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Abstract

This thesis investigates the cost-effectiveness of agricultural non-point source pollution control policies through a biophysical-economic model for the Eden catchment in North-West England. Firstly, the presented thesis extensively reviews agri-environmental policy in the UK and the economic literature on non-point source pollution control. Moreover, in the context of current agricultural reforms in the UK and recent technological progress in agricultural technology, policy recommendations are drawn from a purpose-built biophysical-economic model covering six key non-point source pollutants (nitrogen and phosphorus to both the river and groundwater, sediment, and carbon emissions). The model is implemented in GAMS and characterised by a novel level of biophysical detail in the literature, including six farm types, six livestock types, 10 hydrological connectivity levels, five soil types, four slope types, 45 years of observed weather data, and 25 crops selected from 24 crop rotations. Policies are assessed over a range of abatement ambitions to facilitate evidence for different policymaker objectives. Overall, incentive-based fertiliser input taxes are found to be the most cost-effective policy mechanism in the Eden catchment. Notably, the presented results confirm previous findings in the literature of inelastic fertiliser demand. Consequently, high levels of taxation are required to achieve non-point source pollution abatement. Further, the novel assessment of Precision Agriculture in the context of a detailed catchment-scale biophysical-economic model highlights the necessary preconditions for precision agriculture to be cost-effectively implemented. Modelling of spatially targeted policies moreover highlights the synergies between spatial targeting and precision agriculture in this respect. Policymakers should ensure sufficient heterogeneity in biophysical variables (soil-types, slope-types, and hydrological connectivity levels) to safeguard successful applications of both spatial targeting and precision agriculture.

The Economics of
Agricultural Non-Point Source Pollution Control

Investigating Synergies Between
Spatial Targeting and Precision Agriculture

By

Lioba Marie Wendling

A thesis submitted for the degree of

Doctor of Philosophy
in
Economics

August 2023

Contents

List of Tables

List of Figures

List of Abbreviations

BFI	Base Flow Index	78
BGBM	Below Ground Biomass including GYLD in DM t/ha	98
BIOM	Total Biomass in DM t/ha	98
BPS	Basic Payment Scheme	25
CAP	European Common Agricultural Policy	38
CFEM	Carbon Emissions (from machinery)	120
CRF	Constant Rate Fertilisation	59
CS	Countryside Stewardship	30
CSF	Catchment Sensitive Farming	24
CSS	Countryside Stewardship Scheme	21
CVM	Contingent Valuation Method	63
DEFRA	UK Department of Environment, Food and Rural Affairs	18
DM	Dry Matter	98
EA	UK Environment Agency	22
EF	Efficiency Factor	96
EL	Emission Licenses	42
ELM	Environmental Land Management Schemes	29
ELS	Entry Level Stewardship	24
EPIC	Environmental Policy Integrated Climate model	37
ES	Environmental Stewardship	24
ESA	Environmentally Sensitive Area	18
ESRC	Economic and Social Research Council	76
EWGS	English Woodland Grant Scheme	27
FBEET	Fodder Beet	171
FRfW	Farming Rules for Water	28
FWCF	Fresh Weight Correction Factor	101
FYLD	Forage Yield in DM t/ha	98
FYM	Farm Yard Manure	139
GAMS	General Algebraic Modelling System	53
GDPR	General Data Protection Regulation	61
GRAZE 2	Grazing Grass (2 fertiliser applications)	171
GRAZE 3	Grazing Grass (3 fertiliser applications)	171
GRAZE 4	Grazing Grass (4 fertiliser applications)	139
GRAZE 6	Grazing Grass (6 fertiliser applications)	139
GRAZE LFA	Grazing Grass on LFA Less Favourable Area	171
GYLD	Grain Yield in DM t/ha	61
HAY LFA	Hay on LFA	101
HAY2	Hay (2 cuts)	173
HLS	Higher Level Stewardship	24
LFA	Less Favourable Area	71
LTNM	Lake Taupo Nitrogen Market	45
MAIZE(WC)	Whole-Cropped Maize	173
MIP	Mixed Integer Programming	67
MISC	Miscanthus	173
MPP	Marketable Pollution Permits	41
N	Nitrogen	53
NCS	New Countryside Stewardship	26
NFU	National Farmers Union	26
NGLOAD	Nitrogen to Groundwater	120

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1. Introduction

Over the last three decades, non-point source (NPS) pollution from agriculture has been recognised as a key factor in the significant water quality degradation observed in the EU and across the world (Spofford, Krupnick and Wood, 1986; Buckley and Carney, 2013; Casado *et al.*, 2019). Consequentially, NPS pollution has become a focal concern for agri-environmental policy in Europe and the USA (Hanley, Whitby and Simpson, 1999; Claassen and Horan, 2001). To support these policy efforts, economic research increasingly investigates efficient and cost-effective NPS pollution control policies in agriculture. Research has focussed particularly on biophysical-economic modelling which accounts for the interdisciplinary challenges of examining agri-environmental policies. Several studies for example examine policy measures to reduce diffuse agricultural nitrogen (N) pollution (e.g. Berntsen *et al.*, 2003; Belhouchette *et al.*, 2011; Bourgeois, Ben Fradj and Jayet, 2014). The current once-in-a-generation reform of UK agri-environmental policy following Brexit calls for up-to-date economic evidence on cost-effective policy options to control agricultural NPS pollution. This thesis aims to contribute to this need for evidence by addressing gaps in the literature as outlined in the following section.

1.1. Objective

As touched upon above, the key objective of this thesis is to provide an up-to-date evidence base on the cost-effectiveness of different agri-environmental policies in the UK and support the current work on the UK's agricultural transition (DEFRA, 2020). In addition to UK political developments, the global agricultural sector has seen significant technological advances over the past two decades. Increasing quantitative and environmental demands on food production have prompted substantial innovation in agricultural production (Finger *et al.*, 2019). The progressive use of information technology in the agricultural sector is referred to as "Precision Agriculture" (PA) (see section 3.4.1 for details). Previous empirical economic literature has largely not accounted for PA or has used a limited farm specific modelling framework. This thesis therefore aims to provide insights into PA's influence on catchment-scale yield and NPS outcomes.

In addition to influencing yield and pollution outcomes, technological progress in PA has also extended the possibility frontier of agri-environmental policy. This development specifically applies to spatially targeted agri-environmental policies. Theoretically, numerous studies have shown these interventions to be more efficient and cost-effective than uniformly applied policies, as they account for differences in local biophysical conditions which represent a key variable in agricultural production (Ribaudo, Osborn and Konyar, 1994; Yang *et al.*, 2003; Lungarska and Jayet, 2018). However, previous research has deemed the implementation of spatially targeted agri-environmental policy too costly in the real world due to high monitoring and transaction costs (Lintner and Weersink, 1999). The described new developments in PA provide the data and monitoring powers necessary to reduce implementation costs and make spatially targeted applications of agri-environmental policies feasible in the real world (Gebbers and Adamchuk, 2010). By empirically investigating the economic and environmental impact of PA and spatially targeted agri-environmental policies as well as potential synergies between them, this research will contribute to the evidence base on currently available policy options.

Finally, previous biophysical-economic modelling of agri-environmental policy has necessarily been limited in its detail by current computational capabilities. This fact has led to simplifications of biophysical processes in primary agricultural production which significantly influence key yield and pollution outcomes particularly relating to crop rotations, weather data and hydrological connectivity levels. Using a novel simulated biophysical data set for the Eden catchment in the UK, this thesis extends previous works by explicitly considering hydrological connectivity levels and modelling a novel combination of crop rotations, weather data, soil-, and slope-types (see Table 39, p. 157).

The following section outlines the structure of the presented thesis.

1.2. Thesis Structure

This section provides an overview of the remaining chapters of the thesis. Firstly, chapter 2 provides the UK's agri-environmental policy context from the 1980s to today. Subsequently, chapter 3 reviews the previous economic literature on NPS pollution, agri-environmental policy and agricultural technologies. Chapter 4 describes the theoretical framework and modelling approaches of the biophysical-economic model while chapter 5 analyses the input data and baseline output data for model validation. Chapter 6 presents the results of the scenario analysis and chapter 7 discusses the presented results within the context of the existing literature. Finally, chapter 8 summarises the findings and draws out the resulting policy recommendations before discussing the limitations of the thesis and considerations for future work.

2. Agri-Environmental Policy in the UK

The following chapter contextualises current policy demands through an overview of the last four decades of agri-environmental policy in the UK from its beginnings to the present. This includes environmental policies (e.g.: Water Framework Directive (WFD)) and agricultural policies (e.g.: Single Payment Scheme (SPS), the Basic Payment Scheme)) which are not classified as agri-environmental measures but impact agricutlural production and its environmental externalities.

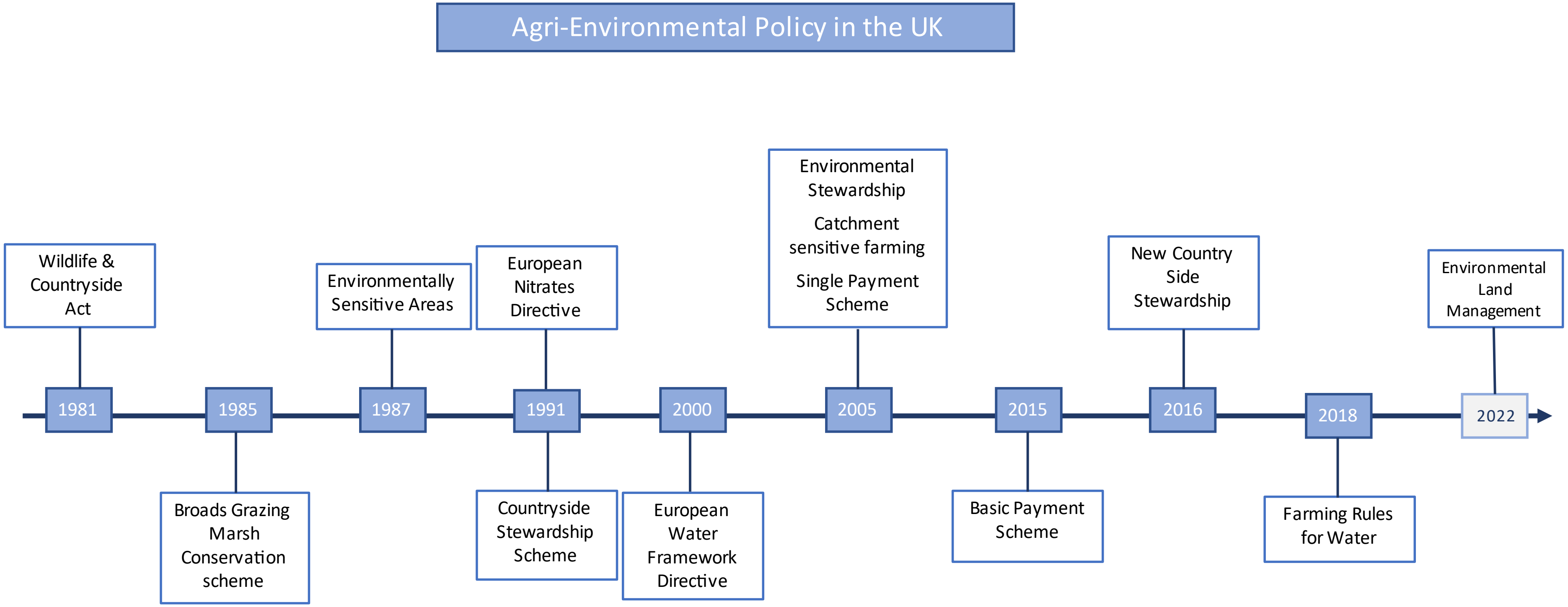
2.1. Agri-Environmental Policy in the UK

Since the first UK agri-environmental policies were introduce in the 1980s, policy objectives have gradually evolved from a production-focussed approach towards seeking to increase environmental benefits (see Figure 1, p. 20 for timeline). Initially, environmental concerns in England focussed on protecting and conserving biodiversity. Among the first agri-environmental policies, the **Wildlife & Countryside Act** introduced protective measures focussed on endangered bird species and National Parks (UK Government, 1981). Farmers were offered income forgone payments to incentivise the reduction of damaging operations. Subsequently, the **Broads Grazing Marsh Conservation Scheme of 1985** used simple hectare based pay-outs for compliance with management restrictions on the Halveragte Marshes in contrast to the previously used forgone-profit-system (Hart and Wilson, 2000, p. 101). With a significantly high uptake of 89% the scheme managed to reduce the degradation of the Marshes and became a model for European measures of the '80s and '90s.

2.2. Environmentally Sensitive Areas (1987)

As European integration deepened and agricultural policy across Europe became increasingly assimilated, UK agri-environmental policy was mainly shaped by European reforms. "Regulation 797/85 on Improving the Efficiency of Agricultural Structures" (1985) was one of the first European Acts to explicitly address the need for conservation of agricultural resources. The adoption of Regulation 797/85 in the UK prompted the introduction of Environmentally Sensitive Areas (ESAs) in 1987 (Hart and Wilson, 2000, p. 101). These sought to define for protection parts of the country with high landscape-, historic-, or wildlife-value by offering incentives to farmers to adopt conservation practices (Natural England, 2019). Farmers in selected areas could sign up for 10-year management agreements with the Department for Environment, Food and Rural Affairs (DEFRA) and receive annual payments on a hectare basis for adhering to conservation management practices. From 1987 to 1994 the number of areas qualifying as ESAs was gradually increased to 22 in England and relatively high uptake up to the end of the programme in 2005 lead to a 10% cover of the English agricultural land (DEFRA, 2006; Natural England, 2012).

Figure 1: Timeline of UK agri-environmental policy



2.3. Countryside Stewardship Scheme (1991)

The ESA programme was supplemented by the Countryside Stewardship Scheme (CSS) in 1991. The CSS aimed to protect the most important areas outside the designated ESAs through the same incentive mechanisms used in the ESA programme and both schemes are now collectively referred to as the classic schemes (Natural England, 2009, p. 2). Carey *et al.*'s (2000) evaluation of CSS found that on average these schemes had a positive environmental effect (mean score of 2.4 on scale of -5 to 5) and a high probability of compliance (mean score of 3.1 on scale of -5 to 5), where scores were assigned according to an appraisal team's judgement of the available evidence. However, the authors report that environmental effectiveness varied significantly between different landscape types (SD 1.5) and notable inconsistencies existed in compliance between agreement holders (SD 1.7). Overall, the classic schemes achieved relatively high participation levels and are credited with slowing the environmental degradation of the British countryside due to increasing agricultural intensification over the 20th century (Natural England, 2009, p. 10). However, as farmers could enter agreements on subsections of their farms, concerns arose over the so-called "halo effect": participants may have shifted intensive practices away from sections under agreement towards other farm areas, thereby relocating environmental degradation as opposed to reducing it (Hart and Wilson, 2000, p. 105).

2.4. Nitrates Directive (1991)

The Nitrates Directive was adopted by the European Commission in 1991 in response to rising water pollution from agriculture across the EU and has since become an integral part of UK agri-environmental policy. It focusses on regulating and limiting agricultural practices related to N fertiliser application and storage as well as livestock management. Firstly, the directive sets out guidance on identifying priority areas for waterbodies which include freshwater and groundwater containing nitrate concentrations greater than 50 mg/l as well as eutrophic freshwaters (European Commission, 2019c). To protect the defined priority areas, "Nitrate Vulnerable Zones" (NVZs) were introduced. NVZs are designated by individual member states to specifically include priority areas on their territory or to extend to the entire national territory. In addition to nationally applicable voluntary Codes of Good Agricultural Practice, farmers in designated NVZs are subject to more stringent regulation. In England, crop specific quantitative, spatial, and temporal limits on N application are imposed to account for varying pollution risks based on seasons and distances to water bodies (DEFRA and EA, 2018b). In addition, farmers are required to record and retain their fertiliser applications in "fertilisation plans" for five years. Enforcement inspections by the Environment Agency (EA) further require farmers to keep risk-N-pollution-maps of the farm holding which detail field locations and slopes, land drains, manure stores, and water bodies (DEFRA and EA, 2018b).

Over the years the cover of NVZs in the UK has gradually increased. However, due to the devolved implementation of NVZs in the UK, their land cover varies significantly between countries. As of 2020 NVZ land cover ranged from 100% (Northern Ireland and Wales) to 55% (England) and 14% of Scotland (Vivid Economics, 2020, p. 19). Evidence on the effectiveness of the Nitrates Directive and NVZs in the UK also shows variation. The 2018 status report from the European Commission on the Nitrate Directive found that the UK soil N surplus was amongst the highest of the member states for the period 2012-14 (European Commission, 2018, p. 4). However, a report from the House of Commons Environmental Audit Committee (2018, p. 45) found a general reduction in N and phosphorous (P) surpluses in UK soils since 2000, indicating that policies of the Nitrates Directive may have positively impacted UK farming practices over time. In a more local study, Macgregor and Warren (2016) investigated the effectiveness of NVZs for the River Eden catchment specifically, which also forms part of this analysis. They found that NVZs had positively influenced farmers' attitudes towards the environmental impact of farming and noted that there has been a significant improvement in the catchment's N concentration parameters since the implementation of the NVZ. However, the authors noted that the observed decline in fertiliser rates is also correlated with significant increases in fertiliser prices over the period and could not be singularly attributed to the establishment of the NVZ. Despite mixed evidence on their effectiveness, NVZs in particular and the Nitrates Directive generally, have remained a fundamental element of UK NPS pollution control and have become part of more recently introduced legislation like the Water Framework Directive (WFD).

2.5. Water Framework Directive (2000)

In late 2000 European water policy was consolidated and extended in its purview under the WFD. The primary goal of the WFD was to achieve "good ecological status" for all European waters by 2015, allowing for extensions until 2027 in specific circumstances (European Commission, 2019b). To accomplish this target, other directives focussing on specific water pollution issues such as the Nitrates Directive, the Industrial Emissions Directive and the

Urban Waste Water Treatment Directive are now coordinated under the WFD (European Commission, 2019a). In contrast to previous water pollution policies, the WFD follows a “river basin management” approach which guides the coordination and implementation of policies according to geographically and hydrologically established watershed boundaries rather than politically-motivated national boundaries (European Commission, 2019a). Management plans are to be created and updated for every river basin subject to European legislation on a six-year-cycle. Although there are no specified policy recommendations, the WFD calls for evidence-based policies to be employed and has spurred significant scientific interest and economic analyses investigating optimal agri-environmental policy design (Collins and McGonigle, 2008). However, the effectiveness of the WFD is difficult to assess, both ex-ante and ex-post, due to the vague definition of the key target of “good status”. The general definition of ecological status levels provided by the directive are insufficiently precise for valuation studies on potential benefits of implementation (Martin-Ortega and Berbel, 2010). In England, seven River Basin Districts (RBDs) were identified and river basin management plans (RBMPS) were published in 2009 and updated in 2015 (DEFRA and EA, 2019). The Solway Tweed RBD for example, encompasses areas in Northeast England and Southeast Scotland including the River Eden catchment which is the case study of this analysis. In the updated RBMPS, the Environment Agency and SEPA (2021) highlight the role advice and guidance as well as catchment partnerships play in increasing the percentage of surface and groundwaters in the RBD meeting a good or better condition than the currently-reported 50%. They specifically highlight the effectiveness of partnerships of farmers, advisory services, and water companies collaborating to tackle the continuing issue of agricultural NPS pollution in the RBD. However, as condition improvements have been offset by newly identified deteriorations, the overall water environment in the RBD has remained stable since 2015 (EA and SEPA, 2021, p. 10). Earlier data on the general status of surface waters in England echoes this finding. Little change is observed in ecological status between 2008-2017 and official estimates suggest about 25% of UK waterbodies will not reach the target of “good status” by 2027 (Priestley and Barton, 2018). Although the status of water protection in the UK has fallen short of the objectives stated by the WFD, the legislation is considered to have been a significant influence in British water policy and an important factor in preventing further water quality degradation.

2.6. Environmental Stewardship (2005)

In 2005 the classic schemes were combined in the new Environmental Stewardship (ES) scheme (Natural England, 2009, p. 11). ES was comprised of two levels of conservation efforts: Entry Level Stewardship (ELS), and Higher Level Stewardship (HLS) (RPA, DEFRA and Natural England, 2019). Land management agreements under ELS included generally simple and effective conservation practices lasting for 5 years while HLS agreements were more complex, long term (10 years) and tailored to the local circumstances. In addition, Organic Entry Level Stewardship (OELS) existed for organic and mixed conventional land management agreements. In line with the previous agri-environmental systems, farmers entering agreements were paid flat rates per ha on land entered into the scheme (Natural England, 2013). Participants chose between different management options which support the main objectives of the scheme and vary in their availability across the country to account for spatial heterogeneity in conservation needs: wildlife conservation, enhancing landscape quality and character, preserving the historic environment, protecting water quality and reducing soil erosion, safeguarding existing soil carbon levels, and providing a response to climate change (Natural England, 2013, p. 9). ES was successful in encouraging wide coverage of areas of arable land with 60% of that arable land being under ELS agreements in 2012 alone (Emery and Franks, 2012). However, evidence from evaluation studies found that the uptake patterns of ELS limit ecological benefits of the scheme which were a primary target. Boundary management constituted up to half of the ELS compensation payments, yet benefits for ornithological biodiversity of boundary management have been found to be limited, thereby limiting the overall ecological benefits of ELS implementation (Davey *et al.*, 2010, p. 470).

2.7. Catchment Sensitive Farming (2005)

The Catchment Sensitive Farming (CSF) programme was introduced in late 2005 with the objective to "encourage action from farmers to help achieve Water Framework Directive […] and SSSI objectives"(CSF Evidence Team, 2014, p. 7). The programme identified priority catchments through which it primarily provides farmers with advice and training on more sustainable practices as well as some financial assistance with the costs of implementing water pollution mitigation measures (CSF Evidence Team, 2014, p. 7). Its third phase ended in 2014; however, CSF officers continue to provide advice and training as well as support farmers through novel agri-environmental schemes like the New Countryside Stewardship programme (see section 2.10, p. 27). Although the selection of broad priority areas was common in previous programmes like ESAs, personalised management advice through the

CSF officers introduced a new layer of spatial targeting at the farm-level. An evaluation of the CSF's effectiveness found that it achieved significant reductions in pesticide levels in rivers and sediment pressures on those rivers (CSF Evidence Team, 2014). Nonetheless, the evaluation highlights that CSF displays three-year lags in achieving environmental impacts in the priority areas as advisors require time to build relationships within local farming communities.

2.8. Single Payment Scheme (2005)

The Single Payment Scheme (SPS) was also implemented in 2005 following the 2003 reform of the Common Agricultural Policy (CAP). The SPS superseded previous European agricultural payments and decoupled them from production-linked targets (European Commission, 2009). The simplification of agricultural support into one payment based on land entitlements sought to encourage farmers to respond to market demand and avoid overproduction issues observed under previous schemes (Massot, 2019). Further, SPS included cross-compliance conditions which farmers had to meet in order to receive full payments. These cross-compliance conditions included statutory management requirements which maintain good environmental conditions on agricultural land like restrictions on water abstraction as well as permit requirements for discharges which affect groundwater (DEFRA, 2012). As the cross-compliance conditions intended to set lower bounds on agriculture-driven environmental degradation, they were relatively unambitious and mainly raised farmer's transaction costs by increasing their administrative obligations. However, these initial conservation measures within the CAP proved insufficient for protecting agricultural landscapes and the 2013 CAP reform shifted further attention and resources towards rural development and environmental conservation including poverty reduction measures in rural areas and promoting low-carbon agricultural practices (Holden *et al.*, 2017, p. 10; Negre, 2019).

2.9. Basic Payment Scheme (2015)

Following the 2013 CAP reform, the SPS was replaced by the Basic Payment Scheme (BPS) in 2015. In a manner similar to the SPS, the operation of the BPS is based on production-decoupled entitlements farmers can claim on their land. However, to address environmental concerns, the BPS includes a greening component which is worth 30% of the total BPS payment and requires farmers above a certain holding size to (RPA, 2019a): (i) implement crop diversification measures, (ii) preserve permanent grassland and (iii) create Ecological

Focus Areas. Ecological Focus Areas include specified agricultural measures which promote ecological and environmental restoration (e.g.: buffer strips, field margins, catch crops, cover crops, and hedges). Despite some overlap with agreements prior to 2012, BPS operated alongside the Environmental Stewardship programmes and continues to compliment the New Countryside Stewardship (NCS) programme. Farm inspections are conducted by the RPA to verify compliance on roughly 1% of the farms that submit BPS claims. Although the inspection rate is significantly lower than that observed in some other European countries (e.g.: 5% inspection rate in Ireland (Department of Agriculture Food and the Marine, 2019, p. 29)) compliance rates in the UK have significantly increased over the period of BPS implementation from 79.08% to 91.06% from 2015 to 2019 respectively[1]. The reduction in non-compliance despite the relatively low probability of inspection may be explained by the increasingly stringent penalties imposed for non-compliance. As found by the Farm Inspection and Regulation Review (2018) significant fines are being issued for minor offences, which has led to dissatisfaction within the farming community. Notwithstanding, these substantial penalties may explain the high compliance rates in accordance with principle-agent theory. In line with criticisms regarding the NCS programme's implementation outlined below, farmers report significant delays in payments of the BPS which lead to uncertainty among producers and hinder production planning (NFU, 2019). Moreover, a 2017 review by the European Court of Auditors raised concerns over the environmental effectiveness of the new greening component. The auditors highlight that the scheme lacks clear and sufficiently ambitious environmental targets and effectively remains an income support system as payments exceed amounts warranted by the environmental requirements (European Court of Auditors, 2017, p. 7). This analysis is further supported by the evaluation of the Alliance Environment and Thünen Institute who find that over 90% of total UK arable land was either already diversified in 2014, exempted from diversification measures or still undiversified in 2014 and 2015; this evaluation indicates that greening policies may have a small impact on promoting change towards environmentally positive farming practices (Alliance Environnement and Thünen Institute, 2017, p. 40). Moreover, some environmental indicators targeted by the greening measures were found to have worsened during the implementation period with, for example, permanent grassland cover in the UK for example decreasing by around 13% between 2014 and 2015 (Alliance Environnement and Thünen Institute, 2017, p. 52).

[1] Source: Information Request to RPA (RFI 5341, 5 February 2020).

2.10. New Countryside Stewardship (2016)

The New Countryside Stewardship (NCS) was introduced in 2016 and encourages agricultural management to promote natural landscape and biodiversity preservation (Zhang *et al.*, 2017). The scheme replaced the ES programme, the English Woodland Grant Scheme (EWGS) and capital grants from the CSF programme (Natural England, 2018). The NCS comprises Mid-Tier and Higher-Tier agreements regarding conservation management between DEFRA and farmers (RPA *et al.*, 2019). For the five-year Mid-Tier agreements farmers can select from 146 options of effective and relatively simple management changes and capital investments which support the scheme's environmental and ecological objectives (see Appendix A, Table 40, p. 169 for details).

As the focus of this thesis is diffuse pollution control, this review concentrates on the management options concerned with reducing agricultural NPS pollution. Of the management options listed under NCS Mid-Tier, 18 can be categorised as targeting agricultural diffuse pollution with 16 of these options being targeted towards specific areas which are generally high risk. In addition to management options which generally provide yearly payments on a hectare basis, the Mid-Tier also includes capital items which provide support over two years for capital farm infrastructure investments with significant environmental or ecological benefits. Two years into the programme, to help facilitate adoption and guide farmers towards relevant options, four specific offers (Arable, Lowland grazing, Mixed farming, Upland) were created. These offers comprise options relevant to the particular land type, but do not include capital items. Applications to these offers are not competitive and are granted to any applicant meeting the requirements. This system is in contrast to all other applications to NCS which are assessed and ranked according to their environmental impact in the local area; in those cases, only the most environmentally effective applications are granted.

The Higher-Tier agreement accommodates more complex and site-specific changes to agricultural management in order to achieve environmental and ecological improvements. The agreements are negotiated between the Rural Payment Agency and farmers in a two-step competitive application process and can last up to 20 years (RPA, 2019b). Although Higher-Tier agreements are more sophisticated and tailored than Mid-Tier agreements, a number of Mid-Tier options and capital items can be included in Higher-Tier agreements.

Despite efforts to simplify the NCS application process, it remains time consuming and requires significant documentation which can be a barrier to adoption. In addition, important issues with the NCS' administrative implementation have been reported, including delays in contract provision from the RPA and late payments (NFU, 2019).

2.11. Farming Rules for Water for England (2018)

In April 2018 *The Reduction and Prevention of Agricultural Diffuse Pollution (England) Regulations* (2018) came into force. These regulations signed eight rules referred to as the Farming Rules for Water (FRfW) into law which specifically address farm fertiliser and soil management to reduce diffuse pollution from agriculture (DEFRA, 2018b). The rules were introduced to achieve water quality targets under the European WFD; however, they are also aligned with the UK government's strategy to implement less-prescriptive and more outcome-focussed agri-environmental policies following the UK's departure from the EU. Although the rules include specified spatial restrictions on fertiliser application and livestock feeder positions, they also require farmers to assess risks for NPS pollution and independently implement appropriate mitigation strategies (DEFRA, 2018b). The "advice led enforcement" of the rules primarily addresses offences through advice issued by the EA and reserves prosecution for persistent offences in order to foster a more collaborative approach to agri-environmental policy between regulators and stakeholders (DEFRA and EA, 2018a, pp. 5, 6). Farm operators have welcomed the exclusion of additional record keeping requirements in the rules as well as the cooperative approach of the advice-led enforcement (NFU, 2018). This focus on outcomes and reducing the administrative burden on stakeholders is likely to promote efficiency and improve acceptance of the policies within the farming community. However, concerns have been raised that the lack of clear definitions could entail diverse interpretations by inspectors across England and thus lead to incongruous enforcement of the FRfW (NFU, 2018). In addition, the possibly subjective readings of central terms in the regulations like "significant risk of pollution" could provide legal loopholes and impact effective enforceability in line with Meran and Schwalbe's (1987) critique of collective fining. Indeed, due to significant uncertainty within the sector regarding the application of the regulation, the EA issued the Regulatory Position Statement (RPS) 252 (2021)[2]. The RPS temporarily amended Rule 1[3] and allowed farms to exceed crop need in fertilisation if

[2] expired on the 1st of March 2022

[3] Rule 1 includes the requirement for land managers to plan the use of manures and fertilisers according to crop need and water pollution risks(DEFRA, 2018b).

contingency plans were in place to reduce the risk of pollution from fertilisation. Subsequently, Defra published statutory guidance on the application of the farming rules for water (DEFRA, 2022c) providing more clarity on the definition of a significant risk of pollution depending on the readily available N content of organic fertilisers.

As farmers adhering to NVZ regulation and BPS cross compliance-conditions are likely to meet the FRfW already (DEFRA and EA, 2018a, p. 8), the additionality and environmental impact of the measures is likely to be low. Bhogal, Anthony and Gooday (2021) modelled the impact of the application of Rule 1. Their results are summarised in Table 1.

Table 1: Bhogal, Anthony and Gooday's (2021) modelled impact of farming rules for water rule 1 on pollution outcomes

Pollutants	Effect on nutrient losses from manure applications	Effect on total loss from UK agriculture
Nitrate leaching	-60%	-1.5%
Ammonia emissions	+ 10%	+2%
P loss	+30%	+5%

While they predict a significant reduction in nitrate losses from organic fertiliser applications, the authors find an increase in ammonia emissions and P losses due to the application of the rules. They highlight the need to balance different pollution risks in NPS pollution regulation, which is exemplified in the pollution swapping demonstrated in Table 1. The rules currently focus on the type of organic manure that is being applied and the timing of the application. However, the authors suggest that the application method and the soil conditions and coverage during application also significantly impact the pollution risk from organic fertilisation. Further evidence of the effectiveness of the FRfW is expected to be available with the first formal review (expected no later than September 2025 (DEFRA, 2022c)).

2.12. Environmental Land Management Schemes (2022)

Over a seven-year transition period from 2021 to 2027, The Environmental Land Management (ELM) schemes are gradually replacing the European CAP in England. While BPS CAP payments are progressively reduced, the offering and funding available under the ELM schemes is increasing (DEFRA, 2020) . This section summarises the published plans for the post-transition offering as outlined in DEFRA's (January 2023) update. Going forward, ongoing financial support in the agricultural sector will come from three key schemes compensating farmers for practices which are environmentally beneficial beyond the regulatory baseline:

1) *Sustainable Farming Incentive (SFI):*
    - Aimed at farmers adopting farming practices which protect nature and enhance farm productivity.
    - Support for specific actions which are grouped into main standards (to date nine standards have been published for 2023).
    - Offer allows farmers to choose specific actions from different standards and is compatible with actions offered under CS.

2) *Countryside Stewardship and CS Plus:*
    - Expanded and refined offer of the existing CS scheme to support actions targeted by habitats, features, and location.
    - CS Plus further includes incentives for land managers to partner locally and deliver results on a larger scale.

3) *Landscape Recovery:*
    - Support for environmentally beneficial, large scale, long-term projects
    - Bespoke agreements are being offered to a smaller number of successful applicants through a competitive process.
    - In 2022 funding was awarded to 22 projects which cover 40 000 hectares collectively with a focus on rivers and habitat protection.
    - Round two, opening in 2023, will focus on protected sites, carbon emission targets and habitat creation.

Over the agricultural transition period, these schemes are complemented by one-off payment schemes which mainly support improvements to farm productivity and resilience. Most relevant to environmental improvements are grants available for investments in equipment, technology and infrastructure which include match-funded support to build slurry storage (DEFRA, 2022b).

The three on-going support schemes aim to respond to recommendations made in the Stacey Review (2018) on UK farm inspection and regulations regarding simplifications and flexibility in the regulatory approach. The review highlighted the need for more simplified, efficient and incentive-led agricultural regulation, having previously identified 182 different regulatory instruments and noted the complexity in existing guidance (Stacey, 2018, p. 43).

Due to the ELM schemes' rapid development and ongoing roll out, the evidence on effectiveness is limited. The report by the National Audit Office (2021, p. 14) further highlights potential uptake issues with only a 5% response rate to SFI pilot trials from eligible farmers. Published results from ELM development trials corroborate evidence from previous policy evaluations (see CSF and WFD above) and suggest that support through advisers plays a key role in maximising environmental benefits from agri-environmental schemes (DEFRA, 2021c).

As outlined above, the scheme design published to date still follows an action-based approach. This method is in contrast to an earlier focus on moving towards payments-by-results with some promising outcomes in early trials (Chaplin, Mills and Chiswell, 2021). Notably, the referenced trials focussed on biodiversity outcomes. The return to action-based schemes may be rationalised by the difficulty of applying payment-by-results to other key agricultural pollution issues such as nutrient pollution in rivers. The NPS nature of river nutrient pollution contributes to these challenges and is further discussed in the following chapter.

3. Literature Review

The following chapter firstly reviews the economic literature on NPS pollution (section 3.1) and policy instruments to control agricultural NPS pollution (section 3.2). Subsequently, section 3.3 discusses the literature on spatially targeted policy applications and section 3.4 reviews previous work on agricultural technologies in economic agri-environmental policy analyses.

3.1. Economic Definition of Non-Point Source Externalities

Environmental externalities are famously defined by Baumol and Oates (1988, p. 17) as situations in which the production or utility functions of an agent (A) are dependent on real variables which are determined by other agents, independently of the welfare implications the chosen variable values entail for A. Namely, a person's welfare may depend on the quality of water at their disposal. Water quality is influenced by the production decisions of farmers in the area, who in turn, however, do not consider water quality impacts in their production decisions.

Griffin and Bromley (1982) specifically focus on agricultural environmental pollution and describe it as a "non-point externality". The authors define non-point externalities as occurring when it is impossible to directly observe and attribute individual externality contributions to different economic agents. Their work underscores the difficulty of observing diffuse pollution which implies significant challenges in tracing it to the polluters and implementing agri-environmental policies (Shortle and Horan, 2017). A further characteristic of NPS pollution, which constitutes an important challenge in control design, is the stochastic nature of the natural processes involved in diffuse pollution (Spofford, Krupnick and Wood, 1986; Halstead *et al.*, 1991). As diffuse pollution levels depend on a number of factors, including transport parameters, geographical characteristics of the area and stochastic environmental variables like precipitation, it is difficult to forecast pollution levels even if all production decisions of polluters could be observed (Shortle and Horan, 2001).

Over the years economic theory and empirical research have sought to address the question of how to efficiently control agricultural NPS pollution. A variety of different policies and application methods have been investigated. The following section will discuss the major policy instruments which have been proposed and review some of the proposed application methods.

3.2. Policy Instruments

Policies to address environmental issues are commonly categorised by their fundamental working mechanism into "command-and-control" and "incentive-based" mechanisms (Hahn and Stavins, 1992). In the context of agricultural pollution, command-and-control policies (also referred to as regulation-based approaches) leave less flexibility for farmers in their production decisions than incentive-based policies (also referred to as market-based approaches) to achieve an environmental goal. Incentive-based policies provide incentives for farmers to meet environmental targets, however, specific production choices remain free. Examples of command-and-control policies include technological and management requirements as well as emission limits and set-aside requirements, whilst incentive-based policies typically comprise taxes, subsidies, and pollution permit markets. Given the scope of this thesis, agri-environmental subsidies are not appraised and are recommended for future research (see section 8.4, p. 166). This section firstly discusses previous economic evidence on the comparative performance of incentive and regulation-based policies (Section 3.2.1), before providing an in depth review of some of the commonly investigated incentive policies (Section 3.2.2). Finally, Section 3.2.3 reviews literature on combining such incentive and regulation-based policies into mixed policy approaches.

3.2.1. Economic Incentive vs Regulation-Based Policies

Griffin and Bromley (1982) were among the first to explicitly consider NPS externalities in their adaptation of Baumol and Oates' framework for point source externalities. The authors focus on the spatial externality of agricultural water pollution which constitutes nutrients and chemicals leaching off agricultural fields into the water system. They extend a static theoretical model for point externality control to account for the unobservability of individual NPS emissions. They show that both least cost incentive and regulation policies can be implemented by focusing efforts on the inputs which determine emissions rather than emissions themselves. The modelled policies specifically include: (i) an incentive policy (tax/subsidy for emission determinants), (ii) regulation standards, (iii) differentiated management incentives for polluting production activities and (iv) a combination of regulation standards and management incentives (see p. 549 f.). The authors find that all four considered policies theoretically constitute allocatively efficient policy outcomes. Nonetheless, they highlight differences in information requirements and potential implementation costs between the instruments. Further, the analysis of Griffin and

Bromley (1982) employs non-stochastic pollution functions and hence does not account for uncertainty in the relationship between inputs and NPS emissions.

These uncertainties are addressed by Shortle and Dunn (1986) who revisit the policies investigated by Griffin and Bromley (1982). Namely, their analysis includes incomplete information on the biophysical run-off process as well as *ex ante* uncertainty about the weather which in turn plays a significant role in the process. Moreover, the authors consider more realistic scenarios such as asymmetric information between farmers and regulators regarding farm profits, multiple polluters, and different levels of farmers' risk aversion. The theoretical analysis confirms the efficiency equivalence of Griffin and Bromley's four policies for the single polluter case without uncertainty or asymmetric information. However, when uncertainty and asymmetric information are accounted for, incentive policies targeting management practices outperform the remaining policy instruments. This is mainly due to the fact that they leave farmers the flexibility to use their expert knowledge in production decisions while also signalling them relatively more information on the expected externalities associated with these decisions than do other policy instruments (see Shortle and Dunn, 1986, p. 675).

Kampas and White's (2004) work also accounts for the stochastic nature of agricultural NPS pollution and additionally investigates the impact of policies' administrative costs on their cost-effectiveness. The authors employ a biophysical-economic model to rank the cost-effectiveness of diffuse N pollution control policies in reaching the European Nitrate Directive target for the Kennet catchment (Southwest England). The range of investigated policies includes (i) emission permits, (ii) an emission tax, (iii) a N input quota, (iv) a targeted N quota, (v) a N tax, (vi) a land tax and (vii) a set-aside requirement (see p. 117). The analysis demonstrates that when administrative costs are ignored, a uniformly applied emission tax is the most cost-effective NPS pollution control. However, when administrative costs are accounted for, N input taxation outperforms emission taxation in terms of efficiency. Moreover, the authors test how sensitive the results are to changes in the assumed level of the policymaker's risk aversion and level of administrative costs. Notably, set-aside requirements are found to become less cost-effective as the regulator's risk aversion increases. The rankings are, however, shown to be robust to changes of up to 30% in the assumed magnitude of administrative costs.

More recently, Wang and Baerenklau (2015) investigated the cost-effectiveness of different nitrate control policy scenarios using a dynamic biophysical-economic model which is calibrated to a representative dairy farm in the San Joaquin Valley (California, USA). The authors simulate a number of regulation-based policies including a nutrient management plan, a field emission limit and a downstream emission limit, as well as two incentive-based measures given by a field emission charge and a downstream emission charge. In line with previous works, their results suggest incentive measures to be more cost-effective in pollution control than regulation-based policies. Further, their analysis finds that emission-based instruments outperform the input-oriented policy. However, these results could be due to the fact that the only input measure simulated is a regulation-based approach. Moreover, the authors do not include administrative costs, which, given Kampas and White's (2004) results discussed above, may explain the favourable performance of emission based policies. Wang and Baerenklau's (2015) work also investigates the impact of alternative production technology choices on the cost of complying to agri-environmental regulation, the details of which are reviewed in section 3.4.

Overall, the reviewed evidence suggests that incentive-based policies generally outperform regulation-based measures. This performance ranking is due to the fact that incentives leave farmers' more flexibility to decide how to achieve pollution reduction in production than command-and-control policies do. As farmers can be assumed to have more information on their costs and revenues, their production decisions are more likely to be cost-minimising than regulations imposed by a government which has imperfect information regarding farmers' costs and revenues (Shortle and Dunn, 1986). This principle is further supported by the findings of more recent empirical studies (Kampas and White, 2004; Wang and Baerenklau, 2015). However, as highlighted by Shortle and Horan (2017), the complex biophysical characteristics of NPS pollution (spatial, temporal, and stochastic variations, unobservability and complex transport pathways for multiple pollutants, see section 3.1) comprise 'wicked challenges' for finding cost-effective NPS pollution control policies. They particularly highlight the fact that economic incentives, whilst remaining theoretically interesting, have been scarcely implemented and largely failed to demonstrate successful real-world results. Therefore, along with authors such as Ribaudo (2015), Shortle and Horan (2017) call further research into alternative approaches including: command-and-control policies, mixed policies, and supporting behavioural change and collective-action through outreach and extension services. Indeed, commentators in the specific debate surrounding incentive and regulation-based policy approaches to NPS pollution have suggested that a combination of economic and regulation-based measures may be more cost-effective than are individual incentive policies (Baumol and Oates, 1988, Chapter 13; Schuler and Sattler, 2010). Further, empirical evidence on such mixed policy instruments is reviewed in section 3.2.3. Firstly, the following section will provide a more detailed review of the different types of economic incentives which are commonly investigated in the literature.

3.2.2. Economic Incentive Policies

As mentioned in the previous sections incentive-based policies include a variety of different measures which all address farmers' incentive structure in different ways to promote agricultural NPS pollution abatement. One of the key differences in incentive-based measures is their target. "Input-based" are distinguished from "ambient" measures, where the former target individual polluters' production choices which are linked to agricultural NPS pollution, while ambient measures are aimed at NPS pollution levels directly and polluters' collective choices (Shortle and Horan, 2013). Another important difference in incentive-based measures is the instrument used to change incentives. Taxes and permit markets can be considered some of the most popular incentive instruments analysed in the economic literature. The following sections firstly review previous economic analyses on environmental taxation of inputs (section 3.2.2.1) and the ambient environment (section 3.2.2.2), before discussing marketable pollution permits in the context of agricultural NPS pollution.

3.2.2.1. Input Tax

As discussed above, the unobservability of agricultural NPS pollution complicates attempts to control NPS emissions directly. Regulating agricultural inputs which are known to impact NPS emissions therefore provides an attractive indirect approach to pollution abatement. Input taxes have thus become a popular incentive-based tool investigated in the literature on agri-environmental policy. The following discussion reviews four studies which analyse the conditions under which input taxes may be a cost-effective measure to control agricultural NPS pollution.

In an early analysis, Larson, Helfand and House (1996) investigate which inputs in particular are most cost-effectively addressed to achieve reduction targets for agricultural nitrate pollution from irrigated Californian agriculture in a second-best scenario. Their results suggest that a water tax is more cost-effective than taxing N and provides welfare results similar to first-best policy outcomes. This finding is explained by the limited substitutability between inputs in the Mitscherlich-Baule production function used (see section 4.5) and the relatively higher elasticity of pollution with respect to water than to N in the employed pollution function. The results are shown to be robust as regards the use of alternative production functions including quadratic and square root functions. However, the numerical analysis does not include a formal treatment of basic production heterogeneity (such as differences in soil quality) which may influence the results. Nonetheless, the study highlights the significance of the elasticities of agricultural output and of the environmental externality with respect to inputs for the cost-effectiveness of an input tax.

Using simulated data from EPIC, Martínez and Albiac (2004) compare the cost-effectiveness of two input taxes to other incentive and regulation-based policies in the context of the European WFD in the Ebro basin in Spain. The policies specifically include a tax on water prices/m^3, a tax on N prices/kg and a tax on N emissions (€/kg), as well a limit on N kg/ha applied varied by crop type. The authors assess these policies based on resulting changes to welfare, farm quasi-rent and N leaching for the irrigation district. In line with Larson, Helfand and House (1996), the results suggest that the cost-effectiveness of input taxation significantly depends on the choice of input. However, conversely to Larson, Helfand and House's (1996) static model results, Martínez and Albiac's (2004) dynamic model results suggest that water taxes are a relatively inefficient instrument of NPS pollution control and N taxation achieves superior pollution abatement at a lower cost to producers. This divergence in results can be explained by the fact that Martínez and Albiac (2004) account for policy effects beyond the period of policy implementation. The authors explain that a water tax leads to a build-up of N in the soil and thereby increases nitrate leaching in the following periods which are omitted from Helfand and House's (1996) static analysis. This highlights the importance of considering the dynamics of biophysical processes in agricultural NPS pollution in policy analysis. In line with the theoretical expectation discussed above, the authors find the incentive-based measure of an emissions tax to be the most cost-effective policy option. Although, their policy ranking suggests that the regulation-based limit on N application outperforms both of the simulated input taxation measures, the authors caution against the significant difficulties of ensuring compliance with the N limit.

Focusing on market dynamics as opposed to biophysical dynamics, Claassen and Horan (2001) investigated agricultural NPS pollution control measures in a flexible price framework. They focus on uniform and non-uniform input taxation in a framework of numerous sub-regions with heterogeneous production and independence in terms of policy setting. Their analytical exposition highlights the "pecuniary externalities" which arise from input taxation when prices are endogenous. These constitute the effects of taxation in one sub-region which are transmitted between different sub-regions through markets. A tax-induced rise in the price of fertiliser in a sub-region for example leads to a local substitution away from fertiliser towards land in the sub-region which in turn entails a fall in the general market price of fertiliser. Consequentially, fertiliser consumption in other sub-regions is likely to increase, leading to a rise in NPS pollution driven by the market price effects which interlink sub-regions (Claassen and Horan, 2001, pp. 5–6). Given the size of this thesis' study catchment (see section 5.1 for details), the possibility of defined sub-regions which could realistically face different prices is limited. Therefore, prices in this thesis are treated as exogenous and Claassen and Horan's (2001) market dynamics points are not quantitatively explored. However, their work highlights the importance for coordination in policy efforts across larger regions to ensure pan-regionally effective outcomes (see Section 3.3 for discussion of the empirical illustration of their model).

More recently, Jayet and Petsakos (2013) also consider the effects of implementing a uniform tax across heterogeneous subregions. They specifically investigate the effectiveness of a N input tax under two wider European policy scenarios and different implementation scales in France. The authors compare the welfare implications of a tax on fertiliser N content in the setting of (i) the CAP at the base year 2002 and (ii) the CAP after its 2003 reform. Moreover, their analysis includes three different applications scales of the N tax: (i) national level, (ii) basin level, and (iii) regional level. They find that N demand is relatively inelastic and that a 100% tax at the national scale only reduces consumption between 50.5% for the base year 2002 scenario and 51.6% for the post 2003 scenario. Their analysis shows that substitution effects occur when the tax is implemented at higher-level scales due to significant regional differences in production practices and fertiliser use, which lead to unintended effects on national N consumption. They suggest that in order to provide efficient N reductions, N taxes should be implemented at smaller scales and possibly combined with N application standards.

Largely, the reviewed studies suggest that input taxation chiefly in the form of N or water taxation can constitute an effective policy intervention; however, the yield and emission elasticities with respect to inputs as well as longer-term biophysical dynamics of pollution should be considered in policy design (Larson, Helfand and House, 1996; Martínez and Albiac, 2004). Moreover, the review has highlighted the potential benefits of mixing incentive-based policies like input taxes with command-and-control measures which has indeed been a separate point of emphasis in the literature (see section 3.2.3). Finally, the question regarding the appropriate choice for application levels of agri-environmental policies raised by Jayet and Petsakos (2013) is further discussed in section 3.3.

Due to the stochastic nature of NPS pollution some commentators argue that excessive uncertainty remains in understanding the relationship between input application and pollution generation. They argue that the success of input taxation in curbing NPS pollution is therefore too uncertain to be relied upon and suggest an approach of ambient taxation instead which is discussed in the following section.

3.2.2.2. Ambient Taxation

In her seminal theoretical contribution, Segerson (1988) proposes an ambient pollution tax as an efficient tool to control NPS pollution. Regulators declare their desired threshold level ($\bar{p}$) of pollution (p) and a tax (t) is imposed on polluters, where the latter could have a positive (tax) or negative (subsidy) value. The magnitude and sign of t is determined by the amount that p exceeds (falls short of) the defined threshold $\bar{p}$. In the case of multiple polluters, the tax becomes a collective tax. Importantly, each potential polluter is charged the entire marginal benefit of lower levels of ambient pollution (B') through the collective tax, as opposed to a fraction (B'/n, where n denotes the number of potential polluters) (Segerson, 1988, p. 95). This approach allows the ambient tax to address issues of moral hazard and ensure that each polluter faces the appropriate marginal incentives, given the uncertain relationship between abatement and ambient pollution levels. Relative to direct regulation and input taxation, the ambient tax is less invasive in firms' production decisions and therefore likely to be more efficient. Moreover, the associated implementation costs are likely to be significantly lower as information only needs to be collected for the ambient level of pollution rather than individual polluters effluents or practices.

Meran and Schwalbe (1987) similarly investigated the issue of enforceable NPS pollution control policies in the context of uncertainty and unobservability of individual contributions. Their model proposes a combination of effluent taxation and collective fining in the context of asymmetric information between polluters and regulators concerning individual pollution emissions. Polluters are taxed based on reported emission levels. If the sum of reported emissions is smaller than the observed level of emissions, all polluters are collectively fined. Supporting Segerson's (1988) analysis, the authors suggest a combination of ambient environmental standards and collective fining if these standards are not met in the context of stochastic pollution functions. However, Meran and Schwalbe highlight two important issues related to these approaches which equally apply to Segerson's (1988) work and its extensions such as that of Xepapadeas (1991). Firstly, the effective enforceability of collective fining requires that every polluter who influences the level of aggregate emissions is known to the regulators and potentially subject to the fine. Secondly, the implementation of a collective fine may be difficult as punishment through criminal law requires evidence of guilt in countries across the world. Such a policy may require a strict application of civil law (e.g., imposing damage payments on polluters for health problems associated with excessive pollution) or more significant legal technicalities. Finally, the authors are concerned about the financial strain that a collective fining approach may impose on firms in the market which is addressed in some extensions of collective fining models.

Indeed, Xepapadeas (1991) builds on Segerson's (1988) notion of a collective ambient pollution tax and extends it to address the excessive financial strain to which it could subject a large group of firms. In contrast to Segerson, Xepapadeas' theoretical model assumes that ambient pollution levels are a deterministic function of individual levels of pollution. Nonetheless, the model also considers the case of asymmetric information where individual pollution contributions are unobservable and only ambient pollution levels can be monitored. The contracts for NPS pollution control between the government and a group of polluters reward polluters with a subsidy for pollution abatement. Similarly to the ambient tax, the magnitude of the subsidy received by individual firms depends on the difference between observed ambient environmental quality (q) and the desired ambient environmental quality $(\bar{q})$ specified by the government. The higher the difference $(\bar{q} - q)$ the higher the subsidy that firms receive. However, when $(\bar{q} > q)$ a randomly chosen polluter is fined while the remaining polluters receive the subsidy. The greater the probability of being fined, the lower the fine required to achieve an optimal environmental outcome.

The efficacy of this "random fining" approach proposed by Xepapadeas (1991) was tested in an experimental study by Alpizar *et al.* (2004). They re-enacted the random fining scenario with a sample of Costa Rican coffee mill managers and a sample of Costa Rican students in a game theoretical laboratory. Their results suggest Xepapadeas' theoretical model over-predicts efficient pollution abatement outcomes and may require further testing. Moreover, Alpizar *et al.* 's (2004) study also established that individuals may perceive collective fining to be ethically preferable to random fining. As random fining involves punishing an agent regardless of their actual pollution contribution it is regarded as more unfair than the traditional collective fining approach.

Indeed, experimental evidence by Spraggon (2002) in favour of the ambient tax for NPS pollution as proposed by Segerson (1988) is not supported by more recent evidence by

Cochard, Willinger and Xepapadeas (2005), who experimentally investigate the efficiency and reliability of four NPS pollution control policies popular in the literature. Specifically, they examine (i) an input tax, (ii) a tax (subsidy) for ambient levels higher (lower) than the social optimum, (iii) a tax if ambient levels are higher than the social optimum and (iv) a collective fine when pollution exceeds the target. In contrast to Spraggon (2002), the authors consider a status quo scenario, as well as assuming an “endogenous externality” where polluters themselves are affected by ambient pollution. The results suggest that an input tax and an ambient tax are highly socially efficient and reliable, while the collective fine is only relatively efficient and varies more between different groups in a given time period. However, the tax/subsidy on ambient pollution is found to reduce social welfare relative to the status quo scenario as well as to be highly variable both between groups and time periods, thus weakening the case for ambient taxation as an optimal policy instrument.

The above review has shown that despite the popularity of the theoretical propositions of ambient taxation for NPS pollution (Segerson, 1988; Xepapadeas, 1991), the experimental evidence questions the efficacy of ambient taxation (Alpízar, Requate and Schram, 2004; Cochard, Willinger and Xepapadeas, 2005). Moreover, Cabe and Herriges (1992) demonstrate that a successful implementation of ambient taxes is highly dependent on polluters having accurate information on the biophysical process of NPS pollution and their contribution to ambient levels of pollution. For example, if producers incorrectly assume that the ambient pollution levels are largely unaffected by their production decisions, an ambient tax effectively becomes a lump sum charge to producers. In such a case of asymmetry between the producers’ and regulators’ information, the effectiveness of ambient tax regimes is limited significantly and they are outperformed in terms of cost-effectiveness by regulation on emission and production technologies, which are generally considered to be less efficient than incentive measures (Cabe and Herriges, 1992, p. 142). In the real world, the requirements to meet informational symmetry between producers and regulators are costly to fulfil and unlikely to represent producers’ reality (Shortle and Horan, 2013). The analysed evidence motivates the exclusion of ambient taxation from the empirical analysis of this thesis. The following section discusses another popular incentive-based measure proposed in the literature: marketable pollution permits (MPPs).

3.2.2.3. Marketable Pollution Permits

MPPs constitute another environmental policy intervention which has become more popular in academic analyses as well as political application over the last three decades. The basic concept is attributed to the 1968 work of John Dales and involves the creation and auctioning of property rights for environmental quality management (Baumol and Oates, 1988, p. 177). In practice, government regulators create a limited number of pollution permits, for N emissions for example, which are distributed or auctioned amongst the relevant polluters of a region and can subsequently be traded among these participating polluters. Over the years, different variations of MPPs, adjusted for the type of targeted pollutants, participating polluters and spatial implementation have been discussed in the economic literature. This section will initially discuss the key theoretical economic concepts related to MPPs before examining empirical work and case studies related to agricultural NPS pollution markets in particular.

The three key theoretical economic design features which are necessary to ensure an efficient MPP system for water quality issues in particular are highlighted by Shortle and Horan (2013, p. 128): (i) a defined tradeable pollution commodity for the different polluters relevant to the water quality issue at hand, (ii) defined trading rules for these commodities between the polluters, as well as (iii) a limit on total supply of pollution commodities to ensure that the overall water quality target can be met. Different approaches to these key features have been proposed in the literature with the most fundamental differences in the first feature, namely, the definition of the tradeable pollution commodity.

For such an approach to define the tradeable pollution commodity, Montgomery (1972) provided the theoretical foundation for two prominent variations in the literature: “pollution licenses” (PL) and “emission licenses” (EL). In a PL system, licenses define the right to pollute such that set environmental quality standards are met at certain monitoring points. Thus, PL systems focus on the environmental impact of emissions and account for spatial differences in the effects pollution has. Consequently, PL markets require polluters to purchase “a portfolio” of licenses for every monitoring point impacted by their emissions. In contrast, EL systems define licenses directly in terms of pollution quantities which polluters are allowed to emit, ostensibly ignoring the spatial heterogeneity of pollution impacts on the environment. Montgomery demonstrates that as a result EL systems cannot reach efficient outcomes under one-for-one trading between different locations. Achieving an efficient outcome in EL markets requires the definition of pollution zones and strong restrictions on the initial license allocations between zones such that environmental quality standards for all monitoring points can be met at least cost. The author shows that PL systems on the other hand achieve an efficient market equilibrium regardless of the initial distribution of licenses.

Both the discussed PL and EL systems have received extensive criticism in the economic literature (Baumol and Oates, 1988, Chapter 12). In PL systems the transaction costs for polluters associated with maintaining "a portfolio" of different licences for the different monitoring points have been deemed prohibitively high. For an efficient market equilibrium in NPS water pollution control in particular, Prabodanie, Raffensperger and Milke (2010) highlight that the heterogeneous time line in which NPS emissions impact receptor points requires the creation of different markets for different impact time scales in addition to the different monitoring point markets. Thus, PL systems are generally not deemed an optimal NPS water pollution control measure. The specific initial allocation of licences required for an efficient market equilibrium in EL systems in turn poses significant policy limitations. Krupnick, Oates and Van de Verg (1983) stress that regulators are, firstly, unlikely to determine the optimal initial allocation of permits correctly as it requires complete information on emissions and abatement costs. Secondly, regulators are excessively restricted by the required initial allocation and unable to respond to political concerns in policy application. The authors therefore propose an alternative system, called pollution offsets (PO), which combines some features from both the PL and EL systems. In line with the EL system, permits in a PO market are defined as pollution quantities that firms are allowed to emit. However, they must be traded such that the environmental quality standards are not violated at any monitoring point. Consequently, as Baumol and Oates (1988, p. 185) highlight, PO permits for different polluters may only be exchanged at the ratio of their "transfer coefficients". Transfer coefficients represent the impact one unit of emissions from a specific polluter has on the environmental quality of a specific receptor point, thus their ratio captures the possible substitution between different PO permits whilst adhering to environmental quality targets at every receptor point. To implement such a PO system regulators require an up-to-date biophysical model to ensure that no transactions violate any environmental standards at any monitoring points; however, transaction costs are significantly reduced relative to a PL system as PO only involves one market which polluters participate in, as opposed to the "portfolio of markets" required by the PL system (Krupnick, Oates and Van De Verg, 1983).

Over the years different variations and extensions of the three outlined theoretical MPPs have been proposed in the literature. Particular attention has been paid to issues like the optimal definition of transfer coefficients (Malik, Letson and Crutchfield, 1993) and the implications of pollutants' spatial heterogeneity for MPP design (Lankoski, Lichtenberg and Ollikainen, 2008). For water pollution specifically, the appropriate way to address point and

NPSs of water pollution in MPP systems has been an important research emphasis. In line with the majority of real world implemented schemes, the market-based water pollution control literature has focussed on MPPs involving trades between point sources and agricultural NPSs (Hansen, Termansen and Hasler, 2019). However, a more recent programme in New Zealand has further sparked interest in MPPs allowing trades exclusively between agricultural NPSs (Shortle, 2013). In the following, key findings from implemented programmes will be discussed focussing initially on point-/NPS-trading and the example of the Pennsylvania Nutrient Credit Trading Program (PNCTP) in the United States (Pennsylvania Department of Environmental Protection, 2020) before analysing aspects of agricultural NPS trading using the example of Lake Taupo in New Zealand (Waikato Regional Council, 2019).

This summary of the PNCTP key features is based on Shortle (2012) who provides an in depth description of the programme which was established in 2005 to reduce agricultural NPS pollution pressures into Chesapeake Bay. The programme allows agricultural non-point pollution sources to generate pollution permits for N and P by adopting management practices which reduce the nutrient flow to the bay beyond a minimum threshold. Point sources may also generate pollution permits for reducing nutrient pollution to the bay. Point source polluters can purchase these permits from farmers or other point source polluters, in order to meet their capped point source pollution allowance. Although no formal trading ratio is applied, restrictions and thresholds result in more than one unit of NPS pollution being abated for every purchased point source permit unit. The effectively higher trading ratio between NPS and point sources mirrors many other trading programmes and can be explained by policymakers' preferences regarding the uncertainty involved in measuring NPS emissions; however, it is not necessarily supported by theoretical evidence on optimal trading ratios (Malik, Letson and Crutchfield, 1993). Economic theory suggests that efficient and effective trading ratios could be 1:1 or lower and heavily depend on the scientific evidence around their design features, therefore, the fact that economic evidence has seldom been consulted in the design of MPPs could be contributing to their limited success (Shortle, 2013, p. 68).

Trades between the PNCTP market participants can be negotiated directly or, since 2010, be completed through a Nutrient Credit Clearinghouse. The low trading volume observed in the PNCTP exemplifies a wider criticism of applying MPPs to water pollution issues. As Fisher-Vanden and Olmstead (2013) highlight, the trading volumes observed in most water quality MPPs are too low to provide efficient market outcomes. The authors summarise a number of factors found in the literature which explain the limited uptake observed across water

MPPs: Firstly, evidence suggests that distrust of the implementation of new measures within the farming community is stifling trade volumes in NPS-point source markets from the supply side. This low supply of NPS pollution reduction permits may be further exacerbated by alternative pollution abatement subsidy schemes available to farmers which crowd out supply side market participation. Moreover, demand from point sources may be low due to disincentivising liability rules being attached to MPP programmes or due the surrounding environmental regulatory framework lacking the stringency to promote point source participation.

The Lake Taupo Nitrogen Market (LTNM) in New Zealand is the first MPP to impose a cap on and to facilitate trade between agricultural NPS polluters (Duhon *et al.*, 2015). This summary of the LTNM is based on Kerr, Greenhalgh and Simmons' (2015) detailed description of the programme that became operational in 2011. The LTNM was introduced as part of legislation which aims to restore the water quality of Lake Taupo to 2001 levels by 2080 and limits the amount of agricultural N leaching into the lake. Annual permits were allocated based on the farm's highest annual N emission levels for the years 2001-5 by which farms may not exceed the annual emission limit indicated by their permit allocation. The N leaching levels were calculated using a nutrient budgeting model and are enforced through a monitoring programme. Farmers can trade permits amongst each other within the Lake Taupo catchment to provide flexibility in the implementation of the N reduction. In addition, the Lake Taupo Protection Trust was set up to permanently purchase and take out of circulation production permits and agricultural land, respectively, within the catchment. Thereby, the total amount of N leaching in the catchment is reduced whilst also reducing the resulting financial burden on the farming community.

The programme has met its preliminary target of a 20% reduction in N emissions in 2015 (Tabaichount *et al.*, 2019). However, it is unclear whether this success is mainly attributable to the Lake Taupo Protection Trust buy-back scheme which is not necessarily linked to an MPP framework and therefore cannot provide empirical support for the use of MPPs in controlling agricultural NPS pollution (Kerr, Greenhalgh and Simmons, 2015). In addition, as Duhon et al. (2015) report, there have been some questions raised over the accuracy with which the nutrient budgeting model captures the farms' N output. Given incomplete data provision from some farms and divergences between the assumptions of the employed model and some farm management styles of the catchment, there could be significant discrepancies between the model output on which the programme crucially relies and real farm N outputs. This issue is related to the inherent unobservability of agricultural NPS pollution and has hindered the effective implementation of other MPP NPS pollution control measures (Fisher-Vanden and Olmstead, 2013). Moreover, although the transaction costs associated with the LTNM are deemed low in comparison to similar international MPPs, they have nonetheless been found to significantly and negatively affect the trade volumes of the programme (Duhon *et al.*, 2015). These significant transaction costs further contribute to the drivers of inefficiently low trade volumes discussed in the context of point-NPS trading and the PNCTP above.

In summary, the theoretical debate surrounding MPPs applied to agricultural NPS water pollution control has provided detailed insights into aspects of MPP design which are crucial to ensure economically efficient outcomes. PLs and ELs, first proposed by Montgomery (1972), have respectively been found to entail excessively high transaction costs for producers and have been shown to fall short of an economically efficient outcome without a specific initial optimal allocation of permits which is practically infeasible for regulators to implement.

A POs system is a hybrid version of the PL and EL systems which was introduced by Krupnick, Oates and Van de Verg (1983) in response to criticisms of the latter systems. In a PO market, trading ratios are determined by the regulators using biophysical models to ensure an efficient economic outcome. Based on variations and extensions of these fundamental theoretical works, a variety of water quality MPP programmes have been implemented over the years. The programmes relevant to agricultural NPS pollution can be categorised into two groups based on the pollution sources involved in trade: point–NPS markets and NPS-NPS markets. Of the first, more widely employed type, the PNCTP has been discussed as a prominent example. The analysis has shown that the programme's efficient functioning has been impeded by low trading volumes which may be attributed to a number of reasons including farmers' distrust of the system, substitute agri-environmental programmes available to farmers as well as a lack of stringency in the general environmental regulatory framework. Low trade volumes which prohibit efficient market solutions have also been a significant issue for the discussed LTNM which to date has been the only implemented NPS-NPS market. In addition, there have been concerns regarding the accuracy with which the nutrient budgeting model underlying the LTNM programme captures the participating farms' N outputs. Moreover, the LTNM programme includes a land-buy-back programme which may be driving the observed reduction in N emissions as opposed to the MPP. The analysis suggests that although there have been promising advances in the theoretical design of market-based approaches to controlling agricultural NPS pollution, real world applications are often not grounded in theoretical evidence and leave significant doubt regarding their efficacy and practicality. Given the systemic issues displayed by implemented MPPs for agricultural NPS pollution control and the limited scope of this thesis, MPPs are not included in the quantitative analysis presented.

The following section discusses studies which investigate the combination of incentive-based measures analysed in this section and command-and-control policies to curb agricultural NPS pollution.

3.2.3. Mixed Instruments

The seminal work of Baumol and Oates (1988, Chapter 13) on environmental externalities includes qualifications to the general economic finding discussed above that incentive-based measures are preferable to command-and-control policies in terms of social welfare outcomes. The authors stress that the stochastic nature of many forms of environmental pollution require time-sensitive changes in behaviours which cannot be achieved by many incentive-based policies such as taxes or subsidies. They demonstrate that when pollution is assumed to be a random variable, taxes can result in higher social costs than command-and-control policies at times of substantial pollution. These higher social costs may be so significant that they outweigh efficiency gains achieved from taxation relative to command-and-control policies during times of normal pollution levels. The authors show that a combination of command-and-control and incentive-based policies leads to an improved social welfare outcome relative to the single policy scenario. Their theoretical analysis is highly relevant to agricultural NPS pollution due to its stochastic nature discussed above. The mixed policy approach is therefore likely to provide an optimal combination of policy mechanisms to respond to random weather events which chiefly influence NPS pollution. Nonetheless, economic analyses of environmental policies to control pollution have traditionally focused on investigating and comparing individually applied policies. However, some more recent contributions have included analyses of so called “mixed instruments” which combine different policy mechanisms such as incentive-based and command-and-control policies (Bennear and Stavins, 2007).

Vatn *et al.* (1997) simulate three agri-environmental policies for Norway individually as well as combined and provide insights into key considerations when planning mixed policy interventions. The investigated policies include: (i) a N tax, (ii) a subsidy for switching from autumn to spring tillage and (iii) a management requirement of cultivating catch crops. When individually applied, the N tax is found to be most cost-effective in terms of social cost per hectare of N abatement, while the spring tillage subsidy is found to provide the smallest reductions in N leaching compared to alternative policies. These results are mirrored in the combined versions of the policies where the combination of the catch crop requirement and the N tax achieve more cost-effective reductions in N than the combination of a spring tillage subsidy and a N tax. The authors highlight that although spring tillage does not effectively reduce N leaching it does significantly reduce soil losses, thus cost-effectiveness rankings will depend on the priorities of policymakers. They further find that the policies affect different types of farms in the study areas in different ways. A N tax for example has greater impacts on milk and beef production than on grain producers who can substitute away from N fertilisation to the use of leguminous cover crops. In contrast, milk producers are not strongly affected by cover crop requirements due to the naturally high percentage of grassland associated with dairy farms. Their findings stress that the interactions of these policy mechanisms need to be taken into account in mixed policy design to avoid unintended consequences.

In the context of UK agri-environmental policy, Aftab, Hanley and Baiocchi (2010) investigate mixed regulation and incentive policies with a biophysical-economic model for the West Peffer catchment (Eastern Scotland). Specifically, the four mixed instruments include: (i) a set-aside requirement with a N tax, (ii) a set-aside requirement with farm stocking density reductions, (iii) farm-stocking density reductions with a N tax and (iv) a set-aside requirement with both a N tax and farm stocking density reductions. These policy combinations were compared to individual versions of the policies, further including emission taxation and emission quotas. The results suggest that mixed policies can be particularly effective when the given geographical or informational circumstances prevent individual approaches from being effective. Moreover, the authors find that the cost-effectiveness of mixed policies further depends on weather conditions and should be favoured in 'wet' weather conditions as opposed to 'average' years.

Aftab, Hanley, and Baiocchi's (2017) analysis of the transferability of NPS pollution control policies between two relatively similar Scottish catchments also includes a comparison of individual and mixed instruments. The policy combinations investigated (details in Table 2) were simulated for four different levels of stringency over ten consecutive years. The policies' stringency is expressed as the likelihood of the catchment exceeding the EU WFD standard of 11.3 mg N/L ambient nitrate concentration and ranged from 10% to 1% (1% being the most stringent).

Table 2: Summary of policies investigated in Aftab, Hanley, and Baiocchi (2017)

Command-and-Control	Incentive-based	Mixed
Land retirement	Input tax	Land retirement & Input tax
Stocking density reduction		Stocking density reduction & Input tax
		Land retirement & Stocking density reduction & Input tax

The authors' results show that the cost-effectiveness ranking of different policies is highly dependent on the stringency of the regulatory target and limited in its transferability between catchments. Individual policies generally tend to be more cost-effective at lower stringency targets. Mixed instruments, in contrast, are generally able to reach more stringent standards for N pollution at lower costs to society. In both catchments the target of 1% non-compliance over 10 years is most cost-effectively reached by a combination of a set-aside, a stocking density reduction, and an input tax. The findings indicate that the choice to combine multiple policies should be guided by the risk aversion of the policymakers. Mixed instruments appear to be preferable for agents seeking to minimise the risk of environmental degradation and maximise the likelihood of achieving the environmental target over time. The authors further support the findings of Kampas and White (2004), reviewed above, that high transaction costs render emission taxes inefficient as policy options in the real world. These results motivate their exclusion from this analysis in favour of lower transaction cost policies.

The reviewed literature has demonstrated that mixed instruments can improve agri-environmental policy cost-effectiveness in particular for more extreme weather scenarios and stringent regulatory targets (Baumol and Oates, 1988; Aftab, Hanley and Baiocchi, 2010, 2017). Moreover, mixed instruments may be used to account for heterogeneous agricultural production in a catchment as different farm types are affected differently by individually applied measures (Vatn *et al.*, 1997). The following section explores the evidence on spatially targeting policies in order to account for the spatial heterogeneities of catchments.

3.3. Application: Uniform and Spatially Targeted Policies

Beyond their underlying economic mechanism, pollution control policies are characterised by their uniform or targeted spatial application. Economic theory reasons that the benefits of policy efforts are maximised cost-effectively if the policies target zones which yield the maximum environmental return for their cost (Claassen, Cattaneo and Johansson, 2008). Numerous studies have tested this conjecture empirically in their investigations on optimal policy design. This section reviews some of the evidence on spatially targeted agri-environmental policies.

Ribaudo, Osborn and Konyar (1994) empirically investigate the effects of spatially targeting agricultural NPS pollution control measures in the context of counties suffering from high levels of diffuse pollution in the USA. In particular, the authors focus on set-aside requirements to improve water quality by reducing nutrient and sediment pollution as well as soil erosion. They simulate four different scenarios with increasing degrees of targeting towards the most polluted areas (measured as crop-land pollution-load potential and distance from a waterbody). Their results demonstrate that the costs (measured as reductions in producer and consumer surplus due to crop price increases) of set-aside requirements fall drastically as they become more spatially targeted. Simultaneously, water quality benefits initially rise significantly as targeting increases, before falling to levels comparable to the minimally targeted scenario for the most targeted scenario (Ribaudo, Osborn and Konyar, 1994, p. 82). These findings suggests that spatial targeting can significantly improve the cost-effectiveness of agri-environmental policy, although the trade-off between cost reduction and environmental benefits for highly targeted scenarios should be considered. This thesis builds on the authors' findings by investigating policies targeted by real pollution potential (i.e., hydrological connectivity (see section 4.6, p. 89)) as opposed to the proxy measure of distance to a waterbody.

Given the difficulty of implementing first-best targeted policies for different pollution sources, Helfand and House (1995) use lettuce production in the Salinas Valley, California USA as an empirical example to evaluate the magnitude of differences between first- and second-best policies (i.e. differentiated and uniformly applied pollution control measures). The modelled policies are summarised in Table 3.

Table 3: Policies modelled by Helfand and House (1995)

Uniform (Second-Best Alternatives)	Spatially Targeted (First-Best)
Input tax on all pollution sources	Input tax differentiated by soil-type and input
Percentage reduction requirement for all inputs	
Tax on single input	
Limit for single input	

The results of their study indicate that the second-best policies of a uniform input tax on a single input, a uniform input tax on different soil-types, and a uniform percentage reduction requirement for all inputs can achieve efficiency outcomes similar to those of the differentiated optimal policy. These findings suggest that such second-best policies could be preferable to first-best spatially targeted policies if significant information requirements and implementation costs are associated with the latter.

Claassen and Horan (2001), provide evidence on the distributional impacts of spatially targeted policies and empirically illustrate their model in the context of corn production in the Northern parts of the Central USA (see section 3.2.1 for the discussion of their theoretical model). In accordance with previous works on the topic, they find that non-uniform taxation is more economically efficient than uniform taxation. The effects of both types of taxes on the different interest groups (consumers/taxpayers, fertiliser producers, owners of capital and labour resources, and landowners) vary. However, the benefits to landowners due to substitution effects from a fertiliser tax are spread more equally across the sub-regions in the case of a non-uniform tax relative to a uniform tax. This distribution relates to the findings of Griffin and Bromley (1982) and contradicts the common perception that non-uniform taxation is less equitable than uniform taxation.

Contrasting uniform policies with differentiated policies in both temporal as well as spatial dimensions, Xabadia, Goetz and Zilberman (2008) propose a dynamic framework to analyse input taxes for managing issues of stock pollution. The analysis also accounts for precision technologies which will be further discussed in section 3.4 of this thesis. Xabadia, Goetz and Zilberman's (2008) theoretical model demonstrates that a dynamic input tax differentiated both technologically and spatially would constitute an optimal policy intervention. Given the practical difficulties of differentiating policies dynamically and spatially the authors consider two second-best alternative cases: (i) a dynamic but spatially uniform input tax and (ii) a static but spatially and technologically differentiated tax. They find the dynamic but spatially uniform input tax affects production at the extensive margin and increases the net benefit of cultivating lower quality land. Therefore, the dynamic but spatially uniform input tax entails greater efficiency losses the greater the changes in production and associated emissions are, and the greater the number of hectares on which these changes take place. Meanwhile, the static but spatially differentiated tax is found to lie in between the initial and final values of its dynamic version. Thus, the static but spatially differentiated tax leads to higher welfare losses if the initial stock value diverges significantly from the steady-state stock value and the decay of the pollutant is small. To quantify the differences in welfare between the policies Xabadia, Goetz and Zilberman (2008) use the issue of waterlogging in the San Joaquin Valley, California USA as a numerical illustration. The empirical work shows a static but spatially differentiated tax leads to a 14% welfare loss relative to the optimal, while a dynamic but spatially uniform policy entails a 36% welfare loss relative to the optimal. These results suggest that spatially differentiating policies may be superior to the imposition of dynamic policies in terms of welfare losses. However, a sensitivity analysis demonstrates that rankings of the policies are highly dependent on the level of land heterogeneity as well as the magnitude of the initial environmental degradation. The importance of considering land heterogeneity in agri-environmental policy design motivates the novel biophysical detail included in this analysis (see section 4.3, p. 74).

Helin *et al.* (2013) also focus on land heterogeneity in their spatially explicit bio-economic model for the southern Finish Lepsämänjoki catchment. The optimisation accounts for key field aspects such as soil-type, slope-type, and distance from forest edge and assesses the combination of spatial targets for water quality improvement and biodiversity conservation in agri-environmental policy. While the conversion of agricultural land into grass set-aside and the reduction of fertilisation are found to be the most cost-effective nutrient abatement measure, cost-effective biodiversity conservation involves converting agricultural land into meadow nectar plant set-aside. The authors show that both objectives can be efficiently combined by optimally targeting the conversion of agricultural land into both grass and meadow plant set-aside. For example, targeting fields with steep slopes and fields close to forest edges significantly reduces the costs of implementing the agri-environmental policies. These findings demonstrate the benefits of combining different environmental goals in policy design but also highlight the importance of spatially targeting policies in order to maximise their cost-effectiveness.

More recently, Lungarska and Jayet (2018) use a biophysical-economic model to investigate the effect of spatially differentiated agri-environmental policy to reduce nitrate leaching in France. The authors simulate an input tax on mineral N fertiliser for different levels of spatial differentiation in polluted areas, namely, (i) a farm and water body specific tax, (ii) a water body specific tax, (iii) uniform tax rates per river-basin-district, and (iv) a nationally uniform tax rate. The different scenarios are assessed in terms of the associated changes to farmers' gross margin, tax revenue, fertiliser application, nitrate leaching, and stocking densities. Their results show that corresponding to theoretical predictions, the more targeted policy entails less significant losses in terms of farm gross margin. However, they also show some limited adverse effects of the input tax including substitution towards manure fertilisation and crops which are less demanding in N but more-polluting. These outcomes highlight the point that the possible substitution effects of spatially targeted approaches need to be considered in policy design – a point more widely applicable to all agri-environmental policies. This thesis reflects the significance of substitution effects stressed by Lungarska and Jayet (2018) in analysing modelled policies' impacts on farmers' land use and fertilisation choices (see section 6.3, p. 138).

Hasler *et al.* (2014) extend their scope beyond a national scale and investigate cost-effective strategies for N and P nutrient abatement in the drainage basin of the Baltic Sea. They implement a non-linear optimisation model in GAMS to investigate the importance of accounting for spatial heterogeneities at the sub-catchment scale in agri-environmental policy design. The investigated policies include six abatement strategies for N and P abatement which appear to be implemented as command-and-control policies. Their results suggest that including spatial heterogeneities in abatement cost calculations significantly improves their accuracy. Moreover, their analysis ranks the cost-effectiveness of policies within the 22 main sub-drainage basins of the Baltic Sea whilst taking into account variation in nutrient retention (a key hydrological characteristic in NPS pollution generation). The authors suggest that once computational powers will allow the cost-effectiveness analysis for the entire Baltic Sea drainage basin to include hydrological characteristics, this should further improve the distribution of policy measures at finer resolutions of the optimisation problem. Their work highlights the importance of including traditionally considered spatial variables like soil-type as well as hydrological characteristics like nutrient retention in agri-environmental policy analysis which are both a focus of this thesis (see chapter 4 for details).

Hasler *et al.* (2019) specifically focus on spatially targeting agricultural NPS N pollution interventions based on heterogeneity in hydrological characteristics of catchments. They also focus on N retention which they define as the extent to which there is a difference between N levels at the source and the recipient water body. Low levels of retention in a catchment imply levels of pollution in recipient water bodies similar to pollution levels at the source, which aids abatement effectiveness. Their biophysical-economic model for the Limfjorden catchment in Denmark suggests that targeting N abatement measures according to heterogeneous levels of N retention of the catchment led to significant reductions in abatement costs. The authors further find these cost savings to be relatively insensitive to the uncertainty in the correct identification of retention levels. Their results underscore the importance of accounting for spatially heterogeneous hydrological characteristics when designing agricultural NPS pollution.

Finally, the research discussed in this section demonstrates that in addition to the underlying mechanisms, the spatial application of agri-environmental policies can significantly impact their cost-effectiveness (Ribaudo, Osborn and Konyar, 1994; Xabadia, Goetz and Zilberman, 2008; Helin *et al.*, 2013; Lungarska and Jayet, 2018). In addition to traditionally considered spatial variables such as soil- and slope-types, the reviewed literature further suggests that hydrological characteristics should inform spatial targets (Hasler *et al.*, 2014, 2019). However, until now little attention has been paid to the synergies between new technological developments in the agricultural sector and NPS pollution control. Therefore, the following section reviews the treatment of technology in previous biophysical-economic studies.

3.4. Technology

In addition to the treatment of spatial heterogeneity, the treatment of technology is a key feature of economic analyses in agri-environmental policy. The emergence of more advanced production technologies changes the parameters for both production externalities and policy interventions. Therefore, an accurate representation of the sector's current technological status is crucial to ensure that economic analyses provide pertinent policy recommendations. However, the majority of previous economic studies considering agricultural NPS pollution control assume unspecified homogeneous production technologies. Notably, the studies which do include a more explicit treatment of technology primarily focus on irrigated agriculture and irrigation precision technologies. Given the low instance of irrigated agriculture observed in the study catchment of this thesis, irrigation technologies do not form part of the presented work. Nonetheless, it is useful to review previous treatments of heterogeneous technologies in the literature. Therefore, this section initially reviews three studies which do include a more explicit treatment of technology before discussing current technological developments in the sector and their representation in the literature.

Khanna, Isik and Zilberman (2002) address the role of new input-efficiency enhancing technologies in their economic model of agricultural NPS pollution control. Specifically, they investigate the cost-effectiveness of subsidies to increase the adoption of such conservation technologies in irrigated cotton production in California. The authors present a framework which allows microunits to choose between two types of technology (traditional and conservation) as well as an input use level from a continuous scale. Their analysis highlights the different effects through which policy measures reduce pollution (see Table 4).

Table 4: Policy effects which reduce pollution (Khanna, Isik and Zilberman, 2002)

Policy Effect	Mechanism
Switching effect	Switching to conservation technology
Intensive margin effect	Reducing input use with a given technology
Extensive margin effect	Cropping pattern changes
Note: created based on (Khanna, Isik and Zilberman, 2002, p. 159)	

They find that while the input tax involves all three effects on abatement, different types of subsidies to support technological adoption are more limited in their pollution-abating incentives. Further, the provision of subsidies may encourage entry to the industry and entail increasing levels of pollution. Moreover, in order to achieve switching effects, significant cost-sharing subsidies may be required which may be prohibitively costly to implement. In line with the results of Helfand and House (1995), Khanna, Isik and Zilberman (2002) find that the differences in abatement costs between the first-best (input taxation) and second-best policy (a combination of an input-reducing and a cost-sharing subsidy restricted to farmers pre-existing in the market) are negligible. Therefore, subsidies to incentivise the adoption of agricultural conservation technologies may represent a cost-effective policy alternative to input taxation, if the subsidies' implementation costs should prove to be lower than those for input taxation. However, in contrast to the interests of these authors on pure conservation technologies, this thesis is focussed on PA which has seen recent technical progress and an associated fall in adoption costs. PA's potentially significant private productivity benefits suggest that the economic rationale for subsidies supporting PA adoption is relatively weak. Therefore, subsidies for PA adoption are not quantitatively considered in this analysis.

As mentioned in section 3.3, Xabadia, Goetz and Zilberman's (2008) work on dynamic spatially differentiated policies also includes an explicit treatment of PA technology for irrigated cotton production in California. Their analytical framework incorporates traditional and precision technologies, where the latter exhibit a higher input-efficiency use and implementation cost, as well as a lower pollution coefficient relative to the former. The theoretical analysis suggests that a dynamic but spatially uniform input tax incentivises production on lower quality land and the use of more-polluting traditional technologies as opposed to precision technologies. The authors' numeric example further demonstrates that a static, spatially differentiated tax entails the highest adoption rate of precision technology (62.4% of farmland) compared to the other modelled second-best policies, as well as the lowest efficiency loss relative to the optimal dynamic spatially differentiated tax (13.8%). The study therefore highlights that the design of agri-environmental policies may significantly affect the technological choices of farmers which in turn impact the cost-effectiveness of policies in achieving environmental targets. This result underscores the importance of accounting for farmers' technological choices in agri-environmental policy analyses and motivates the analysis of PA in the context of policy design in this thesis (see section 4.7, p. 94).

More recently, Wang and Baerenklau (2015) account for technological heterogeneity in irrigated agricultural production in their assessment of nitrate pollution control policies (see also section 3.2.1). They include two different types of irrigation systems as well as two manure handling systems. The modelled manure handling systems include a flush lagoon system and a scrape-tank. The authors assert that the scrape-tank consumes less water in the spreading process, despite being more labour and capital intensive, which is likely to improve leaching outcomes. The representation of irrigation technology includes a furrow irrigation system and a more technologically advanced linear move system which typically improves irrigation efficiency and reduces water usage (Wilson, Coupal and Hart, 1987). Wang and Baerenklau's (2015) findings suggest that the optimal technological choice varies between the different policy interventions and significantly affects the cost-effectiveness of different policies by reducing on-farm compliance costs. While a combination of a flush lagoon and a furrow irrigation system is linked to the lowest losses in farm income under a downstream emission charge, the combination of a flush-lagoon and a linear move system minimises farm income losses under a field emission limit (Wang and Baerenklau, 2015,

p. 146). The authors further account for in-field heterogeneity in terms of irrigation levels (over-, under-, and mean-irrigated sub-fields). They demonstrate that the two irrigation technologies may impact nitrate leaching, yield and water consumption parameters of the three sub-field types in different ways (e.g.: scrape-tank manure handling reduces nitrate leaching from over-irrigated subfields; however, increases nitrate leaching from mean-irrigated subfields in the process). Their results thus highlight the importance of accounting for both technological as well as biophysical heterogeneities in agricultural production. These synergies between in-field heterogeneities in biophysical characteristics and improved agricultural production technologies is embodied by PA which is discussed in the following section.

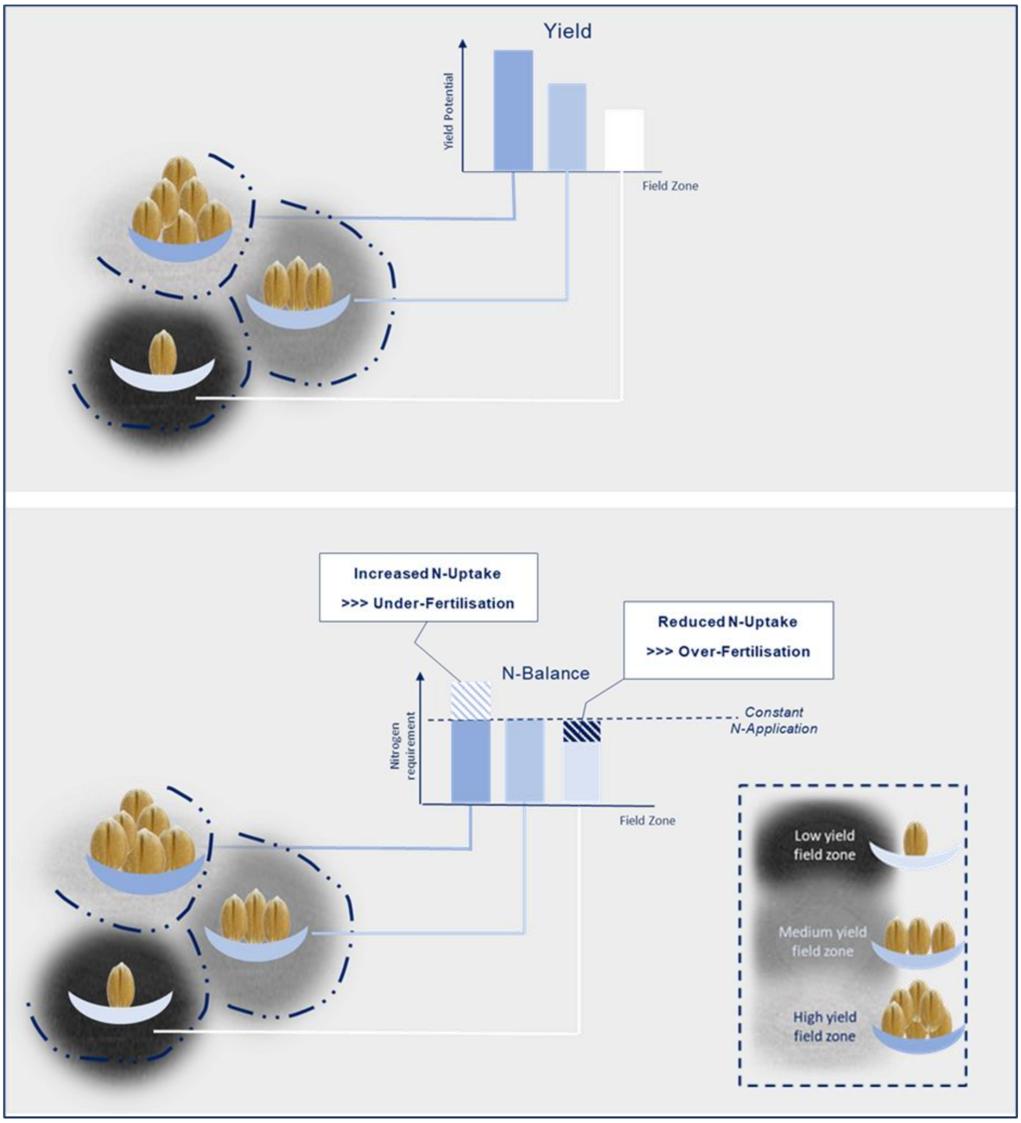
3.4.1. Precision Agriculture

Rising population pressures and heightened environmental awareness across the world have resulted in increasing quantitative and qualitative demands on food production over the past two decades. In turn, these changing demands have spurred significant innovation in agricultural production (Finger *et al.*, 2019). The use of information technology in primary agricultural production has rapidly increased since the late 1990s and early 2000s and has come to be known as "PA". The key objective of PA is to spatially and temporally optimise input use and management practices given localised farming conditions (Pierce and Nowak, 1999, p. 4). Today, numerous PA tools facilitate such tailored and targeted agricultural production using developments in monitoring and sensing technology as well as data collection methods (Balafoutis, Evert and Fountas, 2020). PA is frequently used across both livestock and arable production systems, utilizing for example techniques ranging from the use of milking robots for dairy enterprises to satellite imaging for arable crop monitoring (Fournel, Rousseau and Laberge, 2017; Weersink *et al.*, 2018). More recent innovations further include microbes-based technologies for disease and drought resistance as well as mobile applications for technology rental and sharing (Aulbur *et al.*, 2019). This section initially discusses the focal point of this thesis on variable rate nutrient application (VRNA), provides a summary of the fundamental mechanisms of VRNA, and considers PA adoption before analysing the previous economic research on the use of PA.

As discussed, PA technologies in both the livestock and arable sector have a potential for dual positive impacts on profitability as well as environmental sustainability. Moreover, arable and livestock innovations complement each other as outputs from arable production are inputs in livestock production and vice versa. Due to the limited scope of this thesis, its analysis focusses on PA innovations in the arable sector. These are of particular interest in economic policy analyses due to the strong link between the intensive production margin and environmental outputs in arable production (i.e., changes in fertiliser application on a field significantly impact agricultural diffuse pollution) relative to livestock production, where the extensive margin mainly influences diffuse pollution (e.g., manure production is mainly influenced by the number of cattle on a farm rather than the intensity with which cattle are managed) (Bayrische Landesanstalt für Landwirtschaft, 2019)).

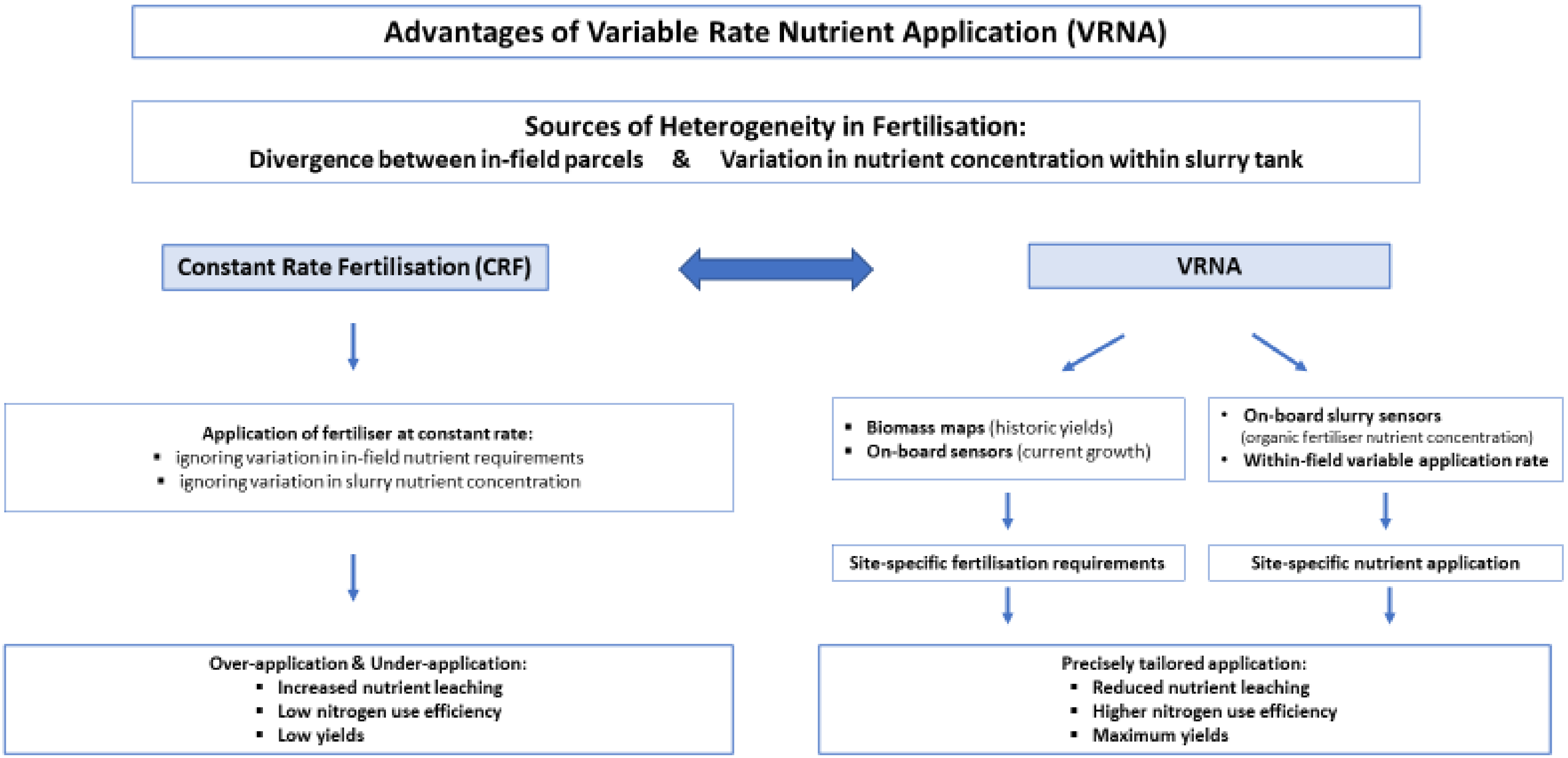
Following Balafoutis et al. (2017) available PA technologies for arable farming can be broadly categorised into: (i) *guidance systems*, (ii) *recording technologies,* and (iii) *reacting technologies*. Guidance technologies include software and appliances that guide agricultural machinery over fields, while recording technologies comprise sensor and satellite equipment which collect spatial data relevant to agricultural production. Finally, reacting technologies use guidance systems and recording technologies to vary the in-field application of agricultural inputs (e.g.: variable rate fertilisation, irrigation, and pesticide application). Crop and soil sensing as well as fertilisation have been a key focus of agricultural research projects, resulting in relatively more available agronomic evidence on their impacts (Balafoutis, Evert and Fountas, 2020). Among reacting PA technologies, variable rate fertilisation specifically has the widest application potential as it is relevant to every crop regardless of irrigation requirements and chosen production method (e.g.: organic or conventional). Therefore, this thesis focusses on PA technologies for arable production systems and variable rate fertilisation technologies in particular.

Figure 2: Effects of constant rate fertilisation in fields with heterogeneous yield potentials



VRNA allows farmers to account for the heterogeneity of in-field conditions when applying fertiliser (Balafoutis *et al.*, 2017). VRNA technologies are based on the principle that soil conditions and plant nutrient requirements differ within fields. As visualised in Figure 2, a uniform application of fertiliser may therefore lead to significant misallocation of nutrients and entail nutrient runoff in low-yield field zones as well as under-application in high-yield field zones. The working mechanisms used in VRNA to achieve this improved allocation of nutrients to plant needs are summarised and contrasted with Constant Rate Fertilisation (CRF) in Figure 3. Firstly, VRNA technologies can use (i) data on previous years' yields through recorded yield maps, (ii) data on current plant growth through onboard sensors for chlorophyll content, for example or (iii) a combination of both to determine the site-specific in-field fertilisation requirements (Schellberg and Lock, 2009). Secondly, software on the tractor and hardware on the fertiliser spreader tailors the application of nutrient contents

Figure 3: Advantages of Variable Rate Nutrient Application (VRNA)



according to the previously determined nutrient requirements. For organic fertiliser (manure and slurry) this process involves further real time measurement of nutrient contents, as nutrient concentration varies significantly within organic fertiliser (Lorenz and Erdle, 2018). In contrast, inorganic fertiliser generally contains constant nutrient concentrations and does not require additional real time sensing. Stamatiadis et al. (2018) found VRNA significantly reduces total fertiliser consumption at constant yields, which positively affected both farm profitability and the environmental impact of farm operations. These dual benefits in economic and environmental terms have led to increasing interest and support for PA technologies from governmental organisations (Ausschuss fuer Bildung Forschung und Technikfolgenabschaetzung, 2006; The Parliamentary Office of Science and Technology, 2015; European Parliamentary Research Service, 2016).

Nonetheless, adoption rates for VRNA have remained low, despite the significant environmental and economic benefits outlined previously, as well as the strong uptake of PA guidance systems across the global farming sector (Bramley and Ouzman, 2018; Lowenberg-Deboer and Erickson, 2019). A recent study of EU farmers finds that the uncertainty regarding performance and higher skill needs associated with sophisticated PA technologies are key drivers of their slow adoption (Barnes *et al.*, 2019). Given the high capital and time investments of acquiring PA technology and the necessary skills for their application, typically risk averse farmers require more certainty regarding financial profitability. The authors suggest that financial incentives, information campaigns, and subsidised skill training would be the most effective policies to boost adoption rates and further exploit the sustainable intensification benefits PA technologies have to offer. In addition, the innovative production technologies of PA require new legislative frameworks to ensure users' safety and privacy (European Parliamentary Research Service, 2016). As the efficiency gains of PA rely on data collection and exchange at unprecedented scales in primary agricultural production, policies regarding data protection in the industry are needed to ensure producers feel confident that their data is secure (Balafoutis, Evert and Fountas, 2020). Within the European Union the application of the General Data Protection Regulation (GDPR) in 2018 has provided some basis for protection for novel agricultural data collected by PA technologies (European Parliament, 2016). However, as Wiseman *et al*. (2019) highlight, whether agricultural data should be classified as personal data and therefore be covered by the GDPR remains controversial. Further clarification of the legislation in this area is important for the continued growth of PA technology in the agricultural sector and could provide an example for future UK policies. However, any policy efforts should be guided by economic cost-effectiveness assessments to ensure a welfare maximising allocation of public resources.

Previous economic assessments of PA have primarily focussed on business level profitability and stress the difficulty of generalising results, as profitability depends on many factors with significant heterogeneity between farms. Schneider and Wagner (2008) conducted field trials on two German farms in Saxony-Anhalt and compare site-specific PA in-field management with uniform management, as part of the government funded German study on the future of sustainable agriculture *preagro.* From the field trials and survey data the authors find on-farm economies of scale of using PA technologies as costs are inversely related to the amount of PA equipment in operation on a farm. However, they caution against blanket statements regarding PA profitability and emphasise the importance of farm-specific characteristics. This opinion is further reflected by Griffin *et al.*'s (2018) more recent review of the PA profitability evidence focussing on equipment efficiency gains to be made through farm investments in PA as well as their return and risk management. They also highlight the individual farm characteristics which influence PA profitability at the farm-level including topographic conditions, changing labour requirements, and compatibility with existing technologies. In particular, a more in-depth analysis of the on-farm economic costs and benefits of VRNA is provided by Heege (2013). He reports the results of published experiments in the UK and Germany which indicate that VRNA improves the efficiency of N usage (Heege, 2013, p. 262). Improved N use efficiency entails improvements in farm profits through gains in yield quantity and quality or cost savings due to reduced N fertiliser consumption. Moreover, higher N use efficiency provides environmental benefits by decreasing N leaching from fertilisation and enhancing groundwater quality. The author calculates that the economic benefit of VRNA technology for winter-wheat corresponds to approximately 45€/ha (Heege, 2013, p. 265). Given purchasing costs of €46,500, annual depreciation, interest and repair costs of 20%, and €300 annual sensor servicing costs, he therefore finds that VRNA technologies become profitable for farmers starting at a fertilised area of 175ha.

In a one farm biophysical-economic model for corn and soybean production in Kentucky USA, Schieffer and Dillon (2015) investigate the interactions between PA and agri-environmental policies. Specifically, they analyse the adoption of (i) an integral valve auto-steer system with GPS receiver, (ii) a VRNA spreader, (iii) automatic section control self-propelled sprayer, and (iv) a combination of all three technologies (Schieffer and Dillon, 2015, pp. 48, 50). They include the interaction effects of PA adoption with input taxes and quantity limits on N and carbon. Their results on VRNA specifically suggest that N application increases through the adoption of PA to increase yields and net returns. Further, the input efficiency gains through PA increase the unit abatement cost of input taxes incurred by producers and lead to increases in N consumption rather than decreases. The authors therefore suggest that PA interaction with incentive based agri-environmental policies can lead to unintended consequences. Importantly, this study approximates N pollution with N consumption and does not consider important biological factors in the impacts of NPS pollution such as variations in soils, slopes, and hydrological connectivity. Higher N applications on less hydrologically connected land could represent a smaller environmental risk than smaller N applications on higher risk land. The authors highlight the need for future analyses of PA in the context of more detailed biophysical modelling. This thesis extends their work by analysing PA in a biophysical model including heterogeneity in geographic variables and the impact of hydrology on agricultural NPS pollution.

As one of the only such works to date, Karpinski (2014) analyses the wider economic impacts of introducing PA technologies across Germany. In her cost-benefit analysis, experts linked to the *preagro* project (Werner *et al.*, 2008) provide valuations of the environmental benefits associated with using PA on an agricultural enterprise in Wulfen (Saxony-Anhalt, Germany) for the years 2005-2007. Further, adjusted benefit transfer and Contingent Valuation Method (CVM) estimates for these environmental benefits were used to include the social value of arable PA technology adoption in the analysis. She estimates a mean benefit of arable PA technology between 24.91€/ha and 244.80 €/ha and finds an introduction of PA across East-Germany to provide a net benefit of €45.6 million. As the estimates rely on the strong assumption that the studied farm in Wulfen is representative for the whole of East-Germany in terms of its biophysical and farm business characteristics, the author cautions against basing policy conclusions on them and calls for further research into the economic impact of a countrywide introduction of PA technologies.

The reviewed literature demonstrates the significant potential of PA technologies to simultaneously support both environmental improvements and rising demands on food security. PA applications in the arable sector and VRNA technologies in particular exhibit a strong capacity to entail both environmental and economic benefits (Heege, 2013; Stamatiadis *et al.*, 2018). However, previous economic assessments of VRNA technologies have largely focussed on issues of business level profitability. A farm-level assessment of PA's environmental impact and interaction with agri-environmental policy excludes crucial biophysical details of the agricultural NPS pollution generation process (Schieffer and Dillon, 2015). Using Germany as a case study, the only previous study including the wider economic and environmental impacts of introducing arable PA technologies at the country scale estimates the societal benefits to be significant (Karpinski, 2014). However, the analysis relies on extensive assumptions which prohibit larger policy conclusions. Given the promising yet indefinite results surrounding the wider benefits of PA technology use in agriculture, the need for further economic research has been well-established globally and highlighted in the UK context in particular (Higgins, Schellberg and Bailey, 2019). Moreover, considering the major shifts in UK agricultural policy due to take place over the course of this decade, such research is becoming increasingly urgent. This thesis therefore seeks to contribute to the literature on wider economic and environmental impacts associated with arable PA technologies using as an example VRNA techniques in a detailed biophysical-economic modelling context.

4. Methodology

This chapter outlines the methodological choices of the thesis in building a biophysical-economic model and assessing agricultural NPS pollution control policies. Section 4.1 reviews commonly employed modelling approaches in the literature, focussing on agent-based modelling and traditional optimisation techniques in mathematical programming. Section 4.2 presents the economic framework of the model, while section 4.3 provides an overview of its biophysical components. The production function data simulation process is explained in section 4.4, while section 4.5 discusses evidence on the appropriate functional forms for production functions in biophysical-economic models. Finally, section 4.6 describes the process of including hydrological connectivity in the model and section 4.7 presents the approach to modelling PA.

4.1. Modelling Approaches

The literature review demonstrates that various modelling approaches are used in the economic literature on agri-environmental policy issues. Most economic analyses employ mathematical programming models to investigate agri-environmental issues instead of econometric models due to reduced aggregate data requirements (Berger, 2001). Traditionally, optimisation techniques in mathematical programming for economic agri-environmental policy analyses have included linear, integer, and non-linear programming models. However, in recent years some studies have used agent-based modelling, a relatively recent mathematical programming approach. This section initially considers agent-based modelling techniques before discussing traditional optimisation techniques and the choice of non-linear programming in this analysis.

Agent-based modelling is a mathematical programming approach used to model complex interactions between agents, which facilitate predictions on the diffusion of environmental innovations and changes in resource usage, for example (Berger, 2001; Maes and Passel, 2017). Due to their versatile nature and evolving applications, controversy remains regarding defining the characteristics and scope of agent-based models (Hanappi, 2017, p. 449). Nevertheless, as demonstrated by Janssen (2005, p. 2 ff.), “Cellular Automata” and “Agents” can be identified as some of the central components of agent-based modelling analyses in environmental and ecological economics. A cell characterises the fundamental unit of Cellular Automata and can assume different states. The states of a cell for the subsequent period are determined via transition rules that depend on the neighbouring cells' states and are defined by the modellers. The spatial dimension of cellular automata facilitates the analysis of inherently spatial agri-environmental issues (Balmann, 1997). The definition of an "agent" in the literature is more controversial, as Crooks and Heppenstall (2012, p. 87) assert. Nonetheless, the authors identify three characteristics that are common in most agents: (i) *autonomy* (they are free to interact and exchange information with other agents), (ii) *heterogeneity* (they can have attributes that distinguish them from other agents like age or qualification), and (iii) *activity* (in simulation agents exercise autonomous influence) (Crooks and Heppenstall, 2012, p. 87). The behaviour and interactions between agents are governed by rules defined by the researchers (Barbati, Bruno and Genovese, 2012).

The described flexibility of agent-based modelling facilitates more realistic representations of behaviour in the real world which may lead to more accurate outcomes in policy analysis (Shortle and Horan, 2013). Moreover, agent-based models like evolutionary algorithms can provide useful approximations when spatially explicit problems exceed the capacity of optimisation techniques (Kling, 2011). Recently, they have been employed to assess agricultural pollution policy issues ranging from Thai pesticide regulation to Chinese land lease policies (Grovermann *et al.*, 2017; Li, Rodriguez and Tang, 2017). Nonetheless, significant issues with the approach remain. Firstly, there are difficulties validating agent-based models as traditional optimisation techniques are unavailable for comparison (Barbati, Bruno and Genovese, 2012). Secondly, agent-based model results are highly dependent on the assumptions made by individual researchers, and techniques to prove the reliability of results are still unavailable (Hanappi, 2017). Consequently, comparisons between models are of limited use in establishing model validity as varying assumptions may be reasonable and contradicting results on the same policy problem are seemingly viable. Moreover, extensive data is required to create agent-based models with behavioural rules that closely match reality (Crooks and Heppenstall, 2012).

Traditional optimisation techniques in mathematical programming are differentiated into linear, integer, and binary programming as well as non-linear programming (Kaiser and Messer, 2011). They all involve either minimising or maximising an objective function, but differ in the functional forms of constraints and objective functions (Williams, 1991). Formerly, linear programming models were commonly used in economic analyses of agricultural production, primarily for farm decision support models (Arfini *et al.*, 2016). Such models describe the farm enterprise as a linear combination of farm activities where technical coefficients measure the contribution of individual activities to the objective and facilitate the maximisation of the objective value (Ten Berge *et al.*, 2000). However, linear functions do not realistically capture complex biophysical relationships between yield and pollution variables inherent to agricultural activities (see section 4.5). As computational powers have advanced, analyses have moved towards positive mathematical programming techniques like integer and non-linear programming models (Arfini *et al.*, 2016).

Integer programming problems require integer solutions to some or all variables and are therefore further differentiated into pure integer programming (PIP) or mixed integer programming (MIP) models (Williams, 1991, p. 154). MIP models are more commonly used as they are less restrictive and generally easier to solve. Integer programming allows optimisation of discrete decision problems and has been predominantly applied to conservation reserve selection in the economic agri-environmental context (Önal and Briers, 2003, 2006; Wang, Önal and Fang, 2018). However, large optimisation problems involving discrete variables suffer from significant solving issues, which limit their applicability for large scale applications and high numbers of integer constraints (Önal *et al.*, 2016; Yao, Zhang and Murray, 2018).

Non-linear programming (NLP) models allow non-linear relationships between variables to be included within the optimisation problem. This approach is particularly useful for agri-environmental issues as they often involve non-linear yield and pollution processes. Their application ranges from analyses concerned with reducing agricultural nutrient pollution in the Baltic Sea (Hasler *et al.*, 2014) to impact assessments of glyphosate bans in Germany (Böcker, Möhring and Finger, 2019). Relative to linear constraints, non-linear constraints require more sophisticated algorithms, including merit functions to balance meeting the constraints and optimising the objective function (Gill, Murray and Wright, 1981, p. 206). Furthermore, models for large catchments, including spatial interdependence, may exceed the capacity of non-linear optimisation techniques (Kling, 2011). Nonetheless, as spatial dependencies can be accounted for outside the optimisation problem, whilst including the essential non-linear yield functions, NLP has become a popular tool in analyses concerned with agricultural production (Aftab, Hanley and Kampas, 2007; Louhichi, Flichman and Boisson, 2010).

Overall, agent-based models may provide interesting exploratory results for issues involving complex behavioural interactions between agents, such as technological diffusion or climate adaptation in the agricultural sector (Berger, 2001; Berger and Troost, 2014). However, the validity and reliability of agent-based model results remain difficult to assess for optimisation problems. Further, farmers' production decisions, which are central to this research, involve limited complex interactions between agents. These interactions are reasonably well understood and have been represented with optimisation techniques in the literature. In addition, as the primary concern of this research is the effectiveness of policy and the impact of PA, as opposed to the diffusion of such new technologies, optimisation techniques are chosen over agent-based modelling. The following section discusses the central economic framework and key theoretical assumptions that underpin the biophysical-economic model.

4.2. Theoretical Economic Model Framework

The economic framework of the analysis builds on the seminal work of Baumol and Oates (1988). In a world of imperfect competition and information, the authors highlight the unrealistic informational requirements associated with achieving optimal environmental policy outcomes - namely, equating the marginal net damage due to agricultural production with its marginal net benefit to society. To overcome the informational issues of optimal policymaking, they suggest the implementation of environmental standards. Policymakers define politically chosen minimum standards that safeguard acceptable conditions for the quality of life. Subsequently, agri-environmental policies can be implemented to achieve the defined standards at minimum cost to society and are thus 'cost-effective' (Ribaudo, Horan and Smith, 1999, p. 23). Given duality, the concept only relies on profit or revenue maximising agents instead of perfect information or competition. Thus, the criterion for policy implementation is shifted from optimality in a first-best world to cost-effectiveness in a second-best world.

Regulatory targets:

In line with previous work, the environmental objective of the policymaker is expressed as a reduction in nutrient leaching (Martínez and Albiac, 2006; Semaan *et al.*, 2007). Following its exit from the European Union, the UK is in the process of developing new regulatory agri-environmental targets. Currently, provisional targets for water nutrient pollution from agriculture are set at a 40% reduction in nutrient load by 2037 (DEFRA, 2022a). A popular approach in the literature is the assessment of daily pollutant concentrations in water bodies in line with the European standard of the Nitrates Directive and WFD (Balana, Vinten and Slee, 2011; Bouraoui and Grizzetti, 2014; Aftab, Hanley and Baiocchi, 2017). However, due to the novel level of biophysical detail and number of observed weather-years included in this analysis (see Table 39, p. 157), the evaluation of daily pollution concentrations was computationally infeasible. In addition, as outlined above, current preliminary UK policy targets are expressed in nutrient load as opposed to concentration. Therefore, this thesis analyses the policies' associated abatement potential in terms of pollutant load to maximise its relevance in supporting current policy development.

Mathematical representation of the non-linear optimisation model:

Formally, the objective of the policymaker is to minimise the cost of achieving a chosen level of pollution abatement through the implementation of an agri-environmental policy. This cost is given by the difference in the unrestricted catchment gross margin and the catchment gross margin after policy implementation (Aftab, Hanley and Baiocchi, 2010), leading to the objective function in equation 1.

$$Min\ (\Pi - \Pi_{r,e}) \qquad (1)$$

Where Π represents catchment gross margin before policy implementation and $\Pi_{r,e}$ represents restricted catchment gross margin after the policy application for a given level of fertiliser application technology e. Equation 2 demonstrates the mathematical representation of restricted catchment gross margin.

$$\Pi_{r,e} = \sum_{f,s,d,h,c} \left(Y_{f,s,d,h,c,e}\, p_c - L_{f,s,d,h,c}\, (k_{f,c,e} + N_{f,s,d,h,c,e}\, p_N\, \tau_N + P_{f,s,d,h,c,e}\, p_P\, \tau_P) \right)$$
$$+ \sum\nolimits_{f,l} [\pi_{f,l,e} - \sum\nolimits_{f,s,d,h,g} \left(L_{f,s,d,h,g}\, (k_{f,g,e} + N_{f,s,d,h,g,e}\, p_N\, \tau_N + P_{f,s,d,h,g,e}\, p_P\, \tau_P) \right)]$$
$$+ \sum\nolimits_{f,g} [Y_{f,g,m,e}\, p_g - Y_{f,g,b,e}(p_g + k_t)] \ + L_{f,s,d,h,a}\psi_a + T \qquad (2)$$

$Y_{f,s,d,h,c,e}$ is the yield of crop c in tonnes grown on the land of farm f, soil s, slope d and hydrological connectivity level h, for a given level of fertiliser application technology e. Prices are represented by p and as appropriate indexed over sale crops c, artificial N or P fertiliser, or forage crops g. τ_N and τ_P represent taxes levied on N and P, respectively. π_l is the gross margin achieved per livestock head, excluding forage costs. $L_{f,s,d,h,c}$, $L_{f,s,d,h,g}$ and $L_{f,s,d,h,a}$represent the farmland of a particular soil-type, slope-type and hydrological connectivity allocated to a sale crop (c), forage crop (g), and set-aside or stocking density reduction (a) respectively. $k_{f,c,e}$ and $k_{f,g,e}$ capture variable costs associated with growing sale crops and forage crops, respectively, which include the cost of crop protection, seed, and plant material as well as labour costs. $N_{f,s,d,h}$ and $P_{f,s,d,h}$ are the fertiliser application levels in kg/ha of N and P, applied respectively. $Y_{g,m}$ represents the forage crop yield in tonnes that is sold within the catchment while $Y_{g,b}$ represents the forage crop yield in tonnes bought from within the catchment incurring an additional transport cost (k_t). ψ_a represents payments for set-aside or stocking density reduction[4], transfer payments for revenue-neutral policies are captured by T.

It is assumed that individual farms maximise their gross margin subject to the constraints of their farm assets and agronomic production requirements such as feeding needs and labour requirements (Schuler and Sattler, 2010; Schönhart *et al.*, 2011; Lungarska and Jayet, 2018). The total gross margin is given by subtracting total variable costs, further specified in Table 5, from total farm revenue (Louhichi *et al.*, 2010, p. 586).

Table 5: Components of farm total gross margin

Total Revenues (TR)	• Sales from agricultural products • Transfer payments
Total variable costs (TVC)	• Cost of fertiliser and fertiliser taxation • Cost of crop protection • Cost of seed and plant material • Cost of animal feed • Cost of employed labour • Cost of contracted PA machinery

A farm's primary asset is its exogenously given land endowment. The land endowment is given in terms of the numbers of hectares of the different soil-slope-type and hydrological connectivity level combinations included in the model, which vary in their yield and pollution generation potential (see section 4.3 for details). A farm's productive capacity is therefore constrained by the size and quality of its land endowment. Moreover, the important spatial aspects of NPS pollution generation are accounted for without an explicitly spatial treatment of the choice variables (i.e., land parcels are not indexed over geographical coordinates), which facilitates computation.

[4] Given the revenue natural policy design and exclusion of subsidies from this analysis, ψ_a is assumed to be zero.

Land use and the level of fertiliser application are the primary choice variables that determine farm gross margin. The four broad land-use choices available to farmers include (i) cultivating sale crops, (ii) cultivating feed crops to meet on-farm livestock feeding requirements or (iii) selling certain feed crops to other farms within the catchment, and (iv) leaving the land as set-aside to receive environmental subsidies. The number of livestock on a farm are endogenously determined by the farm's production choices in growing feed crops to meet the specified livestock feeding requirements. These feeding requirements include hay, silage and pasture grazing needs specific to the six different livestock types included in the model (see Table 6 for description of the livestock types and Appendix A, Table 41 for details of the feeding requirements). Farmers within the catchment may trade fodder beet and maize feed crops amongst each other to meet their livestock feeding requirements. Trades use farm-gate prices with an added transport cost based on haulage weight (SAC Consulting, 2018). Intra-catchment exclusive trading prohibits pollution leakage through bought-in feed crops and accurately represents pollution generated by the catchment's agricultural activities. The N and P pollution associated with livestock grazing is factored into the pollution estimates of grazing and aftermath grazing crops simulated in EPIC. Livestock manure which accrues over the housing period is used for fertilisation and reduces the cost of purchasing artificial fertiliser.

Table 6: Description of included livestock types

Livestock model labels	Description
Dairy	8,500 l all year calving (1 cow)
Sheep1	improved hill breeds (100 ewes tupped)
Sheep2	extensive hill breeds (100 ewes tupped)
Finish1	finishing spring-born suckled calves at 18-20 months (1 steer)
Finish2	forage based finishing dairy steers at 24 months (Holstein)
Suckler	upland suckler cows, calving period Feb-April (1 cow with calf)
Note: livestock descriptions and corresponding grossmargin and forage assumptions sourced from SAC Consulting (2018)	

Multiple farm types are modelled to facilitate an assessment of a policy's impact (Blanco, 2016). The model in this thesis will follow the nine 'robust types' proposed in the UK Farm Classification of DEFRA to aid its policy relevance. These robust farm types include: Cereals, General Cropping, Horticulture, Specialist Pigs, Specialist Poultry, Dairy, Less Favourable Area (LFA) Grazing Livestock, Lowland Grazing Livestock, and Mixed farms (Farm Business Survey and DEFRA, 2014, p. 3). From this list, which is designed for the whole of England, the five types most representative for the Eden catchment are chosen for modelling. This decision was based on the Farm Business Survey[5] data and personal communication with local experts from the River Eden Trust. The chosen farm types are: Cereals, Dairy, LFA Grazing Livestock, Lowland Grazing Livestock, and Mixed Farms, where LFA and Lowland Grazing Livestock include different combinations of sheep, beef finishing, and suckler cows.

Table 7: Modelled farms type distributional attributes

No.	Hypothetical farm position	Farm-type and livestock-type	Soil-type	Slope-type
1	Upland	LFA Grazing Livestock (sheep + suckler)	Less productive	Steeper
2	Lowland	Dairy farm (dairy + some finish)	More productive	Less Steep
3	Upland	LFA Grazing Livestock (sheep + suckler)	Mixed	Mixed
4	Lowland	Lowland Grazing Livestock (dairy + finish)	Mixed	Mixed
5	Lowland	Cereal (sale crops)	More productive	Mixed
6	Lowland	Mixed (sale crops + sheep)	Mixed	Mixed

In addition to heterogeneity of the farm outputs in different main crops and livestock, the model also includes heterogeneity in the inputs through variation in the land qualities allocated to the different modelled farms. Table 7 summarises the modelled farm heterogeneity in terms of the assumed geographical position, livestock produced, and soil slope distribution. As the dominant farm type for the Eden, LFA Grazing Livestock is modelled twice with two different soil-/slope-type distributions. All farms are assumed to be of equal size and should be treated as representative farms of the average farm size for the Northwest of England 77 ha (DEFRA, 2021a). Earlier trials including different farm sizes were computationally costly and did not indicate a significant role of farm size differences in NPS pollution outcomes. However, given the well-documented important impact that differences

[5] http://www.farmbusinesssurvey.co.uk/regional/Reports-on-Farming-in-the-Regions-of-England.asp (accessed 5/5/2020)

in soil, slope and hydrological connectivity have on NPS pollution control, heterogeneity in these variables was prioritised over heterogeneity in farm size.

Modelled policies

Following the literature, the modelled policies include incentive-based, command-and-control measures as well as mixed policy measures. Although transaction costs are not explicitly included in the empirical modelling - in favour of novel biophysical details (see Table 39, p. 157), spatial targeting, and PA - they have informed the choice of policies. Firstly, a nutrient tax on fertilisers is modelled as an incentive-based pollution control policy popular in the literature (Claassen and Horan, 2001; Berntsen *et al.*, 2003; Semaan *et al.*, 2007; Jayet and Petsakos, 2013). This increases the unit cost of crop fertilisation and restricts agricultural production at the intensive margin (Xabadia, Goetz and Zilberman, 2006). Secondly, a set-aside policy is modelled as a command-and-control measure. Set-aside policies require a certain number of parcels to be taken out of production to reduce overall pollution load and create "buffer zones" to aid natural absorption of leached nutrients (Khanna *et al.*, 2003; Yang *et al.*, 2003). A stocking density reduction was tested as an additional regulation-based policy. Stocking density reductions prescribe a maximum grazing livestock unit per hectare. They restrict the intensity of production by (i) a reduction in livestock numbers, (ii) an increase in grazing land sustaining the same number of livestock, or (iii) a combination of both (Aftab, Hanley and Baiocchi, 2017). Moreover, considering the evidence that combining incentive and command-and-control policies may improve their cost-effectiveness (Aftab, Hanley and Baiocchi, 2010), a mixture of set-aside and nutrient tax policies was modelled. Finally, to assess the impact of spatial targeting in agri-environmental policy in the context of technological advances in the sector, the set-aside policy is modelled as a uniform and a spatially targeted application.

The model is implemented in GAMS (GAMS Development Corporation, 2019), in line with numerous studies in the literature (Berntsen *et al.*, 2003; Kampas and White, 2004; Martínez and Albiac, 2006; Hasler *et al.*, 2014; Wang, Önal and Fang, 2018; Böcker, Möhring and Finger, 2019). The non-linear optimisation includes 126,905 single equations and 274,478 single variables at the baseline[6]. Section 4.3 presents details on the biophysical input data for the model.

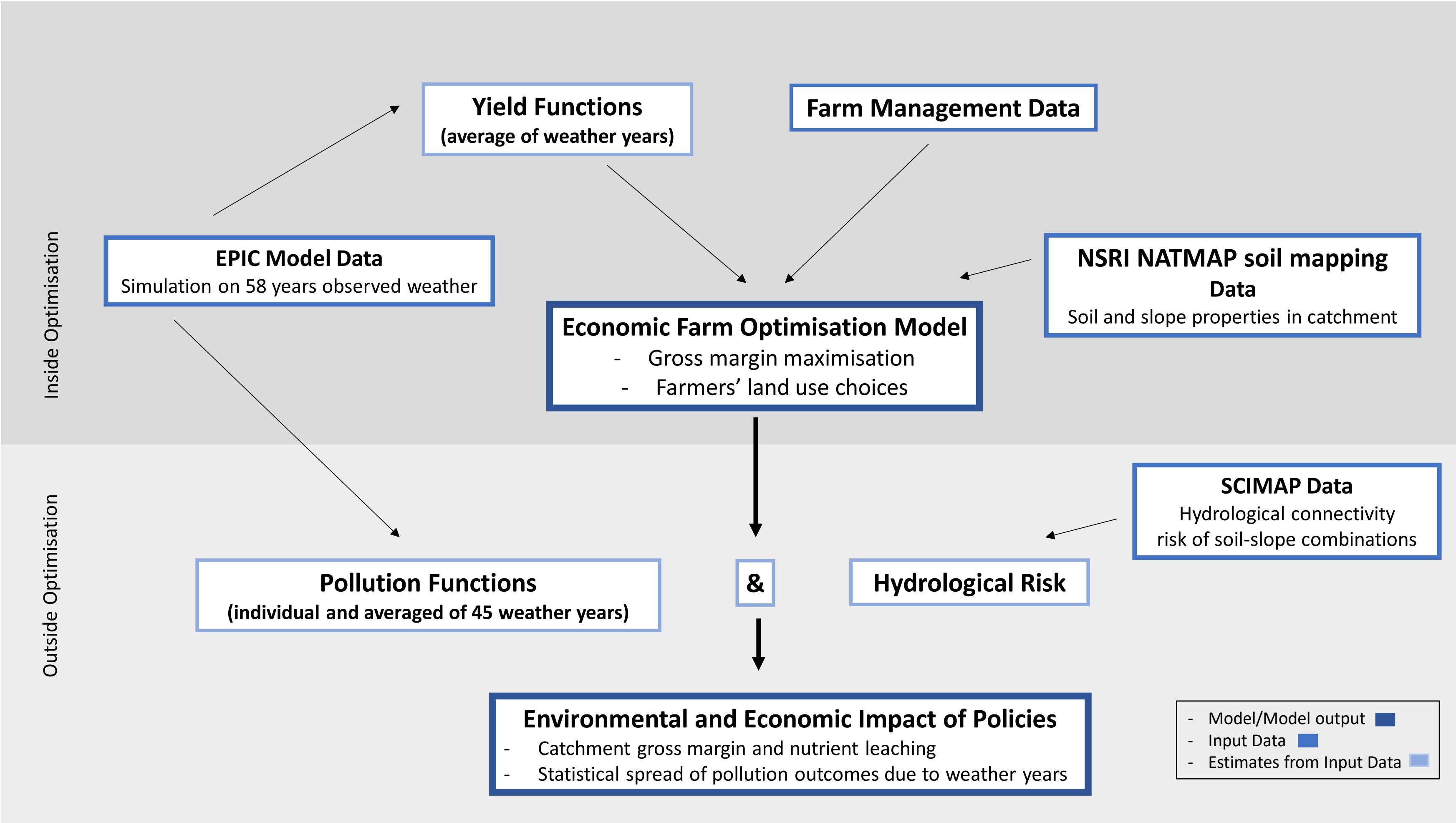
[6] The code for the baseline model is presented in Appendix C from p. 199.

4.3. Biophysical Model Components

Figure 4 (p. 75) provides an overview of the model structure and demonstrates how the different data inputs relate to each other. For the biophysical data, crop-specific yield and pollution functions were estimated based on simulation data from the Environmental Policy Integrated Climate (EPIC) model. For the 58 years of weather data[7], 58 different functions per crop were estimated. Crop-specific yield and pollution functions were averaged across the weather-years. Following data cleaning and testing, 45 weather-years were used in the final model. In the optimisation, the weather-averaged yield functions are used to determine farmers' optimal crop sets and fertiliser application levels. Outside the optimisation, the optimal choice variable levels are used in the average pollution function to calculate the average pollution levels associated with the determined optimal production choices. This structure is facilitated by the exclusion of emission-based policies following the literature review (see section 3.2.3, p. 49 for details). Moreover, outside the optimisation, the estimated weather-year-specific pollution functions were used to determine the statistical variability for the estimated baseline pollution levels (see section 5.4.5, p. 125). Geographical data from NSRI NATMAP[8] provides the soil/slope combinations observed in the catchment. The economic data pertaining to agricultural production in the optimisation is taken from the widely used UK farm management handbooks Redman (2018) and SAC Consulting (2018). Catchment hydrological risk derived from hydrological connectivity data in SCIMAP[9] is used to reflect the environmental risk associated with agricultural pollution from specific slope/soil combinations within the catchment. The hydrological risk estimates are assumed to be exogenous. The following sections explain the simulation process for the yield and pollution data (section 4.4) before discussing the literature on functional forms of the production functions and presenting the functional form chosen for this thesis (section 4.5).

[7] A weather year is defined as daily weather (precipitation, minimum and maximum temperatures, relative humidity, and wind speed variables) data for 365 days https://www.metoffice.gov.uk/services/data (accessed 18/6/2020)
[8] http://www.landis.org.uk/data/series.cfm (accessed 29/4/2020)
[9] http://www.scimap.org.uk/ (accessed 15/6/2020)

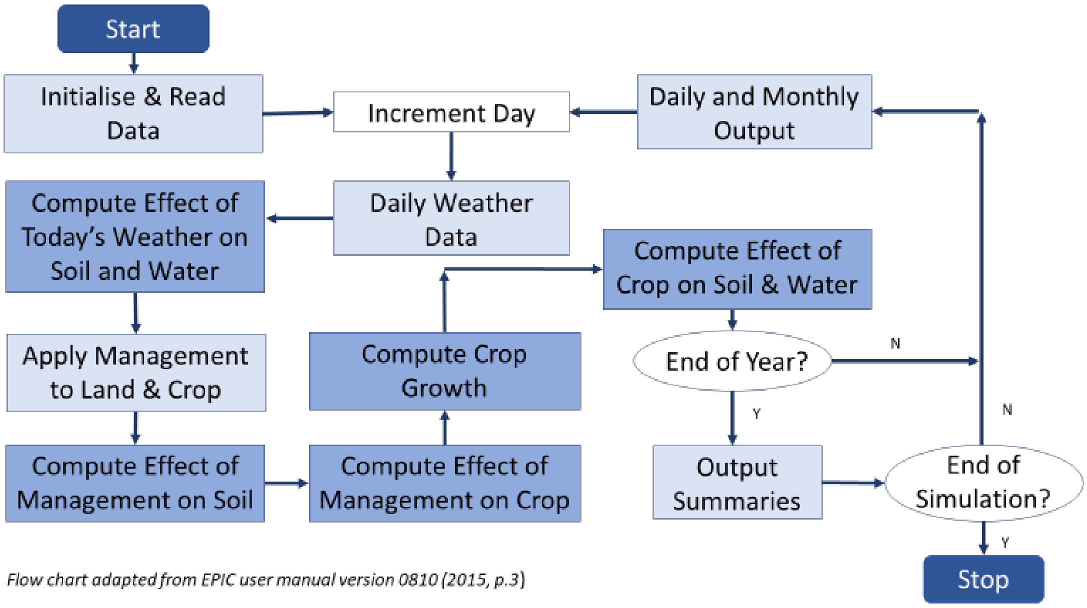
Figure 4: Overview of data inputs in baseline model structure



4.4. Simulation of Yield and Pollution Data

The yield and environmental pollution data are based on simulations from the Environmental Policy Integrated Climate (EPIC) model (Williams, 1990), which were run as part of a wider ESRC funded project (Economic and Social Research Council, 2019) in collaboration with the Durham University Mathematics and Geography departments. Wang *et al.* (2012, p. 1448) provide an overview of the EPIC model components. They explain that EPIC has four main components (pesticide, hydrology, carbon and N cycling, multi-cropping and crop competition) as well as components for weather, erosion, tillage, crop growth, and soil temperature. These allow the model to estimate the effects of different land management practices on key environmental indicators like nutrient leaching and provide important data for assessing policy impacts. Furthermore, EPIC can provide daily estimates and long-term simulations across multiple decades, thereby offering time scale flexibility for policy analyses (Balkovič *et al.*, 2013). In addition, detailed input files allow the model to be calibrated to local conditions of the area of interest. These features have made it a popular foundation for biophysical-economic analyses of agri-environmental policy (Wang *et al.*, 2022). Applications of EPIC in the European context include studies on NPS pollution control in Spain (Martínez and Albiac, 2004), diffuse N pollution in Italy (Semaan *et al.*, 2007), the cost-effectiveness of agri-environmental programs in Austria (Schönhart *et al.*, 2011), as well as soil erosion mitigation strategies in Tunisia (Louhichi, Flichman and Boisson, 2010) in a non-European country. In the following, details of the computational steps involved in the EPIC simulations for this thesis' data are presented before discussing the data inputs required for the simulations.

Figure 5: Flow chart of EPIC simulation process for this project (adapted from EPIC user manual)



Flow chart adapted from EPIC user manual version 0810 (2015, p.3)

Figure 5 was adapted from the EPIC user manual version 0810 (Gerik *et al.*, 2015, p. 3) and illustrates the sequence of computational steps in the EPIC simulation process relevant to this thesis. At the beginning of a simulation, EPIC initialises and reads the data before starting computations for the first day in the simulation (e.g., Day 1). Using the daily weather data for Day 1 (1st January 1954 for this analysis), EPIC computes the effect of Day 1's weather on the chosen soil and water variables. Subsequently, the specified management techniques are applied to the land and the crop to compute their impact on the relevant soil and crop variables. This facilitates the computation of crop growth as well as the crop's impact on the soil and water variables. The Day 1 output variables are then stored and used as inputs to initialise the following increment day (which is Day 2 in this example), with the simulation process then starting again. The process continues until the simulation reaches Day 365, which represents the end of the first simulation year. After which, the output is summarised after computing the effect of crop growth on the soil and water variables to provide the yearly snapshot of the chosen output variables. This yearly snapshot is saved and carried forward, with some outputs reported at the daily or monthly level depending on the variable concerned[10]. The described process is then repeated for the second year of the simulation, starting with simulation day 366. As this study

[10] NPS pollution from agricultural production mainly consists of continuous variables which exhibit changes relevant for economic analyses on a daily basis. However, crop growth variables are only relevant for economic analysis in terms of final yield harvested which only change once or twice in a simulation year on harvest days. Therefore, pollution output is considered at a daily frequency while yield outputs are saved at monthly frequencies.

initially used 58 years' worth of daily weather data, therefore simulation Day 21,170 represents the planned end of the simulation. The model stops at this stage, and the output summaries produced at the end of Day 21,170 are saved as the final simulation output. Figure 6 (see p. 79) details the inputs required for the described simulation steps and provides an overview of the resulting outputs for the Eden catchment.

Weather data:

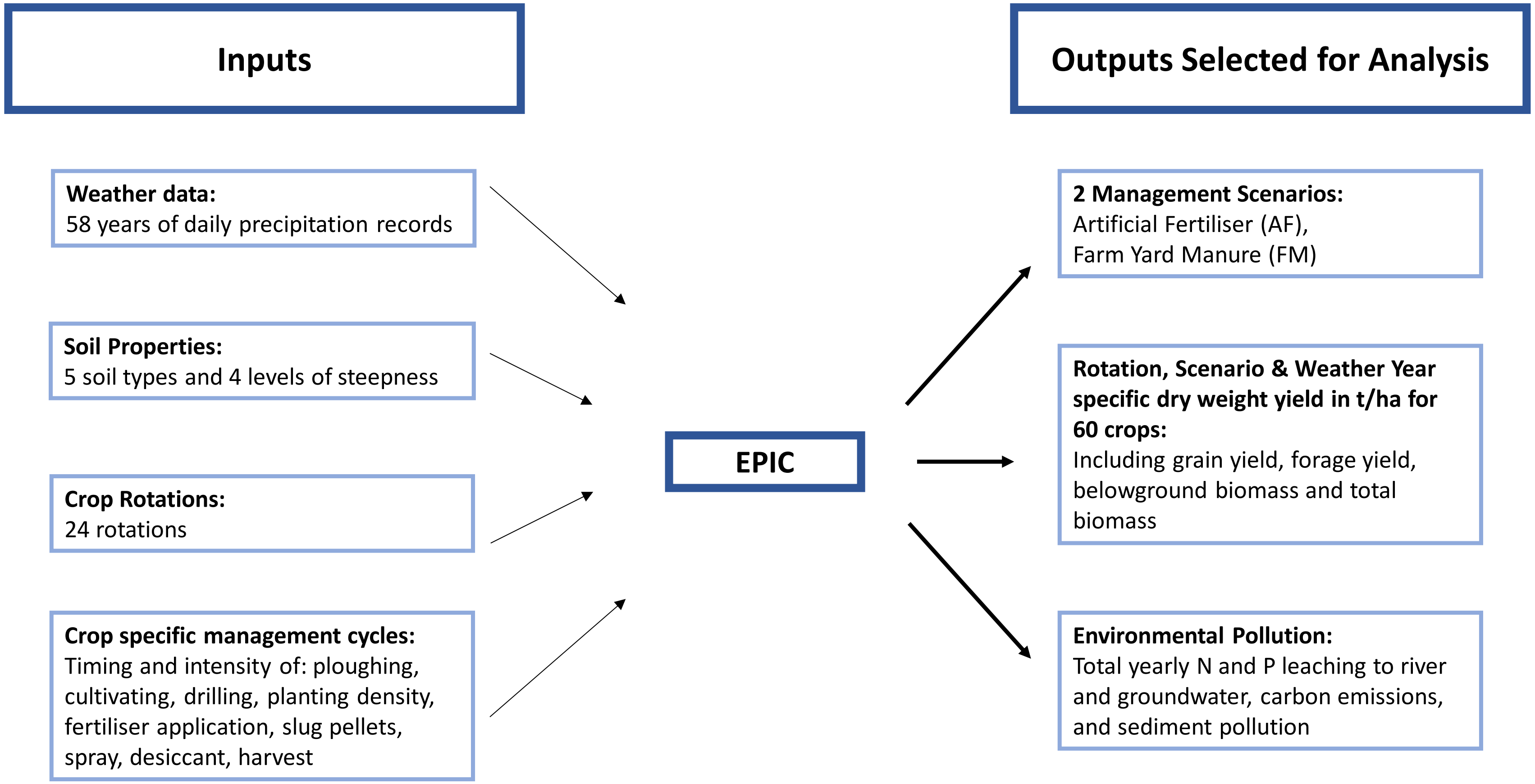
Firstly, 58 years of daily observed weather data (1954-2011) from the UK's Meteorological Office[11] were used as precipitation, minimum and maximum temperatures, relative humidity, and wind speed variables in the simulations for the catchment. As mentioned in section 4.3 (see p. 74), following data cleaning and testing 45 weather-years were used in the final model. The reviewed literature demonstrates that in addition to yields (Basso *et al.*, 2013), weather conditions also significantly impact agricultural NPS pollution and affect the effectiveness of NPS control policies (Aftab, Hanley and Baiocchi, 2010). Therefore, the novel range of real-world weather scenarios used in the biophysical-economic model of this thesis (see Table 39, p. 157) will contribute to the knowledge on the relationship between weather scenarios and NPS pollution control policies.

Soil- and slope-types:

This description of the soil and slope data is based on Reaney (2012). Data on the catchment soils was sourced from NSRI NATMAP soil mapping with links to the Hydrology and Agronomy soil series data[12], which provide a national mapping of UK soil properties. Soils were grouped into five soil-types, and their classifications were based on the two soil properties which are the most relevant to diffuse pollution generation: 'Surface Percentage Runoff' (SPR) and 'Base Flow Index' (BFI). Soil property parameters for the chosen soil-types were either based on an area-weighted

[11] https://www.metoffice.gov.uk/services/data (accessed 18/6/2020)
[12] http://www.landis.org.uk/data/series.cfm (accessed 29/4/2020)

Figure 6: Overview of EPIC simulation inputs and outputs using the Eden catchment as an example



average value or a majority-selected value in the case of categorical data or significant discrepancies between different values. Table 8 provides a summary of the names, descriptions, and areas covered for the chosen soil-types. In addition to prevalent soil-types, degrees of steepness representative of the catchment were also included in the simulations (4 different slopes, see Table 9 for a list of the chosen slopes).

Table 8: Soil-type descriptions and catchment proportions

Soil Label	Classification and Description	Area (ha)	Proportion of Catchment (%)
Soil 1	Wick: light loamy drift with siliceous stones	64,211	51
Soil 2	Newbiggin: reddish medium loamy drift with siliceous stones	45	0.001
Soil 3	Malvern: loamy lithoskeletal basic crystalline rock	19,159	15
Soil 4	Clifton: reddish medium loamy drift with siliceous stones	42,020	33
Soil 5	Winter Hill: mixed eriophorum and sphagnum peat	964	1
Total area		126,400	

Table 9: Slope values and catchment proportions

Slope Label	Slope Values (%)	Area (ha)	Proportion of Catchment (%)
Slope 1	0 – 1.39	11,678	9
Slope 2	1.4 – 4.19	37,641	30
Slope 3	4.2 – 7	30,696	24
Slope 4	7.01 – 12.8	46,384	37

Crop rotations:

Another key influence on agricultural outputs is crop rotations. Crop rotations describe the plantation of different plant species in a particular sequence over time on the same land (Bullock, 1992, p. 309). Since the early days of agriculture, crop rotations have been recognised to improve yields and soil health relative to monoculture practices that grow the same plant species on the same land over extended periods of time (Robinson, 1966; Nevens and Reheul, 2001). The length and composition of crop rotations further affect agricultural output in terms of yield and environmental indicators. In addition, more complex rotations, including leguminous meadows, for example, can improve soil fertility for productive purposes and increase soil organic carbon levels, thereby addressing climate change issues (Triberti, Nastri and Baldoni, 2016).

Based on agronomic expert opinions, various rotations representative of typical systems implemented in the UK were chosen for the simulations. The 24 simulated River Eden catchment rotations range from five to 12 years in length. In addition, 12 long-term monocropping simulations spanning 40 years were simulated, including the different grazing and cutting grass types grown as well as one miscanthus simulation. Details on the rotations are provided in Table 43, Table 44 and Table 45 in Appendix A. The rotations were modelled for every soil-slope-type combination to provide agricultural output and pollution data representative of the catchment. One simulation repeats a rotation over the 58 years of weather data provided. To further maximise the use of the weather data, the number of simulations done per rotation is equal to the length of the rotation (i.e., the number of crops in the rotation), where each simulation starts with a different crop at simulation year 1. This process is illustrated in Table 10 using rotation 9 as an example. Simulation 1 uses the first crop in the rotation (maize in the case of rotation 9) in simulation year 1 or weather data year 1954. The subsequent simulation years plant crops following the order dictated by the rotation and repeat the rotation for the remaining weather data years. Simulation 2 starts with the last crop in the rotation (silage kill in rotation 9) in simulation year 1, before repeating the rotation for the remaining weather data years. Subsequent simulations continue to iterate through the crops in the rotation as starting crops in simulation year 1 until every crop has been used as a starting crop in simulation year 1. This procedure ensures that agricultural outputs for every crop are simulated for every weather-year in the dataset and allows the biophysical-economic model to capture the variability and uncertainty in agricultural production associated with the weather in a particular year.

Table 10: Illustration of simulation weather data use for rotation 9

	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	...	2009	2010	2011
Year of Simulation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**...**	**56**	**57**	**58**
Simulation 1	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	...	MAIZE*	MAIZE*	SIL3 (R)
Simulation 2	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	...	SIL3 (K)	MAIZE*	MAIZE*
Simulation 3	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	...	SIL3	SIL3 (K)	MAIZE*
Simulation 4	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	...	SIL3 (R)	SIL3	SIL3 (K)
Simulation 5	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	SIL3	SIL3 (K)	MAIZE*	MAIZE*	SIL3 (R)	...	MAIZE*	SIL3 (R)	SIL3

*Note: R= Reseed, K=Kill (end of grass in rotation), *=whole-cropped, example crop pair discussed in section 5.2.1, p. 99*

Crop management scenarios:

In addition to weather, soil-type, and degrees of steepness, management practices significantly impact agricultural outputs in terms of yield and environmental indicators. The simulation, therefore, included two different broad management scenarios, which are briefly explained in Table 11. The scenarios include practices traditionally associated with conventional agriculture like the use of artificial fertilisers and a conservation practice, including the use of farmyard manure.

Table 11: Management scenarios in EPIC simulation

Management Scenario	Brief Explanation
Artificial Fertiliser	Fertilisation using synthetic fertiliser
Farmyard Manure	Fertilisation using livestock manure

The majority of the crops included in the model assume artificial fertiliser use, which remains the predominant practice for tillage crops in UK agriculture (DEFRA, 2018a). In addition, 16 tillage crops are simulated with fertilisation using livestock manure. As a by-product of livestock husbandry, manure is often considered a waste product on farms with limited arable farm activities. However, manure contains valuable nutrients and organic matter, which can support soil health indicators such as soil organic carbon stocks (Maillard and Angers, 2014). Particularly in light of the sharp price rises for artificial fertiliser in 2021, there has been more interest in organic fertilisation (AHDB, 2022). Therefore, the simulated farmyard manure crops allow this thesis to capture current agricultural production decisions.

The process of simulating a crop rotation over the 58 years of weather data presented above was repeated for every discussed management scenario. The following section presents analyses of the yield and pollution data received from the simulations. In addition, the following section discusses the literature informing the choice of functional form for the production and pollution functions of the biophysical-economic model.

4.5. Production and Pollution Functions

Economic models of agricultural production and its externalities are built on crop production and pollution functions which capture the biophysical processes involved. As agricultural production and externalities depend on local conditions, the choice of functional form should be guided by both general agronomic theory and local data at hand without any *a priori* assumptions (Frank, Beattie and Embleton, 1990). However, due to the complexity of the concerned natural processes, controversy remains over the appropriate functional forms for the production and pollution functions in these agri-economic models (Jayet and Petsakos, 2013). This section firstly reviews the debate on the issue of functional forms for crop production functions and analyses the appropriate functional form for this thesis. Subsequently, the pollution functions commonly employed in the literature are examined. Examples of the discussed production and pollution functions are presented in Table 12 (see p. 86) and Table 13 (see p. 87) respectively.

Due to the computational simplicity associated with quadratic production functions, several studies apply them in their agri-economic analyses (Martínez and Albiac, 2004, 2006; Louhichi, Flichman and Boisson, 2010). However, early evidence by Ackello-Ogutu, Paris and Williams (1985) suggests that quadratic functional forms overestimate the maximum yield and optimal fertiliser recommendations. Moreover, the authors highlight that a quadratic functional form allows for substitution between inputs (i.e., nutrients) which is contentious within biology. Further, they argue that the presented parameters lack agronomic interpretations.

Empirical evidence largely discredits using a quadratic functional form for agricultural production functions and favours either the von Liebig or the Mitscherlich-Baule functional form (Frank, Beattie and Embleton, 1990; Llewelyn and Featherstone, 1997; Rosenzweig *et al.*, 1999). The von Liebig functional form is based on the Law of the Minimum, which is attributed to the work of Justus von Liebig in 1855 (Harmsen, 2000). His work considers crop growth to be proportional to the supply of the limiting factor *ceteris paribus*, where the limiting factor may be a nutrient, water or light (Ferreira, Zocchi and Baron, 2017). Consequentially, in a two-input factor scenario (e.g. N and water), plant growth displays a linear relationship with the supply of N until the water becomes the limiting factor and crop yield reaches a plateau when neither water nor N are limiting (Llewelyn and Featherstone, 1997). Indeed, some empirical evidence suggests that linear von Liebig specifications better fit real production data than various polynomial specifications (Ackello-Ogutu, Paris and Williams, 1985; Grimm, Paris and Williams, 1987). However, as Paris (1992) stresses, the linear relationship between inputs and plant growth is highly controversial and has produced the Mitscherlich and Mitscherlich-Baule functions as notable extensions adhering to the growth plateau of the Law of the Minimum. He asserts that the single-input Mitscherlich equation addresses the linearity issue by introducing an exponential function. Furthermore, only the Mitscherlich-Baule extension to two or more inputs further introduces a degree of substitution between inputs.

Frank, Beattie and Embleton (1990) test the Mitscherlich-Baule functional form against the discussed alternative specifications and find it preferable. Their findings are supported by Llewelyn and Featherstone (1997), who also include a non-linear extension of the von Liebig functional form in comparing different production functional forms. More recent applications, such as Wang and Baerenklau (2014), also favour the Mitscherlich-Baule specification due to its differentiability and agronomic interpretation. The authors further demonstrate that convergence problems in estimating the Mitscherlich-Baule function reported by Martínez and Albiac (2006) can be overcome by increasing iteration limits of regression models and using complementary methodologies such as data visualisation.

The literature analysis has demonstrated that quadratic production functions exhibit poor yield prediction powers and lack biological interpretations of coefficients (Ackello-Ogutu, Paris and Williams, 1985). Moreover, empirical analyses have shown that the Mitscherlich-Baule specification represents yield behaviour more accurately than the von Liebig specifications (Frank, Beattie and Embleton, 1990; Llewelyn and Featherstone, 1997). Importantly, in contrast to discussed alternatives, the Mitscherlich-Baule functional form is twice differentiable and corresponds to agronomic interpretations[13] (Wang and Baerenklau, 2014). Therefore, the Mitscherlich-Baule functional form should generally be preferred for agricultural production functions. Furthermore, statistical analysis of the simulated yield data used in this thesis suggests that the Mitscherlich-Baule functional form is an appropriate fit for the yield data at hand (see section 5.2.1 for details)[14].

[13] The agronomic interpretation of the functions coefficients is beyond the scope of this thesis.

[14] Statistical fitting of different yield functions was performed with the help of Dr Jonathan Cumming.

Table 12: Examples of production functions

Quadratic: (Rosenzweig *et al.*, 1999) $$Y_i = \alpha_1 + \alpha_2(N_i) + \alpha_3(W_i) + \alpha_4(N_i)^2 + \alpha_5(W_i)^2 + \alpha_6(N_iW_i)$$
Y_i: estimated crop yield; N_i: applied N; W_i: total water amount (precipitation and irrigation); α: parameter.
Linear von Liebig: (Frank, Beattie and Embleton, 1990) $$Y_i = \min\,(Y^*, \beta_1 + \beta_2 N_i, \beta_3 + \beta_4 P_i)$$
Y^*: is the max yield when neither N nor water is limiting; P_i: applied phosphorous; β: parameter.
Non-Linear von Liebig: (Paris, 1992) $$y_i = min\left[m\left(1 - k_N e^{-\beta_N N_i}\right), m\left(1 - k_p e^{-\beta_P P_i}\right)\right] + u_i$$
m: asymptotic plateau common to both inputs; k: parameter; u_i: the experimental error.
Mitscherlich-Baule: (Rosenzweig *et al.*, 1999) $$Y_i = \beta_1[1 - \exp(-\beta_2(\beta_3 + N_i))][1 - \exp(-\beta_4(\beta_5 + W_i))]$$
Y_i: estimated crop yield; N_i: applied N; W_i: total water amount (precipitation and irrigation); $\beta_1 - \beta_5$: parameters

In contrast, to yield functions, the optimal choice for pollution functions in biophysical-economic models has received less explicit attention in the literature. This could be explained by the fact that crop yield as the principal product is of more immediate significance than pollution in agricultural production. Indeed, despite environmental considerations increasingly shaping European agricultural policy since the 1980s, production concerns quickly begin to dominate political agendas in the face of food security issues (Posthumus *et al.*, 2010). This trend is reflected in the less explicit treatment of agricultural pollution functions in the economic literature. Among the studies which do consider pollution functions, some make use of experimental data to estimate them. However, like this thesis, most works rely on simulated data, which facilitates the inclusion of diverse variables and a more holistic representation of diffuse pollution (Vatn *et al.*, 1997). Generally, the choice of pollution function in the literature is data-driven, and frequently studies employ quadratic or square-root polynomial functions to represent nutrient leaching from the soil (Helfand and House, 1995; Martínez and Albiac, 2004). Examples of the functions employed in the literature are presented in Table 13.

Table 13: Examples of pollution functions

Cubic: Nitrate (Lord and Mitchell, 1998) $$Nitrate\ leaching\ potential = a + bN + cN^2 + dN^3$$
a, b, c, d: fitted constants; N: applied nitrogen fertiliser
Restricted quadratic and square-root: Nitrate (Larson, Helfand and House, 1996) $$NO_3 = \beta_0 + \beta_1 N + \beta_2 W + \beta_3 N * W + \varepsilon$$
NO_3: nitrate leached, β: parameters, N: nitrogen applied, W: water applied, ε: disturbance term
Linear: Nitrate (Jayet and Petsakos, 2013) $$e(N) = A \times N + B$$
$e = NO_3 - N\ losses$; A, B: estimated parameters
Linear: Soil Erosion (Schuler and Sattler, 2010) $$A = R \times K \times LS \times CP$$
A: average annual soil loss in t/ha; R: rainfall erosivity index, K: soil erodibility factor; LS: topographic factor (L is slope length, S is slope inclination); C: cropping factor; P: conservation practice factor.

Given the lack of clear evidence in the bioeconomic literature on specific functional forms for pollution functions, the chosen functional forms were based on theoretical relationships between pollutants and fertiliser inputs as well as data exploration. The chosen functions for the six pollution variables of interest in this analysis are presented in Table 14.

Table 14: Functional forms and theoretical reasoning for pollution functions

Pollution Variable	Function of N and or P	Theoretical Reasoning
Sediment mobilised (t/ha)	$\beta_{0,ZLOAD} + \beta_{1,ZLOAD} \times N$	Plant growth is driven by N application. Larger plants with more developed root systems reduce erosion. However, sediment pollution is more strongly influenced by the employed tillage system than the level of fertilisation.
N to River (kg/ha)	$\beta_{0,NRLOAD} + \beta_{1,NRLOAD} \times N$	Increased N application increases the amount of N available on and in the soil, increasing N leaching to the river.
N to groundwater (kg/ha)	$\beta_{0,NGLOAD} + \beta_{,1NGLOAD} \times N$	Increased N application increases the amount of N available on and in the soil, increasing N leaching to groundwater.
P to the river (kg/ha)	$\beta_{0,PRLOAD} + \beta_{1,PRLOAD} \times N + \beta_{2,PRLOAD} \times P + \beta_{3,PRLOAD} \times P \times N$	Increased P application increased P leaching to the river. Increased plant growth through increased N application can reduce the amount of P leaching as larger plants absorb more of the available P.
P to groundwater (kg/ha)	$\beta_{0,PGLOAD} + \beta_{1,PGLOAD} \times N + \beta_{2,PGLOAD} \times P + \beta_{3,PGLOAD} \times P \times N$	Increased P application increased P leaching to groundwater. Increased plant growth through increased N application can reduce the amount of P leaching as larger plants absorb more of the available P.
Carbon emission (kg/ha)	$\beta_{0,CFEM} + \beta_{1,CFEM} \times N + \beta_{2,CFEM} \times P + \beta_{3,CFEM} \times P \times N$	Increased fertiliser application (N and/or P) may increase carbon emissions due to increased machinery use and soil perturbation.

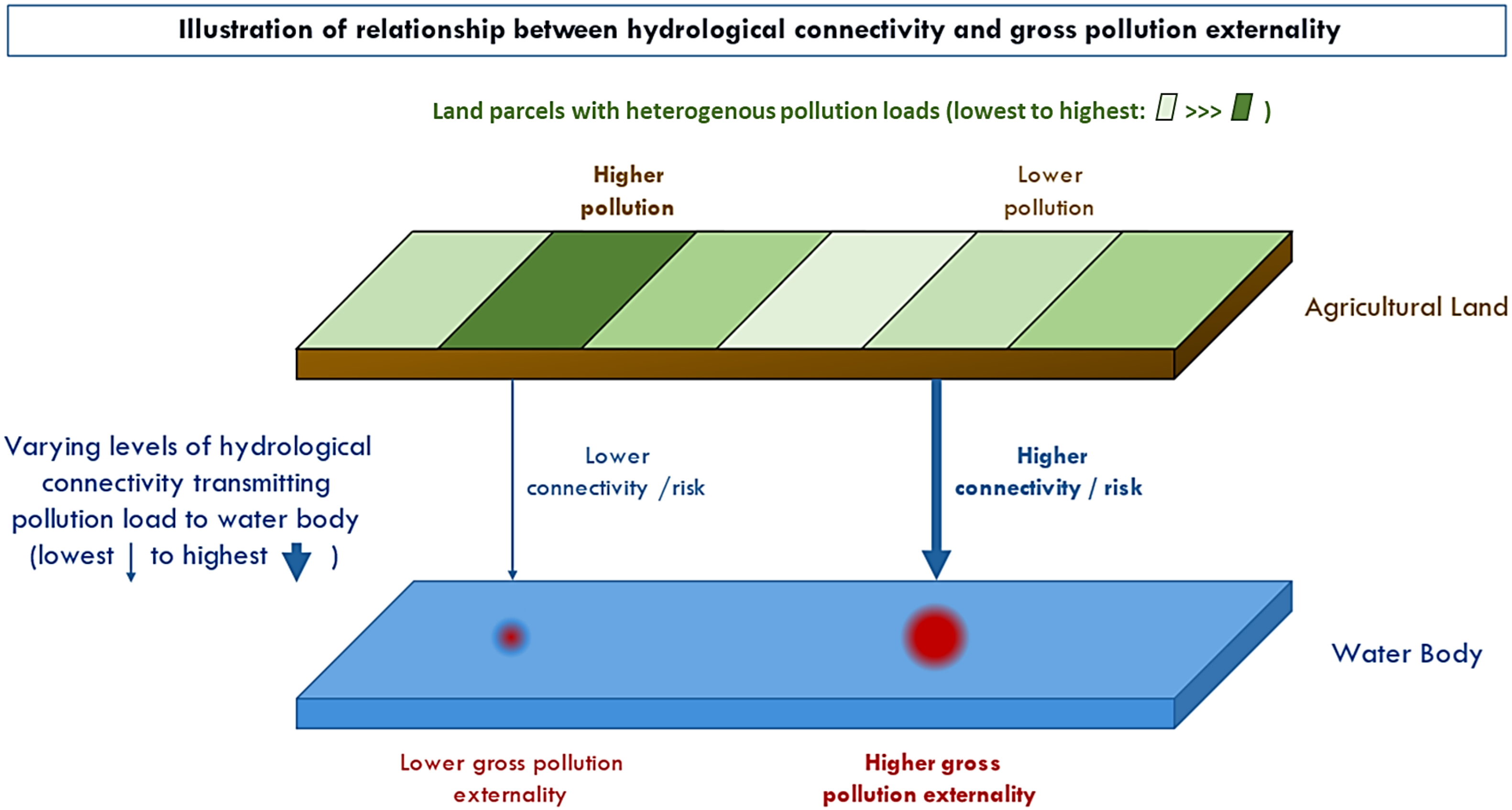
Graphical and statistical summary statistics of the fitted pollution functions are presented in chapter 5. The following section presents the framework and data used to capture hydrological connectivity in this thesis.

4.6. Hydrology Framework

In addition to soil-type, degrees of steepness, and management scenarios, geographical features such as the hydrological connectivity of a land parcel are key predictors of NPS pollution generation (Heathwaite, Quinn and Hewett, 2005). As illustrated in Figure 7 (see p. 90) there is significant variation within the degree of hydrological connectivity of different agricultural fields to water bodies. While some land parcels show direct hydrological pollution pathways to water bodies, other land parcels are not highly connected to a water body. Consequentially, the environmental impact of NPS pollution generated from different land parcels will vary significantly. For example, a field with a soil-/slope-type combination prone to generating NPS pollution may not be hydrologically connected to a water body and therefore not pose a high risk of NPS pollution. However, a land parcel with a relatively low-risk soil-/slope-type combination in terms of NPS pollution generation may be highly connected to a water body and, therefore, in effect, pose a high NPS pollution risk. Previous biophysical-economic models which analyse agri-environmental policies largely fail to capture the hydrological risk component of NPS pollution. However, accurately capturing total NPS pollution generation risk is necessary to effectively design spatially targeted policies. Therefore, this thesis builds on previous works and includes the hydrological connectivity within the catchment in its analysis. The hydrological connectivity data was sourced from SCIMAP[15] with the help of Dr Sim Reaney.

[15] http://www.scimap.org.uk/ (accessed 15/6/2020)

Figure 7: Illustration of relationship between NPS pollution risk and hydrological connectivity



The following description of SCIMAP and its process of predicting hydrological connectivity is based on the SCIMAP documentation (Reaney and Wells, 2014). SCIMAP uses the Network Index (Lane *et al.*, 2004; Lane, Reaney and Heathwaite, 2009), which assesses the risk of the land parcels in a landscape becoming saturated. Further, the Network Index accounts for the probability of a saturated land parcel being connected to a flow path, contributing to NPS pollution in the connected water body. In addition, SCIMAP uses the topographic wetness index (Beven and Kirkby, 1979), which captures spatial heterogeneities in soil moisture across the landscape. The SCIMAP predictions were tested on the Upper Rye catchment in North Yorkshire, which is hydrologically, geomorphologically, and climatologically comparable to the Eden catchment and found to satisfactorily predict hydrological connectivity (Lane, Reaney and Heathwaite, 2009).

Hydrological connectivity is represented as a ranking parameter ranging from 0 – 1, where 0 represents the lowest and 1 the highest hydrological connectivity level for all land covers within the catchment. For the biophysical-economic model, the catchment's agricultural land is divided into intervals of hydrological connectivity at a scale of 0.1[16]. The resulting levels of connectivity are presented in Table 15.

Table 15: Definition of hydrological connectivity Intervals at different scales

Intervals of 0.1
Conn_1 = [0 - 0.1]
Conn_2 = [0.11 - 0.2]
Conn_3 = [0.21 - 0.3]
Conn_4 = [0.31 – 0.4]
Conn_5 = [0.41 – 0.5]
Conn_6 = [0.51 – 0.6]
Conn_7 = [0.61 – 0.7]
Conn_8 = [0.71 – 0.8]
Conn_9 = [0.81 – 0.9]
Conn_10 = [0.91 - 1]

[16] An alternative finer resolution distribution with 100 hydrological connectivity levels was investigated but ultimately not used in the model due to computational constraints. See Appendix A, Figure 33, p. 181 for the finer resolution distribution for intervals of 0.01.

The connectivity levels may be interpreted in line with the following example: At the scale of 0.1 (jumps of 10 percentile), a connectivity level of Conn_3 would imply a level of connectivity within the 21st and 30th percentile, meaning the risk of NPS is between 21 and 30 percentage points higher than the lowest level of NPS pollution.

The data further provides the catchment area in m^2 attributed to a certain soil/slope-type combination and connectivity interval. Therefore, this data facilitates the introduction of hydrological connectivity as an additional index in the biophysical-economic model. The generated NPS pollution calculated by the model is multiplied by the associated hydrological risk factor to reflect the true NPS pollution risk.

The distribution of hydrological connectivity across the agricultural land of the catchment is represented in Figure 8 for intervals of 0.1. The analysis demonstrates that 49.5% of the Eden's agricultural area is characterised by levels of hydrological connectivity within the 21st to 30th percentile above the minimum level of hydrological connectivity.

Figure 8: Distribution of hydrological connectivity levels (intervals of 0.1) across soils and slopes

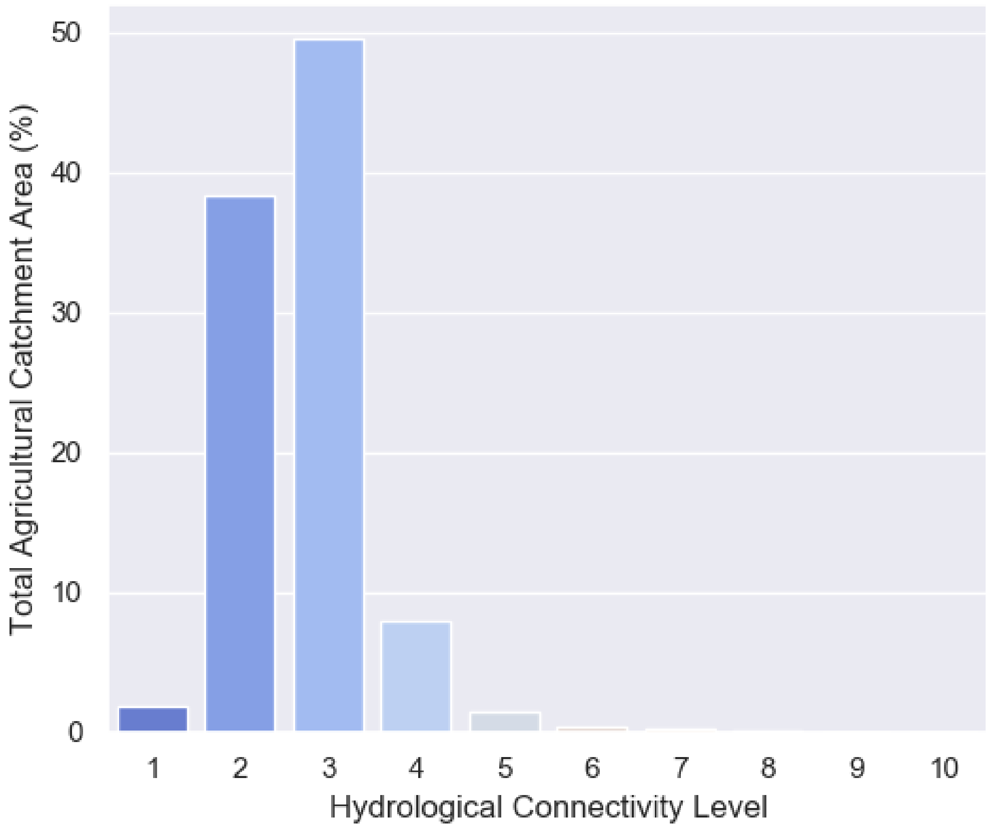


Figure 8 and Figure 9 further demonstrate that the majority of the catchment's agricultural land is characterised by relatively low hydrological connectivity, with 97.68% of the Eden's agricultural area displaying levels of hydrological connectivity equal to or below the 40th percentile on the connectivity ranking. Further, only 0.39% of the agricultural land is classified as relatively high risk based on their hydrological connectivity of within or above the 70th percentile ranking.

Figure 9: Cumulative distribution of hydrological connectivity levels (intervals of 0.1) across soils and slopes

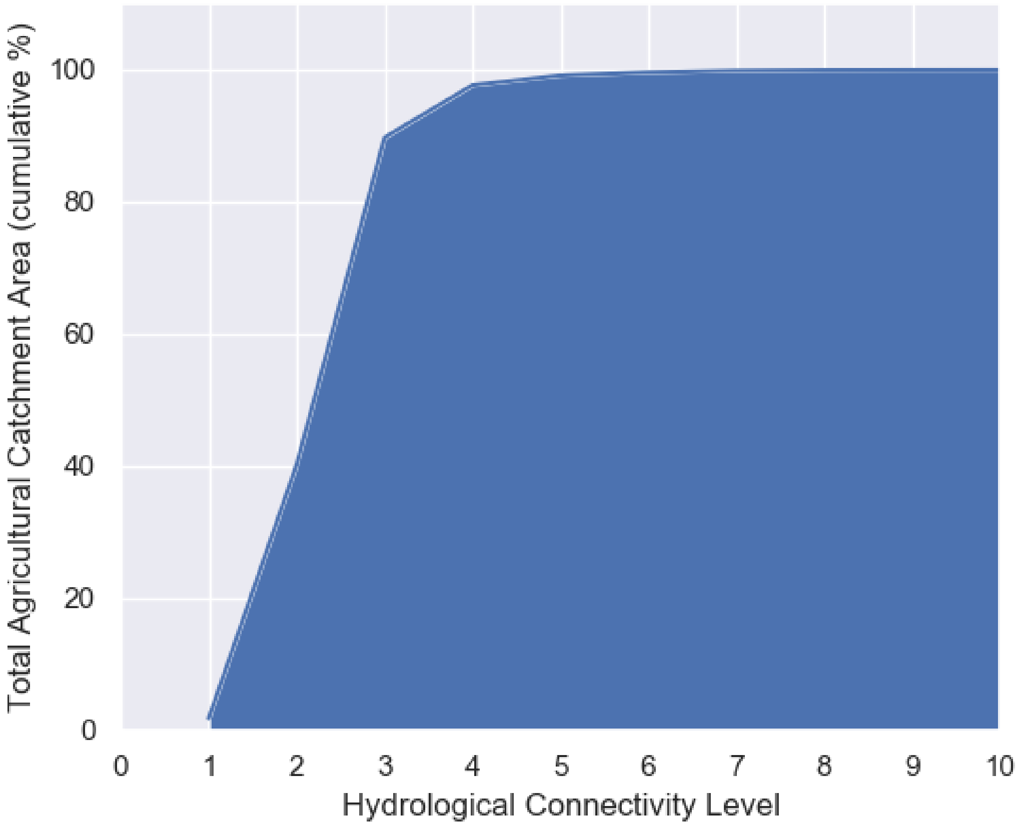


Table 16 shows a more detailed breakdown of the land cover types of the catchment's agricultural land. The land cover types are based on the Centre for Ecology & Hydrology's land cover map of 2007; Appendix A, Table 47, p. 174 provides details of the agricultural land classification (Centre for Ecology & Hydrology, 2021). The 2007 land cover map classification of agricultural land differs only in minor ways from the more recent 2015 land cover map classification in that the 2007 version contains the rough grassland class, which is no longer included in the 2015 land cover map (Centre for Ecology & Hydrology, 2017). Table 16 further demonstrates that, on average, the agricultural land covers of the Eden catchment are characterised by lower levels of hydrological connectivity and relatively little variation. Close to 70% of the catchment agricultural land is classified as improved grassland with an average level of hydrological connectivity within 22 percentage points of the catchment's minimum level of hydrological connectivity. Meanwhile, only 1.6% of the catchment area is classified as neutral grassland with a mean level of hydrological connectivity up to 26 percentage points above the entire catchment's minimum.

Table 16: Mean level of hydrological connectivity by landcover type

Catchment land cover	Area (ha)	Percentage of total agricultural area	Mean level of hydrological connectivity
Arable and Horticulture	22,370	17.7	0.23
Improved Grassland	86,083	68.1	0.22
Rough Grassland	15,875	12.6	0.22
Neutral Grassland	2,002	1.6	0.26
Note: Land covers are defined following the Centre for Ecology & Hydrology Land Cover Map (2007)(Centre for Ecology & Hydrology, 2021)			

4.7. Modelling Precision Agriculture

As discussed in chapter 3 (section 3.4.1), PA firstly facilitates improved data collection on production-relevant variables such as soil heterogeneity and fertiliser requirements relative to conventional agricultural technologies. Secondly, PA allows farmers to optimise their production decisions according to the collected data using VRNA fertilisation, for example. Therefore, in a theoretical economic framework, we can assume that farmers operating with conventional agricultural technologies do so under incomplete information regarding their production functions. PA technologies move farmers from incomplete information towards complete information as they receive more information on the optimal management decisions like hectare-specific fertiliser application levels. Specifically, VRNA technology allows the farmer to apply fertilisers according to the hectare-specific crop requirements and avoid site-specific over- or under-application. Such optimised fertiliser application may lead to fertiliser savings and NPS pollution reductions at the farm-level (Basso *et al.*, 2016). At the cost of obtaining and operating the technology, PA thereby reduces inefficiencies and shifts farmers from inside the production possibility frontier onto the production possibility frontier.

This thesis incorporates PA technology into its biophysical-economic model by building on the economic framework presented. The model focuses exclusively on the impact of PA on N application and does not consider P for three main reasons. Firstly, the N content of manure is, on average, 2.8 times higher than its P content across the different livestock types considered in the model (Crooks *et al.*, 2020). Secondly, the per hectare crop requirement for N generally significantly outweighs the crop requirement for P for grain crops and forage crops (SAC Consulting, 2018). Finally, N's dominance in terms of manure content and crop requirements has led to an exclusive focus on the impact of PA on N in the technical PA literature. To the best of my knowledge, agronomic studies investigating the effects of VRNA, to date, have not included specific treatments of P fertilisation. Given the weight of N in manure composition as well as fertiliser requirements and the lack of reliable evidence regarding the effects PA has on P fertilisation, this thesis' treatment of VRNA focuses on N fertilisation. Therefore, the impact of using PA relative to conventional agricultural technology is modelled by N efficiency factors that capture the improvements in N use associated with using PA.

As discussed in section 3.4.1, quantitatively measuring the exact impact of PA technology on fertiliser efficiency, grain yields, and environmental indicators has been difficult due to the multitude of variables that significantly impact agricultural production. The difficulties associated with capturing all relevant variables in field trials explain the wide range of estimates for N efficiency gains that have been found in the literature on VRNA technology.

A detailed agronomic field trial in Germany, for example, finds that the beneficial effects of VRNA for N fertilisation and N surplus in the soil are highly dependent on additional yield-limiting variables such as water availability in the soil (Zillmann *et al.*, 2006). However, in an earlier field trial on winter wheat, Ehlert, Schmerler and Voelker (2004) find that VRNA entails N fertiliser savings of 10-12%. More recently, Stamatiadis *et al.* (2018) find 38% N fertiliser savings with VRNA relative to a uniform application.

Colaço & Bramley (2018) provide a comprehensive review of the available evidence on sensor-based fertiliser applications. The authors find that most studies report N fertiliser savings ranging from 5% - 45% at relatively constant grain yield levels. This thesis, therefore, uses a range of efficiency factors from 5% - 45% representing the range of efficiency gains in N fertilisation from VRNA technology currently suggested by the literature.

The EPIC simulation assumes conventional agricultural production conditions with imperfect information on the biophysical variables relevant to that agricultural production. Therefore, the production functions obtained from the simulation can be assumed to be inside the production possibility frontier. Under PA use, PA efficiency factors (EF) are applied to the yield functions to simulate the shift towards perfect information and onto the production possibility frontier. This approach demonstrates the range of relative differences between production using PA and conventional technologies currently assumed in the literature. More N reaches the plants to stimulate growth in the PA scenario at equal total N application levels relative to the conventional technology scenario. One, therefore, expects higher yields in the PA scenario but equal levels of pollution relative to the conventional scenario at constant total N application levels. The costs of using PA are modelled as contractor costs per hectare for fertilisation with an added charge for variable rate application net of farmers' average constant rate fertilisation costs per hectare, which are included in the general variable crop costs (Redman, 2018, p. 196). This approach facilitates addressing the research objectives around PA's influence on catchment scale yield and NPS outcomes (see section 1.1, p. 16).

5. Model Baseline

This chapter presents the details of the model baseline. Section 5.1 provides an overview of the study catchment's main characteristics. Sections 5.2 and 5.3 summarise the biophysical and economic data, respectively, which underpins the analysis. Finally, section 5.4 provides the details of the model baseline results.

5.1. Study Catchment: The Eden

The catchment analysed in this thesis is the Eden, located in the Northwest of England. The Eden forms part of the demonstration test catchment network run by DEFRA to investigate cost-effective ways to reduce diffuse pollution from agriculture (Eden DTC - A Defra Demonstration Test Catchment, 2020). It spans 2,310 km^2 and is characterised by various land covers "with four dominant classes: arable; intensive or improved pasture; extensive pasture; and moorland" (Reaney *et al.*, 2011, p. 1021). With an average annual rainfall of 2,800 mm, precipitation levels in the Eden catchment are high relative to the English mean (EA, 2009). Over the period from January 1959 to April 2021, the mean temperature in the Eden was 8.2 °C, including highs of 31.1 °C and lows of -25.4 °C (own calculations based on Met Office (2012)). The location and geographic characteristics of the Eden facilitate a wide representation of the conditions observed in agricultural production across Northern England and Scotland. With respect to agricultural activity, the catchment is livestock intensive and exhibits both upland and lowland farms. In the following, details on the catchment-specific biophysical input data are presented. Section 5.2 discusses the yield and environmental pollution data.

5.2. Biophysical Data

The following sections firstly summarise the yield data (section 5.2.1) used in this analysis before presenting the pollution data (section 5.2.2) employed in this biophysical-economic model.

5.2.1. Yield Data

This section discusses the characteristics of the yield data received from the EPIC simulation, describes the transformation of the raw simulation data into yield functions used in the biophysical-economic model, and presents the results of analyses on the yield functions.

As demonstrated in section 4.4, the output provided by EPIC for each crop includes several variables related to both yield and environmental pollution data. Firstly, we turn to the yield data. The definitions of the variables included in the EPIC yield output files are shown in Table 17. Whether a crop yield is counted as grain yield or forage yield depends on the harvesting methods used in the EPIC simulation, which are pre-defined by the EPIC modellers. Therefore, the variables relevant for the yield of interest in this thesis vary between crops.

Table 17: EPIC variables and definitions

EPIC Variable	Definition
GYLD	Grain Yield (DM t/ha)
FYLD	Forage Yield (DM t/ha)
BIOM	Total Biomass (DM t/ha)
BGBM	Below Ground Biomass including GYLD (DM t/ha)

The EPIC variable combinations relevant to the modelled crop types are presented in Table 18. The combinations were determined based on Gerik *et al*. (2015) and personal communications with the EPIC team. Different management intensity levels were modelled for grazing and cutting grasses, including varying numbers of cuts and, thus, varying numbers of fertiliser applications. The relevant EPIC variable combinations are fixed for every crop across the two management scenarios in Table 11.

Table 18: EPIC yield variables used for each crop

EPIC yield variables used in model	
Crop	**EPIC variable combination**
Winter wheat	GYLD
Whole-cropped winter wheat	GYLD + FYLD
Winter barley	GYLD
Spring barley	GYLD
Winter oil seed rape	GYLD
Spring oats	GYLD
Potatoes	GYLD
Spring beans	GYLD
Whole-cropped maize	GYLD + FYLD
Stubble turnips (July)	FYLD
Stubble turnips (Spring)	FYLD

EPIC yield variables used in model	
Fodder beet	GYLD
Grazing grass (two cuts)	FYLD
Grazing grass (three cuts)	FYLD
Grazing grass (four cuts)	FYLD
Grazing grass (six cuts)	FYLD
Grazing LFA	FYLD
Silage grass (one cut)	FYLD
Silage grass (two cuts)	FYLD
Silage grass (three cuts)	FYLD
Silage grass (four cuts)	FYLD
Silage LFA	FYLD
Hay (two cuts)	GYLD + FYLD
Hay LFA	GYLD + FYLD
Miscanthus	GYLD + FYLD
Note: each crop was modelled in different rotations to capture the impact of crop sequence	

Due to the high number of combinations (crop, rotation, weather-year, soil, slope, and management scenario), 1,985,920 different yearly yield and pollution output files were estimated for the Eden catchment. Several "unique crop pairs" were chosen from the rotations to reduce the output for further analysis to a manageable size. A crop pair denotes two crops grown in a sequence as part of a particular rotation. The optimisation uses the yield and pollution output in a year of the second crop in the pair. Nonetheless, these outputs are also influences by the impacts of the first crop in the pair. Accounting for previous crops when considering NPS pollution and yield is important as soil characteristics (e.g., nutrient availability in the soil) continue to be impacted by the cultivated crop beyond the year of cultivation. The crop pair concept can be illustrated using the second and third crops in Eden rotation 9 from Table 10 (see p. 82, highlighted by a red ellipse) as an example. In this crop pair, silage reseed with three cuts is planted in the current year; therefore, yield and pollution outputs for silage reseed with three cuts are recorded in the model. However, the preceding crop (whole-cropped maize in this example) will significantly impact yield and pollution generated in the current year. Therefore, by defining crop pairs, we can account for and compare the impact farmers' different planting decisions of the previous year have on the current year's environmental and economic indicators. For every management scenario, between 60 and 98 crop pairs were chosen for further analysis. Crop pair choice was informed by obtaining a sample representative of farmers' planting behaviour in the Eden.

For the chosen crop pairs, the relevant EPIC yield variables (see Table 18) were extracted from the EPIC output files in cooperation with Dr Jonathan Cumming. Subsequently, Mitscherlich-Baule yield functions were fitted to the simulated yield data. The Mitscherlich-Baule functional form was chosen based on its theoretical properties (see section 4.5 for a detailed discussion on the preference for a Mitscherlich-Baule functional form) and simple model adequacy tests as opposed to more rigorous tests for non-nested models such as the J-test or the N-test (as investigated by Pesaran (1982)). N and P were chosen as the two varying inputs, and the estimations used range from zero to the defined crop-specific fertiliser maxima (see Appendix A, Table 46 for details). Equation 3 presents the weather-year- (w), soil- (s), and slope- (l) specific yield function where $\beta_{0wsl}, \beta_{1wsl}, \beta_{2wsl}, \beta_{3wsl}, \beta_{4wsl}$ are the estimated coefficients[17] and Y_{iwsl} presents the dry weight EPIC unique crop pair yield in t/ha for the chosen N (N_i) and P (P_j) fertilisation levels in kg/ha.

$$Y_{ijwsl} = \beta_{0wsl}[1 - \exp(-\beta_{1wl}(\beta_{2wsl} + N_i))]\big[1 - \exp\big(-\beta_{3wsl}(\beta_{4wsl} + P_j)\big)\big] \quad (3)$$

As demonstrated in Figure 4 (see p. 75), inside the optimisation of the biophysical-economic model, a yield function fitted as an average over the 45 different weather-years is used in the final model. This approach facilitates computation and accounts for the fact that *ex-ante* farmers cannot predict the year's weather when making crop cultivation and fertiliser application decisions.

Yield Scaling

A few average weather functions showed unrealistically low fertiliser responses for some soil-slope combinations. These were traced to batch errors in the EPIC data. To ensure consistency in the available soil-slope combinations, the yield functions for every unique crop were scaled in Python following the subsequently presented steps:

1) The dry weight yield (t/ha) for the 20 soil-/slope-type combinations were evaluated at maximum P application and five levels of N application ranging from the crop-specific minimum to the crop-specific maximum.
2) The soil-slope combination (r*), which displayed the highest response to N across the application range was chosen as the representative function for the unique crop.

[17] As mentioned in section 4.5 the Mitscherlich-Baule coefficients allow for agronomic interpretation; however, the details of this agronomic interpretation are beyond the scope of this thesis.

3) The scaling factor for each soil-slope combination was determined by subtracting the r* average yield across the N application range from every soil-slope combination of the unique crop.
4) The yield function coefficients β_0, β_1, β_2, β_3, β_4 for all soil-slope combinations were set equal to the r* yield function coefficients. The scaling factor β_5 calculated in step three was added to the yield function resulting in the scaled function:

$$Y_{ijwsl} = \beta_{5\mathrm{wsl}} + \beta_{0w}[1 - \exp(-\beta_{1w}(\beta_{2w} + N_i))][1 - \exp(-\beta_{3w}(\beta_{4w} + P_j))] \quad (4)$$

EPIC yield estimates are reported in dry weight tonnes per ha (Gerik *et al.*, 2015). A dry weight tonne is a conceptual unit that assumes 0% crop moisture content and is used to calculate animal husbandry feeding requirements. The use of dry weight tonnes per ha allows EPIC to be applied in many different geographical settings where there may be significant variation in crop moisture content at harvest. In reality, however, agricultural transactions occur in terms of fresh weight yield (i.e., weight including the typical crop-specific moisture content at harvest). Therefore, yield functions are converted from dry weight to fresh weight through multiplication by a "Fresh Weight Correction Factor" (FWCF). Each crop-specific FWCF is reported in Table 19. Following the recommendation of the EPIC team, the FWCF is based on the typical crop DM content reported by Henry and Morrison (1916).

Table 19: Fresh Weight Correction Factor

Crop	Fresh Weight Correction Factor*	Page reference for crop DM content Henry and Morrison (1916)
Winter wheat	1.109	p. 634
Winter barley	1.093	p. 634
Winter oilseed rape	1.1	p. 636
Spring barley	1.093	p. 634
Spring oats	1.092	p. 634
Potatoes	1.788	p. 645
Spring beans	1.134	p. 636
Whole-cropped maize	1.737	p. 645
Whole-cropped winter wheat	1.702	p. 646
Stubble turnips (July)	1.905	p. 645
Stubble turnips (Spring)	1.905	p. 645
Fodder beet	1.87	p. 644
Grazing Grass LFA	1**	-
Silage LFA	1.728	p. 646
Hay LFA	1.12	p. 639

Crop	Fresh Weight Correction Factor*	Page reference for crop DM content Henry and Morrison (1916)
Silage (one cut)	1.728	p. 646
Silage (two cuts)	1.728	p. 646
Silage (three cuts)	1.728	p. 646
Silage (four cuts)	1.728	p. 646
Hay (two cuts)	1.12	p. 639
Grazing grass (two cuts)	1**	-
Grazing grass (three cuts)	1**	-
Grazing grass (four cuts)	1**	-
Grazing grass (six cuts)	1**	-
*Fresh Weight Correction Factor calculated from 1 + (1 – DM content). **Grazing forage requirements are calculated in kg of DM/ha (SAC Consulting, 2018, p. 72); therefore, grazing grass is not converted to fresh weight.		

Further testing revealed that the absolute fresh weight yield values achieved by the scaled yield functions at average fertiliser application significantly differed from levels expected in the Northwest of England for a number of the modelled crops. This divergence could be explained by deviations for the Northwest of England in the DM content from the values provided by Henry and Morrison (1916). Therefore, an "EPIC correction factor" was calculated for the unique crops which exhibited fresh weight yield values above or below those expected. This step ensures that absolute yield levels reflect the reality of the Northwest of England whilst maintaining the relative yield response to fertilisation, which was found to be realistic. The EPIC correction factor was based on the division of expected yields for the North West of England sourced from SAC Consulting (2018) by the fresh weight yield at mean N and P application averaged across the soil- and slope- types. Notably, DM yield was used for grazing grasses to facilitate forage requirement calculations.

Graphical illustrations of the discussed fresh weight yield functions are presented in Figure 10 to Figure 13. The four chosen crops represent those most commonly cultivated crops (winter wheat: Figure 10; winter barley: Figure 11; spring barley: Figure 12; and oilseed rape: Figure 13)[18] in the North West of England where the Eden catchment is located. The plots show fresh weight yield in tonnes per hectare averaged across weather-years for all slope-types (0-12.8%) and soil-type Newbiggin (soil 2). The plotted fertiliser ranges for N, and P extend from 0 to the specified fertiliser maxima (see Table 46). The plots show a generally strongly positive relationship between N applied and yield. However, the yield response to P application is less

[18] http://www.farmbusinesssurvey.co.uk/regional/Reports-on-Farming-in-the-Regions-of-England.asp (accessed 5/5/2020)

pronounced, which could be explained by P saturation in the soils (see section 6.3). Peaks and troughs observed in the yield functions for spring barley and winter oilseed rape, in particular, may be explained by the variation in steepness levels which are included in the graphs. As discussed further below, agronomic research has shown some negative correlation between slope and yield (Jiang and Thelen, 2004). However, as the strength of the correlation may vary between different crop types, spring barley and winter oilseed rape may therefore be more susceptible to changes in slope than winter wheat and winter barley. This hypothesis is supported by Figure 14 and Figure 15, which show that the fresh weight yield functions for spring barley and winter oilseed rape on Newbiggin soil and slope one (0 - 1.4%) follow a smooth relationship between fertiliser inputs and yield without unexpected peaks and troughs.

Figure 10: Plot of yield function winter wheat (WW4) for artificial fertiliser Scenario, Newbiggin, four slopes (0-12.8%) and N, P fertiliser ranges 0-max

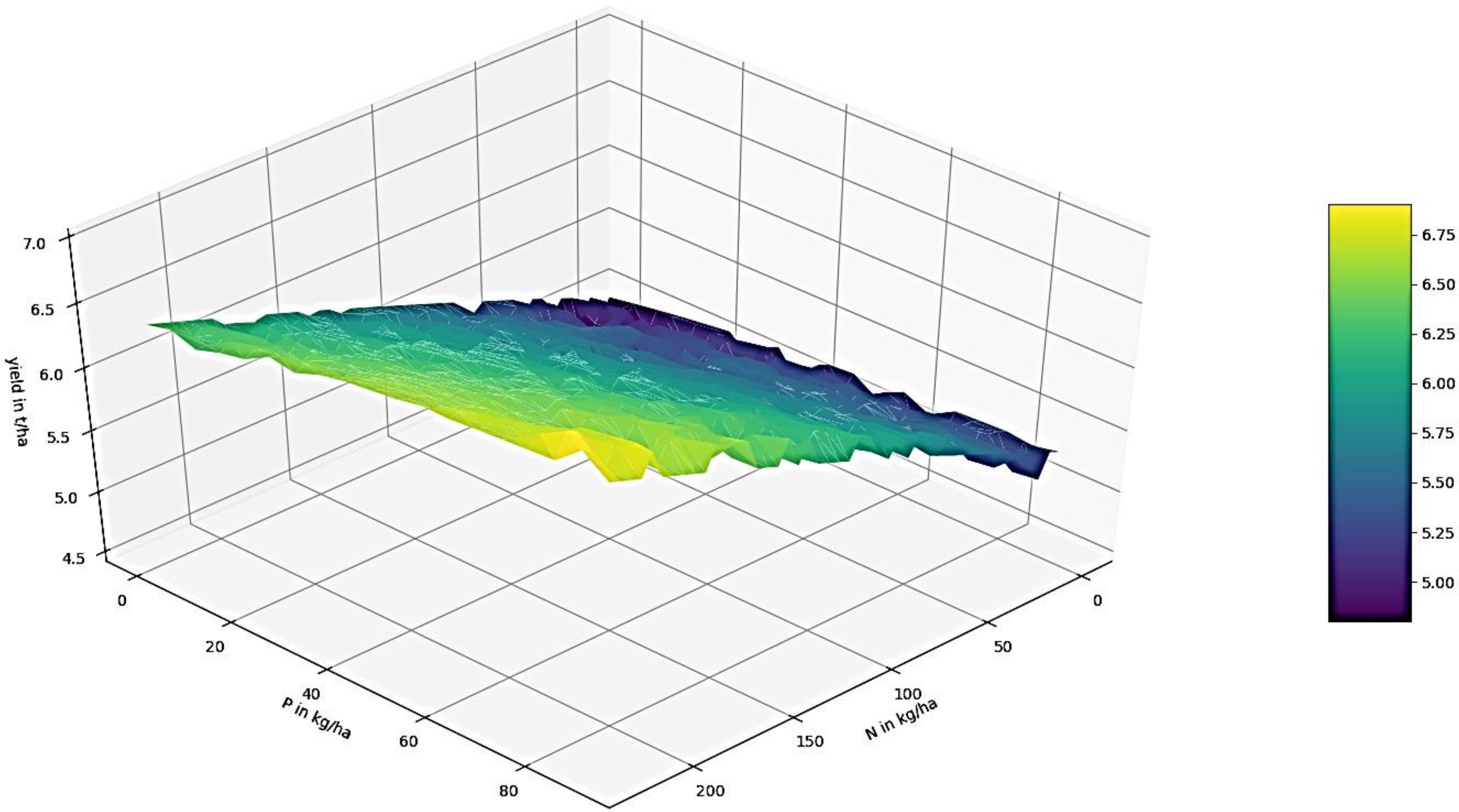


Figure 11: Plot of yield function winter barley (WBAR7) for artificial fertiliser scenario, Newbiggin, four slopes (0-12.8%) and N, P fertiliser ranges 0-max

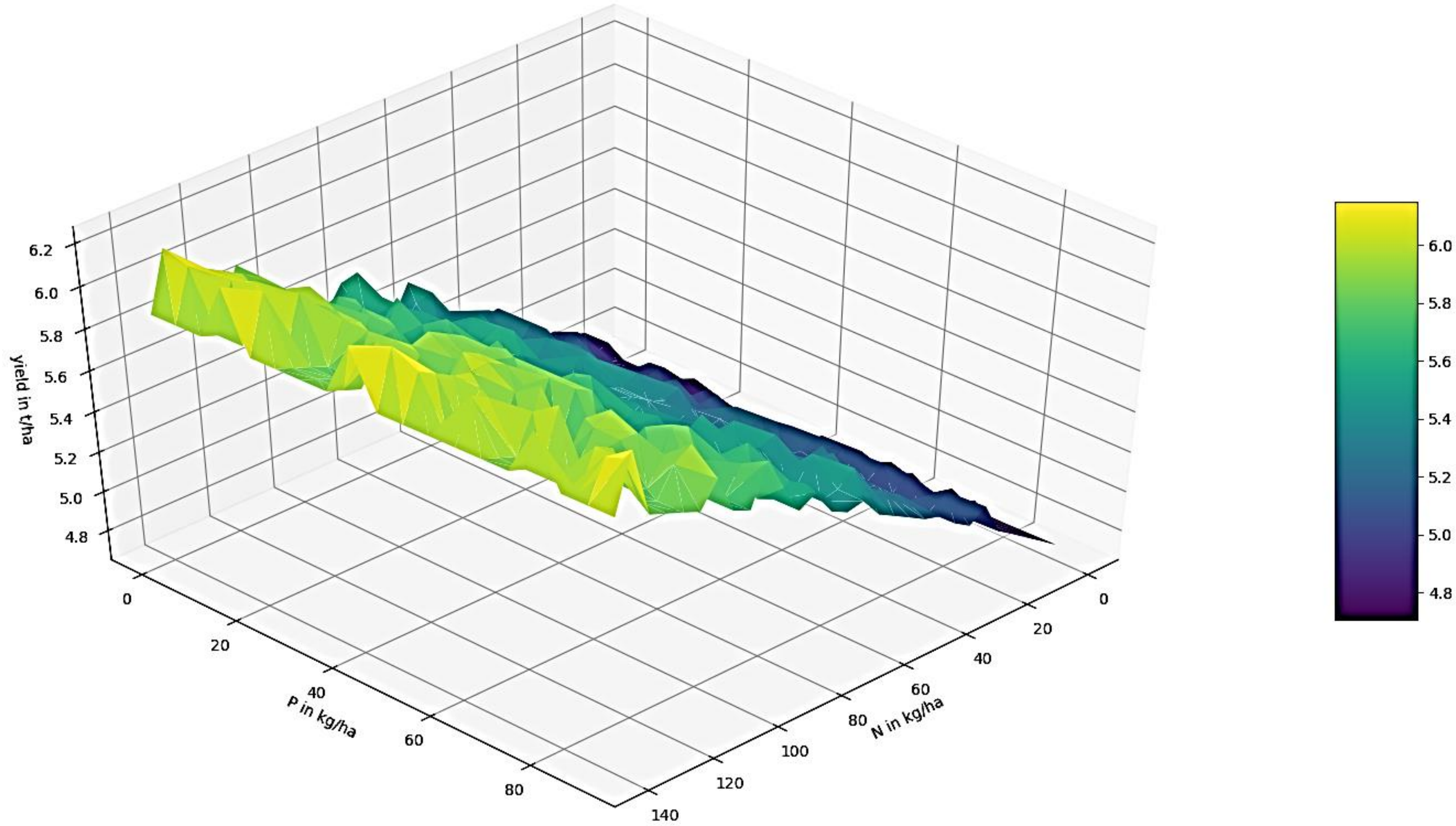


Figure 12: Plot of yield function spring barley (SBAR3) for artificial fertiliser scenario, Newbiggin, four slopes (0-12.8%) and N, P fertiliser ranges 0-max

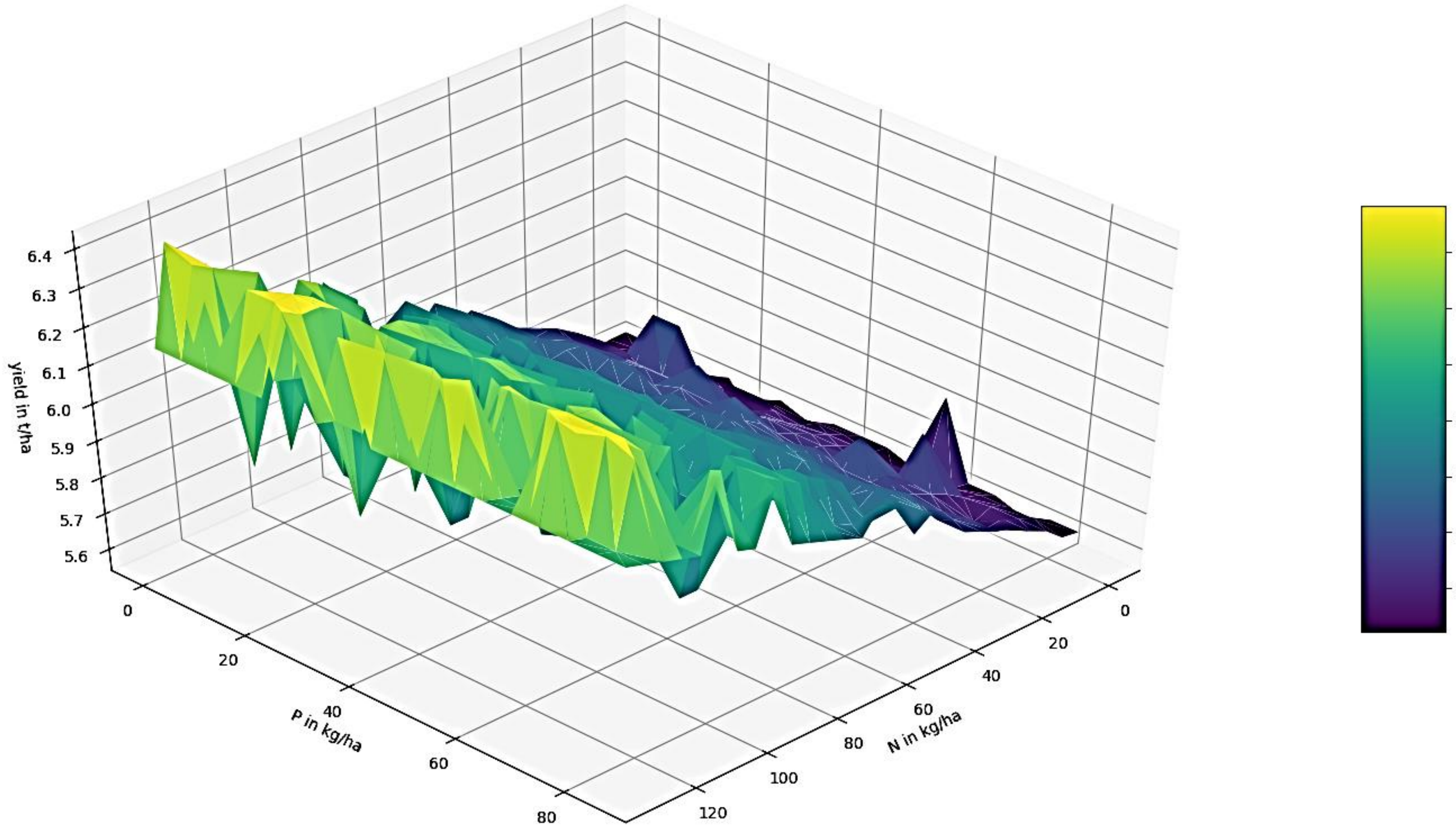


Figure 13: Plot of yield function winter oilseed rape (WOSR1) for artificial fertiliser scenario, Newbiggin, four slopes (0-12.8%) and N, P fertiliser ranges 0–max

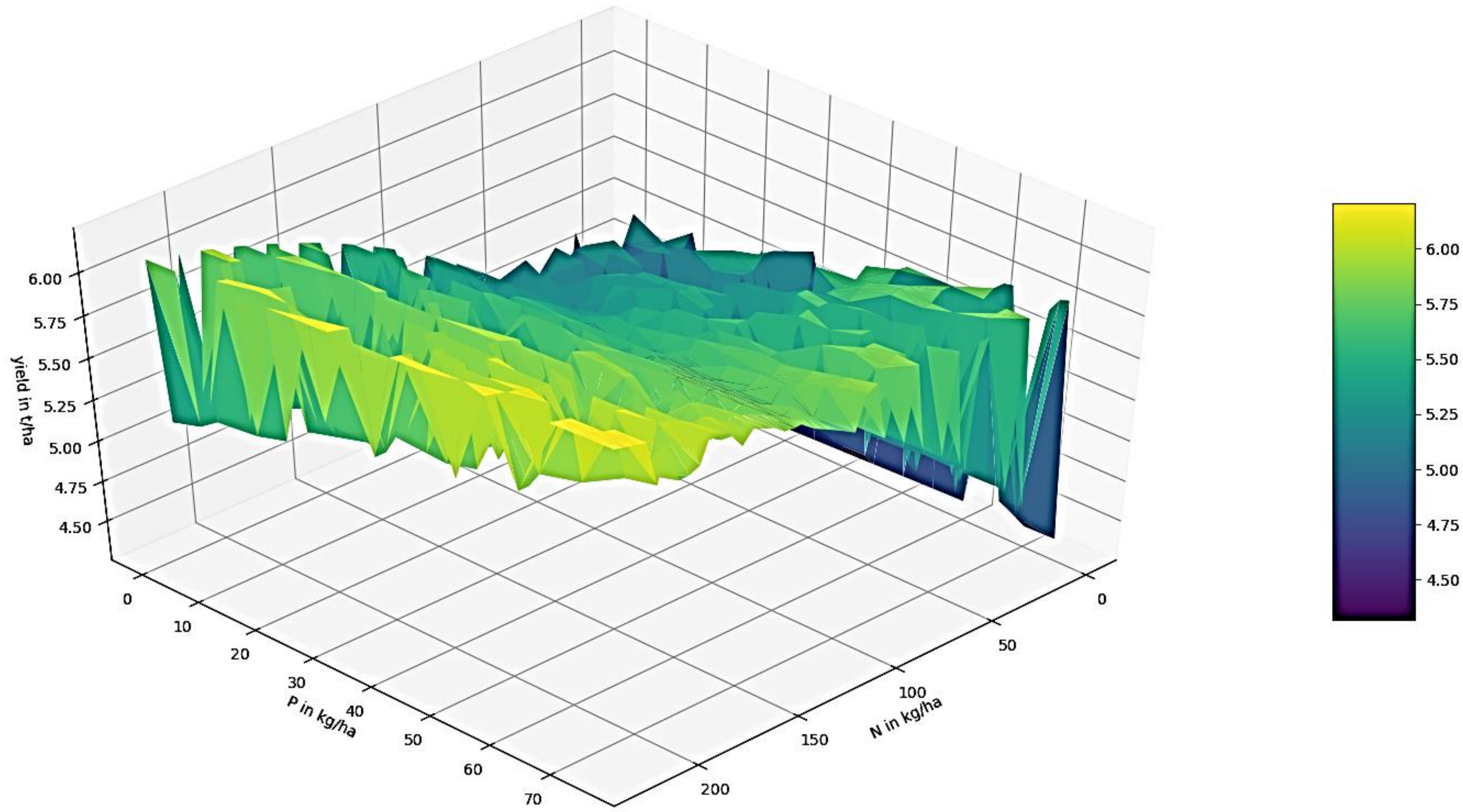


Figure 14: Plot of yield function spring barley (SBAR3) for artificial fertiliser scenario, Newbiggin, slope 1 (0-1.39%) and N, P fertiliser ranges 0-max

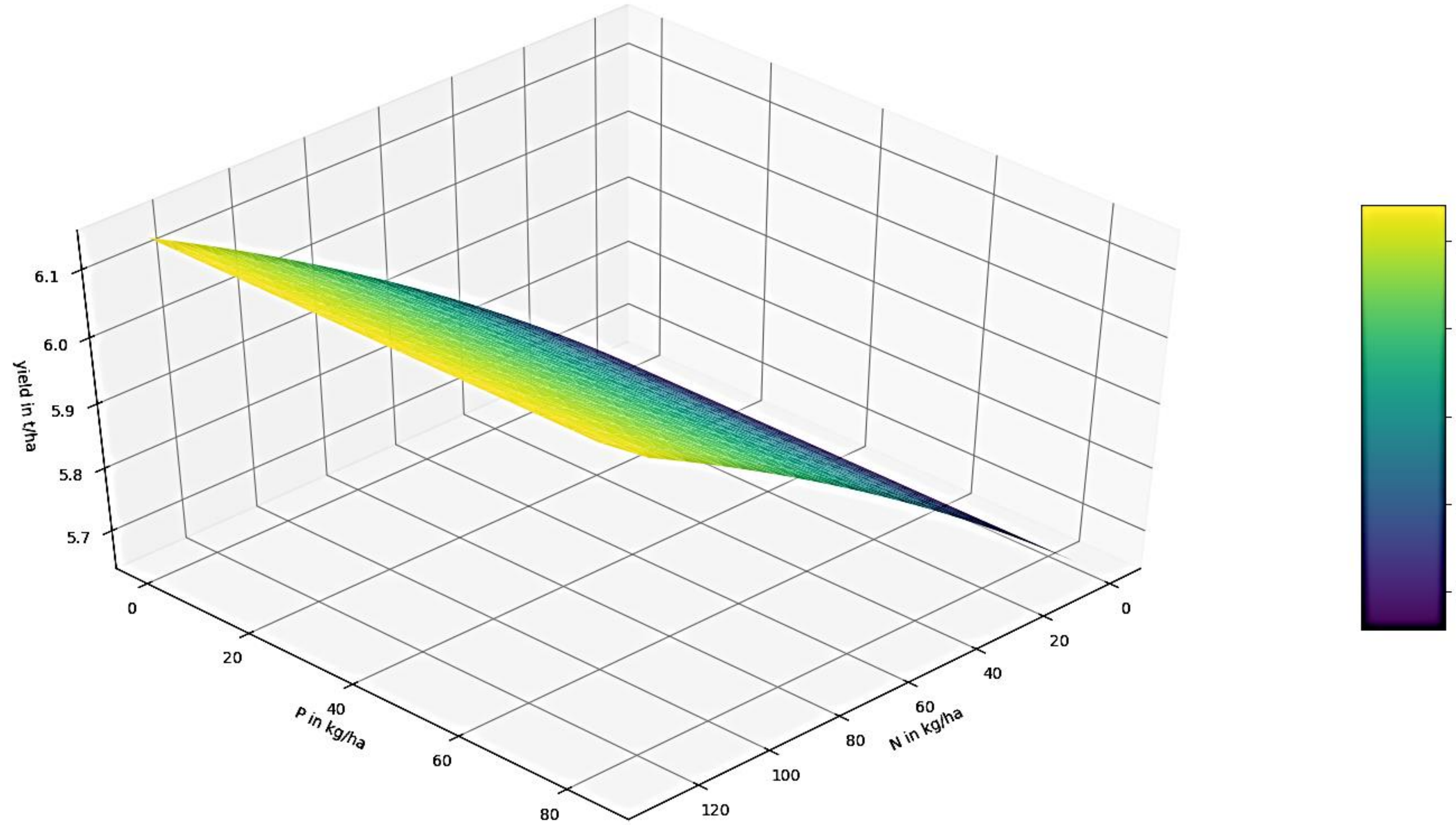
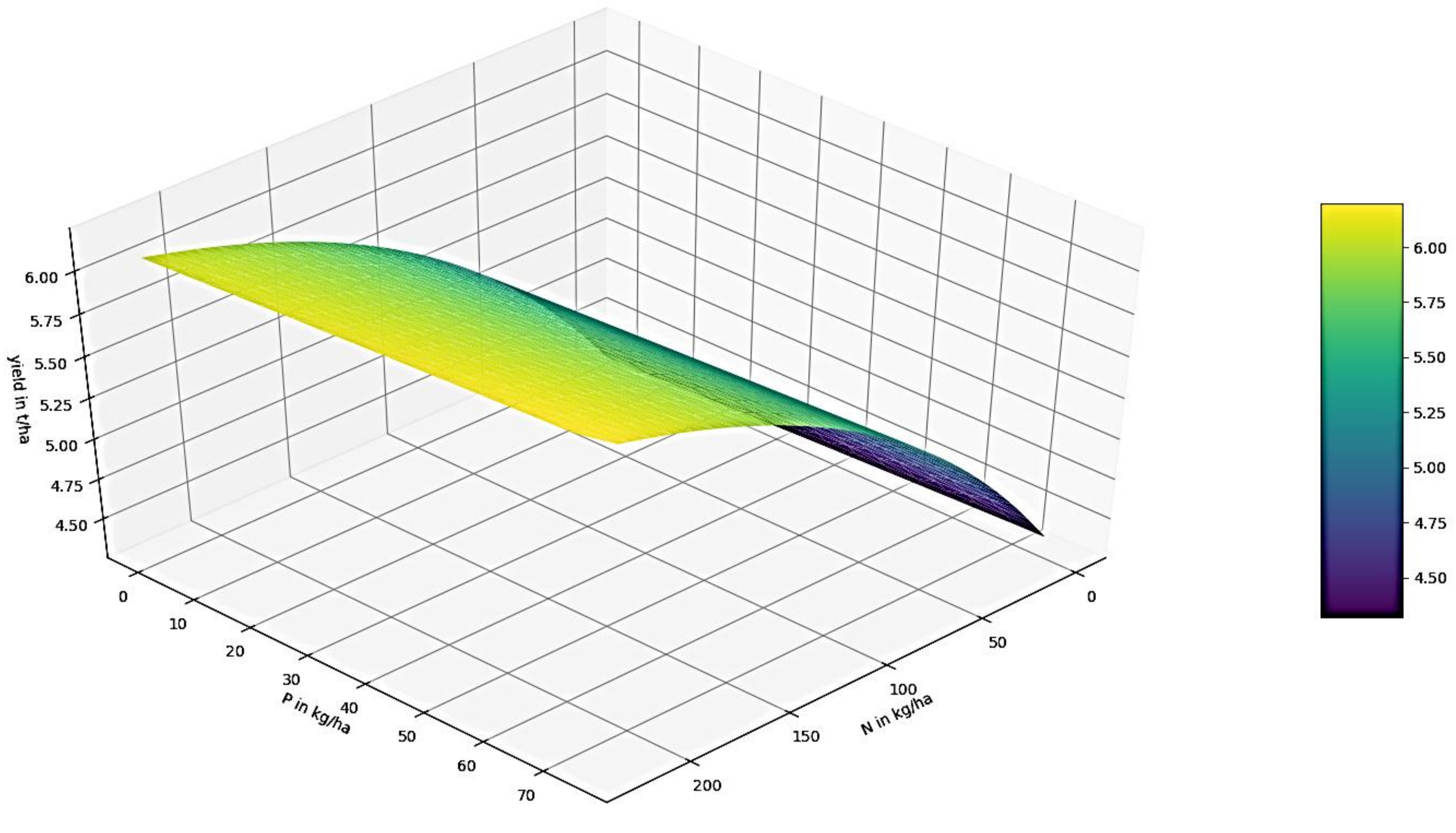


Figure 15: Plot of yield function winter oilseed rape (WOSR1) for artificial fertiliser scenario, Newbiggin, slope 1 (0-1.39%) and N, P fertiliser ranges 0-max



Analysis of the yield data shows that while there is some variation in the productivity of the different soil-types in terms of yield output per hectare (see Table 20) there is less variation in yield across different levels of steepness (see Table 21).

Table 20: Soil productivity ranking for average fertiliser application across all slopes and crops

Sorted by mean (descending)		**Yield in t/ha***			
Ranking	Soil-type	Mean	Median	Max	Min
1	Newbiggin	16.39	6.77	68.87	0
2	Wick	15.32	6.41	67.85	0
3	Clifton	15.19	6.09	65.48	0
4	Malvern	15.11	6.17	69.50	0
5	Winter Hill	14.76	6.33	66.28	0

For fertiliser application, range from crop-defined maximum – 50% of crop-defined maximum. See Table 46 in the appendix for details on the crop-specific fertiliser application maxima.
Note: Calculated using full set of 86 crops, final model includes 25 crops for computational reasons.

The smaller variation in productivity between slope-types relative to the variation between soil-types is aligned with expectation. Agronomic research has shown some negative correlation between slope and crop yields (Jiang and Thelen, 2004); however, these are in part indirect effects of other soil properties (e.g. water availability) which are correlated with slope. Moreover, the strength of the slope-yield relationship varies between crop types, further explaining the lower between-slope variation in yields across all crop types.

Table 21: Slope productivity ranking for average fertiliser application across all soils and crops

Sorted by mean (descending)		**Yield in t/ha***			
	Slope Interval (%)	Mean	Median	Max	Min
1	1.4 – 4.19	15.48	6.46	69.50	0
2	0 – 1.39	15.46	6.53	67.85	0
3	4.2 – 7	15.39	6.47	68.09	0
4	7.01 – 12.8	15.08	6.39	68.87	0

For fertiliser application, range from crop-defined maximum – 50% of crop-defined maximum. See Table 46 in the appendix for details on the crop-specific fertiliser application maxima.

Test of heterogeneity between different crop rotations and crop rotation positions

The Wilcoxon Signed Rank test was used to test the hypothesis that crop rotations and positions within crop rotations significantly impact yield outcomes. The scaled yield functions of the artificial fertiliser scenario (see p. 100) were used to calculate dry weight yield in tonnes per hectare at mean N and P application levels for all soil slope combinations. Specifically, the Wilcoxon Signed Rank test was used to test the null hypothesis that there is no significant difference between the yield distributions of two versions of a crop grown in different crop rotations or placed at different positions within the crop rotation[19]. Out of 208 resulting crop pairs, 178 pairs rejected the null at the 5% significance level, while 30 pairs failed to reject the null of insignificant differences in yield distributions. The results thus suggest that 85% of the crops in the sample show significant differences in yield distributions when placed in different crop rotations or positions within the same rotation. Those results demonstrate the importance of including realistic crop rotations in biophysical-economic models to accurately represent yield and pollution trade-offs. Further, the finding highlights this thesis' contribution in using the EPIC dataset and its uniquely extensive number of crop rotations and different crops in the literature (see Table 39, p.157).

5.2.2. Pollution Data

The six pollution variables chosen for the analysis are presented in section 4.5, along with their chosen functional forms (see Table 14, p.88). The daily and monthly pollution data from the EPIC simulation (see section 4.5 for details) were converted into 45 yearly pollution function estimates corresponding to the 45 included weather-years. These were combined into an average pollution function to facilitate the analysis of general pollution trends.

Due to some EPIC batch inconsistencies, the pollution functions were scaled in Python using the following steps:

1) Slopes were scaled using a step function, where values:
   - between 0.04 - 1 were not scaled
   - greater than 1 were set to 1
   - below 0.04 were set to 0.04

[19]The Wilcoxon Signed rank test was chosen over parametric alternatives as the number of crop pairs constituting the test samples (20) was insufficient to assume normality required for alternative parametric tests. Testing each sample for normality was deemed impractical given the number of crop pair yield samples. See Appendix C, p.243 for the Python code implementation.

2) The intercepts were scaled to an interval of +/- 100% of a realistic value taken from the literature (see section 5.4.4, p. 120 for comparison of final pollution outputs to the literature).

Figure 16 (p. 113) plots examples of the average weather-year pollution function for NRLOAD and ZLOAD. Both are assumed to mainly be functions of N application and plotted here for SIL1_1 on soil 2 (Newbiggin) and slope 1. The displayed relationships of the pollution functions are mostly in line with the expectations outlined in Table 14 (see p. 88). The pollution indicators display slope coefficients which suggest a small relationship between the indicator and N application. Such weak relationships can be explained by two main abstractions which underpin the presented functions. Firstly, the pollution indicators are influenced by numerous stochastic variables such as wind, sunlight, rainfall, and temperature, which are all accounted for and synthesised by EPIC but cannot feasibly be included in the pollution functions of the biophysical-economic model. Therefore, some of the presented pollution functions may be effectively underspecified as other influential variables are not included. Secondly, the plotted functions are averaged over the 45 weather-years, thereby further abstracting from the complexity and variation in the individual weather-year data. These two abstractions may weaken the relationship between pollution indicators and N application relative to the relationships observed in individual weather-year data and functions, including further variables. However, the average weather-year pollution functions remain useful for analysing and identifying broad trends in the relationships between pollutants and fertiliser applications as well as potential synergies and trade-offs.

Figure 17 (p. 114) and Figure 18 (p. 115) present the graphs for the Carbon Emissions (in kg/ha) and Phosphorus to the River (in kg/ha) respectively, which depend on both N and P applications. The carbon emissions captured within the EPIC variable CFEM are assumed to be gaseous and represent soil carbon emissions associated with specific tillage systems (personal correspondence with EPIC team, September 18, 2020). These soil CO_2 emissions are considered the largest contributor to agricultural total carbon emissions and are significantly higher under conventional tillage systems than under conservation tillage systems (Cillis et al., 2018). Carbon emissions from fuel consumption in different tillage systems are not captured. Carbon emissions are positively related to both increased N and P applications. However, the unitary effect of N is larger than that of P. Figure 18 demonstrates that P pollution increases with P application and decreases with N application. This trend may be due to plant growth, which is mainly driven by N application, improving P absorption and reducing P pollution.

Figure 16: Bi-variate pollution functions for SIL1_1 on soil 2 and slope 1 (0-1.39%)

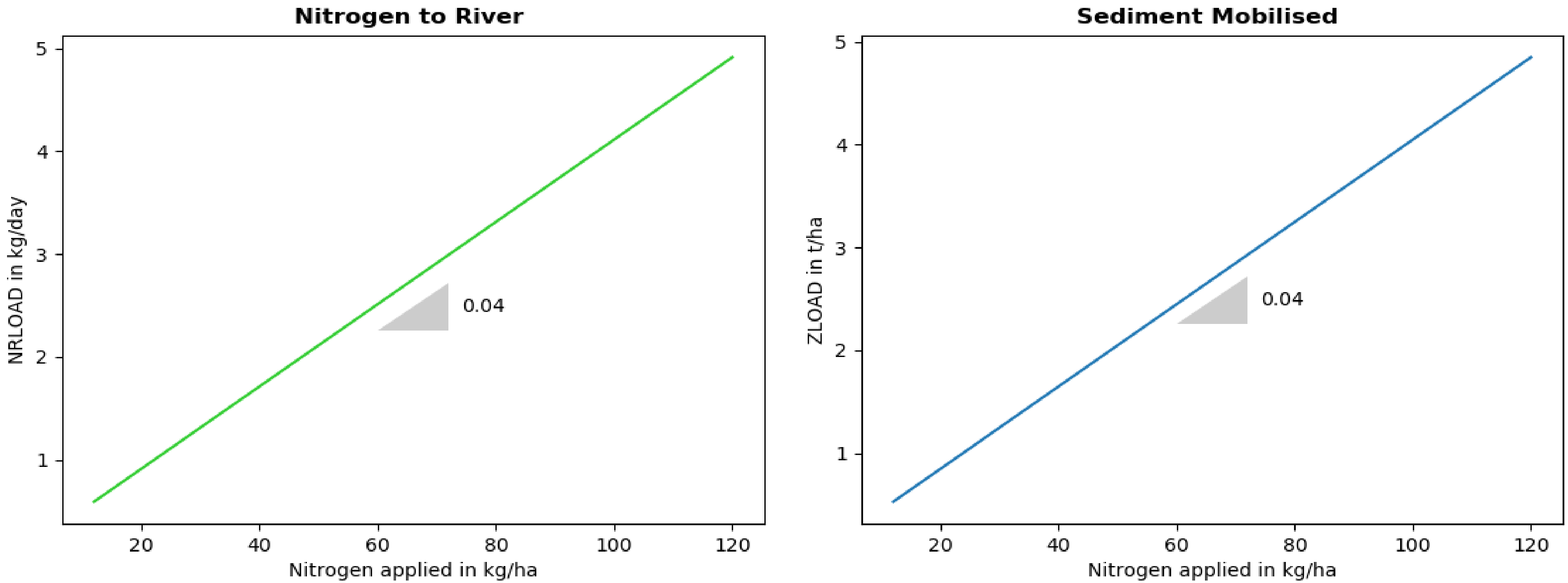


Figure 17: Carbon emission for SIL1_1 on soil 2 and slope 1 (0-1.39%)

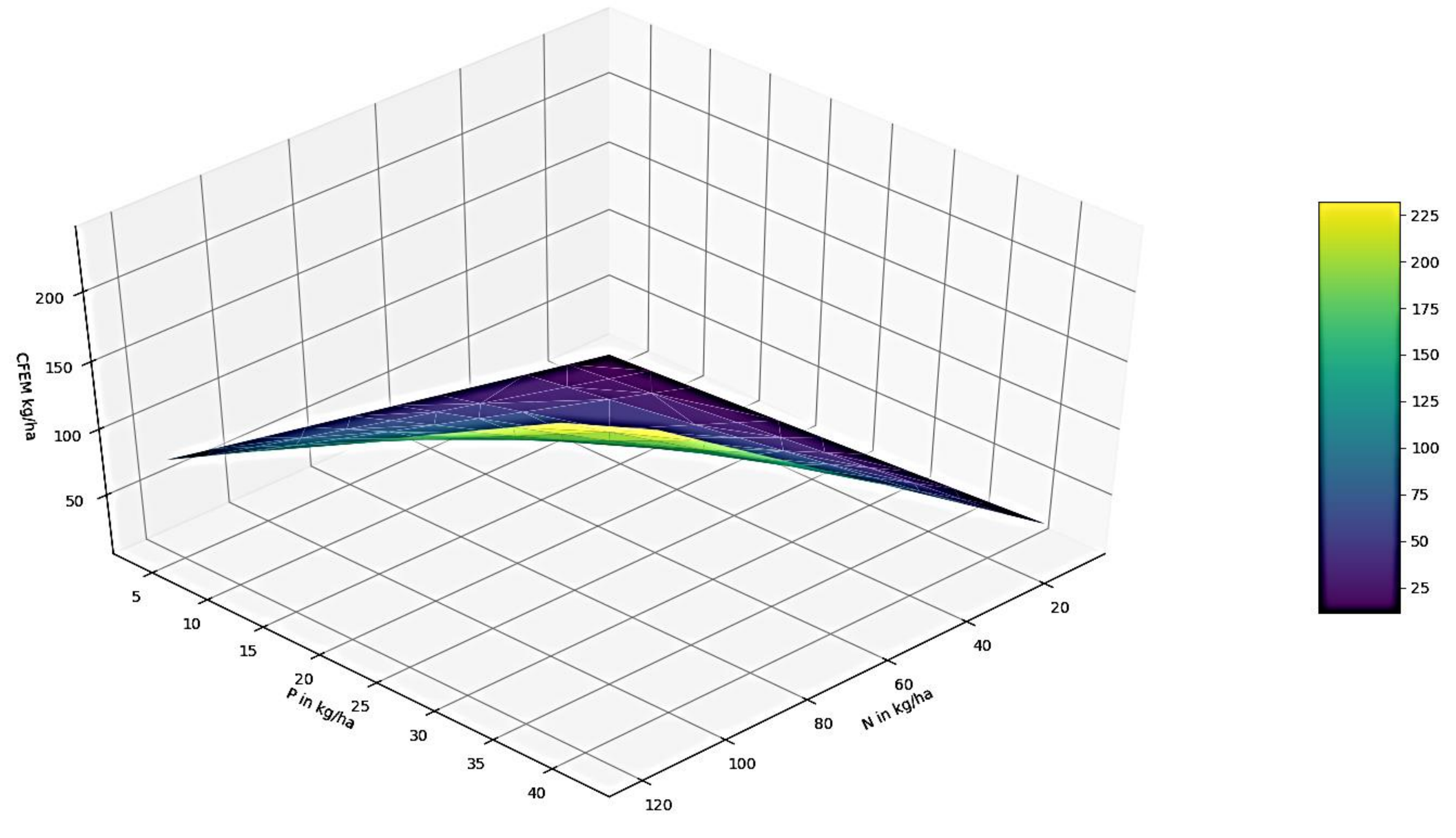
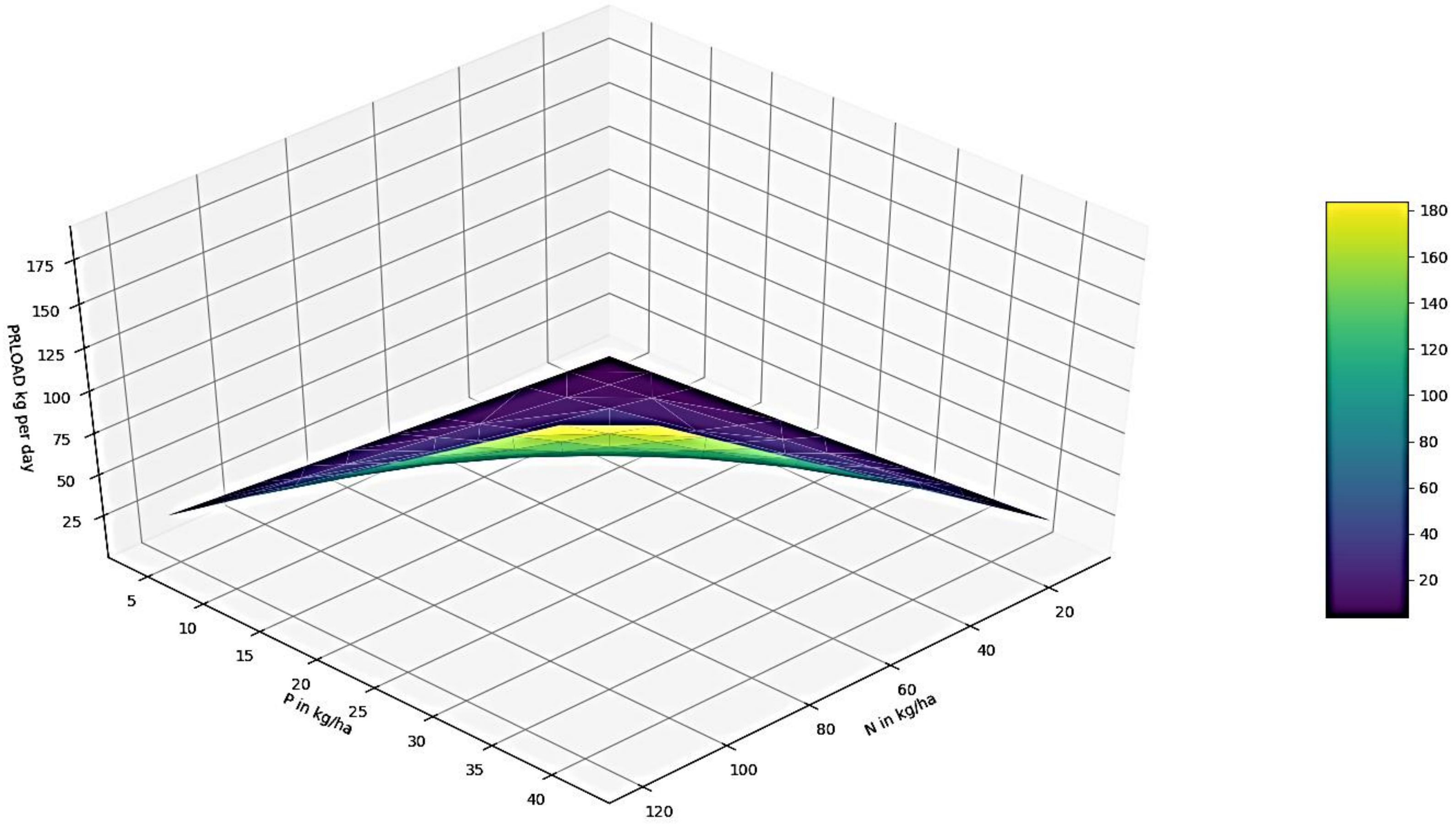


Figure 18: Phosphorus to River SIL1_1 soil 2 slope 1 (0-1.39%)



5.3. Economic Data

The data relating to farm business production was primarily collected from Redman (2018) and SAC Consulting (2018). It includes the gross margins for livestock production, labour costs for livestock and crop production, variable costs for crop production, and farm-gate prices for produced crops. The farm type classification (see section 4.2), according to DEFRA (2014) guidance, used the UK standard output coefficients (SOC) 2013 (European Commission, 2020) converted into pound sterling. At the time of this work, the UK SOC 2013 were still being used for farm-type classification within the UK Farm Business Survey. SOCs measure a farm's average monetary agricultural output for crops and livestock in euros per hectare and head of livestock, respectively. A farm's gross agricultural standard output is calculated by summing the product of the SOCs and the farm's chosen land allocation and herd sizes. Farm types are classified as belonging to the activity which constitutes more than two-thirds of the farm's gross standard output. Farms are designated as "mixed farms" if no single agricultural activity contributes two-thirds of the farm's gross standard output.

5.4. Baseline Catchment Outputs

This section presents and discusses the model's baseline outputs. Section 5.4.1 presents the exogenous land allocation between farms, section 5.4.2 analyses the baseline output mix and crop allocation while section 5.4.3 discusses the baseline livestock output. Finally, section 5.4.4 analyses the baseline pollution outputs before section 5.4.5 presents the sensitivity analysis of pollution outcomes to individual weather-years.

5.4.1. Farmland Allocation

The six representative farms are assumed to be of equal size (21,067 ha). Table 22 summarises the assumed land distribution between farms by the total number of hectares of a particular slope, soil and hydrological connectivity type (see Annex Table 48 for the full distribution).

Table 22: Distribution of slope, soil and hydrological connectivity by farm

	farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
Slope (ha)						
S1	2	2107	1053	1604	5316	1596
S2	1982	8689	10354	4213	4213	8190
S3	6320	98	4213	11036	4458	4571
S4	12763	10173	5447	4213	7079	6710
Soils (ha)						
L1	8427	10161	8182	16832	4898	15711
L3	2107	2267	8466	2107	2107	2107
L4	10460	8427	3962	2107	13840	3225
L2	6	2	24	0	11	2
L5	68	211	433	21	211	21
Hydrological connectivity (ha)						
H1	717	71	44	237	801	481
H2	12041	8176	6557	2564	8562	10672
H3	7929	11122	9810	16618	9222	7840
H4	147	1306	3939	1425	1674	1520
H5	178	240	667	116	407	244
H6	42	85	28	79	199	149
H7	12	30	17	22	170	94
H8	1	22	5	5	26	56
H9	0	10	1	0	6	11
H10	0	5	0	0	1	1

The land allocation was generated through a linear optimisation problem implemented in GAMS (see code in Appendix C p.239). Soil- and slope-types were allocated between the farm types to broadly align with their farming activity and hypothetical position outlined in Table 7 (see p. 72).

5.4.2. Cropland Allocation and Output

The model's land allocation and output were calibrated to the distributions observed in the North West of England in 2019, as published by DERFA (2021a). The baseline calibration was conducted by adding flexibility constraints based on observed data and agronomic rationale to the model[20]. Care was taken to achieve a baseline cropland allocation similar to the observed

[20] Positive Mathematical Programming (Howitt, 1995) would be an alternative calibration approach. This would further reduce the risk of overly restrictive constraints impairing the policy response.

reality in the Eden catchment whilst maintaining enough model flexibility to respond to subsequently implemented scenario shocks. Table 23 compares the baseline distribution of land allocation between crops to the distribution observed in the Northwest of England in 2019 and demonstrates their close alignment. The calibration prioritised the cropland allocation distribution over the output distribution, as the cropland allocation is expected to be more stable and less affected by price volatility than output distributions.

Table 23: Comparison of baseline land allocation to main crop groups to observed catchment land allocation

Main crop groups	Observed percentage of total catchment*	Baseline percentage of total catchment	Baseline percentage point deviation
Barley	3.8	7.1	3.2
Grassland (grazing + cutting)	78.0	77.2	-0.8
Maize	1.4	7.1	5.7
Oilseed Rape	0.5	3.1	2.6
Potato	0.7	0.8	0.1
Wheat	3.7	4.7	1.0
**Calculated from the 2019 Agricultural Facts - Northwest of England by DERFA (2021a)*			

Table 24 compares the average baseline yield by crop group in tonnes per hectare to the average yield expectation in tonnes per hectare as given by SAC Consulting (2018).

Table 24: Comparison of average yield by crop group at the baseline to expectation

Crop group	Average* baseline yield (t/ha)	Average yield expectation** (t/ha)	Percentage difference
Barley	7.3	6.7	9%
Grassland (grazing + cutting)	22.9	23.4	-2%
Maize	44.3	40.0	11%
Oilseed Rape	4.7	4.0	17%
Potato	80.5	65.0	24%
Wheat	8.1	8.0	2%
**Yield averaged across farms, soil, slope, and hydrological connectivity level by crop group* ***Yield expectation based on SAC Consulting (2018)*			

The average baseline yields closely align with expected yields; most crops deviate less than 11%. Oilseed Rape and potato crops show slightly elevated yields (17% and 24% above expectation, respectively). These deviations are unlikely to significantly affect results as they comprise the least prominent crop groups and jointly comprise less than 1.2% of the catchment's land allocation.

5.4.3. Livestock Output

Table 25 compares the baseline distribution of livestock output (defined as the contribution to catchment gross margin) to the distribution of output observed in the North West of England in 2019 (DEFRA, 2021a). The presented output distributions also demonstrate alignment.

Table 25: Comparison of baseline livestock output contributions to actual catchment output contributions

Livestock type	Regional observed percentage output contribution	Baseline output contribution	Baseline percentage point deviation
Beef	8.7	17.2	8.4
Milk	39.3	58.5	19.3
Sheep	7.4	11.5	4.1

Table 26 compares the baseline post-forage livestock gross margin averaged by livestock group to the expectation based on SAC Consulting (2018). The baseline profitability aligns with observed expectations, particularly for beef and dairy, which vary less than 1% from expectation. The baseline sheep post-forage gross margin is, on average, 43% below expectation. This finding could be explained by the fact that sheep grazing in the Eden may be more extensively managed than in the model (less fertiliser and labour input). In general, the gross margin reflects the falling profitability of sheep which has been observed over the past years[21].

[21] Farmers' observed behaviour of continuing to engage in low profit activities such as sheep farming could be seen as a violation of the rationality assumption underpinning this analysis. However, work such as Malawska and Topping's (2016) agent based model investigation demonstrate that analyses of farm behaviour in the context of agri-environmental policies are relatively insensitive to varying assumptions on farmers' rationality. These findings support this thesis' modelling of farmers as rational agents.

Table 26: Comparison of the average livestock gross margin to the expected post-forage gross margin

Livestock groups	Livestock gross margin (£/head*)	Expectation of gross margin (£/head*) †	Percentage deviation from expectation
Beef	267.3	268.3	-0.4
Dairy	1212.9	1222.0	-0.7
Sheep	760.2	1334.0	-43.0
**For sheep £/100 head* *†Calculated based on SAC Consulting (2018)*			

At the baseline, farms are not trading forage crops amongst each other. This behaviour corresponds to limited forage crop trading between farms in the real world due to the low value, which does not support transport costs to other farms.

The farmyard manure produced significantly exceeds the crop needs of the catchment. Assuming that all excess farmyard manure will be applied, the nutrient balance at the baseline amounts to +271 kg/ha of N and +65kg/ha of P. This result reflects the nutrient surplus observed in the published nutrient balance for the Northwest of England of +111.4 kg/ha of N and 10.2 kg/ha of P (DEFRA, 2021b). The larger surplus in the baseline compared to DEFRA-calculated nutrient balances could be explained by the uncertainty involved in the DEFRA statistics. The DEFRA nutrient balances rely on self-reported data from the June Survey regarding artificial fertiliser application (DEFRA, 2021b). We would expect farmers to under-report their use of fertiliser to appear compliant with nutrient management best practices. In addition, rising input costs may have reduced the actual observed housing period in the Eden below the six months assumed by the model.

5.4.4. Pollution Output

This section presents the baseline pollution and fertilisation levels for the catchment. Table 27 presents the baseline total catchment emissions as well as the per hectare average emissions by pollutant for the catchment.

Table 27: Baseline emissions by pollutant averaged across weather-years catchment total and per hectare average

Pollutant	Abbreviation	Catchment total (in '000s)	Catchment average/hectare	unit
Carbon Emission	CFEM	5,404	44.9	kg
Nitrogen to Groundwater	NGLOAD	3,634	28.5	kg
Nitrogen to River	NRLOAD	289	2.5	kg

Pollutant	Abbreviation	Catchment total (in '000s)	Catchment average/hectare	unit
Phosphorus to Groundwater	PGLOAD	406	3.9	kg
Phosphorus to River	PRLOAD	328	2.8	kg
Sediment Mobilised	ZLOAD	320	2.7	t

The presented scaled per hectare pollution values align with the ranges found in the literature (e.g. N leaching (Dybowski *et al.*, 2020), N leaching (Ulén *et al.*, 2007), sediment pollution (da Rocha Junior *et al.*, 2018)). Per hectare pollution is influenced by five key variables within the model: soil-type, slope-type, level of hydrological connectivity, crop grown, and level of fertilisation. The following tables in this section present the different impacts of each of these key variables on baseline average pollution per hectare. Notably, the individual influence of the key variables on pollution outcomes cannot be isolated. Therefore, the averages for the individual variables need to be considered within the context of all other influences.

Firstly, Table 28 differentiates average pollution per hectare by the soil-types included in the model as well as the soil-types' share in total catchment land. The impact of soil-types on average pollution is relatively small and non-uniform across different pollutants at the baseline. This finding may be due to the uneven distribution of soil-types within the catchment. Soils two and five both cover less than 1 % of the catchment area, while soils one, three and four each cover 51%, 15%, and 33% of the catchment, respectively. This uneven distribution is likely to skew average pollution values of the underrepresented soil-types as the distribution of other variables (e.g., crops grown) is less likely to average out. The relatively small absolute differences between soils may further be explained by the fact that the soils are relatively similar in their characteristics (see section 6.3).

Table 28: Average baseline pollution per hectare by soil

Soil	Catchment land Proportion (%)	CFEM (kg)	NGLOAD (kg)	NRLOAD (kg)	PGLOAD (kg)	PRLOAD (kg)	ZLOAD (t)
L1	50.80%	46.79	35.40	2.33	3.44	2.72	2.46
L2	0.04%	28.57	8.93	2.13	4.07	3.15	2.20
L3	15.16%	74.14	64.95	2.91	4.59	3.45	4.27
L4	33.24%	21.82	2.55	1.87	2.10	1.99	1.83
L5	0.76%	63.10	9.44	5.28	9.45	3.25	2.90

Note: Soil pollution values are shaded according to their relative rank within the pollutant where lighter (darker) shading indicates relatively lower (higher) average pollution per hectare.

Table 29 shows the average pollution per hectare for different slope-types. The relative ranking of slope-types varies by pollutants in line with expectations. Sediment pollution is highest for the steepest modelled slope S4, which is explained by the higher risk of erosion associated with steeper slopes (Müller *et al.*, 2014, p. 79). On the other hand, N leaching into the groundwater is found to be lower for steeper slopes. This fact further corresponds with expectation, as water and N is more likely to seep into lower soil layers and leach into groundwater at lower levels of steepness. Steeper slopes, on the other hand, may lead to increased water runoff, which washes N into proximate water bodies (such as rivers). This is less clearly pronounced in slope 1 of the average N leaching to rivers per hectare, most likely due to the low overall catchment proportion of slope 1. Nevertheless, slope 4 has the second highest NRLOAD average pollution load per hectare which corresponds to the expectation outlined above. Notably, P leaching into groundwater is less clearly impacted by slope-type due to its immobility in the soil. Surface water P leaching into rivers (PRLOAD) is driven by its interaction with suspended sediment (Bowes, House and Hodgkinson, 2003) which is reflected in the correlation between PRLOAD and ZLOAD in Table 29.

Table 29: Average baseline pollution per hectare by slope

Slope	Catchment land Proportion (%)	CFEM (kg)	NGLOAD (kg)	NRLOAD (kg)	PGLOAD (kg)	PRLOAD (kg)	ZLOAD (t)
S1	9%	65.53	47.63	3.18	4.64	3.89	3.14
S2	30%	41.59	21.89	2.13	4.29	2.68	2.19
S3	24%	18.45	7.55	1.59	2.48	1.86	1.63
S4	37%	34.53	20.97	2.58	3.17	2.02	3.92

Note: Slope pollution values are shaded according to their relative rank within the pollutant where lighter (darker) shading indicates relatively lower (higher) average pollution per hectare.

Thirdly, the effect of hydrological connectivity on baseline average pollution per hectare is presented in Table 30. In line with expectations, pollution per hectare increases with hydrological connectivity across pollutants. However, as discussed in section 4.6 and presented in the second column of Table 30, the distribution of hydrological connectivity within the catchment is heavily skewed towards low levels of hydrological connectivity. The small amount of highly connected land will likely impact the average pollution calculation.

Table 30: Average baseline pollution per hectare by hydrological connectivity

Hydro	Catchment land Proportion (%)	CFEM (kg)	NGLOAD (kg)	NRLOAD (kg)	PGLOAD (kg)	PRLOAD (kg)	ZLOAD (t)
H1	1.86%	4.86	3.40	0.37	0.42	0.34	0.33
H2	38.43%	16.67	10.14	0.97	1.35	1.08	1.02
H3	49.48%	24.78	13.74	1.44	2.39	1.76	1.90
H4	7.92%	32.36	15.96	2.06	3.37	2.29	1.90
H5	1.46%	49.20	28.07	2.68	4.59	2.85	2.42
H6	0.46%	60.97	32.03	3.57	5.93	4.00	4.18
H7	0.27%	75.98	52.21	4.33	5.96	4.79	5.39
H8	0.09%	89.94	64.10	4.64	7.47	5.62	4.98
H9	0.02%	93.51	62.07	4.75	7.67	5.71	4.69
H10	0.00%	120.51	97.93	5.61	8.39	7.22	5.58

Note: Hydrological pollution values are shaded according to their relative rank within the pollutant where lighter (darker) shading indicates relatively lower (higher) average pollution per hectare.

Table 31 presents the baseline average of pollutants per hectare by the main crop groups. Across pollutants, grassland demonstrates some of the highest per hectare levels of pollution. This result may be explained by grassland being one of the highest input crops in the catchment in terms of fertilisation (see Table 32 for average per hectare nutrient application by crop type).

Table 31: Average baseline pollution per hectare by main crop group

Crop group	CFEM (kg)	NGLOAD (kg)	NRLOAD (kg)	PGLOAD (kg)	PRLOAD (kg)	ZLOAD (t)
Barley	30.40	5.17	2.79	2.85	2.44	2.26
Grassland	67.07	48.03	3.19	5.88	4.10	3.84
Maize	0.62	1.70	0.20	0.13	0.13	0.14
Oilseed rape	46.99	9.90	1.80	3.49	2.07	1.82
Potato	1.36	1.31	0.88	0.65	0.65	0.71
Wheat	47.39	44.26	1.64	2.14	1.99	2.07

Note: crop group pollution values are shaded according to their relative rank within the pollutant where lighter (darker) shading indicates relatively lower (higher) average pollution per hectare.

In addition, grassland fertilisation occurs over up to 6 doses spread throughout the growing season (March – August). This detail contrasts with cereal crops which receive two to three fertilisation doses between October and May. A higher number of fertilisation doses requires increased use of machinery, which therefore explains the elevated carbon emissions per hectare observed for grasslands compared to other crop groups. The relatively high sediment pollution

(ZLOAD) observed for grassland is driven by the assumption that increased N application indirectly reduces erosion by stimulating root system growth (see Table 14).

Maize would typically be expected to be a more-polluting crop as it is a high-input crop. However, the maize grown in the catchment is 100% whole-cropped feeding maize which receives lower inputs and can therefore be expected to be less-polluting. Table 32 demonstrates that average N input, particularly for maize in the catchment, is significantly lower than that of other crop groups. Potatoes show medium-low pollution levels per hectare relative to the other crop groups for nutrient pollution and carbon emissions. Potatoes would usually also be expected to be a relatively more-polluting crop (particularly for sediment pollution) as potato fields are characterised by more pronounced and frequent furrows than cereal fields. However, similarly to maize, their low- to mid-range average N fertiliser application at the baseline drives their low- to mid-range average per hectare sediment pollution levels (see Table 32). Moreover, the fact that potatoes only constitute 1% of overall catchment land use and are grown exclusively on soil 4 - the least polluting soil in terms of sediment pollution at the baseline (see Table 28) – will skew the average potato sediment baseline pollution level relative to other crops.

Table 32: Baseline total and average crop group fertiliser application

Crop Group	Total Nitrogen (kg)	Total Phosphorus (kg)	Land (% of catchment)	Nitrogen (kg/ha)	Phosphorus (kg/ha)
Barley	1,221,418	127,498	7%	137	14
Grassland	23,734,574	5,003,423	77%	244	51
Maize	161,870	427,181	7%	18	48
Oilseed Rape	879,685	174,225	3%	222	44
Potato	81,145	41,842	1%	82	42
Wheat	1,319,525	87,455	5%	222	15

Barley, winter oilseed rape, and wheat show relatively high levels of ZLOAD, pollution given their extended period of crop cover. Analogously to maize and potato, this result is driven by the assumed positive relationship between N application and sediment pollution in this model. The following section presents the sensitivity analysis of pollution outcomes to the different weather-years.

5.4.5. Weather Sensitivity

As outlined in section 5.2.2 (p. 111), the pollution estimates presented above are based on average pollution functions. This section discusses the sensitivity of these pollution estimates to the individual 45 pollution years using the baseline land and fertiliser allocation. Table 33 presents the measures of variability between the pollutants' weather-specific levels.

Table 33: Sensitivity of pollutants across 45 weather-years

Pollutant	Variance	SD	Mean	Maximum	Minimum	Unit
CFEM	3,533.3	59.4	44.9	280.6	0.07	kg/ha
NGLOAD	3,253.1	57.0	28.5	251.4	0.01	kg/ha
NRLOAD	13.1	3.6	2.5	10.8	0.18	kg/ha
PGLOAD	23.0	4.8	3.9	26.6	0.02	kg/ha
PRLOAD	7.9	2.8	2.9	12.6	0.02	kg/ha
ZLOAD	20.1	4.5	2.7	25.4	0.01	t/ha
Note: Estimates based on baseline land allocation and fertiliser input						

Firstly, the range of pollution levels indicated by the maximum and minimum values are considerable. Minima of close to no pollution could be explained by a year of optimal weather conditions. Given the Eden catchment's exceptionally high level of average rainfall (see 5.1, p. 97), a dryer year with moderate rainfall at periods appropriate for supporting plant growth could lead to the very low pollution levels shown. As weather patterns are becoming increasingly extreme and "optimal" weather-years scarcer due to climate change, we expect both the maximum and minimum pollution levels to increase further over the coming years.

Table 34: Annual pollution level deviation from mean by pollutant

Pollutant	Annual pollution levels within mean +/- SD (%)	Annual pollution levels outside mean +/- SD (%)	Annual pollution levels greater than one SD + mean (%)
CFEM	88	12	12
NGLOAD	87	13	13
NRLOAD	91	9	9
PGLOAD	89	11	11
PRLOAD	82	18	15
ZLOAD	93	7	7

Despite the considerable range of the pollution levels for the six pollutants between 82% - 93% of annual pollution levels fall within one SD of their mean (see Table 34). This distribution suggests that while there are significant deviations from mean pollution levels in 18% - 7% of years, most weather-years lead to pollution outcomes relatively close to their mean. The results further demonstrate that the significant deviations from the mean are almost exclusively higher pollution levels rather than lower pollution levels (i.e., the pollution level distribution is right-skewed). Given the potentially significant long-term effects of exceptionally high pollution level events, 7% - 15% of such events for the different pollutants could still represent a significant environmental threat. This finding underlines the importance of using large weather datasets to capture the impacts of weather-years on NPS pollution outcomes. Particularly considering the climate change effects discussed above, the significance of detailed weather-year-specific datasets in biophysical-economic NPS pollution analyses will further increase in the near future.

This chapter has presented the data underlying the baseline scenario of this analysis. It has demonstrated its calibration to reflect the observed reality of the Eden catchment. The description of the uniquely diverse considered variables and their complex interactions were shown to drive the baseline model results. Finally, the sensitivity of pollution levels to individual weather-years was found to be moderate with a right-skew of extreme weather events. Chapter 6 builds on these examined model features and presents the policy scenario results in the context of the baseline features examined in this chapter.

6. Results

This chapter presents the results of the policy evaluation. First, section 6.1 outlines the details of the modelled policies. Next, section 6.2 showcases the policies' pollution and gross margin trade-offs for the main pollutants identified as being of interest. Subsequently, section 6.3 explores the modelled policies' impact on key variables which drive the presented results.

6.1. Modelled Policies

The choice of modelled policies was informed by the review of the previous literature and policy mechanisms (see section 4.1, p. 73). The choices include a range of incentive-based policies, command-and-control policies, and mixed instruments. Table 35 summarises the scenario details of the main modelled policies.

Policies were modelled to levels of stringency beyond realistic levels of implementation to find their maximum pollution abatement potential. For the targeted set-aside policy, the steepest slope (S4) was chosen due to the higher risk of river nutrient and sediment pollution generally associated with steeper slopes (see section 5.4.4.). The maximum targeted set-aside level was set to the total amount of slope 4 available in the catchment (37% of catchment land). Groundwater nutrient pollution may be more-effectively abated by targeting flatter slopes. Policies targeting flatter slopes with set-aside to improve groundwater pollution were not modelled as in the Solway Tweed River Basin District, in which the Eden catchment is situated, around 90% of groundwater is already classified as being in good chemical condition while only 45% of surface waters are in at least good ecological condition (EA and SEPA, 2021). This suggests that surface water pollution is a clear priority within the Eden catchment, an assessment which informed the policy design of this analysis. For the mixed instruments combining an N tax and set-aside policy, the set-aside levels (1%, 2%, and 5%) were chosen based on the most cost-effective combinations found in extensive initial trials.

Table 35: Details of modelled policy scenarios

Modelled Policies	Scenario Description
Non-targeted set-aside	- **Set-aside** 1% - 40% of **catchment agricultural land** ○ Increments of 1 percentage point
Targeted set-aside	- **Set-aside** 1% - 37% of **catchment agricultural land of slope 4** ○ Increments of 1 percentage point
N tax	- **N tax** from 50% - 5,000% ○ Increments of 50 percentage points from 2,000% ○ Increments of 5,000 percentage points to 5,000%
Mixed N tax & 1% set-aside*	- **N tax** from 50% - 5,000% ○ Increments of 50 percentage points from 2,000% ○ Increments of 5,000 percentage points to 5,000% - **Set-aside of 1%** of **catchment agricultural land**
Mixed N tax & 2% set-aside	- **N tax** from 50% - 5,000% ○ Increments of 50 percentage points from 2,000% ○ Increments of 500 percentage points to 5,000% - **Set-aside of 2%** of **catchment agricultural land**
Mixed N tax & 5% set-aside	- **N tax** from 50% - 5,000% ○ Increments of 50 percentage points from 2,000% ○ Increments of 500 percentage points to 5,000% - **Set-aside of 5%** of **catchment agricultural land**
Precision Agriculture	- **Fertiliser efficiency factor** from 5% - 45% ○ Increments of 5 percentage points
P tax*	- **P tax** from 50% - 5,000% ○ Increments of 50 percentage points from 2,000% ○ Increments of 500 percentage points to 5,000%
N tax & P tax	- **N tax** from 50% - 2,000% ○ Increments of 50 percentage points - **P tax** from 50% to 2,000% - Increments of 50 percentage points
*Note: To facilitate visual representation of the results, policies lacking cost-effectiveness were *excluded from summary trade-off graphs for all pollutants*	

Further set-aside variations targeting soil-types and hydrological connectivity were modelled in initial trials. However, they were not shown to be cost-effective and are therefore not reported here. The Eden catchment characteristics which drive this result are further discussed in section 6.3. As an alternative command-and-control policy to set-aside, a stocking density reduction policy was also found to not be cost-effective in initial trials and is therefore not reported. Finally, PA was modelled using the range of efficiency factors following the methodology outlined in section 4.7.

6.2. Policy Trade-offs between Gross Margin and Pollutants

This section examines the modelled policies' high-level results across pollutants before examining unique trends for individual pollutants. For each policy, scenarios of increasing stringency were modelled according to the increments detailed in Table 35.

Figure 19 to Figure 24 show the trade-off between pollution abatement of each identified key pollution variable and social costs for the modelled policies described in Table 35. The trade-offs are modelled as percentage changes from the baseline level of the pollutant and the catchment gross margin (see section 5.4 for details on the baseline). Changes from baseline pollution levels are captured along the x-axis while changes from baseline catchment gross margin are presented along the y-axis. No change from the baseline pollution and catchment gross margin is represented in the upper right corner of the graphs. Each symbol along the graph represents one policy scenario. For a given level of pollution abatement, the policy with the smallest associated reduction in catchment gross margin represents the most cost-effective policy (i.e., in the graphs presented below, policies closer to the x-axis are relatively more cost-effective than alternative policies). The graphs do not include non-optimal model solutions. Moreover, optimal runs at high intervention rates were excluded when they ceased to provide cost-effective abatement options to aid visual representation.

High-level cross-pollutant policy results

Overall, Figure 19 to Figure 24 demonstrate that policies' abatement behaviours are similar across the modelled pollutants (except for NGLOAD which will be addressed in more detail below). Across the pollutants, policies show similar levels of high cost-effectiveness up to the regulatory target of around 20% abatement, which is achieved at a maximum social cost of around 5% of the catchment gross margin.

Generally, a combined N & P tax and an individual N tax provide the most cost-effective abatement for mid- to low-level regulatory targets across pollutants. For higher regulatory targets (above around 30% of abatement), an individually applied N tax provides more cost-effective pollution abatement. The strong disincentive on both N and P application through taxation provides initially strong abatement, before the combined N & P tax becomes too costly and the single input N tax becomes more cost-effective. Notably, the results demonstrate the price inelastic demand for fertiliser, as high levels of N taxation are required to achieve reductions in artificial N application. An N tax of around 800% reduces N consumption by around 10%.

Across the pollutants, an individual set-aside policy generally does not present the most cost-effective option (the exceptions of NGLOAD and carbon emissions are discussed below). Up to a regulatory target of around 25-30% of baseline pollution abatement, spatially targeting the set-aside policy to the highest pollution risk slope-type, provides modest improvements to cost-effectiveness. At higher levels of spatially targeted set-aside farmers are given less choice over which land to take out of production. They are forced to set-aside relatively more productive land of slope-type 4 instead of relatively less productive land of other slope-types in a non-spatially targeted scenario. The more prescriptive targeted set-aside is, therefore, less cost-effective than the non-targeted set-aside at high set-aside levels. The mechanisms driving the limited scope for spatial targeting within the Eden catchment are further explored in section 6.3.

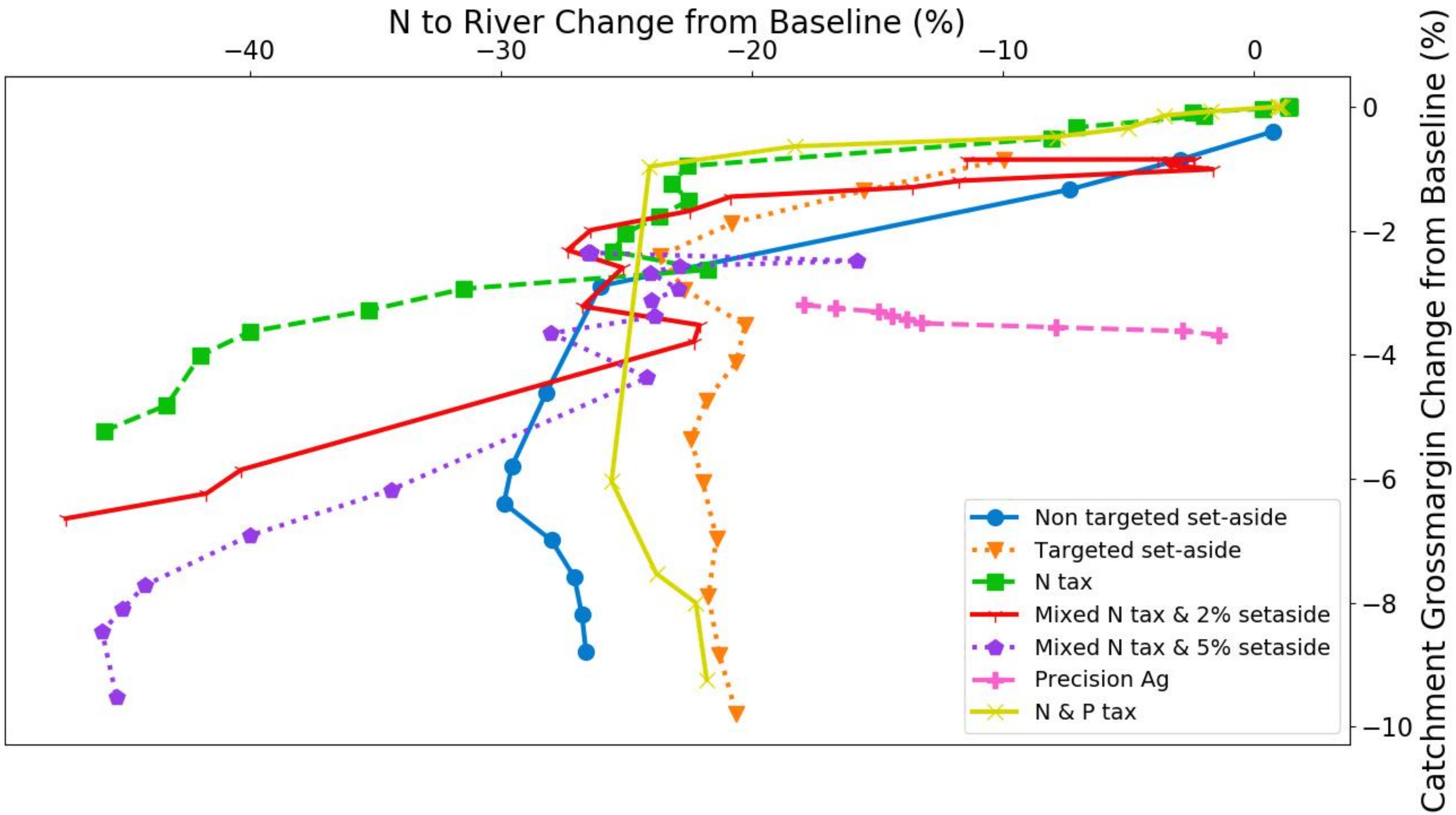
A mixed policy combining set-aside with N taxation is generally found to outperform an individual set-aside policy and shows the highest maximum abatement potential of the modelled policies across most pollutants. A level of 2% set-aside generally outperforms the alternative levels of set-aside modelled (1% and 5%). However, the mixed instrument remains less cost-effective than the modelled N tax (see section 7.2 for further discussion of this result).

PA is shown to provide between around 2% to 20% pollution reduction across the pollutants for the assumed efficiency factors between 5% and 45% at a social cost between 4% and 3%. Efficiency gains show diminishing returns to pollution abatement as efficiency gains up to 20% show the largest marginal pollution abatement of the modelled efficiency factor increments. PA does not individually represent the most cost-effective approach to pollution abatement amongst the modelled policies. However, the Eden catchment characteristics suggest it is not a high-potential location for PA (section 6.3 for more details), reducing its cost-effectiveness in pollution abatement in the Eden catchment.

Individual pollutant results

NRLOAD (Figure 19) largely conforms to the high-level trends described above. Notably, a combined N & P tax increases more sharply in social cost beyond 25% abatement than for other pollutants (excluding NGLOAD). Further, the two mixed instruments demonstrate some reversed pollution abatement potential as the N tax increases. The mechanisms driving these results will be explored in section 6.3.

Figure 19: N to river and gross margin trade-off graph for all cost-effective policies



NGLOAD (Figure 20) shows policy responses similar in their trends to the responses observed for NRLAOD (Figure 19). However, the groundwater responses are more pronounced than the river responses. This difference may be explained by the fact that N is highly mobile in the soil and thus easily leaches into the groundwater (Stahr *et al.*, 2016, p. 174). Therefore, policies targeting N pollution are translated more directly into the groundwater pollution levels. The more pronounced policy responses are showcased by policy failures for all N incentive policies (N tax, N & P tax, and mixed instruments) at lower policy stringency levels than for the other analysed pollutants. These non-cost-effective options have been removed from the graph to aid visual analysis. Set-aside, which targets N pollution at the extensive margin also shows a more pronounced response in groundwater N abatement, achieving around double the river N abatement for groundwater at a given level of social costs. Non-targeted set-aside in particular is shown to have the highest maximum abatement potential at close to 80% groundwater N abatement.

For both P to river (Figure 21) and to groundwater (Figure 22), the combined N & P tax is relatively more cost-effective for medium-ambition P abatement (around 10% - 35% abatement). This is explained by the direct incentive on P application that in contrast to other modelled policies is included in this combined policy. On the other hand, high levels of the N & P tax (beyond around 30%) are excessively costly to farmers and, therefore, less cost-effective. Notably, P to groundwater does not show more prominent policy responses than P to the river, observed for N (Figure 19 and Figure 20). This is explained by the lower soil mobility of P relative to N, with less P therefore likely to leach into the water (Stahr *et al.*, 2016, p. 175).

Figure 20: N to groundwater and gross margin trade-off graph for all cost-effective policies

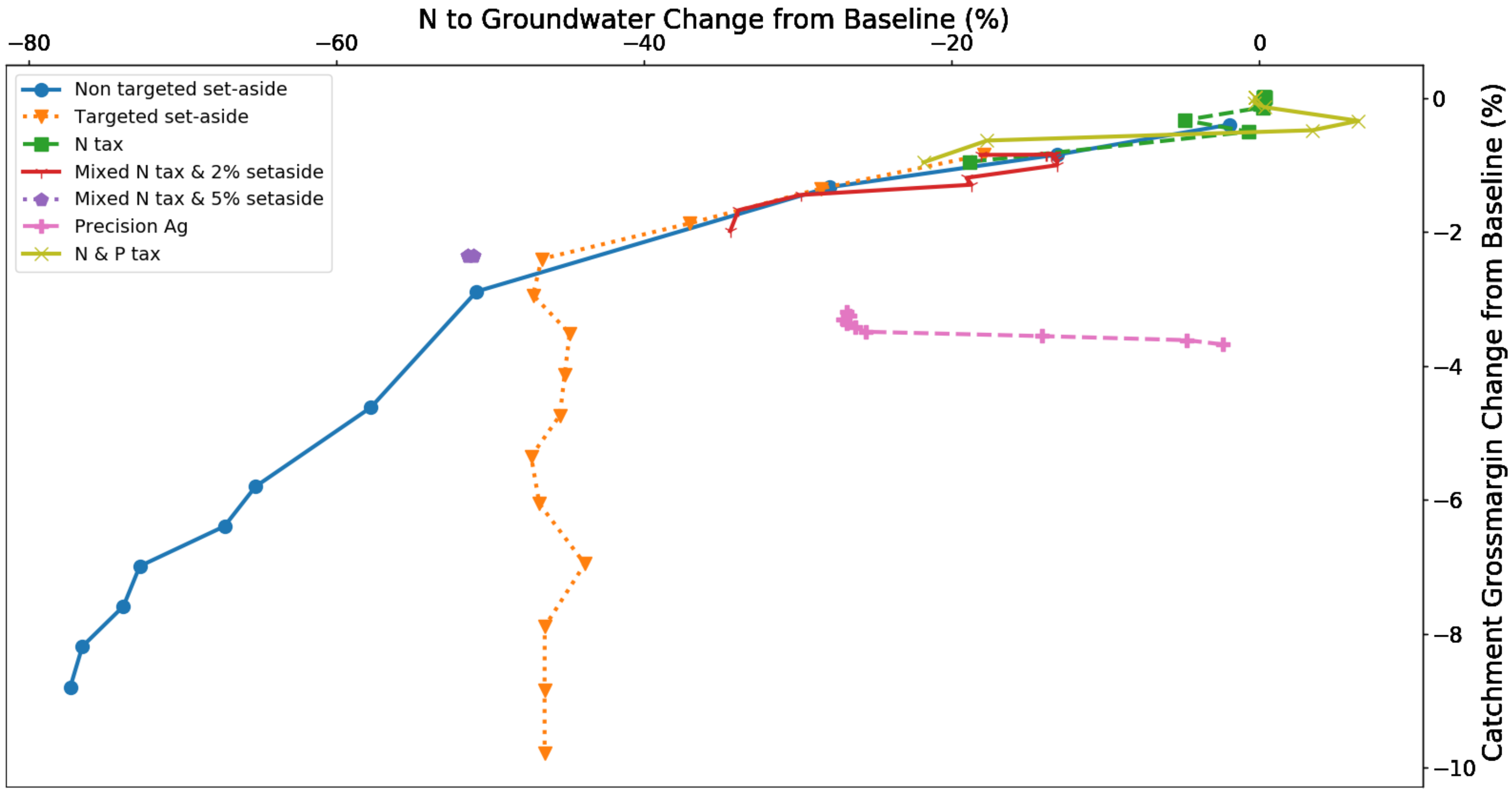


Figure 21: P to river and gross margin trade-off graph for all cost-effective policies

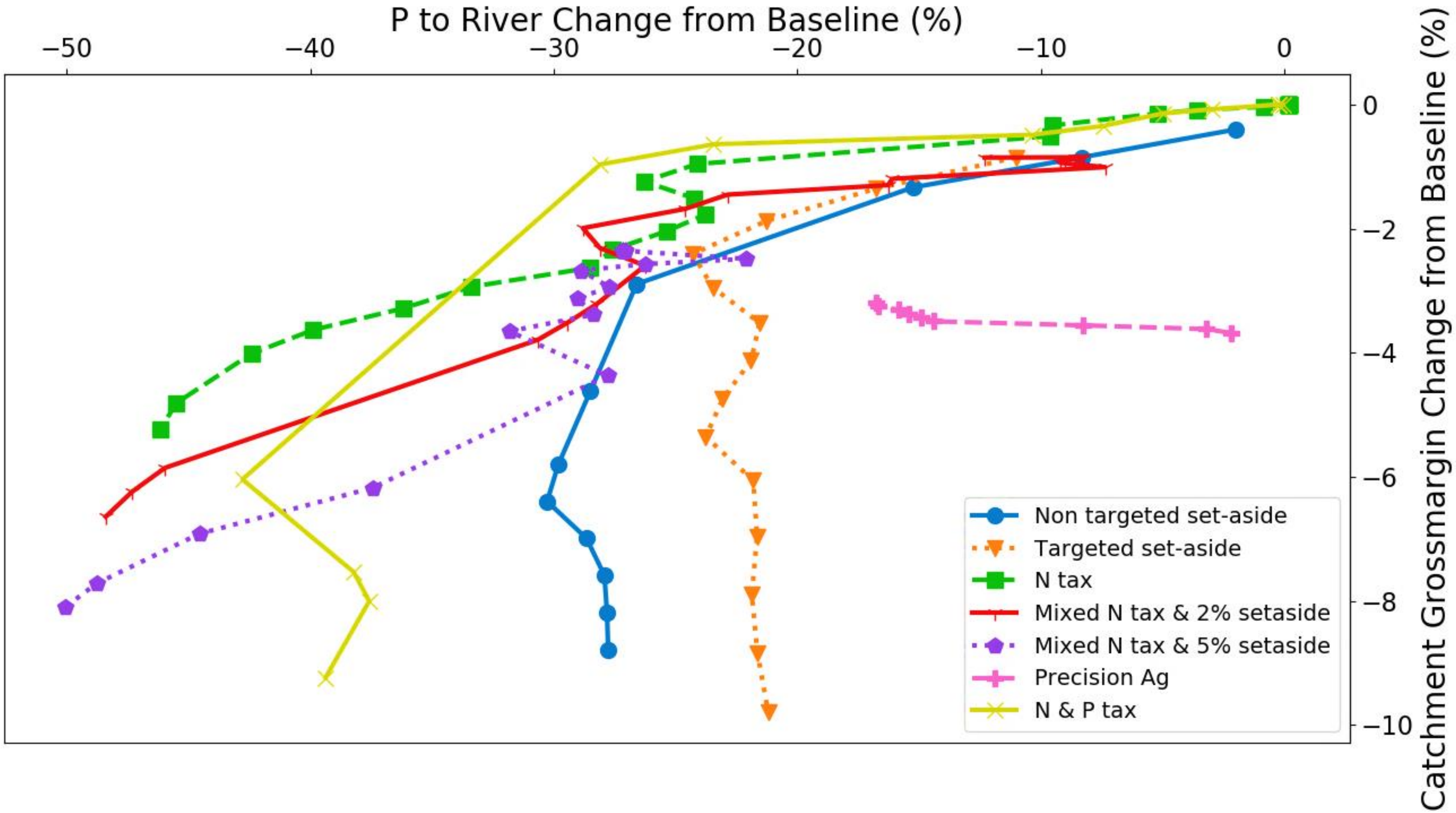


Figure 22: P to groundwater and gross margin trade-off graph for all cost-effective policies

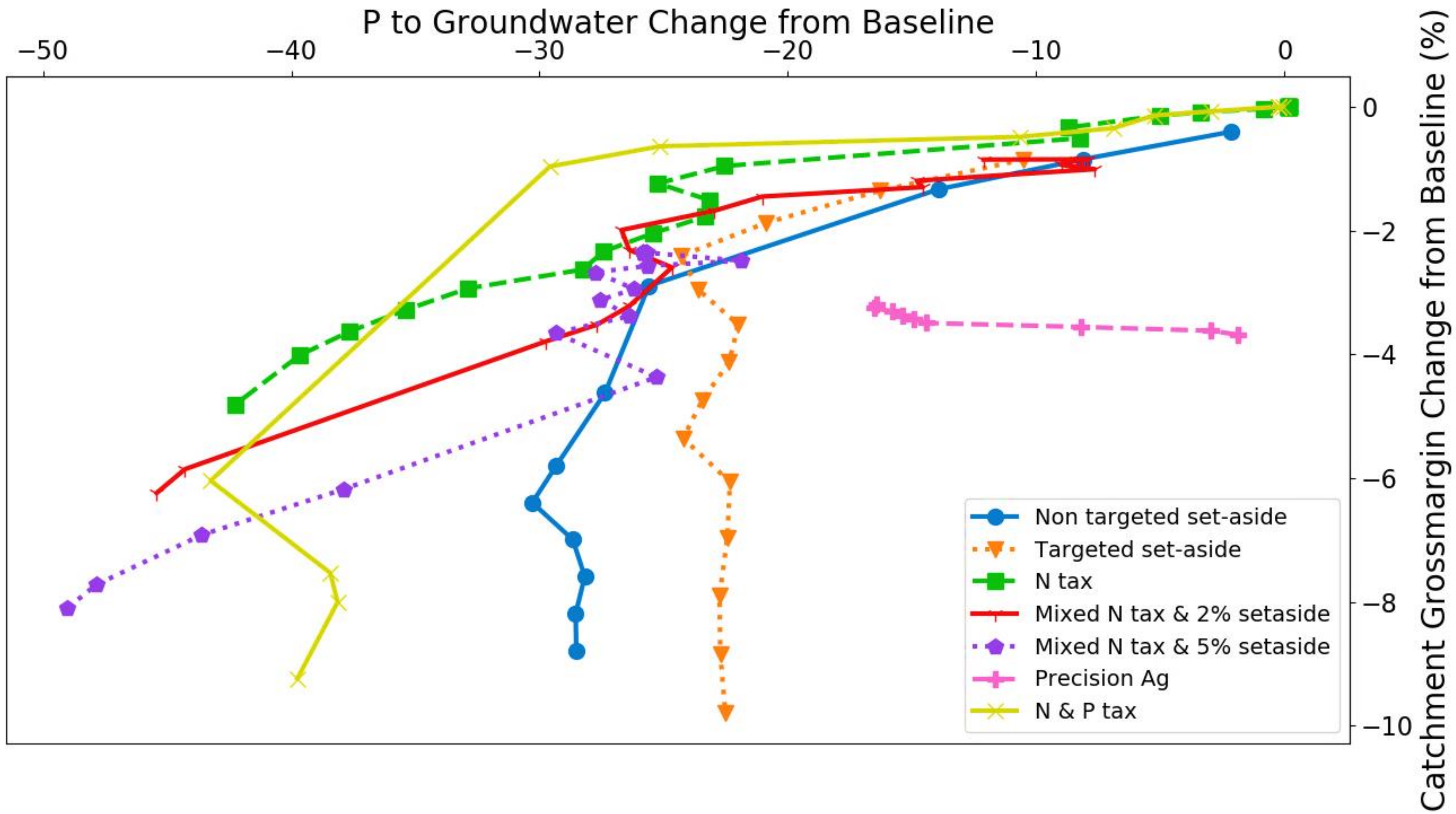


Figure 23: Sediment and gross margin trade-off graph for all cost-effective policies

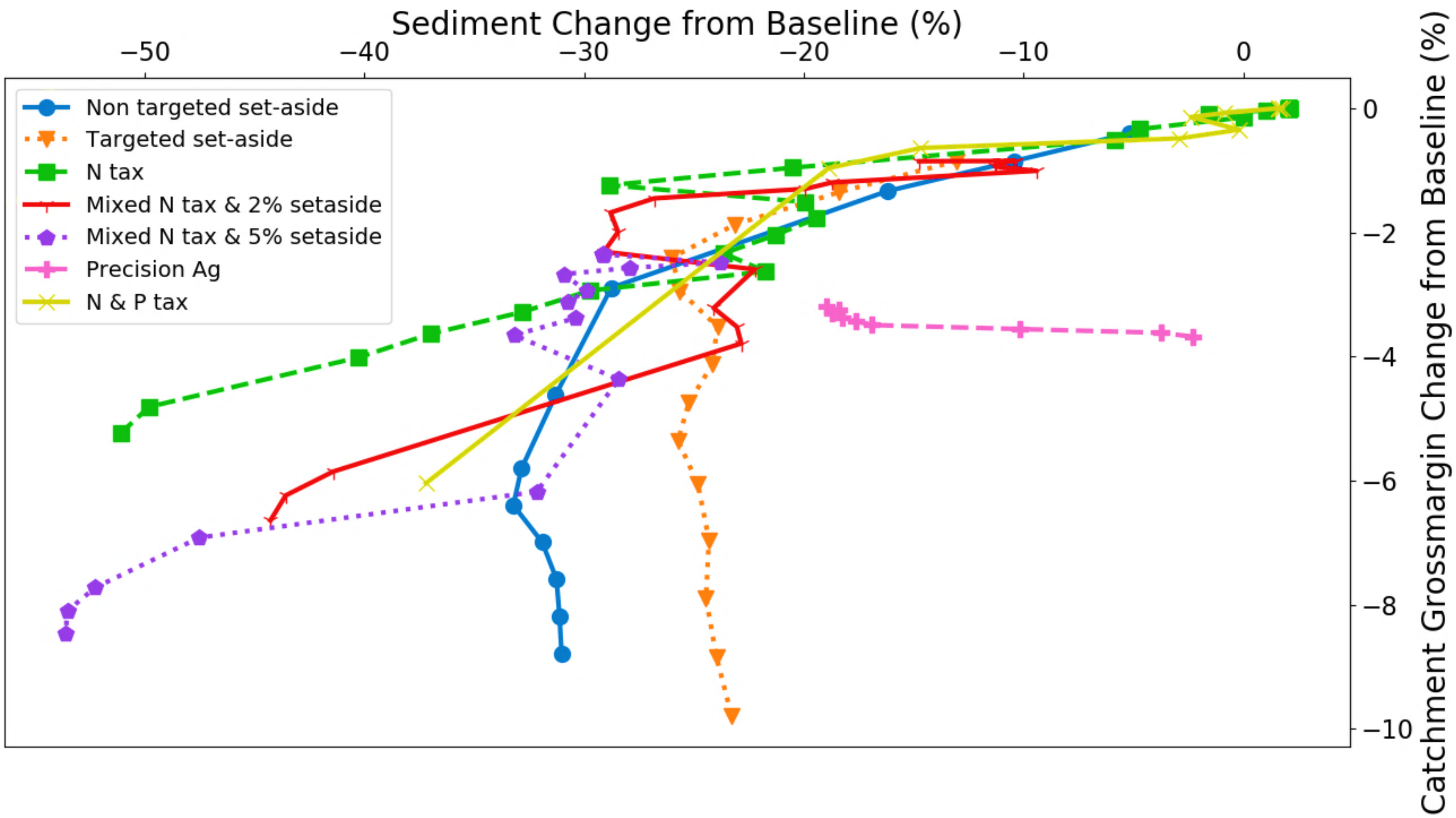
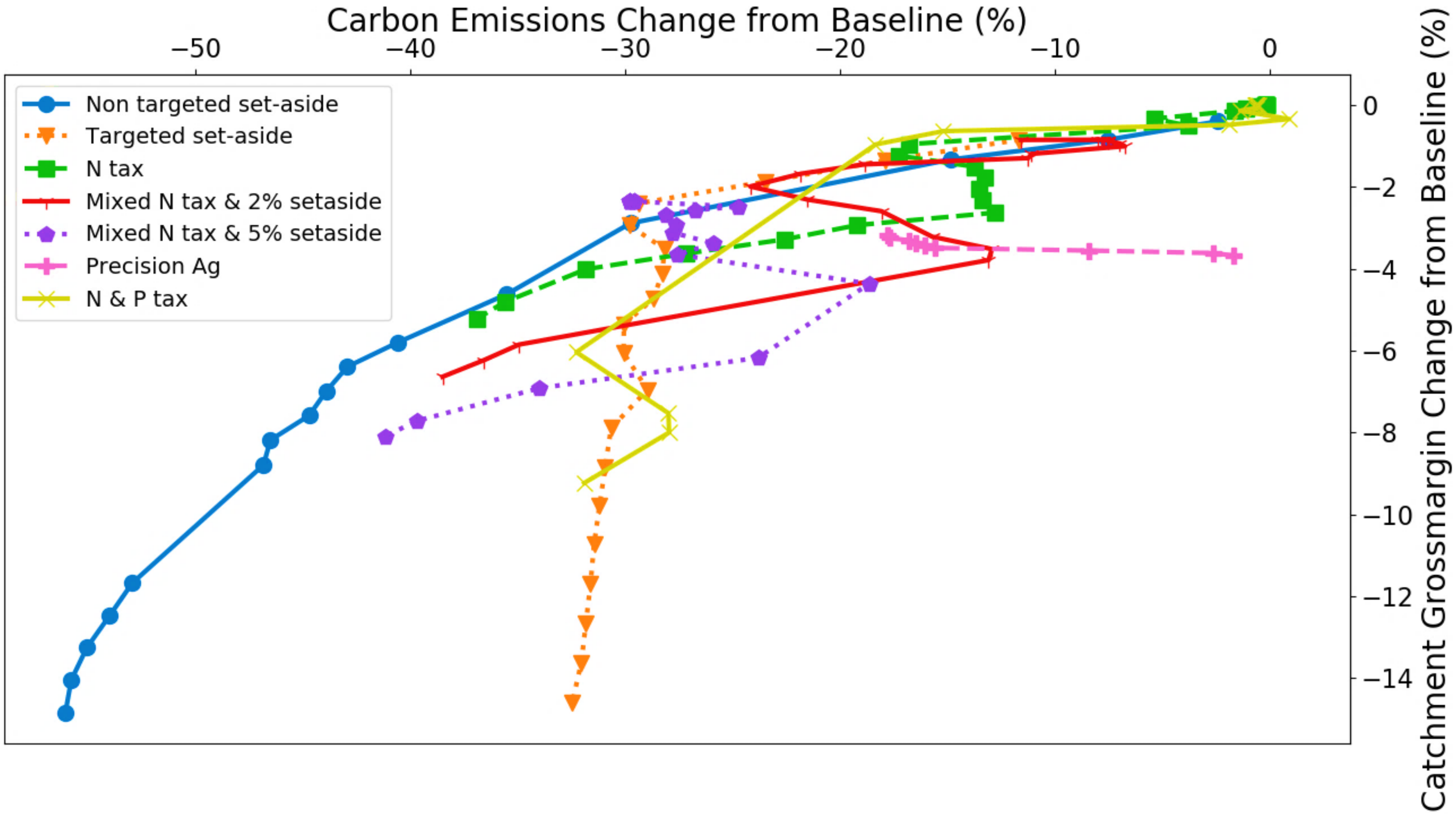


Figure 24: Carbon emissions and gross margin trade-off graph for all cost-effective policies



For sediment abatement (Figure 23), there is less differentiation in cost-effectiveness between the different modelled policies at lower abatement levels than for other pollutants. These findings may be driven by the modelled policies focussing on fertiliser input taxation, which does not directly influence incentives around sediment pollution. Notably, N taxation is the most cost-effective policy for mid- to high-level abatement (around 30-50%) while a mixed N tax with 5% set-aside has the highest abatement potential (53%). This result is not in line with the general expectation that set-aside policies are the most direct intervention for sediment pollution and is further investigated in section 6.3.

Low to medium levels of carbon emission abatement (up to around 30% baseline abatement) are achieved at similar levels of cost-effectiveness through N taxation, N & P taxation, and set-aside. An N tax is less cost-effective for carbon emissions than for other pollutants. Monetary incentives to reduce N application do not directly reduce the number of machine-hours which drive carbon emissions if fertiliser rates are reduced in response to the policy rather than the number of applications. Beyond 30% of baseline carbon emission abatement, non-targeted set-aside is the most cost-effective policy to achieve NPS pollution control and also achieves the maximum abatement potential (at 57%).

6.3. Policy Mechanisms

This section further analyses the policy results presented in section 6.2 through the changes in the key variables of land use, artificial N application and livestock numbers as appropriate. In addition, the impact of general catchment characteristics on the policies' effectiveness is examined.

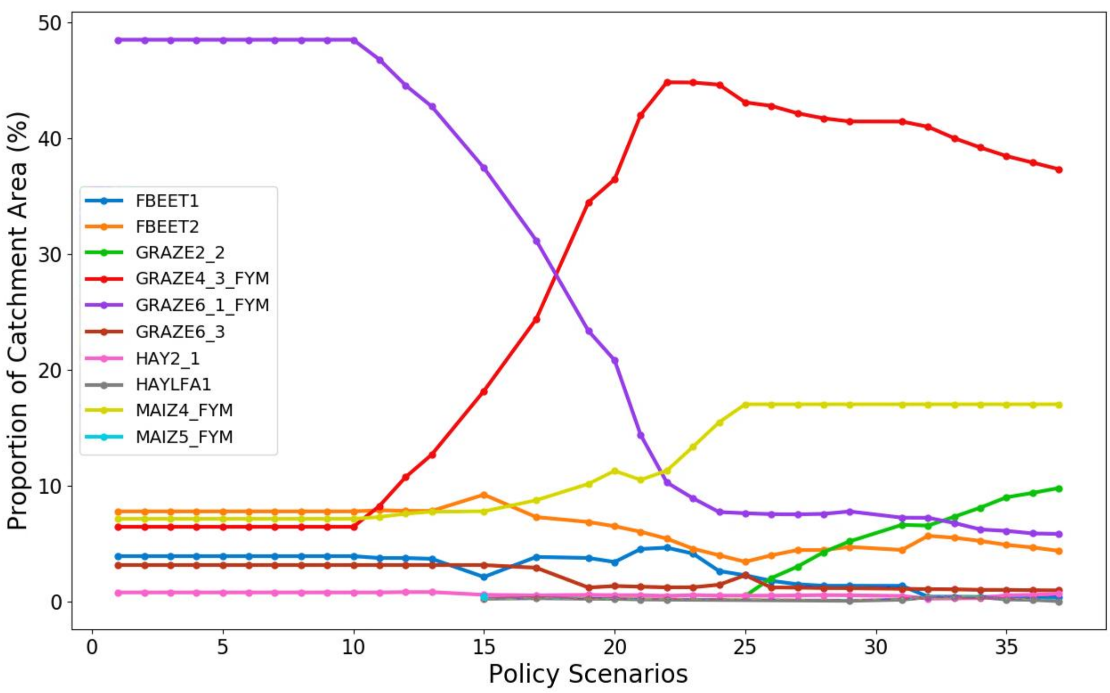
P tax

As mentioned in Table 35 the modelled single P tax did not show significant abatement potential and was therefore excluded from the pollution – gross margin trade-off figures. The ineffectiveness of the P tax is in line with expectations given the low response of yield functions to P application in this analysis (see section 5.2.1). This low response is driven by the immobility of P in the soil, which leads to longer-term soil availability than N. The low yield response is further exacerbated by P saturation in the catchment soils discussed in section 5.4.3, commonly seen across European agricultural land (Stahr *et al.*, 2016, p. 175ff.). Due to the low P yield response, farmers are applying P close to the defined per hectare lower bound at the baseline, which diminishes the scope for further reducing P application in response to a P tax.

N tax

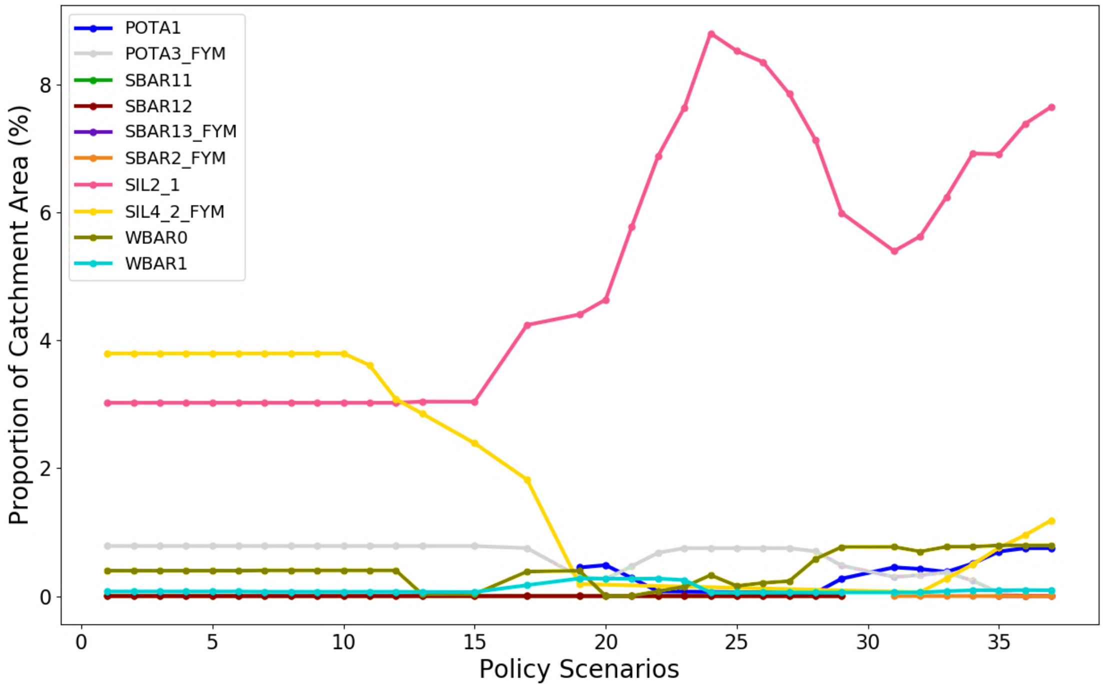
As shown in Figure 19 to Figure 24, the N tax shows consistently increasing abatement across pollutants between levels 500% - 1,000% and 1,200%-1,850% (scenarios 10-20 and 24-37). A temporary trend reversal is seen for an N tax interval between 1,000% and 1,200% across the examined pollutant variables, where the abatement potential is slightly lower (between around 1 and 9 percentage points) than for the previous and following N tax interval. This behaviour is driven by the changes in land use at the extensive margin shown in Figure 25 and Figure 26 (see Appendix B for the remaining crops in Figure 35, p. 183). As the price of artificial fertiliser rises beyond 600% (scenario 11), farms substitute away from the higher-input grazing crop of GRAZE6_1_FYM (Figure 25) and silage crop of SIL4_2_FYM (Figure 26) towards the lower-input grazing crop GRAZE4_3_FYM and SIL2_1 respectively.

Figure 25: Land use change in response to N tax policy scenarios (Part 1)



At the N tax interval between 1,100% and 1,400% (scenario 22-28), the rise in land allocation towards the lower-input silage crop exceeds the fall in the higher-input silage crop.

Figure 26: Land use change in response to N tax policy scenarios (Part 2)



This behaviour further corresponds to the observed shift in the intensive margin (proportion of catchment N fertiliser application in Figure 27 and Figure 28). The intensive production focus shifts away from the higher-input silage crop SIL4_2_FYM towards the lower-input silage crop SIL2_1 whose share in artificial N application increases more sharply around the interval 1,100% and 1,400% (scenario 22-28) than the share of SIL4_2_FYM falls. This result is explained by the fact that as farms shift from higher-input crops to lower-input crops (substitution effect), they initially compensate for their lost yield by increasing production on the lower-input crops at the intensive margin (increasing fertiliser application) as well as the extensive margin (increasing land allocation). This matches the pollution abatement behaviour displayed in the trade-off graphs. Notably, the revenue neutral policy design also reduces farmers' income effect in response to the tax policy. The discussed land use changes at the high taxation levels underline the discussion of the inelastic N demand in section 6.2. Livestock numbers[22] drop by up to 13% across the modelled N tax scenarios.

[22] Measured in Grazing Livestock Units.

Figure 27: Crop share of catchment N fertiliser application for N tax policy scenarios (Part 1)

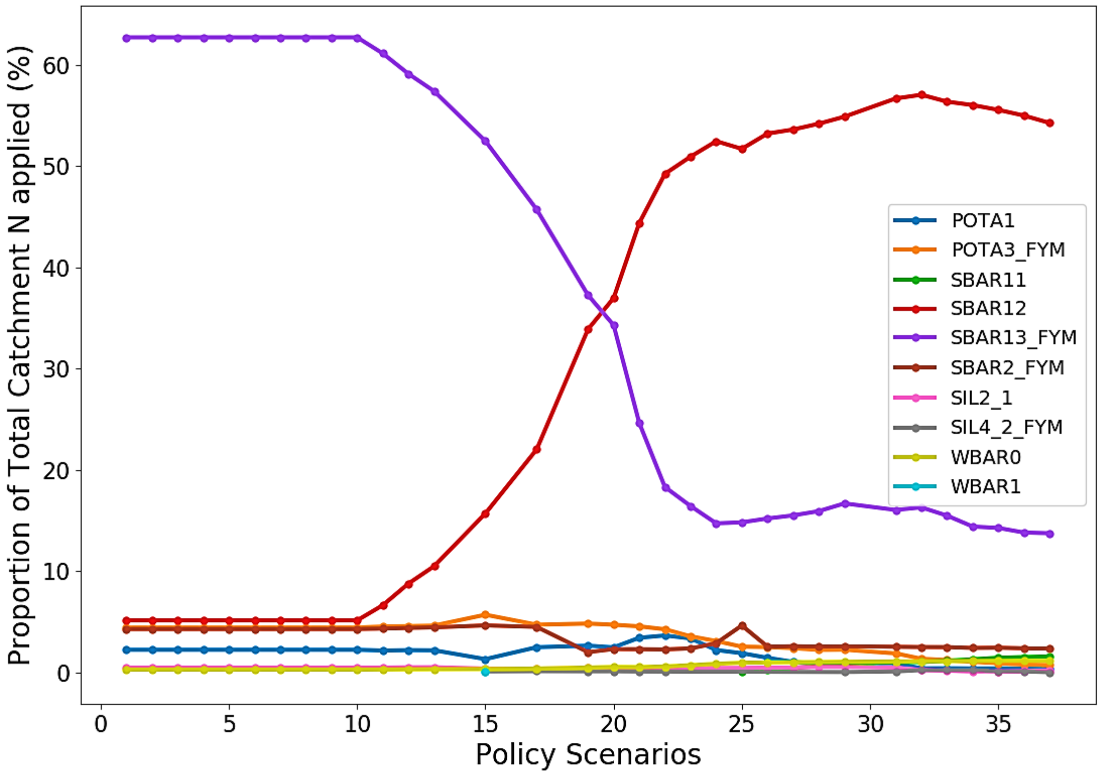
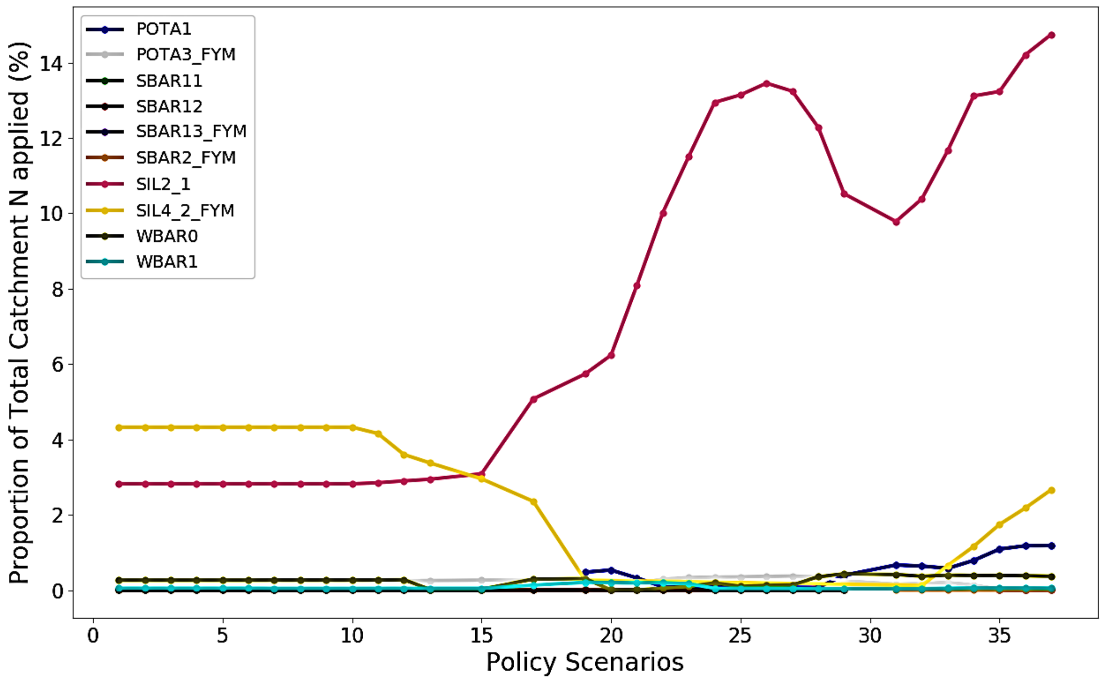


Figure 28: Crop share of catchment N fertiliser application for N tax policy scenarios (Part 2)



The outlined response in land use and fertiliser application to an individual N tax is mirrored in the modelled mixed policies which contain an N tax element (combined N & P tax; mixed N tax & 1%, 2% and 5% set-aside). This finding explains the similar shape in the pollution response.

Combined N & P tax

For the N & P tax, the abatement steadily increases up to around 20% of abatement at a social cost below 2% of the baseline catchment gross margin. Thereafter, the social cost of abatement increases significantly, and an additional abatement of about 10-20% is achieved while sacrificing about 10% of the catchment gross margin. As highlighted in section 6.2, for NRLOAD and NGLOAD the social cost of abatement increases more significantly than for PRLOAD and PGLOAD at higher tax levels and their maximum abatement potential is reached at about 25% of baseline pollution. This outcome is explained by the fact that absolute levels of P application are significantly lower than N application. Therefore, the cost of P represents a smaller proportion of a farm's total costs, and a P tax will be associated with a lower social cost than an N tax. However, as the tax rate increases the combined effect of the N&P tax reduces its cost-effectiveness relative to other policies at higher abatement levels (see section 6.2, p. 129).

Set-aside

Figure 19 to Figure 24 show that set-aside has a high maximum abatement potential, particularly for CFEM and NGLOAD. However, for most pollutants and regulatory targets, set-aside does not represent the most cost-effective abatement tool compared to other modelled policies. This finding is in line with expectation because the social cost of set-aside is greater than the cost of input taxes. For set-aside land, output (yield) actually falls to zero rather than only being reduced due to a less intensive application of inputs.

Further Figure 29 – Figure 31 demonstrate, that in contrast to the N tax, the set-aside policy does not entail a significant shift from higher-input towards lower-input crops. These results are in line with expectations since set-aside acts by restricting the extensive production margin rather than incentivising the intensive production margin.

Figure 29: Land use change in response to non-targeted set-aside policy (Part 1)

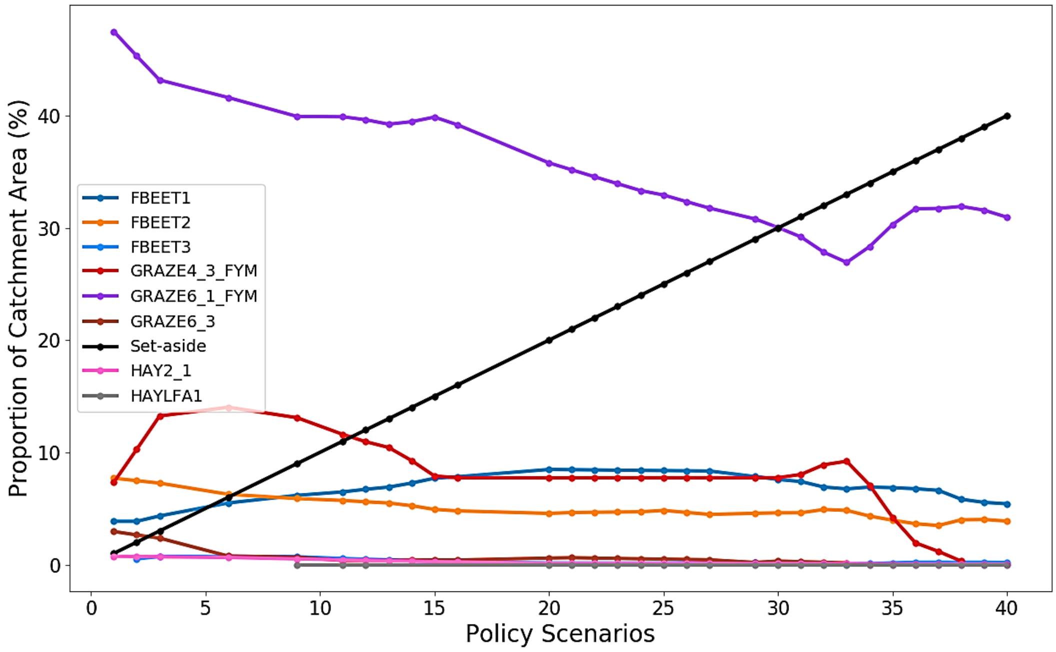
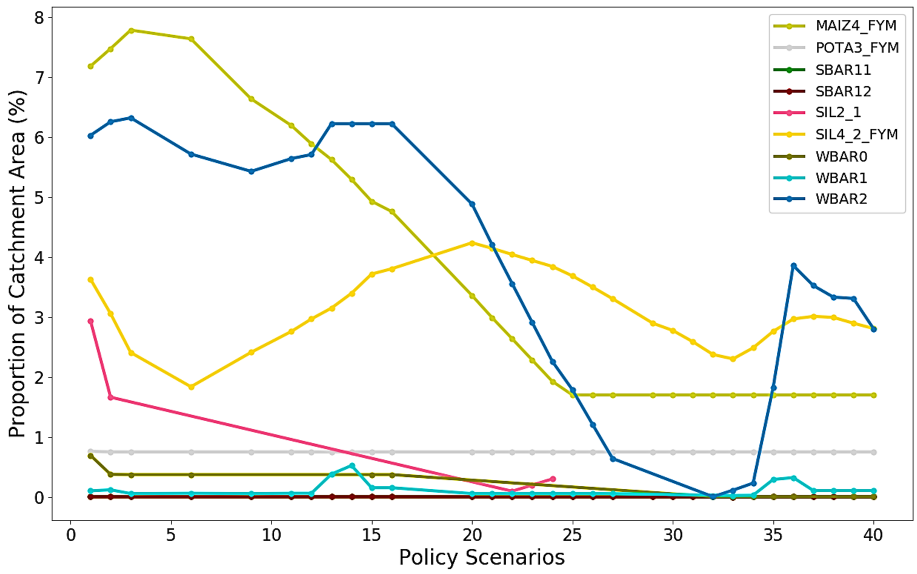


Figure 30 and Figure 31 demonstrate that as the set-aside requirement increases, non-FYM crops tend to be replaced with FYM crops. This finding is driven by the need for farmers to empty their FYM storage[23]. Farms have limited FYM storage available for their herd size and need to

Figure 30: Land use change in response to non-targeted set-aside policy (Part 2)



[23] To aid computation, the model assumes that farms can store up to 80% of the organic N nutrients and 50% of the P nutrients of organics produced on-farm. The higher allowance for N is driven by the higher ratio of N to P in manure. Exact N & P ratios vary widely due multiple factors including different storage and feeding practices (e.g.: covered or uncovered storage, N & P reduced feeding (Pomar et al., 2011)).

spread the FYM produced by their livestock over the land. Therefore, as more land is taken out of production, less land is available to spread FYM and some of the land allocated to non-FYM crops has to be allocated to FYM crops.

Moreover, the proportion of fodder crops generally declines as a proportion of total catchment land. This behaviour is further driven by the up to 47% reduction in livestock numbers over the analysed scenarios as less land is available for extensive livestock rearing. Notably the effect of set-aside on livestock numbers is significantly more pronounced than the impact of an N tax.

Figure 31: Land use change in response to non-targeted set-aside policy (Part 3)

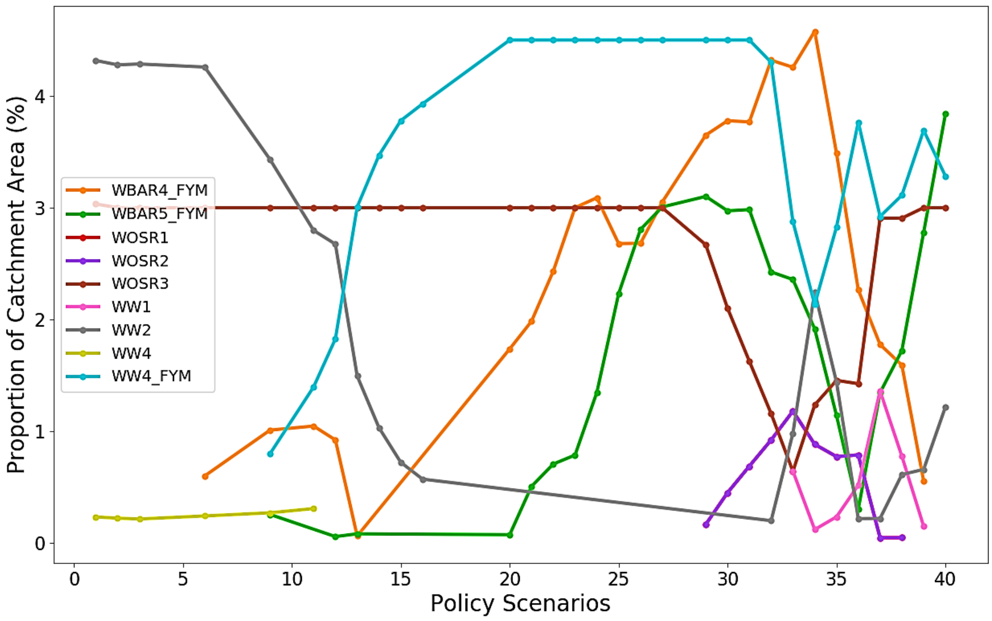


Figure 23 (see p. 136) demonstrates that the non-targeted set-aside does not achieve the highest sediment pollution abatement potential amongst the modelled policies. As highlighted in section 6.2, this result is unexpected, due to the more significant influence tillage systems have on sediment pollution compared to N application. Taking land out of production and thereby eliminating tillage would be expected to reduce sediment pollution more significantly than a change in the level of fertiliser application. However, this finding is explained by the impact of the 78% grassland share in the catchment's land allocation (see Table 23, p.118). Grassland does not require regular tillage throughout the growth cycle and provides permanent soil cover. This fact reduces its potential for sediment pollution relative to the modelled sale crops such as wheat and barley, which require tillage and provide more limited soil coverage. Consequentially, we expect the additional sediment abatement effect of set-aside compared to grassland to be less significant. Given the high proportion of grassland in the catchment at the baseline, this context explains the more limited sediment abatement potential of set-aside in the Eden.

In addition, the fact that sediment pollution in this analysis is primarily modelled as a function of N application may contribute to the lower effectiveness of set-aside in reducing sediment pollution. Although the EPIC simulation accounts for the impacts of tillage systems, the effect of changes to fertiliser application on sediment abatement may be over-estimated due to the functional form linking sediment pollution to N fertiliser application (see Table 14). This assumption may lead to overestimating the maximum abatement potential of policies targeting the intensive margin of N application and explain the relatively lower performance of set-aside on sediment pollution.

Mixed N tax & set-aside

Figure 19 to Figure 24 demonstrate that the mixed instruments of combining an N tax with a set-aside (1%, 2%, and 5% level) display a pollution abatement behaviour similar to an individual N tax. As mentioned in section 6.2, the mixed policies generally provide slightly more cost-effective pollution abatement than an individual set-aside policy for most pollutants and have a higher maximum abatement potential. NGLOAD and CFEM are notable exceptions for the higher maximum abatement potential of mixed N tax and set-aside instruments. This finding is explained by the limited maximum abatement potential of an individual N tax for both pollutants, explained in section 6.2. For NGLOAD, that limitation is driven by failures of N incentive policies due to the more direct N-to-groundwater pathway, as described earlier. For CFEM, an N tax's limited maximum abatement impact is driven by its limited impact on machine hours, as described previously. The modelled mixed instruments do not outperform the analysed N tax in terms of cost-effectiveness. However, they do also provide a higher maximum abatement potential than the individual N tax for most of the examined pollutants (see Table 38, p. 151). The mixed instrument with a 2% set-aside appears to outperform the modelled 5% set-aside mixed instrument for low levels of pollution abatement. However, around an abatement target of 25-30%, the 5% mixed instrument tends to slightly outperform the 2% mixed instrument. Land use changes in response to both mixed instruments are generally very similar (see Appendix B, Figure 42, p. 190 - Figure 47, p. 195). Nonetheless, lower-input crop land share rises at a faster rate in the 2% than the 5% mixed instrument at similar levels of higher-input land shares between scenarios 17 – 25 (N tax levels: 850% - 1,250%) which may explain the slight trend reversal. Moreover, the 5% mixed instrument reaches a higher maximum abatement potential than the 2% mixed instrument.

Examining the underlying responses in terms of land use change and variations in the intensity of fertiliser use confirms that the mixed instruments' responses closely correspond to the N tax responses (see Appendix Figure 42 – Figure 44 for the land use change response). Notably, farmers substitute away from fertiliser-intensive crops towards less intensive crops. This behaviour explains the similarities in the abatement response of mixed instruments to the individual N tax.

Spatial targeting

As outlined in section 3.3, we expect the set-aside policies which are spatially targeted towards the most polluting soils, slopes, and hydrologically connected land to provide significant cost-effectiveness improvements over uniformly applied set-aside policies at low to medium policy stringency levels. However, as mentioned in section 6.1, set-aside policies targeting soils and hydrologically connected land were not cost-effective in early trials. Section 6.2 further demonstrated that a set-aside policy targeted towards the most polluting slope-type, provides pollution abatement at a similar or only marginally smaller social cost than a uniformly applied set-aside policy for low to medium stringency levels across the pollutants in this analysis.[24] The combination of three key characteristics of the Eden catchment contributes to the limited cost-effectiveness of spatial targeting in this analysis:

1) ***The distribution of soils and hydrological connectivity***

Firstly, as outlined in Table 8 and Table 36, the soil distribution is dominated by soil 1 and soil 4 which represent more than 80% of the total catchment. This low level of heterogeneity leads to more homogeneous pollution outcomes and marginal costs of abatement. Therefore, the scope for targeting policies towards soil-types with lower marginal abatement costs is reduced. Analogously, the distribution of hydrological connectivity is also dominated by less-hydrologically-connected land with 90% falling below the 30th and 98% below the 40% percentile of the catchment's maximum level of hydrological connectivity (see Figure 9). Again, this fact leads to more homogeneous pollution outcomes and marginal abatement costs within the catchment and reduces the ability to target policies towards highly hydrologically connected land. Therefore, the distribution of soils and hydrological connectivity within the catchment suggests that spatially targeting policies by soils and hydrological connectivity will not lead to improvements in cost-effectiveness. This theory was confirmed in early trials of set-aside policies targeted towards high pollution-risk soils and high levels of hydrological connectivity.

[24] Livestock numbers are reduced slightly less (by 41%) than under uniform set-aside policy (by 47%) across scenarios.

2) The soil composition

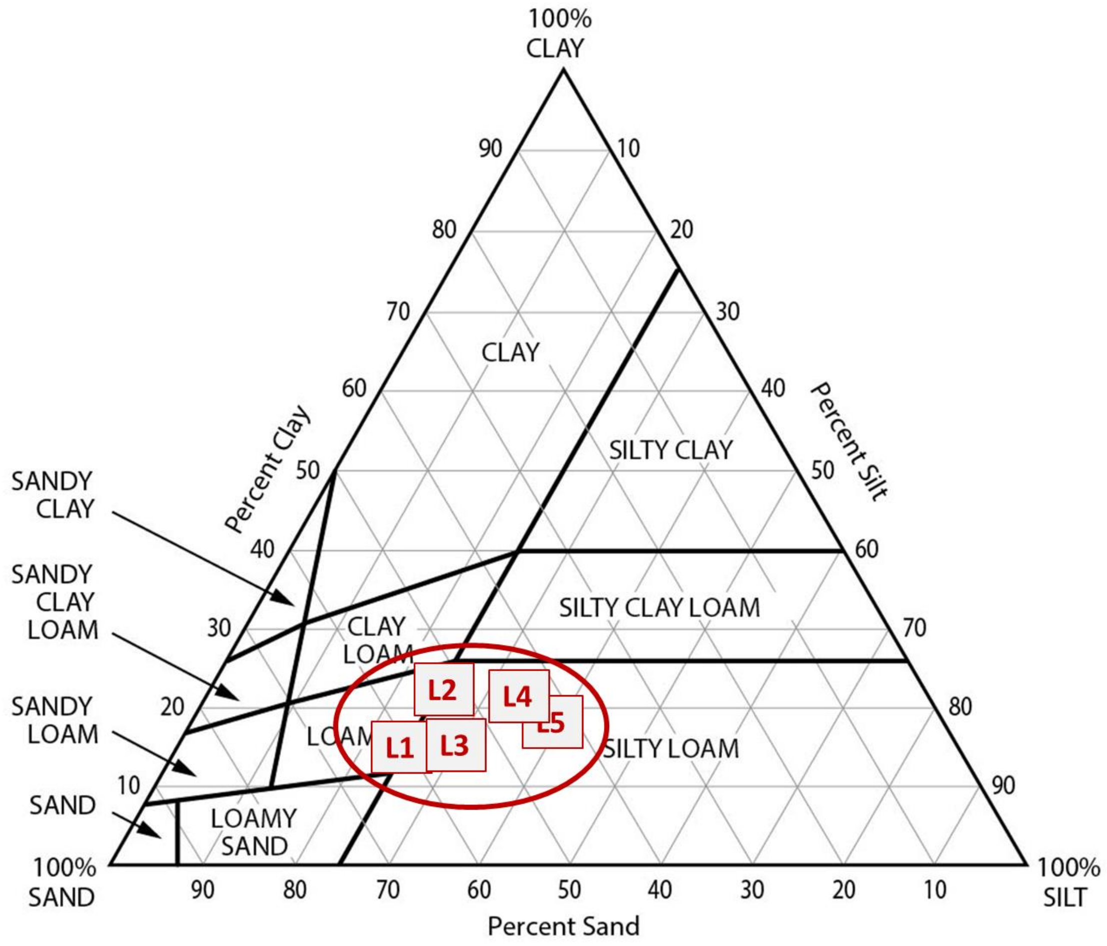
Secondly, the included soils have very similar texture properties as demonstrated in Table 36 which shows the catchment soils' texture proportions in the three key variables: clay, silt, and sand.

Table 36: Composition of soil-types in the Eden catchment

Soil-types	CLAY (%)	SILT (%)	Sand (%)	Proportion of Catchment (%)
L 1	15.6	22.5	61.9	50.80
L 2	21.5	26.8	51.8	0.03
L 3	12.7	30.1	57.2	15.16
L 4	22.7	33.2	44.1	33.24
L 5	23.3	30.7	46.0	0.76

These characteristics are further visually illustrated in Figure 32, which shows the catchment soils in the context of the soil texture triangle. Given that the difference in texture composition between the dominant soils 1 and 4 is 18, 11, and 7 percentage points for sand, silt, and clay, respectively, we would not expect to see large differences in pollution outcomes and marginal abatement costs due to soil-types. These findings further exacerbate the effects of the skewed distribution of soils within the catchment discussed above and reduce the scope for cost-effective spatially targeted policies.

Figure 32: Soil texture triangle (Source: Queensland Government, 2022)



3) *The dominance of grassland in catchment land allocation*

Finally, the catchment slopes detailed in Table 9 show some variation (ranges from 0% to 12.8%) which includes the threshold of 3% at which the pollution potential from tilled agricultural land would be expected to be significant, particularly for sediment pollution (Müller *et al.*, 2014). However, as shown in Table 23 and discussed in detail above (see p. 144), 78% of the catchment is covered by grassland, which provides perennial cover and reduces the sediment load potential from land. This context further explains the relatively small impact of spatial targeting set-aside by slope-type to reduce sediment pollution in the Eden catchment.

Precision agriculture

The implementation of PA has minimal impact on farmers' land use choices (see Appendix B, Figure 48 ,p. 196 and Figure 50, p. 198). Moreover, livestock numbers remain largely unchanged across the modelled scenarios. Table 37 demonstrates that as the PA efficiency factor increases (5% - 45%) artificial N fertiliser consumption in the catchment decreases (0.7% – 3.7%) and overall yield in the catchment increases (0.9% - 7.6%). The PA implementation increases productivity as increased farm outputs are generated with reduced inputs.

Table 37: Effect of Precision agriculture on results - total fertiliser consumption and average yield per hectares

PA efficiency factor scenario (%)	N fertiliser consumption relative to baseline (%)	Yield relative to baseline (%)
5	99.3	100.9
10	99.0	101.8
15	98.2	102.8
20	96.9	103.3
25	96.8	104.0
30	96.6	104.8
35	96.4	105.6
40	96.3	106.6
45	96.3	107.6

As mentioned in section 6.2, the environmental benefits of PA are around 2% to 20% pollution abatement across the pollutants for the increasing levels of assumed efficiency gains. These findings are driven by the reduced fertiliser consumption and the increased yield output. In addition to pollution abatement, PA provides further benefits such as increased data availability and the opportunity to take advantage of automation, which will be discussed in section 7.2.

Currently, the social cost associated with the implementation of PA for pollution abatement (between 4% and 3% of catchment gross margin) is higher than other modelled policy options. As outlined in section 4.7, PA costs are modelled as contractor costs in this analysis. This modelling approach could also represent joint machinery ownership agreements which are popular among smallholder farms, to reduce high capital investment costs and risks associated with PA. The cost of PA implementation will likely decrease going forward as technological advances further reduce capital costs. We expect these cost savings to be passed on directly to joint owners and indirectly to farmers purchasing contractor services through reduced service costs.

The synergies between PA and spatial targeting relate primarily to the catchment preconditions required for their successful implementation. In particular, the distribution of soils and hydrological connectivity outlined above, which limit the Eden catchment's suitability for spatially targeted policies, analogously apply to its suitability for PA implementation. PA requires heterogeneity in catchment characteristics to provide efficiency benefits through targeted input application (Schneider and Wagner, 2008). Notably, this analysis does not model efficiency factors as a function of catchment characteristics which may therefore overestimate the benefits of PA in the Eden catchment, which is further discussed in section 8.3.

This chapter has presented the results of the modelled policy scenarios by looking at the responses of individual pollutants before analysing the individual policy mechanisms. The following chapter synthesises the policy implications of the findings and contextualises them within the literature.

7. Discussion

This chapter discusses the results presented in chapter 6. Section 7.1 compares the modelled policies in a regulatory target matrix, and section 7.2 compares the results to previous findings in the literature reviewed in chapter 3.

7.1. Policy Outcomes

The cost-effectiveness of the modelled policies is ranked in Table 38 for the key pollutants (NRLOAD, PRLOAD, ZLOAD, and CFEM) in the Eden catchment at three levels of pollution abatement (20%, 40%, and maximum abatement potential).

Table 38: Results summary for key modelled policies and pollutants

		20% pollution reduction		40% pollution reduction		maximum pollution potential		
Modelled Policies	Pollutant	Policy rank by pollutant*	Social cost (%)	Policy rank by pollutant*	Social cost (%)	Policy rank by pollutant max abatement potential**	max abatement potential (%)	Social cost at max abatement (%)
Non-targeted set-aside	NRLOAD	2	2.0	4	9.0	4	25.0	9.0
	PRLOAD	4	2.0	4	9.0	5	29.0	9.0
	ZLOAD	3	2.0	4	9.0	4	33.0	9.0
	CFEM	2	2.0	2	6.0	1	56.0	14.5
Targeted set-aside	NRLOAD	2	2.0	5	10.0	6	21.0	10.0
	PRLOAD	4	2.0	5	10.0	6	21.0	10.0
	ZLOAD	2	1.5	5	9.5	5	23.0	9.5
	CFEM	1	1.0	6	14.5	5	32.0	14.5
N tax	NRLOAD	1	1.0	1	3.5	2	47.0	5.0
	PRLOAD	2	1.0	1	3.5	3	46.0	5.0
	ZLOAD	1	1.0	1	4.0	2	51.0	5.5
	CFEM	3	3.0	1	5.0	4	37.0	5.0
Mixed N tax & 2% set-aside	NRLOAD	2	2.0	2	6.0	1	48.0	7.0
	PRLOAD	3	1.5	2	5.0	2	48.0	6.5
	ZLOAD	2	1.5	2	6.0	3	37.0	6.0
	CFEM	1	1.0	3	7.0	3	38.0	7.0

		20% pollution reduction		40% pollution reduction		maximum pollution potential		
Modelled Policies	Pollutant	Policy rank by pollutant*	Social cost (%)	Policy rank by pollutant*	Social cost (%)	Policy rank by pollutant max abatement potential**	max abatement potential (%)	Social cost at max abatement (%)
Mixed N tax & 5% set-aside	NRLOAD	3	2.5	3	7.0	3	46.0	9.5
	PRLOAD	/	/	3	6.5	1	50.0	8.0
	ZLOAD	/	/	3	6.5	1	53.0	8.5
	CFEM	/	/	4	8.0	2	41.0	8.0
Precision Agriculture	NRLOAD	4	4.0	/	/	5	22.0	9.0
	PRLOAD	5	3.0	/	/	7	17.0	0.5
	ZLOAD	4	3.5	/	/	6	19.0	0.5
	CFEM	4	3.5	/	/	7	18.0	0.5
N & P tax	NRLOAD	1	1.0	4	9.0	5	22.0	9.0
	PRLOAD	1	0.5	2	5.0	4	40.0	9.5
	ZLOAD	2	1.5	2	6.0	3	37.0	6.0
	CFEM	1	1.0	5	9.0	6	31.0	9.0

*Note: *ranked by social cost in ascending order, **ranked by max abatement potential in descending order*

The groundwater variables (NGLOAD and PGLOAD see Figure 20 and Figure 22) are excluded for representation purposes in this overview, as surface water pollution is a more pressing issue in the Eden catchment than groundwater pollution (see section 6.1). As illustrated in Figure 19 – Figure 24, the intervals 0-20%, 20%-40% and maximum abatement potential represent points of more consistent policy behaviour and therefore represent appropriate summary points. The following section discusses these policy rankings and findings in more detail in the context of the literature explored in chapter 3.

7.2. Contextualising Results with Previous Findings

Firstly, as highlighted in section 6.2 and demonstrated in Table 38, an individual N tax and N&P tax provide the most cost-effective pollution abatement for low- to mid-level abatement targets. The outperformance of the incentive-based tax policies relative to the regulation-based set aside policies corresponds to findings in the previous literature discussed in section 3.2.1.

This result aligns with the reviewed economic expectation that higher degrees of freedom, which farmers have under incentive-based policies, facilitate lower abatement costs than those under regulation-based policies imposed by a government with imperfect information on farmers' cost curves (Shortle and Dunn, 1986). Kampas and White (2004) also find a N input tax to act as a cost-effective policy option, particularly when transaction costs are accounted for. Without transaction costs, they find an emission tax to be the most cost-effective policy. As outlined above (see section 4.2, p. 73), transaction costs were not explicitly accounted for in the modelling of this thesis in favour of novel biophysical details (see Table 39, p. 157), spatial targeting, and PA. However, the significance of transaction costs did inform the selection of modelled policies and motivated the exclusion of emission taxes (Aftab, Hanley and Baiocchi, 2017, p. 15). Therefore, this thesis also supports the cost-effectiveness ordering of input taxation before set-aside as found by Kampas and White (2004).

Further, demand for N fertiliser is found to be very price inelastic with 800% N tax achieving a 10% reduction in N consumption (see section 6.2). Jayet and Petsakos (2013) generally also find N fertiliser use in France to be relatively price inelastic; however, their results suggest a higher elasticity (100% tax leading to 15%-20% reduction in nitrate emissions at the national to regional level) than the results presented in this thesis. The presented results closely align with Schmidt *et al.* 's (2017) more recent agent-based analysis of N surplus in Switzerland which found an 800% N tax to reduce N surplus by 10%. The authors suggest that the low response to the N tax may be partially explained by the large proportion of dairy and livestock farming in the Swiss agricultural sector which aligns with the described Eden catchment characteristics (see section 5.4.2, p. 117). As Schmidt *et al.* (2017) suggest, the higher gross margins of livestock farms relative to cereal farms lead to less elastic N fertiliser demand.

In addition to N demand elasticity, this thesis' detailed analysis of the N tax response finds that farms shift from higher-input crops to lower-input crops. In the process, as illustrated in section 6.3, they initially compensate for their lost yield by increasing production on the lower-input crops at the intensive margin (increasing fertiliser application) as well as the extensive margin (increasing land allocation). This outcome aligns with Jayet and Petsakos' (2013) findings for a livestock intensive catchment (Basse-Normandie, France). They suggest that an N tax leads to some increases at the extensive margin for permanent meadows (relatively lower-input land allocation) as well as some increases at the intensive margin of these meadows (higher number of livestock on the meadows).

Secondly, mixed policy instruments generally show the highest maximum abatement potential but are not cost-effective at lower abatement levels (see Table 38). This result mirrors Aftab, Hanley and Baiocchi's (2010) finding that mixed instruments' relative cost-effectiveness improves at higher regulatory targets in the Scottish West Peffer catchment. Their results further suggest that single instruments outperform mixed instruments in average weather-years. These conclusions closely align with the findings of this thesis based on average weather-years. Bourgeois, Ben Fradj and Jayet (2014) also find that mixed-policy instruments improve cost-effectiveness for N water pollution abatement in France. The authors consider a N tax and low input crop subsidy instead of the set-aside requirements evaluated above. However, their results also suggest that mixed instruments are not more cost-effective in reducing gaseous (nitrous oxide and ammonia) pollution abatement which is mirrored in the results for carbon emissions in this thesis (see Figure 24, p. 137).

Thirdly, set-aside is generally not found to be cost-effective across the modelled pollutants (see Table 38, p. 151). As mentioned above, this finding corresponds to the economic intuition that command-and-control policies are outperformed by incentive-based policies. Moreover, the observed general decrease in set-aside cost-effectiveness at higher regulatory targets aligns with Kampas and White's (2004) finding that at higher reliability levels set-aside becomes the least cost-effective policy instrument. As discussed in section 6.3, on set-aside land output (yield) falls to zero rather than only being reduced due to a less intensive application of inputs in the alternative modelled policies. As regulatory targets increase, farmers have less choice as to which land to take out of production which increases the policies' social cost.

As discussed in section 6.3, set-aside does not lead to increases at the intensive margin (i.e., farmers are not increasing fertiliser application to compensate for yield losses due to set-aside). However, they do shift towards FYM crops due to limited FYM storage. In contrast, Chakir and Thomas' (2022) recent econometric work on the intensive margin effects of set-aside suggests that as farmers increase set-aside in response to a rise in set-aside subsidy, their fertiliser consumption does increase to compensate for reduced output. In the revenue neutral policy setting model of this thesis, this income effect is not observed as no set-aside subsidy is modelled. Moreover, given the constraints on FYM storage, the share of FYM crops increases in line with set-aside requirements as farms compensate for land taken out of production to empty their manure stores (see p. 143) which may outweigh potential income and substitution effects.

As demonstrated in Table 38 (see p. 151), set-aside does not achieve the highest sediment abatement potential amongst the modelled policies. As outlined in sections 6.2 and 6.3, this result does not align with the expectation that set-aside achieves the highest sediment abatement potential due to its more direct theoretical link to sediment pollution than other modelled policies such as fertiliser taxation. However, Hodge *et al.*'s (2006) report on set-aside options for English agricultural policy suggest that the impact of set-aside measures are highly dependent on individual catchment characteristics. This statement is supported by

Secchi *et al.*'s (2007) modelling work on the cost-effectiveness of an agricultural water pollution abatement policy combination including set-aside for 13 watersheds in Iowa, USA. They find sediment abatement varies significantly between watersheds (6% - 65%) driven by differences in size and environmental conditions of the watersheds. As further outlined in section 6.3 for this thesis the relatively low sediment abatement potential of set-aside policy may be explained by the 78% grassland cover of the assessed Eden catchment.

Spatially targeted set-aside is slightly more cost-effective than uniformly applied set-aside at lower levels; however, the cost-effectiveness ranking inverts at high regulatory targets (see Table 38, p. 151). In the context of irrigated corn production in the Ebro basin of the Iberian Peninsula, Martínez and Albiac (2006) also find that spatially differentiated pollution control policies provide a small welfare improvement compared to a homogeneously applied standard. Notably, their work differentiates between different soil-types as opposed to the slope-targeted policies reported in this thesis. In contrast to the soil-types included in this thesis (see p. 147), the soil-types included in Martínez and Albiac's (2006) analysis show significant differences in key soil characteristics (e.g.: 40 percentage point range in irrigation efficiency level and up to 267% variation in water-holding capacity (m3/ha) (Martínez and Albiac, 2006, p. 525)). Hasler *et al.* (2019) find that spatially targeting NPS N pollution control policies according to heterogeneous hydrological factors (specifically N retention from the root zone to the coast) significantly reduces abatement costs in the Danish Limfjorden catchment. The authors stress that the Limfjorden catchment is characterised by high variation in N retention (spanning from 0 – 100% with a 65% average) and that, in line with the findings of this thesis, spatial targeting has a smaller effect on catchments with lower heterogeneity levels in hydrological connectivity. These findings support the discussion in section 6.3, highlighting that the Eden catchment's limited heterogeneity in the soil-types and hydrological connectivity levels explain why spatially targeted policies by soils and hydrological connectivity were not found to be cost-effective. They further emphasise the contribution of the novel biophysical details included in this thesis' analysis of spatially targeted policies (see Table 39, p. 157 which compares this model with to the previous literature). These details facilitated identifying the preconditions necessary for cost-effectively spatial targeting NPS pollution control policies.

PA shows diminishing returns to abatement and potential for pollution abatement in conjunction with wider policy goals but is not cost-effective on its own (see section 6.3, p. 149). In contrast, Schieffer and Dillon's (2015) simulation of VRNA shows an increased N consumption and carbon footprint due to higher average N application to increase yields and net returns. Their one farm model focusses on cereal production in western Kentucky and includes a limited representation of biophysical conditions (e.g.: two crop rotations, N application as a proxy for N runoff). The model presented in this thesis extends their work as a catchment-scale analysis of PA in an economic model with a novel biophysical detail in the literature (see Table 39, p. 157). The presented results of this thesis which include both increased yield and reduced fertiliser consumption combine the two effects that Heege (2013) highlights as the key VRNA impacts on N use efficiency. However, the presented results also demonstrate that these efficiency improvements of PA do not outweigh the costs associated with them. These findings may be partially explained by the Eden catchment characteristics highlighted in section 6.3 which include its lack of heterogeneity and dominance of grassland. It may be further explained by the fact that farm size is assumed constant in this analysis. Schneider and Wagner's (2008) findings in the context of cereal crop cultivation suggest that VRNA costs per hectare fall as farm size increases. Moreover, as mentioned in section 6.3, this thesis has not considered additional non-monetised benefits associated with PA application. Schneider and Wagner's (2008) survey results suggest these non-monetised benefits of PA may be significant to farmers including time savings, improved information for management decisions, and easier documentation. Quantifying such non-monetised benefits of PA in cost-effectiveness analysis and investigating differences between farm sizes suggests interesting starting points for future research (see section 8.4).

Finally, different crop rotations and positioning in crop rotations lead to significantly different average yield outcomes (see p. 111). These results align with the agronomic findings of Florio and Nosetto (2022) who find that crop rotations significantly impact water-table depth and consequently yields in the south of Córdoba Province (Argentina). Their hydrologically focussed modelling suggests that intense crop rotations can result in water table levels deeper than the optimum depth zone and thereby reduce crop yields. Götze, *et al.*'s (2017) agronomic experimental field trials on crop rotations' impacts on sugar beet yields in Etzdorf (Saxony-Anhalt, Germany) further support their significance in yield outcomes. They find that crop rotations significantly impact the technological yield quality of sugar beet (sugar content and potassium content). Additionally, they find white sugar yield increases with cropping intervals of crop rotations, although they were unable to statistically verify this result. Therefore, both agronomic modelling and experimental studies support the contribution of this thesis demonstrating the importance of detailed crop rotation modelling in biophysical-economic models. Table 39 summarises the key model features of the literature reviewed in this thesis and demonstrates the novel extent of the biophysical details included in this work. Notably, to the best of my knowledge the number of crop rotations included has only been achieved once by Aftab, Hanley and Baiocchi (2017), however, in the context of a smaller number crops, weather-years, as well as soil- and slope-types.

Table 39: Key biophysical model feature comparison of reviewed literature

PAPER	NO. OF CROPS	NO. OF CROP ROTATIONS	NO. OF SOIL-TYPES	NO. OF SLOPE-TYPES	FARM TYPES	HYDROLOGICAL CONNECTIVITY	WEATHER-YEARS	STUDY LOCATION	KEY POLLUTANTS
Aftab, Hanley & Baiocchi (2010)	4	u.s.*	3	u.s.*	4	Not explicit but hydrological model *	9	West Peffer Catchment (Eastern Scotland)	▪ Nitrate
Aftab, Hanley & Baiocchi (2017)	8	34 (M)* 33 (B)*	3	u.s.*	5 (M)* 7 (B) *	Not explicit but hydrological model *	10	Motray Catchment (M)* Brothock Catchment (B)* (Scotland)	▪ Nitrogen
Alpizar *et al.* (2004)	experimental								
Bourgeois, Ben Fradj & Jayet (2014)	14	u.s.*	u.s.*	u.s.*	157	Not explicit but hydrological model *	u.s.*	France	▪ Nitrate ▪ Ammonia ▪ Nitrous Oxid
Cabe & Herriges (1992)	theoretical								
Chakir & Thomas (2022)	Econometric estimation							Department of Meuse (France)	▪ Elasticity of input demand ▪ Intensity of input use/ land unit
Claassen & Horan (2001)	1	u.s.*	4	u.s.*	u.s.*	u.s.*	u.s.*	North Central USA	▪ Nitrogen ▪ Phosphorus
Florio & Nosetto (2022)	4	4	4	3	1	Hydro-economic model	31	South of Cordoba Province (Argentina)	▪ Water table levels

PAPER	NO. OF CROPS	NO. OF CROP ROTATIONS	NO. OF SOIL-TYPES	NO. OF SLOPE-TYPES	FARM TYPES	HYDROLOGICAL CONNECTIVITY	WEATHER-YEARS	STUDY LOCATION	KEY POLLUTANTS
Griffin & Bromley (1982)	theoretical								
Hasler *et al.* (2019)	12	u.s.*	2	u.s.*	90 Sub-catchments	Monitoring and modelled data	u.s.*	Limfjorden catchment (Denmark)	▪ Nitrogen
Hasler *et al.* (2014)	9	u.s.*	u.s.*	u.s.*	22 (regions)	Hydro-economic model	11	Drainage basin of the Baltic Sea	▪ Nitrogen ▪ Phosphorus
Helfand & House (1995)	1	u.s.*	2	u.s.*	1	Not explicit but hydrological model *	1	Salinas Valley/ California (USA)	▪ Nitrate
Helin *et al.* (2013)	3	u.s.*	3	6	1	Not explicit but hydrological model *	u.s.*	Middle Lepsämänjoki Sub -Catchment (Southern Finland)	▪ Nitrogen ▪ Phosphorus ▪ Biodiversity
Jayet & Petsakos (2013)	32	u.s.*	5	u.s.*	14	u.s.*	1	France	▪ Nitrogen
Kampas & White (2004)	u.s.*	u.s.*	u.s.*	u.s.*	1	Not explicit but hydrological model *	u.s.*	Kennet Catchment (South West England)	▪ Nitrate
Khanna, Isik & Zilberman (2002)	1	u.s.*	Beta Distribution (3, 3)		u.s.*	u.s.*	u.s.*	San Joaquin Valley/ California (USA)	▪ Polluted Drainage
Larson, Helfand & House (1996)	1	u.s.*	u.s.*	u.s.*	1	u.s.*	1	Salinas Valley/ California (USA)	▪ Nitrate
Lungarska & Jayet (2018)	9	u.s.*	u.s.*	u.s.*	6 (regions)	u.s.*	u.s.*	France	▪ Surface water Nitrate concentration
MartInez & Albiac (2004)	6	u.s.*	1	u.s.*	u.s.*	Not explicit but nitrogen dynamics in soil	u.s.*	Ebro basin (Iberian Peninsula)	▪ Nitrate

PAPER	NO. OF CROPS	NO. OF CROP ROTATIONS	NO. OF SOIL-TYPES	NO. OF SLOPE-TYPES	FARM TYPES	HYDROLOGICAL CONNECTIVITY	WEATHER-YEARS	STUDY LOCATION	KEY POLLUTANTS
MartInez & Albiac (2006)	1	u.s.*	3	u.s.*	u.s.*	Not explicit but hydrological model *	1	Ebro Basin (Iberian Peninsula)	▪ Nitrate
Meran & Schwalbe (1987)	theoretical								
Ribaudo, Osborn & Konyar (1994)	8	u.s.*	u.s.*	u.s.*	10 (regions)	Not explicit but hydrological model *	u.s.*	USA	▪ Nitrogen ▪ Herbicides ▪ Insecticides
Schieffer & Dillon (2015)	2	2	2	u.s.*	1	u.s.*	30	Western Kentucky (USA)	▪ Nitrogen Run off ▪ Carbon emissions
Schmidt *et al.* (2017)	Agent based model							Switzerland	▪ Nitrogen Farm Gate Balance
Secchi et al. (2007)	u.s.*	u.s.*	u.s.*	7	13	Not explicit but hydrological model *	18	Iowa (USA)	▪ Sediment ▪ Total Nitrogen ▪ Total Phosphorus
Sergerson (1988)	theoretical								
Shortle & Dunn (1986)	theoretical								
Spraggon (2002)	experimental								
Vatn *et al.* (1997)	u.s.*	u.s.*	3	3	4	Not explicit but hydrological model *	20	South Eastern Norway	▪ Nitrogen, ▪ Ammonia, ▪ Phosphorus ▪ Sediment
Wang & Baerenklau (2015)	5	6	9	u.s.*	1	Not explicit but hydrological model *	u.s.*	San Joaquin Valley/ California (USA)	▪ Nitrogen

PAPER	NO. OF CROPS	NO. OF CROP ROTATIONS	NO. OF SOIL-TYPES	NO. OF SLOPE-TYPES	FARM TYPES	HYDROLOGICAL CONNECTIVITY	WEATHER-YEARS	STUDY LOCATION	KEY POLLUTANTS
Xabadia, Goetz, & Zilberman (2008)	Theoretical with numerical example							San Joaquin Valley/ California (USA)	▪ Water logging
Xepapadeas (1991)	theoretical								
This thesis	25	24 (short term) 10 (long term)	5	4	6	10	45	Eden Catchment Northwest England	▪ ZLOAD ▪ NRLOAD ▪ NGLOAD ▪ PRLOAD ▪ PGLOAD ▪ CFEM
*Notes: **(B)***: Brothock Catchment; ***u.s.***: *unspecified – details not explicitly disclosed in paper;* ***Not explicit but hydrological model***: *hydrological connectivity not explicit variable index but hydrological factors included in modelling;* ***(M)***: *Motray Catchment*									

This chapter has summarised the presented results (section 7.1) and discussed the presented results in the context of the reviewed literature (section 7.2). The following chapter summarises each chapter, draws out the key policy recommendations, discusses the thesis' limitations, and highlights areas for future research.

8. Conclusion

This chapter concludes this thesis by firstly outlining the focus points of each chapter (section 8.1) and subsequently highlighting the key policy recommendations drawn from this work (section 8.2). Moreover, the limitations of the thesis are discussed in section 8.3 and points for future research are described in section 8.4.

8.1. Summary

This thesis has investigated the cost-effectiveness of agricultural NPS pollution control policies through a biophysical-economic model for the Eden catchment (North-West England). Chapter 1 provides the context and motivation of this research, namely (i) the current once-in-a-generation reform of agricultural policy in the UK, (ii) the continuously pressing issue of agricultural NPS pollution in the UK, and (iii) the recent technological progress in agriculture expanding the feasibility set of spatially targeted agri-environmental policies and potential use of PA which have not previously been addressed in the literature. Further the chapter outlines the key research objective. Firstly, incentive, regulation-based, and mixed policy instruments are simulated and compared to provide up-to-date policy recommendations (see section 8.2, p. 163). PA and spatially targeted policies are analysed in the novel context of a catchment-scale detailed biophysical-economic model (including hydrological connectivity, crop rotations, and extensive observed weather data). The results highlight the necessary precondition of sufficient catchment heterogeneity in the key biophysical variables (soils, slopes, and hydrological connectivity) to cost-effectively employ both spatially targeted policies and PA (see section 6.3, p. 146). Moreover, the sensitivity analysis suggests that extensive observed weather data is significant for NPS pollution due to years with exceptionally high pollution.

Chapter 2 summarises and describes the developments of agri-environmental policy in the UK from UK leadership on agri-environmental policy issues in the 1980s (see section 2.1) through increasing European influence through the Nitrates Directive and WFD (sections 2.4 and 2.5 respectively) and direct payments (sections 2.8 and 2.9) towards the current post-Brexit UK agri-environmental policies (sections 2.11 and 2.12).

Given the context of UK agri-environmental policy set out in the previous chapter, chapter 3 reviews the economic literature on NPS control policies. Following the definition of NPS externalities (section 3.1), previous evidence on different types of policy interventions is analysed in section 3.2. Economic research exploring application methods of agri-environmental policies are reviewed in section 3.3 and existing work on agricultural technology including PA is explored in section 3.4.

Informed by the review of the existing literature, chapter 4 outlines the methodological details of the biophysical-economic model. The chapter includes the chosen modelling approach of a non-linear optimisation model, the theoretical economic model description (sections 4.1 and 4.2), and the model structure (section 4.3). Moreover, section 4.4 describes the simulation and modelling details of the yield and pollution data using the EPIC model, while section 4.5 discusses the production functions' functional form choice of the Mitscherlich-Baule functional form for yield and polynomial functional form for the pollution functions. Finally, the framework accounting for hydrology using SCIMAP is presented in section 4.6 and the approach to modelling PA through a N efficiency factor is explained in section 4.7.

The model described in the previous chapter is validated in chapter 5. The data used is presented in sections 5.2 and 5.3 relating to the simulated biophysical and economic data collated from various published sources. The model's baseline outputs are compared to observed outcomes in section 5.4 which finds that the proportions of crop land allocation, output, and pollution outcomes generally closely match the observed outcomes of the Eden catchment and expectations from the literature.

Subsequently the scenario model results are reviewed in chapter 6. Section 6.2 presents and discusses the results of the scenario policy analysis focussing on the modelled impacts on the six key investigated pollutants (NRLOAD Figure 19, NGLOAD Figure 20, PRLAOD Figure 21, PGLAOD Figure 22, ZLAOD Figure 23, and CFEM Figure 24). Section 6.3 provides a more detailed analysis of the underlying policy mechanisms driving the key results of the seven modelled policies. These include the land use changes and fertiliser crop share changes in response to the modelled policies. Moreover, the Eden catchment's limited heterogeneity in soil compositions and hydrological connectivity, as well as grassland as its main land cover limit the effectiveness of spatial targeting and PA efficiency.

Chapter 7 initially provides a succinct summary of the policy pollution outcomes in section 7.1 (see Table 38). Section 7.2 then provides a discussion of the previous chapter's key results in the context of the literature reviewed in chapter 3. This discussion is summarised in the following section below to provide the context of the policy recommendations of this thesis.

8.2. Policy Recommendations

This section draws out the policy recommendations from the results discussion of section 7.2.

Firstly, the results presented in section 6.2 suggest that across the analysed pollutants, the modelled policies show high levels of cost-effectiveness for mid – lower regulatory abatement targets. Specifically, up to around 20% of abatement is achieved at a maximum social cost of around 5% of catchment gross margin. These results provide a general reference point for policymakers when balancing the ambition of environmental abatement with political considerations of farmers' economic position.

As outlined in section 7.2, the finding that a combined N&P tax and an individual N tax provide the most cost-effective abatement for mid – low level regulatory targets aligns with the economic intuition concerning incentive- and regulation-based controls and is generally supported by the literature (Shortle and Dunn, 1986; Kampas and White, 2004). This result is surprising given the model also demonstrates that demand for N fertiliser is highly inelastic - further in line with previous work (Schmidt *et al.*, 2017). Policymakers interested in the economically cost-effective option of fertiliser input taxation should therefore be aware of the high levels of revenue neutral N tax required to achieve behavioural change in farmers (800% tax leads to 10% reduction in N consumption). In the revenue neutral context of this analysis the associated social costs are only around 0.5% of catchment gross margin. However, in real world applications perceptions of taxation levels as high as 800% may have strategic implications and warrant political consideration. Moreover, the analysis illustrated in section 6.3 demonstrates that as farmers shift from higher-input to lower-input crops in response to the N tax, they initially compensate for lost yield by increasing production on the lower-input crops at both the intensive and extensive margins. The resulting slight reversal of the N taxes pollution abatement trend should therefore be considered when implementing an N tax to avoid unintended consequences.

As outlined in section 7.2, an individual set-aside policy is not found to be cost-effective particularly at higher regulatory targets, corresponding to the reviewed literature (Kampas and White, 2004). Further, a set-aside policy is not found to provide the highest abatement potential of the modelled policies which may be explained by the individual Eden catchment characteristics given the variable results of set-aside effectiveness in the literature (see section 7.2; Hodge *et al.*, 2006; Secchi *et al.*, 2007). The model results contrast with Chakir and Thomas' (2022) findings, as increasing levels of set-aside are not associated with increasing fertiliser intensity (see section 7.2). However, given the FYM storage constraints that farmers face, they substitute non-FYM crops for FYM crops as set-aside increases. These results suggest that set-aside may not be the economically preferred policy option for the Eden catchment. However, if set-aside is chosen as a policy instrument, unintended consequences - such as increased organic fertilisation intensity on cultivated fields in livestock heavy catchments as the Eden - should be considered. To improve the cost-effectiveness of set-aside, the results suggest that policymakers may wish to combine set-aside to a mixed policy instrument with an N tax particularly at high regulatory targets (Aftab, Hanley and Baiocchi, 2010). Mixed instruments also achieve the highest maximum pollution abetment potential across the analysed pollutants, excluding gaseous CFEM (Bourgeois, Ben Fradj and Jayet, 2014).

Previously, transaction costs of spatially targeted policies were deemed significant and potentially too high for successful real-world implementation (Lintner and Weersink, 1999). However, given technological progress, improved mapping systems and remote sensing, transaction costs of spatially targeted policies have fallen notably and are unlikely to present excessive challenges to successful real-world implementation (Gebbers and Adamchuk, 2010).

Spatially targeted policies according to slope-types are found to provide only insignificant cost-effectiveness improvements with respect to uniformly applied policies, while targeting according to soil-types and hydrological connectivity levels provides no cost-effectiveness benefits and has not been reported. As discussed in section 7.2, this finding can be explained by Eden’s specific catchment characteristics (low level of heterogeneity and significant grassland cover) which the literature supports as a key influence on the cost-effectiveness of spatially targeted policies (Martínez and Albiac, 2006; Hasler *et al.*, 2019). These results highlight the importance of considering catchments’ detailed biophysical characteristics and ensuring they are sufficiently heterogeneous to ensure spatial targeting can be a cost-effective NPS control tool.

PA is shown to lead to increased productivity though reduced fertiliser consumption and increased yields at the catchment scale. Both mechanism are recognised as key impacts of VNRA in the literature based on experimental field evidence (Heege, 2013) as discussed in section 7.2. However, this thesis does not find PA alone to be a cost-effective tool for NPS control as costs of implementation outweigh the achieved productivity benefits. These results may be explained by a number of factors related to the lack of heterogeneity in the Eden catchment and significant grassland cover (78%) outlined above for the spatial targeting results. In catchments which meet the pre-conditions of sufficient heterogeneity, PA therefore may be a potential tool to support NPS pollution control efforts. Moreover, additional non-monetised benefits of PA highlighted in the literature (e.g., time savings, improved data for management decisions, and simplified documentation (Schneider and Wagner, 2008)) have not been quantified in this analysis. Future work is needed to quantify these benefits and accurately assess the economic rationale for investments in PA (see section 8.4). However, the presented results nonetheless suggest policymakers could consider support for PA (in suitable catchments) to promote wider strategic goals given that the private case for farmer investment in PA still appears to be relatively weak while productivity gains and environmental benefits appear promising.

Finally, this thesis has included a novel level of biophysical detail in its modelling (see Table 39). Crop rotations are found to lead to significantly different average yield outcomes (see p. 111) which highlights the need for bioeconomic models including crop rotations to evaluate NPS pollution control policies. The importance of detailed biophysical data in this research is further strengthened by the significance of heterogeneity (e.g., soil, slope, hydrological connectivity types, and weather data) for success in using spatial targeting and PA discussed above. Policy evaluations including targeted policy options should therefore be based on state-of-the-art details in biophysical-economic modelling. The following section explores the limitations of this thesis.

8.3. Limitations

The following describes the key limiting aspects of this thesis which need to be considered when interpreting the results.

Firstly, as discussed in section 6.3, a limitation of this work is the pollution function assumption that sediment pollution is inversely related to N application. Although the assumption is theoretically meaningful given biological processes (see Table 14, p. 88), it produces unrealistic pollution responses to agri-environmental policies. For example, we would expect nil input set-aside to entail lower sediment pollution relative to grassland due to the reduced tillage operations compared to grassland. Moreover, potato crops which have a relatively low N application level in this model (see 5.4.4, p. 124) would be expected to have high sediment values due to the furrows and the limited field coverage they provide during the year. The assumed relationship between N application and sediment pollution may, therefore, limit the possible comparison between set-aside's effect on sediment pollution and the effect of alternative crops.

Secondly, the efficiency factors assumed in the modelling of VRNA are independent of the crop, soil-, and slope-type as well as the heterogeneity of the catchment and weather patterns within the catchment. Realistically, PA technology generally, and VRNA in particular, are highly dependent on these variables. Although it is a meaningful starting point for PA in biophysical-economic modelling, VRNA's more simplistic representation in this thesis may not leverage the extensive biophysical modelling detail included with respect to VRNA analysis. As the current quantified evidence on the interactions between VRNA and particular crop-, soil-, slope-, and hydrological connectivity-types as well as weather variations across field parcels for grassland is still in its infancy, it has not been possible to include more precise assumptions for the Eden catchment at this stage (see section 8.4 for further discussion).

Finally, as outlined above (see section 4.2, p. 73) transaction costs were only considered qualitatively and not explicitly accounted for in favour of the included novel biophysical details, spatial targeting, and PA. Their qualitative consideration informed the modelled policy selection and motivated the exclusion of emission targeting policies following the previous literature (Aftab, Hanley and Baiocchi, 2017, p. 15). Transaction and administration costs significantly impact the cost-effectiveness of policies and influence policymakers' choices. Therefore, although beyond the scope of this thesis, a quantitative appraisal of transaction costs and emission-based policies would give a more holistic picture of policymakers' trade-offs. How the listed limitations could inform future research is further explored in the following section.

8.4. Future Works

This section builds on the discussion of section 8.3 and draws out future areas of research from the presented thesis.

Firstly, as computing power continues to improve, future work could include **additional policy modelling** alongside the extensive biophysical detail included in this thesis. Analysing the emission-based policies discussed above (see section 8.3) would involve an amended model structure. Pollution functions would need to be included inside the optimisation requiring simple functional forms and a significantly larger NLP model. Alongside included transaction costs, this model extension could provide valuable and more complete quantitative insights into policymakers' policy choice sets. Moreover, as the quantitative evidence on the interactions between VRNA and particular geographic features improves, additional policy modelling could include a mixed instrument of PA application and NPS control policies. This work could build on Eskeland and Devarajan's (1995) demonstration of the benefits of combining taxes with automobile regulation to approximate emission tax outcomes whilst avoiding associated monitoring costs. The cited example is transferrable to agricultural nutrient pollution and suggests that combining an input tax with a technological requirement of less-polluting (precision) technology represents a cost-effective alternative to an emission tax with its significant monitoring costs. Using a catchment with the necessary pre-conditions for successful PA application, extending Schieffer and Dillon's (2015) one-farm model of PA combined with an N tax to a more-detailed catchment-scale biophysical model would be a particularly interesting future line of inquiry. Moreover, as outlined above, subsidies were not investigated, given the scope of this thesis. However, modelling the cost-effectiveness of a grant or subsidy for PA technologies in the context of sufficiently heterogeneous catchments could provide important insights given policymaker's interest (BMEL, 2022; Rural Payments Agency, 2023).

In addition to policy modelling, further work is needed on **PA and biophysical interactions modelling**. As PA development and adoption increases, improved data availability will facilitate detailed PA modelling assumptions. Following the discussion of section 8.2 (see p. 164), concrete further work building on the presented analysis should consider **assumptions regarding PA costs and PA's non-monetised benefits.** As explained above, VRNA costs per hectare fall are inversely related to farm size (Schneider and Wagner, 2008). Future work with a wider scope should consider including farm size heterogeneity and investigate its impact on PA cost-effectiveness. As also mentioned above, PA includes numerous non-monetised benefits such as labour savings, inputs reduction, and human capital improvements through improved skills (Sonntag *et al.*, 2022). Quantifying these benefits to provide a more comprehensive assessment of the cost-effectiveness of PA as a tool for both NPS pollution control and productivity enhancement would provide valuable insights for policymakers.

On the biophysical side, **further work is required on the PA efficiency factor and interactions between hydrology and yield outcomes**. Further exploration of more-differentiated PA efficiency factor modelling could provide important insights on PA interactions with biophysical characteristics once the state of agri-environmental evidence has sufficiently progressed (section 8.3). The presented analysis' yield functions assume homogenous weather and rainfall across the catchment and its fields. In reality, we expect rainfall to vary between land parcels so as to introduce further yield heterogeneity. Additionally, given currently uncertain data on the interaction of PA efficiency coefficients with crop-, soil-, slope-, and hydrological connectivity-type, the PA efficiency coefficient is kept constant across the catchment. Further work with more-advanced PA data available could investigate modelling PA performance in a heterogeneous weather catchment and a PA efficiency factor dependent on the level of heterogeneity in crop, soil, slope, and hydrological connectivity types within the catchment's subunits. Finally, further work could extend this thesis by building on the work of Florio &

Nosetto (2022) regarding the interactions between hydrology, crop rotations and topography. Adding an explicit hydrological connectivity interaction in yield functions within the context of the detailed biophysical modelling of this thesis could provide further insights into site-specific NPS pollution control management.

Appendix A

Table 40: Number of Countryside Stewardship Grants available by grant type, land use, and tier

Grant type	No of grants	Land use	No of grants	Tiers, offers & standalone items	No of grants
Option	107	Arable land	36	Higher Tier	240
Capital item	115	Boundaries	17	Mid Tier	146
Supplement	22	Coast	10	Offer: Arable	11
		Educational access	10	Offer: lowland grazing	7
		Flood risk	38	Offer: Mixed farming	14
		Grassland	51	Offer: Upland	8
		Historic environment	15	Standalone capital items	24
		Livestock management	22		
		Organic land	16		
		Priority habitats	92		
		Trees (non-woodland)	22		
		Uplands	227		
		Vegetation control	9		
		Water quality	78		
		Pollinators	24		
		Woodland	27		
Based on information from : (RPA and Natural England, 2019)					

Table 41: Livestock annual forage requirements

Livestock	Grazing forage requirement in DMt/ animal unit	Hay forage requirement in FWt/ animal unit	Silage forage requirement in FWt/ animal unit	Page reference in SAC Consulting (2018)
Dairy	1.83	-	10.97	p. 133
Sheep 1 (100 ewes)	56.67	2.50	-	p. 181
Sheep 2 (100 ewes)	-	2.00	-	p. 179
Suckler	1.67	-	5.62	p. 151
Finish 1	1.61	-	-	p. 163
Finish 2	2.32	-	7.27	p. 171

Table 42: Abbreviations for all crop names in the simulated rotations

Eden Crop Abbreviation	Crop Name
FBEET	Fodder Beet
GRAZE 2	Grazing Grass (2 fertiliser applications)
GRAZE 3	Grazing Grass (3 fertiliser applications)
GRAZE 4	Grazing Grass (4 fertiliser applications)
GRAZE 6	Grazing Grass (6 fertiliser applications)
GRAZE LFA	Grazing Grass on LFA
HAY LFA	Hay on LFA
HAY2	Hay (2 cuts)
MAIZE(WC)	Whole-cropped Maize
MISC*	Miscanthus
POT	Potatoes
SBAR	Spring Barley
SBEANS†	Spring Beans
SIL LFA	Silage on LFA
SIL1	Silage (1 cut)
SIL2	Silage (2 cuts)
SIL3	Silage (3 cuts)
SIL4	Silage (4 cuts)
SOATS	Spring Oats
STURNIP (JULY)*	July Stubble Turnips
STURNIP (SPRING)*	Spring Stubble Turnips
WBAR	Winter Barley
WOSR	Winter Oil Seed Rape
WW	Winter Wheat
WW(WC)	Whole-cropped Winter Wheat
*Note: *Crops which were simulated in the EPIC crop rotations but not featured in the final model (rare crops in Eden or leguminous crops with no fertiliser input)*	

Table 43: Crop rotations No. 1 - 12

Year in Rotation	Rotation Number											
	1	2	3	4	5	6	7	8	9	10	11	12
1	SBAR	WBAR	SBAR	WBAR	SBAR	WW	WW	WW	MAIZE (WC)	WW(WC)	WW(WC)	WW
2	HAY LFA RESEED	SIL LFA RESEED	GRAZE LFA RESEED	WBAR	SOATS	WBAR	WBAR	WBAR	MAIZE (WC)	WBAR	WBAR	SBAR
3	HAY LFA	SIL LFA	GRAZE LFA	SIL 1 RESEED	HAY 2 RESEED	STURNIP (SPRING)	POT	SBAR	SIL3 RESEED	WOSR	STURNIP (SPRING)	FBEET
4	HAY LFA	SIL LFA	GRAZE LFA	SIL 1	HAY 2	SBAR	SBAR	GRAZE 3 RESEED	SIL 3	WBAR	WBAR	SIL3 RESEED
5	HAY LFA	SIL LFA	GRAZE LFA	SIL 1	HAY 2	GRAZE 2 RESEED	SIL3 RESEED	GRAZE 3	SIL 3 KILL	GRAZE 4 RESEED	GRAZE 2 RESEED	SIL 3
6	HAY LFA	SIL LFA	GRAZE LFA	SIL 1 KILL	HAY 2 KILL	GRAZE 2	SIL 3	GRAZE 3		GRAZE 6	GRAZE 2	SIL 3
7	HAY LFA KILL	SIL LFA KILL	GRAZE LFA KILL			GRAZE 2	SIL 3	GRAZE 3 KILL		GRAZE 6	GRAZE 2	SIL 3 KILL
8						GRAZE 2	SIL 3			GRAZE 6	GRAZE 2	
9						GRAZE 2	SIL 3				GRAZE 2	
10						GRAZE 2 KILL	SIL 3 KILL				GRAZE 2 KILL	

Table 44: Crop rotations No. 13-24

Year in Rotation	Rotation Number											
	13	14	15	16	17	18	19	20	21	22	23	24
1	WW	WW	WW(WC)	WW(WC)	WW	WW(WC)	WW	WW	WW(WC)	WW(WC)	WW	WW(WC)
2	WBAR	WBAR	WBAR	WBAR	WBAR	WBAR	WBAR	WBAR	WBAR	WBAR	WBAR	SBAR
3	MAIZE (WC)	WBAR	FBEET	FBEET	SBAR	SBAR	SBAR	SBAR	SBAR	SBAR	SBAR	BEANS
4	SBAR	SIL3 RESEED	GRAZE 4 RESEED	SIL3 RESEED	BEANS	POT	STURNIP (SPRING)	FBEET	MAIZE (WC)	SBAR	STURNIP (JULY)	POT
5	WBAR	SIL 4	GRAZE 4	SIL 4	WW(WC)	SIL3 RESEED	SIL 2 RESEED	SIL3 RESEED	MAIZE (WC)	GRAZE 4 RESEED	MAIZE (WC)	MAIZE (WC)
6	GRAZE 3 RESEED	SIL 4 KILL	GRAZE 4	SIL 4	GRAZE 2 RESEED	SIL 4	SIL 2	SIL 3	SIL3 RESEED	GRAZE 6	MAIZE (WC)	MAIZE (WC)
7	GRAZE 3	POT	GRAZE 4 KILL	SIL 4 KILL	GRAZE 4	SIL 4	SIL 2	SIL 3	SIL 4	GRAZE 6	SIL3 RESEED	FBEET
8	GRAZE 3	SBAR	POT	MAIZE (WC)	GRAZE 4	SIL 4	SIL 2	SIL 3	SIL 4	GRAZE 6	SIL 3	WOSR
9	GRAZE 3	WOSR		MAIZE (WC)	GRAZE 4	SIL 4	SIL 2	SIL 3	SIL 4	GRAZE 6	SIL 3 KILL	
10	GRAZE 3			SBAR	GRAZE 4	SIL 4	SIL 2	SIL 3	SIL 4	GRAZE 6		
11	GRAZE 3 KILL			WOSR	GRAZE 4	SIL 4 KILL	SIL 2 KILL	SIL 3 KILL	SIL 4	GRAZE 6 KILL		
12					GRAZE 4 KILL				SIL 4 KILL			

Table 45: Long-term Eden crop rotations No. 25-35

Rotation Number	Continuous Crop (cultivated for 40 years)
25	HAY LFA RESEED
26	SIL LFA RESEED
27	GRAZE LFA RESEED
28	GRAZE 2 RESEED
29	GRAZE 2 RESEED
30	GRAZE 2 RESEED
31	GRAZE 2 RESEED
32	SIL 2 RESEED
33	SIL 2 RESEED
34	HAY 2 RESEED
35	MISC 1

Table 46: Maximum fertiliser application limits by Eden crop

Crop	Max Nitrogen application (kg/ha)	Max Phosphorous application (kg/ha)
WW	225	90
WW(WC)	225	90
WBAR	140	90
SBAR	132	88
WOSR	225	75
SOATS	121	77
POT	180	120
SBEANS	0	70
MAIZE(WC)	120	75
STURNIP (JULY)	165	105
STURNIP (SPRING)	140	105
FBEET	120	75
GRAZE LFA	90	56
SIL LFA	114	42
HAY LFA	75	35
SIL1	120	42
SIL2	220	60
SIL3	280	60
SIL4	360	70
HAY2	125	50
GRAZE 2	120	35
GRAZE 3	176	40
GRAZE 4	275	50
GRAZE 6	330	50
MISC	150	150

Table 47: Land cover class details

Land cover broad habitat	Details
Arable and Horticulture	Annual crops, perennial crops (e.g.: berries and orchards) and freshly ploughed land.
Improved Grassland	Higher productivity and lack of winter senescence relative to semi-natural grasslands
Rough Grassland	Mix of areas of managed, low productivity grassland, plus some areas of semi-natural grassland.
Neutral Grassland	Determined based on botanical composition and includes semi-improved grasslands managed for silage, hay, or pasture.
Note: Table adapted from Centre for Ecology & Hydrology Appendix 1 (2011, p. 12)	

Table 48: Full distribution of soil, slope, hydrological connectivity allocation by farm (in hectares)

			farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
S1	L1	H1	1.79	3.87	5.6			
S1	L1	H2					522	
S1	L1	H3		1813.21	153.59	407.08		26.11
S1	L1	H4			527.05		111.83	951.12
S1	L1	H5			229.18	101.9		47.92
S1	L1	H6			1.18	1.57	92.63	17.62
S1	L1	H7			1.17		85.93	17.9
S1	L1	H8					8	26.47
S1	L1	H9					4.48	4.68
S1	L1	H10					0.04	0.11
S1	L3	H1		0.39				6.02
S1	L3	H2						273
S1	L3	H3					1180	
S1	L3	H4				1087.98		62.02
S1	L3	H5			1.41		186.45	34.13
S1	L3	H6					5.26	53.78
S1	L3	H7						50.59
S1	L3	H8		0.46			0.84	15.84
S1	L3	H9		2.02				5.9

			farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
S1	L3	H10		2.3				0.5
S1	L4	H1		3.09			9.8	
S1	L4	H2		74.21			372.79	
S1	L4	H3		139.87		2.05	1468.07	
S1	L4	H4		41.88	133.89		894.23	
S1	L4	H5					208	
S1	L4	H6			0.27		69.94	
S1	L4	H7					69.07	
S1	L4	H8		12.71			11.35	
S1	L4	H9		6.45			1.25	
S1	L4	H10		2.27			0.6	
S1	L2	H1		0.06			0.02	
S1	L2	H2					1.07	
S1	L2	H3		1.6			3.98	
S1	L2	H4		0.04			0.94	2.38
S1	L2	H5					1.54	
S1	L2	H6		0.28			0.1	
S1	L2	H7		0.09			0.03	
S1	L2	H8					0.15	
S1	L2	H9					0.01	
S1	L2	H10		0.1			0.03	
S1	L5	H1					0.09	
S1	L5	H2		0.28			2.54	
S1	L5	H3		1.49			2.64	
S1	L5	H4				1.89		
S1	L5	H5				0.91		
S1	L5	H6				0.47		
S1	L5	H7					0.76	
S1	L5	H8				0.46		
S1	L5	H9					0.02	
S2	L1	H1				39.45		
S2	L1	H2	85.01	1357			2067.72	520.26

			farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
S2	L1	H3	951.49	1041.72	2093.84	3572.38	998.74	5041.83
S2	L1	H4		108.7	2461.3			
S2	L1	H5			415			
S2	L1	H6			0.45	76.4		49.15
S2	L1	H7				22.32		18.68
S2	L1	H8				3.96		4.75
S2	L1	H9						0.25
S2	L3	H1		1.42	14.3		6.73	
S2	L3	H2			444.8			765.2
S2	L3	H3		808.23	2268.17		93.6	
S2	L3	H4		398.55	140.45			
S2	L3	H5		9.11				87.83
S2	L3	H6		6.38				25.23
S2	L3	H7			12.92	0.03	2.42	
S2	L3	H8			3.15			4.46
S2	L3	H9		0.75	0.37			
S2	L3	H10		0.02				
S2	L4	H1		45.54				
S2	L4	H2	62.97	2043.02	143.26	10.19	498.01	142.55
S2	L4	H3	878.41	1855.55	2349.06	488.64	24.48	1523.86
S2	L4	H4		671.37			468.63	
S2	L4	H5		212				
S2	L4	H6		76.99				
S2	L4	H7		22.54				
S2	L4	H8		8.12				
S2	L4	H9		0.64				
S2	L4	H10		0.03				
S2	L2	H1			0.27			
S2	L2	H2			5.23			
S2	L2	H3					3.55	
S2	L2	H4			0.6			
S2	L2	H5		0.01	0.14			

			farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
S2	L2	H6			0.05			
S2	L2	H7		0.01	0.01			
S2	L2	H8			0.01			
S2	L2	H9			0.14			
S2	L5	H1						0.59
S2	L5	H2	3.48	19.43				
S2	L5	H3					28.89	3.22
S2	L5	H4		0.56			11.99	
S2	L5	H5					5.9	1.5
S2	L5	H6		1.71			2.7	
S2	L5	H7	0.89					0.24
S2	L5	H8		0.02				0.03
S3	L1	H1	81.98					
S3	L1	H2			936.65	1067.8	247.59	3197.96
S3	L1	H3	1003.04	95.75	760.98	7660.23		
S3	L1	H4	7.32		249.24	334.69		88.74
S3	L1	H5	102					
S3	L1	H6	30.43					
S3	L1	H7	10.61					
S3	L1	H8	0.82					
S3	L3	H1	26.34					8.94
S3	L3	H2	211.97		953.88	148.83	225.32	
S3	L3	H3	965.14		858.06	779.92		26.88
S3	L3	H4	25.18					163.82
S3	L3	H5	21.17					8.11
S3	L3	H6	5.53					1.79
S3	L3	H7						4.41
S3	L3	H8						2.89
S3	L3	H9	0.08					0.17
S3	L4	H1					5.58	77.61
S3	L4	H2	259.81		6.14	170.35	3395.57	88.13
S3	L4	H3	3563.69		438	872.47	306.96	588.89

			farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
S3	L4	H4					165.18	237.82
S3	L4	H5						64.14
S3	L4	H6	0.54				20.28	
S3	L4	H7	0.68				4.4	
S3	L4	H8	0.1	0.1		0.18	0.38	0.49
S3	L4	H9			0.02	0.04		
S3	L2	H1			0.4			
S3	L2	H2			2.85			
S3	L2	H3	0.48		1.37	0.02		
S3	L2	H4			0.28			
S3	L2	H5	0.04		0.07			
S3	L2	H6	0.01		0.02			
S3	L2	H7			0.01			
S3	L2	H8			0.21			
S3	L2	H9	0.07		0.12			
S3	L5	H1					1.32	
S3	L5	H2	0.39			0.39	40.22	
S3	L5	H3		1.79	5.07		42.58	5.19
S3	L5	H4	2.62					5.11
S3	L5	H5				0.34	1.68	0.13
S3	L5	H6				0.47	1.04	
S3	L5	H7				0.03	0.25	
S4	L1	H1	188.64			142.59		387.77
S4	L1	H2	5919.32	984.14		776.28	210.28	5309.98
S4	L1	H3		4735.13		2625.72	549.15	
S4	L1	H4			333			
S4	L1	H5	38.47	13.66				
S4	L1	H6	5.64		14.13			
S4	L1	H7		7.44				
S4	L1	H8	0.16	0.06				
S4	L3	H1	344					
S4	L3	H2		594.49	3232.06	89.88	181.11	2.47

			farm_1	farm_2	farm_3	farm_4	farm_5	farm_6
S4	L3	H3	391.49	442.44	536.44		206.95	502.67
S4	L3	H4	99.37					
S4	L3	H5	16.4			0.05		
S4	L3	H6					5.81	
S4	L3	H7					6.62	
S4	L3	H8					5.56	
S4	L4	H1	70.78	16.75	23.14	50.84	748.48	
S4	L4	H2	5472.91	3103.31	397.31	289.12	764.49	372.85
S4	L4	H3	150.32		342.44	208.98	4312.44	115.82
S4	L4	H4		85.1	93.06		19.69	9.15
S4	L4	H5		4.89	20.81	12.79		
S4	L4	H6			11.51	0.45		1.4
S4	L4	H7		0.02	2.85			2.04
S4	L4	H8		0.27		0.57		0.6
S4	L4	H10						0.01
S4	L2	H1	3.18					
S4	L2	H2	1.81		6.95			
S4	L2	H3			2.87			
S4	L2	H4			0.54			
S4	L2	H5			0.2			
S4	L2	H6			0.02			
S4	L2	H8			1.34			
S4	L5	H1				4.6	28.74	
S4	L5	H2	22.98		427.91	11.04	33.06	
S4	L5	H3	25.08	185.4		0.46		5.06
S4	L5	H4	12.18				1.89	
S4	L5	H5					2.94	
S4	L5	H6					1.35	
S4	L5	H7					0.06	
Total			21066.81	21066.83	21066.81	21066.81	21066.81	21066.76

Table 49: Soil/slope distribution in the catchment

Soil	Slope	Soil/Slope area (ha)	Percentage of total soil-type area	Percentage of total slope-type area
L1	S1	5164	8%	44%
L1	S2	20930	33%	56%
L1	S3	15876	25%	52%
L1	S4	22242	35%	48%
L2	S1	12	27%	0%
L2	S2	10	22%	0%
L2	S3	6	13%	0%
L2	S4	17	37%	0%
L3	S1	2969	15%	25%
L3	S2	5094	27%	14%
L3	S3	4438	23%	14%
L3	S4	6658	35%	14%
L4	S1	3522	8%	30%
L4	S2	11526	27%	31%
L4	S3	10268	24%	33%
L4	S4	16705	40%	36%
L5	S1	12	1%	0%
L5	S2	81	8%	0%
L5	S3	109	11%	0%
L5	S4	763	79%	2%

Figure 33: Distribution of hydrological connectivity levels (intervals of 0.01) across soils and slopes

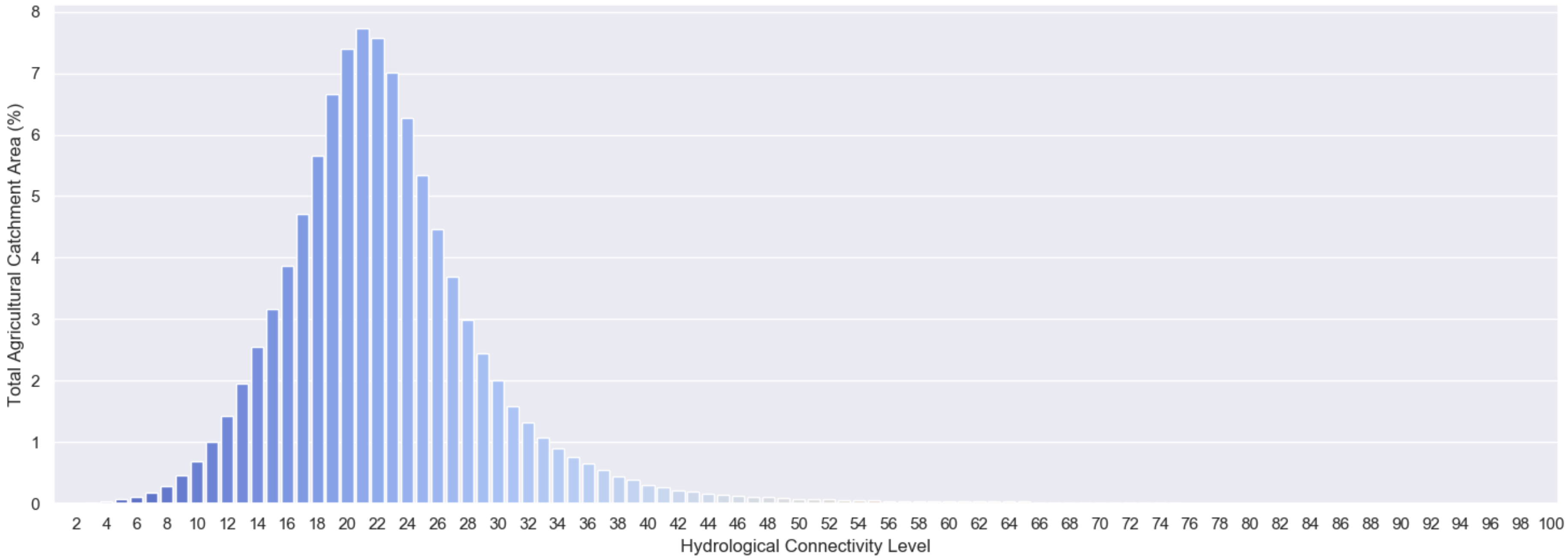
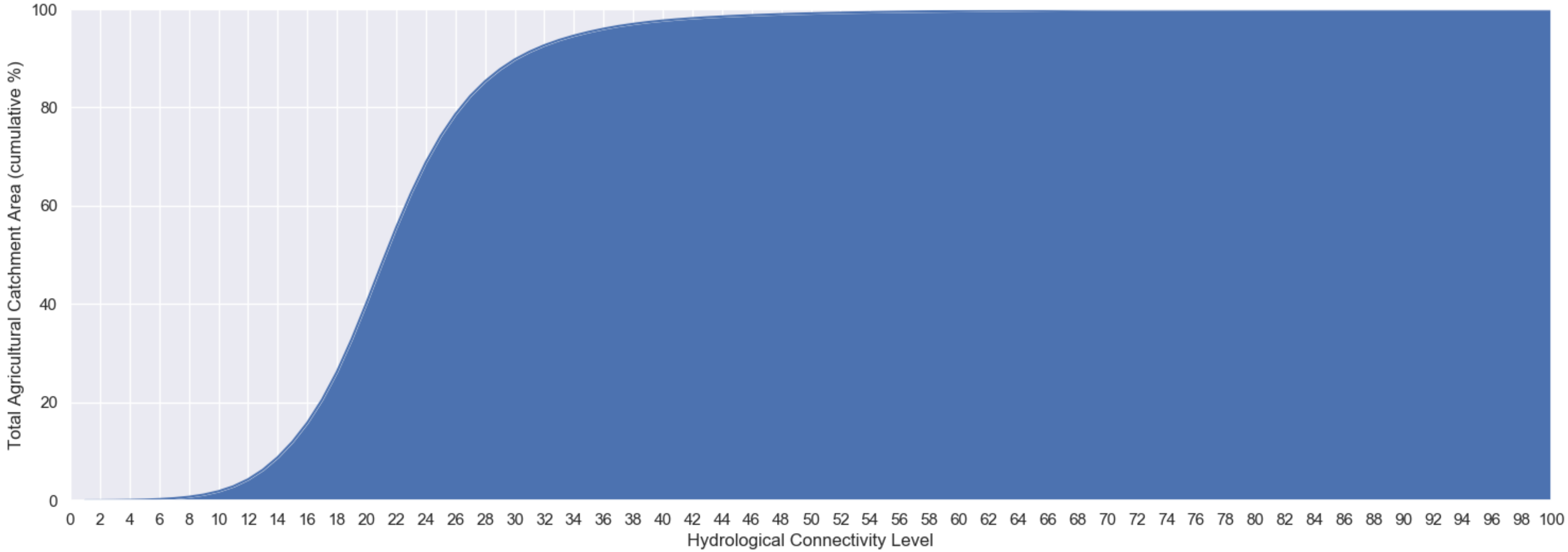


Figure 34: Cumulative distribution of hydrological connectivity levels (intervals of 0.01) across soils and slopes



Appendix B

Figure 35: Land use change in response to N tax policy scenarios (Part 3)

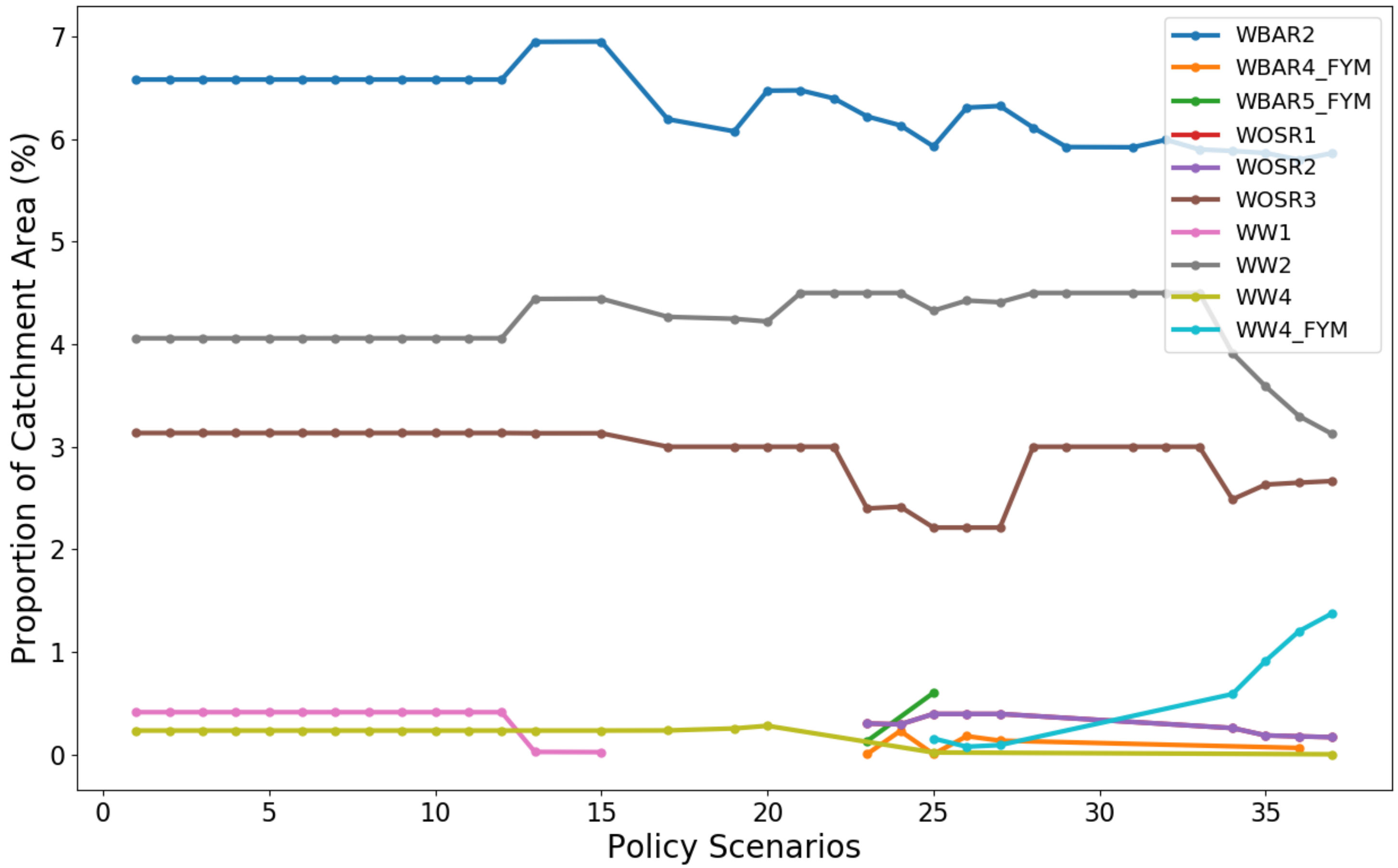


Figure 36: Land use change in response to targeted set-aside policy scenarios (Part 1)

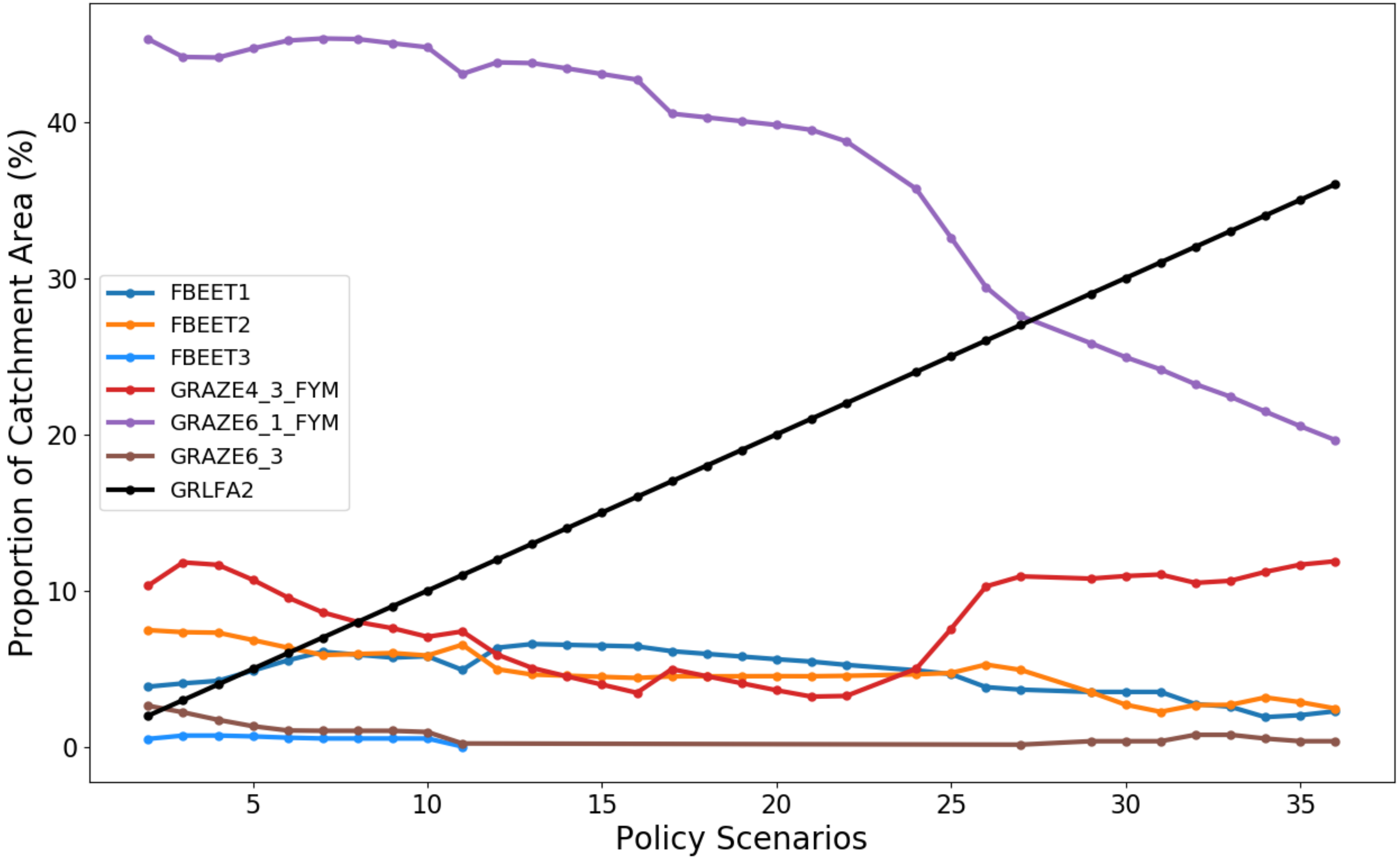


Figure 37: Land use change in response to targeted set-aside policy scenarios (Part 2)

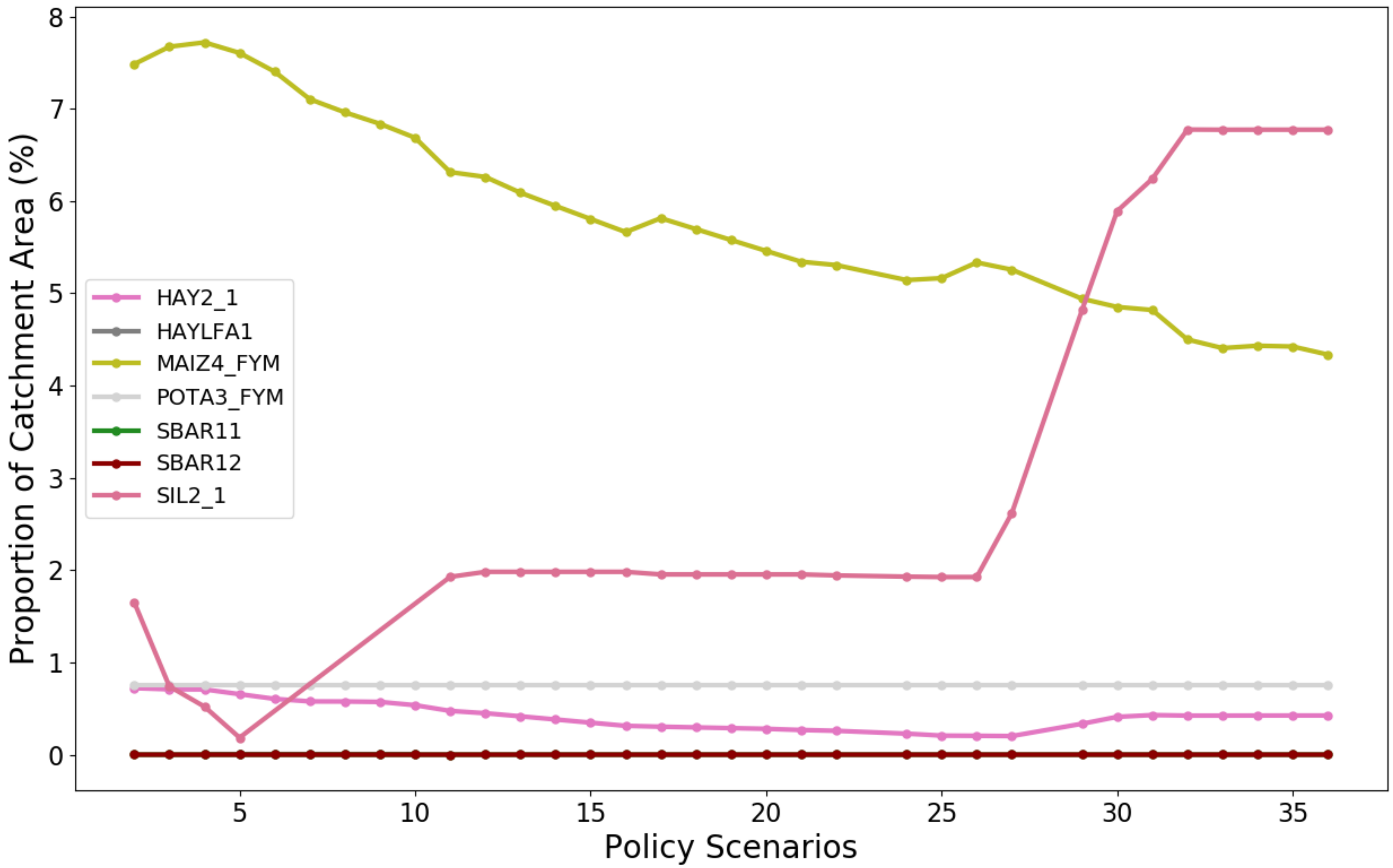


Figure 38: Land use change in response to targeted set-aside policy scenarios (Part 3)

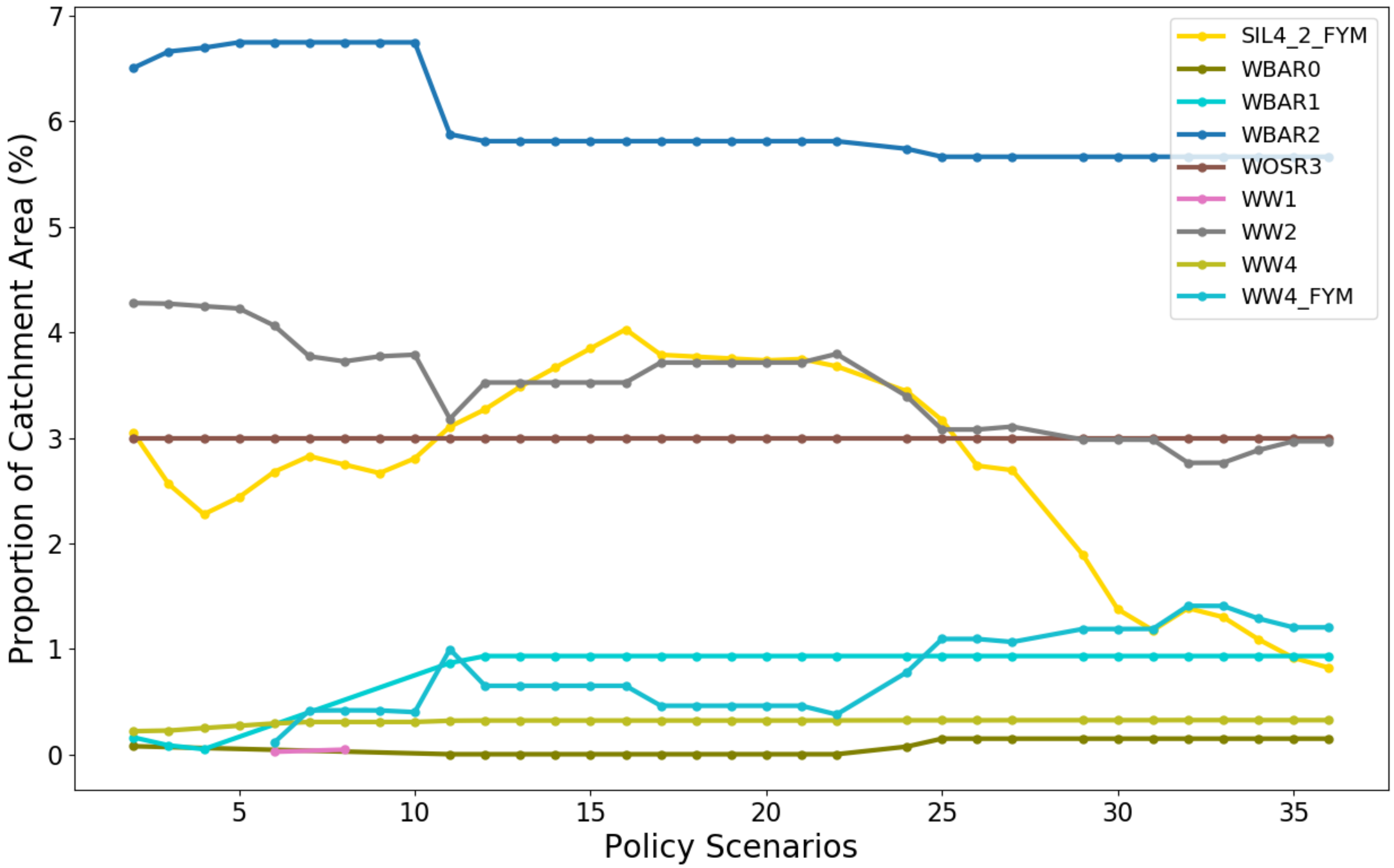


Figure 39: Crop share of catchment N fertiliser application for targeted set-aside tax policy scenarios (Part 1)

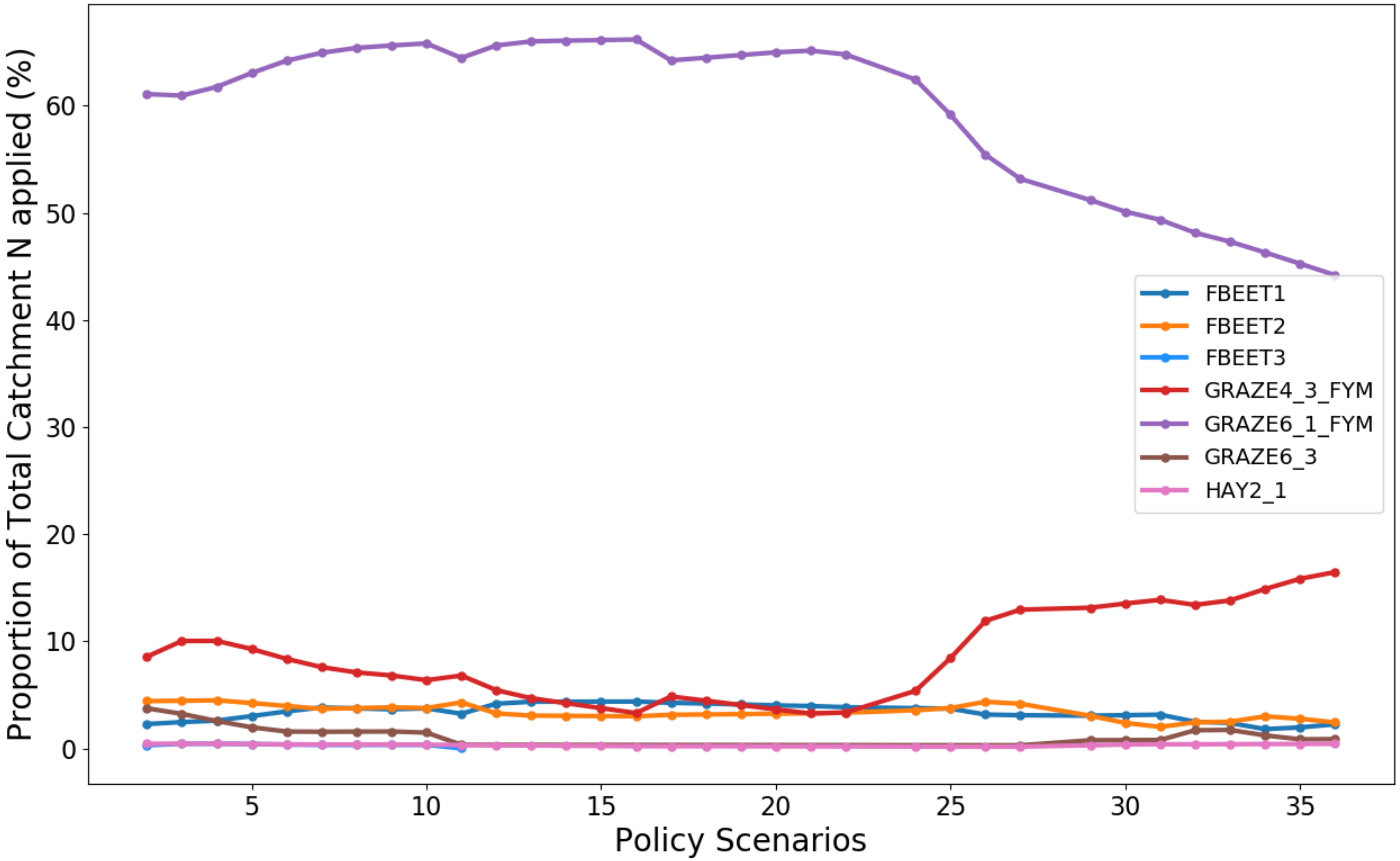


Figure 40: Crop share of catchment N fertiliser application for targeted set-aside tax policy scenarios (Part 2)

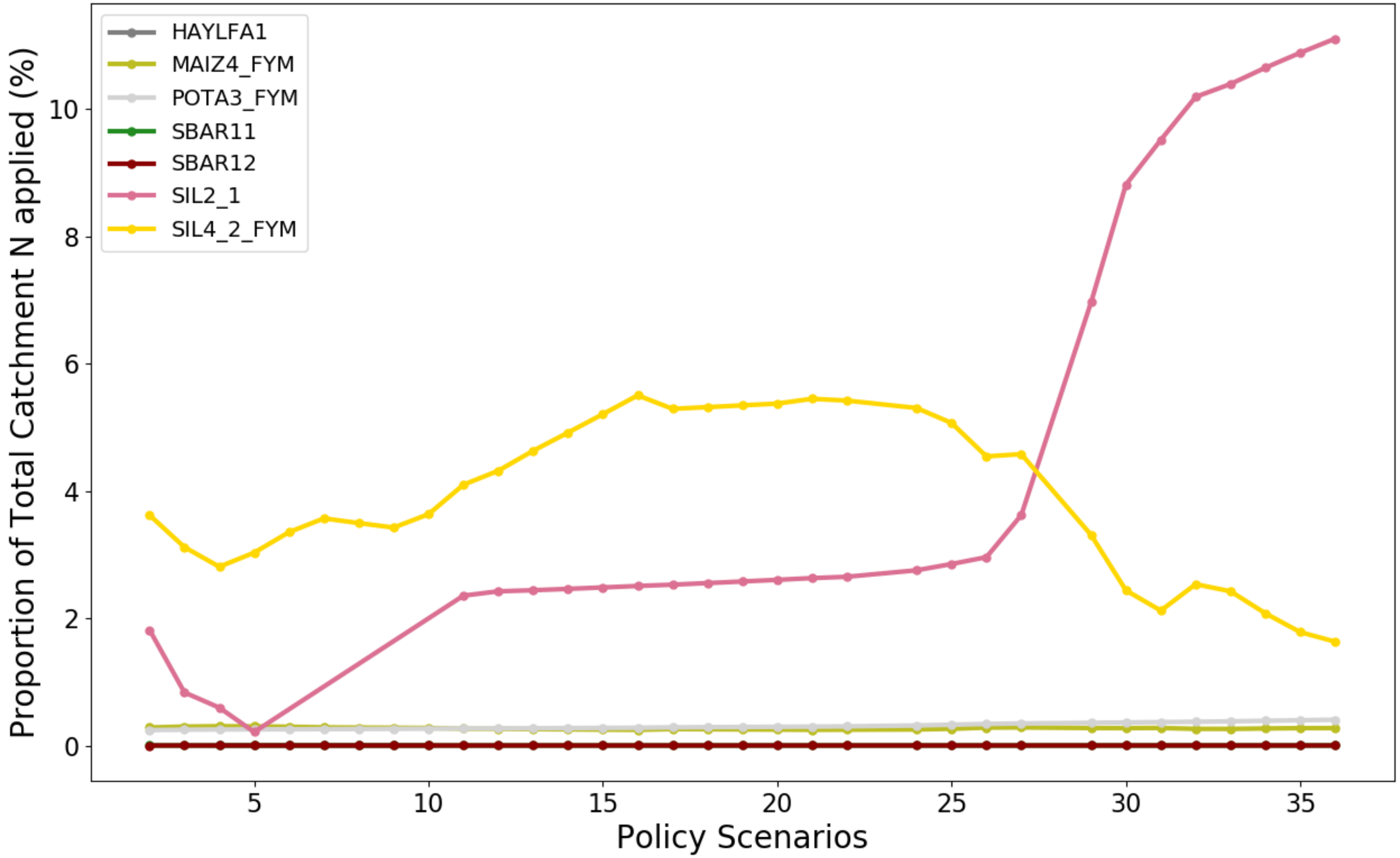


Figure 41: Crop share of catchment N fertiliser application for targeted set-aside tax policy scenarios (Part 3)

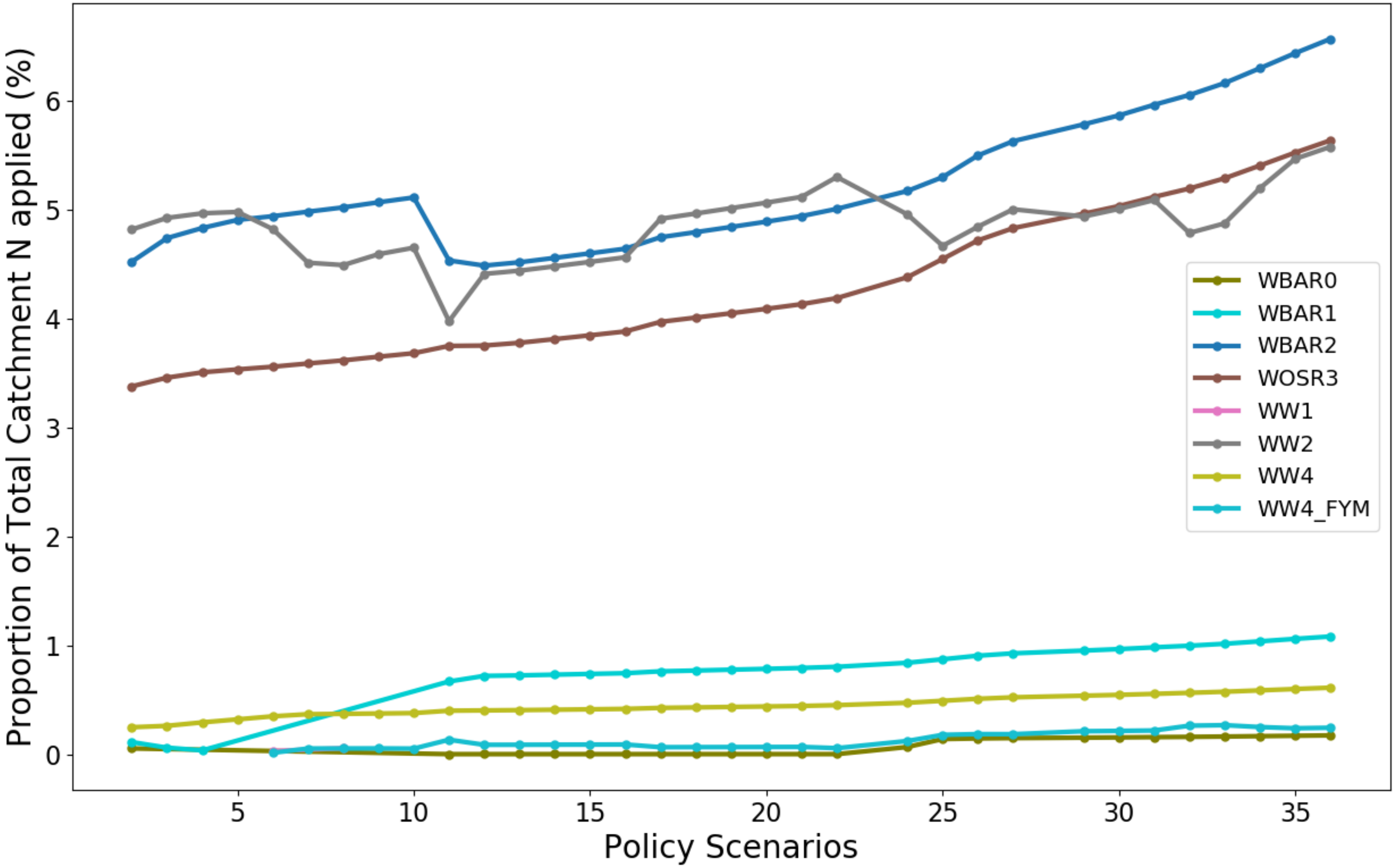


Figure 42: Land use change in response to mixed instrument N tax & 5% set-aside policy scenarios (Part 1)

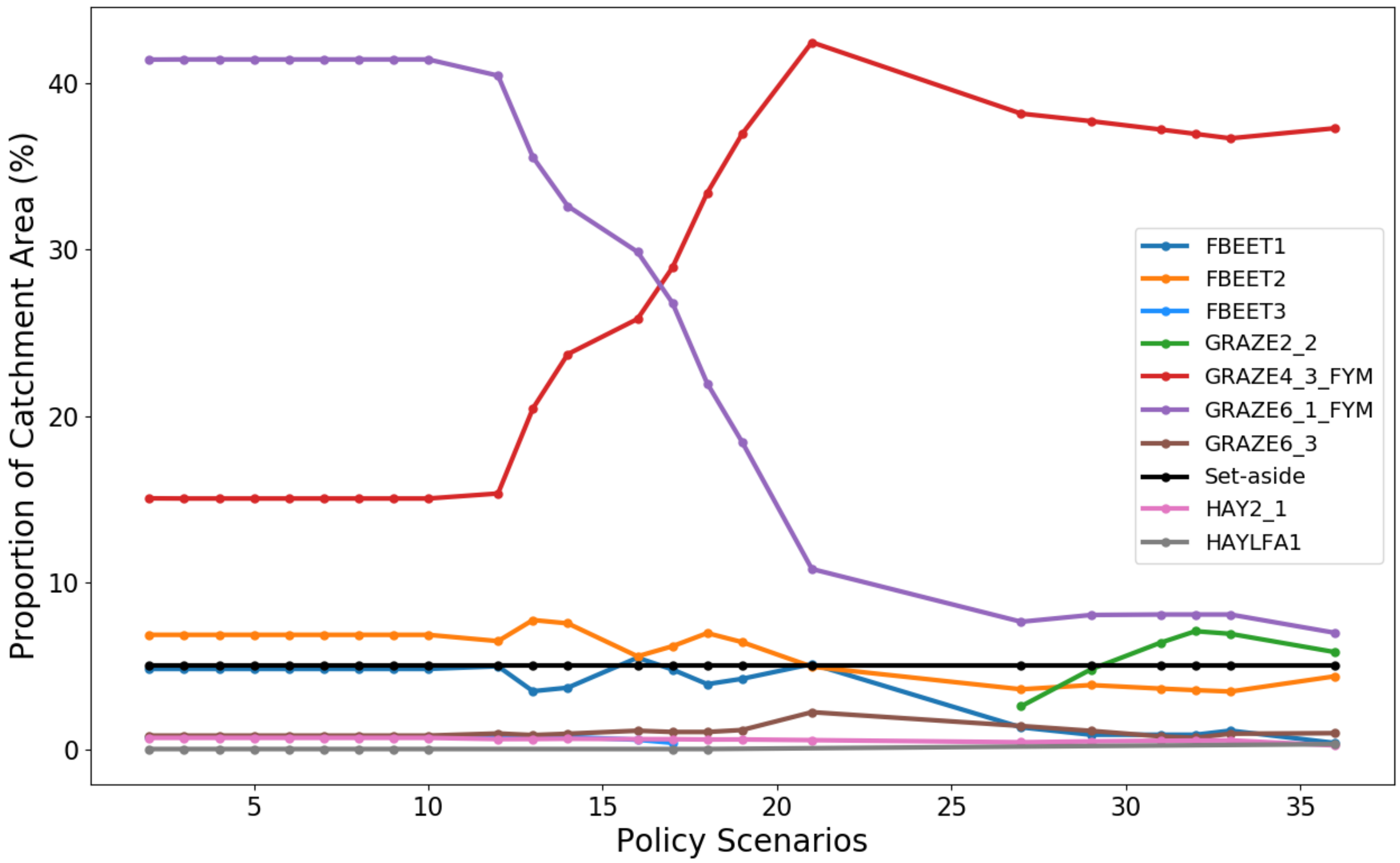


Figure 43: Land use change in response to mixed instrument N tax & 5% set-aside policy scenarios (Part 2)

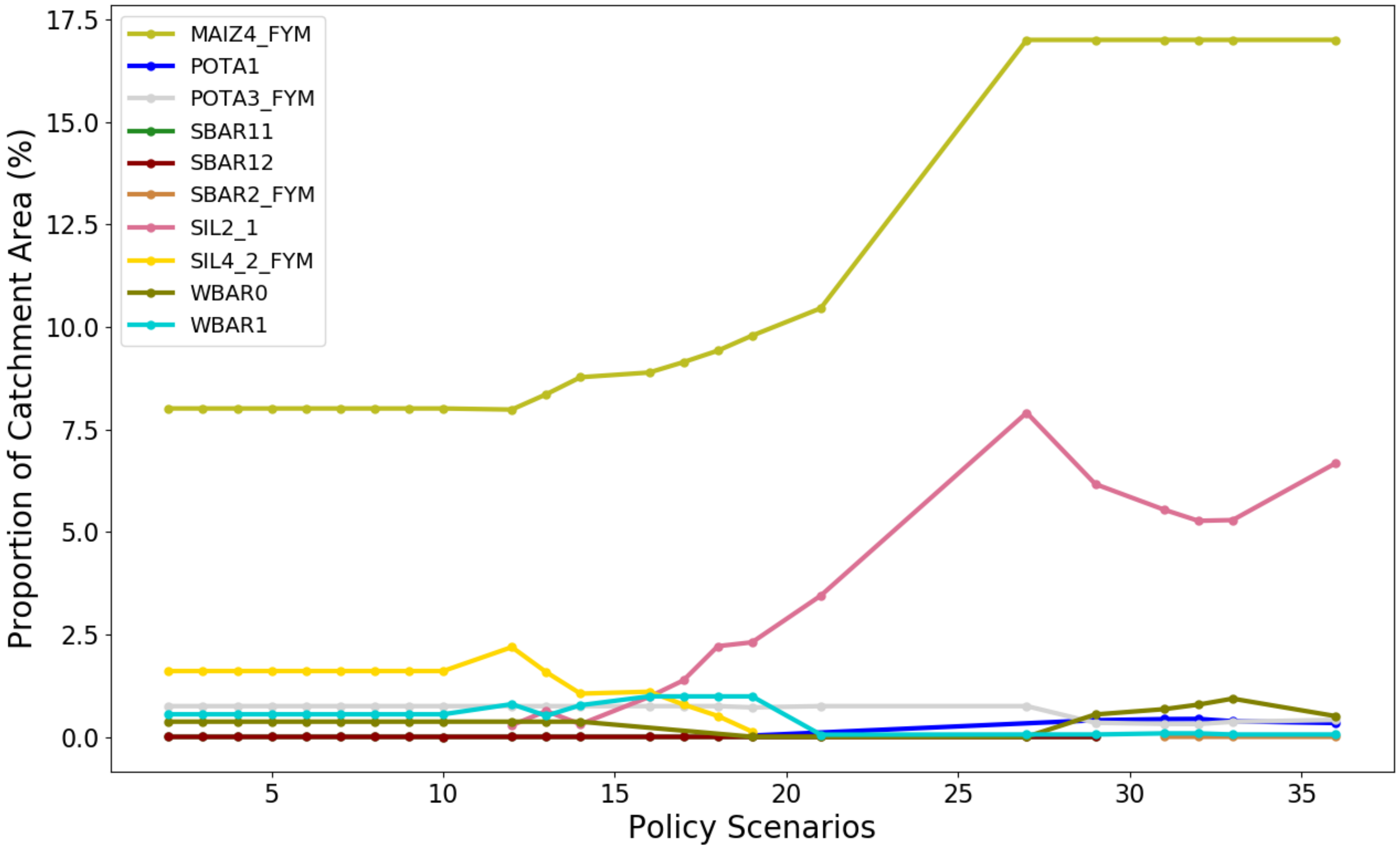


Figure 44: Land use change in response to mixed instrument N tax & 5% set-aside policy scenarios (Part 3)

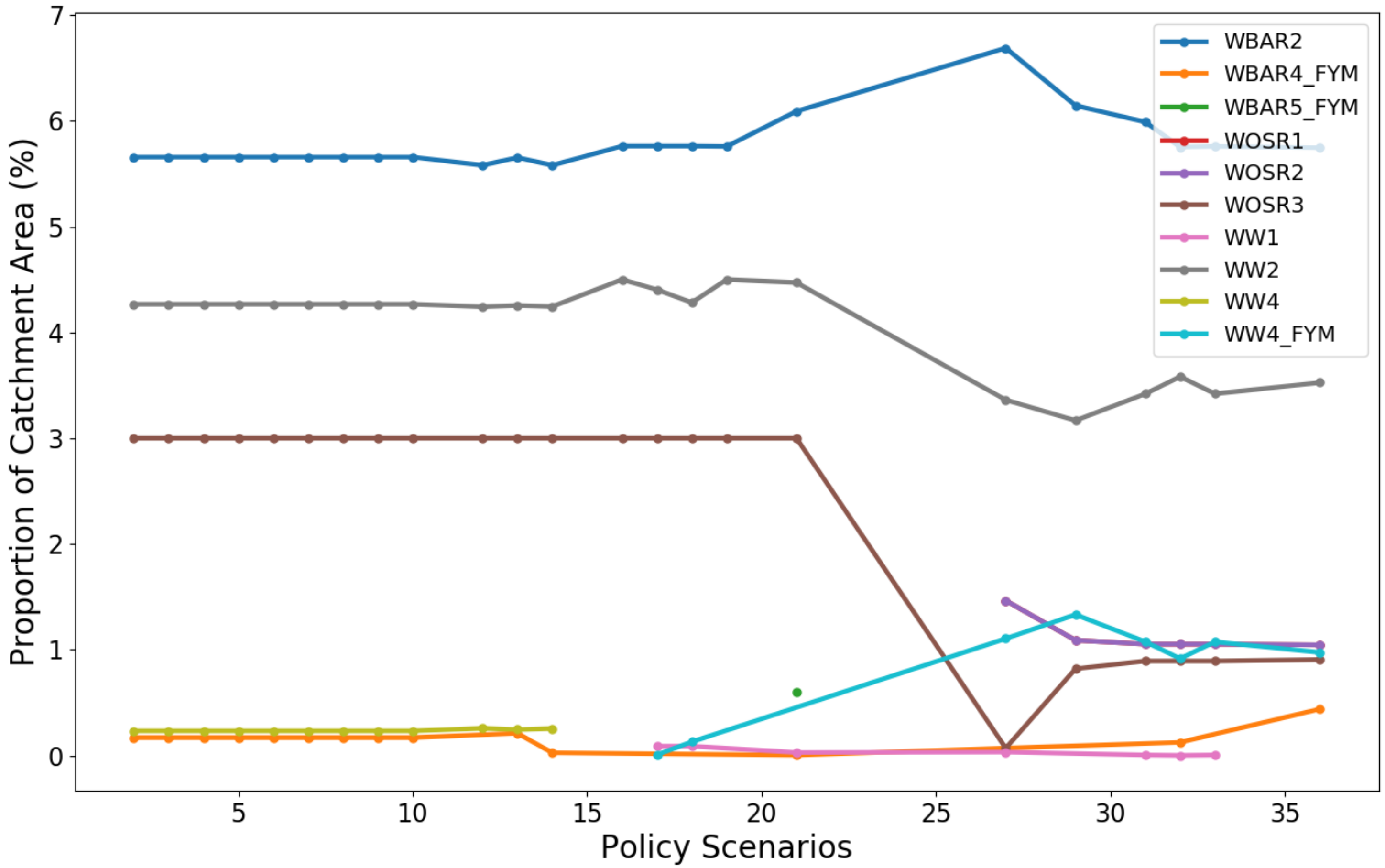


Figure 45: Land use change in response to mixed instrument N tax & 2% set-aside policy scenarios (Part 1)

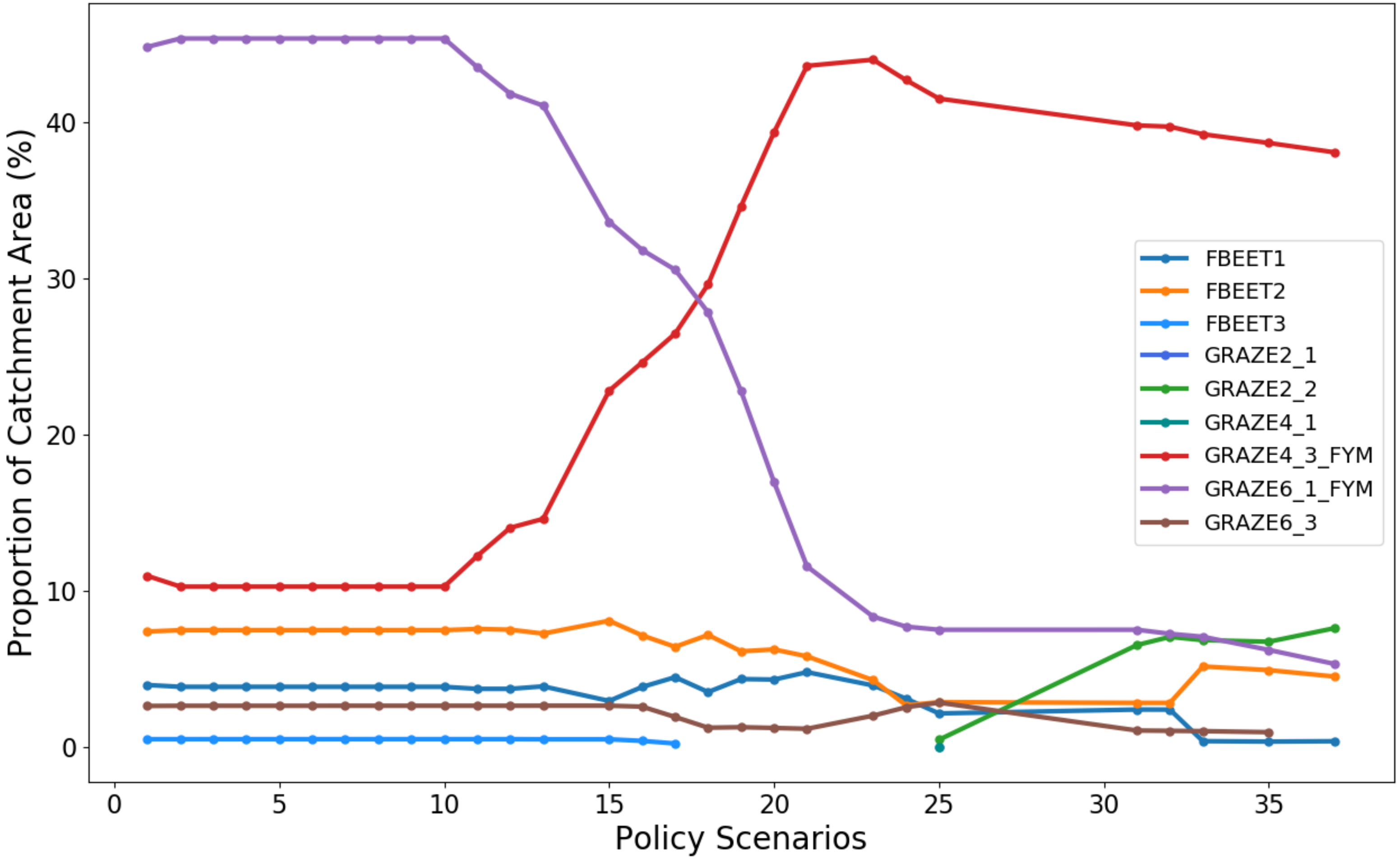


Figure 46: Land use change in response to mixed instrument N tax & 2% set-aside policy scenarios (Part 2)

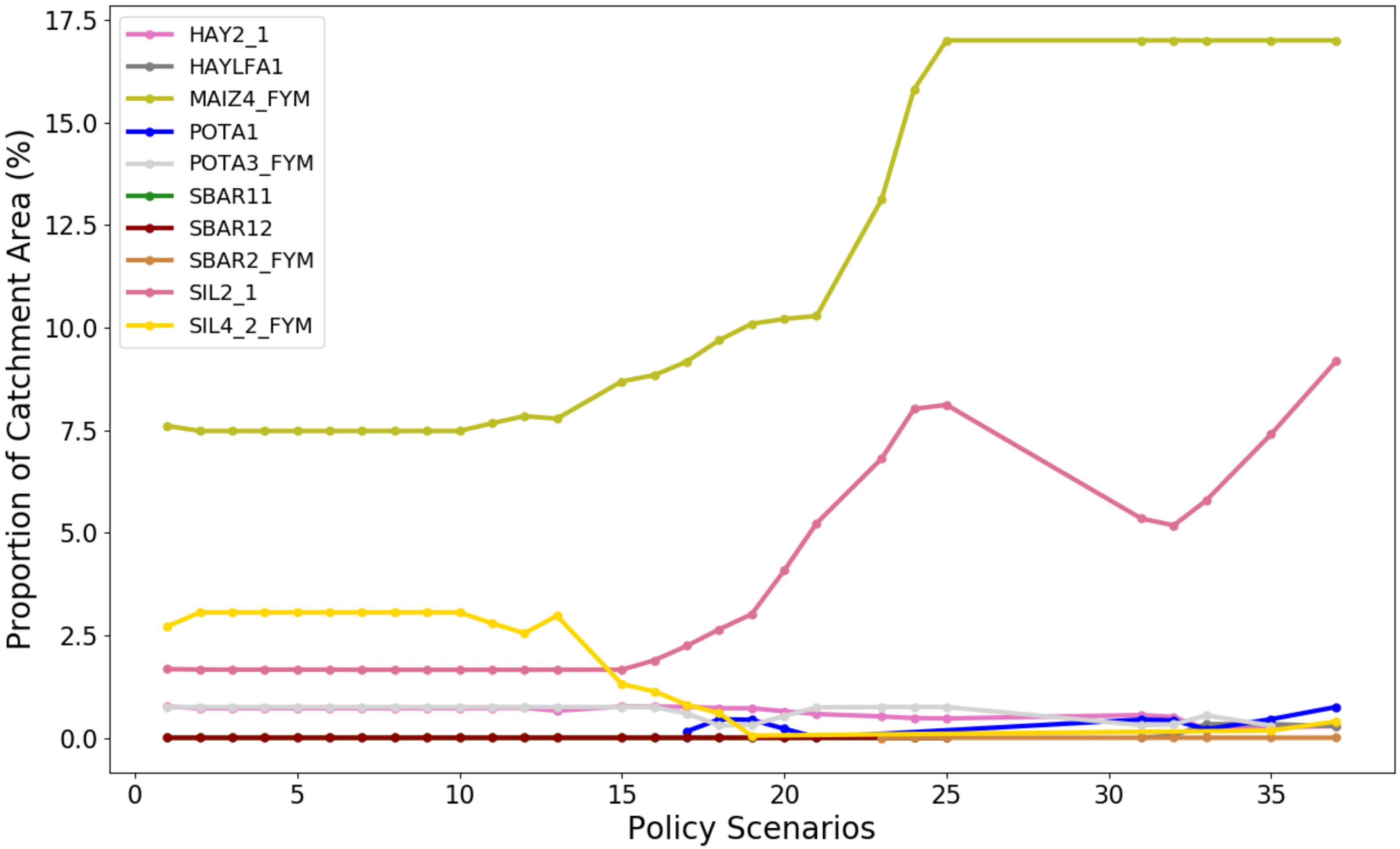


Figure 47: Land use change in response to mixed instrument N tax & 2% set-aside policy scenarios (Part 3)

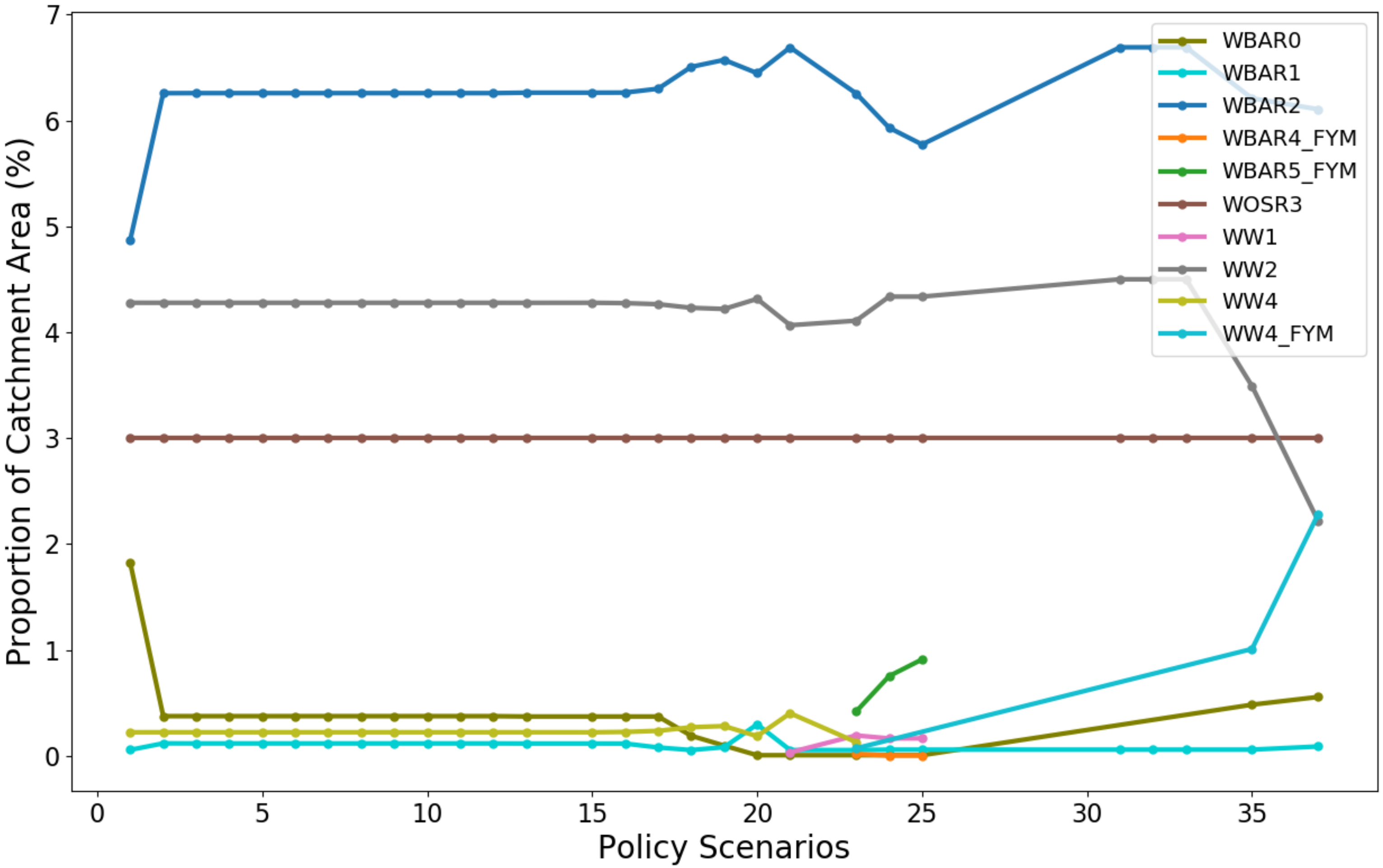


Figure 48: Land use change in response to PA scenarios (Part 1)

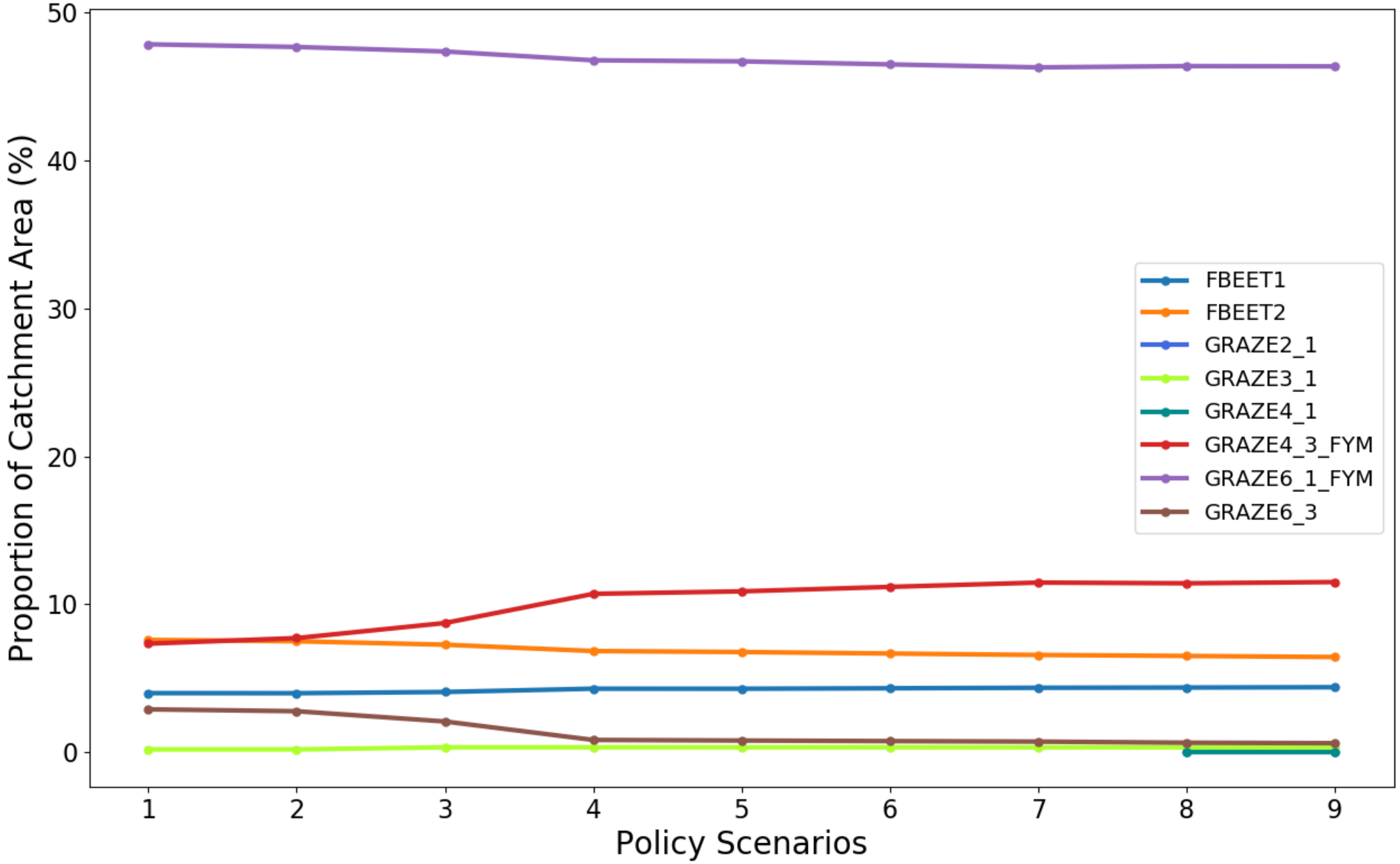


Figure 49: Land use change in response to PA scenarios (Part 2)

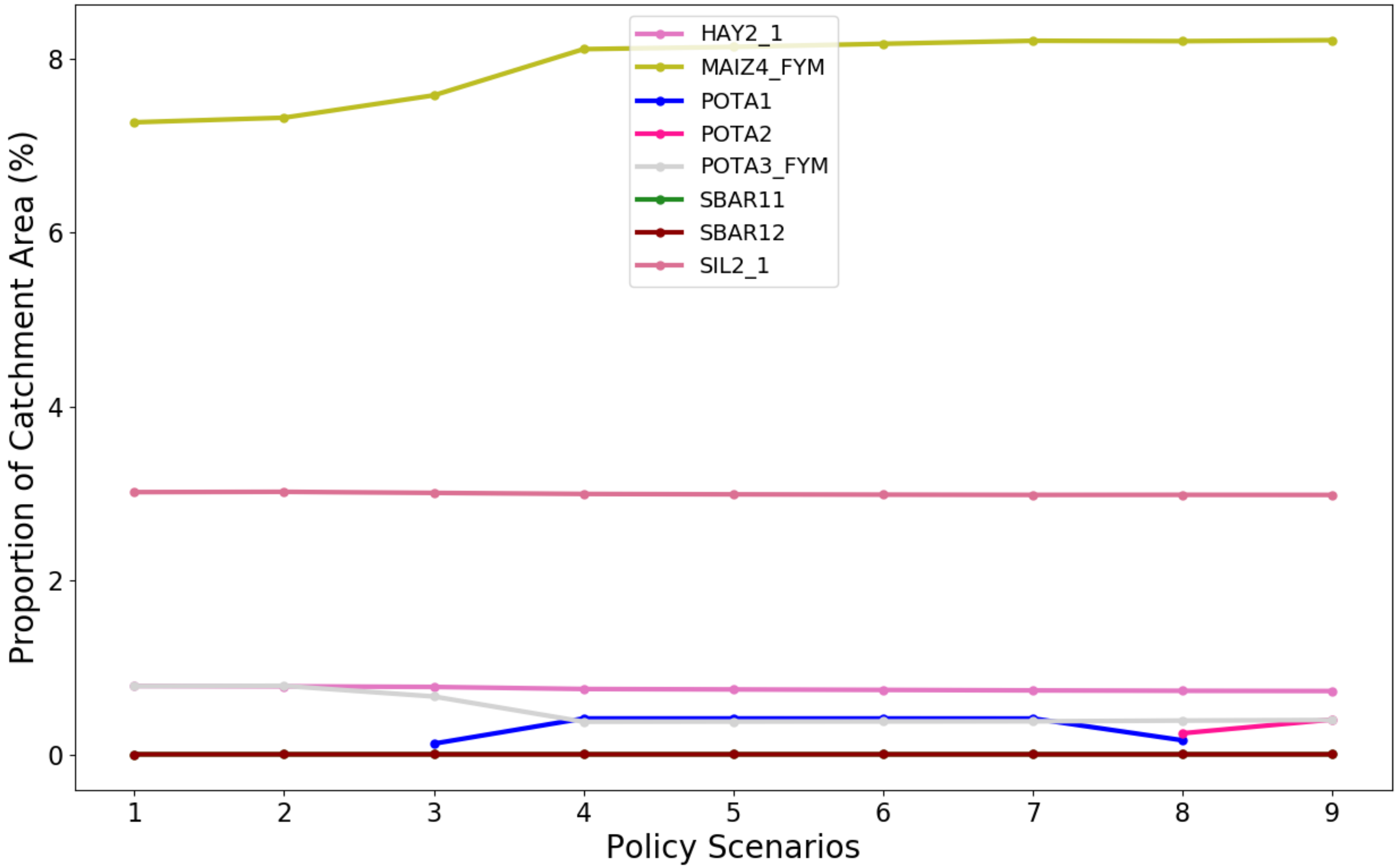
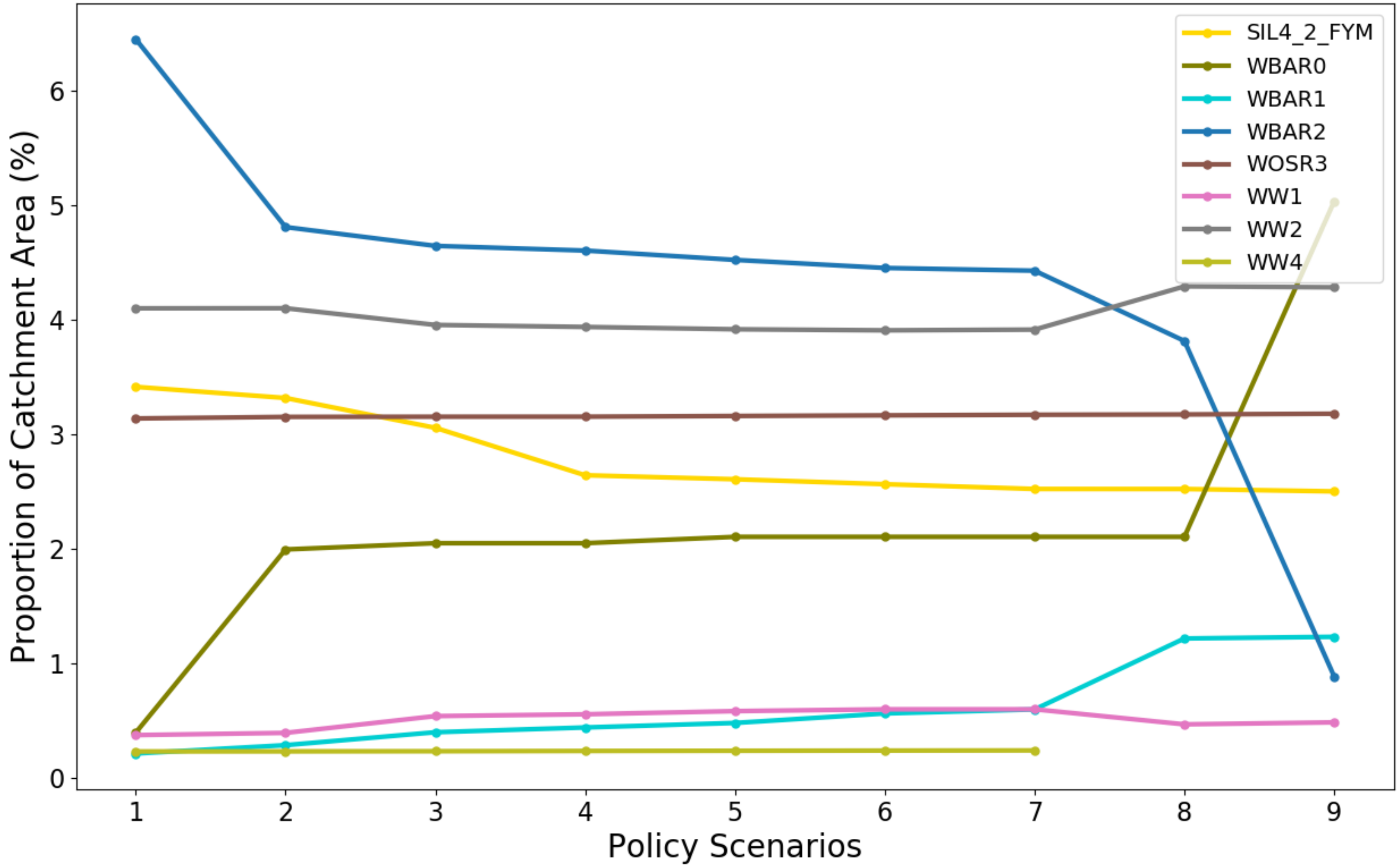


Figure 50: Land use change in response to PA scenarios (Part 3)



Appendix C

This appendix includes the GAMS and Python code for the key results of the presented thesis.

GAMS Code

Firstly, the GAMS code of the baseline model is presented. The baseline model is composed of the main model file (p. 199), the parameters loading file (p. 216), the file with the loop structure and loading of parameters for calculations outside the optimisation (p. 226), and finally the parameters for the results reporting (p. 235). The baseline main model and loop structure code was amended for each policy scenario analysis (including 40 solves per policy scenario). In addition to the main model, the small linear optimisation model used to allocate the catchment land between the representative farms is presented on p. 239.

Main Model Baseline

File name: 'Policies_Base05.gms'

```
$offlisting
$include Parameter_Base05.gms
****Main model****
****run with reslim=12000000000 in command line
Table farm_area (ID, slope, soil, hydro, farm, value) 'number of ha of soil slope type combination per farm from farm area optimisation problem';
$gdxin All_parameters_62.gdx
****read farm area parameter into gdx file
$load farm_area
****load parameter into model
$gdxin
****close gdx file
;
TABLE farm_area_2 (slope, soil, hydro, farm, value) 'number of ha of soil slope type combination per farm';
farm_area_2 (slope, soil, hydro, farm, value)= SUM(ID, farm_area (ID, slope, soil, hydro, farm, value));
****eliminate ID index which is used for reading parameters from Excel into gdx
;
****Limits on minimum and maximum livestock standard output production to include different farm types****199
```

TABLE stan_out_li_lolim (farm, livestock) 'Lower limit for livestock percentage of farm standard output in %'

	dairy	finish1	finish2	suckler	sheep1	sheep2
farm_1	0	0	0	5	5	2
farm_2	50	5	5	0	0	0
farm_3	0	0	0	2	2	1
farm_4	50	5	5	0	0	0
farm_5	0	0	0	0	0	0
farm_6	0	0	0	2	2	1

;

TABLE stan_out_li_uplim (farm, livestock) 'Upper limit for livestock percentage of farm standard output in %'

	dairy	finish1	finish2	suckler	sheep1	sheep2
farm_1	25	25	25	70	70	70
farm_2	80	70	70	25	25	25
farm_3	25	25	25	70	70	70
farm_4	80	70	70	25	25	25
farm_5	5	5	5	5	5	5
farm_6	5	5	10	5	25	25

;

****Limits on minimum and maximum livestock numbers to support farm type implementation****

TABLE farm_live_lolim (farm, livestock)'Lower limit for livestock number per farm'

	dairy	finish1	finish2	suckler	sheep1	sheep2
farm_1	0	0	0	20	10	10
farm_2	50	10	10	0	0	0
farm_3	0	0	0	20	10	10
farm_4	50	10	10	0	0	0
farm_5	0	0	5	0	0	0
farm_6	0	0	0	0	10	10

;

TABLE farm_live_uplim (farm, livestock)'Upper limit for livestock number per farm'

	dairy	finish1	finish2	suckler	sheep1	sheep2
farm_1	20000	20000	20000	20000	20000	20000
farm_2	20000	20000	20000	20000	20000	20000
farm_3	20000	20000	20000	20000	20000	20000
farm_4	20000	20000	20000	20000	20000	20000

```
farm_5              20000    20000     20000    20000    20000     20000
farm_6              20000    20000     20000    20000    20000     20000
;
PARAMETER stan_out_cr_lolim (farm) 'Lower limit on percentage of standard output originating from cash crops'
/
farm_1  =      0
farm_2  =      0
farm_3  =      0
farm_4  =      0
farm_5  =      70
farm_6  =      30
 /
delta 'parameter to block degenerate cycling' / 1/
****Definition of parameters transformed from simple inputs****
farm_land(farm)'Area in hectares allocated to a farm'
catch_land 'Total catchment area in 1000 ha'
crop_var_cost (crop)'variable costs associated with crops (labour, seeding) excluding fertilisation'
crop_buy_cost (crop)'cost of buying crops including transport costs in £100'
live_margin (livestock)'livestock grossmargin net of labour costs in £10'
land_resource (slope, soil, hydro, farm)'binary parameter to indicate land resource 0=no resouce, 1=resource'
set_aside_land 'land in hectares that needs to be set aside';

farm_land(farm)=SUM((slope, soil, hydro),farm_area_2 (slope, soil, hydro, farm, "value"));
crop_var_cost (crop) = crop_cost (crop, 'value')+(crop_lab_requ (crop, 'value') * lab_cost ('value', 'value'));
crop_buy_cost (trade_feed_cr)= crop_price (trade_feed_cr, 'value')+Trans_cost('value', 'value');
live_margin (livestock)=[Live_grmrg (livestock, 'value')- (lab_cost ('value', 'value') * Live_lab_requ (livestock,
'value'))]/10;
land_resource (slope, soil, hydro, farm) = 0+1$farm_area_2 (slope, soil, hydro, farm, 'value');
catch_land=SUM((slope, soil, hydro, farm),farm_area_2 (slope, soil, hydro, farm, "value"))/1000;
display land_resource,  farm_land, catch_land;

TABLE div_constr(farm,group_types_cr) 'Lower limits for % of crop groups which make up crop standard output'
         spcr_lolim  wicr_lolim
farm_1        0           0
farm_2        0           0
farm_3        0           0
```

```
farm_4      0       0
farm_5      10      10
farm_6      5       5
;
TABLE farm_ligm_lolim (farm,livestock)'Lower limit for livestock grossmargin in £100'
         dairy  finish1  finish2 suckler sheep1 sheep2
farm_1    -500  -500     -500  -500   -500  -500
farm_2    -500  -500     -500  -500   -500  -500
farm_3    -500  -500     -500  -500   -500  -500
farm_4    -500  -500     -500  -500   -500  -500
farm_5    -500  -500     -500  -500   -500  -500
farm_6    -500  -500     -500  -500   -500  -500
;
POSITIVE VARIABLES
N_FYM_TOTAL (farm)                    'Total nitrogen in 10000kg available in farm yard manure of farm'
P_FYM_TOTAL (farm)                    'Total phosphor in 10000kg available in farm yard manure of farm'
N_AF (slope, soil, hydro, farm, crop)         'Artificail nitrogen in kg/ha '
P_AF (slope, soil, hydro, farm, crop)         'Artificial phosphor in kg/ha'
N_FYM (slope, soil, hydro, farm, crop)         'FYM nitrogen applied in kg/ha'
P_FYM (slope, soil, hydro, farm, crop)         'FYM phosphor applied in kg/ha'
N_FYM_STOR (farm)                     'FYM nitrogen 10000kg not applied this year and stored on farm'
P_FYM_STOR (farm)                     'FYM phosphor 10000kg not applied this year and stored on farm'
YIELD_DM(slope, soil, hydro, farm, crop)        'Crop yield in t/ha not corrected for fresh weight'
T_YIELD_FW(slope, soil, hydro, farm, crop)          'Crops yield in tonnes corrected for fresh weight excluding
grass which is DM'
CR_TOTAL_COST (slope, soil, hydro, farm, crop)      'Farm cost from crop production in £100'
LAND (slope, soil, hydro, farm, crop)          'Farm land ha of particular slope and soil type allocated to
production of secific crop'
LIVE_NUM (farm, livestock)                'Number of livestock on farm'
SOLD_FEED_crop (farm,trade_feed_cr)            'Silage crops sold to other farm in freshweight t'
FEED_CRREV(farm, trade_feed_cr)              'Revenue from selling feeding crops in £100'
FEED_CRCOST (farm)                    'Farm cost of buying feed crops in £100'
LI_SILBUY_FORAGE_TOTAL_COST (farm, livestock)      'Cost of buyinig feed crops per livestock type in £100'
TOTAL_FORAGE_TOTAL_COST (farm, livestock)        'Total forage costs per livestock type in £100'
BUY_FEED_CROP (farm,trade_feed_cr)            'Silage crops bourght from other farm in freshweight t'
CR_GM(slope, soil, hydro, farm, cash_crop)        'Gross Margin contribution of cash crops in £100'
```

LIVE_HAY_PERC (farm, livestock) 'Percentage of available FW hay yield fed to certain livestock type'

LIVE_GRAZE_PERC (farm, livestock) 'Percentage of available DM grazing yield fed to certain livestock type'

LIVE_SILAGE_PERC (farm, livestock) 'Percetnage of home produced FW silage yield fed to certain livestock type'

FED_SALE_PERC (farm) 'Percentage of available FW silage yield sold to other farms'

FEEDCR_GM(farm,trade_feed_cr) 'Gross Margin contribution of sold feed crops per type in £100'

CR_PERC_STAN_OUTPUT (slope, soil, hydro, farm, crop) 'Percentage of standard ouput attributed to crops including soil slope type indexes'

LI_PERC_STAN_OUTPUT (farm,livestock) 'Percentage of standard output attributed to livestock'

TOTAL_STAN_OUTPUT(farm) 'Total farm standard output in £1000'

LIVE_SILBUY_PERC (farm, livestock) 'Percentage of bought in silage that is consumed by certain animal type'

GRAIN_CR_LAND (farm) 'Total land in ha allocated to grain crops on a farm in 1000 ha'

FARM_T_YIELD_FW(farm, crop) 'Crops yield in tonnes corrected for fresh weight excluding grass which is DM summed over slope, soil, hydro'

CATCH_CROP_LAND (crop) 'Land in the catchment attributed to a certain crop in 1000 ha'

FARM_CR_TOTAL_COST (farm, crop) 'Farm cost from crop production in £100 summed over slope, soil, hydro'

CR_PERC_STOU_FC(farm,crop) 'farm Crop percentage standard output summed over soil, slope, hydro'

FARM_CR_LAND (farm,crop) 'Farm land allocated to a particular crop in ha'

REBATE 'Catchment Grossmaring rebate that farmer recieve from tax'

;

FREE VARIABLES

CATCH_GM 'Catchment farm gross margin in £100,000'

LI_GM(farm, livestock) 'Gross Margin contribution of livestock per type in £100'

N_YLD_FUNCT (slope, soil, hydro, farm, crop) 'Intermediate calculation of the nitrogen yield function parameter'

P_YLD_FUNCT (slope, soil, hydro, farm, crop) 'Intermediate calculation of the phosphorus yield function parameter'

;

EQUATIONS

E1, E2, E3, E6, E7, E10, E11, E12, E13, E14, E15, E16, E17, E18, E19,

E20, E21, E22, E23, E24, E25, E26, E27, E28, E29, E33, E35, E36,

E30, E31, E32, E37, E38, E39, E40, E41, E45, E44, E46, E48, E49, E50,

E51, E52, E53, E54, E55, E56, E57, E58, E59, E61, E62, E63;

****Yield and Fertiliser Constraints****

E1 (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)..

YIELD_DM (slope, soil, hydro, farm, crop) =E= yieldfunc_data (crop, slope, soil, "b5")+ [yieldfunc_data (crop, slope, soil, "b0") * (1 - exp (N_YLD_FUNCT (slope, soil, hydro, farm, crop))) *(1 - exp (P_YLD_FUNCT (slope, soil, hydro, farm, crop)))];

****'Crop yield in dry weight '

E55 (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)..

N_YLD_FUNCT (slope, soil, hydro, farm, crop) =E= yieldfunc_data (crop, slope, soil, "b1") + {yieldfunc_data (crop, slope, soil, "b2") * N_AF (slope, soil, hydro, farm, crop)};

****Nitrogen component of yield function

E56(slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)..

P_YLD_FUNCT (slope, soil, hydro, farm, crop) =E= yieldfunc_data (crop, slope, soil, "b3") + {yieldfunc_data (crop, slope, soil, "b4") * P_AF (slope, soil, hydro, farm, crop)} ;

****Phosphorus component of yield function

E2 (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)..

T_YIELD_FW (slope, soil, hydro, farm, crop) =E= LAND (slope, soil, hydro, farm, crop) *dmfw_corr(crop, 'value') * yield_corr_data(crop,'EPIC_corr') * YIELD_DM (slope, soil, hydro, farm, crop);

****'Crop yield in fresh weight (excluding grazing which remains in dryweight: dmfw_corr =1)'

E57 (farm, crop)..

FARM_T_YIELD_FW(farm, crop)=E= SUM((slope, soil, hydro)$land_resource (slope, soil, hydro, farm), T_YIELD_FW (slope, soil, hydro, farm, crop));

****Calculating the freshweight yield in tonnes of a certain crop type produced per farm

****Land Allocation Constraints****

E3 (slope, soil, hydro, farm)..

SUM (crop, LAND (slope, soil, hydro, farm, crop)) =E= farm_area_2 (slope, soil, hydro, farm, "value");

****'Land allocation constraint'

E54 (crop)..

CATCH_CROP_LAND (crop)=E= SUM ((slope, soil, hydro, farm), LAND (slope, soil, hydro, farm, crop))/1000 ;

****Variable to calculate the catchment land allocated to a particular crop type in 1000 hectares

*****Fertiliser and Manure Calculations****

E6 (farm)..

N_FYM_TOTAL (farm) =E= SUM(livestock, FYM_output (livestock, "N", "value")*LIVE_NUM (farm, livestock))/10000;

****Total nitrogen production from farm yard manure in kg;

E7 (farm)..

P_FYM_TOTAL (farm) =E=   SUM(livestock, FYM_output (livestock, "P", "value")*LIVE_NUM (farm, livestock))/10000;

****Total phosphor production from farm yard manure in kg

E10(farm)..

N_FYM_TOTAL (farm) - N_FYM_STOR (farm) =E= [SUM((slope, soil, hydro, crop)$land_resource (slope, soil, hydro, farm), N_FYM (slope, soil, hydro, farm, crop)* LAND (slope, soil, hydro, farm, crop))/10000];

****Farmyard nutrients applied per ha aggregated over soil, slope, hydro can not exceed the total amount of FYM produced on farm

E11(farm)..

P_FYM_TOTAL (farm) - P_FYM_STOR (farm) =E= [SUM((slope, soil, hydro, crop)$land_resource (slope, soil, hydro, farm), P_FYM (slope, soil, hydro, farm, crop)* LAND (slope, soil, hydro, farm, crop))/10000];

****Farmyard nutrients applied per ha aggregated over soil, slope, hydro can not exceed the total amount of FYM produced on farm

****Costs and Revenues for Cash crops****

E12 (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)..

CR_TOTAL_COST (slope, soil, hydro, farm, crop) =E= LAND (slope, soil, hydro, farm, crop) * [(P_AF (slope, soil, hydro, farm, crop) * fert_cost ('P','value')*(1+P_tax)) + (N_AF (slope, soil, hydro, farm, crop) * fert_cost ('N','value')*(1+N_tax)) + crop_var_cost (crop)]/100 ;

****Crop total cost in 100£/ha

E58(farm, crop)..

FARM_CR_TOTAL_COST (farm, crop)=E= SUM((slope, soil, hydro)$land_resource (slope, soil, hydro, farm),CR_TOTAL_COST (slope, soil, hydro, farm, crop));

****Crop total cost in 100£/ha

****Livestock Feeding Requirements****

E13 (farm, livestock)..

SUM(silage_cr, FARM_T_YIELD_FW(farm, silage_cr)) * LIVE_SILAGE_PERC (farm, livestock)/100+ SUM(trade_feed_cr, BUY_FEED_CROP (farm, trade_feed_cr))* LIVE_SILBUY_PERC (farm, livestock)/100

=E= LIVE_NUM (farm, livestock) * silage_requ (livestock, 'value');

****'Definition of variable for minimum yield required for silage'

E14 (farm)..

SUM (livestock, LIVE_SILAGE_PERC (farm, livestock)) + FED_SALE_PERC (farm) =E= 100+delta*0.001;

****'Imposing constraint that home produced silage percentage fed summed over livestock type plus percentage of home produced silage sold must be smaller than 100'

E15 (farm)..

SUM (livestock, LIVE_SILBUY_PERC (farm, livestock)) =E= 100;

****'Imposing constraint that percentage of bought silage fed summed over livestock type must be 100'

E16 (farm, livestock)..

SUM (graze_cr, FARM_T_YIELD_FW(farm, graze_cr))* LIVE_GRAZE_PERC (farm, livestock)/100 =E= LIVE_NUM (farm, livestock) * Graze_requ (livestock, 'value') ;

****'Definition of variable for minimum yield required for grazing'

E17 (farm)..

SUM (livestock, LIVE_GRAZE_PERC (farm, livestock)) =E= 100+delta*0.001 ;

****'Imposing constraint that graze percentage fed summed over livestock type must equal unity'

E18(farm, livestock)..

SUM(hay_cr, FARM_T_YIELD_FW(farm, hay_cr))* LIVE_HAY_PERC (farm, livestock)/100 =E= LIVE_NUM (farm, livestock) * Hay_requ (livestock, 'value');

****'Definition of variable for minimum yield required for hay' +A3(farm, livestock)

E19 (farm)..

SUM (livestock, LIVE_HAY_PERC (farm, livestock)) =E= 100+delta*0.001;

****'Imposing constraint that hay percentage fed summed over livestock type must equal unity'

*****Trade Allowance for Feeding****

E20 (farm)..

SUM(trade_feed_cr, SOLD_FEED_CROP (farm, trade_feed_cr)) =E= SUM(trade_feed_cr, FED_SALE_PERC (farm)/100 * FARM_T_YIELD_FW(farm, trade_feed_cr)) ;

****'Definition of variable for percentage of silage yield which is sold'

E21 ..

SUM ((farm, trade_feed_cr), BUY_FEED_CROP (farm, trade_feed_cr))- SUM ((farm, trade_feed_cr),SOLD_FEED_CROP (farm, trade_feed_cr))=E=0;

*Constraint allowing only within-catchment trading

****Livestock Revenue and Costs including Feeding Crops****

E22 (farm,trade_feed_cr)..

FEED_CRREV(farm, trade_feed_cr) =E= SOLD_FEED_CROP (farm, trade_feed_cr)* crop_price (trade_feed_cr, 'value')/100;

****'Farm revenue from selling feed crops in 100£'

E23 (farm)..

FEED_CRCOST (farm)=E= SUM(trade_feed_cr, BUY_FEED_CROP (farm, trade_feed_cr) * crop_buy_cost (trade_feed_cr))/100;

****'Farm cost from bought feed crops in 100£'

E24 (farm, livestock)..

LI_SILBUY_FORAGE_TOTAL_COST (farm, livestock) =E= FEED_CRCOST (farm) * LIVE_SILBUY_PERC (farm, livestock)/100;

****'Total cost for silage forage bought in in 100Â£ per animal type'

E25 (farm, livestock)..

TOTAL_FORAGE_TOTAL_COST (farm, livestock) =E= SUM (graze_cr, FARM_CR_TOTAL_COST (farm, graze_cr)) * LIVE_GRAZE_PERC (farm, livestock)/100 + SUM(silage_cr, FARM_CR_TOTAL_COST (farm, silage_cr)) * LIVE_SILAGE_PERC (farm, livestock)/100 + SUM(hay_cr, FARM_CR_TOTAL_COST (farm, hay_cr)) * LIVE_HAY_PERC (farm, livestock)/100 + LI_SILBUY_FORAGE_TOTAL_COST (farm, livestock);

*'Total cost for forage in £100 per animal type (including all 3 different forage types and bought in forage)'

****Farm Type Standard Output Constraint****

E26 (farm) ..

TOTAL_STAN_OUTPUT (farm) =E= [(SUM((slope, soil, hydro, crop)$land_resource (slope, soil, hydro, farm), cr_stan_output_coeff(crop, 'value') * LAND (slope, soil, hydro, farm, crop))) + SUM (livestock, li_stan_output_coeff (livestock, 'value') * LIVE_NUM (farm, livestock))]/1000 ;

****'Calculation of total standard output in £1000'

E27 (farm,livestock)..

LI_PERC_STAN_OUTPUT (farm, livestock)/100 * TOTAL_STAN_OUTPUT (farm) =E= li_stan_output_coeff (livestock, 'value') * LIVE_NUM (farm, livestock)/1000;

****'Calculation of the livestock percentage of the standard output in £1000'

E28 (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)..

CR_PERC_STAN_OUTPUT (slope, soil, hydro, farm, crop)/100 * TOTAL_STAN_OUTPUT (farm) =E= cr_stan_output_coeff(crop, 'value') * LAND (slope, soil, hydro, farm, crop)/1000;

****'Calculation of the crop percentage of the standard output in £1000'

****Gross Margin (Catchment, farm, crop, livestock)****

E29 (slope, soil, hydro, farm, cash_crop)$land_resource (slope, soil, hydro, farm)..

CR_GM (slope, soil, hydro, farm, cash_crop) =E= T_YIELD_FW (slope, soil, hydro, farm, cash_crop) * crop_price (cash_crop, 'value')/100

- CR_TOTAL_COST (slope, soil, hydro, farm, cash_crop);

****'Gross Margin contribution of cash crops in £100

E30 (farm,trade_feed_cr)..

FEEDCR_GM (farm, trade_feed_cr) =E= FEED_CRREV (farm,trade_feed_cr) - (FARM_CR_TOTAL_COST (farm, trade_feed_cr) * FED_SALE_PERC (farm)/100);

****'Gross Margin contribution of sold feed crops per type in £100'

E31(farm, livestock)..

LI_GM (farm, livestock) =E= LIVE_NUM (farm, livestock) * live_margin (livestock) - TOTAL_FORAGE_TOTAL_COST (farm, livestock) ;

****'Farm Gross Margin contribution of livestock per type in £100'

E32 ..

CATCH_GM =E= [(SUM((slope, soil, hydro, farm, cash_crop)$land_resource (slope, soil, hydro, farm), CR_GM (slope, soil, hydro, farm, cash_crop))) + SUM((farm, livestock), LI_GM (farm, livestock)) + SUM((farm, trade_feed_cr), FEEDCR_GM (farm, trade_feed_cr)) +REBATE]/1000;

****CATCH_GM in £100 000

****Bounds****

N_AF.up (slope, soil, hydro, farm, AF_crop) = 0+ N_uplim (AF_crop, 'value') ;

****upper limit on nitrogen in kg/ha for AF crops

P_AF.up (slope, soil, hydro, farm, AF_crop) = 0+ P_uplim (AF_crop, 'value') ;

****upper limit on phosphorus in kg/ha for AF crops

N_AF.fx (slope, soil, hydro, farm, set_aside) = 0 ;

****nitrogen in kg/ha fixed to 0 for set-aside crops

P_AF.fx (slope, soil, hydro, farm, set_aside) = 0 ;

****phosphorus in kg/ha fixed to 0 for set-aside crops

N_AF.lo (slope, soil, hydro, farm, AF_crop) = 0+ N_lolim (AF_crop,'value') ;

****lower limit on nitrogen in kg/ha for AF crops

P_AF.lo (slope, soil, hydro, farm, AF_crop) = 0+ P_lolim (AF_crop, 'value') ;

****lower limit on phosphorus in kg/ha for AF crops

N_AF.up (slope, soil, hydro, farm, FYM_crop) = 0+ N_uplim (FYM_crop, 'value') -FYMcr_FN_fx(FYM_crop,'value');

****upper limit on nitrogen in kg/ha for FYM crops net the amount of FYM applied

P_AF.up (slope, soil, hydro, farm, FYM_crop) = 0+ P_uplim (FYM_crop, 'value') -FYMcr_FP_fx(FYM_crop,'value');

****upper limit on phosphorus in kg/ha for FYM crops net the amount of FYM applied

N_AF.lo (slope, soil, hydro, farm, FYM_crop)= 0+((N_lolim (FYM_crop,'value') - FYMcr_FN_fx(FYM_crop,'value'))$(N_lolim (FYM_crop,'value') > FYMcr_FN_fx(FYM_crop,'value'))) ;

P_AF.lo (slope, soil, hydro, farm, FYM_crop) = 0+((P_lolim (FYM_crop, 'value') - FYMcr_FP_fx(FYM_crop,'value'))$(P_lolim (FYM_crop, 'value') >FYMcr_FP_fx(FYM_crop,'value')));

LI_PERC_STAN_OUTPUT.lo (farm,livestock) = stan_out_li_lolim (farm, livestock);

****farm specific lower limit on the percentage of standard output coming from livestock

LI_PERC_STAN_OUTPUT.up (farm,livestock) = stan_out_li_uplim (farm, livestock);

****farm specific upper limit on the percentage of standard output coming from livestock

N_FYM.fx (slope, soil, hydro, farm, FYM_crop) = 0+FYMcr_FN_fx(FYM_crop,'value');

****fixing the amount of N and FYM crop receives from FYM

P_FYM.fx (slope, soil, hydro, farm, FYM_crop) = 0+FYMcr_FP_fx(FYM_crop,'value');

****fixing the amount of P and FYM crop receives from FYM

N_FYM.fx (slope, soil, hydro, farm, AF_crop) =0;

****setting amount of N an AF crop receives from FYM to 0

P_FYM.fx (slope, soil, hydro, farm, AF_crop) =0;

****setting amount of P an AF crop receives from FYM to 0

N_FYM.fx (slope, soil, hydro, farm, set_aside) =0;

****setting amount of N an AF crop receives from FYM to 0

P_FYM.fx (slope, soil, hydro, farm, set_aside) =0;

E59(farm,crop)..

CR_PERC_STOU_FC(farm,crop) =E= SUM((slope, soil, hydro)$land_resource (slope, soil, hydro, farm),CR_PERC_STAN_OUTPUT (slope, soil, hydro, farm, crop));

E33 (farm)..

SUM(cash_crop,CR_PERC_STOU_FC(farm, cash_crop)) =G= stan_out_cr_lolim (farm);

LIVE_NUM.lo(farm, livestock) = farm_live_lolim (farm,livestock);

LIVE_NUM.up(farm, livestock) = farm_live_uplim (farm,livestock);

N_YLD_FUNCT.lo (slope, soil, hydro, farm, crop) = -50;

P_YLD_FUNCT.lo (slope, soil, hydro, farm, crop) = -280;

N_YLD_FUNCT.up (slope, soil, hydro, farm, crop) = 50;

P_YLD_FUNCT.up (slope, soil, hydro, farm, crop) = 20;

YIELD_DM.lo (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)=0.01;

YIELD_DM.up (slope, soil, hydro, farm, crop)$land_resource (slope, soil, hydro, farm)=70;

LAND.up (slope, soil, hydro, farm, crop)= farm_area_2 (slope, soil, hydro, farm,"value");

LI_GM.lo(farm, livestock)= farm_ligm_lolim (farm,livestock);

LI_GM.up (farm, livestock)=500000;

TOTAL_FORAGE_TOTAL_COST.up (farm, livestock)=1000;

E35 (farm)..

SUM((slope, soil, hydro,spring_crop),LAND (slope, soil, hydro, farm, spring_crop))*100 =G= div_constr(farm,"spcr_lolim")*GRAIN_CR_LAND (farm);

****land allocated to spring crops in a farm must be greater than a certain percentage of the grain crop land

E36 (farm)..

SUM((slope, soil, hydro,winter_crop),CR_PERC_STAN_OUTPUT (slope, soil, hydro, farm, winter_crop)) =G= div_constr (farm,"wicr_lolim");

E37 ..

SUM(osr_crop,CATCH_CROP_LAND (osr_crop))*100=L= 20*SUM(farm,GRAIN_CR_LAND (farm));

E38 ..

SUM(ww_crop,CATCH_CROP_LAND (ww_crop))*100=L= 30*SUM(farm,GRAIN_CR_LAND (farm));

E39..

SUM(pot_crop,CATCH_CROP_LAND (pot_crop))*100=L= 5*SUM(farm,GRAIN_CR_LAND (farm));

E40..

SUM((farm,livestock),LIVE_NUM (farm, livestock)*Graze_LU (livestock, "value")) =L= SUM((farm,forage_cr),SUM((slope, soil, hydro),LAND (slope, soil, hydro, farm, forage_cr))* EPIC_stockden (forage_cr,"value")*stock_den_reduc);

E41..

SUM(maize_cr,CATCH_CROP_LAND (maize_cr))*100=G= 2*(SUM(crop,CATCH_CROP_LAND (crop))-SUM(farm,GRAIN_CR_LAND (farm)));

E44..

CATCH_CROP_LAND ("SBAR11")=E= CATCH_CROP_LAND ("SBAR12") ;

E45..

SUM(bar_crop,CATCH_CROP_LAND (bar_crop))*100=L= 45*SUM(farm,GRAIN_CR_LAND (farm));

E46..

CATCH_CROP_LAND ("WOSR1")=E= CATCH_CROP_LAND ("WOSR2");

E48..

CATCH_CROP_LAND("GRAZE4_1")=E= CATCH_CROP_LAND ("GRAZE2_1");

E49..

SUM(farm, N_FYM_STOR (farm)) =L=0.8*SUm(farm,N_FYM_TOTAL (farm));

****no more than 50% of total N manure produced may be stored

E50..

SUM(farm,P_FYM_STOR (farm)) =L=0.5*SUm(farm,P_FYM_TOTAL (farm));

****no more than 25% of total N manure produced may be stored

E51(farm)..

GRAIN_CR_LAND (farm)=E= SUM((slope, soil, hydro,cash_crop)$land_resource (slope, soil, hydro, farm), LAND (slope, soil, hydro, farm, cash_crop))/1000;

****calculating the area on a farm that is allocated to cash grain crops in 1000 ha

E52..

SUM(maize_cr, CATCH_CROP_LAND (maize_cr))*100=L= 20*(SUM(crop, CATCH_CROP_LAND (crop))-SUM(farm, GRAIN_CR_LAND (farm)));

E53..

SUM(farm, GRAIN_CR_LAND (farm))*100=G=15*SUM(crop, CATCH_CROP_LAND (crop));

E61..

CATCH_CROP_LAND ("GRLFA2")=G= catch_land*Setaside_requ;

E62..

SUM((aside_slope, aside_soil, aside_hydro, farm),LAND (aside_slope, aside_soil, aside_hydro, farm, "GRLFA2")) =G= catch_land*1000*Slope_setaside_requ;

E63..

REBATE =E=SUM((slope, soil, hydro, farm, crop),LAND (slope, soil, hydro, farm, crop) * [(P_AF (slope, soil, hydro, farm, crop) * fert_cost ('P', 'value')*(P_tax)) + (N_AF (slope, soil, hydro, farm, crop) * fert_cost ('N', 'value')*(N_tax))])/100;

****Rebate farms receive from tax in 100£

MODEL Baseline05 /all/ ;

option Savepoint=1;

****save the solution as advanced basis

Baseline05.ScaleOpt = 1;

****enable manual scaling:

execute_loadpoint 'policies_030_1_p';

****provide advanced basis from previous solve of the model

****Manual scaling of variables and equations****

LIVE_NUM.scale(farm,livestock)= 10;

LAND.scale (slope, soil, hydro, farm, crop)=10;

FED_SALE_PERC.scale (farm)=1/100;

LIVE_GRAZE_PERC.scale (farm, livestock) =1/100;

CATCH_CROP_LAND.scale (crop) =1/100;

```
YIELD_DM.scale (slope, soil, hydro, farm, crop)=1/100;
E26.scale (farm)=1/10;
E27.scale (farm,livestock)=1/10;
E28.scale (slope, soil, hydro, farm,crop)=1/10;

****Provide initial values independent of the loaded advanced basis****
TOTAL_STAN_OUTPUT.l('farm_1')  = 33.219 ;
TOTAL_STAN_OUTPUT.l('farm_2')  = 45.647 ;
TOTAL_STAN_OUTPUT.l('farm_3')  = 34.646 ;
TOTAL_STAN_OUTPUT.l('farm_4')  = 45.699 ;
TOTAL_STAN_OUTPUT.l('farm_5')  = 18.252 ;
TOTAL_STAN_OUTPUT.l('farm_6')  = 32.933 ;

LIVE_NUM.l('farm_1','sheep1 ')=  1741.460 ;
LIVE_NUM.l('farm_1','finish2')= 18023.388 ;
LIVE_NUM.l('farm_1','dairy  ')=  3374.541 ;
LIVE_NUM.l('farm_1','suckler')=  4038.058 ;
LIVE_NUM.l('farm_2','finish1')=  4953.307 ;
LIVE_NUM.l('farm_2','finish2')= 14246.002 ;
LIVE_NUM.l('farm_2','dairy  ')= 14838.620 ;
LIVE_NUM.l('farm_3','sheep1 ')=  1993.530 ;
LIVE_NUM.l('farm_3','sheep2 ')=    43.764 ;
LIVE_NUM.l('farm_3','finish2')= 18797.423 ;
LIVE_NUM.l('farm_3','dairy  ')=  3519.464 ;
LIVE_NUM.l('farm_3','suckler')=  1684.591 ;
LIVE_NUM.l('farm_4','finish1')=   4958.906;
LIVE_NUM.l('farm_4','finish2')= 14276.218 ;
LIVE_NUM.l('farm_4','dairy  ')= 14855.391 ;
LIVE_NUM.l('farm_5','finish1')=  1980.534 ;
LIVE_NUM.l('farm_5','finish2')=  1980.534 ;
LIVE_NUM.l('farm_5','dairy  ')=   370.818 ;
LIVE_NUM.l('farm_5','suckler')=  2218.648 ;
LIVE_NUM.l('farm_6','sheep1 ')=  1040.036 ;
LIVE_NUM.l('farm_6','sheep2 ')=   925.409 ;
LIVE_NUM.l('farm_6','finish1')=   478.611 ;
LIVE_NUM.l('farm_6','finish2')=  7147.351 ;
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```
LIVE_NUM.l('farm_6','dairy  ')=   669.104 ;
LIVE_NUM.l('farm_6','suckler')=  4003.329 ;

LI_PERC_STAN_OUTPUT.l('farm_1','sheep1   ')= 41.501  ;
LI_PERC_STAN_OUTPUT.l('farm_1','sheep2   ')=  2.000  ;
LI_PERC_STAN_OUTPUT.l('farm_1','finish2  ')= 25.000   ;
LI_PERC_STAN_OUTPUT.l('farm_1','dairy    ')= 25.000  ;
LI_PERC_STAN_OUTPUT.l('farm_1','suckler  ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_2','finish1  ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_2','finish2  ')= 14.380  ;
LI_PERC_STAN_OUTPUT.l('farm_2','dairy    ')= 80.000  ;
LI_PERC_STAN_OUTPUT.l('farm_3','sheep1   ')= 45.551  ;
LI_PERC_STAN_OUTPUT.l('farm_3','sheep2   ')=  1.000  ;
LI_PERC_STAN_OUTPUT.l('farm_3','finish2  ')= 25.000  ;
LI_PERC_STAN_OUTPUT.l('farm_3','dairy    ')= 25.000  ;
LI_PERC_STAN_OUTPUT.l('farm_3','suckler  ')=  2.000  ;
LI_PERC_STAN_OUTPUT.l('farm_4','finish1  ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_4','finish2  ')= 14.395  ;
LI_PERC_STAN_OUTPUT.l('farm_4','dairy    ')= 80.000  ;
LI_PERC_STAN_OUTPUT.l('farm_5','finish1  ')= 5.000   ;
LI_PERC_STAN_OUTPUT.l('farm_5','finish2  ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_5','dairy    ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_5','suckler  ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_6','sheep1   ')= 25.000  ;
LI_PERC_STAN_OUTPUT.l('farm_6','sheep2   ')= 22.245  ;
LI_PERC_STAN_OUTPUT.l('farm_6','finish1  ')= 0.670   ;
LI_PERC_STAN_OUTPUT.l('farm_6','finish2  ')= 10.000  ;
LI_PERC_STAN_OUTPUT.l('farm_6','dairy    ')=  5.000  ;
LI_PERC_STAN_OUTPUT.l('farm_6','suckler  ')=  5.000  ;

N_FYM_TOTAL.l('farm_1')=  75.710;
N_FYM_TOTAL.l('farm_2')= 128.621;
N_FYM_TOTAL.l('farm_3')=  71.254;
N_FYM_TOTAL.l('farm_4 ')=128.802 ;
N_FYM_TOTAL.l('farm_5')=  18.684;
N_FYM_TOTAL.l('farm_6')=  34.911;
```

```
P_FYM_TOTAL.l('farm_1')=  27.262 ;
P_FYM_TOTAL.l('farm_2')=  51.426 ;
P_FYM_TOTAL.l('farm_3')=  25.400 ;
P_FYM_TOTAL.l('farm_4')=  51.495 ;
P_FYM_TOTAL.l('farm_5')=   6.680 ;
P_FYM_TOTAL.l('farm_6')=  12.430 ;

File gck/%system.fn%.gck/;
put gck;
$onput
NONOPT
BLOCKPIC
BLOCKLIST
$offput
putclose ;
option nlp = gamschk;
option limrow = 0;
option limcol = 0;

SOLVE  Baseline05 maximising  CATCH_GM  using NLP;

$include reporting_Base05.gms
***Report the solver and model status****
Run_stat_base ("model_stat")= Baseline05.modelStat;
Run_stat_base ("solve_stat")= Baseline05.solveStat;

****Unloading reporting output into gdx file ****
execute_unload
'Baseline_out06.gdx',Catch_stats_base,Crop_report_base,farm_live_base,Pol_report_an_base,Fert_report_base,La
nd_report_base,
Li_gm_report_base,Cr_gm_report_base,Catch_gm_report_base,Cr_cost_report_base,
Pol_report_sum_base,total_base,Sediment_soil_tot_base,
  Sediment_slope_tot_base,Sediment_crop_tot_base,Sediment_soil_av_base,
 Sediment_slope_av_base,Sediment_crop_av_base,Run_stat_base,report_catch_base, Crop_report_C_base
,Live_report_base,report_hydro_base ;
;
```

Parameter Loading

File name: 'Parameter_Base05.gms'

$offlisting

****Defining sets and parameters****

SET

alli 'all items'

/ b0, b1, b2, b3, b4,b5,a1, a2, a3,farm_1, farm_2, farm_3,farm_4, farm_5, farm_6,farm_7, farm_8, farm_9, farm_10,farm_11, farm_12, H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, L1, L2,L3, L4, L5, S1, S2, S3,S4, N, P, FBEET1 , FBEET2, FBEET3, GRAZE4_2, GRAZE4_3, GRAZE6_1, GRAZE_6_2, GRAZE2_1, GRAZE2_2, GRAZE2_3,GRAZE3_1,GRAZE3_2,GRAZE3_3,GRAZE4_1, GRAZE6_2,GRLFA1 ,GRLFA2 ,GRAZE6_3, GRLFA3 ,HAY2_1 ,HAY2_2 ,HAY2_3 ,HAYLFA1, HAYLFA2, HAYLFA3, MAIZ1, MAIZ2, MAIZ3, MAIZ4, MAIZ5, MAIZ6, POTA1, POTA2, POTA3, POTA5, SBAR1, SBAR10, SBAR11 ,SBAR12 ,SBAR13 ,SBAR14, SBAR2, SBAR3, SBAR4, SBAR5 ,SBAR6 ,SBAR7 ,SBAR8 ,SBAR9 ,SIL1_1 ,SIL1_2 ,SIL1_3 ,SIL2_1 ,SIL2_2 ,SIL2_3 ,SIL3_1, SIL3_2, SIL3_3, SIL3_4, SIL4_1, SIL4_2 ,SIL4_3 ,SIL4_4 ,SILFA1 ,SILFA2 ,SILFA3, SOATS1, WBAR0, WBAR1, WBAR2, WBAR3, WBAR4, WBAR5, WBAR6, WBAR7, WBAR8, WOSR1, WOSR2, WOSR3, WW1, WW2, WW3, WW4, WWWC1, WWWC2, WWWC4, WWWC5, Land_crop_fl, Land_crop_l, Land_crop_perc, land_prop, crop_cost, crop_price, crop_lab_requ, N_uplim , P_uplim, dmfw_corr,Live_grmrg, Live_lab_requ, Silage_requ, Graze_requ, Hay_requ,crop_Contr_GM, Live_Contr_GM, value, ww, wbar, wosr, sbar, soats, pot, sbeans, maize_wc, ww_wc, sturnip_jul, sturnip_sp, fbeet, frape_cc, wrye_cc, sturnip_cc, must_cc,graze_lfa, sil_lfa, hay_lfa, sil_1, sil_2, sil_3, sil_4, hay_2, graze_2, graze_3, graze_4, graze_6, Li, Cr, Crop_Land_Perc, Crop_standard_output, Livestock_standard_output, TOTAL_ST_OUT_MANUAL,STAN_OUT_PERC_CHK, sheep1,sheep2,finish1,finish2,finish3,dairy,suckler, TOC, WTR_IC, WTR_N, WTG_IC, WTG_N, ZLOAD_IC, ZLOAD_N, CLOAD_IC, CLOAD_N, RSPC_IC, RSPC_N,SAC_YLD, EPIC_corr, NRLOAD_IC, NRLOAD_N, NGLOAD_IC, NGLOAD_N, PRLOAD_I, PRLOAD_N, PRLOAD_P, PRLOAD_N_P, PGLOAD_I, PGLOAD_N, PGLOAD_P, PGLOAD_N_P, DN2O_IC, DN2O_N, CFEM_I, CFEM_N, CFEM_P, CFEM_N_P,labhrs_total 'total farm labour hours', FTE 'Full time equivalent as definded by the DEFRA SLRs for farm size classification', spcr_lolim, wicr_lolim, osr_uplim, FBEET1_FYM, FBEET2_FYM, FBEET3_FYM, GRAZE4_2_FYM, GRAZE4_3_FYM, GRAZE6_1_FYM, GRAZE6_2_FYM, GRAZE2_1_FYM, GRAZE2_2_FYM, GRAZE2_3_FYM, GRAZE3_1_FYM, GRAZE3_2_FYM, GRAZE3_3_FYM, GRAZE4_1_FYM, GRAZE6_3_FYM, GRLFA1_FYM, GRLFA2_FYM, GRLFA3_FYM, HAY2_1_FYM, HAY2_2_FYM, HAY2_3_FYM, HAYLFA1_FYM, HAYLFA2_FYM, HAYLFA3_FYM, MAIZ1_FYM, MAIZ2_FYM, MAIZ3_FYM, MAIZ4_FYM, MAIZ5_FYM, MAIZ6_FYM, POTA1_FYM ,POTA2_FYM, POTA3_FYM, POTA5_FYM, SBAR1_FYM, SBAR10_FYM, SBAR11_FYM, SBAR12_FYM, SBAR13_FYM, SBAR14_FYM, SBAR2_FYM, SBAR3_FYM, SBAR4_FYM, SBAR5_FYM, SBAR6_FYM, SBAR7_FYM, SBAR8_FYM, SBAR9_FYM, SIL1_1_FYM, SIL1_2_FYM, SIL1_3_FYM, SIL2_1_FYM, SIL2_2_FYM, SIL2_3_FYM, SIL3_1_FYM, SIL3_2_FYM, SIL3_3_FYM, SIL3_4_FYM, SIL4_1_FYM, SIL4_2_FYM, SIL4_3_FYM, SIL4_4_FYM, SILFA1_FYM, SILFA2_FYM, SILFA3_FYM, SOATS1_FYM, WBAR0_FYM, WBAR1_FYM, WBAR2_FYM, WBAR3_FYM, WBAR4_FYM, WBAR5_FYM, WBAR6_FYM, WBAR7_FYM, WBAR8_FYM, WOSR1_FYM, WOSR2_FYM, WOSR3_FYM, WW1_FYM, WW2_FYM, WW3_FYM, WW4_FYM, WWWC1_FYM, WWWC2_FYM, WWWC4_FYM, WWWC5_FYM, sc1*sc8, scenario_setup, scenario_results, setaside/

supcrop(Alli) 'superset of crops'/FBEET1_FYM, FBEET2_FYM, FBEET3_FYM, GRAZE4_2_FYM, GRAZE4_3_FYM, GRAZE6_1_FYM, GRAZE6_2_FYM, GRAZE2_1_FYM, GRAZE2_2_FYM, GRAZE2_3_FYM, GRAZE3_1_FYM, GRAZE3_2_FYM, GRAZE3_3_FYM, GRAZE4_1_FYM, GRAZE6_3_FYM, GRLFA1_FYM, GRLFA2_FYM, GRLFA3_FYM, HAY2_1_FYM, HAY2_2_FYM, HAY2_3_FYM, HAYLFA1_FYM, HAYLFA2_FYM, HAYLFA3_FYM, MAIZ1_FYM, MAIZ2_FYM, MAIZ4_FYM, MAIZ5_FYM, MAIZ6_FYM, POTA1_FYM, POTA2_FYM, POTA3_FYM, POTA5_FYM, SBAR1_FYM, SBAR10_FYM, SBAR11_FYM, SBAR12_FYM, SBAR13_FYM, SBAR14_FYM, SBAR2_FYM, SBAR3_FYM, SBAR4_FYM, SBAR5_FYM, SBAR6_FYM, SBAR7_FYM, SBAR8_FYM, SBAR9_FYM, *GRAZE2_1_FYM, SIL1_1_FYM, SIL1_2_FYM, SIL1_3_FYM, SIL2_1_FYM, SIL2_2_FYM, SIL2_3_FYM, SIL3_1_FYM, SIL3_2_FYM, SIL3_3_FYM, SIL3_4_FYM, SIL4_1_FYM, SIL4_2_FYM, SIL4_3_FYM, SIL4_4_FYM, SILFA1_FYM, SILFA2_FYM, SILFA3_FYM, SOATS1_FYM, *SIL2_1_FYM, WBAR0_FYM, WBAR1_FYM, WBAR2_FYM, WBAR3_FYM, WBAR5_FYM, WBAR4_FYM, WBAR6_FYM, WBAR7_FYM, WBAR8_FYM, WOSR1_FYM, WOSR2_FYM, WOSR3_FYM, WW1_FYM, WW2_FYM, WW3_FYM, WW4_FYM, WWWC1_FYM, WWWC2_FYM, WWWC5_FYM, FBEET1, FBEET2, FBEET3, GRAZE4_2, GRAZE4_3, GRAZE6_1, GRAZE6_2, GRAZE2_1, GRAZE2_2, GRAZE2_3, GRAZE3_1, GRAZE3_2, GRAZE3_3, GRAZE4_1, GRAZE6_3, GRLFA1, GRLFA2, GRLFA3, HAY2_1, HAY2_2, HAY2_3, HAYLFA1, HAYLFA2, HAYLFA3, MAIZ1, MAIZ2, MAIZ4, MAIZ5, MAIZ6, POTA1, POTA2, POTA3, POTA5, SBAR1, SBAR10, SBAR11, SBAR12, SBAR13, SBAR14, SBAR2,

SBAR3, SBAR4, SBAR5, SBAR6, SBAR7, SBAR8, SBAR9, *GRAZE2_1, SIL1_1, SIL1_2, SIL1_3, SIL2_1, SIL2_2, SIL2_3, SIL3_1, SIL3_2, SIL3_3, SIL3_4, SIL4_1, SIL4_2, SIL4_3, SIL4_4, SILFA1, SILFA2, SILFA3, SOATS1, *SIL2_1, WBAR0, WBAR1, WBAR2, WBAR3, WBAR5, WBAR6, WBAR7, WBAR8, WOSR1, WOSR2, WOSR3, WW1, WW2, WW3, WW4, WWWC1, WWWC2, WWWC5

/

beta (alli) 'beta coefficients of yield function' /b0, b1, b2, b3, b4,b5/

alpha (alli) 'alpha coefficients for pollution fucntion'/ a1, a2, a3/

scenario (alli) 'scenarios' /sc1*sc8/

ordr (alli) 'ordering scnerio input and output' /scenario_setup,scenario_results/

farm(alli) 'farm types included in the model' /

farm_1 'Sheep & suckler upland farm (less productive soils and more steep slopes)',

farm_2 'Dairy & finish lowland farm (more productive soils and less steep slopes)',

farm_3 'Sheep & suckler upland farm (mixed soils and mixed slopes)',

farm_4 'Dairy & finish lowland farm (mixed soils and mixed slopes)',

farm _5 'Cereal lowland farm (more productive soils and mixed slopes)',

farm_6 'Mixed cereal and sheep farm (mixed soils and mixed slopes)'/

soil(alli) /L1 'Wick', L3 'Malvern', L4 'Clifton', L2 'Newbiggin', L5 'Winterhill' /

aside_soil (soil) 'soil types for spatially targeted set_aside'

/L4 'Clifton', L2 'Newbiggin', L5 'Winterhill'/

slope(alli) /S1 '0-1.39', S2 '1.4-4.19, S3 '4.2-7', S4 '7.01-12.8'/

aside_slope (slope)'slope levels for spatially targeted set_aside' /S4 '4.01-7.3'/

hydro(alli) 'hydrological connectivity/risk levels' /H1, H2, H3, H4, H5, H6, H7, H8, H9, H10/

aside_hydro (hydro)'hydrological connectivity levels for spatially targeted set_aside'/H3, H4, H5, H6, H7,H8, H9, H10/

nutrients (alli) 'in kg per ha' /N, P/

crop (supcrop) 'crops' /SBAR11, FBEET1, SIL1_1, GRAZE6_3, GRLFA2, GRLFA1, HAY2_1, HAYLFA1, MAIZ1, SILFA1, WW1, WBAR0, WOSR1, POTA1, WWWC1, SOATS1, GRAZE2_1,GRAZE2_2,GRAZE3_1,GRAZE4_1,GRAZE6_1_FYM, GRAZE4_3_FYM, FBEET2 ,FBEET3 , SBAR12,SBAR13_FYM ,SBAR2_FYM, SIL2_1, SIL3_1 , SIL3_2_FYM, SIL4_1,SIL4_2_FYM, WW2, WW3, WW4, WW4_FYM, WBAR1, WBAR2, WBAR3_FYM, WBAR4_FYM, WBAR5_FYM, MAIZ4_FYM, MAIZ5_FYM, WOSR2, WOSR3, POTA2,POTA3_FYM,POTA5_FYM, WWWC2, GRLFA3_FYM, GRLFA1_FYM, GRLFA3, HAYLFA2 , HAYLFA3, LT_GRAZFLA/

cash_crop (crop)'non feed crops for sale' / SBAR11, WW1, WBAR0, WOSR1,POTA1, SOATS1,SBAR12 ,SBAR13_FYM ,SBAR2_FYM, WOSR2, WOSR3, WBAR1, WBAR2, WBAR3_FYM, WW2, WW3, WW4, WW4_FYM, POTA2, WBAR4_FYM, WBAR5_FYM, POTA3_FYM, POTA5_FYM/

spring_crop (cash_crop)'spring cereal cash crops' /SBAR11, SBAR12, SBAR13_FYM, SOATS1, SBAR2_FYM/

winter_crop (cash_crop)'winter cereal cash crops' /WW1, WW2, WW3, WW4, WW4_FYM, WBAR0, WBAR1, WBAR2, WBAR3_FYM, WBAR4_FYM, WBAR5_FYM/

osr_crop (cash_crop)'oil seed rape crop' /WOSR1, WOSR2, WOSR3/

ww_crop (cash_crop)'winter wheat sale crop' /WW1, WW2, WW3, WW4, WW4_FYM/

bar_crop (cash_crop)'barley crops' /SBAR11, SBAR12, SBAR13_FYM, WBAR0, WBAR1, WBAR2, WBAR3_FYM, WBAR4_FYM, WBAR5_FYM, SBAR2_FYM/

pot_crop (cash_crop)'potato crop' /POTA1, POTA2, POTA3_FYM, POTA5_FYM/

silage_cr (crop) 'silage crops'

/SIL1_1, FBEET1, FBEET2, FBEET3, MAIZ1, SILFA1, WWWC1, SIL2_1, SIL3_1 , SIL4_1 , SIL4_2_FYM, SIL3_2_FYM, WWWC2, MAIZ4_FYM, MAIZ5_FYM/

graze_cr (crop) 'graze crops'

/GRAZE6_3,GRLFA1, GRAZE2_1, GRAZE2_2, GRAZE3_1, GRAZE4_1, GRAZE6_1_FYM, GRAZE4_3_FYM, GRLFA3_FYM, GRLFA1_FYM, GRLFA3/

hay_cr (crop) 'hay crops' /HAY2_1 ,HAYLFA1 /

forage_cr (crop) 'forage crops'
/GRAZE2_1,GRAZE2_2,GRAZE3_1,GRAZE4_1,GRAZE6_3,GRLFA1,GRAZE6_1_FYM, GRAZE4_3_FYM, HAY2_1 , HAYLFA1, SIL1_1, SIL2_1, SILFA1, SIL4_2_FYM, SIL3_2_FYM, GRLFA3_FYM, GRLFA1_FYM, GRLFA3/

maize_cr (crop) 'maize crops' /MAIZ1 ,MAIZ5_FYM,MAIZ4_FYM/

trade_feed_cr (silage_cr) 'feed crops traded amongst farmers'

/FBEET1,FBEET2,FBEET3,MAIZ1 ,MAIZ5_FYM,MAIZ4_FYM/

set_aside(crop) /GRLFA2/

FYM_crop (crop) /

GRAZE6_1_FYM,MAIZ5_FYM,MAIZ4_FYM,POTA3_FYM,SBAR2_FYM,SIL3_2_FYM,SIL4_2_FYM,WBAR4_FYM, WBAR5_FYM,POTA5_FYM, SBAR13_FYM,WBAR3_FYM,GRAZE4_3_FYM, WW4_FYM,GRLFA3_FYM,GRLFA1_FYM/

AF_crop(crop) /SBAR11, FBEET1, SIL1_1,GRAZE6_3,GRLFA2, HAY2_1, HAYLFA1, MAIZ1, SILFA1, WW1, WBAR0, WOSR1, POTA1, WWWC1, SOATS1, GRAZE2_1, GRAZE2_2, GRAZE3_1, GRAZE4_1, FBEET2 ,FBEET3 , SBAR12, SIL2_1, SIL3_1 , SIL4_1, WW2,WW3,WW4, WBAR1, WBAR2, WOSR2, WOSR3, POTA2, WWWC2, GRLFA3/

pol_crop 'set of crop names used in pollution data'

/FBEET1_FYM, FBEET2_FYM, FBEET3_FYM, GRAZ4_2_FYM, GRAZ4_3_FYM, GRAZ6_1_FYM, GRAZ6_2_FYM, GRAZE2_1_FYM, GRAZE2_2_FYM, GRAZE2_3_FYM, GRAZE3_1_FYM, GRAZE3_2_FYM, GRAZE3_3_FYM, GRAZE4_1_FYM, GRAZE6_3_FYM, GRLFA1_FYM, GRLFA2_FYM, GRLFA3_FYM, HAY2_1_FYM, HAY2_2_FYM, HAY2_3_FYM, HAYLFA1_FYM, HAYLFA2_FYM, HAYLFA3_FYM, MAIZ1_FYM, MAIZ2_FYM, MAIZ4_FYM, MAIZ5_FYM, MAIZ6_FYM, POTA1_FYM,POTA2_FYM,POTA3_FYM,POTA5_FYM, SBAR1_FYM, SBAR10_FYM, SBAR11_FYM, SBAR12_FYM, SBAR13_FYM, SBAR14_FYM, SBAR2_FYM, SBAR3_FYM, SBAR4_FYM, SBAR5_FYM, SBAR6_FYM, SBAR7_FYM, SBAR8_FYM, SBAR9_FYM, SGRAZ2_1_FYM, SIL1_1_FYM, SIL1_2_FYM, SIL1_3_FYM, SIL2_1_FYM, SIL2_2_FYM, SIL2_3_FYM, SIL3_1_FYM, SIL3_2_FYM, SIL3_3_FYM, SIL3_4_FYM, SIL4_1_FYM, SIL4_2_FYM, SIL4_3_FYM, SIL4_4_FYM, SILFA1_FYM, SILFA2_FYM, SILFA3_FYM, SOATS1_FYM, SSIL2_1_FYM, WBAR0_FYM, WBAR1_FYM, WBAR2_FYM, WBAR3_FYM, WBAR5_FYM, WBAR6_FYM, WBAR7_FYM, WBAR8_FYM, WOSR1_FYM, WOSR2_FYM, WOSR3_FYM, WW1_FYM, WW2_FYM, WW3_FYM, WW4_FYM, WWWC1_FYM, WWWC2_FYM, WWWC5_FYM,FBEET1,FBEET2,FBEET3, GRAZ4_2, GRAZ4_3, GRAZ6_1, GRAZ6_2, GRAZE2_1, GRAZE2_2, GRAZE2_3, GRAZE3_1, GRAZE3_2, GRAZE3_3, GRAZE4_1, GRAZE6_3, GRLFA1, GRLFA2, GRLFA3, HAY2_1, HAY2_2, HAY2_3, HAYLFA1, HAYLFA2, HAYLFA3, MAIZ1, MAIZ2, MAIZ4, MAIZ5, MAIZ6,POTA1,POTA2,POTA3,POTA5, SBAR1, SBAR10, SBAR11, SBAR12, SBAR13, SBAR14, SBAR2, SBAR3, SBAR4, SBAR5, SBAR6, SBAR7, SBAR8, SBAR9, SGRAZ2_1, SIL1_1, SIL1_2, SIL1_3, SIL2_1, SIL2_2, SIL2_3, SIL3_1, SIL3_2, SIL3_3, SIL3_4, SIL4_1, SIL4_2, SIL4_3, SIL4_4, SILFA1, SILFA2, SILFA3, SOATS1, SSIL2_1, WBAR0, WBAR1, WBAR2, WBAR3, WBAR5, WBAR6, WBAR7, WBAR8, WOSR1, WOSR2, WOSR3, WW1, WW2, WW3, WW4, WWWC1, WWWC2, WWWC5/

livestock (alli) 'livestock types'

/dairy '8,500 l, all year calving (1 cow)',

sheep1 'improved hill breeds (100 ewes tupped)',

sheep2 'extensive hill breeds (100 ewes tupped)',

finish1 'finishing spring-born suckled calves at 18-20 months (1 steer)',

finish2 'forage based finishing dairy steers at 24 months (holstein)',

suckler 'upland suckler cows, calving period Feb-April(1 cow with calf)'/

value (alli) 'value used in parameter declaration' /value/

crop_dtb(alli) 'crop names used in input database' /ww, wbar, wosr, sbar, soats, pot, sbeans, maize_wc, ww_wc, sturnip_jul, sturnip_sp, fbeet, frape_cc, wrye_cc, sturnip_cc,must_cc, graze_lfa, sil_lfa,hay_lfa, sil_1, sil_2, sil_3, sil_4,hay_2, graze_2, graze_3, graze_4, graze_6, setaside/

product_cat(alli)'product type categories' /Li 'livestock', Cr 'crops'/

yield_corr_cat (alli)'names for yield expectations and corrections' / SAC_YLD, EPIC_corr/

poll_funct_coeff (alli)'pollution function intercept and coefficient names' /TOC, WTR_IC, WTR_N, WTG_IC, WTG_N, ZLOAD_IC, ZLOAD_N, CLOAD_IC, CLOAD_N, RSPC_IC, RSPC_N, NRLOAD_IC, NRLOAD_N, NGLOAD_IC, NGLOAD_N, PRLOAD_I, PRLOAD_N, PRLOAD_P, PRLOAD_N_P, PGLOAD_I, PGLOAD_N, PGLOAD_P, PGLOAD_N_P, DN2O_IC, DN2O_N, CFEM_I, CFEM_N, CFEM_P, CFEM_N_P/

group_types_cr(alli)'crop group types used for diversity constraint' /spcr_lolim,wicr_lolim,osr_uplim/

ID / ID_63_01, ID_63_02, ID_63_03, ID_63_04, ID_63_05, ID_63_06, ID_63_07, ID_63_08, ID_63_09, ID_63_10, ID_63_11, ID_63_12, ID_63_13, ID_63_14, ID_63_15, ID_63_16, ID_63_17, ID_63_18, ID_63_19, ID_63_20, ID_63_21, ID_63_22, ID_63_23, ID_63_24, ID_63_25, ID_63_26, ID_63_27, ID_63_28, ID_63_29,Land_alloc_GAMS_3,Land_alloc_GAMS_4/

;

****Loading Yield Function Data into model from GDX All_parameters_63.gdx created by running Gdx_load.gms****

****define intermediate parameters over intermediate set which contains names of crops used in excel file****

TABLE dtbyieldfunc_data(ID,Crop,Slope, Soil, beta) 'variable costs crop production in ï¿½/ha excluding fertiliser cost';

*read parameter into gdx file

$gdxin All_parameters_63.gdx

*load parameter into model

$load dtbyieldfunc_data

$gdxin

TABLE yieldfunc_data(Crop,Slope, Soil, beta) 'variable costs crop production in ï¿½/ha excluding fertiliser cost';

yieldfunc_data(Crop,Slope, Soil, beta)= SUM(ID, dtbyieldfunc_data(ID,Crop,Slope, Soil, beta));

;

TABLE dtbyield_corr_data(ID,Crop,yield_corr_cat) 'SAC_YLD - expected freshweight yield in t/ha EPIC_corr - correction factor for yield function to reach expected freshweight yield in t/ha';

$gdxin All_parameters_63.gdx

$load dtbyield_corr_data

$gdxin

TABLE yield_corr_data(Crop,yield_corr_cat) 'SAC_YLD - expected freshweight yield in t/ha EPIC_corr - correction factor for yield function to reach expected freshweight yield in t/ha';

yield_corr_data(Crop,yield_corr_cat)=SUM(ID,dtbyield_corr_data(ID,Crop,yield_corr_cat));

crop Parameters

Parameter dtbcrop_cost (ID, crop_dtb, value) 'database variable costs crop production in 100ï¿½/ha excluding fertiliser cost';

$gdxin All_parameters_63.gdx

$load dtbcrop_cost

$gdxin

;

*define set which maps the intermediate names from excel to unique crop pairs used in model files

Set mapindx(crop,crop_dtb) /

SBAR11.'sbar', SBAR12.'sbar',SBAR13_FYM.'sbar',SBAR2_FYM.'sbar', FBEET1.'fbeet', FBEET2.'fbeet', FBEET3.'fbeet', MAIZ1.'maize_wc',MAIZ5_FYM.'maize_wc',MAIZ4_FYM.'maize_wc', SIL1_1.'sil_1', SILFA1.'sil_lfa', SIL2_1.'sil_2', SIL3_1.'sil_3',SIL3_2_FYM.'sil_3', SIL4_1.'sil_4',SIL4_2_FYM.'sil_4', GRAZE2_1.'graze_2', GRAZE2_2.'graze_2', GRAZE3_1.'graze_3', GRAZE4_1.'graze_4',GRAZE4_3_FYM.'graze_4', graze6_3.'graze_6',graze6_1_FYM.'graze_6', HAY2_1.'hay_2', HAYLFA1.'hay_lfa', GRLFA1.'setaside', GRLFA3.'graze_lfa',GRLFA3_FYM.'graze_lfa',GRLFA1_FYM.'graze_lfa', WW1.'ww',WW2.'ww',WW3.'ww',WW4.'ww',WW4_FYM.'ww', WBAR0.'wbar', WBAR1.'wbar', WBAR2.'wbar', WBAR3_FYM.'wbar', WBAR4_FYM.'wbar',WBAR5_FYM.'wbar', WOSR1.'wosr', WOSR2.'wosr', WOSR3.'wosr', POTA1.'pot',POTA2.'pot',POTA3_FYM.'pot',POTA5_FYM.'pot', WWWC1.'ww_wc',WWWC2.'ww_wc', SOATS1.'soats'/

polmap (supcrop,pol_crop)

/FBEET1_FYM.'FBEET1_FYM', FBEET2_FYM.'FBEET2_FYM', FBEET3_FYM.'FBEET3_FYM', GRAZE4_2_FYM.'GRAZ4_2_FYM', GRAZE4_3_FYM.'GRAZ4_3_FYM', GRAZE6_1_FYM.'GRAZ6_1_FYM', GRAZE6_2_FYM.'GRAZ6_2_FYM', GRAZE2_1_FYM.'GRAZE2_1_FYM', GRAZE2_2_FYM.'GRAZE2_2_FYM', GRAZE2_3_FYM.'GRAZE2_3_FYM', GRAZE3_1_FYM.'GRAZE3_1_FYM', GRAZE3_2_FYM.'GRAZE3_2_FYM', GRAZE3_3_FYM.'GRAZE3_3_FYM', GRAZE4_1_FYM.'GRAZE4_1_FYM', GRAZE6_3_FYM.'GRAZE6_3_FYM', GRLFA1_FYM.'GRLFA1_FYM', GRLFA2_FYM.'GRLFA2_FYM', GRLFA3_FYM.'GRLFA3_FYM', HAY2_1_FYM.'HAY2_1_FYM', HAY2_2_FYM.'HAY2_2_FYM', HAY2_3_FYM.'HAY2_3_FYM', HAYLFA1_FYM.'HAYLFA1_FYM', HAYLFA2_FYM.'HAYLFA2_FYM', HAYLFA3_FYM.'HAYLFA3_FYM', MAIZ1_FYM.'MAIZ1_FYM', MAIZ2_FYM.'MAIZ2_FYM', MAIZ4_FYM.'MAIZ4_FYM', MAIZ5_FYM.'MAIZ5_FYM', MAIZ6_FYM.'MAIZ6_FYM', POTA1_FYM.'POTA1_FYM', POTA2_FYM.'POTA2_FYM', POTA3_FYM.'POTA3_FYM', POTA5_FYM.'POTA5_FYM', SBAR1_FYM.'SBAR1_FYM', SBAR10_FYM.'SBAR10_FYM', SBAR11_FYM.'SBAR11_FYM', SBAR12_FYM.'SBAR12_FYM', SBAR13_FYM.'SBAR13_FYM', SBAR14_FYM.'SBAR14_FYM', SBAR2_FYM.'SBAR2_FYM', SBAR3_FYM.'SBAR3_FYM', SBAR4_FYM.'SBAR4_FYM', SBAR5_FYM.'SBAR5_FYM', SBAR6_FYM.'SBAR6_FYM', SBAR7_FYM.'SBAR7_FYM', SBAR8_FYM.'SBAR8_FYM', SBAR9_FYM.'SBAR9_FYM', GRAZE2_1_FYM.'SGRAZ2_1_FYM', SIL1_1_FYM.'SIL1_1_FYM', SIL1_2_FYM.'SIL1_2_FYM', SIL1_3_FYM.'SIL1_3_FYM', SIL2_1_FYM.'SIL2_1_FYM', SIL2_2_FYM.'SIL2_2_FYM', SIL2_3_FYM.'SIL2_3_FYM', SIL3_1_FYM.'SIL3_1_FYM', SIL3_2_FYM.'SIL3_2_FYM', SIL3_3_FYM.'SIL3_3_FYM', SIL3_4_FYM.'SIL3_4_FYM', SIL4_1_FYM.'SIL4_1_FYM', SIL4_2_FYM.'SIL4_2_FYM', SIL4_3_FYM.'SIL4_3_FYM', SIL4_4_FYM.'SIL4_4_FYM', SILFA1_FYM.'SILFA1_FYM', SILFA2_FYM.'SILFA2_FYM', SILFA3_FYM.'SILFA3_FYM', SOATS1_FYM.'SOATS1_FYM', SIL2_1_FYM.'SSIL2_1_FYM', WBAR0_FYM.'WBAR0_FYM',

WBAR1_FYM.'WBAR1_FYM', WBAR2_FYM.'WBAR2_FYM', WBAR3_FYM.'WBAR3_FYM', WBAR5_FYM.'WBAR5_FYM', WBAR6_FYM.'WBAR6_FYM', WBAR7_FYM.'WBAR7_FYM', WBAR8_FYM.'WBAR8_FYM', WOSR1_FYM.'WOSR1_FYM', WOSR2_FYM.'WOSR2_FYM', WOSR3_FYM.'WOSR3_FYM', WW1_FYM.'WW1_FYM', WW2_FYM.'WW2_FYM', WW3_FYM.'WW3_FYM', WW4_FYM.'WW4_FYM', WWWC1_FYM.'WWWC1_FYM', WWWC2_FYM.'WWWC2_FYM', FBEET1.'FBEET1', FBEET2.'FBEET2', FBEET3.'FBEET3', GRAZE4_2.'GRAZ4_2', GRAZE4_3.'GRAZ4_3', GRAZE6_1.'GRAZ6_1', GRAZE6_2.'GRAZ6_2', GRAZE2_1.'GRAZE2_1', GRAZE2_2.'GRAZE2_2', GRAZE2_3.'GRAZE2_3', GRAZE3_1.'GRAZE3_1', GRAZE3_2.'GRAZE3_2', GRAZE3_3.'GRAZE3_3', GRAZE4_1.'GRAZE4_1', GRAZE6_3.'GRAZE6_3', GRLFA1.'GRLFA1', GRLFA2.'GRLFA2', GRLFA3.'GRLFA3', HAY2_1.'HAY2_1', HAY2_2.'HAY2_2', HAY2_3.'HAY2_3', HAYLFA1.'HAYLFA1', HAYLFA2.'HAYLFA2', HAYLFA3.'HAYLFA3', MAIZ1.'MAIZ1', MAIZ2.'MAIZ2', MAIZ4.'MAIZ4', MAIZ5.'MAIZ5', MAIZ6.'MAIZ6', POTA1.'POTA1', POTA2.'POTA2', POTA3.'POTA3', POTA5.'POTA5', SBAR1.'SBAR1', SBAR10.'SBAR10', SBAR11.'SBAR11', SBAR12.'SBAR12', SBAR13.'SBAR13', SBAR14.'SBAR14', SBAR2.'SBAR2', SBAR3.'SBAR3', SBAR4.'SBAR4', SBAR5.'SBAR5', SBAR6.'SBAR6', SBAR7.'SBAR7', SBAR8.'SBAR8', SBAR9.'SBAR9', GRAZE2_1.'SGRAZ2_1', SIL1_1.'SIL1_1', SIL1_2.'SIL1_2', SIL1_3.'SIL1_3', SIL2_1.'SIL2_1', SIL2_2.'SIL2_2', SIL2_3.'SIL2_3', SIL3_1.'SIL3_1', SIL3_2.'SIL3_2', SIL3_3.'SIL3_3', SIL3_4.'SIL3_4', SIL4_1.'SIL4_1', SIL4_2.'SIL4_2', SIL4_3.'SIL4_3', SIL4_4.'SIL4_4', SILFA1.'SILFA1', SILFA2.'SILFA2', SILFA3.'SILFA3', SOATS1.'SOATS1', SIL2_1.'SSIL2_1', WBAR0.'WBAR0', WBAR1.'WBAR1', WBAR2.'WBAR2', WBAR3.'WBAR3', WBAR5.'WBAR5', WBAR6.'WBAR6', WBAR7.'WBAR7', WBAR8.'WBAR8', WOSR1.'WOSR1', WOSR2.'WOSR2', WOSR3.'WOSR3', WW1.'WW1', WW2.'WW2', WW3.'WW3', WW4.'WW4', WWWC1.'WWWC1', WWWC2.'WWWC2'/

;

SET mapindxFYM (FYM_crop, crop_dtb)

/SBAR2_FYM.'sbar', SBAR13_FYM.'sbar', MAIZ5_FYM.'maize_wc', MAIZ4_FYM.'maize_wc', SIL3_2_FYM.'sil_3', SIL4_2_FYM.'sil_4', graze6_1_FYM.'graze_6', WBAR4_FYM.'wbar', WBAR3_FYM.'wbar', WBAR5_FYM.'wbar', POTA3_FYM.'pot', POTA5_FYM.'pot', GRAZE4_3_FYM.'graze_4', WW4_FYM.'ww', GRLFA3_FYM.'graze_lfa', GRLFA1_FYM.'graze_lfa'/

;

PARAMETER

crop_cost(crop,value)'variable costs crop production in 100ï¿½/ha excluding fertiliser cost',

dtbcrop_lab_requ (ID, crop_dtb, value) 'database standard annual labour requirements in h/ha',

crop_lab_requ(crop,value),

dtbcrop_price (ID, crop_dtb, value) 'database crop price farmgate in 100ï¿½/t',

crop_price(crop,value)'crop price farmgate in 100ï¿½/t',

dtbN_uplim (ID, crop_dtb, value) 'database limit of N in kg/ha which can be applied to different crops',

N_uplim(crop,value),

dtbN_lolim (ID, crop_dtb, value) 'database lower limit of N in kg/ha application to different crops',

N_lolim(crop,value),

dtbP_uplim (ID, crop_dtb, value) 'database limit of P in kg/ha application to different crops',

P_uplim(crop,value),

dtbP_lolim (ID,crop_dtb, value) 'database lower limit of P in kg/ha application to different crops',

P_lolim(crop,value),

dtbFert_cost (ID,Nutrients, value)'Fertiliser cost in 100ï¿½/kg',

Fert_cost (Nutrients, value)'Fertiliser cost in 100ï¿½/kg',

dtbDmfw_corr (ID, crop_dtb, value) 'database dry matter fresh weight correction factor based on dry matter content',

Dmfw_corr(crop,value)'dry matter fresh weight correction factor based on dry matter content', cr_stan_output_coeff(crop,value)'standard output coefficient in 1000ï¿½/ha sourced from Eurostat',

dtbSAC_cropgmrg (ID,crop_dtb, value) 'database SAC grossmargin including fertiliser costs in ï¿½/ha',

dtbcr_stan_output_coeff (ID, crop_dtb, value) 'database standard output coefficient in 1000ï¿½/ha sourced from Eurostat',

SAC_cropgmrg (crop, value) 'SAC grossmargin including fertiliser costs in ï¿½/ha';

$gdxin All_parameters_63.gdx

$load dtbcrop_lab_requ

$load dtbcrop_price

$load dtbN_uplim

$load dtbN_lolim

$load dtbP_uplim

$load dtbP_lolim

$load dtbFert_cost

$load dtbDmfw_corr

$load dtbcr_stan_output_coeff

$load dtbSAC_cropgmrg

$gdxin

;

crop_cost(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbcrop_cost(ID, crop_dtb, value)));

crop_lab_requ(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbcrop_lab_requ(ID, crop_dtb, value)));

crop_price(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbcrop_price(ID,crop_dtb,value)));

N_uplim(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbN_uplim(ID,crop_dtb,value)));

N_lolim(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbN_lolim(ID,crop_dtb,value)));

P_uplim(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbP_uplim(ID, crop_dtb,value)));

P_lolim(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbP_lolim(ID,crop_dtb,value)));

Fert_cost (Nutrients, value)= SUm(ID, dtbFert_cost (ID,Nutrients, value));

Dmfw_corr(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbDmfw_corr(ID, crop_dtb,value)));

cr_stan_output_coeff(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbcr_stan_output_coeff(ID, crop_dtb, value)));

SAC_cropgmrg (crop, value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbSAC_cropgmrg (ID,crop_dtb, value)));

display yieldfunc_data, yield_corr_data, crop_cost, crop_lab_requ, SAC_cropgmrg, cr_stan_output_coeff, Dmfw_corr, Fert_cost, P_lolim, N_uplim, N_lolim, P_uplim, crop_price

;

****General Parameters and hydrological risk****

PARAMETER

```
 dtbLab_cost (ID,value,value)'cost of labour in ï¿½/hr',
 Lab_cost (value,value)'cost of labour in ï¿½/hr',
 dtbScale_effect_coeff (ID, farm,value)'scale effect efficienc  for crops',
 Scale_effect_coeff (farm,value)'scale effect efficienc  for crops',
 dtbTrans_cost (ID,value,value)'cost of forage haulage in 100ï¿½/t',
 Trans_cost (value,value)'cost of forage haulage in 100ï¿½/t',
 dtbhydro_fact (ID,hydro,value)'hydrological risk factor for pollution function',
 hydro_fact (hydro,value)'hydrological risk factor for pollution function'
;
$gdxin All_parameters_63.gdx
$load dtbLab_cost
$load dtbScale_effect_coeff
$load dtbTrans_cost
$load dtbhydro_fact
$gdxin
;
Lab_cost (value,value)= SUm(ID, dtbLab_cost (ID,value,value));
Scale_effect_coeff (farm,value)= SUM(ID, dtbScale_effect_coeff (ID, farm,value));
Trans_cost (value,value)= SUm(ID, dtbTrans_cost (ID,value,value));
hydro_fact (hydro,value)= SUM(ID, dtbhydro_fact (ID,hydro,value));

display Lab_cost, Scale_effect_coeff, Trans_cost, hydro_fact

****livestock Parameters****
PARAMETER
 dtbli_stan_output_coeff (ID,livestock, value) 'standard output coefficient in 1000ï¿½/animal unit sourced from
Eurostat',
 li_stan_output_coeff (livestock, value) 'standard output coefficient in 1000ï¿½/animal unit sourced from Eurostat',
 dtbLive_grmrg (ID,livestock, value)'Livestock grossmargin excluding forage costs in 100ï¿½/head',
 Live_grmrg (livestock, value)'Livestock grossmargin excluding forage costs in 100ï¿½/head',
 dtbsilage_requ (ID,livestock, value)'yearly silage requirement in FW t/per animal unit',
 silage_requ (livestock, value)'yearly silage requirement in FW t/per animal unit',
 graze_requ (livestock, value) 'yearly grazing requirement in DM t/per animal unit',
 dtbgraze_requ (ID,livestock, value) 'yearly grazing requirement in DM t/per animal unit',
 dtbhay_requ (ID,livestock, value) 'yearly hay requirement in FW t/per animal unit',
 hay_requ (livestock, value) 'yearly hay requirement in FW t/per animal unit',
```

```
 dtbLive_lab_requ (ID,livestock, value) 'labour hours requirement per livestock type',
 Live_lab_requ (livestock, value) 'labour hours requirement per livestock type',
 dtbSAC_grmg_post_for (ID,livestock, value) 'SAC post-forage grossmargin per animal head in ï¿½',
 dtbFYM_output (ID,livestock, nutrients, value) 'Total kg of nutrient in manure output by livestock over housing
period',
 FYM_output (livestock, nutrients, value) 'Total kg of nutrient in manure output by livestock over housing period',
 dtbEPIC_stockden (ID,crop_dtb, value) 'database stocking density in LU/ha assumed in EPIC',
 EPIC_stockden(crop,value)'Stocking density in LU/ha assumed in EPIC',
 dtbGraze_LU (ID,Livestock, value) 'Livestock unit (LU) system is a reflection of the annual energy requirements of
different livestock'
 dtbFYMcr_FN_fx (ID,crop_dtb, value) 'Amount of FYM N in kg/ha applied to each FYM crop',
 Graze_LU (Livestock, value) 'Livestock unit (LU) system is a reflection of the annual energy requirements of different
livestock',
 SAC_grmg_post_for (livestock, value) 'SAC post-forage grossmargin per animal head in ï¿½',
 FYMcr_FN_fx (FYM_crop, value) 'Amount of FYM N in kg/ha applied to each FYM crop',
 dtbFYMcr_FP_fx (ID,crop_dtb, value) 'Amount of FYM P in kg/ha applied to each FYM crop',
 FYMcr_FP_fx (FYM_crop, value) 'Amount of FYM P in kg/ha applied to each FYM crop'
;
$gdxin All_parameters_63.gdx
$load dtbli_stan_output_coeff
$load dtbLive_grmrg
$load dtbsilage_requ
$load dtbhay_requ
$load dtbLive_lab_requ
$load dtbgraze_requ
$load dtbSAC_grmg_post_for
$load dtbFYM_output
$load dtbEPIC_stockden
$load dtbGraze_LU
$load dtbFYMcr_FN_fx
$load dtbFYMcr_FP_fx
$gdxin
;
li_stan_output_coeff (livestock, value) = SUM(ID, dtbli_stan_output_coeff (ID,livestock, value));
Live_grmrg (livestock, value) = SUM(ID, dtbLive_grmrg (ID,livestock, value));
silage_requ (livestock, value)= SUM(ID, dtbsilage_requ (ID,livestock, value));
```

```
hay_requ (livestock, value)=SUM(ID, dtbhay_requ (ID,livestock, value));

graze_requ (livestock, value)= SUM(ID,dtbgraze_requ (ID,livestock, value));

Live_lab_requ (livestock, value) = SUM(ID, dtbLive_lab_requ (ID,livestock, value));

SAC_grmg_post_for (livestock, value) = SUM(ID,dtbSAC_grmg_post_for (ID,livestock, value));

FYM_output (livestock, nutrients, value) = SUM(ID, dtbFYM_output (ID,livestock, nutrients, value));

EPIC_stockden(crop,value) = SUM(ID, sum(mapindx(crop,crop_dtb), dtbEPIC_stockden(ID,crop_dtb,value)));

Graze_LU (Livestock, value)= SUM(ID, dtbGraze_LU (ID,Livestock, value));

FYMcr_FN_fx (FYM_crop, value)= SUM(ID, sum(mapindxFYM(FYM_crop,crop_dtb), dtbFYMcr_FN_fx (ID,crop_dtb,
value)));

FYMcr_FP_fx (FYM_crop, value)= SUM(ID, sum(mapindxFYM(FYM_crop,crop_dtb), dtbFYMcr_FP_fx (ID,crop_dtb,
value)));


display li_stan_output_coeff, Live_grmrg, silage_requ, graze_requ, hay_requ, Live_lab_requ, SAC_grmg_post_for,
FYM_output, EPIC_stockden, Graze_LU, FYMcr_FN_fx, FYMcr_FP_fx

$include Loops_Base05.gms

****include file with specification of scenarios and reporting sets and parameters
```

Loading Additional Parameters and Scenario Loop structure

File name: 'Loops_Base05.gms'

```
PARAMETER
N_tax N tax as fraction of price of N /0/
*N_tax_scen(scenario) 'N tax multiplier'  /sc1=0/
Setaside_requ Set aside requirement as a fraction of the total available agricultural land /0/
*Setaside_scen (scenario) 'Set aside requirement multiplier'/sc1=0/
Stock_den_reduc 'Stocking density proportion of original EPIS stocking density'/1/
*Stock_den_reduc_scen (scenario) stocking density reduction multiplier/sc1=1/
P_tax P tax as fraction of price of N /0/
*P_tax_scen(scenario) 'P tax multiplier'  /sc1=0/
Slope_setaside_requ 'Set aside requirement multiplier for particular slope'/0/
*Slope_setaside_scen (scenario)/sc1=0/
;
$ontext
**used in scenarios to save scenario parameters
PARAMETER
sN_tax saving N initial value,
sSetaside_requ saving Setaside requirement initial value,
sStock_den_reduc saving initial stocking density reduction value,
sP_tax saving N initial value,
sSlope_setaside_requ saving initial stocking density reduction for specific slope value,
;
sN_tax=N_tax;
sSetaside_requ=Setaside_requ;
sStock_den_reduc=Stock_den_reduc;
sP_tax=P_tax;
sSlope_setaside_requ=Slope_setaside_requ;
$offtext
$offlisting

****Definition of parameters for calculations outside the optimisation for summary purposes****
SET
OUT1 /OUT_60_01,OUT_60_02, OUT_60_03,OUT_60_04,OUT_60_05,OUT_60_06/
OUT2 / OUT_60_04_AF,OUT_60_04_FYM/
```

```
Year / 1969 * 2013/

;

****Loading Pollution Data****

TABLE mdtbpollution_data (OUT1,OUT2,Slope, Soil, pol_crop,Year, poll_funct_coeff) 'pollution function intercepts and coefficients';

$gdxin OUT_parameters_60.gdx

$load mdtbpollution_data

$gdxin

;

TABLE pollution_data (Slope, Soil, Crop,Year, poll_funct_coeff) 'pollution function intercepts and coefficients';

pollution_data (Slope, Soil, Crop,Year, poll_funct_coeff)= SUM((OUT1,OUT2), sum(polmap (supcrop, pol_crop), mdtbpollution_data (OUT1, OUT2, Slope, Soil, pol_crop, Year, poll_funct_coeff)));

display pollution_data

;

*****Loading SLR data for farm size classification

PARAMETER

 dtbSLR_crop_coeff (OUT1,crop_dtb, value) 'standard labour requirement coefficient in hrs/ha sourced from DEFRA 2014',

 SLR_crop_coeff(crop,value),

 dtbSLR_live_coeff (OUT1,livestock, value) 'Standard Labour Requirement coefficient for livestock in hrs per head',

 SLR_live_coeff (livestock, value) 'Standard Labour Requirement coefficient for livestock in hrs per head'

;

$gdxin OUT_parameters_60.gdx

$load dtbSLR_crop_coeff

$load dtbSLR_live_coeff

$gdxin

;

SLR_crop_coeff(crop,value) = sum(OUT1, sum(mapindx(crop, crop_dtb), dtbSLR_crop_coeff (OUT1, crop_dtb, value)));

SLR_live_coeff (livestock, value)= SUM(OUT1, dtbSLR_live_coeff (OUT1,livestock, value));


display SLR_crop_coeff,  SLR_live_coeff

;

SET

report 'terms used in report writing'

/Land_crop_f '% of land attributed to a crop group by farm',

Land_crop_l '% of land attributed to a crop group by soil type',

Land_crop_perc '% of land attributed to a crop group over the catchment',
```

Land_alloc 'Land.l'

Crop_standard_output 'Crop standard output in ï¿½',

STAN_OUT_PERC_CHK 'Sum of crop and livestock standard output percentage shares',

TOTAL_ST_OUT_MANUAL 'Total standard output per farm in ï¿½'

Forage_Totcost 'Total forage cost in ï¿½1000 per animal'

SAC_dev_Liprofit 'Percentage difference between the SAC and model post forage and labour gross margin'

Farm_total_area 'Farm area in ha'

Farm_size 'Farm size measured in full time yearly labour requirement following FBS standard'

Crop_land_perc 'Percetnage of total farm land allocated to a particular crop'

Cr_perc_stan_out 'Percentage of crops to total standard output summed over the soil, slope, hydro'

YLD_check 'Checking yield for excessively high yielding crops'

******************Crops******************

Av_YLD 'Average yield in tonnes per ha by soil, slope and hydro type'

AVYLD_FSLC 'Calculating the average yield per hectare only including used sets averaged over hydrology'

AVYLD_FSC 'Calculating the average yield per hectare only including used sets averaged over hydrology, soil'

AVYLD_FC 'Calculating the average yield per hectare only including used sets averaged over hydrology, soil,slope'

AVYLD_C 'Calculating the average yield per hectare only including used sets averaged over hydrology, soil,slope,farm'

Avha_cropsrev 'Average crop revenue per hectare'

Fert_cost 'Average crop fertiliser costs per hectare'

Crop_cost 'Other crop costs per hectare'

P_level_FLSH 'level of P application in kg/ha'

N_level_FLSH 'level of N application in kg/ha'

P_level_FLS 'level of P application averaged over hydrological connectivity in kg/ha'

N_level_FLS 'level of N application averaged over hydrological connectivity in kg/ha'

Pup_lim 'Phosphor upper limit in kg/ha'

Plo_lim 'Phosphor lower limit in kg/ha'

Nup_lim 'Nitrogen upper limit in kg/ha'

Nlo_lim 'Nitrogen lower limit in kg/ha'

P_level 'level of P application averaged over soil, slope, farm and hydrological connectivity in kg/ha'

N_level 'level of N application averaged over soil, slope, farm and hydrological connectivity in kg/ha'

P_level_LS 'level of P application averaged over farm and hydrological connectivity in kg/ha'

N_level_LS 'level of N application averaged over farm and hydrological connectivity in kg/ha'

P_level_FLSCH 'level of P application in kg/ha'

N_level_FLSCH 'level of N application in kg/ha'

Poll_value 'level of pollutant'

M_N_AF_rep 'Marginal N artificial fertiliser report'

M_P_AF_rep 'Marginal P artificial fertiliser report'

M_N_FYM_rep 'Marginal N farmyard manure fertiliser report'

M_P_FYM_rep 'Marginal P farmyard manure fertiliser report'

M_N_YLD_FUNCT 'Marginal N yield function value report'

M_P_YLD_FUNCT 'Marginal P yield function value report'

N_AF_rep 'N artificial fertiliser report'

P_AF_rep 'P artificial fertiliser report'

N_FYM_rep 'N farmyard manure report'

P_FYM_rep 'P farmyard manure report'

N_YLD_FUNCT 'N yield function value report'

P_YLD_FUNCT 'P yield function value report'

Crop_profit 'Grossmargin achieved per t of crop averaged over soil, slope, farm, hydro'

Number 'Number of unique crops within a crop group'

Dev_from_exp 'Average percentage deviation from the SAC expected yield'

SAC_expect 'per ha SAC yield expectation'

labhrs_total 'total labour hours needed by farm'

li 'livestock standard output'

cr ' crop standard output'

very_small '<0.5 FTE spare time, 0.5<1 FTE part time'

small '1<2 FTE full time'

medium '2<3 FTE full time'

large '3<5 FTE full time'

very_large '>=5 FTE'

Out_percdev 'output percentage deviation from expectation'

total

average

model_stat 'model status number'

solve_stat 'solver status number'

******************Livestock******************

No 'Number of livestock per farm (in 100ewes tupped for sheep)'

Li_gmrg 'Pre forage and labour cost livestock gross maring in ï¿½ per animal'

Li_labcost 'Annual labour cost in ï¿½ per animal'

Li_profit 'Post forage and labour cost livestock grossmargin in ï¿½ per animal'

Li_stan_out 'Livestock standard output in ï¿½'

Li_gm_coeff 'Difference between pre-forage grossmargin and livestock labour costs in ï¿½ per animal'

milk 'dairy category for catchment output contribution'

sheep 'sheep category for catchment output contribution (sheep1, sheep2)'

beef 'beef category for catchment output contribution (finish1, finish2, suckler)'

Out_contr 'Percentage contribution to catchment output'

DEFRA_dt 'Defra data on the real-world situation in the catchment'

live_out_perc 'percentage of livestock output as percentage of total in the catchment'

live_out 'livestock output of the catchment'

cr_out 'crop output of the catchment'

feedcr_out 'feed crop sale output of the catchment'

catch_out 'catchment output'

barley, wheat, maize, potato, oilseed_rape, grazing, setaside

land_perc 'percentage of catchment land allocated to a crop group defined by DEFRA'

exp_land_perc 'expected percentage of catchment land allocated to a crop group as defined by DEFRA'

land_percdev 'percentage points deviation of model land allocation from expectation'

N_FYM_par 'parameter to calculate the mean N FYM application'

P_FYM_par 'parameter to calculate the mean P FYM application'

tot_appl 'total fym in kg applied'

tot_prod 'total fym in kg produced on farm'

excess_kg 'excess amount of fym in kg produced that is not applied'

excess_perc 'excess amount of fym produced that is not applied as percentage of total produced'

stock_den 'farm stocking density (livestock units per hectare)'

*******************Pollution****************************

TOC 'Organic carbon in soil profile (in kg/ha) '

WTR 'Water to river WTR (in m3)'

WTG 'Water to deep percolation (in m3)'

ZLOAD 'Sediment mobilised (in t / ha)'

CLOAD 'C to river (in kg per day)'

RSPC 'CO2 respiration (in kg/ha)'

NRLOAD 'N to River (load, in kg per day'

NGLOAD 'N to groundwater (load, in kg per day)'

PRLOAD 'P to river (in kg per day) '

PGLOAD 'P to groundwater (load, in kg / day)'

DN2O 'Nitrous oxide loss (in kg/ha)'

```
CFEM            'Carbon emission (in kg/ha)'
TOC_HR            'Organic carbon in soil profile with hydrological risk (in kg/ha) '
WTR_HR            'Water to river WTR with hydrological risk (in m3)'
WTG_HR            'Water to deep percolation with hydrological risk (in m3)'
ZLOAD_HR            'Sediment mobilised with hydrological risk (in t / ha)'
CLOAD_HR            'C to river with hydrological risk (in kg per day)'
RSPC_HR            'CO2 respiration with hydrological risk (in kg/ha)'
NRLOAD_HR            'N to River with hydrological risk (load, in kg per day'
NGLOAD_HR            'N to groundwater with hydrological risk (load, in kg per day)'
PRLOAD_HR            'P to river with hydrological risk (in kg per day)  '
PGLOAD_HR            'P to groundwater with hydrological risk (load, in kg / day)'
DN2O_HR            'Nitrous oxide loss with hydrological risk (in kg/ha)'
CFEM_HR            'Carbon emission with hydrological risk (in kg/ha)'
Neg_pol_aux            'Auxiliary variable to count neg pollution values'
Neg_pol            'Counts of negative pollution values for soil/slope/crop type'
hydro_ck,land_ck
/
pol_vars  (report)  'pollution variables'/
TOC            'Organic carbon in soil profile (in kg/ha) '
WTR            'Water to river WTR (in m3)'
WTG            'Water to deep percolation (in m3)'
ZLOAD            'Sediment mobilised (in t / ha)'
CLOAD            'C to river (in kg per day)'
RSPC            'CO2 respiration (in kg/ha)'
NRLOAD            'N to River (load, in kg per day'
NGLOAD            'N to groundwater (load, in kg per day)'
PRLOAD            'P to river (in kg per day)  '
PGLOAD            'P to groundwater (load, in kg / day)'
DN2O            'Nitrous oxide loss (in kg/ha)'
CFEM            'Carbon emission (in kg/ha)'
TOC_HR            'Organic carbon in soil profile with hydrological risk (in kg/ha) '
WTR_HR            'Water to river WTR with hydrological risk (in m3)'
WTG_HR            'Water to deep percolation with hydrological risk (in m3)'
ZLOAD_HR            'Sediment mobilised with hydrological risk (in t / ha)'
CLOAD_HR            'C to river with hydrological risk (in kg per day)'
RSPC_HR            'CO2 respiration with hydrological risk (in kg/ha)'
```

NRLOAD_HR 'N to River with hydrological risk (load, in kg per day'

NGLOAD_HR 'N to groundwater with hydrological risk (load, in kg per day)'

PRLOAD_HR 'P to river with hydrological risk (in kg per day) '

PGLOAD_HR 'P to groundwater with hydrological risk (load, in kg / day)'

DN2O_HR 'Nitrous oxide loss with hydrological risk (in kg/ha)'

CFEM_HR 'Carbon emission with hydrological risk (in kg/ha)'

P_level_FLSCH 'P level for farm, soil, slope, crop, hydrology'

N_level_FLSCH 'P level for farm, soil, slope, crop, hydrology'

/

farmsizes (report) 'Defra farm size classification by SLRs fulltime equivalent'

/ very_small '<0.5 FTE spare time, 0.5<1 FTE part time', small '1<2 FTE full time', medium '2<3 FTE full time', large '3<5 FTE full time', very_large '>=5 FTE'/

standardout (report) 'Standard output categories'

/li 'livestock standard output'

cr 'crop standard output'

/

fym_report (report) 'Categories for farm yard manure statistics'

/

tot_appl 'total fym in kg applied'

tot_prod 'total fym in kg produced on farm'

excess_kg 'excess amount of fym in kg produced that is not applied'

excess_perc 'excess amount of fym produced that is not applied as percetnage of total produced'

/

livestock_dtb (report) 'set used to read in livestock parameter from the input data' / milk, sheep, beef/

crop_group_dtb (report) 'set used to read in expected land use percentage of catchment'/barley, wheat, maize, potato, oilseed_rape, grazing,setaside/

chk_report(report)'set used to check crop yield average calculations'/hydro_ck,land_ck/

**define mappings to match crop sets used in input file "database" to the model crop sets

mapindx2(crop_dtb,crop)

/sbar.'SBAR11', sbar.'SBAR12', sbar.'SBAR13_FYM', sbar.'SBAR2_FYM', fbeet.'FBEET1', fbeet.'FBEET2', fbeet.'FBEET3', maize_wc.'MAIZ1', maize_wc.'MAIZ4_FYM', maize_wc.'MAIZ5_FYM', sil_1.'SIL1_1', sil_2.'SIL2_1', sil_3.'SIL3_1', sil_3.'SIL3_2_FYM', sil_4.'SIL4_1', sil_4.'SIL4_2_FYM', sil_lfa.'SILFA1', graze_2.'GRAZE2_1', graze_2.'GRAZE2_2', graze_3.'GRAZE3_1', graze_4.'GRAZE4_1', graze_4.'GRAZE4_3_FYM', graze_6.'GRAZE6_3', graze_6.'GRAZE6_1_FYM', hay_2.'hay2_1', hay_lfa.'HAYLFA1', graze_lfa.'GRLFA1', graze_lfa.'GRLFA1_FYM', graze_lfa.'GRLFA3_FYM', graze_lfa.'GRLFA3', ww.'WW1', ww.'WW2', ww.'WW3', ww.'WW4', ww.'WW4_FYM', wbar.'WBAR0', wbar.'WBAR1', wbar.'WBAR2', wbar.'WBAR3_FYM', wbar.'WBAR4_FYM', wbar.'WBAR5_FYM', wosr.'WOSR1', wosr.'WOSR2', wosr.'WOSR3', pot.'POTA1', pot.'POTA2', pot.'POTA3_FYM', pot.'POTA5_FYM', ww_wc.'WWWC1', w_wc.'WWWC2', soats.'SOATS1'/

mapindx3 (livestock_dtb, livestock)

/ milk.'dairy', sheep.'sheep1', sheep.'sheep2', beef.'finish1', beef.'finish2', beef.'suckler'/

mapindx4 (crop_group_dtb, crop) /barley.'SBAR11', barley.'SBAR12', barley.'SBAR13_FYM', barley.'SBAR2_FYM', barley.'WBAR0', barley.'WBAR1', barley.'WBAR2', barley.'WBAR3_FYM', barley.'WBAR4_FYM', barley.'WBAR5_FYM', wheat.'WW1', wheat.'WW2', wheat.'WW3', wheat.'WW4', wheat.'WW4_FYM', maize.'MAIZ1', maize.'MAIZ5_FYM', maize.'MAIZ4_FYM', potato.'POTA1', potato.'POTA2', potato.'POTA3_FYM', potato.'POTA5_FYM', oilseed_rape.'WOSR1',oilseed_rape.'WOSR2',oilseed_rape.'WOSR3', grazing.'GRLFA1', grazing.'GRLFA3', grazing.'GRAZE2_1', grazing.'GRAZE2_2', grazing.'GRAZE3_1', grazing.'GRAZE4_1', grazing.'GRAZE4_3_FYM', grazing.'GRAZE6_3', grazing.'GRAZE6_1_FYM', grazing.'hay2_1', grazing.'HAYLFA1', grazing.'SIL1_1', grazing.'SIL2_1', grazing.'SIL3_1', grazing.'SIL3_2_FYM', grazing.'SIL4_1', grazing.'SIL4_2_FYM', grazing.'SILFA1', grazing.'FBEET1', grazing.'FBEET2', grazing.'FBEET3', setaside.'GRLFA1'

/;

PARAMETERS

dtbcatch_out_contr (OUT1,livestock_dtb, value) 'Percentage contribution to output in the North West region for livestock based on DEFRA (21) Agriucltural Facts -North West (NW)',

catch_out_contr(livestock_dtb, value) 'Percentage contribution to output in the North West region for livestock based on DEFRA (21) Agriucltural Facts -North West (NW)',

dtbLive_output (OUT1,livestock, value) 'Output per head of livestock in ï¿½ (per 100 ewes tupped for sheep)',

Live_output (livestock, value) 'Output per head of livestock in ï¿½ (per 100 ewes tupped for sheep)',

dtbLand_expect_dtb (OUT1, crop_group_dtb, Value) 'Percentage of catchment land allocated to particular crop based on DEFRA (2021) Agricultural Facts - North West (NW)',

Land_expect_dtb (crop_group_dtb, Value) 'Percentage of catchment land allocated to particular crop based on DEFRA (2021) Agricultural Facts - North West (NW)',

$gdxin OUT_parameters_60.gdx

$load dtbcatch_out_contr

$load dtbLive_output

$load dtbLand_expect_dtb

$gdxin

;

catch_out_contr(livestock_dtb, value) = SUM(OUT1, dtbcatch_out_contr (OUT1,livestock_dtb, value));

Live_output (livestock, value)= SUM(OUT1, dtbLive_output (OUT1,livestock, value));

Land_expect_dtb (crop_group_dtb, Value)=SUM(OUT1, dtbLand_expect_dtb (OUT1, crop_group_dtb, Value));

display catch_out_contr, Live_output, Land_expect_dtb

****Defining parameters for reporting****

PARAMETERS

Catch_stats_base (report,report) 'Parameter for reporting catchment statistics relative to the FBS data'

Crop_report_base (Alli,Alli,report) 'Costs, revenues'

farm_live_base (farm,livestock,report) 'Number of livestock heads per farm (sheep in 100 ewes tupped)'

report_catch_base (Alli,report) 'costs, revenues and pollution contributions of different production activities catchment scale'

Crop_report_C_base (Alli,report) 'Crop statistics by unique crop for whole catchment'

Live_report_base (Alli,Alli,report) 'Nos, costs, revenues, profits associated with livestock'

total_base (report) 'Parameter for reporting totals of certian variables so only need one index'

report_hydro_base (Alli,Alli,Alli,Alli,Alli, report) 'calculation at hydrological risk area scale'

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,report) 'Pollution parameter reporting yearly'

Fert_report_base (slope, soil, hydro,farm,crop,report) 'Fertiliser application reporting'

Land_report_base (slope, soil, hydro, farm, crop) 'Land allocation reporting'

Li_gm_report_base (farm, livestock) 'Livestock grossmargin reporting'

Cr_gm_report_base (slope, soil, hydro, farm, cash_crop) 'Crop grossmargin reporting'

Catch_gm_report_base 'Catchment grossmargin reporting'

N_tax_rep_base 'Calculated check of the current % of the N tax'

Cr_cost_report_base   (slope,soil, hydro,farm, crop) 'Crop cost in 10Â£ per tonnes'

Fert_cost_report_base 'N tax as proportion of N cost'

Setaside_report_base 'Setaside as proportion of total catchment area'

Setaside_slope_report_base 'Setaside of particular slope type as proportion of total catchment area'

Pol_report_sum_base (report) 'Pollution parameter averaged over the years'

Pol_report_chng_base (report) 'Percentage change in the pollution parameter relative to the baseline'

Sediment_soil_av_base (soil,report) 'Average sediment pollution by soil type'

Sediment_slope_av_base (slope,report) 'Average sediment pollution by slope type'

Sediment_crop_av_base (crop,report) 'Average sediment pollution by crop type'

Sediment_soil_tot_base (slope,soil, hydro,farm,crop,report) 'Total sediment pollution by soil type per ha'

Sediment_slope_tot_base (slope,soil, hydro,farm,crop,report) 'Total sediment pollution by soil type per ha'

Sediment_crop_tot_base (slope,soil, hydro,farm,crop,report) 'Total sediment pollution by soil type per ha'

Run_stat_base (report) 'Reporting of model and solver status for the solve in GAMS number'

;

TABLE farmsize_def (farmsizes, value) 'FTE bounds below which farm is classified as a particular farmsize'

	value
very_small	1
small	2
medium	3
large	5
very_large	5 ;

Parameters for Results Reporting

Filename: 'Reporting_Base05.gms'

****report catchment wide output statistics****

total_base ("live_out")= round((SUM((farm,livestock), LI_GM.l(farm, livestock)*Live_output (livestock, "value"))),2);

total_base ("cr_out")= round((SUM((slope, soil, hydro, farm, cash_crop), T_YIELD_FW.l (slope, soil, hydro, farm, cash_crop) * crop_price (cash_crop, 'value')*100)),2);

total_base ("feedcr_out")= round((SUM((farm, trade_feed_cr), SOLD_FEED_CROP.l (farm, trade_feed_cr)* crop_price (trade_feed_cr, 'value')*100)),2);

total_base ("catch_out") =round((total_base ("live_out")+total_base ("cr_out")+total_base ("feedcr_out")),2);

total_base ("stock_den")$SUM((slope,soil, hydro,farm,forage_cr),LAND.l (slope,soil, hydro,farm,forage_cr))=round(SUM((farm, livestock),LIVE_NUM.l (farm, livestock)*Graze_LU (Livestock, "value"))/SUM((slope,soil, hydro,farm,forage_cr),LAND.l (slope,soil, hydro,farm,forage_cr)),2);

report_catch_base (livestock, "live_out_perc") =round(SUM(farm, LI_GM.l(farm, livestock)*Live_output (livestock, "value"))/total_base ("catch_out")*100,2);

Crop_report_C_base (crop,"Crop_land_perc")$SUM((slope, soil, hydro, farm),farm_area_2 (slope, soil, hydro, farm,"value"))= SUM((slope, soil, hydro,farm), LAND.l (slope,soil, hydro,farm,crop))/SUM((slope, soil, hydro, farm),farm_area_2 (slope, soil, hydro, farm,"value"))*100;

****calculate catchment wide metrics of activities****

Catch_stats_base (livestock_dtb,"Out_contr")= round(sum(mapindx3 (livestock_dtb, livestock),report_catch_base (livestock, "live_out_perc")),2) ;

Catch_stats_base (livestock_dtb,"DEFRA_dt") =round(catch_out_contr (livestock_dtb, "value"),2);

Catch_stats_base (livestock_dtb,"DEFRA_dt") =round(catch_out_contr (livestock_dtb, "value"),2);

Catch_stats_base(livestock_dtb, "Out_percdev")= round((Catch_stats_base (livestock_dtb,"Out_contr")-Catch_stats_base (livestock_dtb,"DEFRA_dt"))/Catch_stats_base (livestock_dtb,"DEFRA_dt")*100,2);

Catch_stats_base (crop_group_dtb,"exp_land_perc") = round(Land_expect_dtb (crop_group_dtb, "Value"),2);

Catch_stats_base (crop_group_dtb,"land_perc") = round(sum(mapindx4(crop_group_dtb,crop), Crop_report_C_base (crop,"Crop_land_perc")),2);

Catch_stats_base (crop_group_dtb,"land_percdev")$Catch_stats_base (crop_group_dtb,"exp_land_perc")=round((Catch_stats_base (crop_group_dtb,"land_perc") - Catch_stats_base (crop_group_dtb,"exp_land_perc"))/Catch_stats_base (crop_group_dtb,"exp_land_perc")*100,2);

report_hydro_base(slope,soil, hydro,farm,crop,"Av_YLD")$LAND.l (slope,soil, hydro,farm, crop) = dmfw_corr(crop, 'value') * yield_corr_data(crop,'EPIC_corr') * YIELD_DM.l (slope, soil, hydro, farm, crop);

Crop_report_base(farm, crop,"AVYLD_FC")$SUM((slope,soil, hydro),LAND.l (slope,soil, hydro,farm,crop)) = (SUM ((slope,soil, hydro), report_hydro_base(slope,soil, hydro,farm,crop,"Av_YLD")*LAND.l (slope,soil, hydro,farm,crop)))/ SUM((slope,soil, hydro),LAND.l (slope,soil, hydro,farm,crop));

Crop_report_base(farm, crop,"SAC_expect")= yield_corr_data(Crop,"SAC_YLD") ;

Crop_report_base(farm, crop, "Cr_perc_stan_out") = SUM ((slope, soil, hydro), CR_PERC_STAN_OUTPUT.l (slope, soil, hydro, farm, crop));

****report key livestock metrics****

Live_report_base (farm, livestock, "Li_profit")$LIVE_NUM.l (farm, livestock)= round(LI_GM.l (farm, livestock)*1000/LIVE_NUM.l (farm, livestock),2);

Live_report_base (farm, livestock, "SAC_dev_Liprofit")$LIVE_NUM.l (farm, livestock) = round(((LI_GM.l (farm, livestock)*1000/LIVE_NUM.l (farm, livestock))-SAC_grmg_post_for(livestock, "value"))/SAC_grmg_post_for(livestock, "value")*100,2);

farm_live_base (farm,livestock,"No") = round(LIVE_NUM.l (farm, livestock),2);

farm_live_base (farm, livestock, "Li_profit") = round(Live_report_base (farm, livestock, "Li_profit"),2);

farm_live_base (farm, livestock, "SAC_dev_Liprofit") = round(Live_report_base (farm, livestock, "SAC_dev_Liprofit"),2);

****report total pollution levels in relevant units****

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"TOC")$LAND.l (slope,soil, hydro,farm,crop) = pollution_data (Slope, Soil, Crop,Year, "TOC")*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"WTR")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "WTR_IC") + pollution_data (Slope, Soil, Crop,Year, "WTR_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"WTG")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "WTG_IC") + pollution_data (Slope, Soil, Crop,Year, "WTG_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"ZLOAD")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "ZLOAD_IC") + pollution_data (Slope, Soil, Crop,Year, "ZLOAD_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"CLOAD")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "CLOAD_IC") + pollution_data (Slope, Soil, Crop,Year, "CLOAD_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"RSPC")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "RSPC_IC") + pollution_data (Slope, Soil, Crop,Year, "RSPC_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"NRLOAD")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "NRLOAD_IC") + pollution_data (Slope, Soil, Crop,Year, "NRLOAD_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"NGLOAD")$LAND.l (slope,soil, hydro,farm,crop) =(pollution_data (Slope, Soil, Crop,Year, "NGLOAD_IC") + pollution_data (Slope, Soil, Crop,Year, "NGLOAD_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"PRLOAD")$LAND.l (slope,soil, hydro,farm,crop) =(pollution_data (Slope, Soil, Crop,Year, "PRLOAD_I") + pollution_data (Slope, Soil, Crop,Year, "PRLOAD_N") * N_AF.l(slope, soil, hydro, farm, crop) + pollution_data (Slope, Soil, Crop,Year, "PRLOAD_P") * P_AF.l(slope, soil, hydro, farm, crop) + pollution_data (Slope, Soil, Crop,Year, "PRLOAD_N_P") * P_AF.l(slope, soil, hydro, farm, crop) * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"PGLOAD")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "PGLOAD_I") + pollution_data (Slope, Soil, Crop,Year, "PGLOAD_N") * N_AF.l(slope, soil, hydro, farm, crop) + pollution_data (Slope, Soil, Crop,Year, "PGLOAD_P") * P_AF.l(slope, soil, hydro, farm, crop) + pollution_data (Slope, Soil, Crop,Year, "PGLOAD_N_P") * P_AF.l(slope, soil, hydro, farm, crop) * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"DN2O")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "DN2O_IC") + pollution_data (Slope, Soil, Crop,Year, "DN2O_N") * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"CFEM")$LAND.l (slope,soil, hydro,farm,crop) = (pollution_data (Slope, Soil, Crop,Year, "CFEM_I") + pollution_data (Slope, Soil, Crop,Year, "CFEM_N") * N_AF.l(slope, soil, hydro, farm, crop) + pollution_data (Slope, Soil, Crop,Year, "CFEM_P") * P_AF.l(slope, soil, hydro, farm, crop) + pollution_data (Slope, Soil, Crop,Year, "CFEM_N_P") * P_AF.l(slope, soil, hydro, farm, crop) * N_AF.l(slope, soil, hydro, farm, crop))*LAND.l (slope,soil, hydro,farm,crop)*hydro_fact (hydro,'value');

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"P_level_FLSCH")$LAND.l (slope,soil, hydro,farm,crop)=P_AF.l(slope, soil, hydro, farm, crop)*LAND.l (slope,soil, hydro,farm,crop);

Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"N_level_FLSCH")$LAND.l (slope,soil, hydro,farm,crop)=N_AF.l(slope, soil, hydro, farm, crop)*LAND.l (slope,soil, hydro,farm,crop);

****report levels of fertiliser application in kg/ha****

Fert_report_base (slope, soil, hydro, farm, crop,"N_AF_rep") = N_AF.l (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"P_AF_rep") = P_AF.l (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"N_FYM_rep") = N_FYM.l (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"P_FYM_rep") = P_FYM.l (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro,farm,crop,"N_YLD_FUNCT") = N_YLD_FUNCT.l (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro,farm,crop,"P_YLD_FUNCT") = P_YLD_FUNCT.l (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"M_N_AF_rep") = N_AF.m (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"M_P_AF_rep") = P_AF.m (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"M_N_FYM_rep") = N_FYM.m (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro, farm, crop,"M_P_FYM_rep") = P_FYM.m (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro,farm,crop,"M_N_YLD_FUNCT") = N_YLD_FUNCT.m (slope, soil, hydro, farm, crop);

Fert_report_base (slope, soil, hydro,farm,crop,"M_P_YLD_FUNCT") = P_YLD_FUNCT.m (slope, soil, hydro, farm, crop);

****Report levels of key variables across scenarios****

Land_report_base (slope, soil, hydro, farm, crop) =LAND.l (slope, soil, hydro, farm, crop);

Li_gm_report_base(farm, livestock) =LI_GM.l(farm, livestock);

Cr_gm_report_base (slope, soil, hydro, farm, cash_crop)= CR_GM.l(slope, soil, hydro, farm, cash_crop);

Cr_cost_report_base (slope,soil, hydro,farm, crop)=CR_TOTAL_COST.l (slope, soil, hydro, farm, crop);

Catch_gm_report_base = CATCH_GM.l;

****Calculate pollution averaged over weather years and summed over slope, soil, hydro, farm, and crop ****

Pol_report_sum_base("TOC") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"TOC"))/card(Year);

Pol_report_sum_base("WTR") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"WTR"))/card(Year);

Pol_report_sum_base("WTG") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base (slope, soil, hydro, farm, crop, Year,"WTG"))/card(Year);

Pol_report_sum_base("ZLOAD") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"ZLOAD"))/card(Year);

Pol_report_sum_base("CLOAD") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"CLOAD"))/card(Year);

Pol_report_sum_base("RSPC") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"RSPC"))/card(Year);

Pol_report_sum_base("NRLOAD") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"NRLOAD"))/card(Year);

Pol_report_sum_base("NGLOAD") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"NGLOAD"))/card(Year);

Pol_report_sum_base("PRLOAD") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"PRLOAD"))/card(Year);

Pol_report_sum_base("PGLOAD") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"PGLOAD"))/card(Year);

Pol_report_sum_base("DN2O") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"DN2O"))/card(Year);

Pol_report_sum_base("CFEM") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"CFEM"))/card(Year);

Pol_report_sum_base("P_level_FLSCH") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"P_level_FLSCH"))/card(Year);

Pol_report_sum_base("N_level_FLSCH") = SUM((slope, soil, hydro, farm, crop, Year),Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"N_level_FLSCH"))/card(Year);

****Calculate where sediment pollution is most significant****

Sediment_soil_tot_base (slope, soil, hydro, farm, crop,"total")$LAND.l (slope, soil, hydro, farm, crop) = SUM(Year,Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"ZLOAD")/LAND.l (slope, soil, hydro, farm, crop))/card(Year);

Sediment_slope_tot_base (slope, soil, hydro, farm, crop,"total") $LAND.l (slope, soil, hydro, farm, crop) = SUM(Year,Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"ZLOAD")/LAND.l (slope, soil, hydro, farm, crop))/card(Year);

Sediment_crop_tot_base (slope, soil, hydro, farm, crop,"total") $LAND.l (slope, soil, hydro, farm, crop) = SUM(Year,Pol_report_an_base(slope, soil, hydro, farm, crop, Year,"ZLOAD")/LAND.l (slope, soil, hydro, farm, crop))/card(Year);

Sediment_soil_av_base (soil,"average")= SUM((slope,hydro, farm, crop), sediment_soil_tot_base (slope, soil, hydro, farm, crop,"total"))/(card(slope)*card(hydro)*card(farm)*card(crop));

Sediment_slope_av_base (slope,"average") = SUM((soil, hydro, farm, crop), sediment_slope_tot_base (slope, soil, hydro, farm, crop,"total"))/(card(soil)*card(hydro)*card(farm)*card(crop));

Sediment_crop_av_base (crop,"average") = SUM((slope, soil, hydro, farm), sediment_crop_tot_base (slope, soil, hydro, farm, crop,"total"))/(card(slope)*card(hydro)*card(farm)*card(soil));

Land Allocation Linear Optimisation Programme

```
****Model to optimally allocate land to different farms in line with constraints****

Set

Alli 'All items set'

/value, L1, L2 , L3 , L4 , L5 ,S1 , S2 , S3 , S4, H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, farm_1 , farm_2 , farm_3 ,
farm_4, farm_5, farm_6,area,catch_total,farm_total/

soil(alli)   'soil types' /L1 'Wick', L2 'Newbiggin', L3 'Malvern', L4 'Clifton', L5 'Winterhill' /

slope(alli) 'slopes'   /S1 '0-0.8', S2 '0.81-2.4', S3 '2.41-4.0', S4 '4.01-7.3'/

hydro(alli) 'hydrological connectivity/risk levels'     /H1, H2, H3, H4, H5, H6, H7, H8, H9, H10/

value (alli) 'value used in parameter declaration'   /value/

farm(alli) 'farms in the main model'        /farm_1, farm_2, farm_3, farm_4, farm_5, farm_6/

report(alli) 'set used for reporting'          /value, catch_total, farm_total/

;

*read in the connectivity data from csv:

*call excel file and specify the cell frame from which the parameter should be read

$call gdxxrw.exe edenTableConn10.csv par=land_data rng=A1:D201 cDim=1 rDim=3

*define intermediate parameter over intermediate set which contains names of crops used in excel file

Table land_data (slope, soil, hydro, value) 'land available to be allocated between the farms in m^2';

*read parameter into gdx file

$gdxin edenTableConn10.gdx

*load parameter into model

$load land_data

$gdxin

display land_data

;


Parameter

Farm_size   'min size of representative farms in ha'            /21066.81/;

TABLE

Farm_soil_prop (farm, soil) 'minimum proportion of farm land belonging to certain soil'

          L1     L2     L3     L4     L5

farm_1    0.4    0      0.1    0      0

farm_2    0      0      0.1    0.4    0.01

farm_3    0.2    0      0.1    0.1    0.001

farm_4    0.2    0      0.1    0.1    0.001

farm_5    0      0      0.1    0.4    0.01
```

farm_6	0.2	0	0.1	0.1	0.001

;

TABLE

Farm_slope_prop (farm, slope) 'minimum proportion of farm land that should belong to certain soil'

	S1	S2	S3	S4
farm_1	0	0	0.3	0.3
farm_2	0.1	0.3	0	0
farm_3	0.05	0.2	0.2	0.2
farm_4	0.05	0.2	0.2	0.2
farm_5	0.05	0.2	0.2	0.2
farm_6	0.05	0.2	0.2	0.2

;

POSITIVE VARIABLES

ALLOC_LAND (slope, soil, hydro, farm)'land allocated to farms in ha'

T_FARM_LAND (farm) 'Total land allocated to a farm (over soil, slope, hydro type)'

LAND_PROP (slope, soil, hydro, farm) 'Proportion of land in ha of particular slope, soil, hydro type available allocated to particular farm(0-1)'

FARM_PROP (slope, soil, hydro, farm) 'Proportion of total farm land in ha that is particular slope, soil, hydro combination'

SURPLUS_LAND (slope, soil, hydro) 'Land that has not been allocated in ha'

;

FREE VARIABLES

SUM_SURPLUS 'Surplus land in ha summed over slope, soil, hydro'

;

EQUATIONS

E1, E2, E3, E4, E5, E6, E7, E8;

E1 (slope, soil, hydro)..

SUM(farm, ALLOC_LAND (slope, soil, hydro, farm)) =L= land_data (slope, soil, hydro, "value")*0.0001;

****The land allocation summed over farms must equal the available land data scaled for model performance

E2 (slope, soil, hydro, farm) ..

LAND_PROP (slope, soil, hydro, farm)*(land_data (slope, soil, hydro, "value")*0.0001)=E= ALLOC_LAND (slope, soil, hydro, farm);

****The land allocation is defined by land data multiplied by the proportion of land (0-1) of particular slope, soil, hydro type allocated to farm.

E3 (farm)..

T_FARM_LAND (farm) =E= SUM((slope, soil, hydro), ALLOC_LAND (slope, soil, hydro, farm));

****The total land allocated to a farm is given by the land allocation summed over slope, soil, hydro.

E4 (slope, soil, hydro, farm)..

ALLOC_LAND (slope, soil, hydro, farm) =E= FARM_PROP (slope, soil, hydro, farm)*T_FARM_LAND (farm);

****The land allocation is defined by the total land allocated to a farm multiplied by the proportion of land (0-1) of particular slope, soil, and hydro type allocated to a farm.

E5 (slope, soil, hydro)..

(land_data (slope, soil, hydro, "value")*0.0001)- SUM(farm, ALLOC_LAND (slope, soil, hydro, farm)) =E= SURPLUS_LAND (slope, soil, hydro);

****Non-allocated land by slope, soil, and hydro is given by the subtraction of the allocated land summed over farms from the land data.

E6..

SUM_SURPLUS =E= SUM((slope, soil, hydro), SURPLUS_LAND (slope, soil, hydro));

****Total non-allocated land is given by non-allocated land summed over slope, soil, and hydro.

E7 (soil, farm)..

SUM((slope, hydro), FARM_PROP (slope, soil, hydro, farm)) =G= Farm_soil_prop (farm, soil);

****'The proportion of total farm land in ha summed over slope and hydro combination must be greater than the minimum proportion of farm land belonging to certain soil'

E8 (slope, farm)..

SUM((soil, hydro), FARM_PROP (slope, soil, hydro, farm)) =G=Farm_slope_prop (farm, slope);

****'Proportion of total farm land in ha summed over soil and hydro combination must be greater than the minimum proportion of farm land belonging to certain slope'

****Defining bounds****

SUM_SURPLUS.lo=0;

****The non-allocated land lower bound is 0.

T_FARM_LAND.fx (farm) = Farm_size;

****The overall farm size is fixed to the representative farm size.

****Model definition****

MODEL land_alloc /all/ ;

****Running GAMSCK****

File gck/%system.fn%.gck/;

put gck;

```
$onput
NONOPT
$offput
putclose ;
option nlp = gamschk;
option limrow = 0;
option limcol = 0;

SOLVE  land_alloc minimising  SUM_SURPLUS  using LP;
****Solve statement
PARAMETER
farm_area (Alli, Alli, ALli, Alli, Alli) 'Parameter to report the land allocation between the farms to read into GAMS';
****Definition of farm area parameter for output generation

farm_area (slope, soil, hydro, farm, "value") = round (ALLOC_LAND.L (slope, soil, hydro, farm),2);
*unload the land allocation in a gdx file to read into main model
execute_unload 'Land_alloc_GAMS_4.gdx', farm_area;
```

Python Code

This section firstly presents the Python code used to implement the Wilcoxon Signed Rank test of yield heterogeneity between crops in different rotations from p. 243. This test for heterogeneity is discussed in the main text on p. 111. Subsequently, the Python code implementing the weather year sensitivity analysis presented in the main text section 5.4.5 is presented below from p. 249.

Wilcoxon Signed Rank Test

```
import pandas as pd
pd.options.mode.chained_assignment = None
import numpy as np
from numpy import mean, absolute
from tqdm import tqdm
import xlrd
import seaborn as sns
import matplotlib.pyplot as plt


# Loading the yield function data set:
df = pd.read_fwf(
    r'C:\Users\lioba\OneDrive - Durham University\Work\PhD\Data\EPIC\Yield
Function\YLD_checks_May_June2020\AF\AF-ave_2.fwf')
#Maximum Nitrogen applied in kg/ha
N_max = {}
wb = xlrd.open_workbook(
    r'C:\Users\lioba\OneDrive - Durham University\Work\PhD\Data\EPIC\Yield
Function\YLD_checks_May_June2020\N_P_response_AF.xlsx')
sh1 = wb.sheet_by_index(0)
row_count = sh1.nrows
for i in range(1, row_count):
    cell_value_crop = sh1.cell(i, 0).value
    cell_value_id = sh1.cell(i, 1).value
    N_max[cell_value_crop] = cell_value_id

# Minimum Nitrogen applied in kg/ha
N_min = {}
for i in range(1, row_count):
    cell_value_crop = sh1.cell(i, 0).value
    cell_value_id = sh1.cell(i, 2).value
    N_min[cell_value_crop] = cell_value_id
# Maximum Phosphorus applied in kg/ha
P_max = {}
for i in range(1, row_count):
    cell_value_crop = sh1.cell(i, 0).value
    cell_value_id = sh1.cell(i, 3).value
    P_max[cell_value_crop] = cell_value_id

# Minimum Phosphorus applied in kg/ha

# creating lists of the N and P values corresponding to the particular crop in order to add as a column to the
dataframe:
N_max_lst = []
```

```
for i in df.index:
    N_max_lst.insert(i, N_max[df.iat[i, 2]])

N_min_lst = []
for i in df.index:
    N_min_lst.insert(i, N_min[df.iat[i, 2]])

P_max_lst = []
for i in df.index:
    P_max_lst.insert(i, P_max[df.iat[i, 2]])

# check the length of the columns is correct:
if len(N_min_lst) == len(N_max_lst) == len(P_max_lst) == len(df):
    print("Correct number of columns")
else:
    print("Error in column length")

# add the columns to the dataframe:
df["N_min"] = N_min_lst
df["N_max"] = N_max_lst
df["P_max"] = P_max_lst
df["N_Q1"] = ((df["N_max"] - df["N_min"]) / 4) + df["N_min"]
df["N_Q2"] = ((df["N_max"] - df["N_min"]) / 2) + df["N_min"]
df["N_Q3"] = ((df["N_max"] - df["N_min"]) / 4 * 3) + df["N_min"]

# dropping crops which are not in the model:
df.drop(df.loc[df['CROPS---'] == 'BEAN1'].index, inplace=True)
df.drop(df.loc[df['CROPS---'] == 'BEAN2'].index, inplace=True)
df.drop(df.loc[df['CROPS---'] == 'STUR1'].index, inplace=True)
df.drop(df.loc[df['CROPS---'] == 'STUR2'].index, inplace=True)
df.drop(df.loc[df['CROPS---'] == 'STUR3'].index, inplace=True)
graze4_1_iidx = list(range(100, 120))
print(len(graze4_1_iidx))
for i in range(0, 20):
    df.drop(graze4_1_iidx[i], inplace=True)

# Extracting the list of crops present in the file:
crop_dbl_lst = []
crop_dbl_lst = df.iloc[0:-1, 2]
print(len(crop_dbl_lst))

# reindexing the dataframe:
df.index = range(0, len(crop_dbl_lst) + 1)

# print the column names in order to specify them:
print(df.head(0))
# calculate the YLD_min,Q1,Q2,Q3,max:
df["YLD_min"] = df["----B0--"] * (1 - np.exp(df["------B1---"] + df["-----B2---"] * df["N_min"])) * (
            1 - np.exp(df["-----B3---"] + df["----B4-----"] * df["P_max"]))
df["YLD_Q1"] = df["----B0--"] * (1 - np.exp(df["------B1---"] + df["-----B2---"] * df["N_Q1"])) * (
            1 - np.exp(df["-----B3---"] + df["----B4-----"] * df["P_max"]))
df["YLD_Q2"] = df["----B0--"] * (1 - np.exp(df["------B1---"] + df["-----B2---"] * df["N_Q2"])) * (
            1 - np.exp(df["-----B3---"] + df["----B4-----"] * df["P_max"]))
df["YLD_Q3"] = df["----B0--"] * (1 - np.exp(df["------B1---"] + df["-----B2---"] * df["N_Q3"])) * (
            1 - np.exp(df["-----B3---"] + df["----B4-----"] * df["P_max"]))
df["YLD_max"] = df["----B0--"] * (1 - np.exp(df["------B1---"] + df["-----B2---"] * df["N_max"])) * (
            1 - np.exp(df["-----B3---"] + df["----B4-----"] * df["P_max"]))

# calculate percentage change in yield between minimum and maximum N application:
df["YLD_perc_chng"] = (df["YLD_max"] - df["YLD_min"]) / df["YLD_min"] * 100
```

```
# rank the percentage change in yields within each unique crop
df["response_rank"] = df.groupby("CROPS---")["YLD_perc_chng"].rank("dense", ascending=False)
df["AV_YLD"] = (df["YLD_min"] + df["YLD_Q1"] + df["YLD_Q2"] + df["YLD_Q3"] + df["YLD_max"]) / 5


# check that the rank function has given the correct value
print(len(df) / 20)  # =86
rank_min_names = df.groupby("CROPS---")["response_rank"].idxmin()
rank_min_names.index = range(0, len(rank_min_names + 1))
chng_max_names = df.groupby("CROPS---")["YLD_perc_chng"].idxmax()
chng_max_names.index = range(0, len(chng_max_names + 1))

if len(rank_min_names) == len(chng_max_names):
   print("correct lengths")
else:
   print("error")
for i in range(0, len(chng_max_names)):
   if rank_min_names[i] != chng_max_names[i]:
      print(f'Error: rank:{rank_min_names[i]} change max:{chng_max_names[i]}')
# repeating the list of highest ranked indexes 20 times to create list that is the same length as the dataframe.
Facilitates use of the appropriate element for every crop
rank_repeat = rank_min_names.repeat(20)
rank_repeat.index = range(0, len(rank_repeat))
rank_repeat = rank_repeat.astype(int)
if len(rank_repeat) != len(df):
   print('error')
# creating empty column for B5 coefficient:
df["B5"] = 0
# filling B5 column by subtracting the average of the highest ranked index from the other averages
for i in range(0, len(df)):
   df.iloc[i, 22] = df.iloc[i, 21] - df.iloc[rank_repeat[i], 21]
# replacing B0-B4 of the other crops with the B0-B4 from the highest ranked index:
for i in range(0, len(df)):
   df.iloc[i, 3] = df.iloc[rank_repeat[i], 3]
   df.iloc[i, 4] = df.iloc[rank_repeat[i], 4]
   df.iloc[i, 5] = df.iloc[rank_repeat[i], 5]
   df.iloc[i, 6] = df.iloc[rank_repeat[i], 6]
   df.iloc[i, 7] = df.iloc[rank_repeat[i], 7]

# Minimum Phosphorus applied in kg/ha
P_min={}
for i in range (1, row_count):
   cell_value_crop = sh1.cell(i,0).value
   cell_value_id = sh1.cell(i,4).value
   P_min[cell_value_crop] = cell_value_id
#creating lists P values corresponding to the particular crop in order to add as a column to the dataframe:
P_min_lst=[]
for i in df.index:
   P_min_lst.insert(i, P_min[df.iat[i, 2]])
#check the length of the columns is correct:
if len(P_min_lst) ==len(df):
   print("Correct number of columns")
else:
   print("Error in column length")

#add the columns to the dataframe:
df["P_min"] = P_min_lst
df["N_Q2"] = ((df["N_max"]-df["N_min"])/2) + df["N_min"]
df["P_Q2"] = ((df["P_max"]-df["P_min"])/2) + df["P_min"]

#drop N and P min and max columns from the data frame
```

```
df.drop("N_min", axis=1, inplace=True)
df.drop("P_min", axis=1, inplace=True)
df.drop("N_max", axis=1, inplace=True)
df.drop("P_max", axis=1, inplace=True)
df.drop("YLD_min", axis=1, inplace=True)
df.drop("YLD_Q1", axis=1, inplace=True)
df.drop("YLD_Q2", axis=1, inplace=True)
df.drop("YLD_Q3", axis=1, inplace=True)
df.drop("YLD_max", axis=1, inplace=True)
df.drop("YLD_perc_chng", axis=1, inplace=True)
df.drop("response_rank", axis=1, inplace=True)
df.drop("AV_YLD", axis=1, inplace=True)
#calcualte the required YLD value for N and P Q2:
# recalculating the YLD values to reflect the scaled functions:

df["YLD_Q2"] = df["B5"] + (df["----B0--"] * (1 - np.exp(df["------B1---"] + df["-----B2---"] * df["N_Q2"])) * (
        1 - np.exp(df["-----B3---"] + df["----B4-----"] * df["P_Q2"])))

#create copy of the dataframe:
df2=df.copy()
df2.drop("N_Q1", axis=1, inplace=True)
df2.drop("N_Q3", axis=1, inplace=True)
df2.drop("----B0--", axis=1, inplace=True)
df2.drop("------B1---", axis=1, inplace=True)
df2.drop("-----B2---", axis=1, inplace=True)
df2.drop("-----B3---", axis=1, inplace=True)
df2.drop("----B4-----", axis=1, inplace=True)
df2.drop("B5", axis=1, inplace=True)

# calculate the soil average per unique crop:
df2_soil_av = df2.groupby(['CROPS---',"L"], as_index= False)[["YLD_Q2"]].mean()

#adding crop group columns to data frame:
#reading in crop croup dictionary data:
wb=xlrd.open_workbook(r'C:\Users\lioba\OneDrive - Durham University\Work\PhD\Data\EPIC\Yield
Function\YLD_checks_May_June2020\N_P_response_AF.xlsx')
sh2=wb.sheet_by_index(1)
row_count = sh2.nrows
#creating crop group dictionary:
crop_group={}
for i in range (1, row_count):
    cell_value_crop = sh2.cell(i,0).value
    cell_value_id = sh2.cell(i,1).value
    crop_group[cell_value_crop] = cell_value_id


import scipy
from scipy.stats import wilcoxon

#creating list with crop group names corresponding to the dataframe df2:
crop_group_lst=[]
for i in df2.index:
    crop_group_lst.insert(i, crop_group[df2.iat[i,2]])

#check the list length is correct:
if len(crop_group_lst) != len(df2):
    print("Error in list length")

#adding crop group to the data frame as a column:
df2["crop_group"] = crop_group_lst
#count the number of unique crops in each crop group:
```

```
group_members=df2.groupby("crop_group" )[["CROPS---"]].nunique()
group_members["crop_group"] =group_members.index
group_members.index=range(0, len(group_members))
#check the numbers of unique crops in each crop group add up to 86:
sum_check=group_members.sum(axis=0)
print(sum_check)

#determine indexes from which the crop group starts in df2:
group_members["idx_range"] = 0.0000

group_members.iat[0,2]= group_members.iat[0,0]*20
for i in range(1,len(group_members)):
   group_members.iat[i,2]= (group_members.iat[i,0] * 20) + group_members.iat[(i-1),2]
group_members["idx_range"] =group_members["idx_range"].astype(int)

group_members["idx_start"] =0.00
for i in range(1,len(group_members)):
   group_members.iat[i,3]=  group_members.iat[(i-1),2]
group_members["idx_start"] =group_members["idx_start"].astype(int)

#sort the dataframe by crop_group and reindex:
df2.sort_values(["crop_group", "CROPS---", "S", "L"], axis=0, inplace=True)
df2.index = range(0, len(df2))

test_results ={}
for i in tqdm(list(range(0,1720,20))):
   crop1=df2.iloc[i:i+20,5]
   iterable_lst=[x for x in range(0,1720,20) if x != i]
   for j in iterable_lst:
      crop2 = df2.iloc[j:j + 20, 5]
      #add the output to the dictionary:
      w, p = wilcoxon(crop1, y=crop2, zero_method='wilcox', correction=False, alternative='two-sided')
      test_results[df2.iat[i,2], df2.iat[j,2]]= w, p
#create a dataframe with the results in two columns and the crop pair as the index
results_df = pd.DataFrame.from_dict(test_results,orient="Index")
results_df.columns = ["statistic","p_value"]
#create transposed version of the first dataframe where crop pairs are in the columns
results_df_2 = pd.DataFrame.from_dict(test_results)
#extract the names of the columns from the dataframe as a list of tuples
index_lst = list(results_df_2.head(0))
#separate the tuples into two list of tuples:
crop_pair1=[x[0]for x in index_lst]
crop_pair2=[x[1]for x in index_lst]
#add the lists to the original results dataframe as columns
results_df["crop_1"]=crop_pair1
results_df["crop_2"]=crop_pair2
#reindex the original dtaframe to remove the crop pairs from the index:
results_df.index = range(0, len(results_df))

#create new column with crop group corresponding to the unique crop
results_df["crop_group_1"]= "empty"
results_df["crop_group_2"]= "empty"
#fill the new columns using the crop_group dictionary and the crop1 and crop2 columns:
for i in results_df.index:
   results_df.iat[i,4] = crop_group[results_df.iat[i,2]]
   results_df.iat[i,5] = crop_group[results_df.iat[i,3]]
#create a copy of the dataframe
results_final_df = results_df.copy()
#create a list of the index of all rows for which the crop groups for crop1 and crop 2 are not equal:
index_to_drop=[]
for i in range(0,len(results_final_df)-1):
```

```
    if results_final_df.iat[i,4] != results_final_df.iat[i,5]:
        index_to_drop.append(i)

#drop all rows for which the crop groups for crop1 and crop 2 are not equal:
for i in index_to_drop:
    results_final_df.drop([i], inplace=True)
#reindex the final data frame:
results_final_df.index=range(0, len(results_final_df))
results_final_df.to_excel("YLD_Wilcoxon_Signed_Rank_AF_scaled_YLD_functions_2_2_21.xlsx")
```

Sensitivity Analysis

```
####using data including the scaling of the pollution functions
import numpy as np
import gdxpds
import pandas as pd
gdx_file= r'C:\Users\lioba\OneDrive - Durham University\Work\GAMS-
modeling\Crop_test_July2020\Section4_2_poll_19.gdx'

#extract the parameters in the gdx file into an ordered dictionary of dataframes
dataframes = gdxpds.to_dataframes(gdx_file,r'C:\GAMS\win64\29.1\GMSPython')
#create a list of all the parameters contained in the dictionary:
parameter_lst=list(dataframes)
#save annual pollution
pol_df_an=dataframes['pol_report']
pol_df2_an=dataframes['pol_report']

#average over years
pol_df=pol_df_an.groupby(['slope','soil','hydro','crop','report'], as_index=False)['Value'].mean()
pol_df2=pol_df2_an.groupby(['slope','soil','hydro','crop','report'], as_index=False)['Value'].mean()
#read in the land data
gdx_file2= r'C:\Users\lioba\OneDrive - Durham University\Work\GAMS-
modeling\Crop_test_July2020\Baseline05_p.gdx'
#extract the parameters in the gdx file into an ordered dictionary of dataframes
dataframes2 = gdxpds.to_dataframes(gdx_file2,r'C:\GAMS\win64\29.1\GMSPython')
parameter_lst2=list(dataframes2)
df_land=dataframes2['LAND']
#calculate total catchment size
total=df_land['Level'].sum()
#drop unnecessary columns
df_land.drop(['Marginal',  'Lower',  'Upper',  'Scale'],axis=1, inplace=True)
#rename the columns
df_land.columns.values[0] = "Slope"
df_land.columns.values[1] = "Soil"
df_land.columns.values[2] = "Hydro"
df_land.columns.values[3] = "Farm"
df_land.columns.values[4] = "Crop"
df_land.columns.values[5] = "Land"
#eliminate spaces in columns so accessible through calling
df_land.columns = df_land.columns.str.strip()

#calculate the % of each soil type of the catchment:
soil_type_df=df_land.groupby("Soil", as_index=False)['Land'].sum()
soil_type_df['Percentage']=soil_type_df['Land']/total
#sum over farms to get rid of them
df_land=df_land.groupby(["Slope","Soil","Hydro","Crop"], as_index=False)['Land'].sum()

#caluclate how much of each soil type is of what slope type:
soil_slope_df=df_land.groupby(["Soil","Slope"], as_index=False)['Land'].sum()
#soil_slope_df['Soil_tot']=000
#for i in range(0, len(soil_slope_df)):


soil_slope_df.iat[i,3]=soil_type_df.iat[soil_type_df.Soil[soil_type_df.Soil==soil_slope_df.Soil[i]].index.values.astype(int
),1]
#calculate the % of each hydrological connectivity of the catchment:
hydro_type_df=df_land.groupby("Hydro", as_index=False)['Land'].sum()
hydro_type_df['Percentage']=hydro_type_df['Land']/total

print(soil_type_df.Soil[soil_type_df.Soil==soil_slope_df.Soil[5]].index.values.astype(int))
#calcute the mean across the weather years:
```

```
pol_tot=pol_df.groupby(['slope','soil','hydro','crop','report'], as_index=False)['Value'].mean()
pol_tot=pol_tot.groupby('report', as_index=False)['Value'].sum()

#add the land data to the yearly averaged pollution data
pol_df=pol_df.merge(df_land, left_on=['slope','soil','hydro','crop'], right_on=['Slope','Soil','Hydro','Crop'])
pol_df.drop(['Slope','Soil','Hydro','Crop',],axis=1, inplace=True)

#add the land data to the yearly pollution data
pol_df_an.rename({'slope':'Slope', 'soil':'Soil', 'hydro':'Hydro', 'crop':'Crop'}, inplace=True)
pol_df_an=pol_df_an.merge(df_land, left_on=['slope','soil','hydro','crop'], right_on=['Slope','Soil','Hydro','Crop'])
pol_df_an.drop(['Slope','Soil','Hydro','Crop'],axis=1, inplace=True)

#averaged across years:
#read in the map for the crop groups
mapindx4 ={
'SBAR11':'barley','SBAR12':'barley','SBAR13_FYM':'barley','SBAR2_FYM':'barley','WBAR0':'barley','WBAR1':'barley','
WBAR2':'barley','WBAR3_FYM':'barley',
'WBAR4_FYM':'barley','WBAR5_FYM':'barley','WW1':'wheat','WW2':'wheat','WW3':'wheat','WW4':'wheat','WW4_FYM'
:'wheat','MAIZ1':'maize',
'MAIZ5_FYM':'maize','MAIZ4_FYM':'maize','POTA1':'potato','POTA2':'potato','POTA3_FYM':'potato','POTA5_FYM':'p
otato','WOSR1':'oilseed_rape','WOSR2':'oilseed_rape',
'WOSR3':'oilseed_rape','GRLFA1':'grazing','GRLFA3':'grazing','GRAZE2_1':'grazing','GRAZE2_2':'grazing','GRAZE3
_1':'grazing','GRAZE4_1':'grazing','GRAZE4_3_FYM':'grazing',
'GRAZE6_3':'grazing','GRAZE6_1_FYM':'grazing','HAY2_1':'grazing','HAYLFA1':'grazing','SIL1_1':'grazing','SIL2_1':'g
razing','SIL3_1':'grazing','SIL3_2_FYM':'grazing',
'SIL4_1':'grazing','SIL4_2_FYM':'grazing','SILFA1':'grazing','FBEET1':'grazing','FBEET2':'grazing','FBEET3':'grazing','
GRLFA2':'setaside'}
units = {'ZLOAD':"t/ha", 'NRLOAD':"kg/day", 'NGLOAD':"kg/day",'PRLOAD':"kg/day", 'PGLOAD':"kg/day",
'CFEM':"kg/ha"}
description = {'ZLOAD':"Sediment Mobilised , 'NRLOAD':"Nitrogen to River ", 'NGLOAD':"Nitrogen to Groundwater
",'PRLOAD':"Phosphorus to River ", 'PGLOAD':"Phosphorus to Groundwater ", 'CFEM':"Carbon Emission
",'P_level_FLSCH':'P applied','N_level_FLSCH':'N applied'}

pol_df['crop_group']=pol_df['crop'].map(mapindx4)


#calculate pollution per hectare
pol_df['Pol_ha']=pol_df['Value']/pol_df['Land']
#average by soil
soil_df=pol_df.groupby(['soil','report'], as_index=False)['Pol_ha'].mean()
soil_df=soil_df.pivot(index='soil', columns='report', values='Pol_ha')

slope_df=pol_df.groupby(['slope','report'], as_index=False)['Pol_ha'].mean()
slope_df=slope_df.pivot(index='slope', columns='report', values='Pol_ha')

hydro_df=pol_df.groupby(['hydro','report'], as_index=False)['Pol_ha'].mean()
hydro_df=hydro_df.pivot(index='hydro', columns='report', values='Pol_ha')

crop_group_df=pol_df.groupby(['crop_group','report'], as_index=False)['Pol_ha'].mean()
crop_group_df=crop_group_df.pivot(index='crop_group', columns='report', values='Pol_ha')

#whole catchment averages per hectare:
catch_df=pol_df.groupby(['report'], as_index=False)['Pol_ha'].mean()

#######for yearly pollution

pol_df_an['crop_group']=pol_df_an['crop'].map(mapindx4)

#calculate pollution per hectare
pol_df_an['Pol_ha']=pol_df_an['Value']/pol_df_an['Land']
#average by soil
```

```
soil_df_an=pol_df_an.groupby(['soil','Year','report'], as_index=False)['Pol_ha'].mean()
#soil_df=soil_df.pivot(index='soil', columns='report', values='Pol_ha')

slope_df_an=pol_df_an.groupby(['slope','Year','report'], as_index=False)['Pol_ha'].mean()
#slope_df=slope_df.pivot(index='slope', columns='report', values='Pol_ha')

hydro_df_an=pol_df_an.groupby(['hydro','Year','report'], as_index=False)['Pol_ha'].mean()

crop_group_df_an=pol_df_an.groupby(['crop_group','Year','report'], as_index=False)['Pol_ha'].mean()
#crop_group_df=crop_group_df.pivot(index='crop_group', columns='report', values='Pol_ha')


#whole catchment averages per hectare
catch_df_an=pol_df_an.groupby(['report','Year'], as_index=False)['Pol_ha'].mean()
catch_df_an.rename({'report':'report','Year':'Year','Pol_ha':'Mean_pol_ha'},axis=1, inplace=True)
catch_df_an['Max']= pol_df_an.groupby(['report','Year'], as_index=False)["Pol_ha"].max().iloc[:,2]
catch_df_an['Min']= pol_df_an.groupby(['report','Year'], as_index=False)["Pol_ha"].min().iloc[:,2]

#variance from the individual year
df_pol_var_all=pol_df_an.groupby('report', as_index=False)["Pol_ha"].var()
df_pol_var_all.rename({'report':'report','Pol_ha':'Variance'},axis=1, inplace=True)
df_pol_var_all['Std']=np.sqrt(df_pol_var_all['Variance'])

#adding the mean, max and min values
df_pol_var_all_withmean=df_pol_var_all.merge(catch_df, left_on=['report'], right_on=['report'])
df_pol_var_all_withmean.rename({'report':'report','Variance':'Variance','Std':'Std','Pol_ha':'Mean_ha'},axis=1,
inplace=True)
df_pol_max=pol_df.groupby(['report'], as_index=False)['Pol_ha'].max()
df_pol_max.rename({'report':'report','Pol_ha':'Max_ha'},axis=1, inplace=True)
df_pol_max['Min_ha']=pol_df.groupby(['report'], as_index=False)['Pol_ha'].min().iloc[:,1]

#final output dataframe for output to Excel
df_final_poll_spread =df_pol_var_all_withmean.merge(df_pol_max,left_on=['report'], right_on=['report'] )

#add the upper and lower range of SD +/- mean to the data frame:
df_final_poll_spread['mean_plus_SD']=df_final_poll_spread['Mean_ha']+df_final_poll_spread['Std']
df_final_poll_spread['mean_minus_SD']=df_final_poll_spread['Mean_ha']-df_final_poll_spread['Std']
#create new data frame with the SD range around the mean to calculate percentage of #results outside mean +/- SD
df_pol_range=pol_df_an.merge(df_final_poll_spread, left_on=['report'], right_on=['report'])
df_pol_range['Out_range']=(df_pol_range['Pol_ha'] < df_pol_range['mean_minus_SD'] )|(df_pol_range['Pol_ha'] >
df_pol_range['mean_plus_SD'])
df_pol_range['Top_outlier']=(df_pol_range['Pol_ha'] > df_pol_range['mean_plus_SD'])

df_pol_range_group=df_pol_range.groupby(['report'], as_index=False)['Out_range'].sum()
df_pol_range_group['all']=df_pol_range.groupby(['report'], as_index=False)['Out_range'].count().iloc[:,1]
df_pol_range_group['In_range']=df_pol_range_group['all']-df_pol_range_group['Out_range']
df_pol_range_group['In_range_perc']=df_pol_range_group['In_range']/df_pol_range_group['all']*100
df_pol_range_group['Out_range_perc']=df_pol_range_group['Out_range']/df_pol_range_group['all']*100
df_pol_range_group['Top_outlier']=df_pol_range.groupby(['report'], as_index=False)['Top_outlier'].sum().iloc[:,1]
df_pol_range_group['Above_range_perc']=df_pol_range_group['Top_outlier']/df_pol_range_group['all']*100

file = r'C:\Users\lioba\OneDrive - Durham
University\Work\PhD\Data\Output_trials\GAMS_EXCELoutputs_29072023.xlsx'
with pd.ExcelWriter(file, engine='openpyxl', mode='a', if_sheet_exists='replace') as writer:
  df_pol_range_group.to_excel(writer, sheet_name='Spread_significance2' , startrow=0, index=True)
```

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