Agricultural Non-Point Source Pollution Control – Synergies between Spatial Targeting and Precision Agriculture

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Abstract

This paper investigates the cost-effectiveness of agricultural non-point source (NPS) pollution control policies through a biophysical-economic model for the Eden catchment (N-W England). In the context of current UK agricultural reforms and recent technological progress in agricultural technology, policy recommendations are drawn from a purpose-built biophysical-economic model covering six key NPS pollutants (nitrogen and phosphorus to both the river and groundwater, sediment, and carbon emissions). The model is 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.

Incentive-based fertiliser input taxes are found to be the most cost-effective policy mechanism. Notably, the presented results confirm previous findings in the literature of inelastic fertiliser demand. Consequently, high levels of taxation are required to achieve NPS pollution abatement. The novel assessment of Precision Agricutlure (PA) in the context of a catchment-scale biophysical-economic model highlights the synergies in necessary preconditions for PA and spatial targeting to be cost-effective. Policymakers should ensure sufficient heterogeneity in biophysical characteristics and land cover to safeguard successful spatial targeting and PA.

Key words: Precision Agriculture, Non-Point Source Pollution, Non-Linear Optimisation

JEL Code: Q52, Q16

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

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evidence on cost-effective policy options to control agricultural NPS pollution. Further, the progressive use of information technology in agriculture has influenced yield and pollution outcomes as well as extended possibilities on agri-environmental policy. This paper contributes to this need for evidence by addressing the following gaps in the literature: (1) assessing Precision Agriculture (PA) and its synergies with spatially targeted policies and (2) extending previous work by explicitly considering hydrological connectivity levels and modelling a novel combination of crop rotations, weather data, soil-, and slope-types in ranking NPS pollution control options.

2. Methods

2.1. Study catchment

The catchment analysed 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 (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.

2.2. Theoretical model

This papers' theoretical structure builds on Baumol and Oates (1988) work, appraising policies based on their cost-effectiveness in a second best world as opposed to optimality in a first-best world. 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.

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

$Y_{f,s,d,h,c,e}$ 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[2], 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 (including costs of: fertiliser including taxation, crop protection, seed and plant material, animal feed excluding forage, employed labour, and contracted PA machinery) from total farm revenue which includes sales from agricutlural products and transfer payments (Louhichi *et al.*, 2010, p. 586).

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. A farm's productive capacity is therefore constrained by the size and quality of its land endowment.

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 (see Table 1 for description of the livestock types). Farmers within the catchment may trade fodder beet and maize feed crops amongst each other to meet their livestock feeding requirements. Intra-catchment exclusive trading prohibits pollution leakage through bought-in feed crops and accurately represents pollution generated by the catchment's agricultural activities. Livestock manure which accrues over the housing period is used for fertilisation and reduces the cost of purchasing artificial fertiliser.

Table 1: 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)	

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

The model in this paper will follow the nine 'robust types' proposed in the UK Farm Classification of DEFRA to aid its policy relevance. The five types most representative for the Eden catchment are chosen: 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 8 (Appendix) 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 catchment, 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, 2021)[3].

2.3. 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, 2022). Due to the novel level of biophysical detail and number of observed weather-years included in this analysis, the evaluation of daily pollution concentrations popular in the literature was computationally infeasible. In addition, as outlined above, current preliminary UK policy targets are expressed in nutrient load as opposed to concentration. Therefore, this paper analyses the policies' associated abatement potential in terms of pollutant load to maximise its relevance in supporting current policy development.

2.4. 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, 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). Secondly, a set-aside policy is modelled as a command-and-control measure (requiring land to be taken out of production). A stocking density reduction was tested as an additional regulation-based policy. Stocking density reductions prescribe a maximum grazing livestock unit per hectare. 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. Table 2 summarises the details of the modelled policies.

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

Table 2: Modelled policy scenarios

Modelled Policies	Scenario Description
Non-targeted set-aside	- **Set-aside** 1% - 40% of **catchment agricultural land** o Increments of 1 percentage point
Targeted set-aside	- **Set-aside** 1% - 37% of **catchment agricultural land of slope 4** o Increments of 1 percentage point
N tax	- **N tax** from 50% - 5,000% o Increments of 50 percentage points from 2,000% o Increments of 5,000 percentage points to 5,000%
Mixed N tax & 1% set-aside*	- **N tax** from 50% - 5,000% o Increments of 50 percentage points from 2,000% o 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% o Increments of 50 percentage points from 2,000% o 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% o Increments of 50 percentage points from 2,000% o Increments of 500 percentage points to 5,000% - **Set-aside of 5%** of **catchment agricultural land**
Precision Agriculture	- **Fertiliser efficiency factor** from 5% - 45% o Increments of 5 percentage points
P tax*	- **P tax** from 50% - 5,000% o Increments of 50 percentage points from 2,000% o Increments of 500 percentage points to 5,000%
N tax & P tax	- **N tax** from 50% - 2,000% o 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*	

The model is implemented as a non-linear optimisation 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.

2.5. 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.

2.6. Weather data

A novel range of 58 years of daily observed weather data (1954-2011) from the UK's Meteorological Office[4] were used as precipitation, minimum and maximum temperatures, relative humidity, and wind speed variables in the simulations for the catchment. Following data cleaning and testing 45 weather-years were used in the final model. 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).

2.7. 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[5], 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). Table 3 provides a summary of the names, descriptions, and areas covered for the chosen soil-types.

Table 3: 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 3 demonstrates relatively similar loamy characteristics between the different soil types and their uneven distribution within the catchment (84% of soil is given by soils 1 &4). In addition to prevalent soil-types, degrees of steepness representative of the catchment were also included in the simulations (4 different slopes, see Table 4 for a list of the chosen slopes).

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

Table 4: 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

2.8. Management scenarios and crop rotations

The two management practices include conventional agriculture like the use of artificial fertilisers and a conservation practice, including the use of farmyard manure. For both management practices, 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. The Wilcoxon Signed Rank test was used to test the hypothesis that crop rotations and positions within crop rotations significantly impact yield outcomes. 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 paper' contribution in using the EPIC dataset and its uniquely extensive number of crop rotations and different crops.

2.9. Production and Pollution Functions

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. 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. 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 each 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 catchment.

Mitscherlich-Baule yield functions were fitted to the simulated yield data. The Mitscherlich-Baule functional form was chosen based on its theoretical properties 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. 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 , $\beta_5$represents a scaling factor, 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.

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

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.

With respect to pollution functions, six pollution variables were chosen for the analysis. The daily and monthly pollution data from the EPIC simulation were converted into 45 yearly pollution function estimates corresponding to the 45 included weather-years. These were combined into an average scaled pollution function to facilitate the analysis of general pollution trends. The linear and quadratic 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 9 (Appendix).

2.10. 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). Previous biophysical-economic models which analyse agri-environmental policies largely fail to capture the hydrological risk component of NPS pollution required for 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[6]. For a detailed description of SCIMAP see Reaney and Wells (2014). 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[7]. The resulting levels of connectivity are presented in Table 10 (Appendix). 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 (see Figure 1, Appendix).

2.11. Weather sensitivity

As outlined above, the pollution estimates are based on average pollution functions. The sensitivity of these pollution estimates to the individual 45 pollution years was tested using the baseline land and

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

[7] An alternative finer resolution distribution with 100 hydrological connectivity levels was investigated but ultimately not used in the model due to computational constraints. See **Error! Reference source not found.**, **Error! Reference source not found.**, p. 181 for the finer resolution distribution for intervals of 0.01.

fertiliser allocation. Table 5 presents the measures of variability between the pollutants' weather-specific levels.

Table 5: 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, 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 6: 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 6). 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.

2.12. Precision Agriculture

The assessment of PA focusses on Variable Rate Nitrogen Application (VRNA) specifically and assumes that through improved information, farmers adopting PA shift from within the production possibility frontier (PPF) onto the PPF. Following Colaço & Bramley (2018)'s comprehensive review of agronomic evidence, VRNA is modelled as an efficiency factor applied to the yield functions ranging from 5%-45%.

3. Results

Table 7 summarises the results at key environmental reduction targets for each chosen pollutant. 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. This result aligns with the 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. While transaction costs were not explicitly accounted for in modelling, they informed policy selection.

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%. Jayet and Petsakos (2013) generally also find N fertiliser use in France to be relatively price inelastic; although, their results suggest a higher elasticity (100% tax leading to 15%-20% reduction in nitrate emissions at the national to regional level). 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.

In addition to N demand elasticity, this paper' detailed analysis of the N tax response finds that farms shift from higher-input crops to lower-input crops. In the process, 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).

Across the pollutants, an individual set-aside policy generally does not present the most cost-effective option. 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 paper, 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 which may outweigh potential income and substitution effects.

As demonstrated in Table 7, set-aside does not achieve the highest sediment abatement potential amongst the modelled policies. This result does not align with the expectation due to set-aside's more direct theoretical link to sediment pollution than other modelled policies such as fertiliser taxation. 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 is supported by Secchi *et al.*'s (2007) modelling work on 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. For this paper the relatively low sediment abatement potential of set-aside policy may be explained by the 78% grassland cover of the assessed Eden catchment.

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. In the context of irrigated corn production in the Ebro basin of the Iberian Peninsula, Martínez and Albiac (2006) also find that pollution control policies spatially differentiated by soil-type provide a small welfare improvement compared to a homogeneously applied standard. Hasler *et al.* (2019) find that spatially targeting NPS N pollution control policies according to heterogeneous hydrological factors 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 paper, spatial targeting has a smaller effect on catchments with lower heterogeneity levels in hydrological connectivity. These findings highlight 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.

Table 7: 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

		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 (%)
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
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*

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. However, the mixed instrument remains less cost-effective than the modelled N tax.

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 which closely align with our findings. Bourgeois, Ben Fradj and Jayet (2014) also find that mixed-policy instruments improve cost-effectiveness for N water pollution abatement in France.

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. 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). This paper extends their work as a catchment-scale analysis of PA in an economic model with a novel biophysical detail in the literature. This paper finds both increased yield and reduced fertiliser consumption which 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 explained by the Eden catchment characteristics which include its lack of heterogeneity and dominance of grassland. They further demonstrate the synergies between PA and spatial targeting relate which primarily relate 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). The limited cost-effectiveness of PA 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.

4. Conclusions

The presented bio-physical model for the Eden catchment, firstly provide a general reference point for policymakers when balancing the ambition of environmental abatement across the six analysed pollutants with political considerations of farmers' economic position. 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.

In line with expectations, a combined N&P tax and an individual N tax provide the most cost-effective abatement for mid – low level regulatory targets (Shortle and Dunn, 1986; Kampas and White, 2004). The model also demonstrates that demand for N fertiliser is highly inelastic (800% tax leads to 10% reduction in N consumption) (Schmidt *et al.*, 2017). 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.

A set-aside policy is not found to provide cost-effective abatement or the highest abatement potential of the modelled policies which may be explained by the individual Eden catchment characteristics. 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 abatement potential across the majority of analysed pollutants.

Spatially targeted policies according to slope-types are found to provide only insignificant cost-effectiveness improvements with respect to uniformly applied policies. 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.

This precondition of sufficient heterogeneity required for successful implementation of spatially targeted policies equally applies to PA. Analogously to spatially targeted policies, PA is not found to be cost-effective as implementation costs outweigh the achieved productivity benefits (reduced fertiliser consumption and increased yields at the catchment scale). These results may be explained by 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 may contribute towards NPS pollution control and productivity efforts.

Finally, this paper has included a novel level of biophysical detail in its modelling. Crop rotations are found to lead to significantly different average yield outcomes. 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.

Appendix

Table 8: 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

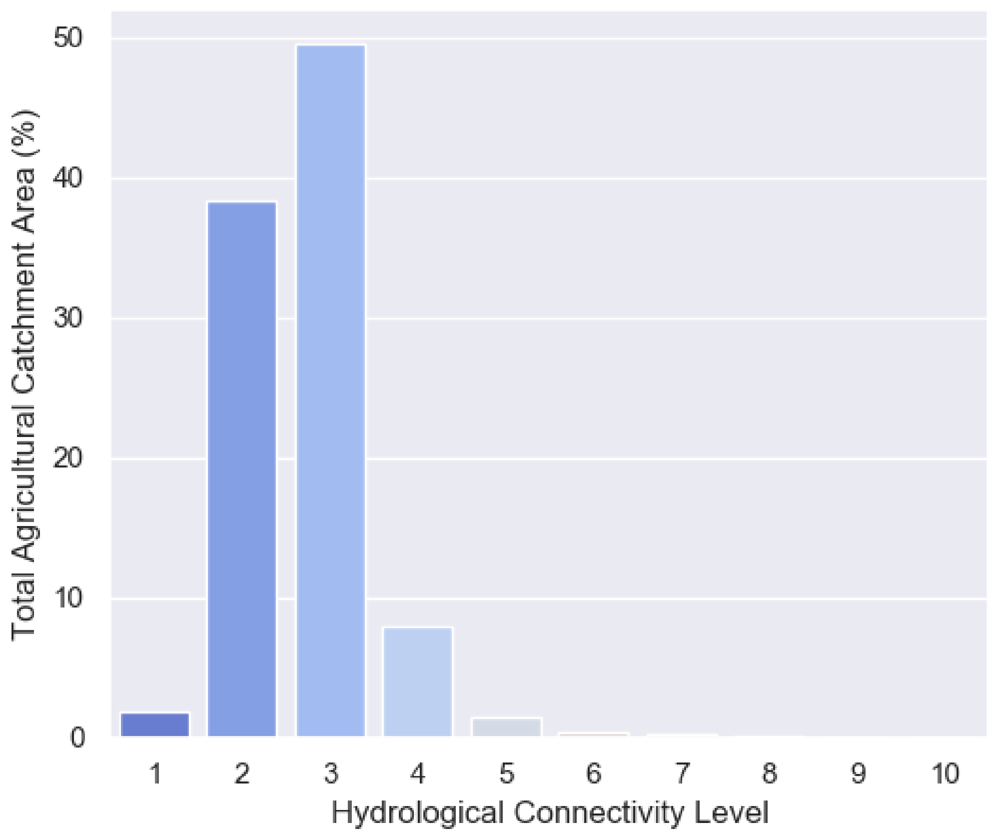
Table 9: Functional forms and theoretical reasoning for pollution functions

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.

Table 10: 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]

Figure 1: Distribution of hydrological connectivity levels (intervals of 0.1) across soils and slopes



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