Transferability of Policies to Control Agricultural Nonpoint Pollution in Relatively Similar Catchments

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Abstract

The EU's WFD requires cost-effective compliance with good ecological and chemical status across EU surface waters. Previous studies have modelled single catchments or been limited by their realism when investigating multiple catchments. We investigate whether the cost-effectiveness ranking of policy instruments to control agricultural nonpoint nitrate pollution (NP) is consistent across two relatively similar catchments. Transferability may interest regulators seeking to identify policies implementable in relatively similar catchments, rather than setting high transaction cost catchment specific policies. Detailed nonlinear stochastic biophysical economic optimisation models of two catchments are constructed. We estimate the distribution of daily river pollution for 10 years in each catchment without assuming an underlying pollutant distribution that is likely to distort policy ranking. We report consistency of policy rankings and outperformance in distinct regulatory target ranges in both catchments as well as pollution swapping. The transferability evidence may not be as robust as policymakers would like. Mixed instruments are cost-effective at higher regulatory targets and display characteristics suited to uniform application across catchments. Our study would benefit from improved modelling of farming heterogeneity, groundwater hydrology and policy transaction costs. Further research is required to identify catchment characteristics that determine transferability across a broader set of catchments.

1. Introduction

The EU's Water Framework Directive (WFD) (2000/60) requires cost-effective compliance with good ecological and good chemical status (GECS) across all EU surface waters. Several key principles underlie the Directive's aims including the polluter pays principle and the management of rivers on a river basin basis. In Scotland's rivers diffuse nutrient pollution from agriculture is the single most important pollution pressure (SEPA, 2007) since 24.3% of all rivers and 45% of estuaries fail to meet WFD targets due to such pollution (SEPA, 2005). In this paper, we estimate the cost-effectiveness of policies to control agricultural nonpoint nitrate pollution (NP) in two relatively similar mixed farming Scottish catchments with a diffuse nitrate pollution problem, the Motray and Brothock.

At present a variety of policy mechanisms to achieve GECS are being assessed by UK regulators. Since cost-effectiveness is a WFD criteria and there is evidence of the cost-effectiveness of economic instruments in the literature (see below), regulators have considered the role economic instruments can play (NERA, 2006). However, concerns exist over the environmental effectiveness, transactions costs and political acceptability of economic instruments to reduce nutrient pollution. Thus presently, regulators have employed a range of managerial controls (regulatory codes of good practice, general binding rules, best management practices etc.), including limits on fertiliser applications and timings, limitations on stocking rates etc. (under various cross-compliance schemes).

There is a growing consensus among UK policy makers/regulators[1] (DEFRA, EA and SEPA) and catchment stakeholders (rivers trusts, farmers' unions etc.) that a one size fits all agricultural diffuse pollution policy for catchments characterised by different agricultural systems, weather patterns etc. is inappropriate and cost-ineffective. However, unfortunately the high transaction costs of formulating and enforcing catchment specific policies may also be arguably prohibitively expensive. Thus recent and on going research in the UK[2] has focused on identifying cost-effective policies that can be applied to similar catchments, i.e. with similar agricultural systems, weather patterns and hydrogeology.

Economists have undertaken numerous single catchment studies to assess the cost-effectiveness of instruments to control NP. Yet, for practicality and wider consistency, regulators are looking for cost-effective policies that are in general consistently efficient

[1] Department for Environment, Food & Rural Affairs (DEFRA), Environment Agency (EA) and Scottish Environment Protection Agency (SEPA).

[2] E.g. DEFRA's Demonstration Test Catchment research platform.

across relatively similar water bodies[3]. We investigate the characteristics and consistency of policies, in particular mixed instruments, to control NP in two relatively similar catchments. The transferability of cost-effective policy instrument rankings across catchments is not something economists have addressed conclusively as previous cross catchment studies have been limited by their realism, modelling assumptions, simulated regulatory policies and/or ability to model farmer's response to them.

Moreover, cost-effective instrument ranking has not always been consistent in the empirical literature. This inconsistency could be attributed to differences in biophysical economic modelling sophistication, realism, assumptions (scale, resolution, fate, transport and hydrological modelling, heterogeneity, soil dynamics, livestock management, crop rotations, input substitution, transformation of regulatory concentration standards into load (mass) equivalents, farmer's behavioural response options etc.), economic incentives (prices, subsidies etc.), regulatory restrictions, geophysical catchment characteristics (Martinez and Albiac, 2004), and/or importantly the catchment weather patterns that drive the stochastic NP processes etc. In considering the stochastic nature of NP studies have made different distributional assumptions in estimating deterministic equivalents in chance-constrained optimisation models. Such differences affect the cost-effectiveness of regulatory instruments and render a comparison of NP policies in separate studies inappropriate, e.g. it is not meaningful to compare results of a study in semi-arid Spain (Martinez and Albiac, 2004) or California (Larson et al., 1996) with a high rainfall UK catchment (Kampas and White, 2004). Thus, in this research the modelling, assumptions and policy options were kept consistent enough to compare two separate catchments that differ in terms of scale, soils, crop rotations, arable to grassland ratio, agricultural activities, diffuse pollution levels, and

[3] The high transaction costs/political acceptability of tailoring policies to individual catchments necessitates this. Moreover, in practice operational EU "river-basin areas" can be considerably larger, e.g. Scotland comprises of only two river-basin (Scottish-Government, 2015).

importantly weather – but not drastically. Thereby allowing a meaningful comparison to help identify consistently cost-effective instruments across two relatively similar[4] catchments.

By using nonlinear stochastic biophysical economic modelling this paper 1) examines the cost-effectiveness and transferability of policies to control NP in two relatively similar catchments based on estimates of daily river concentration (mg/L) for 10 continuous years; 2) accounts for physical mixing, retention and lags in the diffuse pollutant transport process without assuming an underlying pollutant distribution - which is likely to distort instrument cost-effectiveness; 3) investigates the characteristics of mixed instruments (MI), comprising of economic instruments and managerial/regulatory controls, that make them more suited to being applied across catchments; and; 5) estimates pollution swapping (or substitution) of catchment phosphorus (P) and potassium (K) consumption from implementing policies to control NP. This is important as farmer's response to regulation may have unintended consequences and actually prevent attainting GECS.

2. Previous Work

Past research on the economics of NP control has largely focussed on single instrument policies and concluded that economic instruments are generally cost-efficient under a range of restrictive conditions (Balana et al., 2011; Shortle and Horan, 2001; Weersink et al., 1998). Previous studies have also detailed the efficiency gains of using policies that combine two or more economic incentives to control NP. However, in practice the information, monitoring and enforcement transaction costs of such policies have prevented their uptake. One study reported the superiority of MI in 'wet weather' conditions and improvements in their relative cost-effectiveness at higher regulatory targets (RT) under 'mean weather' (Aftab et al., 2010). These results were based on weekly averages of NP for just one representative 'wet' and 'mean' year's weather, which may not realistically capture the stochastic nature of NP over

[4] Identifying a set of relatively similar catchment characteristics that ensure the cost-effective transferability of policies is beyond the scope of this study. This would require an assumptions/methodologically consistent analysis of numerously more catchments with different characteristics.

time. This paper improves on these limitations and uses more realistic modelling assumptions to determine whether the cost-effectiveness of MI and other policies across relatively similar catchments is consistent and thus more broadly implementable.

Previous large-scale studies have provided valuable insights and modelled catchments by using either an econometric or applied general equilibrium approach. However, both approaches have their limitations. Econometric studies have been limited by: extremely broad classifications of land use incapable of differentiating between crops, grassland, livestock or setaside etc. (Langpap et al., 2008); unrealistically large land units of assessment (Wu et al., 2004); not permitting land use to change in response to policies (Fezzi et al., 2010). While an applied general equilibrium approach requires numerous simplifying assumptions, such as arbitrarily converting the loads of different pollutants into one generic nutrient unit (Brouwer et al., 2008). A few cross catchment comparison studies have used a biophysical economic modelling approach. These have been limited by: the absence of livestock and manure management (Brady, 2003); a simple linear economic model and infeasible high transaction costs policies (Volk et al., 2008); very small study areas as well as the assumption that livestock types and amounts remain constant (Vatn et al., 1997)[5]. More importantly, these studies estimate average pollutant loads[6] and do not consider pollutant concentration, river mixing and the probability of achieving a concentration standard with a specific certainty as well as its impact on the cost-effectiveness of policies. Most assume an arbitrary average annual load reduction equates to compliance with an environmental concentration standard. Pollutant loads are not necessarily reliable proxies for concentration and environmental impact. There is a trade-off between the complexity/realism and the scale of modelling (Brady, 2003). Generally, an econometric approach is restrictive in: capturing diffuse pollution processes; the type of policies that can be simulated and the ability to model farmers' behavioural response to policies. Whereas landscape scale

[5] It compares annual pollutant loads in two catchments with a combined area of 4313ha.

[6] Although Volk et al. estimate the concentration of total N they do not report how the stochastic variation impacts on the cost-effectiveness of policies (Volk et al., 2008).

biophysical economic approach is more interdisciplinary, data intensive and, as discussed earlier, involves assumptions that can vary across studies and affect the cost-effective rankings of policies.

Most of the diffuse water pollution chance constrained (stochastic), biophysical economic literature (Elofsson, 2003; Milon, 1987) involves imposing a deterministic equivalent on the optimisation problem by assuming that the distribution of pollution estimates are normal (Gren et al., 2000), log-normal (Kampas and White, 2004) or truncated normal (Kataria et al., 2009). The normality assumption is motivated by the central limit theorem, i.e., the statistics of sample loads will asymptotically converge to a normal distribution, while the log-normality[7] and truncated normal assumption is justified by the need to avoid the possibility of negative pollution loads. Alternatively, a distribution-free approach uses the Chebyshev's inequality to approximate the probabilistic constraint (Wets, 1983). The literature is inconclusive and often contradictory as to which distribution should be used. Besides probabilistic programming models are sensitive to such distributional assumptions (Gren et al., 2002; Kampas and White, 2004; Xu et al., 1996; Zhu et al., 1994). More recent research has estimated that the assumed distribution can bias results by as much as 60% (Kataria et al., 2009). Moreover, a review of environmental data concluded there was little support for a general use of either the log-normal or normal distribution (Reimann and Filzmoser, 2000).

Although numerous studies have investigated controlling P (Goetz and Keusch, 2005; Iho and Laukkanen, 2012; Johansson et al., 2004; Schleich et al., 1996), and the joint management of P and nitrogen (N) pollution has been conceptually considered (Heathwaite et al., 2000), few empirical studies have used detailed biophysical economic modelling to consider the trade-off between their consumption (Kampas et al., 2002; Vatn et al., 1997). We consider the consequences of policies to control diffuse N pollution on farm P and K

[7] A 'theory of successive random dilutions' attempts to explain how lognormal distributions may arise from physical processes responsible for generating pollutant concentrations in the environment (Ott, 1990). However, more recent work by the US EPA has confirmed that such environmental datasets are not necessarily lognormally distributed (Simon, 2014).

consumption. Coordinating policies targeted at different agricultural externalities is critical (Aftab et al., 2007). This also emphasises the importance of attaining a final ecological outcome, the stated WFD intention, instead of realising a specific nutrient standard. K, unlike N and P, is not usually a limiting macronutrient in rivers and less likely to contribute to eutrophication. However, the amount of K in rivers is known to play a role in species composition and impact river ecology, even though previous studies have highlighted the possible contribution of elevated K to river eutrophication (Czernas, 1978; Leentvaar, 1980).

3. Study Area

The relatively similar catchments are approximately 39.03km apart and share reasonably similar farming practice, weather, ground water base flow and comparable soil profiles (table 1). The Motray is entirely underlain by lavas and tuffs, rising to over 300 m, with lower areas mantled by fluvioglacial deposits. While the Brothock is underlain mostly by a permeable geology of sandstones in the lower areas, supporting fertile soils and mixed farming, while the upper catchment, rising to 150 m, is underlain by lavas and supports a mix of rough grazing and forestry. The catchments suffer from low flow in summer from surface water potato irrigation. Both catchments are also in Nitrate Vulnerable Zone (NVZ)[8] designated areas and infrequent SEPA spot sampling indicates a risk of exceeding the WFD nitrate standard from NP (see 4.4). Information on catchment crops, rotations, tillage and livestock was collected from Scottish Agricultural College regional field agronomists as well as surveys of farmers in the catchments.

4. Biophysical Economic Modelling

4.1 Farming Activities

Six main arable crops (winter wheat, spring barely, winter barley, winter oilseed rape, ware potatoes and seed potatoes), seven different livestock types (dairy, sheep, lowland suckler and four types of beef cattle), and three types grasslands (permanent grazing grass,

[8] NVZ require a maximum of 250kg N/ha/yr of organic manure and 170kg N/ha/yr averaged over the farm; fertiliser management plans and restrictions on the storage/application of slurry.

temporary grassland (silage) and hay) were modelled[9]. Crop-soil specific production functions were derived from the literature (Chambers and Johnson, 1990). Farms also had the option to purchase silage from the market. Livestock waste is accounted for as a source of N, P and K on grassland and relevant farm subsidies (e.g. Scottish Beef Calf Scheme), were included. Potatoes are the only irrigated crop and the variable costs of contracting the supply of irrigation water is incorporated. Catchment agronomic practices and parameters, crop rotations and the existing baseline scenario were taken from the literature and catchment farm survey data. Field level crop data for both catchments were collected from the IACS-SAF database (2000-2010) while livestock numbers were based on lower resolution parish level data (2008-2010). Approximately 150 crop rotations in each catchment were considered. For practical reasons these were simplified to catchment specific crop-pair rotations. Crop-pairs account for the N applied to both crops in a two crop rotation. The Motray was modelled as 34 crop-pair and the Brothock as 33 catchment specific crop-pair rotations for each of the three catchment specific soil types. Considering the previous crop in the rotation accounts for soil N dynamics (Martinez and Albiac, 2004).

4.2 Farming Heterogeneity

The Motray's (4743 ha) and Brothock (3580 ha) was modelled as 5 and 7 farms respectively. The farms represent hypothetical aggregated land use categories since individual farm data are not made available due to confidentiality concerns. They denote heterogeneity in farming practice across catchments in terms of farming knowledge, experience, spatial characteristics, preferences and capital/infrastructure considerations etc. (Wossink et al., 2001). These heterogeneous farms differ in terms of acreage, distribution of soil types, crop mix, crop rotations, livestock types, stocking densities, arable to grassland ratios, amount of non-agricultural sources of NPS nitrate pollution from forestry, rough grazing and urban areas (FRU). Modelling farm heterogeneity allows more realistic approximation of farms' responses to regulatory policies, especially since farming practice is notoriously varied.

[9] Spring oats, a relatively minor crop, was the only catchment crop that as not modelled. Note all crops are conventionally tilled.

4.3 Pollutant flux

Fluctuations in daily river N concentrations are driven by temporal interactions between farm management practices, stochastic weather patterns and crop growth demands. The link between land use and nitrate run-off was simulated using NITCAT (DEFRA, 2001). Regressing the N load estimates of catchment specific crop/soil combinations against a range of nitrogen input levels provided nitrogen leaching functions. Three separate soil classes for each catchment were determined based on HOST[10] classification, profile water column, and representative soil type. Daily water balance was calculated for 4 catchment-specific crop transitions (crop-pair rotations) using the IRRIGUIDE model (Bailey and Spackman, 1996) for 10 years from 1985/6 to 1993/4[11]. Four water balance classes appropriately approximated reality without excessively complicating the aggregation of estimates at the catchment scale. Each crop-pair was assigned to the most appropriate water balance class.

Daily time series of water balance and nitrate loss from soils units via rapid (shallow) and slow (deep) drainage pathways were routed using the EveNFlow (Anthony et al., 2009) model. EveNFlow is a semi-distributed, catchment scale, conceptual model of effective rainfall delivery to a river system by building on: SLIMMER (Anthony et al., 1996), an elution model; a crop water use/drainage model based on elements of the MORECS (Field, 1983) and IRRIGUIDE (Bailey and Spackman, 1996) models, and crop-soil specific leaching functions from NITCAT. This framework simulates a daily time-series of river flow and nitrate-N concentrations and was validated by the EUROHARP project (DEFRA, 2005). Soil retention, transfer delays and mixing of base flow helped reproduce the river hydrograph and concentrations resulting from mixing the two drainage pathways. Although sewage inputs were not considered emissions from FRU were factored. This framework[12] estimated daily

[10] Hydrology of Soil Types classification of the soils of the UK, assigns soils to classes on the basis of their physical properties and their effects on the storage and transmission of soil water (Boorman et al., 1995).

[11] This time period afforded the best river flow, river N sampling and continuous weather data in both catchments.

[12] Further details of the modeling framework can be found in the online appendix at WEB ADDRESS.

average nonpoint N pollution in the river for 10 years of continuous weather in each catchment.

4.4 Water quality calibration

Infrequent spot ambient water quality sampling by SEPA reveals that the EU nitrate standard is breached around 49% of the time in the Motray (Figure 1). However, since this includes contribution from sewage treatment works and other sources not captured by our modelling this figure is likely to overestimate agricultural NP. Moreover, in-stream measurements may also overestimate actual pollution because there is a bias towards sampling in winter months that are more prone to diffuse N peaks. Brothock sampling revealed the standard is violated approximately 11% of the time. Generally, the simulated baseline provides a reasonable fit to the actual data, especially the winter patterns, which are more likely to violate the nitrate standard. Comparing SEPA's actual river concentration data with the distribution of modelled river concentration (Figure 2 with Figure 1) suggests the modelled data reproduces key features of the river's actual N concentration distribution. Moreover, simulated hydrograph peaks and troughs reasonably matched actual in-stream flow patterns. Overall considerable effort was made to improve the realism of the biophysical catchment processes relative to previous studies.

4.5 Underlying pollutant distribution assumption

We do not assume any underlying distribution and instead empirically estimate the distribution of daily river N concentration using 10 years' continuous weather data. Generating a large sample of river concentration under different regulatory policies provides a more realistic approximation of the natural variability in the stochastic diffuse pollution process (formation, transport and fate) in each catchment. This way we avoid any bias in the ranking of regulatory instruments from imposing distributional assumptions about the pollutant. We also compared the nonparametric kernel density of the empirical (modelled) river concentration with an assumed normal, truncated normal and log-normal distribution[13] and report the results in section 5.5. Moreover, our methodology is also superior to imposing a standard on the leachate in or below the root zone - a common assumption in the literature due to the difficulty of modelling pollutant fate and transport to the receiving water body. It also avoids having to convert the EU WFD nitrate standard (concentration - mg/L) into a mass equivalent which requires making simplifying and distorting assumptions (Kampas and White, 2004). Nor do we assume that the distribution of the pollution load (mass - mg) in the root zone approximates the distribution of N concentration in the river, which is likely to distort instrument cost-effectiveness and policy ranking. Also, since our approach does not involve approximating the deterministic equivalent of a probabilistic constraint in a chance constrained programming framework, therefore we don't have to estimate the correlation coefficient between emissions (Kampas and White, 2003).

4.6 Economic modelling

(1) Minimise

$$\sum_f \Pi_f - \sum_f \left[\sum_{r,c,s} \left(Y_{frcs} P_c - w^n N_{frcs} L_{frcs} \right) + \sum_b a_{fb} P_b - w^n \left(\sum_{r,t,s} u_{frts} m_{frts} \right) - \sum_c C_{fc} L_{fc} - \sum_k A_{fk} R_k + T_f \right]$$

Catchment farms are modelled as economic decision makers $\left(f\right)$, who are assumed to maximise individual farm profits $\left(\Pi_f\right)$, by endogenously determining land and fertiliser (NPK) allocation to productive activities[14] on each soil type, in response to different regulatory controls. The regulator's policy objective is to minimise the catchment abatement cost of achieving a particular RT (probability of exceeding the EU 11.3 mg N/l ambient nitrate concentration regulatory standard), i.e. the difference between the unrestricted catchment profit $\left(\sum_f \Pi_f\right)$ and the catchment profit different pollution control policies. Thus, (1)

[13] The parameters for the normal and lognormal distributions were estimated from the data's mean and the mean of the log, respectively, whereas those of the truncated normal over the interval of concentration greater that 2 mg/L (arbitrarily chosen) were obtained by maximum likelihood. The nonparametric density, which closely follows the data, was obtained using a normal kernel with a bandwidth of 0.5. Empirical frequency refers to the number of observations that exceed the standard.

[14] Productive activity refers to crops, livestock production (grassland) and LR.

determines the social cost of regulation (Baumol and Oates, 1988; Beavis and Walker, 1983). If a policy achieves a particular RT at lower social cost than another policy, then it is more cost-effective and in a second best world more efficient (Ribaudo et al., 1999). Π_f is the outcome of an unrestricted run of the model without any regulation, other than existing mandatory restrictions (NVZ etc.), on farm f. Catchment profit in the objective function is the sum of the return to each producer's management and allocation of resources minus the cost of total farm nitrogen consumption ($\sum_{r,c,s} w^n N_{frcs} L_{frcs}$ (arable crops), $w^n \sum_{r,t,s} u_{frts} m_{frts}$ (silage and grazing grass)), cost of land retirement ($\sum_k A_{fk} R_k$) and all other crop specific secondary farming costs C_{fc} including the cost of potato crop irrigation, sprays, K and P fertiliser application, etc. Land retirement area A_{fk} and the per hectare cost of land retirement, R_k are indexed over land retirement type k (permanent, temporary good and temporary bad).

Exogenous terms in (1) include P_c the market price of arable crop c, and P_b the market return from livestock unit[15] (LU) type b. Agricultural prices were set to the 2009/10 price level (SAC, 2009). The number of livestock on each farm is represented by a_{fb}. w^n is the market price of nitrogen fertiliser, N_{frcs} and L_{frcs} is respectively the nitrogen applied and land allocated to arable crop c (excluding grasslands) on soil type s in crop pair rotation r. Likewise, Y_{frcs} is the yield for each crop, soil, rotation combination on each farm. Whereas m_{frts} and u_{frts} refer respectively to land and nitrogen allocated to grassland type t (permanent, temporary, and hay). T_f refers to all transfer payments (positive for IT). Such transfer payments are not included in estimates of abatement costs. The non-linear optimization model was written in GAMS (Brooke et al., 1998) and solved using the

[15] A livestock unit is defined in terms of the metabolised energy requirement. With one unit being the maintenance of a mature 625 kg Friesian cow and the production of a 40–45 kg calf, and 4500 l of milk at 36 g/kg of butterfat and 86 g/kg s.n.f. Based on this the LU unit values of all livestock are calculated, e.g.: suckler cow (1 LU), ewe (0.15 LU), male cattle < 2 years (0.6 LU), male cattle > 2 years (1 LU).

CONOPT 3 solver[16] (Stolbjerg-Drud, 1993). Overall the model estimates the cost-effectiveness of policy control instruments to attain RTs. The 10% RT means the NP standard must be met at least 90% of the time etc. The social (resource) cost of policy controls are reported as percentage reductions from the baseline profitability. Figure 3 provides a diagrammatic representation of the biophysical economic modelling.

We simulated the following policies: 1) nitrogen input taxation (IT); 2) farm livestock stocking density reduction (SDR), and; 3) a minimum percentage farm permanent land retirement (LR) requirement. Three types of MI policy packages that combine economic incentives with managerial controls (regulation), were simulated: a) LR with IT, b) SDR and IT and c) LR, SDR with IT. All of the control instruments were uniformly applied and simulated as iterative runs of the model. Impractical high transaction cost policies such as emission taxation (Aftab, 2010) and nitrogen input quotas were also simulated but their results are not reported.

4.7 Land use and livestock calibration

The model's baseline allocation was calibrated to farm level survey data on cropping and livestock intensities. Both catchment models' baseline simulations reflected actual farm practice in each catchment. The Motray's baseline percentage deviation from actual average catchment data was: -0.38% for arable crops and 2.99% for catchment livestock units (LU). The Brothock's baseline percentage deviation from actual average catchment data was: -11.79% for arable crops and -7.94% for catchment livestock units. The Motray's baseline arable to grassland ratio is 2.6 to Brothock's 4.45.

5. Results

Figures 4 and 5 illustrate the social cost of regulation as a percentage reduction from baseline catchment profit, £3.26m and £2.59m, under different pollution control policies for the Motray and Brothock respectively. The strictness of nitrate RT increases when moving from left to right along the x-axis in both figures. The probability of the standard being

[16] Robustness checks were undertaken and results were verified by using the MINOS 5 solver.

exceeded is the number of days in the 3650 days of simulation that violate the standard. MI are represented by discontinuous lines. The highest pollution level for each simulated control policy is represented by top left-most starting point of its line. The control policies deliver different minimum levels of compliance, e.g. the MI: [SDR (1.98) + IT] over achieves the 10% RT by ensuring at least 8% compliance at all times. Table 2 ranks each policy's relative cost-effectiveness and associated reduction in catchment profit relative to the catchment baseline. The 10%, 5%, 3% and 1% RTs were arbitrarily chosen to illustrate the effect of progressively stricter enforcement, with the 1% RT being the tightest.

5.1 Motray results

In figure 4, among single instrument stand-alone policies IT is clearly most efficient while LR is the least cost-effective at mitigating pollution. Both stand-alone SDR and LR are inefficient at achieving the 10% and 5% targets and incapable of achieving stricter RTs unless essential crop rotation constrains are relaxed - unfeasible given the role of crop rotations in minimising crop disease. The efficiency difference between economic and managerial policies as well as between SDR and LR increases as the RT is tightened.

Interestingly, as the RT is increased MI outperform. IT is the most cost-effective control instrument until the 16% RT after which there is a 'cross-over' and [LR (0.99%) + IT] becomes more efficient. From the 15% target onwards various MI optimise social cost. Both two instrument mixed instruments (2MI), [SDR + IT] and [LR + IT], are more cost-effective at delivering the 15% RT and higher RTs. In fact, even though [SDR (1.98) + IT] over achieves and actually meets the 5% RT, it is still more efficient than IT at the 10% target. This efficiency difference between the two instruments extends from 0.46% at the 10% RT to 16.03% at the 1% RT. At the extreme, 2% RT and 1% RT, the three instrument mixed instrument (3MI) [LR + SDR + IT] policy packages excels. E.g. at the strictest 1% RT the efficiency gain between IT and [LR (0.96%) + SDR (1.97) + IT][17] is 17.95%. Thus adding a

[17] [LR (0.96%) +SDR (1.97) + IT] refers to a MI comprising of the requirement to retire 0.96% of farmland, a maximum stocking density of 1.97 GLU/ha on grassland and an N input tax.

further control instrument to the MI policy package improves efficiency as regulatory stringency is increased. Additionally, this efficiency gap widens considerably as the RT increases (figure 4 and table 2). Overall, across the RT considered in table 2, [SDR (1.98) + IT] is clearly the most efficient overall. Overall, the 'crossovers' are insignificant and policies tend to outperform in very distinct RT ranges. Such distinct cost-effectiveness frontiers make it easier to set RT specific policies.

5.2 Brothock results

The Brothock exhibits greater clustering of instruments in a narrower efficiency range, i.e. the difference in cost-effectiveness of policies is not as well defined (figure 5). LR is the least and IT is the most efficient single instrument. IT is marginally the most efficient control policy until the 10% RT after which various MIs maintain a small efficiency advantage. In table 2, [SDR (1.98) + IT] is marginally more efficient at the 5%, 3% and 1% level. The 3MI [LR (0.2%) + SDR (2.1) + IT] is clearly the most cost-effective policy at the strictest 1% level, delivering a cost saving of 0.82% over IT. Thus overall, within the considered RT range the [SDR + IT] MI is the most efficient. Two additional MI were simulated in the Brothock catchment: [SDR (2.1) + IT] and [LR (0.2%) + SDR (2.1) + IT]. These additional MI were set at SDR and LR levels that were "optimal" for the Brothock - illustrating that efficiency gains from tailoring instrument levels to each catchment. SDR is considerably more efficient in the Brothock and even outperforms IT from the 2% RT onwards.

Intriguingly, a pattern of instrument efficiency frontiers emerges which is entirely consistent with the Motray frontier. IT is the most cost-effective control instrument for small reductions in diffuse pollution from the baseline (14%-9% RT), whereas 2MI [SDR (2.1) + IT and SDR (1.98) + IT] outperform in achieving mid-range abatement (8%-2% RT), and 3MI [LR (0.2%) + SDR (2.1) + IT] is most cost-effective at the strictest regulatory target (1% RT). Such efficiency frontiers are catchment specific and depend on catchment characteristics.

5.3 Cross catchment comparison

In both catchments MIs outperform IT, SDR and LR at stricter RTs and their efficiency gain increases at higher RT. The efficiency gain MIs provide is relatively greater in the Motray, but instrument ranking remains largely, but not convincingly, consistent in both catchments. Unfortunately, this consistency is not as robust as policy makers would like. Intriguingly, for approximately the first 40% of pollution reduction in both catchments IT remains the most efficient instrument – reflecting the superiority of IT in making small reductions from baseline level of pollution in both catchments. Significantly, in table 2, MI policies, especially 3MIs, display the least variation in social cost across the RTs (e.g. from the 10% to the 1% RT in the Motray IT's resource cost increases from -3.77% to -23.42%, whereas with [LR (0.96%) +SDR (1.97) + IT] it rises from -4.05% to -5.47%). Suggesting it may be easier and more politically acceptable for regulators to raise the RT with MI than with single instruments like IT or LR[18], due to the relative smaller reduction in catchment profit.

5.4 Comparative control instrument levels

Table 3 compares the instrument levels required to induce compliance with the same RT in each catchment. The result that higher probabilities of achieving E^* (stricter RT) require higher instruments levels and that they are relatively greater in the Motray is self-explanatory - given its higher baseline pollution. E.g. a 332.62% higher IT achieves the 10% RT, rising to 572.16% at the 1% target, in the Motray than in the Brothock. This difference between catchments instrument levels is less apparent with managerial controls - particularly, LR at the 5% RT where the Motray's 18.66% LR requirement is comparable to the Brothock's 17.95% LR requirement.

Also, the instrument level difference between catchments is considerably less for MI. The difference in the IT component of the instruments 2MI [SDR + IT] and 3MI [LR + SDR + IT] is 44.23% and only 13.45% respectively at the 3% target. Intriguingly, the difference between instrument levels required to achieve the same RT in both catchments is the smallest with

[18] Compare the increased percentage reduction in the Brothock's resource profit using LR in moving from the 10% RT (-6.5) to the 1% RT (-36.94).

3MI, i.e. an IT difference of 19.23%, 13.45% and 28.84% at the 5%, 3% and 1% RT respectively. Thus, the evidence suggests MIs are more suited to being applied uniformly as blanket policies across different catchments than IT. Uniform policies have lower transaction costs than spatially targeted ones, are arguably more enforceable in practice and perceived to be fairer. This may explain the reluctance of policy makers to adopt economic controls in isolation. Our results suggest it may be easier to impose a uniform MI policy than a uniform IT policy across different catchments. Detailed water quality metrics and their interpretation can be found in the supporting supplementary material.

5.5 Estimated pollutant distribution bias

Figure 1 compares the modelled daily baseline river concentration histograms of both catchments. By comparing the nonparametric kernel density of the empirical (modelled) river concentration with an assumed normal, truncated normal and log-normal distribution we found that in the Motray all three assumed distributions underestimate the probability of exceeding the 11.3 mg/L standard, whereas in the Brothock they overestimate the probability. This illustrates the bias from assuming an incorrect underlying distribution. This bias is as much as -19.15% with the normal in Motray and 31.88% when assuming a lognormal distribution in the Brothock. Such substantial errors are likely to be economically and environmentally costly. Real data seldom follows standard distributions; excessive peakedness (with many outliers) and multimodality are more common - as shown in the actual data (Figure 2). Multimodality occurs naturally in meteorological data (Mardia and Jupp, 2000; Zoccatelli et al., 2011), and is a key driver of river pollution. Furthermore, using a crude one−sided Chebyshev inequality produces very large upper bounds on the probability of exceeding the threshold. The inequality provides very limited information and appears excessively conservative when contrasted with real data.

5.6 Associated P and K consumption

Farmers tend to apply fertilisers in fixed ratios or purchase fertiliser mixes containing N, P and K in recommended ratios. Assuming this, the models estimate the application or load of

P and K to each crop/soil combination (including grassland) based on the optimal application of N[19]. Thus allowing an estimate of the impact of NP control policies on catchment consumption of P and K at both the intensive and extensive margin inclusive of the P and K content of livestock waste. This is important as regulatory policies, may affect the intensity of production and land allocation (proportion of arable to livestock activity) in catchments and thus the relative use of N, P and K. The purpose of this analysis is not to identify cost-effective ways to control P and K emissions, but to simply consider the possible consequences of policies to control NP on P and K losses (pollution swapping).

The Motray's baseline N load was 751.22t with a P:N ratio of 0.42 and a K:N ratio of 0.47; whereas the Brothock's baseline N load was 624.82t with a P:N ratio of 0.41 and a K:N ratio of 0.49. As expected, in the Motray, achieving higher nitrate RT also reduces catchment P consumption (table 4). The greatest reduction in catchment P consumption is associated with IT, whereas LR and in particular SDR do not reduce P utilization as much. Therefore, the LR and SDR components in MIs explain the slightly greater P consumption when compared to stand alone IT. The fact that IT primarily reduces catchment pollution by decreasing the intensive margin whereas LR affects the extensive margin may explain the results. SDR works by either reducing livestock numbers or increasing the farmland that that sustains livestock or both depending on which is most profitable. Thus at lower N regulatory targets SDR may only lower P consumption loads on grassland and not affect arable land P consumption, thereby achieving less P reduction.

Similarly, in the Brothock the P load falls as the N regulatory target is tightened. However, interestingly, in the Brothock results produce two differences. Firstly, LR produces greater P reduction than IT. This can be explained by the considerably high levels of LR, mostly at the expense of winter wheat, which are required to meet the nitrate RT. Secondly, using [SDR + IT] and in particular stand-alone IT produces a sharp increase in catchment P consumption at the strictest 1% regulatory target - even exceeding the baseline P load in the case of IT.

[19] In practice substitution between N, P and K is limited.

3MI, which has a smaller IT component, does not produce a spike in P consumption. This is because at high N input prices it is more profitable to substitute away from winter wheat to seed potatoes. Therefore, an unintended consequence of IT is that, while it reduces catchment N consumption, it unfortunately provides a perverse incentive to shift from winter wheat (NPK/ha ratio 200:70:70) to seed potatoes (NPK/ha ratio 90:200:150) - which requires relatively less N but more P. Both P and N are nutrients that contribute to eutrophication and achieving GECS. This highlights the risk of pollution swapping and the need to consider the broader impact of policies as they may paradoxically provide perverse incentives that produce detrimental water quality consequences from pollution swapping.

The results for K are similar but not as pronounced as the P results. They are similar in that Motray's K consumption decreases at higher N regulatory targets; this reduction is greatest with IT and less so with LR. Among the single instruments considered SDR produces the least reduction in K consumption. 2MI and especially 3MI display much lower catchment K application. Again the Brothock displays a similar increase in K consumption at the highest 1% RT – although not as significant as the P increase. Overall, this is evidence of the need to coordinate environmental regulation and consider the complementary regulation of other polluting nutrients. As clearly, controlling N may inadvertently change P and K consumption and prevent attaining the intended ecological outcome.

6. Discussion

Regulation will simpler if consistently cost-effectives policies across a range of water bodies with similar characteristics can be identified. In this paper, we investigate the consistency of policy cost-effectiveness across two relatively similar catchments. We account for the stochastic nature of NP by empirically estimating the distribution of daily ambient river nitrate concentration using 10 years of continuous weather data, without making distorting a priori distributional assumptions. This provides a more realistic assessment of the uncertainty associated with regulatory controls. Additionally, we estimate instrument cost-effectiveness based on the distribution of river concentration as opposed to pollution loads (mass) in the root zone. We contend that modelling the entire biophysical processes realistically and imposing environmental standards at the point of environmental impact (river) is critical to policy analysis. The significance of our results are in the detail, i.e., policy ranking is only just broadly consistent, even in two relatively similar catchments. That is, the cost-effectiveness ranking of policies is may not be as robust as policy makers would like.

Interestingly, policies tend to outperform in very distinct RT ranges - even though the instrument levels required to meet RTs differ in catchments. Initial pollution reduction is most cost-effectively achieved by IT, higher RTs required 2 instrument MIs, whereas the strictest RTs require 3 instrument MIs. Thus indicating that cost-effective rankings are probably RT dependent. Such distinct cost-effectiveness frontiers should make it easier to determine optimal control policies for specific RTs. The presence of crossovers did not significantly alter the ranking of policies or the identification of efficiency frontiers. Results confirm the previous literature in that single instruments display efficient abatement fatigue at higher RTs and that the relative cost-effectiveness of MIs improves as the RT is tightened.

A key result is that the difference between instrument levels required to achieve the same RT in both catchments is the smallest with 3MI. Thus MIs are arguably more suited to being applied as uniform policies across different catchments than IT. Interestingly, MIs also display the least variation in catchment resource cost across RTs, implying it might easier to raise environmental quality (higher RT) with a MI policy. The standard deviation of river pollution under MIs is also less than IT in both catchments. In considering the impact of policies to control diffuse N pollution on farm P and K consumption our results suggest that IT does significantly reduce P and K consumption, but LR and SDR do not. However, at the strictest RT, IT produced perverse land allocation incentives that may produce spikes in the consumption of P and K. Another benefit of MIs was the absence of such spikes. It is apparent that there are trade-offs between policies to control NP and the consumption of P and K, which in turn can paradoxically prevent meeting GECS – providing another reason to coordinate policy across pollutants. Admittedly consumption of P & K is a proxy for pollutant loads entering the river and future research would benefit from modelling P and K river concentrations or better yet ecological impact. Whilst in a sense a favourable case has been considered here (i.e. relatively comparable catchments in geographical proximity), the results suggest that an overall consistent ranking is found across policy instruments. Unfortunately, it may not be as as robust as regulators and stakeholders would like or assume. Differences in the absolute level of instruments across catchments are considerable but intuitively correct. Ideally policy packages should be tailored to specific catchments, as the efficiency gains are theoretically considerable – however real world transaction costs may render this infeasible at present.

The advantages of MI are reinforced when you consider a) the secondary environmental benefits from the managerial component of MIs, and b) the political sensitivity of implementing economic instruments in isolation. Properly managed LR can help mitigate NP pollution while promoting farmland biodiversity (Burt and Haycock, 1993; Ribaudo et al., 1994). CAP has imposed minimum LR and SDR conditions in the past and LR maybe return under recent 'greening' of CAP. Unfortunately, reliable transaction cost estimates of implementing and enforcing such regulatory policies are not available and thus not considered. Nor have we factored the stochastic nature of crop yields or the transition period between policy implementation and its impact. Our analysis would benefit from improved modelling of farming heterogeneity and groundwater hydrology. More research is required to analyse the consistency of our results across catchments of differing similarity and to identify the defining catchment characteristics that determine the transferability of policy cost-effectiveness.

7. Conclusion

The paper investigates the transferability of instruments to control NP by comparing the cost-effective ranking of regulation in two relatively similar agricultural catchments. We use an approach, which does not necessitate making a priori assumptions about the underlying distribution of daily stochastic pollutant concentration in rivers. Our results suggest that policy instrument ranking is broadly but not convincingly consistent across relatively similar catchments but that policies outperform in distinct regulatory target ranges. Notably we find that MI policies display characteristics more suitable to wider application across catchments (especially at higher RTs), the enforcement of stricter RTs over time and where there are ecological concerns about pollution swapping and the consumption of other polluting nutrients.

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Figure 1: Comparison of the modelled daily baseline river concentration histograms of both catchments

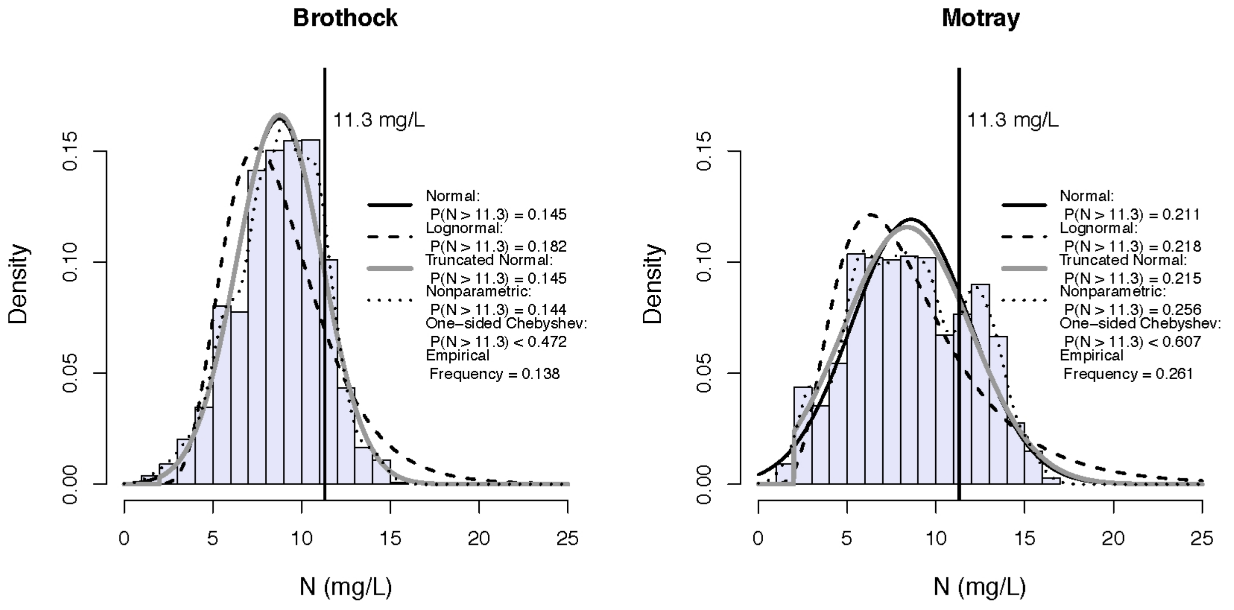

Figure 2: Comparison of the actual sampled river concentration histograms of both catchments

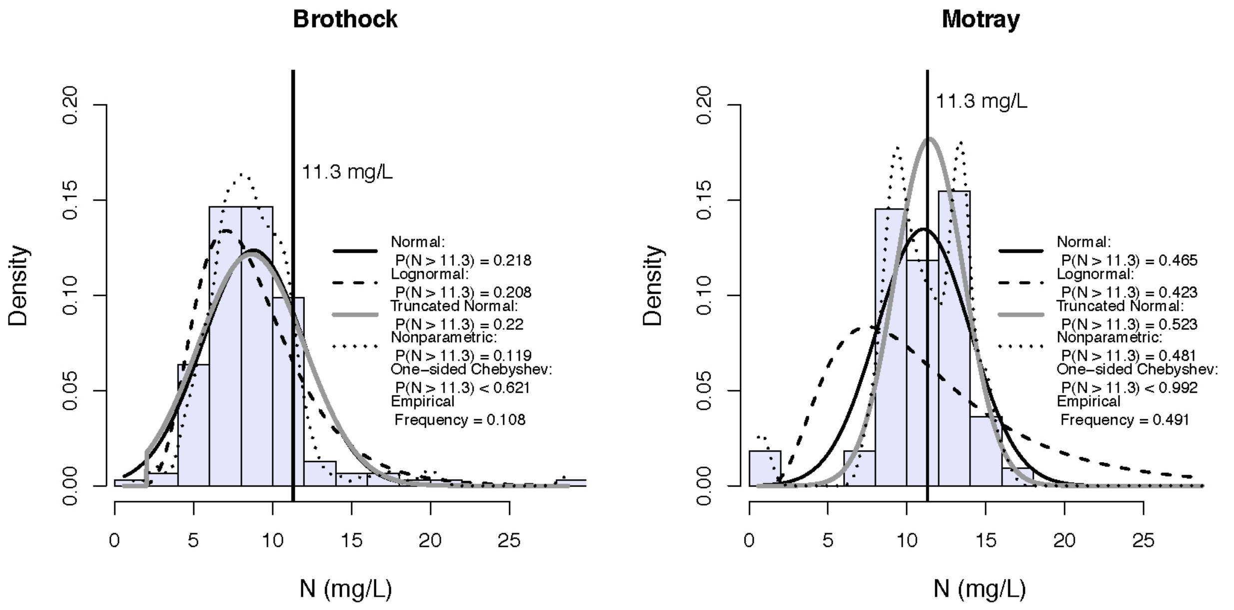

Figure 3: Diagrammatic representation of the biophysical economic modelling

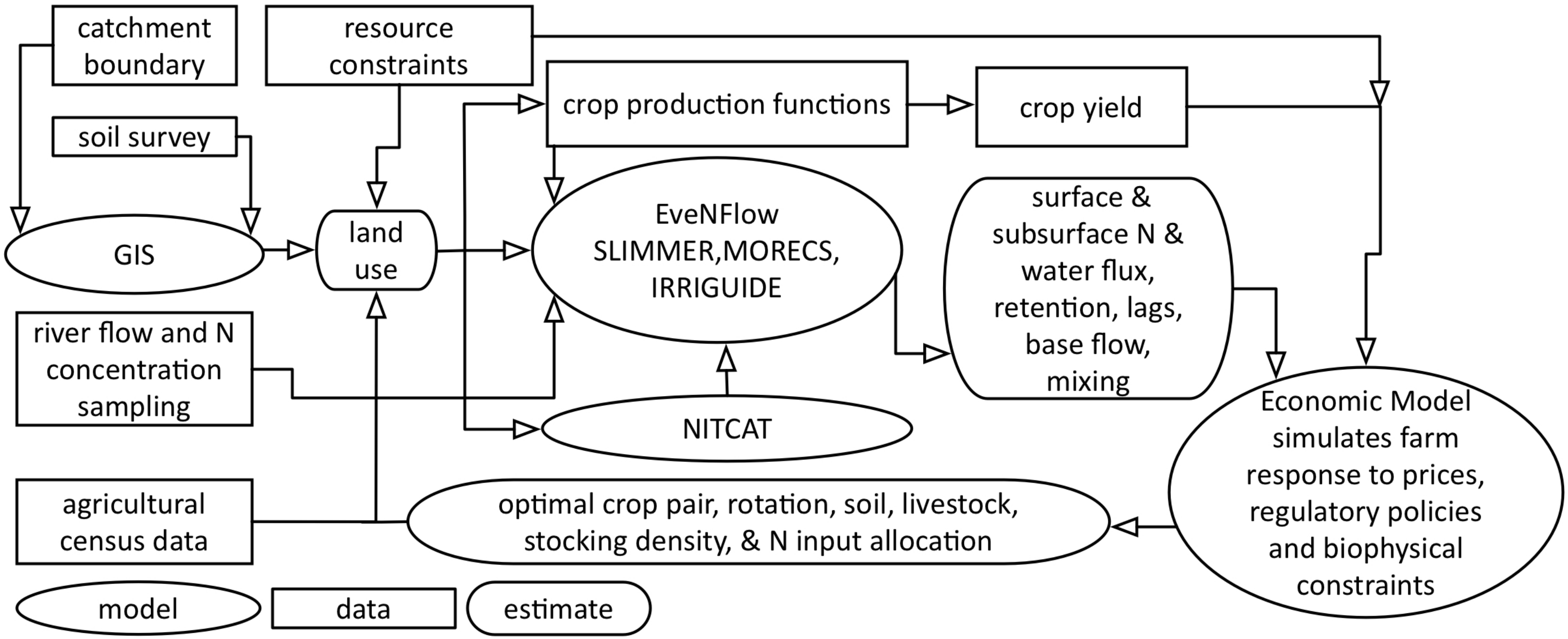

Figure 4: MOTRAY - REGULATORY TARGETS AND ASSOCIATED CATCHMENT SOCIAL COST

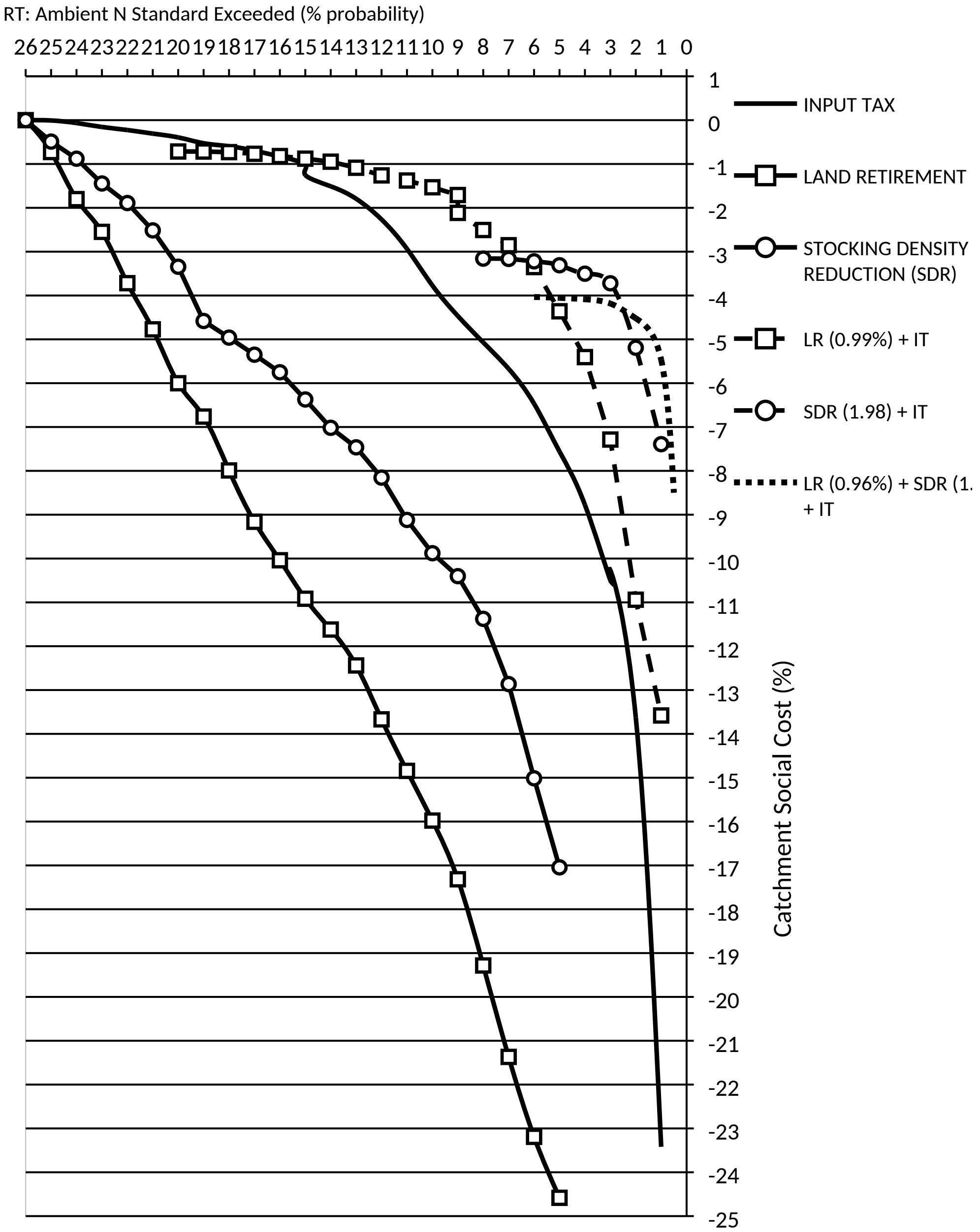

Figure 5: BROTHOCK - REGULATORY TARGETS AND ASSOCIATED CATCHMENT SOCIAL COST

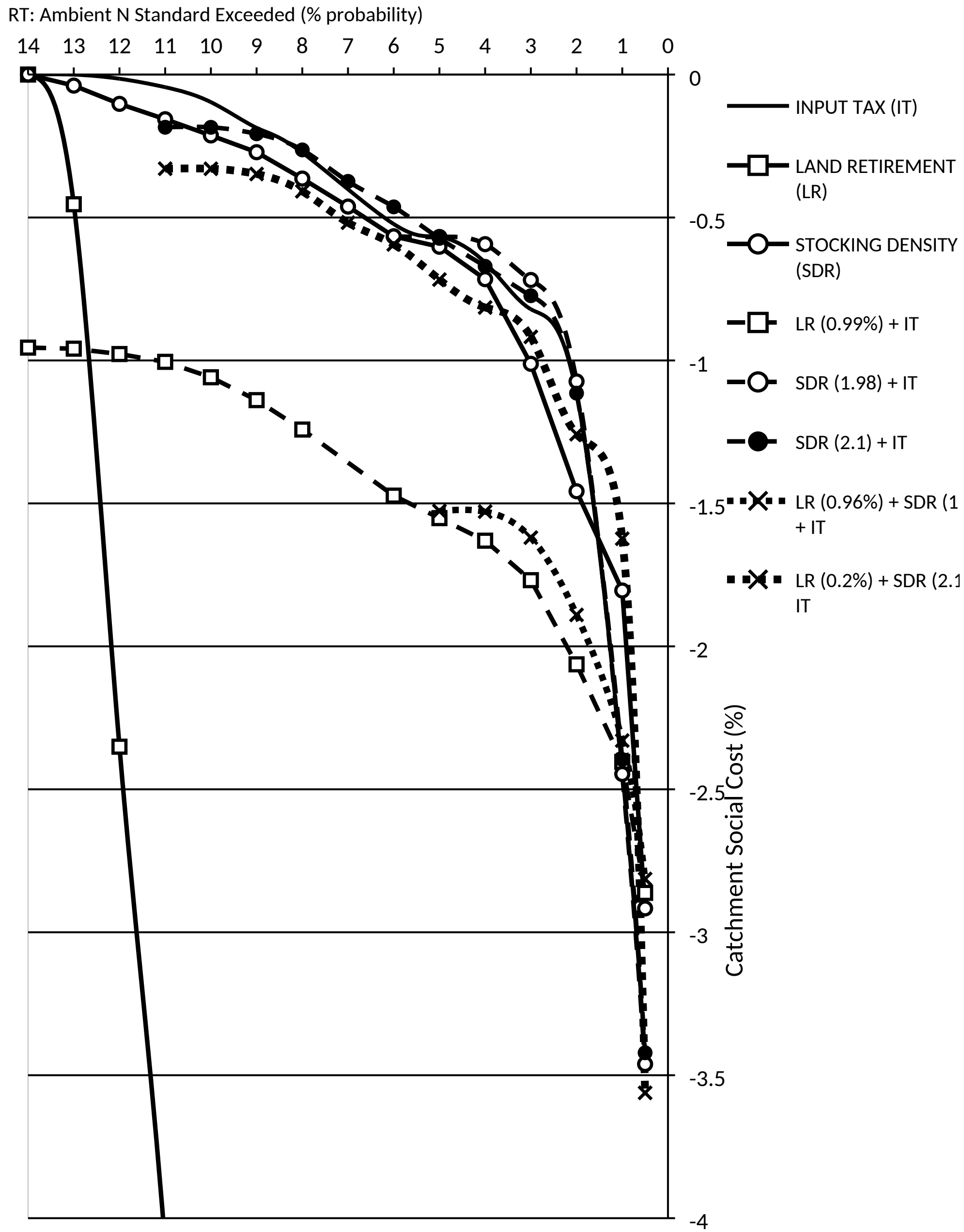

Table 1: Catchment characteristics

Catchment	Motray			Brothock		
Size (km^2)	58.3			44.3		
Arable area* (ha)	4743			3580		
Average annual rainfall (mm)	720			708		
Representative soil classes	Mountboy	Sourhope	Auchenblae	Balrownie	Vinny	Corby
Profile water column (mm)	353	337	219	344	316	193
HOST class	18	22	5	18	16	5
Agricultural area (%)	38	39	23	68	28	4

* Excluding rough grazing and forestry

Table 2: Comparative Catchment Ranking of Control Instruments and Associated Percentage Reduction in Catchment Resource Profit

Catchment	Motray				Brothock			
	Regulatory Target							
Percentage of time	**10**	**5**	**3**	**1**	**10**	**5**	**3**	**1**
Input Tax (IT)	2 (-3.77)	4 (-7.56)	4 (-10.50)	4 (-23.42)	1 (-0.10)	3 (-0.57)	3 (-0.82)	6 (-2.44)
Land Retirement (LR)	4 (-15.98)	6 (-24.58)	NA	NA	8 (-6.50)	8 (-18.85)	8 (-26.81)	8 (-36.94)
Stocking Density Reduction (SDR)	3 (-9.88)	5 (-17.04)	NA	NA	3 (-0.21)	4 (-0.60)	5 (-1.01)	2 (-1.80)
LR (0.99%) +IT	1 (-1.53)	3 (-4.36)	3 (-7.29)	3 (-13.58)	5 (-1.06)	7 (-1.55)	7 (-1.01)	4 (-1.80)
SDR (1.98) + IT	OA	1 (-3.31)	1 (-3.72)	2 (-7.39)	OA	1 (-0.57)	1 (-0.72)	7 (-2.45)
SDR (2.1) + IT					2 (-0.18)	2 (-0.57)	2 (-0.77)	5 (-2.40)
LR (0.2%) +SDR (2.1) + IT					4 (-0.33)	5 (-0.72)	4 (-0.92)	1 (-1.62)
LR (0.96%) +SDR (1.97) + IT	OA	2 (-4.05)	2 (-4.18)	1 (-5.47)	OA	6 (-1.53)	6 (-1.62)	3 (-2.33)

(): Associated percentage reduction in catchment resource cost

OA: over achieves regulatory target; NA: does not achieve regulatory target

Note: in the case of SDR and LR not achieving regulatory target does not mean that the two control instruments are incapable of achieving the regulatory target, but only at a very significant cost farming. In terms of the optimisation it means relaxing numerous constraints that are probably not practical (e.g. pest control) or acceptable (high cost) to farmers.

Table 3: Comparative Control Instrument Levels in Motray and Brothock

Catchment	Motray				Brothock			
	Regulatory Target (percentage of time)							
Percentage of time	**10**	**5**	**3**	**1**	**10**	**5**	**3**	**1**
Input Tax (IT)	373	500	573	726	40.38	76.92	90.38	153.84
Land Retirement (LR)	14.05	18.66	NA	NA	6.40	17.95	22.4	26.9
Stocking Density Reduction (SDR)	24.5	33.18	NA	NA	3.42	8.96	13.58	20.52
LR (0.99%) + IT	103.84	369.23	469.23	626.92	42.30	70.84	90.38	117.30
SDR (1.98) + IT	OA	56.84	96.15	442.30	OA	5.76	51.92	105.77
SDR (2.1) + IT					1.92	75	82.69	117.30
LR (0.2%) +SDR (2.1) + IT					1.92	75	82.69	117.30
LR (0.96%) +SDR (1.97) + IT	OA	19.23	53.84	134.61	OA	0	40.39	105.77

All values are percentage increases relative to baseline levels in each catchment, except SDR for which actual values are presented.

Table 4: Changes in Phosphorus (P) Consumption Load Associated with Policies to Control Diffuse N Pollution

Catchment	Motray				Brothock			
RT (percentage of time)	**10**	**5**	**3**	**1**	**10**	**5**	**3**	**1**
	PHOSPHORUS							
Input Tax (IT)	-19.03	-23.20	-24.69	-31.68	-4.11	-8.29	-9.76	1.34
Land Retirement (LR)	-14.76	-21.51	NA	NA	-4.90	-14.09	-20.25	-28.18
Stocking Density Reduction (SDR)	-9.61	-14.61	NA	NA	-0.74	-1.94	-3.02	-4.48
LR (0.99%) +IT	-12.16	-19.26	-23.26	-27.61	-4.96	-9.13	-10.36	-13.20
SDR (1.98) + IT	OA	-9.45	-12.89	-22.17		-2.44	-6.90	0.93
SDR (2.1) + IT					-0.85	-8.13	-9.20	1.44
LR (0.2%) +SDR (2.1) + IT					-0.96	-8.22	-9.29	-12.76
LR (0.96%) +SDR (1.97) + IT	OA	-6.95	-10.07	-16.54	OA	-2.64	-6.58	-12.54
	POTASSIUM							
Input Tax (IT)	-24.75	-30.28	-31.88	-39.33	-4.46	-8.81	-10.34	-7.28
Land Retirement (LR)	-13.48	-22.48	NA	NA	-4.10	-12.12	-19.99	-31.06
Stocking Density Reduction (SDR)	-9.09	-15.42	NA	NA	-0.68	-1.74	-2.69	-4.02
LR (0.99%) +IT	-12.58	-24.90	-29.74	-34.10	-5.21	-9.55	-10.85	-13.84
SDR (1.98) + IT	OA	-9.56	-13.53	-28.72		-2.29	-7.13	-7.52
SDR (2.1) + IT					-0.82	-8.63	-9.71	-7.15
LR (0.2%) +SDR (2.1) + IT					-0.91	-8.71	-9.79	-13.47
LR (0.96%) +SDR (1.97) + IT	OA	-6.51	-10.15	-17.43	OA	-2.32	-6.60	-13.06

Phosphorus and Potassium load reductions are presented as percentage reductions from catchment specific baseline phosphorus and potassium loads respectively. Motray's phosphorus (P) baseline load was 313.516 tonnes; Brothock's load was 256.135. Motray's potassium (K) baseline load was 352.608 tonnes; Brothock's load was 306.016 tonnes.

Glossary

DEFRA	Dept. of Environment Food and Rural Affairs	LR	Land Retirement	P	Phosphorus
EA	Environment Agency	LU	Catchment Livestock Units	RT	Regulatory Target
FRU	Forestry, Rough grazing and Urban areas	MI	Mixed Instruments	SDR	Stocking Density Reduction
GECS	Good Ecological and good Chemical Status	N	Nitrogen	SEPA	Scottish Environmental Protection Agency
IT	Input Taxation	NP	Nonpoint nitrate pollution	2MI	Two instrument mixed instrument
K	Potassium	NVZ	Nitrate Vulnerable Zone	3MI	Three instrument mixed instrument

SUPPLEMENTARY MATERIAL: Motray and Brothock Modelling Methodology

The modelling of river flow and nitrate concentrations was done using a version of the EveNFlow model, developed by ADAS.

Daily time series of water and nitrate exiting soil units via rapid (shallow) and slow (deep) drainage pathways were routed by the EveNFlow model, introducing transfer delays, to reproduce the river hydrograph and concentrations resulting from the mixing of waters from the two drainage pathways. EveNFlow is a semi-distributed, catchment scale, conceptual model of the delivery of effective rainfall to a river system. The model is constructed so that it may be parameterised in catchments where observed flow data limited or unavailable. Parameterisation of the model requires information on the areas of soils of each HOST class within a catchment or long-term estimates of the BFI from observed flows (Boorman *et al.*, 1995; NERC, 1998). The BFI is conceptualised as a measure of the proportion of flow that travels via the deeper, slower routes to the river system.

The flow routing methodology is based upon an exponential model of the drainage from a non-linear catchment soil water store or reservoir, as derived by Kirkby (1975), in which the instantaneous rate of discharge from the store is calculated as:

$$Q_t = Q_0 \cdot e^{\left(\frac{S_t}{M}\right)} \qquad (1)$$

where Q_t is the rate of discharge at time t, Q_0 is the rate of discharge when the soil store is saturated, S_t is the catchment soil moisture store, and M is the master recession constant, representing the rate at which the soil store empties and hence the recession of the river hydrograph.

The store is representative of an exponential decline in lateral transmissivity of the soil with depth (Beven *et al.*, 1994). Thus, the change of the rate of discharge is nonlinear with respect to the rate of change of the catchment store. This nonlinear description enables the model to represent the delivery of water to a river channel via rapid flow routes such as macropores.

In the EveNFlow model, the discharge equation (1) has been simplified to give:

$$Q_t = e^{\left(\frac{S_t}{M}\right)} \qquad (2)$$

In this form there is no explicit identification of the state of saturation, and rapid run-off associated with saturation excess overland flow is assumed to be adequately represented by the extension of the soil transmissivity profile above a virtual soil surface.

The instantaneous volume of water in the catchment soil store is calculated as:

$$S_t = M \cdot \log_e Q_t \qquad (3)$$

and the mass balance of the catchment soil store is calculated as:

$$\frac{dS}{dt} = H - Q_t \qquad (4)$$

where effective rainfall H is the soil drainage, and represents a constant intensity inflow of water from the root zone to the store.

Kirkby (1975) showed that the instantaneous discharge at time $t+\Delta t$ is equal to:

$$Q_{t+\Delta t} = \frac{1}{\frac{1}{Q_t} + \frac{\Delta t}{M}} \text{ where } H = 0 \qquad (5)$$

and

$$Q_{t+\Delta t} = \frac{H}{1-\exp\frac{-H\cdot\Delta t}{M}+\frac{H}{Q_t}\cdot\exp\frac{-H\cdot\Delta t}{M}} \quad \text{where } H>0 \qquad (6)$$

The volume of water discharged to the river system during the time step Δt is calculated by use of equation (13) to determine the net change in the catchment soil water store, taking into account of effective rainfall:

$$\int_t^{t+\Delta t} Q_t = M\cdot\left(\log_e \frac{Q_t}{Q_{t+\Delta t}}\right)+H\cdot\Delta t \qquad (7)$$

In this modified form, the parameter *M* is used to represent the effect of the combined time delay associated with the lateral movement of water from hillslopes to the river channel and the in-river routing to the mouth of the catchment. The greater the value of *M*, the greater the apparent residence time of the water associated with a particular drainage event.

In the modified version of the EveNFlow model used here, each area of a given soil type within a catchment was represented by two EveNFlow soil water stores. The first was driven by additions of both the rapid and slow drainage from the soil profile, and the second by additions of only the slow soil drainage. Total routed flow from the soil area is the output from the first store. The contribution from only rapid flow is the difference in the outputs between the two stores. The contribution from only slow flow is the output from the second store.

Each catchment store S must be initialised. Each simulation begins on September 1st, when the initial value of the soil moisture store can be estimated from the low flow index Q_{95} as follows:

$$S_{t=0} = M\cdot\log_e(Q_{95}\cdot\overline{H}) \qquad (8)$$

where $\overline{H}$ is the daily mean effective rainfall over the simulation period.

The rate parameter M for the stores may be determined from iterative optimisation of the fit between the modelled and observed hydrograph. In EveNFlow however, the rate parameter is *not* reliant on an observed flow time series for calibration, but from catchment scale observations of hydrograph shape.

The BFI is a numerical separation of the river hydrograph into a rapid flow and base flow component. The BFI is the volume of base flow, expressed as a proportion of total flow. This published statistic (NERC, 1998), is determined from long-term records of observed flow. The EveNFlow model is based on the observation that the annual BFI and Q_{95} of hydrographs simulated using the modified flow model are uniquely related to the value of the rate parameter M, for a given effective rainfall time-series. Flow is simulated on a daily time-step using a given input rainfall time-series and first estimates of M and the BFI of the hydrograph are calculated. An iterative procedure in the form of a simple bisection method (Press *et al.*, 1992) is invoked that successively modifies the estimate of M until the BFI of the simulated hydrograph equals the target BFI for the response group HOST class. Parameterisation of M is based only on the match between the BFI of the simulated hydrograph and the BFI predicted for the soil water store by the HOST database, not by reference to standard model fit criteria. The target BFI of the infiltration excess surface runoff store is set at 0.10, and a separate recession parameter *M* is calculated for this store. This value is based upon information in the Flood Studies Report (NERC, 1975) for the response of rivers to storm runoff from urban areas.

The BFI is used to parameterise M in the EveNFlow system, following studies of hydrograph index variability that have demonstrated that BFI is more stable than Q_{95}, and that the BFI for individual years are consistently close to the long-term value except in years of extreme drought (Gustard *et al.*, 1987).

The total flow from a catchment is calculated by area weighting of the sum of rapid and slow soil drainage derived flows for each soil area within the catchment.

The methodology described above separates the river hydrograph into components derived from rapid and slow drainage. To simulate mixed nitrate concentrations, the EveNFlow stores were then paired with nitrogen stores. For each store, the nitrogen in storage was increased daily by the quantities in the rapid or slow drainage, as appropriate. The nitrogen in the stores was assumed to be mixed perfectly in the volumes of water held by the EveNFlow stores. Hence, nitrogen was removed from the stores and input to the modelled rivers each day, in proportion to the ratio of the predicted total discharge from and current volume of water in the stores.

Finally, a proportion of nitrate was calculated retained by plant uptake and bio-chemical processes including denitrification. The proportion of nitrate in the river system remaining after retention was calculated as:

$$P = e^{\frac{-1 \cdot K \cdot 0.26 \cdot \left[10^{0.0293 \cdot T}\right]}{V}} \qquad (9)$$

where *K* is an empirical retention parameter, *T* is the daily average air temperature, and *V* is the river velocity, calculated according to the methodology of Round et al. (1998).

For further details of the EveNflow methodology, underlying modelling and validation please refer to: Anthony, S., M. Silgram, et al. (2009). "Modelling nitrate river water quality for policy support." International Journal of River Basin Management **7**(3): 259-275.

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