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A framework for predicting delivery of phosphorus from agricultural land using a decision-tree approach

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Abstract Diagnostic models such as the P Indicators Tool have been used to predict the risk of P losses from different areas of agricultural land to watercourses. These models embody the source–mobilization–delivery–impact framework as a simple logical summary of process understanding. however, the assessment of P delivery has been neglected in the past. An alternative, decision-tree approach to predict the delivery of P to water bodies is presented here. The approach was developed as part of the DEFRA PEDAL project (http://www.lec.lancs.ac.uk/cswm/projects) and makes use of national coverage data held within a GIS at the 1 km^2 scale, in combination with a "field toolkit" of measurements and qualitative observations. For all catchments, monitoring of total P loads in receiving waters has occurred over recent years enabling evaluation of the modelling and field toolkit approach.

Key words decision tree; delivery; phosphorus; prediction

INTRODUCTION

The problem of diffuse pollution of waterways by sediments and nutrients has become widely scrutinized in recent years, not least due to legislative pressures related to the Water Framework Directive (Heathwaite *et al.*, 2005a; Neal & Jarvie, 2005). The role of phosphorus (P) loss from agricultural farmland to water bodies is reasonably well understood and it has been shown (Vollenweider & Kerekes, 1982) that P is the main nutrient involved in eutrophication as the major limiting nutrient in surface waters (Young *et al.*, 1999). Implications of high P inputs to water are therefore clear in environmental terms, in that ecosystem health may suffer due to a reduction in available oxygen or drinking water quality may be affected (Sharpley & Rekolainen, 1997).

In the UK, this problem is exacerbated by the presence of high concentrations of P in soils (Withers *et al.*, 2001), sometimes referred to as a "national P surplus" and the potential for this P to be delivered to water courses in a highly effective manner (Heathwaite *et al.*, 2005b; Wood *et al.*, 2005). Furthermore, additions of P to farmland are numerous, including the application of manures, inorganic fertilisers and biosolids (Withers *et al.*, 2001). Consequently, one goal of P research is to further understanding of the delivery of these forms to surface waters, in an attempt to define how much of the stored P in the system is being exported from agricultural land.

The processes controlling delivery of P are complex. Mobilization and transfer of P associated with particulates is thought to be significant where surface runoff is evident (Haygarth & Jarvis 1999; Heathwaite *et al.*, 1998) and less so through well-drained soils (Heathwaite & Dils, 2000), whereas removal of soluble P may be important through both surface and subsurface pathways (Heathwaite, 1997). Recent research has pointed to the importance of the relationship between P and colloids (Heathwaite *et al.*, 2005b), and the role of buffers in the retardation of delivery to channels (Heathwaite *et al.*, 1998), as well as the interaction of different P forms with soil and water in different hydrological pathways (Haygarth *et al.*, 1998). Consequently, though much progress has been made in recent years to understand the processes involved in P mobilization (Preedy *et al.*, 2001; McDowell & Sharpley 2002; Haygarth *et al.*, 2005), the mobilization, transfer, delivery continuum is still poorly understood in a quantitative sense (Haygarth *et al.*, 2005).

A great deal of recent work has concentrated on modelling P delivery at a range of spatial and temporal scales. Such work has again been driven by the need for tools to aid decision-making and support policy at a national scale (Heathwaite *et al.*, 2005a). Models range from process-based, spatially distributed tools such as INCA-P (Wade *et al.*, 2002) to empirically-based models that are lumped in both time and space (Johnes, 1996). All of these approaches, however, suffer from problems of equifinality, in that many different combinations of the parameters used to predict P, will provide acceptable predictions (Beven & Freer, 2001) and there is uncertainty surrounding model predictions, as has been demonstrated for a wide range of environmental models (Franks & Beven 1997; Zak *et al.*, 1997; Brazier *et al.*, 2000; Freer *et al.*, 2004).

As a consequence of the lack of quantitative process understanding, efforts to predict the delivery of P are limited, particularly by the lack of data that describe observed delivery. In part this may be due to the lack of a globally accepted definition of delivery which is entirely independent of mobilization (Beven *et al.*, 2005). This problem occurs as most approaches to predict delivery, such as the Export Coefficient Approach of Johnes (1996), also rely upon predictions of mobilization. As quantification (measured or modelled) of P mobilization is far from being consistent across all studies, a certain paradox is evident, which may only be solved (in a practical sense, given current understanding) by standardizing not only what is meant by delivery, but also mobilization.

Herein a way forward is suggested that may begin to solve the problem of both defining and subsequently predicting P delivery, using available data from both quantitative and qualitative sources. The approach needs to be as parsimonious as possible, given the lack of data, yet still able to provide predictions that differentiate between the numerous combinations of soil, slope and land use in the UK that may lead to a wide range of observed delivery. To this end, fuzzy approaches are appropriate (see Freer *et al.*, 2004; Kisi, 2004; Schmidt & Hewitt, 2004; Sen & Altunkaynak, 2004; for examples) as they permit the incorporation of a range of data types and qualities in the model framework (Schärer *et al.*, 2005).

Aims and objectives

This paper aims to present an initial description of a decision-tree approach to predicting annual P delivery within "data-rich" first-order catchments in lowland, agricultural Britain. The approach aims to use existing derived data sets, held at the national scale in combination with data collected using a field "toolkit" to define delivery relative to a standardized estimation of P mobilization. The work is part of the DEFRA funded Phosphorus Export and Delivery from Agricultural Land "PEDAL" project, that seeks to define and implement a pragmatic approach to quantify phosphorus delivery in the UK.

METHODOLOGY

Existing data sets

Catchment data Five "data-rich" sites have been identified as providing the highest quality observations of P at a range of spatial scales from 0.3 km^2 to 4 km^2 within first-order catchments. The catchments are known as Rosemaund Farm, Cliftonthorpe, Redesdale, Den Brook and Drewston (Table 1). Monitoring at these sites provides time series of rainfall, flow and P data from a variety of different soil, slope and land use combinations and therefore reflects a good range of agricultural practice within the UK. All scales of observation are sub first-order, in terms of the surface channel drainage network, therefore the effects of point sources on the P signal are taken to be minimal and all P observations are taken to represent delivery from diffuse sources. It is assumed that the effects on delivery of remobilized P from channel sediments is minimized by the choice of first-order catchments with limited channel networks. However, it is also recognized that in-stream processes, though poorly understood, may be significant. Findings of the DEFRA funded "PARIS" project, which seeks to further understanding of P in channel sediments, will therefore be incorporated into the decision tree approach, when they become available.

Table 1 Data used in the decision tree.

Catchment	Catchment area (ha)	DESPRAL value (mg L^{-1})	BFI%	Mean annual rainfall (mm)	Connectivity (accelerating/retarding factors)
New Cliftonthorpe	95.5	266	0.61	690	High
Upper Cliftonthorpe 1	62.5	250	0.61	690	Medium
Upper Cliftonthorpe 2	37.5	281	0.61	690	Medium
Belmont	150	1020	0.52	691	Medium
Jubilee	30.6	960	0.52	691	Medium
Redesdale 2	440	180	0.2	989	Low
Redesdale 3	190	103	0.2	989	Low
Redesdale 4	110	182	0.2	989	Low
Den Brook	22	2230	0.31	1048	High
Drewston	48	2629	0.79	1201	Low

Time series data Data describing rainfall, flow and P time series were available from ten channel monitoring sites across the five catchments. These data were sourced from ADAS (in the case of the Redesdale, Rosemaund and Cliftonthorpe sites) and the Institute of Grassland and Environmental Research—IGER—for the Den Brook and Drewston sites, covering a total of 13 years of observations (see Walling *et al.*, 2002 for further details). Rainfall data were captured with tipping-bucket raingauges and flow data were captured on a 15-min timestep on a continuous basis. Pump samples and grab samples were taken to characterize base flow P concentrations on long timesteps throughout the year; flow triggered pump samples were taken during storms to capture event dynamics. All samples were analysed for total phosphorus (TP), total dissolved phosphorus (TDP), and total particulate phosphorus (TPP) after filtering at 0.45 μm. To calculate the annual loads used in this paper, a simple linear rating curve procedure was used.

Soil P status is not easily defined due to the wealth of ways in which it is described in the literature (Quinton *et al.*, 2003), many of which are not necessarily comparable for the same soils (Neyroud & Lischer, 2003). Consequently, a pragmatic decision has been taken for this work to characterize soil P status using the DESPRAL test developed by ADAS (Hodgkinson, personal communication). Use of this test is an attempt to standardize quantification of the P content of the soil that is available for mobilization across sites used in the study. Such an approach is supported by the findings of Quinton *et al.* (2003) who show that a strong positive relationship exists between available P concentrations from such soil P tests and measured P in overland flow under laboratory conditions. Table 1 describes the DESPRAL values determined for each soil type at each site.

GIS data sets Derived data held at the national scale with a 1 km^2 resolution were thought to be the most useful data sets with which to develop a methodology that could be applied throughout England and Wales. Previous work modelling soil erosion has demonstrated the utility of these data (Brazier *et al.*, 2001a,b), though has also stressed that the coarse resolution leads to high levels of uncertainty within the data sets. Thus, the following data sets are used as the "best-available" data, within a framework that permits the inclusion of improved spatial or temporal resolution data when it becomes available. The core data set used here is known as MAGPIE (Miles *et al.*, 1996) describing land use types, dominant soils, management practices and average annual rainfall. These data are supplemented by a digital elevation model (DEM) with a 10-m resolution and topographic map from the OS panorama database as well as soil characteristic data and the Hydrology of Soil Types (HOST) classification (Boorman *et al.*, 1995) from the National Soil Inventory (NSI) NatMap database.

Field Toolkit

An important element of predicting delivery is an understanding of the connectivity of the hillslopes with the catchment, to the channel where P is delivered. Consequently a "field toolkit" is being developed to assess connectivity and therefore factors which accelerate or retard P delivery within each catchment. The approach involves field visits to provide a visual assessment of delivery within a catchment to complement the

GIS and time series data described above. An example of the visual assessment for the Den Brook catchment is shown in Fig. 1(a) and (b). Results of the visual assessment for each catchment are built into the decision tree (see Fig. 2).

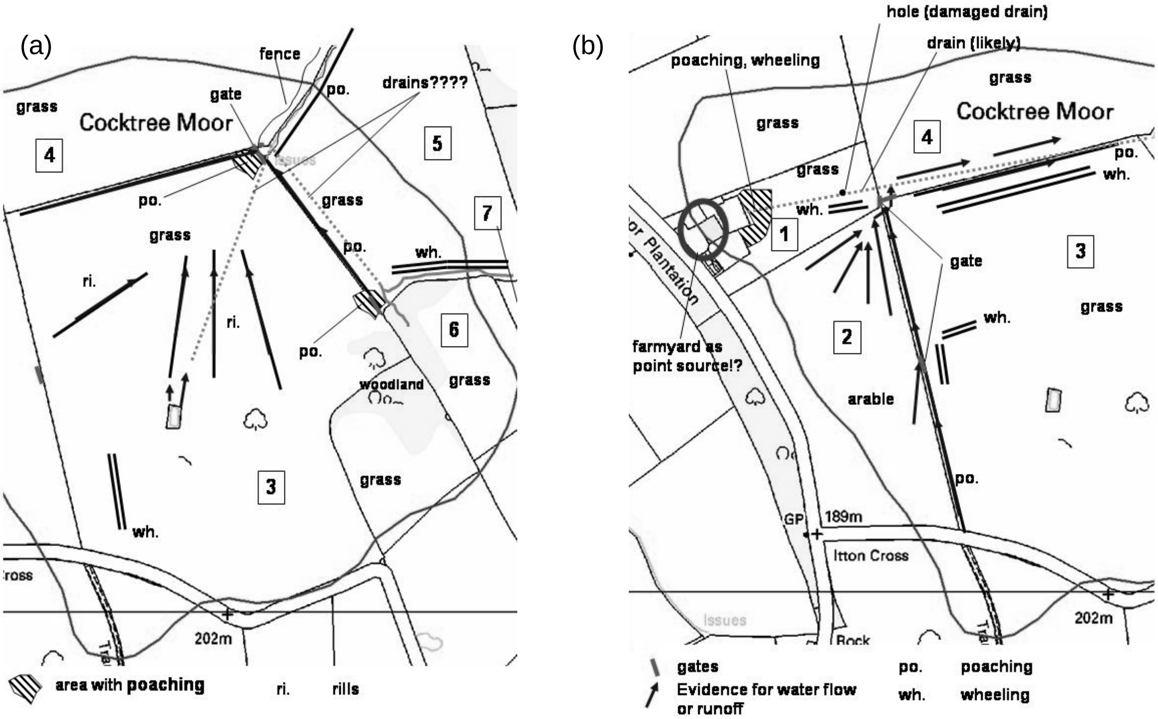

Fig. 1 A visual assessment of factors accelerating and retarding P delivery at the Den Brook catchment.

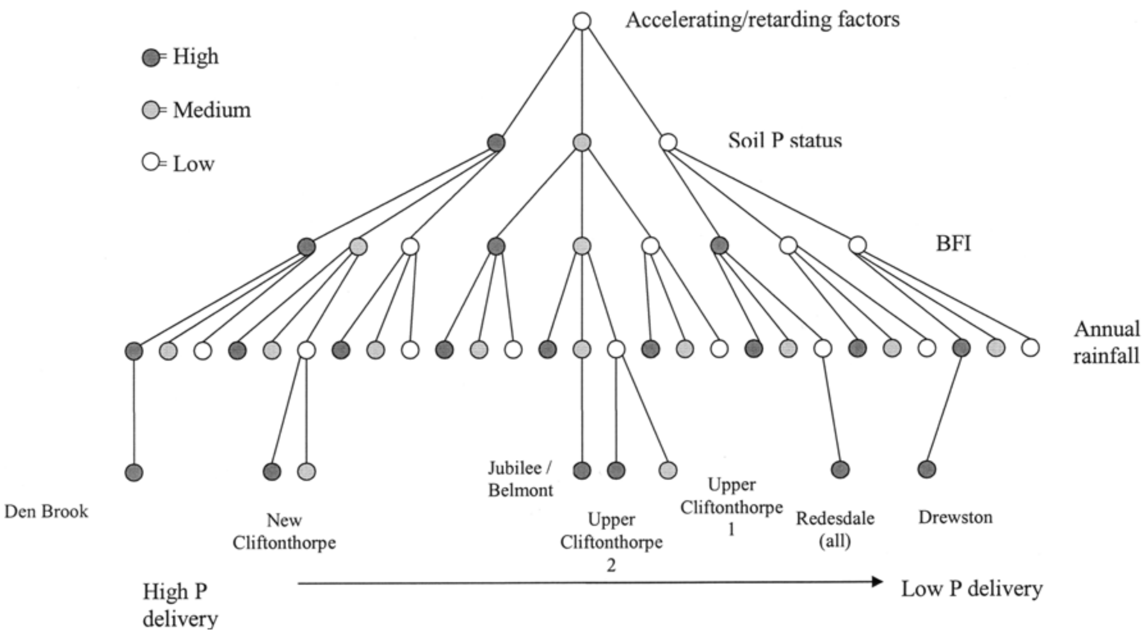

Fig. 2 A decision tree to predict TP delivery from first-order catchments.

Modelling approach

Ultimately, the model will be built around two decision trees. One will estimate annual TPP delivery (i.e. >0.45 μm), the other annual TDP (i.e. <0.45 μm delivery. For the purpose of this paper, the decision tree used to estimate TDP will be used as an example to predict which catchments have the highest delivery rates for each year within the data set. These predictions will then be evaluated against the ranking of observed delivery described in Table 2. The decision tree for TDP may contain a number of input parameters as shown in Fig. 2. However, it is advisable to limit the number of parameters to as few as possible, so as to reduce the complexity and

Table 2 Observed annual delivery coefficients from all catchments for TDP and with ranking based upon average TDP delivery from each catchment.

Catchment	Year	TPP delivery coefficient	TDP delivery coefficient	Rank based on average TDP delivery from each catchment
New Cliftonthorpe	1996–1997	1.17	2.57	1
	1997–1998	0.57	2.57	
	1998–1999	1.29	2.45	
	1999–2000	0.77	1.92	
Upper Cliftonthorpe 1	1998–1999	0.79	2.28	2
	1999–2000	0.43	2.21	
Upper Cliftonthorpe 2	1998–1999	0.89	1.58	6
	1999–2000	0.63	1.55	
Belmont	1994–1995	0.22	0.76	7
	1995–1996	0.52	1.41	
	1996–1997	0.66	2.22	
	1997–1998	0.75	1.50	
	1998–1999	0.54	1.86	
	1999–2000	0.55	1.60	
Jubilee	1994–1995	0.77	1.21	8
	1995–1996	0.12	1.33	
	1996–1997	0.10	0.61	
	1997–1998	0.87	2.43	
	1998–1999	0.45	2.22	
	1999–2000	0.58	1.13	
Redesdale RD2	1994–1995	0.52	1.15	4
	1995–1996	0.27	2.49	
	1996–1997	0.42	1.47	
Redesdale RD3	1994–1995	1.43	2.77	3
	1995–1996	0.39	1.13	
	1996–1997	0.35	2.17	
Redesdale RD4	1994–1995	0.83	1.08	9
	1995–1996	0.71	0.66	
	1996–1997	0.22	1.28	
Den Brook	2002–2003	0.33	1.68	5
Drewston	2002–2003	0.01	0.17	10

increased uncertainty that additional parameters add (Beven, 2000). Consequently, the initial formulation of the decision tree to predict TPP requires information on:

(a) BFI (Base Flow Index) from 30 year annual averages;
(b) local annual rainfall;
(c) soil P status (DESPRAL data);
(d) connectivity of acceleration and retardation factors within the catchments.

An assessment of the relative (high, medium or low) value of each variable at each step of the decision tree for each year of monitored data at each catchment is then made. Currently this decision is made manually, based upon the range of data that are evident for all five of the catchments considered, so for example, Drewston is ranked high in terms of mean annual HER (641 mm), New Cliftonthorpe is ranked low (231 mm), whereas the Redesdale catchments are ranked medium (508 mm). Clearly, this approach is subjective, and will alter as more data become available for other catchments. However, at this stage it provides a realistic means to classify catchments which can be updated as more information becomes available.

RESULTS

Defining delivery

Accepting that the DESPRAL test describes P available for mobilization from a soil the results from DESPRAL analysis of soil P status (Table 1) have been used to define delivery from each catchment scale observed for each year. These results are shown in Table 2 for delivery of TPP and TDP. Thus, the working definition of P delivery described above is illustrated for five “data-rich” catchments at a range of spatial scales on an annual basis. Ranking the catchments in order of delivery demonstrates that the highest delivery catchment is Redesdale 2 (1994–1995) and the lowest delivery catchment is Drewston (2002–2003). It must be noted that this observed delivery coefficient is not explicit about the *absolute* delivery of P, rather it describes the proportion of the available P that is delivered. Despite their different characteristics, the other catchments all fall broadly in between these two extremes, providing a data set with which to evaluate predictions made using the decision tree approach.

Predicting delivery

Initial construction of the decision tree allows prediction of which catchments are likely to deliver the most P in a relative sense. Thus, Fig. 2 describes the results of the preliminary predictions by illustrating the position of each catchment on a continuum from high to low delivery. Predictions for each spatial scale demonstrate that the highest delivery coefficients are expected to occur in the Den Brook and New Cliftonthorpe catchments, whereas the lowest deliveries are predicted to be in the Redesdale and Drewston catchments. The remaining catchments fall within the mid-range of delivery predictions, with no clear difference between the Jubilee and Belmont catchments and the two Upper Cliftonthorpe catchments.

DISCUSSION

There is some agreement between predictions and observed delivery data, for example, Drewston is ranked consistently low in terms of both TPP and TDP and is also predicted to deliver relatively low levels of P, whereas New Cliftonthorpe is ranked highly in terms of observed P delivery, which matches initial predictions. However, not all predictions are supported by the observed data; for instance the Redesdale catchments are all predicted to deliver relatively low amounts of P, whereas in reality there is significant variation between these catchments, although it should be noted that in absolute terms, the catchments do produce very low P delivery coefficients. This may be due to the lack of discrimination that is possible using annual data, as it is likely that specific events within years contribute large proportions of the annual P values that are used here. Consequently, further work with this approach will employ event-based data, in an effort to capture event and seasonal dynamics within the decision tree that may permit better predictions of annual variation at each site, which are not shown here.

At this stage the visual assessment of the connectivity of catchments is in its infancy, and is simply used to assess whether the catchment connectivity (i.e. whether delivery is retarded or accelerated) is high, medium or low. Further work is needed to refine this approach, in order to provide more discrimination between catchments, as for example, the Upper Cliftonthorpe catchments are predicted to behave quite similarly, largely due to the same GIS data being used in the decision tree. However, the visual assessment provides the opportunity to incorporate directly observed, on-site data, which in theory, should identify distinctions between neighbouring catchments such as these.

Further improvements might be made to predictions with the direct usage of a fuzzy classification system for each decision, rather than the discrete “high-medium-low” approach shown here. As much of the data involved are either qualitative (in the case of the visual assessment) or highly uncertain (in the case of national data describing BFI), next steps in model development will attempt to be explicit about these data quality issues, by using fuzzy values at each decision in the tree, and finally producing a fuzzy output describing delivery. This may be a number describing P delivery, but with an associated range of uncertainty or a distribution of likely P delivery from a catchment for any given year (Schärer *et al.*, 2005).

CONCLUSIONS

The decision-tree approach presented provides a means by which catchments can be ranked on the predictions of delivery, with some agreement with the observed ranking of delivery. Not all predictions match observations, so it is suggested that forthcoming, event-based decision-trees are developed to permit more accurate and also absolute predictions of both TPP and TDP delivery in headwater catchments.

The approach is conceptually simple being split down two practically justifiable decision-trees; it employs very few parameters (in this example only four) and therefore reduces the likelihood of high levels of uncertainty associated with more complex, physically-based models. Furthermore, the decision tree structure is easily updated if further data are collected or more appropriate means of defining mobilization are developed. This flexibility is seen as a key factor given the large amount of research that is ongoing within this field, much of which may ultimately be used to improve predictions via a decision tree approach.

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