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biomass and climate change impacts in the
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An assessment of tropical dryland forest
ecosystem biomass and climate change
impacts in the Kavango-Zambezi (KAZA)
region of Southern Africa.

Ruusa-Magano David

Thesis submitted for the degree of Doctor of Philosophy

Department of Geography

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Abstract

The dryland forests of the Kavango-Zambezi (KAZA) region in Southern Africa are highly susceptible to disturbances from an increase in human population, wildlife pressures and the impacts of climate change. In this environment, reliable forest extent and structure estimates are difficult to obtain because of the size and remoteness of KAZA (519,912 km²). Whilst satellite remote sensing is generally well-suited to monitoring forest characteristics, there remain large uncertainties about its application for assessing changes at a regional scale to quantify forest structure and biomass in dry forest environments. This thesis presents research that combines Synthetic Aperture Radar, multispectral satellite imagery and climatological data with an inventory from a ground survey of woodland in Botswana and Namibia in 2019. The research utilised a multi-method approach including parametric and non-parametric algorithms and change detection models to address the following objectives: (1) To assess the feasibility of using openly accessible remote sensing data to estimate the dryland forest above ground biomass (2) to quantify the detail of vegetation dynamics using extensive archives of time series satellite data; (3) to investigate the relationship between fire, soil moisture, and drought on dryland vegetation as a means of characterising spatiotemporal changes in aridity. The results establish that a combination of radar and multispectral imagery produced the best fit to the ground observations for estimating forest above ground biomass. Modelling of the time-series shows that it is possible to identify abrupt changes, longer-term trends and seasonality in forest dynamics. The time series analysis of fire shows that about 75% of the study area burned at least once within the 17-year monitoring period, with the national parks more frequently affected than other protected areas. The results presented show a significant increase in dryness over the past 2 decades, with arid and semi-arid regions encroaching at the expense of dry sub-humid, particularly in the south of the region, notably between 2011-2019.

Keywords: Above ground biomass, Remote sensing, Synthetic Aperture Radar (SAR), Multispectral data, Climate change, Dryland forest change, Burned area mapping, Biodiversity

DECLARATION

I confirm that no part of the material presented in this thesis has previously been submitted for a degree in this or any other university. In all cases the words of others, where relevant, have been fully acknowledged.

Ruusa-Magano David

Durham University – 2021

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Dedicate to my parents Mrs Helena Johannes and Mr David Joseph

“Let the b-pressure go up, it will surely come down”

Publications arising from the thesis

This thesis is presented as a collection of papers and chapters. The Supplementary information is presented at the end of each paper/chapter. The reference list and appendices are presented at the end of the thesis. The analytical codes of the thesis have been written in R and Google Earth Engine (Appendix B), and the substantial codes will be uploaded to GitHub. Details and the current status of each paper are shown below:

Remote sensing for monitoring tropical dryland forests: A review of current research, knowledge gaps and future directions for Southern Africa

Chapter 2 is published by *Environment Research Communications*, DOI:

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The estimation of above ground biomass is improved by combining Sentinel-1 SAR and Sentinel-2 multispectral imagery in the dryland forests of Southern Africa.

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Identifying and understanding dryland forest changes and disturbances in Southern Africa using Landsat and MODIS time series and field vegetation data

In progress: Intended for submission to *International Journal of Applied Earth Observation and Geoinformation*.

A spatio-temporal drought and fire analysis for semi-arid dryland ecosystems in southern Africa using moderate resolution satellite imagery.

In progress: Intended for submission to *Remote Sensing in Ecology and Conservation*.

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1 INTRODUCTION AND RESEARCH CONTEXT

1.1 Background and Motivation

Tropical forests play an important role in global carbon storage and are therefore an important natural component of climate change mitigation (Baccini et al., 2017). Tropical dryland forests (TDFs) make up ca. 40% of all tropical forest region, however, they are facing threats both from human-induced and natural factors (Murphy et al., 1986). During the 20th century, substantial change in TDFs through land-cover conversion and modification has been unprecedented throughout Sub-Saharan Africa, resulting in loss of forest biodiversity and land degradation (Eva et al., 2006; Petheram et al., 2006). Brink et al. (2009) noted that the greatest amount of deforestation in Africa is taking place in dryland forests, accounting for about 70% of forest loss between 1975 and 2000 compared to moist tropical forest loss which accounted for 16% of forest loss. Deforestation in Southern Africa is a major concern, with ca. 1.4 million ha of net forest loss annually, contributing to increased land degradation and the ensuing impacts on the balance of ecosystem function (Lesolle, 2012). According to Intergovernmental Panel on Climate Change (IPCC), these changes have impacts on carbon emissions to the atmosphere and forest biodiversity loss, reducing the region's adaptive capacity and resilience to the impact of high temperatures and varying precipitation (IPCC, 2014).

Tropical countries are beginning to develop policies and initiate projects to reduce greenhouse-gas emissions from deforestation and forest degradation (e.g., REDD+), seeing forests both as environmental resources and carbon sinks (Gibbs et al., 2007; UNCCD, 2015). For these, resource managers, stakeholders, governments, and United Nations (UN) agencies need high-quality reliable information on biomass carbon stocks, forest structure, and the REDD+ -related research in TDFs monitoring (Gizachew et al., 2017; UNCCD, 2009). Recently, the UN called for all to mobilise to deliver 17 Sustainable Development Goals (SDGs) by 2030, including the aim to ensure the conservation, restoration, and sustainable

30 use of forests (SDG 15; UN, 2015). These objectives require the ability to localise,
31 measure, and monitor forest change at both community and regional levels.

32 The UN argues that to mitigate climate change and biodiversity loss, and to stop
33 degradation and deforestation processes, action must be taken at all levels: people,
34 local, regional, global, and by all countries: poor, middle-income, and rich (UN,
35 2011). Recently, ecologists have embraced remote sensing to study forest change
36 and biodiversity and have used this to prepare conservation responses to potential
37 threats (Schulte to Bühne & Pettorelli 2018; Dawson et al., 2016). However, remote
38 sensing in tropical forests faces challenges including accessibility to and/or the
39 suitability of different remote sensing data; methods for relating vegetation
40 structural changes to remotely sensed proxies across different ecosystem types;
41 and access to suitable data for validating the estimates of forest changes to detect
42 trends in dryland forests (Lehmann et al., 2015; Privette et al., 2005).

43 This study was designed and undertaken to further understand the large-spatial
44 and temporal-scale variation of dryland forests dynamics, focussing on the
45 development of an integrated assessment method for use in the context of climate
46 change. In line with the multiple threats forced by climate change and
47 anthropogenic activities, and the challenges of using remote sensing in these
48 landscapes, this research examined these issues in Kavango Zambezi Conservation
49 Area (KAZA) in Southern Africa. This focus constitutes the research gap that this
50 study addresses, by assessing and estimating forest biomass and structural
51 parameters, fire, and climatic impacts at a regional scale using novel application of
52 remote sensing.

53 This chapter introduces with fundamental aspects of the research problem and
54 aims to demonstrate the appropriateness of remote sensing as the best tool to
55 address fundamental questions about changes in dryland forests.

56 1.2 Conceptual frameworks

57 Many of the unique properties of TDFs relate to their rainfall regimes. TDFs are
58 characterised by prolonged dry seasons of six months or more, with rainfall less
59 than 100 mm, which in turn determines the distinctive phenology of the forest

60 (Murphy et al., 1986). The definition of “dryland forest” remains debatable and
61 controversial, which contributes to be difficulty in accurately assessing and
62 measuring its distribution patterns and status (Blackie et al., 2014). The lack of a
63 clear and comprehensive understanding of general terms including “drylands” and
64 “forests” makes it a challenge to explicitly define dryland forests (Charles-D et al.,
65 2015). Given the fact that dryland forests progressively grade into other vegetation
66 types such as wet forests, woodlands and savannas, also makes clear definitions
67 complex (Putz et al., 2010). Walter et al. (1971) noted that the accuracy of
68 estimates of all tropical forest areas is constrained by uncertainty in the
69 distribution of open woodlands in dryland areas, which are extensive in Africa,
70 Australia, and Latin America.

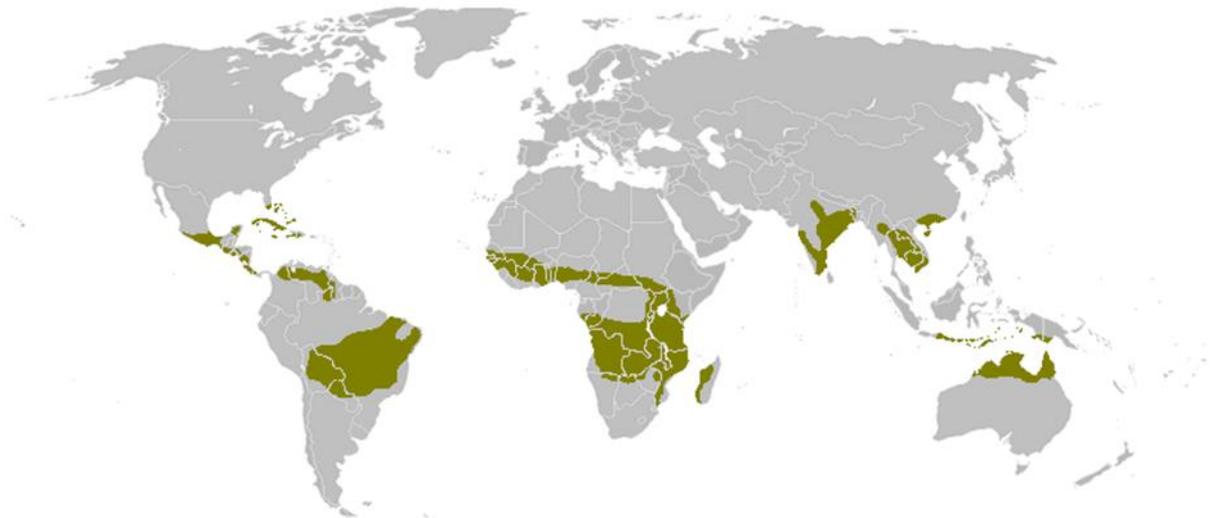
71 In the general literature, many different names have been applied to TDFs,
72 including savanna forests, Sudanian woodland and miombo woodland in Africa,
73 monsoon forest in Asia, neotropical dry forests in South America (Chidumayo,
74 2013; Linares-Palomino et al., 2011; Suresh et al., 2011). The neotropical dry
75 forests in South America have a plethora of names from “caatinga” in northeast
76 Brazil, to “bosque tropical caducifolio” in Mexico, and “cuabal” in Cuba, which in
77 part hinders comparisons (Mayes et al., 2017; Sánchez-Azofeifa et al., 2005). For
78 example, Dexter et al. (2015) identified dry deciduous forest in India (Suresh et al.,
79 2011), miombo woodland in southern Africa (Chidumayo, 2013), and deciduous
80 dipterocarp forest in continental Asia (Bunyavejchewin et al., 2011) as a form of
81 savanna, and not TDFs, despite the formal classification as TDFs by these studies,
82 and the FAO (FAO, 2001).

83 There are several definitions currently available for TDFs, but there is still a lack of
84 consensus in developing a common understanding. Mooney et al. (1995) defined
85 TDFs as forests occurring in the tropical regions characterised by pronounced
86 seasonality in rainfall, where there are several months of severe, or even absolute
87 drought. A widely accepted definition is that of the FAO, that has identified TDFs as
88 a Global Ecological Zone (GEZ), which includes the drier type of miombo and
89 Sudanian woodlands, savannah (Africa), caatinga and chaco (South America), and
90 dry deciduous dipterocarp forest and woodlands (Asia) (FAO, 2001).
91 Sánchez-Azofeifa et al. (2005) broadly defined TDFs as a vegetation type typically

92 dominated by deciduous trees (at least 50% of trees present are drought
93 deciduous), where the mean annual temperature is ≥ 25 °C, total annual
94 precipitation ranges between 700 and 2000 mm, and there are three or more dry
95 months every year (precipitation < 100 mm per month).

96 For the scope of this present study, TDFs are defined as forests occurring in
97 tropical regions which include the drier type of miombo and Sudanian woodlands,
98 savanna forests (Africa), caatinga and chaco (South America), and dry deciduous
99 dipterocarp forest and woodlands as defined by FAO (see: Fig. 1.1). The thesis
100 adopted the definition of FAO because it recognises forests occurring in the dry
101 tropical climate globally, then those based entirely on climate definitions. The
102 current climate does not define the biogeography of TDFs, particularly in the
103 context of future unprecedented climate change (IPCC, 2007). If climates become
104 sufficiently warmer and drier in the tropics, dry forests may expand into areas that
105 are currently dominated by rain forests (Putz et al., 2010). The research however
106 acknowledges the diverse definitions and views of different researchers on the
107 topic, such as those pointed out by Dexter et al. (2015) and Murphy et al. (1986).

108



109

110 Fig. 1. 1 The graphic illustration shows the relative distribution of tropical dry forests.
111 Source: FAO, (1999). Reproduced with permission.

112

113

114 1.3 Importance of dryland forests

115 TDFs provide ecosystem services to more than two billion people, including
116 providing habitat for numerous rare and endemic organisms, supporting
117 significant crop production, and forage for wildlife and domestic livestock
118 (Petheram et al., 2006). The dryland ecosystem (including dry forests) harbors
119 considerable biodiversity in terms of species richness, endemism, and functional
120 diversity of plants and animals that sometimes even exceeds that of moist forests
121 (Pennington et al., 2018). Furthermore, TDFs are known to play an important role
122 in supporting the agricultural systems on which millions of rural subsistence
123 farmers depend, and so TDFs are central to achieving broader food security
124 (Chidumayo et al., 2010; Sunderland et al., 2015).

125 Beyond subsistence farming, TDFs contribute to the direct and indirect provision
126 of various products, including timber and non-timber products to their inhabitants
127 (Petheram et al., 2006). Other ecosystem services provided include flood control,
128 tourism revenue, pollination, local diets with wild fruits, bushmeat, and medicinal
129 plants (Djouidi et al., 2015; Safriel et al., 2006). In dry forested regions, majority of
130 people use firewood and charcoal from TDFs as a source of energy (Sunderland et
131 al., 2015). Drylands have major global climate benefits; their carbon storage
132 (including soil carbon) accounts for more than one-third of global stocks (Durant
133 et al., 2012; Pennington et al., 2018). The capacity to store carbon depends on
134 many factors including climate, past land use, and opportunity for management
135 change (UN, 2011). Growing pressure on dryland forests to meet human and
136 socioeconomic development needs means that TDFs are increasingly being utilised
137 unsustainably, and so the degradation of these resources poses a serious problem
138 (Petheram et al., 2006).

139 1.4 Threats to tropical dryland forests

140 1.4.1 Degradation/Deforestation

141 For more than 20 years, TDFs have been recognised among the world's most
142 threatened ecosystems when compared across all major tropical forest types

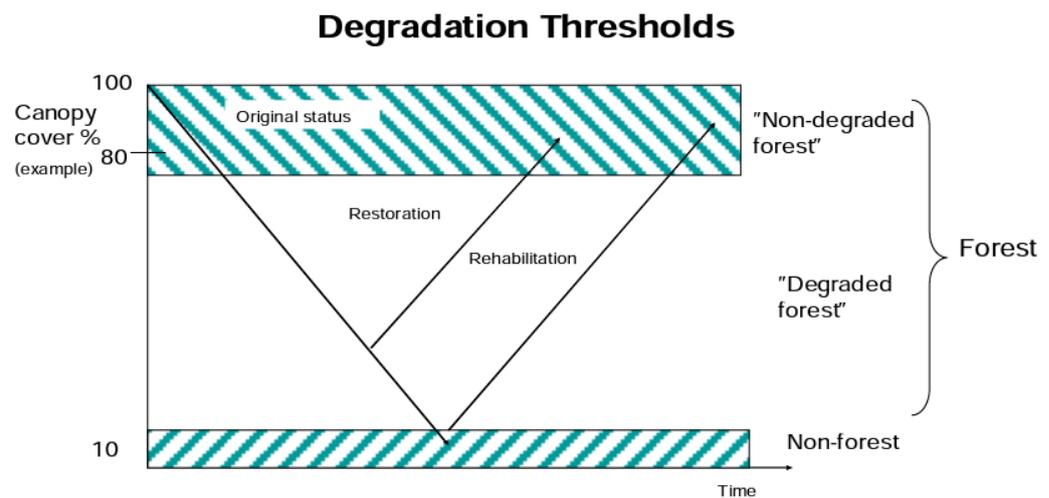
143 (Janzen, 1988). These activities may take place either abruptly (land cover
144 conversion) or gradually (land cover modification) (Hayward et al., 2001; Lambin
145 et al., 2003). Land cover conversion is defined as a shift from one land cover class
146 to another, whilst modification is subtle changes in continuous properties within
147 classes (e.g., plant biomass, canopy cover, leaf area) (Hansen et al., 2012). Human
148 activity causes deforestation through logging of timber and clearing of the forest
149 where extraction exceeds regeneration.

150 Land degradation, which is sometimes used synonymously with desertification in
151 dryland areas, is a term that refers to the many processes that drive the decline or
152 loss in biodiversity, ecosystem functions or productivity (Scholes et al., 2018).
153 Land degradation includes the degradation of all terrestrial ecosystems (e.g., dry
154 land, semi-arid land, rain-soiled areas in sub-humid areas or grassland, rangeland,
155 forest, and wetland) (Xie et al., 2020). Forest degradation is land degradation that
156 occurs within forest land and is most often loosely defined as a loss of particular
157 forest attributes that negatively affect the structure or function of the stand or site
158 (IPCC, 2003; ITTO, 2003; Scholes et al., 2018; Simula, 2009). Lund, (2009) provides
159 a detailed review of more than 50 definitions of forest degradation. FAO, (2011)
160 defines forest degradation as the change process caused by natural disturbance,
161 and human-induced that leads to the reduction of the capacity of a forest to
162 provide goods and services. Services might include biomass, carbon sequestration,
163 water regulation, soil protection, and biodiversity conservation. According to
164 Simula, (2009) land degradation acts synergistically with forest degradation.
165 Figure 1.2 shows degradation thresholds which shows that degradation can
166 usually be reversible through restoration and management interventions. On the
167 other hand, degradation is sometimes long-term or permanent leading to the
168 irreversible loss of forest (Lund 2009). As shown in Fig. 1.2, it's considered forest
169 degradation when there is a reduction of the canopy cover or carbon stock within a
170 forest, provided that the canopy cover stays above 10% (FAO, 2000). The status of
171 degraded areas is distinguished in terms of the degree of degradation (e.g.,
172 slightly/moderately/severely degraded), as it could help identify priority areas for
173 preventive or corrective action when monitoring changes. The ability to identify a
174 degraded forest is essential to help develop techniques to establish systems for
175 monitoring forest degradation and practical approaches to restore forest cover and

176 structure, species composition and forest regeneration as well as rehabilitation
177 (see: Fig. 1.2 and 1.3) (Chazdon et al., 2016;). In this study, land degradation and
178 vegetation degradation are used to describe degradation taking place in forests
179 and non-forests, while forest degradation was used to refer to degradation largely
180 taking place in forested areas.

181 Biggs et al. (2008) reported that degradation of dryland landscapes in Southern
182 Africa happen through alteration of intact ecosystems, for example, the
183 fragmentation of habitats, the modifications of forests to pasture, and conversion
184 of extensive land uses to intensive ones, causes a severe loss in biodiversity. Forest
185 degradation has been described using variables such as changes in canopy cover,
186 understory tree density, plant or animal species richness, biomass loss from
187 extensive standing forests, and changes in vegetation attributes as measured
188 against a baseline undisturbed condition (Thompson et al., 2013; Washington-
189 Allen et al., 2008). These changes can be caused by natural disturbance such as
190 wildfire, storms or drought, and also can be human-induced such as via harvesting,
191 road construction, poor agricultural practices, or grazing, which may each vary in
192 extent, severity, and frequency. While deforestation is the rapid transformation
193 from forest to the non-forest area, forest degradation is usually a gradual process
194 though it may be induced by quick, single events such as hurricanes, and it is
195 typically more difficult to discern and quantify than deforestation (Thompson et
196 al., 2013).

197 These alterations in land-cover/land-use could also impact global and regional
198 climate through alterations in the length of the growing seasons, changes in the
199 climatic regimes, including extreme high temperatures or rainfall, and increases in
200 perturbation regimes such as fires, which in turn impact the structure and function
201 of the dryland forest (Le Houérou, 1996; Naik, 2015). Along with deforestation,
202 forest degradation contributes to global carbon emissions, and reporting on both is
203 required by the United Nations Framework Convention on Climate Change
204 (UNFCCC) through incentives for developing countries through the REDD+
205 programme (UNFCCC, 2009).



206

207 Fig. 1. 2 Illustration of the degradation thresholds within forest and non-forest typically
 208 caused by disturbances which vary in terms of the extent, severity, quality, origin, and
 209 frequency (Simula, 2009).

210 1.4.2 Climate and drought

211 TDFs are known to be extremely vulnerable to predicted changes in climate
 212 (Huang et al., 2017), and the effects of these changes are already being experienced
 213 in biodiversity showing significant shifts in species ranges in Africa (McClellan et al.,
 214 2005). There is now abundant evidence from models and observations that
 215 suggest rainfall regimes in the seasonal tropics are changing to hotter and drier
 216 conditions, with predicted elevated temperatures (Chadwick et al., 2016; Dai,
 217 2013), likely exacerbating the risk of further land degradation (Huang et al., 2016).
 218 Dryland CO₂ uptake is strongly associated with variations of both precipitation
 219 and temperature, and changes in aridity. The effectiveness of each is impacted by
 220 deforestation, widespread increases in plant disturbances, and declines in
 221 ecosystem function (Williams et al., 2013). Dryland vegetation responses to
 222 environmental perturbations depends upon the frequency and magnitude of
 223 disturbances (e.g., temperature, precipitation, fire, land use), and the resilience of
 224 the ecosystem concerned (see: Fig. 1.2) (Lambin et al., 2010).

225 African dryland forests are identified as the most threatened and least protected
 226 ecosystem on the continent, largely as a result of population growth, climate
 227 change, and poor environmental governance and policy frameworks (Brink et al.,

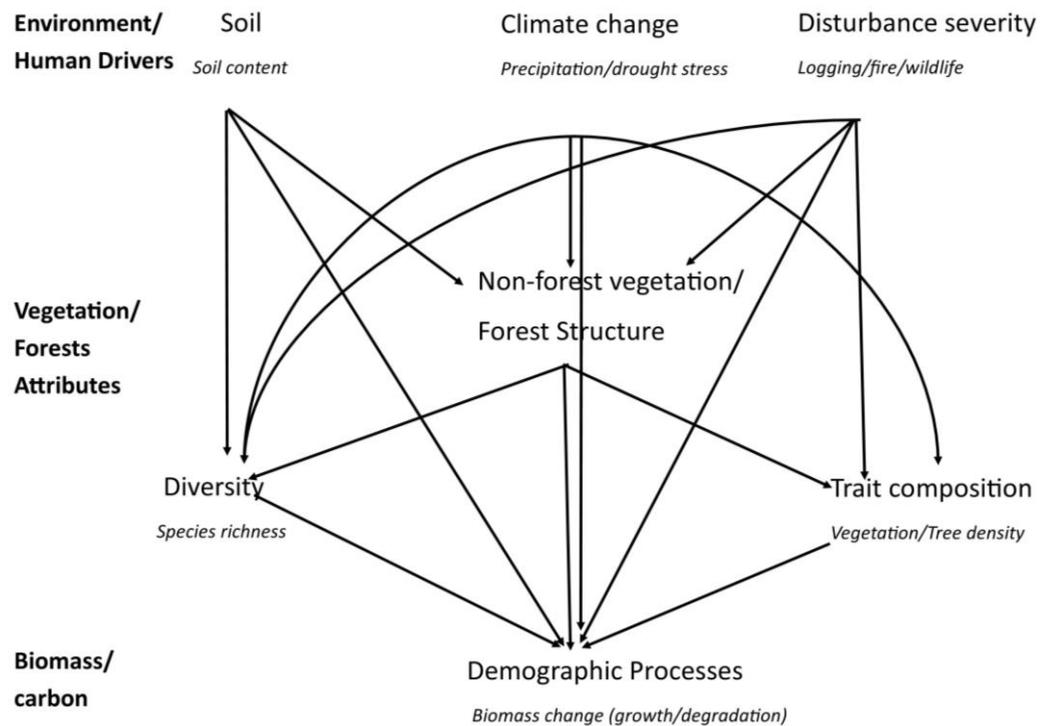
228 2009). The IPCC reported that when climate threats are coupled with a growing
229 population and future changes in land use could lead to severe dry forest biome
230 shifts and biomass degradation, particularly in Southern Africa (King, 2014; Niang
231 et al., 2014). The role of climatic variation, land-use practices, and disturbance
232 regimes, such as herbivory, has been identified by several studies to be among the
233 main drivers of ongoing changes in dryland ecosystems leading to forest
234 degradation and land cover change in Southern Africa (Fig. 1.3) (Anyamba et al.,
235 2002; Prince, 2012; Privette et al., 2005; Shackleton et al., 2010). Biodiversity in
236 the region has responded with significant recorded shifts in species ranges,
237 impacting species composition and productivity (IPCC, 2014; King, 2014). Given
238 that the availability of water is a determinant of forest resources in drylands, these
239 types of change affect forest tree cover, demographic processes, biological
240 diversity, trait composition, habitat quality, and in turn movements of wildlife
241 (Naidoo et al., 2016). Fig. 1.3 provide a schematic representation of factors
242 controlling temporal and spatial heterogeneity of biomass plants. This schematic is
243 not exhaustive but provides a framework of changes in vegetation land cover and
244 main dryland forest attributes, i.e., composition, structure and function, which is
245 addressed in this research. This thesis report on the development of open access
246 codes to map forest structural parameters such as biomass and monitor changes in
247 dryland forests because of climate change and other disturbances such as
248 fire/logging. The changes are mapped using a combination of ground and Earth
249 observation data including multispectral and synthetic aperture radar (SAR)
250 satellite imagery at a regional scale of Kavango Zambezi region.

251 On a regional level, few studies have evaluated the forest structural parameters
252 and changes in dryland forests of Southern Africa (David et al., 2022a). Majority of
253 these studies are done in Republic of South Africa, for example, Mathieu et al. 2013
254 and Naidoo et al. (2015) found in dryland forests in Kruger National Park that
255 Woody vegetation cover is accurately mapped with Synthetic Aperture Radar
256 (SAR) data, however these studies observe an overestimation of woody cover
257 below 20% as a results of surface contributions to the signal, such as roughness in
258 radar retrievals (Mathieu et al. 2013; Santoro et al. 2011). There is, however, very
259 limited spatial information on structural parameters such as above ground
260 biomass distribution and forest changes in other part of Southern Africa. To date in

261 most of Southern Africa, most quantitative spatial data on forests are available
262 from products developed globally, such as the pantropical African savanna
263 biomass map (Bouvet et al., 2018), tree density map (Glick et al., 2016), global
264 forest height map (Simard et al., 2011), Global Land Cover Map (Arino et al., 2012),
265 and global tree cover maps (Hansen et al., 2013; Sexton et al. 2013). However,
266 there is unreliability regarding the accuracies of these maps at regional scales,
267 particularly in open forest ecosystems such as savannas and dry forests, because
268 these products were developed primarily to track tropical forest losses (Bastin et
269 al., 2017). Underestimation for the woody cover above 60% has been observed
270 likewise in other studies (Bouvet et al. 2018) because of saturation in dense
271 canopies.

272 To identify changes to dryland forest, and their drivers, and to separate these from
273 long- and short-term trends, it is essential to select remote sensing data with good
274 temporal coverage (time series data) but also with a sufficiently frequent revisit
275 period and spatial resolution. This is however not an easy task, since the
276 availability of remote sensing data for long-term monitoring purposes is
277 constrained by sensor characteristics (e.g., revisit time) and then the data utility
278 can be significantly influenced by environmental factors (e.g., cloud cover)
279 (Donoghue, 2000; Kuplich et al., 2013).

280



281

282 Fig. 1. 3 Conceptual framework depicting the key abiotic factors (disturbance and soil
 283 resource availability) and biotic factors (vegetation/forest structure, diversity, and
 284 trait composition) controlling temporal and spatial heterogeneity of demographic processes
 285 (biomass growth, and degradation). Physical damage by wildfire, mega-herbivores, e.g.,
 286 elephants, and deforestation e.g., logging/coppicing are one of the main disruptions to the
 287 ecosystems. Forest structure (e.g., plot basal area, tree density) is based on all alive trees
 288 in the selected plots, while diversity and trait composition are based on the individuals of
 289 that demographic group (i.e., vegetation recruits). The dryland forests ecosystem has an
 290 option of closed woodland form and open grass form depending on the soil resource
 291 availability, climate, disturbances, and anthropogenic disruption e.g., fire. (Reproduced
 292 from Van-der-Sande et al., 2017).

293 1.5 Application of remote sensing

294 1.5.1 Optical and Synthetic-Aperture Radar (SAR) remote 295 sensing in dryland forests

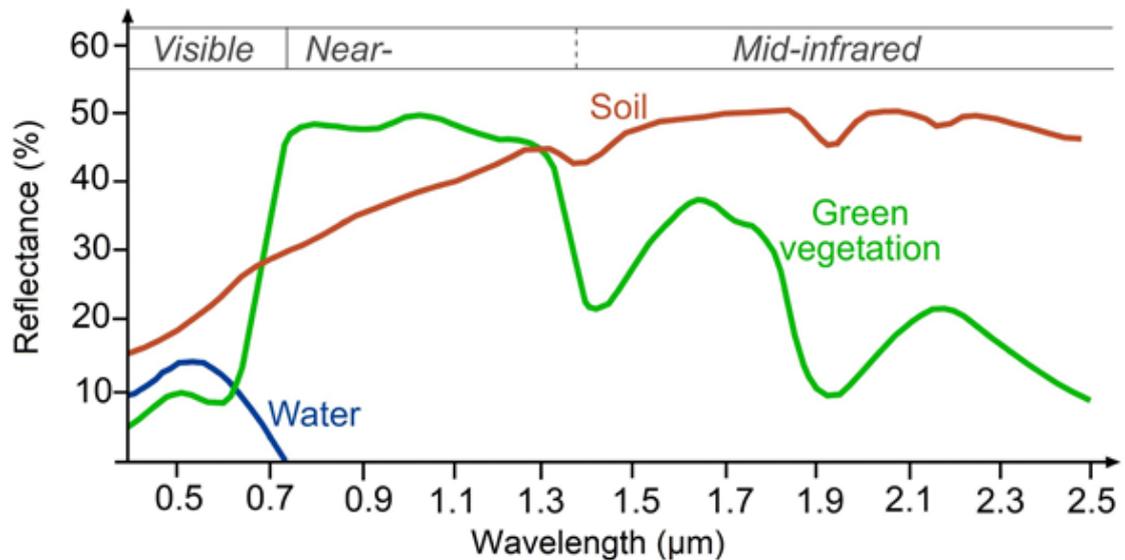
296 Remote sensing has contributed greatly to the mapping and understanding of the
 297 tropical forest ecosystems in relation to local and global environmental change

298 (Foody, 2003). Advances in the remote detection of burned areas (Zhang et al.,
299 2011), land-use and land-cover (De Oliveira et al., 2019), forest structure (Hyde et
300 al., 2006), biomass (Cutler et al., 2012) and biodiversity (Rampheri et al., 2020)
301 have also changed the understanding with regards to forest functioning. From the
302 TDF resources perspective, satellite remote sensing has been used to provide three
303 levels of information. The first is information on the spatial extent of forest cover
304 and forest change patterns; the second level comprises information on forest type;
305 and the third provides information on the biophysical and biochemical properties
306 of forests (Boggs, 2010; Higginbottom et al., 2018; Wood et al., 2012). Several
307 studies have established the many advantages of remote sensing over traditional
308 field investigation methods for measuring and monitoring tropical forests (Hyde et
309 al., 2006; Puhr et al., 2000). The most obvious advantages include the potential to
310 survey large areas rapidly or over longer periods at low cost, especially in remote,
311 inaccessible, and sometimes dangerous environments (Rumiano et al., 2020).

312 In general terms, Earth Observation (EO) platforms have carried two types of
313 sensor: optical and active SAR. The optical systems measure reflected radiation of
314 one or more discrete wavelengths located in the spectral range 400–3000 nm,
315 wherein the wavelengths are notably several orders of magnitude smaller than the
316 leaves, needles, and branches that make up a forest canopy, and so these
317 components absorb and scatter radiation (Boyd et al., 2005). Synthetic-Aperture
318 Radar (SAR) systems measure backscattered microwave radiation at wavelengths
319 between 1 cm and 1000 cm, characterising scattering from leaves, branches, stems
320 trunks and the ground (Mitchard et al., 2009). Optical remote sensing systems may
321 provide information on the amount of foliage and its biochemical properties, while
322 SAR (microwave) systems provide information on woody biomass and forest
323 structure (Armston et al., 2009; Higginbottom et al., 2018). Many SAR sensors can
324 both transmit and receive microwaves with two different polarisations, which
325 enhances the information provided, particularly that which describes surface
326 roughness and geometric regularities in the forest stand (Kasischke et al., 1997).
327 Therefore, satellite remote sensing signals provide additional proxy information
328 that can be linked to forest parameters and health indicators, as well as
329 disturbance factors when using vegetation indices.

330 1.5.2 Vegetation Indices

331 In satellite remote sensing for forests, vegetation indices, biophysical variables,
332 and data transformations are often used for data analyses (Morley et al., 2019;
333 Yengoh et al., 2015). The various materials of the earth's surface absorb and reflect
334 different amounts of energy at different wavelengths. The magnitude of energy
335 that an object reflects or emits across a range of wavelengths is called its spectral
336 response pattern (Aggarwal, 2004). The graph below illustrates the spectral
337 response patterns of soils, water, and vegetation (Fig. 1.4). The healthy vegetation
338 has a unique spectral reflectance signature that is dictated by various plant
339 attributes. The visible reflectance of plants is mainly characterised by absorption
340 of the leaf pigments like chlorophyll, carotenoids and xanthophylls (Gibson et al.,
341 2013). Stressed vegetation will give off a different spectral
342 signature corresponding to the effect of the stress on the various leaf pigments.
343 Knowing the typical spectral response characteristics makes it possible to
344 distinguish forests, crops, and soils, and to evaluate their condition (e.g., stressed
345 plants) using remotely sensed images (Ranjan et al., 2012). In the case of
346 vegetation, the measured spectral reflectance values from two or more
347 wavelengths are usually used to estimate vegetation indices. NDVI is one of such
348 indices, commonly used to distinguish live green plant canopies, calculated as a
349 ratio of near-infrared to red vegetation reflectance (Rouse, 1974; Tucker, 1979).
350 NDVI has been used as a proxy of vegetation greenness and has been shown to
351 relate closely to leaf area index (LAI), biomass, and the fraction of
352 photosynthetically active radiation absorbed by vegetation (fAPAR) (Curran,
353 1980).



354

355 Fig. 1. 4 Spectral signatures as functions of wavelength for vegetation, soil and water.

356 Source: <https://seos-project.eu/classification/classification-c01-p05.html/> (accessed 02
357 May 2021).

358 Ringrose et al. (1994) and Turner et al. (1999) indicate that the strength of the
359 relationships between forest LAI and vegetation indices, such as the NDVI, is site-,
360 time- and species-specific and that above a LAI of about 5 or 6, NDVI may not be
361 sensitive to LAI variation. Several well-known limitations of NDVI for robust
362 estimation of biomass in drylands exist. NDVI is sensitive to green components and
363 insensitive to woody components where the majority of carbon is stored (Tucker,
364 1979). Also, Above Ground Biomass (AGB) production is not always uniformly
365 linked to either greenness or plant structure (herbaceous and woody
366 compositions), as moisture content and vegetation species composition have been
367 shown to impact the biomass-NDVI relationship (Asner et al., 2009; Wessels et al.,
368 2006). These observations may help explain reportedly weak relationships
369 between NDVI and tropical forest canopies, particularly for areas with complex
370 and high vegetation amounts as in TDFs (Foody et al., 2001; Sader et al., 1989). For
371 example, Madonsela et al. (2018) investigated the interactions between seasonal
372 NDVI and woody canopy cover in the savanna of the Kruger National Park (NP) to
373 model tree species diversity using a factorial model and found that the interaction
374 between NDVI and woody canopy cover was insignificant. It is also widely
375 reported that the NDVI signal is influenced by woody canopy foliage, underlying
376 canopy background, and soil moisture in sparse vegetative areas (LAI <3), which

377 reduces the apparent NDVI signal and seasonal variations in vegetation phenology
378 (Pettorelli et al., 2005; Wagenseil et al., 2006).

379 These challenges have led to the development of alternative formulations which
380 include correction factors or constants introduced to account for or minimise, the
381 varying background reflectance (Gitelson et al., 1996; Huete et al., 1999). The
382 Enhanced Vegetation Index (EVI) is a modification of NDVI that provides
383 complementary information about the spatial and temporal variations of
384 vegetation while minimising many of the contamination problems present in the
385 NDVI, such as those associated with canopy background and atmospheric
386 influences (Huete et al., 2002). Other closely related indices include the Simple
387 Ratio (SR), the Green Normalised Difference Vegetation Index (GNDVI), Soil-
388 Adjusted Vegetation Index (SAVI) amongst others. Xue et al. (2017) provides a
389 detailed review of vegetation indices. Critically, an increase in availability of EO
390 data with improved spatial, spectral, and radiometric resolution combined with
391 the machine or deep learning techniques and development in computational
392 resources would enhance the potential dryland forest information to be exploited
393 (Ali et al., 2015). The constraint in spectral, spatial, and radiometric resolutions of
394 remote sensing data may result in different saturation values of AGB depending on
395 vegetation characteristics (Zhao et al., 2016). The spatial resolution of images such
396 as NOAA AVHRR, SPOT Vegetation, and MODIS imagery data particularly at 1-8 km
397 spatial resolution has been reported to result in poor spectral purity and limited
398 identification of broad forest types such as coniferous and lack sufficient spatial
399 details, particularly for less abundant species broad-leafed forests (Immitzer et al.,
400 2018; Xu et al., 2021). Stratoulis et al. (2015) showed that the 10 m spatial
401 resolution of Sentinel 2 allows for detecting fragmented patches in the lakeshore
402 ecosystems but argued that enhanced spectral and spatial capabilities provide
403 further potential in habitat monitoring and classification of environmentally
404 complex areas. Other studies such as Wulder et al. (2004) and Xu et al. (2021)
405 concluded that medium-high resolution Earth observation satellites can be used to
406 produce more accurate results of forest species composition and land cover use
407 classification by providing detailed spectral features of the canopy of tree species
408 (Salajanu and Olson, 2001). Dube et al. (2014) have concluded that fine spatial
409 resolution data with improved spectral bands (e.g., red edge) contains more

410 spectral information critical for accurately predicting forest metrics such as
411 biomass in South Africa. Other remotely sensed studies estimated forest biomass
412 at different scales and concluded that coarse spatial resolution optical sensors are
413 useful for biomass mapping at continental and global scales rather than at local
414 scales because the limited spatial detail of these coarse-resolution images misses
415 the biomass variability in heterogeneous forests (Avitabile et al., 2012; Dube et al.,
416 2014; van der Wer et al., 2006; Zhang and Kondragunta, 2006; Zhu and Liu, 2015).
417 Lu (2006) demonstrated that the use of coarse spatial resolution sensors (i.e.,
418 Landsat, MODIS etc.) for AGB estimation resulted in poor prediction accuracy due
419 to the presence of mixed pixels together with a mismatch between the size of field
420 measurements and the pixel (Avitabile et al., 2012). Various statistical methods,
421 vegetation indices and textures have been explored to reduce the impacts of data
422 saturation in Landsat imagery on AGB estimation accuracy (Lu et al., 2016).
423 Studies such as Basuki et al. (2013) and Kajisa et al. (2009) observed that the
424 application of statistical methods, spectral mixture analysis and integrating radar
425 data with Landsat images improves forest AGB estimation accuracy significantly.
426 Time series of Landsat imagery is another alternative explored that can result in
427 more accurate AGB estimation and reduce saturation effects compared to the use
428 of a single NDVI (Gasparri et al., 2010; Zhu and Liu, 2015).

429

430 1.5.3 Forest biomass and structural parameters

431 1.5.3.1 Forest biomass estimation in dryland forests

432 Biomass, in general, includes the above-ground and below-ground living mass, and
433 is usually expressed as dry weight (Lu, 2006). AGB includes all living biomass
434 above the soil surface that includes the stem, stump, branches, bark, seeds, and
435 foliage. Measuring forest biomass and its change acts as an indicator of climate
436 change and forest health (Pause et al., 2016), however, the majority of studies on
437 biomass have focused on boreal and temperate forests (Dong et al., 2003; Naidoo
438 et al., 2006). Studies on TDFs are limited because they are dynamic with complex
439 species composition and structure, coupled with environmental conditions which
440 are difficult to assess and model (McElhinny et al., 2005). AGB estimation requires

441 field measurements as a prerequisite for developing estimation models, but field
442 measurements are often difficult to implement, especially in remote areas (Lu,
443 2006; Wingate et al., 2018), and they cannot provide the spatial distribution of
444 biomass across large areas. Thus, remote sensing techniques offer the most
445 practical approach to estimating dryland forest biomass and monitoring changes in
446 forest structure, overcoming the limitations of sample size, timeliness, expense,
447 and access (Lu, 2006; Lucas et al., 2015).

448 With increasing concern regarding greenhouse gas emissions, there is a need to
449 better quantify the biomass of forests associated with regeneration and clearance
450 (FAO, 2011; UN, 2011). Such information needs to be obtained at scales ranging
451 from entire regions to individual forest stands (e.g., for carbon accounting
452 purposes). However, assessments of biomass are typically obtained by applying
453 species-specific allometric equations to forest inventory data (Chave et al., 2005).
454 Although many studies have investigated the ability to estimate the biomass of
455 forests, including tropical moist forests (Asner et al., 2009), dryland forests
456 (Gizachew et al., 2016), temperate forests, and boreal forests (Dong et al., 2003)
457 from remotely sensed data, a number of problems have been encountered. Of key
458 concern is the generalisation of relationships derived for the accurate prediction of
459 biomass at a specific location or time period (e.g., generalisation between images
460 of one location acquired over a period of time to estimate characteristics at
461 another location) (Woodcock et al., 2001). This problem is common in less well
462 studied ecosystems such as dryland forests and can substantially limit the
463 contribution remote sensing can make to environmental studies. Overall, regional
464 variations in forest biomass arise as a result of differences in tree stem density,
465 growth and disturbances rates, and other species-specific attributes, such as wood
466 density (Asner et al., 2009).

467 1.5.3.2 Application of optical and SAR sensor in forest biomass

468 Different remote sensing sensors have been successful in forest biomass studies
469 (Gizachew et al., 2016; Powell et al., 2010). However, in the tropics, where the
470 cloud cover is common, optical data could not be used over large areas. Optical
471 sensors are also less sensitive to variations within dense forests, and can only

472 provide spectral and horizontal distribution and not the vertical distribution (e.g.
473 tree height or difference between single-story and multi-story vertical structural
474 classes) of canopy elements in forests (Joshi et al., 2016). Under these conditions,
475 radar remote sensing provides an alternative (Michelakis et al., 2014; Paradzayi et
476 al., 2013). SAR has the advantage that it includes: the ability to collect data in all
477 weathers, and during day and night; the sensor penetrates cloud, vegetation, dry
478 soil, sand, dry snow; the data is sensitive to surface roughness, dielectric
479 properties and moisture content; and the reflected signal is sensitive to
480 polarisation and frequency (HH, VV, HV, and VH), and can be used for volumetric
481 analysis (Balzter, 2001; Mitchard et al., 2009). However, radar remote sensing also
482 has limitations including uncertainties in estimation, expensive datasets,
483 difficulties in data processing, and data saturation problems (Balzter, 2001;
484 Mitchard et al., 2009). Furthermore, Light Detection and Ranging (LiDAR) has
485 become popular for deriving tree height variables closely related to the AGB
486 (Unger et al., 2014), and a few studies have combined optical and LiDAR for AGB
487 mapping (Lu et al., 2012). However, the applicability of this technique is limited to
488 local regions because of its high economic costs and labour-intensive collection
489 (Gibbs et al., 2007). Alternatively, other authors have explored the combination of
490 optical and SAR (e.g., Cutler et al., 2012; Wingate et al., 2018). Combining
491 frequently available SAR observations with less frequent (due to cloud cover)
492 optical remote-sensing data may provide a sound information source in the
493 tropics, but there remain few studies of this nature in tropical dryland forests.

494 Accurate delineation of biomass distribution at scales from local (ca. 1×10^{-1} km)
495 to pantropical is significant in reducing the uncertainty of carbon emissions and
496 sequestration, understanding their roles in influencing land degradation, and
497 wider environmental processes (Foody, 2003). However, the lack of spatially
498 explicit maps of biomass and forest structural parameters over dryland forests
499 areas in Southern Africa is one of the largest sources of uncertainty in estimates of
500 carbon emissions (Midgley et al., 2011; Timothy et al., 2016). With regards to
501 tropical forests, forest biomass and structure are often relatively well studied in
502 the tropical rainforests as compared to dryland forests, but rainforests are
503 progressively shifting to TDFs, especially in South America and Africa, often

504 irreversibly because of fire events (Zhao et al., 2021). This phenomenon justifies
505 the importance of studying TDF carbon stocks.

506

507 1.5.4 The benefits and challenges of remote sensing in 508 dryland forests

509 The development of the Earth observation satellites during the past decades has
510 enhanced our ability to assess the status and dynamics of vegetation change as
511 well as impacts of climate change at a large scale (Nicholson, 2011). In forest
512 ecosystems, identifying changes in canopy cover with remote sensing generally re-
513 quires data at frequent intervals because the spectral signature changes rapidly
514 with regrowth. Optical sensors provide the best alternative for vegetation change
515 mapping and biomass estimation to field sampling due to global coverage and
516 repeatability, given the ability to estimate characteristics such as forest type and
517 leaf area index (LAI) (Lu, 2006; Symeonakis et al., 2018). Such sensors are
518 however limited in the degree to which they can generate structural information
519 and are restricted by cloud occlusion which is particularly problematic in tropical
520 regions (Herold, 2007; Symeonakis et al., 2018). Light Detection Ranging (LIDAR)
521 and Hyperspatial data can observe tree crowns, basal area, tree height and
522 biomass but cannot cover large areas (Falkowski et al., 2008, Blackburn, 2007).
523 The selection of suitable satellite data depends on the ecological characteristics of
524 the ecosystems, spatial and temporal scales of interest (Estes et al., 2018). As the
525 region of interest and temporal extent increases, the volume of data, and the
526 complexity of image-processing becomes significant and an obstacle to many
527 researchers and operational users with limited access to high-performance
528 computing infrastructures (Smith et al., 2019).

529 Due to the inherent trade-offs between spatial and temporal resolution in EO data,
530 and geographic coverage, the vegetation patterns on both spatial and temporal
531 domains have been revealed by various technological advances resulted in the
532 growing availability of remote sensing data and methods (Toth and Józków, 2016;
533 Zhou et al., 2020). The application of non-parametric machine learning regression

534 algorithms, such as decision trees, random forests (RF), support vector machines
535 (SVMs), and k-nearest neighbour have become more predominant and
536 demonstrate the ability to outperform widely used parametric approaches, such as
537 polynomial and multiple linear regression variables used with remotely sensed
538 data in a forest environment (Breiman, 2001; Latifi et al., 2010). Non-parametric
539 machine and deep learning models are sufficiently versatile to uncover
540 complicated nonlinear relationships and able to extract combinations of the input
541 data that are difficult to describe explicitly by humans, particularly, in areas with
542 high structural variability such as dryland forests (Hastie et al., 2009; Shao et al.,
543 2017). Machine and deep learning have been used by many remote sensing studies
544 to provide in-depth forest investigation from the perspectives of hyperspectral
545 image analysis, interpretation of SAR/ LiDAR images, interpretation of high-
546 resolution satellite images and classification, and multimodal data fusion (e.g., the
547 fusion of Hyperspectral, SAR, LiDAR and optical data (Guirado et al., 2020; Shao et
548 al., 2017; Trier et al., 2018). Improved techniques in remote sensing such as
549 Vegetation Indices, VOD, and machine and deep learning have been utilised to
550 estimate dryland forest attributes globally and other dryland ecosystems,
551 however, very few of these focused on the local and regional scale of Southern
552 Africa (e.g., Symeonakis et al., 2020).

553 The uncertainties reported in many dryland forests studies relating to remote
554 sensing (Bastin et al. 2017), could be decreased following further development,
555 application, and comparison of these improved approaches in future works at
556 local, regional, and continental studies in dryland forest ecosystems. It has been
557 discovered that there is plausible trade-off between spatial resolution, image
558 coverage and frequency in data acquisition, and many studies has shown that
559 coarse spatial resolution optical sensors are useful for biomass mapping at
560 national and global scale rather than at local scale (Wulder et al. 2004; Lu, 2006).
561 For example, Dube et al., (2014) used spaceborne multispectral RapidEye sensor
562 with a fine spatial resolution have the potential to satisfactorily predict intra-and-
563 inter species predicting forest metrics, such as biomass in areas of closed and
564 dense vegetation. The RapiEye have the capability to provide a better prediction
565 for biomass because they contain more spectral information critical for vegetation
566 mapping in comparison to the existing broadband multispectral images (Dube et

567 al., 2014). The rise of innovative and high-performance computing facilities and
568 web-based software tools such as Google Earth Engine (GEE) platform and
569 growing use of machine learning algorithms helps to overcome many barriers,
570 enabling large volumes of data to be integrated, processed, and analysed for large
571 areas and over long time periods (Warren et al., 2015). For a detailed review of
572 machine learning and deep learning for remote sensing and Sustainable
573 Development Goals, see Zhu et al. (2017) and Holloway and Mengersen (2018).
574 Also, more information on research trends, benefits, and challenges of remote
575 sensing in dryland forests are provided in David et al., 2002a, (Chapter 2). Using
576 the new advances in data management and cloud computing capabilities of Google
577 Earth Engine led to a recent discovery that forests in drylands exceeds previous
578 estimates by over 40% (Bastin et al., 2017).

579 1.5.5 Google Earth Engine platform

580 The Google Earth Engine (GEE) platform provides pre-processed satellite imagery,
581 enabling large volumes of data to be integrated, processed, and analysed for large
582 areas and over long time periods (Warren et al., 2015). The platform provides
583 online access to extensive imagery including the entire Landsat archive, complete
584 archives of data from MODIS, Sentinel-1 and Sentinel-2. GEE also co-locates climate
585 forecast data, land cover data, and many other environmental and socioeconomic
586 data covering much of the planet. All processing and computations are done on-
587 the-fly in the cloud which allows the user to process data in close to real-time
588 (Hansen et al., 2013). The catalogue is continuously updated, and users can request
589 the addition of new datasets to the public catalogue, or they can upload their
590 private data via a REST (representational state transfer) interface using either
591 browser-based or command-line tools (Gorelick et al., 2017).

592 GEE's functionality affords a unique opportunity to overcome the limitations
593 imposed by the volume of data and the scale of analysis that would otherwise
594 prevent analysis in many organisations in tropical dryland regions (Hansen et al.,
595 2013; Shelestov et al., 2017). Although GEE has removed many computational and
596 analysis barriers, the technology is not yet comprehensive. The approach is still
597 evolving and there are shortcomings around the challenges of completing analysis

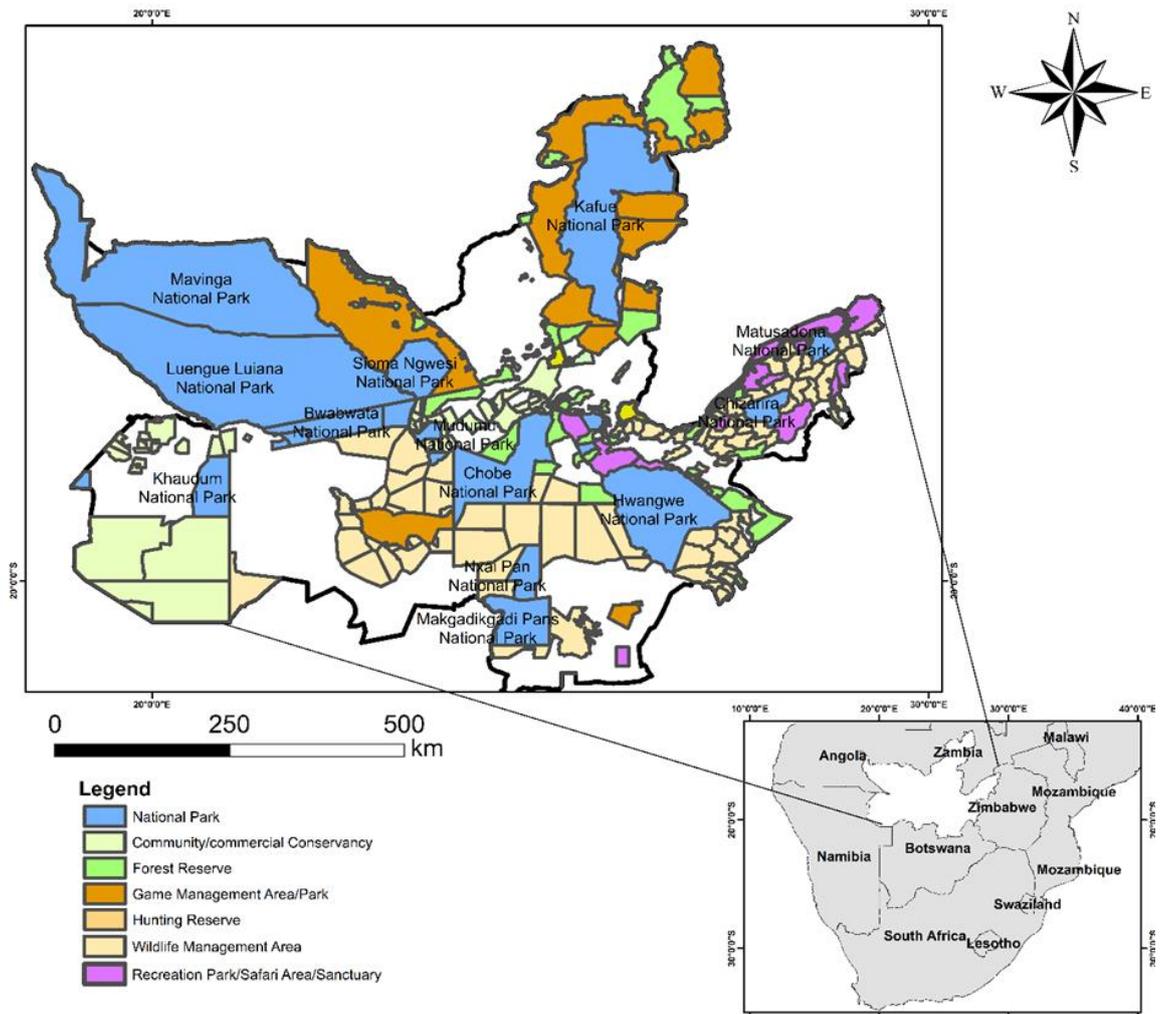
598 that would normally be better suited to a GIS environment, such as the intersection
599 of raster- and vector-based datasets. This thesis has, therefore, utilised other
600 analytical software such as R and ArcGIS since GEE allows files and data to be
601 imported and exported for use elsewhere.

602

603 1.6 The world's largest conservation park

604 The Kavango-Zambezi Transfrontier Conservation Area (KAZA TFCA) was
605 established in 2011 by its member states of Angola, Botswana, Namibia, Zambia,
606 and Zimbabwe, with support from World Wide Fund for Nature (WWF) and the
607 Peace Parks Foundation (WWF, 2016). KAZA TFCA is the World's largest
608 transfrontier conservation area covering a land area of 519,912 km² (200,739 sq.
609 mi, equivalent to the area of Spain or Thailand) (Murphy, 2008). About 71% of
610 KAZA is protected to create economic development and conserve the unique
611 biodiversity within the region, and only 29% of the land is not protected.

612 One key aim of KAZA is to connect and coordinate efforts across protected areas
613 and create free movement for wildlife within its borders, without political
614 boundaries hampering the ability to meet conservation objectives (Cumming,
615 2008). KAZA links several conservation areas including 20 protected national
616 parks, 103 wildlife management areas, 85 forest reserves, 11 game management
617 areas, 11 sanctuaries, and communal lands (Fig. 1.5) (Karidozo et al., 2016). The
618 area hosts the largest population (ca. 250,000) of the African elephant, one quarter
619 (25%) of the African wild dog population, amongst other wildlife, and a human
620 population of 2,677,086 (Karidozo et al., 2016). The growing human population
621 and increasing wildlife population in KAZA have given rise to human
622 encroachment and increased human-wildlife conflict (Stoldt et al., 2020).



623

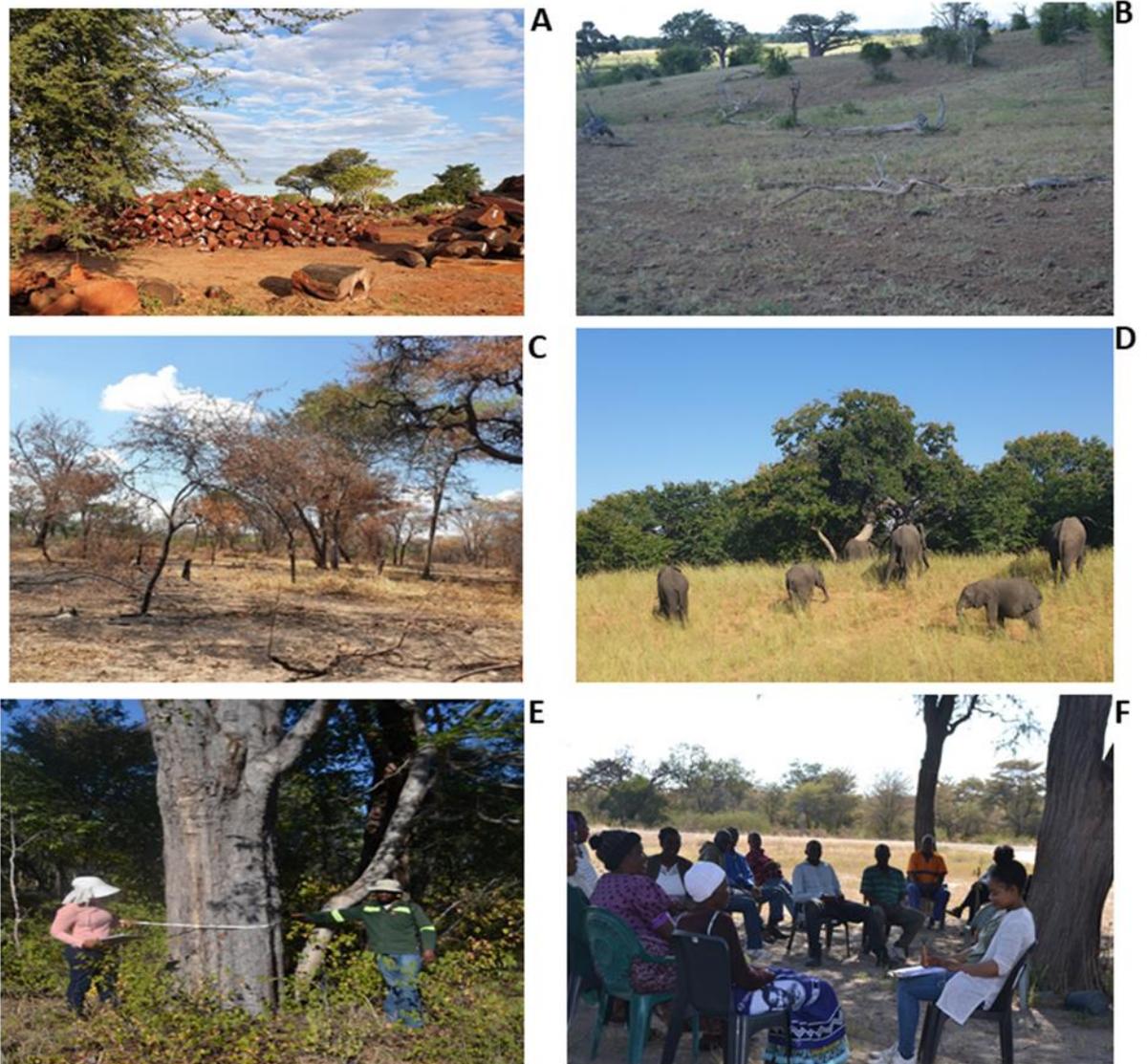
624 Fig. 1. 5 Map of the study area showing KAZA region in Southern Africa and the and land
 625 management classes as designated by the World Database on Protected Areas (WDPA).

626 1.6.1 Rationale of the study

627 It is important to acknowledge the inherent pressure on dryland resources from
 628 the perspective of the local population that depends on these ecosystems for
 629 livelihoods, even in the remote and protected areas of the KAZA region. The
 630 vegetation structure of KAZA consists of desert shrubs in the southwest, and
 631 dryland forest in the northeast, with Baikiaea, miombo, mopane, and acacia
 632 woodland species occupying by far the greatest portion of the area (Cumming,
 633 2008). Within this region, forest loss and degradation are a major concern because
 634 TDFs are already severely degraded as a result of competing land use, and from
 635 overuse (Kamwi et al., 2020; Shackleton et al., 2010), as shown by field photos
 636 collected in 2019, from Namibia and Botswana (Fig. 1.6).

637 These changes do not only directly impact wildlife species distribution, but can
638 also undermine efforts to maintain, expand and link wildlife populations and
639 economic sustainability (Naidoo et al., 2016). Dryland vegetation in arid, semi-arid,
640 and dry sub-humid areas of Southern Africa are highly sensitive because
641 precipitation is scarce and typically more or less unpredictable, temperatures are
642 high, humidity is low and soils generally contain small amounts of organic material
643 (King, 2014; Meadows, 2006; Niang et al., 2014).

644 For KAZA, no large-scale study exists that provides spatially explicit and up-to-date
645 information on both the protected areas and forests throughout the region, that
646 also includes detailed information on forest biomass, vegetation density, fire and
647 drought impact, and land degradation (Cumming, 2008). This hampers efforts to
648 mitigate the threats against KAZA. For example, many species (flora and fauna) are
649 identified as endangered or threatened and would almost certainly merit Alliance
650 for Zero Extinction (ACE) ranking (IUCN, 2020). For example, the *Baikiaea*
651 *plurijuga* (Zambezi Teak) is on the International Union for Conservation of Nature
652 (IUCN) red list due to overexploitation through logging and fire damage in Zambia
653 and Namibia. The Zambezi and Kavango East regions within KAZA have low levels
654 of income and high levels of poverty and are the most heavily forested regions in
655 Namibia (USAID, 2010). A large part of the Zambezi region's land surface is state-
656 run protected areas, where there is an ongoing land-use pressure, agricultural
657 expansion, and conversion of closed woodland into secondary woods and shrubs
658 (Kamwi et al., 2015). Due to the remoteness of the area, wildlife dangers, and the
659 fact that KAZA extends across international borders, continuous and in-situ field
660 sampling to measure and assess vegetation characteristics is an effectively
661 impossible and expensive task. With a view on time and expense, satellite remote
662 sensing is therefore here considered as an appropriate methodology for measuring
663 changes in the dryland of KAZA, building on a limited number of localised previous
664 studies (e.g., Schultz et al., 2018). This study provides an initiative for a significant
665 advancement in mapping the dryland forests using remote sensing technology.



666

667 Fig. 1. 6 Example of ground data captured during a field campaign in February to May 2019; (A)
 668 deforestation in Zambezi state forest in Namibia; (B) forest degradation in Chobe National Park in
 669 Botswana; (C) Burned forest for cultivation near the protected area of Mudumu NP, Namibia; (D)
 670 elephant browsing; (E) Sampling diameter at breast height of all tree per plot; (F) Meeting and
 671 interviews with community members concerning dryland forests.

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675 1.7 Aims and Objectives

676 Aims

677 The fundamental aim of this thesis is to estimate and characterise forest
678 parameters, disturbance, and land cover change in the context of climate change in
679 the KAZA region of Southern Africa. Throughout the thesis, the goal is to explore
680 the use of novel application of remote sensing approaches and the fusion of
681 multiple remote sensing data from optical and SAR sensors. The research seeks to
682 consider their combination to ascertain the potential insights into the spatial and
683 temporal change of dryland forests that remote sensing is able to provide. To
684 address the aim, the thesis will tackle the following objectives:

685 Objectives

686 **Objective 1:** Provide a systematic review of the scientific literature related to the
687 use of remotely sensed data within the context of dryland forests, with a focus on
688 Southern Africa.

- 689 ○ Provide a detailed overview of the current approaches and limitations for
690 monitoring dryland forests using optical and radar remote sensing data.
- 691 ○ Quantify general trends in remote sensing data studies focusing on
692 monitoring dryland forests in Southern Africa.
- 693 ○ Identify research gaps and make recommendations for monitoring dryland
694 forests using remote sensing data.

695

696 **Objective 2:** To assess the feasibility of using remote sensing data derived from
697 SAR, multispectral, and ground measurements to estimate dryland forest above
698 ground biomass.

- 699 ○ Develop empirical models to determine the relationship between field-
700 measured AGB and Sentinel-1 SAR backscatter coefficients, S Sentinel-2,
701 and Landsat-8 multispectral reflectance in the dryland forest environment.

702 The focus will be on the contribution and prediction potential of SAR data,
 703 multispectral bands, and their spectral indices, both individually and in
 704 combination.

705 ○ Develop parametric and non-parametric models for estimating and testing
 706 the accuracy of AGB estimation and mapping.

707 ○ To compare these models to different published biomass estimates in the
 708 dryland forest environment.

709 ○ To discuss the suitability of different models for land and wildlife
 710 management at different spatial scales (regional to global).

711 **Objective 3:** Investigate the evidence for water stress conditions across KAZA and
 712 to test the utility of structural breaks for detecting dryland forest changes using
 713 two methods: (1) BFAST and (2) BEAST change detection in the dryland forests of
 714 KAZA.

715 ○ Spatial characterisation of climatic data with vegetation indices as a proxy
 716 indicator of climate variability to improve understanding of vegetation
 717 response to drought.

718 ○ Compare the common vegetation index NDVI with GNDVI to evaluate their
 719 respective sensitivities and performance in detecting changes.

720 ○ To characterise changes in trends and phenological patterns using Breaks
 721 for Additive Seasonal and Trend (BFAST), and Bayesian Estimator of Abrupt
 722 change, Seasonality, and Trend (BEAST).

723 **Objective 4:** Investigate the relationship between fire and different climate effects
 724 on vegetation spectral characteristics at the regional scale of KAZA.

725 ○ To characterise drought conditions using climatic data (SPEI, root soil
 726 moisture, temperature, and precipitation) and explore the variability of
 727 drought using monitoring indicators (i.e., the drought duration, severity,
 728 and magnitude)

- 729 ○ To characterise the frequency, seasonality, and extent of fires through time
730 on different land use management in the KAZA region
- 731 ○ To investigate the spatiotemporal changes in aridity in the KAZA region
732 from 2002 to 2010 and 2011 to 2019

733 1.8 Thesis Structure

734 The thesis comprises six chapters structured as follows.

735 **Chapter 1** has introduced the general background, motivation and critically
736 examines concepts and remote sensing of TDFs.

737 **Chapter 2** presents a detailed review of the scientific literature related to the use
738 of remotely sensed data including synthetic aperture radar (SAR) and optical
739 sensors within the context of dryland forests, with a focus on Southern Africa. The
740 research presents examples of the literature from 1997 to 2020 that summarises
741 past achievements, current efforts, and geoinformation knowledge gaps.

742 **Chapter 3** assesses the combination of synthetic-aperture radar (SAR) and
743 multispectral data to estimate in dryland forests. Different parametric and non-
744 parametric models for estimating parameters are developed and resulting maps
745 accuracy is tested with ground measurements and different published biomass
746 models in the dryland forest environment.

747 **Chapter 4** examines water stress conditions on vegetation and changes in dryland
748 forests using multiple data streams for time series assessment over National parks
749 and surrounding communal areas within KAZA. BFAST and BEAST algorithms
750 were applied to evaluate their sensitivity to detect changes in trend and
751 seasonality in tropical dryland forests. Different vegetation indices suitability in
752 drylands were tested.

753 **Chapter 5** seeks to investigate the relationship between fire and different climate
754 effects on vegetation spectral characteristics at the regional scale of KAZA. The
755 chapter investigating the impacts, severity, and characteristics of drought a
756 conditions in drylands. The fire dynamics are also investigated at the regional scale

757 of KAZA. The purpose is to expand the understanding from Chapter 4, linking it to
758 climate and fire.

759 **Chapter 6** draws together the key findings presented in Chapters 2-5, addressing
760 the research aim, bringing the findings into the wider research context, and
761 contains the primary recommendations and conclusions of the research presented
762 in the thesis.

763

764

765

766 **2 REMOTE SENSING FOR MONITORING TROPICAL**
767 **DRYLAND FORESTS: A REVIEW OF CURRENT**
768 **RESEARCH, KNOWLEDGE GAPS AND FUTURE**
769 **DIRECTIONS FOR SOUTHERN AFRICA**

770

771 Chapter 2 is published by *Environment Research Communications*, DOI:
772 <https://doi.org/10.1088/2515-7620/ac5b84>

773 Chapter 2 is also published as a policy brief by n8agrifood for policy makers,
774 <https://policyhub.n8agrifood.ac.uk/activity/rapid-evidence-synthesis-training/>, DOI:
775 10.5281/ZENODO.5566492

776

777 **Title:** Remote sensing for monitoring tropical dryland forests: A review of current
778 research, knowledge gaps and future directions for Southern Africa

779

780

781 Authors: Ruusa M. David, Nick J. Rosser, Daniel N.M. Donoghue

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784 Department of Geography, Durham University, Science Laboratories, DH1 3LE
785 Durham, UK

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788 **Author Contribution**

789

790 David Ruusa- Design the research, perform the data analysis, interpret the results,
791 wrote the manuscript, and revised the manuscript. Nick Rosser- Contributed to the
792 research design, manuscript editing and supervision. Daniel Donoghue-
793 Contributed to the research design, manuscript editing and supervision.

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801 **Abstract**

802 Climate change, manifest via rising temperatures, extreme drought, and associated
803 anthropogenic activities, has a negative impact on the health and development of
804 tropical dryland forests. Southern Africa encompasses significant areas of dryland
805 forests that are important to local communities but are facing rapid deforestation
806 and are highly vulnerable to biome degradation from land uses and extreme
807 climate events. Appropriate integration of remote sensing technologies helps to
808 assess and monitor forest ecosystems and provide spatially explicit, operational,
809 and long-term data to assist the sustainable use of tropical environment
810 landscapes. The period from 2010 onwards has seen the rapid development of
811 remote sensing research on tropical forests, which has led to a significant increase
812 in the number of scientific publications. This review aims to analyse and synthesise
813 the evidence published in peer review studies with a focus on optical and radar
814 remote sensing of dryland forests in Southern Africa from 1997-2020. For this
815 study, 137 citation indexed research publications have been analysed with respect
816 to publication timing, study location, spatial and temporal scale of applied remote
817 sensing data, satellite sensors or platforms employed, research topics considered,
818 and overall outcomes of the studies. This enabled us to provide a comprehensive
819 overview of past achievements, current efforts, major research topics studies, EO
820 product gaps/challenges, and to propose ways in which challenges may be
821 overcome. It is hoped that this review will motivate discussion and encourage
822 uptake of new remote sensing tools (e.g., Google Earth Engine (GEE)), data (e.g.,
823 the Sentinel satellites), improved vegetation parameters (e.g., red-edge related
824 indices, vegetation optical depth (VOD)) and methodologies (e.g., data fusion or
825 deep learning, etc.), where these have potential applications in monitoring dryland
826 forests.

827 **Keywords:** Remote sensing, Dryland forests, Southern Africa, Forest monitoring,
828 SAR, Optical, Systematic review

829

830 2.1 Introduction

831 2.1.1 Tropical dryland forest

832 Approximately 40% of the Earth's tropical and subtropical land surface is covered
833 by open or closed forests. Of this, tropical dryland forests account for the largest
834 share at 42%; the remaining 33% is moist forest, and only 25% is rain forest
835 (Murphy et al., 1986; Janzen, 1988). The largest proportion of dryland forests
836 ecosystems are found in Africa, accounting for 60 - 80% of the total biome area
837 (three times the area covered by African rain forest) (Bodart et al., 2013; Bullock et
838 al., 1995). Dryland forests hold a significant amount of terrestrial organic carbon
839 that may contribute more to climate mitigation and adaptation than previously
840 appreciated (Valentini et al., 2014). Dryland forests also provide diverse ecosystem
841 services, including water regulation and erosion control, the provision of food, fuel,
842 and tourism opportunities (Djouidi et al., 2015; Schröder et al., 2021). On the other
843 hand, dryland forests are subject to prolonged dry seasons and their rate of
844 conversion to secondary forests has historically been higher than other tropical
845 forest types (Pennington et al., 2018). According to the Intergovernmental Panel
846 on Climate Change (IPCC), these changes have impacts on carbon emissions to the
847 atmosphere and forest biodiversity loss that reduce adaptive capacity and
848 resilience to the impact of high temperatures and varying precipitation (IPCC,
849 2014).

850 The definition of “dryland forest” remains debatable and controversial, which
851 contributes to the difficulty in accurately assessing and measuring its distribution
852 patterns and status (Blackie et al., 2014). The lack of a clear and comprehensive
853 understanding of general terms including “drylands” and “forests” makes it a
854 challenge to explicitly define dryland forests (Charles-D et al., 2015). Given the fact
855 that dryland forests progressively grade into other vegetation types such as moist
856 tropical forests, woodlands, and savannas, also makes clear definitions complex
857 (Putz et al., 2010). Walter et al. (1971) noted that the accuracy of estimates of all
858 tropical forest areas is constrained by uncertainty in the distribution of open
859 woodlands in dryland areas, which are extensive in Africa, Australia, and Latin
860 America.

861 In the scientific literature, many different names have been applied to tropical
862 dryland forests, including savanna forests, Sudanian woodland and miombo
863 woodland in Africa, monsoon forest in Asia, neotropical dry forests in South
864 America (Chidumayo, 2013; Linares-Palomino et al., 2011; Suresh et al., 2011). The
865 neotropical dry forests in South America have a plethora of names from “caatinga”
866 in northeast Brazil, to “bosque tropical caducifolio” in Mexico, and “cuabal” in
867 Cuba, which in part hinders comparisons (Mayes et al., 2017; Sánchez-Azofeifa et
868 al., 2005). For example, Dexter et al. (2015) identified dry deciduous forest in India
869 (Suresh et al., 2011), miombo woodland in southern Africa (Chidumayo, 2013),
870 and deciduous dipterocarp forest in continental Asia (Bunyavejchewin et al., 2011)
871 as a form of savanna, and not TDFs, despite the formal classification as TDFs by
872 these studies, and the FAO (FAO, 2001). The Caatinga and Chaco vegetation in
873 Latin America is also considered by some authors as part of the dry forests
874 (Gasparri and Grau, 2009; Pennington and Ratter, 2006), although Olson et al.,
875 (2001) classifies these regions as a shrubland ecosystem.

876 There are several definitions currently available for TDFs, but there is still a lack of
877 consensus in developing a common understanding. Mooney et al. (1995) defined
878 TDFs as forests occurring in the tropical regions characterised by pronounced
879 seasonality in rainfall, where there are several months of severe, or even absolute
880 drought. Sánchez-Azofeifa et al. (2005) broadly defined TDFs as a vegetation type
881 typically dominated by deciduous trees (at least 50% of trees present are drought
882 deciduous), where the mean annual temperature is ≥ 25 °C, total annual
883 precipitation ranges between 700 and 2000 mm, and there are three or more dry
884 months every year (precipitation < 100 mm per month). A widely accepted
885 definition is that of the FAO, which has identified TDFs as a Global Ecological Zone
886 (GEZ), experiencing a tropical climate, with a dry period of 5 to 8 months and
887 annual rainfall ranges from 500 to 1500 mm; GEZ includes the drier type mbo and
888 Sudanian woodlands, savannah (Africa), caatinga and chaco (South America), and
889 dry deciduous dipterocarp forest and woodlands (Asia) (FAO, 2001). For the scope
890 of this review, the FAO. (2001) definition of TDFs was followed because it
891 recognises forests occurring in the dry tropical climate globally including areas
892 with relatively open canopies such as woodlands, and woody stands, then those
893 based entirely on climate definitions. The growing body of evidence suggests that

894 the current climate does not define the biogeography of TDFs or determine biome
895 distributions (Staver et al., 2011; Sunderland et al., 2015), particularly in the
896 context of future unprecedented climate change (IPCC, 2007). If climates become
897 sufficiently warmer and drier in the tropics, dry forests may expand into areas that
898 are currently dominated by moist tropical forests (Putz et al., 2010).

899

900 2.1.2 Recent research trends on tropical dry forests

901 2.1.2.1 Geographical research trends on tropical dry forests

902 Studies have pointed out that dryland forests generally receive a lower number of
903 scientific publications and are under-represented in research in comparison with
904 tropical moist forests (Miles et al., 2006; Quesada et al., 2009). Global reviews on
905 dryland forests addressed the imbalance in the geographical coverage of dryland
906 forest publications using remote sensing with certain tropical countries such as
907 Latin America receiving the highest publications on dryland forests in comparison
908 to most places in Africa (Blackie et al., 2014; Schröder et al., 2021). To investigate
909 the geographical distribution of tropical dry forest studies, the study initially
910 searched for publications in ISI web of knowledge and Scopus on tropical dryland
911 forests from Asia, Africa, America, and Australia. This search was conducted by
912 using the keywords 'Dry Forest', 'Dryland Forest' 'Savan* Woodland', 'Savan* Tree',
913 'Dryland Vegetation', 'Dry Vegetation' 'Satellite', 'Remote Sensing', 'Optical', 'Radar',
914 'Image', 'SAR', 'Earth Observation', 'country/continent e.g., Africa'. In the search
915 period from 1997 to 2020, the study identified 1662 papers for Africa, 1639 for
916 Australia, 1338 for America, and 1134 for Asia. In Africa, when the search was
917 narrowed to individual countries, the results showed that about 743 publications
918 are from the Republic of South Africa (RSA) while 355 publications were from the
919 Sahel region of Nigeria. The study also investigated scientific publications from
920 other Southern African countries with dryland forest and 369 publications were
921 identified, including from Botswana (87), Zimbabwe (69), Mozambique (60),
922 Namibia (68), Zambia (49), Angola (24), Lesotho (6), Swaziland (5). When the
923 review combined the scientific publications from the above 8 Southern African
924 countries, the results were 369 publications, indicating that publications on

925 dryland forests for the Republic of South Africa were 2.01 times higher than all 8
926 Southern African countries combined. These results confirm that much less
927 progress has been made in developing objective methods for assessing the rates of
928 deforestation/conservation and threats to dryland forests ecosystems in most
929 Southern African countries except for the Republic of South Africa.

930 The dryland forests in other parts of the world like Latin America are increasingly
931 well studied at local, regional, national and continental scale, particularly with
932 regards to carbon/biomass (Chazdon et al., 2016; Marín-Spiotta et al., 2008), fire
933 (Campos-Vargas et al., 2021; White, 2019; Pereira et al., 2014), climate change
934 (Mendivelso et al., 2014; Castro et al., 2018; González-M et al., 2021), floristic and
935 diversity composition (Alvarez-Añorve et al., 2012; Gillespie et al., 2000),
936 ecosystem services (Castillo et al., 2005; Paruelo et al., 2016), Payment for
937 Environmental Services (PES) (Alcañiz and Gutierrez, 2020; Corbera et al., 2009),
938 novel conservation approaches (e.g., sustainable intensification for
939 protected/conservation areas) (Méndez et al., 2007; Reynolds et al., 2016) and has
940 the most comprehensive forest change/deforestation and biophysical aspects
941 including species population changes, with extensive use of remote sensing (do
942 Espírito-Santo et al., 2020; Gasparri and Grau, 2009; Stan and Sanchez-Azofeifa,
943 2019; Trejo and Dirzo, 2000; Portillo-Quintero et al., 2012). In terms of reviews,
944 many remote sensing reviews are providing valuable information on TDF's
945 biophysical, ecological and socioeconomic at a regional level of Latin America
946 (Castro et al., 2003; Metternicht et al., 2010; Portillo, 2010; Sanchez-Azofeifa et
947 al., 2003; Sánchez-Azofeifa et al., 2005; Sánchez-Azofeifa et al., 2013; Stan and
948 Sanchez-Azofeifa, 2019; Quijas et al. 2019), and Australia (Lawley et al., 2016;
949 Moore et al., 2016; Fensham et al., 2002). Also, reviews of current progress on
950 dryland forests in individual countries can be found in many neotropics countries
951 such as Mexico (Castillo et al., 2005; Curry, 2020), Venezuela (Fajardo et al., 2005;
952 Rodríguez et al., 2008), and Costa Rica (Frankie et al., 2004; Stoner et al., 2004)
953 enabling the identification of knowledge gaps and aiding in the development of a
954 policy-relevant approach to conservation of these forests (Miles et al., 2006).

955 Latin America is one of the best-represented areas for remote sensing research in
956 dryland forests, for example, Portillo-Quintero and Sánchez-Azofeifa. (2010)

957 utilised remote sensing data at continental America, dryland forests ecoregion, and
958 neotropics countries to show that 66% of tropical dry forest in the region has
959 already been converted and that in some countries the conversion rate is as high as
960 86% and 95%, respectively. Aide et al. (2012) using Moderate Resolution Imaging
961 Spectroradiometer (MODIS) satellite data estimated that 200,000 km² of woody
962 vegetation of Latin American and the Caribbean region were lost due to
963 deforestation between 2001 and 2010. Nanni et al. (2019) utilised MODIS satellite
964 data at 250 m spatial resolution to assess reforestation at the regional level and
965 reported that the reforestation hotspots cover 167,667.7 km² (7.6 %) of Latin
966 America between 2001 and 2014. While there are continental studies in Africa
967 utilising remote sensing on biophysical parameters such as biomass/deforestation
968 (Bouvet et al., 2018; Bodart et al., 2013), as compared to Latin America, these
969 studies may not consider the empirical observations of dryland forests
970 extent/change per region or country level. In addition, most continental studies in
971 Africa rather focus the attention on tropical rainforest in Central Africa (e.g., core
972 Congolese forest) which may under-represent dryland forest (e.g., Aleman et al.,
973 2018). Global applications often report general land use/cover change which
974 results in inaccurate or poor estimates of dryland forest (Smith et al., 2019;
975 Aleman et al., 2018).

976 Several studies using optical and passive microwave instruments in the African
977 Sahel (Horion et al., 2014; Brandt et al., 2016; Olsson et al., 2005; Tian et al., 2017)
978 has reported that the density/size of woody vegetation stands have increased, with
979 few areas in northern Nigeria reported to experience logging and agricultural
980 expansion into forest reserves. Deforestation in Southern Africa is a major concern,
981 with ca. 1.4 million ha of net forest loss annually, contributing to increased land
982 degradation and the ensuing impacts on the balance of ecosystem function
983 (Lesolle, 2012). A global study by Tian et al. (2017) utilising the optical Normalised
984 Difference Vegetation (NDVI) index and passive microwave VOD across tropical
985 drylands has reported a decreasing trend in woody vegetation in Southern African
986 countries such as Botswana and Zimbabwe. Mitchard and Flintrop. (2013)
987 conducted a coarse-scale analysis of changes in woody vegetation from 1982 to
988 2006 using NDVI time series from the Global Inventory Modeling and Mapping
989 Studies (GIMMS) dataset and found that significant woody encroachment is

990 occurring in most west African countries, but, in contrast, in Southern Africa, a
991 rapid reduction in woody vegetation (deforestation) is occurring. Bodart et al.
992 (2013) used Landsat satellite imagery between 1990 and 2000 to estimate forest
993 cover and forest cover changes in the African continent and found that 84% of the
994 total deforested area occurred in the dry ecosystems of the Southern African
995 region, with large spatially concentrated areas of forest loss found in Angola,
996 Mozambique, Tanzania, Zambia and Zimbabwe, and isolated hotspots found in
997 Nigeria and the border of the humid forest in Ghana. While such global and
998 continental level studies are useful to highlight and reinforce the need to direct
999 more attention and resources to these threatened/poorly studied ecosystems,
1000 research efforts on forest change/deforestation and climate change impacts of
1001 dryland forests at the regional level of Southern Africa are much harder to come by
1002 (Blackie et al., 2014).

1003 2.1.2.2 Remote Sensing approaches research trends in tropical dry 1004 forests

1005 In recent decades, satellite remote sensing or Earth observation (EO) has proved a
1006 valuable tool in forest ecology, owing to its capability to perform systematic,
1007 frequent, and synoptic observation of the Earth, resulting in large data volumes
1008 and multiple datasets at varying spatial and temporal scales (Donoghue, 2002; Zhu,
1009 2017). There are several sensors including multi-spectral scanners, laser scanners
1010 (LiDAR), hyper-spectral scanners as well as satellite-borne Synthetic Aperture
1011 Radar (SAR), that provide information on the colour and structure of forest
1012 environments (Donoghue, 2002). EO has been applied to mapping the distribution,
1013 changes in cover and condition including deforestation, desertification, fire
1014 damage, and climate impact (Dogru et al., 2020; Smith et al., 2019). Additionally,
1015 these data have been used to estimate biophysical characteristics such as total
1016 above ground biomass (AGB), leaf area index (LAI), woody area index, tree
1017 diameter, and canopy height which are key inputs into a variety of ecological
1018 models, as well as calculations of carbon balance and primary production (Barbosa
1019 et al., 2014; Donoghue, 2000). The continuous forest metrics obtained using EO
1020 data can be extracted at leaf and crown level to evaluate spectral elements of leaf
1021 or species properties and at stand-level and plot-level, or beyond to understand

1022 the variation between and among species, and through time (Muraoka et al., 2009).
1023 Monitoring of dryland forest cover and forest metrics using EO data also helps to
1024 improve the understanding of the ecological drivers behind land cover change
1025 dynamics (Chambers et al., 2007; Veldkamp et al., 2001).

1026 Biomass has extensively been estimated based on the spectral reflectance values
1027 from two or more wavelengths, and the sensitivity of optical and near-infrared
1028 wavelengths to photosynthetic canopy cover has long been used for vegetation
1029 analyses (Rouse, 1974; Tucker, 1979). Spectral vegetation indices (VIs), including
1030 the NDVI index, are commonly used as a proxy of vegetation cover and have been
1031 shown to relate closely to LAI, biomass, and the fraction of photosynthetically
1032 active radiation absorbed by vegetation (fAPAR) (Curran, 1980). Several well-
1033 known limitations of NDVI for robust estimation of biomass in drylands exist. NDVI
1034 is sensitive to green components and insensitive to woody components where the
1035 majority of carbon is stored (Tucker, 1979). Also, AGB production is not always
1036 uniformly linked to either greenness or plant structure (herbaceous and woody
1037 compositions), as moisture content and vegetation species composition have been
1038 shown to impact the biomass-NDVI relationship (Asner et al., 2009; Wessels et al.,
1039 2006). These observations may help explain reportedly weak relationships
1040 between NDVI and tropical forest canopies, particularly for areas with complex
1041 and high vegetation amounts as in TDFs (Foody et al., 2001; Sader et al., 1989). For
1042 example, Madonsela et al. (2018) investigated the interactions between seasonal
1043 NDVI and woody canopy cover in the savanna of the Kruger National Park (NP) to
1044 model tree species diversity using a factorial model and found that the interaction
1045 between NDVI and woody canopy cover was insignificant. These challenges have
1046 led to the development of alternative formulations which include correction
1047 factors or constants introduced to account for or minimise, the varying
1048 background reflectance (Gitelson et al., 1996; Huete et al., 1999). The Enhanced
1049 Vegetation Index (EVI) is a modification of NDVI that provides complementary
1050 information about the spatial and temporal variations of vegetation while
1051 minimising many of the contamination problems present in the NDVI, such as
1052 those associated with canopy background and atmospheric influences (Huete et al.,
1053 2002). Other closely related indices include the Simple Ratio (SR), the Green
1054 Normalised Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index

1055 (SAVI) amongst others. Xue et al. (2017) provides a detailed review of vegetation
1056 indices.

1057 Although vegetation monitoring has been largely based on the multispectral
1058 “greenness” indices, which have proven invaluable for monitoring biophysical and
1059 biogeochemical parameters, it has been widely reported in the literature that they
1060 suffer from several weaknesses in dryland ecosystems (Tian et al., 2016; Shi et al.,
1061 2008). Other remote sensing systems such as the passive microwave-based
1062 satellite systems capture the biomass signal in the parameter termed vegetation
1063 optical depth (VOD) which has been used to monitor changes in vegetation
1064 dynamics (Andela et al., 2013; Brandt et al., 2018a; Brandt et al., 2018b). Unlike the
1065 optical remote sensing-based vegetation indices that are sensitive to chlorophyll
1066 abundance and photosynthetically active biomass of the leaves, the vegetation
1067 information (e.g., VOD) deriving from passive microwave instruments is sensitive
1068 to the water content in the total aboveground vegetation, including both the
1069 canopy (e.g. woody plant foliage) and non-green woody (e.g. plant stems and
1070 branches) components due to greater penetration and sensitivity (Liu et al., 2011;
1071 Shi et al., 2008). The passive microwave observations VOD is relatively insensitive
1072 to signal degradation from solar illumination and atmospheric effects and provide
1073 a valuable alternative tool for rapid monitoring of carbon stocks and their changes
1074 (Jones et al., 2011). One of the advantages of passive microwave-derived VOD is
1075 that it continues to distinguish biomass variations at a relatively high biomass
1076 density, as compared to optical-based vegetation indices which are likely to
1077 become saturated over dense canopies (Jones et al., 2011; Liu et al., 2015). The
1078 main disadvantage of passive microwave observations is the relatively coarse
1079 spatial resolution (>10km), as compared to satellite data in the visible and near-
1080 infrared parts of the spectrum; however, these data still have highly useful
1081 applications at regional and global scales (Liu et al., 2015; Rahmoune et al., 2013;
1082 Owe et al., 2001). Some recent global and local studies from Latin America and
1083 Africa in the dryland ecosystems found VOD to be more robust against the NDVI
1084 drawbacks of saturation effect and continues to distinguish structural differences
1085 for vegetation with a near-closed canopy when used as a proxy for vegetation
1086 productivity (van Marle et al., 2015; Cui et al., 2015; Liu et al., 2011; Tian et al.,
1087 2016). Apart from the VOD and NDVI, an intercomparison between several

1088 vegetation indices including other passive microwave-based vegetation indices,
1089 such as the Microwave Polarisation Difference Index (MPDI) (Becker & Choudhury,
1090 1988), and the Microwave Vegetation Indices (MVIS) (Shi et al., 2008) would be of
1091 benefit in monitoring dryland biomes.

1092 2.1.3 Review focus justification

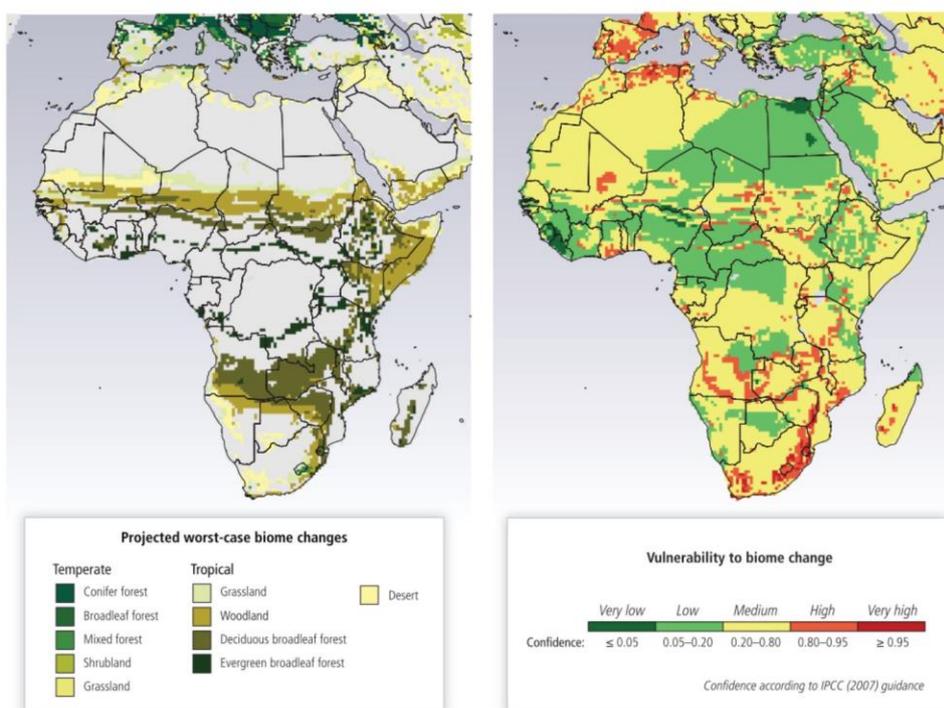
1093 The majority of the residents of Southern Africa are poor and about 75% of them
1094 live in rural areas with high reliance on dryland forests (Bond 2010). Additionally,
1095 these dryland areas display a high susceptibility to bush encroachment (O'Connor
1096 et al., 2014) and economic reliance on tourism (Ferreira 2004) and forest products
1097 (Kamwi et al., 2020), which means that both agriculture and tourism development
1098 encroach on the dryland forests, resulting in loss of forest biodiversity and land
1099 degradation (Eva et al., 2006; Petheram et al., 2006). Across Southern Africa,
1100 sustainable management of dryland ecosystems is hindered by complex land
1101 tenure due to historical legacy, weak links between policy and woodland use and
1102 management, and cultural drivers (Balint and Mashinya, 2006; Dewees, 1994).
1103 Also, the dryland ecosystems of Southern Africa are dominated by private land
1104 ownership, a high concentration of wildlife and human populations, and
1105 agriculture where TDFs occur (Child et al. 2012). This review focuses on Southern
1106 Africa because there is a gap in knowledge on carbon storage, biomass, and the
1107 long-term trend of forest distribution and degradation in dryland forests. Much of
1108 the research on dryland forests in Southern African has concentrated on
1109 livelihoods, community forest management, and conservation/development trade-
1110 offs (Chidumayo et al., 2010; Chidumayo and Gumbo, 2010; Chidumayo, 2019;
1111 Djoudi et al., 2015, Dewees 1994; Du Preez, 2014; Ryan et al., 2016), leaving forests
1112 highly vulnerable to deforestation and degradation (Keenan et al., 2015). The
1113 social and economic aspects are important given the large numbers of African
1114 people that rely on dry forests for their livelihoods and a range of goods and
1115 services. However, the gap in biophysical aspects, threats status, and adaptation to
1116 climate change identified for Southern African TDFs at the regional and national
1117 level (Blackie et al., 2014; Sunderland et al., 2015), presents an urgent need for an
1118 assessment of the effectiveness of the EO scientific foundation on current
1119 understanding of TDFs in Southern Africa; this can aid in the development of

1120 policy-relevant approaches and long-term, regional perspective for planning and
1121 conservation of the TDFs.

1122 With the prospects of multiple free datasets from optical and SAR sensors being
1123 available; combining information from optical sensors on photosynthetic activity
1124 (e.g., through various vegetation indices) with SAR-derived information on forest
1125 structure and volume brings the benefits of higher spectral resolution and
1126 compensating for the shortcomings of using single data products alone. Based on
1127 this hypothesis, this review focuses on examining the studies using optical and SAR
1128 sensors, both individually and the combination of the two types of EO data in
1129 monitoring tropical forests. While forest distribution, carbon storage, and reducing
1130 emissions from deforestation and forest degradation (REDD+) related research
1131 exists in African dryland forests, the geographical focus has tended to be confined
1132 to several West/Central African countries, whereas Southern Africa is relatively
1133 poorly analysed (Lewis et al., 2013; Sunderland et al., 2015). Although numerous
1134 reviews have been conducted discussing the application of optical and radar
1135 remote sensing, they are either concentrated on mangroves forests (Kuenzer et al.,
1136 2011; Wang et al., 2019), rain forests (Dupuis et al., 2020), or ecosystem services
1137 (Barbosa et al., 2015). To date, reviews on remote sensing and EO in Southern
1138 Africa have focused on research conducted in the Republic of South Africa (RSA)
1139 (Hoffman et al., 2000; Mutanga et al., 2016; Mutanga et al., 2009).

1140 As shown in Fig. 2.1, the climate threats coupled with a growing human population
1141 and future anticipated changes in land use are predicted to lead to severe dry
1142 forest biome shifts and degradation across the whole of Southern Africa, hence the
1143 need to expand the geographical scope of this review from previous work (IPCC,
1144 2014; King, 2014). This paper provides a systematic review of the scientific
1145 literatures related to the use of Earth observation data including SAR and optical
1146 sensors used to study dryland forests, with a focus on Southern Africa. To achieve
1147 this, examples from the literature that summarise past achievements, current
1148 efforts, and knowledge gaps are presented. The objectives of this review are to (i)
1149 to provide a detailed overview of the current approaches and limitations for
1150 monitoring dryland forests using optical and radar remote sensing data. (ii) to
1151 provide a critical evaluation and synthesis of the literature monitoring dryland

1152 forests using remote sensing data and discuss how EO data can contribute to
 1153 dryland forest monitoring and forest conservation in Southern Africa. (iii) to
 1154 identify knowledge gaps and make recommendations for research that will
 1155 enhance monitoring of dryland forests using remote sensing data.



1156

1157 Fig. 2. 1 (a) Projected biome change from the periods 1961–1990 to 2071–2100 using the
 1158 MC1 Dynamic Vegetation Model. (b) Vulnerability of ecosystems to biome shifts based on
 1159 historical climate (1901–2002) and projected vegetation (2071–2100) (source: IPCC,
 1160 2014).

1161

1162 2.2 Remote sensing applications in dryland forest

1163 2.2.1 Optical data

1164 In broad terms, the satellite platforms developed over the past 40 years (since
 1165 1972) have carried two broad types of sensor systems; passive optical and active
 1166 synthetic aperture radar (SAR). Successful change detection and parameter
 1167 estimation over tropical dryland forests require: (a) correct selection and
 1168 application of sensor type; (b) coupling with field observation data for calibration

1169 and validation, and (c) data integration and appropriate techniques for modelling
1170 (Fig. 2.2). Optical sensors have been widely used for land cover and forest resource
1171 mapping, providing access to long-term data dating back to the launch of Landsat
1172 ERTS (Earth Resources Technology Satellite) satellites in 1972. Landsat and
1173 several other coarse/medium spatial resolution optical sensor missions (National
1174 Oceanic and Atmospheric Administration (NOAA) - Advanced Very High-
1175 Resolution Radiometer (AVHRR); the National Aeronautics and Space
1176 Administration (NASA) -Aqua/Terra- Moderate Resolution Imaging
1177 Spectroradiometer (MODIS); Indian Remote Sensing Satellites-1C/1D (ISRO-IRS-
1178 1C/D), Sentinel-2) provide well-calibrated, nadir-viewing, near-global systematic
1179 coverage which have built up a valuable archive of image data that can be used to
1180 analyse ecosystem dynamics (Congalton, 2018; Donoghue, 2000). In 2014, ESA
1181 launched the Multispectral Instrument (MSI) onboard Sentinel-2 as part of its
1182 Copernicus EO mission. Sentinel-2 MSI uses two identical satellite sensors to
1183 measure the Earth's reflected radiance with a revisit time of 5 days and a fine
1184 spatial resolution of 10 - 20 m pixel size. The length of the Sentinel-2 archive is
1185 short (from 2015), compared to the Landsat mission from 1972-present, NOAA-
1186 AVHRR 1979-present; Satellite Pour l'Observation de la Terre VEGETATION
1187 (SPOT/VGT) (1998-present), IRS-1C/1D (ISRO-IRS-1C/D) (1995-2010), ENVISAT -
1188 Medium Resolution Imaging Spectrometer (MERIS) (2002-2010) and the NASA -
1189 MODIS (2000-present) and the French Space Agency (CNES-Centre national
1190 d'études spatiales) high-resolution SPOT satellite constellation (6 m - 20 m pixel
1191 size) - SPOT-1 in 1986-1990, SPOT-2 in 1990-2009, SPOT-3 in 1993-2009; SPOT-4
1192 in 1990-2013; SPOT-5 in 2002-present; SPOT-6 in 2012-present; SPOT-7 in 2014-
1193 present. The VEGETATION 1 (VGT 1) (1998-2012) and VEGETATION 2 (VGT 2)
1194 (2002-2014) instrument on the SPOT 4 and SPOT 5 (SPOT/VGT) satellites
1195 provided global daily monitoring of vegetation cover, and it is successor the
1196 European PROBA-V satellite (2013-present), with a pixel size of 1 km, 300 m and
1197 100 m are supplied by the VEGETATION image Processing Centre (CTIV) of VITO
1198 (Belgium), which can be accessed through the internet site <http://free.vgt.vito.be>.
1199 Although a large number of satellite sensors have been launched that are capable
1200 of observing land dynamics, and their pixel size has decreased from 80 m of the
1201 Landsat-1 to 0.41-1.65 m of the GeoEye-1 satellites (Aguilar et al., 2013), very few

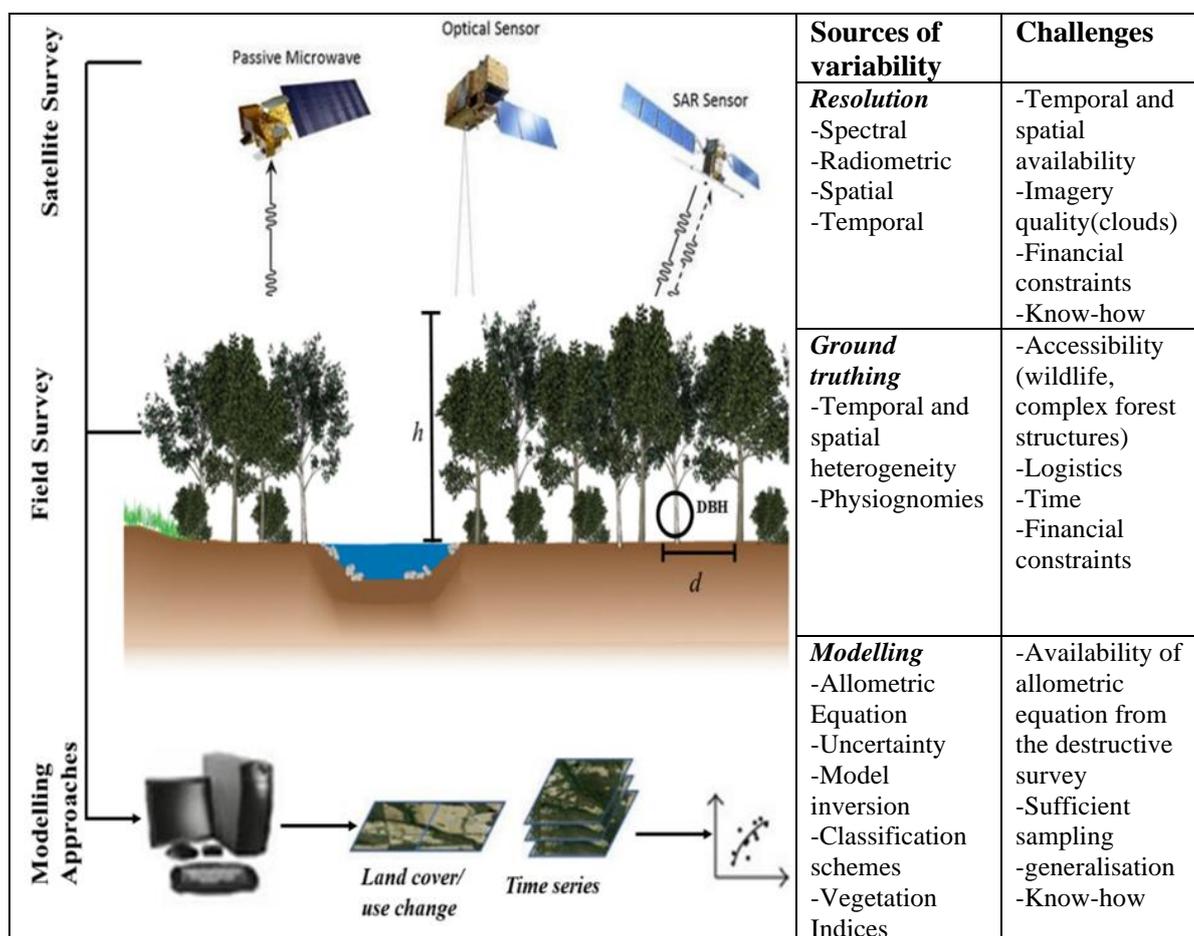
1202 sensors provide well-calibrated multispectral, nadir-viewing observations and
1203 even fewer systematically capture all global data and provide a long-term archive
1204 of data free of charge to the public. Except for AVHRR and Landsat, no other sensor
1205 or sensor line offers the chance of long-term monitoring of an area to be monitored
1206 back in time to the 1970s, covering about four decades.

1207 There are several non-systematic commercial high-resolution satellites that allow
1208 the detection of individual trees or populations. Maxar Technologies Inc. launched
1209 4 very fine resolution satellites - WorldView-1 in 2007, WorldView-2 in 2009,
1210 WorldView-3 in 2010, and WorldView-4 in 2019 that acquire images with spatial
1211 resolution of 0.5, 0.41, and 0.31 m, respectively. From 2009 onward, Planet labs
1212 launched a swarm of micro-satellites including PlanetScope (PS), RapidEye (RE),
1213 and SkySat (SS) Earth-imaging constellations with multispectral imaging capability
1214 with the aim of acquiring daily image capture for any part of the world at a spatial
1215 resolution of 3.125 m to 6.5 m (Marta, 2018). In 2011 and 2012, the Space Agency
1216 of France (CNES) launched the Pléiades – fine resolution optical imaging satellite
1217 constellation (Pléiades-1A and Pléiades-1B), with a fine spatial resolution of 0.7 –
1218 2.8 m. Other very fine-resolution commercial space imaging satellites include
1219 Earlybird (1997), GeoEye (2008), EROS-A (1998), IKONOS (1999), QuickBird
1220 (2001), OrbView (2001) (Maglione, 2016). In Africa, South Africa started satellite
1221 developments in the 1990s, with the successful launch of SunSat-1 with a spatial
1222 resolution of 15 m in 1999 and SumbandilaSat low orbit satellite with a high fine
1223 resolution of 6.25 m in 2009 (Cho et al., 2012; Mutanga et al., 2016). While the first
1224 Nigerian satellite, a microsatellite called NigeriaSat-1, was successfully launched
1225 into low earth orbit in 2003, followed by Nigeriasat-2 with a higher spatial
1226 resolution of 2.5 – 5 m, built by Surrey Satellite Technology Limited (SSTL) of UK
1227 (Agbaje, 2010).

1228 Nevertheless, the use of data acquired by higher spatial resolution optical sensors,
1229 particularly at regional and global scales, can be limited by their relatively high
1230 cost, huge data volumes, and low frequency of data acquisition compounded
1231 further in tropical regions where cloud cover is prevalent (Lehmann et al., 2015;
1232 Zhu et al., 2012). The temporal resolution of sensors has also increased from, for
1233 example, 16 days for Landsat to nearly 1 day for the NOAA-AVHRR, NASA-

1234 Aqua/Terra-MODIS, NOAA-AVHRR, SPOT, SPOT/VGT (PROBA-V), and/or
 1235 ENVISAT-MERIS data, but with a coarse spatial resolution of 250 m to 1 km (Arino
 1236 et al., 2007; Herold et al., 2008). Although lacking fine spatial detail, the daily
 1237 temporal resolution of such sensors enables frequent estimation of deforestation,
 1238 detection of disturbances using dense time series data, and enables gaps due to
 1239 cloud cover to be overcome (Mbow et al., 2015). It is important to mention that the
 1240 acquisitions of some satellites such as NOAA-AVHRR, IRS-1C/1D, and MERIS
 1241 ceased operations, however, the Sentinel, MODIS, SPOT-VGT, and Landsat series
 1242 continue to operate, with ongoing continuity of data collection ensured with the
 1243 recent launch of Landsat-9 in September 2021.

1244



1245 Fig. 2. 2 Interaction mechanisms for dryland forest canopies and source of variability and
 1246 challenges related to each stage of remote sensing monitoring tropical dryland forest
 1247 extents. Adapted from Barbosa et al., 2014.

1248

1249

1250 2.2.2 Synthetic Aperture Radar (SAR)

1251 SAR sensors for civilian applications first appeared in 1978 with NASA's SeaSat but
1252 have grown in importance as a tool for forest studies. SAR sensors can operate at
1253 different frequencies and polarisations; these system parameters provide
1254 information on the roughness and scattering properties of forest canopies and data
1255 can be captured day and night independent of weather conditions (Durden et al.,
1256 1989). Since SAR can penetrate cloud, rain, smoke, and haze, and it is a valuable
1257 source of data when atmospheric conditions hamper optical data capture,
1258 particularly in the tropical dryland forest such as Southern Africa where the cloud
1259 and smoke from forest fires are prominent features (Le Canut et al., 1996). Radar
1260 signals are sensitive to moisture, variations, surface roughness, and vegetation
1261 structure properties, whereas data from optical systems use characteristics related
1262 to reflected solar illumination or surface temperature (for thermal infrared
1263 sensors) as a basis for discrimination of the land cover (Kasischke et al., 1997;
1264 Mitchard et al., 2009). Cloud cover-free SAR images have great potential in the
1265 dryland tropical areas but have been used less often for forest monitoring
1266 applications compared to optical imagery, partly because of the scarcity of data
1267 (Castro et al., 2003). Since the launch of the Sentinel-1A and B, dense SAR time-
1268 series data are now available over tropical forest areas freely and openly, with
1269 systematic acquisitions at a 10 m spatial resolution and a 6 - 12 day revisit time
1270 (dependent on the location) in all weather conditions.

1271 Over the last 30 years, several satellite-borne SAR has been launched, including the
1272 United State Spaceborne Imaging Radar-Synthetic Aperture Radar (SIR-C/X-SAR),
1273 European Remote Sensing (ERS-1/-2), Advanced Synthetic Aperture Radar (ASAR),
1274 Japanese Earth Resources Satellite (JERS-1), Advanced Land Observation Satellite
1275 (ALOS/PALSAR-1/-2), German TerraSAR-X, and the Canadian RADARSAT-1/-2
1276 (Shimada, 2018). Depending on the sensor configuration, a single channel
1277 (wavelength/frequency) or multiple channels may be recorded in either single or
1278 multiple polarisations. Generally, studies have reported that the longer the
1279 wavelength (e.g. P (30–100 cm) and L (15–30 cm)), the further is its penetration

1280 into the forest and the greater the importance of scattering beyond the upper
1281 canopy (Huang et al., 2015). Besides the greater sensitivity of longer radar
1282 wavelengths to forest structure, different studies indicate that cross-polarised
1283 backscatter (HV-horizontally transmitted, and vertically received, VH-vertically
1284 transmitted and horizontally received) often exhibits greater sensitivity to forest
1285 biomass than like-polarised backscatter (co-polarised bands: HH-horizontally
1286 transmitted and horizontally received, VV-vertically transmitted and vertically
1287 received) (Kasischke et al., 1997).

1288 2.2.3 Limitations of optical and radar, and benefits of 1289 combining sensors

1290 Despite the different generations and types of satellite sensors, no one sensor
1291 currently meets fully the requirements of a comprehensive forest resource
1292 assessment EO system. The selection of an appropriate source of data requires first
1293 the identification of the ecological question being asked, identification of the
1294 limitations and advantages of each sensor. The varying temporal, spatial, spectral,
1295 and radiometric resolutions unique to the individual sensor system, result in
1296 different advantages and disadvantages to the monitoring of dryland ecosystems
1297 (Lu, 2006). Optical data are limited in the monitoring of this forest type. For
1298 example (1) cloud and smoke severely limit the use of optical products (Le Canut
1299 et al., 1996); (2) Dramatic seasonal changes in the dryland forests conditions
1300 including droughts and leaf shedding make it unsuitable for systematic all-season
1301 monitoring of this forest type (Boggs, 2010). One of the reasons for this is
1302 associated with the seasonality of the tropical vegetation: during the wet season,
1303 cloud-free satellite imagery is difficult to acquire, while during the dry season
1304 when the imagery is more available, the leaf-off configuration of the forest causes
1305 misclassification with savanna shrubland or grassland; (3) Optical data is sensitive
1306 at the early stages of growth but as forest canopies close, reflected radiation is no
1307 longer sensitive to biomass as the reflectance signal saturates at higher biomass
1308 values (Lu, 2006); (4) Passive optical sensors only detect the surface top layer,
1309 meaning that forest canopy obscures the understory, and similarly grasses/crops
1310 obscure soil; (5) Changes in the spectral properties of the soil and atmosphere can

1311 also hinder the inference of forest cover properties (Santos et al., 2002; Wang et al.,
1312 1998).

1313 Similarly, there are a number of challenges to analysing and interpreting radar
1314 images for tropical forest applications, which include: (1) Difficulty in interpreting
1315 radar backscatter, including, for example, speckle, which is unwanted random
1316 noise inherent in all SAR images, which may increase measurement uncertainty
1317 and make interpretation difficult (Klogo et al., 2013); (2) Topography is a major
1318 limitation in mountainous regions due to geometric and radiometric effects such as
1319 radar shadowing caused by foreshortening and layover when the satellite is not
1320 able to illuminate the whole ground surface (Mitchard et al., 2009); (3) SAR
1321 observations often lack a long-term and dense time series because they demand a
1322 relatively high energy provision on satellite platforms. Until recently, satellite-
1323 based SAR data for multi-temporal assessments over large areas were constrained
1324 by coarse spatial and temporal coverage at medium resolution, although this now
1325 may be overcome with acquisitions from the recently launched C-band Sentinel-1
1326 and L-band ALOS-2 satellite missions (Reiche et al., 2016).

1327 Rather than using EO data from a single satellite sensor, the synergy of remotely
1328 sensed data from multiple sensors, particularly SAR systems with those acquired
1329 by optical sensors, has been shown to be beneficial for forest resource assessment
1330 (Lehmann et al., 2015). Because optical data is capable of measuring the
1331 reflectance of the topmost layer of the forest canopy and SAR data deliver useful
1332 within-canopy biophysical parameters without being affected by cloud cover and
1333 weather conditions, one dataset may compensate for the shortcomings of the other
1334 (Reiche et al., 2016). Previous research indicated that integration of optical and
1335 radar can improve land and forest cover characterisation (Symeonakis et al.,
1336 2018). For example, the fusion of optical and radar sensor data has the potential to
1337 improve AGB estimation because it may compensate for the mixed pixels in a
1338 tropical forest area. In addition to the spectral synergy afforded, the cloud
1339 penetrating capability of microwave radar sensors allows areas that have missing
1340 optical data to be included in analyses, particularly if multi-temporal methods are
1341 being employed (Reiche et al., 2016).

1342 2.3 Methodology

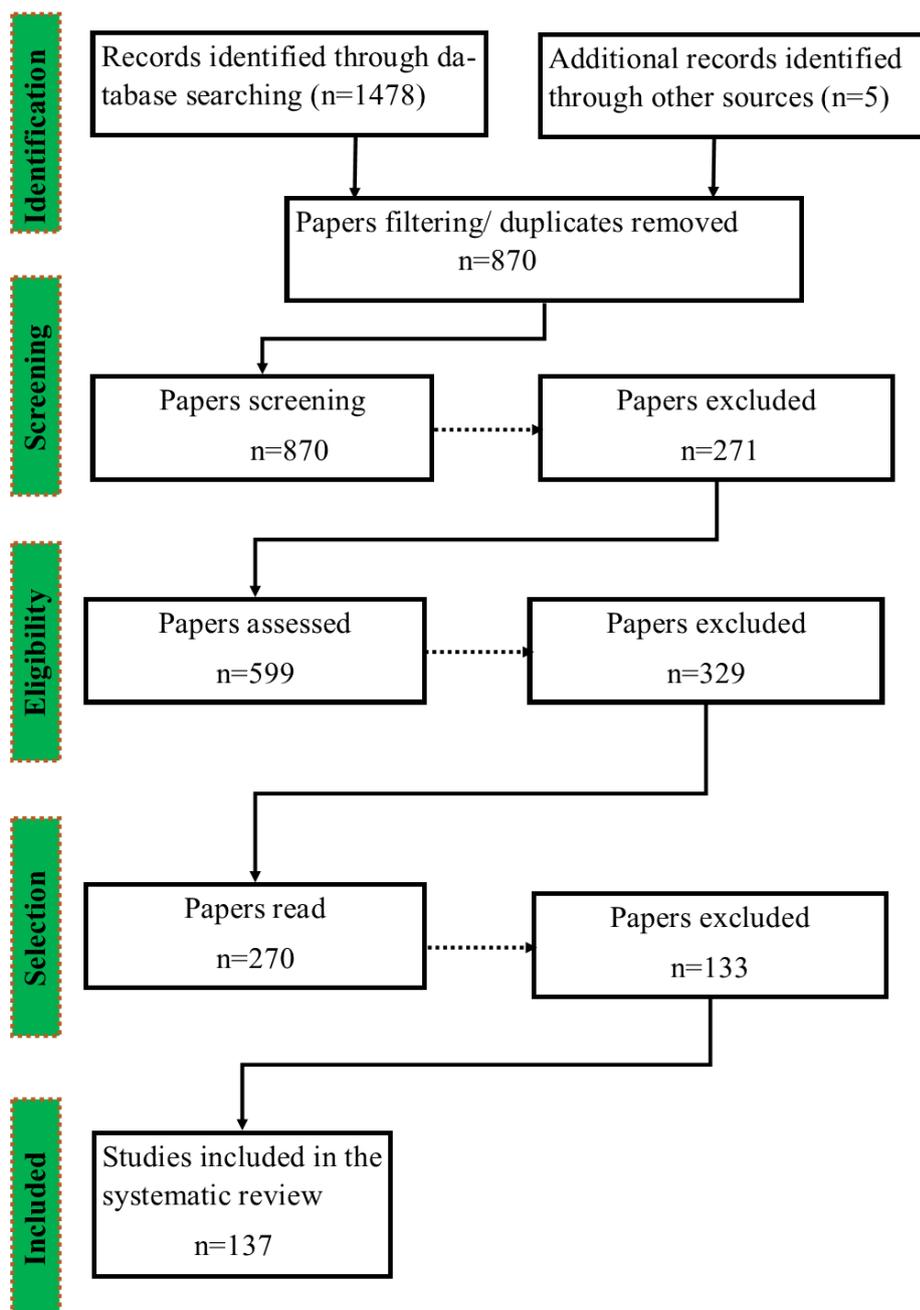
1343 This review focused on scientific papers studying tropical dryland forests
1344 and made use of remote sensing data to monitor and estimate changes in dryland
1345 forests. Airborne remote sensing studies were excluded from this review process,
1346 since the review's major focus lies on satellite Earth observation of dryland forests
1347 and because the acquisition of airborne sensors have low area coverage and high
1348 cost per unit area of ground coverage (e.g., the airborne hyperspectral images),
1349 making them spatially and temporally limited in most African countries. The
1350 systematic search approach taken to querying the literature was carried out by
1351 making use of selective keyword searches in the form of structured queries using
1352 field tags and Boolean operators through the Web of Science
1353 (<http://apps.webofknowledge.com>) and Scopus (<http://www.scopus.com>)
1354 databases. At each query, terms and keywords such as '*Dryland forests*', '*Savan**',
1355 '*Woodland*', '*Tree*', '*Vegetation*', '*Satellite*', '*Remote Sensing*', '*Optical*', '*Radar*',
1356 '*Image*', '*SAR*', and '*Earth Observation*' were used to produce an extensive list of
1357 articles, where * is a wildcard search. The results were further refined with
1358 keywords such as '*Forest change*', '*Degradation*', '*Deforestation*', '*Trend*',
1359 '*Biodiversity*', '*Phenology*', '*Biomass*', '*Structural parameter*', and also keywords
1360 representing the countries in Southern Africa, such as '*Botswana*', '*Namibia*',
1361 '*Mozambique*', '*South Africa*', to provide a comparison in terms of the numbers of
1362 studies undertaken across the region. Within the context of this review, all
1363 research articles were categorised into eight categories, including: 'Land-use/land-
1364 cover', 'Forest cover/types', 'Biomass', 'Forest structure', 'Biodiversity/habitats',
1365 'Phenology', 'Plant traits', and 'Disturbances'. Articles with a publication date
1366 between 1997 and 2020 were considered, capturing a period of two decades
1367 within the review, based on a broad set of inclusion criteria:

- 1368 1. The paper should address dryland forests and remote sensing as either
1369 main or secondary subjects.
- 1370 2. The selection terms and keywords should exist as a whole in at least one of
1371 the fields: title, keywords, and abstract.
- 1372 3. The paper should be published in a peer-reviewed scientific journal.

1373 4. The paper should be written in the English language.

1374 During the data extraction process and literature search, the research aimed to
1375 find studies meeting the criteria for peer-reviewed publications, available through
1376 the chosen indexed bibliographic databases. For this reason, the literature search
1377 did not include general non-scientific reports, books, grey literature, thesis
1378 documents or dissertations, extended abstracts, or presentations. The initial steps
1379 of the search process returned 1,478 published articles. Additional publications
1380 were added to the total set of studies by identifying relevant literature found in the
1381 reference lists of these selected papers that conform to the inclusion criteria. The
1382 review methodology was guided by the Guidelines for Systematic Review and
1383 Evidence Synthesis in Environmental Management (Collaboration for
1384 Environmental Evidence, 2013). A systematic review and meta-analysis were
1385 undertaken and framed based on the PICO (population, intervention, comparison,
1386 outcomes) model (McKenzie et al., 2019) and reported using PRISMA (Preferred
1387 Reporting Items for Systematic reviews and Meta-Analyses) flow diagram (Moher
1388 et al., 2009). The 1,478 articles were reduced to 870 articles as only the studies
1389 that had a full text available in English, papers published in peer-reviewed journals
1390 were selected for inclusion in the review, and all repetitions across databases were
1391 removed. Initially, the titles and abstracts were screened to assess eligibility, by
1392 searching for predefined keywords and terms of the abstract or summary,
1393 identifying terms 'dry or dryland forests and the country or countries where the
1394 research took place. In this way, studies not conducted in Southern Africa or
1395 dryland forests were filtered out, which reduced papers from 870 to 599 papers.
1396 The screening was followed by a full-text assessment that reduced the papers to
1397 270 by excluding studies that, for example, mentioned the term 'dryland forest'
1398 once in the abstract but did not investigate dryland forests, as outlined in the
1399 PRISMA flow diagram in Fig. 3.3. The search was subsequently refined by assigning
1400 the papers to each of the study aims they addressed and to each category for the
1401 variables identified in the search protocol, reviewing the methodologies of each
1402 publication, excluding them from further analysis if they did not meet the inclusion
1403 criteria on review. These steps reduced the total number of entries to 137
1404 scientific publications. The selected literature was reviewed systematically,
1405 searching for specific information regarding the publication temporal

1406 development, study location, remote sensing sensor/platform used, spatial and
 1407 temporal coverage, remote sensing product (e.g., biophysical indices) used, and
 1408 application areas of the study (e.g., land cover, forest biomass). The parameters
 1409 used to extract relevant information from the remaining 137 identified scientific
 1410 publications are in Table 2.1. Fig. 3.3 is a PRISMA schematic representation of the
 1411 methodology used and the derivation of the final number of articles selected.



1412

1413 Fig. 2. 3 PRISMA follow diagram (Moher et al., 2009) showing the flow of information
 1414 through the different phases of the systematic review

1415

1416

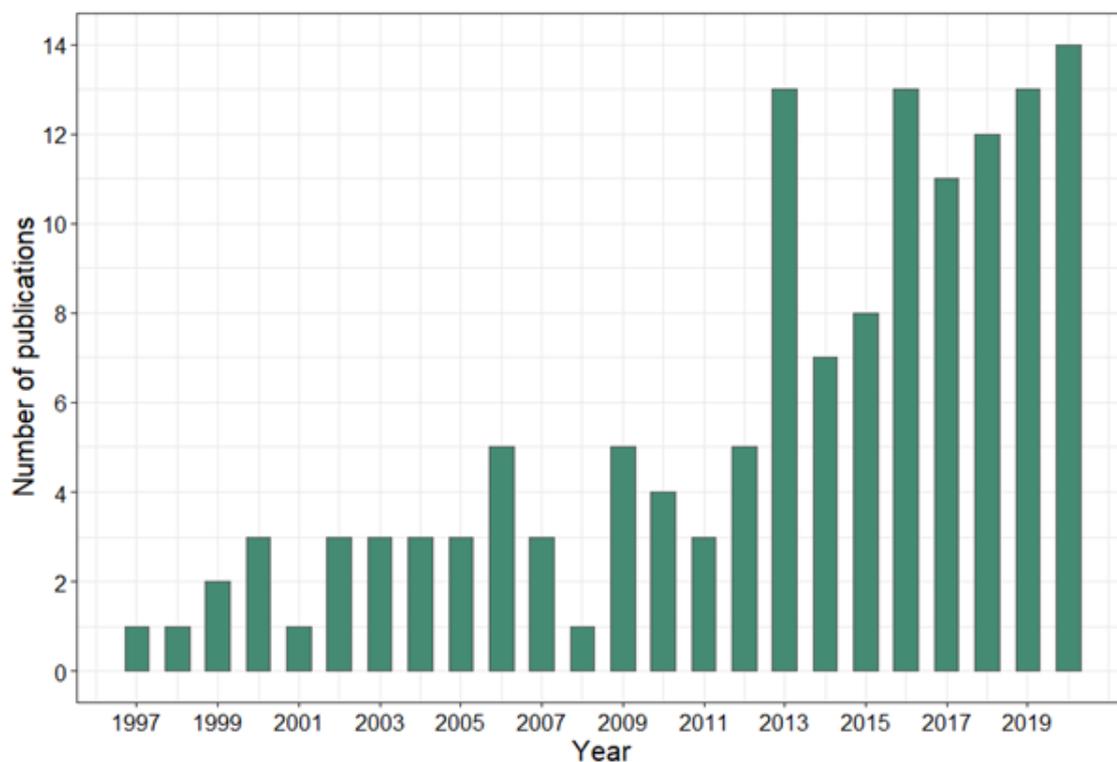
1417 Table 2. 1 Parameters used to extract relevant information for this review

General information
Paper Id
1st author's institution
Research institute city
Publication year
Publishing Journal
Journal category
No of Citation
Study type
Site specific information
Location of the study area
Study country
Forest management area
Predominant forest type
Information on remote sensing data
Sensor Type
Instrument name
Image resolution
Time period observed
Temporal resolution of EO data
Database used
Information on research
Research topic considered: Forest cover/type, disturbance, phenology, biodiversity/habitats, plant traits, land cover/land use
Parameters examined in the study
Examined object scale
Applied methodology
Information on validation and accuracy of results
Database used

1418 2.4 Results

1419 2.4.1 Temporal development of publications and author 1420 affiliations

1421 From the literature search, the cumulative number of published research papers
1422 integrating remote sensing data in dryland forests of Southern Africa grew
1423 exponentially from 2 in 1997 to 155 in 2020. The temporal development of the 137
1424 investigated research articles is illustrated in Fig. 2.4. The graphic shows that the
1425 number of studies has increased significantly over the last 23 years, with the
1426 majority of the studies published from 2013. More than 105 (80%) of articles were
1427 published from 2009 to 2020 and only 4 (3%) of articles were published before
1428 2000. The growth in number is also related to the increased availability of remote
1429 sensing platforms, sensors, data, for example, Landsat 8 in 2013 and Sentinel
1430 satellite in 2014, respectively.

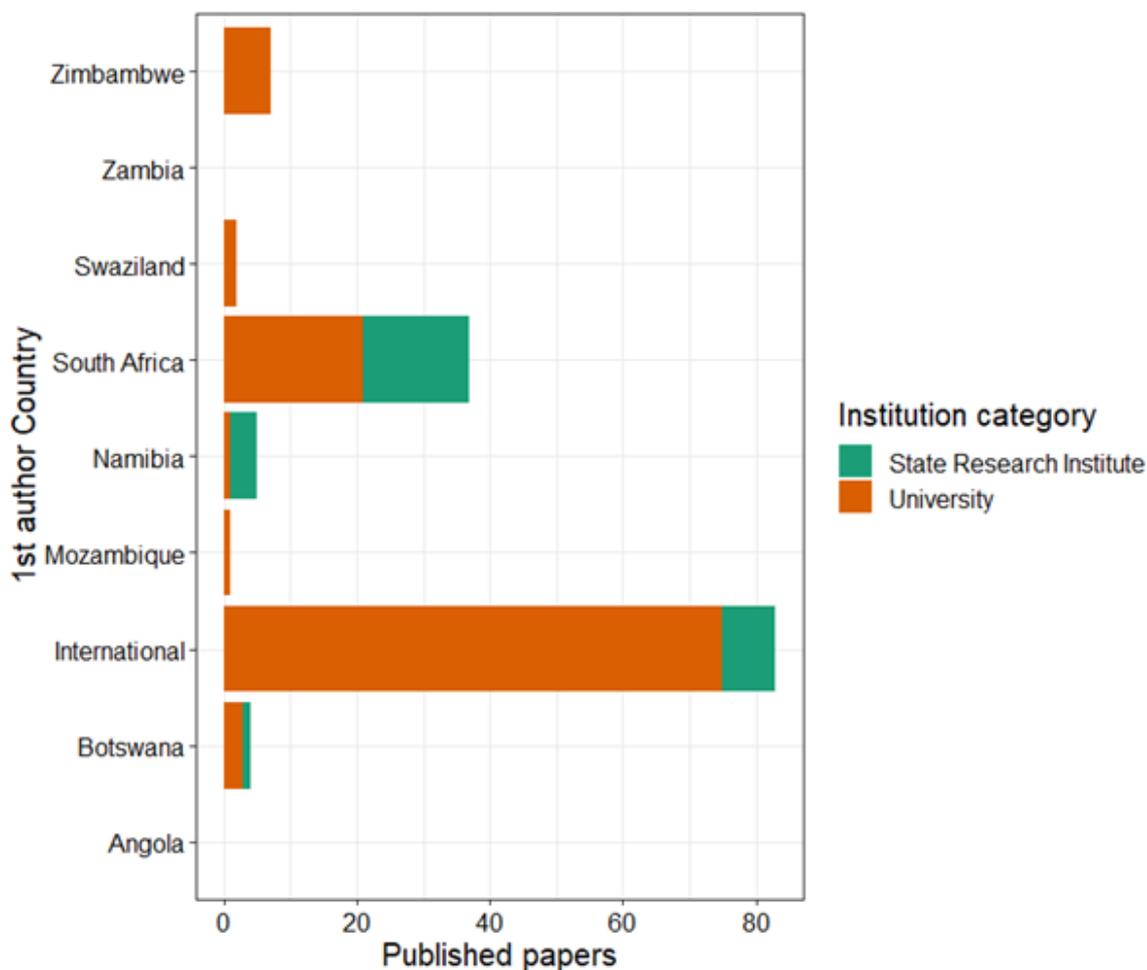


1431

1432 Fig. 2. 4. Number of papers included in the review integrating remote sensing and dryland
1433 forests in Southern Africa published annually between 1997 and 2020.

1434

1435 In the review, only studies within Southern Africa were considered; however, the
1436 majority of first authors, 83 (61%) of 137 investigated papers, are mainly
1437 scientists from international research institutions outside of the focus region,
1438 mainly the USA, UK, Portugal, Germany, and The Netherlands (Fig. 2.5). Conversely,
1439 the majority of first author institutions from Africa, 37 (27%) of published papers,
1440 were from RSA research institutions. The state funded research institutions in
1441 Southern Africa shown in Fig. 2.5 include South African Council for Scientific and
1442 Industrial Research (CSIR), South African National Space Agency (SANSA), Water
1443 Resource Commission of South Africa, South Africa Agricultural Research Council,
1444 Range and Forage Institute, Botswanan Harry Oppenheimer Okavango Research
1445 Centre, Desert Research Foundation of Namibia, and Namibia Ministry of
1446 Environment and Tourism. Considering the 137 studies conducted, about 120
1447 (90%) of the first authors are affiliated with either International and RSA
1448 institutions, but no first authors were from Zambia, Lesotho, or Angola.



1449

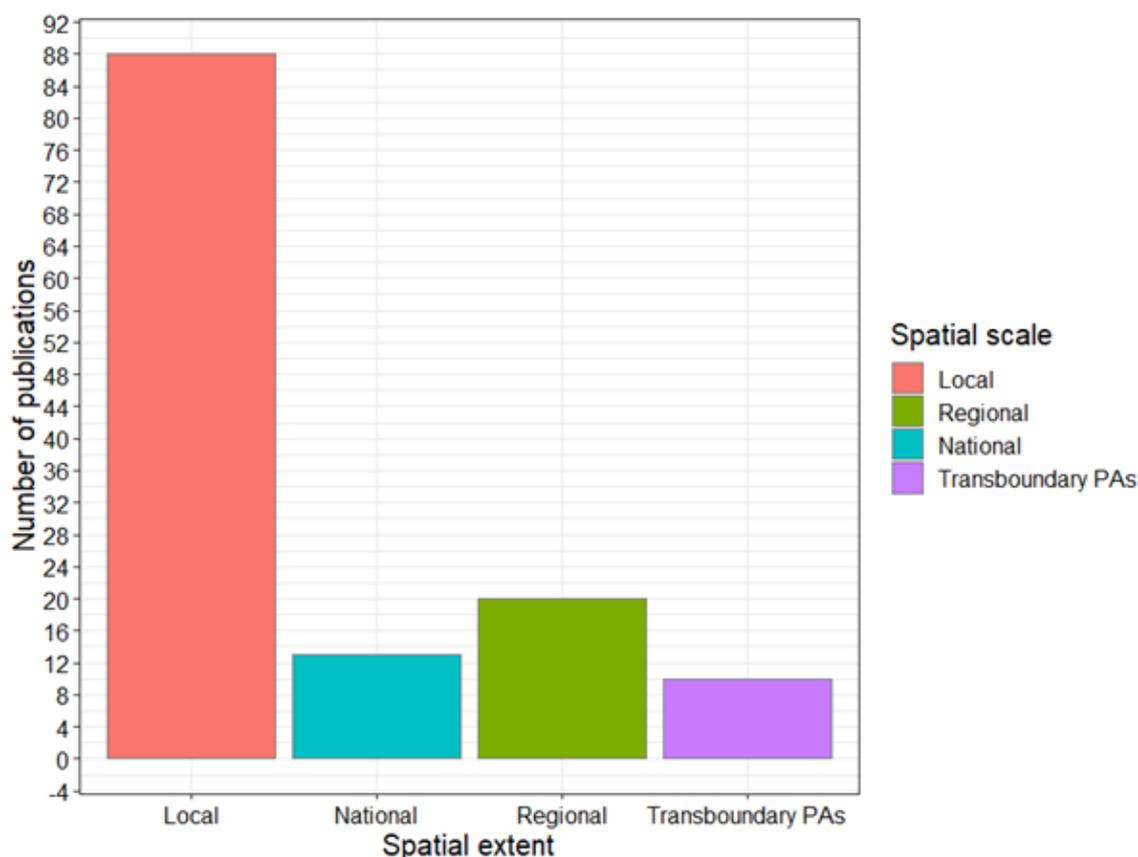
1450 Fig. 2. 5. Number of papers by research institutions.

1451

1452 2.4.2 Spatial coverage, spatial extent, and investigated 1453 protected areas

1454 Looking at the spatial scale of the study areas, the research distinguished between
1455 studies done at a local community level in a single country, termed local scale, and
1456 studies done at more than one local community or province termed regional scale.
1457 Also studies done at the national level and the whole of Southern Africa were
1458 considered. If a study covered more than three countries, it was counted as an
1459 analysis of Southern Africa. The spatial extent of the studies in the review is shown
1460 in Fig. 2.6. The majority 88 (64%) of the investigated studies focused on a local
1461 scale, despite the need for regional scale information on dryland forest
1462 distribution. From Fig. 2.6, out of 137 investigated research papers, 20 (15%) and

1463 13 (9%) research papers covered regional and national scales, respectively. Only
 1464 10 (7%) out of 137 research papers dealt with transboundary protected areas,
 1465 while 6 (4%) of research papers were covering Southern African, considering the
 1466 region as a whole, using mainly multispectral data of large spatial resolution of
 1467 1km to 8km (MODIS, SPOT, and AVHRR) to generate information on phenology,
 1468 and vegetation condition (fire or drought), as shown in Fig. 2.8.



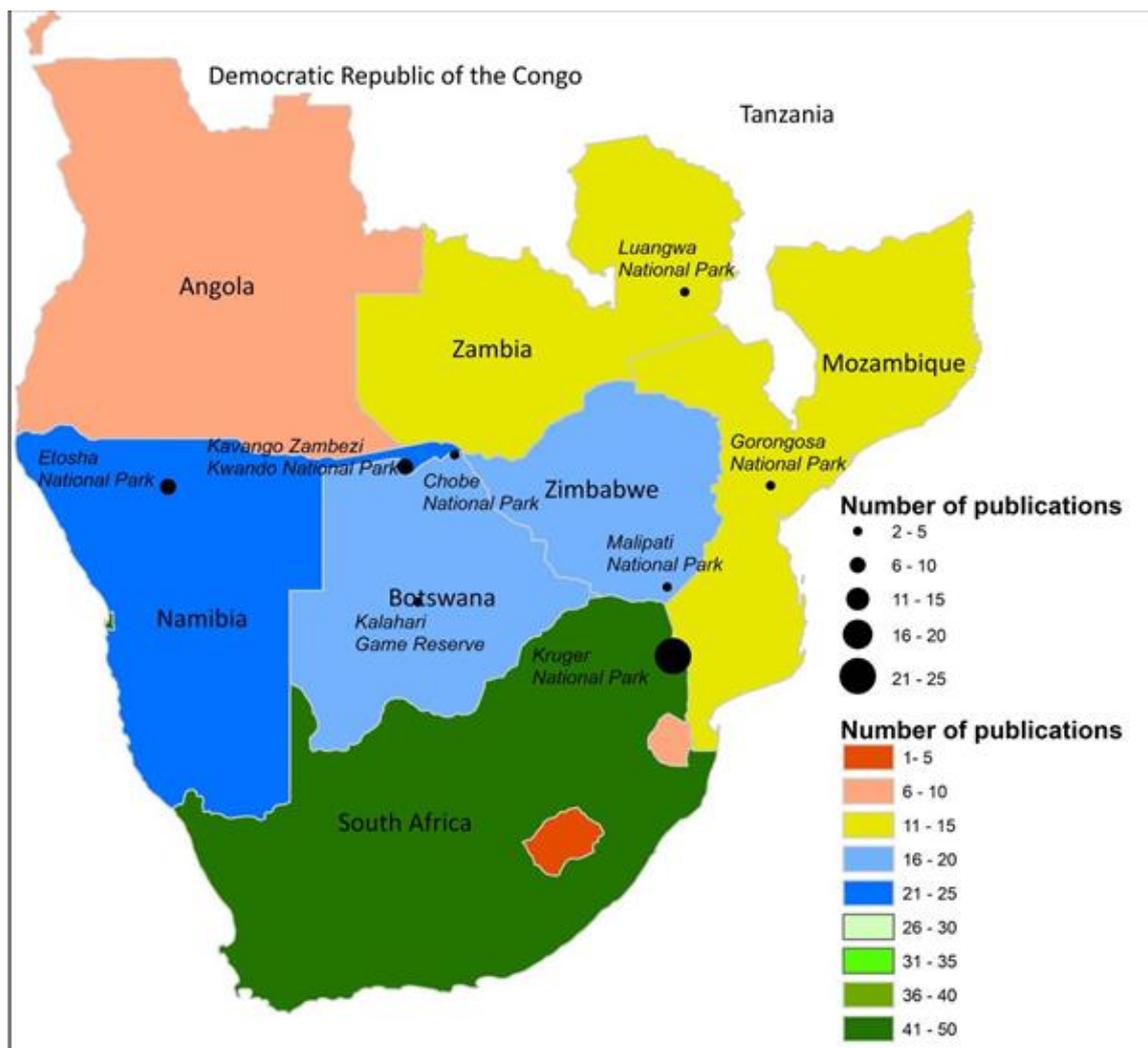
1469

1470 Fig. 2. 6. Spatial extent of investigated studies.

1471

1472 From Fig. 2.7, it is evident that considerable gaps in geographical focus of research
 1473 on tropical dryland forests mapping still exist in Southern Africa. With respect to
 1474 spatial coverage of the research, most studies, 50 (36%) of research papers were
 1475 carried out in RSA, followed by Namibia and Botswana, with 22 (16%) and 18
 1476 (13%) of research papers, respectively. Swaziland, Angola, and Lesotho were the
 1477 least frequently investigated, each with < 10 papers. Angolan dryland forests are
 1478 even less well studied with 4 (6%) of research papers, despite being found

1479 extensively in that country. Fig. 2.7 also shows the location of the most frequently
1480 studied protected areas. By far, the most studied was the Kruger National Park
1481 (NP) in RSA, involving research by local and foreign researchers from as far afield
1482 as the USA, the UK, and beyond. With this interest in the Kruger NP, there is,
1483 unfortunately, a lack of attention on other conservation areas and parks in
1484 Southern Africa. Kruger NP was the only subject of more than one-third, 23 (37%)
1485 of the 61 of all reviewed papers on protected areas. The second most frequently
1486 studied protected areas are the Etosha NP in Namibia with 6 (8%) of papers,
1487 Chobe NP with 4 (7%) of papers, and Kwando, Kavango and Zambezi
1488 transboundary NP with 8 (13%) of papers). Malipati Safari Area, South Luangwa
1489 NP, Gorongosa NP, and Central Kalahari Game Reserve were each studied 3 (5%)
1490 and 2 (3%) times.



1491

1492 Fig. 2. 7. Number of studies per country and National Park in Southern Africa. (Note: The
 1493 data are not scaled to the proportion of dryland forest area of countries, and National
 1494 Parks with fewer or no publications are not shown. Source: FAO, (1999). Reproduced with
 1495 permission).

1496 To identify land surface changes and the drivers behind these, as well as short- and
 1497 long-term trends, it is essential that EO temporal coverage has sufficiently frequent
 1498 revisit periods and resolutions. Nonetheless, this is not an easy task since the
 1499 availability of remote sensing data for long-term monitoring is constrained by
 1500 sensor characteristics (e.g., revisit time) and environmental factors (e.g., cloud
 1501 cover). Looking at the temporal resolution of the EO datasets used, the research
 1502 distinguished between data acquired at a single point in time on a monthly basis,
 1503 termed mono-temporal analyses, and on a single annual basis, termed mono-
 1504 annual analyses. In addition, multi-temporal and multi-annual to separate monthly

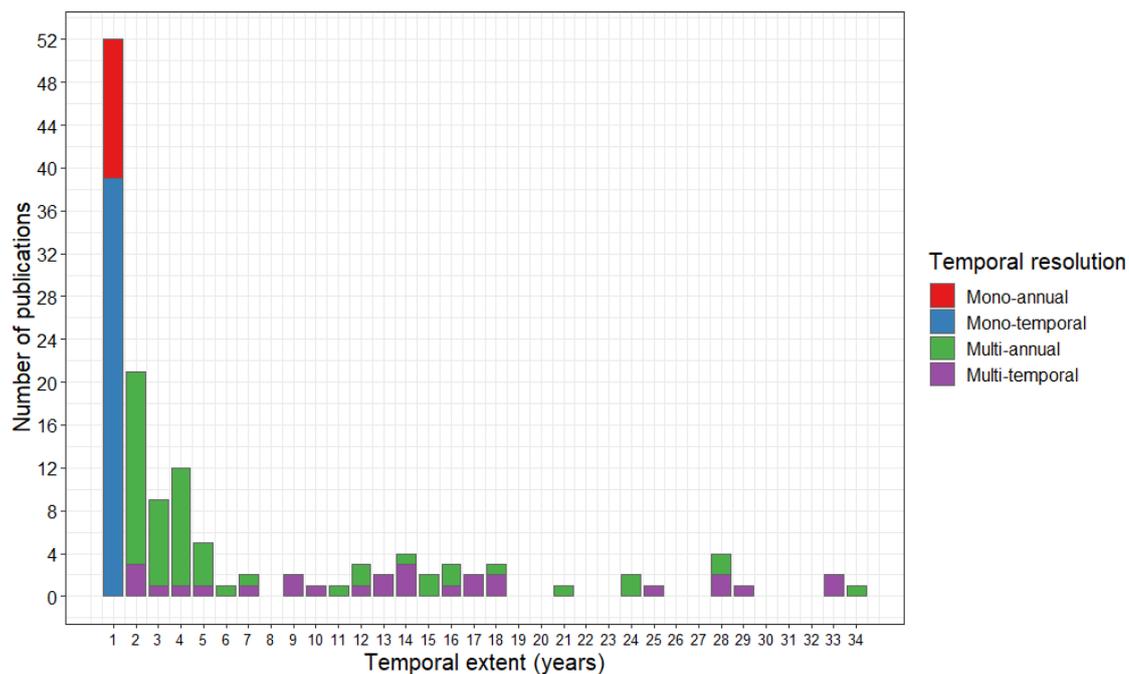
1505 and yearly analyses studies were considered. From Fig. 2.8 it is seen that the
1506 majority of published material has focused on a single temporal period. The
1507 majority of studies involved mapping over two or more years (multi-
1508 temporal/multi-annual) comparing images at two or more different times, with a
1509 bi-temporal approach based on discrete classification (e.g., Chiteculo et al., 2018;
1510 Coetzer-Hanack et al., 2016; Matavire et al., 2015). Although the bi-temporal
1511 approach is mathematically simple and does not require large data storage, it is
1512 less useful compared to the time series approach that can provide a more
1513 comprehensive understanding of the complexity of the Earth's land surface
1514 dynamics. Very few studies feature time series analysis, which is required to
1515 perform continuous long-term monitoring of changes in a tropical forest
1516 ecosystem. The majority of articles on time series analysed multi-annual data,
1517 which masks within-year variations, as compared to the detail provided at a
1518 monthly temporal scale (e.g., Akinyemi et al., 2019; Venter et al., 2020; Verlinden et
1519 al., 2006a; Wessels et al., 2006). Only 22 (16%) out of the 137 studies analysed
1520 more than 15 years and only 11 (8%) studies covered more than 20 years using
1521 monthly time series (e.g., Bunting et al., 2018; Schultz et al., 2018).

1522

1523

1524

1525



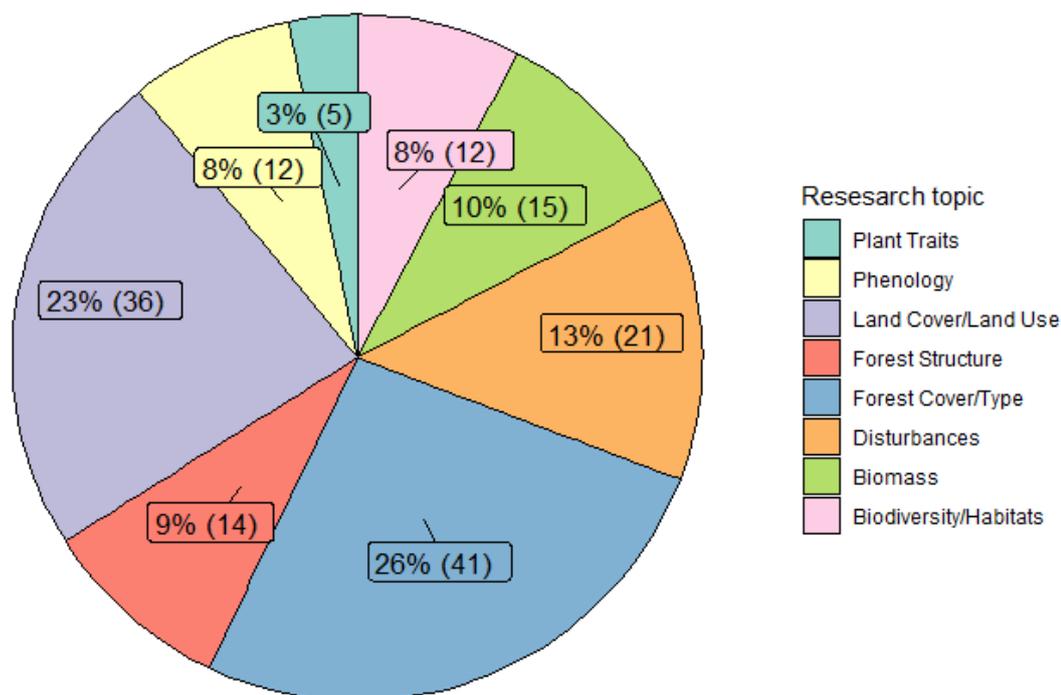
1526

1527 Fig. 2. 8. Temporal duration of studies included in the review integrating remote sensing
 1528 and dryland forests in Southern Africa between 1997 and 2020.

1529

1530 2.4.3 Research topics

1531 The study classified the large number of research topics into eight broad
 1532 categories that cover the diversity of research into dryland forests. The eight
 1533 categories, and the number of studies belonging to each of them, are shown in Fig.
 1534 2.9.



1535

1536 Fig. 2. 9. Research topic categories of reviewed articles between 1997 and 2020. Note that
 1537 some studies cover different topics, which may result in multiple entries.

1538

1539 2.4.3.1 Land cover/land use

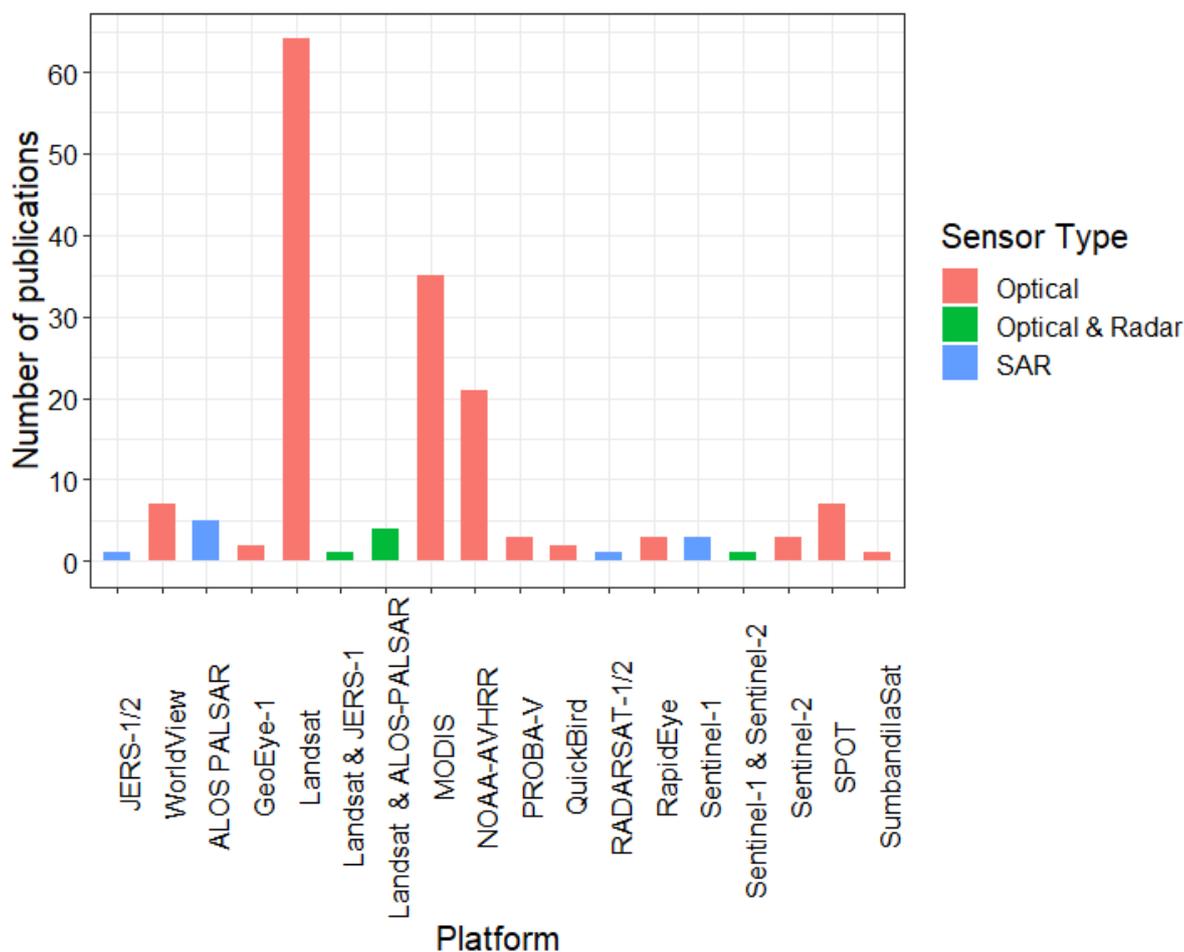
1540 Land-cover change is one of the most researched areas using EO in Southern
 1541 Africa, with 36 (23%) publications making it the second most common topic. Land-
 1542 use/cover describing land surface classification, typically represented in thematic
 1543 maps of different dryland vegetation were considered. Land-use/cover changes
 1544 with a specific focus on other dryland vegetation such as rangelands, grassland,
 1545 coastal vegetation, or plantation forests without covering dryland forests were
 1546 excluded. The majority of publications on land-use/land-cover used optical data.
 1547 For example, Landsat data have been used by more than 90% of publications,
 1548 except Daskin et al. (2016) and Hüttich et al. (2011) which used RapidEye and
 1549 MODIS data. Only one publication used a combination of Radar and optical data
 1550 (Symeonakis et al., 2018). Sentinel data have not been utilised for land cover and
 1551 land use study in the reviewed papers, probably due to the relatively recent
 1552 availability of these data. Looking at scale, the majority of papers on land-cover
 1553 change focused on the local scale in Southern Africa, but there is still a general lack

1554 of synthesis of land-use /cover change assessment at the regional, national or
1555 subcontinental scale (Fig. 2.6).

1556 2.4.3.2 Forest cover/type

1557 The majority of publications, 46 (31%) of studies cover the topic “Forest
1558 cover/type”. The forest cover/type comprises the generation of a forest/non-forest
1559 mask (Dlamini, 2017; Heckel et al., 2020), forest cover change estimation (Erkkilä
1560 et al., 1999; Ringrose et al., 2002), forest type discrimination between dryland
1561 forests (McCarthy et al., 2005), forest health assessment (Herrero et al., 2020),
1562 woody cover (Boggs, 2010; Ibrahim et al., 2018), and tree species classification
1563 (Adelabu et al., 2013; Hüttich et al., 2009). The majority of forest type/cover
1564 mapping was undertaken with optical multi-spectral data including Landsat,
1565 MODIS, and AVHRR and a few studies used high-resolution data such as RapidEye,
1566 GeoEye, and WorldView. On the other hand, a few studies on forest cover/type
1567 mapping used a combination of multispectral and spaceborne SAR data (X-band, C-
1568 band, and L-band) such as Landsat and JERS-1 (Bucini et al., 2009), Landsat and
1569 ALOS PALSAR (Higginbottom et al., 2018; Naidoo et al., 2016) and Sentinel-1 and -
1570 2 (Heckel et al., 2020) (Fig. 2.10).

1571 A few studies on forest cover/type mapping relied on field data (Bucini et al., 2009;
1572 Ibrahim et al., 2018; Schultz et al., 2018) or forest inventory plots (Heckel et al.,
1573 2020). Most studies did not include detailed field measurements (species
1574 composition, density, frequency, dominance, and basal area, percentage soil cover,
1575 total height) and had very few field samples (Gessner et al., 2013). Other studies
1576 relied on fine resolution EO data (Dlamini, 2017; Higginbottom et al., 2018), and
1577 published maps (Westinga et al., 2020) as reference data to validate their results.
1578 The majority of studies did not perform any form of accuracy assessment or
1579 validation of quantitative estimates (e.g., Campo-Bescós et al., 2013; Harris et al.,
1580 2014). Forest cover and species mapping is essential for many forestry-related
1581 tasks and play a key role in sustainable forest management; the importance of
1582 these topics can be seen in the fact that they are addressed across all countries in
1583 Southern Africa, with the majority of studies conducted in RSA, followed by
1584 Namibia and Botswana (Fig. 2.11).



1585

1586 Fig. 2. 10. Number of studies based upon platform and sensor type. Note that studies
 1587 investigating forest change with multiple platforms were counted multiple times.

1588

1589 2.4.3.3 Forest biomass and structures

1590 Fifteen research papers (10%) studied forest biomass, and fourteen publications
 1591 (10%) assessed “forest structure”. Studies on biomass included the estimation of
 1592 AGB (Dube et al., 2018; Mutanga et al., 2006), and changes in carbon stock (Gara et
 1593 al., 2017). Some of the publications used National Forest Inventory (NFI) data
 1594 (Halperin et al., 2016; Verbesselt et al., 2007), and field-based samples (Mareya et
 1595 al., 2018; Tsalyuk et al., 2017) to estimate biomass in Southern Africa.

1596 Forest structure in the review includes research on stand structure (Mathieu et al.,
 1597 2013), canopy cover (Erkkilä et al., 1999; Huemrich et al., 2005), canopy gaps
 1598 (Cho et al., 2015), and stand density (Adjorlolo et al., 2013). The majority of studies

1599 on “forest structure” in Southern Africa dealt with canopy cover (e.g., Adjorlolo et
1600 al., 2014; Yang et al., 2000). Very few studies considered vertical forest structure
1601 including tree height and tree crown diameter (e.g., Verlinden et al., 2006b).
1602 Mareya et al. (2018) utilised freely available fine resolution Google satellite
1603 imagery in combination with object-based image analysis (OBIA) to estimate tree
1604 crown areas in miombo forests and found the overall accuracy to be low and
1605 unsuitable when high accuracy is required. Some of the “forest structure”
1606 publications are also assigned to the research topic “biomass”, which discusses the
1607 relevance of forest structure for biomass (Meyer et al., 2014). Forest structure is
1608 also a very important parameter when it comes to habitat suitability, species
1609 diversity, biodiversity estimation, and conservation studies and thus some
1610 publications cover both topics (e.g., Akinyemi et al., 2019).

1611 The methods applied in the biomass and forest structure publications are diverse.
1612 Most studies employed some sort of regression analysis between in-situ field data
1613 and EO data, with the most popular methods being random forests, support vector
1614 machines, kriging, linear and generalised linear models (Berger et al., 2019;
1615 Carreiras et al., 2013; Halperin et al., 2016; Mutanga et al., 2006; Wingate et al.,
1616 2018). Williams et al. (2013) utilised the simple ensemble model to analyse
1617 biomass dynamics and found that biomass distributions can diagnose disturbance
1618 processes in miombo woodlands. Most studies utilised the normalised difference
1619 vegetation index (NDVI) in dryland forest mapping to correlate with biomass
1620 (Gizachew et al., 2016; Wessels et al., 2006), but very few studies considered other
1621 vegetation indices such as red-edge (RE)-computed indices (e.g., Dube et al., 2018;
1622 Gara et al., 2016). For the most part, optical sensors were used to derive forest
1623 biomass and structures, only four papers utilised radar data, and one paper used a
1624 combination of radar and optical data to estimate biomass (Wingate et al., 2018).
1625 More research is needed to explore the improvement of forest AGB and forest
1626 structure estimation through multi-sensor (optical and radar) data fusion.

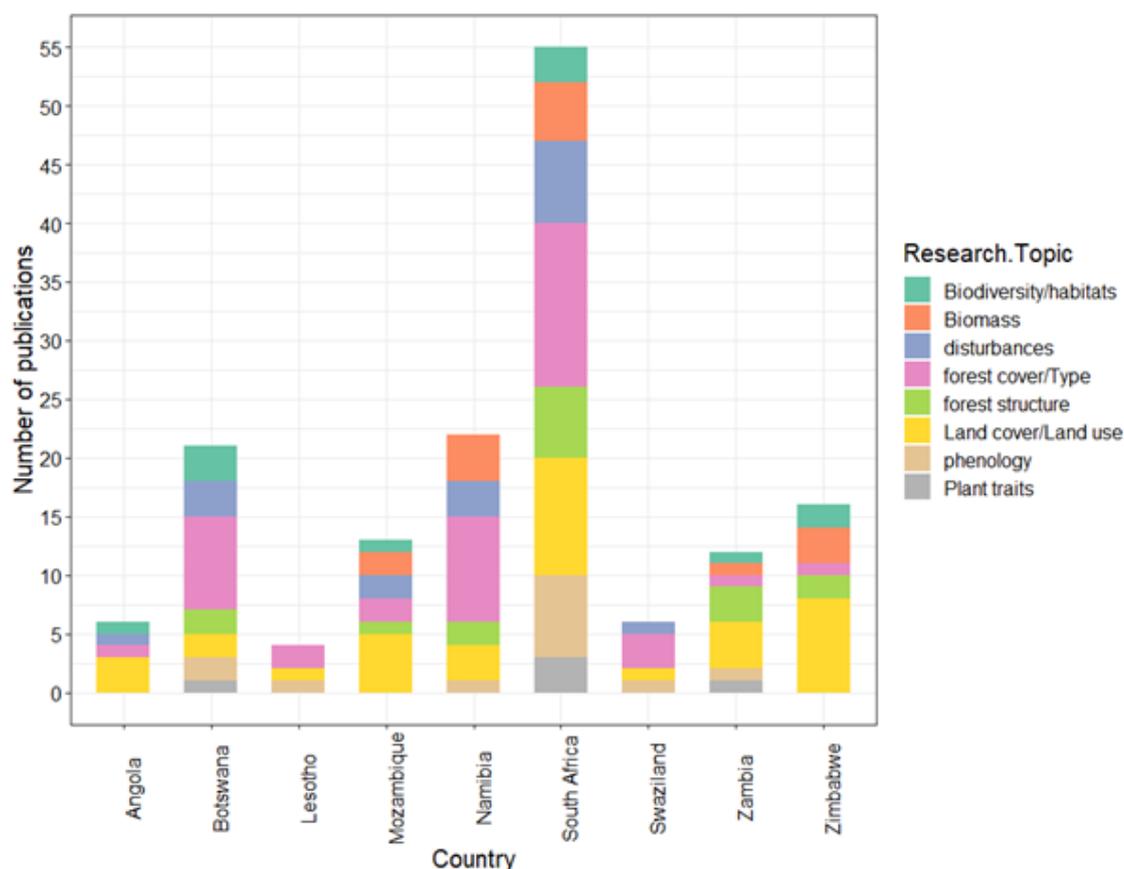
1627 2.4.3.4 Climate change and disturbances

1628 Here the study refer to dryland forests stress monitoring e.g., damage due to fire,
1629 climate/weather-related hazards including drought events, floods, extreme

1630 temperatures as part of climate change and disturbances. Twenty-one papers
1631 (13%) investigated disturbances to forest cover. Among the different forms of
1632 disturbance, fire damage was the most commonly studied (Mayr et al., 2018;
1633 Pricope et al., 2012; Roy et al., 2019; Silva et al., 2003). In the context of threats of
1634 climate change, other disturbances included drought (Lawal et al., 2019;
1635 Marumbwa et al., 2021; Urban et al., 2018) and floods (Pricope et al., 2015). A
1636 regional studies Lawal et al. (2019) used gridded climate data from the Climate
1637 Research Unit and GMMS NDVI to characterise the impact of drought to vegetation
1638 in southern Africa from 1981 to 2005; They found that the responses of vegetation
1639 varied according to season and biome, and showed that droughts had extensive
1640 impacts over the central parts of South Africa and Namibia, and the southern
1641 border of Botswana and the western parts of Zambia. In this review, only studies
1642 that investigated climate change in terms of temperature/drought in dryland
1643 forests where satellite data are a primary or secondary source of data were
1644 considered. Although there are a number of studies on climate change modelling in
1645 Southern Africa, the results show that there is a striking lack of studies
1646 investigating climate change into dryland forest change and stress monitoring.

1647 The sensors used to detect disturbances differs, with most studies using MODIS
1648 (Alleaume et al., 2005; Archibald et al., 2009; Chongo et al., 2007; Giglio et al.,
1649 2009), two publications used SPOT-VGT (Silva et al., 2003; Verbesselt et al., 2006),
1650 and one Landsat and Sentinel-2 (Roy et al., 2019). Only two publications utilised
1651 SAR data. Mathieu et al. (2019) investigated SAR Sentinel-1A C-band images for
1652 detecting surface fires in the Kruger NP, while Williams et al. (2013) used ALOS
1653 PALSAR to analyse known disturbance agents in tropical woodlands in
1654 Mozambique. The research by Urban et al. (2018) used Sentinel-1 SAR time series
1655 NDVI from Sentinel-2 and Landsat-8 to derive surface moisture for drought
1656 monitoring in the Kruger NP between 2015 and 2017. A combination/fusion of
1657 SAR and Optical data for detecting disturbances is not tested by any study. Only
1658 one study used field data as input data for validation (Alleaume et al., 2005), while
1659 two studies used forest inventory data (Verbesselt et al., 2006; Verlinden et al.,
1660 2006a).

1661 2.4.3.5 Biodiversity, plant traits, and phenology



1662

1663 Fig. 2. 11. Research topic by country. Note that the order of the mentioned topics has
 1664 changed when compared to Fig. 2.9 as some studies were conducted in several countries.

1665

1666 Twelve (8%) of the reviewed publications dealt with research questions in the
 1667 context of forest biodiversity. Almost half of the papers on forest biodiversity
 1668 examined plant species diversity (Adjorlolo et al., 2014; Chapungu et al., 2020;
 1669 Mapfumo et al., 2016). Others looked at animal species and habitat suitability (e.g.,
 1670 Cáceres et al. (2015) for birds, Ducheyne et al. (2009) for tsetse flies, impala (Van
 1671 Bommel et al., 2006), and elephants (Marston et al., 2020). Forest biodiversity is
 1672 often related to structural canopy parameters. Most studies, nine (75%) of twelve
 1673 used Landsat to derive parameters such as plant canopy height, species
 1674 occurrence, richness, and diversity. Three (25%) of the studies used MODIS data
 1675 (e.g., Fullman et al. (2014) used MODIS at 250 m pixel resolution and a Moving
 1676 Standard Deviation Index (MSDI) to detect elephant-modified vegetation along the
 1677 Chobe riverfront in Botswana; Akinyemi et al. (2019) utilised 1 km spatial

1678 resolution of SPOT - VGT and PROBA-V annual time series of 18 years to
1679 understand species diversity and richness assessment based on the Vegetation
1680 Degradation Index in Palapye Botswana.; Adjorlolo et al. (2014) investigated the
1681 utility of SPOT-5 multispectral data to assess tree equivalents and total leaf mass to
1682 model grazing and browsing capacity in KwaZul-Natal province in RSA.

1683 Five papers (3%) dealt with different plant characteristics, known as plant
1684 functional traits. These include canopy chlorophyll content (Cho et al., 2012), leaf
1685 nitrogen concentration (Cho et al., 2013), and vegetation water content (Verbesselt
1686 et al., 2006), and Leaf Area Index (LAI) (Scholes et al., 2004). Plant functional traits
1687 including vegetation biophysical and biochemical properties (e.g., pigment levels,
1688 nitrogen content) are often related to patterns of biodiversity. Huemmrich et al.
1689 (2005) explored monthly MODIS data at 1 km spatial resolution over two years to
1690 estimate LAI and the fraction of absorbed photosynthetically active radiation
1691 (FAPAR) and found that ground-measured LAI values correspond well with MODIS
1692 LAI, and showed a discrepancy with FAPAR. Cho et al. (2012) utilised variogram
1693 analysis and the red edge shift from SumbandilaSat and SPOT 5 to estimate canopy
1694 chlorophyll content in Dukuduku forest in Southern Africa and found that
1695 SumbandilaSat provides additional information for quantifying stress in vegetation
1696 as compared to SPOT image data. All studies on plant traits were undertaken at the
1697 local scale.

1698 Looking at research categories per country, biodiversity/habitat publications were
1699 mainly undertaken in Botswana and RSA (Fig. 2.11). All studies in the context of
1700 forest biodiversity and plant traits covered only mono-temporal and multi-annual
1701 classifications. Only two studies utilised multi-annual time series (Akinyemi et al.,
1702 2019; Verbesselt et al., 2006), and one study used MODIS multi-temporal time
1703 series over two years (Huemmrich et al., 2005). All of these studies focused on a
1704 coarse resolution of 1 km.

1705 Phenology is also strongly linked to plant traits, but analysis puts more emphasis
1706 on the seasonal variations including growing season (green-up date) (Archibald et
1707 al., 2007; Whitecross et al., 2017), end of the season, and length of the season
1708 (Davis et al., 2017). To date, phenological research in Southern African dryland
1709 forests is limited, and more than half of the published papers on phenology focused

1710 only on examples from RSA. In the few studies that have analysed phenology, most
1711 studies dealt with estimating leaf flush and early-greening dates (Chidumayo,
1712 2001; Higgins et al., 2011). For example, Archibald et al. (2007) developed an
1713 intricate algorithm that used MODIS NDVI products and field-based parameter
1714 estimates to predict green-up dates for grass and tree components at a site in the
1715 Kruger NP in RSA. Jolly et al. (2004) compared a water balance model to a 3-year
1716 NDVI time series and found the deviation between the onset of leaf flush predicted
1717 by the model and empirical data was between 10 and 40 days.

1718 2.5 Discussion

1719 2.5.1 Temporal extent

1720 In this article, the current research with EO on dryland forests, with a particular
1721 focus on Southern Africa were synthesised. Although the volume of scientific
1722 literature has demonstrated a sharp increase, the use of remote sensing is still
1723 limited, and up until 2013, the number of publications on this topic was relatively
1724 small. Substantial research on the dryland forests of Southern African is mainly
1725 based on single-date observations, and comparing classified images at two or more
1726 different times. Maps that relate successive land cover change between two dates
1727 typically lack information regarding underlying processes and do not enable
1728 insights on the nature of the transformations present, such as the rate or
1729 persistence of change (Lambin et al., 2003). Time series analysis on dryland
1730 forests, which enables tracking changes is scarce, only 22 (16%) out of 137 studies
1731 feature time series lengths that exceed 15 years and only 11 (8%) studies that
1732 cover more than 20 years. Longer time series of remote sensing data afford the
1733 ability to assess the dynamics of forest structures, biodiversity, degradation,
1734 disturbance from climatic extremes, and change in phenology, in which a gap still
1735 exists.

1736 2.5.2 Spatial scale

1737 Another finding that stands out from the analyses is that there are very few studies
1738 at the national and regional levels. Despite new sensor and EO data availability, it

1739 is clear that a systematic and consistent regional monitoring of dryland forests is
1740 not yet fully exploited and is still in its infancy in Southern Africa. In fact, the
1741 majority of publications 88 (64%) concentrated their research efforts on local
1742 scale investigations (Fig. 2.6). Desanker et al. (2001) and Geist (2002) also
1743 emphasised that Southern Africa is limited to local-scale studies, thereby lacking a
1744 simultaneous analysis of the impacts of these changes at a larger scale. To fully
1745 assess regional and long-term implications for tropical dryland forest change
1746 studies, analyses on large(r) scales are needed, ideally with higher spatial
1747 resolutions and longer temporal duration.

1748 2.5.3 Accuracy assessment

1749 Through evaluation of the literature, the review identified that the assessment of
1750 accuracy for thematic/classified maps and statistical data to be another important
1751 issue, with only 54 (39%) of the studies appearing to have performed some form of
1752 accuracy assessment. The results show there is limited information on sources of
1753 error and uncertainty levels of the estimates provided by most studies. The review
1754 found that most forest and vegetation-related scientific outputs in Southern Africa
1755 are not yet strongly linked to field measurements and forest inventory data.
1756 Among the reviewed studies, very few studies utilised field test sites/ ground-
1757 based independent datasets for accuracy assessment, while other studies
1758 estimated uncertainties using other procedures e.g., using a sample of finer spatial
1759 resolution remote sensing data, or did not report the map uncertainty. Some
1760 studies employed root-mean-square error to assess model accuracy (RMSE) (e.g.,
1761 Adjorlolo and Mutanga, 2013; Higginbottom et al., 2018), while many studies used
1762 an error matrix to assess map uncertainties, which was employed for instance (e.g.,
1763 Adelabu et al., 2013; Hüttich et al., 2011). However, some studies used sample
1764 points below the desirable target number of validation points per class (e.g., Cabral
1765 et al., 2011), while studies briefly mentioned that a confusion matrix was
1766 calculated but did not report how many sample points were used for validation
1767 (e.g., Chagumaira et al., 2016). Congalton. (1988) suggests planning to collect a
1768 minimum of 50 samples for each map class for maps of less than 1 million acres in
1769 size with less than 12 classes. It has been empirically confirmed that a good
1770 balance between statistical validity and practicality for larger area maps or more

1771 complex maps can be achieved with about 75 to 100 sample sites per class
1772 (Congalton & Green, 2009).

1773 Globally, owing to TDFs low commercial importance in comparison to other
1774 tropical forests such as moist forest, they are often not assessed by field surveys, or
1775 surveyed regularly by governments (Keenan et al., 2015). Independent validation
1776 data for dryland forest estimations are rarely available because acquiring
1777 appropriate field survey data is a time-consuming and expensive task. In Southern
1778 Africa, these areas are often remote and dangerous to visit in the field, due to the
1779 hazard posed by wildlife and if present, unexploded landmines, almost
1780 impracticable to obtain independent validation data for large(r) area studies,
1781 especially for many protected areas. Despite challenges to obtain ground-based
1782 observation, effective integration of these data and remote sensing methods will be
1783 key to accurately mapping and monitoring dryland forest across a range of spatial
1784 scales and in reporting the accuracy of models. However, the applicability of
1785 remotely measured geospatial data is reliant on quality and translating remote
1786 sensing data into accurate and meaningful information is often a challenge prone
1787 to errors (Congalton et al., 2009; Donoghue, 2002). In this context, it is critical to
1788 ensure the validity of these data and their suitability for each particular
1789 application, particularly where coarse spatial maps can be misleading. In addition,
1790 characterising dryland forest for large areas of Africa cannot entirely rely on global
1791 and pantropical monitoring studies for dry forest estimation because global forest
1792 monitoring generally underestimates, and in some instances overestimates,
1793 dryland biomes (Bastin et al., 2017).

1794 2.5.4 Research topics and geographical focus

1795 The classification of studies into eight broad subject categories revealed forest
1796 cover/types 41 (26%) and land cover/land use 36 (23%) to be the most commonly
1797 researched topics. Topics receiving less attention included phenology, plant traits,
1798 and biodiversity/habitats, and disturbances with regards to climate change (Fig.
1799 2.9). With regards to disturbances, fire damage was the most commonly studied
1800 but there is a missing body of literature on the climate change impact on the
1801 composition, biodiversity, and ecological health of dry forest ecosystems in most

1802 countries of Southern Africa. The thesis also found an interesting, non-uniform
1803 spatial distribution of dryland vegetation and forest studies using spaceborne
1804 remote sensing, particularly when considering disparities among countries and
1805 across protected areas. The distribution of research categories by country reveals
1806 that RSA is, by far the most studied nation across all categories in Southern Africa
1807 (Fig. 2.7). It should be noted that care should be taken here not to assume that the
1808 number of studies equates to research quality, which remains difficult to articulate
1809 from a review of this nature. However, the dryland forests of Mozambique,
1810 Lesotho, Swaziland, and Zambia are noticeably very poorly studied. Studies on the
1811 dryland forests of Angola are even less frequent, receiving relatively little global
1812 attention, and the few studies conducted on its forests were mostly conducted by
1813 researchers from Portuguese Universities (Catarino et al., 2020; Leite et al., 2018).
1814 The focus of publications tended to be biased towards conservation and national
1815 parks, particularly as a large proportion of studies were undertaken in the Kruger
1816 NP, leaving many other private and international protected areas relatively
1817 understudied. Transboundary conservation areas, such as Kavango-Zambezi
1818 (KAZA), have received relatively little attention but merit further research in terms
1819 of the vast dryland forests extent, biodiversity, species abundance and diversity,
1820 and the potential for this area to form important corridor areas for wildlife
1821 animals. There is a further concern as a result of such gaps because some of the
1822 dryland forests, and species to which they are home, notably in countries like
1823 Angola and Zambia, are listed on the IUCN red list and would almost certainly
1824 merit Alliance for Zero Extinction (AZE) ranking (Cumming, 2008). Furthermore,
1825 future efforts to estimate important variables such as forest cover and biomass
1826 need not be restricted by country boundaries. Future studies, based on medium-
1827 fine resolution EO and validated with field data, will provide information to
1828 improve the understanding of African dryland vegetation and its management.

1829 2.5.5 Vegetation indices, optical, SAR, and fusion of optical 1830 and SAR sensors

1831 The most commonly used vegetation index was the NDVI, with more than half of
1832 the studies, 84 (54%) of papers utilising this index, but only 13 (8%) of papers
1833 used Enhanced Vegetation Index (EVI) and soil-adjusted vegetation index (SAVI).

1834 Other vegetation indices such as the Green Normalised Difference Vegetation Index
1835 (GNDVI) and Sentinel red-edge related indices and passive microwave
1836 observations such as Vegetation Optical Depth were not utilised in studies
1837 considered in this review. One major problem commonly encountered in the less
1838 studied ecosystems, such as dryland forests, is that of generalising or transferring
1839 knowledge and methods derived from remotely sensed imagery over both space
1840 and time (Foody et al., 2003). For example, commonly used vegetation indices and
1841 classification schemes are in general mainly been calibrated on other, better-
1842 studied ecosystems, such as temperate or rain forests, and this has led to poor
1843 accuracy results when extrapolated, to for example, tropical dryland forests. This
1844 phenomenon justifies the importance of utilising a range of vegetation indices
1845 when studying dryland forests using EO data. Imagery from optical sensors is most
1846 commonly used, out of all sensor types, providing the data used in 90% of papers
1847 reviewed, followed by SAR data with 6%. The fusion of optical and radar data was
1848 rarely used, with only 4% of publications exploring this. The most frequently used
1849 platforms are Landsat, followed by MODIS and AVHRR. Imagery taken by the
1850 Sentinel-1/2 satellites only makes up a small portion of the remote sensing data on
1851 dryland forests. For example, Sentinel-2 was only used by 2% of investigated
1852 studies, but this may reflect the relatively short period (since 2015) when these
1853 data have been available.

1854 2.5.6 Remote sensing platforms and cloud-based computing

1855 Most of the EO data used in the publications reviewed were downloaded, and are
1856 available at no cost from a number of online portals, including the Oak Ridge
1857 National Laboratory (ORNL), the United States Geological Survey (USGS)
1858 Distributed Active Archive System (DAAC) and Earth Explorer (EE) tool. The lack
1859 of remote sensing research centres in most Southern African research institutions
1860 may contribute to limit the number of African Scientists engaged in monitoring
1861 forests resources. For example, most studies in RSA made use of remote sensing
1862 data through the University of the Witwatersrand, Satellite Application Centre
1863 (SAC), the South African National Space Agency (SANSA), and the Council of
1864 Science and Industrial Research (CSIR). The development of remote sensing
1865 capacity at local universities has inevitably contributed to RSA universities and

1866 research institutions conducting the majority of studies in Southern Africa (Fig.
1867 2.5). To improve EO data access, and the skills to handle and interpret this across
1868 Southern Africa, there is a need to increase the number of local institutions that
1869 distribute the remote sensing data, and who have the capacity to access and use
1870 innovative web-based platforms such as the Google Earth Engine (GEE) and
1871 Amazon Web Services to overcome some of the logistical and financial constraints
1872 of this type of research.

1873 Southern African countries face considerable technical challenges with remote
1874 sensing, particularly in respect to REDD+-related research on dryland forests
1875 monitoring. Freely available tools, for example, the cloud-based geospatial analysis
1876 platform Google Earth Engine (GEE), make it easier to access powerful computing
1877 resources for processing and analysing pre-processed large-scale datasets
1878 (Shelestov et al., 2017). However, only nine papers (6%) out of 137 used GEE to
1879 access or analyse remote sensing data. The “near real-time” remote sensing data
1880 offered by GEE is of particular interest for monitoring changes and automating the
1881 analysis of time-series, when detecting and tracking trends in surface reflectance
1882 properties. With increasing spatio-temporal coverage of satellite data and
1883 computational platforms that reduce the need for costly local infrastructure (e.g.,
1884 GEE), there is an opportunity to overcome the limitations previously enforced by
1885 large volumes of data and the scale of analysis, whereby the knowledge of dryland
1886 forest dynamics can be improved in the upcoming years.

1887 2.6 Conclusion

1888 This review summarises research progress towards the use and integration of
1889 remote sensing data within the context of monitoring dryland forests in Southern
1890 Africa, using a systematic review methodology that focused on 137 most relevant
1891 research articles. The study has systematically reviewed the temporal and spatial
1892 coverage of these studies, their application area, and the remote sensing platforms
1893 and sensors used. Based on the results, the following conclusions can be drawn.
1894 There is a broad range of topics covered by research on dryland forests, from
1895 which land-use/land-cover and forest cover and disturbances from the fire were
1896 the most frequently studied. However, there is still a relative lack of studies

1897 assessing dryland forest structure, phenology, biodiversity/habitats, plant traits,
1898 and disturbance from climatic extremes, suggesting additional research is
1899 required. The majority of studies relied on single-date or annual data and bi-
1900 temporal discrete classification; only a very few studies employed time series
1901 analysis.

1902 The thesis considers some of the limitations of the research reviewed, which
1903 indicates a need for more frequent use of field and inventory data, a greater use of
1904 validation/accuracy assessments, and testing other vegetation indices beyond
1905 NDVI and EVI such as the Vegetation Optical Depth and Sentinel-2 red-edge related
1906 indices. In addition, further improvements should focus on for extensive
1907 combination and fusion of SAR and optical data in order to have a temporally and
1908 spatially consistent data set necessary for several applications in dryland forests.
1909 Given the state of decline of woody vegetation condition in Southern Africa, long-
1910 term monitoring of monthly time series of EO data at regional and transboundary
1911 scale clearly hold potential to capture dryland forests dynamics and to understand
1912 their current status and future trends. A significant move from EO predictions that
1913 are extremely site-dependent to large(r) ecoregional level monitoring approach
1914 that integrates a range of remotely-sensed data of sufficiently fine spatial and
1915 temporal resolution with field measurements and using machine/deep learning
1916 models could provide a sound basis for assessing dryland forest-related changes
1917 and dynamics. Information inferred from these kinds of models would be
1918 extremely useful for the current knowledge, management and conservation of the
1919 dryland forests as well as for understanding their responses to disturbance
1920 (natural or anthropogenic) and climatic change at regional to sub-continental level.
1921 Finally, there is significant geographical heterogeneity in study coverage; whilst
1922 there is substantial research on the forests in the Kruger NP and across RSA, the
1923 same cannot be said for other areas of Southern Africa. The EO interventions not
1924 only assess deforestation rate, but also support other forest related REDD+
1925 activities such as sustainable forest management which reduce forest degradation
1926 and enhance forest carbon stocks at a range of scales, transcending both provincial
1927 and national boundaries e.g., Kavango-Zambezi Transfrontier Conservation Area
1928 (KAZA TFCA). Nevertheless, REDD+-related research on dryland forests in most
1929 Southern African countries and protected areas has been limited, with clear gaps

1930 across Angola, Mozambique, Zambia, and Zimbabwe. Finally, Africa has the
1931 potential to emulate other continents, such as Latin America, that have made
1932 notable progress in employing freely available remote sensing data to monitor
1933 tropical dryland forest area change and biomass on a large scale.

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1942 York.

1943

1944 **3 IMPROVING ABOVE GROUND BIOMASS ESTIMATES OF**
1945 **SOUTHERN AFRICA DRYLAND FORESTS BY**
1946 **COMBINING SENTINEL-1 SAR AND SENTINEL-2**
1947 **MULTISPECTRAL IMAGERY.**

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1967

1968 **Title:** Improving above ground biomass estimates of Southern Africa dryland
1969 forests by combining Sentinel-1 SAR and Sentinel-2 multispectral imagery.

1970

1971

1972 Authors: Ruusa M. David, Daniel N.M. Donoghue, Nick J. Rosser

1973

1974

1975 Department of Geography, Durham University, Science Laboratories, DH1 3LE
1976 Durham, UK

1977

1978

1979

1980 **Author Contribution**

1981

1982 David Ruusa- Design the research, perform the data analysis, interpret the results,
1983 wrote the manuscript, and revised the manuscript. Nick Rosser- Contributed to the
1984 research design, manuscript editing and supervision. Daniel Donoghue-
1985 Contributed to the research design, conducting fieldwork, manuscript editing and
1986 supervision.

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1997 **Abstract**

1998 Having the ability to make accurate assessments of above ground biomass (AGB) at
1999 fine spatial resolution is invaluable for the management of dryland forest
2000 resources in areas at risk from deforestation, forest degradation pressure and
2001 climate change impacts. This study reports on the use of satellite-based synthetic-
2002 aperture radar (SAR) and multispectral imagery for estimating AGB by correlating
2003 satellite observations with ground truth data collected on forest stands from
2004 dryland forests in the Chobe National Park, Botswana. The study undertooks
2005 nineteen quantitative experiments with Sentinel-1 (S1), Sentinel-2 (S2) and
2006 Landsat 8 OLI (LC8) and tested simple and multivariate regression including
2007 parametric (linear) and non-parametric (random forests) algorithms, to explore
2008 the optimal approaches for AGB estimation. The largest AGB value of 145 Mg/ha
2009 was found in northern Chobe while a large part of the study area (85%) is
2010 characterised by low AGB values (< 80 Mg/ha), with an average estimated at 51
2011 Mg/ha. The results show that the AGB estimated using SAR backscatter values
2012 from vertical transmit receive (VV) polarisation is more accurate than that based
2013 on horizontal receive (VH) polarisation, accounting for 58% of the variance
2014 compared to 32%. Nevertheless, the combination of S1 SAR and S2 multispectral
2015 image data produced the best fit to the ground observations for dryland forests
2016 explaining 83% of the variance with an accuracy of 89%. Furthermore, the optimal
2017 AGB model performance was achieved with a multivariate random forest (MRF)
2018 regression trees algorithm using S1 (SAR) and S2 (multispectral) image data ($R^2 =$
2019 0.95 ; $RMSE = 0.25$ Mg/ha). From the 11 vegetation indices tested, GNDVI,
2020 Normalised Difference Red Edge (NDRE1), and NDVI obtained the highest linear
2021 relationship with AGB ($R^2 = 0.71$ and $R^2 = 0.56$, $p < 0.001$), however, GNDVI and
2022 NDRE1 improved the AGB estimation at medium to high-density forests compared
2023 to NDVI. The GRVI and EVI were the least correlated with AGB ($R^2 = 0.09$ and $R^2 =$
2024 0.31) at a significance level of $p < 0.001$, respectively. The thesis shows that NDVI
2025 saturates in areas with >80 Mg/ha AGB, whereas the inclusion of SAR backscatter
2026 and optical red edge bands (B5) significantly reduces saturation effects in areas of
2027 high biomass. GNDVI and red edge (B5) derived vegetation indices have more
2028 potential for estimating AGB in dryland forests than NDVI. This study results
2029 demonstrate that dryland AGB can be estimated with a reasonable level of

2030 precision from open access Earth observation data using multivariate random
2031 forest regression.

2032 **Keywords:** Dryland forests, Above ground biomass, Random forest, Linear
2033 regression, Sentinel, SAR, Southern Africa, Chobe, Conservation

2034 3.1 Introduction

2035 Dryland forests in Southern Africa are currently experiencing high rates of forest
2036 loss as a result of overexploitation, wildfire, and herbivory, and are projected to
2037 experience the impacts of climate change (Miles et al., 2006). Although large
2038 uncertainties surround the contribution of tropical savanna forests and open
2039 woodland (hereafter referred to as dryland forests) to the global carbon budget,
2040 recent studies have shown that dryland above ground biomass (AGB) is a more
2041 dominant driver of variations in the global carbon cycles when compared with
2042 moist tropical forests (Ahlström et al., 2015; Poulter et al., 2014). However,
2043 wildfires and a high density of mega-herbivores in most protected/conservation
2044 areas (particularly elephants, *Loxodonta africana*) can have a significant impact on
2045 tree cover and structural diversity by modifying vegetation structure through
2046 grazing and physical damage thereby making trees less tolerant to fire (Ben-
2047 Shahr, 1996; Shannon et al., 2011). With these pressures degrading the dryland
2048 forests, techniques are urgently needed to measure, map, and monitor the forest
2049 stand parameters reliably and to produce this information at appropriate scales to
2050 support conservation and management actions. AGB estimates from sub-tropical
2051 dryland forests have received less attention than many other biomes and so
2052 estimates of AGB remain highly uncertain, despite the importance of these areas as
2053 carbon stores and for ecosystem services (Pennington et al., 2018; Olson and
2054 Dinerstein, 2002). For instance, studies of tropical moist forests are well
2055 represented in the scientific literature (Salis et al., 2006; Williams et al., 2008),
2056 primarily because they have the highest carbon (C) uptake of the World's forests
2057 (Olson and Dinerstein, 2002). The largest proportion of dryland forests ecosystems
2058 are found in Africa, accounting for 60 - 80% of the total biome area (three times
2059 the area covered by African rain forest) (Bodart et al., 2013; Bullock et al., 1995),
2060 which provides a significant carbon stock for the African continent.

2061

2062 AGB is recognised as an essential terrestrial climate variable (ECV) by the Global
2063 Climate Observing System (GCOS) led by the UN Framework Convention on
2064 Climate Change (UNFCCC) (Bojinski et al., 2014). In addition, having information
2065 on AGB, and other biophysical structural parameters such as canopy height and
2066 habitat density in dryland forests can feed into a wide range of activities related to
2067 carbon accounting and conservation purposes (Wulder et al., 2012). Information
2068 about the distribution of biomass at local, regional, and global scales can also
2069 detect land changes due to factors such as deforestation (a reduction in a
2070 woodland area) and forest degradation (Harris et al., 2012; Saatchi et al., 2011).
2071 However, at the same time, dryland forests experience an increase in woody
2072 carbon stock, including widespread regrowth following shifting cultivation, bush
2073 encroachment, and a reduction in browsing megaherbivores (McNicol et al., 2018).
2074 Southern Africa, particularly the KAZA region, is experiencing large-scale shifts in
2075 vegetation cover, biomass degradation, and increased vulnerability to climate
2076 change which hold significant implications for forest ecosystem function
2077 (Cumming, 2008; King, 2014; Niang et al., 2014). Yet, the location and rates of the
2078 AGB and biomass loss and regrowth, and the above ground woody carbon stocks
2079 are largely unknown (David et al., 2022a).

2080 Estimates of biomass using conventional techniques based on field measurements
2081 are the most accurate ways of collecting biomass data. However, extensive
2082 fieldwork is not feasible due to the inaccessibility, and logistical challenges of such
2083 field surveys which limit the number of plots that can reasonably be surveyed
2084 which impact AGB characterisation over large areas (Næsset et al. 2016). Biomass
2085 measurements based on Earth observation measurements are obtained through
2086 statistically-based integration of tree-level allometric equations with biophysical
2087 or structural information derived from satellite data (Boisvenue & White, 2019).
2088 The shortcoming of utilising satellite imagery for AGB estimation is related to
2089 selecting suitable models and data availability (Houghton et al., 2009; Lu, 2006). In
2090 terms of optical sensors, Landsat is one of the most utilised datasets because it
2091 provides freely accessible imagery, at a high temporal coverage with a medium
2092 spatial resolution (Dogru et al., 2020). In their study within miombo forests,
2093 Gizachew et al. (2016) identified a linear relationship between AGB and Landsat 8

2094 derived spectral variables, concluding that the approach was suitable for
2095 monitoring and reporting of biomass baselines in low-biomass, open-canopy
2096 woodlands for REDD+ projects. The launch of the Sentinel-2 series satellites
2097 through the EU Copernicus program provides new opportunities to enhance forest
2098 monitoring in tropical countries on a large scale (ESA, 2020). Compared to
2099 Landsat, the Sentinel-2 data provides four additional spectral bands strategically
2100 positioned in the red-edge region that are expected to contribute to improved AGB
2101 estimation and mapping (Li et al., 2021; Mutanga et al., 2012). Previous studies
2102 that compared Sentinel 2 to Landsat 8 found Sentinel 2 to have spatial and spectral
2103 capabilities that improved the estimation of AGB in different vegetations (Sibanda
2104 et al., 2016; Forkuor et al., 2018). Such optical sensors are however limited in the
2105 degree to which they can generate structural information because they have
2106 difficulty penetrating beyond upper canopy layers and optical data can be
2107 obscured by frequent cloud cover (Hyde et al., 2006). Certain limitations related to
2108 data saturation also exist, particularly at sites with high woody cover, or those
2109 areas with complex vegetation structures such as dryland vegetation, as so many
2110 satellite sensors can be insensitive to large AGB variations (Lu et al., 2012; Powell
2111 et al., 2010). Optical sensors are also limited in their ability to estimate higher
2112 biomass levels as they are more sensitive to canopy density/cover rather than
2113 canopy height (Joshi et al., 2016). Biomass saturation for low and medium spatial
2114 resolution passive optical sensors such as the Moderate Resolution Imaging
2115 Spectroradiometer (MODIS) or Landsat is a well-recognised problem (Steininger,
2116 2000; Zhao et al., 2016).

2117 Space-borne Synthetic Aperture Radar (SAR) sensors such as Sentinel 1, TerraSAR-
2118 X, ALOS PALSAR can be used to estimate AGB through cloud, as well as provide
2119 detailed vegetation structural information from backscatter (Berninger et al.,
2120 2019; Lucas et al., 2008). SAR data has the advantage that it includes the ability to
2121 collect data in all weathers, during both day and night; the sensor has the
2122 capability to penetrate through cloud and forest canopy; data are sensitive to
2123 surface roughness, dielectric properties, and moisture content (Balzter, 2001;
2124 Santos et al., 2002). The radar backscatter and the reflected signal is sensitive to
2125 polarisation and frequency (HH, VV, HV, and VH), and can be used for volumetric
2126 analysis rather than just the colour and density of leaves and so has the potential

2127 to be more sensitive to AGB in the woodlands of savanna (Balzter, 2001; Mitchard
2128 et al., 2011). Recent research has shown that SAR data are suitable for classifying
2129 vegetation types and assessing biomass at regional scales (Omar et al., 2017). Minh
2130 et al. (2016) used SAR tomography to model tropical forest biomass and height in
2131 central French Guiana and found a high correlation between the backscatter signal
2132 and AGB in the high-biomass forest areas. In Africa, Bouvet et al. (2018) created an
2133 ALOS PALSAR map at 25-m spatial resolution using an L-band PALSAR mosaic
2134 produced by JAXA and in situ data, to estimate AGB over the whole of Africa.
2135 Conversely, the saturation problem is also common in radar data at the middle to
2136 high biomass levels, depending on wavelength and forest type, as documented by
2137 Balzter (2001) and Lucas et al. (2008). The saturation level has been found to vary
2138 as a function of the wavelength and polarisation of the incident radiation and
2139 studies have reported saturation at approximately 30 - 50 Mg/ha, 60–100 Mg ha
2140 and 100–150 Mg ha for C-, L- and P-band respectively (Lucas et al., 2006; Lucas et
2141 al., 2015). Water content, forest spatial structure, and surface geometry (terrain
2142 slope) derive errors and can cause saturation (Balzter, 2001). Studies have
2143 successfully demonstrated the capabilities of Light Detection And Ranging (LiDAR)
2144 for measuring vegetation distribution and estimating associated biophysical
2145 parameters (Popescu, 2007). LiDAR can be used to directly estimate a spatially
2146 explicit 3D canopy structure as a laser pulse emitted from the LiDAR sensor can
2147 penetrate the multi-layered tree canopies reaching the ground, which has great
2148 potential for improving the estimates of vegetation parameters (Pearse et al.,
2149 2019). This leads to more accurate estimations of basal area, tree height and stem
2150 volumes (Pirotti, 2011), but such approaches remain intensive and unsuited to
2151 regional or global coverage (Gibbs et al., 2007). For the direct derivation of
2152 biomass from optical, radar and LiDAR data, no single data type can fulfil all
2153 requirements with each limited by either weather, saturation, and other bio-
2154 physical conditions (Kellndorfer et al., 2010). Given these limitations, research
2155 exploring the fusion of different data types is crucial to develop accurate AGB maps
2156 (Koch, 2010).

2157 To assess and monitor forest structural parameters, various approaches to reduce
2158 the impacts of data saturation in optical imagery in AGB estimation have also been
2159 explored. Vegetation indices and textures generated from optical and airborne

2160 LiDAR data are often used as an alternative (Zhao et al., 2016). Many factors
2161 influence data saturation, ranging from spectral, spatial, and radiometric
2162 resolutions, vegetation type, or topographic features, which may lead to different
2163 saturation values of AGB (Lu et al., 2016). For example, Lu et al. (2004) compared
2164 different vegetation indices in the moist tropical region of the Brazilian Amazon
2165 and found that vegetation indices including near-infrared (NIR) improved
2166 correlations with AGB in relatively simple forest stand structures. Gizachew et al.
2167 (2016) used Landsat 8 derived NDVI to estimate total living biomass (TLB) in the
2168 miombo woodlands of Liwale district, south-eastern Tanzania. Despite its wide
2169 application, NDVI has major limitations for modelling the spatial variability of
2170 biomass including its instability. The NDVI signal is influenced by the underlying
2171 canopy background, varying with soil colour, canopy structure, leaf optical
2172 properties, and atmospheric conditions (Tucker, 1979; Pettorelli et al., 2005).
2173 Madonsela et al. (2018) investigated the interactions between seasonal NDVI and
2174 woody canopy cover in the savanna of the Kruger National Park (KNP) to model
2175 tree species diversity using a factorial model and found that the interaction
2176 between NDVI and woody canopy cover was insignificant. NDVI is known to give
2177 poor estimates in the growing seasons and in estimates of areas with high-density
2178 wood cover. These challenges have led to the development of alternative
2179 formulations which include correction factors or constants introduced to account
2180 for or to minimise the varying background reflectance, such as the Enhanced
2181 Vegetation Index (EVI) (Huete et al., 1999). Xue et al. (2017) reviews other closely
2182 related indices that include the Normalised Burn Ratio (NBR), the Green
2183 Normalised Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index
2184 (SAVI), the Transformed Soil Adjusted Vegetation Index (TSAVI) and the Green Red
2185 Vegetation Index (GRVI) amongst others. Some studies have demonstrated that the
2186 use of vegetation indices derived from the NIR narrow and red-edge bands
2187 situated between red and near-infrared at wavelengths 680–780 nm can yield a
2188 higher accuracy of AGB estimation as compared to conventional NDVI (Cho et al.,
2189 2007; Laurin et al., 2016). Ramoelo et al. (2015) and Li et al. (2021) found a strong
2190 correlation between biomass and the red edge position for a rangeland and
2191 grassland ecosystem in South Africa and China, respectively. Comparable research
2192 in dryland forested regions remains extremely limited (Michelakis et al., 2014;
2193 Forkuor et al., 2020),

2194 thus this study has tested vegetation indices derived from the NIR narrow and red-
2195 edge bands, GNDVI, EVI, NDVI, NBR, NBR2, SAVI, MSAVI in dryland forest of
2196 Southern Africa. In this study vegetation indices such as NDVI, GNDVI, NBR, and
2197 NDRE (Table 3.2) were selected because they all use a NIR band but differ in terms
2198 of the second band, e.g., NDVI utilised the red band, GNDVI the green band, NBR
2199 the SWIR2 and NDRE the red-edge band. Furthermore, it is important to choose a
2200 suitable method to estimate forest AGB. The linear and multiple regression (LR and
2201 MLR) method has been the most commonly utilised statistical algorithm for AGB
2202 estimation in past research (Propastin, 2012). However, it is documented that the
2203 linear regression method does not effectively explain the complex nonlinear
2204 relationship between biomass and Earth observation data and has been known to
2205 be unreliable at values beyond a saturation point of the canopy reflectance (Lu,
2206 2006; Pühr and Donoghue, 2000). Also, identifying suitable variables for
2207 developing a multiple regression model is critical because some variables are
2208 weakly correlated with AGB or are likely to suffer from multicollinearity (Jong et
2209 al., 2003). Thus, understanding the performance and contribution of multiple
2210 sources of data and methods for forest biomass estimation has the potential to
2211 exploit the strengths of each and can help minimise the limitations of single
2212 sensors.

2213 Several assessments have indicated that global forest cover datasets based on
2214 satellite data have clear limitations for characterising forest structural parameters
2215 in areas where the tree canopy is open, such as in savannas (McElhinny et al.,
2216 2005). Approaches that integrate forest structural parameters and remote sensing
2217 need to be replicated and tested across different regions, and geographic scales
2218 (Lehmann et al., 2015; Mitchard et al., 2013). Furthermore, Foody et al. (2003) and
2219 Woodcock et al. (2001) have pointed out concerns of generalising or transferring
2220 methods and results derived from remotely sensed imagery over both space and
2221 time. Many studies lack field data to build and validate AGB models, particularly in
2222 tropical dryland forests where national forest inventory data is not available
2223 (Grainger, 1999; Schimel et al. 2015). To the best of the author's knowledge, there
2224 are very few studies that have tested the combination of synthetic-aperture radar
2225 (SAR) and multispectral data to map AGB in Southern African dryland forests. Such
2226 structural diversity maps are an invaluable data source for monitoring and

2227 managing biodiversity of forests and conservations of wildlife habitats and
2228 corridors reducing the isolation of wildlife populations. Such maps also contribute
2229 to the ecological functioning and health of savanna ecosystems. This study aims to
2230 assess the feasibility of using remote sensing data derived from SAR, multispectral,
2231 and ground measurements to estimate AGB in an area of typical African dryland
2232 forests. The study developed parametric and non-parametric models for
2233 estimating and testing the accuracy of AGB estimation and mapping. The models
2234 developed by this thesis are compared to different published biomass models in
2235 the dryland forest environment (Avitabile et al., 2016; Baccini et al., 2017; Bouvet
2236 et al., 2018). The study presents a novel remote-sensing approach of dataset
2237 combination and methodology, that can, in principle, be applied to the estimation
2238 and mapping of AGB in dryland forest sites worldwide.

2239 3.2 Materials and methods

2240 3.2.1 Study area

2241 This study area is situated in Chobe National Park, in the north-east of Botswana
2242 covering an area of around 10,589 km² (18.7°S and 24.5°E) (see: Fig. 3.1) within
2243 the Kavango Zambezi Transfrontier Conservation Area (KAZA) of Southern Africa.
2244 KAZA is the World's largest conservation area with an enclosed area of 519,912
2245 km². KAZA is shared by Angola, Botswana, Namibia, Zambia, and Zimbabwe and
2246 links together over 36 proclaimed protected areas including national parks, forest
2247 reserves, and wildlife management areas. Chobe National Park was chosen as the
2248 field site because it is one of the largest protected areas in Botswana featuring an
2249 impressive population of large mammals and several endemic plant species,
2250 including large areas of the dryland forests and globally significant wetlands.
2251 Within these habitats, there is a broad range of vegetation types ranging from low
2252 herbaceous to high-density woody cover (McIntyre, 2010). The largest population
2253 of African elephants (>150,000) is in northern Botswana drawn by the Chobe River
2254 basin which serves as a source of surface water in the dry season when animals
2255 converge on this stretch of water (Fullman, 2009).

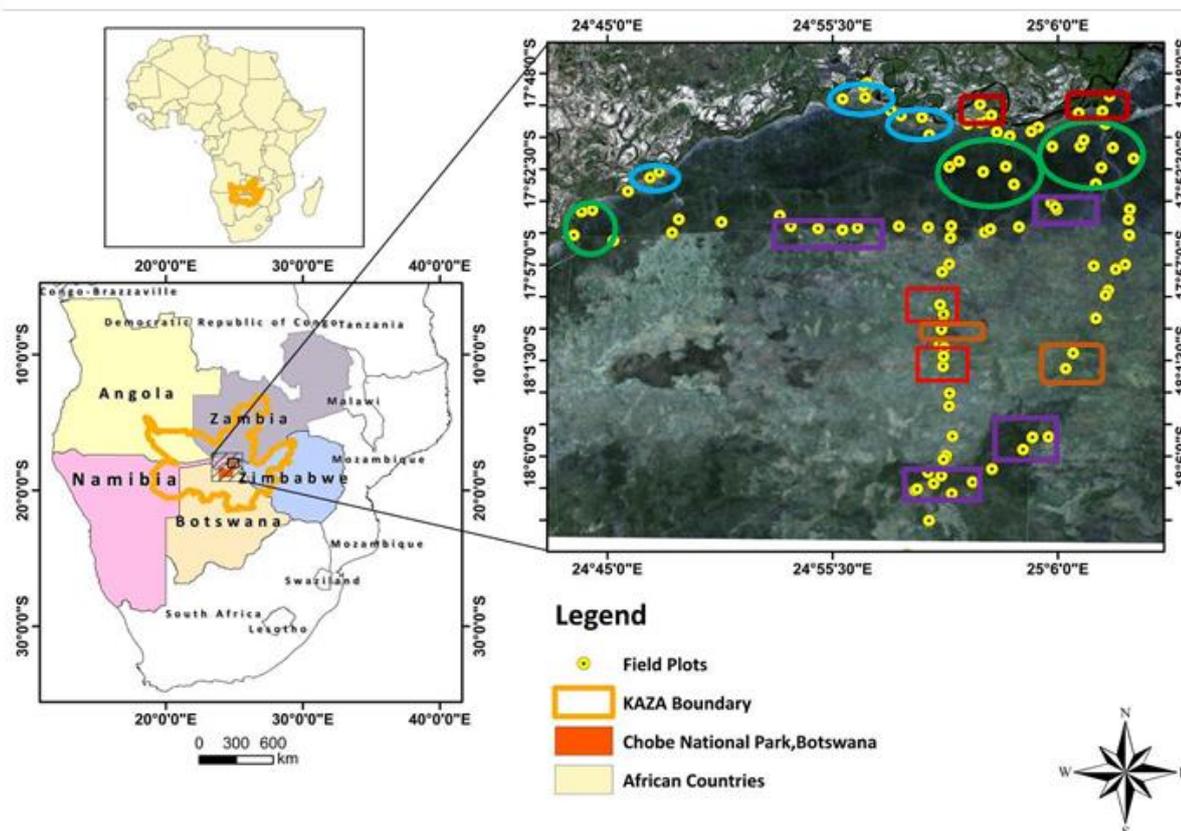
2256 Chobe NP is a relatively flat area with an average elevation of 980 m. The climate is
2257 semiarid with a highly variable mean annual rainfall of about 600 - 700 mm,

2258 mainly falling between November and March and a mean annual temperature of
2259 21.8 °C (Fullman and Child, 2013). There is a general absence of rainfall in the dry
2260 season (April–October). The nearest permanent water source is the Chobe River
2261 forming the northern boundary of the park and the political border between
2262 Botswana and Namibia. A high concentrations of large mammalian herbivores
2263 including elephant, giraffe (*Giraffa camelopardalis* (L.)), impala (*Aepyceros*
2264 *melampus*), and buffalo (*Syncerus caffer*) are found along the Chobe River front
2265 during the dry season when seasonal pans are dry (Melton, 1985). Vegetation in
2266 Chobe National Park is dominated by savanna grassland and low-density
2267 woodland. Within these habitats, there is a broad array of vegetation types from
2268 low herbaceous to high-density woody cover (McIntyre, 2010). The vegetation
2269 found on the banks of the river is riparian woodland including *Capparis tomentosa*,
2270 *Trichilia emetica*, *Acacia nigrescens*, and *Croton megalobotrys*. Because of the
2271 intense pressure from elephants, vegetation along the Chobe riverfront has been
2272 heavily impacted and is now dominated by low shrubs and very few large trees
2273 (Fullman and Child, 2013). Often, the remains of dead trees suggest they have been
2274 ring-barked, heavily browsed and toppled by elephants causing mortality. In the
2275 south of the Chobe River, the most dominant woodland species are *Baikiaea*
2276 *plurijuga*, *Burkea africana*, *Ochna pulchra* (Mosugelo et al., 2002).

2277 The high population of elephants has a wider destructive influence on vegetation,
2278 especially within the Chobe River basin as they migrate to neighbouring countries
2279 including Angola, Zambia, and Namibia. According to the United Nations
2280 Framework Convention on Climate Change (UNFCCC) many of the countries of
2281 southern Africa, including Botswana, Zambia, and Namibia, has been classified as
2282 highly vulnerable to climate change and its effects (McGann, 2004). The visible
2283 forest loss, especially that along the Chobe River frontage, has caused concerns
2284 among stakeholders regarding dryland forest degradation pressure and
2285 accompanying loss of biodiversity (see: Fig. 3.2A-F) (Nichols et al., 2017). In
2286 addition to climate change and wildlife damage, it is estimated that 55% of year-
2287 old saplings across all woodland species are killed by fire in Chobe National Park
2288 (Fidzani, 2014). The KAZA region has been identified as biodiversity hot spot and
2289 estimates of dryland forest cover and distribution not only are important tools to
2290 help conservation and sustainable management of forests but also because of the

2291 risk to dryland forest areas from several potential threats: climate change, forest
 2292 fragmentation, fire, conversion to agriculture, and increasing wildlife population
 2293 density (Cumming, 2008).

2294



2295

2296 Fig. 3. 1. Location of the study area highlighting the countries (Botswana, Namibia, Angola,
 2297 Zambia and Angola) and Chobe National Park where the field work was conducted. The
 2298 coloured polygons around the sampled points indicate the type of vegetation structural
 2299 formation and a range of land cover types that field sites represent (e.g., green-coloured
 2300 circle: closed forests, purple-coloured square: open forests, orange-coloured square:
 2301 shrubs, red-coloured square: grassland).

2302

2303 3.2.2 Fieldwork and sampling design

2304 Fieldwork was carried out during March 2019, which is the growing season, when
 2305 the vegetation photosynthetic activity is still high. Sentinel-2 (S2) and Landsat 8
 2306 OLI (LC8) wet season images (February - April) were acquired then classified into

2307 four classes (forests, open woodland, shrubs, and grassland) as these classes
2308 represent the main land cover types in the study area of Chobe NP. The allocation
2309 of field plots followed a stratified random sampling approach based on the four
2310 strata (forest, open woodland, scattered trees with low herbaceous cover, and non-
2311 forest) that represent broad vegetation types, and capture change between key
2312 land cover types well. Measurements were collected from a total of 101 individual
2313 sample plots throughout the savanna landscape of Chobe National Park. The
2314 sample plots were widely distributed across Chobe NP (Fig. 3.1) and encompassed
2315 relatively homogeneous tracts across a range of typical ecosystems (e.g., savanna
2316 grasslands, shrubs) and structural formations (open woodland to closed forest).
2317 Data from 61 of the 101 plots surveyed represented forest, and 40 samples
2318 described represented non-forest land cover types. Examples of the collected
2319 ground truth of typical forest cover types and recent vegetation degradation
2320 activities through herbivory, drought, and burning captured during the field
2321 campaign in 2019 are shown in Fig. 3.2. Within the 61 sample plots, a total of 4337
2322 individual trees were measured. Table 3.1 presents stand parameters statistics
2323 based upon this survey for dryland forests. Fig. A. 1 shows the density and
2324 histogram plots of Aboveground biomass (AGB) and Carbon stock (Mg/ha) of each
2325 field plot within savanna forest.

2326 Prior to fieldwork, the size of field sampling plots was defined based on S2 with 10,
2327 20 m and LC8 multi-temporal data with 30 m pixel resolution, respectively. Hence,
2328 plot sizes of (20 m × 20 m, 0.04 ha) and (10 m × 10 m, 0.01 ha) were considered
2329 adequate in this study to ensure correspondence between field-measurement and
2330 pixel size in the image. This area was large enough to contain almost the complete
2331 diversity of the known plant community. 0.04 ha plots have been widely applied in
2332 the National Forest Monitoring Plan in Botswana (Manatsha and Malebang, 2016)
2333 and in different forests elsewhere (Baker et al., 2004; Carreiras et al., 2013) as it
2334 normally encompasses a representative sample of trees within a single stand and
2335 allows detection of changes in vegetation structure.

2336 The field measurements of stand characteristics included: mean height, diameter
2337 at breast height (DHB), tree density, canopy closure, and tree species. Sample plots
2338 were circular and the UTM coordinates at the centre of each plot were recorded in
2339 the field with a hand-held Garmin GPS 64S. Tree height of each individual tree was

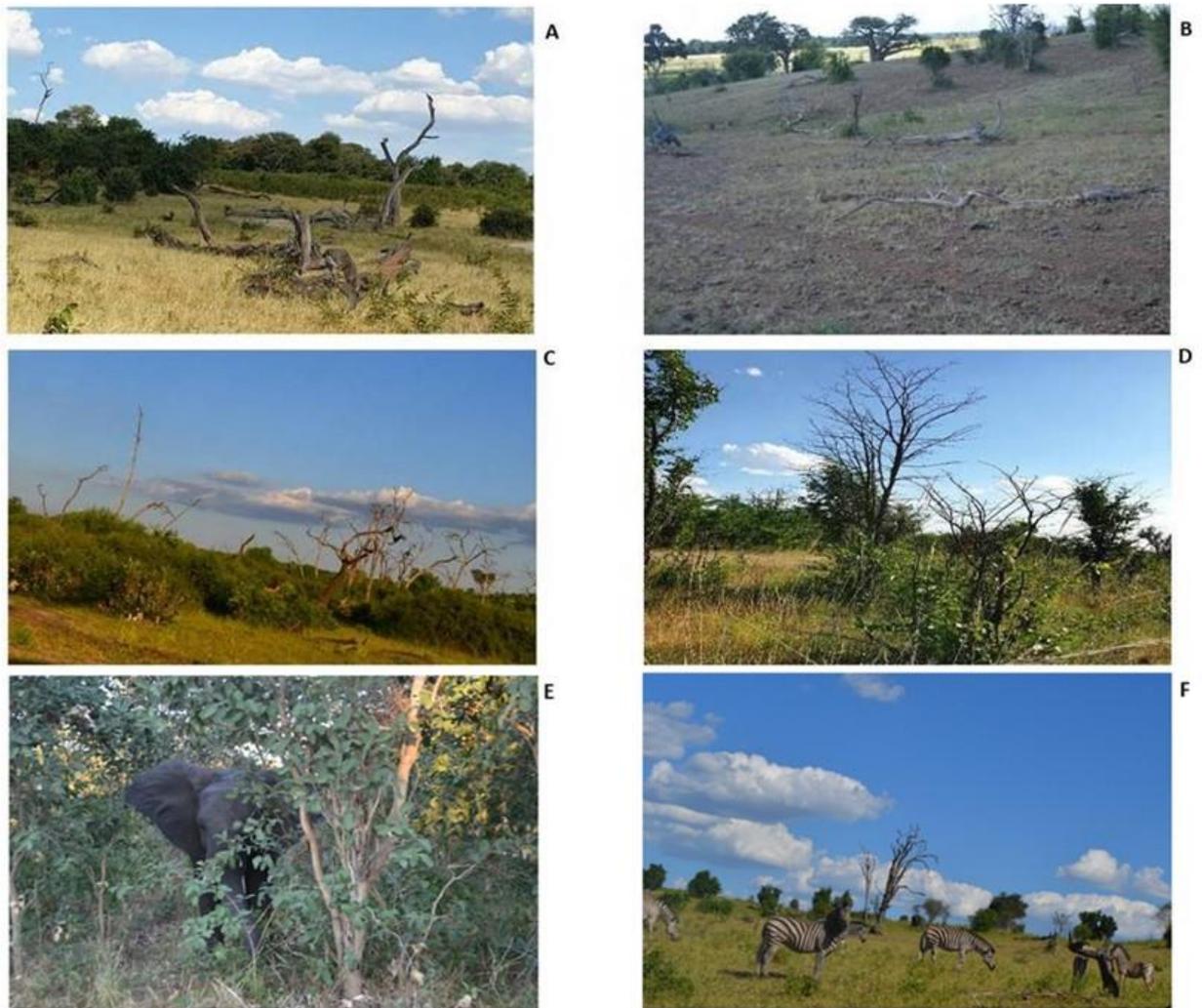
2340 measured using an ultrasonic Vertex III hypsometer which requires finding a
 2341 suitable position to observe each tree tip (Božić et al., 2005), while stem diameter
 2342 was measured using a Diameter above Breast Height (DBH) tape. All trees with a
 2343 stem diameter of >3 m and >1.5 m height were recorded. Fractional vegetation
 2344 cover (FVC) of shrubs between 1 and 6 m in height was estimated visually within
 2345 all plots in the field. In the case of multi-stemmed species, such as *Burkea Africana*,
 2346 *Compretum collinum* and *Baikiaea plurijuga*, individual stems are recorded as an
 2347 individual.

2348

2349 Table 3. 1. Summary statistics for field sample data in Chobe National Park.

Variables	AGB (Mg/ha)	Carbon Stock (Mg/ha)	BA (m ² /ha)	MDBH (cm)	MH (m)	TD (no. trees/ha)
Minimum	2.07	1.03	0.62	4.73	3.14	103.50
Maximum	166.98	83.49	35.42	30.07	15.23	4297.20
Mean	54.99	26.93	11.18	8.78	5.58	1183.40
S.D.	44.27	22.34	8.80	4.69	1.87	1019.68

2350 *AGB= above ground biomass, MDBH=mean diameter at breast height, BA=basal area,
 2351 MH= mean height, TD= tree density, S.D. =standard deviation.



2352

2353 Fig. 3. 2. Examples of collected ground truth captured during a field campaign in Chobe
 2354 National Park in 2019. The photos represent typical forest cover types and recent
 2355 degradation activities resulting from A: drought impacts, B: Trees toppled by elephants
 2356 causing mortality, C and D: Trees destroyed by wildfire, and E and F: elephant and
 2357 herbivory browsing.

2358 3.2.3 Satellite image data collection

2359 The imagery included Sentinel-1 Synthetic Aperture RADAR (S1-SAR), Sentinel-2
 2360 Multispectral Instrument (MSI) data, and Landsat 8 - Operational Land Imager
 2361 (OLI) were all accessed via Goggle Earth Engine (GEE) (Table 3.2). The GEE
 2362 platform provides pre-processed top and bottom-of-atmosphere reflectance data,
 2363 enabling large volumes to be integrated, processed, and analysed for extensive
 2364 areas over long time periods (Warren et al., 2015). The Sentinel 1 and 2 data were
 2365 acquired as close in time to the fieldwork as shown in Table A 1.

2366 3.2.3.1 Sentinel-1 image pre-processing

2367 S1 is a C-band SAR remote sensing satellite launched into orbit on 03.04.2014.
2368 There are four imaging modes (Stripmap [SM], Interferometric Wide swath [IW],
2369 Extra Wide swath [EW], and Wave [WV]), but the level-1 Interferometric Wide
2370 (IW) Ground Range Detection (GRD) were also used in the study. Radar data were
2371 analysed using the single co-polarisation with vertical transmit/receive and dual-
2372 band co-polarisation, with vertical transmit and horizontal receive (VV + VH) from
2373 Sentinel-1A and 1B C-band SAR. Within GEE, S1 images are pre-processed using
2374 the S1 Toolbox (ESA, 2020) to an analysis-ready format using border and thermal
2375 noise removal, radiometric calibration, and orthorectification (Google, 2020).
2376 Radar data is not significantly affected by cloud cover, so a considerable number of
2377 complete images can be obtained each month. However, radar data can be affected
2378 by recent rainfall or wind and so an image from a period of good weather
2379 (14.3.19), close to the field data collection date, was selected for analysis. The date
2380 closest to the date of field collection (February-March 2019) was selected because
2381 2019 was an extreme drought year in Southern Africa including Chobe NP, and
2382 there was minimal recorded rainfall or soil moisture in the area during the time
2383 period, hence soil moisture will have a minimal influence on the backscatter
2384 (Chikoore and Jury, 2021; Lucas et al., 2006; Liu and Zhou, 2021).

2385 3.2.3.2 Sentinel-2 image pre-processing

2386 S2 MSI data, processed to level-2A were used. These data have been orthorectified
2387 and radiometrically corrected providing Bottom-Of-Atmosphere (BOA) corrected
2388 reflectance values (ESA, 2013). S2 images were further pre-processed with an
2389 automatic cloud masking procedure using QA bands provided for the S2 2A
2390 product, masking both opaque and cirrus cloud cover. Ten of the thirteen bands
2391 from S2 (4 visible, 4 red edge, 2 short-wavelength infrared (SWIR)), were
2392 extracted for pre-processing and analysis. The 20 m bands of S2 (SWIR and red
2393 edge bands) were resampled to 10 m using the cubic convolution algorithm. S2
2394 spectral indices, (see: Table 3.2 for all indices and their derivation) were used to
2395 create the “indices” datasets. Previous studies suggested that numerous spectral
2396 vegetation indices provided more information than the individual spectral bands
2397 for retrieval of forest structure (Lu et al., 2012). Eleven spectral vegetation indices

2398 from S2 previously shown useful for biomass modelling and estimation were
2399 computed (Hawryło et al., 2018).

2400 3.2.3.3 Landsat 8 image pre-processing

2401 LC8 was launched on 11.03.13 and provides multispectral images at 30 m
2402 resolution with a 16-day return cycle. The study used LC8 Level 2 Tier 1 ortho-
2403 rectified collections from 15.03.19. These data are derived from L8's OLI/TIRS
2404 sensors and have been orthorectified and atmospherically corrected to obtain
2405 surface reflectance. The LC8 reflectance orthorectified product was used because
2406 GEE has already converted digital number (DN) values into surface reflectance
2407 data as a result of standardising across image products to a common radiometric
2408 scale (Chander et al., 2009). A cloud masking procedure was applied using the
2409 Function of Mask (FMask) band included with the Landsat data (Zhu and
2410 Woodcock, 2012). Eight spectral indices from LC8 were computed as "indices"
2411 datasets. As shown in Table 3.2, a total of 39 initial variables were used for the
2412 statistical analysis of the forest parameter estimation in this study.

2413 3.2.3.4 Land Cover Classification

2414 In order to allocate field plots throughout landscape using a stratified random
2415 sampling approach, the sentinel 2 images in 2019 were independently classified
2416 into four main land cover classes in GEE using a RF classifier because of its
2417 robustness (Belgiu et al., 2016; Breiman, 2001). Based on the prior knowledge of
2418 the study area, spectral clusters from the classification were assigned to four
2419 general land cover classes: Forests, open forests, grassland, and shrubs. A total of
2420 367 ground points were randomly distributed on the study area, and they were
2421 split equally into 50% of points as reference points for image classification and the
2422 remaining 50% of points used for accuracy assessment.

2423

2424 Table 3. 2. Description of predictor variables for the AGB estimation.

<i>Satellite</i>	<i>Band</i>	<i>Description, wavelength, spatial resolution)</i>
S1 GRD (14.03.2019)	<i>VV - Vertical transmit-vertical channel</i>	<i>5.6 cm (10 m)</i>
	<i>VH - Vertical transmit-horizontal</i>	<i>5.6 cm (10 m)</i>

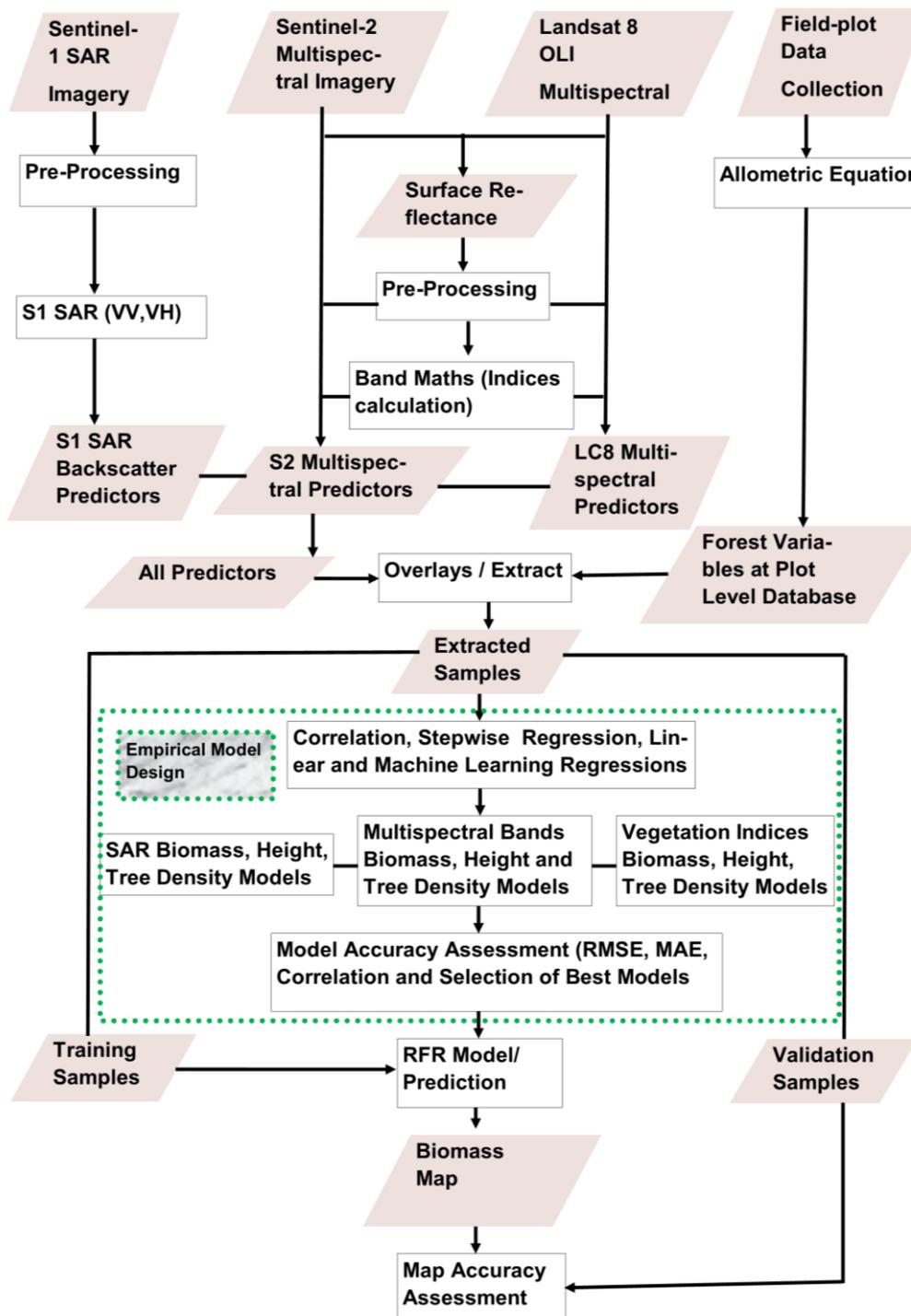
	<i>channel</i>	
	<i>Band 1 – Coastal aerosol</i>	<i>0.443nm - (60 m)</i>
	<i>Band 2 – Blue</i>	<i>0.490nm -(10 m)</i>
	<i>Band 3 – Green</i>	<i>0.560nm - (10 m)</i>
	<i>Band 4 – Red</i>	<i>0.665nm -(10 m)</i>
S2 SR (14.03.2019)	<i>Band 5 – Vegetation red edge</i>	<i>0.705 nm -(20 m)</i>
	<i>Band 6 – Vegetation red edge</i>	<i>0.740 nm - (20 m)</i>
	<i>Band 7 – Vegetation red edge</i>	<i>0.783 nm - (20 m)</i>
	<i>Band 8 – NIR</i>	<i>0.842 nm - (20 m)</i>
	<i>Band 8A – Narrow NIR</i>	<i>0.865 nm - (20 m)</i>
	<i>Band 11 – SWIR</i>	<i>1.61 nm - (20 m)</i>
	<i>Band 12 – SWIR</i>	<i>2.19 nm - (20 m)</i>
LC8 OLI TOA (15.03.2019)	<i>Band 1 Coastal</i>	<i>0.43 - 0.45 nm (30 m)</i>
	<i>Band 2 Blue</i>	<i>0.45 - 0.51 nm (30 m)</i>
	<i>Band 3 Green</i>	<i>0.53 - 0.59 nm (30 m)</i>
	<i>Band 4 Red</i>	<i>0.63 - 0.67 nm (30 m)</i>
	<i>Band 5 NIR</i>	<i>0.85 - 0.88 nm (30 m)</i>
	<i>Band 6 SWIR 1</i>	<i>1.57 - 1.65 nm (30 m)</i>
	<i>Band 7 SWIR 2</i>	<i>2.11 - 2.29 nm (30 m)</i>
Vegetation Indices	<i>Normalised vegetation index (NDVI)</i>	<i>(NIR -R)/(NIR + R)</i>
	<i>Green red vegetation Index (GRVI)</i>	<i>(G-R)/(G + R)</i>
	<i>Enhanced Vegetation Index (EVI)</i>	<i>2.5NIR-RED(NIR+6RED-7.5 BLUE)+1</i>
	<i>Green NDVI (GNDVI)</i>	<i>(NIR - G)/(NIR + G)</i>
	<i>Normalised Difference NIR/SWIR2 (NBR)</i>	<i>NIR-SWIR/NIR+SWIR</i>
	<i>Normalised Difference SWIR1/SWIR2 (NBR2)</i>	<i>(SWIR1 - SWIR2) / (SWIR1 + SWIR2)</i>
	<i>Soil-adjusted vegetation index (SAVI)</i>	<i>(NIR - R)/(NIR + R + L)*1.5</i>
	<i>Modified Soil-adjusted vegetation index (MSAVI2)</i>	<i>(2 * NIR + 1 - sqrt ((2 * NIR + 1)² - 8 * (NIR - R))) / 2.</i>
	<i>Normalised Difference Index 45 (NDI45)</i>	<i>B5-B4/B5+B4</i>
	<i>Inverted red-edge chlorophyll index (IRECI)</i>	<i>RE3 -R/(RE1/RE2)</i>
	<i>Normalised difference red edge index (NDRE1)</i>	<i>(NIR -RE1)/(NIR + RE1)</i>

2425 *RE: Red-edge; NIR: Near infra-red; SWIR1: Short-wave infra-red 1; SWIR2: Short-wave
2426 infra-red 2.

2427 3.2.4 Methods and modelling

2428 A full overview of the methodological approach for AGB is shown in Fig. 3.3. For all
2429 forest parameters, analysis was undertaken using S1 backscatter values (VV and
2430 VH polarisations) the reflectance values from individual spectral bands (B2-12),

2431 and spectral vegetation indices from S2 and LC8 OLI (NDVI, GRVI, EVI, GNDVI,
 2432 NBR, NBR2, SAVI, MSAVI2, NDI45, IRECI, and NDRE1) as shown in Table 3.2. All
 2433 models and their combinations are shown in Table 3.3 and 3.4.



2434

2435 Fig. 3. 3. Overview of methodological approach

2436 3.2.4.1 Calculation of AGB at the tree level

2437 Locally defined allometric equations are not available for most of the species in the
 2438 study area; AGB in kilograms per tree was estimated using the following
 2439 generalised biomass estimation model (Eq. 3.1) developed for tropical dry forests
 2440 (Chave et al., 2005).

$$\begin{aligned}
 AGB_{est} &= \exp(-2.187 + 0.916 \times \ln(\rho D^2 H)) \\
 &\equiv 0.112 \times (\rho D^2 H)^{0.916}
 \end{aligned}
 \tag{Eq.3.1}$$

2441 Where AGB is the above ground biomass in kg per tree; H = height (m);
 2442 D = diameter at breast height; ρ = wood density (g cm^{-3}).

2443 The AGB of each individual tree was first calculated based on wood density, and
 2444 then the total AGB per plot was summed based on the number of trees and the
 2445 proportion between species. The wood density for species was obtained from the
 2446 World Agroforestry Database (worldagroforestry, 2019). The biomass values were
 2447 produced using the allometric equation developed by Chave et al. (2005) using
 2448 Statistical Package R software (version 4.1.1) (R Core Team, 2013). Three tree-
 2449 specific variables (tree wood density, DBH, height) were then generated and
 2450 normalised by the area of the plots to estimates AGB in Mg/ha. The allometric
 2451 model accounts for uncertainty and error in the estimation due to both data
 2452 measurement and model uncertainty by averaging out the tree-level uncertainties
 2453 at the stand scale, which is typically less than 10% of the mean as detailed in Chave
 2454 et al., 2014. According to Baker et al. (2004) and Chave et al. (2005) excluding
 2455 wood density and height would result in a poor overall AGB prediction and
 2456 overestimation of the forest AGB. Rahman et al., 2021 showed that the generic
 2457 allometric models overestimated AGB between 22% and 167% compared to the
 2458 species-specific models and AGB was overestimated by up to 20% when using plot
 2459 top height and underestimated by 8% using plot average height data from
 2460 databases rather than individual tree heights in the mangroves (Rahman et al.,
 2461 2021).

2462 The allometric equation used in the study was specifically developed for tropical
 2463 dryland forests and already includes the uncertainty and correction factor. The

2464 dryland forest model typically achieves 90% accuracy in AGB stock estimation and
2465 the standard error in estimating stand biomass was 12.5% if height is available,
2466 and 19.5% if height is not available for dryland forests (Chave et al., 2005).
2467 Therefore, this research used species-specific models and individual tree
2468 measurements including DBH, tree height and wood density as independent
2469 variables in the allometric equation to reduce uncertainty and improved the
2470 quality of the AGB prediction. This study didn't calculate the allometric equation
2471 uncertainty since the error due to the DBH, height, and wood density
2472 measurements are already calculated and factored in one error term of the
2473 allometric equation (Chave et al., 2004). The average and total AGB and carbon
2474 stocks per land cover class (i.e., closed forest, open forest) were estimated, as well
2475 as the total AGB and carbon stock in the forests of Chobe NP. The amount of carbon
2476 in biomass was determined by multiplying by a factor of 0.5 to obtain the amount
2477 of carbon existing in dry wood biomass, assuming biomass is approximately 50%
2478 of dry weight (Brown and Lugo, 1982; Chave et al., 2005). Table 3.1 presents plot
2479 summary statistics (minimum, maximum, mean, and standard deviation) for the
2480 variables of interest. The density and histogram plots of AGB and carbon stock
2481 (Mg/ha) of each field plot with woodland trees are presented in the supplementary
2482 materials as Fig. A3.

2483 3.2.4.2 Extraction of remote sensing data at field plot location

2484 Each circular field plot had a radius of 10 and 20 m, and for each plot location, the
2485 coordinates of each plot centre were established with GPS. Field plot location data
2486 were then overlaid on the SAR and S2 images to create a vegetation plot region-of-
2487 interest (ROI) map, based upon plot centre GPS position. Although the coordinates
2488 of each plot centre were collected with a high-quality device with GPS and
2489 GLONASS sensors, there may be small positional errors, especially when
2490 differential corrections are unavailable (errors up to 8–10 m are common). To
2491 compensate for possible positional errors, a 20 m radius buffer was created
2492 around the plot centre. This buffer was used to collect biomass image spectra. All
2493 pixels inside each 20 m buffer were extracted, with several metrics computed
2494 (mean, minimum, maximum, and standard deviation) (see Table 3.1), and these
2495 data were used to establish relationships with the AGB at plot level. As the original
2496 Sentinel data mosaic had a 10 m resolution and the buffer around each plot centre

2497 was set to 20 m, the extracted values per plot were those located approximately on
2498 a 4×4 -pixel window size, thus extracting from a 40×40 m area.

2499 3.2.4.3 Selection of relevant predictors

2500 The selection of suitable variables is critical for developing biomass estimation
2501 models, as some variables are weakly correlated with AGB, or the variables can be
2502 co-dependent. Selected variables should be significantly correlated with AGB, but
2503 independent (Lu, 2006). In order to obtain valid predictor variables, correlation
2504 analysis was first used for candidate variable selection. Pearson correlation
2505 coefficients (p) and scatterplots were used to examine the nature of the AGB
2506 correlation, then variables were accepted for further analysis based on their
2507 significance ($P < 0.05$). In addition to the p -value, the variation inflation factor
2508 (VIF) generated for each predictor variable was used to minimise multicollinearity
2509 in the model. The VIF measures the increase in the variance of an estimated
2510 regression coefficient due to collinearity, indicating how much larger the variance
2511 is compared to when the independent variables are not linearly related in the
2512 model (Fox, 2015). A VIF of 1, indicates no collinearity and several studies have
2513 used a $VIF < 10$ to avoid serious multicollinearity between the chosen predictor
2514 variables. Generally, a VIF greater than 10 indicates high collinearity with other
2515 predictor variables in the model and interpreting the regression estimates
2516 associated with a high VIF predictor variable can lead to unstable estimates (James
2517 et al., 2013; O'Brien, 2007). VIF has been used in the field of remote sensing to
2518 check multicollinearity in a model with independent predictors (Tu et al., 2018;
2519 Yang et al., 2012). To test for collinearity between the selected variables, a
2520 variance inflation factor (VIF) threshold of 10 was applied.

2521 3.2.4.4 Model development and selection

2522 Different statistical models were developed including parametric linear regression
2523 and non-parametric machine learning using random forest regression in the R
2524 programming platform. The dataset was first subjected to linear regression
2525 (Simple linear (SL) regression, Multivariate linear (ML) regression, and STEPWISE-
2526 AIC regression) to determine the optimum model (Bozdogan, 1987). Since biomass
2527 is usually nonlinearly related to remotely sensed variables, to improve the

2528 nonlinear estimation of the biomass model, non-parametric random forest (RF)
2529 models are widely used in satellite-based estimation of the forest AGB (Nandy et
2530 al., 2017; Wu et al., 2014). RF does not make a priori assumptions regarding the
2531 probability distribution of variables, and thus offers a significant advantage over
2532 parametric statistical models which assume a Gaussian distribution. Ensemble
2533 learning methods like RF (Breiman, 2001) play a significant role in remote sensing
2534 and forest mapping because of their robustness, processing ability for high-
2535 dimensional features, and ability to handle complex relationships between
2536 independent variables in biomass estimation modelling (Belgiu et al., 2016; Adam
2537 et al., 2014).

2538 A challenge is to select the fewest number of predictors that offer the best
2539 predictive power and help in the interpretation of the final model. 12 experiments
2540 were conducted to explore the suitability of different datasets (SAR, optical
2541 spectral bands, and indices) and their combinations, in estimating AGB. To
2542 overcome the challenge of selecting the fewest number of predictors that offer the
2543 best predictive power and to help in the interpretation of the final model, the RF
2544 was used to rank the predictor variables. This was followed by a backward feature
2545 elimination method (BFE) as part of the evaluation process for the final model
2546 selection (Guyon and Elisseeff, 2003). The BFE starts with all the possible
2547 predictors and progressively drops the least promising variable, in this case, the
2548 SAR, optical spectral bands, and indices. The model optimisation and comparison
2549 was based on absolute and relative measures of fit: by calculating the accuracy
2550 assessment (Acc%) and error statistics for the models including Root Mean
2551 Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage
2552 Error (MAPE), coefficient of determination (R^2), adjusted R^2 (R^2_{adj}), and Akaike
2553 information criterion (AIC) and VIF. The concordance index was adopted to rank
2554 the effectiveness of the ML and RF models (Gerds et al., 2012). The smallest subset
2555 of variables with the highest coefficient of determination (R^2), accuracy, adjusted
2556 R^2 (R^2_{adj}), and lowest RMSE, VIF, and AIC were then selected to predict the AGB.
2557 Table 3.4 details the 19 multivariate models and the datasets used for estimating
2558 AGB.

2559 The RF regression tree algorithm was selected to model forest parameters after
2560 analyses showed that it performed better than ML regression algorithms. The

2561 decision tree-based models such as random forests, make no assumptions
2562 regarding the distribution of the input data and can capture non-linear
2563 relationships between the response and predictor variables (Breiman, 2001; Liaw
2564 and Wiener, 2002). It is essential to optimise the model with the best combination
2565 of parameters. For RF, only two parameters need to be tuned: *n*tree (with a default
2566 value of 500 trees) that controls the number of trees to grow (*k*), and *m*try (with a
2567 default value is 1/3 of the total number of the predictors) that controls the number
2568 of variables randomly sampled at each split (*m*). The study identified the number of
2569 trees (*k* = 1000) and *m*try (the default was accepted) because it minimised the
2570 error rate and produced the best results for AGB estimation in this study.

2571 3.2.4.5 Model Validation

2572 The field dataset (*n* = 101) was randomly split 70/30 for training and validation,
2573 respectively (Ismail et al., 2006). The training dataset was used to optimise the
2574 random forest regression and train the prediction model, and to assess the
2575 goodness of fit of each model, the accuracy and the reliability of the prediction
2576 model were assessed using the 30% validation sample. A regression equation
2577 developed from the training data set (*n* = 71) was then used to predict AGB on the
2578 independent test data set (*n* = 30). Validation techniques such as leave one out for
2579 cross-validation and k-fold cross-validation are widely used in previous studies to
2580 assess the model performance using reference data (Fassnacht et al., 2014). Cross-
2581 validation is very similar to the out-of-bag (OOB) estimate, which is a formal
2582 approach to quantify the predictive performance of a model, automatically
2583 accounting for model complexity (Hastie et al., 2009). The sensitivity of the model
2584 to the selection of the training and validation datasets was evaluated using a
2585 repeated k-fold cross-validation and bootstrapping where the data are randomly
2586 divided and spatially independent. The k-fold cross-validation procedure was used
2587 to test for overfitting by partitioning the data *K* times (*K*=5), using the shuffle
2588 option of three repetitions (*S*=3) when splitting the samples into 5 folds. In
2589 addition, to assess the model uncertainty, a 1000 runs of bootstrapping was used.
2590 The random forest regression performance in estimating AGB was compared with
2591 the commonly utilised multiple linear regression. The correlation between
2592 measured and predicted AGB from the independent validation plots was examined.

2593 3.3 Results

2594 3.3.1 Land cover classification

2595 The results of the land cover classification are presented in Fig. A. 5. Open forests
 2596 were the dominant form of land-cover occupying 43%, followed by grassland with
 2597 25%, forests with 23% and shrubs with a total of 9% of the land total area (see
 2598 Table A 2). The difficulty was experienced in the separation of forests and open
 2599 woodland due to difficulty in interpreting them. As shown in Table A 3, the overall
 2600 classification accuracy was 97% and the Kappa statistic of 60% which denotes a
 2601 good agreement between classes indicating generally low misclassification error,
 2602 with the highest confusion arising between forests and open woodland. The
 2603 validation overall accuracy was 67% which is reasonable for the random
 2604 stratification purpose. A total of 101 ground plots were surveyed in Chobe NP. A
 2605 total of 61 of the 101 plots surveyed represented forest, and 40 samples
 2606 represented non-forest land cover types as shown in Fig. 3.2.

2607 3.3.2 Simple linear regression (SLR)

2608 Table 3.3 summarises the strength of the linear relationship between all variables
 2609 derived from S1, S2, and LC8 data. S1 VV polarisation is substantially more
 2610 sensitive to AGB ($R^2 = 0.58$ and $RMSE = 0.70$ Mg/ha) as compared to VH
 2611 polarisation ($R^2 = 0.32$ with $RMSE = 0.89$ Mg/ha) at 99% confidence level. Among
 2612 the S2 spectral bands, the highest coefficient of determination for AGB was
 2613 obtained using spectral bands blue (B2), green (B3), red edge 1 (B5) ($R^2=0.73$,
 2614 $R^2=0.73$, and $R^2=65$ at p-value 0.001, respectively). The relationships of S1
 2615 polarisations and selected S2 spectral bands (B3 and B5) with AGB are shown in
 2616 Fig. A. 4A-D. S2 spectral indices Green Normalised Difference Vegetation Index
 2617 (GNDVI) and Normalised Difference Red Edge (NDRE1) and Normalised Difference
 2618 Vegetation Index (NDVI) obtained the highest linear relationship with AGB ($R^2 =$
 2619 0.71 and $R^2 = 0.56$) at 99% confidence level, respectively.

2620

2621 Table 3.3. Simple linear relationship of satellite-based predictors with AGB. The
 2622 backscatter polarisation, spectral bands, and indices with a strong linear relationship with

2623 AGB are highlighted in bold. The $R^2 > 0.5$ is considered to indicate relatively a strong
 2624 relationship between the variable (Silvy et al., 2020).

<i>Modelling Group</i>	<i>Response</i>	<i>Bands/Predictors</i>	<i>Intercept</i>	<i>Slope</i>	R^2	<i>RMSE error Mg/ha</i>	<i>AIC</i>
S1	AGB	VV	9.35	0.51	0.58***	0.70	104.06
		VH	39.04	-0.04	0.32***	0.89	125.95
S2		B2	6.69	-72.99	0.73***	0.56	83.15
		B3	6.98	-47.73	0.73***	0.56	83.23
		B4	6.15	-36.09	0.63***	0.66	98.48
		B5	7.37	-31.21	0.65***	0.64	95.61
		B6	10.84	-30.22	0.41***	0.83	119.68
		B7	8.76	-18.05	0.15*	1.0	136.30
		B8	7.65	-13.86	0.09*	1.03	139.47
		B8A	8.12	-14.32	0.09*	1.03	139.50
		B11	9.97	-24.19	0.57***	0.71	104.50
		B12	7.079	-20.75	0.57***	0.71	104.89
		NDVI	-1.70	8.52	0.56***	0.72	106.40
		GRVI	3.48	5.93	0.09*	1.03	139.29
		EVI	-0.73	10.44	0.31***	0.90	126.56
		GNDVI	-4.09	12.43	0.71***	0.59	87.38
		SAVI	-1.72	13.53	0.39***	0.84	121.01
MSAVI	-0.82	11.82	0.36***	0.87	123.34		
NBR	1.52	7.29	0.46***	0.80	115.79		
NBR2	-0.05	15.86	0.52***	0.75	109.86		
NDI45	0.80	10.04	0.33***	0.89	125.54		
IRECI	1.18	5.24	0.35***	0.87	123.96		
NDRE1	-0.52	9.67	0.56***	0.72	105.92		
NDRE2	0.59	28.63	0.46***	0.80	115.71		
LC8		B2	10.62	-78.30	0.52***	0.75	109.72
		B3	7.77	-49.61	0.54***	0.73	108.16
		B4	6.27	-34.78	0.48***	0.78	113.80
		B5	7.25	-12.48	0.07.	1.05	140.65
		B6	8.27	-21.99	0.41***	0.83	119.50
		B7	6.29	-22.15	0.43***	0.81	117.58
		NDVI	-2.59	10.42	0.52***	0.75	110.38
		GRVI	2.98	11.42	0.26***	0.93	130.16
		EVI	-2.40	11.77	0.43***	0.82	118.29
		GNDVI	-5.89	16.90	0.62***	0.67	99.53
		NBR	-0.27	13.80	0.44***	0.81	117.44
		NBR2	0.24	7.89	0.44***	0.81	116.71
SAVI	-3.95	19.95	0.45***	0.80	116.47		
MSAVI	-2.98	18.43	0.42***	0.82	118.37		

2625 Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

2626 3.3.3 Multivariate linear (ML) regression models

2627 Table 3.4 presents the multivariate relationships and validation results of the 19
 2628 experiments conducted with S1 SAR signals, S2, and LC8 spectral bands, and
 2629 indices for AGB. The results show that the relationship strength with AGB, and

2630 associated errors, are improved when the polarisation variables are combined.
2631 Further improvements were attained when predictors are combined, from either a
2632 single sensor or by integrating both sensors. Taking the linear relationship from S1
2633 VV and VH polarisation, with R^2 of 0.58 and 0.32 respectively, the R^2 increased to
2634 0.61 when combined. On the other hand, a combination of both S1 and S2 bands
2635 generated a higher R^2 of 0.85 and reduced the RMSE to 0.42 Mg/ha with an
2636 increased estimation accuracy of 90%. A step-wise regression obtained the highest
2637 R^2 of 0.95, a very low RMSE of 0.25 Mg/ha, and the highest accuracy of 94% for S1
2638 backscatter and S2 spectral variables.

2639

2640 However, although the models with all S2 and LC8 spectral variables and stepwise-
2641 regression models have high R^2 values and low errors, they were excluded from
2642 estimation because of high co-dependence between spectral bands and indices,
2643 resulting in a high VIF (Table 3.4). A backward stepwise approach is useful to
2644 reduce the number of parameters within the model in a systematic way. Based on
2645 R^2 , MAE, and RMSE, the most suitable predictive model was obtained with S1 SAR
2646 VV polarisation, the green (B-3) and red edge spectral band (B-5) of S2, explaining
2647 82% of the variance but with a VIF of less than 10 for AGB (Table 3.4). The
2648 inclusion of SAR data with optical data strengthens the relationship between
2649 biomass and remote sensing variables, and consequently improves the model
2650 performance as shown in Table 3.4. The results of the repeated k-fold cross-
2651 validation shown in Supplementary materials in Fig A 3, show that the model fit is
2652 not sensitive to the selection of training and validation sampling. The results of the
2653 bootstrap validation in Fig A. 4 indicate that the model performance was stable
2654 across bootstrap replicates. The bootstrap distribution, errors, and intercepts
2655 correspond very closely to the linear model estimates, see Table 3.5 and 3.6 for
2656 parameter values. If the predicted bootstrapping R^2 was found to be significantly
2657 smaller than the original multiple linear model R^2 , that would indicate that the
2658 model was over-fitted which is not the case with the linear model. The lower = .025
2659 and upper = .975 of the 95-percent confidence interval for the coefficients of the
2660 multiple linear and the bootstrap regression are shown in Table 3.6. The bootstrap
2661 approach yields a similar estimation for AGB without relying on assumptions, and
2662 this helps to confirm the stability of the model coefficients for the multiple linear
2663 regression used in this study.

2664 Table 3.4. Multivariate linear relationship and validation results of 19
 2665 experiments/models conducted for AGB modelling (label a-k represents S1 and S2) and
 2666 (label l-p represents LC8). The best model is highlighted in grey.

AGB Model Label	Variables	R^2	RMSE (Mg/ha)	MAE	MAPE	ACC %	AIC	VIF
a	S1 bands all	0.61	0.68	0.55	0.21	0.84	102.8	1.46
b	S2 bands all	0.79	0.50	0.41	0.14	0.88	88.48	67.70
c	S2 bands & S1 bands all	0.85	0.42	0.35	0.12	0.90	77.25	77.17
d	S2 indices all	0.85	0.42	0.35	0.12	0.89	83.39	19063.24
e	Step regression S1 bands, S2 bands & indices all	0.95	0.25	0.19	0.06	0.94	47.79	11600.7
f	Step backward selection with selected S1 & S2 B3, B5, S1 VH, S1 VV, GRVI, GNDVI, NDRE1, NDI45	0.88	0.38	0.31	0.10	0.90	61.92	2927.90
g	Step backward selection with selected S2 Bands & indices B3, B5, GRVI, GNDVI, NDRE1, NDI45	0.82	0.46	0.36	0.13	0.89	74.34	2493.00
h	Step Backward Selection with selected S1 & S2 B3, B5, S1 VV, S1 VH, GNDVI, NDRE1	0.84	0.43	0.37	0.13	0.89	69.13	1143.50
i	Step Backward Selection with selected S1 Bands & S2 indices GNDVI, NDRE1, S1 VV, S1 VH	0.82	0.45	0.38	0.14	0.88	69.98	9.8
j	Step Backward Selection with selected S1 & S2 Bands B3, B5, S1 VV, S1 VH	0.83	0.45	0.37	0.13	0.89	69.15	10.1
k	Selected AGB model B3, B5, S1 VV	0.82	0.45	0.36	0.13	0.90	67.92	9.9
l	LC8 bands all	0.68	0.62	0.47	0.18	0.87	102.00	75.28
m	LC8 Indices all	0.69	0.60	0.45	0.18	0.87	104.28	9408.0
N	Step regression LC8 bands and indices	0.72	0.57	0.42	0.17	0.88	99.23	11926.0
o	Step backward selection with selected LC8 bands & indices B3, B4, B7, GNDVI, NBR2	0.68	0.61	0.45	0.18	0.87	98.97	282.24
p	Step backward with selected LC8 indices GNDVI, NBR2	0.67	0.62	0.47	0.19	0.86	94.94	9.1

2667

2668 Table 3. 5. Summary statistics and coefficients of linear and bootstrap regression for AGB

	Linear Regression	Bootstrap
--	-------------------	-----------

<i>R</i>²	0.82	0.80
<i>RMSE</i>	0.45	0.42
<i>MSE</i>	0.36	0.32
<i>Intercept</i>	8.65	8.54
<i>B3</i>	-52.46	-56.11
<i>B5</i>	13.15	13.66
<i>SI-VV</i>	0.26	0.23

2669

2670 Table 3. 6. Confidence intervals (95 %) of linear and bootstrap regression for AGB

	2.5%	97.5%	2.5%	97.5%
	Linear Regression	Linear Regression	Bootstrap	Bootstrap
<i>Intercept</i>	7.58	9.72	7.47	9.65
<i>B3</i>	-78.68	-26.23	-74.88	-37.35
<i>B5</i>	-5.12	31.42	0.13	26.83
<i>SI-VV</i>	0.15	0.38	0.11	0.36

2671

2672 3.3.4 Comparing parametric and non-parametric machine 2673 learning for estimating stand parameters

2674

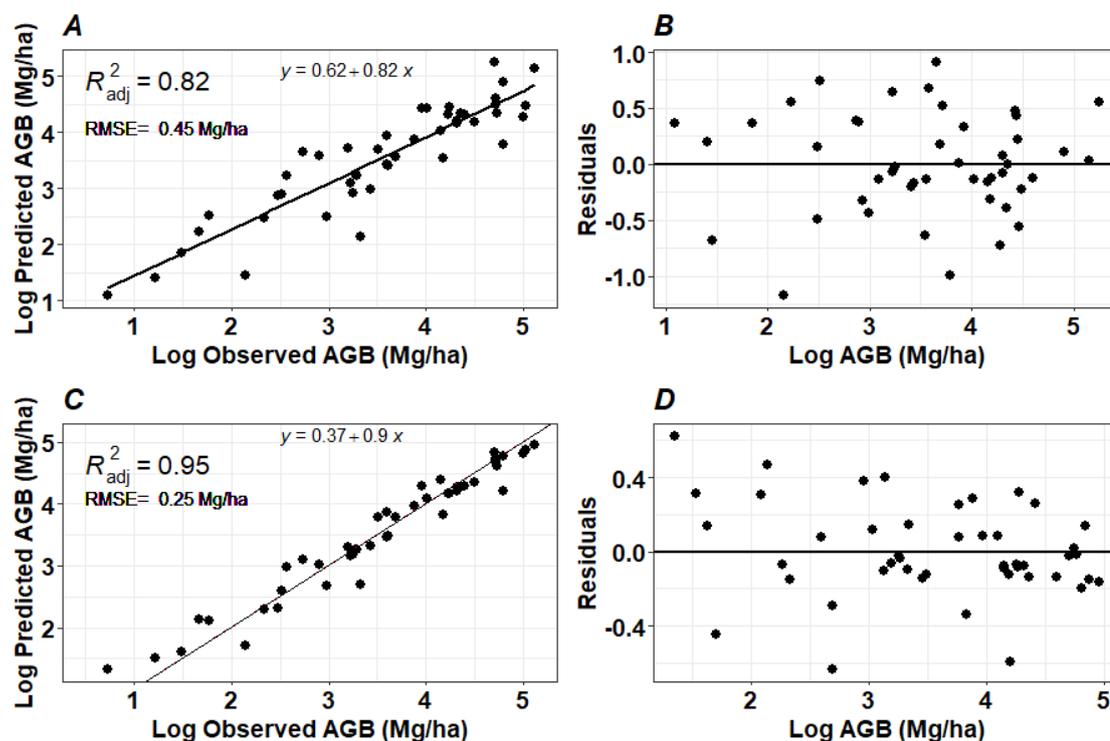
2675 Table 3.7 shows the summary statistics for the ML and RF regression models for
2676 AGB using the three optimum predictor variables (S1 VV polarisation, S2 green
2677 (B3), and red edge (B5)) hereafter referred to as S1S2), from the final models. It
2678 can be seen that features derived from the MRF regression model offer the most
2679 accurate estimates for all forest parameters compared to the ML regression model.
2680 Graphical illustrations for the performance of the AGB models are presented in Fig.
2681 3.4 that show the ML and RF fitted regression models for AGB and the associated
2682 residuals. The plots of observed vs predicted AGB and residuals, indicate that the
2683 RF residuals were rather stable across medium and high AGB values and had an

2684 average around zero compared to ML that under predicted AGB across the same
 2685 data range. It can also be seen that low AGB values are not estimated well by any of
 2686 the regression methods, although RF still had a more accurate estimation than the
 2687 ML regression model. For AGB, the RF regression has the highest R^2 of 0.95 and an
 2688 RMSE of 0.25 Mg/ha compared to ML regression model with an R^2 of 0.82 and
 2689 RMSE of 0.45 Mg/ha. Based on R^2 , RMSE, MSE, and concordance between predicted
 2690 and observed value, the MRF regression performed better than the ML and so the
 2691 MRF regression model was used for estimating forest stand parameters. Graphical
 2692 illustrations for the performance of the AGB models are presented in Fig. 3.4.

2693 Table 3. 7. Summary diagnostics for the AGB models developed by ML and RFR regression
 2694 methods using the S1S2 model. In this study, the best model throughout the study was the
 2695 RF regression model, highlighted in grey.

<i>Model Type</i>	R^2	<i>RMSE</i>	<i>MSE</i>	<i>Concordance</i>
<i>ML Regression AGB</i>	0.82	0.45	0.21	0.88
<i>RF Regression AGB</i>	0.95	0.25	0.06	0.95

2696



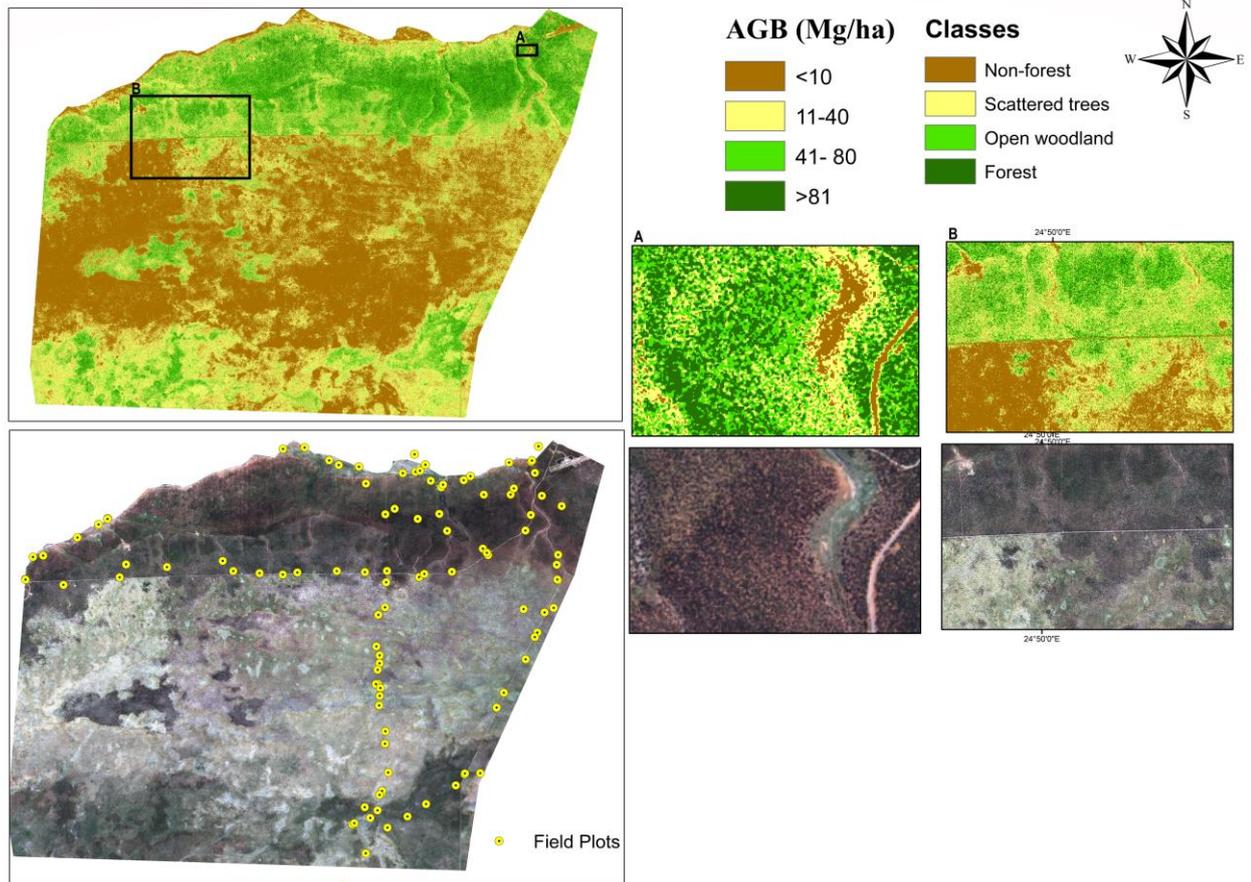
2697

2698 Fig. 3. 4. Optimal AGB model. A: Observed and predicted AGB using ML regression. B: ML
 2699 regression standardised residuals. C: Observed and predicted AGB using MRF regression.
 2700 D: MRF regression standardised residuals.

2701

2702 3.3.5 Spatial distribution of AGB

2703 Fig. 3.5 maps the spatial distribution of the AGB estimations across the study area using
2704 the RF regression-based model and S1 SAR and S2 spectral bands (S1S2). The
2705 distribution of AGB ranges from 4.0 Mg/ha to 145 Mg/ha, which closely corresponds to
2706 the range of values measured in the field where the highest AGB values were 167
2707 Mg/ha. The estimated AGB map revealed that the highest AGB values range from 80 to
2708 145 Mg/ha in northern Chobe, while a large part of the study area (80%) is characterised
2709 by low AGB values < 80 Mg/ha, with an average AGB estimated at 51 Mg/ha. In the
2710 southern part of the study area, there is a mixture of high and low-density forests, as
2711 shown in both the modelled maps and S2 imagery. Similarly, the lowest AGB estimates
2712 were found in the central part of the study area, which is consistent with field conditions
2713 where grassland, shrubs, and scattered trees are found, as a result of degradation
2714 associated with overgrazing and wildfire. The field photos corresponding to the mapped
2715 land cover types are shown in Fig. 3.6A, which shows an example of a typical forest
2716 plot where AGB ranges from 80 Mg/ha to 145 Mg/ha, as shown in dark green colour in
2717 Fig. 3.5A. Fig. 3.6B represents an open woodland with AGB ranging from 41 Mg/ha to
2718 80 Mg/ha, shown in light green colour in Fig. 3.5. The field photo in Fig. 3.6C shows an
2719 example of scattered trees with herbaceous cover, corresponding to AGB ranges
2720 between 11 Mg/ha and 40 Mg/ha, as shown in yellow colour in Fig. 3.5. Fig. 3.6D
2721 represents non-forest land cover with occasional scattered trees and/or shrubs which
2722 matches AGB values of <10 Mg/ha.



2723

2724 Fig. 3. 5. Modelled AGB maps of a dryland forest landscape of the study area and the RGB
 2725 432 S2 image (10 m).

2726



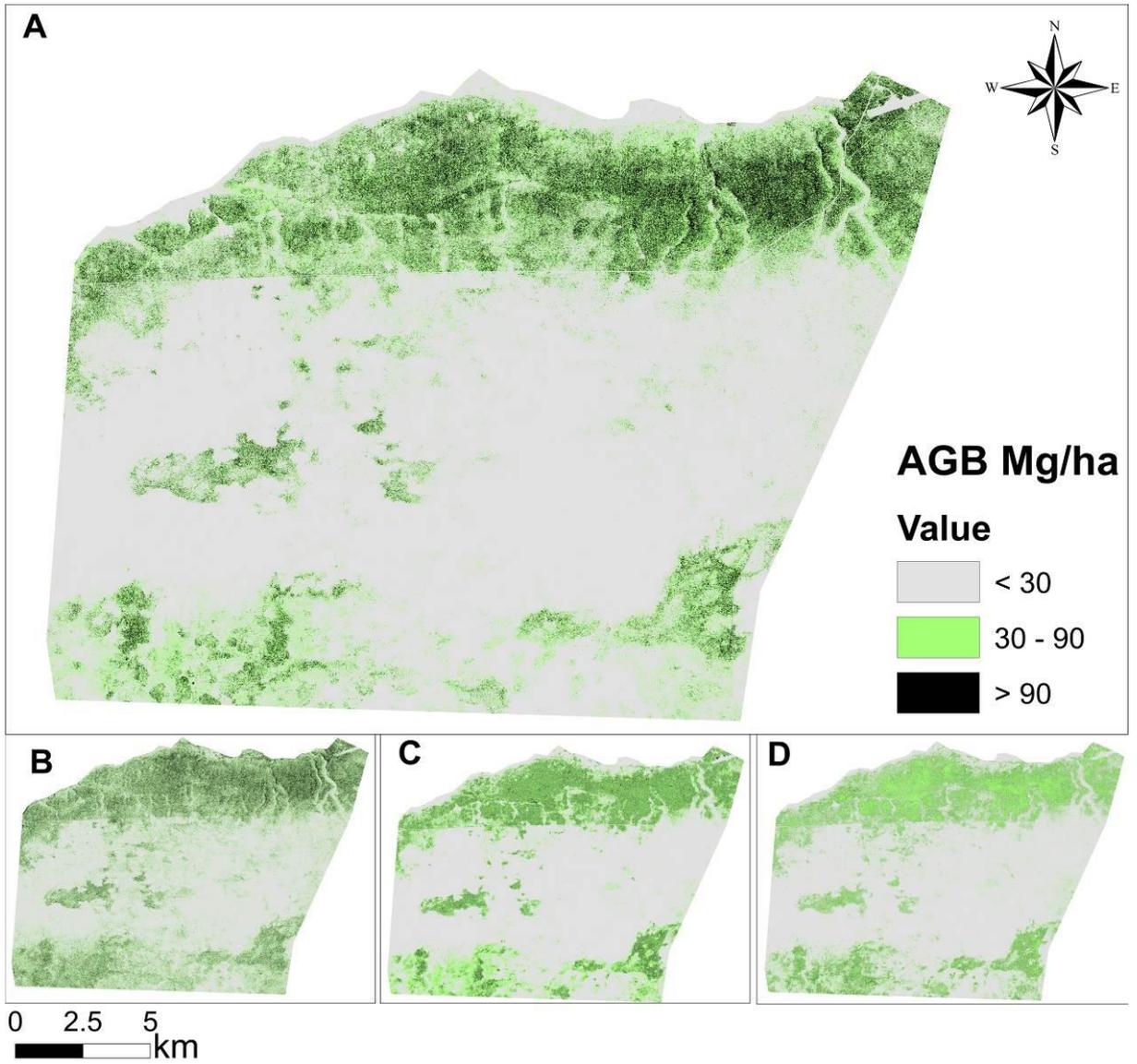
2727
 2728

Fig. 3. 6. Examples of dryland forest types and their respective ground pictures across

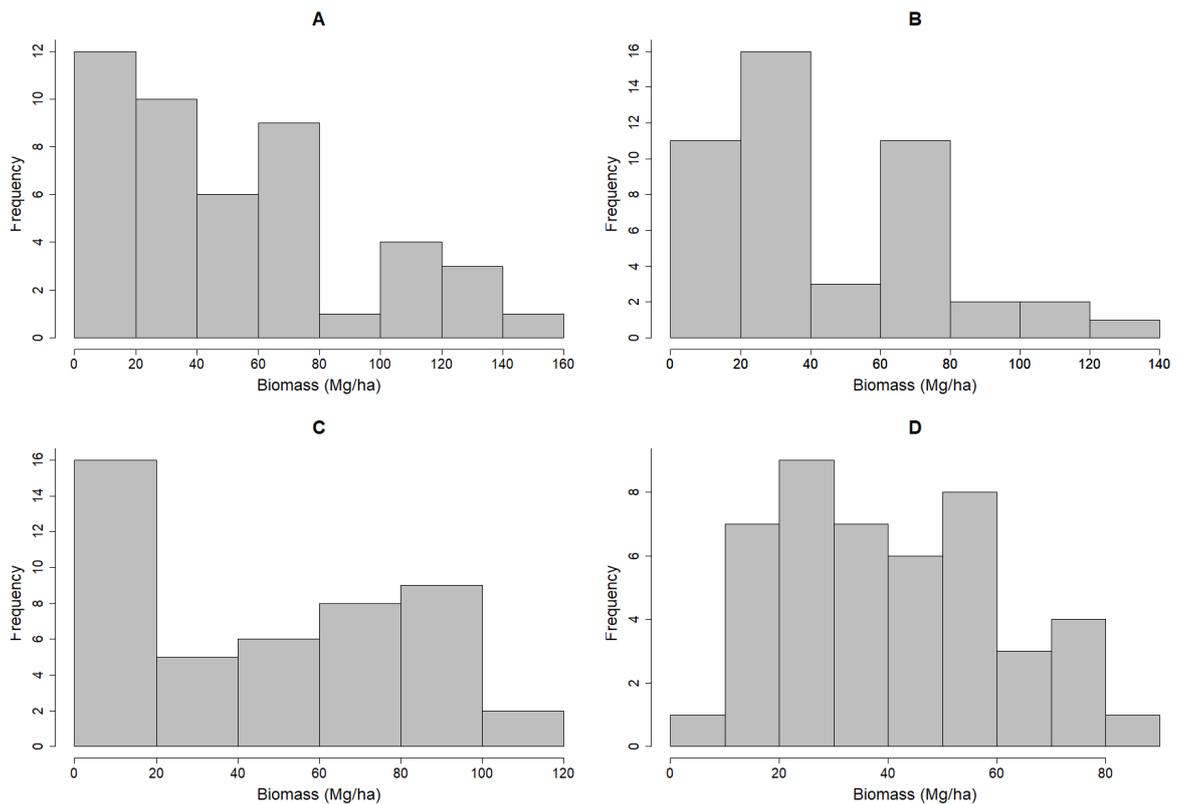
2729 Chobe National Park. A: closed canopy forest. B: open canopy woodland. C: scattered trees
2730 with low herbaceous cover. D: non-forest land cover.

2731

2732 This study selected and compared the combination of S1 C-band SAR, LC8 and S2
2733 optical data (S1S2), S1 polarisations and vegetation indices (NDRE1 and NDVI)
2734 that were suitable for forest structural parameter estimation. The results in Fig. 3.7
2735 show that the combination of S1 C-band SAR and S2 optical data estimated
2736 medium to high biomass density with a higher level of accuracy as compared to
2737 either sensor alone. A saturation effect for the S2 NDVI (S2NDVI) model was
2738 observed, wherein the sensitivity to biomass variability declines when biomass
2739 density exceeds 80 Mg/ha (see Fig. 3.7A). The saturation points for S1 polarisation
2740 (Fig. 3.7B) and NDRE1 (Fig. 3.7C) models were higher in comparison to NDVI. The
2741 combination of S1 backscatter values and S2 red edge position bands (S1S2) are
2742 capable of estimating biomass > 80 Mg/ha (black colours) and did reduce the
2743 saturation effect in high-density forest areas as shown in Fig. 3.7B. The maps in Fig.
2744 3.7 confirm that the S1S2 model produced the best fit with the ground
2745 observations for dryland forests, while reducing the under-estimation of large AGB
2746 values estimated by the S2NDVI model. The study observed a small but noticeable
2747 over-estimation for low values of biomass areas in the S2-NDVI model, although
2748 this was more prevalent in the degraded and fragmented vegetation areas e.g.,
2749 along the Chobe River frontage (see: Fig 3.7).



2750



2751

2752 Fig. 3. 7. A: AGB maps and histograms with the A: S1S2 model. B: S1 VV model. C: Modelled
 2753 AGB map with NDRE1 model. D: Modelled AGB map with the NDVI model (the NDVI model
 2754 saturates at values >80 Mg/ha).

2755

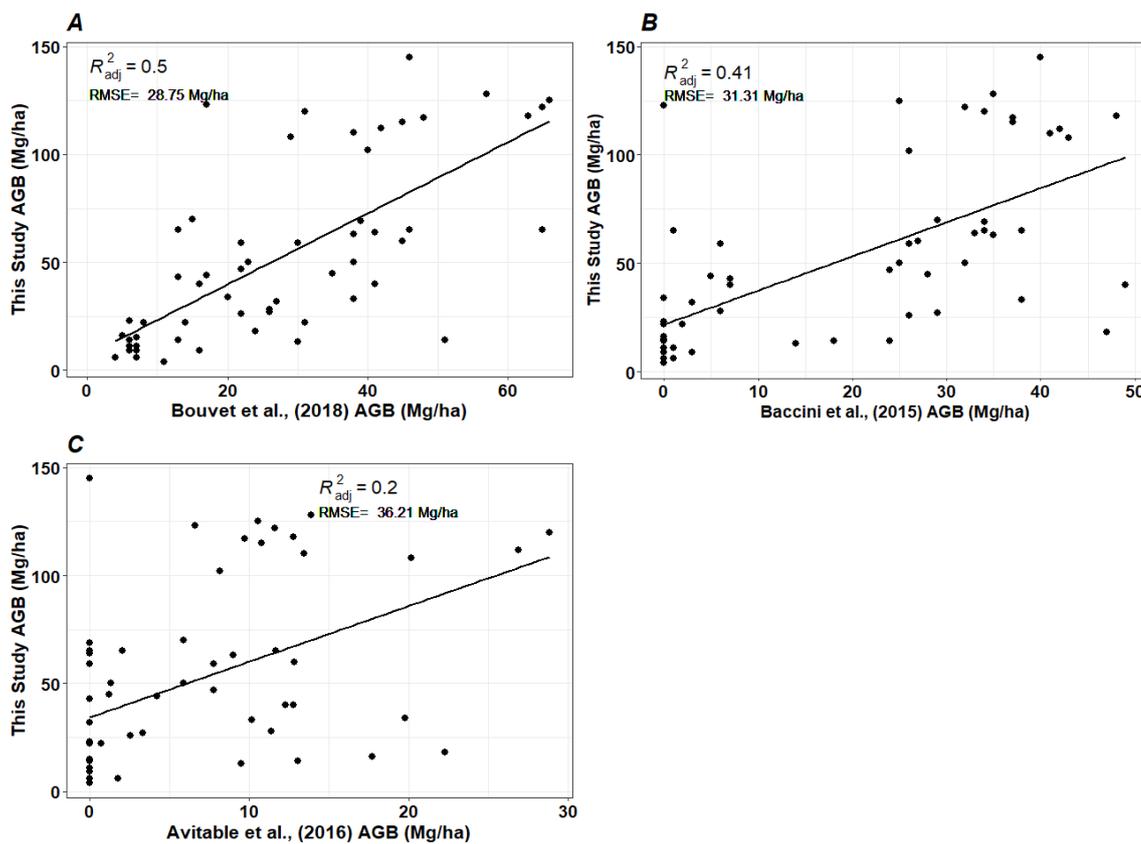
2756 In addition to cross-validation, the AGB map was evaluated by comparison with
 2757 the most recent published pan-tropical AGB datasets (Avitabile et al., 2016; Baccini
 2758 et al., 2017; Bouvet et al., 2018). The differences between models were analysed as
 2759 displayed in Fig. 3.8, 9, and 10. Avitabile et al. (2016) integrated two existing global
 2760 datasets of AGB from Saatchi et al., (2011) and Baccini et al. (2012) to create an
 2761 improved pan-tropical AGB map at 1 km resolution, using an independent
 2762 reference dataset of field observations to reduce bias and improve the accuracy.
 2763 Baccini et al. (2017) used Landsat data to produce an AGB map at 30 m resolution,
 2764 while Bouvet et al. (2018) used an ALOS PALSAR mosaic produced by JAXA in
 2765 2010 to produce an AGB map at 25 m resolution for continental Africa.

2766 Fig. 3.8 shows a comparison between this study AGB estimates with these three
 2767 published pan-tropical AGB datasets. A comparison with Avitabile et al. (2016)
 2768 predicts low AGB values in the 0 to 30 Mg/ha range with a very low R^2 of 0.20 and

2769 a precision of 36.21 Mg/ha. The result from Bouvet et al. (2018) using ALOS
2770 PALSAR shows the highest agreement with this study with a coefficient of
2771 determination R^2 of 0.50, compared to Baccini et al. (2017) which reported
2772 precision for the AGB estimates of 31.31 Mg/ha and an R^2 of 0.41. The pan-tropical
2773 maps all exhibited a high RMSE and a low R^2 when compared with this study,
2774 which has AGB estimates with R^2 of 0.95 and RMSE of 0.25.

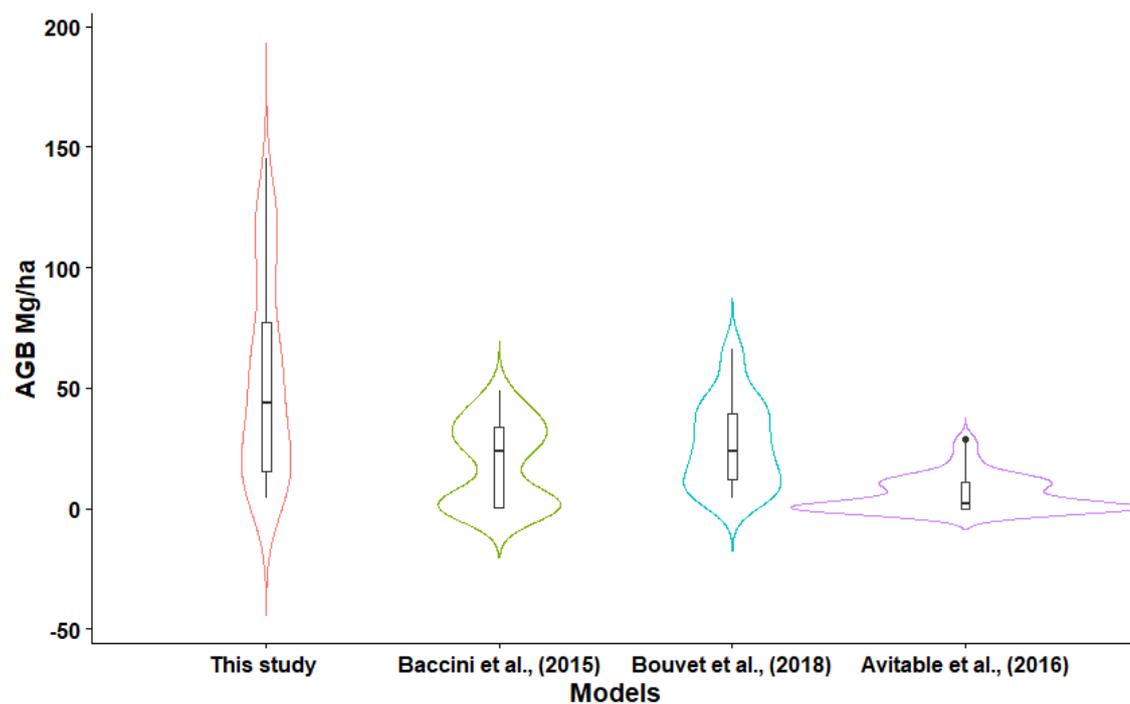
2775 Fig. 3.9 shows the spread, and distribution of the AGB from this study and three
2776 published pan-tropical AGB datasets. The mean AGB varied from 5.92 Mg/ha with
2777 the Avitabile et al. (2016), 18.5 Mg ha⁻¹ for Baccini et al., (2015), 26.7 Mg/ha for
2778 Bouvet et al., (2018) to the highest 51 Mg/ha for this study (Fig. 3.9). The lowest
2779 median is observed in Avitabile et al. (2016) and a relatively high variance is
2780 observed in this study. Some bimodality is suggested by Avitabile et al. (2016) and
2781 Baccini et al., (2015). This study and Bouvet et al., (2018) have a similar AGB
2782 spread and the highest mean AGB estimation, with this study estimating a AGB of
2783 145 Mg ha compared to 66 Mg/ha from Bouvet et al., (2018), 49 Mg/ha from
2784 Baccini et al., (2015) and 28.8 Mg/ha from Avitabile et al. (2016). Bouvet et al.
2785 (2018) was derived by limiting the model-based inversion method in predicting
2786 AGB of forest plots to not exceed 85 Mg/ha for dryland ecosystem, and this could
2787 explain the low AGB estimation in the high-density forest of the study area.

2788



2789

2790 Fig. 3. 8. Comparison between A: This Study AGB estimates and the AGB estimates from
 2791 Bouvet et al. (2018). B: This Study AGB estimates and the AGB estimates from Baccini et al.
 2792 (2017). C: This Study AGB estimates and the AGB estimates from Avitabile et al. (2016).



2793

2794 Fig. 3. 9. Comparison of AGB distribution (Mg/ha) among the different AGB estimates from
2795 this study, Avitabile et al. (2016), Baccini et al. (2017), and Bouvet et al. (2018). The
2796 models are arranged from the highest median AGB to the lowest. The horizontal line of the
2797 box plot for each model represents the median and the width of violin plot represents the
2798 proportion of the data using a kernel probability density.

2799

2800 3.4 Discussion

2801 3.4.1 Relationship between S1 SAR, S2, and LC8 with AGB

2802 In this study, simple linear regression models from S1 backscatter, S2, and LC8
2803 spectral coefficients were statistically significant ($p < 0.001$). However, the simple
2804 models estimating the AGB from all sensors provided low R^2 values and high RMSE
2805 that are considered unreliable for estimating forest structure parameters for
2806 practical forest management and habitat mapping. The RMSE observed in this
2807 study is lower than other AGB studies reported in the region, but it is similar to
2808 Mutanga et al. (2012) who predicted biomass using a similar sized plot from
2809 homogeneous areas (20 m × 20 m) to compute 3 NDVIs from the WorldView-2 red
2810 edge and NIR bands and yielded an RMSE of 0.441 kg/m². The highest R^2 was
2811 generated using multivariate models that employed both SAR and optical data
2812 (S1S2) highlighted in grey in Table 3.4, indicating the responsiveness of SAR to
2813 forest parameters particularly when sensors are used in combination for
2814 monitoring structural parameters in dryland forests, as reported by Townsend
2815 (2002).

2816 In terms of the radar polarimetric parameters, VV polarisation showed a better
2817 correlation and relationship with AGB and is shown to be more useful for the AGB
2818 estimations as compared to VH. However, the combination of VV and VH
2819 polarisation improves the R^2 and lowers the RMSE. This result is not consistent
2820 with the results obtained by Liu et al. (2019) but it is similar to the results of Omar
2821 et al. (2017) and (Pham et al. (2020) who found VV polarisation to perform better
2822 in estimating AGB and sensitive to the increase in AGB as compared to VH.
2823 Nizalapur and Madugundu, (2010) used backscatter intensities obtained in X, C, L
2824 and P- bands from DLR-ESAR data in Indian tropical forests, in which VV was

2825 found to correlate with biomass when compared to HH, HV and VH polarisations.
2826 The selection of VV polarisation and their strong correlation with AGB and forest
2827 parameters estimation also aligns with the studies by Ouaadi et al. (2020) and
2828 Wijaya et al. (2015).

2829 Further, it could be observed that the SAR data was better at detecting
2830 aggregations of individual trees in the savanna landscape than its optical
2831 counterpart, while overestimating AGB and tree density cover in this area. This
2832 effect was also shown in a study that was conducted in the Sahel dryland
2833 ecosystems using S1/2 data (Zhang et al., 2019). The overestimation of AGB was
2834 reduced from the combined use of S1 and S2 as compared to the single use of any
2835 of the sensors.

2836 For optical data, although NDVI and EVI remain two of the most widely used
2837 vegetation indices, they were outperformed by the NDRE1 and GNDVI in
2838 estimating AGB, for dryland forests. The results are in agreement with the study by
2839 Wang et al. (2007) that tested the capabilities of GNDVI for estimating the Leaf
2840 Area Index (LAI), which were tested under different circumstances, and found that
2841 GNDVI performed better than the conventional NDVI in both circumstances. The
2842 results also align with the study by Otsu et al. (2019) who found that GNDVI
2843 performed best in distinguishing broad leaf from needle leaf forests as compared
2844 to NDVI. Another study by Yoder et al. (1994) used the green channel in a
2845 vegetation index and found that it had a better correlation with the photosynthetic
2846 activity of the tree canopy in miniature Douglas-firs as compared to the red
2847 channel. The main reason for the difference in the performance of NDVI and GNDVI
2848 is likely because the former is more sensitive to low chlorophyll concentrations,
2849 while GNDVI is more sensitive to high chlorophyll concentrations and so is more
2850 accurate for assessing chlorophyll content at the tree crown level (Gitelson et al.,
2851 1996). Besides the use of the green channel in a vegetation index, the red edge
2852 band is found to be more effective in estimating AGB at high canopy density as
2853 compared to conventional vegetation indices because it covers chlorophyll
2854 absorption and leaf cell structure reflection (Mutanga and Cho., 2012, Eitel et al.,
2855 2011).

2856 The study found that a combination of S1 polarisation, S2 green, and red edge
2857 bands, have led to the mitigation of data saturation in high-density biomass, when
2858 compared to S2 NDVI models that saturate at biomass levels above 80 Mg/ha. The
2859 saturation of the relationship between biomass and the NDVI due to strong
2860 absorption in the red wavelength is a well-recognised problem (Zhao et al., 2016).
2861 SAR acquired across the range of frequencies (namely C-, L- and P-band) has a
2862 demonstrated capacity to quantify biomass up to a saturation level after which
2863 sensitivity is lost, depending on the frequency used. For example, it is reported that
2864 the C-band radar backscatter response saturates at biomass values of 30 Mg/ha to
2865 50 Mg/ha, and the L-band backscatter is generally reported to occur between 70
2866 Mg/ha and 150 Mg/ha and P-band backscatter can measure from 100 Mg/ha
2867 up to 200 Mg/ha (Lucas et al., 2015). For this study, the synergy between the two
2868 data sources, particularly the inclusion of SAR backscatter values from VV
2869 polarisation and the red-edge (B5) spectral bands have reduced saturation effects
2870 typical in optical and radar backscatter remote sensing data for the dense or
2871 mature forest with complex stand structures in dryland forest (Liu et al., 2019).

2872 3.4.2 Selection of suitable algorithms and methods

2873 The estimations derived from the machine learning algorithm showed the ability
2874 for improved the estimation of all forest parameters including AGB. Although the
2875 results from ML regression models exhibited a strong linear relationship, this
2876 study found that the RF regression algorithm performed better than ML
2877 regression, reducing the RMSE for the estimation models by almost 50% in all
2878 instances. In this study, ML regression derived relationships between observed
2879 and estimated AGB and residuals show some linearity, that is, overestimations and
2880 underestimations for the low and high biomass observations, respectively. This
2881 demonstrates the problem of using linear regression models, as identified by Zhao
2882 et al. (2016) who used Landsat and linear regression to estimate biomass
2883 saturation values in the Zhejiang Province of Eastern China.

2884 Even though MRF regression models reduce the overestimation and
2885 underestimation of biomass compared to ML regression models in this study, there
2886 remains room for improvement. Specifically, the RF regression model estimated
2887 medium and high-density forests with good accuracy but showed variation in low-

2888 density forests <30 Mg/ha. Most of these low-density forest plots include
2889 understoreys and low herbaceous cover such as grassland, open forest, and burned
2890 woodlands, often with relatively low canopy density. Therefore, soil and moisture
2891 conditions under the canopy would have a significant impact on surface
2892 reflectance and considerably influence AGB estimation. These results are similar to
2893 numerous studies that assessed dryland forests using radar backscatter signals
2894 and decision tree models (Baccini et al., 2004; Santos et al., 2002; Wang et al.,
2895 1998) which all found that variations in understorey and ground conditions had an
2896 impact on the interaction of microwave radiation with vegetation cover. Using
2897 Radar C- and L-band, Wang et al. (1998) noted that the sensitivity of SAR to surface
2898 parameters is most pronounced for co-polarisation signals C-VV and C-HH angles
2899 at low biomass levels, with a sensitivity decrease for high biomass stands. This was
2900 also an issue in this study because data were acquired during the wet season
2901 where errors associated with moisture are likely (Mitchard et al., 2013).

2902

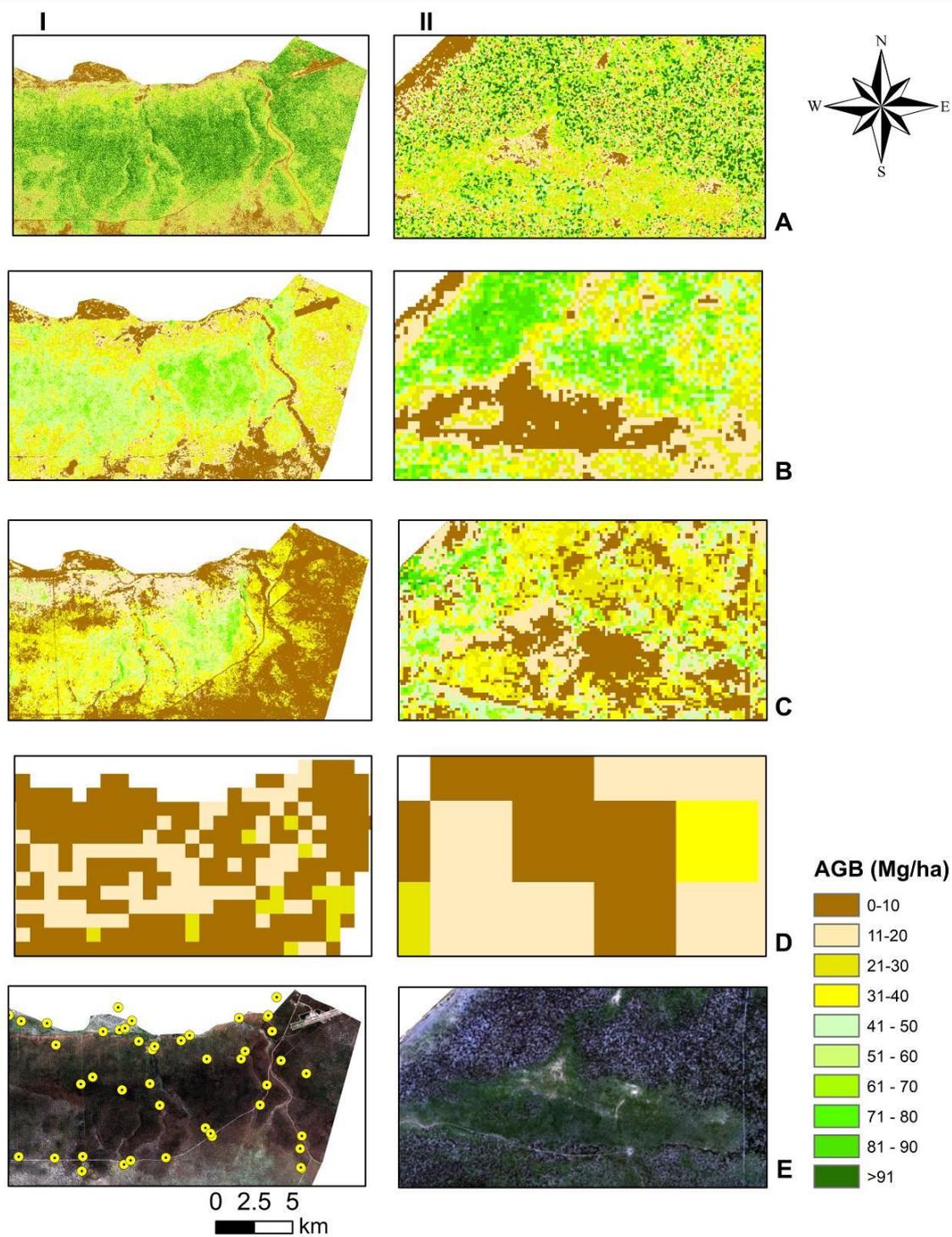
2903 3.4.3 Comparing regional AGB estimates with pan-tropical 2904 maps

2905 The spatial distribution of high values of AGB (>145 Mg/ha) closely corresponds to
2906 field measurements, with the forests in the northern part of Chobe National Park
2907 found to have the highest AGB values. This can be attributed to the predominance
2908 of species with large DBH such as Zambezi teak (*Baikaea Pluijuga*). Also, the
2909 impacts of fire on the northern part of Chobe Park are better controlled than the
2910 southern areas, as they commonly experience a higher burning frequency (Dube,
2911 2013).

2912 Fig. 3.10 (I) shows a detailed view of a subset of forests in the northern part of the
2913 study area, dominated by high density forests. The inability to estimate AGB
2914 heterogeneity and a large under-estimation of biomass in dryland forests can be
2915 clearly seen in the AGB map of Avitabile et al. (2016) when compared to all the
2916 other AGB datasets. In contrast, Baccini et al. (2017) using Landsat imagery
2917 underestimate AGB in the area of high-density forest around the airport situated to
2918 the northeast of the study area (0-10 Mg/ha). Bouvet et al. (2018), using ALOS

2919 PALSAR, predict higher levels of biomass than Baccini et al. (2017) around the
2920 airport area (10-30 Mg/ha), but these estimates are lower than this study
2921 estimates of >80 Mg/ha. This study estimates higher biomass stocks in large areas
2922 of northern Chobe > 80 Mg/ha particularly when compared to Bouvet et al. (2018)
2923 and Baccini et al. (2017).

2924 The area shown in Fig. 3.10(II) is along the Shimwanza Valley, characterised by
2925 bare ground, gullies, tall shrub savanna, and open woodland with a mixture of
2926 medium and large trees. Results showed very large discrepancies from the pan-
2927 tropical map in this area. For example, it can be seen that Bouvet et al. (2018)
2928 underestimated a large portion of large and mature individual trees and were not
2929 able to characterise the variability in dryland forests or the patterns of open
2930 woodland. In addition, Bouvet et al., (2018) estimated high biomass of 50 Mg/ha to
2931 70 Mg/ha in the degrading forest along the Chobe River frontage (see: Fig. 3.9B).
2932 The S2 image reveals that there are actually fewer trees in this area with more
2933 bare ground in between. The S1S2 model from this study was able to clearly show
2934 the fine details of trees in different AGB ranges, with a mix of very low biomass
2935 (due to different degrees of degradation) to intermediate biomass for certain areas
2936 with very large but scattered trees, as shown in S2 imagery (see: Fig. 3.10E).
2937 Baccini et al. (2017) shows a broad range of AGB (low to intermediate) similar to
2938 this study AGB estimates in the Chobe River frontage; although their study
2939 estimated lower biomass in high-density forest areas (see: Fig. 3.10C).



2940

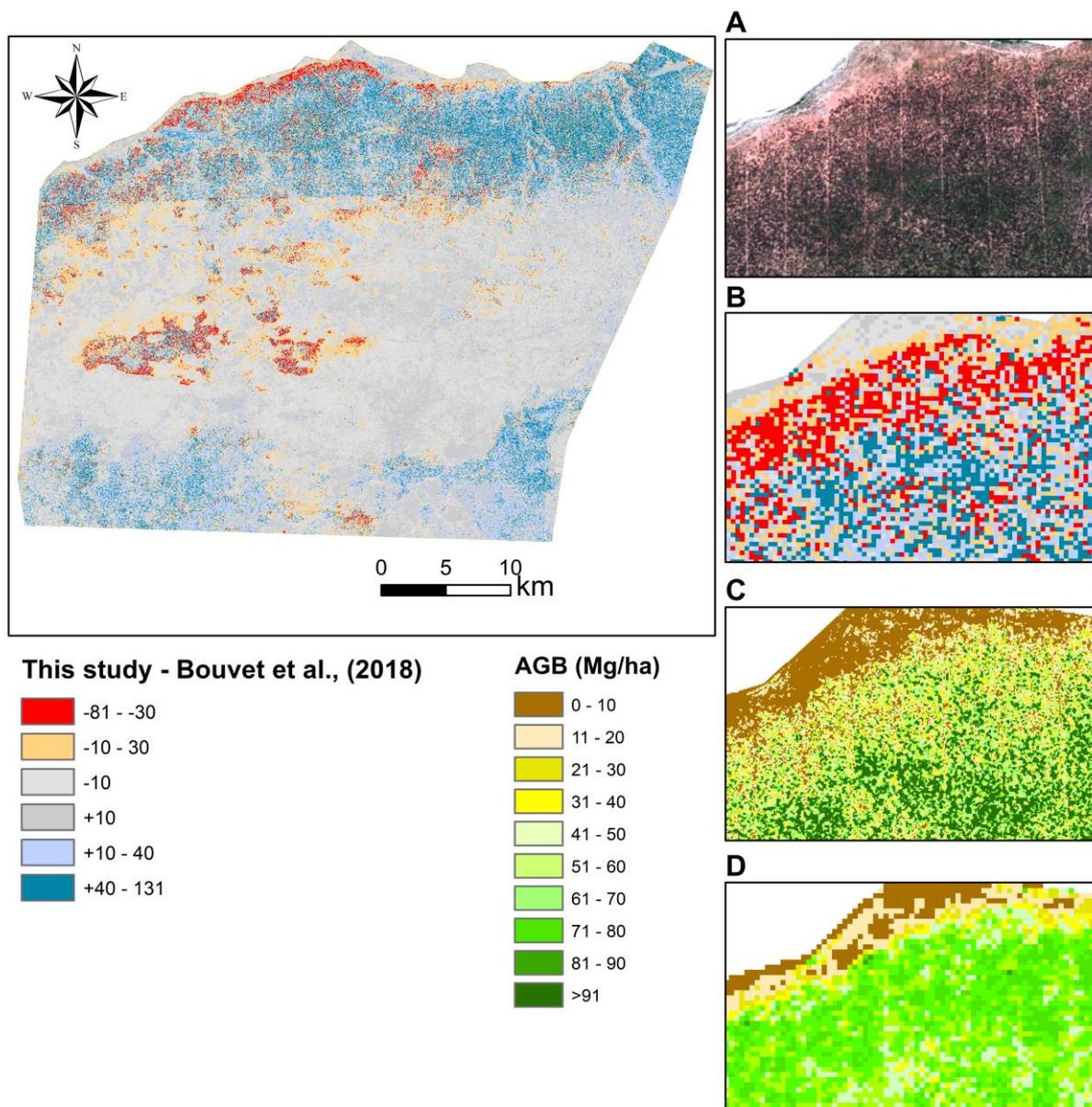
2941 Fig. 3. 10. Biomass map in a subset of forests in the (I) northern part of the study area and
 2942 (II) Shimwanza valley. A: estimated AGB map by this study. B: estimated AGB map by
 2943 Bouvet et al. (2018). C: estimated AGB map by Baccini et al. (2017). D: estimated AGB map
 2944 by Avitabile et al. (2016). E: RGB 432 S2 image.

2945 3.4.4 Suitability of different models for land and wildlife 2946 management

2947 Optical Landsat imagery utilised by Baccini et al. (2017) was able to capture broad-
2948 scale information on forest biomass but was less able to describe fine-scale
2949 disturbance. Where it captured the patterns of biomass fragmentation, it mostly
2950 overly overestimated AGB (Baccini et al., 2017). While Bouvet et al. (2018), using
2951 ALOS PALSAR L-band, was effective in mapping biomass structural density, but it
2952 was less capable at distinguishing biomass from degraded habitat areas, and
2953 largely failed to capture biomass variability and relatively small-scale changes
2954 associated with features such as roads, which were captured by this study and to a
2955 larger extend by Baccini et al. (2017) (see: Fig. 3.11). The large discrepancies in
2956 biomass distribution from Pan-tropical datasets can also be attributed to forest
2957 masks derived from different land cover maps which excluded certain
2958 woodland/vegetation types from their estimation. For example, Avitabile et al.
2959 (2016) used the GLC2000 map from Bartholomé & Belward. (2005) as a forest
2960 mask, while Bouvet et al. (2018) masked out forest classes (broadleaf evergreen
2961 closed to open forest) using the ESA CCI Land Cover 2010 map from ESA (2014),
2962 which can have a large impact on the estimation of biomass and carbon stocks in
2963 dryland forests. The AGB map generated by this study is the most accurate and
2964 detailed published for the study area and complements the global products,
2965 therefore facilitating regional to international reporting of biomass and carbon
2966 dynamics. This is in agreement with (Lucas et al., 2008) who utilised ALOS PALSAR
2967 data and the Landsat-derived Foliage Projected Cover (FPC) in Queensland,
2968 Australia, and reported that the combination of radar and optical data has the
2969 ability to allow better assessment of deforestation patterns, regeneration and
2970 woody thickening, tree death from climate change, and biomass change. In
2971 addition, the AGB model from this study showed that biomass for dryland forests
2972 exceeds estimates derived from pan-tropical products which underestimate
2973 biomass and forests in dryland ecosystems of less-studied areas such as the KAZA
2974 region, which are often neglected in this type of analysis (David et al., 2022a). The
2975 sensor fusion explored here complements this study and encouragingly suggests a
2976 high potential for separating biomass in dryland cover types that are structurally
2977 distinct but spectrally similar, which are notably those areas that are challenging

2978 to distinguish through optical remote sensing alone (Buhne and Pettoirelli, 2018;
2979 Treuhaft et al., 2004).

2980 In addition to sensor integration, issues of scale are critical for biomass and habitat
2981 mapping, where the adequacy of spatial resolution is key (Buhne and Pettoirelli,
2982 2018). For example, biomass mapping at a regional scale utilising the fusion of
2983 optical and radar data in this study reduced the saturation effect at high AGB
2984 values above 80 Mg/ha, allowing the identification of habitat fragmentation, and
2985 small-scale degradation patterns of biomass compared to broader scale maps.
2986 Maps of AGB, if sufficiently detailed, can assist conservation managers,
2987 practitioners, and policymakers to formulate specific practices (e.g., corridor
2988 planning, tree thinning, fire control, biodiversity surveys, etc.) that are appropriate
2989 to support the conservation of forest habitats and their management. Many
2990 countries presently lack the capacity to produce their own local maps of forest
2991 biomass and so must rely on existing biomass maps founded upon broader pan-
2992 tropical and global datasets. Whilst the AGB maps produced by Baccini et al.
2993 (2017) and Bouvet et al. (2018) may be used to meet national-scale emissions
2994 reporting requirements when no finer scale information is available, these maps
2995 need to be validated against local forest stock surveys or local/regional AGB maps
2996 from higher resolution satellite imagery. Given the decision-making on
2997 sustainability at national and subnational levels, this study contends that the pan-
2998 tropical and global data sets are unable to provide finer scale mapping of aspects
2999 that are relevant to wildlife habitat and biodiversity in dryland forests. These
3000 results support the assertion that countries should not rely on pan-tropical
3001 datasets but should rather estimate biomass and carbon stocks at the regional and
3002 local level, which in turn feeds into meeting the United Nations' Sustainable
3003 Development Goals (SDGs), as suggested by Mitchard et al. (2013). This is essential
3004 for land and forest management in these areas, particularly in protected zones,
3005 given the vulnerability to anthropogenic pressure, disturbance from wildlife, and
3006 climatic fluctuations.



3007

3008 Fig. 3. 11. A: RGB 432 S2 image. B: S2 a difference map between this study and Bouvet et
 3009 al., 2018 (This study -Bouvet et al., (2018), C: This study AGB map. D: Bouvet et al., 2018
 3010 AGB map.

3011

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3013

3014

3015 3.5 Conclusion

3016 This study combined satellite-based synthetic-aperture radar (SAR) and
3017 multispectral imagery with ground truth data to map above ground biomass
3018 throughout the dryland forests in the Chobe region of Botswana. The main finding
3019 from the results is that using a combination of data types (SAR and multispectral
3020 sensors) it is possible to estimate above ground biomass in dryland forests with a
3021 good level of precision. The estimations of AGB reveal that the highest biomass
3022 values of 80-145 Mg/ha were found in northern Chobe where the dominant tree
3023 species are *Baikiaea plurijuga*, *Burkea africana*, and *Pterocarpus angolensis*. A large
3024 part of the study area (85%) is characterised by low AGB values (< 80 Mg/ha). In
3025 Southern Chobe and along the Chobe River frontage area, a high burning frequency
3026 and degradation associated with overgrazing and elephant damage may have
3027 contributed to the generally low AGB values observed. Three main conclusions can
3028 be drawn from this study:

3029 First, combining freely available SAR and multispectral imagery (S1 and S2) has
3030 the potential to estimate biomass at local and regional levels with a good level of
3031 precision compared to using single sensors alone. The research observed that the
3032 relatively fine resolution of Sentinel (10 m pixels) reduced the mixed pixel
3033 problem observed in medium spatial resolution data (30 m pixels; e.g. Landsat 8),
3034 which led to an increase in the precision of biomass estimation. The results
3035 demonstrated that SAR backscatter in conjunction with the strategically positioned
3036 optical bands (red edge wavebands) significantly improved forest stand parameter
3037 estimations and the reduced saturation effect in areas of high biomass in dryland
3038 forests. The NDRE1 and GNDVI yielded a higher linear relationship than NDVI,
3039 while GRVI and EVI yielded the lowest correlation with AGB.

3040 Secondly, dryland forest ecosystems and conservation organisations can use global
3041 and continental datasets as sources of information that could provide early
3042 warnings of regional-scale ecological change. However, regional and local studies
3043 are critical and serve to provide useful information in evidence-based decision
3044 making for improved estimation of carbon stocks, monitoring the impacts of
3045 climate change, and the conservation of dryland forest habitats under pressure.

3046 Finally, after comparing and analysing the effects of the various empirical models
3047 using ML and RF regression approaches, this study found that the decision tree
3048 model (RF regression algorithm) is the most robust for estimating AGB in dryland
3049 forests, as compared to linear analysis. The precise and timely quantification of
3050 AGB can help improve the understanding of dryland forest habitats and to plan and
3051 monitor land and forest resources in conservation areas, which are critical for
3052 wildlife function and sustainable land management at present and into the future.

3053 3.6 Acknowledgments

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3060 Authority Michael Flyman, and University of Namibia (Katima Branch) Dr.
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3062 Kamwi who helped with data collection.

3063

3064

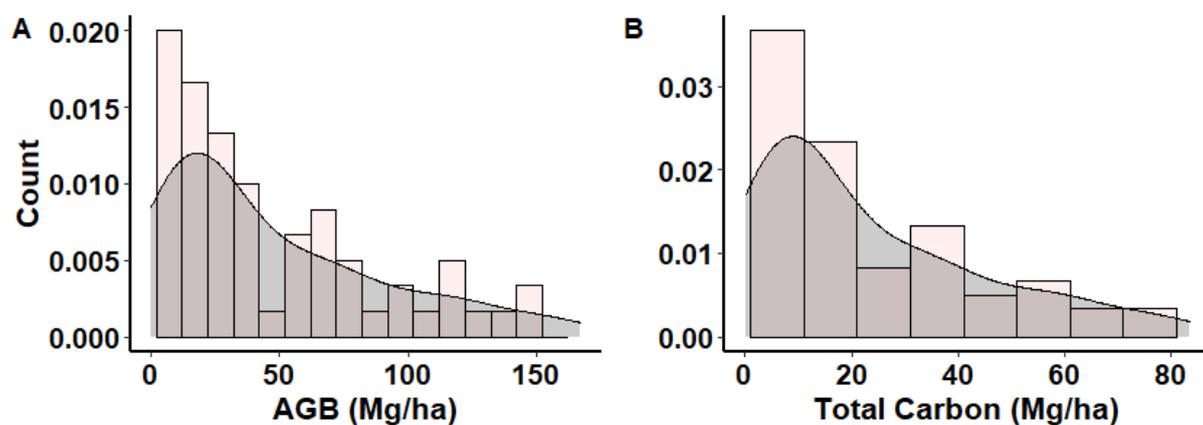
3065

3066 3.7 Supplementary Information 1

3067 Table A. 1. Image acquisition date and scene ID.

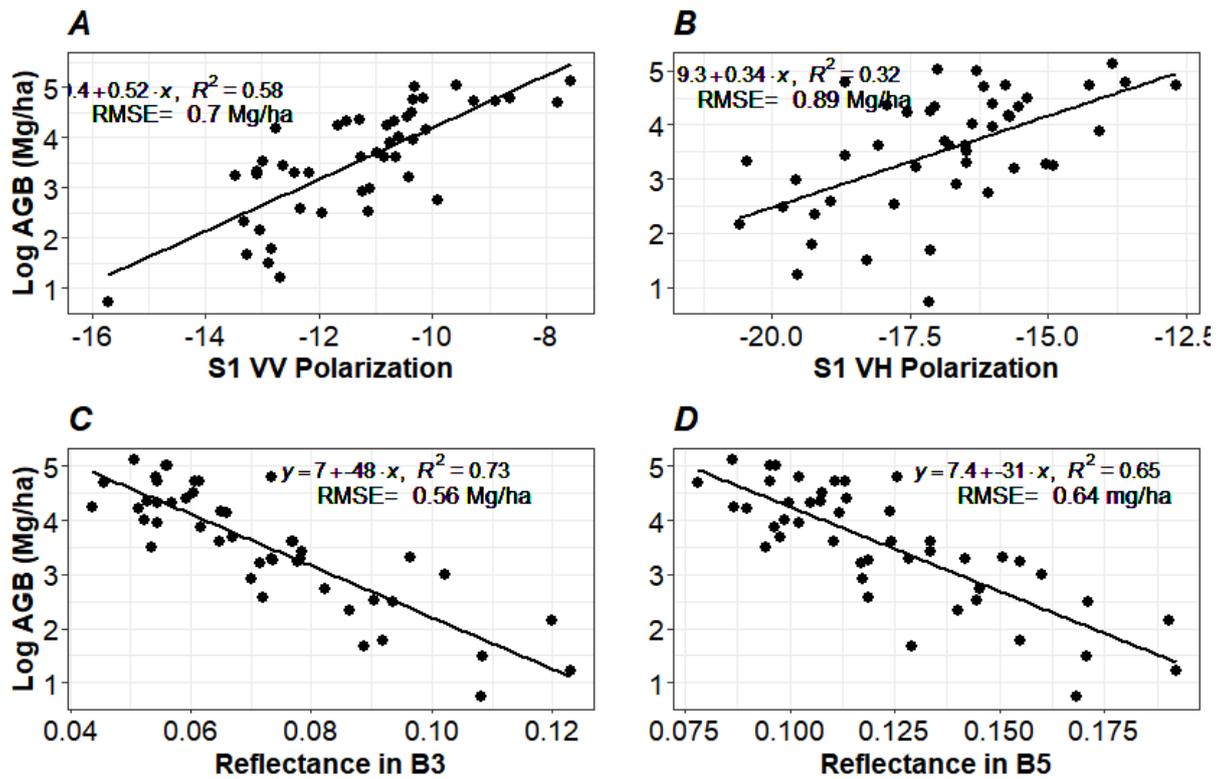
<i>Satellite</i>	<i>Cloud cover</i>	<i>Acquisition Date</i>	<i>Satellite Name</i>
S1	0	15/03/2019	COPERNICUS/S1_GRD
S2	0	14/03/2019	COPERNICUS/S2_SR/20190314T080709_20190314T083245_T35KKA
LC08	0	15/03/2019	LANDSAT/LC08/C01/T1_SR/LC08_174072_20190315

3068



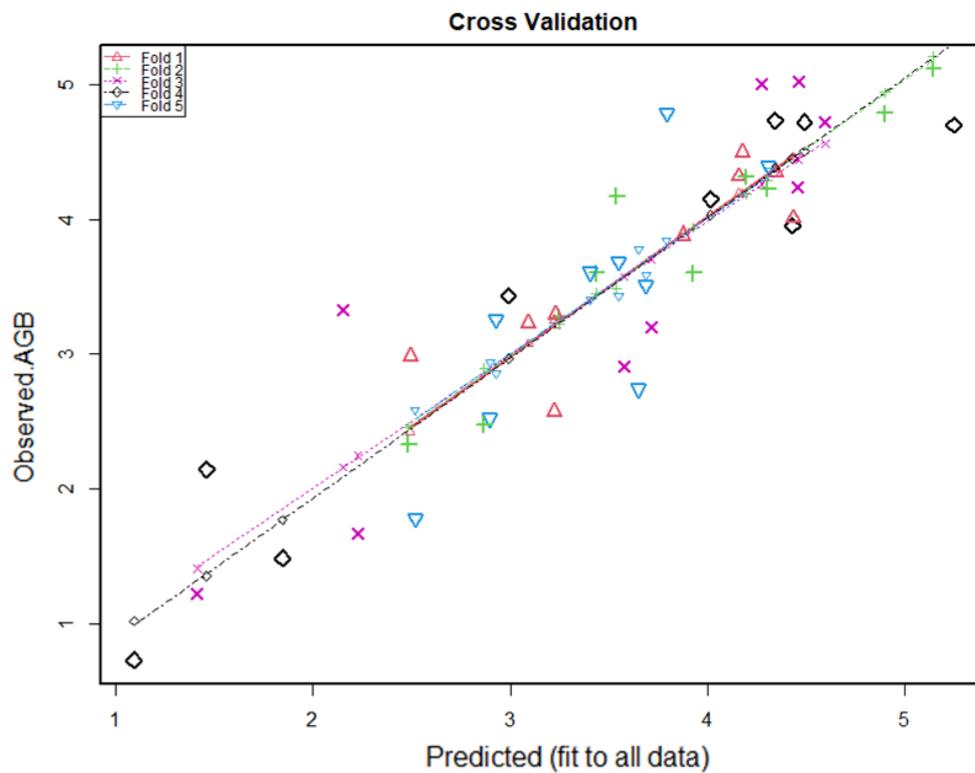
3069

3070 Fig A. 1. Density and histogram plots A: Aboveground biomass (AGB); B: Carbon stock
 3071 (Mg/ha) of each field plot with woodland trees.



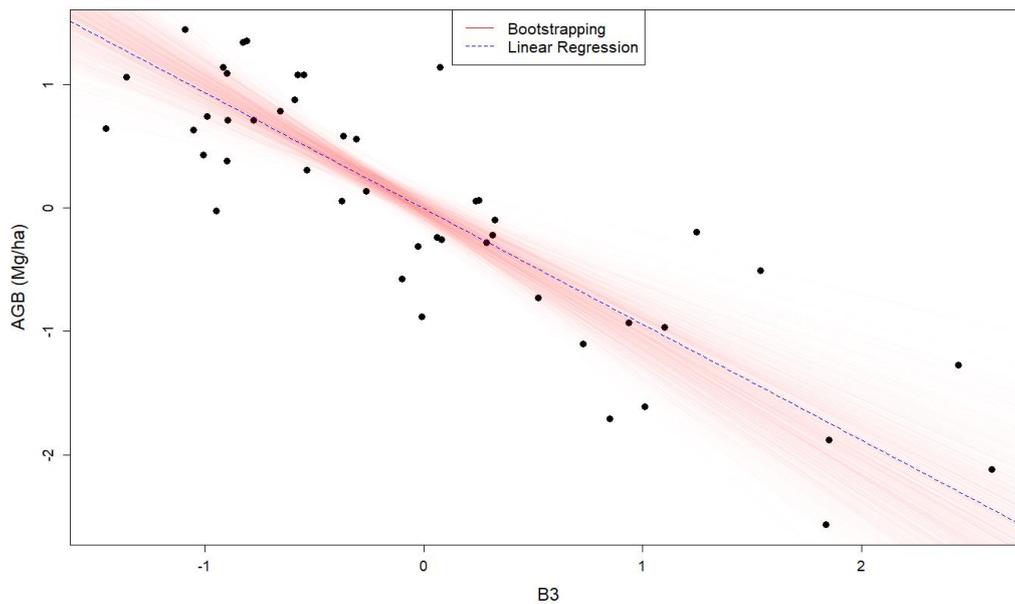
3072

3073 Fig A. 2. Relationships of S1 polarisations and S2 spectral bands with stand forest
 3074 parameters in the study area. A: S1 VV polarisation vs AGB. B: S1 VH polarisation vs AGB.
 3075 C: S2 B3 vs AGB. D: S2 B5 vs AGB.



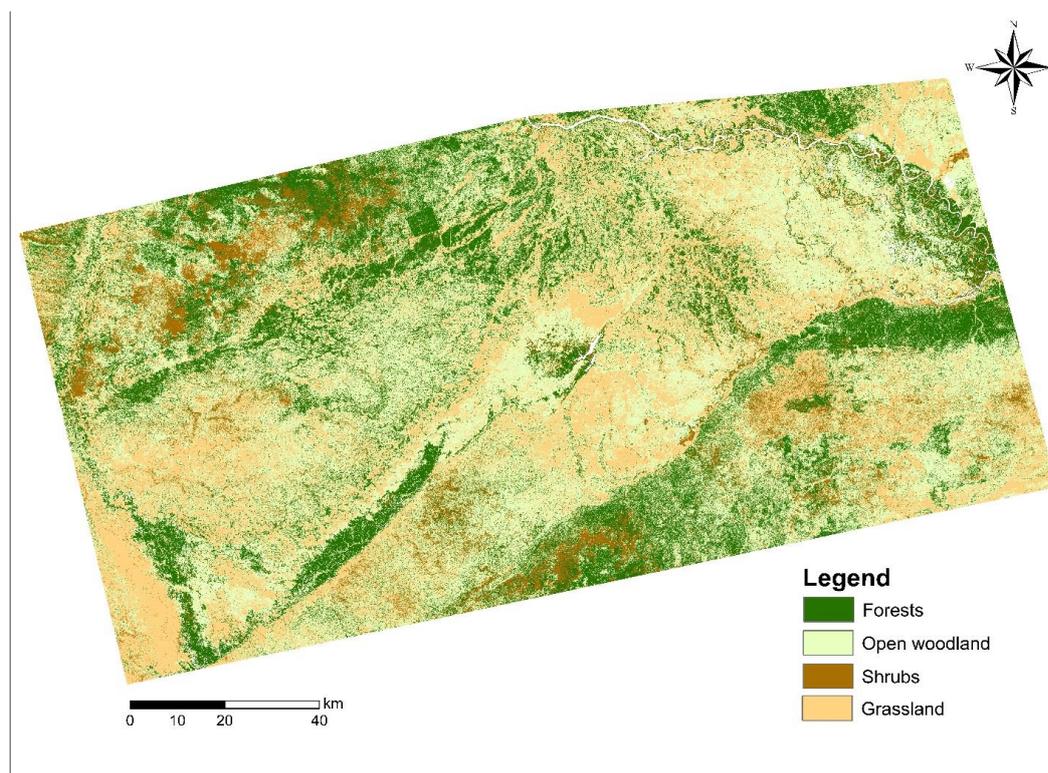
3076

3077 Fig A. 3. Dispersion diagram of the observed versus predicted biomass at each fold on a log
 3078 scale using 70% of the training data.



3079

3080 Fig A. 4. Linear and Bootstrap regression of Sentinel 2 Band 3 on a standardised scale.



3081

3082 Fig A. 5. Land cover classification map of Zambezi region in Namibia and Chobe District in
3083 Botswana for 2019

3084

3085

3086 Table A. 2. Area statistics of the land cover classes.

Land cover classes	Total Area (km²)	Percentage (%)
Forests	4,475	23
Open woodland	8,216	43
Grassland	4,910	25
Shrubs	1,719	9
Sum	19,321	100%

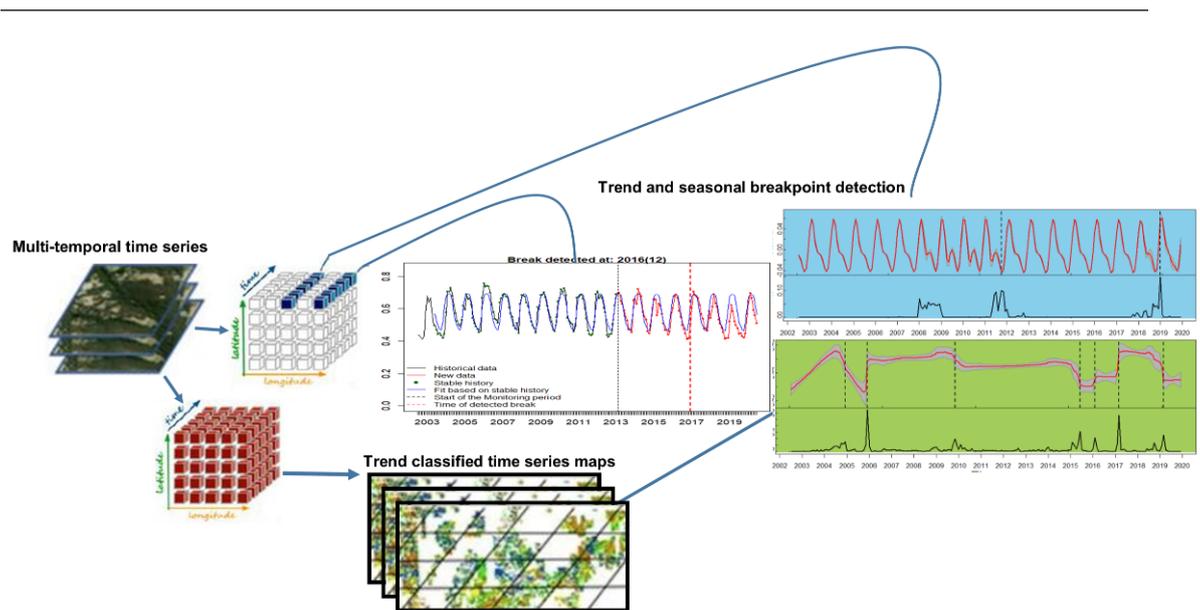
3087

3088 Table A. 3. Accuracy assessment of the land cover classification

Accuracy	Percentage (%)
Overall Accuracy	97%
Validation Overall Accuracy	67%
Kappa coefficient	60%

3089

3090 **4 IDENTIFYING AND UNDERSTANDING DRYLAND**
 3091 **FOREST CHANGES AND DISTURBANCES IN SOUTHERN**
 3092 **AFRICA USING LANDSAT AND MODIS TIME SERIES**
 3093 **AND FIELD VEGETATION DATA**



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3095

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3097

3098 Chapter 4 Manuscript in progress: Intended for submission to *International Journal of*
3099 *Applied Earth Observation and Geoinformation*.

3100

3101 **Title:** Identifying and understanding dryland forest changes and disturbances in
3102 Southern Africa using Landsat and MODIS time series and field vegetation data.

3103

3104 **Author contributions**

3105

3106 David Ruusa- Design the research, perform the data analysis, interpret the results,
3107 wrote the manuscript, and revised the manuscript. Nick Rosser- Contributed to the
3108 research design, manuscript editing and supervision. Daniel Donoghue-
3109 Contributed to the research design, conducting fieldwork, manuscript editing and
3110 supervision.

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3117 **Abstract**

3118 The Kavango Zambezi (KAZA) Transfrontier Conservation Area is sensitive to
3119 water availability, and drought, in addition to anthropogenic disturbances, impacts
3120 vegetation cover in the region. An effective method for change detection to
3121 examine vegetation response across KAZA needs to account for seasonal as well as
3122 abrupt changes over at fine temporal resolutions (e.g., monthly) rather than yearly
3123 basis. In this study, an approach that quantifies dryland forest change by
3124 combining Landsat and MODIS imagery with climate data, validated against
3125 ground-based measurements collected from Namibia and Botswana was
3126 presented. The Breaks for Additive Seasonal and Trend (BFAST), and Bayesian
3127 Estimator of Abrupt change, Seasonality and Trend (BEAST) algorithms were
3128 applied to evaluate their ability to detect changes in both long-term trend and
3129 seasonality based upon the MODIS normalised difference vegetation (NDVI) and
3130 Green normalised difference vegetation (GNDVI) time series. The results
3131 demonstrate that there is a close relationship between the ground survey data and
3132 the estimated changepoints. The Bayesian analysis (BEAST) was found to give the
3133 best performance in identifying abrupt changes associated with fire, drought, and
3134 seasonal changes driven by climate and clear-cutting events as compared to
3135 BFAST. BFAST failed to detect seasonal shifts in the entire study period. GNDVI
3136 was an effective dataset for detecting both small and large magnitude changes (e.g.,
3137 deforestation, fire, and drought), while the NDVI was most effective in detecting
3138 large magnitude changes, particularly those that resulted in complete land-cover
3139 class changes (e.g., deforestation). The study found that the NDVI was more
3140 influenced by canopy background variations and herbaceous layers when
3141 detecting changes with regrowth of herbaceous layers than the GNDVI. Tropical
3142 dryland forests in KAZA are highly dynamic and water-sensitive with high rates of
3143 deforestation and widespread degradation, which mainly result in abrupt
3144 vegetation changes, continuous vegetation recovery and regrowth. The approach
3145 presented can accurately identify the vegetation changes, phenological variations
3146 and time of disturbance in both the spatial and temporal domains. Therefore, it can
3147 contribute to the understanding of forest decline and habitat changes and their

3148 vulnerability in the context of land cover change, climate change and sustainable
3149 development policies in tropical dryland forests.

3150 **Keywords:** Change detection, Time-series decomposition algorithm, Forest
3151 disturbance, Bayesian estimators, BFAST, Abrupt change, Southern Africa

3152 4.1 Introduction

3153 Tropical dryland forests experience a high degree of pressure from human activity
3154 but monitoring forest degradation in these systems is challenging due to high
3155 canopy complexity, phenology, climatic variability, and diverse degradation
3156 drivers (Grainger, 1999, McElhinny et al., 2005, McNicol et al., 2018). Protected
3157 Areas (PAs) underpin global efforts to preserve the Earth's biodiversity and
3158 maintain functional terrestrial and aquatic ecosystems (Wiens et al., 2009). The
3159 Kavango Zambezi Transfrontier Conservation Area (KAZA TFCA) is the largest
3160 "hyper" hotspot for endemism and conservation support. However, the tropical
3161 savanna forests and woodlands (hereafter referred to as "dryland forest") face an
3162 increasing number of threats, ranging from those originating from climate,
3163 disturbance by large mammalian herbivores, to those associated with the
3164 increasingly invasive competition for diminishing resources. These multiple
3165 threats have led to deforestation and degradation of protected landscapes, which
3166 directly impacts wildlife species distributions (Cumming, 2008). Changes in
3167 climate regimes and competition for the available natural habitats have
3168 contributed to the escalation of human-wildlife conflict (HWC) in the KAZA region,
3169 especially in Namibia and Botswana (FAO, 2009). Furthermore, climate modelling
3170 of Africa has shown that dryland forest in and around KAZA TFCA is among the
3171 world's most vulnerable at warming levels of 1.5–2.0° (IPCC, 2014).

3172 Monitoring long-term ecological processes in these PAs is therefore crucial to
3173 ecological conservation and biodiversity (FAO, 2009). The possibility that arises
3174 when changes are not monitored routinely is that the adverse impacts may have
3175 already occurred and it may be too late to reverse the change or even adapt to it
3176 (Sheffield et al., 2008). This will lead to large-scale destruction of important
3177 habitats for many species and a dramatic decrease in wildlife habitats. Thus, for
3178 conservation goals to be met, it is essential to detect whether vegetation changes

3179 and degradation are occurring within the forests of PAs and their causes.
3180 Assessment of the regional impacts of land use and land cover (LULC) change are
3181 fundamental for determining the appropriate policy responses to forest decline,
3182 increased human-wildlife conflicts, and managing of animal movement patterns
3183 and wildlife corridors in KAZA TFCA (Stoldt et al., 2020). Such efforts are equally
3184 important for enhancing forest carbon sequestration and avoiding deforestation
3185 for developing nations, as encouraged by Reducing Emissions from Deforestation
3186 and forest Degradation (REDD+) schemes.

3187 In Africa, almost all remaining dryland forests in PAs are threatened by
3188 deforestation and degradation and so should be given high conservation priority
3189 (Clark et al., 2008). Although the focus in detecting forest cover loss using different
3190 indices soon after they occur overwhelmingly remains in humid forests (Janzen,
3191 1988; Masiello et al., 2020), dryland forests are beginning to receive more
3192 attention. However, published studies on dryland forests in Africa are generally
3193 concentrated on the Sahel in West Africa (Liu et al., 2017), while most studies in
3194 Southern Africa have been confined to Kruger NP (Bucini et al., 2010).
3195 Unfortunately, the forests in PAs of other parts of Southern Africa such as KAZA
3196 TFCA have received far less attention. An additional challenge is understanding the
3197 sensitivity and therefore suitability of conventional satellite-based NDVI
3198 measurements in detecting large and small-scale forest disturbances and seasonal
3199 change in highly heterogeneous forest environments such as drylands (Blackie et
3200 al., 2014). The lack of historical disturbance events in KAZA TFCA constitutes a
3201 challenge for in-depth temporal and spatial analysis which is crucial to ecological
3202 conservation and biodiversity. This is raising concerns that disturbances within
3203 the dryland, natural resources and wildlife habitat management areas might
3204 increasingly interfere with continuous and sustainable provisioning of ecosystem
3205 services to society and wildlife.

3206 The availability of MODIS satellite data and new automated data processing
3207 techniques that provide high-quality continuous time-series data represent a
3208 major advancement for the automated monitoring at monthly rather than annual
3209 intervals which potentially masks considerable within-year variations. The daily
3210 temporal resolution of the MODIS NDVI has a significant advantage over Landsat
3211 data for monitoring the disturbance and recovery state. The limitation of MODIS

3212 based Vegetation Indices (VIs) for change detection is associated with the
3213 moderate spatial resolution. With the advancement of cloud computing,
3214 particularly the Google Earth Engine (GEE) platform, which provides an archive of
3215 data including MODIS and Landsat with associated data processing capacity at no
3216 cost (Gorelick et al., 2017), has become a valuable tool for change monitoring in
3217 tropical environments. Access to such temporally rich time series has also led to an
3218 increase in methods that aim to track the occurrence of disturbance events at
3219 regional scale. It is reported that disturbance rates in dryland forests have
3220 increased in recent decades, and there is evidence that climate change and past
3221 land use both have contributed to the disturbance increasing rate (Wilcox, et al.,
3222 2011). Continuous disturbances in an area consisting of natural habitats result in
3223 habitat fragmentation and reduce its ability to support the ecosystems and
3224 surroundings that are essential for their sustainability (Visscher, 2006). The
3225 accurate reconstruction of past forest disturbance dynamics at spatial, temporal,
3226 and thematic scales offered by time series will allow ecological analyses to help
3227 provide a better understanding of disturbance regimes (Senf et al., 2017). The
3228 dense time series information enables the quantification and characterisation of
3229 disturbances in terms of disturbance magnitude, duration, and attribution of
3230 recent disturbance activities (Kennedy et al., 2012). Before the availability of time
3231 series analysis, forest change detection mapping was done using bi-temporal
3232 differences or supervised image classifications (David et al., 2022a). Bi-temporal
3233 image classifications were able to detect large-scale deforestation, but they are less
3234 useful for assessing small-scale deforestation, degradation, and regrowth because
3235 they fail to capture the dynamic behaviour of vegetation during the year and over
3236 longer time periods (Hamunyela et al., 2020; Zhu and Woodcock, 2014). Moving
3237 from a relatively static, bi-temporal view of change toward a more continuous view
3238 of ecosystem dynamics can improve understanding regarding the disturbance's
3239 spatiotemporal patterns, their causes, and consequences (Kennedy et al. 2014).
3240 Effective change detection ideally identifies variations at the seasonal scale while
3241 simultaneously detecting abrupt, and subtle changes in any long-term trends.
3242 Breaks For Additive Seasonal and Trend (BFAST), BFAST Seasonal and Bayesian
3243 Estimator of Abrupt change, Seasonality and Trend (BEAST) algorithms have been
3244 developed to do this (Verbesselt et al., 2012; Zhao et al., 2019). However, their

3245 effectiveness in tropical dryland forests, where vegetation response is typically
3246 aseasonal, has yet to be assessed.

3247 This paper aims to provide a systematic assessment of vegetation dynamics and
3248 spatially detailed patterns of change in the dryland forests. To do this, the research
3249 employs multiple data streams for the time series assessment of forest change over
3250 parks and surrounding areas within KAZA TFCA from 2002–2019. The premise is
3251 that by taking advantage of the different characteristics of vegetation indices and
3252 different change detection model, change detection results could be improved in
3253 dryland forests. The general objective was to investigate the evidence of water
3254 stress conditions and assess the suitability of the change detection model on
3255 MODIS time series data for mapping forest disturbances (e.g., clear-cutting,
3256 drought) in dynamic and diverse tropical dryland forests. Specifically, this paper
3257 reports three steps: (1) spatial characterisation of climatic data with vegetation
3258 indices as a proxy indicator of climate variability to improve understanding of
3259 vegetation response to drought; (2) Compare the commonly used NDVI vegetation
3260 index with GNDVI and evaluate their sensitivities and performances in detecting
3261 changes; and (3) Characterise changes in trends and phenological patterns using
3262 BFAST and BEAST algorithms. (4) Quantify and identify the LULC change,
3263 locations, types, and trends of the land cover during the 19-year period in
3264 communal and protected areas of Zambezi region. Ideally, such an analysis will
3265 provide conservation efforts with frequently updated information for monitoring
3266 disturbances and potentially deforested areas, allowing targeted mitigation actions
3267 to be taken.

3268

3269 4.2 Materials and methods

3270 4.2.1 Study area

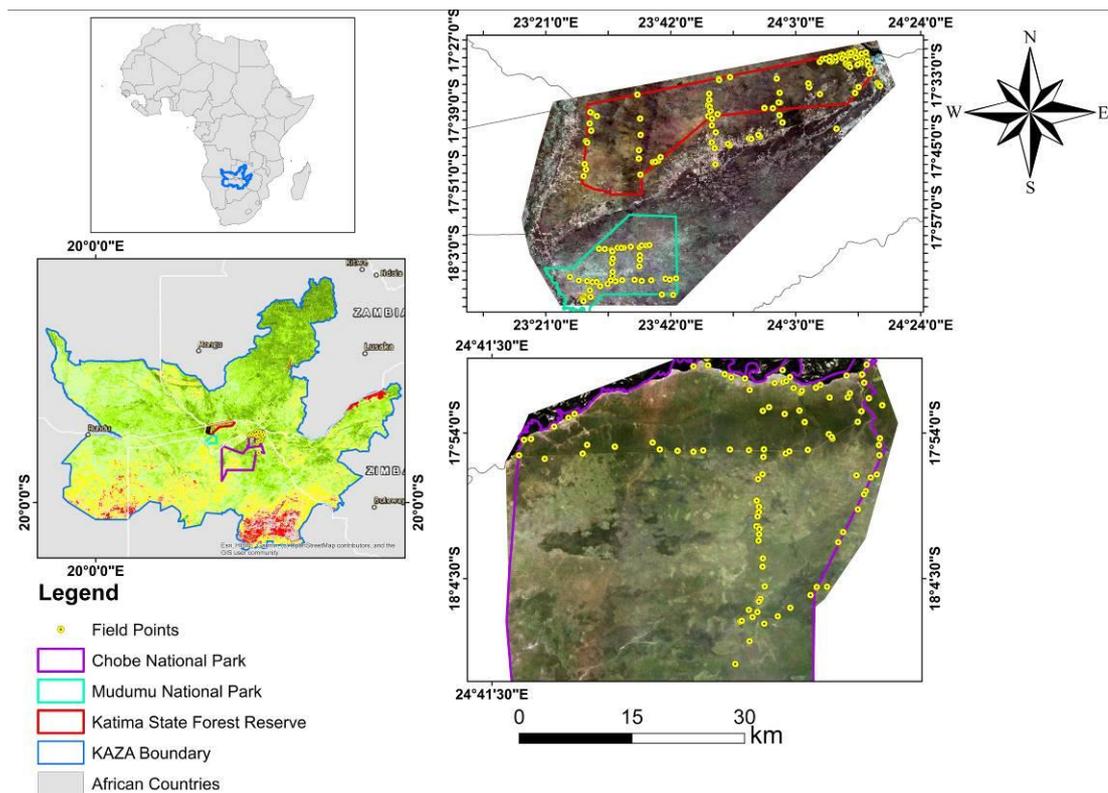
3271 The KAZA TFCA (18.00°S, 23.00°E) in Southern Africa, is an iconic PA that inhabits
3272 a rich ecology and enormous wildlife. KAZA TFCA is established in March 2013
3273 with an enclosed area equivalent to the size of France at 519,912 km² (Cumming,
3274 2008), and is situated in the Kavango and Zambezi River basins- and is shared by

3275 Angola, Botswana, Namibia, Zambia, and Zimbabwe. Within this area, 371,394 km²
3276 are under conservation and the remaining 148,520 km² are mainly used for
3277 agricultural activities including rangeland.

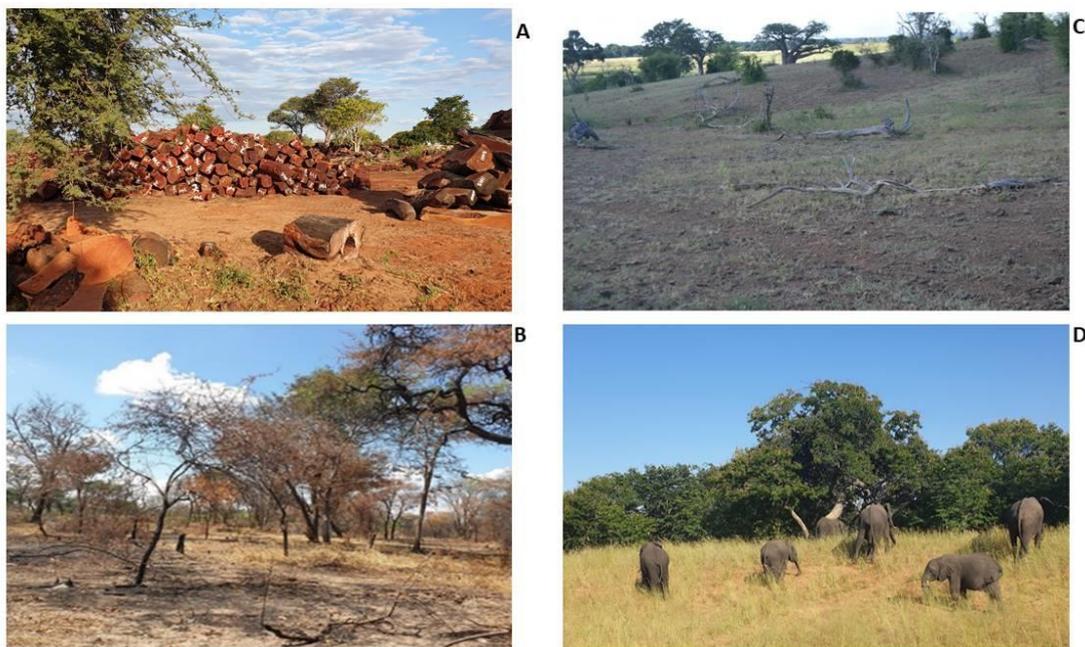
3278 This conservation area is considered to be an important means to create economic
3279 development and conserve the unique biodiversity by establishing links between
3280 fragmented habitats with a particular focus on large-scale migrations of wildlife
3281 (WWF, 2016). KAZA links together over 36 proclaimed PAs including national
3282 parks (NPs), forest reserves, community conservancies, and wildlife management
3283 areas. PAs carry substantial populations of large mammals and several plant
3284 endemic plant species, including large areas of the dryland forests, and globally
3285 significant wetlands. The dryland vegetation domain in KAZA ranges from forest
3286 formations with a dense canopy cover to shrubs and grasslands ranges, which are
3287 also considered a biodiversity hotspot. However, these areas are under severe
3288 pressure from agricultural expansion and settlement, wildlife, large-scale burning,
3289 and timber harvesting (NACSO, 2014) (see: Fig. 4.1). This study focuses on the
3290 Namibian and Botswanan components of the KAZA TFCA. In particular, the study
3291 was conducted in three protected areas situated in the Okavango Zambezi region:
3292 (a) Chobe NP in Botswana, (b) Zambezi state forest (ST) in Namibia, and (c)
3293 Mudumu NP in Namibia. The selection of study sites depended on the ecological
3294 importance and the land conservation practices implemented within the region.
3295 The selection of sites in Namibia included state-run protected areas such as
3296 Zambezi state forest (red-coloured polygon), a conserved forest area which was
3297 traditionally protected by the government and residents in the area (see: Fig. 4.1).
3298 Zambezi state forest is designed to be only used sustainably used for timber and other
3299 forest products but has now been pushed back by human settlement (Bollig and
3300 Vehrs, 2021). The Mudumu National Park (Aqua-coloured polygon) is one of the
3301 largest protected areas in the Zambezi region established as a core wildlife area
3302 with animals migrating from the park to surrounding communal conservancies,
3303 where they can be used for quota hunting or through tourism (O'Connell et al.,
3304 2000). The unprotected surrounding communal area including the communal
3305 conservancies that depend on agriculture and tourism development and both
3306 encroach on the dryland forests (Hank, 2003).

3307 The Chobe NP, in the north-east of Botswana (18.7°S, 24.5°E), features the largest
3308 number of elephants in KAZA; the number of elephants in northern Botswana
3309 alone is estimated at more than 156,000 (Junker, 2009). The Chobe River basin
3310 serves as a source of surface water for the Chobe District and in the dry season,
3311 animals converge on this stretch of water from Northern Botswana (Hanks, 2003).
3312 Chobe NP contrasts with the Namibian component of KAZA TFCA. The Zambezi
3313 Region (17.8° S, 23.9° E), in the heart of KAZA, is a long strip of land with multiple
3314 land uses, containing several national parks much smaller by comparison to Chobe
3315 NP. The Mudumu NP, in north-eastern Namibia, and is bordered by the Kwando
3316 River. The park is in the centre of KAZA TFCA and as there is no boundary fence, it
3317 acts as a corridor for large game species such as African elephants, as migrating
3318 between Botswana, Zambia, Angola, and Zimbabwe. The Zambezi ST area is
3319 surrounded by conservancies and communally governed areas. The Zambezi ST
3320 generally features very high population densities with consequent overgrazing and
3321 widespread unsustainable wood harvesting with many areas considered now
3322 degraded.

3323 Topography in both parks is relatively flat characterised by low elevations ranging
3324 from 910 to 1100 m above sea level (Omphile et al., 2002). Climatically, the sites
3325 have similar rainfall patterns throughout the year, and so the KAZA region has a
3326 subtropical dry climate characterised by highly variable rainfall. The annual
3327 average rainfall is approximately 650 mm, with almost all falling between
3328 November to March, followed by a dry season from April to October. Daytime
3329 temperatures increase towards the end of the dry season, when the heat soars and
3330 the expectation of rain is high. Average temperatures range between 15.2°C -
3331 30.2°C.



3332



3333

3334 Fig. 4. 1. Location of the study area in KAZA TFCA. The yellow circles show sampling sites
 3335 in Zambezi ST, and Mudumu NP Namibia (top), and Chobe NP (bottom). Examples of
 3336 sample plots representing disturbance types and recent degradation activities captured
 3337 during a field campaign in 2019 are shown, A) clear-cut deforestation of forest area in
 3338 Zambezi ST Namibia, B) Burned forest for cultivation near protected area of Mudumu NP,
 3339 Namibia, C) the visible forest loss, especially the woodland along the Chobe riverfront, D)
 3340 high population of elephants destructive influence on vegetation.

3341 4.2.2 Fieldwork and sampling design

3342 Survey fieldwork was undertaken to record forest tree stands and observe the
3343 different land cover types present in the study area during the growing season (1st
3344 February - 30th April 2019). The field samples of the five main land cover classes
3345 (forests, open woodland, shrubs, grassland, and bare land) were collected at three
3346 sites in the KAZA TFCA region; one park was located in Botswana, the Chobe NP.
3347 The other two sites are located in Namibia - the Mudumu NP, and Zambezi ST (see:
3348 Fig. 4.1). These sites were chosen because dryland forests within and around the
3349 PAs are particularly susceptible to disturbance and drought, warranting particular
3350 attention (Feng et al., 2013). However, these areas are often remote and dangerous
3351 to visit in the field, due to the hazard posed by wildlife and if present, unexploded
3352 landmines (see: Fig. 4.1). Another challenge is there are very little plot data in the
3353 dryland forests, which are more sensitive to inter-annual variations in climate than
3354 humid forests (Grainger, 1999). This is particularly true for the forest in the KAZA
3355 region that experienced several extreme droughts in recent.

3356 The allocation of plots followed a stratified random sampling approach based on
3357 the four strata (forest, open woodland, scattered trees with low herbaceous cover,
3358 and non-forests). The plot sizes of (20 m × 20 m) and (10 m × 10 m) were
3359 considered adequate to enable sampling a good number of trees in each plot.
3360 Smaller plot sizes of (10 m × 10 m) were adopted only in areas of very high tree
3361 density that were dangerous to visit due to the hazard posed by wildlife. In total,
3362 measurements were collected from 271 individual sample plots randomly
3363 distributed throughout the dryland landscape. A total of 101 plots in Chobe NP,
3364 115 plots in Zambezi ST, and 50 plots in Mudumu NP were visited. In Botswana, 61
3365 sample plots represent woody vegetation, 40 sample plots represented non-
3366 woodland cover, while in Namibia 95 sample plots represent woody vegetation,
3367 and 75 represented non-woodland cover. The total number of individual trees
3368 measured was 4337 in Botswana, 2400 trees in Zambezi ST, and 1600 trees in
3369 Mudumu NP. For each tree inside the plot, mean height, diameter at breast height
3370 (DHB), tree density, canopy closure, and tree species were recorded. The UTM
3371 coordinates at the centre of each plot were taken with the hand-held GPS. Although
3372 the coordinates of each plot centre were collected with a high-quality device with

3373 GPS and GLONASS sensors, there may be small positional errors, especially when
3374 differential corrections are unavailable (errors up to 8–10 m are common). The
3375 images used in this chapter have a spatial resolution of 30 m for Landsat and 500m
3376 for MODIS data which have a coarser pixel size which compensated for the
3377 possible positional error of the GPS used. Heights of individual trees were
3378 measured using an ultrasonic Vertex III hypsometer which requires finding a
3379 suitable position to observe each tree tip (Božić et al., 2005), while stem diameter
3380 was measured using a Diameter above Breast Height (DBH) tape. The diameters of
3381 all the trees in each plot were measured at breast height, which is at 1.37 m above
3382 the ground surface. All trees with a stem diameter >3 cm and 1.5 m height were
3383 recorded. Field surveys of woody plants were conducted on sites where damage to
3384 plants was specifically observed to identify where drought had an obvious impact.

3385 4.2.3 CHIRPS precipitation data

3386 Climate data were selected under the assumption that plant growth in the region is
3387 limited by water availability, temperature, and/or incident radiation (Field et al.,
3388 1995). Changes in either of these parameters might induce changes in vegetation
3389 productivity and the proxy NDVI signal. For this region, water availability is
3390 determined by the amount of precipitation, and so the study confined this
3391 parameter to precipitation as productivity here is water rather than temperature
3392 limited (Nemani et al., 2003). However, for most parts of Africa, and especially the
3393 semi-arid lands, the network of climatological stations is not dense enough to
3394 provide a coherent spatial picture of climate variability. As a result, the spatial
3395 characterisation of the effects of drought events on the land surface is not well
3396 defined. The study used satellite-based monthly precipitation estimates from the
3397 Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product
3398 ($0.05^\circ \times 0.05^\circ$). CHIRPS data span from 1981 to the present. CHIRPS incorporates
3399 in-situ station data and CHPclim, 0.05° resolution satellite imagery to represent
3400 sparsely gauged locations such as Southern Africa (Funk et al., 2015a). To be
3401 consistent with MODIS VIs, the CHIRPS rainfall data from 2002 to 2019 was used.

3402 4.2.4 Vegetation indices from remote sensing imagery

3403 The vegetation datasets used in this study include NDVI and GNDVI greenness
3404 vegetation indices derived from the MODIS sensors. The vegetation indices use the
3405 wavelength and intensity of the reflected light within the visible and near-infrared
3406 wavelengths to measure the density of green leaf vegetation, acting as proxies for
3407 leaf area index (LAI), fractional vegetation cover, and photosynthetic capacity
3408 (Broge et al., 2001). Generally, the plant is under stress when there is a change in
3409 the health condition of the plant foliage, reflected by a corresponding decrease of
3410 LAI. Under stress conditions, plants increase their reflectance in the green and red
3411 portions as leaves become yellowish or chlorotic. This has led to the suggestion
3412 that the VIS portion is the most consistent leaf reflectance indicator of plant stress
3413 (Carter, 1993).

3414 The Normalised Difference Vegetation Index (NDVI) is a commonly used
3415 vegetation index that measures green healthy vegetation as it utilises the regions
3416 of the electromagnetic spectrum most associated with high absorption of
3417 chlorophyll in the red band, and high reflectance of NIR by mesophyll layers in
3418 green leaf biomass (Rouse, 1974). It is calculated as a normalised ratio between
3419 Red and NIR reflectance values (Eq. 4.1). Higher NDVI values suggest higher
3420 amounts of photosynthetic active biomass. The NDVI was used in this study
3421 because it is a biophysical parameter that correlates with the photosynthetic
3422 activity of vegetation and is an indicator of the greenness of the biomes (Robinson
3423 et al., 2017; Tucker, 1979). NDVI is also able to offer valuable information to
3424 monitor vegetation health, drought effects, changes in plant growth, land
3425 degradation, deforestation, change detection/monitoring, and in relating large-
3426 scale inter-annual variations in vegetation to climate (Smith et al., 2019).
3427 Restrictions, however, have existed due to the effects of external factors, for
3428 example, soil and dead material, solar and viewing geometry as well as
3429 meteorological events, all of which pose a challenge in carrying out a proper
3430 assessment (Zhu et al., 2012). Particularly, in drylands with generally low
3431 vegetation canopy cover, the soil background tends to significantly influence NDVI,
3432 leading to a need for further development of vegetation indices. The study includes
3433 another greenness index, which is a variation of the NDVI and designed to reduce

3434 saturation issues identified with this index. The GNDVI is computed similarly to the
 3435 NDVI, but the Green band is used instead of the Red band (Eq. 4.2) (Gitelson et al.,
 3436 1996). Thus, GNDVI is more sensitive to chlorophyll concentration than NDVI and
 3437 ranges from 0 to 1.0. It is related to the proportion of photosynthetically absorbed
 3438 radiation and is linearly correlated with Leaf Area Index (LAI) and biomass (Hunt
 3439 et al., 2008). By exploring various combinations of available spectral bands, the
 3440 study additionally examined the sensitivity of other indices such as MSAVI, EVI to
 3441 find the most sensitive VI to detect changes in the dryland forest. MSAVI and EVI
 3442 were outperformed by GNDVI and thus GNDVI is presented in comparison to NDVI.

3443

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (\text{Eq. 4. 1})$$

$$\text{GNDVI} = \frac{\text{NIR} - \text{Green}}{\text{NIR} + \text{Green}} \quad (\text{Eq. 4. 2})$$

3444 Table 4. 1. Characteristics of the main datasets used in this study

<i>Climate Data</i>					
<i>Dataset</i>			<i>Timespan</i>	<i>Resolution</i>	<i>Source</i>
MODIS	8-day	Terra	2002-2019	500m	GEE
Surface	Reflectance	(MOD09A1.006)			
Climate Hazards Group	InfraRed	Precipitation with Station Data (CHIRPS)	2002-2019	0.05 degrees	GEE
<i>MODIS vegetation Data</i>					
Terra Surface Reflectance 8-Day Global 500m			2002-2019	500m	GEE

(MOD09A1.006)			
<i>LANDSAT Data</i>			
Landsat 5 ETM sensor- Surface Reflectance	2002-2012	30m	GEE
Landsat 8 OLI sensor- Surface Reflectance	2013-2019	30m	GEE

3445 4.2.5 Landsat Imagery

3446 In the Google Earth Engine platform, 2004 Landsat-5 TM (Thematic Mapper and 2019
3447 Landsat-8 OLI (Operational Land Image) surface reflectance 30 m spatial resolution
3448 satellite images were utilised for landcover cover classification over the study region
3449 (Gorelick et al., 2017). For both Landsat 5 and Landsat 8 data, only optical 30 m spatial
3450 resolution spectral bands (visible and infrared) were selected for classification. Bands 1
3451 and 9 were not used due to strong atmospheric absorption. The study aims to use
3452 Landsat images from 2002 for the classification, however, the year 2002 had 0 images
3453 available for the study site, while 2003 had 5 images available for the study area, and
3454 they only cover 1/5 of the study area. Therefore, the Landsat images for 2004 were used
3455 because it was the closest date to 2002 with a total of 35 available images which cover
3456 the whole study area. In 2019, a total of 84 images were available and selected for
3457 classification.

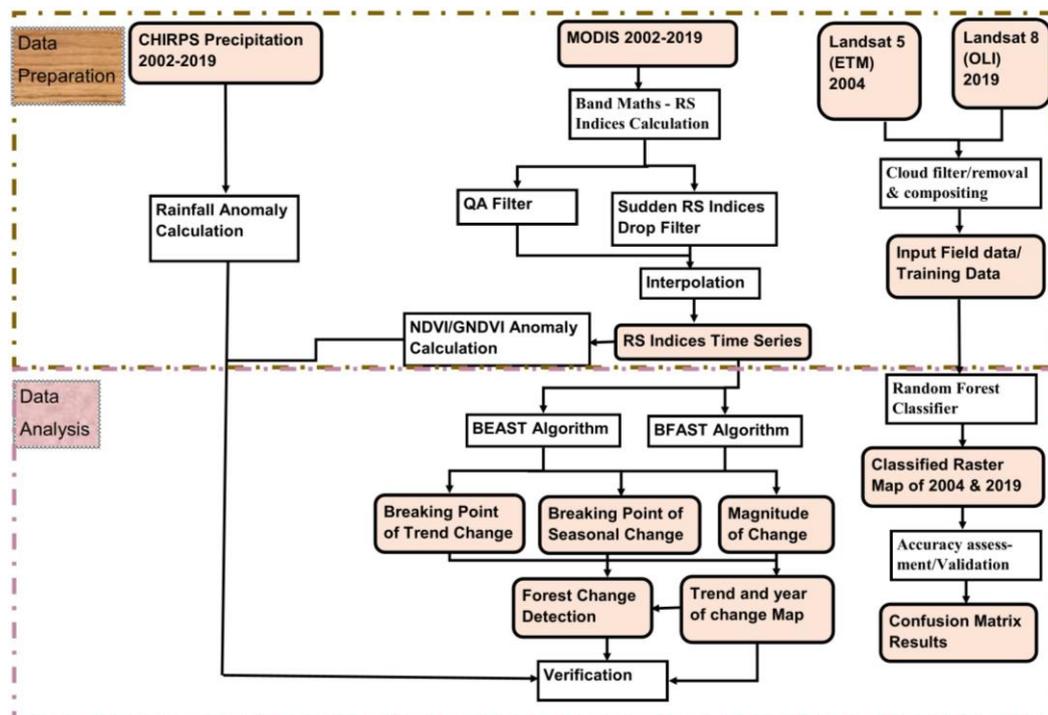
3458 4.2.6 Validating data

3459 The ground field sample points were used to validate the change detected by the
3460 algorithms. The verification was carried out quantitatively using field data
3461 collected from the field and the classified/change maps by generating a confusion
3462 matrix to assess the effectiveness of the land cover classification generated by the
3463 Random Forest classification in section 4.3.5. The BFAST change detection was
3464 validated using an area change using sample-based estimates in section 4.3.6.
3465 Additional verification was also conducted through visual interpretation of the
3466 Landsat surface reflectance 30 m spatial resolution satellite images
3467 (LANDSAT/LT05/C01/T1_SR) and (LANDSAT/LC08/C01/T1_SR) that are
3468 atmospherically corrected using LEDAPS and using LaSRC to ensure the data

3469 consistency and comparability (see: Table 4.1) (Claverie et al., 2015). The
3470 acquisition date of the Landsat image in which the disturbance event was first
3471 visible was used as a surrogate time for when the disturbance has occurred, and
3472 such data was used to verify the detected changes of BFAST and BEAST and note
3473 the timing of the change. This interpretation is commonly used by other
3474 comparable studies on change detection using BFAST (Cohen et al., 2010; Dutrieux
3475 et al., 2015). Using high resolution data, Cohen et al. (2010) used visual detection
3476 of a large proportion of historic change processes in the forest. Their study
3477 highlighted the importance of visual interpretation technique of change points
3478 using high resolution images and photo interpretation because historic events can
3479 be very difficult to ascertain. For example, DeVries et al. (2015) and Hamunyela et
3480 al. (2016) visually examined the Landsat image time series data to validate forest
3481 change occurred for a specific pixel detected using BFAST algorithm. Zhao et al.
3482 (2019) developed the BEAST algorithm (also tested in this study) and visually
3483 validated the ground-reference data on disturbances and changepoints by
3484 interpretation of multisource imagery.

3485 4.3 Methods

3486 An overview of the methods for this research is shown in Fig. 4.2. The four main
3487 steps were as follows: (1) high-quality NDVI time series data preparation. A time
3488 series was first pre-processed to remove noise and obtain an uninterrupted data
3489 stream. (2) Temporal and spatial analysis of climate and vegetation time series to
3490 detect anomalies and drought impacts. (3) Trend and seasonal breakpoint
3491 detection using BFAST and BEAST algorithms. (4) Validation of the change
3492 detection algorithms and discussion of the potential factors driving vegetation
3493 change.



3494

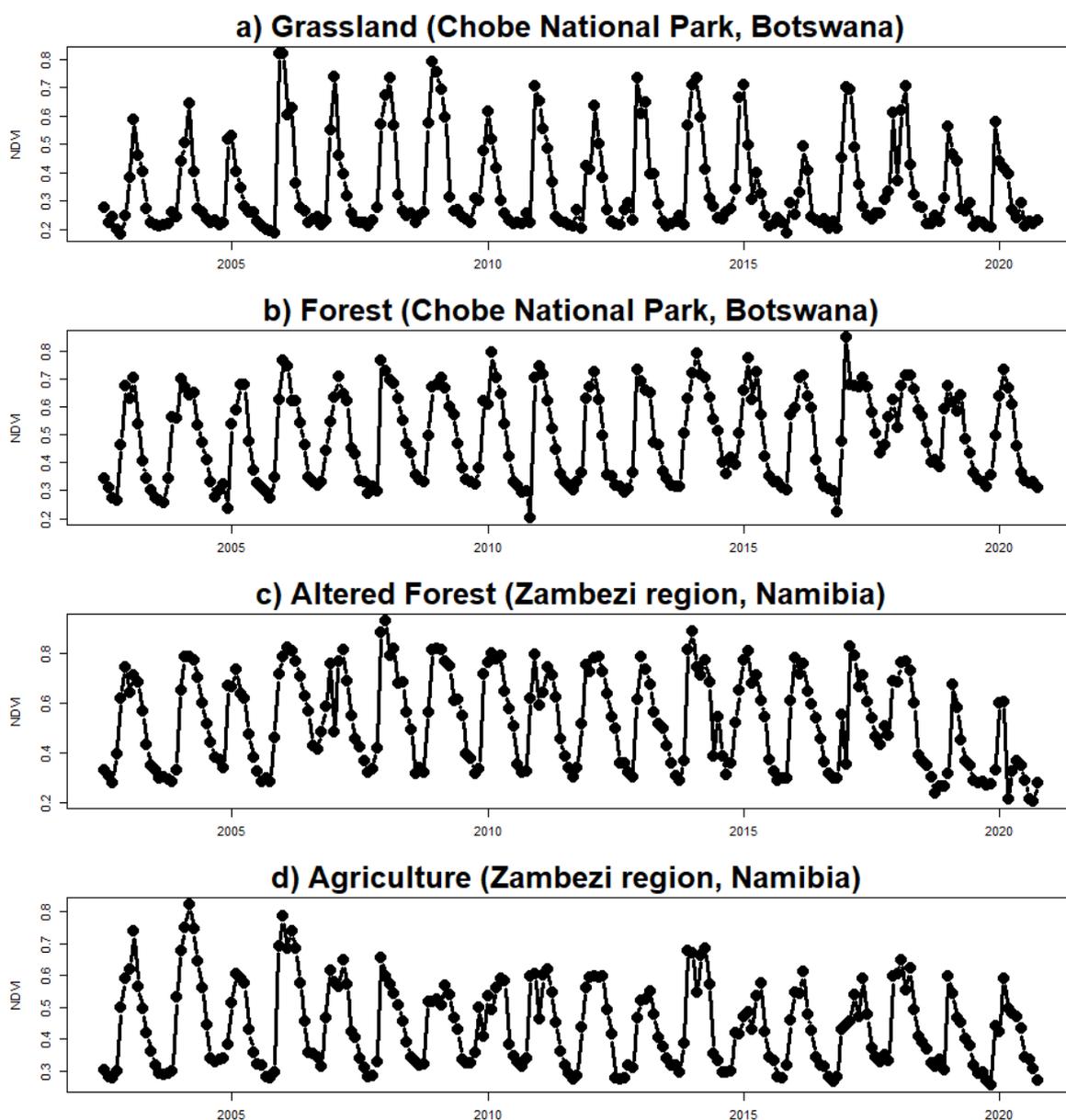
3495 Fig. 4. 2. Flow chart of data and methods.

3496

4.3.1 Preparation of high-quality MODIS datasets

3497 Satellite image time series are rarely complete. Noise in a time series is brought
3498 about by cloud contamination and other factors such as snow or device
3499 malfunction (Vermote et al., 2002). Tropical environments such as Southern Africa
3500 present a unique challenge for optical time series analysis, primarily owing to
3501 fragmented data availability, persistent cloud cover, and atmospheric aerosols.
3502 Pre-processing is necessary to reduce this noise because it may conceal actual
3503 trends in a time series. In this study, although the monthly maximum value
3504 composite (MVC) method has been used to decrease cloud and other atmospheric
3505 effects in the original VIs data (Holben, 1986), residual noise resulting from poor
3506 atmospheric conditions, cloud cover, aerosol loading and unfavourable sun sensor
3507 surface viewing geometries remain (Huete et al., 2002). Therefore, the
3508 corresponding MODIS quality assurance (QA) data layer was used to help identify
3509 and remove low-quality observations, and only the time points in a time series that
3510 are higher quality, cloud-free, and have nadir-view pixels with minimal residual
3511 atmospheric aerosols are retained. The cloud-contaminated pixels and extreme off-
3512 nadir sensor view angles are considered lower quality were excluded from the
3513 composite.

3514 In addition to the QA data, to retain good quality values throughout the time series,
3515 an assessment for data transmission errors, such as line drop out or moving from
3516 cloudy to clear sky conditions, which can cause localised Vegetation Indices (VIs)
3517 to increase or suddenly drop, were conducted. These fluctuations in VIs are not
3518 compatible with the gradual process of plant regrowth. The algorithm uses a
3519 threshold of 20% as an acceptable percentage increase in VIs for regrowth from
3520 fire or drought for arid/semi-arid dryland grassland though to dryland forests
3521 (Viogy et al., 1992). A low filtering threshold means that most MODIS VIs pixels
3522 with high-frequency noise related change are included, while a high filtering
3523 threshold produces a smoother temporal profile and can smooth out important
3524 changes. This study used a 20% threshold to reject fluctuations attributed to data
3525 errors. By utilising the MVC, QA data, and implementing the test for sudden drops,
3526 the observation points contaminated by noise were detected and discarded from
3527 the time series. The presence of contaminants such as clouds and cloud shadows,
3528 caused anomalous values which can be detected and removed to some degree,
3529 leaving gaps in the time series (see: Fig. B. 1). As with noise, robustness to missing
3530 data is therefore a crucial component to evaluate when considering change
3531 detection methods, especially when applying change detection to parts of the
3532 world with persistent cloud such as Southern Africa. The missing values at those
3533 points were then filled by implementing a linear average interpolation method
3534 (see: Fig. B. 1). However, this method still requires a time series of images with low
3535 cloud cover. The linear interpolation method has been proven to be efficient, and
3536 most of the time it is better than non-linear interpolations for predicting missing
3537 values in ecological phenomena time series (Gnauck, 2004). Fig. 4.3 shows the time
3538 series of the main land cover present in the study area, including forest, grassland,
3539 altered forest, and agricultural land.



3540

3541 Fig. 4. 3. Time series representing forest, grassland, altered forest, and agricultural land.

3542

3543

4.3.2 Vegetation and precipitation time series anomaly

3544 Here, satellite data was used to first quantify the extent and severity of rainfall
 3545 anomalies and droughts with respect to long-term patterns, with a baseline of 17
 3546 years, and then to investigate the impacts of droughts and water stress on the
 3547 dryland forest vegetation. The study focused on summer vegetation activity during
 3548 the growth period. Hence the main season of interest here is January–March (JFM)
 3549 since it is a period that contributes significantly to the summer rainy season across

3550 Southern Africa and approximately coincides with the mature phase of El Niño
3551 (Lyon et al., 2007).

3552 For this study, to identify and map the spatial extent of drought response in
3553 vegetation, the NDVI and GNDVI anomalies for a different season (the growing
3554 season is presented) for the KAZA region are calculated relative to a base period of
3555 2002–2019. The anomalies are constructed by subtracting the growing season VIs
3556 (calculated over 2002–2019) from the long-term mean patterns for that period
3557 (e.g., month or seasons). The departures from a base mean period are used to
3558 detect periodic temporal patterns in VIs. This isolates the variability in the
3559 vegetation signal and establishes a meaningful historical context to determine
3560 relative drought severity. The NDVI and GNDVI anomaly was calculated using
3561 MODIS data. The 2010 to 2019 period is presented because it is representative of
3562 the record of the 21st century where drought events are extreme.

3563 4.3.3 Change detection algorithms

3564 Remote multispectral and hyperspectral measurements, especially in recent
3565 years, have been an imperative source of data for drought and vegetation dynamics
3566 assessment. Satellite remote sensing complements traditional ground-based data
3567 collection through synoptic spatial coverage and reduced costs (Galiatsatos et al.,
3568 2020). Numerous time-series methods have been introduced to study the temporal
3569 trends in pixel values across remote sensing images addressing the detection of
3570 temporal-scale changes including *seasonal, abrupt, and gradual* changes. These
3571 methods include BFAST (Verbesselt et al., 2010a), LandTrendr (Kennedy et al.,
3572 2010), Estimating Segments in Trend (DBEST) (Jamali et al., 2015), and BEAST
3573 (Zhao et al., 2019). These change detection methods detect when a pixel value
3574 drastically changes, indicating a change in surface reflectance, and thus, in land
3575 cover or land use (Zhu, 2017).

3576 Producing forest cover change information requires approaches that also account
3577 for intra-annual seasonal or cyclic signals to identify changes in the phenological
3578 patterns, which indicates species' responses to environmental conditions (Menzel
3579 et al., 1999). The study utilised BFAST and BEAST algorithms because the two
3580 approaches use a season-trend decomposition model to take account of both inter-

3581 and intra-year variation in a time series, unlike other methods. These algorithms
3582 consider seasonal changepoints in plant phenology caused by changes in
3583 temperature and rainfall regimes as opposed to other trend detection methods
3584 such as Detecting Breakpoints and Estimating Segments in Trend (DBEST) which
3585 do not consider seasonality if any.

3586 4.3.3.1 BFAST

3587 BFAST is a widely used method for detecting trends and seasonal breaks in time
3588 series. The BFAST approach iteratively decomposes a time series to find both trend
3589 and seasonal changes in vegetation dynamics over a univariate time-series object
3590 (Verbesselt et al., 2010b). The function fits a model to the data by Ordinary Least
3591 Square (OLS) fitting on a stable history period, and to check for stability of that
3592 same model during the monitoring period. The nonlinearity in the trend
3593 component is also simplified into a number of individual trend segments, in order
3594 to identify sudden structural shifts. The trend is composed of segments with
3595 gradual changes, separated from each other by relatively brief, abrupt changes
3596 (Verbesselt et al., 2010a). The discrepancy between the model predictions and the
3597 data during the monitoring period is estimated using a moving sum of residuals
3598 (MOSUM) window to test whether one or more breakpoints occur. When observed
3599 data significantly deviate from the model, a break is detected (DeVries et al., 2015).
3600 The hypothesis of structural stability is rejected when the MOSUM
3601 window significantly deviates from 0 and crosses a boundary defined by the
3602 functional central limit theorem (Zeileis et al., 2005). The difference between the
3603 intercept and slope terms of consecutive models is used to calculate change
3604 magnitude between breakpoints (Verbesselt et al., 2010a). Having a sufficiently
3605 long stable history period for model fitting is critical for accurate detection of
3606 change. The history period needs to be free of disturbances and is referred to as a
3607 'stable history'. Verbesselt et al. (2012) provide a guideline of a stable history
3608 equal to or longer than two years for change monitoring with BFAST. Detailed
3609 descriptions of BFAST can be found in Verbesselt et al. (2010a).

3610 4.3.3.2 BEAST

3611 The Bayesian estimator of abrupt change, seasonal change, and trend (BEAST) is a
3612 recent algorithm that fits both linear and nonlinear trends and disentangles trends
3613 from seasonality; it further pinpoints abrupt shifts in the two isolated signals
3614 (Zhao et al., 2019). The model structure of BEAST applies a Bayesian ensemble
3615 modeling technique to aggregate numerous competing models to reduce
3616 uncertainty, overfitting, and model misspecification. From the numerous
3617 competing candidate models, BEAST evaluates how probable each of them is to be
3618 a true model and synthesises these into an average to capture multiple and subtle
3619 phenological changes (Zhao et al., 2019). BEAST algorithm uncovers complex
3620 nonlinear dynamics from time-series of any variables, such as LAI, climatic data, or
3621 soil moisture. To detect the rate of change in trends, BEAST infers the sign of the
3622 change (e.g., greening, or browning) as well as the associated error and probability
3623 of having a phenological shift, greening or browning at any time. Time series
3624 decomposition was performed using BFAST R package and RBEAST R package in R
3625 version 4.0.3 (R Development Core Team, 2013). Detailed descriptions of BEAST
3626 can be found in Zhao et al. (2019).

3627 4.3.4 Land cover classification

3628 Figure 4.2 presents a flow chart to classify land cover from Landsat data using
3629 Random Forest (RF) classifier. The less-cloudy, multiple-temporal Landsat images
3630 for the selected years (2004 and 2019), were collected and merged over the study
3631 area. This study used Quality Assurance bands and Function of Mask (Fmask)
3632 algorithm (Zhu and Woodcock, 2012) to mask out cloud and cloud shadows. The
3633 Quality Assurance (QA) band sets a cloud score threshold, and any pixel scoring
3634 higher than the threshold will be masked and merged with another image from the
3635 same area that doesn't have any clouds. Essentially, a cloud score greater than 0.2
3636 for a pixel shows that the pixel is a cloud (Housman et al., 2018). The composite
3637 algorithm in Earth Engine library was also used to reduce the effect of the cloud
3638 (Lück and van Niekerk, 2016). In the end, all imagery used for land cover detection
3639 used in this study are free of clouds. Before land cover classification, a spatial
3640 clipping operation was performed on images to extract the exactly defined area of
3641 study sites within GEE.

3642 Ground surveys to collect data on forests, open forests, agriculture,
3643 shrubs/grassland and other land cover classes were conducted in fieldwork in
3644 Namibia in 2019, see section 4.2.2 for details on fieldwork and sampling design. A
3645 total of 165 points were visited and collected from the field, and additional points
3646 of 498 points were randomly added. A total of 674 points were available for the
3647 land cover mapping. Half of the 674 points collected for training the classifiers (i.e.,
3648 'train' points on GEE), and the other half (341 points) were used for accuracy
3649 assessment. Additional ground truth data for land cover classification training and
3650 verification for 2004 was also collected through Landsat, Sentinel 2, high-
3651 resolution Google Earth, and Open Street Map using a visual interpretation. These
3652 sources were selected because they are freely accessible, consist of high-quality
3653 images, and this technique was also used by previous studies (Rwanga and
3654 Ndambuki, 2017). Based on local knowledge, this study categorised land cover into
3655 five groups, including forest, open forests/shrubs, agriculture/barren, water, and
3656 urban areas.

3657 The classification of multi-temporal satellite imagery was performed on a per-pixel
3658 basis using RF classification (Li et al., 2017). The classifiers are trained with the
3659 spectral characteristics of these known areas, by assigning each pixel to the five
3660 target classes including forest, open forests/shrubs, agriculture/barren, water, and
3661 urban areas. RF is a popular method of classification and clustering based on an
3662 ensemble of decision trees (DT). RF was used because it overcomes problems of
3663 overfitting experience by other decision trees (DT) classifiers such as Classification
3664 and Regression Tree (CART) (Cánovas-García et al., 2017). RF is a development of
3665 the CART method by applying bagging and random feature selection to DT, which
3666 is to randomly select several trees that have many iterations so that they resemble
3667 forests (Breiman, 2001).

3668

3669 4.3.5 Accuracy assessment

3670 Once the Land cover classification is completed, the final step is to conduct an accuracy
3671 assessment to quantitatively assess the effectiveness of the method in correctly assigning
3672 the pixels to the proper land cover classes. Accuracy assessments are one of the most

3673 important steps of classification because it validates the output classification product as
3674 well as the quality of the data itself, by comparing the pixels of the classified image
3675 with ground truth data (Congalton et al., 1983). In this study, the full set of 165 training
3676 data visited and collected in the field and 498 added training data were divided into two
3677 subsamples, one used for algorithm training and the other used for error testing so that
3678 the same sample is never used for both training and testing (Geiß et al., 2017). For each
3679 classification accuracy assessment, this study used the popular measures extracted from
3680 confusion matrix reports, such as overall accuracy (OA), producer accuracy (PA) and
3681 user accuracy (UA) (Janssen and Vanderwel, 1994; Story and Congalton, 1986). An
3682 error matrix is generated by comparing the Land cover types calculated by the algorithm
3683 for a given pixel with the true Land cover class identified by the ground truth sample.
3684 The error matrix is a simple grid that lists the target classes and their respective number
3685 of correct and incorrect pixel classifications (Congalton et al., 1983). The uncertainty in
3686 estimated classification accuracy depends on the uncertainty in the true accuracy of the
3687 classifier, the number of samples and the accuracy of the observed ground truth
3688 (Carlotto, 2009). An overall classification error including kappa coefficient,
3689 commission and omission statistics were also calculated (Fung and LeDrew, 1988).

3690 4.3.6 Validation of estimated forest changes and disturbance

3691 The BFAST change detection was conducted to provide precise estimates of changed
3692 and unchanged forest areas. To evaluate the accuracy of the change map and validate
3693 the estimates of the predicted change for the whole study area, the study used 341 points
3694 in total, 165 points were visited and collected in the field and 176 points were randomly
3695 added as detailed in the above section. A change analysis using a stratified random
3696 sampling design was conducted to provide precise estimates of disturbances in the study
3697 area. Stratification was on patterns of past disturbances selected according to "the risk
3698 of disturbances". The communal areas that are unprotected were assigned "High risk",
3699 the Zambezi State Forest that is semi-protected (red-coloured polygon) was assigned
3700 "Medium risk" and the Mudumu National Park (Aqua-coloured polygon) that is
3701 protected was assigned "Low risk" (see: Fig. 4.1). The accuracy of detected changes and
3702 unchanged estimates from BFAST was independently identified using various
3703 information sources including ground observation data collected from the field in 2019,
3704 land cover classification and image interpretation of high spatial resolution satellite
3705 imagery including Landsat, Google Earth images, and Sentinel 2. The study used the

3706 method of accuracy assessment as recommended by the GOFC-GOLD, 2014 guidelines
3707 to help identify and quantify uncertainty in the level and rate of disturbances in dryland
3708 forest areas (GOFC-GOLD, 2014). Watt et al. (2020) and Galiatsatos et al. (2020)
3709 utilised this method to develop monitoring, reporting and verification (MRV) systems to
3710 quantify and validate the accuracy of the change in forest cover carbon and carbon
3711 emissions in Guyana. This study adopted this method to validate the estimated changes
3712 because it allows the generation of detailed, consistent, transparent, and verifiable
3713 assessment of forest area change (GFOI, 2016).

3714

3715

3716

4.4 Results

3717

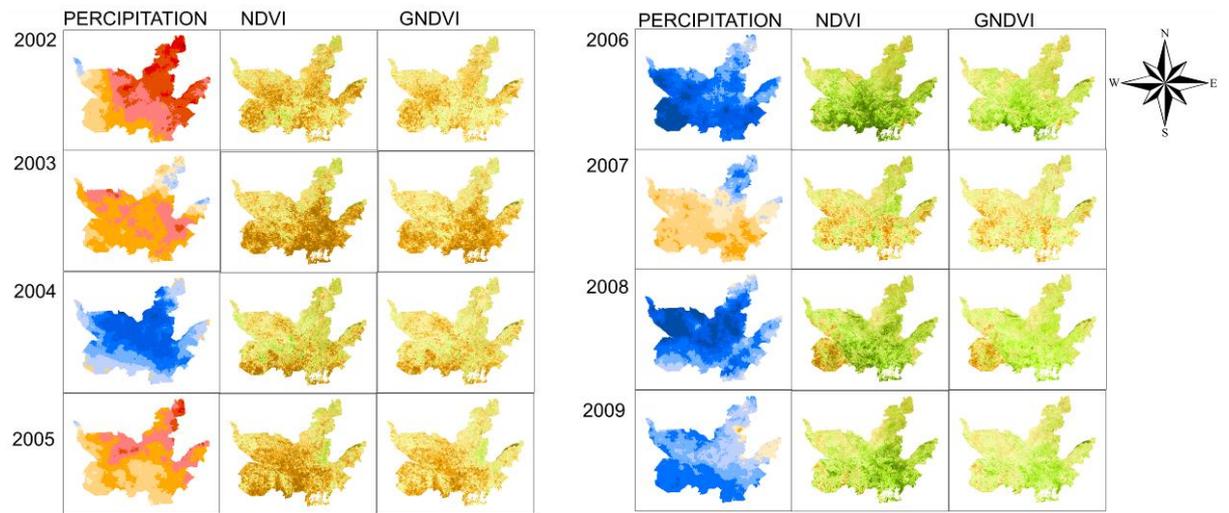
4.4.1 Spatial pattern of vegetation and drought stress in

3718

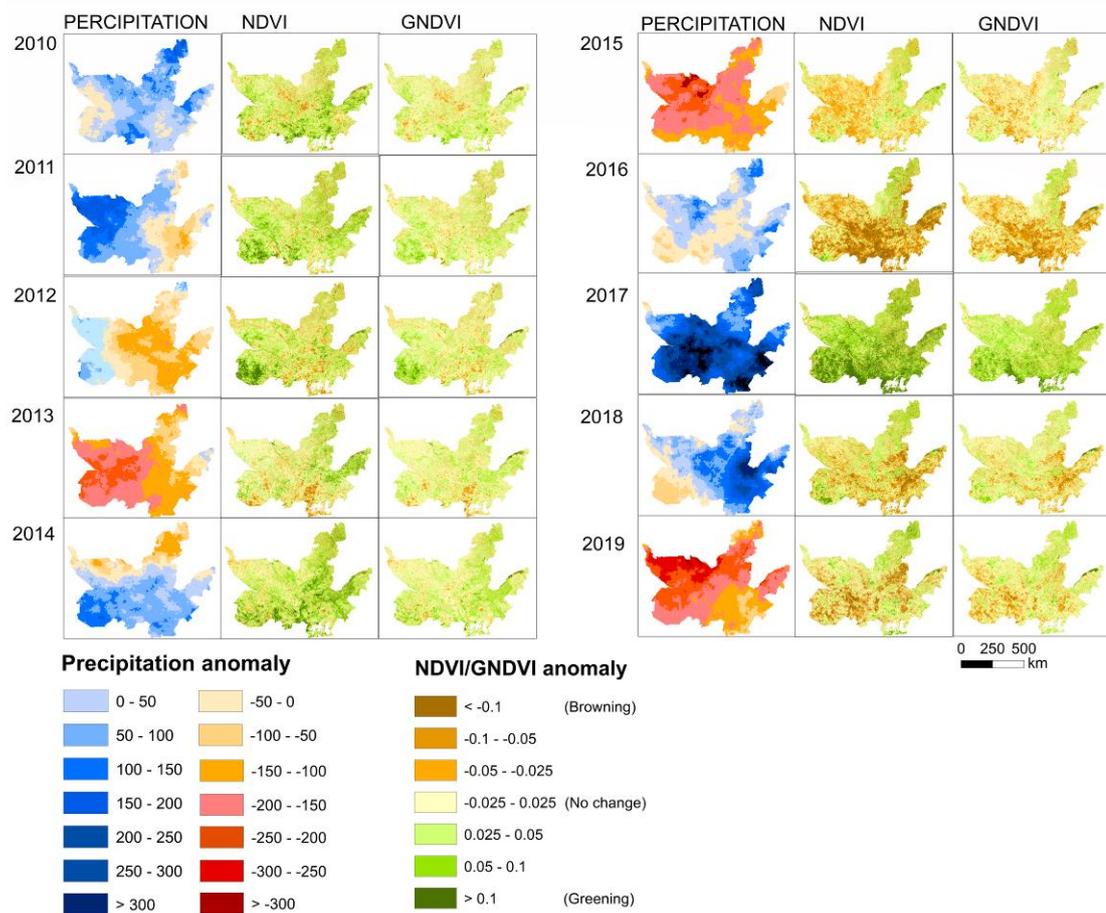
KAZA TFCA

3719 To provide insights into the relationship between precipitation and disturbances,
3720 and the general vegetation dynamics response to drought, the spatial and temporal
3721 variations of the VIs (NDVI and GNDVI) anomaly for the growing seasons of 2002
3722 to 2019 were plotted as shown in Fig. 4.4. The spatial pattern of both NDVI and
3723 GNDVI anomaly shows vegetation productivity increased (green to dark green
3724 colours; > 0.05) in 2006, 2008, and 2017 which correspond to higher than average
3725 rainfall in these years. Regionally, negative seasonal vegetation anomalies (NDVI
3726 and GNDVI) were mainly caused by large-scale droughts. The anomalies of
3727 precipitation in the JFM season (see: Fig. 4.4) remained negative over the entire
3728 KAZA region in 2002-2003, 2015-2016, and 2019 (red to dark red colours). The
3729 centre of the maximum rainfall deficit was mostly concentrated eastward of KAZA
3730 in 2016 and 2018. For vegetated land areas in KAZA, precipitation is a dominant
3731 factor controlling the growing season in the region, as indicated by the anomaly in
3732 vegetation and rainfall (see: Fig. 4.4). A close comparison indicates that the
3733 extreme droughts in 2015 and 2019 (red to dark red colours) greatly reduced
3734 vegetation productivity (brown colours in NDVI and GNDVI) which is coincident
3735 with severe water stress in these years. The lag in vegetation greenness between
3736 drought stress and browning rates extending to 2016, stands out based on the
3737 extent of severe decrease of greenness regardless of rainfall returning to normal.

3738



3739



3740

Fig. 4. 4. Spatial pattern of ndvi and gndvi and precipitation anomalies for the 21st century

3741

from 2010 through 2019.

3742

3743 4.4.2 Comparison of the sensitivity of BFAST and BEAST
3744 algorithms

3745 The study examined and compared the effectiveness of two time-series
3746 decomposition algorithms (BFAST and BEAST) on three events to illustrate the
3747 proposed methodology, which included: 1. Clear-cut and burnt forest, 2. Drought
3748 impact and degradation forest, and 3. A stable, recovering forest. Table 4.2 shows
3749 the dates of detected trend and seasonal breakpoints identified using BFAST and
3750 BEAST algorithms for both NDVI and GNDVI time series.

3751

3752 Table 4. 2. Dates of trend and seasonal breakpoint detection relative to BFAST and BEAST
3753 algorithms. The Bold date represents the seasonal shift with the highest probability with a
3754 vertical dotted line.

<i>Clear-cut and burnt forest</i>			
		<i>Trend change Date</i>	<i>Seasonal change Date</i>
<i>BFAST</i>	<i>NDVI</i>	<i>2003, 2005, 2018</i>	<i>0</i>
	<i>GNDVI</i>	<i>2003, 2005, 2009, 2018</i>	<i>0</i>
<i>BEAST</i>	<i>NDVI</i>	<i>2003, 2005, 2007, 2017, 2018</i>	<i>2015-2017</i>
	<i>GNDVI</i>	<i>2003, 2005, 2006, 2007, 2009, 2017, 2018</i>	<i>2015-2017, 2019</i>
<i>Degrading Forest</i>			
<i>BFAST</i>	<i>NDVI</i>	<i>0</i>	<i>0</i>
	<i>GNDVI</i>	<i>2004, 2005, 2017</i>	<i>0</i>
<i>BEAST</i>	<i>NDVI</i>	<i>2004, 2005, 2015, 2017, 2019</i>	<i>2008-2009, 2012-2013</i>

	<i>GNDVI</i>	<i>2004, 2005, 2010, 2015, 2016, 2017, 2019</i>	<i>2008-2009, 2011-2013, 2018-2019</i>
<i>A stable, recovering forest</i>			
<i>BFAST</i>	<i>NDVI</i>	<i>0</i>	<i>0</i>
	<i>GNDVI</i>	<i>0</i>	<i>0</i>
<i>BEAST</i>	<i>NDVI</i>	<i>2017</i>	<i>2008, 2010-2011, 2015-2016</i>
	<i>GNDVI</i>	<i>2017</i>	<i>2006, 2008, 2015-2016</i>

3755

3756 4.4.2.1 Clearing of forest to non-forest

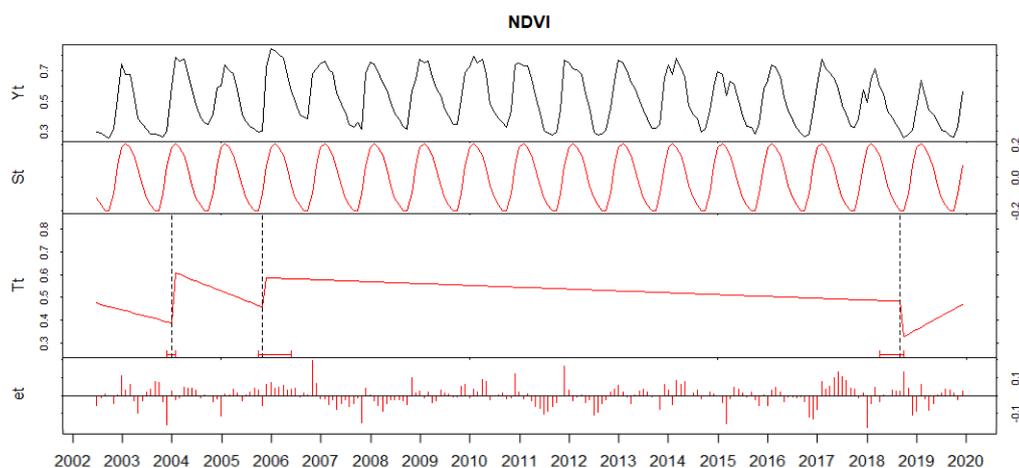
3757 Fig. 4.5 and 6 show a forest stand plot that was forest initially, however the forest
3758 experienced a series of disturbances including a fire event around 2017 causing a
3759 sudden loss in forest cover, and a clear-cut activity that resulted in complete forest
3760 loss between 2018 and 2019. There were also major drought events that took
3761 place in 2002-2003, 2005, 2015 and 2019 (see: Fig. 4.4). Photos taken in February-
3762 May 2019 of each corresponding stand forest plot and Landsat time series images
3763 illustrating changes are shown in the supplementary information (see: Fig. B. 1 and
3764 B. 2).

3765 4.4.2.1.1 BFAST algorithm application on a Clear-cut and burnt forest:

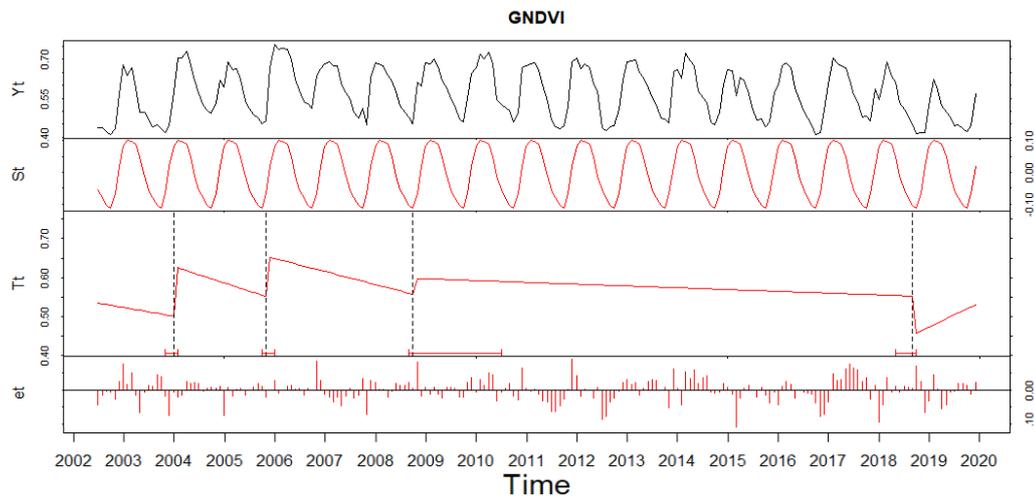
3766 As shown in Fig 4.5, BFAST algorithm decomposed the NDVI time series and fitted
3767 seasonal, trend, and remainder components. BFAST algorithm applied on the NDVI
3768 time series detected three breakpoints in the trend component. BFAST predicted a
3769 disturbance around 2003 and 2005 because of severe drought in the region, which
3770 caused the forest to be stressed and the NDVI to decrease significantly. BFAST
3771 algorithm run on the NDVI time series also identified the occurrence of a

3772 breakpoint from clear-cut forest conversion to non-forest at the end of 2018.
 3773 Around 2017 this location undergoes burning which triggered disturbance around
 3774 the plot, however, BFAST failed to identify this trend in the NDVI trajectory.
 3775 Furthermore, BFAST algorithm applied to the NDVI time series also failed to
 3776 identify the disturbance in forest caused by a moderate drought event in 2007 and
 3777 its recovery in 2009.

3778 On the other hand, BFAST algorithm run on the GNDVI time series produced four
 3779 breakpoints in the trend component: three breakpoints in 2003, 2005 as a result of
 3780 severe drought and deforestation towards the end of 2018. Further, using the
 3781 GNDVI time series, BFAST identified the abrupt changes caused by vegetation
 3782 recovery in 2009 that are not identified by the NDVI time series trajectory as
 3783 shown in Fig 4.5. Even though using GNDVI time series, BFAST identified the
 3784 vegetation recovery in 2009, it also failed to identify the breakpoint caused by a
 3785 moderate drought event in 2007. BFAST algorithm did not detect abrupt changes
 3786 in the seasonal component of NDVI and GNDVI time series (Fig. 4.5).



3787



3788

3789 Fig. 4. 5. Example of the corresponding BFAST algorithm output for NDVI and GNDVI
 3790 extracted from a forest stand that underwent conversion from clear-cut to non-forest
 3791 vegetation. The vertical dotted lines represent the dates of detected breakpoints, while the
 3792 red horizontal bars represent the associated confidential intervals. The raw time series
 3793 (Yt), the seasonal component (St), the trend component (Tt), and the noise (et)
 3794 component, are also shown. The location of the corresponding pixels, field photo taken in
 3795 Namibia in 2019 and Landsat time series images illustrating changes are shown in the
 3796 supplementary information (see: Fig. B. 1 and B. 2).

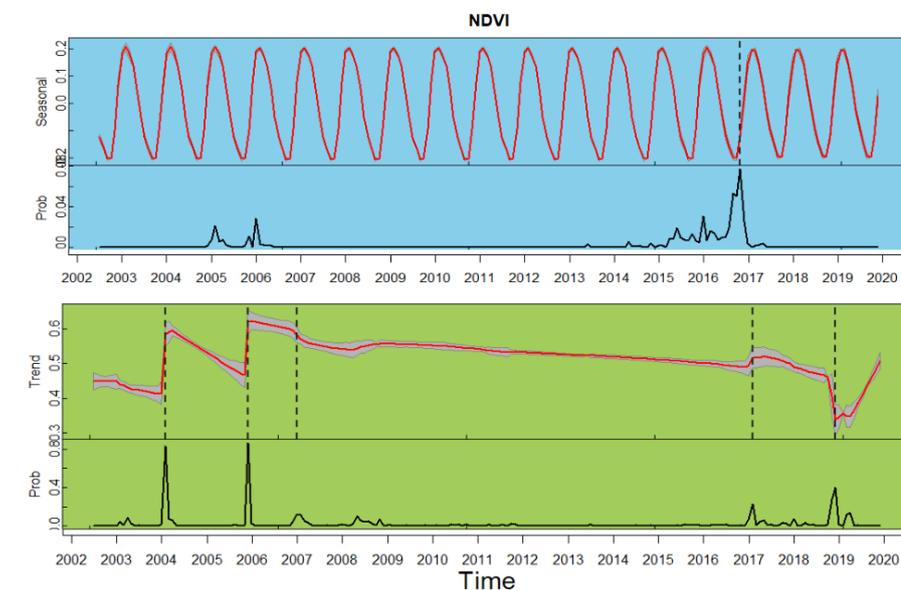
3797 4.4.2.1.2 BEAST algorithm application on a Clear-cut and burnt forest:

3798 Fig. 4.6 shows BEAST algorithm applied to the NDVI and GNDVI time series to
 3799 detected phenological and trend changes. BEAST algorithm applied on the NDVI
 3800 time series detected five breakpoints in the trend component. The four
 3801 breakpoints including two breakpoints in 2003 and 2005 as a result of severe
 3802 drought, one breakpoint in 2018 from deforestation and one abrupt change caused
 3803 by 2009 moderate drought, similar to the changes identified by BFAST on the
 3804 GNDVI time series in Fig. 4.5. However, the application of BEAST algorithm on the
 3805 NDVI time series also detected one breakpoint in the trend component in 2017 as a
 3806 result of vegetation increase (due to increase in rainfall in 2017) following the fire
 3807 event in 2017 that neither application of BFAST was able to detect.

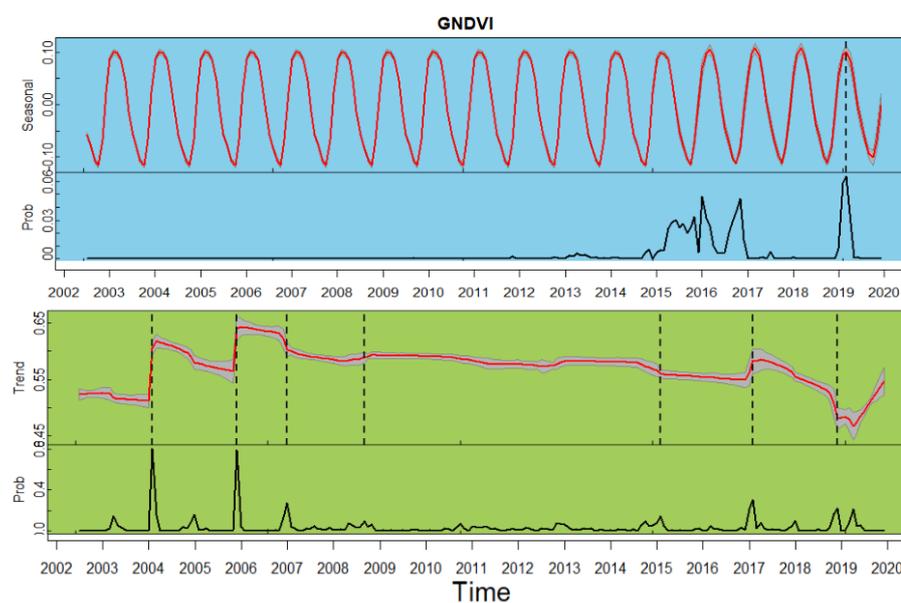
3808 The application of BEAST algorithm to the GNDVI time series detected the
 3809 occurrence of five breakpoints, two from drought in 2003 and 2005, the fire event
 3810 of 2017, the forest clear-cut in 2018, and vegetation increase in 2017, similar to
 3811 exploring the NDVI signal with BEAST algorithm. However, BEAST algorithm

3812 applied to the GNDVI time series was also able to uncover the beginning of
 3813 vegetation disturbance and the vegetation recovery, for example it captures the
 3814 correct year of the subtle decrease in forest cover in 2007 due to 2007 drought and
 3815 its recovery in 2009. Similarly, it detects another decrease in forest cover due to
 3816 drought in 2015 and its recovery in 2017 that was not detected using BEAST on
 3817 NDVI time series. For both indices, BEAST algorithm detected phenological
 3818 changes resulting from the 2015-2016 drought. BEAST applied to the GNDVI time
 3819 series further detected a seasonal shift associated with 2019 logging and drought
 3820 (see: Fig. 4.6). In contrast, BFAST algorithm uncovered a stable seasonal trajectory
 3821 (see: Fig. 4.5), suggesting no phenological change during this period (2002-2019).

3822



3823



3824 Fig. 4. 6. Example of the decomposition generated by the application of BEAST algorithm
3825 for the NDVI and GNDVI time series extracted from a forest stand that underwent
3826 conversion from clear-cut to non-forest vegetation. Seasonal and Trend represent the best
3827 fitted seasonal and trend signals (red line), respectively. The vertical dotted lines
3828 represent the dates of detected breakpoints in the trend/seasonal components, while the
3829 black lines at the bottom panels represent the probabilities of the changepoint in the
3830 seasonal/trend components. The location of the corresponding pixels, field photo taken in
3831 Namibia in 2019 and Landsat time series images illustrating changes are shown in the
3832 supplementary information (see: Fig. B. 1 and B. 2).

3833

3834 4.4.2.2 Drought impact and degraded forest

3835 Fig. 4.7 and 8 show the results from modelling a forest stand plot that has
3836 undergone multiple disturbances from drought coupled with wildlife grazing and
3837 mega-herbivore pushovers, as a result of its location near to the Chobe river
3838 frontage. Photos taken in February-May 2019 of each corresponding stand forest
3839 plot and Landsat time series images, both illustrating changes are shown in the
3840 supplementary (see: Fig. B. 3 and B. 4).

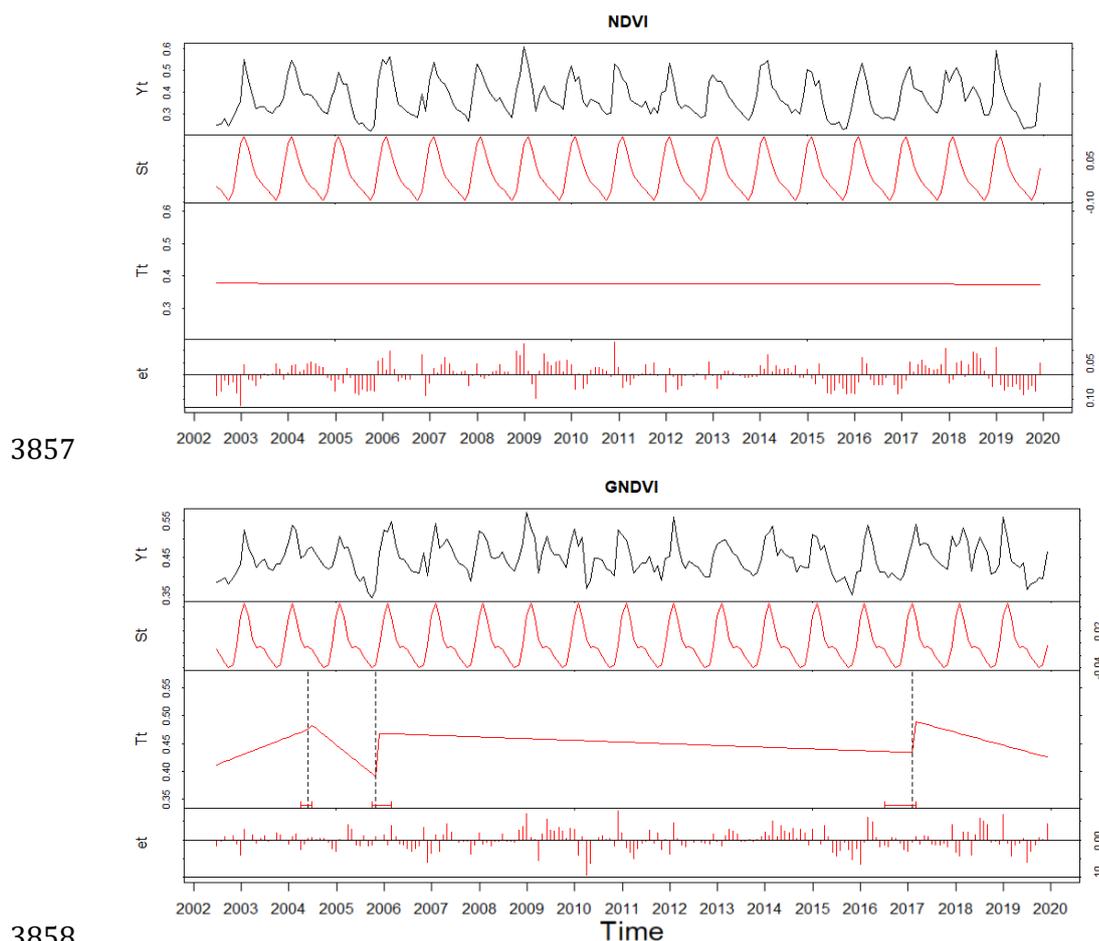
3841

3842 4.4.2.2.1 BFAST algorithm application on a degraded forest:

3843 Fig. 4.7 presents BFAST algorithm decomposition of the NDVI and GNDVI time
3844 series. BFAST was not able to capture any meaningful information relating to
3845 disturbances to the forest from the trend and seasonal components throughout the
3846 period of 2002 to 2019. None of the severe climatic events or moderate drought
3847 years were identified, and the NDVI trend appeared stable when using BFAST
3848 algorithm. This is despite the original time series showing some instances of an
3849 NDVI drop during this period.

3850 However, using BFAST algorithm on the GNDVI time series, three breakpoints
3851 were detected in 2004, 2005 and 2017. The two abrupt changes in 2004 and 2006,
3852 correspond to the drought event in 2003 and 2005 (or to an increase in rainfall in
3853 2004 and 2006 after the drought), were detected (see: Fig. 4.4 and 7). The

3854 breakpoint in 2017 represent a vegetation increase as a result of rainfall increase
 3855 in 2017. BFAST did not detect abrupt changes in the seasonal component of NDVI
 3856 and GNDVI time series as shown in Fig. 4.7.



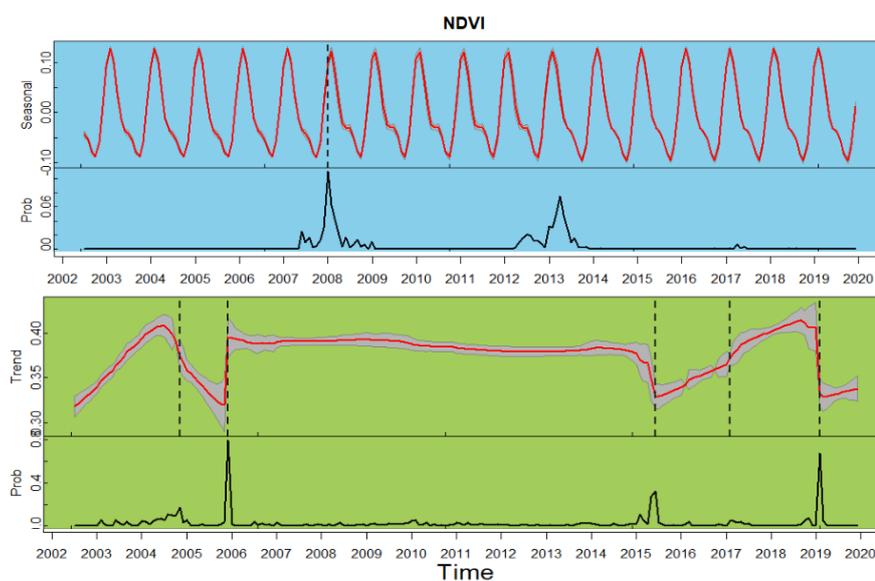
3857
 3858
 3859 Fig. 4. 7. Example of the corresponding BFAST for NDVI and GNDVI extracted from a forest
 3860 stand of a degraded forest. The vertical dotted lines represent the dates of detected
 3861 breakpoints, while the red horizontal bars represent the associated confidential intervals.
 3862 The raw time series (Yt), the seasonal component (St), the trend component (Tt), and the
 3863 noise (et) component, are also shown. The location of the corresponding pixels, field photo
 3864 taken in Botswana in 2019 and Landsat time series images illustrating changes are shown
 3865 in the supplementary information (see: Fig. B. 3 and B. 4).

3866

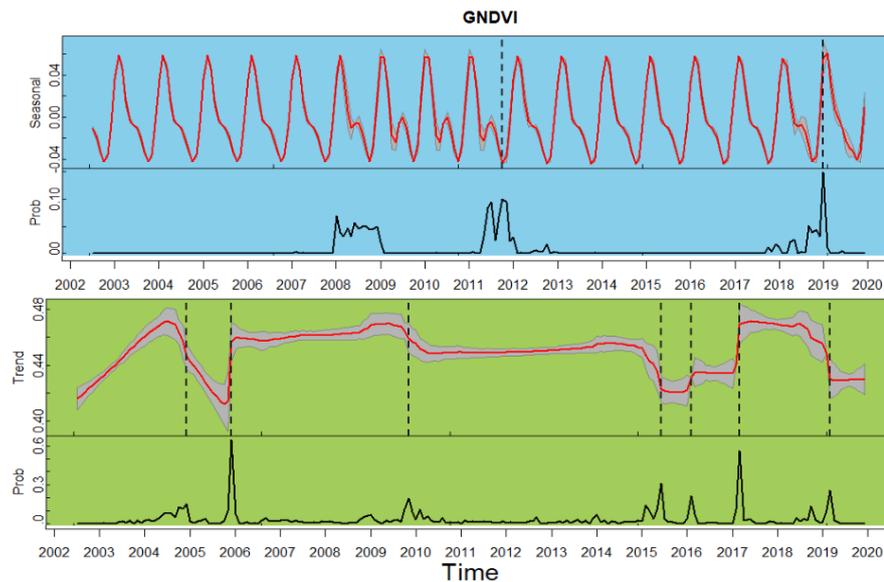
3867 4.4.2.2.2 BEAST algorithm application on a degraded forest:

3868 BEAST algorithm applied to the NDVI time series (Fig. 4.8) detected five
 3869 breakpoints as a result of extreme effects of the 2005, 2015, 2019 droughts and the
 3870 increase in rainfall in 2004, 2006, and 2017, which BFAST algorithm applied to the

3871 same time series did not detect, as shown in Fig. 4.7. The application of BEAST
 3872 algorithm to the GNDVI time series was able to detect seven breakpoints, including
 3873 the similar extreme droughts as shown with the NDVI, which were timed to similar
 3874 dates. The increase in rainfall in 2008, and the drought stresses of 2010-2012,
 3875 which both have a smaller magnitude of abrupt change, were also identifiable in
 3876 the trend within the GNDVI, but not in the NDVI. BEAST algorithm was also able to
 3877 describe the magnitude of drought impacts and recovery more clearly than when
 3878 using BFAST. The drought impact detected by applying BEAST algorithm to the
 3879 GNDVI time series in 2010, which is smaller in terms of the magnitude of the
 3880 abrupt change, was not detected when using NDVI by either algorithm, as shown in
 3881 Fig. 4.8. The Bayesian approach (BEAST) detected a phenological shift in 2008
 3882 when applied to the NDVI time series. Three seasonal shifts resulting from changes
 3883 in precipitation in 2008, 2010, and the 2019 drought, were noticeable in BEAST-
 3884 derived seasonal trend of the GNDVI time series as shown in Fig. 4.8.



3885



3886

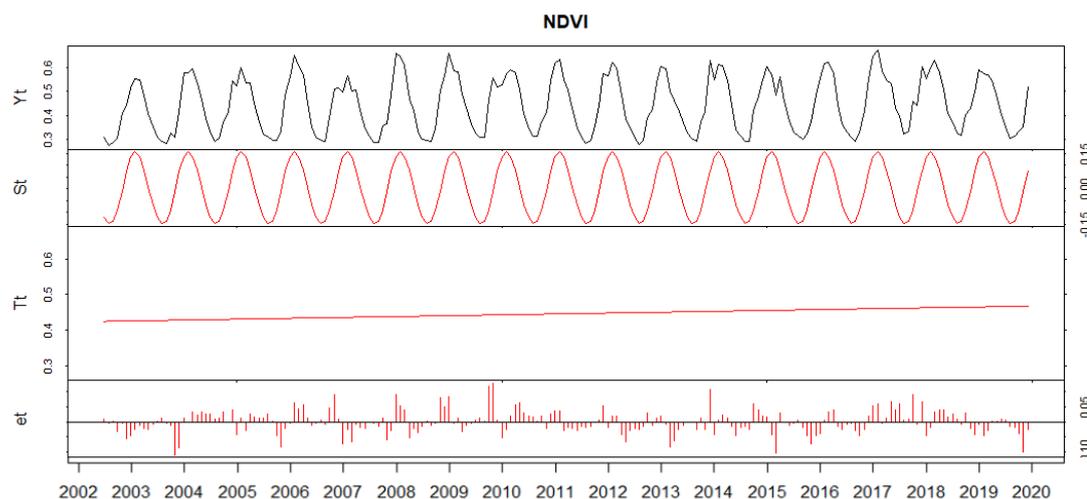
3887 Fig. 4. 8. Example of the decomposition generated by the application of BEAST algorithm
 3888 for the NDVI and GNDVI time series extracted from a forest stand of a degraded forest.
 3889 Seasonal and Trend represent the best fitted seasonal and trend signals (red line),
 3890 respectively. The vertical dotted lines represent the dates of detected breakpoints in the
 3891 trend/seasonal components, while the black lines at the bottom panels represent the
 3892 probabilities of the changepoint in the seasonal/trend components. The location of the
 3893 corresponding pixels, field photo taken in Botswana in 2019 and Landsat time series
 3894 images illustrating changes are shown in the supplementary information (see: Fig. B. 3 and
 3895 B. 4).

3896 4.4.2.3 Stable forest

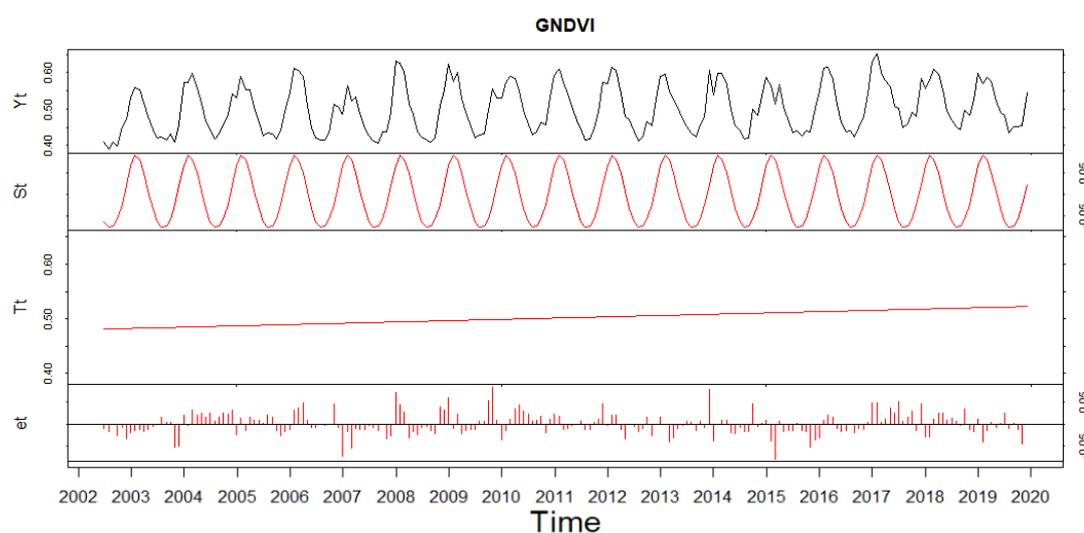
3897 Fig. 4.9 and 10 show the results from modelling a forest stand plot that has
 3898 experienced limited human and wildlife disturbance and is considered to be stable.
 3899 Photos taken in February-May 2019 of each corresponding stand forest plot and
 3900 Landsat time series images, both illustrating changes are shown in the
 3901 supplementary (see: Fig. B. 5 and B. 6).

3902 4.4.2.3.1 BFAST algorithm application on a stable forest:

3903 BFAST algorithm detected no breakpoints in trend and seasonality using both the
 3904 NDVI and GNDVI time series. Both indices show a gradual increase in the forest
 3905 cover. In both indices, the application of BFAST failed to detect any seasonal
 3906 change.



3907



3908

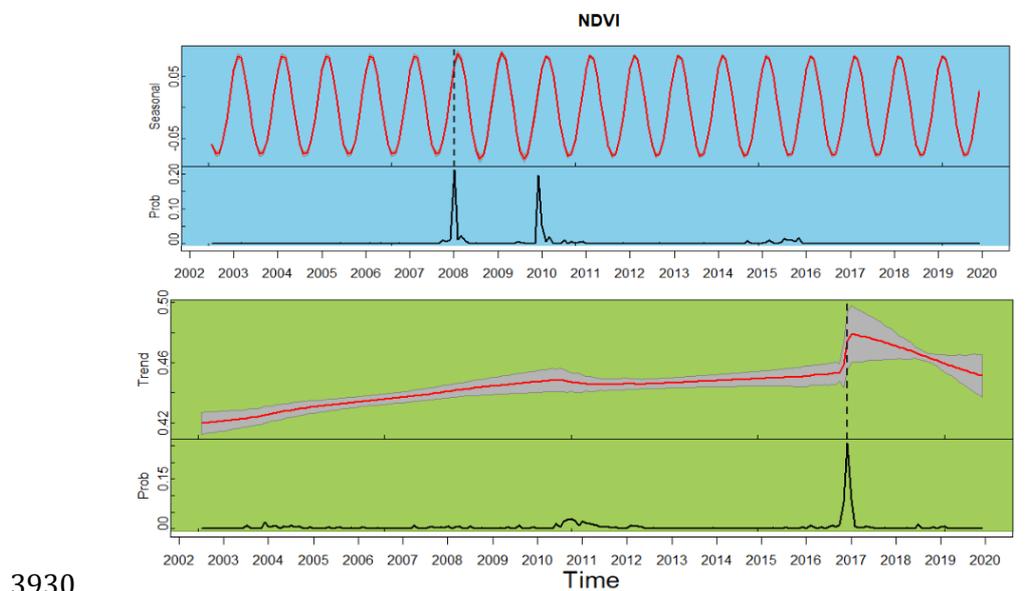
3909 Fig. 4. 9. Example of the corresponding BFAST algorithm output for NDVI and GNDVI
 3910 extracted from a forest stand that considered stable. The vertical dotted lines represent
 3911 the dates of detected breakpoints, while the red horizontal bars represent the associated
 3912 confidential intervals. The raw time series (Y_t), the seasonal component (S_t), the trend
 3913 component (T_t), and the noise (e_t) component, are also shown. The location of the
 3914 corresponding pixels, field photo taken in Namibia in 2019 and Landsat time series images
 3915 illustrating changes are shown in the supplementary information (see: Fig. B. 5 and 4. 6).

3916

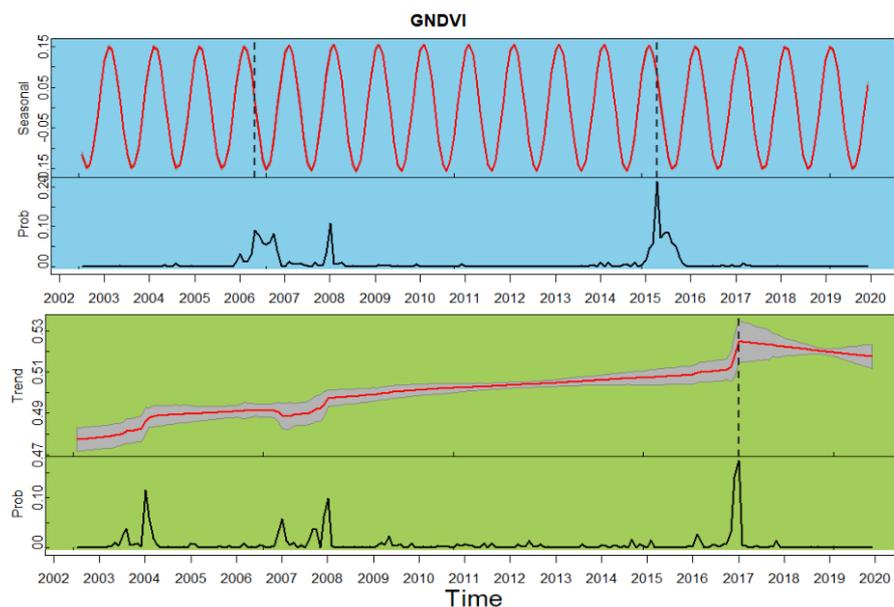
3917 4.4.2.3.2 BEAST algorithm application on a stable forest:

3918 BEAST algorithm showed a gradual increase in forest, and no abrupt trend as a
 3919 result of a disturbance was identified in in either the NDVI or the GNDVI time

3920 series as shown in Fig. 4.10. One exception was an abrupt change as a result of
 3921 forest cover increases was evident in 2017, as indicated by a high probability of
 3922 this change in both indices, which was associated with plentiful rainfall in 2017. In
 3923 terms of a seasonal signal, both indices show the phenological shifts around the
 3924 2008 and 2015-2016 drought events, although the GNDVI time series was able to
 3925 detect a larger number of seasonal shifts. These seasonal changes are detected in
 3926 severe drought years that were followed by an increase in rainfall. For example,
 3927 the seasonal shift in the 2005 drought was followed by an increase in rainfall in
 3928 2006, and the seasonal shift in the 2015-2016 drought was followed by relatively
 3929 high levels of precipitation in 2017, as shown in Fig. 4.4 and 4.10.



3930



3931

3932 Fig. 4. 10. Example of the decomposition generated by the application of BEAST algorithm
 3933 for the NDVI and GNDVI time series extracted from a forest stand that considered stable.
 3934 Seasonal and Trend represent the best fitted seasonal and trend signals (red line),
 3935 respectively. The vertical dotted lines represent the dates of detected breakpoints in the
 3936 trend/seasonal components, while the black lines at the bottom panels represent the
 3937 probabilities of the changepoint in the seasonal/trend components. The location of the
 3938 corresponding pixels, field photo taken in Namibia in 2019 and Landsat time series images
 3939 illustrating changes are shown in the supplementary information (see: Fig. B. 5 and B. 6).

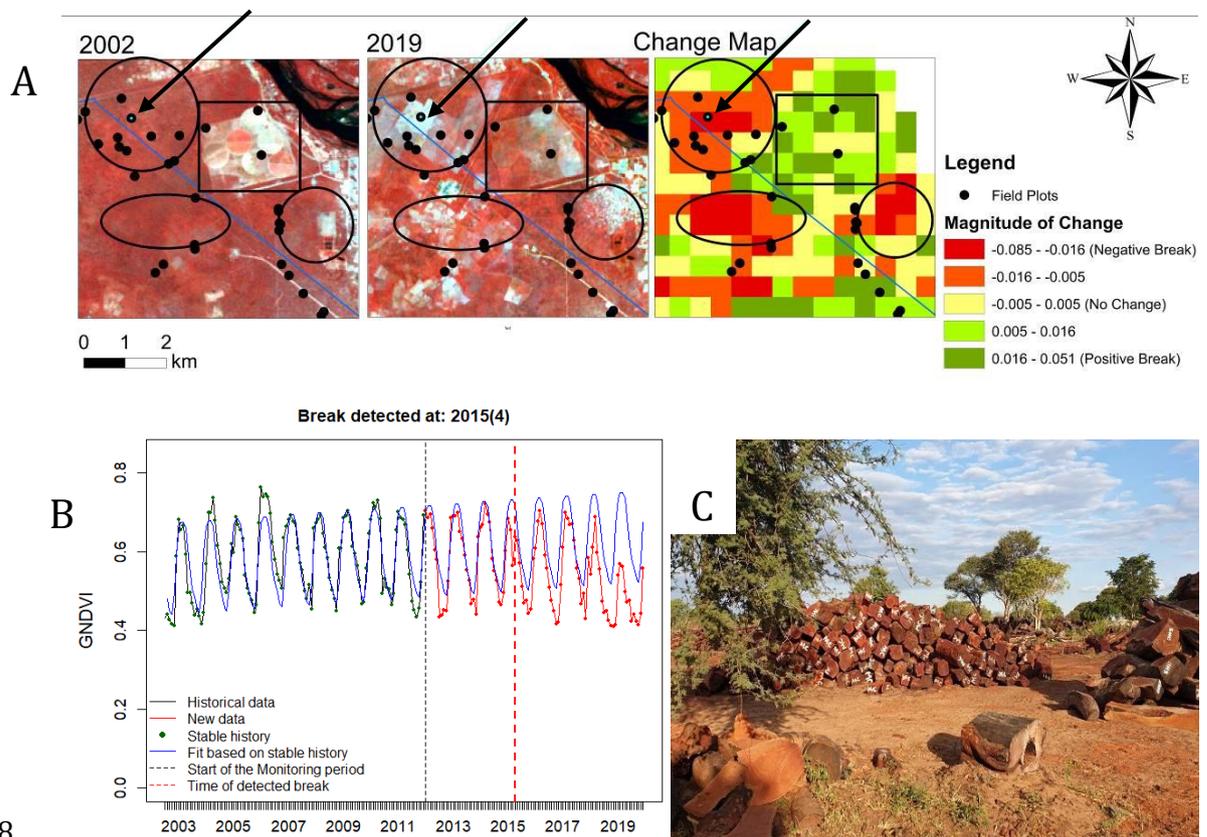
3940

3941 4.4.3 Robustness of predicting forest dynamics using 3942 breakpoints and change magnitude

3943 The examples shown in Fig. 4.11 demonstrate the differences in magnitude of
 3944 GNDVI that were commonly observed to be associated with varying degrees of
 3945 forest cover change. The cumulative probability of each of the change classes
 3946 (deforestation, degradation, vegetation regrowth, or no-change) detected from the
 3947 application of BFAST algorithm using the MODIS time series from 01/01/2010 to
 3948 31/12/2019 is shown in Fig. 4.11 and 12. The study only shows the breakpoints
 3949 from 2010 to 2019 as these years help to highlight the impact of exceptional
 3950 drought events (Fig. 4.4), fire, and large-scale forest clear-cutting events in the
 3951 Mudumu NP and Zambezi ST, resulting in a negative breakpoint magnitude. Fig.
 3952 4.11A presents 2002 Landsat 5 (LC5) ETM, 2019 Landsat 8 (LC8) OLI images, and
 3953 the cumulative change map overlaid with field points collected with land cover and
 3954 vegetation measurement (black-coloured circles) mapped in Zambezi ST. The
 3955 results of the survey plot (black circle coloured blue) shown with an arrow are
 3956 represented in Figure 4. 11 A-C. Figure 4. 11A shows the Landsat image in 2002
 3957 and 2019 with the survey plot undisturbed (forest) in 2002, and when it is turned
 3958 into a non-forest in 2019. A cumulative change map of MODIS produced with
 3959 BFAST in Figure 4. 11 A shows the negative break of the same survey plot.
 3960 Similarly, figure 4. 11 B shows the time series of the forest pixel with a negative
 3961 break detected in April 2015, while Figure 4. 11 C represents the actual
 3962 photograph of the survey plot with cut-down trees on the ground. This approach
 3963 used prior knowledge of disturbances such as clearing, and BFAST allowed the

3964 most significant change event in the time series to be detected. Prior knowledge of
3965 disturbances such as clearing was used in this approach and BFAST allowed the
3966 most significant change event in the time-series to be detected. For mapping
3967 cumulative change, the probability of the deforestation class increased with
3968 decreasing change magnitude, showing a strong negative relationship with change
3969 magnitude, whilst the probability of the degradation class showed a weak negative
3970 relationship with change magnitude. The probability of vegetation growth class
3971 increased with increasing change magnitude, showing a positive relationship with
3972 change magnitude.

3973 Maps showing the time of the changepoint event and the magnitude of the GNDVI
3974 change are displayed in Fig. 4.11 and 12. Fig. 4.11A shows the negative breakpoint
3975 with high mean negative magnitude of change due to forest logging and clear-
3976 cutting to almost no vegetation between 2018 and 2019 as shown by the top circle.
3977 Other breakpoints with high mean negative magnitude due to forest clearing for
3978 agriculture and urban areas are also observed and shown with the two bottom
3979 circles. The breakpoint with positive mean magnitude is observed in a square
3980 showing an agricultural area (farmland) that was abandoned and vegetation
3981 regrowth gradually increased by 2019 (Fig. 4.11A). As shown by the plot shown by
3982 the black arrow (see: Fig. 4.11A), the negative break in the forest pixel is detected
3983 in April 2015 and is associated with extreme drought, as shown by the red vertical
3984 line in the GNDVI time series in Fig. 4.11B. Another disturbance in the forest stand
3985 plot caused a large reduction in GNDVI in 2019 as a result of forest clear-cutting
3986 for timber, as also illustrated in the change map (Fig. 4.11A), the time series (Fig.
3987 4.11B), and the field photo taken in 2019 (Fig. 4.11C).



3988

3989 Fig. 4. 11. A: 2002 LC5 ETM, 2019 LC8 OLI image and a map of the magnitude of change in
 3990 the trend component from 01/01/2010 to 01/12/2019 generated by BFAST algorithm in
 3991 and around the Zambezi ST and Mudumu NP; the colour scale represents the magnitude
 3992 and direction of change. The circles here represent abrupt changes with a negative
 3993 magnitude; a square represents a vegetation regrowth with a positive magnitude, and the
 3994 arrow shows a forest stand plot for a forest disturbed by drought and subsequent forest
 3995 canopy clearing. Fig.4.11. B: MODIS time series from 01/01/2002 to 31/12/2019 for a plot
 3996 shown by an arrow in Fig. 4.11. A. Fig. 4.11. C: Shows the photograph of the selected plot
 3997 (location coordinate is 17.49°S, 24.21°E) in Fig. 4.11. A, with logged for timbers
 3998 photographed during a field campaign in Zambezi ST near the border of Namibia and
 3999 Zambia in 2019.

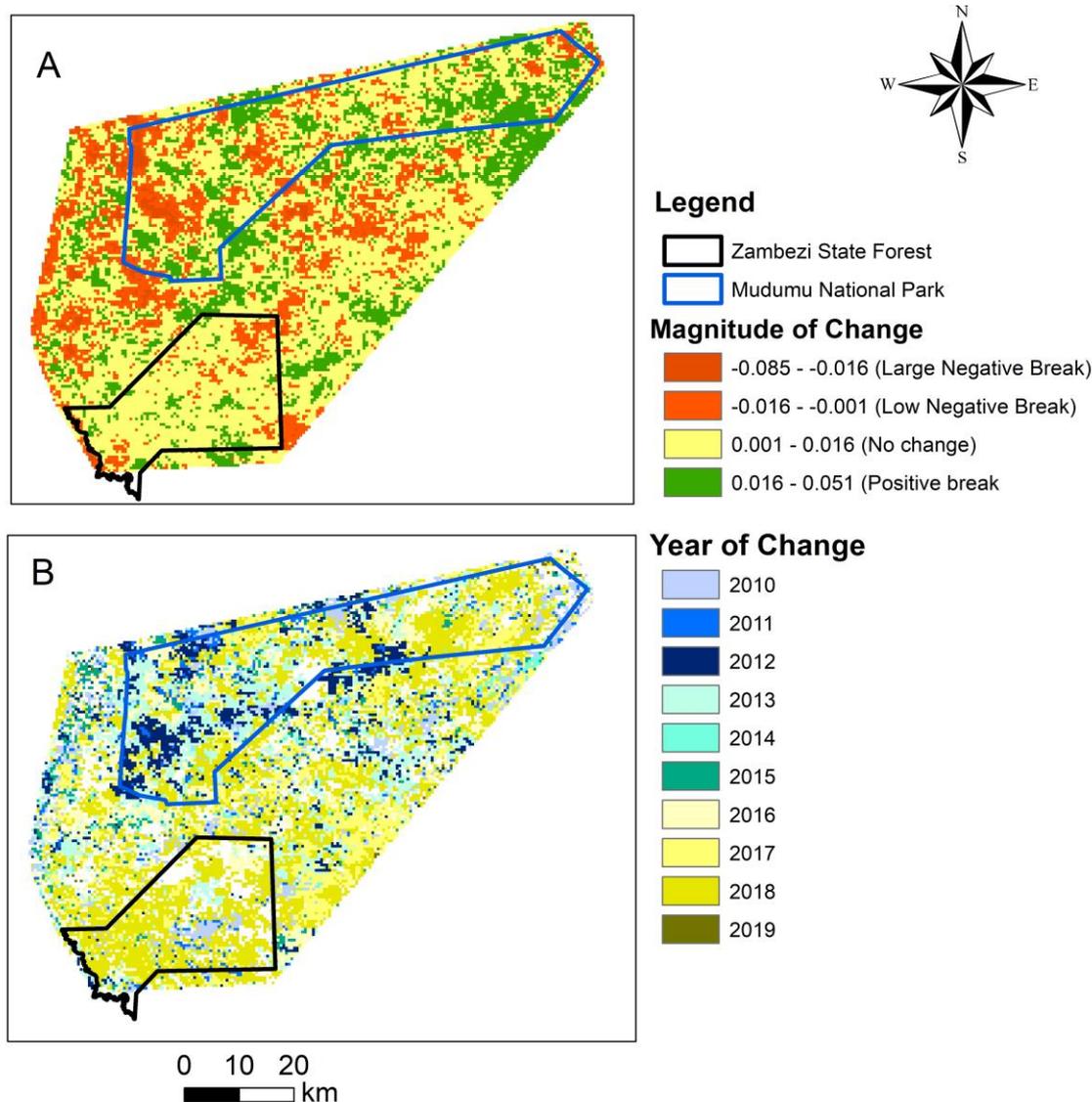
4000

4001 4.4.4 Spatial pattern of predicted forest changes using 4002 breakpoints and magnitude

4003 Fig. 4.12 presents the spatial pattern of the extracted trend classification, showing
 4004 the predicted magnitude of change in the trend component and the estimated date
 4005 of change generated from BFAST algorithm applied to the GNDVI time series on the

4006 Zambezi region, Namibia. The final disturbance map showing disturbed versus
4007 undisturbed areas highlights distinct spatial patterns across the study area. Fig.
4008 4.12A shows the predicted abrupt change in the trend component. It can be seen
4009 that the Mudumu NP remains undisturbed, although there are distinct spatial
4010 patterns of forest degradation indicated by low magnitude negative breakpoints at
4011 the edge of the park, around the communal villages in Sobbe conservancy.
4012 Examining the disturbance map, forest decline from clear-cutting and forest
4013 conversion to agricultural land were observed in Zambezi ST and in the
4014 community conservancy and communal area surrounding the Zambezi SF and
4015 Mudumu NP. The disturbance trends and extreme vegetation loss from
4016 deforestation and clear-cuts are shown by extreme magnitude negative breaks and
4017 vegetation degradation (Fig. 4.12A). Although most of the clear-cuts are associated
4018 with an extreme magnitude negative breakpoint, some cases are associated with a
4019 low magnitude negative/positive breakpoint. This is shown, for example, in areas
4020 with forest clear-cuts replaced by matured shrubs in the northernmost section of
4021 the study area (Zambezi ST) near the border between Namibia and Zambia.

4022 The map also shows continuous patches of forest showing a positive magnitude
4023 breakpoint, which denotes a forest recovery, vegetation regrowth that follows an
4024 earlier event, and vegetation less affected by disturbance as shown by positive
4025 magnitude of change in Fig. 12 A. More than 50% of the breakpoint dates are in the
4026 period between 2016 and 2019, with 2018 having the highest number of
4027 breakpoints. The high percentage of breakpoints detected in this period, and a
4028 negative magnitude, reflect both the impact of the 2015/2016 and 2018/2019
4029 droughts, coupled with clear-cutting of the forest stands.



4030

4031 Fig. 4. 12. A. shows the magnitude of change in the trend component and the predicted
 4032 time of change generated by BFAST; red colour represents negative breakpoint typically
 4033 associated with vegetation loss. Green colour represents positive breakpoint associated
 4034 with vegetation gain. The turquoise polygon shows Zambezi ST, and the black polygon
 4035 shows Mudumu NP. B: shows the estimated year of change from 2010 to 2019.

4036

4037 4.4.5 Validation of spatial pattern of predicted forest 4038 changes and disturbances

4039 The BFAST model was used to estimate forest disturbance for the complete study
 4040 area (Fig. 4.12). The validation assessment used a weighted average of the within-
 4041 stratum estimates to ensure the weights are proportional to size of high, medium

4042 and low 'risk of change' strata. The results of the comparable land cover classes for
4043 the BFAST time series analysis and the interval-based per-pixel Random Forest
4044 classification are shown in Tables 4.3 and 4.4. The complete tables with all the area
4045 change classes for the two approaches are in the supplementary material (Tables
4046 B.2, B.3 and B.4). The land cover classes for the interval-based per pixel
4047 classification in Table B.3 were calculated based on post-classification
4048 reorganisation of land cover area transition table (Table B. 4), where the similarly
4049 classified class areas were summed together.

4050 The results are presented in Table 4.4 and both methods show a land transition
4051 from forest to non-forest (deforestation) in the region. The interval-based per-
4052 pixel classification estimated that the conversion of forest to non-forest land was
4053 87,251 ha. The BFAST time series estimates of deforestation are corresponding to
4054 the two-interval pixel-based classification showing an area change of 99,911 ha
4055 (SE 9,753 ha) throughout the entire 2002–2019 period. The two-interval
4056 classification estimated that the total unchanged forest area was 147,875 ha. These
4057 values are higher as compared to 106,390 ha of unchanged forest land estimated
4058 by BFAST time series analysis. The interval-based pixel-based classification which
4059 bases the change estimates on differencing between images at only two points in
4060 time has little capability to distinguish forest degradation, which is the progressive
4061 reduction/losses in forest cover that do not qualify as deforestation. As a result, it
4062 is likely that the interval-based classification does not detect forest degradation as
4063 well as BFAST (time series) approach. The BFAST time series analysis captures the
4064 subtle change of forest conversion to the degraded forest with an estimate of
4065 33,131 ha (SE 6,859 ha). In addition, BFAST time series analysis found that
4066 approximately 23,409 ha (SE 556,8 ha) of degraded forest was converted to forest
4067 land. However, the degraded forest estimates from the BFAST time series are not
4068 comparable with the two-based interval per pixel classification because it does not
4069 detect degradation (see: Table 4.4). The BFAST algorithm can iteratively estimate
4070 and characterize temporal changes (time) and characterizes the spatial change by
4071 its magnitude and direction ("deforestation", "degradation" and "no change"). The
4072 sample-based estimates and validation of BFAST used in this study also provide
4073 the standard error for the continuous changes. For this study, the standard error
4074 for the non-disturbed forest class was lower as compared to the disturbed classes

4075 (see: Table 4. 3). It is also important to note that the region has no Landsat images
 4076 available in 2002, and few images for the year 2003, therefore the two-interval
 4077 classification used the starting year of 2004, which can account for some difference
 4078 in land cover class areas. In summary, BFAST (time series) approach at one level
 4079 agrees with a two-interval traditional classification when identifying discrete
 4080 change but it also identifies areas of more subtle change and so adds value to the
 4081 analysis and interpretation. In broad terms, the two approaches agree where direct
 4082 comparison is possible, but the differences also help to stimulate important
 4083 questions about the differences.

4084

4085 Table 4. 3. Area changes of BFAST using sample-based estimates and the observed
 4086 disturbance change rates.

Change identified by BFAST	Area Hectares (ha)	Standard Error (ha)	2.5 % (ha)	97.5 % (ha)
Non-disturbance (no change) <i>(Stable Forest)</i>	106,390	9,817	87,148	125,631
Non-disturbance -low negative change <i>(Stable forest to Degradation)</i>	33,132	6,859	19,688	46,576
Non-disturbance -large negative change <i>(Stable Forest to Deforestation)</i>	99,911	9,753	80,795	119,027
Low negative break -large negative change <i>(Degradation to Deforestation)</i>	59,515	8,154	43,533	75,497
Low negative changes -non-disturbance	23,409	556,8	12,497	34,322

<i>(Degradation to Stable Forest)</i>				
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4087

4088 Table 4. 4. Types of changes identified by BFAST and Random Forest classification for the
4089 period 2004 and 2019.

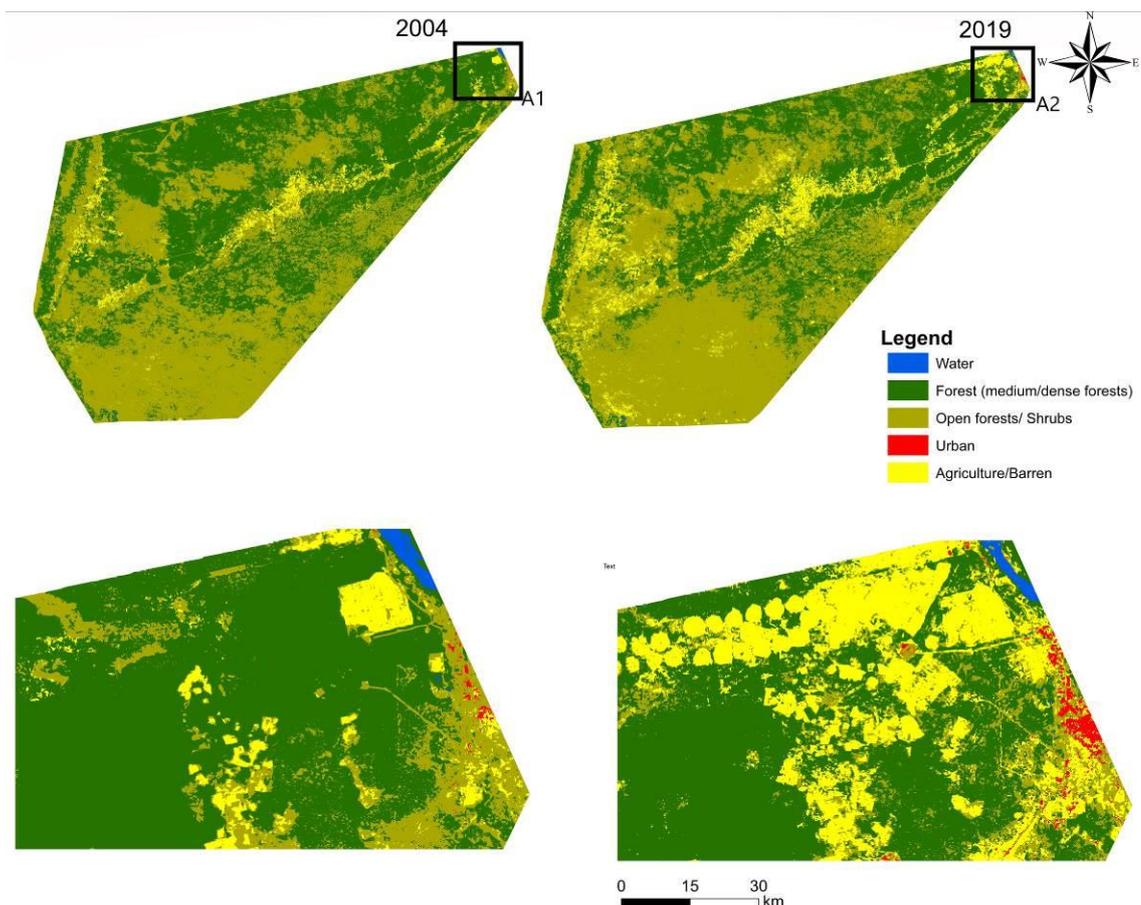
Type of Changes	Two interval Classification 2004 and 2019 Area(ha)	BFAST Time Series analysis 2002 to 2019 Area (ha)
Forest	147,875	106,390
Forest to Non-forest	87,251	99,911
Forest to Degraded Forest	-	59,515
Degraded Forest to Forest	-	33,131
Degraded Forest to Non-forest	-	23,409
Non-forest-Forest	41,447	54,517

4090

4091 4.4.6 Land cover classification

4092 The land cover classifications using the RF algorithm, in 2004 and 2019, are illustrated
4093 in Fig. 4.13. To quantify the land use changes over the years, the study analysed the
4094 error matrix which showed any classification errors that may have occurred such as a
4095 pixel being misclassified. Table 4.6 presents the confusion matrix and accuracy
4096 assessment for land cover classification in the years 2004 and 2019. For classification
4097 accuracy, Landis and Koch et al (1977) suggested the Kappa result with values ≤ 0
4098 indicate no agreement and 0.01–0.20 denote none to slight, 0.21–0.40 fair, 0.41– 0.60
4099 moderate, 0.61–0.80 indicate substantial, and 0.81–1.00 as almost perfect agreement
4100 (Sim and Wrigh, 2005). The accuracy assessment on the 2004 and 2019 classified

4101 images showed an overall classification accuracy of 82% and 88%, and an overall
 4102 Kappa Statistic of 0.74 and 0.83, respectively. The classification results and Kappa
 4103 statistics obtained in this study show a very good agreement between classes which is
 4104 considered sufficient for the land cover map in the Zambezi region. The five classes that
 4105 were used (forest, open forests/shrubs, agriculture/barren, water, and urban areas)
 4106 resulted in 100% accuracy for the water and urban areas, and 90% for agriculture.
 4107 However, accuracy was somewhat lower in the other two classes of forest and open
 4108 forest/shrubs areas, with 82% and 76% accuracy, respectively (Table 4.6). The reason
 4109 for the high accuracy of water was due to the small area comprised of water and urban
 4110 areas. The two classes had a low number of training sample pixels because the training
 4111 points were distributed proportionally to the study area. The classification for forests,
 4112 open forest/shrubs and agriculture/barren exhibited low scores in both user accuracy and
 4113 producer accuracy. The reason for the low accuracy of open forests/Shrubs was due to
 4114 this class being often mixed with forests and agriculture/barren in this study, reducing a
 4115 large percentage of accuracy (more than 20% reduction).



4116

4117 Fig. 4. 13. Land cover classification in 2004 and 2019; panel A1 and A2 are zoom in of land
 4118 cover in 2004 and 2019.

4119

4120 Table 4. 5. Confusion matrix of land cover classification in 2004 and 2019 using Random

4121 Forest.

Specification	Ground Truth								
	Class Name	Water	Forest	Open Forests/ Shrubs	Urban	Agriculture	Total	User's Accuracy	Error of commission (%)
Classified Map	2004								
	Water	21	0	0	0	0	21	1	0
	Forest	3	111	20	0	2	154	0.82	0.16
	Open Forests/ Shrubs	1	23	101	2	6	133	0.76	0.24
	Urban	0	0	0	22	0	22	1	0
	Agriculture	0	0	1	2	26	29	0.90	0.1
	Total	25	134	122	26	34	341		
	Producer's Accuracy	0.84	0.83	0.83	0.85	0.76	Overall Accuracy	0.82	
	Error of omission (%)	0.16	0.17	0.17	0.15	0.24	Kappa coefficient	0.74	
2019									
Classified Map	Water	27	0	0	0	0	27	1	0
	Forest	0	40	10	0	1	51	0.78	0.21
	Open Forests/ Shrubs	0	8	109	0	9	126	0.87	0.13
	Urban	0	0	2	24	0	26	0.92	0.07

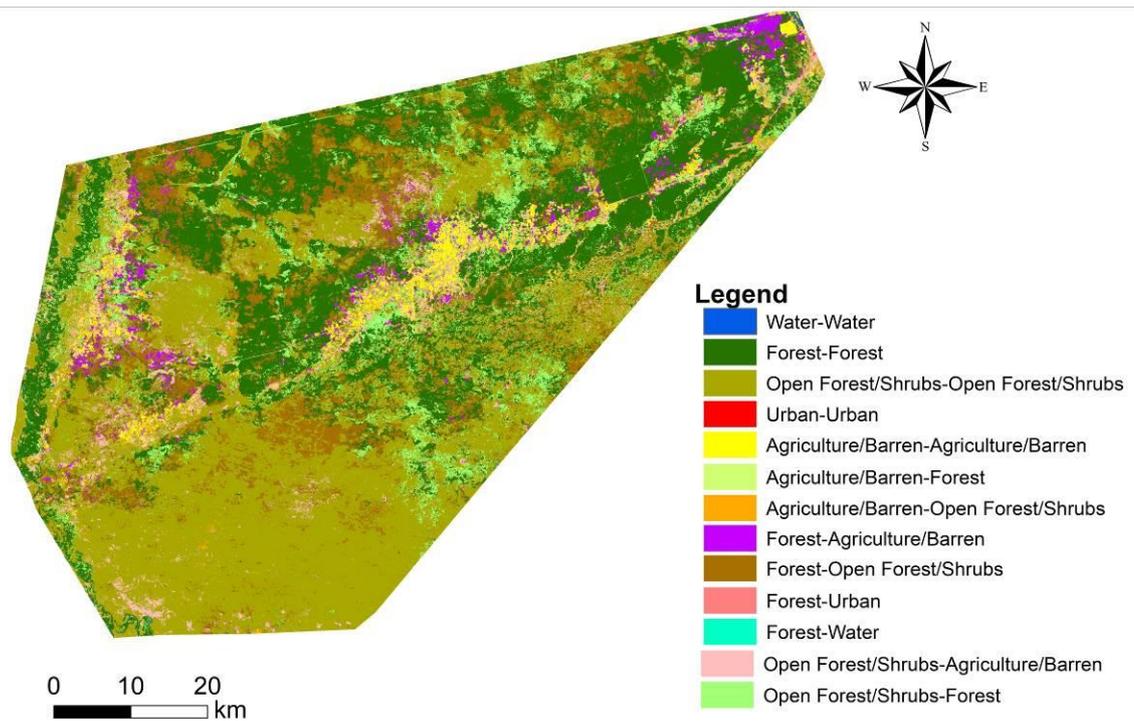
Agriculture	0	1	9	0	101	111	0.91	0.09
Total	27	49	130	24	111	341		
Producer's Accuracy	1	0.82	0.84	1	0.91	Overall Accuracy	0.88	
Error of omission (%)	0	0.18	0.16	0	0.09	Kappa coefficient	0.83	

4122

4123

4.4.7 Land cover change detection

4124 The land cover change map conversion from 2004 to 2019, is illustrated in Fig. 4.14. In
4125 general, open forest/shrubs were the dominant land cover type followed by forests in both
4126 years. In the northeast of the Zambezi State Forests, there was a significant change as
4127 forested areas were replaced by barren/agricultural land as a result of forest logging. A
4128 closer inspection of the classified maps revealed that most of the agricultural expansion
4129 occurs primarily around the communal areas in the northern part of the study area, in
4130 comparison to the southern part where protected areas such as Mudumu National Park
4131 are found. The conversion from forests to open forest/shrubs was significant with
4132 76345.98 ha (15%) and occurred mainly in the Mudumu National Park in the Southern
4133 part and Zambezi State Forest in the northern part of the region. Table B 1 presents the
4134 land cover change matrix between 2004 and 2019. Three major changes were an increase
4135 in open forests/shrubs and agricultural/barren land and a reduction in forest land. In
4136 2004, agricultural/barren land accounted for only 2.8% (143,77.87 ha) of total land. In
4137 2019, this figure increased to 8.47% (429,36.31 ha) (see: Table B 1). On the contrary,
4138 forest land experienced a significant decline of 9.04%, from 46.41% (235,140.91 ha) to
4139 37.37% (189,334.60 ha) of the total area in 2004 and 2019, respectively (see: Table B 1).
4140 The forest loss mainly was due to conversion to open forest/shrub (76,345.9), followed by
4141 agricultural/barren land (10,634.1 ha) (see Fig. 4.14). At the same time, other land uses
4142 are also converted to forest. For example, 40,172.9 ha of open forests/shrubs was
4143 converted to forest, followed by agricultural/barren land (236,77.1 ha) (see Fig. 4.14).



4144

4145 Fig. 4. 14. Changed areas for the epoch (2004–2019) in the study area

4146

4147

4.5 Discussion

4148

4.5.1 Effectiveness of BFAST and BEAST algorithms for

4149

characterising change in dryland forests

4150

4.5.1.1 Trend

4151 Despite BFAST and BEAST algorithms being able to handle unfiltered data, the
 4152 study found in the preliminary testing phase of the analysis that the use of filtered
 4153 MODIS time series yields accurate results and improved forest change detection, as
 4154 compared to the unfiltered data (see supplementary: A1). Identified changes that
 4155 occur in the trend component indicate both gradual and abrupt changes in land
 4156 cover, while changes occurring in the seasonal component indicate phenological
 4157 variation. In terms of deforestation, BFAST and BEAST algorithms identify a
 4158 consensus in time of breakpoints of larger magnitude, such as those associated
 4159 with clear-cutting of the forest to non-forest. This agreement shows that both
 4160 algorithms can be used to detect large-scale disturbances in the dryland forest. In

4161 terms of drought, BEAST algorithm was found to be the most successful in
4162 identifying abrupt changes from vegetation disturbance caused by drought. BFAST
4163 algorithm performed well in detecting abrupt changes of some known large
4164 magnitude drought events, however, BFAST did not identify abrupt changes in
4165 forest response for most drought and fire events, especially the lower magnitude
4166 of change. A study by Watts et al. (2014) reported that BFAST did not detect abrupt
4167 changes in vegetation as a result of well-known flood events. In this study, the
4168 advantage of BEAST was the capability to detect the impact of exceptional climatic
4169 conditions in both high and low magnitude drought years of 2002/03, 2005,
4170 2010/11, 2015/16, and 2019 on forest stand development. Conversely, BFAST
4171 algorithm was not able to detect such abrupt changes, as was seen in an example of
4172 a fire event in 2017 that resulted in a known disturbance within the forest plot. In
4173 this study, when using BFAST, sometimes 'minor changes', such as beginning or
4174 end of periods of disturbance and recovery are not included in the identified trend,
4175 and these breakpoints are often (incorrectly) counted as false positives. With such
4176 limitations in the performance of BFAST algorithm, disturbance or drought events
4177 can therefore be easily missed. A similar problem was found in a study by Wu et al.
4178 (2020), where BFAST algorithm was applied to an NDVI time series to detect
4179 changes within forest areas in China. They found that BFAST algorithm failed to
4180 detect slow urban expansion which resulted in a partial forest cut within the pixel,
4181 until the whole area of the pixel was changed.

4182 By comparing MODIS vegetation indices in detecting disturbance and trends in
4183 dryland forests, GNDVI outperformed NDVI in both algorithms. Particularly, BEAST
4184 algorithm generated change model using the GNDVI time series performed better
4185 overall. Both NDVI and GNDVI predicted large-scale clear-cut deforestation events
4186 accurately. However, GNDVI was more sensitive to detecting the abrupt changes
4187 due to droughts, fire, and small-scale disturbances. The analysis of the NDVI time
4188 series sometimes failed to detect abrupt changes in areas that did not undergo
4189 complete land cover class changes. The sensitivity of NDVI to background
4190 variations in the canopy and herbaceous layers could explain why the use of NDVI
4191 failed to detect disturbances and drought impacts in these areas (Huete et al.,
4192 2002). For stable or recovered forests, BFAST and BEAST algorithms performed
4193 similarly in detecting gradual changes using NDVI and GNDVI time series. The

4194 similarity in the performance of the two indices can be attributed to the fact that
4195 the study area is covered in trees and less of herbaceous layer (see supplementary:
4196 D1 and D2 for field photo and LC8 time series images). The gradual increase in
4197 forest cover of the stable forest can be a result of limited disturbance from fire,
4198 wildlife, and logging. This suggests that the dryland forest can quickly recover from
4199 drought in areas where multiple disturbances have not been experienced.

4200 4.5.1.2 Phenology

4201 In this research study area, the dryland forests have a very pronounced seasonality
4202 controlled mainly by humidity, with a rapid response to the onset of the rainy
4203 season, reflected in the abrupt changes in NDVI and GNDVI responses. The
4204 interannual variation in precipitation caused the change detection algorithms to
4205 flag breakpoints related to dryland forest phenology (Grogan et al., 2016, Zhao et
4206 al., 2019). BEAST algorithm detected phenological changes resulting from drought
4207 years followed a large increase in precipitation and clear-cut deforestation in NDVI
4208 and GNDVI time series (Table 4.2). BFAST also failed to detect any seasonal change
4209 using both NDVI and GNDVI time series. The ability of BFAST algorithm to capture
4210 seasonal changes triggered by interannual variations or disturbances in the
4211 dryland biomes is limited. Studies that tested BFAST algorithm on different forest
4212 types also reported poor performance in detecting seasonal changes. This included
4213 limitations in identifying changes in the amplitude of the seasonal curve, or
4214 changes in the number of seasons in which tropical dryland forests were
4215 characterised by high inter-annual seasonal variability (Gao et al., 2021, Grogan et
4216 al., 2016).

4217 The difference in the performance of the algorithms tested here can be attributed
4218 to the fact that BEAST incorporates non-linear change models (Burkett et al.,
4219 2005). BEAST not only detects the changepoints, but also quantifies their
4220 probability of being true, providing a confidence measure to interpret the changes
4221 in both trend and seasonality. A shortcoming of BFAST algorithm is that by relying
4222 on linear segments to describe underlying fluctuating trends, the model assumes
4223 vegetation trends are quasi-linear processes (i.e., regular, or stable seasonality)
4224 (Grogan et al., 2016). Deterministic models used within BFAST algorithm often do
4225 not therefore capture nonlinear behaviour as thresholds and complex interactions

4226 among ecosystem processes are unaccounted for (Burkett et al., 2005). For
4227 example, Jamali et al. (2014) accounted for non-linear vegetation changes in the
4228 Sahel using a polynomials fitting-based scheme to an annual NDVI time series and
4229 found it to describe general non-linear change trajectories. It has been widely
4230 observed that vegetation dynamics and land cover change can often occur in a non-
4231 linear pattern (Lambin et al., 1997). Additionally, climatic variations and change in
4232 moisture regimes, such as short- or long-term changes in rainfall patterns or
4233 temperature, may also drive nonlinear progressions in vegetation cover (Foley et
4234 al., 2003).

4235 These results demonstrate that accounting for variations at the seasonal scale
4236 while simultaneously uncovering complex nonlinear trends in forest dynamics is
4237 important, particularly for dryland forests where seasonality may vary
4238 significantly in amplitude from year to year. Projected rapid climate change is of
4239 major concern in these regions, especially when viewed with other population
4240 stresses such as habitat conversion, the impacts of fire, and herbivores
4241 disturbances. In KAZA, it is reported that competition between wild species occurs
4242 when habitats become degraded, especially by elephants (FAO, 2009). These
4243 synergistic stresses are likely to prove to be the greatest challenge to wildlife
4244 conservation in the 21st century, hence tracking the occurrence of disturbance
4245 events and phenological shift events as they occur is an essential task in PAs
4246 conservation efforts.

4247 4.5.2 Spectral index sensitivity in dryland forests

4248 The study found that BFAST and BEAST change models using the GNDVI time
4249 series performed better than the more commonly used NDVI. Comparing results
4250 from NDVI and GNDVI and related these to the precipitation anomaly shows that
4251 the maximum differences in vegetation index performance occurred over the
4252 dryland forest relative to the grassland, and then shrubs. There is a general
4253 agreement between indices in areas undergoing browning and greening in the
4254 non-forested area (see: Fig. 4.4). GNDVI had the best performance in distinguishing
4255 browning and greening of forest from herbaceous layers affected by droughts. For
4256 example, analysis of the NDVI was able to detect a strong greening in forest areas
4257 in the severe droughts of 2015-2016 and 2019. These results are similar to a study

4258 by Loranty et al., (2018) that found positive decadal trends in NDVI in Siberian
4259 forests that ranged from sparse to dense canopy cover, which correspond to
4260 increases in understory productivity rather than an increase in forest cover. This
4261 study results also concur with the study by Otsu et al. (2019) that found that
4262 GNDVI performed best in distinguishing broad leaf from needle leaf forests as
4263 compared to NDVI. Another study by Yoder et al. (1994) used the green channel in
4264 a vegetation index and found that it had a better correlation with the
4265 photosynthetic activity of the tree canopy in miniature Douglas-fir trees as
4266 compared to the red channel. The main reason for the difference in the
4267 performance of NDVI and GNDVI is likely because the former is more sensitive to
4268 low chlorophyll concentrations, while GNDVI is more sensitive to high chlorophyll
4269 concentrations and so is more accurate for assessing chlorophyll content at the
4270 tree crown level (Gitelson et al., 1996). A study by Grogan et al., (2016) tested
4271 BFAST on Land Surface Water Index (LSWI) and used NDVI on dry-deciduous and
4272 evergreen forests and found that the LSWI time series outperformed the more
4273 commonly used NDVI and EVI indices.

4274 In conjunction with observations from the field, these results indicate that
4275 understory vegetation likely exerts a strong influence on NDVI. It has been shown
4276 in other research that different plant functional types, including canopy
4277 background variations and herbaceous vegetation, also have a pronounced
4278 seasonal effect on the NDVI signal, while also not being directly correlated with
4279 woody cover (Grogan et al., 2016, Prince, 1991). This is apparent in my
4280 observations and suggests that the NDVI pattern of a higher-than-average anomaly
4281 during the growing season of 2015 and 2019 may correspond primarily to
4282 increases in understory productivity rather than an increase in forest cover. For
4283 this study, a possible explanation for this is that tropical vegetation greenness can
4284 recover rapidly soon after forest clearing as the low herbaceous cover such as
4285 grassland and saplings grow vigorously due to increased light levels, resulting in
4286 reduced sensitivities to detect disturbances in greenness-based indices such as
4287 NDVI. The use of VIs for biophysical parameter retrievals is therefore a challenging
4288 task and there remains much work in understanding VI sensitivity across and
4289 within dryland biomes (Huete et al., 2002). Ground field validation test sites are
4290 essential in this regard and help provide valuable insight in interpreting spatial

4291 and temporal variability in VI that arises from vegetation-related properties,
4292 including LAI, canopy structure, and understory vegetation. Hence, both soil
4293 characteristics and the reflectance of lower plant communities may lead to
4294 misinterpretations of the open dry forest dynamics and an under or
4295 overestimation of ecosystem productivity in similar semiarid environments.

4296 4.5.3 Land cover classification and spatial pattern of forest 4297 changes using breakpoints and magnitude

4298 This study applied remote sensing techniques to classify satellite imagery of the
4299 Zambezi region of Namibia in 2004 and 2019. Despite the good classification
4300 obtained in this study, there were some general issues which may have reduced
4301 the accuracy of the overall classification. For example, the spectral signature of
4302 forests was mixing with the signature of open forests/shrubs, resulting in low
4303 producer's accuracies for both classified map due to their noisy Landsat spectral
4304 signatures and difficulty in interpreting them. A similar problem was also
4305 encountered by Lu et al. (2003) and Zhao et al. (2016). To overcome this mixed
4306 pixel problem, higher spatial resolution multispectral images such as SPOT images
4307 reduced the mixed pixel problem, resulting in improved forest classification
4308 accuracy (Lu et al., 2008). However, using higher spatial resolution with pixel-
4309 based tree species classification approaches also increased spectral variations,
4310 especially in savannas with open forests, because of their complex forest stand
4311 structure and canopy shadows, resulting in poor classification accuracies (Lu and
4312 Weng, 2005; Myeong e al., 2001; Pu et al., 2018; McElhinny et al., 2005).
4313 Incorporation of these relatively medium spatial resolution images such as Landsat
4314 with 30-meter spatial resolution with other data sources such as digital elevation
4315 models (along with their derivatives such as slope and aspect), spatial texture, and
4316 SAR can improve classification accuracy (Myeong e al., 2001).

4317 In this study, the LULC change trajectories included the conversions to-and-from
4318 land cover classes. Unchanged areas, particularly forest land and open
4319 forest/shrub land, are of exceptional importance for biodiversity management,
4320 providing forest habitat and increases connectivity between forest patches for
4321 wildlife population dynamics, and migratory species (Stoldt et al., 2020; Wegmann
4322 et al., 2015; Wintle et al., 2019). In addition, unchanged areas provide timber and

4323 non-timber product supply, and carbon storage in the study area (David et al.,
4324 2022a). The large areas of unchanged forest land may provide an indication of the
4325 effectiveness of intensified efforts for forest protection and biodiversity
4326 management such as forest fire protection programs and awareness creation on
4327 the sustainable use of forests implemented by the Government (Russell-Smith et
4328 al., 2017). Conversely, the large area of forest conversion to open forests/shrubs
4329 and agricultural/Barren land could also indicate the degradation of forests from
4330 continuous drought events and logging of forests for timbers from the Chinese
4331 companies in the Zambezi region (Asanzi et al., 2014; Chikoore and Jury, 2021;
4332 Weng et al., 2015). The most valuable timber tree species in Namibia include
4333 *Pterocarpus angolensis*, *Baikiaea plurijuga*, and *Guibourtia coleosperma*. However,
4334 the harvest of these trees has increased because of the high demand for timber
4335 from dense tropical hardwood species from Chinese (Asanzi et al., 2014).

4336 Making full use of the opportunities that the Landsat and MODIS archive provides,
4337 this study provides an assessment of land cover change and forest disturbances in
4338 the KAZA region, from 2002/2004 to 2019, explored with change detection
4339 algorithms. The main aim was to quantify and identify the Land cover change,
4340 locations, types, and trends of the land cover during the 19-year period in
4341 communal and protected areas of Namibia. Methodologically, this study showed
4342 that dryland forest disturbances associated with deforestation and degradation
4343 can be mapped reliably with both BFAST and BEAST change detection algorithms.
4344 In terms of the performance of indices utilised, this study suggests that the GNDVI
4345 was found to have the best performance in monitoring degradation and detecting
4346 disturbances from droughts and fires as compared to NDVI. This study found the
4347 NDVI is less sensitive to changes in dryland forests as compared to GNDVI, and this
4348 result is consistent with studies that found that metrics based on the short-wave
4349 infrared (SWIR) outperform NDVI in temperate and savanna ecosystems in the
4350 USA (Jin and Sader, 2005, Kennedy et al., 2010, Zhu, Woodcock and Olofsson,
4351 2012).

4352 Thematically, this study yielded three main insights. First, the study found diverse
4353 spatial patterns of forest disturbances are more prevalent in the communal areas
4354 and state forests such as the Zambezi ST, particularly when compared to protected
4355 areas such as Mudumu NP. These changes are driven by different disturbance

4356 agents, including both natural processes (e.g., drought) and anthropogenic impacts
4357 (e.g., timber logging, fire). This suggests disturbance attribution is central for
4358 understanding the drivers and impacts of forest degradation. According to land
4359 cover change analysis in Fig. 4.13, agricultural/barren land has increased
4360 dramatically during 2004 to 2019. Agricultural/ barren land may be caused by (1)
4361 cut trees for households and wood processing businesses, or (2) slash-and-burn
4362 agricultural activities (Kamwi et al., 2017) and (3) timber trade (Asanzi et al.
4363 2014). That unsuitable farming practice is mainly taken by local ethnic groups
4364 living in the province, while the tree logging is due to a strong presence of logging
4365 companies primarily from China (Nott et al, 2019). This is in agreement with
4366 previous studies on land cover and land use analysis such as Kamwi et al. (2017)
4367 that found agricultural expansion to be the most predominant driver in the same
4368 study area.

4369 Second, the study found large areas of the dryland forest in the Zambezi ST have
4370 experienced major disturbances from 2016 to 2019 from clear-cut of forests
4371 coupled with fire, and extreme drought events, suggesting deforestation and
4372 degradation is a widespread phenomenon in KAZA. Similar to the research
4373 presented by Kamwi et al. (2015), the land cover analysis from this study (see: Fig.
4374 4.13 and Fig.4.14) found that small-holder agriculture and shifting cultivation was
4375 largely responsible for breakpoints of large magnitudes in the communal areas of
4376 the Zambezi region detected by BFAST change detection (see: Fig 4. 12). The
4377 BFAST change detection also detected vegetation disturbances/degradation, stable
4378 vegetation, and vegetation regrowth, and these level of disturbances, trend and
4379 direction of change were not detected by the bi-temporal classification. Third, a
4380 clear association between forest disturbance and precipitation was found. Forest
4381 disturbance was particularly widespread during severe drought years such as
4382 2015-2016 and 2019. This study results also showed positive magnitude
4383 breakpoints, which represented forest recovery and vegetation regrowth, which
4384 could be attributed to increased precipitation and lack of disturbance in protected
4385 areas such as Mudumu NP, as compared to community conservancies and the
4386 Zambezi SF. This study disturbance maps, land cover change and field observations
4387 suggest that drought, forest logging, agricultural expansion, large herbivore
4388 disturbance, and increased fire may explain some of the observed pattern by the

4389 BFAST and BEAST change detection algorithms (Kamwi et al., 2017); Nott et al,
4390 2019), (also see: Fig. B2, B3, B4 and B5). Similar patterns of increases in forest
4391 disturbance during drought seasons were found both in the Amazon and the Gran
4392 Chaco of Argentina (Bullock et al., 2020, De Marzo et al., 2021).

4393 Previous land cover mapping research in the KAZA region has shown contrasting
4394 results. Kamwi et al. (2015) reported forest and woodlands are expanding in
4395 communal land in the Zambezi region, while Meyer et al. (2021) reported that
4396 woodland cover reduced by 2.1% within the same study area and time period of
4397 1990 to 2010. The land cover mapping from this study shows that forests reduced
4398 by 9% in the same region between 2004 and 2019. The deforestation and
4399 widespread degradation identified in this study are consistent with findings by
4400 McNicol et al. (2018) that found Southern African woodland is highly dynamic with
4401 widespread degradation and deforestation, but also extensive vegetation
4402 regrowth. The further step on assessing the magnitude of change reported in this
4403 study demonstrates first that forest change occurs in an incremental manner, and
4404 second, by making use of the magnitude parameter, that conventional bi-temporal
4405 classification studies could further be improved and complimented by extent and
4406 severity of forest disturbances derive here (DeVries et al., 2015). The ability to
4407 describe these change processes with high temporal detail highlights the
4408 advantage of a time series change detection approach used here and the additional
4409 information they provide to conventional bi-temporal classification maps of forest
4410 versus non-forest maps conducted in KAZA region (Kamwi et al., 2017, Meyer et
4411 al., 2021, Fox et al., 2017).

4412 4.6 Conclusion

4413 This study evaluated the applicability of BFAST and BEAST algorithms to detect a
4414 range of abrupt, gradual, and seasonal changes using MODIS vegetation index (VI)
4415 time series data in tropical dryland forests in Southern Africa from 2002–2019.
4416 The change detection algorithms complemented the bi-temporal Land cover
4417 change detection in Zambezi region from 2004 and 2019. The study has shown
4418 that analysis of monthly MODIS VI time series, climate data, and field validation
4419 can effectively describe and help to interpret longer-term changes of vegetation

4420 dynamics. Changes occurring in the trend component identified indicate both
4421 gradual and abrupt changes, while giving insights into the influence of drought and
4422 phenological variation on the forest. Four main conclusions can be drawn from this
4423 study:

4424 First, dryland forests are highly dynamic and water sensitive with high rates of
4425 deforestation and widespread degradation, but also continuous vegetation
4426 recovery and regrowth are identified in protected areas compared to unprotected
4427 areas.

4428 Second, BEAST algorithm was found to give the best performance overall, correctly
4429 identifying abrupt changes of vegetation response to fire and drought impacts.
4430 BFAST did not perform well in identifying abrupt changes resulting from fire and
4431 low magnitude drought events. Based on the results, the best decomposition of
4432 trend and seasonal breakpoints were given by BEAST using the GNDVI.

4433 Third, BEAST algorithm outperformed BFAST algorithm in detecting seasonal
4434 changes driven by climatic and clear-cutting events. BEAST algorithm detected the
4435 abnormality of deforestation and climate-driven changes in seasonality, which
4436 helped identify the potential drivers of these phenological shifts. However, BFAST
4437 failed to detect any seasonal changes within the entire study period (2002-2019)
4438 using either the NDVI or GNDVI.

4439 Fourth, conventional NDVI was highly influenced by canopy background variations
4440 and herbaceous layers, as compared to the GNDVI. NDVI performed best in the
4441 robust detection of areas with complete land cover class changes, while GNDVI
4442 performed well in detecting changes within areas of partial (low magnitude
4443 change) and complete land cover class changes. The analysis suggests that GNDVI
4444 is more sensitive to chlorophyll concentration in vegetation when the leaf area
4445 index is moderately high as is the case in tropical dryland forests, while NDVI is
4446 more sensitive to forest types with low chlorophyll concentrations.

4447 Finally, the study shows that the droughts that took place in 2015 and 2019 were
4448 longer and more extreme than the droughts in 2002-2003, 2005, 2007 and 2011-
4449 2013. Overall, the results also show that a large part of the growing season and

4450 phenology is highly influenced by seasonal and inter-annual variations in climatic
4451 conditions, particularly in the case of severe drought in the KAZA region.

4452 These results highlight the importance of complementing the conventional bi-
4453 temporal classification studies on Land cover change with improved time series
4454 change detection algorithms to detect the magnitude, extent, and severity of forest
4455 disturbances with high temporal detail. The study also showed the importance of
4456 considering the sensitivities of VIs used in forest monitoring when trying to
4457 identify non-linear dynamics of dryland forests. Two extreme record droughts in
4458 less than two years (2015-2016 and 2018-2019) are evidence of the negative
4459 impacts of extremes of climate variability and climate change in the region.
4460 Therefore, an in-depth assessment of the intensity, spatial coverage, and
4461 geography of impacts of future droughts are of fundamental importance to the
4462 region. The approach described above is transferable to other tropical forest areas
4463 with high inter-annual variability that is influenced by seasonal climatic variations
4464 and disturbance. These methods are subject to further tests with other datasets of
4465 higher spatial resolution such as Landsat, Sentinel, or simulated datasets, to ensure
4466 their efficacy.

4467 4.7 Acknowledgments

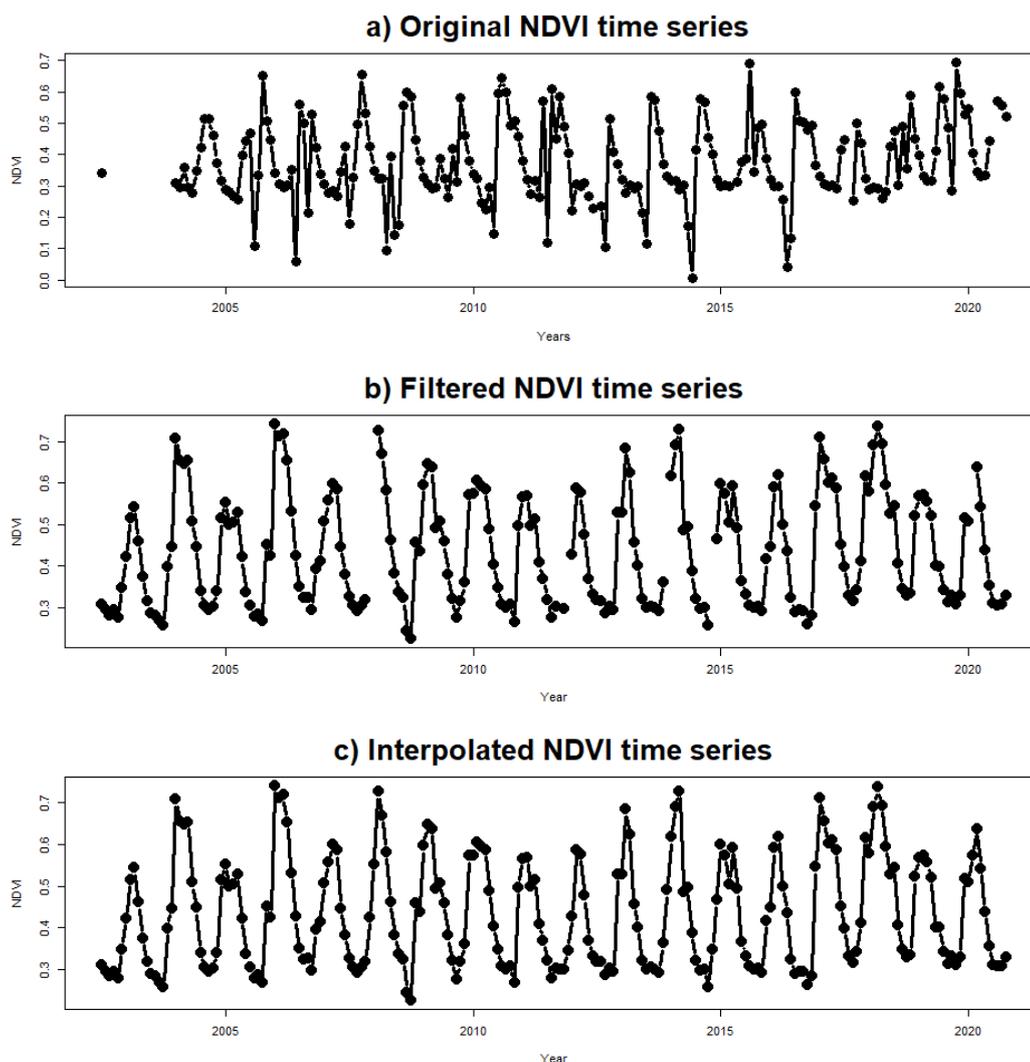
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4476 collection in the field.

4477

4478

4479 4.8 Supplementary Information 2

4480 MODIS Data Processing and Filtering



4481

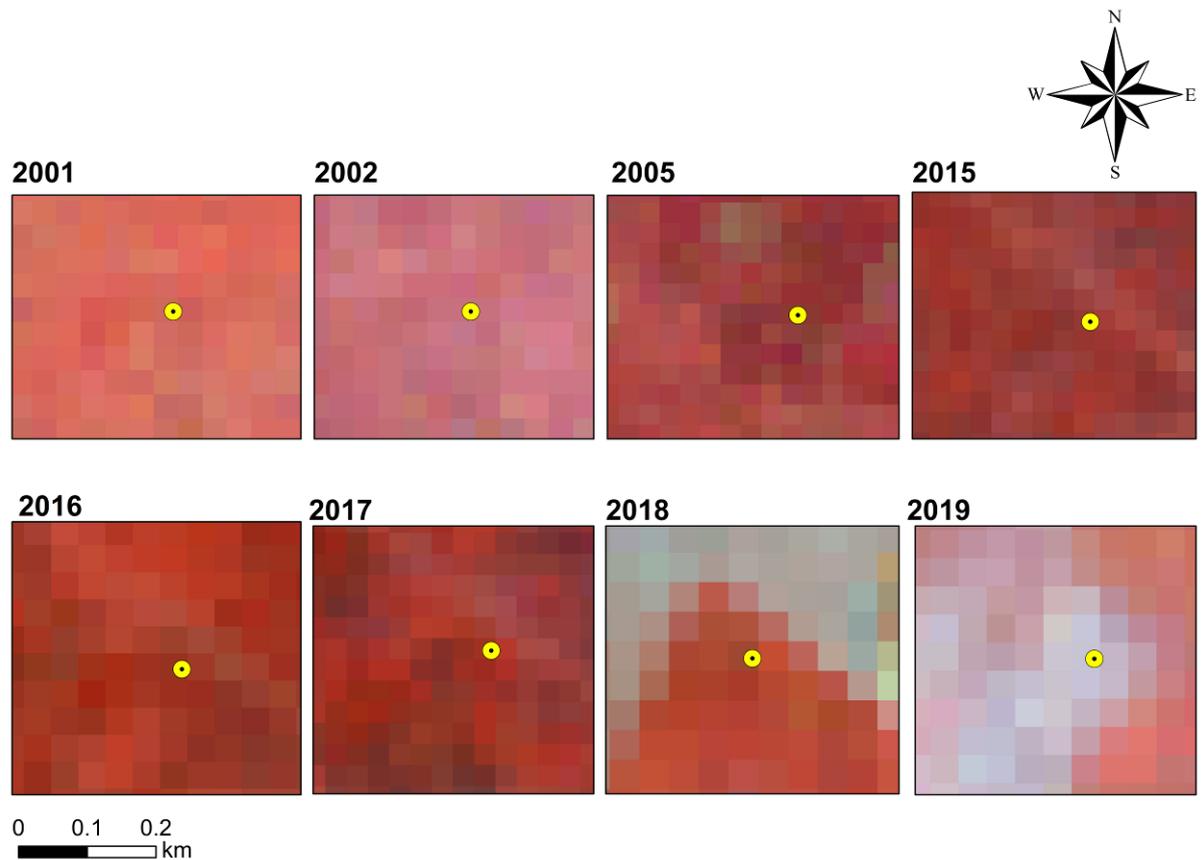
4482 Fig. B 1. Temporal profiles of raw and cleaned MODIS NDVI data for a forest plot: (a)
 4483 original time series after MCV method; (b) time series retained after filtering, and (c) time
 4484 series with linear interpolation on filtered points over a 17-year period.

4485

4486 Clear-cut and burnt forest

4487 Fig. B 2. A and B shows field photo evidence of a deforestation event in a dryland forest
 4488 dominated by *Baikiaea plurijuga* species, the area was burned in 2017 and clear-cut for

4489 timbers in around 2018-2019. The photo location coordinate is 17.49°S, 24.21°E taken
 4490 from ground survey in Namibia in 2019.



4491
 4492 Fig. B 3. Shows the corresponding time series of Landsat images with no cloud cover in the
 4493 pixels documenting changes in the forest (forest to shrubs) from 2015 to 2019,
 4494 respectively. The yellow dot represents the location ID (coordinate: 17.49°S, 24.21°E). The
 4495 year 2002 and 2005 was included because it is a drought year and 2001 was used as a
 4496 baseline year.

4497

4498 **Drought impacts and degraded forest**

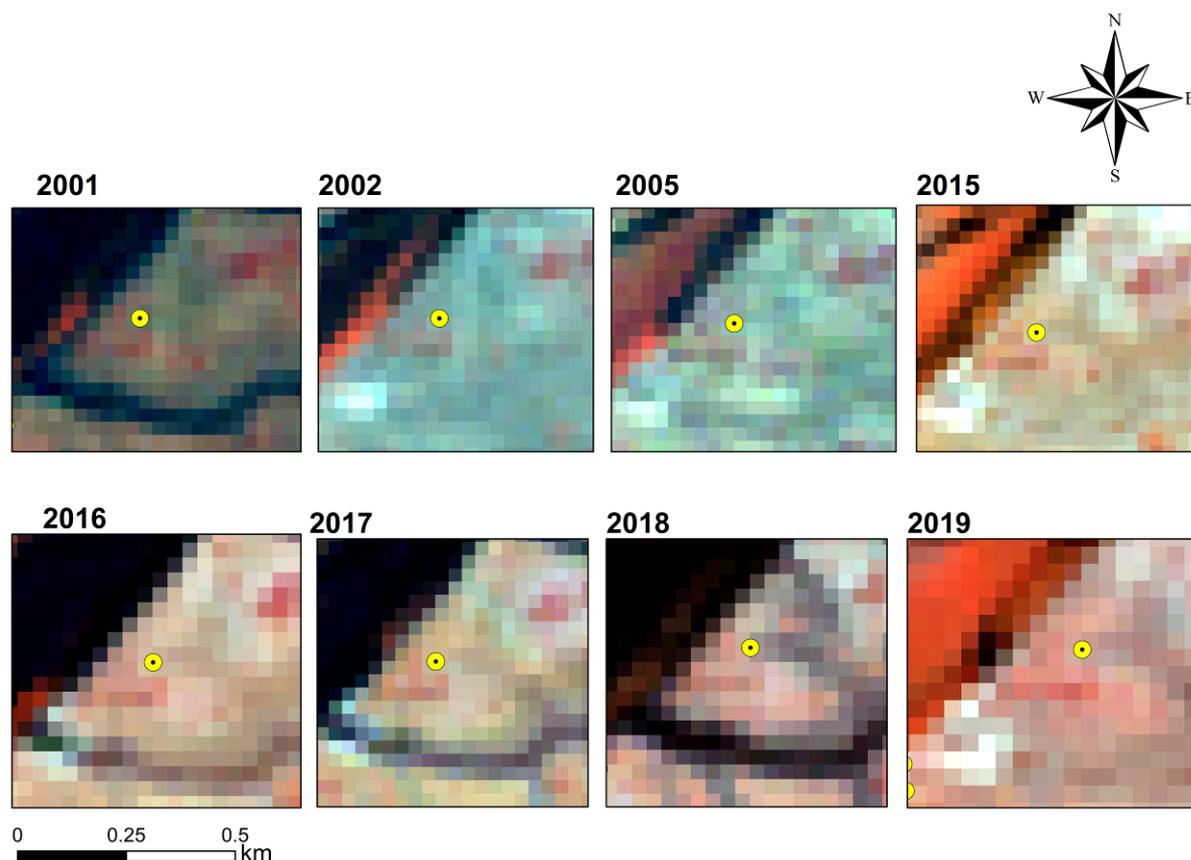
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4500

4501 Fig. B 4. shows field photo evidence of a degrading forest dominated by baobabs and
 4502 riparian woodlands species near Chobe River frontage. The photo location coordinate is
 4503 17.80°S, 24.95°E taken from ground survey in Botswana in 2019.

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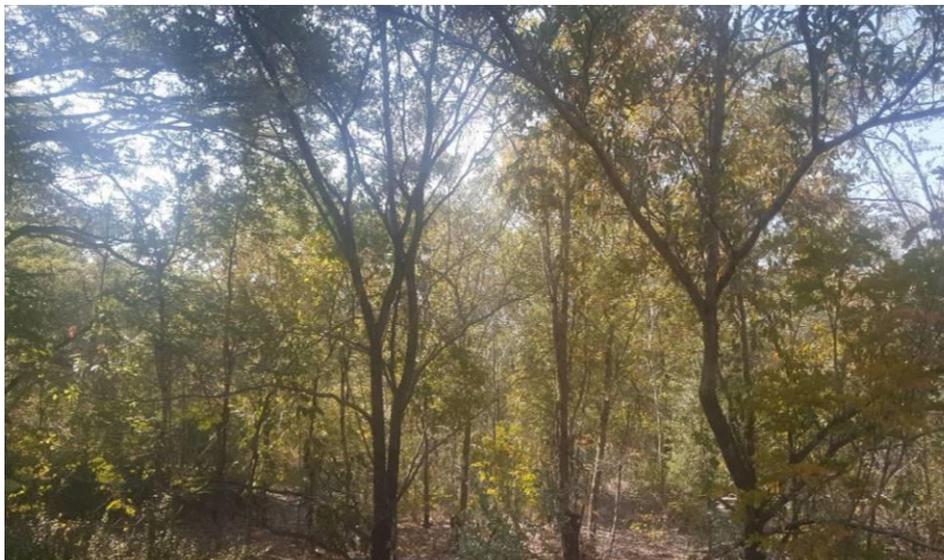
4506

4507 Fig. B 5. shows the corresponding time series of Landsat images with no cloud cover in the
 4508 pixels documenting changes in the plot from 2015 to 2019, respectively. The yellow dot
 4509 represents the location ID (coordinate: 17.80°S, 24.95°E). The year 2002 and 2005 was
 4510 included because it is a drought year and 2001 was used as a baseline year.

4511

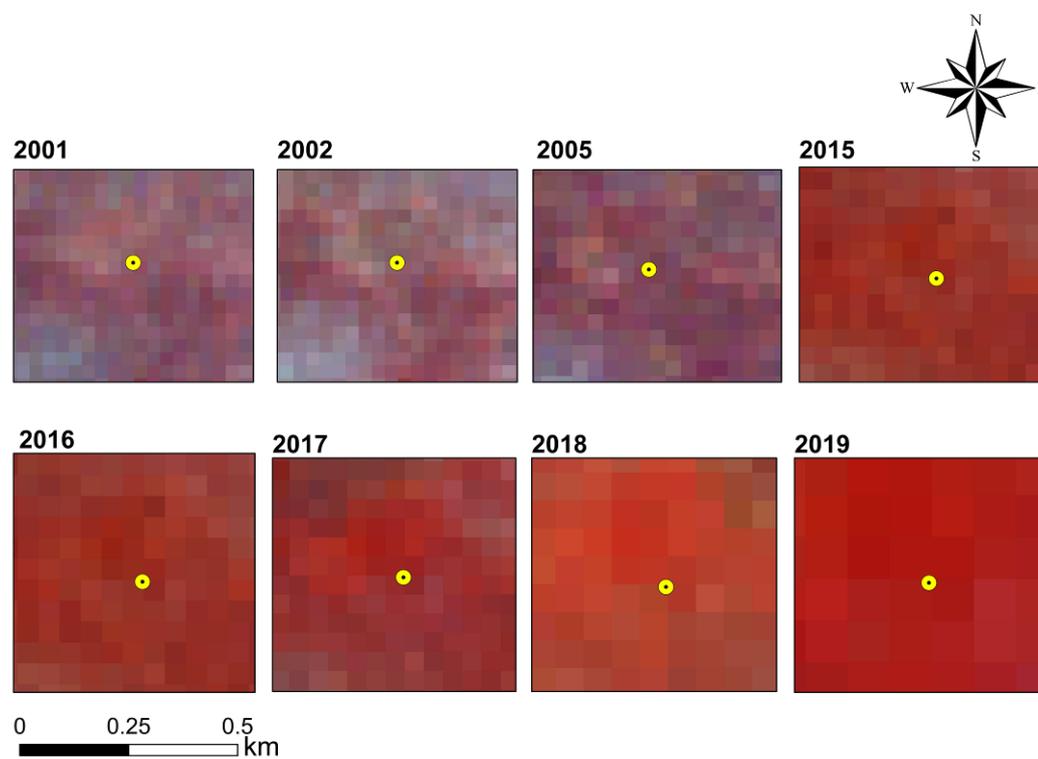
4512 A stable and recovering forest

4513



4514

4515 Fig. B 6. Shows field photo evidence of a forest that has not experienced any disturbance
4516 for the period of the study. The photo location coordinate is 17.57°S, 24.28°E taken from
4517 ground survey in Botswana in 2019.



4518

4519 Fig. B 7. shows a time series of LC8 images from 2015 to 2019 is shown below. The yellow
 4520 dot represents the location ID (coordinate: 17.57°S, 24.28°E). The year 2002 and 2005
 4521 was included because they are drought years and 2001 was used as a baseline year

4522 Table B. 1. Land cover areas in the study area per year (2004 and 2019) in km² and
 4523 hectares.

Class name	2004 Area (km ²)	2004 Area (ha)	2004 Area (%)	2018 Area (km ²)	2018 Area (ha)	2019 Area (%)
Water	5	508	0	6	600	0
Forest	2,351	2351,411	46	1,893	189,335	34
Open forests/Shrub	2,564	256,410	51	2,735	273,512	54
Urban	3	262	0	3	318	0
Agriculture	143	14,378	3	429	42,934	8

4524

4525 Table B. 2. Area changes of BFAST (2002-2019) using sample-based estimates and the
 4526 observed disturbance change rates in hectares.

Change identified by BFAST	Area (ha)	Standard Error (ha)	2.5 % (ha)	97.5 % (ha)
Non-disturbance (No change) <i>(Stable Forest)</i>	106,390	9,817	87,148	125,631
Low negative changes (no change) <i>(Degradation)</i>	90,929	10,636	70,083	111,776
Large negative changes (No change) <i>(Non-forest)</i>	38,873	7,162	24,836	52,910
Non-disturbance -Low negative changes <i>(Stable forest to Degradation)</i>	33,132	6,859	19,688	46,576
Non-disturbance -Large negative	99,911	9,753	80,795	119,027

changes <i>(Stable Forest to Deforestation)</i>				
Low negative changes -Large negative changes <i>(Degradation to Deforestation)</i>	59,515	8,154	43,533	75,497
Low negative changes -Non-disturbance <i>(Degradation to Stable Forest)</i>	23,409	556,8	12,497	34,322
Large negative changes -Low negative changes <i>(Deforestation to Degradation)</i>	48,537	8,353	32,167	64,908
Large negative changes -Non-disturbance <i>(Deforestation to Stable Forest)</i>	5,980	2,966	167	11,792
Total	506,676			

4527

4528 Table B. 3. Area changes for the Random Forest classification in the Zambezi region in
4529 hectares.

Change identified by two-interval classification	Area (ha)
Forest-Forest	147,876
Non-forest-Non-forest (no change)	201,157
Forest - Non- Forest	87,251

Non-forest - Forest	41,447
Non-forest - Non-Forest (change)	28,944
Total	506,676

4530

4531 Table B. 4. Area-based transition among land cover categories for the Random Forest
4532 classification for the period 2004–2019 in the Zambezi region in hectares.

4533

4534

Land cover class Change	Re-organisation	Area Change (ha)	Area Change (%)
Agriculture-Agriculture	Non-forest-Non-forest (no change)	8,501	2
Agriculture-Forest	Non-forest - Forest	1,109	0
Agriculture-Open forest/Shrub	Non-forest -Non-Forest (change)	4,707	1
Agriculture-Urban	Non-forest -Non-forest (change)	58	0
Agriculture-Water	Non-forest -Non-forest (change)	4	0
Forest-Agriculture	Forest to Non-forest	10,634	2
Forest-Forest	Forest-Forest	14,7876	29
Forest- Open forest/Shrub	Forest to Non-forest	76,346	15
Forest-Urban	Forest to Non-forest	16	0
Forest-Water	Forest to Non-forest	256	0
Open forest/Shrub -Agriculture	Non-forest -Non-forest (change)	23,677	5
Open forest/Shrub -Forest	Non-forest - Forest	40,173	8
Open forest/Shrub - Open Forest/Shrub	Non-forest-Non-forest (no change)	192,313	38
Open forest/Shrub -Urban	Non-forest -Non-forest (change)	205	0
Open forest/Shrub -Water	Non-forest -Non-forest (change)	34	0
Urban-Agriculture	Non-forest -Non-forest (change)	115	0
Urban-Forest	Non-forest - Forest	5	0
Urban- Open forest/Shrub	Non-forest -Non-forest (change)	101	0
Urban-Urban	Non-forest-Non-forest (no change)	39	0
Urban-Water	Non-forest -Non-forest (change)	1	0
Water-Agriculture	Non-forest -Non-forest (change)	7	0
Water-Forest	Non-forest - Forest	161	0

Water- Open forest/Shrub	Non-forest -Non-forest (change)	36	0
Water-Urban	Non-forest -Non-forest (change)	0	0
Water-Water	Non-forest-Non-forest (no change)	305	0
Total		506,676	100

4535

4536 **5 A SPATIO-TEMPORAL DROUGHT AND FIRE ANALYSIS**
4537 **FOR SEMI-ARID DRYLAND ECOSYSTEMS IN SOUTHERN**
4538 **AFRICA USING MODERATE RESOLUTION SATELLITE**
4539 **IMAGERY.**

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4552 Chapter 5 Manuscript in progress: Intended for submission to *Remote Sensing in*4553 *Ecology and Conservation*.

4554

4555 **Title:** A spatio-temporal drought and fire analysis for semi-arid dryland
4556 ecosystems in southern Africa using moderate resolution satellite imagery.

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4561 **Author contributions**

4562

4563 David Ruusa- Design the research, perform the data analysis, interpret the results,
4564 wrote the manuscript, and revised the manuscript. Nick Rosser- Contributed to the
4565 research design, manuscript editing and supervision. Daniel Donoghue-
4566 Contributed to the research design, conducting fieldwork, manuscript editing and
4567 supervision.

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4587 **Abstract**

4588 The dryland ecosystem of Southern Africa is fire-prone and has a long history of
4589 recurrent droughts that in turn, affect its ecology, structure, function and
4590 distribution. This chapter presents a spatiotemporal analysis of drought, water
4591 stress, fire impacts on dryland vegetation between 2002 and 2019 for the largest
4592 conservation area: Kavango-Zambezi Transfrontier Conservation Area (KAZA). To
4593 disentangle the relative contribution of climatic and fire regimes to dryland
4594 vegetation, Normalised Difference Vegetation Index (NDVI), precipitation data,
4595 temperature data, evapotranspiration, Root Soil Moisture (RSM) and Active Fire
4596 and Burned Area data products were used. For drought condition, this study shows
4597 most severe drought was in 2002/2003, 2005, 2015/2016 and 2018/2019. The
4598 worst drought with the longest duration and highest magnitude was recorded in
4599 2019. In the KAZA region, about 149,410 km² of land is burned on an annual basis
4600 over the period 2002–2019, however significant differences were observed in the
4601 fire patterns among the five countries of KAZA. Fire incidence was higher in Angola
4602 and Zambia where burning is not strictly controlled; midrange fire incidences were
4603 observed in Namibia where fire control policy and awareness programs were
4604 introduced in 2006; and fire incidence was lower in Botswana and Zimbabwe,
4605 where there are effective and strict fire management policies. These results reveal
4606 that the areas with high dryland forests (or high tree cover), high rainfall, and long
4607 dry season length coincide with areas of high fire frequency resulting in relatively
4608 large burned areas. The combination of drought, water stress and high fire
4609 frequency observed in this study has led to an increase in land area classified as
4610 arid and semi-arid at the expense of dry sub-humid and humid land classes, which
4611 were reduced by 10% in the period 2002 to 2019. These findings have important
4612 implications on wildlife habitat management and climate change in Southern
4613 Africa's dryland forest ecosystems.

4614 **Keywords:** Dryland vegetation, climate change, soil moisture, drought, forest fire,
4615 Southern Africa, remote sensing

4616

4617 5.1 Introduction

4618 5.1.1 Drought stress on dryland vegetating

4619 Drought is a regular and recurrent feature of Southern African climate, and climate
4620 change scenarios predict large-scale biogeographical shifts in vegetation in
4621 response to the severe drought and intense moisture surplus which will be
4622 exacerbated by higher temperatures (Diffenbaugh et al., 2017). Growing evidence
4623 suggests that the effects of drought on vegetation under warmer conditions can be
4624 severe, as highlighted by recent observations of regional-scale woody-plant die-off
4625 across Southern Africa (Naidoo et al., 2013), the Sahel (Anyamba et al., 2005), and
4626 more widely around the globe (De Jong et al., 2013). In Southern Africa's arid and
4627 semiarid areas, droughts are a frequent occurrence and can have severe ecological
4628 and economic consequences (Mason et al., 2000). While these events may be short
4629 duration followed by recovery during subsequent years of higher rainfall, in some
4630 cases droughts can trigger substantial and irreversible ecological and
4631 socioeconomic changes (Ellis et al., 1988).

4632 The effects of drought on vegetation can vary considerably across ecosystems,
4633 depending on plant adaptations and interactions with other ecological processes
4634 (Engelbrecht et al., 2007). The responses of vegetation to variations in climate are
4635 expected to be most sensitive and extreme in tropical open woodlands and forests
4636 in arid and semi-arid ecosystems (Watson et al., 1996). Tropical open woodlands
4637 (hereafter called "dryland forest or woodland") are forests comprising mixtures of
4638 trees, shrubs, and grasses in which the tree canopies do not form a continuous
4639 closed cover (Grainger, 1999). There is evidence that anomalies in tropical
4640 vegetation greenness are linked to global inter-annual variations in sea surface
4641 temperature (SST), land surface temperature and precipitation, as evidenced in the
4642 dryland forests (Huang et al., 2017). The xeric areas of the dryland biome often
4643 have unreliable rainfall and are often subject to a substantial multi-year rainfall
4644 deficit. Furthermore, the impacts of drought tend to be aggravated by
4645 deforestation, land degradation, growing water demand and extremes of
4646 temperature, as a result of climate variability, anthropogenic activities and global
4647 warming (Dale et al., 2001). For example, Chagnon et al. (2004) found a large shift
4648 in local rainfall and seasonality with increases in deforested areas in the Amazon,

4649 associated with local atmospheric circulation that were changed by gradients in
4650 vegetation. Monitoring drought stress in vegetation is a critical component of
4651 proactive drought planning designed to mitigate the impact of this natural hazard.
4652 Although it is not possible to avoid drought, its impacts can be managed through
4653 preparedness planning. The success of drought preparedness and management
4654 depends, among others, on how well the droughts are defined and drought
4655 characteristics (e.g., intensity and duration) are quantified temporally and
4656 spatially.

4657 A drought is a naturally recurring hazard and can alternatively be defined as a
4658 temporary, recurring reduction in the precipitation in an area. Droughts have a
4659 slow initiation and they are usually only recognised when the drought is already
4660 well established. The deficiency in precipitation is the main causes of all drought
4661 types, including: meteorological, agricultural, hydrological, and socioeconomic.
4662 Meteorological drought relates to precipitation deficiencies in absolute totals for a
4663 given period and is one of the primary causes of wider drought. On the other hand,
4664 agricultural drought is characterised by a soil moisture deficit and changed plant
4665 behaviours during the plant-growing period. The longer and the more spatially
4666 extensive this deficiency, the more likely the occurrence of other types of droughts,
4667 such as hydrological that is a reduction of streamflow, lake or reservoir storage,
4668 and a lowering of ground-water levels. Socioeconomic drought occurs when the
4669 demand for an economic good exceeds supply as a result of a weather-related
4670 shortfall in water supply (Maliva et al., 2012). Drought indices derived from
4671 meteorological data can be used to monitor not only meteorological droughts but
4672 also agricultural and hydrological droughts, and to categorise the seriousness of
4673 the drought, which is important for a wide range of management and planning
4674 decisions. Drought indices commonly applied around the world are summarised by
4675 Svoboda et al. (2016). Consequent impacts of warm droughts could include a
4676 reduction in habitat for wildlife, enhanced opportunities for invasion by exotic
4677 species, formation of novel communal areas, imbalances in the hydrologic cycle,
4678 and temporal disruptions to ecosystem goods and services (Rands et al., 2010).

4679 5.1.2 Fire impacts on dryland vegetation

4680 In addition to drought, within the forest-dryland mosaics other natural
4681 disturbances that affect forests include large pulses of forest disturbances from
4682 agents such large mammalian herbivore damage, insect outbreaks, strong winds
4683 and wildfires (Geist et al., 2004). Fire is considered a major determinant of the
4684 ecology and distribution of Africa's dryland forests and the frequency and severity
4685 of large wildfires has increased during some extremely dry years in past decades
4686 (Archibald et al., 2018). The burning of natural vegetation is common and
4687 widespread throughout the tropics and is considered to be a significant source of
4688 aerosol, trace gas and particles to the global atmosphere (Frost, 1999). Within the
4689 tropical landscape, 42% of CO₂ emissions are estimated to come from Africa, 29%
4690 from Asia, 23% from South America, and 6% from Oceania (Andreae et al., 1998).
4691 In Africa, fire is generally viewed as key to ecosystem structure and function. For
4692 example fire is used to maintain grasslands by suppressing bush encroachment
4693 (Chidumayo, 1997). In Southern Africa, fire is started either by people or by
4694 lightning, and is intensified by a prolonged annual dry season combined with
4695 relatively rapid rates of fuel accumulation. Often, fires originate outside of
4696 protected areas but later burn uncontrolled into protected areas. Uncontrolled
4697 wildland fires can destroy extensive landscapes, posing a major threat to the
4698 survival of dryland tree species, human life and property, encouraging society and
4699 policy makers to take measures that mitigate its effects (Turner et al., 1999).

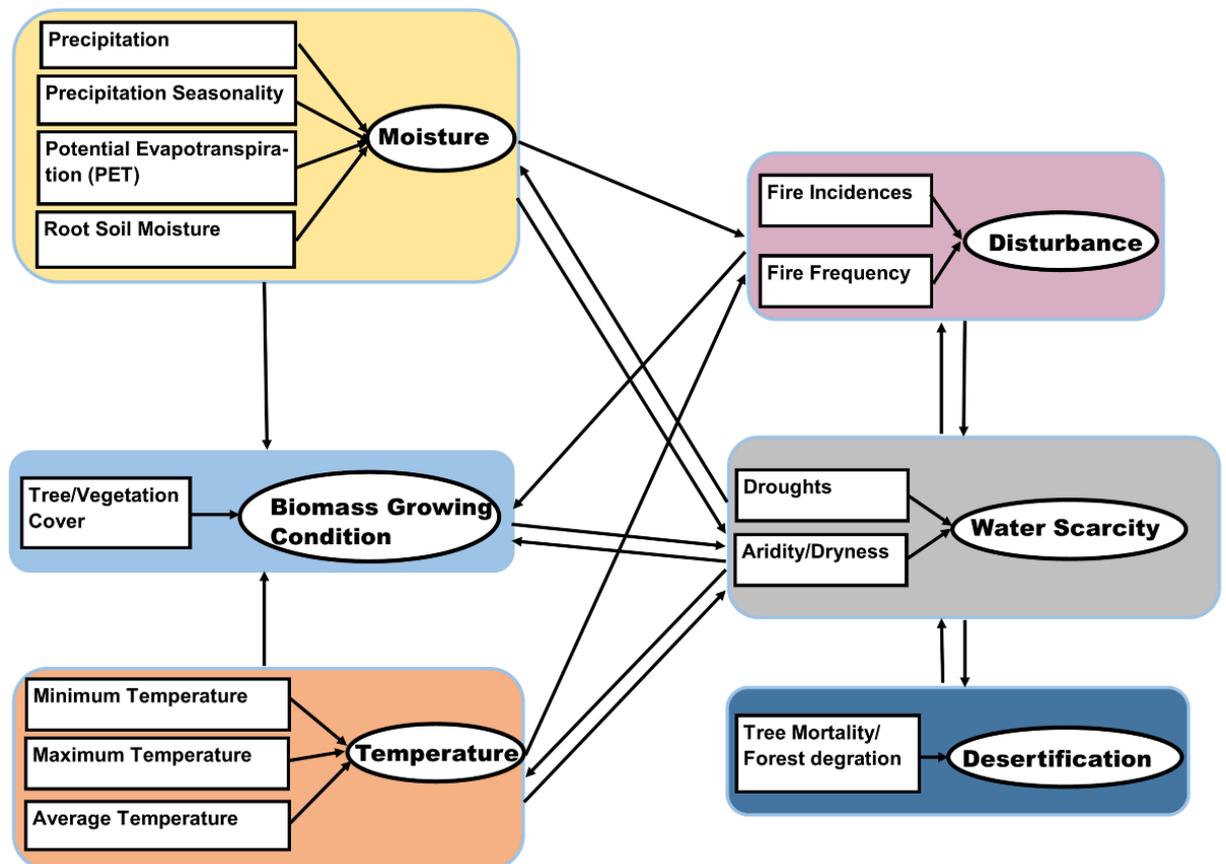
4700 The fire regime of an area is defined by several variables, including the patterns of
4701 frequency, season, type, severity and extent. All of these characteristics are
4702 intricately linked to ecosystem structure and function, and are highly dependent
4703 on weather and climate oscillations (Archibald et al., 2009; Gill, 1975). Reliable
4704 observed data on fire frequency (or, alternately, the reciprocal of the fire return
4705 time) for calculating biomass burned at regional scales are fundamentally
4706 important (Frost, 1999). This is partly because biome characteristics, mainly
4707 biomass loads and moisture levels, determine fire behaviour, but also fire alters
4708 vegetation structure, composition and development (Bond et al., 2005; Hantson et
4709 al., 2016). On the other hand, climate affects fire occurrence through temperature
4710 and precipitation cycles, but climate is also affected by fire through by gaseous

4711 emissions (Bojinski et al., 2014). These mutual influences between vegetation,
4712 climate and fire highlight the importance of having long-term burned area (BA)
4713 and climate information that serves as an input for a holistic vegetation analysis.
4714 Therefore, better fire observations and improved estimates of fire impacts will
4715 reduce uncertainty and improve prediction for future ecosystem feedbacks on
4716 atmosphere interactions.

4717 Recent research has also pointed out a decline of forest resilience to wildfires
4718 because of an intensification of the interactions between extreme droughts and fire
4719 (Brando et al., 2019). Fire and grazing regimes, in conjunction with changes in
4720 climate characteristics affecting soil moisture status, relative humidity, or drought
4721 stress, will have the greatest influence on grassland-woody species boundaries
4722 (Barros et al., 2018). A drying climate, in combination with non-adapted and
4723 unsustainable land-use therefore increases the risk of desertification (Geist et al.,
4724 2004). Intensifying disturbance regimes are thus expected to be among the most
4725 severe impacts of climate change on forest ecosystems and can bring forests to a
4726 threshold for massive die-off (Turner, 2010). The killing of plants causes
4727 substantial vegetation change and limits productivity, thereby causing shifts in
4728 plant communities resulting in species loss (Williams et al., 2013). Such forest
4729 disturbances significantly affect the global carbon cycle by, for example, vegetation
4730 loss or changing forest phenology. This is raising concerns that disturbances to
4731 dryland natural resources in these areas might increasingly interfere with
4732 sustainable provision of ecosystem services and wildlife habitat management in
4733 the tropics (Scholes et al., 2004).

4734 A drying climate, in combination with unsustainable land use practises, in already
4735 water-scarce regions, increases the risk of drying conditions (Reynolds et al.,
4736 2007). Desertification is a complex phenomenon, driven by socio-economic and
4737 climate-related processes, such as increasing aridity and more frequent and/or
4738 severe droughts (Reynolds et al., 2007) (Fig. 5.1). Desertification is not confined to
4739 drylands, however, they are some of the most vulnerable regions to land
4740 degradation processes due to the delicate balance between natural resources (e.g.,
4741 limited rainfall, low soil moisture, high temperature, low vegetation productivity)
4742 (Vogt et al., 2011) (Fig. 5.1). Consequently, an important contribution in the fight
4743 against desertification is to quantify whether the extent of drylands has changed

4744 and, if this process has taken place, where and to what degree it has occurred
 4745 (UNCCD, 1994). In addition, this knowledge would allow natural resource
 4746 managers to implement best management practices under drought conditions and
 4747 other decision makers to better target assistance and response activities (e.g., early
 4748 detection of hot spots for wildfires) in a timely manner.



4749

4750

4751 Fig. 5. 1. Conceptual model depicting theoretical relationships among moisture availability,
 4752 temperature, plant growing conditions, and disturbance (fire frequency), water scarcity
 4753 (droughts) and their effects on dryland vegetation cover directly or indirectly as it
 4754 characterises desertification.

4755

4756

4757 The interrelations between dryland fire regimes and vegetation dynamics are
 4758 indeed complex; they are conditioned by various climatic, biotic and anthropogenic
 4759 factors involving different feedbacks. Although many studies have been

4760 undertaken in southern Africa (see (Chidumayo, 1997; Korontzi et al., 2003), very
4761 few of these have investigated the combined effects of all these on dryland
4762 vegetation cover. The majority of research on the potential impacts on fire regimes
4763 and climate change on drylands has focused on the Amazon and West Africa (e.g.,
4764 Sahel) (Aragão et al., 2007; Herrmann et al., 2005; Samanta et al., 2011). By
4765 contrast, the regional studies that analyse the impacts of climate and fire on
4766 dryland forests and vegetation in many parts of Southern Africa have been more
4767 sparse (Blackie et al., 2014). There is, to my knowledge, no study that has
4768 investigated drought and fire impacts on dryland vegetation cover across the KAZA
4769 region over a long-term basis. A study published by Pricope et al. (2012), did
4770 consider fire frequency from 2000 to 2010 in KAZA region, but only focused on the
4771 central part, while Mpakairi et al. (2019) only focused on Zimbabwean component
4772 of KAZA. Neither study considered the whole region and were solely based on fire
4773 analysis without incorporating vegetation information.

4774 This chapter analyses trends of fire regimes of all the five of the national
4775 constituents of KAZA, noting that each country manages fire differently. Some aim
4776 to prevent fires, others legislate for seasonal prescribed burns, and others witness
4777 more uncontrolled fires in protected and unprotected areas. To investigate the
4778 drivers underlying the observed long-term vegetation cover change in the KAZA
4779 region, a conceptual model was constructed (see: Fig. 5.1) based on the knowledge
4780 that there are direct and indirect effects of climate, soil moisture, and fire on
4781 woody vegetation cover. Fire disturbance and soil moisture were included in the
4782 climate-vegetation analyses because they are considered an Essential Climate
4783 Variable (ECV) by the Global Climate Observing System (GCOS) program, which
4784 encourages the generation of long-term time series of ECVs to better understand
4785 climate trends (Bojinski et al., 2014; Mason et al., 2009). The present study was
4786 designed to investigate the relationship between moisture availability as a function
4787 of effective rainfall, rainfall seasonality, evapotranspiration, and root soil moisture,
4788 temperature, fire incidence and frequency, drought and vegetation index. This was
4789 used to characterise spatiotemporal changes in aridity in the KAZA region using
4790 long-term time series from both ground and satellite observations from 2002 to
4791 2019.

4792 5.2 Aims and Objectives

4793 Aims

4794 The aims of this study are to investigate the relationship between fire and different
4795 climate effects on vegetation spectral characteristics at the regional scale of KAZA.

4796 Objectives

4797 ○ To characterise drought conditions using climatic data (SPEI, root-soil
4798 moisture, temperature, and precipitation) and explore the variability of
4799 drought using monitoring indicators (i.e., the drought duration, severity and
4800 magnitude)

4801 ○ To characterise the frequency, seasonality, and extent of fires through time
4802 on different land use management in KAZA region

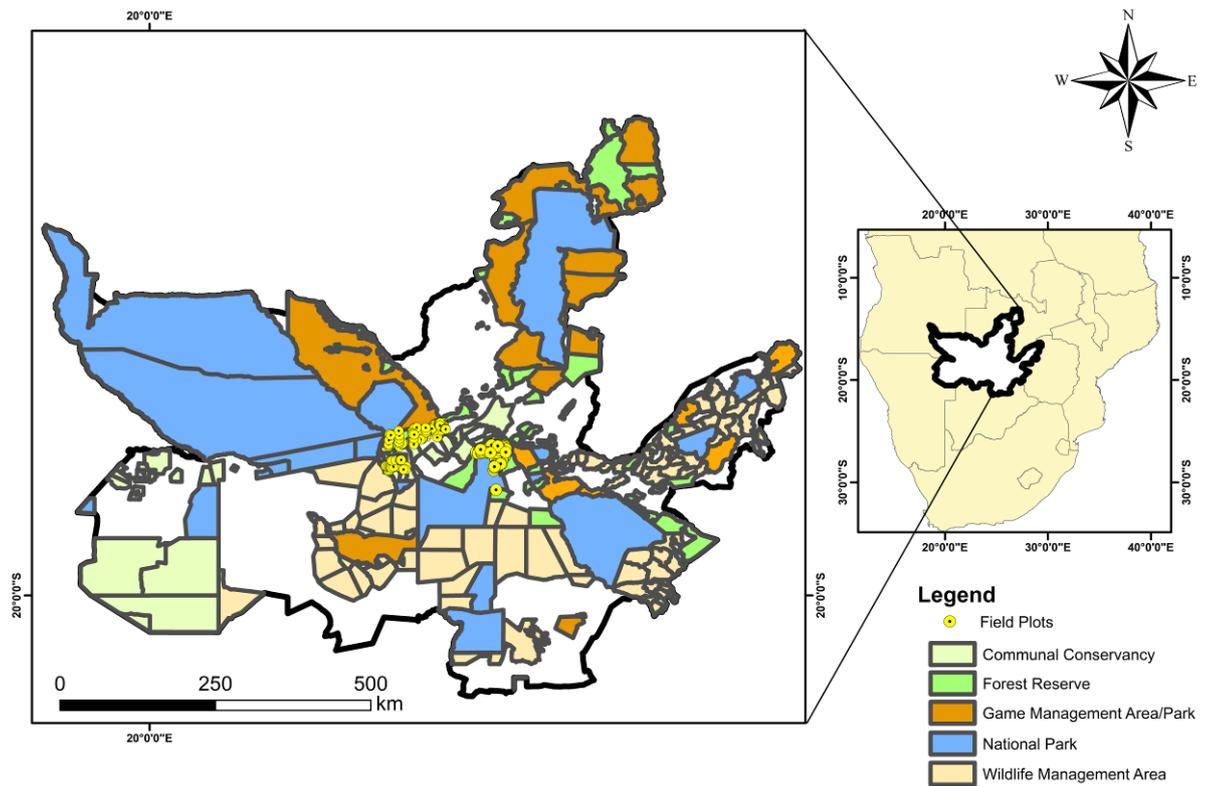
4803 ○ To investigate the spatiotemporal changes in aridity in KAZA region from
4804 2002 to 2010 and 2011 to 2019

4805

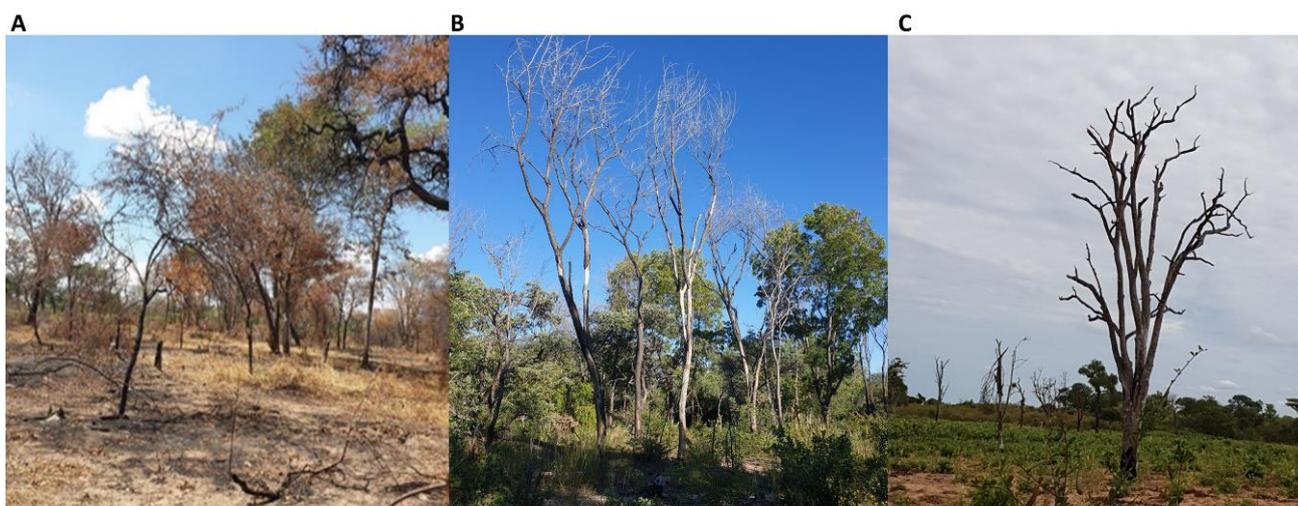
4806 5.3 Materials and methods

4807 5.3.1 Study Area

4808 The Kavango Zambezi Transfrontier Conservation Area (KAZA TFCA) (18.00°S
4809 23.00°E) in Southern Africa, is a large multi-nationally managed network of
4810 national parks (NP), wildlife and game management areas, forests reserves and
4811 communal. The KAZA TFCA is the largest transfrontier conservation area in the
4812 world, and encompasses an area of approximately almost 520 000 km² shared by
4813 Botswana, Namibia, Zambia, Zimbabwe, and Angola (KAZA, 2014). The KAZA was
4814 established to improve the cooperative management of shared resources, to
4815 improve links between wildlife habitats, to create economic development to the
4816 local communities adjacent to protected areas through tourism. KAZA was also
4817 intended as a means to contribute to peace and friendly relationships between
4818 participating countries through cooperation in nature protection and development
4819 (Stoldt et al., 2020). The region hosts the largest elephant population (*Loxodonta*
4820 *africana*) in the world and it is characterised by large-scale migrations of
4821 megafauna such as buffalo (*Syncerus caffer*), leopard (*Panthera pardus*), zebra
4822 (*Equus quagga*). The region is home to numerous red-listed tree species, and
4823 contains the world-heritage listed Okavango Delta (Matswiri, 2017; Naidoo et al.,
4824 2012). The largest portion of KAZA is generally water- and nutrient-poor due to its
4825 location in the Kalahari Basin, and has a climate that is characterised by a single
4826 rainy season and a long dry season (see: Fig. 5.4), with an annual rainfall average
4827 of 300–950 mm from 1983 to 2019 (see: Fig. 5.3). During the dry season, as most
4828 natural pans dry up, water is mostly available at a large number of artificial
4829 waterholes across parts of the landscape and most animals migrate between
4830 seasons to other parts of KAZA converging to rivers such as Zambezi and Chobe
4831 Rivers in northern Botswana, and Gwaii river in Zimbabwe (Cumming, 1981;
4832 Tshipa et al., 2017). This rainfall seasonality provides a fire-prone climate such
4833 that the drylands of Africa are thought to experience the most extensive biomass
4834 burning in the world (Lehmann et al., 2014).



4835



4836

4837 Fig. 5. 2. Location of the study area in KAZA Conservation Area Southern Africa, showing
 4838 the yellow circles representing the sampling sites, protected areas and land management
 4839 classes as designated by the World Database on Protected Areas (WDPA). Examples of
 4840 sample plots representing degradation from fire captured during a field campaign in 2019
 4841 are shown, A) Burned Forest for cultivation near the protected area of Mudumu NP,
 4842 Namibia, B) Forest scorched by wildfire with dead trees that could not recover in the
 4843 Zambezi state forests (ST) C) forest or woodland burned down to create a field.

4844 5.3.2 Fieldwork and Sampling Design

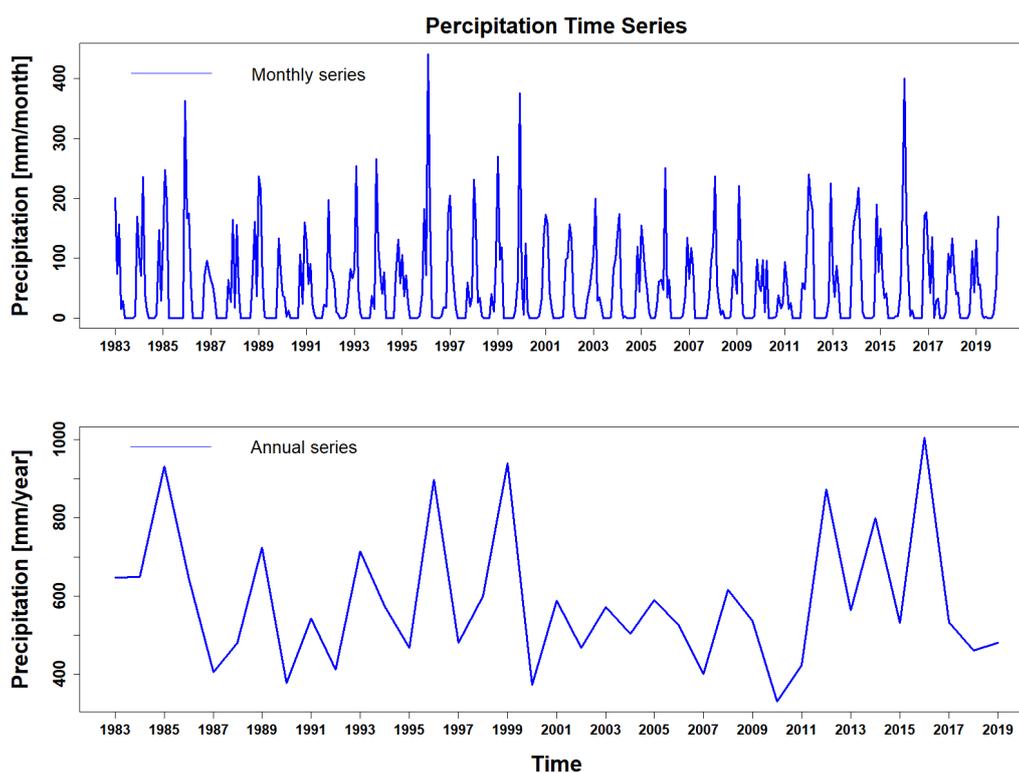
4845 Field work was undertaken to measure forest stand characteristics from three
4846 locations with different land cover characteristics to provide ground validation in
4847 the KAZA region. The 2019 was one of the most severe droughts this century,
4848 which caused major impacts on vegetation and generated an economic shock felt
4849 throughout the region. Measurements were made in forests and woodlands,
4850 shrubland areas, and grassland agricultural land. One was located in Botswana,
4851 which is within the Chobe NP (18.7°S, 24.5°E). The other two sites were located in
4852 Namibia, Mudumu NP and Zambezi ST (17.8° S, 23.9° E) (Fig. 5.2). These sites were
4853 chosen because dryland forests within and around the protected area have been
4854 particularly susceptible to disturbance and drought during the 21st century, with
4855 severe events in 2015 and 2019, warranting particular attention. For this reason,
4856 survey fieldwork was undertaken to record forest tree stand characteristics, and to
4857 observe the different land cover types present in the study area during the
4858 growing season (1st February - 30th May 2019). The 2019 was one of the most
4859 severe droughts this century, which caused major impacts on vegetation and
4860 generated an economic shock felt throughout the region. At each sample plot, and
4861 before the biophysical measurements, plot information such as land use, land
4862 cover, vegetation type, soil, and disturbance history (e.g., evidence of fire) was
4863 recorded (Fig 5.2). Also, information about regeneration, deadwood, and stumps
4864 was collected. Field sites were chosen to cover a range of landscapes given the
4865 constraints of road accessibility, wildlife danger, and public access restrictions
4866 allowed. Measurements were collected from a total of 250 individual sample plots.
4867 Field surveys of woody plants were conducted on sites where damage was
4868 specifically observed to identify sites where drought had an obvious impact. These
4869 sites can be used for further long-term monitoring.

4870 5.3.3 Ground-based Climate Data

4871 5.3.3.1 Rainfall Data

4872 The climate in the region is considered subtropical with an annual rainfall of about
4873 600-700 mm, dry winters, and hot, wet summers (Fig. 5.3 and 4). The daily and
4874 monthly rainfall data values recorded at Kasane and Kavimba have been used in

4875 this study (Table 5.1). The data set spans a period of 60 years from 1960 to
 4876 2019/20 from Kasane meteorological gauging station, and a period of 46 years
 4877 from 1971 to 2017 for Kavimba meteorological police gauging station. The Kasane
 4878 meteorological station data have a consistent and longer record and so was used in
 4879 this study. All the rainfall observation data were from the Botswana Department of
 4880 Meteorological Service (BDMS) Data Network.



4881

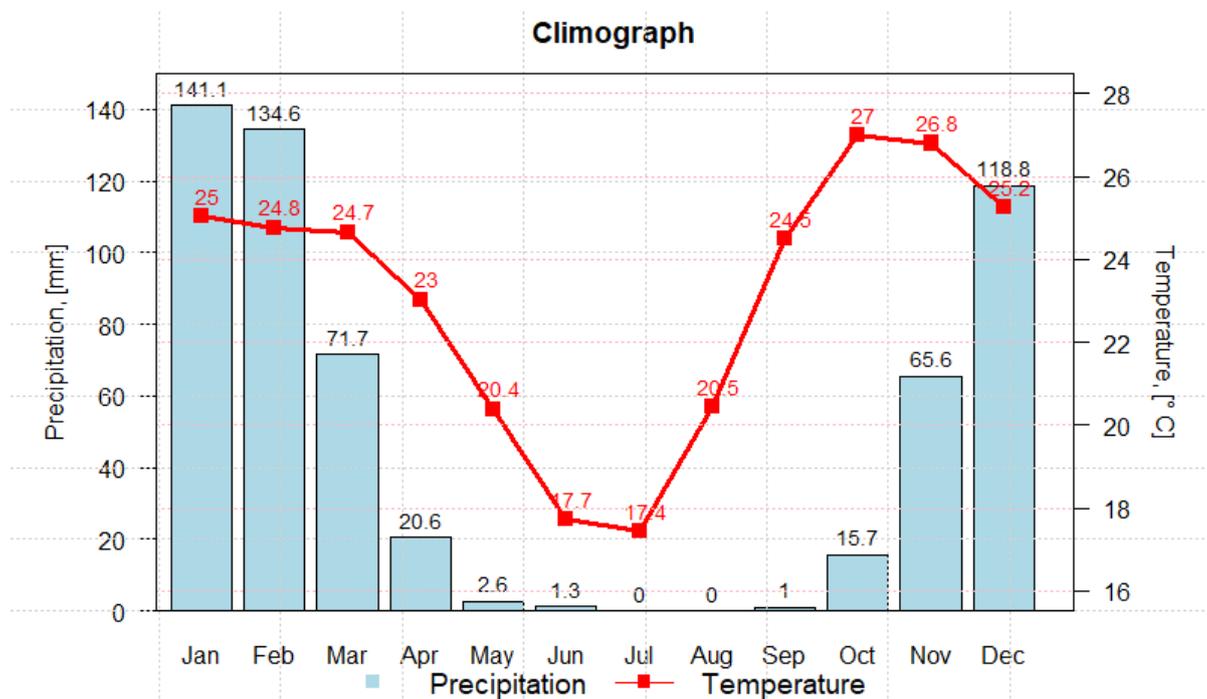
4882 Fig. 5. 3. Monthly (top) and annual (bottom) precipitation (mm) for the period 1983 to
 4883 2019 using data obtained from Kasane meteorological station in Botswana.

4884

4885 5.3.3.2 Temperature Data

4886 Monthly meteorological data (minimum and maximum temperature) were
 4887 acquired from BDMS. A long record of temperature data was obtained from Kasane
 4888 and Pandamatenga meteorological stations. The temperature data from the Kasane
 4889 meteorological station is used in this study because it has a longer timespan
 4890 covering 38 years from 1982/3 to 2019/20, compared to Pandamatenga
 4891 meteorological station which is continuous only since 1989 (Table 5.1).

4892 The climograph in Fig. 5.4 shows that rains in the region are expected in
 4893 November, peaking in January and February and ending around March. These are
 4894 warm summer months, with temperatures and humidity high. January averages
 4895 the highest amount of precipitation and October observes the highest temperature.



4896

4897 Fig. 5. 4. Climograph of average monthly precipitation and temperature from 1983 to 2019
 4898 using data obtained from Kasane meteorological station in Botswana.

4899

4900 Table 5. 1. Weather stations in the study area.

Station Name	Data Type	Data Span	Data length
Kasane	Precipitation	1960 to 2019/20	60
Kavimba	Precipitation	1971 to 2017	46
Kasane	Max and Min Temperature	1982/3-2019/20	38
Pandamatenga	Max and Min Temperature	1989-2020	31

4901

4902

4903 5.3.4 Remote sensing based rainfall - Climate Hazards Group 4904 Infrared Precipitation with Station Data (CHIRPS)

4905 The characteristics of the main satellite-based data used in this study is shown in
4906 Table 5.2. Drought monitoring has been historically carried out using ground-
4907 based observations (Chen et al., 2002). However, many regions do not have
4908 adequate gauge instruments, particularly in Africa (e.g., remote regions or
4909 agricultural areas) to obtain detailed precipitation, temperature, relative humidity
4910 and wind speed data, necessary for accurate assessment of drought (Washington-
4911 Allen et al., 2006). Furthermore, gauge (point) data do not capture the spatial
4912 variability of drought events. Satellite measurements overcome the limitations of
4913 gauge-based meteorological observation through continuous spatial observation
4914 that allows drought conditions to be determined where gauge sampling is
4915 otherwise unavailable. Often satellite-only rainfall estimates are merged with
4916 gauge-based observations for calibration and validation. This results in merged
4917 data sets, which exploit the strengths of each of the data source, and so improve
4918 the overall quality of key environmental variables (Xie et al., 1995).

4919 Climate Hazards Group Infrared Precipitation (CHIRP) with Station Data (CHIRPS)
4920 is a recently-developed, high-resolution, daily, pentadal, decadal, and monthly
4921 precipitation dataset, from 1981 to near present. It was created by the US
4922 Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre,
4923 with collaborators at the University of California, Santa Barbara, Climate Hazards
4924 Group (Funk et al., 2015a). It was developed for drought early warning and
4925 environmental monitoring to support the Famine Early Warning Systems Network
4926 (FEWS-NET). It was produced by blending a set of satellite-only precipitation
4927 estimates with monthly and pentadal station observations. The CHIRP is based on
4928 infrared cold cloud duration (CCD) estimates calibrated with the Tropical Rainfall
4929 Measuring Mission Multi-Satellite Precipitation Analysis v.7 (TMPA 3B42 v.7) and
4930 the Climate Hazards Group Precipitation Climatology (CHPclim). The estimates are
4931 available at a resolution of $0.05^\circ \times 0.05^\circ$ resolution, or at a coarser resolution of
4932 $0.25^\circ \times 0.25^\circ$ (Funk et al., 2015). The fine resolution $0.05^\circ \times 0.05^\circ$ dataset was used
4933 in this study.

4934

4935 5.3.5 Root Soil Moisture (GLEAM)

4936 GLEAM stands for Global Land Evaporation Amsterdam Model, and is designed to
4937 estimate land surface evaporation and root-zone soil moisture from satellite
4938 observations and re-analysis data (Miralles et al., 2011). The potential evaporation
4939 is computed from surface net radiation and near-surface air temperature data
4940 using a Priestley & Taylor equation. The root-zone soil moisture (SM_{root}) is
4941 calculated using a multi-layer running water balance model, which combines
4942 observed precipitation and soil moisture observations (Martens et al., 2017).
4943 GLEAM v3.3b provides global monthly potential and actual evaporation,
4944 evaporative stress conditions and root zone soil moisture spanning the
4945 approximately 18-year period between 2003–2020 at a spatial resolution of 0.25°.
4946 The vegetation fractional cover in v3.5b comes from MOD44B and uses the latest
4947 version of CERES radiation (v4.1), AIRS temperature (v7.0), MSWEP precipitation
4948 (v2.8), and ESA-CCI soil moisture (v5.3) (Martens et al., 2017). GLEAM datasets
4949 have already been comprehensively evaluated and used for multiple drought
4950 analysis and monitoring applications (Peng et al., 2019; Vicente-Serrano et al.,
4951 2018). For this study, the GLEAM root zone soil moisture was used. GLEAM
4952 datasets are openly available globally at daily temporal resolution and 0.25° spatial
4953 resolution for 1980–2019 (<https://www.gleam.eu/#downloads/> (accessed 10 July
4954 2020).

4955 5.3.6 Vegetation Indices from Remote Sensing Imagery

4956 Vegetation indices uses vegetation reflectance in the near and shortwave infrared
4957 regions for reducing the effects of irradiance and exposure, and enhancing the
4958 contrast between vegetation and the ground (Xue et al., 2017). NDVI has been
4959 widely used in many studies to monitor drought impacts on vegetation and forests,
4960 predict agricultural production, assist in hazardous fire zone prediction, and to
4961 map desert encroachment which defines the vegetation growth status (Anyamba et
4962 al., 2005; Myneni et al., 1997; Xulu et al., 2018). The NDVI was used in this study
4963 because it is a biophysical parameter that correlates with the photosynthetic
4964 activity of vegetation and is an indicator of the greenness of the biomes (Robinson
4965 et al., 2017; Tucker, 1979). NDVI is also able to offer valuable information to
4966 monitor vegetation health, drought effects, changes in plant growth, land

4967 degradation, deforestation, change detection/monitoring, and in relating large-
 4968 scale inter-annual variations in vegetation to climate (Smith et al., 2019). As
 4969 shown in Eq. 5.1, vegetation reflectance is at a minimum in the visible (red) part of
 4970 the electromagnetic spectrum due to absorption of radiation by chlorophyll
 4971 pigments, whereas maximum reflection is in the Near Infra-Red (NIR) spectral
 4972 region owing to refraction of radiation by leaf cellular structure. The NDVI index
 4973 outputs values range between -1.0 and 1.0, and has been shown to correlate well
 4974 with leaf area index (LAI), and fraction of photosynthetically active radiation
 4975 absorbed by vegetation (fAPAR) (Fensholt et al., 2004; Tucker, 1979). Negative
 4976 values are mostly due to clouds, snow, water, and values near zero are generally
 4977 generated from rock and bare soil. Lower NDVI values often correspond to
 4978 stressed or sparse vegetation. Shrubs and grasslands have moderate values (0.2 to
 4979 0.5) and high values (0.5 to 0.8) are typical of healthy vegetation with different
 4980 densities. I analysed the NDVI patterns during the growing season (January –
 4981 March) using 2002 to 2019 time series data from the MODIS (MYD09A1.006) 8-
 4982 day product, with a 500 m spatial resolution.

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (\text{Eq. 5. 1})$$

4983 where NIR is the near infrared range of the electromagnetic spectrum (841–876
 4984 nm) and RED is the red spectrum of the electromagnetic spectrum (620–670 nm),
 4985 respectively, as measured by the MODIS sensor.

4986 5.3.7 Product of burnt area MODIS MCD64A1

4987 Satellite-based strategies for large-area burn assessment may rely on two types of
 4988 remote sensing data including postfire reflectance images and active fires and can
 4989 be used in combination or separately (Fraser et al. 2000). So, this study used
 4990 Burned Area Products of 500 m spatial resolution for analysing spatial dynamics of
 4991 burned areas and FIRMS Active Fire Products was used for seasonal temporal
 4992 variations. This is because Active Fire Products are unable to estimate burned
 4993 areas with an acceptable degree of accuracy due to coarse resolution of 1 km

4994 spatial resolution, and untrivial spatial and temporal sampling issues as stated by
4995 Giglio et al. (2006b). The burnt area data were obtained from the MODIS burnt
4996 area sensor monthly product MCD64A1 v.6, and was accessed via Google Earth
4997 Engine (GEE). MCD64 (Giglio et al., 2009) is the latest product from the MODIS
4998 Burnt Area product, and was updated as reported in Giglio et al., (2018). This is a
4999 global grid-level 3 product at 500 m spatial resolution containing per-pixel burnt-
5000 area and quality information. It is based on an automated hybrid approach that
5001 employs 500 m surface reflectance imagery coupled with 1 km MODIS active fire
5002 observations. The algorithm applies dynamic thresholds to composite images
5003 generated from a burn sensitive vegetation index, which in turn are derived from
5004 MODIS shortwave infrared surface reflectance band 5 and 7, and a measure of
5005 temporal texture (Giglio et al., 2016). Data layers include a recording of burn date,
5006 data uncertainty, quality assurance and the first and last day of reliable change in
5007 the year. The date on which the burn occurred with values assigned to unburnt
5008 land pixels is encoded in a single data layer as the ordinal day of the calendar year.
5009 The data layer also contains additional values reserved for missing data and water
5010 grid cells. Overall, the MCD64A1 has improved the detection of burnt areas,
5011 provides better detection of small fires and has proven adaptability to different
5012 regional conditions in multiple ecosystems.

5013 5.3.8 MODIS MCD14ML Active Fire Product

5014 Fire point location were obtained from the Aqua & Terra MODIS wildland fire data,
5015 with a spatial resolution of 1 km, Collection 6, from January 2002 to December
5016 2019, available from the NASA Fire Information for Resource Management System
5017 (FIRMS) at <https://firms.modaps.eosdis.nasa.gov/download/> (accessed 21 March
5018 2020). The data have a 1-day temporal resolution, and the location of the fire
5019 nominally corresponds to the centre of a 1x1 km pixel, signalled by the algorithm
5020 as containing one or more fires within that pixel. A full description of the
5021 algorithms used to acquire the data can be found in Davies et al. (2008). FIRMS
5022 was developed to provide a simpler and faster means to obtain MODIS active fire
5023 locations and expand the distribution of MODIS fire data to a broader range of fire
5024 and forest monitoring organisations around the world. In this study, active fire
5025 products were used to determine fire seasons by determining the months when

5026 fire activity is very high. The fire seasons were determined from the cumulative
 5027 ratio of active fires on a regional scale detected during each month across the
 5028 seventeen years of observation (2002-2019) and the proportion of this number to
 5029 the overall number of fires. FIRMS is an extension to the MODIS Rapid Response
 5030 (MRR) system for near-real-time active fire information in a format that is easy to
 5031 use, and for users that could not handle image files (Ilavajhala et al., 2014).

5032 Table 5. 2. Characteristics of the main datasets used in this study.

<i>Dataset</i>	<i>Timespan</i>	<i>Resolution</i>	<i>Source</i>
<i>Climate Data</i>			
<i>Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS)</i>	2002-2019	0.05 degrees	GEE
<i>High resolution Standardised Precipitation Evapotranspiration Index (SPEI) dataset for Africa</i>	2002-2016	5 km	CHIRPS and GLEAM
<i>The Global Land Evaporation Amsterdam Model (GLEAM v3.3b)</i>	2003-2019	0.25° x 0.25°	GLEAM
<i>Rainfall Data</i>	1975-2020	-	Botswana department of Meteorological Service (BDMS)
<i>Minimum and Maximum Temperature Data</i>	1983-2020	-	Botswana department of Meteorological Service (BDMS)
<i>Vegetation Data</i>			
<i>MODIS 8-day time series (MOD13Q1)</i>	2002-2020	250m	GEE (MODIS09, 2020).
<i>MODIS Terra Surface Reflectance 8-Day Global 500m (MOD09A1.006) and (MYD09A1.006)</i>	2002-2019	500m	GEE (MODIS09, 2020).
<i>Fire Data</i>			

<i>MODIS burnt area (MCD64A1)</i>	<i>2002-2019</i>	<i>500m</i>	<i>GEE (MODIS09, 2020).</i>
<i>MODIS wildland fire point data</i>	<i>2002-2019</i>	<i>500m</i>	<i>FIRMS</i>

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5.4 Methods

5037

5.4.1 Calculating the standardised precipitation

5038

evapotranspiration index (SPEI) from ground observation

5039 Satellite-based drought indices are capable of characterising spatial and temporal
5040 variability of drought based on the magnitude, duration, and intensity, and so they
5041 represent promising tools for monitoring drought at regional scales, which is
5042 important for developing a drought watch system for an area. A variety of drought
5043 indices have been developed to quantify whether or not a region is experiencing a
5044 drought, and to categorise the seriousness of that drought. Dryness severity was
5045 quantified using the multiscalar Standardised Precipitation Evapotranspiration
5046 Index (SPEI), calculated from ground meteorological data (rainfall and
5047 precipitation) from the Kasane meteorological station. Drought severity is
5048 predominantly caused by either precipitation decreases or increases in
5049 temperature induced evapotranspiration. Hence, precipitation does not represent
5050 the only control on ecologically and socially relevant water resources, such as
5051 stream flow, reservoir storage, and soil moisture (Cook et al. 2004). SPEI is used to
5052 measure environmental water stress by combining information from both
5053 evaporation and precipitation. The SPEI is a drought indicator that determines
5054 deviations from a location's average water balance (the ratio of temperature and
5055 precipitation) over a specified timeframe which is then fitted to a statistical
5056 distribution (Vicente-Serrano et al. 2012). The SPEI was quantified based on the
5057 Hargreaves equation (Hargreaves, 1994) using the 'SPEI' package (Bergueria et al.,
5058 2014) in the R software package. Due to the complex computation of Potential
5059 Evapotranspiration (PET), which involves several variables, including surface
5060 temperature, air humidity, soil, incoming radiation, water vapour pressure, and
5061 ground-atmosphere latent and sensible heat fluxes, this study made use of
5062 Hargreaves' and Samani's temperature-based method for PET estimation. The
5063 Hargreaves approach has the advantage of only requiring data on monthly mean
5064 minimum and maximum temperatures.

5065

5066 The SPEI was chosen over the commonly used Standardised Precipitation Index
5067 (SPI) because it includes PET as well as precipitation (Stagge et al. 2014). PET is
5068 the amount of evapotranspiration that could occur if enough water were available
5069 (Oudin et al. 2005). For example, Dutrieux et al., (2015) used SPI and they found it
5070 to perform poorly in tropical dry forest and concluded SPI was not the ideal way to
5071 include moisture conditions in the dryland environment. Limitations of SPI, which
5072 considers rainfall anomalies alone without including evaporative demand have
5073 also been discussed by Trenberth et al. (2014). The SPEI is calculated based on the
5074 accumulated difference between precipitation (P) and temperature used to
5075 compute potential evapotranspiration (PET). The SPEI can comprehensively
5076 reflect the change in surface water balance, hence automatically capturing the
5077 well-known temporal lag of vegetation response to rainfall (Stagge et al. 2014;
5078 Potop et al., 2014). Since SPEI is a standardised variable it can be used to compare
5079 droughts over different spatial and temporal scales. SPEI produces a graph with
5080 values ranging from 2 to -2 (Table 5.3).

5081 This study places emphasis on moderate to extreme droughts and the SPEI index
5082 scale is given as: extreme drought (≤ -2); severe drought (-2 to -1.5); and,
5083 moderate drought (-1.5 to -1). A continuously negative SPEI generally implies an
5084 abnormally drier climate/drought period based on intensity, severity, magnitude,
5085 and duration, while positive values correspond to abnormally wet periods. It
5086 should be noted that drought ends when the SPI/SPEI approaches zero and
5087 progresses to a positive value. For this study, the duration of the drought is
5088 considered as the number of months for which the drought has occurred, whilst
5089 the magnitude of the indices indicates the severity of the drought. Vegetation has
5090 been found predominantly responsive to short-term drought time scales, hence 1,
5091 3 and 12 months were determined as an appropriate time scales for
5092 contextualizing meteorological, vegetation/crop and hydrological drought on
5093 vegetation (Vicente-Serrano et al. 2012). Two data periods were used in the SPEI
5094 analysis. The 1983–2019 period was used as the baseline period based on
5095 availability of the high-quality observed data for temperature and rainfall. The
5096 2002–2019 time period was used in SPEI analysis to investigate sensitivity of the
5097 vegetation to drought events.

5098 Table 5. 3. Categories of dry and wet conditions indicated by SPEI values.

SPEI	Category
2 and above	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
−0.99 to 0.99	Near Normal
−1.0 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
−2 and less	Extremely dry

5099

5100

5101

5.4.2 Calculation of the satellite-based aridity index (AI)

5102 The degree of dryness is not determined by precipitation alone. If the temperature
5103 is high/low, evaporation is either large or small. Therefore, the degree of dryness
5104 is normally expressed as the ratio of PET and precipitation, giving the aridity
5105 index, which is an important indicator of regional climate. The study adopted the
5106 aridity index (AI) recommended by the United Nations Educational, Scientific and
5107 Cultural Organisation (UNESCO), the Global Environment Monitoring System
5108 (GEMS), the Global Resource Information Database (GRID), and the Desert Cure
5109 and Prevention Activity Centre (DC/PAS), to reflect the aridity changes of the KAZA
5110 region. The AI was calculated using the following form (Eq. 5.2).

$$AI = \frac{PRE}{PET} \quad (\text{Eq. 5. 2})$$

5111 where PET is the Potential Evapotranspiration (in mm) and PRE is the
5112 precipitation (in mm). The aridity index (AI) has been widely used to divide
5113 climate zones and to assess changes in aridity trends. Under this quantitative
5114 indicator, drylands are defined as regions with $AI < 0.65$ and are further divided
5115 into subtypes of: hyper-arid ($AI < 0.03$); arid ($0.03 \leq AI < 0.2$); semiarid ($0.2 \leq AI <$
5116 0.5); dry subhumid ($0.5 \leq AI < 0.65$); and, humid ($AI > 0.65$) regions, as shown in
5117 Table 5.4 (Middleton et al., 1997).

5118

5119 AI was calculated using the MODIS data products MOD16A2 v.6
 5120 Evapotranspiration/Latent Heat Flux product, which is an 8-day composite
 5121 product produced at 500 m resolution. The algorithm used for the MOD16A2
 5122 product is based on the logic of the Penman-Monteith equation, which includes
 5123 inputs of daily meteorological reanalysis data along with MODIS data on vegetation
 5124 property dynamics, albedo, and land cover. The pixel values for the PET layer are
 5125 the sum of all values in the 8 days within the composite period.

5126 Table 5. 4. UNESCO (1979) aridity classification and bioclimatic index thresholds

<i>Threshold</i>	$0.03 \leq AI < 0.2$	$0.2 \leq AI < 0.5$	$0.5 \leq AI < 0.65$	$AI > 0.65$	$AI > 0.75$
<i>Arid conditions</i>	<i>Arid</i>	<i>Semi-arid</i>	<i>Dry sub-humid</i>	<i>Humid</i>	
<i>Desertification risk</i>	<i>Risk</i>				<i>No risk</i>

5127

5128 5.4.3 Evaluation Criteria

5129 Most of the currently employed indexes in climate and drought regionalisation
 5130 reflect meteorological variables, without taking the diversity of landscape (such as
 5131 soil condition) into consideration. Therefore, a single index is insufficient for a
 5132 nationwide drought regionalisation program. In this respect, the regionalisation
 5133 indexes presented above that can be used to reflect climate wetness and assess
 5134 agricultural and plant droughts were developed. The SPEI at fine spatial resolution
 5135 based on CHIRPS and GLEAM v3 (root zone soil moisture) is compared temporally
 5136 and spatially to the CHIRPS precipitation dataset. In addition, the NDVI can also
 5137 serve as an indicator for drought and vegetation health and was used to assess the
 5138 performance of drought indices (Vicente-Serrano et al., 2013; Aadhar and Mishra,
 5139 2017). Furthermore, root zone soil moisture is an ideal hydrological variable for
 5140 plant (soil moisture) drought monitoring.

5141

5142 A critical issue for identifying and quantifying droughts is the local historic
 5143 climatic distribution (i.e., what is “normal”?). The sample size must be large
 5144 enough to guarantee that sample statistics are reasonable approximations of the
 5145 corresponding population parameter (Maliva et al., 2012). For a region to receive
 5146 its long-term average annual precipitation in a year should be a rare event; most
 5147 years will be either wetter or drier than the mean or median. To facilitate direct
 5148 comparison between SPEI, precipitation, NDVI and RSM, both precipitation, NDVI
 5149 and RSM are standardised by subtracting their corresponding (2002–2019) mean
 5150 and are expressed as the resulting anomalies in terms of numbers of standard
 5151 deviations (Eq. 5.3). The monthly and seasonal standardised anomalies (*std.*
 5152 *anomaly*) for vegetation and climate parameters were computed using Eq. 5.3,
 5153 below

$$\text{std.anomaly} = \frac{x_i - \bar{x}}{\delta} \quad (\text{Eq. 5.3})$$

5154 where x_i is the value of NDVI/climate at a particular time (month/season), \bar{x} and
 5155 δ are the average (monthly/seasonal) and standard deviation (monthly/seasonal),
 5156 respectively, over the study time period, 2002-2019. This standardisation has been
 5157 applied by many studies to evaluate drought indices (e.g., Anderson et al., 2011;
 5158 Mu et al., 2013; Zhao et al., 2017).

5159

5160

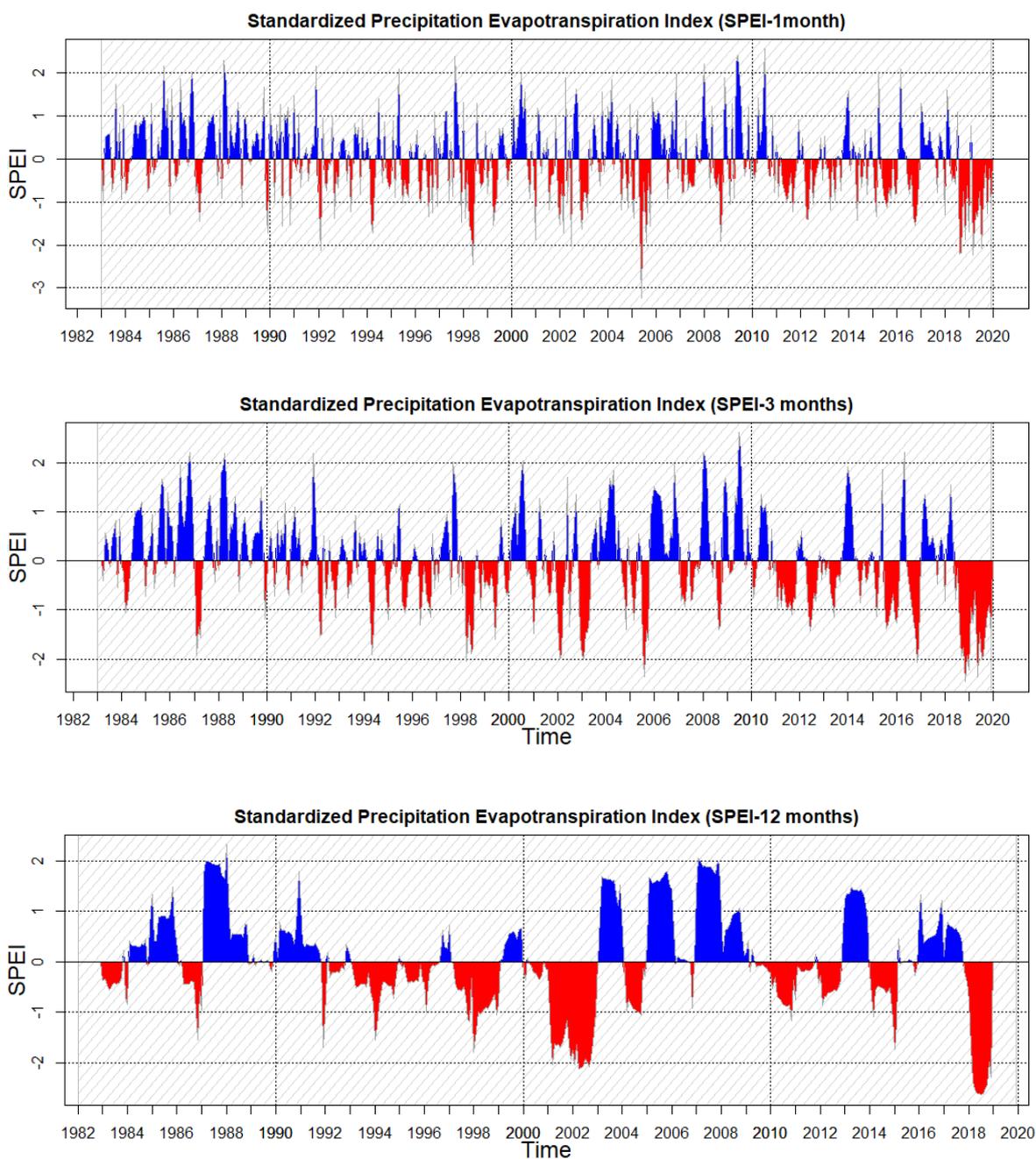
5161 5.5 Results

5162 5.5.1 Temporal analyses drought and water stress

5163 5.5.1.1 Drought index at different scales

5164 To demonstrate the temporal variation of drought at different time scales (1, 3 and
5165 12 months) for the study period (1982–2019) in the KAZA region, the SPEIs were
5166 generated and presented in Fig. 5.5. All three timescales had SPEI values close to
5167 the extreme drought level of -2 for the entire hydrological year of 2019. In general,
5168 the index data show the same pattern of variability for each timescale, with
5169 different durations and magnitudes of drought. Also, the frequency of occurrence
5170 of droughts was higher for the shorter, compared to the longer timescales; hence,
5171 the meteorological droughts (1-month) show the highest frequency of occurrence,
5172 followed by agricultural droughts (3-months), and lastly the hydrological droughts
5173 (12-months). The number of drought events observed at the 3- and 12-month time
5174 scales were 77, compared to 80 in the 1-month time scale (Supplementary, Table C
5175 1). It takes a shorter time (at most 1-month) of prevailing water deficiency for a
5176 meteorological drought to develop, hence the high variability of droughts.
5177 However, at the longer timescales the drought lasts longer and the SPEI magnitude
5178 increases. The variability shows that at the 12-month timescale, SPEI was found to
5179 be of greater severity and magnitude compared to the 1- and 3-month timescales.
5180 The SPEI event with the greatest magnitude at the 12-month scale was found in
5181 2019 with the SPEI value >2.5 (Fig. 5.5).

5182



5183

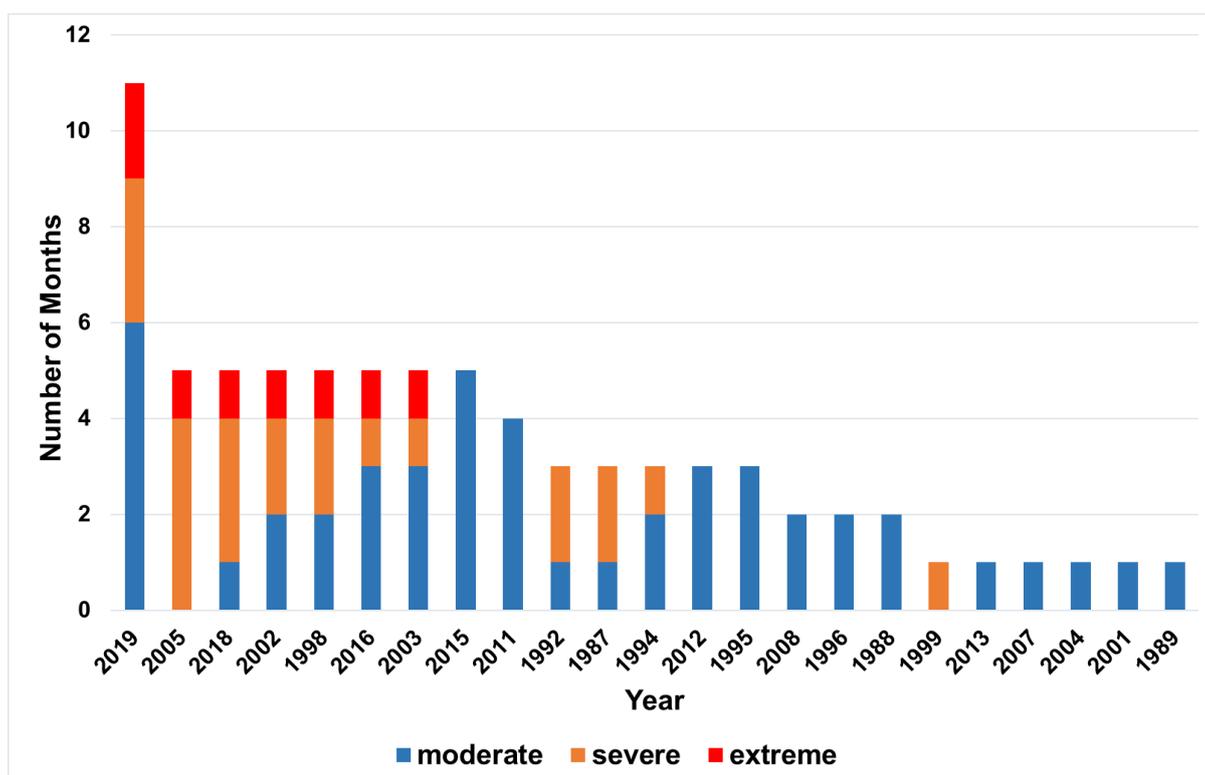
5184

5185 Fig. 5. 5. SPEI for 37 years calculated from ground precipitation and temperature at
 5186 different timescales. SPEI index scale is given as, extreme drought (≤ -2), severe drought
 5187 (-2 to -1.5) and moderate drought (-1.5 to -1).

5188

5189 Given that it takes up to 3 months for most vegetation to be fully developed, a
 5190 water deficiency accumulation of at least 3 months during the growing season will
 5191 adversely impact vegetation and crop yields, thus quickly developing into an
 5192 agricultural drought. On the other hand, a longer period of water deficit

5193 accumulation or depletion of water storage in rivers and reservoirs is required for
 5194 a hydrological drought to occur. Fig. 5.6 shows the number of droughts per year at
 5195 a time scale of 3 months, including the drought categories. For the period under
 5196 observation (1983–2019), drought was more extreme in 1998/1999, 2002/2003,
 5197 2005, 2015/2016 and 2018/2019. Severe drought was also observed in 1987,
 5198 1992, 1994, and 1999. The SPEIs calculated for 2019 show the worst drought and
 5199 accompanying effects on crops and vegetation ever recorded over the Southern
 5200 African region.



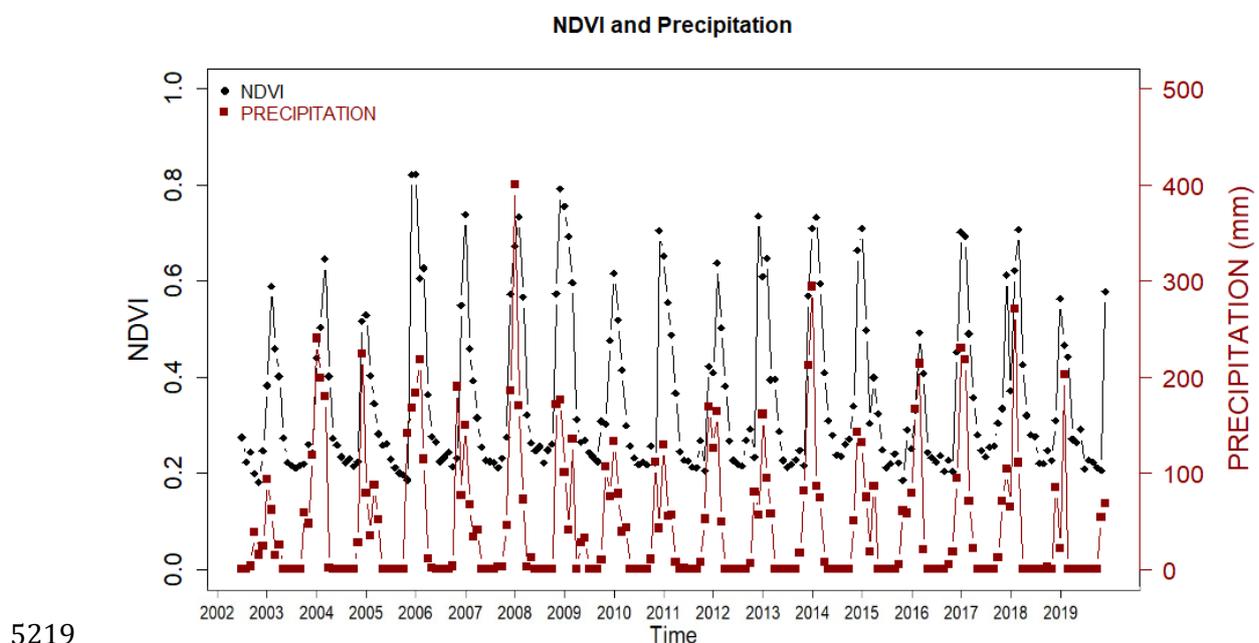
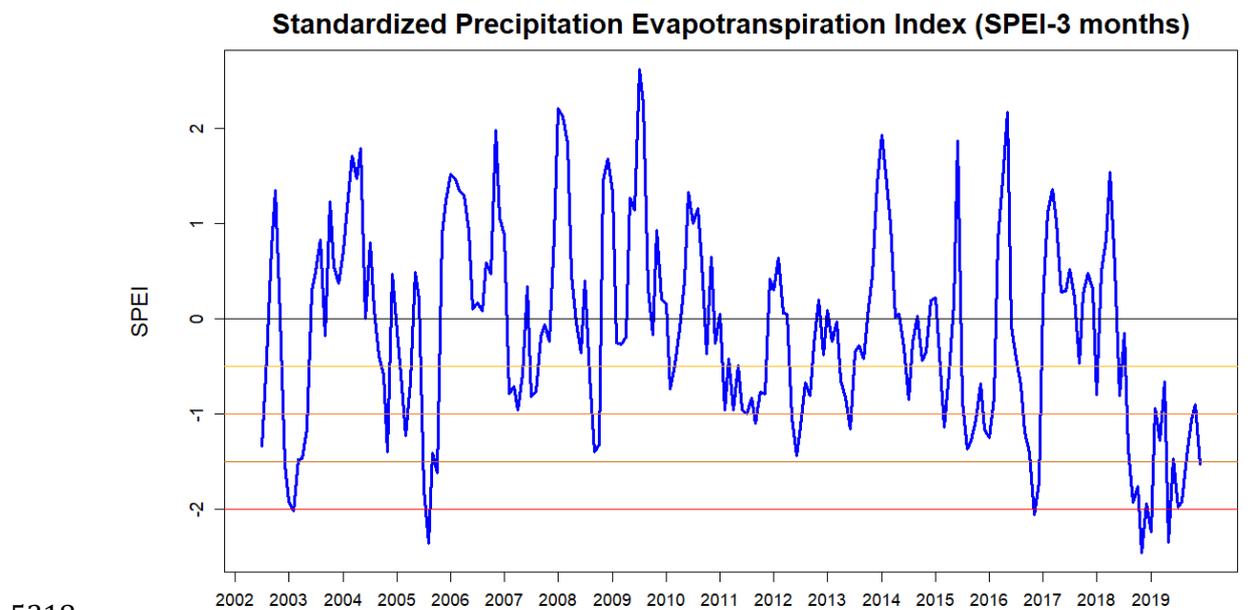
5201

5202 Fig. 5. 6. Number of drought events for the years that experienced droughts in the period
 5203 of 1983 to 2019 using a 3-month time scale, ranked by number of drought months.

5204 5.5.1.2 Drought index, precipitation and vegetation relationship

5205 To contextualise the drought impacts on vegetation, the 3-month SPEI,
 5206 precipitation from the ground station, and monthly NDVI values of a forested area
 5207 between 2002 and 2019 were plotted to determine the interplay between
 5208 vegetation and climate variability. Monthly NDVI varied closely as a function of
 5209 rainfall distribution, as shown in Fig. 5.7. Low NDVI values appear to coincide with
 5210 large drops in SPEI and these correspond to abnormally dry years as shown in the
 5211 graph of precipitation. The lowest NDVI range was recorded in 2002-2003, 2005,

5212 2010/2012, 2015/2016, and 2019, corresponding to the low rainfall values and
 5213 drought years, visible in the SPEI data. Similarly, the highest NDVI was observed in
 5214 2004, 2006, 2008 /2009, and 2017, which are associated with good rainfall in the
 5215 growing season. The SPEI values show that 2019 experienced extreme drought
 5216 with a negative anomaly from the mean conditions reaching the level of -2, and this
 5217 corresponds with reduced NDVI and rainfall levels.



5221 Fig. 5. 7. Top: SPEI from 2002 through 2019 calculated from ground precipitation and
 5222 temperature at 3 months timescales. SPEI index scale is given as, extreme drought (≤ -2),

5223 severe drought (-2 to -1.5), and moderate drought (-1.5 to -1). The different vertical line
5224 colours represent the drought scale (yellow colour shows mild drought and red colour
5225 shows extreme drought). Bottom: Temporal variation of the NDVI (black circles) and
5226 inverted monthly precipitation from ground station data (red squares) from 2002 through
5227 2019.

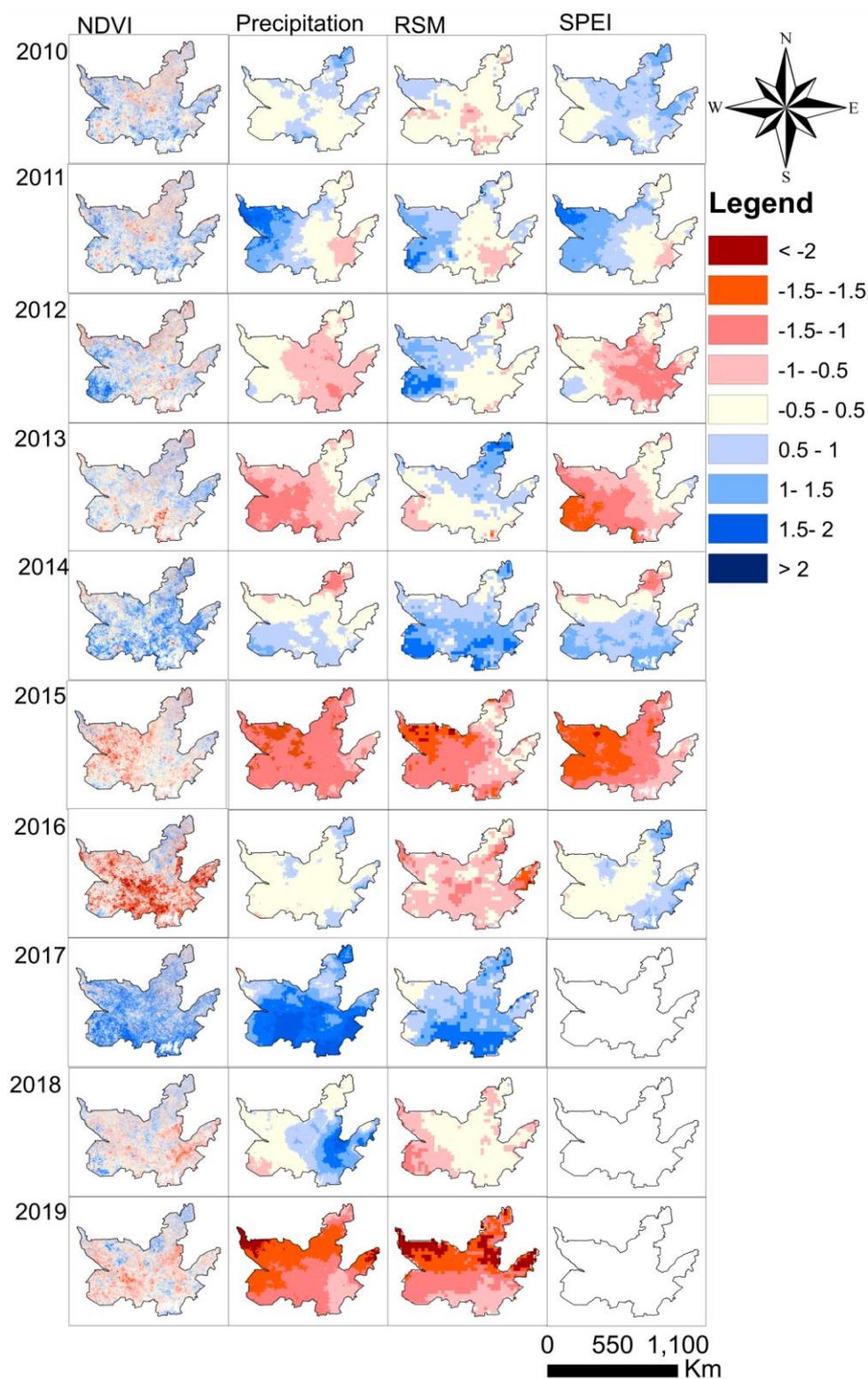
5228

5229 5.5.2 Spatial analyses of drought and water stress on 5230 vegetation

5231 The precipitation, SPEI and RSM dataset are compared with NDVI to gain more
5232 insight into their significance, and to assess which climatic variables explain spatial
5233 patterns of forest and vegetation in this region. Fig. 5.8 shows the results of the
5234 spatial and temporal comparison from 2010 to 2019 for NDVI, precipitation, and
5235 RSM. Noter that SPEI maps end in 2016 due to lack of data availability. In general,
5236 these four variables reflect a progressive dry-out during the events from 2010-
5237 2019. The period between 2010 to 2019 was chosen because it is the period with
5238 more years experiencing severe drought events. For example, a severe drought is
5239 revealed by the SPEI in 2012, with values < -1 , mostly in the west of the KAZA
5240 region, coinciding with a decline in NDVI in this area. The drought of 2012 in
5241 western KAZA could be exacerbated by low rainfall values in 2011 which lead to a
5242 considerable decrease in RSM and SPEI values. However, in 2012, the eastern part
5243 of KAZA experienced an increase in vegetation cover, despite receiving less than
5244 average rainfall. The high NDVI in eastern KAZA corresponds to high RSM with
5245 values >1.5 in the same area, which can be attributed to high rainfall, wet
5246 conditions, as reflected in the in SPEI and high RSM values from 2011 in the
5247 eastern KAZA. In 2013, extremely low rainfall was recorded which is reflected by a
5248 severe drought in SPEI with values <-1.5 over almost the whole of the KAZA region.
5249 This drought resulted in a decreased vegetation productivity, although not as
5250 severely as the RSM which was still high for most parts of KAZA. In 2015, the entire
5251 KAZA region experienced extremely low precipitation, with a value <-1 . This
5252 resulted in a strong and extreme drought, as shown by the SPEI and RSM, with
5253 extremely low values <-1.5 across $>80\%$ of KAZA. The 2015 drought event
5254 impacted vegetation in the region severely, with an NDVI value <-1 in $>50\%$ of
5255 KAZA. Precipitation returned to normal in 2016, which corresponds to the SPEI

5256 data, as there was no drought or dry condition experienced in 2016. However, the
5257 NDVI progressively declined through 2016, which is explained by RSM values <-1
5258 across the whole of KAZA, despite precipitation and SPEI showing a different
5259 pattern.

5260 The slight increase in NDVI values in northern KAZA corresponds to the very few
5261 areas with average RSM in 2016. The RSM reflected the main drought conditions
5262 that are shown also by negative values in NDVI, rather than rainfall or SPEI. The
5263 extreme drought of 2015-2016 is followed by a high level of precipitation in 2017
5264 over almost the entirety of KAZA region, showing wet condition values of >1.5 .
5265 This corresponds to an increase in NDVI and RSM over most of the region,
5266 although most dryland forest in northern and central KAZA remained negative. In
5267 2019, the whole of the region received extremely low precipitation with values
5268 <1.5 . This resulted in a distressing drought with extremely low RSM values
5269 coinciding with a decline in NDVI. The location of the maximum precipitation and
5270 RSM deficit is concentrated in the north and east of KAZA in both 2015 and 2019.
5271 While the wetter conditions were mostly concentrated in south of KAZA, where it
5272 is more arid with less dryland forest such as in 2014 and 2017. RSM was useful in
5273 explaining the spatial-temporal patterns of vegetation lag effects and revealing the
5274 cumulative effect of climate anomalies on vegetation conditions, that were not
5275 explained by precipitation or SPEI.



5276

5277 Fig. 5. 8. Spatial distribution of PRECIPITATION, NDVI, SPEI and RSM anomalies expressed
 5278 as numbers of standard deviations sampled from the monthly data in the growing season
 5279 from 2010 to 2019. Extreme droughts (≤ -2), severe drought (-2 to -1.5) and moderate
 5280 drought (-1.5 to -1), mild droughts (-1 to -0.5) and no drought (-0.5 to 0.5). The map
 5281 shows the whole of KAZA region as represented by the study area in Fig. 5.2.

5282 Comparisons of climate variables against the NDVI values show that reduced NDVI
5283 uniformly coincide with extremely high temperatures and with low precipitation.
5284 Similarly, low SPEI values (< -0.5) moisture coincides with low NDVI values
5285 (Fig. 5.9). SPEI values indicate that the drought event of 2019 was the worst with
5286 SPEI values falling below -1 , followed by the drought event of 2015. The root soil
5287 moisture shows that the dry forest vegetation corresponds strongly to the drought
5288 events of 2019 and 2015, with both years experiencing the lowest root-soil
5289 moisture resulting in low NDVI values. In contrast, high NDVI values are captured
5290 for the year 2017 strongly responding to the high moisture availability as
5291 illustrated by the high value of precipitation, root soil moisture, and SPEI. The max
5292 and average temperature also show a sharp contrast of the drought years (2015
5293 and 2019) and the wet years (2017 and 2014). The drought year (2019 and 2015)
5294 has the highest average and maximum temperatures, with low NDVI values
5295 coinciding with extremely high temperatures. On the other hand, the high NDVI
5296 values of wet years (2017 and 2014) correspond with the lowest average and
5297 maximum temperature. There is a lag observed in dryland vegetation productivity
5298 in some years following drought events such as 2016 and 2013, in which the NDVI
5299 remain very low despite an increase in precipitation and positive values in SPEI.
5300 The min temperature does not uniformly coincide with the NDVI deviation, with
5301 low NDVI values weakly responding to both low and high min temperatures
5302 (Fig. 5.9).

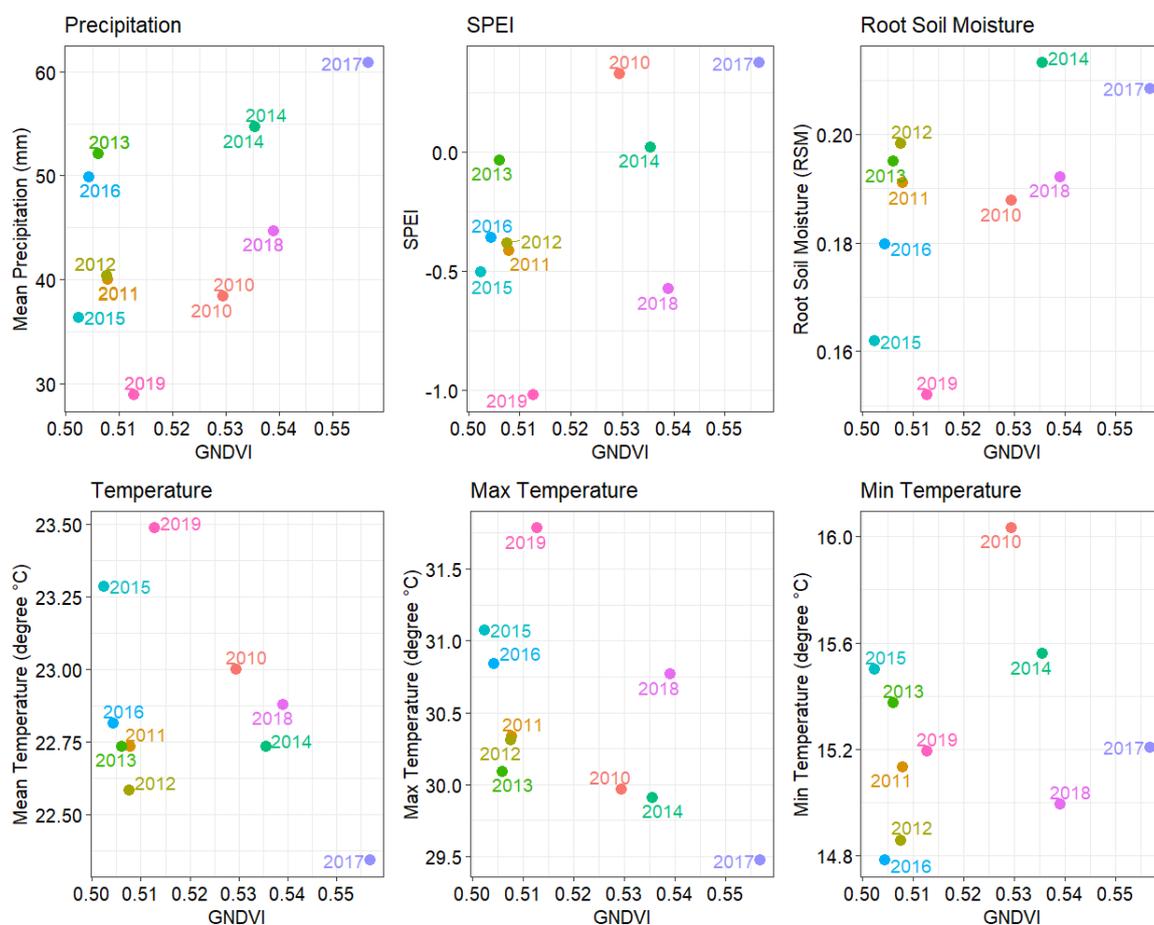
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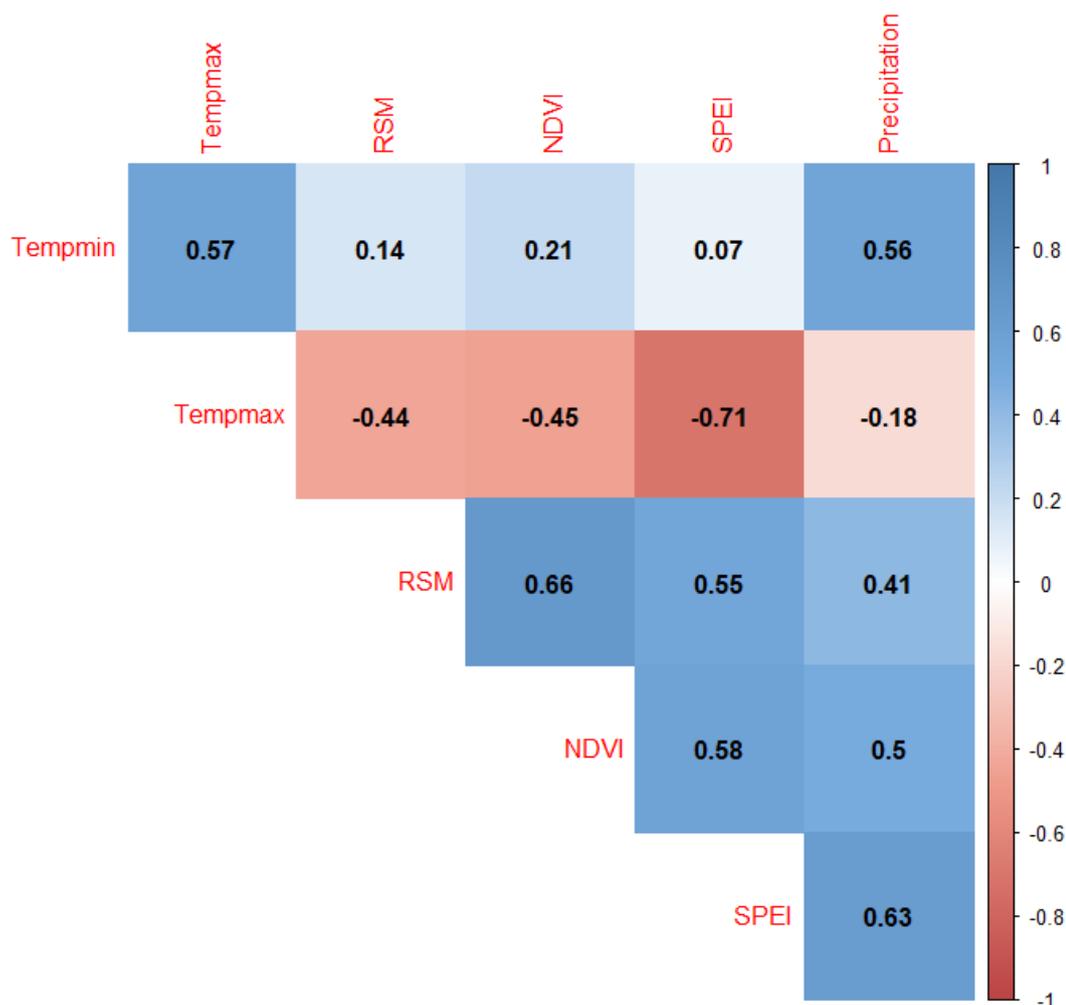


5308

5309 Fig. 5. 9. Association between climate variables and NDVI from the Kavango Zambezi
 5310 region. The average daily mean, maximum temperatures, precipitation, SPEI and Root Soil
 5311 Moisture were calculated from the monthly data in the growing season from 2010 to 2019.

5312

5313 The correlations of NDVI, precipitation, SPEI, root soil moisture, minimum
 5314 temperature and maximum temperature are presented in Fig. 5.10. The NDVI
 5315 shows a strong correlation with the root soil moisture ($r = 0.66$), highlighting the
 5316 constraints imposed by root soil moisture deficit on dryland vegetation. The
 5317 results also indicate a higher correlation between NDVI and SPEI ($r = 0.58$), as well
 5318 as the NDVI and precipitation ($r = 0.50$), reaffirming the consistent mechanism of
 5319 influence of drier conditions. The NDVI - maximum temperature correlation ($r = -$
 5320 0.45) was also notable. The SPEI index showed a strong negative correlation with
 5321 maximum temperature ($r = -0.71$), and a positive correlation with precipitation
 5322 ($r = 0.63$).



5323

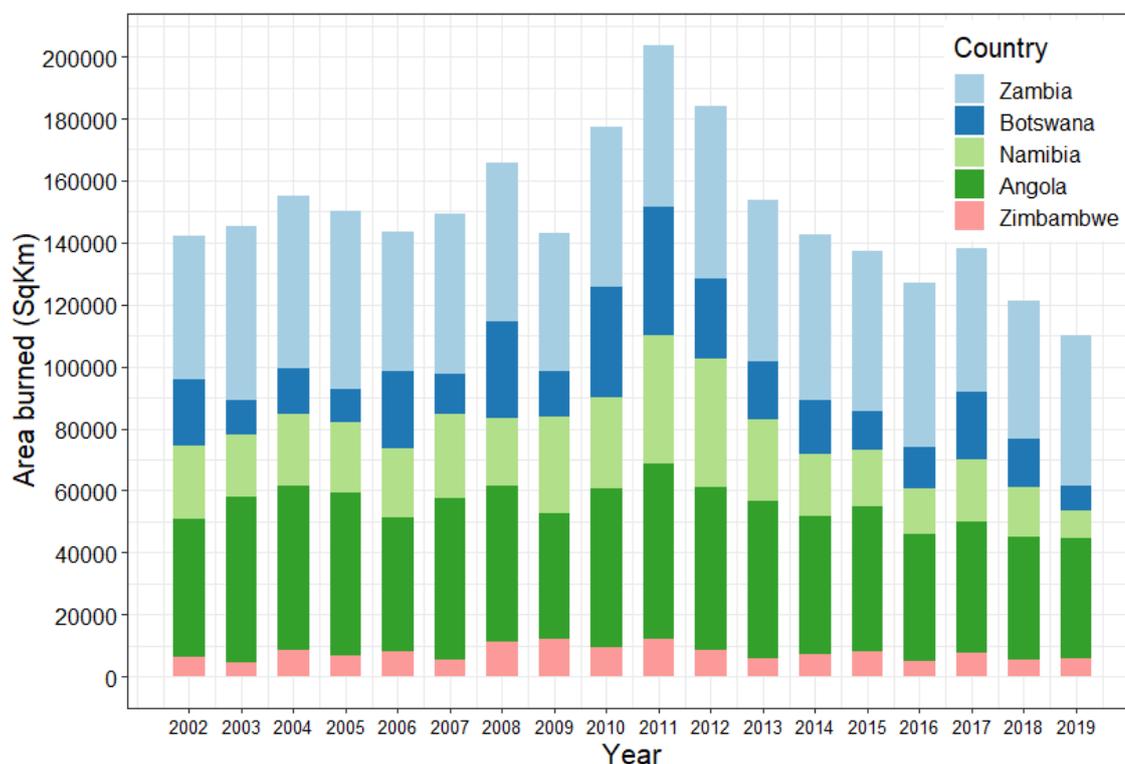
5324 Fig. 5. 10. Pearson's correlation of the NDVI, precipitation, SPEI, root soil moisture,
5325 minimum temperature and maximum temperature.

5326 5.5.3 Temporal analyses of fire

5327 5.5.3.1 Fire seasonality and extent

5328 Fig. 5.11 shows the area burnt for each country in the KAZA region. Every year,
5329 between 110,173 km² (21%) and 203,849 km² (39%) of the land area in the KAZA
5330 region were burnt on an annual basis in the period 2002 to 2019. The year 2011
5331 experienced the highest degree of burning with 203,849 km² (39%), followed by
5332 2010 and 2012 with 177,493 km² (34%) and 184,186 km² (36%), respectively.
5333 The year 2019 experienced the lowest burning with only 110,173 km² (21%). In
5334 KAZA region, a mean 149,410 km² of land is burnt on an annual basis in the period
5335 2002–2019. Most of this burnt area is situated in Angola and Zambia, with an
5336 average of 47,492 km² (32%; Angola) to 50,935 km² (35%; Zambia), respectively,

5337 of the land area burnt on an annual basis between 2002 and 2019 respectively. The
 5338 average area burnt annually in Namibia, Botswana, and Zimbabwe was lower,
 5339 varying between 23,806 km² (16%; Namibia), 19,554 km² (13%; Botswana) and
 5340 7,623 km² (5%; Zimbabwe), respectively (see supplementary: Fig. C. 1 and Table C
 5341 1).

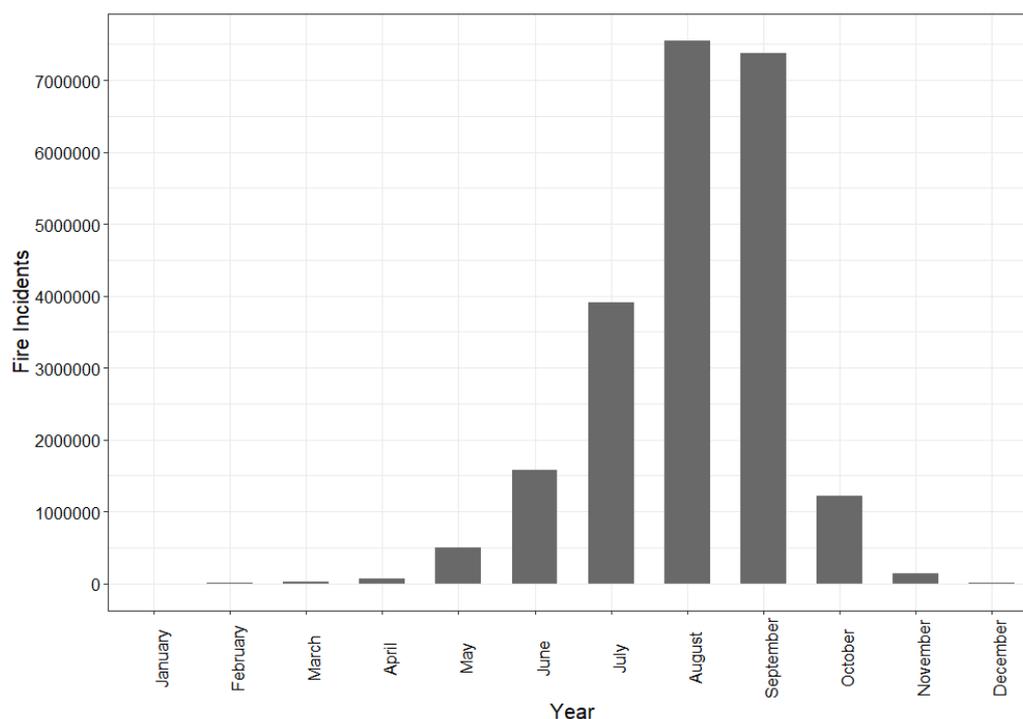


5342

5343 Fig. 5. 11. Total area burnt annually for each country of KAZA from 2002 to 2019 in
 5344 km² based on the MODIS Burnt Area product data.

5345 Fig. 5.12 shows the cumulative monthly seasonal distribution of fires in KAZA
 5346 between 2002 to 2019, as determined from an analysis of the 1 km FIRMS fire
 5347 activity data. The FIRMS data are reported to have considerable amount of
 5348 uncertainty on individual fire number/size distribution. Therefore, FIRMS point
 5349 data were used as complementary to MODIS burned data (Mouillot et al., 2014).
 5350 Vegetation burning in the KAZA region occurs mainly in the dryland forests during
 5351 the dry season between May to October each year. The highest degree of burning is
 5352 experienced during the late dry season, with the months of August and September
 5353 representing the peak months for fire incidences. More than 96% of the incidences
 5354 are due to dry season fires from May to October. There is a relatively low level of
 5355 fire incidences in the months of November, December, January, February, March

5356 and April (Fig. 5.12). Looking at burning incidences per individual country,
 5357 Namibia, Botswana and Zimbabwe have the highest levels in September, while
 5358 Zambia and Angola have the highest levels in August (see supplementary, Fig. C .
 5359 2). On a regional scale, August shows the highest burning rate followed by
 5360 September because Zambia and Angola experience the highest burning incidences
 5361 on an individual basis in comparison to the other three countries (Botswana,
 5362 Namibia and Zimbabwe) combined, as shown below (Fig. 5.12).



5363

5364 Fig. 5. 12. Cumulative monthly fire incidences for the whole of KAZA from 2002 to 2019
 5365 using FIRMS fire activity data.

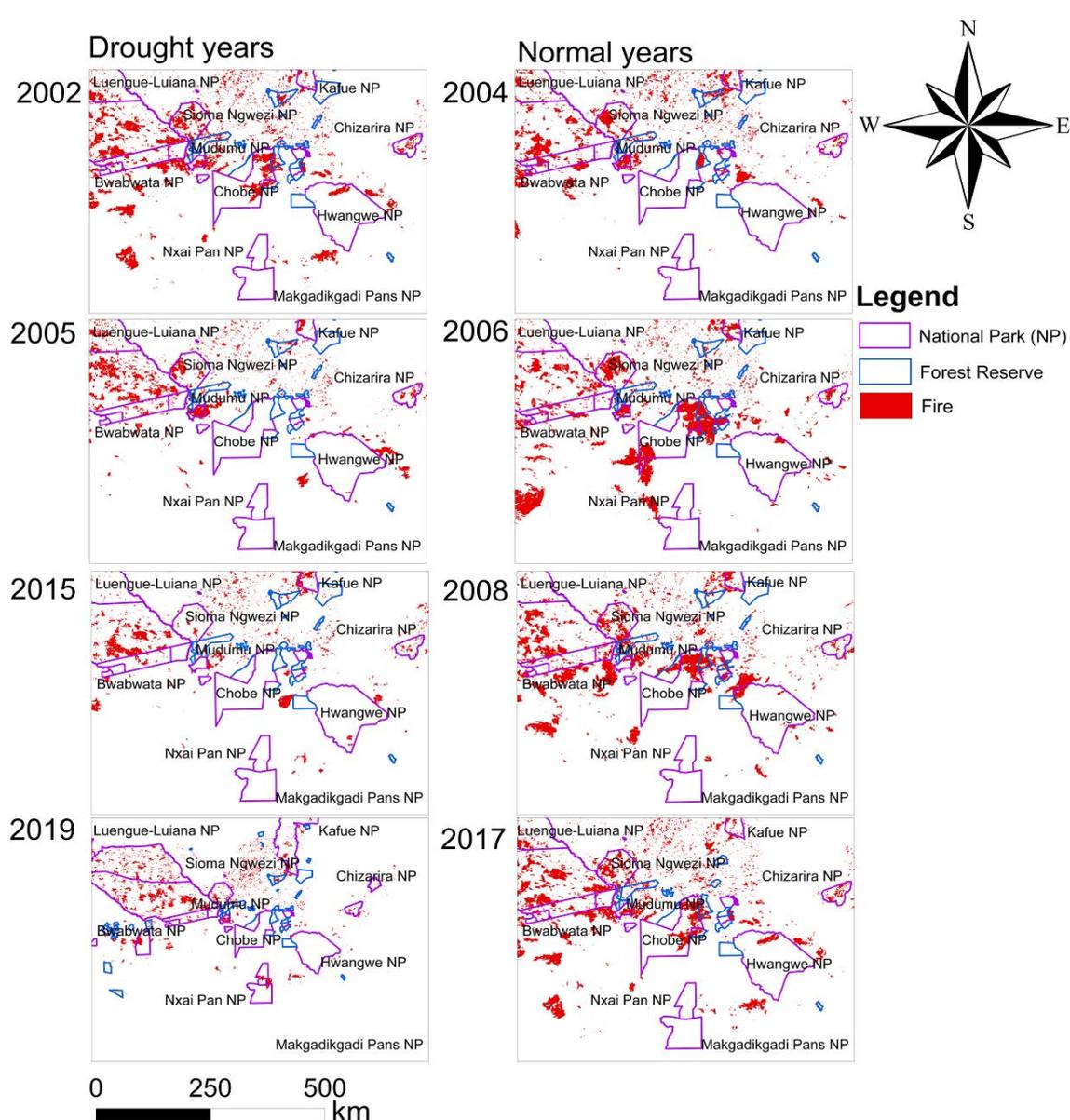
5366

5367 5.5.4 Spatial analyses of fire seasonality and extent

5368

5369 Fig. 5.13 shows comparison between the fires burnt in September in drought and
 5370 wet years. Data from the month of September are used because it represents the
 5371 peak month for fire incidences in most of the KAZA countries. Spatial analysis
 5372 indicates that the years with extreme drought, including 2002, 2005, 2015 and
 5373 2019, experience the lowest extent of area burnt as compared to normal and wet
 5374 and less drought affected years. The burnt area was greatest in the wet years of
 5375 2004, 2006, 2008-2010 and 2017, and in the very low drought years (2011 to

5376 2013) for all the five countries in the study area, and most of the burnt area is
5377 situated within National Parks. As shown in Fig. 5.13, the Chobe NP has no fire
5378 incidences during the drought years, but fire intensified in the normal/wet years. It
5379 can be noted that the northeastern section of Chobe NP (near Kasane Forest
5380 Reserve) is more prone to fire than the north and southern part of the park. The
5381 national parks including Chobe NP, Mudumu NP, Sioma Ngwesi NP and Luengue-
5382 Luiana NP and Kafue NP are more vulnerable to fires in wet years as compared to
5383 drought years. The Nxai Pan NP and Makgaikgadi Pans NP of Botswana and
5384 Hangwe NP of Zimbabwe has little to no fire incidence in most years. The
5385 National Parks in Angola, Zambia, and Namibia including Sioma Ngwesi NP and
5386 Luengue-Luiana NP, Kafue NP and Mudumu NP experience severe burning in both
5387 dry and wet years, even though the national parks are more vulnerable to fire in
5388 wet years as compared to drought years.



5389

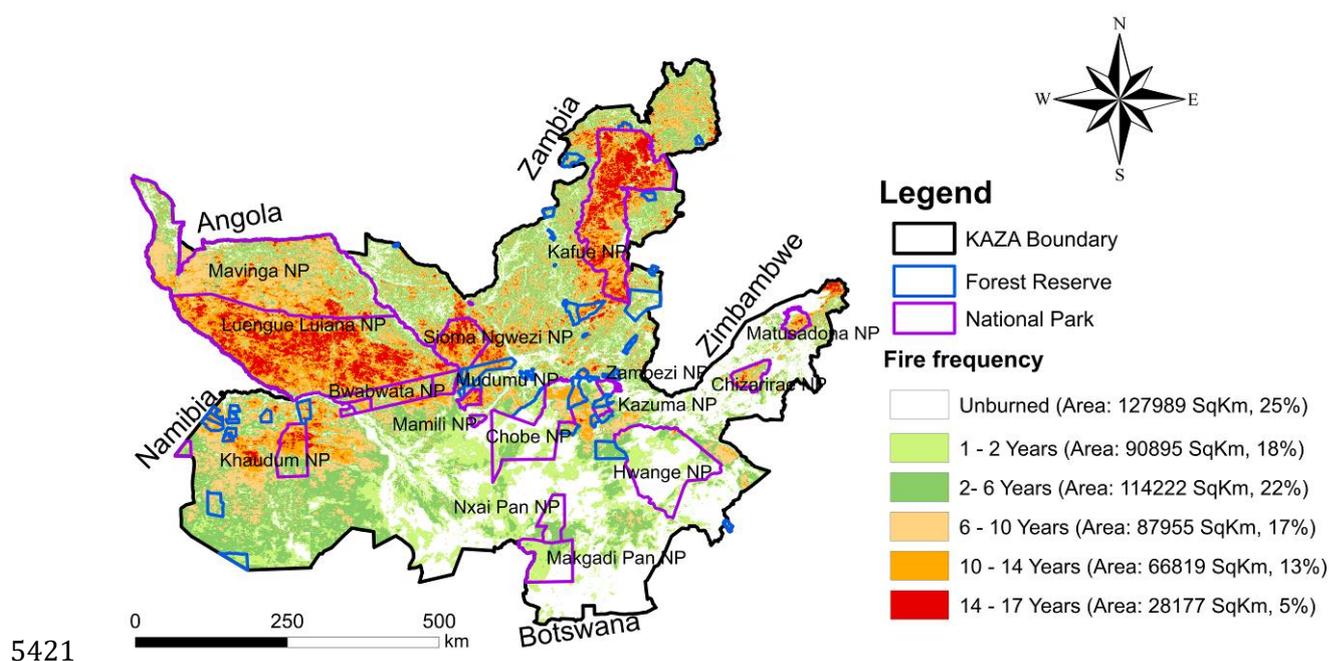
5390 Fig. 5. 13. Burnt area derived from the September month of MODIS MCD64A1 product for
 5391 selected drought years (2002, 2005, 2015 and 2019) and wet years (2004, 2006, 2008 and
 5392 2017) based on SPEI data.

5393

5394 **5.5.5 Fire frequency index**

5395 Fire-affected pixels were considered as those area that burnt at least once in the
 5396 17-year monitoring period. As shown in Fig. 5.14, between 2002 and 2019, about
 5397 390,678 km² (75%) of the land area is classified as fire-affected at least once, and
 5398 127,989 km² (25%) of the area is not affected by fire (Fig. 5.14). Of the 390,678
 5399 km² (75%) of fire-affected area, 90,895 km² (18%) of the area burnt only once or

5400 twice during the 17 years, indicating a low overall fire frequency overall. The
 5401 majority of the area, 114,222 km² (22%), burnt 2-6 times, while 87,955 km² (17%)
 5402 burnt 6-10 times over the same period. About 28,177 km² (13%) burnt frequently,
 5403 >10-14 times, and 28,177 km² (5%) burnt every in >14 of the 17 years indicating a
 5404 high frequency overall (Table C 2). The national parks are affected by higher levels
 5405 of fire occurrence than other protected areas such as forest reserves. The fire
 5406 frequency map shows that Zambia including Sioma Ngwezi NP and Luengue-
 5407 Luiana NP, Kafue NP experienced high rates of fire return with many of the same
 5408 areas burning every year, during the monitoring period, with very large areas
 5409 burnt in >14 out of 17 years. In Namibia, Mudumu, Bwabwata and Khaudum NPs
 5410 also experienced very high rates of fire return for the majority of their total area
 5411 ranging returning in 10 to 17 years. In Botswana and Zimbabwe, fire return is
 5412 generally <6 years, with the exception of the Northeasten Chobe NP, Chizarirae NP
 5413 and Matusadona NP, which had a fire return of between 6 to 14 years. Hwange NP
 5414 in Zimbabwe experienced a fire return >6 years for a very small proportion of the
 5415 northeast area adjacent but outside Hwange NP, and the two parks at the
 5416 southernmost tip of Botswana (Makgadimkadi Pan NP, and Nzai Pan NP) have the
 5417 lowest fire reoccurrence of <6 times out of the 17 monitored years. A large portion
 5418 of the 25% of unburnt pixels were recorded south of Zambezi River in Botswana
 5419 and Zimbabwe. By comparison, the fire return and incidence of burning are higher
 5420 in Botswana than in Zimbabwe.



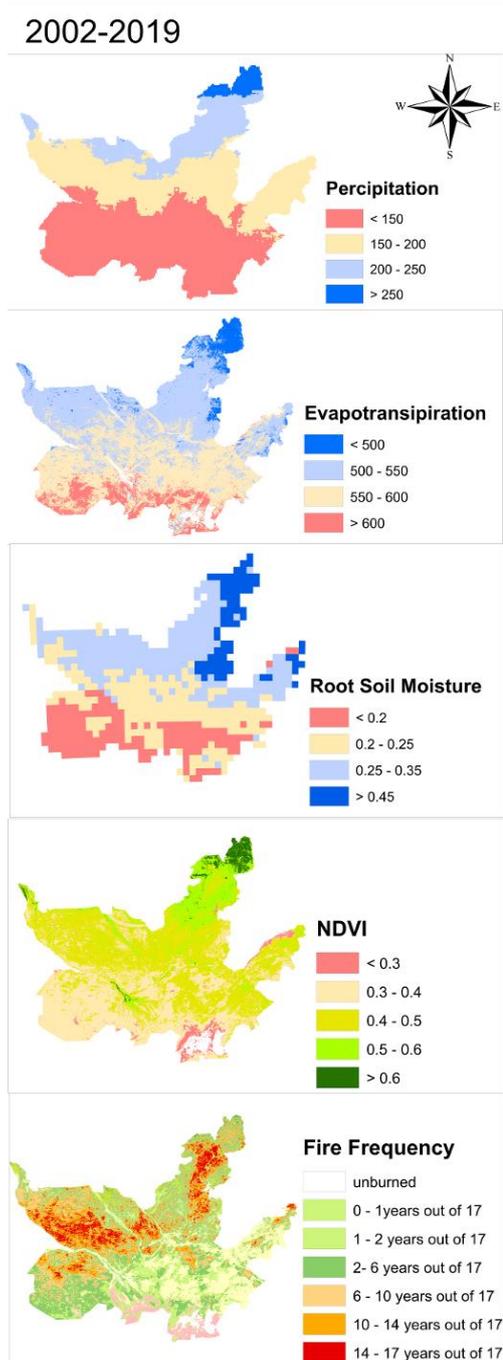
5422 Fig. 5. 14. The area affected by fire determined from monthly using MODIS Burnt Area data
5423 from 2002 to 2019 for different land categories in the region. Colours indicate the number
5424 of times pixels were classified as burnt. White areas represent pixels that were classified
5425 as unburnt over the time period.

5426 Fig. 5.15 shows climate, fire and vegetation indices data from 2002 to 2019. Very
5427 high and extremely low burnt areas coincide with a certain combination of climatic
5428 factors. A comparison of the distribution of these climatic data and burnt areas,
5429 with the spatial distribution of NDVI values, an index of 'greenness' of the
5430 vegetation also derived from the MODIS sensor, shows that burning is closely
5431 related to areas with proportions of high dryland forests. The areas with high
5432 dryland forests (or high tree cover), high rainfall, and dry season length
5433 correspond to areas with high fire frequency and large burnt areas (Fig. 5.15). For
5434 example, areas with high dryland tree cover and vegetation with NDVI >0.4
5435 receiving mean annual precipitation >150 mm were burnt in approximately 6 to
5436 17 out of the 17 monitored years, here it was common that the same areas burned
5437 frequently and recurrently. The areas with low tree cover and vegetation with
5438 NDVI <0.4 receiving mean annual precipitation <150 mm were burnt 1 to 6 times
5439 out of 17 years. The very dry areas, such as the succulent deserts, burnt once and,
5440 in most cases, remained unburnt in the 17 years. The precipitation variations
5441 corresponded with the highest degree of spatial similarity to the root soil moisture,
5442 and with consistent high rainfall in northern part of KAZA, and the extremely low
5443 rainfall (<150 mm) in the southern part of the region.

5444 In contrast, the potential evapotranspiration has the lowest variation in the
5445 northern part of the study area (>550 mm) and highest variations in the south
5446 (<5500 mm). This is consistent with the root soil moisture, which have high
5447 variations (>0.25) in the northern part of the region in comparison to the northern
5448 side with very low soil moisture (<0.25). The northern part of the region is
5449 situated in the countries with the largest dryland forest cover, Angola and Zambia,
5450 which is consistent with high NDVI (light and dark green colours in Fig. 5.15).
5451 However, these areas also have a very high rate of burning in consecutive years,
5452 with a fire return of between 14 to 17 years within 17 years, as shown by the fire
5453 frequency index. The high fire return rate is also prevalent in other areas with
5454 dryland forests, such as the forest reserves and national parks in Namibia and

5455 Botswana (e.g., Mudumu, Chobe NP, Zambezi ST and Kasane forest reserves),
 5456 which display a fire return of between 6 to 14 in 17 years, with proportions of
 5457 their areas experiencing fire recurrences in more than 14 years. The south of
 5458 Zambezi River shows a very low fire frequency and a large portion of the 25% of
 5459 unburnt pixels from 2002 to 2019 are recorded here (see supplementary: Table C
 5460 2).

5461

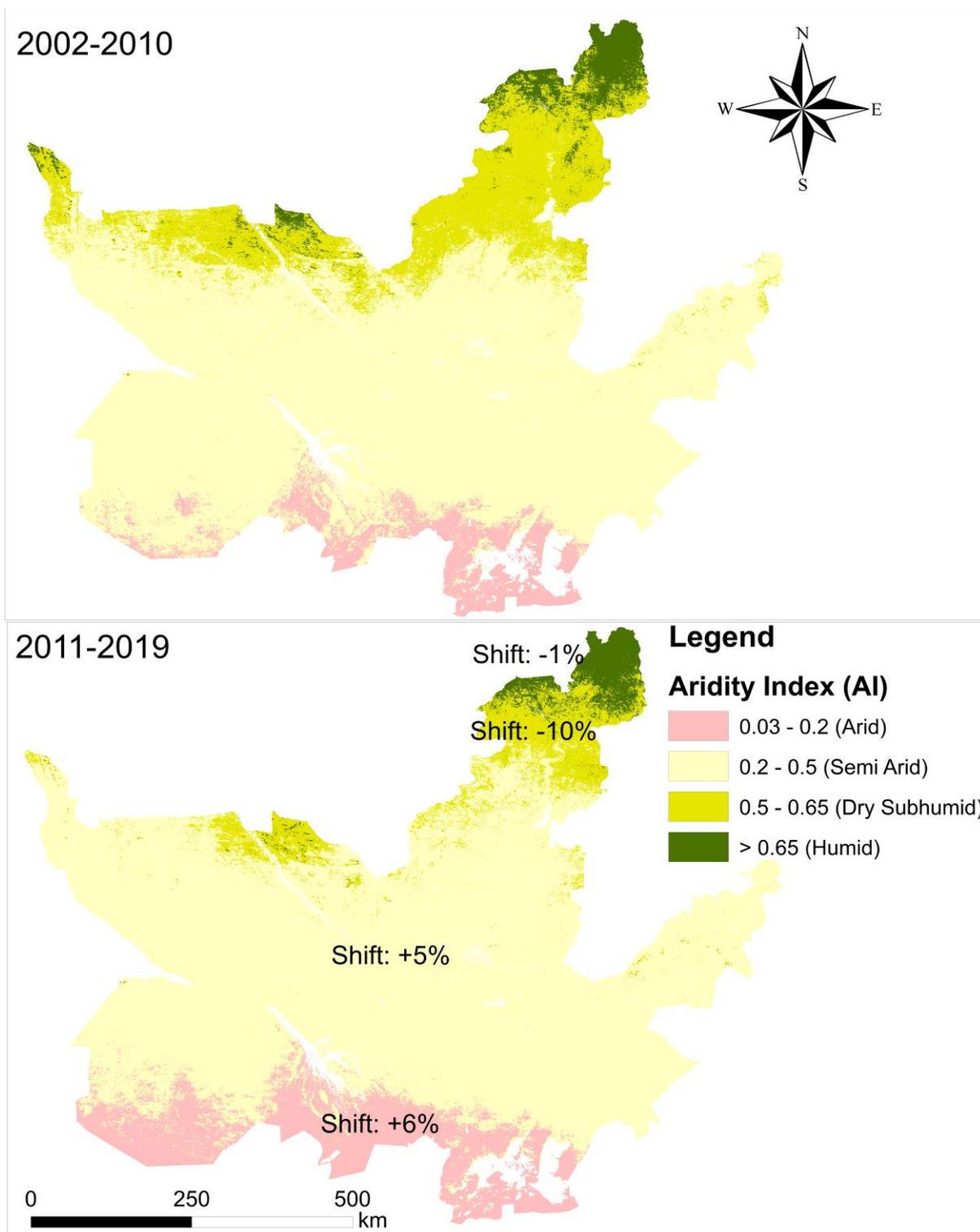


5462

5463 Fig. 5. 15. Areas where the fire frequency is under varying degrees of climatic condition
5464 (precipitation, potential evapotranspiration, root soil moisture), and NDVI sampled from
5465 the averaged monthly-mean of the growing season of 2002 to 2019.

5466 5.5.6 Spatiotemporal changes in the Aridity Index

5467 Fig. 5.16 presents the spatiotemporal aridity changes in the whole of the KAZA
5468 region to explore whether frequent drought and fire dynamics in recent years have
5469 led to increased dryness, and subsequent vegetation change. A subset of the AI
5470 data over the last 9 years of the period (2011–2019) is compared with the first 9
5471 years (2002 - 2010) to highlight these temporal changes. The temporal changes of
5472 AI showed a significant increasing dryness since 2002. Observed areal changes
5473 (Fig. 5.16) are apparent, with the change to drier subtypes being dominant and
5474 mainly located in southern side of the region as compared to the northern side in
5475 the period of 2002-2010, as compared to 2011-2019. An increase in the drying
5476 variations and changes in the aridity index were observed in transition zones
5477 between arid, semi-arid, and sub-humid regions between 2011 and 2019. The arid
5478 and semi-arid regions have increased at the expense of neighbouring dry sub-
5479 humid areas, and represented 5.56% and 4.84%, respectively. The sub-humid
5480 areas experienced a significant decrease of approximately 10% of the KAZA land
5481 area. The largest expansion of drylands occurs in semiarid regions, which account
5482 for nearly half of the total dryland expansion and cover >70% of the region (Table
5483 C 3). The AI indicator detected areas with increasing aridity to be mainly in
5484 southern KAZA, and these areas are shifting towards more arid and hotter classes,
5485 while northern the KAZA areas with semi humid regions are shifting into semi-arid
5486 regions and, therefore, increasing climatological drying risk.



5487

5488 Fig. 5. 16. Spatial distribution of averaged aridity over KAZA region for 2002-2010 and
 5489 2011-2019.

5490

5491 5.6 Discussion

5492 5.6.1 Drought impacts on vegetation

5493 Temporal analysis of the SPEI index, precipitation and soil moisture anomalies all
5494 reveal that the 2019 drought event surpasses the severity of events in 2002, 2005,
5495 2010, and 2015, which were all considered severe drought events. The results
5496 show that the dryland vegetation in the region has a strong correlation with
5497 precipitation and closely responds to variability in precipitation and drought (see:
5498 Fig. 5.7). A study by Caylor et al. (2005) showed that vegetation in the Kalahari
5499 region depends on the stochastic distribution of rainfall events and interannual
5500 variation in rainfall that can induce shifts in vegetation structure with prolonged
5501 periods of wet (or dry) regime. Comparing the satellite-based rainfall anomalies
5502 (CHIRPS) with ground-based rainfall observations also indicates that the results
5503 are not sensitive to the precipitation data used in this analysis. The multi-year
5504 spatial patterns of change in climate, soil moisture and vegetation were
5505 categorised from 2002 through 2019 (see: Fig 5.8). Fig 5.8 shows the results of
5506 2010 to 2019 as this period was more affected by drought impacts as compared to
5507 the period 2002-2009. As shown in Fig. 5.8, the severity and extensiveness of the
5508 2015 and 2019 drought resulted in considerable precipitation and soil water
5509 deficit, which caused a significant change in dryland forest vegetation. A similar
5510 pattern was seen by Liu et al. (2013) who found climate variability to be extreme
5511 in dryland trees and grassland in the KAZA region. The browning hotspots are
5512 concentrated in unprotected woodland and grassland, although significant
5513 browning patterns were also observed in protected national parks (e.g., Chobe NP
5514 and Kafue NP). On the one hand, some large-scale browning patterns are not
5515 corresponding to the low precipitation values and drought years, which implies
5516 that they could not be directly associated with climate change (see: Fig. 5.8).
5517 Agricultural expansion, deforestation, and frequent fire burning could be
5518 associated with these changes, particularly in Namibia and Zambia.

5519 The lag in greening rate in dryland biomes can be seen in some years following
5520 drought (e.g., 2016), with most dryland trees suffering drastically reduced growth
5521 rates despite an increase in rainfall and a subsequent lack of a dry spell, as shown
5522 in the SPEI of 2016 (see: Fig. 5.8 and 5.9). The root soil moisture data explained the

5523 consistent decrease in vegetation productivity in 2016, despite precipitation and
5524 the SPEI showing a positive trend, indicating that RSM root soil moisture is one of
5525 the major controlling factors that helps to explain changes in vegetation cover
5526 across the KAZA region, as indicated by Caylor et al. (2005). Sporadic, erratic and
5527 extremely poor rainfall accompanied by high temperatures in preceding years,
5528 seems to have resulted in an absence of soil water storage with root soil moisture
5529 levels becoming very low, resulting in potential carry-over effects on plants.
5530 Although SPEI considers the effects of both temperature and precipitation, and has
5531 been very useful in detecting vegetation drought in many studies (Marumbwa et
5532 al., 2020; Vicente-Serrano et al., 2015), the RSM showed a better performance in
5533 explaining the climatic relationship with vegetation vulnerability to prolonged
5534 drought resulting in lack of moisture in plant roots (see: Fig. 5.8 and 9). This
5535 finding is similar to Anderegg et al. (2013) and Case et al. (2019) who also
5536 observed lag-effect patterns between drought stress and extended multiyear tree
5537 disturbances in 2015-2016 in temperate forests in North America and dryland
5538 woodland in Kruger NP. These results confirm that MODIS-derived VIs time series
5539 coupled with climatic variables, soil moisture and ground measurements of forest
5540 stands can provide insights into the influence of water stress on dryland biomes.

5541 5.6.2 Fire

5542 Changes in fire regime were analysed in conjunction with climate data as the
5543 climate variability and change also modify the risks of fires, pest and pathogen
5544 outbreaks, which each negatively affect vegetation (IPCC, 2014). The data show
5545 that every year, between 110173 km² (21%) and 203849 km² (39%) of the land
5546 area in the KAZA region were burned in the period 2002 to 2019. The year 2011
5547 experienced the highest amount of burning with 203849 km² (39%), and 2019
5548 experienced the lowest burning with only 110173 km² (21%). The results show an
5549 increase in annual precipitation in the study region has led to a potential increase
5550 in fire incidence, and the reoccurrence of drought events have exacerbated fire
5551 incidences in the wet years. During wet years (2004, 2006, 2008-2009 and 2017)
5552 and less drought prone years (2011 to 2013), fire incidence in the KAZA was
5553 greatest across protected areas. By comparison, dry years of 2002-2003, 2005,
5554 2015-2016 and 2018-2019 show unusually low fire incidence and notably, 2019

5555 which experienced extreme drought conditions also experienced the lowest
5556 number of fire incidences (see: Fig. 5.11 and 13). The findings of this study are in
5557 agreement with Fox et al. (2017) who analysed fire incidences in Chobe NP from
5558 2001 to 2013, and found more active fires recorded in years with higher rainfall. In
5559 addition, during wet seasons or low drought years, fire is also used to remove
5560 biomass from land being cleared for agriculture, shifting cultivation, weed and
5561 disease control, or, afterwards, for removal of the previous-year's agricultural
5562 waste (Eriksen, 2007; Frost, 1999). However, inverse results were found in the
5563 Amazon, where many studies demonstrate that fire incidence and extent increases
5564 in drought years (Aragão et al., 2007; Nobre et al., 2009)..

5565 One explanation for the high incidence of fire in wet years is that in the KAZA
5566 region, more than 90% of fire incidences are due to dry season fires in June to
5567 October, the highest number of burning incidences occur in the late dry season
5568 between August and September (see Fig. 5.12), and the end of dry season affects
5569 the amount of fuel available in wet years (see: Fig 5.4). During the dry season, the
5570 herbaceous vegetation is either dry/dead (annual grasslands), and deciduous trees
5571 have shed their leaves, thereby contributing to the build-up on the surface of
5572 ignition sources after only a few weeks of dry weather (Higgins et al., 2000;
5573 Lehmann et al., 2014). This evidence suggests that most fires in the region are set
5574 by people, because there are few thunderstorms in the late dry season months that
5575 might naturally trigger fires. The late dry seasons are normally hot, windy with
5576 extremely dry conditions, which means the fires can spread easily and are difficult
5577 to control, and subsequently burn large areas (Archibald et al., 2010). On the other
5578 hand, severe drought conditions with very low rainfall does not permit the
5579 accumulation of sufficient fuel to become a source of ignition and then to sustain
5580 extensive fires (Stott, 2000). The fieldwork of 2019 revealed that a frequent late
5581 dry season fire transforms woodland into open, tall grass savanna with only
5582 isolated fire-tolerant canopy trees. This suppresses the regrowth of woody plants
5583 resulting in scattered understorey trees and shrubs. Similarly, in the Amazon, huge
5584 and successive fires have substantially increased forest disturbances and favoured
5585 the occurrence of short-life-cycle pioneer species (Nobre et al., 2016).

5586 Between 2002 and 2019, about 390678 km² (75%) of the land area was classified
5587 as fire-affected at least once, and 127989 km² (25%) of the area was not affected

5588 by fire (see: Fig. 5.14). Even though all of the KAZA member countries have fire
5589 suppression policies that largely date back to colonial days, the striking difference
5590 in fire incidence and extent of area burnt is due to the different types of fire laws,
5591 and the enforcement of these laws. The national parks are more affected by high
5592 fire occurrence as compared to other protected areas, such as forest reserves,
5593 game reserves and wildlife management areas. The fire frequency map shows that
5594 a large portion of the 75% burned pixels were located in the Zambian and Angolan
5595 areas of KAZA. The two countries experienced high rates of fire return, with many
5596 of the same areas burning every year, in the last two decades, with very large areas
5597 burned in 14 to 17 years out of 17 years. Within Angola, anthropogenic fire is
5598 thought to be a significant cause of deforestation and the fire incidence rate is
5599 significantly higher during the dry season, which has a negative impact on forest
5600 resources and biodiversity in Kuando-Kubango Province (the Angolan component
5601 in KAZA), as recorded by United States Forest Service report (Zweede et al., 2006).
5602 Although there is legislation and regulation on fire control in Angola, these are
5603 rarely enforced, and so uncontrolled dry-season burning for clearing land and to
5604 flush animals for hunting are common practices (USAID, 2013). In Zambia, fire is
5605 perceived as an important land management tool in agricultural and caterpillar
5606 breeding. The Zambian State Forestry Department and local NGOs encourage
5607 burning earlier in the dry season to enable fire suppression in the late dry season
5608 across most national parks and other protected areas. Even though there is
5609 existing state law on fire regimes in Zambia, these laws are not strictly followed,
5610 again due to the difficulty of enforcement, and potentially a lack of understanding
5611 of the laws in many remote rural areas (Eriksen, 2007). A separate study by
5612 Archibald et al. (2010) also reported similar results, whereby Angola and Zambia
5613 have the highest burnt areas amongst Southern African countries, with much of
5614 their area burned >4 in the 8-year period monitored.

5615 In Namibia, fire return periods for most of areas are midrange compared to other
5616 areas of KAZA (e.g., Mudumu, Bwabwata and Khaudum NP experienced high rates
5617 of fire return for most of its total area ranging from 10 to 17 years out of the 17
5618 years). In Namibia, a fire management project that includes the establishment of a
5619 community fire break, and the implementation of awareness programs on fire, to
5620 manage and reduce wildfires was established in 1996 through the Namibia-

5621 Finland Forestry Programme (NFFP) (Verlinden et al., 2006). In addition, an
5622 innovative integrated fire management program (Integrated Rural Development
5623 and Nature Conservation Caprivi Program) was implemented between 2006 and
5624 2010 to support national parks and forestry agencies via decentralization of fire
5625 management decision-making to include community members in decision-making
5626 (Russell-Smith et al., 2017). Fire management in the Namibian section of the
5627 Wildlife Dispersal Area (WDA) has progressed significantly through collaborative
5628 efforts between the Directorate of Forestry, NGOs and local communities (KAZA,
5629 2014). According to Verlinden et al. (2006), the implementation of fire
5630 management into schools and community meetings, through awareness raising
5631 interventions in Namibian were very effective and the results appear to show a
5632 significant decrease in burned area in comparison to the prior era.

5633 A large portion of the 25% of unburned pixels from 2002 to 2019 are recorded in
5634 Zimbabwe and south of Zambezi River around the Makgadikgadi Pans National
5635 Park and Nxai Pan National Park in Botswana. This is due to the generally drier
5636 environment with low precipitation and low tree cover as both Makgadikgadi Pans
5637 National Park and Nxai Pan National Park are physically and ecologically part of
5638 the “Kalahari Desert,” and possibly due to better controlled fire regimes in these
5639 areas (Chinamatira et al., 2016; EMA, 2007). The incidence of burning is lower in
5640 Botswana than in Zimbabwe, despite the higher human population density in the
5641 latter. In the two countries, the fire return is generally low with <6 years
5642 experiencing burning from 17, with the exception of northeast of Chobe NP, the
5643 northeast of Hwange NP, Chizarirae NP and Matusadona NP, which have a fire
5644 return of between 6 and 14 years. This is in line with the findings by Mpakairi et al.
5645 (2019) who reported fire hotspots in Chizarira, Matusadona NP and northeast of
5646 Hwange NP. Botswana has a fire suppression management strategy through the
5647 use of fire breaks and firefighting crews including the military, police and
5648 volunteer members of the general public, mobilised through the District
5649 Commissioner (Dube, 2013). The Zimbabwean component have strict laws on fire
5650 management and control in place, dating back to colonial days bolstered by recent
5651 laws passed in 1998 (Zweede et al., 2006). The Zimbabwean Environmental
5652 Management Authority passed regulations on fire suppression in 2007, such that
5653 anyone caught setting a wildfire outside a residential or commercial premises

5654 during the dry summer period from 31 July to 31 October of each year are
5655 arrested, face expulsion from the area, or can be fined by decree (Chinamatira et
5656 al., 2016; EMA, 2007).

5657 5.6.3 Changes in aridity

5658 Understanding the long-term areal change in the aridity is essential for taking
5659 early action to prevent the aggravation of drying conditions. The results shown in
5660 Fig. 5.16 confirm that the KAZA region is becoming drier in the 20th century, and
5661 there is an increased risk of arid conditions as result of enhanced warming,
5662 wildfires and the rapidly growing human population in the drylands of KAZA
5663 region. Such an expansion of arid areas detected in this study is in agreement with
5664 the projection by IPCC (2007) that by 2020, most African countries are projected
5665 to be exposed to increased water stress due to climate change and this would lead
5666 to reduced carbon sequestration and enhanced regional warming, resulting in
5667 increased warming trends over the drylands. In the scientific literature, there are
5668 many publications dealing with aridity changes, but as there is no study of aridity
5669 change at a regional scale across KAZA, it is difficult to make detailed comparisons.
5670 At regional scale, climate shifts can be notably different to those observed at global
5671 scale. The most relevant precursor to this study aridity maps can be the global
5672 maps produced by Huang et al. (2017). Huang et al. (2017) compared aridity data
5673 over 10 years, from 1996 to 2005, to a 10 year period between 1948 to 1957. Their
5674 study found that most vegetation change from dry sub-humid to semi-arid
5675 occurred in the area of the KAZA region in Southern Africa. In comparison to this
5676 study, an increase in the drying variations and changes in the aridity index were
5677 observed in the arid and semi-arid regions represented by 5.56% and 4.84%
5678 between 2002 to 2019 (this study), as compared to 1.16% and 2.32% in the arid
5679 and semi-arid regions between 1948 to 1957 observed in Huang et al. (2017).

5680 Another global study by Spinoni et al. (2015) compared AI from 1951 to 2010
5681 using FAO AI and the KG climate classification. Their study found that the extent of
5682 arid lands increased in Africa by 1.95%, followed by Asia (0.55%) and decreased in
5683 the North and South Americas by -0.47 and -70%, respectively. Their study found
5684 that that the arid lands in Southern Africa are larger by the end of the period 1981
5685 to 2010, as compared to the period 1951-1980, and the largest increase in arid

5686 regions of Southern Africa were located in the KAZA region (Southern Zambia,
5687 Zambezi region of Namibia and western Zimbabwe) as compared to any other part
5688 of Southern Africa. These findings more or less agree with the results presented
5689 here, with one exception: the shifts identified in this study were found to be larger
5690 in dry-sub-humid and humid area, with 10.40% of the regional land area becoming
5691 arid compared to the previously published 1.95% at a continental scale. The
5692 difference could be attributed to the difference in data, as this study used high-
5693 resolution precipitation and PET data at a much smaller scale, while the global
5694 studies used a more coarser resolution Global Precipitation Climatology Centre
5695 (GPCC) and the Climatic Research Unit (CRU) for precipitation and PET. This
5696 difference could also be due to the fact that the thesis considered data up to 2019,
5697 and the 21st century recorded the worst drought periods, notably in 2012-2013,
5698 2015-2016 and 2018-2019.

5699 As a result of the multiple effects of consecutive droughts, many countries such as
5700 Namibia and Angola, declared a state of emergency in response to drought 3 times
5701 in a period of 6 years, with the drought of 2019 declared as the worst in the last 90
5702 years (Shikangalah, 2020). In addition, projected aridification-prone areas overlap
5703 with regions at risk of severe drought, marked soil moisture depletion, and shifts
5704 in potential vegetation distributions. This suggests that, compared with globally
5705 averaged aridity changes, the KAZA region show a much drier climate than most
5706 regions in Africa, and globally. The results sows that if future precipitation
5707 extremes become more severe, this region is likely to have vegetation that is more
5708 unstable or may even to experience extreme vegetation shifts that will be hard to
5709 adapt to, as predicted by (IPCC, 2014). Therefore, being able to understand areas at
5710 risk of risk of drying conditions through drought indices should give land
5711 managers information that may allow the implementation of mitigation or
5712 adaptation measures, which can be fundamental in terms of dryland vegetation
5713 sustainability.

5714

5715 5.7 Conclusion

5716 This study detected spatial and temporal patterns of climate, burnt areas and
5717 dryland vegetation across KAZA, using a combination of ground-data and remote
5718 sensing imagery to understand the ecological effects of climate and fire. The long-
5719 term climate, fire, and vegetation data analysis led to the following conclusions:

5720 First, the extreme droughts of 2015 and 2019 resulted in considerable
5721 precipitation and soil water deficits. Dryland forest vegetation is to be more
5722 susceptible to changes in soil moisture trends, as opposed to changes in rainfall
5723 and drought index.

5724 Second, at decadal time scales, interannual variability in fire frequency and burnt
5725 area is likely to be driven largely by variation in rainfall, vegetation distribution
5726 and dry season length. The areas with high tree cover, high rainfall, and less severe
5727 drought season coincide with areas of high fire frequency and large burned areas,
5728 while low tree cover (e.g., succulent deserts), low rainfall and extended severe
5729 drought conditions correspond to areas with low fire frequency.

5730 Finally, the detected aridification-prone areas overlap with regions at risk of
5731 severe drought, marked soil moisture depletion, and shifts in potential vegetation
5732 distribution. The KAZA region has become drier due to aridification in the period
5733 between 2002 to 2019 as a consequence of both drought and wildfire, which
5734 critically affect agriculture, water quality, vegetation productivity, and biodiversity.

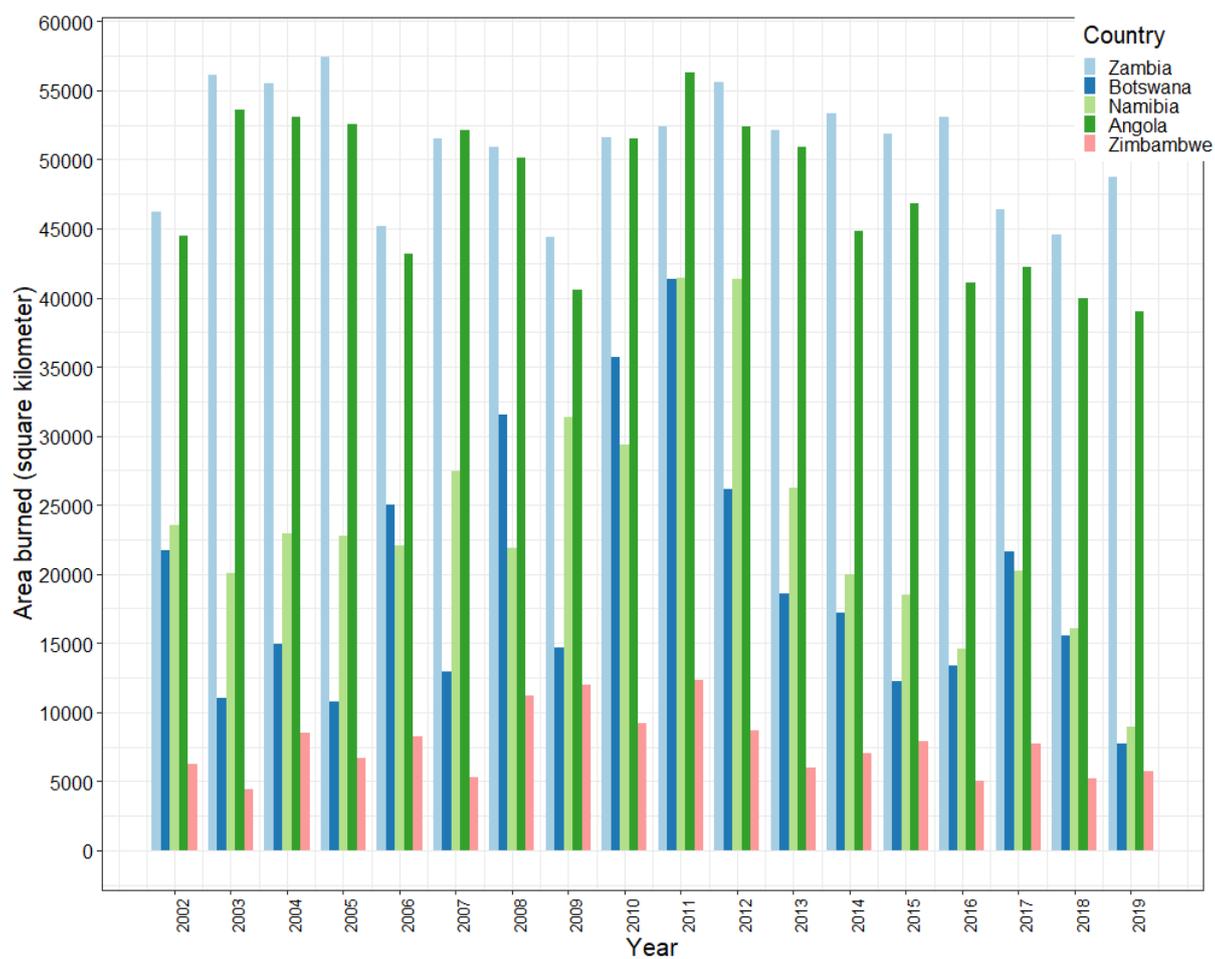
5735 The identification of the areas with significant trends of change is extremely
5736 important in tropical dryland areas where low levels of field data are available and
5737 limited financial resources can be invested in monitoring and assessment, as is the
5738 case in much of the KAZA region. The detailed relationship between remotely
5739 sensed drought/fire indicators and vegetation stress at the regional scale shown
5740 here allow us to make several suggestions to move towards a more impact-
5741 oriented drought and fire monitoring approach, with the potential to provide early
5742 warnings in to devise more practical measures to control aridity in vulnerable
5743 areas.

5744

5745

5746 5.8 Supplementary Information 3

5747 Temporal analyses: burned area

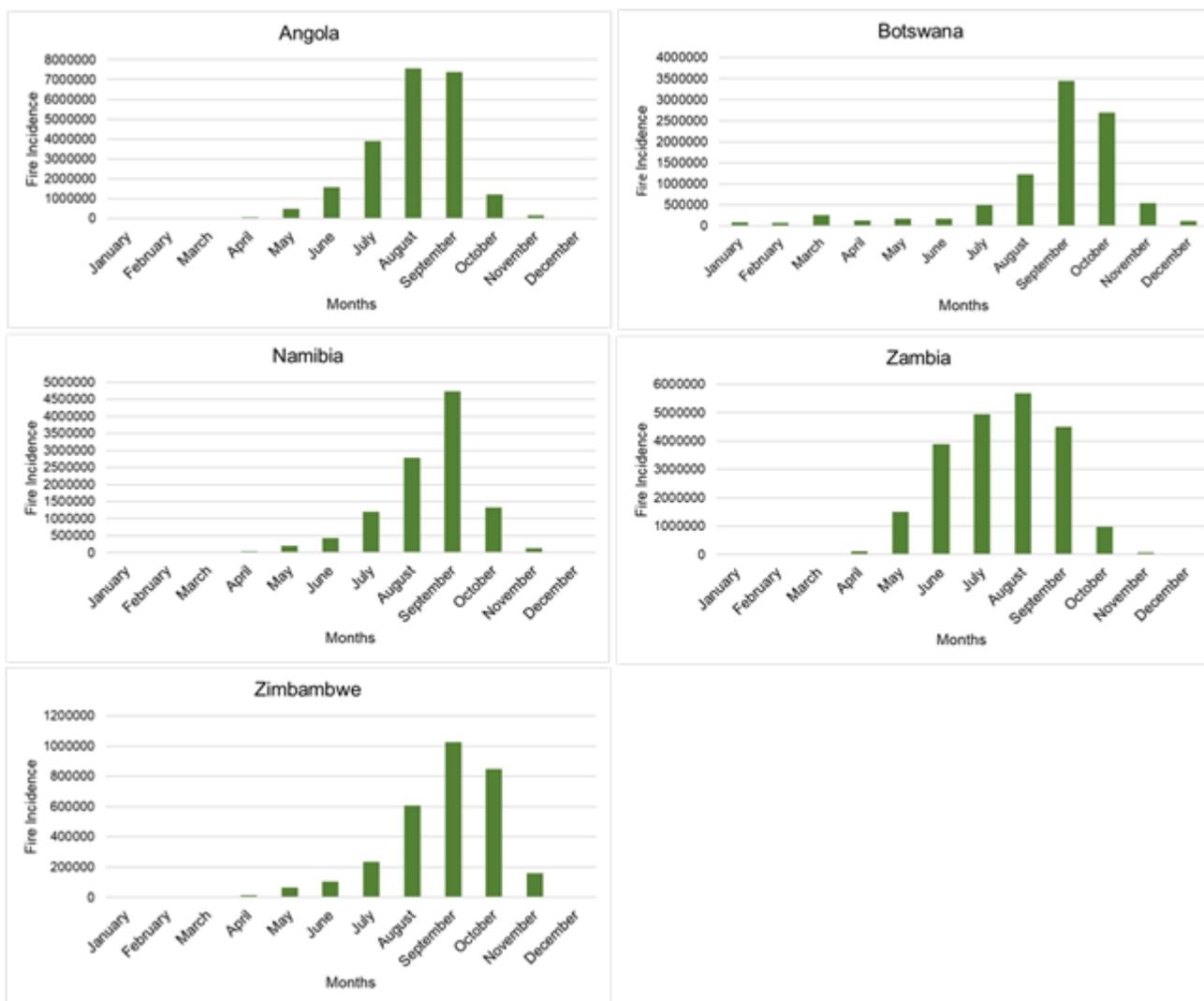


5748

5749 Fig C 1. Total area burned annually for each country of KAZA from 2002 to 2019 in
 5750 km² based on the MODIS Burned Area product data.

5751

5752



5753

5754 Fig C 2. Cumulative monthly fire frequency for all the countries from 2009 to 2019 using
5755 MODIS Active Fire product.

5756 Spatial analyses: burned area

5757 Table C 1. Estimates of the total area of burnt and unburnt areas in km² and their % from
5758 2002 to 2017 in KAZA region

Year	Burnt area(km ²)	Burnt (%)	Unburnt (km ²)	Unburnt (%)
2002	142235	27	376463	73
2003	145168	28	373530	72
2004	154911	30	363783	70
2005	1501678	29	368530	71

2006	143703	28	374995	72
2007	149365	29	369333	71
2008	165706	32	352991	68
2009	142975	28	375723	72
2010	177493	34	341205	66
2011	203849	39	314849	61
2012	184186	36	334511	64
2013	153835	30	364863	70
2014	142463	27	376234	73
2015	137259	26	381439	74
2016	127181	25	391516	75
2017	138072	27	380626	73
2018	121363	23	397335	77
2019	110173	21	408525	79

5759

5760 Table C 2. Recorded areal fire frequencies of burnt and unburnt areas in km² and their %

5761 from 2002 to 2017 in KAZA region

Year	Area (km²)	Area (%)
Unburnt	127989	25
1-2	90895	18
2-6	114222	22
6-10	87955	17

10-14	66819	13
14-17	28177	5

5762

5763 Table C 3. KAZA shifts of AI per class from 2001-2010 to 2011-2020

Class (SbAI)	2001-2010 (km²)	2001-2010 (%)	2011-2020 (km²)	2011-2010 (%)	Shift %
Arid	33957	6.75	61897	12.31	5.56%
Semi-Arid	368016	73.13	392072	77.97	4.84%
Dry Sub-humid	82464	16.39	35369	7.03	-9.36%
Humid	18769	3.73	13503	2.7	-1.04%

5764 Drought

5765 Table C 4. Drought years and drought categories of SPEI at different time scales

Year	SPEI1				SPEI3				spei2			
	moderate	severe	extreme	Σ	moderate	severe	extreme	Σ	moderate	severe	extreme	Σ
1983	2	-	-	2	-	-	-	-	-	-	-	-
1984	-	-	-	-	1	-	-	1	1	-	-	1
1985	1	-	-	1	-	-	-	-	-	-	-	-
1986	-	-	-	-	-	-	-	-	-	-	-	-
1987	1	-	-	1	1	2	-	3	3	1	-	4
1988	-	-	-	-	2	-	-	2	-	-	-	-
1989	-	1	-	1	1	-	-	1	1	-	-	1
1990	2	2	-	4	-	-	-	-	-	-	-	-
1991	-	-	-	-	-	-	-	-	-	-	-	-
1992	2	-	1	3	1	2	-	3	2	1	-	3
1993	1	-	-	1	-	-	-	-	-	-	-	-
1994	1	1	-	2	2	1	-	3	2	1	-	3
1995	2	-	-	2	3	-	-	3	1	-	-	1
1996	5	-	-	5	2	-	-	2	3	-	-	3

1997	2	-	-	2	-	-	-	-	-	-	-	-
1998	1	2	1	4	2	2	1	5	5	-	1	6
1999	1	1		2	-	1	-	1	2	-	-	2
2000	1	-	-	1	-	-	-	-	-	-	-	-
2001	2	1		3	1	-	-	1	1		-	1
2002	2	4	1	7	2	2	1	5	4	2	1	7
2003	1	-	-	1	3	1	1	5	4	3	1	8
2004	2	-	-	2	1	-	-	1	1			1
2005	2	2	1	5	-	4	1	5	-	3	1	4
2006	1	-	-	1	-	-	-	-	-	-	-	-
2007	-	-	-	-	1	-	-	1	1		-	1
2008	1	-	-	1	2	-	-	2	-	-	-	-
2009	2	-	-	2		-	-	-	-	-	-	-
2010	-	-	-	-	-	-	-	-	-	-	-	-
2011	2	-	-	2	4		-	4	3	-	-	3
2012	3	-	-	3	3		-	3	2	-	-	2
2013	2	-	-	2	1		-	1	1	-	-	1
2014	1	-	-	1	-	-	-	-	-	-	-	-
2015	5	-	-	5	5		-	5	4	-	-	4
2016	2		1	3	3	1	1	4	3	1	1	5
2017		-	-	-	-	-	-	-	-	-	-	-
2018	1	1	2	4	1	3	1	5	2		2	4
2019	4	1	2	7	6	3	2	11	4	6	2	12
Σ	55	16	9	80	47	22	8	77	50	18	9	77

5766

5767 **6 DISCUSSION**

5768

5769

5770 6.1 Introduction

5771 Changes in climate, land-cover, and land-use intensification have contributed to
5772 land degradation and desertification in tropical forest ecosystems (Allen et al.,
5773 2010; Brink et al., 2014; Brown et al., 2002). Extreme climate events and human-
5774 induced environmental changes such as deforestation can act synergistically (Le
5775 Houérou, 1996). In tropical dryland ecosystems, deforested and degraded areas
5776 can affect regional climate, and the regional climate, in turn, can amplify
5777 deforestation and forest degradation (Chagnon et al., 2004; Huang et al., 2017).
5778 Climate change and anthropogenic processes appear to amplify fire occurrence
5779 and spreading, and land degradation in dryland tropical forest ecosystems (Fox et
5780 al., 2017).

5781 As a consequence forests, plant species, and biomass have experienced changes in
5782 their species range, abundances, and shifts in their seasonality, resulting in an
5783 impacts on biodiversity and forest ecosystem services (Desanker et al., 2001).
5784 Severe dry forest biome shifts and land degradation as a result of climate change
5785 are predicted to be most severe in Southern Africa (IPCC, 2014; King, 2014).
5786 Already deforestation in Southern African countries is high, with about 1.4 million
5787 ha net forest loss annually (Darkoh, 2009; Lesolle, 2012). In Southern Africa, a
5788 range of policy options have been advocated to reduce the continuing loss and
5789 degradation of dryland forests, including expansion of protected area networks,
5790 improving governance and better management of dryland forests (Cumming,
5791 2008; Hanks, 2003; KAZA, 2014). However, high-quality, long-term, and reliable
5792 information on dryland forests and ecosystems over large areas are needed to
5793 estimate and manage the impacts of forest changes on biodiversity, biomass
5794 carbon stocks and dryland ecosystem functions accurately.

5795 There are significant advantages to forest analysis, such as remote sensing to
5796 better improve estimates of forest changes and biomass, characterise forest
5797 structures, and to understand the dynamics of tropical dryland forests in the
5798 context of climate changes (Andela et al., 2013; Donoghue, 2002; Lu, 2006).

5799 However, such approaches that integrate forest studies and remote sensing need
5800 to be replicated and tested across different regions, geographic scales, and over
5801 relevant time periods to change (decades) (Lehmann et al., 2015; Mitchard et al.,
5802 2013). Existing literature shows limitations in terms of methodological
5803 inconsistency and generalisation, and constraints on the spatial and temporal
5804 scales of investigation which limits the actual effectiveness of integrating remote
5805 sensing into the tropical dryland forest assessment (Foody et al., 2001; Woodcock
5806 et al., 2001).

5807 Given these challenges, this thesis set out to overcome such limitations to
5808 contribute to the ability to characterise above ground biomass, forest structural
5809 parameters, land cover change, and disturbances in the context of climate change
5810 in the dryland forests of the Kavango Zambezi Transfrontier Conservation Area
5811 (KAZA TFCA) of Southern Africa. KAZA is a conservation area with over thirty-six
5812 protected areas including national parks, game reserves, community conservancies
5813 and game management areas. It established to merge fragmented wildlife habitats
5814 into an interconnected mosaic of protected areas and transboundary wildlife
5815 corridors, to enhance the free movement of animals across international
5816 boundaries and to create economic development in the region (Cumming, 2008;
5817 Stoldt et al., 2020). However, the region is experiencing large-scale shifts in
5818 vegetation cover, biomass degradation and increased vulnerability to climate
5819 change, manifesting through altered disturbance regimes which hold significant
5820 implications for forest biodiversity and ecosystem function of this region. By
5821 addressing the above limitations, the thesis explored the use of novel application of
5822 improved satellite remote sensing approaches and datasets including optical and
5823 SAR, and their combination, that can in principle improve estimates of forest
5824 biomass and structural parameters, disturbances, and climatic impacts at a
5825 regional scale.

5826 The research presented here was structured around three research priorities
5827 identified in a systematic review (chapter 2, David et al., 2022a). Specifically, the
5828 review identified a need to address (i) the feasibility of combining SAR, optical
5829 remote sensing data and ground measurements to estimate the forest stand
5830 parameters, (ii) vegetation dynamics, and spatially detailed patterns of change
5831 using different remote sensing proxies, (iii) characterisation of spatiotemporal

5832 changes in climate and fire using different climatic and vegetation time series data
5833 at regional scale. By combining improvements across each of the three research
5834 priorities, this thesis aims to combine ground measurements and multiple remote
5835 sensing including climate, fire, and vegetation data to enable estimates of forest
5836 biomass, and changes in dryland forests, across different spatial and temporal
5837 scales.

5838 6.2 Suitability of remote sensing data

5839 6.2.1 Combining sensors

5840 Remote sensing techniques can be applied to detect changes, estimate forest
5841 structural parameters including biomass, and to monitor the extent in tropical
5842 dryland forest cover at different spatial scales, from individual trees, large blocks
5843 of the unbroken canopy, to regional and pantropical or even global extents (Baccini
5844 et al., 2004). However, there are large discrepancies in the methodologies used to
5845 quantify forest structural changes in tropical dryland forests, including attempts to
5846 relate forest cover and biomass to optical remote sensing measurements (Mitchell
5847 et al., 2017; Sexton et al., 2016). In the research presented in this thesis, the use of
5848 the medium to coarse resolution optical data, such as NASA's MODIS sensor,
5849 demonstrate an approach to monitoring forest cover change and degradation due
5850 to clear-cutting, fire, and drought (chapter 4 & 5), but also showed that certain
5851 types of change remain difficult to detect. The quantitative assessment of the
5852 ability of sensors with different spatial resolutions, and the integration of multiple
5853 datasets from optical and SAR sensors, to improve estimates of forest biomass and
5854 structures in the dryland ecosystems are limited and have not been carried out in
5855 Southern Africa (Chapter 2, David et al., 2022a). Consequently, there is an
5856 opportunity to exploit the benefits of different remote sensing in this context,
5857 alongside a need to consider the trade-offs between spectral and spatial resolution,
5858 and geographic coverage, when estimating biomass and forest structural
5859 parameters in dryland forests ecosystems (chapter 2, David et al., 2022a).

5860 This thesis combined freely available Sentinel 1 (S1) SAR, Sentinel 2 (S2) and
5861 Landsat 8 (LC8) multispectral imagery to estimate biomass at regional level and
5862 the relatively fine resolution of S2 (10 m pixels) which reduced the mixed pixel

5863 problem observed in medium spatial resolution data (30 m pixels; e.g. LC8), and
5864 led to an increase in the precision of biomass estimation compared to using single
5865 sensors alone (Chapter 3, David et al., 2022b). In this research, AGB is more
5866 accurately estimated when adding Sentinel 1 SAR and Sentinel 2 to a Random
5867 Forest algorithm (instead of using multispectral or SAR on its own). For example,
5868 this research found that SAR data was better at detecting aggregations of
5869 individual trees in the dryland landscape than optical data. But this research also
5870 found that SAR data alone overestimated AGB in the dryland area (Fig 3.7, Chapter
5871 3, David et al., 2022b). A similar problem of SAR overestimating AGB was noted by
5872 other studies such as Zhang et al. (2019), and this problem was overcome by fusing
5873 SAR and multispectral data in this thesis (Fig 3.7, Chapter 3, David et al., 2022b).
5874 The comparison of recently published pan-tropical AGB datasets (Avitabile et al.,
5875 2016; Baccini et al., 2017; Bouvet et al., 2018) with the regional scale maps
5876 produced in this thesis, using a combination of optical and SAR datasets with DBH
5877 and tree height measurement of more than 4300 tree ground-validation, resolves
5878 realistic spatial patterns in estimated biomass for the study area (Fig. 3.5, chapter
5879 3, David et al., 2022b). Here, S1 SAR and S2 data were combined to show in fine
5880 detail AGB ranges, including a mix of very low biomass (due to different degrees of
5881 degradation) to intermediate biomass for certain areas with very large but
5882 scattered trees, through to higher biomass areas in high-density forests (Fig.3.7,
5883 chapter 3, David et al., 2022b).

5884 Partly, this study has improved biomass estimation by investigating the
5885 capabilities and correlation of AGB with diverse spectral bands from Sentinel 2,
5886 Landsat 8, and radar backscatter polarisation from Sentinel 1 SAR data. For optical
5887 data, although NDVI and EVI remain two of the most widely used vegetation
5888 indices, they were outperformed by the red edge index (NDRE1) and the green
5889 channel index (GNDVI) in estimating AGB for dryland forests (Table 3.3, Chapter 3,
5890 David et al., 2022b). NDVI is utilised in biomass mapping by different studies such
5891 as (Cunliffe et al., 2020; Gizachew et al., 2020), however this study detected
5892 saturation in NDVI when the spectral values remain insensitive to increases in
5893 forest AGB value beyond 80 Mg/ha (Fig. 3.7, Chapter 3, David et al., 2022b).
5894 Gitelson et al., 1996 found the green channel index to be much more sensitive to
5895 the Chlorophyll concentration and enabled precise estimation of pigment

5896 concentration than the original "red" NDVI. The red edge-based indices were found
5897 to have a better correlation with the photosynthetic activity of the tree canopy and
5898 leaf cell structure reflection (Cho et al., 2008; Mutanga and Skidmore, 2004).

5899 There has been concern that structural variation and understory herbaceous cover
5900 reduce measurement precision when mapping from remotely sensed estimates in
5901 semi-arid savanna and dryland forests (Baccini et al., 2004; Santos et al., 2002).
5902 Combining information from optical sensors that describe photosynthetic activity
5903 (e.g., through various vegetation indices) with SAR-derived information on forest
5904 structure and biomass in winter months, brings the benefits of higher spectral
5905 resolution, and compensates for the shortcomings of using single data products
5906 alone that are commonly subject to saturation, temporal gaps, and clouds cover
5907 (chapter 3, David et al., 2022b). Comparing the performance of ML and RF
5908 regression algorithm and considering the collinearity between predictor variables
5909 also improved biomass mapping and reduced uncertainty in the models. ML
5910 regression overestimated low values, and underestimated high biomass values,
5911 which is also common in previous studies using ML (Fuchs et al., 2009; Zheng et al.,
5912 2007). RF had a positive impact on the biomass estimation accuracy, and
5913 performed better than ML regression, reducing the RMSE for the estimation
5914 models by almost 50%. Therefore, it is important to assess the ability of combining
5915 improved methods and freely available optical and SAR data with sample plot
5916 survey data/forest inventory to characterise large-area biomass distributions to
5917 provide regional estimates of forest carbon stocks. Although this study has
5918 improved AGB estimation in dryland forests, there is room for improvement, for
5919 example RF regression model estimated medium and high-density forests with
5920 good accuracy but showed variation in low-density forests that include
5921 understoreys and low herbaceous cover such as grassland often with relatively low
5922 canopy density. This study did not consider multitemporal seasonal time series
5923 data and texture information from images in AGB modelling which provides
5924 additional information on seasonal variations and reduce the impacts of
5925 heterogeneity as suggested by studies in temperate and evergreen broad leaf
5926 forests (Sarker and Nichol, 2011; Zhu and Liu, 2015). Incorporation seasonal time
5927 series and textural information in AGB modelling in dryland forests could improve
5928 biomass modelling and is a topic for future research. Despite these limitations, this

5929 study aimed to improve the performance of the regional forest biomass model and
5930 can provide a reference and support for future plans of relevant forestry
5931 departments.

5932 6.2.2 Spatial scale

5933 In sensor integration, issues of scale are critical for biomass and habitat mapping,
5934 where the adequacy of spatial resolution to the problem in hand is key. Pan-
5935 tropical and global maps derived from satellite imagery can show large uncertainty
5936 in the extent and distribution of tropical dryland forest recorded, and typically
5937 underestimate the extent of forest cover and biomass in dryland areas (Bastin et
5938 al., 2017). This is illustrated by the substantial spatial disagreements between
5939 recent satellite-based global (Giri et al., 2005) and pantropical forest maps
5940 (Mitchard et al. (2013), and is further hindered by the relative scarcity of large-
5941 scale studies assessing forest cover in dryland biomes (Chapter 2; David et al.,
5942 2022a). The distribution of AGB and precision varied between this study and
5943 pantropical maps (Fig. 3.9, Chapter 3 David et al., 2022b). The observed
5944 discrepancies may have arisen due to satellite data characteristics (such as spatial
5945 resolution), unavailability of cloud-free images, availability of ground-truth
5946 information, and forest definitions (such as tree cover thresholds) used in the
5947 analyses (De Sy et al., 2012). In the research presented in this thesis, comparing
5948 three recent pan-tropical forest maps to estimate above ground biomass (AGB)
5949 revealed important differences: 0-30 Mg/ha using the pan-tropical AGB map (1 km
5950 resolution), 0-50 Mg/ha using Landsat (30 m), 0-70 Mg/ha using ALOS PALSAR
5951 (25 m); and 0-145 Mg/ha from this study using combined optical and SAR (10 m)
5952 (Fig. 3.8, Chapter 3, David et al., 2022b). This research has a high mean estimate of
5953 biomass of 51 mg/ha in comparison to Bouvet et al. (2018) using radar data, that
5954 estimated mean biomass of 26.7 Mg/ha which is 50 % less compared to this study
5955 mean biomass (Fig. 3.9, Chapter 3, David et al., 2022b). Avitabile et al. (2016) only
5956 estimated the mean biomass of 5.92 Mg/ha for the study area and predicted AGB
5957 values in the 0 to 30 Mg/ha range.

5958 In this research, biomass mapping at a regional scale using SAR backscatter in
5959 conjunction with the strategically positioned optical bands (red edge wavebands)
5960 improved estimation at high AGB values and allowing the identification of small-

5961 scale degradation patterns of biomass such as roads compared to either sensor
5962 alone (Fig. 3.11, chapter 3, David et al., 2022b). In addition, the AGB model from
5963 this study showed that biomass for dryland forests exceeds estimates derived from
5964 pan-tropical products which underestimate biomass and forests in dryland
5965 ecosystems of less-studied areas such as the KAZA region, which are often
5966 neglected in this type of analysis (Chapter2; David et al., 2022).

5967 However, the advent of free Landsat data combined with improving computational
5968 and data storage capabilities mean that large area Landsat land cover products are
5969 increasingly being generated. In this study, a large volume of Landsat data using
5970 high quality training data derived from the field survey was demonstrated using
5971 Google Earth Engine and Random Forest classifier (Fig. 4.13-4.14, Chapter 4). A 30
5972 m Landsat land cover map was generated and was able to detect large scale
5973 deforestation and changes with an acceptable classification accuracy >80%
5974 (Chapter 4). This study used medium spatial resolution Landsat data because land
5975 cover maps based on coarse spatial resolution imagery (nominally at 500 or 250
5976 m) limits the ability for detecting changes and provide a highly generalised
5977 representation of land cover and ultimately land cover change, over large areas
5978 (Hamunyela et al., 2020; Zhu and Woodcock, 2014). Using a two point in time
5979 classification is useful to detect changes in land cover, however such bi-temporal
5980 change detection approach can have some limitation of potentially masking
5981 considerable within-year vegetation dynamic and variations (Chapter 2; David et
5982 al., 2022a). For example, this type of change estimates risks interpreting natural
5983 phenological change as actual changes in the land cover (DeVries et al., 2015).
5984 Therefore, this study has moved from a relatively static, bi-temporal view of
5985 change toward a more continuous mapping of vegetation dynamics to improve the
5986 detection of disturbance's spatiotemporal patterns using change detection
5987 algorithms of BFAST and BEAST (Chapter 4). These change detections algorithms
5988 were useful in assessing small scale deforestation, degradation, and regrowth by
5989 capturing vegetation changes during the year and over longer time-periods at the
5990 regional scales (Chapter 3, David et al., 2022b). Such large area analyses on change
5991 detection conducted in this research can be used to adjust and update global land
5992 cover and biomass estimates. The pan-tropical and global maps are limited in their
5993 spatial resolution and temporal coverage, and most of them provide inadequate

5994 information for policymaker regarding restoration intervention efforts that are
5995 needed for regional- or local-scale restoration projects (Abbas et al., 2020). At
5996 regional-to-national scales, the adoption and application of satellite technology is
5997 highly variable across countries in the tropics. For example, many countries across
5998 Southern African are faced with scarcities of technology, finances, and computer
5999 time limitations, preventing the use of conventional downloaded high-resolution
6000 satellite data (chapter 2, David et al., 2022a). To overcome these limitations, the
6001 thesis utilised the recent developments in cloud computing platforms, such as
6002 Google Earth Engine (GEE), which have greatly increased access to pre-processed
6003 optical, SAR, and climatic datasets, enabling a comprehensive analysis of multiple
6004 threats including deforestation, and degradation from fire and climatic impacts on
6005 vegetation at regional scale (chapter 3, 4 & 5).

6006 6.2.3 Temporal scale

6007 To characterise vegetation and climate interactions, changes in forest cover must
6008 be quantified over different temporal scales, to capture both short term and
6009 gradual changes experienced by dryland ecosystems (chapter 2, David et al.,
6010 2022a). The study has shown that the impact of degradation varies from fine-scale
6011 structural changes in canopy, to broad-scale rapid loss of biomass (chapter 3 David
6012 et al., 2022b). Several methods and techniques are proposed in the literature to
6013 address land cover characterisation and forest cover change. Mapping changes
6014 through comparing images at two different times, based on discrete classification,
6015 are one of the most common forms of remote sensing change detection utilised
6016 (Jensen, 1996). This is despite change detection between two dates (pre-and post-
6017 disturbance imagery) is generally limited to the detection of broad-scale changes
6018 (chapter 2, David et al., 2022a).

6019 Change detection is more powerful, however, when the signal is analysed over a
6020 long time period (decadal, or longer) in a continuous and consistent manner,
6021 providing an improved signal-to-noise ratio, detection of subtle/transient changes
6022 in forest cover or phenology and condition (Huang et al., 2009; Verbesselt et al.,
6023 2012). Here, the ability to make precise estimates of change in dryland forest
6024 distribution was improved by combining a long high frequency time-series of
6025 MODIS data with pixel-based break detection (chapter 4). The abrupt changes (e.g.,

6026 deforestation), gradual change (e.g., forest degradation), and other slow processes
6027 (e.g., seasonal changes) in response to wildfire, disease, and climate variability
6028 were each detected effectively (chapter 4). In the research presented in this thesis,
6029 the fire estimates in the KAZA region reveal that between 2002 and 2019, about
6030 390,678 km² (75%) of the landmass is classified as fire-affected for at least one
6031 time in the monitored period, leaving 127,989 km² (25%) of the area not affected
6032 by fire. This showed that national parks are more affected by high fire occurrence
6033 than other protected areas (chapter 5). As shown in this thesis, the failure of
6034 vegetation to recover and browning intensification following drought years
6035 reaffirm the consistent multiple threats from severe drought, soil moisture deficit,
6036 and high fire reoccurrence on dryland vegetation responses (chapter 4 & 5).
6037 Consequently, this combined approach to change assessment using long term
6038 monitoring (> decadal), as used here, allows spatiotemporal aridity information to
6039 be extracted, thereby enabling quantification of vegetation shifts and increased
6040 risks of land degradation and drying risk that cumulatively occur over many years
6041 in the dryland forest ecosystems (chapter 4 & 5). In addition to visual detection
6042 validation of historic change using high resolution data proposed by Cohen et al.
6043 (2010), this study demonstrated that the change estimates and precision from
6044 BFAST can be validated and improve using a stratum-based estimate of variance
6045 that will be more precise than using simple random sampling (Stehman and
6046 Czaplewski, 1998; Stehman, 2009; Potapov *et al.*, 2014). As shown in this study
6047 (Chapter 4), the large-scale changes such as clear felling of woodland for
6048 agriculture are comparable while more subtle changes such as land degradation
6049 were detected by BFAST better than interval-based per-pixel classification. Since
6050 this study used a rather small sample size (341 points), the change estimates need
6051 to be tested with training data of a larger sample size to be conclusive. In addition,
6052 the research conducted here can be improved with recently developed new
6053 algorithm such as Continuous Change Detection and Classification (CCDC) that
6054 make better use of the temporal domain of Landsat data to improve both
6055 continuous change detection and land cover classification at medium spatial
6056 resolution and high temporal frequency (Zhu and Woodcock, 2014) . CCDC use all
6057 available Landsat clear observation data to classify land cover from multiple time
6058 period. In addition to land cover classification from any time period in history, it
6059 can monitor large scale deforestation and small-scale changes such as degradation

6060 in near real time as the algorithms updates the time series model every time new
6061 observations are available (Arévalo et al., 2020).

6062 6.2.4 Ecological relevance of mapping changes

6063 There are two parts to the problem that this research has addressed; one was to
6064 show changes within the forest ecosystems (deforestation and degradation) and
6065 the other was to characterise forest structural parameters and to estimate biomass
6066 distribution in the forest. In both situations, methodologically consistent
6067 approaches were identified as one of the important needs to improve upon current
6068 monitoring of dryland forests (Mitchell et al., 2017); (chapter 2, David et al.,
6069 2022a). At the regional scale, monitoring poses a number of methodological
6070 challenges including the lack of quantitative, spatially explicit, and statistically
6071 representative methods, which have previously resulted in simplistic
6072 representations (Coppin et al., 2004). Therefore, as shown in this thesis, testing
6073 different models and their suitability to characterise trends and phenological
6074 patterns can reveal suitable algorithms for estimating dryland forest covers
6075 (chapter 4). Furthermore, Foody et al. (2003) and Woodcock et al. (2001) have
6076 pointed out concerns of generalising or transferring methods derived from
6077 remotely sensed imagery over both space and time, based on lessons learned in far
6078 better-studied ecosystems. Generalisation also limits the interpretation of change
6079 patterns and the impacts that these changes will have on the biodiversity of
6080 forests, conservation of wildlife habitats conservation, and dryland ecological
6081 function (chapter 2, David et al., 2022a).

6082 Whilst models based on remote sensing data can show promising results in
6083 different ecosystems (e.g., rain forests), it can fail to detect non-linear vegetation
6084 patterns (e.g., degraded areas) in largely climate and fire-driven ecosystems, such
6085 as drylands, as shown here (chapter 4). This observation justifies the importance
6086 of testing and utilising a range of sensors and vegetation indices for forest
6087 structure parameter and change detection estimation. The results in this thesis,
6088 reveals that spectral indices based on the red edge spectral region and green
6089 normalised vegetation index (GNDVI) have a stronger relationship skill in
6090 describing dryland forests than conventional NDVI (chapter 3 & 4). Consequently,
6091 there is good reason to believe that NDVI is not an ideal indicator of stress

6092 response in dryland forests despite the widespread use of this index in studies of
6093 forest health decline. In the research presented in this thesis, indices based on fire,
6094 such as the fire frequency index, and several climatological indices, such as SPEI
6095 and the aridity index, were tested in dryland forest cover to assess vegetation
6096 response to environmental change over large areas (chapter 5). This was
6097 undertaken because testing different algorithm and sensor combinations can help
6098 detect specific strengths and limitations for a dryland ecosystem, particularly
6099 where climate change and variability negatively affecting dryland vegetation and
6100 biomass (chapter 3, 4 & 5).

6101 Oliveira et al. (2021), working in Brazil, modelled biomass in tropical dryland
6102 forests using linear regression, and recommended testing the ability of non-
6103 parametric machine learning algorithms over linear regression analysis in dryland
6104 forests. Some image classification algorithms and traditional statistical approaches
6105 make unrealistic assumptions about the distributional properties of forests, and
6106 are unable to describe underlying fluctuating trends as these models assume
6107 vegetation trends to be quasi-linear (i.e., regular, or stable seasonality) (Grogan et
6108 al., 2016). In this research, multivariate machine learning models, integrated with
6109 stepwise-regression methods, enabled better adjustment and fit to ground
6110 measurement, which was tested against more than 4300 individual trees (Chapter
6111 3, David et al., 2022b). This approach enabled both the interpretation and
6112 validation of remotely sensed forest structure and biomass estimates, providing a
6113 very high R^2 of 0.95 and a low RMSE error of 0.25 Mg/ha (Chapter 3, David et al.,
6114 2022b).

6115 Despite prior concerns raised over the need to use ground truth verification for
6116 estimating biomass and changes in forest mapping (Grainger, 2008), there are few
6117 vegetation-related studies that link vegetation estimates to field measurements
6118 and forest inventory data (Chapter 2, David et al., 2022a). As shown in this thesis,
6119 obtaining field data for validation of remote sensing data in dryland ecosystems of
6120 protected areas, such as National parks, can be challenging because many areas are
6121 very remote and often dangerous to visit due to hazardous, and if present and in
6122 some cases unexploded landmines (chapter 3, David et al., 2022b). Consequently,
6123 most detected changes in the spectral signature that occur due to an increase in
6124 woody biomass, deforestation and forest degradation in the dryland ecosystems of

6125 Southern Africa have not been validated (chapter 2, David et al., 2022a). The
6126 optical sensors at 250 m-1 km resolution (e.g., MODIS) used here make consistent
6127 and frequent measurements over large areas building a long time series, which
6128 helps identify locations of active forest change ('hotspots') with good precision and
6129 that was validated against ground-truth data (chapter 4). However, where
6130 possible, important areas of change and in particular for key forest structural
6131 parameters, such as AGB that are needed for baseline carbon stock maps, there are
6132 benefits to further ground measurement for validation and finer spatial resolution
6133 data. Maps of AGB, if sufficiently detailed, can assist conservation managers,
6134 practitioners, and policymakers to formulate specific interventions (e.g., corridor
6135 planning, tree thinning, fire control, biodiversity surveys) that are appropriate to
6136 support the conservation of forest habitats and their management.

6137 6.3 Recommendation for policy and practice

6138 Dryland forests in protected areas such as KAZA face an increasing number of
6139 threats ranging from those originating from climate change and competing
6140 economic pressures, especially when they span international borders. Learning
6141 from this research and past experience on dryland forests in KAZA (Cumming,
6142 2008; WWF, 2016), there are often conflicting views related to the amount of
6143 biomass and changes in forest cover in dryland ecosystems. These differences are
6144 however not confined to science only, but also between the understanding of
6145 dryland monitoring programmes and policies (Appendix A: N8 AgriFood policy
6146 brief). These challenges present also an opportunity for a mutual benefit; with
6147 more freely accessible data, such as that explored in this thesis, scientists and
6148 policy makers may now refine their focus to share knowledge on the management
6149 of forestry, and the interface with land uses, including wildlife management and
6150 ecosystem function (Sexton et al., 2016). Based on the findings of this research,
6151 along with the challenges and lessons learnt throughout, there are three
6152 recommendations that can be made for policy and practice, which can
6153 subsequently be used in decision making of the KAZA region, and beyond, in
6154 Southern Africa more widely.

6155 First, a large part of the knowledge base for dryland forest landscapes in Southern
6156 Africa is derived from research generated outside of Africa (chapter 2, David et al.,
6157 2022a), and so there is an opportunity to change academic narratives by working
6158 in partnership with local organisations to foreground local research and
6159 knowledge. Given the growing technical capacity for monitoring, reporting and
6160 verification, there is a need to shift the focus to producing and sharing transparent
6161 research maps with resource managers. Technology platforms such as the cloud-
6162 based image-analysis pipeline using freely available remote sensing imagery, as
6163 used here, is an opportunity to overcome the limitations previously enforced by
6164 data scarcity, volumes and costs, and can enhance substantially the collective
6165 knowledge of dryland forest environments (chapter 3, 4 &5). Sharing of research
6166 outputs and often captivating satellite imagery with the news media to inform
6167 citizens and to create awareness about the extent and location of deforestation
6168 hotspots is a potentially important component of the KAZA monitoring
6169 programme. If such information can influence local practitioners and public
6170 opinion, it can exert pressure on policymakers in democratic societies to
6171 strengthen enforcement and to tighten regulations around forest management and
6172 protection. Improved monitoring of forest cover itself is unlikely to produce any
6173 change in behaviour unless it is linked to research, forest management and
6174 practice, and all key stakeholders in these regions (Olsson et al., 2019).

6175 Second, the process of monitoring dryland forests could be enhanced through the
6176 greater involvement of stakeholders in the modelling process itself. Building on the
6177 existing regional networks in the KAZA region, workshops could be facilitated
6178 between academic scientists, decision makers and practitioners to identify current
6179 gaps in knowledge, data requirements and training needs. Most studies in KAZA
6180 region on drought, fire and vegetation analyses are done at local level (e.g., within
6181 a single community) and others cover only a part of the KAZA region (Mpakairi et
6182 al., 2019; Pricope et al., 2012), making it impossible to compare to a regional
6183 perspective. Similar research studies on tropical dryland forest change analyses at
6184 large(r) scales (chapter 3, 4 & 5) are needed, ideally retaining fine spatial
6185 resolutions and a longer temporal duration. A significant proportion of studies in
6186 Southern Africa have been undertaken in Kruger National Park, leaving many other
6187 national parks and protected areas in KAZA relatively understudied. Furthermore,

6188 future efforts to estimate changes in important variables such as forest cover and
6189 biomass, need not be restricted by country boundaries but can extend across the
6190 less well studied private and international protected areas (chapter 2, David et al.,
6191 2022a). Such workshops would allow stakeholders and other users to have an
6192 opportunity to present their work, examine the research outputs in their area of
6193 interest with reference to existing or predicted scenarios of future change.
6194 Consequently, such structures can harness a wealth of existing research and
6195 expertise and help to provide a support network to stimulate high quality
6196 published outputs from scientists, and to facilitate input from local experts and
6197 practitioners (Appendix A: N8 AgriFood policy brief).

6198 Lastly, the KAZA region concept recognises that borders are political rather than
6199 ecological and aims to ensure that key ecological processes continue to function
6200 where borders have previously divided ecosystems and/or wildlife migration
6201 corridors. Based on my own engagement with stakeholders such as WWF Namibia
6202 and the KAZA secretariat, Botswana, there is a willingness to work together and
6203 support research, across KAZA region to ensure such information will continue to
6204 support future conservation efforts and economic development in countries such
6205 as Angola, Botswana, Namibia, Zambia, and Zimbabwe. Such interdisciplinary
6206 knowledge and evidence-based policy, generated through partnership and data
6207 sharing, is urgently needed. In this region, climate change will cause large-scale
6208 shifts in vegetation cover and biomass degradation resulting in increases in the
6209 vulnerability of ecosystems across large areas of dryland forest in Southern Africa,
6210 which represents risks faced by all stakeholders.

6211 6.4 Future work

6212 The work presented in this thesis offers a platform to improve the understanding
6213 of biomass, disturbance patterns, and climate change relationships in dryland
6214 forest ecosystems. The thesis considered the factors that cause changes in forest,
6215 biodiversity, and ecological function. Numerous spectral indices have been
6216 developed to assess vegetation cover and growth dynamics, which provide useful
6217 insights for applications in forestry, biodiversity conservation, agriculture, and
6218 other related fields. However, most of these indices are derived from a limited

6219 selection of species and are typically developed in often quite different regions and
6220 ecosystems. The research presented in this thesis tested optimum spectral indices
6221 from multispectral data in dryland forests that improve the ability to effectively
6222 estimate forest stand characteristics (chapter 3, David et al., 2022b), identify shifts
6223 in vegetation dynamics and the timing of key phenological events (chapter 4), and
6224 helps us to assess forest health and vulnerability to different stressors, including
6225 fire and climate change (chapter 5).

6226 One potential future avenue for research is different sensors. For example,
6227 airborne imaging spectroscopy can provide up to 2000 contiguous narrow-band
6228 spectral information across the solar spectrum, often at fine spatial resolution
6229 (Morley et al., 2020). Asner et al. (2016) used airborne imaging spectroscopy and
6230 satellite data trained on spectroscopy data to estimate water lost from California's
6231 forest ecosystems over the drought years between 2011 and 2015. To detect a
6232 decline in forest cover and shifts in the timing of phenological events requires
6233 spectral indices that are sufficiently sensitive to chlorophyll content, and in
6234 particular to capture the response of trees to a stress event. Therefore, further
6235 research could explore the potential to relate dryland forest cover to hyperspectral
6236 data, to identify more sensitive spectral bands corresponding to different
6237 vegetation species, and to identify the most important wavelength regions for
6238 predicting drought and fire-sensitive species.

6239 Optical sensors have recently been presented as a viable alternative for estimating
6240 biomass and carbon stock in tropical forests, due to their global coverage,
6241 frequency of capture, and cost-effectiveness (Kumar et al., 2015). Furthering the
6242 research presented in this thesis, the primary challenge of MODIS data, despite its
6243 high temporal resolution, is the large spatial resolution of between 250 m and 500
6244 m. The temporal resolution of Landsat (16-days, and now 8 days with the recent
6245 launch of Landsat 9), which is often occluded by cloud cover can be a major
6246 obstacle, despite the relatively fine spatial resolution of 30 m. The integration of
6247 MODIS with Landsat to combine fine spatial and temporal resolutions could
6248 therefore be used in future to improve the mapping of forests patterns of changes
6249 and disturbances.

6250 On the other hand, there is a need to incorporate satellite imagery with a fine
6251 spatial resolution information for estimating biomass and carbon stock. For
6252 example, the thesis has shown that Sentinel-2 data show a better ability to improve
6253 the estimation of above ground biomass and forest structure in tropical dryland
6254 forests as compared to Landsat-8 (Chapter 3, David et al., 2022b). Despite
6255 improvements in the spatial precision of optical data, such as Sentinel-2, improved
6256 characterisation of forest structure may not be possible using multispectral
6257 imagery alone due to the spectral similarities between structural classes.
6258 Furthering the research presented in this thesis by improving the characterisation
6259 of forest structure using a fusion of data such as that from airborne light detection
6260 and ranging (LiDAR), collected from airborne platforms, SAR, and/or other forms
6261 of optical data, could further advance the understanding of the detailed structural
6262 information and accurate vertical distribution of canopy in tropical dryland forests.
6263 Li et al. (2017) highlighted that metrics derived from a LiDAR point cloud led to
6264 improved biomass estimates at nearly all resolutions in comparison to raster-
6265 derived metrics in the drylands of the US. Despite these benefits, LiDAR data are
6266 not widely available in many dryland ecosystems, particularly in developing
6267 countries, and the acquisition of new data sets can be prohibitively expensive.
6268 However, new satellites such as the Global Ecosystems Dynamics Investigation
6269 (GEDI) LiDAR and the Multi-footprint Observation Lidar and Imager (MOLI)
6270 promise space-borne imaging with laser altimetry, which can contribute to the
6271 development biomass, forest distribution, and its relationship with climate in
6272 tropical dryland forests (Coyle et al., 2015; Kimura et al., 2017). MOLI includes
6273 LIDAR to measure canopy height, vegetation phenology, vegetation indices, and an
6274 optical imager to measure the position of the canopy for improving biomass
6275 estimation (Sakaizawa et al., 2018). GEDI estimates mean aboveground biomass
6276 density at 1 km grid and provides metrics of tree height and canopy cover at a
6277 footprint of 25 m (Dubayah et al., 2020), and can be used in fusion with other
6278 existing radar data such as Sentinel-1, ALOS PALSAR, along with other optical data
6279 sets such as from Landsat and Sentinel-2. The successful unification of forested
6280 vegetation monitoring data with detailed information on three-dimensional (3-D)
6281 structure would represent a significant improvement in the capacity of ecologists
6282 and decision makers to estimate the impacts of forest cover change on

6283 biodiversity, wildlife habitat, and forest management approaches more widely, and
6284 should be a core focus of future research.

6285

6286 6.5 Conclusion

6287 In this thesis, the close integration of field data, Sentinel-1 SAR, Landsat-8 and
6288 Sentinel-2, regional climate and MODIS time-series data, has enabled a more
6289 precise estimation of biomass and forest stand structural parameters, which has
6290 enabled the quantification of changes in vegetation patterns. The long-term
6291 changes and trends identified enabled the characterisation of various influences,
6292 from climate, fire and animals to be assessed in terms of their impact on forest
6293 biodiversity and dryland ecosystem function. The KAZA region has the highest
6294 population of elephants in Africa, which have a destructive influence on forest
6295 diversity and density, forest structure, and the wider landscape. The increasing
6296 human population, occurrence of wildfires, and changing climate variability, set in
6297 a wider context of limited levels of development, are aggravating forest and
6298 vegetation decline. Such declines risk the loss of dryland tree species, wildlife, and
6299 pose a significant threat to dryland biodiversity. Ongoing monitoring of changes
6300 within dryland forest ecosystems integrating open-access Earth observation data
6301 alongside improved methods of analysis is vital in the context of future climate
6302 change, and the expected impacts of this on dryland forest areas. The key findings
6303 of the research are therefore summarised as follow: The thesis has demonstrated
6304 that using a combination of radar backscatter in conjunction with strategically
6305 selected multispectral optical imagery at fine resolution (10 m pixels) significantly
6306 improved above ground biomass and forest stand structural parameter
6307 estimations, and reduced saturation effects in areas of high biomass, across large
6308 areas with mixed forest stands compared to using single sensors alone. This part of
6309 the thesis highlighted the importance of considering spatial scale when mapping
6310 forest characteristics that are relevant to management of biodiversity and wildlife
6311 in dryland forests, which can help improve the wider understanding of these
6312 habitats. The study demonstrated that long-term monthly time-series analysis in
6313 combination with change detection models (Breaks for Additive Seasonal and

6314 Trend (BFAST) and the Bayesian analysis (BEAST)) can identify abrupt and
6315 gradual changes associated with fire, drought and seasonality driven by climate
6316 changes and clear-cutting. Critically, the results emphasised the importance of
6317 considering the sensitivity of the chosen vegetation indices, and the need to adopt
6318 advanced change detection methods, such as BEAST algorithm, that can fully
6319 characterise the complex non-linear dynamics of dryland forest ecosystems. This
6320 research has demonstrated that an analysis of long-continuous time series data
6321 describing drought, water stress and fire impacts across large spatial scales can
6322 reveal regional trends in vegetation change, drying patterns, and the expansion of
6323 drylands (arid and semi-arid). These findings highlighted the importance of a
6324 precise and timely assessment of the intensity and geography of impacts of
6325 droughts within and across conservation areas, both at present and into the future.
6326 This approach therefore creates a valuable evidence base for understanding the
6327 multiple and interacting impacts on forest biodiversity, wildlife and ecosystem
6328 function at a regional-scale, which has hitherto not been possible, and which is
6329 essential for more effective management of these critical ecosystems.

6330

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Appendix A

A policy brief published with N8 AgriFood at <https://policyhub.n8agrifood.ac.uk/>



Remote sensing could enable more evidence-based policy to monitor and manage tropical dryland forests

Key Messages

- Remote sensing and Earth Observation technologies help to assess and monitor forest ecosystems and provide spatially explicit, operational, and long-term data to assist the sustainable use of tropical environment landscapes.
- However, few studies assess carbon storage or biomass, and there is little research on EO methods for assessing REDD+ initiatives in dryland forests in most Southern African countries.
- Africa has the potential to emulate other continents, such as Latin America, that have made notable progress in employing freely available remote sensing data to monitor tropical dryland forest area change and biomass on a large scale.
- Greater use of a wider range of EO products could enable more evidence-based policy to prioritise sustainable use of forests, enabling the policy community to learn what works to reduce deforestation and forest degradation, to improve livelihoods in a changing climate.

The Research

Researchers have assessed the evidence base for a number of tropical dryland forests-remote sensing options, asking how remote sensing technology was used to monitor and estimate changes in dryland forests in southern Africa. The researchers considering evidence from over 130 peer-reviewed papers including research on land-use/land-cover, forest cover/types, biomass, forest structure, biodiversity/habitats, phenology, plant traits, and disturbances from drought and fire. It considered publication trends over time, study location, remote sensing sensor/platform used, spatial and temporal coverage, remote sensing product (e.g., biophysical indices) used, and application areas of the study (e.g., land cover, forest biomass).

Key findings and evidence

Publication trends	Although the volume of scientific literature has demonstrated a sharp increase, the use of remote sensing is still limited, and up until 2013, the number of publications on tropical dryland forests was relatively small.
Time scales	Time series analysis on dryland forests, which enables tracking changes is scarce, only 22 (16%) out of 137 studies feature time series lengths that exceed 15 years and only 11 (8%) studies that cover more than 20 years. Longer time series of remote sensing data afford the ability to assess the dynamics of forest structures, biodiversity, degradation, disturbance from climatic extremes, and change in phenology, in which a gap still exists.

Spatial scales	Despite new sensor and EO data availability, it is clear that a systematic and consistent regional monitoring of dryland forests is not yet fully exploited and is still in its infancy in Southern Africa. In fact, the majority of publications 88 (64%) concentrated their research efforts on local scale investigations. To fully assess regional and long-term implications for tropical dryland forest change studies, analyses on large(r) scales are needed, ideally with higher spatial resolutions and longer temporal duration.
Geographical focus	The Republic of South Africa is, by far the most studied nation across all categories in Southern Africa and the dryland forests of Angola, Mozambique, Lesotho, Swaziland, and Zambia are noticeably very poorly studied. In terms of National Parks, a large proportion of studies were undertaken in the Kruger National Park, leaving many other private and international protected areas relatively understudied. Future efforts to estimate important variables such as forest cover and biomass need not be restricted by country boundaries.
Research categories	Most studies focused on forest cover/types 41 (26%) and land cover/land use 36 (23%) categories while there is limited research on forest biomass and structures, disturbances from drought, phenology, plant traits, and biodiversity/habitats.
Vegetation indices	More than half of the studies, 84 (54%) of papers utilised the normalized difference vegetation index (NDVI), and few studies used other vegetation indices. Testing other vegetation indices beyond NDVI such as the Sentinel-2 red-edge related indices is needed in tropical dryland forests.
Remote sensing sensors	Imagery from optical sensors is most commonly used, out of all sensor types. More than 90% of papers investigated used optical sensors, 6% used SAR data and only 4% used a combination of SAR and Optical sensors. Further improvements should focus on extensive combination and fusion of SAR and optical data.
Validation and accuracy assessments	Our results show there is limited information on sources of error and uncertainty levels of the estimates provided by most studies, with only 54 (39%) of the studies appearing to have performed some form of accuracy assessment. Evidence indicates a need for more frequent use of field observation and inventory data, a greater use of validation/accuracy assessments.
Use of innovative remote sensing platforms	Only nine papers (6%) out of 137 used cloud-based geospatial analysis platforms such as Google Earth Engine (GEE) to access or analyse remote sensing data. The web-based platforms that reduce the need for costly local infrastructure (e.g., GEE), is an opportunity to overcome the limitations previously enforced by data scarcity, large volumes of data, and the scale of analysis.

Limitations

- There is limited information on sources of error and uncertainty levels of the estimates provided by most studies assessed. As a result, for some interventions, there is not sufficient evidence to determine whether the number of studies done equates to research quality, which remains difficult to articulate from a review of this nature.
- One major problem encountered is that commonly used vegetation indices and classification schemes are generalised from better-studied ecosystems, such as temperate and rain forests and this has led to poor accuracy results when extrapolated to, for example, tropical dryland forests, making it difficult to create robust syntheses for decision-makers in policy and practice.

Find out more

For more information, please contact:
 Ruusa-Magano David
 Email: ruusa-magano.david@durham.ac.uk
 Department of Geography, University of Durham
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N8 AgriFood Food Systems Policy Hub
 Email: policy@n8agrifood.ac.uk
 Website: <https://policyhub.n8agrifood.ac.uk>

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Appendix B

The analytical codes used in this thesis have been written in R and Google Earth Engine developed by Ruusa David. The substantial code will be uploaded in GitHub.

CHAPTER 2

2A. R CODE FOR ANALYSING AND PLOTTING DATA

This part of the R code is for analysing data for the systematic review

Number of papers integrating remote sensing and dryland forests in Southern Africa.

Install needed packages through the pkgTest which is a helper function to load packages and install packages only when they are not installed yet.

```
pkgTest <- function(x)
{
  if (x %in% rownames(installed.packages()) == FALSE) {
    install.packages(x, dependencies= TRUE)
  }
  library(x, character.only = TRUE)
}
neededPackages <- c("sp","zoo", "ggplot2", "dplyr")
for (package in neededPackages){pkgTest(package)}
```

#Load the library

```
library(ggplot2)
library(dplyr)
library(tidyverse)
library(sf)
```

```
library(scales)
library(ggrepel)
```

#path to data

```
path=("C:/ ")
```

#Read the data

```
No_study_SA <-read.csv(paste(path,"File.csv",sep="",collapse=""))
```

#Create the chart

```
No_study_SA_plot1<- ggplot(No_study_SA, aes(y = NoPublication, x = Year,
width=.60)) + geom_col(fill = "aquamarine4", colour = "grey38", width=.85)
```

```
No_study_SA_plot2<- No_study_SA _plot1 + labs(x = "Year", y = "Number of
publications")+scale_x_continuous(breaks=seq(1997,2020,2))+scale_y_continuous
(breaks = breaks_width(2))+theme_bw()+geom_smooth(method = "lm",
colour="red", linetype="dashed", size=1.5,se=FALSE)
```

```
No_study_SA_plot2<- No_study_R_topic_country_plot2 +
theme(text=element_text(family="Tahoma",colour="black", size = 15),
axis.text.x=element_text(colour="black", size =12),
axis.text.y=element_text(colour="black", size = 12))
```

#run lm to get the intercept and slope

```
lm(formula = NoPublication ~Year, data = No_study_SA_plot2)
```

#plot a trend line on the line graph

```
No_study_SA_plot2<- No_study_SA _plot2 + geom_abline(intercept = -1100.7132 ,
slope = 0.5509 , colour="red", linetype="dashed", size=1.5)
```

#Plot the Chart

```
No_study_SA_plot2
```

Number of papers by research institutions.

#Read the data

```
No_study_Inst <-read.csv(paste(path," File.csv ",sep="",collapse=""))
```

#Create the Chart

```
No_study_Inst_plot1<- ggplot(No_study_Inst (x = NoPublication, y  
=Institution.Category, fill = Institution.Type)) + geom_col()
```

```
No_study_Inst_plot2<- No_study_R_topic_country_plot1 + labs(x = "Published  
papers", y = "1st author Country")+ scale_fill_brewer(palette = "Dark2")  
+theme_bw()
```

```
No_study_Inst_plot2<- No_study_R_topic_country_plot2 +  
theme(text=element_text(family="Tahoma",colour="black", size = 15),  
axis.text.x=element_text(colour="black", size = 12),  
axis.text.y=element_text(colour="black", size = 12))
```

```
No_study_Inst_plot2<- No_study_Inst_plot2 +  
guides(fill=guide_legend(title="Institution category"))
```

#Plot the Chart

```
No_study_Inst_plot2
```

Spatial extent of studies.

#Read the data

```
No_study_S_extent <-read.csv(paste(path," File.csv ",sep="",collapse=""))
```

#Create the chart

```
No_study_S_extent_plot1<- ggplot(No_study_S_extent, aes(x =Scale, y  
=NumberofPublication, fill = fct_inorder(Scale))) +  
geom_col(colour = "grey50",width=0.9)
```

```
No_study_S_extent_plot2<- No_study_R_topic_country_plot1 + labs(x = "Spatial  
extent", y = "Number of publications")+ scale_colour_brewer()  
+scale_y_continuous(breaks = breaks_width(4))+ theme_bw()
```

```
No_study_S_extent_plot2<- No_study_S_extent_plot2 +  
theme(text=element_text(family="Tahoma",colour="black", size = 15),  
axis.text.x=element_text(colour="black", size =12),  
axis.text.y=element_text(colour="black", size = 12))
```

```
No_study_S_extent_plot2<- No_study_S_extent_plot2 +  
guides(fill=guide_legend(title="Spatial scale"))
```

#Plot the Chart

```
No_study_S_extent_plot2
```

Temporal duration of studies.

#Read the data

```
No_study_T_extent <-read.csv(paste(path," File.csv ",sep="",collapse=""))
```

#Create the chart

```
No_study_T_extent_plot1<- ggplot(No_study_T_extent, aes(x = Year, y  
=NoPublication, fill = TemporalResolution, width=.85)) +  
geom_col(colour="grey39", size=0.60)
```

```
No_study_T_extent_plot2<- No_study_T_extent_plot1 + labs(x = "Temporal extent  
(years)", y = "Number of publications")+ scale_fill_brewer(palette = "Set1")  
+scale_x_continuous(labels = 1:34, breaks = 1:34)+scale_y_continuous(breaks =  
breaks_width(4))+ theme_bw()
```

```
No_study_T_extent_plot2<- No_study_T_extent_plot2 +  
theme(text=element_text(family="Tahoma",colour="black", size = 15),  
axis.text.x=element_text(colour="black", size =10),  
axis.text.y=element_text(colour="black", size = 12))
```

```
No_study_T_extent_plot2<- No_study_T_extent_plot2  
+guides(fill=guide_legend(title="Temporal resolution"))
```

#Plot the Data

```
No_study_T_extent_plot2
```

Research topic categories

#Read the data

```
No_study_R_topic <-read.csv(paste(path," File.csv.csv",sep="",collapse=""))
```

Add label position #Note, calculate this before adding % sign to the number of publication

```
No_study_R_topic <- No_study_R_topic %>%
```

```
arrange(desc(Research.focus)) %>% mutate(midpoint =
cumsum(Number.of.Publication) - 0.5*Number.of.Publication)
```

```
mycols <- c("#0073C2FF", "#EFC000FF", "#868686FF",
"#CD984CFF", "#007672FF", "#EFC000CC", "#896686FF", "#CD529CFF")
```

```
ggplot(No_study_R_topic, aes(x = "", y = Number.of.Publication, fill =
Research.focus)) +
```

```
geom_bar(width = 1, stat = "identity", colour = "white") + coord_polar("y", start =
0)+
```

```
geom_text(aes(y = midpoint, label = Number.of.Publication), colour = "white")+
```

```
scale_fill_manual(values = mycols) + theme_void()
```

#add columns for percentage

```
No_study_R_topic <- No_study_R_topic %>%
```

```
mutate(Research.focus = factor(Research.focus,
```

```
levels = Research.focus[length(Research.focus):1]),
```

```
cumulative = cumsum(Number.of.Publication),
```

```
midpoint = cumulative - Number.of.Publication / 2,
```

```
labels = paste0(round((Number.of.Publication/ sum(Number.of.Publication))
* 100, 0), "%", " (", Number.of.Publication, ")"))
```

Get the Pie Chart positions

```
No_study_R_topic <- No_study_R_topic %>% mutate(csum =
rev(cumsum(rev(Number.of.Publication))),
```

```
pos = Number.of.Publication/2 + lead(csum, 1),
```

```
pos = if_else(is.na(pos), Number.of.Publication/2, pos))
```

#Plot the chart

```
ggplot(No_study_R_topic, aes(x = "", y = Number.of.Publication, fill =
fct_inorder(Research.focus))) +
```

```
geom_col(width = 1, colour = 1) +
```

```
coord_polar(theta = "y") +
```

```
scale_fill_brewer(palette = "Set3") +
```

```
geom_label_repel(data = No_study_R_topic,
  aes(y = pos, label =labels),
  size = 4.5, nudge_x = 0.14, show.legend = FALSE) +
guides(fill = guide_legend(title = "Resesarch topic")) +
theme_void()
```

Number of studies based upon platform and sensor type.

#Read the data

```
No_study_R_sensor <-read.csv(paste(path," File.csv ",sep="",collapse=""))
```

#Create the chart

```
No_study_R_sensor_plot1<- ggplot(No_study_R_sensor, aes(x =InstrumentName, y =
=NumberofPublication, fill = Sensor.Type,width=.60)) +
```

```
geom_col()
```

```
No_study_R_sensor_plot2<- No_study_R_sensor_plot1 + labs(x = "Platform", y =
"Number of publications")+ scale_colour_brewer(palette = "Greens")
+scale_y_continuous(breaks = breaks_width(10))+ theme_bw()+theme(axis.text.x
= element_text(angle = 90))
```

```
No_study_R_sensor_plot2<- No_study_R_sensor_plot2 +
theme(text=element_text(family="Tahoma",colour="black", size = 15),
```

```
axis.text.x=element_text(colour="black", size =12),
```

```
axis.text.y=element_text(colour="black", size = 12))
```

```
No_study_R_sensor_plot2<- No_study_R_sensor_plot2 +
guides(fill=guide_legend(title="Sensor Type"))
```

#Plot the Chart

```
No_study_R_sensor_plot2
```

Research topic by country

#Read the data

```
No_study_R_topic_country<-read.csv(paste(path,"Article
Assessment_reseracharea_bycountry_2.csv",sep="",collapse=""))
```

#Create the chart

```
No_study_R_topic_country_plot1<- ggplot(No_study_R_topic_country, aes(x =
Country, y =Publications, fill = Research.Topic,width=.60)) + geom_col()
```

```
No_study_R_topic_country_plot2<- No_study_R_topic_country_plot1 + labs(x =
"Country", y = "Number of publications")+ scale_fill_brewer(palette =
```

```
"Set2")+theme_bw()+scale_y_continuous(breaks =  
breaks_width(5))+theme(axis.text.x = element_text(angle = 90))  
No_study_R_topic_country_plot2<- No_study_R_topic_country_plot2 +  
theme(text=element_text(family="Tahoma",colour="black", size = 15),  
axis.text.x=element_text(colour="black", size =12),  
axis.text.y=element_text(colour="black", size = 12))
```

#Plot the Chart

```
No_study_R_topic_country_plot2
```

CHAPTER 3

3A. GOOGLE EARTH ENGINE CODE FOR DOWNLOADING IMAGES, CLASSIFICATION AND CHANGE DETECTION

Google Earth Engine Code for downloading Landsat, Sentinel 1 and 2
images, satellite image classification and change detection

Image classification for Landsat 2004

<https://code.earthengine.google.com/5f543641fb703ab0bbf23ea869e3d4a8?noload=1>

Image classification for 2018 code

<https://code.earthengine.google.com/57348f290a26907372d530f21762c718?noload=1>

Perform a Change detection

<https://code.earthengine.google.com/d7618eedeaf46fcf53a7de56df0af330?noload=1>

Landsat image code

<https://code.earthengine.google.com/421117de52df03e0fabf48edac554aae?noload=1>

Sentinel image code

<https://code.earthengine.google.com/33b7477b23ad3a8bf1f220486c283da1?noload=1>

3B. R CODE FOR ESTIMATING FOREST STAND PARAMETERS

This part of the R code is for estimating forest stand parameters

Estimates for forest stand parameters using Chave et al., 2005 allometric Equation

ESTIMATES FOREST STAND PARAMETERS

Install needed packages through the pkgTest

```
pkgTest <- function(x)
{
  if (x %in% rownames(installed.packages()) == FALSE) {
    install.packages(x, dependencies= TRUE)
  }
  library(x, character.only = TRUE)
}
neededPackages <- c("rgeos "," raster ", "ggplot2", "dplyr")
for (package in neededPackages){pkgTest(package)}
```

#Load the library

```
library(rgdal)
library(raster)
library(rgeos)
library(ggplot2)
library(rcompanion) #for transforming
library(Hmisc) # compute significance levels for pearson
library(dplyr) # to use select
library(ggpubr) #for ggscatterForest
library(ggpmisc)
library(corrplot) #Forest correlation
library(MASS) #for BOXCox Transformation
library(devtools)
library(ithir) #To check regression prediction
library(MASS)
library(car)#for vif to test multicollinearity
```

```

library(performance) #To test model performance
library(randomForest)
library(DAAG) #for k fold validation in linear regression
to test multicollinearity
library(performance)

```

#Apply the allometric equation from Chave et al., 2005 for dry forest

```

ForestPlots <- plotdata %>%
  mutate(BasalArea_m2 = 0.0001*pi*(DBH/2)^2,
         standBasalArea_m2=0.0001*pi*(DBH/2)^2/0.05*20,
         WoodDensity = 0.79,

```

#Estimate DBH

```

AGB_kg_Chave_DBH = WoodDensity*exp(-
0.667+(1.784*log(DBH))+(0.207*(log(DBH))^2)-(0.0281*(log(DBH))^3)))

```

#Estimate with DBH and total tree height (H)

```

AGB_kg_Chave_H_DBH = exp(-2.187+(0.916*log(WoodDensity*DBH^2*Height))),

```

CALCULATE/ ESTIMATES OF STAND LEVEL PARAMETERS

(including DBH, Basal Area, Height, AGB, Carbon etc)

```

StandPhysicalParams <- Plotmeta %>%
  group_by(ForestID) %>%
  mutate(PlotArea_m2 = pi * PlotSize^2,
         scalingFactor = 10000/PlotArea_m2) #convert to hectare

```

```

StandForestParams <- ForestPlots %>%
  group_by(ForestID) %>%
  summarise(DBH_mean = mean(DBH, na.rm = T),
            DBH_sd = sd(DBH, na.rm = T),
            DBH_median= median(DBH, na.rm = T),
            BA_mean = mean(BasalArea_m2, na.rm = T),
            BA_sum = sum(BasalArea_m2, na.rm = T),
            BA_sd = sd(BasalArea_m2, na.rm = T),

```

```

standBA_sum=sum(standBasalArea_m2, na.rm = T),
standBA_mean=mean(standBasalArea_m2, na.rm = T),
Height_mean = mean(Height, na.rm = T),
Height_median = median(Height, na.rm = T),
Height_sd = sd(Height, na.rm = T),
Tree_Density = n(),
AGB_kg_sum_Chav_Height_DBH = sum(AGB_kg_Chave_H_DBH, na.rm = T),
AGB_kg_sum_Chav_DBH =sum(AGB_kg_Chave_DBH, na.rm = T))
standParams <- left_join(StandPhysicalParams,StandForestParams, by =
"ForestID") %>%
mutate(Tree_DensityHa = Tree_Density*scalingFactor,
BA_m2Ha = BA_sum*scalingFactor,
AGB_kgHa_Chav_H = AGB_kg_sum_Chav_Height_DBH*scalingFactor,
AGB_tHa_Chav_H = AGB_kgHa_Chav_H/1000,
AGB_tCHa_Chav_H = AGB_tHa_Chav_H*0.5,

AGB_kgHa_Chav_DBH = AGB_kg_sum_Chav_DBH*scalingFactor,
AGB_tHa_Chav_DBH = AGB_kgHa_Chav_DBH/1000,
AGB_tCHa_Chav_DBH = AGB_tHa_Chav_DBH*0.5)

```

Plots of forest stand parameters

```
library (cowplot)
```

```
library(ggpubr)
```

#Stand forest DBH

```
Stand_DBH <-
```

```
ggplot(aes(ForestID, DBH_mean),
```

```
data = standParams[1:78,]) +
```

```
geom_col(aes()) +
```

```
theme_bw() +
```

```
theme(panel.grid.major.x = element_blank(),
```

```
text = element_text(size=12),
```

```
axis.text.x = element_text(angle = 55, hjust = 1)) +
```

```
labs(x = "Plot ID", y = "Mean DBH (cm)") +  
geom_errorbar(aes(ymin=DBH_mean-DBH_sd, ymax=DBH_mean+DBH_sd),  
width=.5)
```

Stand forest Basal Area

```
Stand_BA <-  
ggplot(aes(ForestID, BA_mean),  
data = standParams[1:78,]) +  
geom_col(aes()) +  
theme_bw() +  
theme(panel.grid.major.x = element_blank(),  
text = element_text(size=12),  
axis.text.x = element_text(angle = 55, hjust = 1)) +  
labs(x = "Plot ID", y = "Mean Basal Area (m2)") +  
geom_errorbar(aes(ymin=BA_mean-BA_sd, ymax=BA_mean+BA_sd),  
width=.5)
```

Stand forest Height

```
Stand_Height <-  
ggplot(aes(ForestID, Height_mean),  
data = standParams[1:78,]) +  
geom_col(aes()) +  
theme_bw() +  
theme(panel.grid.major.x = element_blank(),  
text = element_text(size=12),  
axis.text.x = element_text(angle = 55, hjust = 1)) +  
labs(x = "Plot ID", y = "Mean Tree Height (m)") +  
geom_errorbar(aes(ymin=Height_mean-Height_sd, ymax=Height_mean+Height_sd),  
width=.5)
```

Stand forest Tree Density

```
Stand_Density <-
```

```

ggplot(aes(ForestID, Tree_DensityHa),
  data = standParams[1:78,]) +
geom_col(aes()) +
theme_bw() +
theme(panel.grid.major.x = element_blank(),
  text = element_text(size=12),
  axis.text.x = element_text(angle = 55, hjust = 1)) +
labs(x = "Plot ID", y = "Tree Density (Trees ha-1)")

```

Above Ground Biomass using DBH for CHAVE

```

Stand_AGB_tha_DBH_Chav <-
ggplot(aes(ForestID, AGB_tHa_Chav_DBH),
  data = standParams[1:78,]) +
geom_col(aes()) +
theme_bw() +
theme(panel.grid.major.x = element_blank(),
  text = element_text(size=12),
  axis.text.x = element_text(angle = 55, hjust = 1)) +
labs(x = "Plot ID", y = "AGB with DBH; (t ha-1)")

```

```

Stand_AGB_tCha_DBH_Chav <-
ggplot(aes(ForestID, AGB_tCha_Chav_DBH),
  data = standParams[1:78,]) +
geom_col(aes()) +
theme_bw() +
theme(panel.grid.major.x = element_blank(),
  text = element_text(size=12),
  axis.text.x = element_text(angle = 55, hjust = 1)) +
labs(x = "Plot ID", y = "Total Carbon with DBH; (t C ha-1)")

```

Stand forest AGB with Height

```

Stand_AGB_tha_H_Chav <-
  ggplot(aes(ForestID, AGB_tHa_Chav_H),
    data = standParams[1:78,]) +
  geom_col(aes()) +
  theme_bw() +
  theme(panel.grid.major.x = element_blank(),
    text = element_text(size=16),
    axis.text.x = element_text(angle = 55, hjust = 1)) +
  labs(x = "Plot ID", y = "AGB (Mg/ha)")

```

```

Stand_AGB_tCha_H_Chav <-
  ggplot(aes(ForestID, AGB_tCHa_Chav_H),
    data = standParams[1:78,]) +
  geom_col(aes()) +
  theme_bw() +
  theme(panel.grid.major.x = element_blank(),
    text = element_text(size=16),
    axis.text.x = element_text(angle = 55, hjust = 1)) +
  labs(x = "Plot ID", y = "Total Carbon (Mg/ha)")

```

#Plot the forest stand parameters Individually

```

plot_grid(Stand_DBH)
plot_grid(Stand_BA)
plot_grid(Stand_Height)
plot_grid(Stand_Density)
plot_grid(Stand_AGB_tha_H_Chav)
plot_grid(Stand_AGB_tCha_H_Chav, labels = "auto",
  label_size = 18,
  align = "v")
plot_grid(Stand_AGB_tha_DBH_Chav)
plot_grid(Stand_AGB_tCha_DBH_Chav)

```

#Plot the forest stand parameters in one Figure

```
StandFigure <- hist(Stand_AGB_tha_H_Chav,Stand_AGB_tCha_H_Chav,  
  ncol = 1, nrow = 2, align = "v", axis = "r",labels="auto", label_size = 18)  
StandFigure
```

PLOT THE DENSITY AND HISTOGRAM PLOTS FOR AGB AND CARBON

3.1 Create density and histogram plots for Aboveground biomass (AGB)of each field plot with woodland trees.

```
AGB<-ggplot(standParams[1:78,], aes(x=AGB_tHa_Chav_H)) +  
  geom_histogram(aes(y =..density..),  
    breaks=seq(2, 170, by = 10),  
    col="Black",  
    fill="#FF6666", alpha = .1 ) + theme_bw()+  
  geom_density(alpha=.2, fill="black") +  
  # labs(title="AGB (Mg/ha)") +  
  labs(x="AGB (Mg/ha)", y="Count") +  
  theme(axis.line = element_line(size=1, colour = "black"),  
    panel.grid.major = element_blank(),  
    panel.grid.minor = element_blank(),  
    panel.border = element_blank(),  
    panel.background = element_blank(),  
    plot.title=element_text(size = 20,face="bold"),  
    text=element_text(size = 16),  
    axis.text.x=element_text(colour="black", size = 14,face="bold"),  
    axis.text.y=element_text(colour="black", size = 14,face="bold"),  
    axis.title.x = element_text(colour="black", size=16, face="bold"),  
    axis.title.y = element_text(colour="black", size=16, face="bold"),  
    axis.text=element_text(colour="black", size=14))
```

3.2 CARBON: Create density and histogram plots Carbon stock (Mg/ha) of each field plot with woodland trees.

```

carbon<-ggplot(standParams[1:78,], aes(x=AGB_tCHa_Chav_H)) +
  geom_histogram(aes(y =..density..),
    breaks=seq(1.03, 84, by = 10),
    col="black",
    fill="#FF6666", alpha = .1
  ) + theme_bw()+
  geom_density(alpha=.2, fill="black") +
  # labs(title="AGB (Mg/ha)") +
  labs(x="Total Carbon (Mg/ha)", y="") +
  theme(axis.line = element_line(size=1, colour = "black"),
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    panel.border = element_blank(),
    panel.background = element_blank(),
    plot.title=element_text(size = 20,face="bold"),
    text=element_text(size = 16),
    axis.text.x=element_text(colour="black", size = 14,face="bold"),
    axis.text.y=element_text(colour="black", size = 14,face="bold"),
    axis.title.x = element_text(colour="black", size=16, face="bold"),
    axis.title.y = element_text(colour="black", size=16, face="bold"),
    axis.text=element_text(colour="black", size=14))

```

Plot the density and histogram plot for carbon

```
carbon
```

#Combine all the plots

```
ggarrange(AGB, carbon,
```

```

  labels = c("A", "B"),common.legend=TRUE,legend = "top",# specify the legend
  position and specify whether they should share the common legend or not.

```

```

  ncol = 2, nrow = 2) # column and row numbers

```

2. Estimates the AGB using Linear Model (Raster data)

#Read the csv data

```
S2chobezam_wo.num<-read.csv(paste(path,"File.csv",sep="",collapse=""))
```

#Transform the data for normality

```
S2chobezam_wo.num$AGBL<-log(S2chobezam_wo.num$AGB_tHa_Chav_H)
```

#display histogram for transformed AGB

```
hist(S2chobezam_wo.num$AGBL)
```

#choose variables to work (Sentinel 1, Sentinel 2 and Landsat 8 bands and indices)

```
S2chobezam_wo.num=dplyr::select(S2chobezam_wo.num,AGBL,B2,B3,B4,B5,B6,B7,B8,B8A,B11,B12,S1_VH,S1_VV,ndvi,grvi,evi,savi,msav,nbr,nbr2,gndvi,nR1,nR2,nR3,nR4,ndi45,ireci,srtm)
```

#read in Raster data-sentinel

NB: Load Sentinel 1, Sentinel 2, and Landsat 8 tif files. Below is an example of Sentinel 2 data loaded in r

```
S2_chobe<-list.files ("Path/", pattern = ".tif$", full.names = TRUE)
```

#stack all bands

#covariates are of the same scale in terms of resolution and extent.

```
S2_03_chobe<- stack(S2_chobe[])
```

Linear Model prediction

```
hv.MLR.rh <-lm(AGBL~B3+B5+S1_VH+S1_VV, data =S2chobezam_wo.num)
```

```
vif(hv.MLR.rh)
```

```
summary(hv.MLR.rh)
```

#Estimate AGB using Linear Model

#predict from raster data

```
map.MLR1<- exp(predict(S2_03_chobe,hv.MLR.rh,format = "GTiff", datatype = "FLT4S", overwrite = TRUE)) # backtransform the log data to original
```

```
plot(map.MLR1, main = "S2 Biomass prediction with linear model")
```

including all bands and indices, and choose the right variables

```
tempD <- data.frame(cellNos = seq(1:ncell(S2_03_chobe)))  
vals <- as.data.frame(getValues(S2_03_chobe))  
tempD <- cbind(tempD, vals)  
tempD <- tempD[complete.cases(tempD), ]  
cellNos <- c(tempD$cellNos)  
gXY <- data.frame(xyFromCell(S2_03_chobe, cellNos, spatial = FALSE))  
tempD <- cbind(gXY, tempD)  
str(tempD)
```

backtransform the log data to original scale with exp

```
map.MLR <- exp(predict(hv.MLR.rh, newdata = tempD))  
map.MLR <- cbind(data.frame(tempD[, c("x", "y")]), map.MLR) #include x and y  
coordinates
```

#rasterise the predictions for mapping

```
map.MLR.r <- rasterFromXYZ(as.data.frame(map.MLR[, 1:3])) #include the cell  
numbers  
plot(map.MLR.r, main = "S2 Biomass prediction with glm forest")
```

Validate the AGB using Linear Model

validate the Linear model

#split the data 70 and 30% for validation

```
set.seed(123)  
training <- sample(nrow(S2chobezam_wo.num), 0.7 *  
nrow(S2chobezam_wo.num))
```

#display the calibration data

```
training
```

#fit the model

```
hv.MLR.rh <-lm(AGBL~B3+B5+S1_VH+S1_VV+gndvi+ndi45, data
=S2chobezam_wo.num,y=TRUE, x=TRUE)
```

```
AGB.pred.F <- predict(hv.MLR.rh, S2chobezam_wo.num)
```

#Evaluate the model with goof:

```
goof(observed = S2chobezam_wo.num$AGBL, predicted= AGB.pred.F,plot.it =
TRUE)
```

#Check model performance

```
model_performance(hv.MLR.rh)
```

#Evaluate the calibration model

```
AGB.pred.C <- predict(hv.MLR.rh, S2chobezam_wo.num[training, ])
```

```
goof(observed = S2chobezam_wo.num$AGBL[training], predicted
= AGB.pred.C,plot.it = TRUE)
```

#Evaluate the validation model

```
AGB.pred.V <- predict(hv.MLR.rh, S2chobezam_wo.num[-training, ])
```

```
goof(observed = S2chobezam_wo.num$AGBL[-training], predicted
= AGB.pred.V,plot.it = TRUE)
```

set the CRS to +zone=35 +south +datum=WGS84

```
crs(map.MLR.r) <- "+proj=utm +zone=35 +south +datum=WGS84 +units=m
+no_defs +ellps=WGS84 +towgs84=0,0,0"
```

#Export the map

```
writeRaster(map.MLR.r, filename="Path", datatype = "FLT4S", overwrite = TRUE)
```

Estimated AGB vs Field-based AGB for Linear Models (Calibration Data: 70%)

#Plot the predicted vs the observed for Linear Model

#fit the model

```
chobe.MLR<-lm(AGBL~B3+B5+S1_VV, data =S2chobezam_wo.num)
```

```
summary(chobe.MLR)
```

```
predicted AGB <- predict(chobe.MLR, S2chobezam_wo.num)
goof(observed = S2chobezam_wo.num$AGBL, predicted= predicted_AGB)
```

#plot the model

```
gg0 <- ggplot(S2chobezam_wo.num,aes(
AGBL,predicted_AGB))+geom_point(aes()) #colour by forest types
gg0<-gg0+geom_point( size=4)
gg1 <- gg0 + geom_smooth(method="lm",se=FALSE,
colour="black")#+geom_abline(linetype="dashed",col="red")
gg1
glm1<- gg1+stat_regline_equation (aes(label = paste(..adj.rr.label., sep =
"~~~~")), label.x.npc = "left", label.y.npc = 0.95,hjust=0,size=5.5,face="bold")
#include Y
```

Calculate RMSE

```
chobe.MLR1 <-lm(AGBL~predicted_AGB, data =S2chobezam_wo.num)
rmse <- round(sqrt(mean(resid(chobe.MLR1 )^2)), 2)
```

#plot the rmse

```
gg<-glm1 + geom_text(aes(x=0.5, y=4.8,size=30, label= paste("RMSE= ", rmse,
"Mg/ha"), hjust=0))
gg<-gg+theme_bw()
gg<-gg + labs(y="Predicted AGB (Mg/ha)", x = "Observed AGB (Mg/ha)", title = "(a)
MLR AGB Model")
rmse_xy<-gg + theme(
plot.title = element_text(colour="black", size=20, face="bold.italic"),
axis.title.x = element_text(colour="black", size=20, face="bold"),
axis.title.y = element_text(colour="black", size=20, face="bold"),
axis.text=element_text(colour="black", size=20, face="bold")
)
rmse_xy
```

#Calculate the residuals

```

chobe.MLR <-lm(AGBL~B3+B5+S1_VV, data =S2chobezam_wo.num)

predicted_AGB <- predict(chobe.MLR, S2chobezam_wo.num)

err<-predicted_AGB- S2chobezam_wo.num$AGBL

df<-data.frame(residuals=err, fitted.values=predicted_AGB )

df2<-df[order(df$fitted.values),]

plot(residuals~fitted.values, data=df2, ylab="Residuals", xlab="AGB (Mg/ha)",
      main="(a MLR AGB residuals ", cex.lab=2.0, cex.main=2.0,
      cex.axis=2.0,pch=19,cex=1.4, font = 2, font.lab=2,font.main=4) +abline(0,0,
      col="black")

```

Estimated AGB vs Field-based AGB for Linear Models (Validation Data: 30%)

#Plot the predicted vs the observed for Linear Model

#fit the model

```

chobe.MLR<-lm(AGBL~B3+B5+S1_VV, data =S2chobezam_wo.num)
summary(chobe.MLR)
predicted_AGB <- predict(chobe.MLR, S2chobezam_wo.num)
goof(observed = S2chobezam_wo.num$AGBL, predicted= predicted_AGB)

```

#plot the model

```

gg0 <- ggplot(S2chobezam_wo.num,aes(
AGBL,predicted_AGB))+geom_point(aes()) #colour by forest types
gg1 <- gg0 + geom_smooth(method="lm",se=FALSE,
colour="black")#+geom_abline(linetype="dashed",col="red")

gg1

glm1<- gg1+stat_regline_equation (aes(label = paste(..adj.rr.label., sep =
"~~~~")), label.x.npc = "left", label.y.npc = 0.95,hjust=0,face="bold") #include Y

```

Calculate RMSE

```
chobe.MLR1 <-lm(AGBL~predicted_AGB, data =S2chobezam_wo.num)
rmse <- round(sqrt(mean(resid(chobe.MLR1 )^2)), 2)
```

#plot the rmse

```
gg<-glm1 + geom_text(aes(x=0.5, y=4.8, label= paste("RMSE= ", rmse, "Mg/ha"),
hjust=0))
```

```
gg<-gg+theme_bw()
```

```
gg<-gg + labs(y="Predicted AGB (Mg/ha)", x = "Observed AGB (Mg/ha)", title =
"AGB Model (a) Linear regression")
```

```
gg
```

```
rmse_xy<-gg + theme(
  plot.title = element_text(colour="black", size=20, face="bold.italic"),
  axis.title.x = element_text(colour="black", size=16, face="bold"),
  axis.title.y = element_text(colour="black", size=16, face="bold"),
  axis.text=element_text(colour="black", size=14)
)
```

```
rmse_xy
```

#Calculate the residuals

```
chobe.MLR <-lm(AGBL~B3+B5+S1_VV, data =S2chobezam_wo.num)
```

```
predicted_AGB <- predict(chobe.MLR, S2chobezam_wo.num)
```

```
err<-predicted_AGB- S2chobezam_wo.num$AGBL
```

```
df<-data.frame(residuals=err, fitted.values=predicted_AGB )
```

```
df2<-df[order(df$fitted.values),]
```

#Plot the residuals

```
plot(residuals~fitted.values, data=df2, ylab="Residuals", xlab="AGB (Mg/ha)",
```

```
  main="AGB residuals (a) Linear regression ", cex.lab=1.5, cex.main=1.5,
  cex.axis=1.5) +
```

```
  abline(0,0, col="black")
```

Validate Estimated AGB vs Field-based AGB for Linear Models

#split the data 70 and 30% for validation

```
training <- sample(nrow(S2chobezam_wo.num), 0.7 *  
nrow(S2chobezam_wo.num))
```

#fit the model

```
chobe.MLR <- lm(AGBL~B3+B5+S1_VV, data =S2chobezam_wo.num[-training,])
```

```
summary(chobe.MLR)
```

```
predicted_AGB <- predict(chobe.MLR, S2chobezam_wo.num[-training,])
```

```
goof(observed = S2chobezam_wo.num[-training,]$AGBL, predicted=  
predicted_AGB)
```

```
RF.pred.C <- predict(chobe.MLR, newdata =S2chobezam_wo.num[training, ])
```

#calibration

```
goof(observed = S2chobezam_wo.num$AGBL[training], predicted = RF.pred.C,  
plot.it=TRUE)
```

#Validation

```
MLR.pred.V <- predict(chobe.MLR, newdata = S2chobezam_wo.num[-training, ])
```

```
goof(observed = S2chobezam_wo.num$AGBL[-training], predicted  
=MLR.pred.V,plot.it = TRUE)
```

Estimates the AGB using Random Forest Model (Raster data)

#Split the data into calibration and validation dataset

```
set.seed(123)
```

```
training <- sample(nrow(S2chobezam_wo.num), 0.7 *  
nrow(S2chobezam_wo.num))
```

#fit the RF model

```
chobe.rf.mod <- randomForest(AGBL~B3+B5+S1_VV, data  
=S2chobezam_wo.num,mtry=3,importance=TRUE,ntree=1000)
```

```
print(chobe.rf.mod)
```

#Plot variable importance

```
varImpPlot(chobe.rf.mod)
```

#check the model residuals

```
S2chobezam_wo.num$residual <- S2chobezam_wo.num$AGBL-  
predict(chobe.rf.mod,  
newdata = S2chobezam_wo.num, plot.it=True)  
hist(S2chobezam_wo.num$residual)  
mean(S2chobezam_wo.num$residual)
```

backtransform the log data to original

```
map.RF.r1 <- exp(predict(S2_03_chobe, chobe.rf.mod, "Chobe Biomass_RF.tif",  
format = "GTiff", datatype = "FLT4S", overwrite = TRUE))
```

#Plot the data

```
plot(map.RF.r1 , main = "Random Forest model predicted Biomass")
```

Estimated AGB vs Field-based AGB for Random Forest Model (Calibration Data: 70%)

#Plot the predicted vs the observed

#fit the model

```
chobe.rf.mod <- randomForest(AGBL~B3+B5+S1_VV, data  
=S2chobezam_wo.num,mtry=3,importance=TRUE,ntree=1000, trace=true)  
print(chobe.rf.mod)  
predicted_AGB <- predict(chobe.rf.mod, S2chobezam_wo.num)  
goof(observed = S2chobezam_wo.num$AGBL, predicted= predicted_AGB)
```

#plot the model

```
gg0 <- ggplot(S2chobezam_wo.num,aes(  
AGBL,predicted_AGB))+geom_point(aes()) #colour by forest types  
gg0<-gg0+geom_point( size=4)
```

```

gg1 <- gg0 + geom_smooth(method="randomForest",
colour="black")+geom_abline(linetype="dashed",col="red")

gg1<-gg1+geom_abline(intercept = 0,slope=1,col="black")

glm1<- gg1+stat_regline_equation (aes(label = paste(..adj.rr.label., sep =
"~~~~")), label.x.npc = "left", label.y.npc = 0.9,hjust=0,size=5.5,face="bold")
#include Y

```

Calculate RMSE

```

chobe.rf.mod1 <-randomForest(AGBL~predicted_AGB, data
=S2chobezam_wo.num,importance=TRUE,ntree=1000)

rmse_function<-function(pred,actual){
  sqrt(sum(pred-actual)^2)
}

rmse<-round(rmse_function( predicted_AGB,S2chobezam_wo.num$AGB),2)

rmse

```

#plot the rmse

```

gg<-glm1 + geom_text(aes(x=0.5, y=4.3,size=30,face="bold", label= paste("RMSE=
", rmse, "Mg/ha"), hjust=0))

gg<-gg+theme_bw()

gg<-gg + labs(y="Predicted AGB (Mg/ha)", x = "Observed AGB (Mg/ha)", title = "(b)
RFR AGB Model")

```

```

gg

rmse_xy<-gg + theme(
  plot.title = element_text(colour="black", size=20, face="bold.italic"),
  axis.title.x = element_text(colour="black", size=20, face="bold"),
  axis.title.y = element_text(colour="black", size=20, face="bold"),
  axis.text=element_text(colour="black", size=20, face="bold")
)

rmse_xy

```

#Calculate the residuals

```

chobe.rf.mod <-randomForest(AGBL~B3+B5+S1_VV, data
=S2chobezam_wo.num,mtry=3, importance=TRUE,ntree=1000)

```

```

print(chobe.rf.mod)
predicted_AGB <- predict(chobe.rf.mod, S2chobezam_wo.num)
err<-predicted_AGB- S2chobezam_wo.num$AGBL
df<-data.frame(residuals=err, fitted.values=predicted_AGB )
df2<-df[order(df$fitted.values),]

```

#Plot the residuals

```

plot(residuals~fitted.values, data=df2, ylab="Residuals", xlab="AGB (Mg/ha)",
     main="(b) RFR AGB residuals ", cex.lab=2.0, cex.main=2.0,
     cex.axis=2.0,pch=19,cex=1.4, font = 2, font.lab=2,font.main=4) +
     abline(0,0, col="black",lwd=2.5)

```

Validate Estimated AGB vs Field-based AGB for Random Forest Model

#split the data 70 and 30% for validation

```

training <- sample(nrow(S2chobezam_wo.num), 0.7 *
nrow(S2chobezam_wo.num))

```

#fit the model

```

chobe.rf.mod <-randomForest(AGBL~B3+B5+S1_VV, data
=S2chobezam_wo.num,mtry=3,importance=TRUE,ntree=1000)
print(chobe.rf.mod)
predicted_AGB <- predict(chobe.rf.mod, S2chobezam_wo.num)
goof(observed = S2chobezam_wo.num$AGBL, predicted= predicted_AGB)

```

Internal validation

```

RF.pred.C <- predict(chobe.rf.mod, newdata =S2chobezam_wo.num[training, ])
goof(observed = S2chobezam_wo.num$AGBL[training], predicted = RF.pred.C,
plot.it=TRUE)

```

#External validation

```

RF.pred.V <- predict(chobe.rf.mod, newdata = S2chobezam_wo.num[-training, ])

```

```
goof(observed = S2chobezam_wo.num$AGBL[-training], predicted =  
RF.pred.V,plot.it = TRUE)
```

Computing variables correlation

(i) PEARSON CORRELATION WITH S2 BANDS

#Read the csv data

```
S2chobezam_wo.num<-read.csv(paste(path," File.csv ",sep="",collapse=""))
```

#Choose the variable (Sentinel 1, Sentinel 2 and Landsat 8 bands and indices)

```
S2chobezam_wo.num2=dplyr::select(S2chobezam_wo.num,AGBL,  
B2,B3,B4,B5,B6,B7,B8,B8A,B11,B12,S1_VH,S1_VV,ndvi,grvi,evi,savi,msav,nbr,nbr2,  
gndvi,nR1,nR2,nR3,nR4,ndi45,ireci,srtm, HeightL, DenHAL)
```

compute the correlation matrix

```
cor2<-rcorr((as.matrix(S2chobezam_wo.num2)))
```

compute variable p-values

```
cor2$P
```

(ii) CREATE A SCATTER PLOTS FOR CORRELATION

#SAR sentinel 1 scatterplot

#Plot S1 VV and AGB

```
S1_VV <- ggplot(data = S2chobezam_wo.num, aes(x=S1_VV, y = AGBL))+  
geom_point(aes())  
S1_VV<-S1_VV+geom_point( size=4)  
S1_VV<-S1_VV+geom_smooth(method = "lm", se=FALSE, colour="black", formula =  
y ~ x) #to exclude the line in the middle set (se=FALSE),
```

Get equation and r-squared as string

#make a function to plot the equation

```
lm_eqn <- function(S2chobezam_wo.num){  
  m <- lm(AGBL~S1_VV, S2chobezam_wo.num);  
  eq <- substitute(italic(y) == a + b %.% italic(x)*" ~ ~italic(r)^2 ~ "=" ~r2,  
    list(a = format(unname(coef(m)[1]), digits = 2),  
      b = format(unname(coef(m)[2]), digits = 2),  
      r2 = format(summary(m)$r.squared, digits = 2)))  
  as.character(as.expression(eq));}  
S1_VV_eq <- S1_VV + geom_text(x = -15.0, y = 4.8, size=5.5,label =  
lm_eqn(S2chobezam_wo.num), parse = TRUE)  
S1_VV_eq
```

Calculate RMSE

```
S1_VV_model<-lm(AGBL~S1_VV, data=S2chobezam_wo.num)
rmse <- round(sqrt(mean(resid(S1_VV_model)^2)), 2)
```

Plot RMSE

```
S1_VV_rmse<-S1_VV_eq + geom_text(aes(x=-16.0, y=4.5, size=35,label=
paste("RMSE= ", rmse, "Mg/ha"), hjust=0))+theme_bw()
S1_VV_rmse_xy <- S1_VV_rmse + labs(y="AGB (Mg/ha)", x="S1 VV
Polarisation",title="(a) Sentinel-1 Backscatter Value on VV")
S1_VV_rmse_xy<-S1_VV_rmse_xy + theme(text = element_text(size = 14))
S1_VH_rmse_xy
```

#Sentinel 2 scatterplot

#Plot Sentinel 2 variable ands AGB

```
B2 <- ggplot(data = S2chobezam_wo.num, aes(x =B2, y = AGBL))+
geom_point(aes())
```

```
B2<-B2+geom_smooth(method = "lm", colour="black", formula = y ~ x) #to
exclude the line in the middle set (se=FALSE),
```

#Get equation and r-squared as string

#make a function to plot the equation

```
lm_eqn <- function(S2chobezam_wo.num){
  m <- lm(AGBL~B2, S2chobezam_wo.num);
  eq <- substitute(italic(y) == a + b %.% italic(x)*", "~italic(r)^2~"="~r2,
    list(a = format(unname(coef(m)[1]), digits = 2),
          b = format(unname(coef(m)[2]), digits = 2),
          r2 = format(summary(m)$r.squared, digits = 2)))
  as.character(as.expression(eq));
}
```

```
B2_eq <- B2 + geom_text(x = 0.06, y = 2, label = lm_eqn(S2chobezam_wo.num),
parse = TRUE)
```

Calculate RMSE

```
B2_model<-lm(AGBL~B2, data=S2chobezam_wo.num)
rmse <- round(sqrt(mean(resid(B2_model)^2)), 2)
```

Plot RMSE

```
B2_rmse<-B2_eq + geom_text(aes(x=0.05, y=1.5, label= paste("RMSE= ", rmse,
"mg/ha"), hjust=0))+theme_bw()
B2_rmse
B2_rmse_xy <- B2_rmse + labs(y="AGB (Mg/ha)", x="Reflectance in
B2",title="Sentinel 2")
B2_rmse_xy<-B2_rmse_xy + theme(text = element_text(size = 14))
```

Simple and Multivariate regression models

CREATE THE SIMPLE MODEL FOR AGB USING SAR S1, S2 SPECTRAL BANDS, S2 INDICES. NB: Only showed certain models, the rest of the models can be provided upon request

#B3

```
B2_lm <-lm(AGBL~B2, data =S2chobezam_wo.num)
summary(B2_lm)
r2(B2_lm)
model_performance(B2_lm)
```

#B3

```
B3_lm <-lm(AGBL~B3, data =S2chobezam_wo.num)
summary(B3_lm)
r2(B3_lm)
model_performance(B3_lm)
```

#B5

```
B5_lm <-lm(AGBL~B5, data =S2chobezam_wo.num)
summary(B5_lm)
r2(B5_lm)
model_performance(B5_lm)
```

#NDVI

```
ndvi_m <-lm(AGBL~ndvi, data =S2chobezam_wo.num)
summary(ndvi_lm)
r2(ndvi_m)
model_performance(ndvi_m)
```

#GRVI

```
grvi_m <-lm(AGBL~grvi, data =S2chobezam_wo.num)
summary(grvi_lm)
```

```
r2(grvi_m)
model_performance(grvi_m)
```

#S1 VV

```
S1_VV_lm <-lm(AGBL~S1_VV, data =S2chobezam_wo.num)
summary(S1_VV_lm)
r2(S1_VV_lm)
model_performance(S1_VV_lm)
```

#S1 VH

```
S1_VH_lm <-lm(AGBL~S1_VH, data =S2chobezam_wo.num)
summary(S1_VH_lm)
r2(S1_VH_lm)
model_performance(S1_VH_lm)
```

**#CREATE THE MULTIVARIATE MODEL AND PREDICTION FOR ABOVE
GROUND BIOMASS USING SAR S1, S2 SPECTRAL BANDS, S2 INDICES
COMBINATIONS.** *NB: Only showed certain models, the rest of the models can be provided
upon request*

a)model SAR S1

```
sar.model<-lm(AGBL~S1_VH+S1_VV, data=S2chobezam_wo.num)
summary(sar.model)
r2(sar.model)
model_performance(sar.model)
vif(sar.model)
```

b)Sentinel 2 bands

```
sentinel2.model<-lm(AGBL~B3+B5+B4+B5+B6+B7+B8+B8A+B11+B12,  
data=S2chobezam_wo.num)
```

```
summary(sentinel2.model)
r2(sentinel2.model)
model_performance(sentinel2.model)
vif(sentinel2.model)
```

c) Sentinel 2 and Sentinel 1 bands

```
sentinel2SAR.model<-
lm(AGBL~B3+B5+B4+B5+B6+B7+B8+B8A+B11+B12+S1_VV+S1_VH,
data=S2chobezam_wo.num)
summary(sentinel2SAR.model)
r2(sentinel2SAR.model)
model_performance(sentinel2SAR.model)
vif(sentinel2SAR.model)
```

d) S2 indices only

```
S2ind.model<-
lm(AGBL~ndvi+grvi+evi+savi+msav+nbr+nbr2+gndvi+nR1+nR2+nR3+nR4+ndi4
5+ireci, data=S2chobezam_wo.num)
summary(S2ind.model)
r2(S2ind.model)
model_performance(S2ind.model)
vif(S2ind.model)
```

CHAPTER 4

GOOGLE EARTH ENGINE CODE FOR THE VEGETATION INDICES

Google Earth Engine Code for the vegetation Indices time series time series

<https://code.earthengine.google.com/fe5b816a2cde4a03c63183cb3f1b2cfb?noload=1/>*/

Code generated for calculating different vegetation Indices using 8 day MODIS at 500m, developed by-Ruusa David August 2020

*/

//add the shapefile to the map

```
Map.addLayer(Chobe, ndviVis,'NDVI 8 days')
```

```
Map.addLayer(Chobe, ndviVis,'NDVI 8 days')
```

// mask out cloud and bad pixels

```
var maskclouds = function(image) {  
  return image.updateMask(image.select("SummaryQA").eq(0));  
};
```

```
var maskcloudsQC = function(image) {  
  var QA = image.select('StateQA')  
  var bitMask = 1 << 10;  
  return image.updateMask(QA.bitwiseAnd(bitMask).eq(0))  
}
```

// Load MODIS image collection

```
var MODIS = ee.ImageCollection("MODIS/006/MOD09A1")  
.filterDate('2019-12-01', '2019-12-31')  
.map(maskcloudsQC).max().clip(Chobe);
```

//create a function to calculate NDVI

```
var addNDVI = function(image){
  var newImg = image.normalisedDifference(['sur_refl_b02',
'sur_refl_b01']).double()
  .rename('ndvi');
  return newImg.
  set({
    'system:index' : image.get('system:index'),
    'system:time_start' : image.get('system:time_start')
  });
};
var ndvi =addNDVI(MODIS);
```

//Define visualisation parameters

```
var ndviVis = {
  min: 0.0,
  max: 1.0,
  palette: [
    'FFFFFF', 'CE7E45', 'DF923D', 'F1B555', 'FCD163', '99B718', '74A901',
    '66A000', '529400', '3E8601', '207401', '056201', '004C00', '023B01',
    '001E01', '011D01', '011301'
  ], };
Map.addLayer(ndvi, ndviVis,'NDVI 8 days')
```

//create EVI function

```
var addEVI = function(image) {
  return image.expression(
    '(NIR-RED) / (NIR + 6*RED - 7.5*BLUE + 1)',
    {
      'NIR': image.select('sur_refl_b02'),
```

```

    'RED': image.select('sur_refl_b01'),
    'BLUE': image.select('sur_refl_b03')
  }
).rename('evi') }
var evi = addEVI(MODIS)
Map.addLayer(evi,ndviVis,'EVI 16 days')

```

//create a function to calculate GNDVI

```

var addGNDVI = function(image){
  var newImg = image.normalisedDifference(['sur_refl_b02',
'sur_refl_b04']).double()
  .rename('gndvi');
  return newImg.
  set({
    'system:index' : image.get('system:index'),
    'system:time_start' : image.get('system:time_start')
  }); };
var gndvi =addGNDVI(MODIS);
Map.addLayer(gndvi, ndviVis,'GNDVI 16 days')

```

//Export the NDVI data

```

Export.image.toDrive({
  image:ndvi ,
  folder: 'ChobeMODIS_1',
  fileNamePrefix: 'ND_12_2020',
  description:"Modis_ndvi_8_days_02_500m",
  region: Chobe,
  crs:"EPSG:32735 ",
  scale: 500,
  maxPixels:1e13
});

```

//Export the EVI data

```
Export.image.toDrive({  
  image: evi,  
  folder: 'ChobeMODIS_1',  
  fileNamePrefix: 'EV_12_2020',  
  description:"Modis_evi_8_days_02_500m",  
  region: Chobe,  
  crs:"EPSG:32735 ",  
  scale: 500,  
  maxPixels:1e13  
});
```

//Export the GNDVI data

```
Export.image.toDrive({  
  image: gndvi,  
  folder: 'ChobeMODIS_1',  
  fileNamePrefix: 'GN_12_2020',  
  description:"Modis_gndvi_8_days_02_500m",  
  region: Chobe,  
  crs:"EPSG:32735 ",  
  scale: 500,  
  maxPixels:1e13  
});
```

**R CODE FOR ANALYSING TIME SERIES OF DIFFERENT
VEGETATION INDICES, AND CLIMATE DATA**

This part of the R code is for analysing time series of different
vegetation indices, climate data with change detection algorithms

*Script for gap filling Vegetation Index e.g. NDVI values derived
from MODIS composites.*

Script for gap filling site level NDVI values derived from MODIS composites.

Install needed packages through the pkgTest

```
pkgTest <- function(x)
{
  if (x %in% rownames(installed.packages()) == FALSE) {
    install.packages(x, dependencies= TRUE)
  }
  library(x, character.only = TRUE)
}
neededPackages <- c("r imputeTS "," (lubridate )
for (package in neededPackages){pkgTest(package)}
```

load Libraries

```
library(tidyverse)
library(imputeTS)
library(lubridate)
```

#Read the data

```
MODIS<-read.csv(paste("File.csv",sep="",collapse=""))
```

Convert date to Date format

```
MODIS$Date <- as.Date(MODIS$Date, "%d.%m.%Y")
```

Plot all the land cover types (forest, grassland, water etc) to analyse the data

```
ggplot(MODIS %>% filter(NDVI > -1)) +
  geom_point(aes(Date, NDVI, col = PlotType)) +
  facet_wrap(~PlotType, ncol = 1)
```

Plot one land cover types (forest, grassland, water etc) for all the 12 months to see data distribution

```
ggplot(MODIS %>% filter(NDVI > -1) %>% filter(PlotType == "grass")) +
  geom_point(aes(Date, NDVI, col = PlotType)) +
```

```
facet_wrap(~month)
```

```
# In this section, remove the lowest 1% of values in each month
```

```
# this method assumes low values are contamination and not real change so use with caution
```

```
# 1% could be changed to 5% by swapping 'probs=0:100/100' for 'probs=0:20/20' or by selecting
```

```
MODISa <- MODIS %>%  
  filter(NDVI > -1) %>%  
  group_by(PlotType,month) %>%  
  mutate(quantile = as.integer(cut(NDVI, quantile(NDVI, probs=0:100/100),  
include.lowest=TRUE)),  
         NDVI=replace(NDVI, quantile==1, NA)) %>%  
  drop_na(NDVI) %>%  
  ungroup() %>%  
  select(!c(Year,month))
```

```
# Reformat data in preparation for gap filling
```

```
## Expand data frame to include all date values for every site id
```

```
MODISb <- MODISa %>%  
  complete(Date = seq(floor_date(min(MODISa$Date),unit = "month"),  
                     floor_date(max(MODISa$Date), unit = "month"), by = "month"),  
          nesting(ForestID,PlotType))  
ggplot(MODISb) +  
  geom_point(aes(Date, NDVI, col = PlotType)) +  
  facet_wrap(~PlotType, ncol = 1)
```

```
# Reformat data and fill missing metadata values
```

```
MODISb <- MODISb %>%  
  mutate(DATE = as.Date(Date,"%Y-%m-%d"),  
         DOY = lubridate::yday(DATE)) %>%  
  separate(Date, into = c("YEAR","MONTH","DAY"), sep = "([-])")
```

```
MODISb <- MODISb %>%  
  group_by(ForestID) %>%  
  fill(PlotType, .direction = "updown")
```

check how many na values are there in the NDVI series?

```
sum(is.na(MODISb$NDVI))
```

Gap fill missing NDVI data

This first stage will only be carried out where there is 1 missing value. if there are 2 or more

consecutive missing values then this first step will not fill the gap

```
MODISb <- MODISb %>%  
  arrange(DATE) %>%  
  group_by(ForestID) %>%  
  mutate(GapFill1 = na_interpolation(NDVI, option = "stine", maxgap = 1))
```

#check how many na values are there in the NDVI series?

```
sum(is.na(MODISb$GapFill1)) # in this dataset we have no filled all of the missing data
```

If there are still missing values then we can fill gaps based on the next nearest matching month from a different year

using the linear interpolation between the values in

```
MODISb <- MODISb %>%  
  arrange(DATE) %>%  
  group_by(ForestID, MONTH) %>%  
  mutate(GapFill2 = na_interpolation(GapFill1, option = "linear"))
```

check how many na values are there in the NDVI series?

```
sum(is.na(MODISb$GapFill2))
```

Plot restulant data

```
ggplot(MODISb) +  
  geom_point(aes(DATE, GapFill2, col = PlotType)) +  
  facet_wrap(~PlotType, ncol = 1)
```

investigate difference in Gapfill 1(filled from the month immediately adjacent to missing value)

and 2(filled from nearest matching month)

```
ggplot(MODISb %>% filter(ForestID == "STATE128")) +  
  geom_point(aes(DATE, GapFill2), col = "red") +  
  geom_point(aes(DATE, GapFill1), col = "blue") +  
  geom_point(aes(DATE, NDVI), col = "black") +  
  ylab("NDVI")
```

Write csv for future use

```
write_csv(MODISb, "modis_ndvi_2000_2020_Gapfilled.csv" )
```

Script for BFAST and BEAST algorithm on time series data

load Libraries

```
library(tidyverse)  
library(imputeTS)  
library(lubridate)  
library(zoo)  
library(bfast)  
library(strucchange)  
library(ggplot2)  
library(tidyverse)  
library(Rbeast)  
library(sp)  
library(stringr)
```

```
library(raster)
library(devtools)
library(bfastSpatial)
library(rgdal)
```

Read MODIS and climate monthly data

```
modisall<-read.csv(paste("File.csv",sep="",collapse=""))
str(modisall)
```

#convert the date from factor to DATE format

```
modisall$DATE=as.Date(modisall$DATE, "%d/%m/%Y")
```

#convert the csv to a dataframe

```
modisall.df<-as.data.frame(modisall)
```

aggregate the data and calculate average based on plottype and location(e.g., Namibia and Botswana)

```
mean<-aggregate(modisall.df[,13:18],
list(PlotType=modisall.df$PlotType,Location=modisall.df$Location,
Date=modisall.df$DATE ), mean)
```

#Plot Different types of land cover/ forest types

create the time series for mediumforest

```
NDVI_QA_zammedium.ts <- ts(
  data = meanmedium.zam$NDVI_QA,
  start = c(2002, as.numeric(format(meanmedium.zam$NDVI_QA[1], 07))),
  end = c(2020,as.numeric(format(meanmedium.zam$NDVI_QA[1], 10))),
  frequency = 12 #number of observations per year)
plot(NDVI_QA_zammedium.ts ,type='b', ylab="NDVI",xlab="Year", main =" Average
of mediumforest plots (n=48)",cex=2.0,lwd = 3.5, pch=16,cex.main =
2.0,cex.lab=3.5)
```

create the time series for closedforest

```

NDVI_QA_zamclosed.ts <- ts(
  data = meanclosed.zam$NDVI_QA,
  start = c(2002, as.numeric(format(meanclosed.zam$NDVI_QA[1], 07))),
  end = c(2020,as.numeric(format(meanclosed.zam$NDVI_QA[1], 10))),
  frequency = 12 # number of observations per year

plot(NDVI_QA_zamclosed.ts ,type='b',ylab="NDVI",xlab="Year", main =" Average of
closedforest plots (n=16), Zambezi Namibia",cex=2.0,lwd = 3.5, pch=16,cex.main =
2.0,cex.lab=3.5)

```

#create the time series for agriculture

```

NDVI_QA_zamagri.ts <- ts(
  data = meanagri.zam$NDVI_QA,
  start = c(2002, as.numeric(format(meanagri.zam$NDVI_QA[1], 07))),
  end = c(2020,as.numeric(format(meanagri.zam$NDVI_QA[1], 10))),
  frequency = 12 # number of observations per year)

plot(NDVI_QA_zamagri.ts ,type='b', ylab="NDVI",xlab="Date", main =" Average of
agricultural plots (n=7)",cex=2.0,lwd = 3.5, pch=16,cex.main = 2.0,cex.lab=3.5)

```

#Alternatively choose a single plot type

```

mean_Chobe001<-mean%>% dplyr::filter(
  ForestID=="STATE035")

```

#create the NDVI time series for the chosen plot

```

NDVI_Chobe001.ts <- ts(
  data = mean_Chobe001$NDVI,
  start = c(2002, 7),
  end = c(2019,12),
  frequency = 12 # number of observations per year)

plot(MSAVI_Chobe001.ts ,type='b', ylab="MSAVI",xlab="Year", main =" Disturbed
forest plot",cex=2.0,lwd = 3.5, pch=16,cex.main = 2.0,cex.lab=3.5)

#axis(side=1, at=c(2002:2020))

axis(side=1, at=seq(2002, 2019, by=1))

#box()

```

#create the GNDVI time series for the chosen plot

```
GNDVI_Chobe001.ts <- ts(  
  data = mean_Chobe001$GNDVI,  
  start = c(2002,7),  
  end = c(2019,12),  
  frequency = 12 #number of observations per year)  
plot(MSAVI_Chobe001.ts ,type='b', ylab="MSAVI",xlab="Year", main =" Disturbed  
forest plot",cex=2.0,lwd = 3.5, pch=16,cex.main = 2.0,cex.lab=3.5)  
#axis(side=1, at=c(2002:2020))  
axis(side=1, at=seq(2002, 2019, by=1))  
#box()
```

#create the EVI time series for the chosen plot

```
EVI_Chobe001.ts <- ts(  
  data = mean_Chobe001$EVI,  
  start = c(2002, 7),  
  end = c(2020,6),  
  frequency = 12 # number of observations per year)  
plot(EVI_Chobe001.ts ,type='b', ylab="EVI",xlab="Year", main =" Disturbed forest  
plot",cex=2.0,lwd = 3.5, pch=16,cex.main = 2.0,cex.lab=3.5)
```

#Run BFAST algorithm on NDVI

define the ratio of distance between breaks (time steps) and length of the time series

```
rdist <- 15/length(NDVI_Chobe001.ts)  
fit <- bfast(NDVI_Chobe001.ts, h=rdist,  
  season="harmonic", max.iter=1)  
plot(fit, xlab="DATE", main="NDVI",axes=F)
```

#Run BEAST algorithm on NDVI

```
fit <- beast(NDVI_Chobe001.ts,12)
```

```
plot(fit,xlab="", main="NDVI",axes=FALSE,labels=F)
```

#Run BFAST algorithm on GNDVI

```
rdist <- 15/length(GNDVI_Chobe001.ts) #I tried 25 , but 15 work best  
fit <- bfast(GNDVI_Chobe001.ts, h=rdist,  
            season="harmonic", max.iter=1)  
plot(fit, main="GNDVI")
```

#Run BEAST algorithm on GNDVI

```
fit <- beast(GNDVI_Chobe001.ts,12)  
plot(fit,main="GNDVI")
```

Script for SPATIAL ANALYSIS OF BFAST ALGORITHM (RASTER ANALYSES)

PREPROCESS and ANALYSE THE RASTER DATA WITH BFAST

Define path to files

```
VlpathGNDVI <- "Path/"
```

Load list of raster file names

```
MODIS8GNDVI.fileList <- list.files(VlpathGNDVI , pattern = "*.tif")
```

load individual files into a raster brick

```
MODIS8dayGNDVI <-  
do.call("brick",lapply(paste0(VlpathGNDVI,"/",MODIS8GNDVI.fileList[1:216]),  
                      FUN = function(x){  
                        r <- raster(x)  
                      })
```

#project the raster

```
crs(MODIS8dayGNDVI)
```

#rename the files

```
names(MODIS8dayGNDVI) <- MODIS8GNDVI.fileList
```

create object for original names

```
MODISnamesGNDVI <- names(MODIS8dayGNDVI)
```

```
# Create object for each part of the required name
```

```
band <- str_sub(MODISnamesGNDVI, 1,2)
```

```
month <- str_sub(MODISnamesGNDVI, 4,5)
```

```
year <- str_sub(MODISnamesGNDVI, 7,10)
```

create a new object with the new layernames

```
MODISnamesGNDVI.new <- paste(band,month,year,sep = ".")
```

relabel modis data with new names

```
names(MODIS8dayGNDVI) <- MODISnamesGNDVI.new
```

reorder the raster brick according to new names

```
MODIS8dayGNDVI.reordered <- subset(MODIS8dayGNDVI,  
order(MODISnamesGNDVI.new))
```

```
names(MODIS8dayGNDVI.reordered)
```

**# Save the stacked image data in a single file, .grd with ENVI header file
preserves the layer names**

```
MODISStackGNDVI <-
```

```
writeRaster(MODIS8dayGNDVI.reordered,paste0(VIpathGNDVI,"/MODIS_NDVIsta  
ck.grd"), format="raster",overwrite=TRUE)
```

```
s<-hdr(MODISStack, format = "ENVI")
```

```
par(mar=c(1,2,2,1))
```

#assign dates from 2002 to 2019

```
dtGNDVI<-c('2002-01-01','2003-01-01','2004-01-01','2005-01-01','2006-01-01',
```

'2007-01-01','2008-01-01','2009-01-01','2010-01-01','2011-01-01','2012-01-01',
'2013-01-01','2014-01-01','2015-01-01','2016-01-01','2017-01-01','2018-01-01',
'2019-01-01','2002-02-01','2003-02-01','2004-02-01',
'2005-02-01','2006-02-01','2007-02-01','2008-02-01','2009-02-01','2010-02-01',
'2011-02-01','2012-02-01','2013-02-01','2014-02-01','2015-02-01','2016-02-01',
'2017-02-01','2018-02-01','2019-02-01',
'2002-03-01','2003-03-01','2004-03-01','2005-03-01','2006-03-01','2007-03-01',
'2008-03-01','2009-03-01','2010-03-01','2011-03-01','2012-03-01','2013-03-01',
'2014-03-01','2015-03-01','2016-03-01','2017-03-01','2018-03-01','2019-03-01',
'2002-04-01','2003-04-01','2004-04-01',
'2005-04-01','2006-04-01','2007-04-01','2008-04-01','2009-04-01','2010-04-01',
'2011-04-01','2012-04-01','2013-04-01','2014-04-01','2015-04-01','2016-04-01',
'2017-04-01','2018-04-01','2019-04-01',
'2002-05-01','2003-05-01','2004-05-01','2005-05-01','2006-05-01','2007-05-01',
'2008-05-01','2009-05-01','2010-05-01','2011-05-01','2012-05-01','2013-05-01',
'2014-05-01','2015-05-01','2016-05-01','2017-05-01','2018-05-01','2019-05-01',
'2002-06-01','2003-06-01','2004-06-01',
'2005-06-01','2006-06-01','2007-06-01','2008-06-01','2009-06-01','2010-06-01',
'2011-06-01','2012-06-01','2013-06-01','2014-06-01','2015-06-01','2016-06-01',
'2017-06-01','2018-06-01','2019-06-01',
'2002-07-01','2003-07-01','2004-07-01','2005-07-01','2006-07-01','2007-07-01',

```

'2008-07-01','2009-07-01','2010-07-01','2011-07-01','2012-07-01','2013-
07-01',
'2014-07-01','2015-07-01','2016-07-01','2017-07-01','2018-07-01','2019-
07-01',
'2002-08-01','2003-08-01','2004-08-01',
'2005-08-01','2006-08-01','2007-08-01','2008-08-01','2009-08-01','2010-
08-01',
'2011-08-01','2012-08-01','2013-08-01','2014-08-01','2015-08-01','2016-
08-01',
'2017-08-01','2018-08-01','2019-08-01',
'2002-09-01','2003-09-01','2004-09-01','2005-09-01','2006-09-01','2007-
09-01',
'2008-09-01','2009-09-01','2010-09-01','2011-09-01','2012-09-01','2013-
09-01',
'2014-09-01','2015-09-01','2016-09-01','2017-09-01','2018-09-01','2019-
09-01',
'2002-10-01','2003-10-01','2004-10-01',
'2005-10-01','2006-10-01','2007-10-01','2008-10-01','2009-10-01','2010-
10-01',
'2011-10-01','2012-10-01','2013-10-01','2014-10-01','2015-10-01','2016-
10-01',
'2017-10-01','2018-10-01','2019-10-01',
'2002-11-01','2003-11-01','2004-11-01','2005-11-01','2006-11-01','2007-
11-01',
'2008-11-01','2009-11-01','2010-11-01','2011-11-01','2012-11-01','2013-
11-01',
'2014-11-01','2015-11-01','2016-11-01','2017-11-01','2018-11-01','2019-
11-01',
'2002-12-01','2003-12-01','2004-12-01','2005-12-01',
'2006-12-01','2007-12-01','2008-12-01','2009-12-01','2010-12-01','2011-
12-01',
'2012-12-01','2013-12-01','2014-12-01','2015-12-01','2016-12-01','2017-
12-01',
'2018-12-01','2019-12-01')# corresponding dates to all rasters
my_datesGNDVI <- as.Date(dtGNDVI, format = "%Y-%m-%d")

```

define the function that will be applied across the brick using the calc function

```
bfmRaster = function(pixels)
{
  tspx <- timeser(pixels, my_datesGNDVI) # create a timeseries of all pixels
  bfm <- bfastmonitor(tspx, response ~ trend + harmon, order = 3, start =
c(2014,1)) # run bfast on all pixels
  return(c(bfm$breakpoint, bfm$magnitude))
}
```

calc function

```
bfmRGNDVI <- calc(MODIS8dayGNDVI.reordered, bfmRaster)
names(bfmRGNDVI ) <- c('time of break', 'magnitude of change')
plot(bfmRGNDVI ) # resulting time and magnitude of change
```

Ensure the raster images have correct number of rows and columns

```
rGNDVI<- raster(ncol= 210, nrow=166)
sGNDVI <- stack(lapply(1:216, function(x) setValues(rGNDVI,
runif(ncell(rGNDVI))))))
MODIS8dayGNDVI.reordereds <- setZ(MODIS8dayGNDVI.reordered,
my_datesGNDVI)
MODIS8dayGNDVI.reordereds
getZ(MODIS8dayGNDVI.reordereds)
plot(MODIS8dayGNDVI.reordereds[[1]])
```

Define path to files to export

```
VlpathGNDVI_out <- "path/"
```

#Define output path

```
outsGNDVI <- file.path(VlpathGNDVI_out ,
"bfmSpatial_start2010,1_gndvi_until2019.tif")
```

#Run the bfmSpatial on raster data starting 2010

```
bfmSpatial(MODIS8dayGNDVI.reordereds, start = c(2010, 1),formula =
response~harmon,order = 1, filename = outsGNDVI)
```

**PREPARE THE RASTER DATA AND EXTRACT THE
MAGNITUDE**

#Read in the data

```
gndvistate2010_ha1 <- brick("File.tif")  
plot(gndvistate2010_ha1,1, main="Monitoring period 2013-2020, gndvi ")
```

extract change raster

```
change_gndvistate2010_ha1 <- raster(gndvistate2010_ha1, 1)  
# extract magn raster  
magn_gndvistate2010_ha1 <- raster(gndvistate2010_ha1, 2)  
# make a version showing only breakpoing pixels  
magn_bkpgndvistate2010_ha1 <- magn_gndvistate2010_ha1  
magn_bkpgndvistate2010_ha1[is.na(change_gndvistate2010_ha1)] <- NA  
op <- par(mfrow=c(1, 3))  
plot(magn_bkpgndvistate2010_ha1, main="Magnitude: breakpoints")  
plot(magn_gndvistate2010_ha1, main="Magnitude: all pixels")
```

extract and rescale magnitude and apply a threshold

```
magn09thresh_gndvistate2010_ha1 <- magn_gndvistate2010_ha1  
magn09thresh_gndvistate2010_ha1 [magn_gndvistate2010_ha1 > 0.00] <- NA
```

compare all magn rasters

```
op <- par(mfrow=c(2, 2))  
plot(magn09thresh_gndvistate2010_ha1, main="magnitude")  
plot(magn09_sieve_gndvistate2010_ha1, main="pixel sieve")  
plot(magn09_areasieve_gndvistate2010_ha1, main="0.5ha sieve")  
plot(magn09_as_rook_gndvistate2010_ha1, main="0.5ha sieve, rook's case")
```

```
changeSize_queengndvistate2010_ha1 <-  
clumpSize(magn09_areasieve_gndvistate2010_ha1)
```

```
changeSize_rookgndvistate2010_ha1 <-  
clumpSize(magn09_areasievegndvistate2010_ha1, directions=4)
```

#Calculate the change size

```
op <- par(mfrow=c(1, 2))
```

```
plot(changeSize_queengndvistate2010_ha1, col=bpy.colours(50), main="Clump  
size: Queen's case")
```

```
plot(changeSize_rookgndvistate2010_ha1, col=bpy.colours(50), main="Clump size:  
Rook's case")
```

```
changeSize <- clumpSize(magn09_areasievegndvistate2010_ha1,  
f=250000/10000)
```

```
plot(changeSize, col=bpy.colours(50), main="Pixel size gndvi (hectares)")
```

#export path

```
writeFormats()
```

```
GNDVI_VIpath <- "path/"
```

**#Write the year of change and magnitude of change raster and export it out
for further analysis in ArcGIS**

```
MODISStack <- writeRaster(changegndvistate2010_ha1,paste0(File.tif"), format =  
"GTiff",overwrite=TRUE)
```

```
MODISStack <- writeRaster(magngndvistate2010_ha1,paste0(File.tif"), format =  
"GTiff",overwrite=TRUE)
```

CHAPTER 5

GOOGLE EARTH ENGINE CODE FOR FIRE

Google Earth Engine Code for the fire time series

<https://code.earthengine.google.com/7a868676bc7ac534247a19d7cdc6b150?noload=1>

```
/*////////////////////////////////////
```

```
Code geerated for MODIS Burned Area Monthly at 500m, developed by-Ruusa  
David August 2020
```

```

*////////////////////////////////////
//This is a code to get the monthly Burned pixels
//Get list of images
var MODISBurn_Image = ee.ImageCollection(MonthlyBurnedArea)
  .filterDate('2019-09-01', '2019-09-30') //define the month, change this to the
month of your choice
  .filterBounds(kaza).mean().clip(kaza); //get the mean and clip the data

//Get the burn date
var MODISBurn_Image = MODISBurn_Image.select('BurnDate');
var firesVis = {
  min: 325.0,
  max: 400.0,
  palette: ['red', 'orange', 'yellow'],};

//Display on the map
Map.addLayer(MODISBurn_Image, firesVis, 'Fires');
print(MODISBurn_Image)
print('ImageList')

//export the burned data out
Export.image.toDrive({
  image: MODISBurn_Image,
  folder: 'MCD64A1_fireUncertainty_2019',
  description:"MCD64A1_fire_2019_12_500m",
  region: kaza.geometry().bounds(),
  crs:"EPSG:32735 ",
  scale: 500,
  maxPixels:210984237950});

//This is a code to get the uncertainty of the Burned pixels

```

// Get list of images to test

```
var MODISUncertainty_Image = ee.ImageCollection(MonthlyBurnedArea)
  .filterDate('2019-12-01', '2019-12-30')
  .filterBounds(kaza).mean().clip(kaza);
```

//Get the uncertainty burn date

```
var MODISUncertainty_Image = MODISUncertainty_Image.select('Uncertainty');
var firesVis = {
  min: 325.0,
  max: 400.0,
  palette: ['red', 'orange', 'yellow'],};
```

//Display on the map

```
Map.addLayer(MODISUncertainty_Image, firesVis, 'Fires');
print(MODISUncertainty_Image)
print('ImageList')
```

```
//export the uncertainty out
```

```
Export.image.toDrive({
  image: MODISUncertainty_Image,
  folder: 'MCD64A1_fireUncertainty_2019',
  description:"MCD64A1_fireUncertainty_2019_12_500m",
  region: kaza.geometry().bounds(),
  crs:"EPSG:32735 ",
  scale: 500,
  maxPixels:210984237950});
```

GOOGLE EARTH ENGINE CODE FOR THE CLIMATE DATA

Google Earth Engine Code for the climate time series

<https://code.earthengine.google.com/93b50f3bd714cb527ce6573fbd1f23dc?noload=1>

```
/*////////////////////////////////////
```

Code generated for comparing Ground precipitation and satellite based precipitation, developed by-Ruusa David June 2019

```
*////////////////////////////////////
```

```
//Add the ground precipitation on the map
```

```
Map.addLayer(gpcc1981)
```

```
Map.addLayer(gpcc2016)
```

```
//extract all the climate data
```

```
var collections = [ {
```

```
  name: 'CHIRPS', scale: 5000,
```

```
  collection: ee.ImageCollection('UCSB-CHG/CHIRPS/PENTAD')
```

```
},
```

```
{
```

```
  name: 'gpcc', scale: 3000,
```

```
  collection: ee.ImageCollection('users/ruusadavid2/gpccCollection_1891')
```

```
},
```

```
{
```

```
  name: 'cru', scale: 3000,
```

```
  collection: ee.ImageCollection('users/ruusadavid2/cruCollection')
```

```
},
```

```
{
```

```
  name: 'CFSV2', scale: 5000,
```

```
  collection: ee.ImageCollection('NOAA/CFSV2/FOR6H')
```

```
  .select('Precipitation_rate_surface_6_Hour_Average')
```

```
  .map(function(i) {
```

```
    return i.multiply(60 * 60 * 6) // convert to mm by 6 since it is in mm/second and is a 6 hour basis
```

```
    .copyProperties(i, ['system:time_start'])
```

```
  }) }];
```

//create a function to define the the range of date to be mapped through

```
function getDates(start, stop, step) {  
  return ee.List.sequence(start, stop).map(function(year) {  
    return ee.List.sequence(1, 12, step).map(function(month) {  
      return ee.Date.fromYMD(year, month, 1)  
    })  
  }).flatten()  
}
```

//create a function to compute the sum and mean through all precipitation bands in all images

```
function compute(start, stop, step) {  
  var dates = getDates(start, stop, step)  
  var features = collections.map(function(c) {  
    return dates.map(function(d) {  
      var p = c.collection  
        .filterDate(d, ee.Date(d).advance(step, 'month'))  
        .sum()  
        .reduceRegion(ee.Reducer.mean(), southAfrica, c.scale).values().get(0)  
      return ee.Feature(null)  
        .set('system:time_start', ee.Date(d).millis())  
        .set(c.name, p)  
    })  
  })  
  return ee.FeatureCollection(ee.List(features).flatten())  
}
```

//define the the time period to be computed on

```
var monthly = compute(1981, 2016, 1)  
var annual = compute(1981, 2016, 12)
```

//set a function to define the chart titles, x and y axis titles

```
function chart(features, title) {  
  var chart = ui.Chart.feature.byFeature(features, 'system:time_start')  
  chart.setOptions({  
    vAxis: { title: 'Precipitation [mm]' },  
    title: title  
  })  
  print(chart)  
}
```

//create the charts

```
chart(monthly, 'Monthly precipitation in Southern Africa Subcontinent (2001-  
2015)')  
  
chart(annual, 'Raingauge and satellite-based annual precipitation in Central  
Angola, coordinates[18.71,-11.00](1981-2016)')
```

R CODE FOR ANALYSING TIME SERIES OF VEGETATION DATA AND CLIMATE DATA

This part of the R code is for analysing time series of Vegetation Data and Climate Data

ANALYSE AND PLOT THE GROUND RAINFALL AND TEMPERATURE

#Load the Library

```
library(corr)  
library(dplyr)  
library(tidyverse)  
library(igraph)  
library(ggraph)
```

```
library(Hmisc )
library(corrplot)
library(sp)
library(zoo)
library(xts)
library(hydroTSM)
library(ggplot2)
library(dplyr)
```

#Import the data

```
precip8<-read.csv(paste("File.csv",sep="",collapse=""))
```

#prepare the data

#convert to data frame

```
x<-as.data.frame(precip8)
```

Convert date to Date format

```
x$Dates=as.Date(x$Date, "%d.%m.%Y")
```

```
#anyDuplicated(x$Dates)
```

```
#duplicated(x$Dates) | duplicated(x$Dates, fromLast = TRUE)
```

#create a zoo object for time series

```
x<- zoo(x$Rainfall,x$Dates)
```

#plot rainfall

```
plot(x, main="rainfall", ylab="precipitation (mm)", xlab="Time")
```

#find the number of years

```
( nyears <- yip(from=start(x), to=end(x), out.type="nubr" ) )
```

#plot the prepared data with hydroplot

```
hydroplot(x, var.type="Precipitation", main="at Chobe National Park",
```

```
pfreq = "dm", from="1975-01-01")
dwi(x)
```

#Analyse the rainfall time series data

#Monthly analysis

```
monthlyfunction(x, FUN=median, na.rm=TRUE)
cmonth <- format(time(x), "%b")
months <- factor(cmonth, levels=unique(cmonth), ordered=TRUE)
```

#Boxplot of the monthly values

```
boxplot( coredata(x) ~ months, col="lightblue", main="Monthly Precipitation",
        ylab="Precipitation, [mm]", xlab="Month")
```

#Average seasonal values of precipitation

```
seasonalfunction(x, FUN=sum, na.rm=TRUE) / nyears
```

#Extracting the seasonal values for each year

```
m<-monthlyfunction(x, FUN=sum, na.rm=TRUE)
( DJF <- dm2seasonal(x, season="DJF", FUN=sum) )
( MAM <- dm2seasonal(x, season="MAM", FUN=sum) )
( JJA <- dm2seasonal(x, season="JJA", FUN=sum) )
( SON <- dm2seasonal(x, season="SON", FUN=sum) )
```

#Extract the seasonal values for each year

```
hydroplot(x, pfreq="seasonal", FUN=sum, stype="default",ylab="Precipitation
(mm)",lwd=2)
```

Mean winter (DJF) values of streamflow for each year of 'x'

```
dm2seasonal(x, FUN=sum, season="DJF")
dm2seasonal(x, FUN=sum, season="MAM")
dm2seasonal(x, FUN=sum, season="JJA")
```

```
dm2seasonal(x, FUN=sum, season="SON")
```

Selecting only a three-year time slice for the analysis

```
x <- window(x, start=as.Date("1975-01-01"))
```

```
#Plotting the selected time series
```

```
hydroplot(x, FUN=sum, ptype="ts", pfreq="ma",  
var.unit="mm",ylab="Precipitation",lwd=1.8)
```

Create the Climograph from the rainfall and temperature data

#Read the Precipitation and Temperature data

```
preciptemp<-read.csv(paste("File.csv",sep="",collapse=""))
```

#convert to data frame

```
y<-as.data.frame( preciptemp)
```

Convert date to Date format

```
Dates=as.Date(y$Date, "%d.%m.%Y")
```

#create a zoo for time series

```
z <- zoo(y[, 2:4], as.Date(as.character(y[, 1]), format="%d.%m.%Y"))
```

```
colnames(z) <- c("Precipitation", "Max Temperature", "Min Temperature")
```

extracting individual ts of precipitation, maximum and minimum temperature

```
pcp <-z[,1]
```

```
tmx <- z[,2]
```

```
tmn <-z[, 3]
```

Plotting the climograph

```
m <- climograph(pcp=pcp, tmx=tmx, tmn=tmn, na.rm=TRUE, main="Monthly  
Precipitation, Min and Max Temperature")
```

```
plot(z, main = "Monthly Rainfall, Maximum and Minimum  
Temperature",xlab="Years", lwd=2, col=c("blue", "red","black"),cex.axis  
=1.5,cex.main = 2)
```

**CALCULATING SPEI FROM GROUND RAINFALL AND
TEMPERATURE**
**#Calculating SPEI using Ground rainfall and temperature from Kasane Chobe
Botswana**

#Read the data

```
raintemp<-read.csv(paste("File.csv",sep="",collapse="")) #with all data and  
outliers removed
```

#convert points into dataframe

```
raintemp<-data.frame(raintemp)  
str(raintemp)
```

#calculate potential evapotranspiration

```
raintemp$PET<-hargreaves(Tmin=raintemp$Tempmin,  
Tmax=raintemp$Tempmax, lat =-17.82947 )  
raintemp$PET
```

#calculate climatic water balance

```
raintemp$CIWaBAL<-raintemp$Precip-raintemp$PET  
raintemp$CIWaBAL  
CIWaBAL<-raintemp$Precip-raintemp$PET
```

**#calculate standardised precipitation evapotranspiration index, and define
the scale by 1 moth or two months or 12 etc**

```
SPEI1<-spei(raintemp$CIWaBAL,1) #for 1 month  
raintemp$SPEI1.dataframe=as.data.frame(fitted(SPEI1)) #convert to dataframe  
par(mar=c(5, 4, 4, 6) + 0.1)
```

#calculate SPEI for 1 month

```
plot.spei(spei(ts(raintemp$CIWaBAL,  
freq=12,start=c(1983,1)),1,ref.start=c(1983,1),ref.end=c(2020,10)),main  
="Standardised Precipitation Evapotranspiration Index (SPEI-1 months)",textSize  
= 8 )
```

```
mtext(side=1, line=2, "Time", font=2,cex=1.2)
```

#calculate SPEI for 2 month

```
plot.spei(spei(ts(raintemp$CIWaBAL,  
freq=12,start=c(1983,1)),2,ref.start=c(1983,1),ref.end=c(2020,10)),main  
="Standardised Precipitation Evapotranspiration Index (SPEI-2 months)",textSize  
= 8 )
```

```
mtext(side=1, line=2, "Time", font=2,cex=1.2)
```

#calculate SPEI for 12 month

```
plot.spei(spei(ts(raintemp$CIWaBAL,  
freq=12,start=c(1983,1)),12,ref.start=c(1983,1),ref.end=c(2020,10)),main  
="Standardised Precipitation Evapotranspiration Index (SPEI-12 months)",textSize  
= 8 )
```

```
mtext(side=1, line=2, "Time", font=2,cex=1.2)
```

#Plot all three SPEI timescale (1,3,12 months) in one plot

```
par(mar=c(5, 4, 5, 6) + 0.1)
```

```
par(mfrow=c(1,1))
```

#Plot first plot for 1 month

```
plot.spei(spei(ts(raintemp$CIWaBAL,  
freq=12,start=c(2002,7)),1,ref.start=c(2002,7),ref.end=c(2019,12)),main  
="Standardised Precipitation Evapotranspiration Index (SPEI-1month)",textSize  
=12, xlab="", ylab="", axes=FALSE, )
```

```
#mtext(side=1, line=2, "Time", cex=1.5)
```

```
mtext(side=2, line=2, "SPEI", cex=1.5)
```

```
axis(side=1, at=seq(2002, 2019, by=1),cex.axis = 1.0, cex.lab = 1)
```

```
box()
```

#Plot second plot for 2 months

```
plot.spei(spei(ts(raintemp$CIWaBAL,  
freq=12,start=c(1983,1)),3,ref.start=c(1983,1),ref.end=c(2019,12)),main  
="Standardised Precipitation Evapotranspiration Index (SPEI-3 months)",textSize  
=12, xlab="", ylab="", axes=FALSE, )
```

```

mtext(side=1, line=2, "Time", cex=1.5)
mtext(side=2, line=2, "SPEI", cex=1.5)
axis(side=1, at=seq(1982, 2019, by=1),cex.axis = 1.0, cex.lab = 1)
box()

```

#Plot second plot for 22 months

```

plot.spei(spei(ts(raintemp$CIWaBAL,
freq=12,start=c(1982,1)),12,ref.start=c(1982,1),ref.end=c(2019,12)),main
="Standardised Precipitation Evapotranspiration Index (SPEI-12 months)",textSize
=12, xlab="", ylab="", axes=FALSE, )
mtext(side=1, line=2, "Time", cex=1.5)
mtext(side=2, line=2, "SPEI", cex=1.5)
axis(side=1, at=seq(1982, 2019, by=1),cex.axis = 1.0, cex.lab = 1)
box()

```

ANALYSE THE CLIMATE DATA AND VEGETATION DATA (NDVI)

#Plotting climate and NDVI

#Read the data

```

preciptemp<-read.csv(paste("File.csv",sep="",collapse=""))
head( preciptemp)

```

#Covert the data to a dataframe

```

y<-as.data.frame( preciptemp)

```

#Covertto the Date understood by r

```

y$Dates=as.Date(y$Date, "%d.%m.%Y")
tail( preciptemp)

```

Plot first set of data (NDVI in this case) and draw its axis

```

plot(y$Dates, y$NDVI, pch=16, axes=TRUE, ylim=c(0,1), xlab="", ylab="",
      cex.axis = 1.3, cex.lab = 2, type="b",col="black", main="NDVI and Precipitation")
#axis(2, ylim=c(0,1),col="black",las=1) # las=1 makes horizontal labels

```

```
mtext("NDVI",side=2,line=2.5, cex=1.5)
```

```
box()
```

Allow a second plot on the same graph

```
par(new=TRUE)
```

Plot the second plot (precipitation) and put axis scale on right

```
plot(y$Dates, y$Precip, pch=15, xlab="", ylab="", ylim=c(0,500), axes=FALSE,  
type="b", col="dark red", )
```

add labels

```
mtext("PRECIPITATION",side=4,col="dark red",line=4, cex=1.5)
```

```
axis(4, ylim=c(500), col="dark red",col.axis="dark red",las=1,cex.axis = 1.3, cex.lab  
= 2)
```

Draw the time axis

```
mtext("Time",side=1,col="black",line=2.5, cex= 1.8)
```

Add Legend

```
legend("topleft",legend=c("NDVI","PRECIPITATION"),bty = "n",  
text.col=c("black","dark red"),pch=c(16,15), col=c("black","dark red"))
```

ANALYSE THE RELATIONSHIP BETWEEN CLIMATE DATA (SOIL MOISTURE, SPEI, RSM, PRECIPITATION, TEMPERATURE) AND VEGETATION DATA

#Read the data

```
modis8<-read.csv(paste("XFile.csv",sep="",collapse=""))
```

#Create a function to plot

```
flattenCorrMatrix <- function(cormat, pmat) {  
  ut <- upper.tri(cormat)  
  data.frame(  
    row = rownames(cormat)[row(cormat)[ut]],  
    column = rownames(cormat)[col(cormat)[ut]],
```

```

cor =(cormat)[ut],
p = pmat[ut]
)
}
s2corAll3<-rcorr(as.matrix(modis8.num[]))
flattenCorrMatrix(s2corAll3$r,s2corAll3$P)

```

Mark the insignificant coefficients according to the specified p-value significance level

```

cor_5 <- rcorr(as.matrix(modis8.num))
M <- cor_5$r
p_mat <- cor_5$P
col <- colourRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD",
"#4477AA"))
corrplot(M, method = "colour", col = col(200),
type = "upper", order = "hclust",
addCoef.col = "black", # Add coefficient of correlation
# Combine with significance level
p.mat = p_mat, sig.level = 0.01,
# hide correlation coefficient on the principal diagonal
diag = FALSE )

```