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The Catchment Runoff Attenuation Flux Tool, a minimum information requirement nutrient pollution model

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Abstract. A model for simulating runoff pathways and water quality fluxes has been developed using the minimum information requirement (MIR) approach. The model, the Catchment Runoff Attenuation Flux Tool (CRAFT), is applicable to mesoscale catchments and focusses primarily on hydrological pathways that mobilise nutrients. Hence CRAFT can be used to investigate the impact of flow pathway management intervention strategies designed to reduce the loads of nutrients into receiving watercourses. The model can help policy makers meet water quality targets and consider methods to obtain "good" ecological status.

A case study of the 414 km^2 Frome catchment, Dorset, UK, has been described here as an application of CRAFT in order to highlight the above issues at the mesoscale. The model was primarily calibrated on 10-year records of weekly data to reproduce the observed flows and nutrient (nitrate nitrogen – N; phosphorus – P) concentrations. Data from 2 years with sub-daily monitoring at the same site were also analysed. These data highlighted some additional signals in the nutrient flux, particularly of soluble reactive phosphorus, which were not observable in the weekly data. This analysis has prompted the choice of using a daily time step as the minimum information requirement to simulate the processes observed at the mesoscale, including the impact of uncertainty. A management intervention scenario was also run to demonstrate how the model can support catchment managers investigating how reducing the concentrations of N and P in the various flow pathways. This mesoscale modelling tool can help policy makers consider a range of strategies to meet the European Union (EU) water quality targets for this type of catchment.

1 Introduction

The mesoscale is classed as catchments that vary between 10 and 1000 km^2 (Blöschl, 1996). Uhlenbrook et al. (2004) states that "The satisfactory modelling of hydrological processes in mesoscale basins is essential for optimal protection and management of water resources at this scale". It is therefore important that government policies on pollution abatement be implemented at this scale. The EU Water Framework Directive (WFD; definitions of further abbreviations can be found in Table A1) (European Parliament, 2000) has required catchments to meet in-stream standards in order to obtain "good" ecological status. Therefore, all surface water bodies must meet exacting water quality and ecological targets (Withers and Lord, 2002). There is a need for a framework that helps inform policy makers and regulators how to understand the source of nutrient pollution at the scale of their interest.

Numerous models have been developed to simulate water and nutrient fluxes at the mesoscale (e.g. INCA: Wade et al., 2002, 2006; PSYCHIC: Davison et al., 2008; SWAT: Arnold, 1994). These models have been used to underpin policy decisions and feed into the decision-making processes with regards to the catchment land use, as well as assess the impacts of any changes including source control or modified agricultural practices (Whitehead et al., 2013). However, these models tend to be too complex for informed end users to use and the simulations are prone to having greater parameter uncertainty than simpler models (McIntyre et al., 2005; Dean et al., 2009). Conversely, export coefficients can be an oversimplification of reality and omit the role of event-driven nutrient losses (Johnes, 1996; Hanrahan et al., 2001). A series

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of recent catchment-scale studies have investigated the role of residence time and its variability in the export of nutrients (particularly nitrate and conservative tracers, e.g. chloride; Botter et al., 2011; Hrachowitz et al., 2013; Van der Velde et al., 2010) in small catchments ($< 10\,km^2$) to identify travel time distributions. These studies focussed on small research catchments with more extensive data sets, including high-resolution digital elevation models. Moreover, their scope was limited firstly in terms of the number of different nutrients investigated and secondly in the number of flow pathways; for example Van Der Velde et al. (2010) only considered a single pathway (shallow groundwater) that transported nitrate from the catchment to the stream, without any representation of overland flow in their model.

High-frequency (defined here as containing sub-daily data) water quality monitoring data sets are becoming increasingly available with newly developed auto-analysers and sondes (for example, Cassidy and Jordan, 2011; Owen et al., 2012; Wade et al., 2012) and from high-frequency samplers (Evans and Johnes, 2004; Bowes et al., 2009a).

It is vital that models should aid catchment planners when considering alternative strategies to attain policy objectives (Cuttle et al., 2007; DEFRA, 2015). This study aims to show that modelling must include sufficient processes to reflect nutrient losses from the catchment, which must be based primarily on soil and hillslope processes such as overland flow, subsurface soil flow and slower groundwater dynamics (in temperate catchments). Hence the model must represent both chronic nutrient losses (seasonal fluxes) and acute losses (storm-driven fluxes) (these terms were defined by Jordan et al., 2007). To this end a minimum information requirement (MIR) modelling approach was developed which (i) uses the simplest model structure that achieves the current modelling goals and (ii) uses process-based parameters that are physically interpretable to the users so that the impact of any parameter change is clear (Quinn et al., 1999; Quinn, 2004). Hence the MIR approach led to the development of CRAFT (Catchment Runoff Attenuation Flux Tool), a parsimonious lumped model that capitalises on the mixing effects of aggregation and homogenisation of processes observed at the mesoscale.

The MIR approach

The MIR approach was developed partly as a response to a perceived excessive number of parameters in the established water quality and sediment transport models (Quinn et al., 1999; Quinn, 2004) and partly to address the issue of excessive model complexity to end-user needs. In principle, MIR models are based on how much information can be gained from localised and experimental studies on nutrient loss, so that the most pertinent process components can be retained in the model and be easily manipulated and assessed by an end user.

Models derived through the MIR approach must be suitable for use in the decision-making process in order to become a valuable tool. In this approach the issues that require addressing include (i) the complexity of the model, (ii) linking nutrient losses and hydrological flow pathways, and (iii) the ability to simulate both acute and chronic nutrient fluxes.

In the MIR approach, the modelling of runoff is kept as simple as possible, although key runoff processes that influence nutrient and sediment loads are retained (Quinn, 2004). By creating a meta-model of more complex process based models, a minimum number of processes are retained in the model structure that are required to satisfy a model goal: in this case the simulation of meso-catchment-scale diffuse pollution. A series of simple equations are implemented in MIR models with a parsimonious number of parameters. The TOPCAT MIR family of models (Quinn, 2004; Quinn et al., 2008) were developed using this approach to simulate various sources of sediments and nutrients. Heathwaite et al. (2003) developed a simple spatial index model called the PIT (Phosphorus Indicators Tool) for estimating diffuse P losses from arable lands into waterways. A series of decision support system (DSS)-based models were developed in Australia, commencing with E2 (Argent et al., 2009), then WaterCAST and finally SourceCatchments (Storr et al., 2011; Bartley et al., 2012). These have similar features to an MIR, including a daily simulation time step to predict sediment and nutrient concentrations (C) and fluxes (i.e. $C \times$ daily flow), containing only two flow and nutrient pathways termed "event mean" (i.e. storm flow) and "dry weather" (i.e. baseflow), both assigned fixed C values for each sediment and nutrient simulated.

It is important that models are seen as useful in terms of the decision-making process and its relationship to land use through a feedback mechanism between the regulators (DEFRA, 2015) and the land owners (e.g. farmers as in Cuttle et al., 2007) or holders of discharge consents into receiving watercourses (e.g. water companies) (Whitehead et al., 2013). Modelling can highlight any potential problems such as changes in nutrient form, known as pollution swapping (Stephens and Quinton, 2009). In essence, the model shows how catchment management decisions impact nutrient concentrations and fluxes at the scale of assessment.

2 Methods

2.1 Catchment description

The case study focusses on the $414.4\,km^2$ River Frome catchment (Fig. 1), which drains into Poole Harbour, with its headwaters in the North Dorset Downs (Bowes et al., 2011; Marsh and Hannaford, 2008; Hanrahan et al., 2001). Nearly 50 % of the catchment area is underlain by permeable chalk bedrock, the remainder consisting of sedimentary formations such as

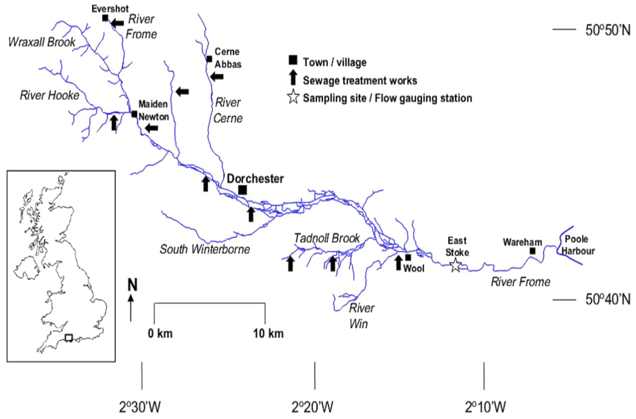

Figure 1. Schematic map of Frome Catchment showing monitoring points (from Bowes et al., 2009a).

tertiary deposits along the valleys of the principal watercourses (including sand, clay and gravels). There are some areas of clay soils in the lower portion of the catchment. However, most of the soils overlaying the chalk bedrock are shallow and well drained. The land use breakdown is dominated by improved grassland (ca. 37 %, comprising hay meadows, areas grazed by livestock and areas cut for garden turf production) and ca. 47 % tilled (i.e. arable crops primarily cereals) usage (Hanrahan et al., 2001). The major urban area in the catchment is the town of Dorchester (2006 population over 26 000; Bowes et al., 2009b) otherwise the catchment is predominantly rural in nature.

From 1965 to 2005, the mean annual catchment rainfall was 1020 mm and mean runoff 487 mm (Marsh and Hannaford, 2008). At East Stoke, the UK Environment Agency (EA) has recorded flows since 1965. The Centre for Ecology and Hydrology (CEH) and Freshwater Biological Association collected water quality samples at this same location at a weekly interval from 1965 until 2009 (Fig. 1) (Bowes et al., 2011); see Sect. 2.1.2 below.

Hanrahan et al. (2001) calculated both export coefficients for diffuse sources of TP and load estimates for diffuse and point sources (comprising wastewater treatment plants (WWTPs) (serving Dorchester plus other towns), septic systems and animal wastes). The total annual TP (total phosphorus) export from diffuse sources in the catchment was estimated to be 16.4 t P yr^{-1}, a yield of 0.4 kg P ha^{-1} yr^{-1}. Point source loads from WWTPs, septic systems and animals added an extra 11.5 t P yr^{-1} (from the data in Table 2 in Hanrahan et al., 2001) to the catchment export, giving a total load of 27.9 t P yr^{-1}. Nitrogen (as nitrate) export from the catchment in the mid-1980s was estimated by Casey et al. (1993) to be 21.6 kg N ha^{-1} yr^{-1}, with 7 % of this originating from point sources in the catchment.

2.1.1 Meteorological data

Forcing data (precipitation) were supplied by the EA for the period 1997 to 2006, which was therefore chosen as the modelling period. A single rain gauge, Kingston Maurwood (ST718912), located ca. 4 km downstream of Dorchester, was used for the modelling, as this gauge had the most complete record and was centrally located in the catchment. Daily mean and 15 min interval flow data were also provided from East Stoke gauging station for the same time period. Potential evapotranspiration (PET) was derived using an algorithm developed to calculate a daily PET based on monthly temperature patterns in order to obtain a daily PET time series which, when totalled for the year, would match the estimated annual PET (465 mm yr^{-1}). Given the dominance of winter runoff in the Frome catchment, the model predictions are unlikely to be sensitive to input values of PET.

2.1.2 Monitoring data sets

Two sets of water quality monitoring data were used in this study, with daily flows recorded by the Environment Agency at East Stoke gauging station. The data were compared and analysed so that the MIR model could be defined. The attributes of the data are described in Table 1, and long-term statistics relating to nutrient concentrations are listed in Table 2. The first is the CEH/Freshwater Biological Association long-term data set (LTD) of water quality for the River Frome (Bowes et al., 2011; Casey, 1975; open access via gateway.ceh.ac.uk). After March 2002, the introduction of P-stripping measures at Dorchester WWTP produced a step reduction in SRP concentrations and reduced SRP loads by up to 40 %, according to the analysis of Bowes et al. (2009b). The second data set (Table 1) is a high-frequency data set (HFD) described in Bowes et al. (2009a) which was also collected at East Stoke over a shorter period using a stratified sampling approach and EPIC™ water samplers (Salford, UK). High-resolution measurements may be prone to localised "noise" that can introduce errors into the observations (Bowes et al., 2009a). Unravelling trends, seasonality and noise may require signal processing techniques to extract meaningful time series data and perform trend analysis (e.g. Kirchner and Neal, 2013).

2.1.3 Temporal runoff and nutrient behaviour in the Frome catchment (LTD and HFD)

The flow time series of the LTD (daily mean flows, DMF) and HFD (sub-daily) flows were compared over the HFD monitoring period, and both time series of flows are shown in Fig. 2a along with the residuals. For most of the period, both sets of flows closely matched ($\rho = 0.98$) except perhaps during runoff events of less than a day where the HFD flows were sometimes higher as indicated by the positive residuals. The analysis suggests that, for modelling purposes including

Table 1. Attributes of Frome water quality monitoring data sets.

Data set	Time period	Sampling frequency	Average number of observations per year	Measurements
Long-term data set (LTD) CEH/Freshwater Biological Association (Bowes et al., 2011)	1965–2009	Weekly	48	TP, TDP, nitrate, SRP
High-frequency data set (HFD) (Bowes et al., 2009a)	1 Feb 2005 to 31 Jan 2006	Sub-daily	> 1000 (see Table 2 for actual total)	TP, TON, SRP, instantaneous flows

Table 2. Long-term nutrient concentration statistics in the LTD and HFD data sets.

Data set/nutrient (time period)	Number of observations	10th percentile concentration ($mg\,L^{-1}$)	Mean concentration ($mg\,L^{-1}$)	90th percentile concentration ($mg\,L^{-1}$)
LTD nitrate (7 Jan 1997–21 Nov 2006)	384	4.6	5.6	6.9
LTD TP (7 Jan 1997–28 Feb 2002)	176	0.13	0.21	0.30
LTD SRP (7 Jan 1997–28 Feb 2002)	183	0.08	0.14	0.20
HFD TON (12 Dec 2004–31 Jan 2006)	1454	4.5	5.5	6.7
HFD TP (14 Jan 2004–31 Jan 2006)	2290	0.09	0.17	0.24
HFD SRP (1 Feb 2005–31 Jan 2006)	1340	0.06	0.09	0.14

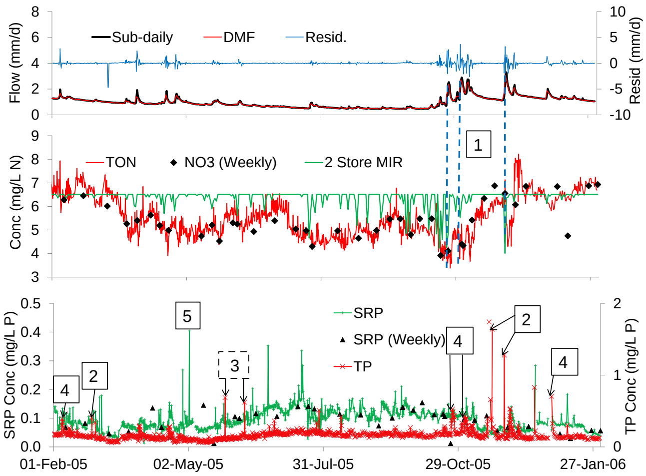

Figure 2. Time series plots from the sub-daily HFD data set from the Frome at East Stoke monitoring point showing **(a)** flow data from the catchment outlet comparing the daily mean (DMF) with sub-daily flows by showing the residual, **(b)** TON and (LTD) nitrate data, the results of a two-store MIR model of nitrate (green line), **(c)** (HFD) TP and (HFD and LTD) SRP data.

load estimation, a daily time step can capture the variability in the observed data without the need to use an hourly time step.

For nitrate it is assumed that nitrite concentrations were negligible in the LTD data set (Bowes et al., 2011) so that TON concentrations (equivalent to nitrate plus nitrite) were effectively equal to nitrate. This allows the HFD TON data to be directly compared against the observed (weekly LTD) nitrate data. The patterns observed visually (i.e. locations of the peak C's) in the weekly and high-frequency nitrate/TON time series were very similar, indicating that the weekly monitoring data were probably sufficient to estimate the range of nitrate/TON concentrations in the catchment in order to assess compliance with EU WFD quality standards (in this case ensuring that $C \leq 11.9\,mg\,L^{-1}$ N). In Fig. 2b it can be seen that there were a few spikes in the HFD above concentrations measured by the LTD, with those measured during recession spells in the flows generally being less than $1\,mg\,L^{-1}$ N in magnitude. There was also no evidence that high flows would generate correspondingly high nitrate concentrations; in fact, in Fig. 2b a dilution effect can be clearly observed during several events in autumn 2005 (indicated by "1", with the dashed blue line linking the concentration time series to the corresponding events in the hydrograph in Fig. 2a), with lower concentrations persisting in some cases for several days after the event. This indicates that concentrations of nitrate in the combined slower baseflow/sewage effluent must have been higher than concentrations in rapid overland flow.

For phosphorus the HFD SRP data were compared visually with the LTD SRP data in Fig. 2c, and again the patterns in both data sets were broadly similar, with increasing concentrations during the summer period between May and November 2005. HFD TP concentrations are also shown in Fig. 2c by the red line. Between November 2004 and March 2006 there was a gap in the LTD TP data for operational reasons discussed in Bowes et al. (2011). Several key points arising from the HFD data are as follows:

i. Some of the spikes in TP concentration, for example in February and mid-December 2005, were during the falling limb or low-flow periods of the hydrograph and were not associated with significant storm runoff events. Corresponding spikes in SRP concentration were not usually prominent at these times, except for one in January 2006. Examples are indicated by "2" in Fig. 2c. Some spikes were also observed during medium-flow periods on several occasions in summer 2005, without corresponding SRP spikes but during a period where SRP concentrations were increasing. Examples are indicated by "3" in Fig. 2c.

ii. Three events between November 2005 and 1 January 2006 generated high concentrations of PP that coincided with the storm peak in the flow hydrograph ($> 1\,\mathrm{mg\,L^{-1}}$ P). This could indicate a faster mobilisation of PP into the channel system during wet conditions in autumn–winter 2005 compared to summer storms. Haygarth et al. (2012) observed similar peaks in PP in smaller headwater catchments due to sheet flow events. Examples are indicated by "4" in Fig. 2c. Some smaller "type 4" events were also observed between February and April 2005.

iii. Some SRP concentration spikes were not simultaneously observed in the TP concentrations; these may have been due to WWTP discharges or leaky septic tanks (the high sampling frequency allowed for this to be observed; Bowes et al., 2009a). Examples of these are indicated by "5" in Fig. 2c.

SRP concentrations during the summer months tended to increase by approximately $0.07\,\mathrm{mg\,L^{-1}}$ P, indicating chronic sources of nutrients in the catchment, whereas acute sources tended to be associated with runoff events or other events in the catchment not associated with high flows. Bowes et al. (2011) also observed this phenomenon in the LTD data set and suggested that the probable cause was a combination of lower flows with less dilution of SRP in the river originating from point sources (WWTPs) in the catchment. Jordan et al. (2007) attributed acute sources of TP in their $5\,\mathrm{km^2}$ agricultural catchment in Northern Ireland to applications of slurry and inorganic P during periods of low rainfall (with no associated runoff events).

Of the 12 runoff events observed between February 2005 and February 2006, 9 were classified as "type 4" events in terms of TP, where a corresponding increase in TP C was also observed (Fig. 2c). The total annual loads (1 February 2005–31 January 2006) of TP and SRP were estimated from the HFD using simple baseflow separation and load analysis techniques as carried out by Haygarth et al. (2005) and Sharpley et al. (2008) in order to estimate the percentage

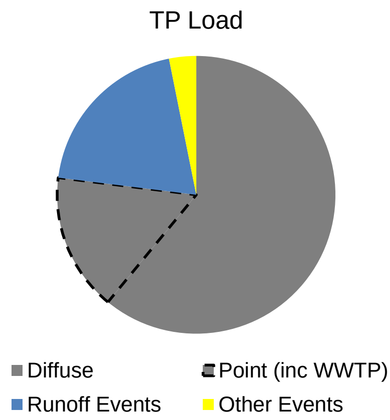

Figure 3. Pie chart showing proportion of 2005–2006. Observed TP load from different event and diffuse sources calculated from the HFD data set.

of the annual TP load generated by events. These loads (with the percentage contributed from the nine runoff events in brackets) were estimated to be 27.8 t TP (20.0 %) and 13.1 t SRP (17.7 %) respectively.

The total annual TP loads are shown in Fig. 3 as a pie chart that indicates the percentages due to event and non-event sources. The percentage of the SRP load from point sources (mostly WWTPs) was estimated to be 34 % based on Bowes et al. (2011) and is indicated by the dashed segment (i.e. 4.5 t P). Making the further assumption that PP = TP − SRP allowed the PP load to be estimated as well (here the "PP" load estimate will probably include a component of unreactive, organic P, so it will be an overestimate) to be 14.8 t PP (22.1 % from events).

The HFD data set shows the range of concentrations that are seen in reality which are often missed in weekly and monthly data sets. These data also show the problem of noise and incidental events that are not correlated with storms. Hence the mesoscale model requires a structure that can address the identifiable seasonal and event-driven patterns but equally should not be expected to exhibit high goodness-of-fit metrics.

2.2 Model description

2.2.1 Developing CRAFT using the MIR approach

The justification for including some processes and omitting others is a difficult task in modelling. Hence it is worth firstly reviewing the MIR process to date. CRAFT has evolved from the model TOPCAT-NP (Quinn et al., 2008). In terms of the hydrology, TOPCAT-NP contained a dynamic store model and a constant (flow and concentration) groundwater term. TOPCAT-NP also contained a time-varying soil-leaching model for N and SRP (with an associated soil adsorption term for SRP).

In terms of nutrient process modelling (in TOPCAT-NP), a meta-modelling exercise of the physically based model EPIC (simulating flow, SS, N and P) (Williams, 1995) and the N-loss model SLIM (**S**olute **L**eaching **I**ntermediate **M**odel) (Addiscott and Whitmore, 1991) was carried out and is published in Quinn et al. (1999). Herein a case was made to reduce many of the soil hydrological and chemical processes. Multiple simulation of EPIC showed that both the annual exports and the daily losses could be readily simulated by a leaching function and knowledge of how much N or P was being applied and available for mobilisation. Based on these earlier studies, the final version of TOPCAT could simulate flow, N and P at a number of research locations (hence the suffix "-NP"). It included a leaching model; hence a soil nutrient store and a leaching term based on a soil type parameter were required to determine the flux into the store.

Essentially the MIR formulation is thus a series of mass balance equations that sum the flux of nutrients $F = Q \cdot C$ from each store over time to obtain a nutrient load. In order to study nutrient pools and/or explicit soil flux processes, a physically based model is required (e.g. Arnold, 1995; Van der Velde, 2010; Hrachowitz et al., 2013). The HFD data set (Sect. 2.1.2) described above is used to estimate the likely origin and magnitude of nutrient fluxes in the catchment and help inform our choice of model structure in terms of processes and stores. The second simplest form of an MIR water quality model (other than merely using a constant concentration of nutrients in all the stores) is the EMC/DWC formulation (Argent et al., 2009) with two stores: (i) "dry weather", i.e. baseflow, and (ii) "event mean", i.e. overland flow events in this case. Each store is represented by a single, constant C value, i.e. DWC and EMC, respectively.

The results of modelling nitrate using a two-store MIR model can be seen in Fig. 2b by the green line. The two C parameters are $6.5\,\mathrm{mg\,L^{-1}\,N}$ (DWC) and $2\,\mathrm{mg\,L^{-1}\,N}$ (EMC). Here, the "flow" component of the MIR is able to reproduce events (here with lower nitrate C) reasonably well, but the background nitrate C is not reproduced well during the summer–autumn period since the model overpredicts it between July and November 2005. A similar phenomenon could be demonstrated using the SRP data set with this structure of MIR model. The modelling of the Frome catchment using a CRAFT MIR will be revisited later, but this exercise neatly illustrates how an MIR model can be too simple to represent all the phenomena that are detectable in the observations. Thus TOPCAT-NP's constant (flux and C) groundwater term was hence too simple for this study.

The signals observed in the HFD data set are examined slightly more deeply in order to further develop the conceptual MIR model processes (particularly for P). Nine of the 12 events discussed above were classified as type 4 events in terms of TP, where a corresponding increase in the TP C was also observed (Fig. 2c). These should be incorporated in an MIR model, if it is to be a useful predictive tool for modelling P event fluxes and TP loads, by generating TP (as PP) from runoff events. In Fig. 2c it can be seen that the TP C's during type 4 events were quite variable (highest in late autumn–winter 2005), so using a constant C value in the overland flow/surface process store in an MIR model would be an oversimplification.

The type 2 and 3 events discussed above generated spikes of relatively high TP C's and type 5 events generated spikes of SRP C's that were not associated with significant catchment rainfall, or flow events observed at the outlet (Fig. 2c). Therefore, in terms of total annual P loads, the type 2 and 3 events contributed a very small percentage of the total (mainly due to the low flows at the time of occurrence) and may have been generated by incidental losses.

In Fig. 2b it was shown with the HFD TON signal that many of the runoff events were categorised as type 1 where dilution of the TON, presumably due to overland flow, was observed. A similar analysis to that carried out with the TP data was not appropriate, as it was clear that the TON C in overland flow during events must have been lower than the observed C in the baseflow in order to have caused the dilution patterns. Thus the MIR model should capture (i) a dilution signal and (ii) the observed variations in TON C's, particularly the decrease observed between later winter and summer (i.e. in the winter 2005–2006 period from ca. 7 to ca. $4\,\mathrm{mg\,L^{-1}\,N}$ followed by a recovery back up to $7\,\mathrm{mg\,L^{-1}\,N}$). The two-store MIR model shown in Fig. 2c was unable to reproduce any seasonal patterns at all in the observed TON HFD data.

Therefore, it was decided that an additional flux term (and store) was required in the model to represent a time-varying baseflow component from deeper groundwater (GW). This modification also had a similar beneficial effect on the modelling of the SRP concentrations. The shape of the flow hydrograph and some background information on the catchment physical characteristics (Casey et al., 1993; Marsh and Hannaford, 2008) suggested that an improved representation of the subsurface flow processes was important in the Frome catchment. In mesoscale catchments such as this, a physically based leaching function (as used in TOPCAT-NP; Quinn et al., 2008) thus also becomes redundant as the "minimum requirement" is to know the concentration of the nutrients at the outlet and it is assumed that fluxes of N and P are being generated at some location in the catchment throughout the year, due to the (assumed uniform) spatial distribution of intensive agricultural land uses. These fluxes are thus incorporated into a soil flux store in the final MIR, with this flux assigned constant C's of SRP and N.

The development of the conceptual model discussed above led to an MIR structure for CRAFT that represents the complex hydrological system in the simplest manner feasible. The upper pane of Fig. 4 shows that the model comprises three dynamic storages and the associated flow and transport pathways (or fluxes). The lower pane in Fig. 4 shows the flow and nutrient transport pathways that exist in a catchment such as the Frome using a conceptual cross section of

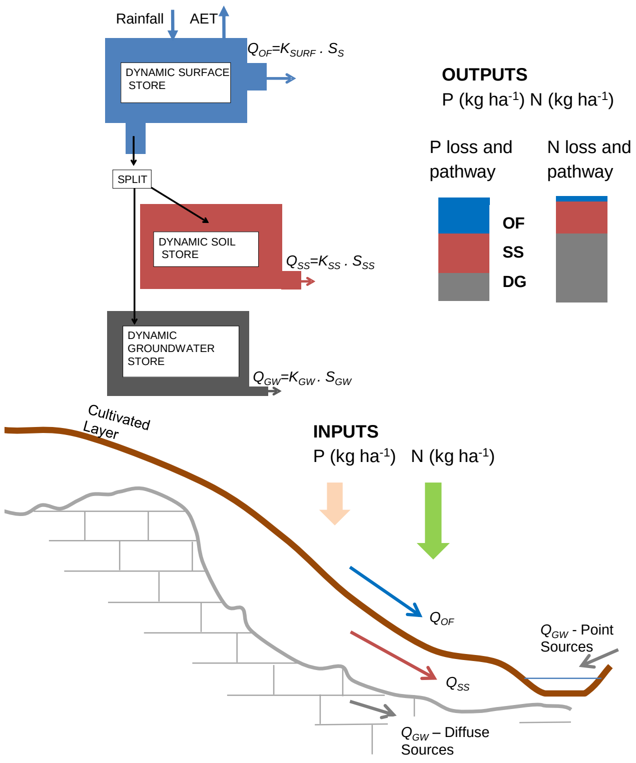

Figure 4. Conceptual diagram of CRAFT (top) and a hillslope (bottom), showing the dominant flow and nutrient transport pathways.

a hillslope. Here, inputs and outputs of N and P in the catchment are shown diagrammatically. There are three flow pathways shown: (i) an overland flow component which also represents processes in the cultivated near surface layer (down to several centimetres depth); (ii) a faster subsurface component encapsulating agricultural soils that may have been degraded by anthropogenic activities and perhaps enhanced flow connectivity (e.g. through field drains); and (iii) a slower groundwater component encapsulating any background flow in the catchment due to deeper flow pathways, wastewater treatment plant (WWTP) discharges (assumed constant), and other non-rainfall-driven constant fluxes including any generated within either the channel or the riparian areas. We will refer below to the pathways as (i) overland flow (OF), (ii) fast subsurface soil (SS) flow and (iii) the slow, deeper groundwater (DG) flow respectively. It has been argued above that the composition of SRP and nitrate fluxes must be dominated by the DG and SS pathways. The TP flux includes a PP component that is generated by the OF pathway in the model (as discussed above).

2.2.2 Water flow pathways

There are six parameters that require estimation or calibration to control the water flow pathways. Their values are shown in Table 3 below.

The uppermost dynamic surface store (DSS) is conceptualised to permit both crop management and runoff connectivity options to be examined. The DSS store is split into two halves, with the upper half representing a cultivation (tillage) layer that generates overland flow and the lower half controlling the evapotranspiration. Firstly, a water balance updates the storage (S_S) and then computes the overland flow from the surface store (Q_{OF}) through the following equations, where R is rainfall and D is drainage to the lower half of the store. Note that all stores are in units of length (e.g. m) and all flux rates (e.g. R, D, Q_{OF}) are in units of length per time step (e.g. m day^{-1})

$$S_S(t) = S_S(t-1) + R(t) - Q_{OF}(t-1) - D(t-1), \quad (1)$$

$$D(t) = \mathrm{Min}(S_{DMAX}, S_S(t)), \quad (2)$$

$$Q_{OF}(t) = (S_S(t) - D(t)) \cdot K_{SURF}. \quad (3)$$

The parameter S_{DMAX} can be used to deliberately partition excess water between surface and subsurface flows, which is crucial for investigating connectivity options and possible pollution-swapping effects. The lower half of the DSS represents the soil layer (below the cultivated layer) and also accounts for losses due to actual evapotranspiration E_T. The parameter limiting the size of the store is called S_{RZMAX}. The storage of water in the store (S_{RZ}) at each time step is updated by the following mass balance:

$$S_{RZ}(t) = S_{RZ}(t-1) + D(t) - E_T(t). \quad (4)$$

Any excess water present in the store above S_{RZMAX} will cause percolation (Q_{PERC}), which then cascades into the subsurface SS and DG stores. S_{RZ} is then reset to S_{RZMAX}:

$$Q_{PERC}(t) = \mathrm{MAX}(0, (S_{RZ}(t) - S_{RZMAX})). \quad (5)$$

Both the SS and DG stores are dynamically time-varying and generate fast (Q_{SS}) and slow groundwater flows to the outlet (Q_{GW}) respectively. A dimensionless parameter K_{SPLIT} (0,1) apportions active drainage from the lower surface store towards either store; that is, a water balance for the storage (S_{SS}) in the SS store can be written as

$$S_{SS}(t) = S_{SS}(t-1) - Q_{SS}(t-1) + Q_{PERC}(t) \cdot K_{SPLIT}. \quad (6)$$

The equation for the storage in the DG store (S_{GW}) is identical except that $(1 - K\,S_{PLIT})$ is substituted for K_{SPLIT} and S_{GW} for S_{SS}.

The flow (Q_{SUB}) from either subsurface store is described by Eq. (7), where K is a recession rate constant (d^{-1}) and S is the storage (in m). Therefore, Q_{SUB} at time t is given by

$$Q_{SUB}(t) = K\,S(t-1). \quad (7)$$

In the DG store the initial storage S_{GW0} is set by the user by rearranging Eq. (7) in terms of the groundwater discharge Q_{GW0} at the start of the simulation (assumed to be equal to the observed flow in a dry spell):

$$S_{GW0} = Q_{GW0}/\mathrm{KGW}, \quad (8)$$

Table 3. Hydrological model parameters: bounds and performance metrics (baseline simulation).

	S_{DMAX} (md^{-1})	S_{RZMAX} (m)	K_{SURF} (–)	K_{SPLIT} (–)	K_{GW} (d^{-1})	K_{SS} (d^{-1})
"Expert" value	0.02	0.019	0.08[a]	0.56	0.0011	0.041
Lower bound	1	1	0	0	0.0001	0.02
Upper bound	100	500	5	1	0.02	1
NSE (–)	0.80					
MBE (%)	1.00					

[a] K_{SURF} was reduced to 0.012 in the MI scenario.

where $Q_{\mathrm{GW0}} \equiv$ observed runoff on first day of simulation ($\mathrm{m\,d^{-1}}$), following the assumption above.

Lastly, the total modelled runoff at each time step at the outlet is calculated (Q_{mod}):

$$Q_{\mathrm{mod}} = Q_{\mathrm{OF}} + Q_{\mathrm{SS}} + Q_{\mathrm{GW}}. \tag{9}$$

2.2.3 Nutrient fluxes

Users must now add a sensible range of input nutrient concentrations to the model in order to simulate loads (i.e. $C \times Q$). They are encouraged to set and alter these values and see the impact instantaneously. The nutrient transport processes are conservative, and users are encouraged to understand the link between land use management and the level of nutrient loading, assuming that they have a working knowledge of the relevant terms and processes.

In general, nutrients are modelled in CRAFT by either a constant concentration assigned to each flow pathway or by using an uptake factor (or "rating curve") approach (e.g. Cassidy and Jordan, 2011; Krueger et al., 2009), where the concentration is directly proportional to the overland flow rate (Eq. 10). A conceptual model of the flow and transport pathways in the catchment that are incorporated into CRAFT is shown in the lower part of Fig. 4.

In the uptake factor approach, the concentration vector (units $\mathrm{mg\,L^{-1}}$) of different nutrients ($\boldsymbol{n}$) in overland flow (C_{OF}) is given by

$$C_{\mathrm{OF}}(\boldsymbol{n}) = \mathrm{MAX}(K(\boldsymbol{n}) \cdot Q_{\mathrm{OF}}, C_{\mathrm{OFMIN}}(\boldsymbol{n})), \tag{10}$$

where Q_{OF} is the overland flow, $K(\boldsymbol{n})$ represents the slope of the relationship between flow and nutrient ($\boldsymbol{n}$) concentration in the observed data (i.e. uptake factor) and $C_{\mathrm{OFMIN}}(\boldsymbol{n})$ is the minimum concentration. This is included in Eq. (10) to prevent unrealistically low concentrations being used in the model during low-flow periods, i.e. below the measurable limit. Krueger et al. (2009) used this type of equation to model TP concentrations in high flows generated by enrichment of sediment with P.

The daily nutrient load is calculated by the mixing model described by Eq. (11), where $\boldsymbol{L}(\boldsymbol{n})$ is the vector of the nutrient loads (NO_3, SRP and TP, denoted by $\boldsymbol{n}$), C_{SS} and C_{GW} are the constant concentrations in the dynamic soil and dynamic groundwater zones respectively:

$$\boldsymbol{L}(\boldsymbol{n}) = C_{\mathrm{OF}}(\boldsymbol{n}) \cdot Q_{\mathrm{OF}} + C_{\mathrm{SS}}(\boldsymbol{n}) \cdot Q_{\mathrm{SS}} + C_{\mathrm{GW}}(\boldsymbol{n}) \cdot Q_{\mathrm{GW}}. \tag{11}$$

The concentration vector of the nutrients in the catchment outflow ($\boldsymbol{C}(\boldsymbol{n})$) can be calculated directly from the vector $\boldsymbol{L}(\boldsymbol{n})$ using Eq. (12):

$$\boldsymbol{C}(\boldsymbol{n}) = \boldsymbol{L}(\boldsymbol{n}) / Q_{\mathrm{MOD}}. \tag{12}$$

Nitrate and SRP concentrations are calculated at each time step using Eqs. (11) and (12). The TP concentration is calculated with Eq. (13):

$$C_{(\mathrm{TP})} = \frac{L(\mathrm{SRP}) + L(\mathrm{PP})}{\mathrm{QMOD}}. \tag{13}$$

CRAFT can thus capture the mixing effects of N and P losses associated with several hydrological flow pathways at the mesoscale. The above equations that remain in the MIR for CRAFT do not contain the following:

i. The myriad of nutrient cycling processes occurring in the N and P cycles. Sect. 2.1.2 shows the observable processes at the catchment outlet and Fig. 3 the nutrient apportionment at this scale. However, the MIR captures the integrated effect of the processes and how these might change over time.

ii. Riparian processes. It is argued the impact of these is not observable at the outlet. The net effect of riparian processes is integrated into the soil and groundwater concentration values.

iii. Within-channel processes such as plant uptake and the bioavailability of nutrient from bed sediments. Again, the impacts of these processes are not identifiable in the HFD time series. Unless the evidence of impact is clear, they are not included in the MIR process.

2.3 Modelling and calibration

Flow and nutrients were simulated with CRAFT for a 10-year baseline period – 1 January 1997 to 31 December 2006

– using a daily time step. A comparison of the model performance at predicting the SRP and TP concentrations was curtailed at the end of February 2002. However, for nitrate the model performance over the full 10-year period was assessed.

The performance of the calibrated CRAFT model at reproducing observed stream flow at the catchment outlet was assessed by a combination of visual inspection of the modelled against observed runoff and the use of the Nash–Sutcliffe efficiency (NSE) evaluation metric. The original aim of the hydrological model calibration was to maximise the value of the NSE whilst ensuring that the MBE (mass balance error) was less than 10 %. The parameters K_{SURF}, K_{GW}, K_{SS}, K_{SPLIT}, S_{RMAX} and S_{DMAX} were adjusted iteratively to enable this and obtain a single "expert" parameter set for the baseline simulation (values shown in Table 3). The calibration strategy involved firstly obtaining an acceptable simulation of overland flow. In order of process representation: K_{SURF} and S_{DMAX} control the generation of overland flow (S_{DMAX} must be adjusted to less than the maximum rainfall rate to initiate overland flow, and then K_{SURF} controls the flow volume), K_{SPLIT} is then used to proportion recharge to the two subsurface stores, S_{RMAX} controls the timing and volume of recharge events, and finally K_{GW} and K_{SS} are adjusted to reproduce the observed recession curves in the hydrographs (K_{SS} being the more sensitive of the two).The sensitivity of the model was then assessed by running a Monte Carlo analysis of 100 000 simulations, where the six parameters were randomly sampled from a uniform distribution (the upper and lower bounds are shown in Table 3).

Simulations with a MBE greater than 10 % were rejected. The top 1 % of simulations meeting both criteria were thus chosen as "behavioural" and a normalised likelihood function ($L(Q)_i$) was calculated using Eq. (14) with the SSE (Beven, 2009) (sum of square errors) values determined above for each simulation i:

$$L(Q)i = \mathrm{SSE}i / \sum \mathrm{SSE}. \tag{14}$$

Lastly, weights were assigned to the behavioural flows based on the likelihood of each simulation. These weighted flows were then used to compute the upper and lower bounds (here the 5th and 95th percentile flows were chosen) applied to the modelled flows (Q_{mod}).

The NSE metric is suitable for assessing flow simulation performance but is less suitable for nutrient concentrations due to the occurrence of negative NSE values, partly as a result of calculating variance terms using sparse observed data (where the sample mean is unlikely to reflect the true mean). Therefore, the nutrient model parameters were calibrated by assessing the performance of the model against the weekly concentration data in the LTD, using the following metrics to determine an "expert" parameter set:

– Visually comparing the time series of nitrate, SRP and TP against the observed data and adjusting the nutrient model parameters to obtain a best fit between modelled and observed time series.

– Optimising the errors between modelled and observed mean and 90th percentile concentrations with the aim of reducing these below 10 % if possible. The mean and 90th percentile concentrations were chosen as these represent the concentrations over the range of flows (mean) and events (90th percentile) and therefore allow the model performance under all flow regimes to be assessed.

A further sensitivity analysis was then performed using the flows from the behavioural hydrology simulations (discussed above) and re-running the nutrient model (without adjusting the "expert" parameter values for the nutrients) to determine a set of upper and lower bounds (5th and 95th percentile values) to the predicted concentrations and their associated loads ($Q \cdot C$).

2.4 Management intervention scenario

For a model to be effective at the management level it needs to be able to demonstrate the impacts of changes in local scale in land management. Here the local land use change is assumed to occur at all locations. Nevertheless, CRAFT can show the magnitude and proportion of the nutrients lost by each hydrological flow pathway. It is equally possible to show the concentration of each nutrient at each time step, as this helps educate the end user.

In order to demonstrate the impact of a catchment management intervention strategy, the following changes were made to the catchment as a runoff and nutrient management intervention (MI) scenario. For simplicity a combination of land use changes were applied and the output expressed as the changes in export loads for each pathway at the outlet, shown below:

i. The modelled overland flow was reduced by reducing the value of the K_{SURF} parameter to 0.012, representing a management intervention that removes or disconnects the agricultural pollution "hotspots".

ii. Nutrient loads in the rapid subsurface zone were reduced by reducing the values of C_{SS}(SRP) and $C_{\mathrm{SS}}(\mathrm{NO_3})$ by 50 % (i.e. halving the impact of diffuse sources linked to the outlet by this flow pathway) to represent improved land management with reduced fertiliser loads. No change to the DG nitrate concentration was made as, firstly, any changes in land management may take decades to be observed in the deeper groundwater (Smith et al., 2010) and, secondly, recent improvements to WWTPs have only targeted reducing SRP loads and not nitrate loads (Bowes et al., 2009b, 2011).

Table 4. Nutrient modelling parameters from the baseline and MI scenarios (only values that were modified from the baseline in the MI scenario are shown in parentheses).

Parameter	Nitrate ($mg\,L^{-1}$ N)	SRP ($mg\,L^{-1}$ P)	PP ($mg\,L^{-1}$ P)
C_{OFMIN}	0.4	0.01	0.01
C_{SS}	8.0 (4.0)	0.03 (0.15)	
C_{GW}	4.5	0.22 (0.08)	
K_{SR}(N)[a]	0	70	700

[a] Units of ($mg\,day\,m^{-4}$) $\times 10^3$.

iii. Background loads of SRP in the catchment are reduced by lowering C_{GW}(SRP) to represent the reduction in deeper groundwater concentration caused by lower leaching rates from the soil store and making improvements to WWTPs in the catchment to reduce SRP loads. Bowes et al. (2009b) found that a 52 % reduction in the SRP export from point sources had taken place since 2001 in the catchment (up to 70 % of the SRP load from each improved WWTP is assumed to be stripped out). In terms of the total (point and diffuse) SRP load, Bowes et al. (2011) estimated that it had been reduced by 58 % between 2000 and mid-2009, which was due to further improvements to the smaller WWTPs in the catchment as well as a reduction in diffuse sources of up to 0.1 $kg\,P\,ha^{-1}\,yr^{-1}$. Figure 3 shows that point sources (in 2005–2006) were thus estimated to contribute 16 % of the annual TP load.

3 Results

The baseline model results are shown in Fig. 5 as time series plots of modelled and observed flow at East Stoke along with the modelled and observed nitrate, TP and SRP concentrations for a selected 2-year period. The years chosen have average followed by wet hydrological conditions. To further illustrate the model performance at predicting flow and concentrations, the upper panes in Fig. 5 show a corresponding time series plot of the absolute error (i.e. observed flow or concentration minus modelled flow or concentration).

3.1 Baseline simulation

The hydrology model parameters used by the baseline simulation are shown in Table 3. The model results from CRAFT were as follows: the NSE for the baseline hydrology simulation was 0.80, and the mass balance error was overpredicted by 1.0 %. In the Frome catchment the percentage of overland flow (which includes surface runoff and near-surface runoff through the ploughed layer) according to the calibrated model was very small (2.2 % of the annual total runoff of 516 $mm\,yr^{-1}$). This value may be low but, as stressed

Table 5. Nutrient modelling results from "expert" calibration in the baseline scenario (1997–2006[a]).

Data set	C_{mod} mean ($mg\,L^{-1}$)	Error (%)	C_{mod} 90th ($mg\,L^{-1}$)	Error (%)	R^2 (–)
LTD nitrate	6.0	5.4	7.1	3.3	0.04
LTD TP[a]	0.14	−58	0.21	−50	0.02
LTD SRP[a]	0.13	−4.9	0.21	5.0	0.22

[a] Calculated up until 28 February 2002 only.

before, it is difficult to see the overland flow signal at the mesoscale. Here, an overland flow component has been retained (by setting K_{SURF} and K_{SR} to the values shown in Tables 3 and 4) due to an assumption that P is being lost via this process, i.e. from the knowledge arising from research studies (e.g. Owen et al., 2012; Bowes et al., 2009a; Heathwaite et al., 2005). Values for the parameters K_{SR}(PP) and K_{SR}(SRP) were determined in the baseline simulation based on some events (as suggested in Figs. 2 and 3) where runoff-driven TP spikes were observed.

3.2 Runoff

It is possible to optimise the parameter values in the model to generate either a smaller mass balance error or a larger value of the NSE metric (over 0.8 is possible with this model and data, as evidenced by the Monte Carlo simulation results). Here a compromise was sought between both these metrics, retaining the overland flow process (discussed above) and a good visual fit with the observed flows.

The behavioural flows from the Monte Carlo simulation are shown in Fig. 6 as dotted lines representing the upper (95th percentile) and lower (5th percentiles) prediction bounds. There were 511 simulations classed as "behavioural". The envelope of the predicted flows indicates that most of the observed flows during the 10-year period of data could be reproduced, supporting the choice of runoff processes represented in CRAFT for this particular catchment. Some events may have been either missed or overpredicted, which could be due to limitations with using a single rain gauge in the forcing data for the model. Table 6 shows the minimum, median and maximum flows extracted from these time series. The table shows that the model outputs are sensitive to the parameter values.

3.3 Nutrients

3.3.1 Nitrate

The observed nitrate concentrations in Fig. 2b indicated that concentrations of nitrate in overland flow are much smaller than concentrations in baseflow, and the model parameter $C_{OFMIN}(NO_3)$ (see Eq. 10) was set to 0.4 $mg\,L^{-1}$ N (Table 4). In the baseline scenario, the proportion of nitrate loads generated by overland flow was thus fairly negligible (< 1 %)

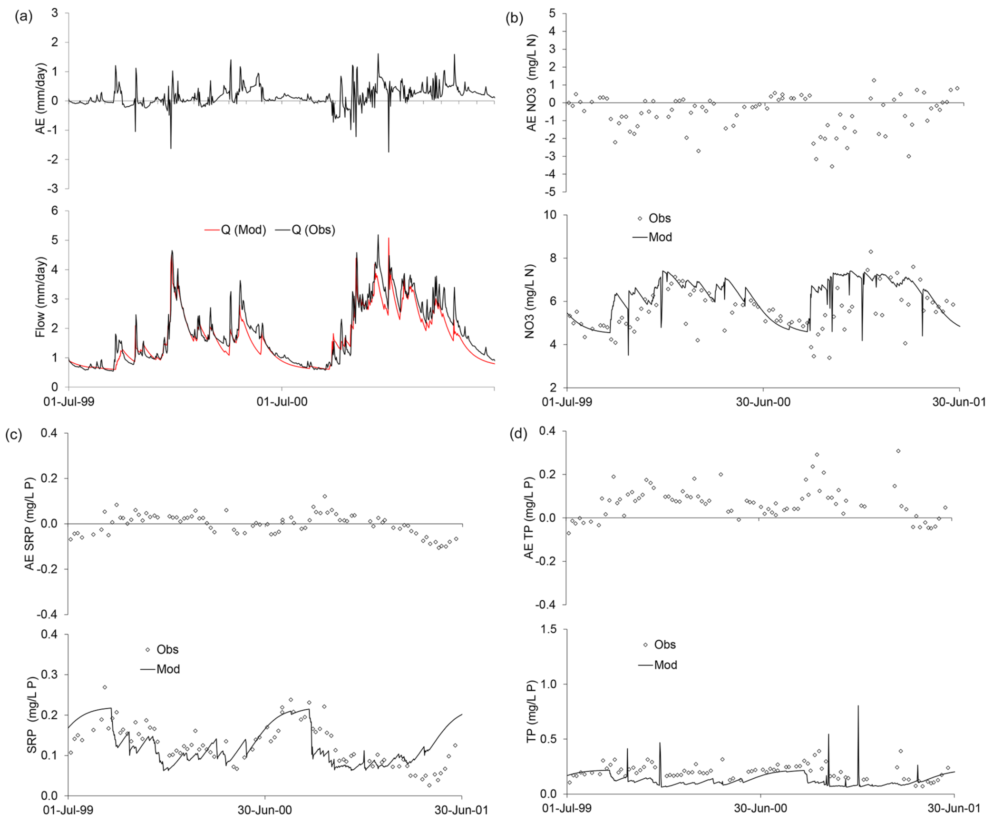

Figure 5. Time series plots of modelled (from "expert" calibration) and observed (LTD) flows and nutrient data, with the absolute error (AE) (observed minus modelled) shown above: **(a)** flows, **(b)** nitrate, **(c)** TP and **(d)** SRP. Two years of data shown only.

Table 6. Sensitivity analysis results (1997–2006).

Eval, mean (min–max) C and Q	"Expert" (baseline)	5th percentile behavioural	Median behavioural	95th percentile behavioural
Q (mm d^{-1})	1.4 (0.46–6.4)	1.1 (0.08–4.5)	1.4 (0.20–5.6)	1.7 (0.41–8.8)
TP C^a (mg L^{-1} P)	0.14 (0.06–1.9)	0.14 (0.07–0.22)	0.21 (0.11–1.2)	0.23 (0.19–3.9)
SRP C^a (mg L^{-1} P)	0.13 (0.06–0.22)	0.14 (0.07–0.22)	0.20 (0.10–0.22)	0.22 (0.17–0.38)
Nitrate C (mg L^{-1} N)	6.0 (1.7–7.5)	4.5 (0.73–5.0)	4.8 (2.2–6.6)	5.9 (4.5–7.3)
TP yield[a] (kg P ha^{-1} yr^{-1})	0.69	0.72	1.11	1.31
SRP yield[a] (kg P ha^{-1} yr^{-1})	0.62	0.72	1.10	1.28
Nitrate yield (kg N ha^{-1} yr^{-1})	33.2	22.8	26.1	32.1

[a] Calculated up until 28 February 2002 only.

and the nitrate loads were split fairly evenly between the SS and DG pathways according to the model. The load from the DG contributed around 31 % of the total load, compared to 43 % of the modelled runoff originating from this pathway. This implies that a significant proportion of nitrate drains from the shallow subsurface (SS) immediately after storm events, probably through either enhanced connectivity due to agricultural drains or recharge into the underlying chalk aquifer (Bowes et al., 2005). The DG component includes nitrate loads from the WWTPs in the catchment which were estimated to contribute around 7 % (1.5 kg N ha^{-1} yr^{-1}) of the total load based on monitoring data from the mid-1980s (Casey et al., 1993) and 14 % of the modelled DG load.

Overall, CRAFT reproduced a moving average of the observed nitrate LTD concentrations reasonably well, and mean concentrations were within 10 % of the observed (Table 5). The fit between modelled and observed nitrate in terms of absolute errors (Fig. 5b upper panel) was not so good due to timing errors in predicting the onset of dilution, although visually (Fig. 5b lower panel) the model appeared to simu-

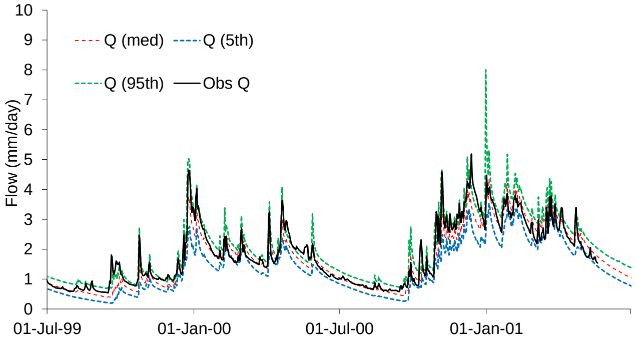

Figure 6. Time series plot of modelled (using Monte Carlo sampling to determine parameter values) 5th and 95th percentile and median flows, as well as the observed flows.

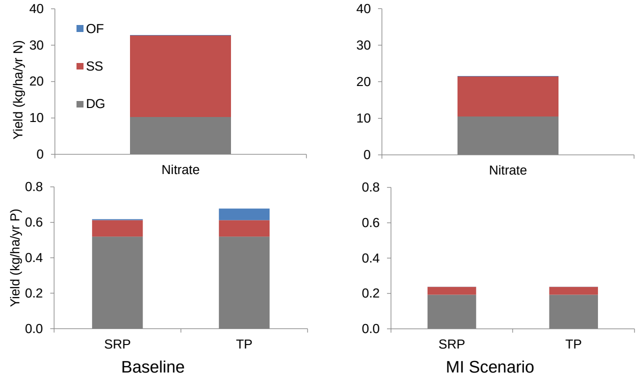

Figure 7. Comparison of the nutrient yields (N and P) from the baseline (left) and MI scenario (right).

late the seasonal patterns of nitrate fairly well. Table 6 shows the uncertainty in nitrate loss arising from the hydrological model in terms of the 5th, 95th percentiles and medians of modelled concentrations and yields.

3.3.2 Phosphorus

Bowes et al. (2009b) estimated that, between 1991 and 2003, SRP provided 65 % of the TP load in the Frome catchment. In the baseline scenario, the DG component in the model generated almost 4 times the load of SRP compared to the SS component (Fig. 7). This seems plausible as the DG component also included the SRP loads from the WWTPs, in addition to the SRP originating from springs and seeps from shallow groundwater. Again, the K_{SPLIT} parameter in the flow model had a large influence on SRP loads by adjusting the ratio between the SS and DG components of these. The model errors, identifiable from the panels above the time series plots (Fig. 5), may have been caused by timing issues leading to periods of overprediction and underprediction of SRP concentrations. Visually, the SRP concentrations showed a close match, and the seasonal patterns and trends were simulated (Fig. 5c). Any spikes in the observed data which were not reproduced by the model appear not to have been caused by actual hydrological runoff events (as seen in Fig. 2 and discussed above). Modelled concentrations (on sample days only) were within 10 % of the observed SRP concentrations for both the mean and 90th percentile values but underpredicted the mean and 90th percentile TP concentrations by around 50 % (Table 5). This may be due to an additional source or sources of P not being accounted for in the model (e.g. within-channel river dynamics and/or conversion of SRP to entrained particulate forms of P as suggested by Bowes et al., 2009a). Table 6 shows the uncertainty in the TP and SRP losses arising from the hydrological model in terms of the 5th, 95th percentiles and medians of modelled concentrations and yields.

However, these results showed that high concentrations of TP associated with the transport of PP during runoff events were predicted by the Monte Carlo and expert simulations (over 1.9 mg L^{-1} P), which was similar to the type 2 events identified in the HFD data set, where TP concentrations reached 1.75 mg L^{-1} P in late 2005. The LTD data set did not contain many spikes of this magnitude in the TP concentrations; however the HFD data did measure occasional high concentrations of TP associated with runoff events (e.g. those indicated by a “4” in Fig. 2c). Figure 2c and the model results in Fig. 5 show that the issue of fitting TP at the mesoscale is problematic and is unlikely to be improved by having a more complex model.

In the baseline scenario the modelled proportion of TP (i.e. PP) generated by overland flow was about 11 %, which is quite high considering that only 1.2 % of the modelled runoff is generated via this pathway. The PP concentrations generated by the model were calibrated by adjusting the value of the K_{SR}(PP) parameter (Table 4).

The export yields (load per unit area) for each nutrient to show the impact of the flow pathways at transporting nutrients were also calculated (see Fig. 7 and Table 6). This aggregation lends itself to comparisons with previous studies. The baseline simulation predicted a TP export of 0.69 kg P ha^{-1} yr^{-1}, which is slightly more than both the export rate estimated by Hanrahan et al. (2001) for diffuse and point sources in the catchment of 0.62 kg P ha^{-1} yr^{-1} (for calendar year 1998). SRP loads were modelled by Bowes et al. (2009b) and the SRP export was predicted to be 0.44 kg P ha^{-1} yr^{-1} between 1996 and 2000 (of which WWTP discharges accounted for 49 %), compared to CRAFT-modelled baseline SRP export of 0.62 kg P ha^{-1} yr^{-1} (between 1997 and February 2002). Similar historical estimates for nitrate export were not available to compare with the model estimate of 32.8 kg N ha^{-1} yr^{-1} over the period 1996–2005, except a single year from the HFD data set where the TON export was estimated to be 20.2 kg N ha^{-1} yr^{-1} (Bowes et al., 2009a). Table 6 shows the uncertainty in terms of the 5th, 95th percentiles and medians of modelled concentrations and yields.

3.4 Management intervention scenario

The yields of nitrate and TP are summarised by the use of bar charts in Fig. 7, which illustrate the fluxes under the baseline conditions (left bars) and the MI scenario (right bar), and the relative contribution of each of the three flow pathways to these, which provides valuable source apportionment information for policy makers.

The results show that the amount of PP generated by the overland flow pathway (denoted by the blue rectangle in the baseline scenario bar in Fig. 7) has reduced to almost zero due to the reduction in overland flow, and the difference between TP and SRP export is negligible as a result. This indicates that a limited amount of "pollution swapping" is predicted, and as a result the proportions of PP and SRP comprising TP have changed from 8.8 and 92.2 % to 0 and 100 % respectively under the MI scenario. Nitrate and TP loads are predicted to decrease by 34.4 and 65.0 % respectively. Under the MI scenario, the nitrate concentration in the DG flow component (which includes point sources) was not reduced (it was assumed that WWTP improvements targeted P and not N). Both nitrate and SRP loads in overland flow were negligible (< 0.1 %) under the baseline scenario and have been reduced to effectively zero by drastically reducing the amount of overland flow generated. SRP loads due to point sources were included in the DG component and the predicted DG load was reduced by 63 %. The export of SRP via the faster SS component was also reduced by 55 % (to $0.045\,\mathrm{kg\,P\,ha^{-1}\,yr^{-1}}$) under the MI scenario. These reductions in the SRP loads from different components compare well to the overall reductions since the 1990s in point and diffuse sources in the catchment (Bowes et al., 2009b, 2011).

4 Discussion and conclusions

This paper has explored the role of MIR modelling methods at the mesoscale. Specifically, it has explored the information content of flow and nutrient data within a case study that helps justify the choice of model structure and time step. The MIR approach to modelling is thus the minimal parametric representation to model phenomena at the mesoscale as a means to aid catchment planning/decision making at that scale. The approach is based on observations made in research studies in the Frome catchment. The MIR model that was developed, CRAFT, thus focussed on key hydrological flow pathways which are observed at the hillslope scale. The nutrient components were kept very simple, neglecting all nutrient cycling aspects. CRAFT deliberately avoids a spatial representation of local land use in this particular case study. This implies that the lumping process is appropriate for circumstances where the local variability is lost when aggregated. The model can be used in a semi-distributed form if the land use patterns justify such a new model structure and this form may help to identify the sources of the fluxes in the overall model for some applications. Future developments of CRAFT will also permit the investigation of many features such as riparian fluxes and also the impact of attenuation on sediments and nutrient fluxes when routed through ponds and wetlands.

High-frequency data (such as in the HFD data set) for all nutrient parameters are desirable at all locations if affordable. However, it is shown here that, at the mesoscale, these data tend to reflect the "noise", incidental losses and within-channel diurnal cycling in the system that have a limited effect on the overall signal and loads. For the Frome case study, a daily time step in CRAFT could simulate the dominant seasonal and storm-driven nutrient flux patterns and thus aid the policy maker in considering a variety of policy decisions. It is stressed that collecting the longest possible high-frequency data set, particularly for all forms of nutrients, is still of the utmost importance for effective water quality monitoring and identifying the full range of observed concentrations, including incidental losses (see Fig. 2c). There may be some evidence here that collecting higher-resolution data for nutrients helps to explain the distribution values and addresses the issues of "noise" and diurnal variability (e.g. the fluctuations in P concentrations observed in the River Enborne by Wade et al., 2012; Halliday et al., 2014) in the data sets. Even so, it may still be beneficial to aggregate sub-daily data to daily data as a means to optimise the capabilities of a process based model, such as CRAFT, and make use of all the relevant information actually contained in high-frequency monitoring data.

The Frome case study revealed a number of interesting factors, leading to the exploration of a management intervention (MI) scenario. The mean annual SRP concentration that has to be attained in order to comply with the WFD standards for P is $0.06\,\mathrm{mg\,L^{-1}}$ P, which was achieved by the MI scenario (modelled mean $= 0.053\,\mathrm{mg\,L^{-1}}$ P) by reducing the SRP concentrations in the model's flow pathways to reduce the modelled SRP load by 61.7 %. There are no explicitly defined guidelines for nitrate, except that the maximum concentration must not exceed $11.9\,\mathrm{mg\,L^{-1}}$ N, which is imposed on all surface waters in the EU under the terms of the 1991 Nitrates Directive. In terms of nitrate management in the Frome catchment, the observed data from 1997 to 2006 indicated that concentrations (at least in surface water) were below the limit, without any reductions due to nutrient and/or runoff management. CRAFT was able to reproduce the seasonality in the observed nitrate concentrations and also make predictions of the likely reductions in concentrations and yields, due to improved management of diffuse sources in the catchment. This MI scenario reduced mean concentrations from 6 to $4.3\,\mathrm{mg\,L^{-1}}$ N at the outlet of the Frome. Recent studies of long-term trends (Smith et al., 2010; Bowes et al., 2011) have shown that nitrate concentrations have been observed to be rising in the Frome since the 1940s; however, over the simulation period, the rate of increase has slowed down and CRAFT could predict the weekly time series reasonably well as a result. The MI scenario shows that interventions to reduce concentrations of nitrate in rapid subsurface flow can have a significant impact at reducing the total nitrate load by 34 %, although this may occur at the expense of pollution swapping, leading to increased nitrate fluxes to deep groundwater. Interventions to reduce the concentration of nitrate in flows originating from deeper groundwater were not investigated, as these improvements could take decades to be observable at the monitoring point at the catchment outlet (Smith et al., 2010).

The results of this case study may best be viewed as event-driven export coefficients when the origin of the nutrient is tied to the pathway that generated it. This informs the user as to the aggregate effect of local policy changes and the importance of storm size and frequency. Whilst we have shown that those impacts are still uncertain, further intervention in order to guarantee the success of new policies is encouraged (Cuttle et al., 2007). Equally, locally observed environmental problems caused by high nutrient concentrations may well be lost due to mixing effect at the mesoscale (i.e. catchment outlet).

CRAFT has been shown to fit the dominant seasonal and event-driven phenomena. The benefits of using CRAFT are twofold. Firstly, it is a useful tool which conveys the mixed effect of land use and hydrological process at the mesoscale for policy makers. The modelling process assumes that the policy maker or informed end user will then manipulate the model to see the likely impacts of regulations. The burden is still on the user to translate policy into the likely local impact – for example, reduction in N and P loading, more efficient use of N and P in soils, and the acute loss of P from well-connected flow pathways. Once the parameters are changed, the net effect at the mesoscale can then be seen instantaneously. The user is encouraged to try many scenarios and explore the parameter space. Secondly, its interactive graphical user interface allows an instantaneous view of the changes made to the model parameters, which in itself is informative. The range of the fluxes seen can inform the user about the uncertainty of the model when making decisions and can alert them to unexpected outcomes such as pollution swapping.

The sensitivity and uncertainty analysis carried out with the hydrological model showed the impact on the resultant nutrient fluxes. CRAFT is intended to be just one of many required for setting policy at the mesoscale. Equally, despite the uncertainty in the model, the outputs should encourage the user in that a range of local scale polices can have a large impact on the final nutrient flux at the mesoscale. When used with other model tools and observed data, the CRAFT mesoscale model can play a key role in evaluating land use change and the need to conform to WFD targets.

Appendix A:

Table A1. Nomenclature.

CEH	Centre for Ecology and Hydrology
DG	Deep groundwater (store)
DSS	Dynamic surface store
DTC	Demonstration test catchments
DWC	Dry weather concentration (i.e. in baseflow)
EMC	Event mean concentration (i.e. in overland flow)
HFD	High-frequency data set of nitrogen and phosphorus, recorded several times per day in the River Frome
LTD	Long-term data set of weekly nitrogen and phosphorus measurements also in the River Frome, modelled by the baseline scenario
MBE	Mass balance error
MI	Management intervention (scenario)
MIR	Minimum information required
$\boldsymbol{n}$	Vector of nutrients simulated by the model (e.g. N and P)
NSE	Nash–Sutcliffe efficiency (model performance metric)
PP	Particulate phosphorus (i.e. the insoluble fraction
SRP	Soluble reactive phosphorus (from samples filtered using 0.45 µm paper)
SS	Subsurface soil (store)
TON	Total oxidised nitrogen (nitrate + nitrite).
TP	Total phosphorus (soluble + insoluble forms)
WFD	Water Framework Directive
WWTP	Wastewater treatment plant (sewage treatment works)

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