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Research article

Modelling the impacts of agricultural management practices on river water quality in Eastern England

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A B S T R A C T

Agricultural diffuse water pollution remains a notable global pressure on water quality, posing risks to aquatic ecosystems, human health and water resources and as a result legislation has been introduced in many parts of the world to protect water bodies. Due to their efficiency and cost-effectiveness, water quality models have been increasingly applied to catchments as Decision Support Tools (DSTs) to identify mitigation options that can be introduced to reduce agricultural diffuse water pollution and improve water quality. In this study, the Soil and Water Assessment Tool (SWAT) was applied to the River Wensum catchment in eastern England with the aim of quantifying the long-term impacts of potential changes to agricultural management practices on river water quality. Calibration and validation were successfully performed at a daily time-step against observations of discharge, nitrate and total phosphorus obtained from high-frequency water quality monitoring within the Blackwater sub-catchment, covering an area of 19.6 km^2. A variety of mitigation options were identified and modelled, both singly and in combination, and their long-term effects on nitrate and total phosphorus losses were quantified together with the 95% uncertainty range of model predictions. Results showed that introducing a red clover cover crop to the crop rotation scheme applied within the catchment reduced nitrate losses by 19.6%. Buffer strips of 2 m and 6 m width represented the most effective options to reduce total phosphorus losses, achieving reductions of 12.2% and 16.9%, respectively. This is one of the first studies to quantify the impacts of agricultural mitigation options on long-term water quality for nitrate and total phosphorus at a daily resolution, in addition to providing an estimate of the uncertainties of those impacts. The results highlighted the need to consider multiple pollutants, the degree of uncertainty associated with model predictions and the risk of unintended pollutant impacts when evaluating the effectiveness of mitigation options, and showed that high-frequency water quality datasets can be applied to robustly calibrate water quality models, creating DSTs that are more effective and reliable.

1. Introduction

Agricultural diffuse water pollution remains a notable global pressure on surface water and groundwater quality (Carpenter et al., 1998; Vörösmarty et al., 2010; European Environment Agency, 2012), and trends suggest that agricultural expansion will continue to exacerbate those pressures well into the 21st Century (Tilman et al., 2001). Legislation has been introduced in many parts of the world to protect water bodies from agricultural diffuse water pollution and to improve water quality, including the Nitrates Directive and Water Framework Directive (WFD) in Europe (Council of the European Union, 1991, 2000), and the Clean Water Act in the United States (United States Environmental Protection Agency, 2002). The WFD seeks to improve or maintain water quality through the establishment of River Basin Management Plans (RBMPs) and the development of Programmes of Measures (PoMs), which can be implemented to ensure that each water body within a river basin district achieves good ecological and chemical status (Council of the European Union, 2000). Member states committed to achieving this status by 2015 but many water bodies were not expected to meet the necessary water quality standards before this deadline (European Environment Agency, 2012). According to Solheim et al. (2012), 56% of rivers, 44% of lakes, 67% of transitional waters and 49% of coastal waters that have been classified in

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Europe do not achieve a good ecological status or potential and 6% of rivers, 2% of lakes, 10% of transitional waters, 4% of coastal waters and 25% of groundwater bodies by surface area are of a poor chemical status. Agricultural diffuse water pollution is cited as a significant pressure in 40% of rivers and coastal water bodies and one-third of lakes and transitional water bodies. Such poor water quality has consequences for the health of aquatic ecosystems, biodiversity, human health, the use of water in industry and agriculture and as a resource for public water supply and recreation (Carr and Neary, 2008).

In Europe, agricultural diffuse water pollution contributes 50–80% of the total nitrogen load and approximately 50% of the total phosphorus load in surface water bodies (European Environment Agency, 2005; Kronvang et al., 2009). In the United Kingdom (UK) specifically, agricultural diffuse water pollution is estimated to be responsible for 61% of the total nitrogen load and 28% of the total phosphorus load experienced within surface water bodies (Hunt et al., 2004; White and Hammond, 2007). Nutrient enrichment within surface waters due to the oversupply of phosphorus and nitrogen in agriculture increases the risk of eutrophication (Richardson and Jørgensen, 1996; Withers and Lord, 2002; Carr and Neary, 2008). While phosphorus pollution has implications for ecosystem health, nitrate pollution also has implications for the supply of water and human health (Withers and Lord, 2002). To protect human health, water is considered to be unfit for human consumption under the Drinking Water Directive applied within Europe if it contains a nitrate concentration above 50 mg L^{-1} (equivalent to 11.3 mg NO_3-N L^{-1}) (Council of the European Union, 1998), but many surface water and groundwater bodies within the UK contain concentrations of nitrate that approach or exceed this limit (European Environment Agency, 2012).

To develop PoMs that can be implemented under the WFD, authorities responsible for establishing RBMPs must be able to assess the effectiveness of potential mitigation options. Given the limited resources available to monitor and quantify the impacts of mitigation options in-field, and the need to provide timely evidence to inform policy, water quality models which can quantify the impacts of mitigation options on nutrient losses have been increasingly applied as Decision Support Tools (DSTs) within Decision Support Systems (Collins and McGonigle, 2008; Volk et al., 2008). This approach can be used to develop targeted mitigation plans, identify critical source areas and times, assess the cost-effectiveness of mitigation options, identify pollution swapping and involve stakeholders in the development of suitable management plans (Bouraoui and Grizzetti, 2014). Effective dialogue and engagement between stakeholders and scientific experts is essential to ensure that the PoMs are appropriate, cost-effective and sustainable and to maximise the effectiveness of the mitigation practices that are introduced (Van Ast, 2000; Gerrits and Edelenbos, 2004).

The Benchmark Models for the Water Framework Directive project established a set of criteria to assess which models have the potential to assist in the implementation of the WFD (Saloranta et al., 2003). As part of this project, the suitability of the Soil and Water Assessment Tool (SWAT) water quality model for assessing the impacts of mitigation options proposed to meet WFD targets on water quality was examined by Bärlund et al. (2007). Rode et al. (2008) and Volk et al. (2009) also applied SWAT to examine the potential for changes in catchment management to ensure that water bodies achieve WFD targets. SWAT has been widely and successfully applied to assess the impacts of agricultural mitigation options on water quality and can therefore be considered to be an appropriate DST for assisting authorities in managing catchments to achieve statutory water quality targets (e.g. Santhi et al., 2006; Hu et al., 2007; Ullrich and Volk, 2009; Lam et al., 2011; Moriasi et al., 2011; Glavan et al., 2012; Aouissi et al., 2014; Boithias et al., 2014; Santhi et al., 2014). Examples of mitigation options that have been modelled include buffer strips, nutrient management plans, alternative tillage techniques, alternative crop rotations and changes in land use.

In this study, based in the River Wensum catchment in Eastern England (Fig. 1), the availability of a high-quality, high-frequency dataset of water quality enabled the performance of SWAT in simulating multiple pollutants at a daily time-step to be assessed. SWAT was also used to investigate the impacts of agricultural mitigation options on long-term water quality at a daily resolution and to assess the uncertainties of the predicted impacts of mitigation options on water quality. The unique water quality dataset applied within this study is derived from continuous monitoring at a 30-min temporal resolution. Such a monitoring strategy reduces the uncertainty associated with estimates of in-stream nutrient loads relative to datasets derived from fewer samples collected at longer time intervals and ensures that the model applied within this investigation has been robustly calibrated. This lower uncertainty allows the model to be applied with a higher degree of confidence, creating a more effective and reliable DST.

There is no standard or universally accepted metric applied to assess model performance but Moriasi et al. (2007) suggested that models should achieve a Nash-Sutcliffe Efficiency (NSE) coefficient of greater than 0.5 for flow, nitrogen and total phosphorus at a monthly time-step for performance to be considered satisfactory. If we consider this performance criterion to apply at all time-steps, over half of the 115 SWAT hydrological assessments and 37 SWAT pollutant loss studies summarised by Gassman et al. (2007), achieved this level of model performance, but some studies reported poor results for all variables particularly at a daily time-step and it is in this context that we consider the performance of SWAT within the River Wensum catchment.

Since 2010, the River Wensum catchment has been the focus of the Wensum Demonstration Test Catchment (DTC) Project which aims to provide evidence to test the hypothesis that it is economically feasible to reduce agricultural diffuse water pollution through the introduction of agricultural mitigation practices whilst maintaining agricultural productivity (Wensum Alliance, 2014). The Blackwater sub-catchment has been selected as a pilot area where the effects of changes in management will be investigated and is considered to be representative of the rest of the River Wensum catchment. To identify the mitigation options that are most relevant for the River Wensum catchment, there has been close cooperation and engagement between local land owners, farm managers, environmental organisations, government agencies and scientific experts. With knowledge gained from these stakeholders, the aim of this investigation is to apply SWAT to the Blackwater sub-catchment to quantify the long-term impacts of potential changes to agricultural practices on water quality, to assess the uncertainties of those predictions and to identify mitigation options that have the potential to be applied within similar arable catchments to improve water quality. This is one of the first studies to quantify the impacts of agricultural mitigation options, both singly and in combination, on long-term water quality for nitrate and total phosphorus at a daily time-step, in addition to providing an estimate of the uncertainties of those impacts.

In the remaining parts of this paper, a brief review of the study area, the datasets used and the methodology adopted in applying SWAT to the Blackwater sub-catchment is provided. A detailed summary of the mitigation options that were selected and modelled is also supplied. The results of model calibration and validation and the impacts of each agricultural measure on water quality, both singly and in combination, are also presented and discussed. Finally, conclusions and a summary of findings are

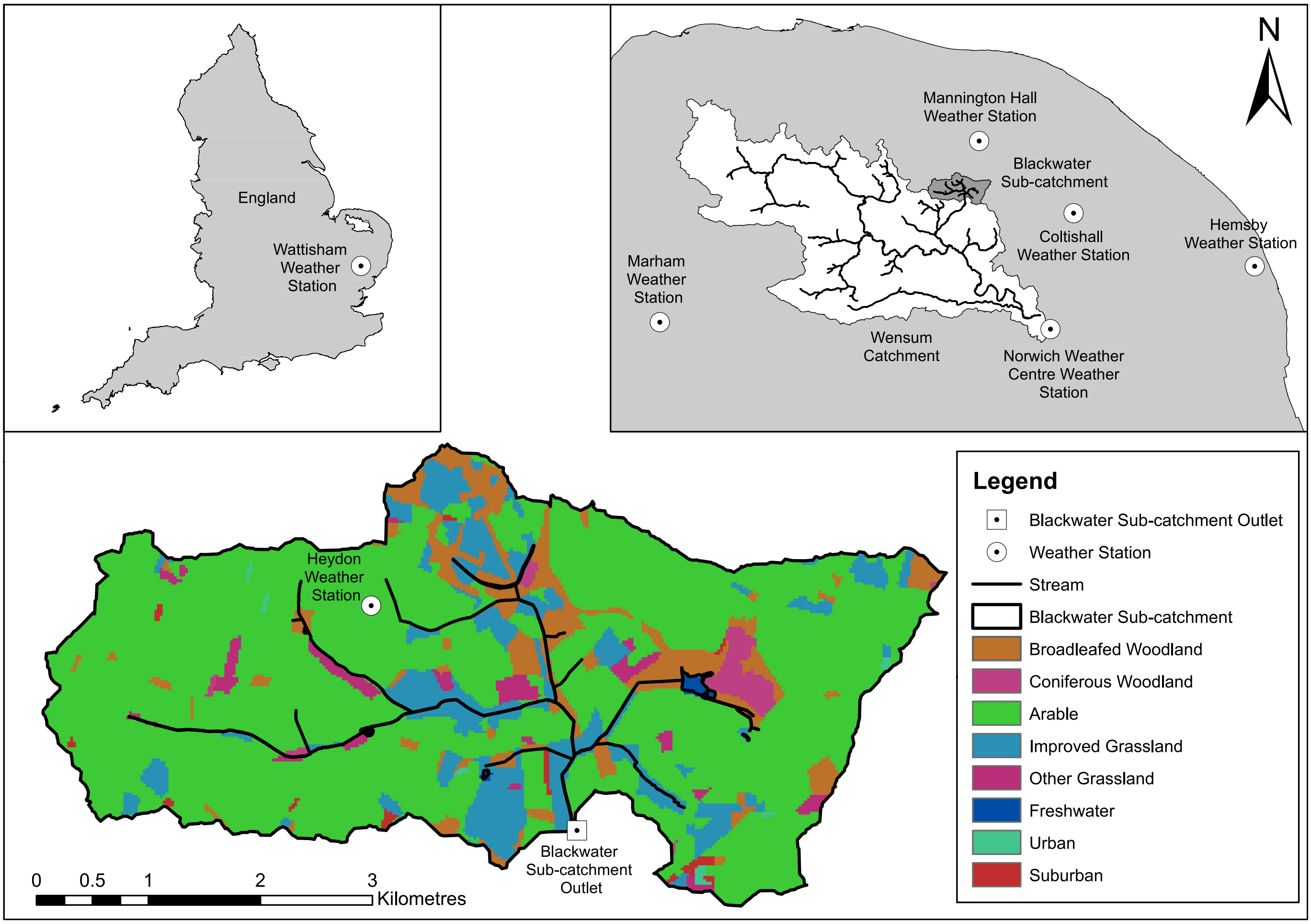

Fig. 1. A map of the location and land cover of the Blackwater sub-catchment in relation to the River Wensum catchment within England. The locations of the weather stations used in this investigation and the outlet of the sub-catchment are also shown. Based upon LCM2007 © NERC (CEH) 2011. Contains Ordnance Survey data © Crown Copyright 2007. © third party licensors.

provided.

2. Materials and methods

2.1. Study area

The River Wensum has a total catchment area of 675 km^2 and is designated a Special Area of Conservation (SAC), a Drinking Water Protected Area and 71 km of the riparian zone are designated as a Site of Special Scientific Interest (SSSI) (Natural England, 1993; English Nature, 2005; Environment Agency, 2009). The importance of the River Wensum has also been recognised by the UK Biodiversity Action Plan, which designates the river as a priority chalk river habitat (Biodiversity Reporting and Information Group, 2007). The catchment has a temperate maritime climate and had a mean annual rainfall of 714 mm and an annual rainfall range of 542.6–878.8 mm during 1981–2010 (Met Office, 2014).

This study focuses on the Blackwater River, a tributary of the Wensum, which drains an area of 19.6 km^2 (Fig. 1). The characteristics of the Blackwater sub-catchment are typical of the wider River Wensum catchment and other catchments found in Eastern England. The topography of the sub-catchment is relatively subdued, with elevation ranging from 28 to 70 m above sea level, and 95% of the sub-catchment area has a slope of 5% or less. Streamflow within the Blackwater sub-catchment is derived from groundwater flow, lateral flow in the soil zone, surface runoff and contributions from an extensive tile drain network (Howson, 2012). During periods of low rainfall, streamflow is sustained by baseflow, with a baseflow index similar to that of the Wensum catchment as a whole equal to 0.80 (Outram et al., 2014). At the outlet of the Blackwater sub-catchment during the period from 1 December 2011 to 30 June 2014, 30-min resolution data recorded a daily mean discharge of 0.112 m^3 s^{-1} and daily mean concentrations of 6.16 mg NO$_3$-N L^{-1} and 0.089 mg P L^{-1} for nitrate and total phosphorus, respectively. Cretaceous Chalk deposits underlay the majority of the sub-catchment, with some Pleistocene Crag deposits on the south-eastern edge of the sub-catchment boundary (Hiscock, 1993). The bedrock geology is overlain by superficial deposits of Quaternary glacial origin composed of boulder clay, sands and gravel that attain a thickness of greater than 20 m (Hiscock, 1993; Hiscock et al., 1996).

2.2. The SWAT model and inputs

SWAT is a semi-distributed and physically based water quality model that operates at a continuous time-step (Arnold et al., 2012). The model is designed to simulate the effects of changes in management practices on surface water and groundwater hydrology, diffuse pollution and sediment erosion within catchments. Within SWAT, a catchment is divided into multiple sub-catchments which are then further divided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, slope and soil characteristics (Arnold et al., 2012). Physical processes in SWAT are split into two phases: (i) the land-based phase; and (ii) the channel-based phase (Neitsch et al., 2011). The former includes climate, hydrology, plant growth, erosion, nutrient cycles, pesticides and management practices. The latter routes water, sediment, nutrients and pesticides through the channel network. Input variables define physical properties within the model and parameters are used to define and perform management practices. The model simulates all of the key physical processes found within the Blackwater sub-catchment and is therefore considered to be a suitable model to apply. In order to construct a SWAT model of the Blackwater sub-catchment, ArcSWAT version 2012.10.0.14 was applied (Texas A&M University, 2015). The methodology applied to construct the model is available for reference in Winchell et al. (2013). Readers are referred to Neitsch et al. (2011) for a detailed review of the physical processes modelled within SWAT and Arnold et al. (2014) for a detailed overview of the model input requirements and outputs. Gassman et al. (2007) provide a detailed summary of over 250 previous publications relating to SWAT. Krysanova and Arnold (2008), Douglas-Mankin et al. (2010) and Tuppad et al. (2011) review the historical development and applications of the model and Arnold et al. (2012) present an overview of a methodology that can be adopted when applying the model. The model is subject to ongoing development and future landscape unit and grid-based versions will allow a more detailed spatial representation of catchment practices to be implemented within SWAT (Arnold et al., 2010; Bosch et al., 2010; Bonumá et al., 2014; Rathjens et al., 2015).

2.2.1. *Catchment agricultural practices*

Data from the Agricultural Census conducted by The Department for Environment, Food and Rural Affairs (Defra) was obtained for the River Wensum catchment for the period 1993–2010 in a 2 km grid square format. Data for the Blackwater sub-catchment was used to identify those crops commonly grown within the sub-catchment (Fig. 2) and to identify an appropriate crop rotation plan to implement within the SWAT model of the sub-catchment (Defra, 2016; EDINA, 2014). Based on this analysis, it was found that the most commonly grown crops within the catchment were wheat, barley, oilseed rape, spring beans and sugar beet. The Salle Estate, which is located in the Blackwater sub-catchment, manages 2000 ha of arable land and operates a seven-year crop-rotation that includes those crop types identified in the agricultural census data (Salle Farms Ltd, 2014). Listed in order of cultivation, the seven-year crop-rotation operated within the sub-catchment and applied within the SWAT model consists of winter barley, winter oilseed rape, winter wheat, sugar beet, spring barley, spring beans and winter wheat (Table 1). The rotation was initiated at different starting points within the rotation based on crop-type and was distributed randomly within the model because actual crop distributions within the sub-catchment were unknown. The Defra RB209 Fertiliser Manual was used to identify appropriate fertiliser application rates for each crop included in the crop-rotation (Defra, 2010a). The timings of planting, harvesting, field tillage and fertiliser application were determined from UK Agriculture (2014) for all crops except sugar beet where the source used was British Sugar (2014).

To assess the impacts of mitigation options on agricultural diffuse water pollution and water quality within the Blackwater sub-catchment, a variety of mitigation options have been introduced on the Salle Estate as part of the Wensum DTC Project (Lovett et al., 2015). The mitigation options include the introduction of a cover crop during the autumn and winter months which is intended to protect soils from erosion when they would otherwise be bare, to reduce the leaching of nutrients from soils during wet winter months and, when destroyed, to act as a ‘green manure’, slowly releasing nutrients to the surrounding soil for subsequent crops (Rubæk et al., 2011). The use of strip tillage to establish autumn and spring-sown crops, with the intention of reducing sediment and nutrient loss in surface runoff, has been introduced as an additional mitigation option in some pilot areas of the sub-catchment.

2.2.2. *Meteorological data*

The meteorological inputs required to perform simulations within SWAT include daily observations of precipitation, mean wind speed, maximum and minimum temperature, solar radiation and mean relative humidity (Arnold et al., 2014). If no observations are available, SWAT includes a weather generator which has the capacity to generate estimates of meteorological variables.

Observations of meteorological variables recorded from January 1980 to June 2014 were obtained from UK Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data for application within the model (Met Office, 2012). Observations of daily minimum and maximum temperature, wind speed and relative humidity were obtained from the MIDAS weather station located at Marham (MIDAS Station ID: 409), which is sited approximately 40 km to the south-west of the Blackwater sub-catchment. Observations of daily sunshine hours recorded at Marham weather station were used to estimate a daily record of incident solar radiation for the sub-catchment. Where observations of

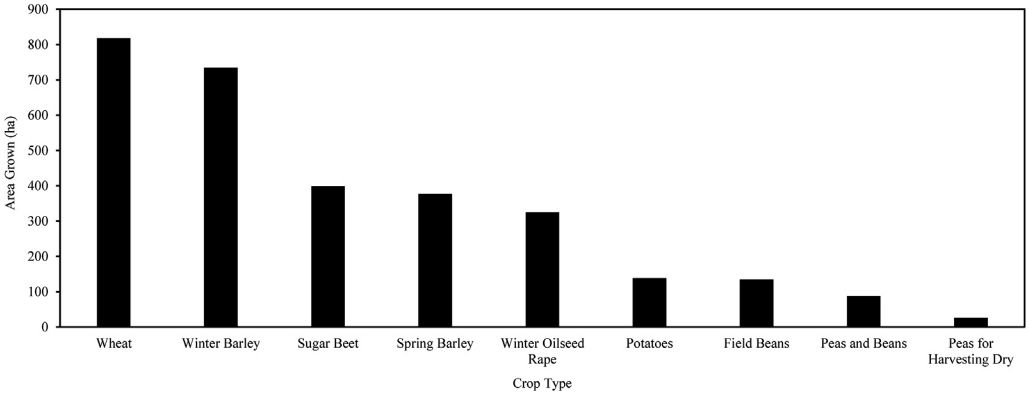

Fig. 2. The area of each crop type grown within the Blackwater sub-catchment according to the 2010 Agricultural Census conducted by the Department for Environment, Food and Rural Affairs (Defra, 2016; EDINA, 2014).

Table 1
The seven year crop-rotation scheme and management operations applied within the SWAT model of the Blackwater sub-catchment.

Year	Month	Day	Management operation	Description
1	9	15	Tillage	Generic fall ploughing operation
1	9	30	Tillage	Roterra harrow tillage operation
1	10	1	Cultivation	Plant winter barley
2	3	1	Fertiliser application	Apply 40 kg ha^{-1} elemental nitrogen
2	3	1	Fertiliser application	Apply 60 kg ha^{-1} phosphate
2	4	1	Fertiliser application	Apply 70 kg ha^{-1} elemental nitrogen
2	7	31	Harvest	Harvest winter barley
2	8	15	Tillage	Generic fall ploughing operation
2	8	31	Tillage	Roterra harrow tillage operation
2	9	1	Cultivation	Plant winter oilseed rape
3	3	1	Fertiliser application	Apply 60 kg ha^{-1} elemental nitrogen
3	3	1	Fertiliser application	Apply 50 kg ha^{-1} phosphate
3	4	1	Fertiliser application	Apply 60 kg ha^{-1} elemental nitrogen
3	7	31	Harvest	Harvest winter oilseed rape
3	9	15	Tillage	Generic fall ploughing operation
3	9	30	Tillage	Roterra harrow tillage operation
3	10	1	Cultivation	Plant winter wheat
4	3	1	Fertiliser application	Apply 40 kg ha^{-1} elemental nitrogen
4	3	1	Fertiliser application	Apply 60 kg ha^{-1} phosphate
4	5	1	Fertiliser application	Apply 120 kg ha^{-1} elemental nitrogen
4	8	31	Harvest	Harvest winter wheat
4	9	15	Tillage	Generic fall ploughing operation
5	3	17	Fertiliser application	Apply 50 kg phosphate
5	3	31	Tillage	Roterra harrow tillage operation
5	4	1	Cultivation	Planting sugar beet
5	4	1	Fertiliser application	Apply 40 kg ha^{-1} elemental nitrogen
5	5	1	Fertiliser application	Apply 40 kg ha^{-1} elemental nitrogen
5	10	31	Harvest	Harvest sugar beet
5	11	15	Tillage	Generic fall ploughing operation
6	1	31	Tillage	Roterra harrow tillage operation
6	2	1	Cultivation	Plant spring barley
6	4	1	Fertiliser application	Apply 70 kg ha^{-1} elemental nitrogen
6	4	1	Fertiliser application	Apply 45 kg ha^{-1} phosphate
6	8	31	Harvest	Harvest spring barley
6	11	15	Tillage	Generic fall ploughing operation
7	1	31	Fertiliser application	Apply 40 kg ha^{-1} phosphate
7	1	31	Tillage	Roterra harrow tillage operation
7	2	1	Cultivation	Plant spring beans
7	8	31	Harvest	Harvest spring beans
7	9	15	Tillage	Generic fall ploughing operation
7	9	30	Tillage	Roterra harrow tillage operation
7	10	1	Cultivation	Plant winter wheat
8	3	1	Fertiliser application	Apply 40 kg ha^{-1} elemental nitrogen
8	3	1	Fertiliser application	Apply 60 kg ha^{-1} phosphate
8	5	1	Fertiliser application	Apply 120 kg ha^{-1} elemental nitrogen
8	8	31	Harvest	Harvest winter wheat

daily sunshine hours are missing from the Marham record, observations recorded at the nearby MIDAS weather stations located at Coltishall (MIDAS Station ID: 429), Norwich Weather Centre (MIDAS Station ID: 408), Hemsby (MIDAS Station ID: 433) and Wattisham (MIDAS Station ID: 440), selected in order of their proximity to the sub-catchment and the availability of data, were used to interpolate the missing data. Observations of daily precipitation were obtained from the MIDAS weather station located at Heydon (MIDAS Station ID: 4807) (Fig. 1). Where observations of precipitation are missing from the Heydon record, observations recorded at the nearest MIDAS weather station, located at Mannington Hall (MIDAS Station ID: 24219), were used to interpolate the missing data using the nearest-neighbour technique.

2.2.3. Water quality data

As part of the Wensum DTC Project, automated equipment including a pressure transducer housed in a stilling well, a Nitratax Plus SC sensor and a Phosphax Sigma analyser, have been used to continuously monitor river stage, nitrate and total phosphorus concentrations, respectively, at 30-min intervals at the outlet of the Blackwater sub-catchment since April 2011 (Fig. 1). Quality assurance and quality control procedures, including the comparison of high-frequency data to laboratory analysed spot samples, were conducted to ensure the validity of data included in this study. Flow gauging using an electromagnetic open channel flow meter was conducted on 16 occasions during high, moderate and low flow events which, in combination with observations of river stage from the pressure transducers, was used to develop a power law stage-discharge rating curve which was applied to estimate daily mean discharge, nitrate load and total phosphorus load exported from the sub-catchment during the period 1 December 2011 to 30 June 2014. These estimates were applied within this study to perform model sensitivity analysis, calibration and validation. To identify the importance of any relationship between sediment transport and total phosphorus concentrations within the sub-catchment, 467 in-stream grab samples collected at the outlet of the Blackwater sub-catchment during the period October 2010 to March 2015 were used to develop a log-log regression model and conduct a linear regression *t*-test to test the hypothesis that the relationship between the concentration of total suspended solids and the concentration of total phosphorus was significant.

2.2.4. Geographical datasets

The digital terrain model applied within this study has a resolution of 5 m and was obtained from the NEXTMap British Digital Terrain Model Dataset (Itermap Technologies, 2007). Land cover within the study area was identified from the Land Cover Map 2007 (LCM2007) raster dataset which has a resolution of 25 m and divides land cover into 23 distinct classes based on the Broad Habitats defined within the UK Biodiversity Action Plan (Morton et al., 2011). According to LCM2007, land cover within the Blackwater sub-catchment is largely arable with 86.05% of the land area utilised for agricultural purposes (Morton et al., 2011). The dominance of the arable farming industry within the sub-catchment is reflected by the fact that 74.22% of the land area is utilised for growing crops and 11.83% as grazing pasture. Woodland, other areas of grassland and heathland, urban areas and surface water bodies including wetland environments account for the remaining area.

A map of soil types within the sub-catchment was derived from the National Soil Map (NATMAP) vector dataset which displays the spatial occurrence of 300 distinct Soil Associations throughout England and Wales (Cranfield University, 2014a). Each Soil Association is composed of multiple Soil Series and possesses distinct properties. According to NATMAP, five different Soil Associations are present within the Blackwater sub-catchment. Burlingham 1, Wick 2 and Wick 3 cover 83.72% of the sub-catchment and are composed of loamy soils, Beccles 1 covers 16.17% of the sub-catchment and is composed of loamy over clayey soils and Isleham 2 covers 0.11% of the sub-catchment and is composed of sandy soils (Cranfield University, 2014b). The properties of each Soil Association, as required by SWAT, have been determined from the Horizon Fundamentals, Horizon Hydraulics, NSI Textures and NSI Profile datasets (Cranfield University, 2014c, d). The properties required by SWAT for each layer of each soil type include the depth of soil layer, moist bulk density, available water capacity, saturated hydraulic conductivity, sand, silt, clay and organic carbon content, maximum rooting depth within the soil profile, the fraction of porosity from which anions are excluded, moist albedo of the soil surface and erodibility (Arnold et al., 2014).

2.2.5. Model calibration and validation

In order to conduct a sensitivity analysis and to perform model calibration and validation, the Sequential Uncertainty Fitting version 2 (SUFI-2) optimisation algorithm (Abbaspour et al., 2004, 2007) was applied within the SWAT Calibration and Uncertainty Program (SWAT-CUP) version 5.1.6.2 (Abbaspour, 2014). SUFI-2 is based on the concept of equifinality, which posits that multiple models (i.e. multiple parameter sets) provide equally acceptable predictions and as such, parameter values are treated as uncertain (Beven, 1993; Beven and Freer, 2001). Model parameters selected for calibration were first assigned an initial global uncertainty range within SWAT-CUP (Table 2). Sensitivity analysis was then performed to identify those parameters that model outputs were sensitive to. In general, a parameter should be included in calibration if sensitivity analysis identifies that there is a 95% probability that the sensitivity of a variable to a particular parameter is significant. Only sensitive parameters were included in the calibration of the model at a daily time-step against observations of discharge and nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment. Using the sensitive parameters, five iterations of 1000 simulations were performed to calibrate the model. The parameter ranges were updated after each iteration, as identified by the SUFI-2 optimisation algorithm, until prediction uncertainty and model performance was considered satisfactory. The model was applied at a daily time-step during the period from 1 December 2011 to 30 June 2014, of which 1 December 2011 to 31 March 2013 and 1 April 2013 to 30 June 2014 were used as calibration and validation time periods, respectively. An initial warm-up period of four years was applied during calibration and validation to ensure that the model achieved a steady-state and to eliminate any initial bias. Validation involved evaluating model performance against observations recorded outside of the calibration time-period and was utilised as an additional test of model performance.

2.3. Objective functions

Moriasi et al. (2007) recommend that three quantitative statistics are used as objective functions to evaluate model performance, including the Nash-Sutcliffe Efficiency (NSE) coefficient, percentage bias (PBIAS) and the ratio of the root mean square error to the standard deviation of the measured data (RSR). Each of these statistical measures is defined below.

2.3.1. Nash-Sutcliffe efficiency coefficient

The Nash-Sutcliffe Efficiency (NSE) coefficient proposed by Nash and Sutcliffe (1970) is defined by Equation (1).

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)^2} \tag{1}$$

where: n is the total number of observations, Y_i^{obs} is the value of the observed variable at the ith time-step, Y_i^{sim} is the value of the simulated variable at the ith time-step and $\overline{Y^{obs}}$ is the mean value of the measured data considered.

NSE is a normalised statistic that describes the degree of the ‘goodness-of-fit’ between model predictions and observations and can vary between $-\infty$ and 1, where a value of 1 represents a perfect fit. An NSE value of between 0 and 1 is generally recognised as acceptable model performance, whilst a value of less than 0 indicates that the mean of the measured data is a better predictor of a variable compared to the model and indicates unsatisfactory model performance.

2.3.2. Percent bias

Percent bias (PBIAS) is described as the average tendency of simulated data to overestimate or underestimate a variable relative to observations and is defined by Equation (2). The optimum value of PBIAS is zero, indicating perfect agreement between model simulations and observations. A negative PBIAS value indicates overestimation and a positive value indicates underestimation.

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)*100}{\sum_{i=1}^{n}\left(Y_i^{obs}\right)} \tag{2}$$

2.3.3. Ratio of the root mean square error to the standard deviation of the measured data (RSR)

RSR is described as the ratio of the Root Mean Square Error (RMSE) to the standard deviation (STDEV) of observed data and is defined by Equation (3) (Moriasi et al., 2007).

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)^2}\right]} \tag{3}$$

Table 2
The model parameters identified as significant by the sensitivity analysis and the initial and final calibrated ranges of each parameter.

Parameter	Description	Initial range	Final range
ALPHA_BF	Baseflow recession constant (1/day)	0–1	0.16–0.5
GW_DELAY	Groundwater delay time (days)	0–500	420–490
CH_N2	Manning's roughness coefficient for the main channel	0–0.3	0.03–0.081
CH_K2	Effective hydraulic conductivity of main channel alluvium (mm hr^{-1})	0–100	28–55
ALPHA_BNK	Baseflow recession constant for bank storage (1/day)	0–1	0.73–0.96
GW_REVAP	Groundwater evaporation coefficient	0.02–0.2	0.03–0.1
SURLAG	Surface runoff lag coefficient	1–24	1–4.18
REVAPMN	Threshold depth of water in the shallow aquifer required for the movement of water from the shallow aquifer to the unsaturated zone to occur (mm)	0–500	66–200
OV_N	Manning's roughness coefficient for overland flow	−0.2 to 0.2[a]	−0.035 to 0.087 [a]
CN2 AGRL	Runoff curve number for agricultural land	−0.2 to 0.2[a]	−0.15 to −0.05 [a]
CN2 FRSD	Runoff curve number for deciduous forest	−0.2 to 0.2[a]	−0.13 to 0.093 [a]
CN2 PAST	Runoff curve number for pasture land	−0.2 to 0.2[a]	−0.23 to −0.082 [a]
SOL_AWC	Available water capacity of soil layer (mm H_2O/mm soil)	−0.2 to 0.2[a]	0.16–0.39 [a]
SOL_Z	The depth from the soil surface to the bottom of soil layer (mm)	−0.2 to 0.2[a]	−0.041 to 0.028 [a]
DDRAIN	Depth to the sub-surface drain (mm)	900–1100	1060–1130
CDN	Denitrification exponential rate coefficient	0–0.1	0.033–0.059
ANION_EXCL	Fraction of void space from which anions are excluded	0.5–0.75	0.68–0.76
SDNCO	Fraction of field capacity above which denitrification takes place	0.9–1	0.94–0.96
SOL_NO3	Initial nitrate concentration in the soil layer (ppm)	0–100	69–96
SOL_SOLP	Initial soluble phosphorus concentration in the soil layer (ppm)	0–100	36–70
GWSOLP	Concentration of soluble phosphorus in groundwater (ppm)	0–0.25	0.06–0.19
SOL_BD	Moist bulk density of soil layer (g cm^{-3})	−0.2 to 0.2[a]	−0.25 to −0.054 [a]
RCN	Concentration of nitrogen in rainfall (mg L^{-1})	0–15	3.7–7
CMN	Rate factor for mineralisation of active organic nutrients in humus	0.001 −0.003	0.0017 −0.0023
NPERCO	Nitrate percolation coefficient	0–1	0.21–0.47
CH_ERODMO	The level of resistance to channel erosion	0–1	0.83–0.96
HLIFE_NGW	Half-life of nitrate in groundwater (days)	0–200	130–200
PHOSKD	Phosphorus soil partitioning coefficient (m^3 Mg^{-1})	100–200	150–180
TDRAIN	Time to drain soil to field capacity (hours)	0–72	46–64
ESCO	Soil evaporation compensation factor	0–1	0.86–1
SHALLST_N	Initial concentration of nitrate in shallow aquifer (ppm)	0–1000	130–310
ERORGP	Phosphorus enrichment ratio	0–0.1	0.0017–0.03

[a] A relative change which has been applied to the original value of the parameter where the value is multiplied by 1 plus a number from within the defined range.

RSR can vary from an optimum value of zero, indicating that there is no error between measured and simulated data, up to large positive values (Moriasi et al., 2007). A small RSR indicates a good model performance.

2.3.4. Model performance criteria

Moriasi et al. (2007) suggest that for a model to be considered to perform satisfactorily in simulating discharge, nitrate and total phosphorus loads at a monthly time-step, it must achieve a NSE of >0.5, a RSR of $<$ 0.7 and a PBIAS of ±25% for discharge and a NSE of >0.5, a RSR of $<$ 0.7 and a PBIAS of ±70% for nitrate and total phosphorus loads.

2.4. Mitigation scenarios

As part of the Wensum DTC Project, stakeholders, including farmers and farm-advisers, were consulted to identify and select potential agricultural mitigation options that can be applied within the Blackwater sub-catchment to improve water quality. The Farm Scale Optimisation of Pollutant Emission Reductions (FARMSCOPER) tool, described in detail by Zhang et al. (2012) and Gooday et al. (2014), was also applied to the sub-catchment to evaluate the impacts of potential mitigation options. FARMSCOPER is a spreadsheet-based DST which can identify the impacts of mitigation options on losses of multiple pollutants at the farm scale and assess the costs of each mitigation option (ADAS, 2015). Input requirements include mean annual precipitation, soil type and general farm type, based on the robust farm types classification scheme used by the UK Government (ADAS, 2015; Defra, 2010b). More detailed livestock and cropping information can be included if required. Since application within this project, the tool has undergone considerable development and it can now evaluate the impacts of mitigation options on biodiversity, energy and water use and can be applied at catchment and national scales (ADAS, 2015). The options identified as being suitable by stakeholders and the results provided by FARMSCOPER were broadly similar and were selected for evaluation in this study (see Table 3).

The control scenario (S0) is considered to represent current conditions and practices within the catchment and is used as the baseline scenario against which all other mitigation scenarios are assessed. Under scenario S0, a generic ploughing operation (primary tillage) is conducted on agricultural land within the model prior to establishing a crop. Primary tillage involves the aggressive mixing of surface materials and a mixing or burying of crop residues, pesticides and fertilisers leaving a rough soil surface. Primary tillage is followed by a further pulverisation of surface materials (secondary tillage) with a harrow (the Roterra harrow in the SWAT model). Secondary tillage involves a less aggressive mixing of soils,

Table 3
The agricultural measures scenarios applied within the SWAT model of the Blackwater sub-catchment.

Number	Name	Description
S0	Control scenario	Baseline scenario representing current conditions and practices
S1	Buffer strip (2 m)	Establishment of 2 m wide buffer strip on arable land
S2	Buffer strip (6 m)	Establishment of 6 m wide buffer strip on arable land
S3	Conservation tillage	A reduced tillage practice compared to the control scenario
S4	Zero tillage	No field tillage and the direct drilling of crops
S5	No tile drains	Removal or blockage of field drainage systems from all arable land
S6	Red clover cover crop	Introduction of a red clover cover crop to the crop rotation scheme
S7	Combined scenario	Buffer strip (6 m) (S2) and red clover cover crop (S6) scenarios combined

and pulverises soils into a finer material, removing air pockets and preparing the seedbed for cultivation (see Table 4). Such a detailed regime of tillage practice is not often conducted in SWAT. Under scenario S0, tile drains are included on all areas of arable land. Sandy soils (i.e. Isleham 2) where tile drains would otherwise have been excluded are not under arable land use anywhere within the catchment.

Scenarios S1 and S2 involve the introduction of buffer strips of 2 m and 6 m width, respectively, to areas of arable land within the sub-catchment. Scenario S1 represents a compulsory practice required under cross compliance rules in order to qualify for payments under Common Agricultural Policy schemes (Defra, 2015). Scenario S2 represents a voluntary practice that can be introduced in order to qualify for payments under the Entry Level Stewardship Scheme by achieving good environmental conditions (Natural England, 2014). Scenarios S3 and S4 consider the use of alternative tillage practices within the sub-catchment. Conservation or reduced tillage (S3) involves a less aggressive mixing of soils relative to the control scenario, whereas no tillage (S4) involves the direct drilling of seeds into soils without any cultivation. The mixing depth and mixing efficiency of each tillage technique considered by the SWAT model is provided in Table 4. Scenario S5 involves the removal or blockage of subsurface tile drainage systems from areas of arable land within the sub-catchment in order to simulate the slowing of runoff and solute transport. Under scenario S6, a red clover cover crop was applied within the modelled sub-catchment on two occasions during the crop rotation scheme when arable land would otherwise have been bare prior to the planting of spring crops. The two occasions are between the harvesting of winter wheat and the cultivation of sugar beet from the 1 September to 31 March and between the harvesting of spring barley and the cultivation of spring beans from 1 September to 31 January. Under this scenario, the red clover cover crop is terminated within the model at the end of the growing period and is ploughed back into the field to form a ‘green manure’. Finally, to assess the impacts of mitigation options on water quality when introduced in combination, a red clover cover crop (S6) and buffer strips of 6 m width (S2), the two mitigation options that were considered to be most effective at reducing nitrate and total phosphorus losses individually within the Blackwater sub-catchment, respectively, were modelled together under scenario S7. Each mitigation scenario was implemented across all areas of arable land within the sub-catchment.

To quantify the impacts of each mitigation option on long-term water quality, each scenario was run within the SWAT model at a daily time-step for the period 1990–2009, with an initial warm-up period of four years from 1986 to 1989. The period from 1990 to 2009 was used because precipitation during this period reflected full climatic variability, including droughts and wet periods. A total number of 1000 simulations were performed to simulate discharge, and nitrate and total phosphorus loads at a daily time-step under each scenario. This relatively long time period was used in order to consider the response of the sub-catchment to each measure under a variety of conditions over the long term.

3. Results and discussion

3.1. Calibration and validation

Sensitivity analysis identified that the parameters listed in Table 2 were required to be included in model calibration. In order to calibrate the model against observations of discharge, and nitrate and total phosphorus loads, five iterations of 1000 simulations were performed. The initial and final calibrated ranges of each parameter are provided in Table 2.

3.1.1. Discharge simulation

The model performance in simulating daily mean discharge at the outlet of the Blackwater sub-catchment during the calibration and validation time periods is shown in Figs. 3 and 4. When evaluated at a daily time-step, the model achieved NSE, PBIAS and RSR values of 0.77, −6.0% and 0.48, respectively, during the calibration period and values of 0.68, −24.8% and 0.57, respectively, during the validation period (Table 5). The 95% prediction uncertainty range bracketed 86% and 87% of observed flow data during calibration and validation periods, respectively, indicating that the model achieved a relatively good fit between predictions and observations overall. To evaluate the model performance at a monthly time-step against the performance criteria suggested by Moriasi et al. (2007), daily data were aggregated into monthly time-series. According to those criteria, the model can be considered to perform very well in simulating discharge at both daily and monthly time-steps during the calibration and validation periods (see Table 5). The negative PBIAS values achieved during both time periods indicate that the model tends to overestimate discharge. This overestimation is pronounced during prolonged dry periods in 2013 and 2014 and may indicate a deficiency in simulating baseflow during periods of drought.

Table 4
The mixing depth and efficiency of each tillage technique applied within the model.

Tillage technique	Mixing depth (mm)	Mixing efficiency (fraction)
Generic ploughing operation	150	0.95
Conservation tillage	100	0.25
Roterra harrow	5	0.80

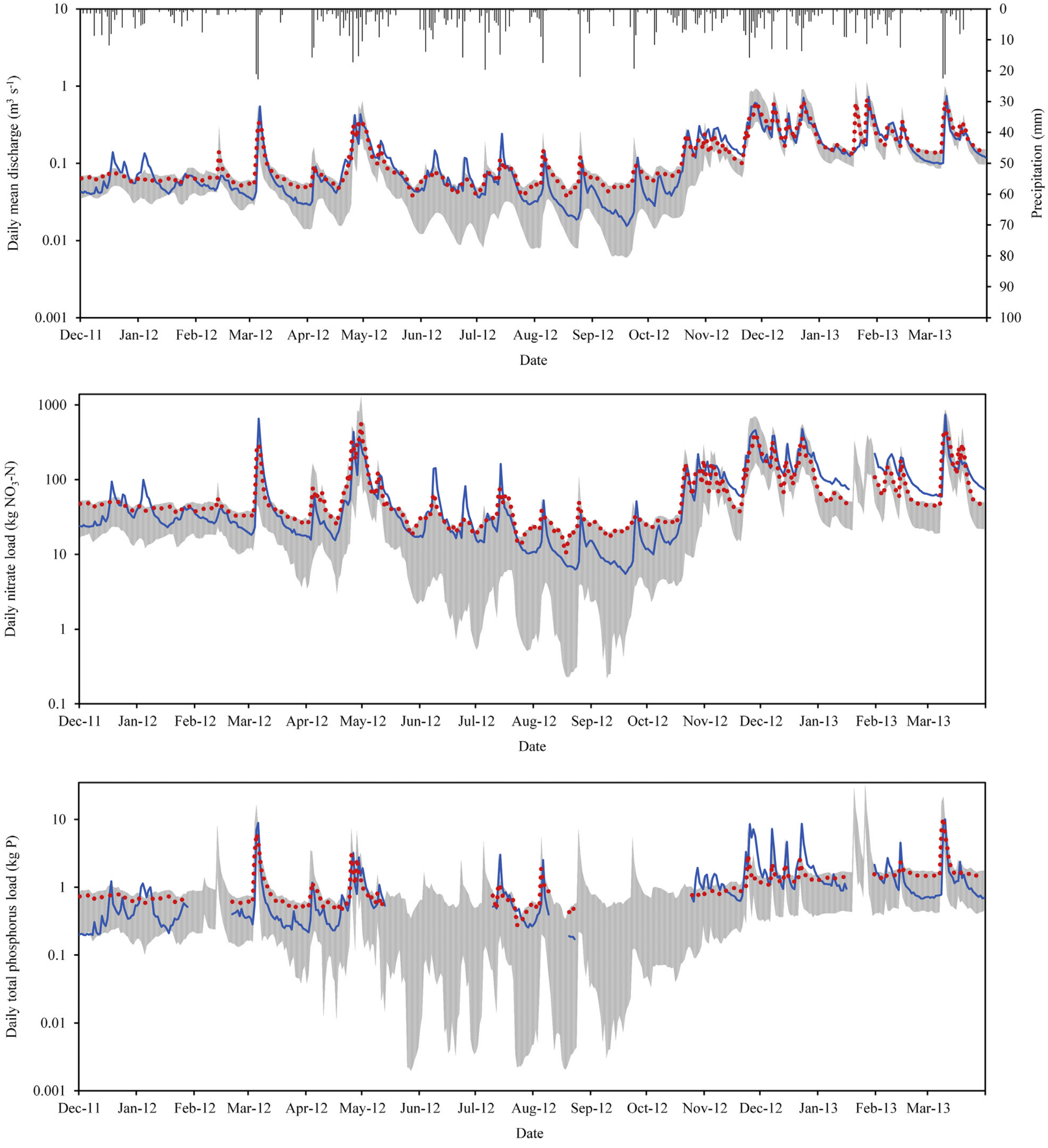

Fig. 3. Observed (solid line) and the best simulated (dotted line) daily mean discharge, nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment during the calibration time period (1 December 2011–31 March 2013). The 95% confidence interval is represented by the hatched area and the daily rainfall amount recorded at Heydon weather station is plotted in the top panel for reference.

3.1.2. *Nitrate simulation*

The model performance in simulating daily nitrate loads during the calibration and validation time periods is shown in Figs. 3 and 4, respectively. When evaluated at a daily time-step, the model achieved NSE, PBIAS and RSR values of 0.72, 5.6% and 0.53, respectively, during the calibration period and values of 0.46, 4.2% and 0.74, respectively, during the validation period (Table 5). The 95% prediction uncertainty range bracketed 76% and 72% of observed nitrate load data during calibration and validation periods, respectively, indicating that the model achieved a relatively good fit between predictions and observations overall. According to the criteria set out in Moriasi et al. (2007), the model performs very well in simulating nitrate loads during the calibration and validation periods if evaluated at a monthly time-step (see Table 5). When evaluated at a daily time-step however, there is a notable decline in model performance during the validation period.

A visual inspection of Fig. 4 indicates that the model generally performs well in simulating nitrate loads during the validation period however there is an observed tendency to underestimate some peaks in nitrate loads. Although the model tends to

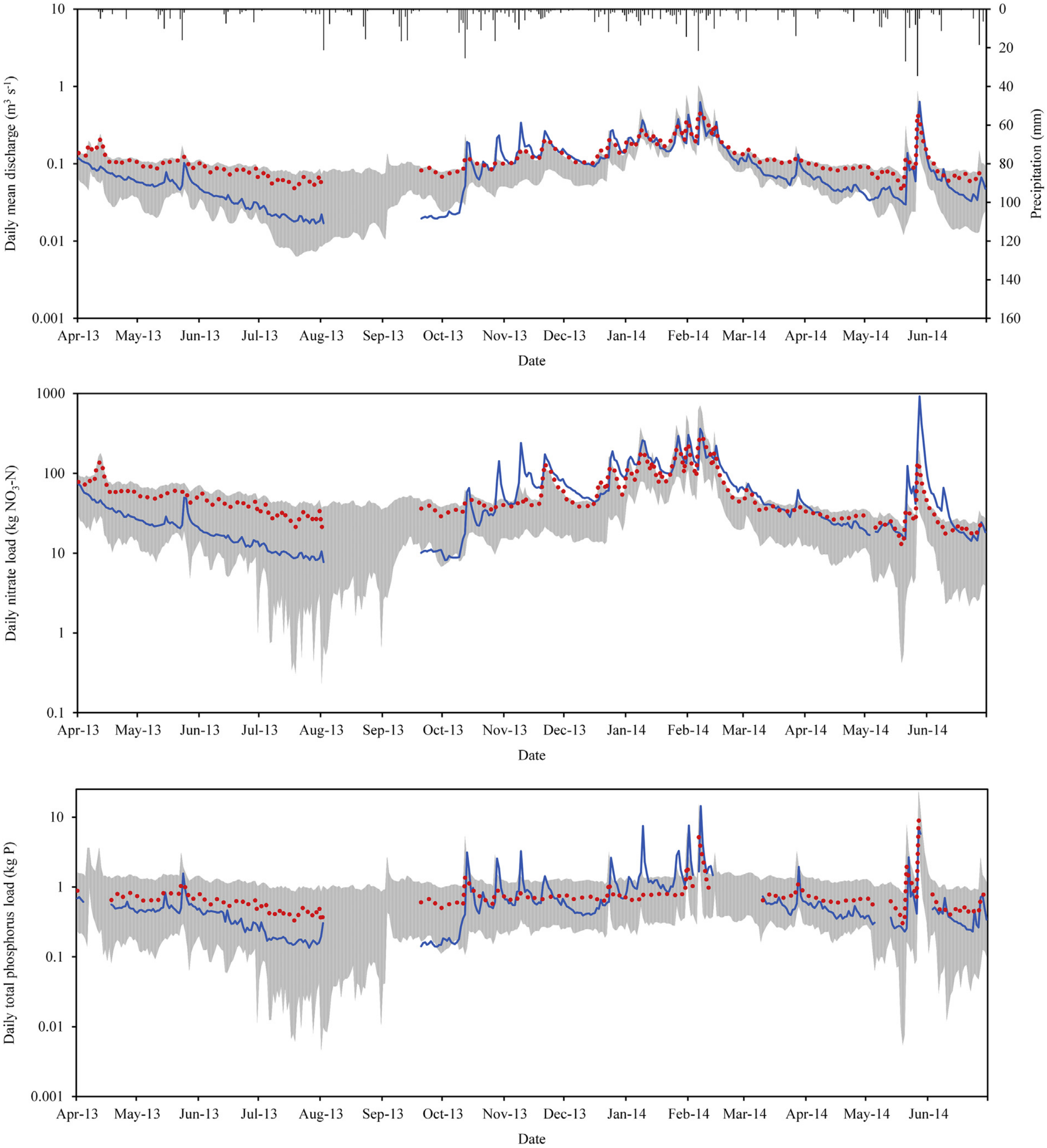

Fig. 4. Observed (solid line) and the best simulated (dotted line) daily mean discharge, nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment during the validation time period (1 April 2013–30 June 2014). The 95% confidence interval is represented by the hatched area and the daily rainfall amount recorded at Heydon weather station is plotted in the top panel for reference.

overestimate discharge in general, it failed to reproduce a number of peaks in discharge (e.g. during March 2012, June–August 2012 and October–December 2013) which appears to translate into an underestimation of nitrate loads. Four factors that may contribute to this deficiency are: (i) rating curve uncertainty under high-flow conditions due to a limited number of flow gauging observations recorded during storm events (McMillan et al., 2010); (ii) difficulties in modelling responses to extreme conditions (Zhang et al., 2014); (iii) difficulties in modelling antecedent conditions within a catchment (Yatheendradas et al., 2008); and (iv) incorrect timing of management practices (e.g. fertiliser application and tillage).

The model also greatly underestimates the mass of nitrate exported from the sub-catchment in response to 35 mm of rainfall recorded at Heydon weather station on 27 May 2014. This is the largest amount of precipitation to have occurred within the sub-catchment on any single day since 2008. During the three consecutive days following this event, nitrate loads observed at the sub-catchment outlet were over 7, 5 and 4 times the mass predicted by the best simulation respectively. It is possible that the response observed within the sub-catchment may result from an incidental loss of nitrate from a farm or from the connection of a previously unconnected nitrate source or so-called legacy stores (Outram et al., 2016) within the system. Such occurrences are difficult to account for within SWAT. If model performance in simulating

Table 5
The statistical performance of the model in simulating mean discharge, nitrate and total phosphorus loads at monthly and daily time-steps at the outlet of the Blackwater sub-catchment during the calibration (1 December 2011–31 March 2013) and validation (1 April 2013–30 June 2014) periods, respectively. NSE is the Nash-Sutcliffe Efficiency coefficient, PBIAS is percentage bias and RSR is the ratio of the root mean square error to the standard deviation of the measured data. The numbers enclosed in brackets are benchmark values suggested by Moriasi et al. (2007).

Variable	NSE	PBIAS (%)	RSR
Daily time-step:			
Calibration:			
Flow	0.77	−6.0	0.48
Nitrate	0.72	5.6	0.53
Total Phosphorus	0.44	0.8	0.75
Validation:			
Flow	0.68	−24.8	0.57
Nitrate	0.46	4.2	0.74
Total Phosphorus	0.36	−2.9	0.80
Monthly time-step:			
Calibration:			
Flow	0.95 (>0.5)	−5.9 (±25)	0.23 (<0.7)
Nitrate	0.86 (>0.5)	5.6 (±70)	0.37 (<0.7)
Total Phosphorus	0.63 (>0.5)	0.8 (±70)	0.61 (<0.7)
Validation:			
Flow	0.92	−15.6	0.28
Nitrate	0.81	−4.7	0.43
Total Phosphorus	0.60	8.5	0.64

nitrate loads at a daily time-step during the validation period is evaluated with these three outliers removed, NSE, PBIAS and RSR values of 0.68, −1.43% and 0.56 are achieved, respectively.

According to the criteria set out by Moriasi et al. (2007), the model can be considered to perform very well in simulating nitrate loads at a monthly time-step during the calibration and validation periods (see Table 5). Moriasi et al. (2007) recommend that, in general, the model performance criteria should be less strict when considering a shorter time-step. For the purposes of this investigation, the model is therefore considered to perform adequately in simulating nitrate loads at daily and monthly time-steps.

3.1.3. Total phosphorus simulation

The model performance in simulating daily total phosphorus loads during the calibration and validation time periods can be observed in Figs. 3 and 4, respectively. A visual inspection indicates that the model generally performs well in simulating total phosphorus loads in baseflow, however it fails to reproduce a number of peak events during the calibration and validation periods.

The sediment transport component of the SWAT model was not calibrated within this investigation because sediment observations were not available at daily or sub-daily resolutions. 467 stream water samples were, however, collected at the outlet of the Blackwater sub-catchment from October 2010 to March 2015 as part of the Wensum DTC Project and were used to develop a log-log regression model to test the hypothesis that there is a significant relationship between the concentration of total suspended solids and the concentration of total phosphorus (Fig. 5). A linear regression *t*-test found that this relationship has a P-value of >0.001 and is statistically significant. Because of the significance of this relationship and the sensitivity of total phosphorus losses to the transport of sediment during storm events, the lack of high-resolution data means that sediment losses may not be adequately simulated by the model. This observation may account for the apparent deficiency of the model in simulating total phosphorus loads during storm events. Other explanations which may account for the poor performance of the model in reproducing peak total phosphorus events are that: (i) the general representation of fertiliser practice within the model is not sufficiently accurate for total phosphorus at a daily resolution; and (ii) the accumulation of sediment and sediment-associated nutrients within complex tile drainage networks and their subsequent removal during storm events is difficult to reproduce within a generalised model. For example, Kronvang et al. (1997) investigated the transport of sediment and phosphorus in an arable catchment in Denmark and found that the majority of losses occurred during storm events, with subsurface drainage found to be an important pathway.

Despite the above deficiencies, when evaluated at a daily time-step the model achieved NSE, PBIAS and RSR values of 0.44, 0.8% and 0.75, respectively, during the calibration period and values of 0.36, −2.9% and 0.80, respectively, during the validation period (Table 5). The 95% prediction uncertainty range bracketed 85% and 92% of observed total phosphorus load data during calibration and validation periods, respectively, indicating that the model achieved a relatively good fit between predictions and observations overall. Although the model does not achieve the satisfactory performance criteria suggested by Moriasi et al. (2007) when simulating total phosphorus loads at a daily time-step, the small percentage bias values achieved during the calibration and validation time periods indicate that the model simulates overall total phosphorus loads with reasonable accuracy (Table 5). When evaluated at a monthly time-step, the model performance in simulating total phosphorus loads does achieve the satisfactory performance criteria (Table 5). The priority of this investigation is to achieve good model performance in simulating losses of total phosphorus over the long-term. Given the good performance in this respect, for the purposes of this investigation it is therefore considered that the model performs adequately in simulating total phosphorus loads at both daily and monthly time-steps.

3.2. Agricultural mitigation options

The satisfactory performance of the model in simulating discharge and nitrate and total phosphorus loads suggests that the model can be applied with high confidence to assess the impacts of agricultural mitigation options on water quality within the Blackwater sub-catchment.

3.2.1. Mitigation scenario impacts

Buffer strip scenarios S1 and S2 achieved small reductions in the amount of nitrate lost from the sub-catchment relative to the control scenario (S0) (Fig. 6a). Scenarios S1 and S2 reduced mean annual nitrate losses by 2.3% and 4.6%, respectively, for buffer strips of 2 m and 6 m width. A reduction in the total area of land utilised for agricultural purposes and the reduction in the total amount of fertiliser applied to land within the sub-catchment that results is most likely to be responsible for the reduction in nitrate losses observed under these scenarios. A proportion of the simulated reductions are also likely to result from a reduction in the amount of nitrate lost in surface runoff due to wider buffer strips. In comparison, Glavan et al. (2012) found that introducing buffer strips of 4 m width to arable land and grassland within SWAT reduced losses of total nitrogen by 21.2% and attributed this reduction largely to a drop in the amount of total nitrogen lost in surface runoff. In another study, Lam et al. (2011) found that introducing buffer strips of 10 m width to arable land and pasture land along the main river channel reduced total nitrogen losses by 12.9% and attributed this reduction largely to denitrification within groundwater in the locality of the vegetative buffer. Scenarios S1 and S2 achieved notable reductions in the amount of total phosphorus lost from the sub-catchment relative to the control scenario (S0) (Fig. 6b). Scenarios S1 and S2 reduced mean annual total phosphorus losses by 12.2% and 16.9%, respectively, reflecting an increase in the width of buffer strips from 2 m to 6 m. Increasing the width of buffer strips acts to

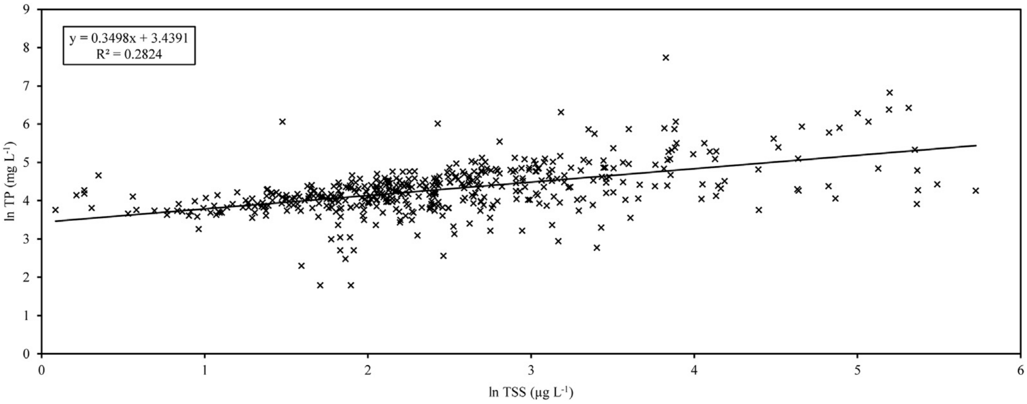

Fig. 5. Log-log regression model of the relationship between the concentration of total suspended solids (TSS) and the concentration of total phosphorus (TP) at the outlet of the Blackwater sub-catchment according to stream water samples collected during 1 October 2010–31 March 2015.

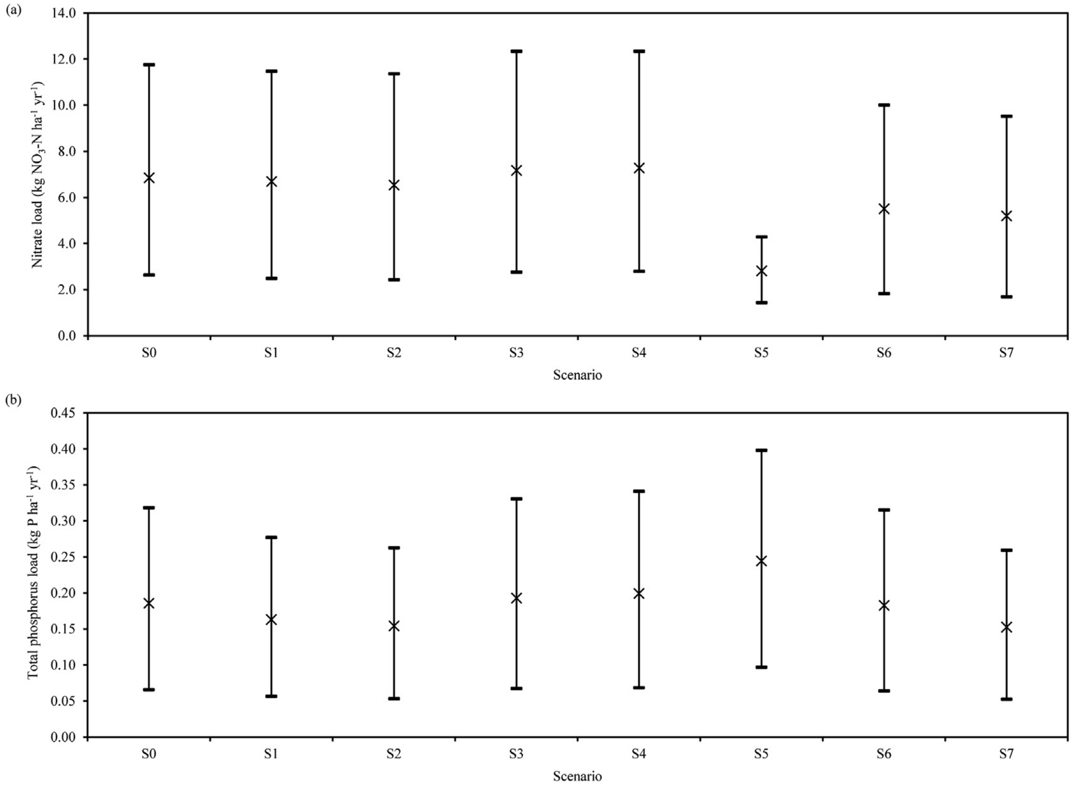

Fig. 6. (a) The mean annual nitrate load and (b) the mean annual total phosphorus load exported from the Blackwater sub-catchment during the period 1990–2009 under each mitigation scenario. The upper and lower bounds of the 95% prediction uncertainty range are also shown at the end of each line. The ' × ' represents the mean value of each scenario.

slow surface runoff, causing more sediment-associated phosphorus to drop out before the runoff enters a stream. In comparison, Glavan et al. (2012) found that introducing buffer strips of 4 m width to arable land and grassland within SWAT reduced losses of total phosphorus by 47.7% and Lam et al. (2011) found that introducing buffer strips of 10 m width to arable land and pastureland along the main river channel reduced total phosphorus losses by 5.3%. Again, it is considered that the effectiveness of buffer strips is dependent on local factors. As evidenced by our study and the findings of others, including Cho et al. (2010), it is clear that the effectiveness of buffer strips varies, depending on local conditions, the width of the buffer strip and the extent of the area to which they are applied. For mean annual losses, the 95% prediction uncertainty range within which 95% of the 1000 model predictions fell, ranged from 2.5 kg NO_3-N ha^{-1} yr^{-1} to 11.5 kg NO_3-N ha^{-1} yr^{-1} and 0.06 kg P ha^{-1} yr^{-1} to 0.28 kg P ha^{-1} yr^{-1} under scenario S1, and from 2.4 kg NO_3-N ha^{-1} yr^{-1} to 11.4 kg NO_3-N ha^{-1} yr^{-1} and 0.05 kg P ha^{-1} yr^{-1} to 0.26 kg P ha^{-1} yr^{-1} under scenario S2 (Fig. 6). Relative to control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range respectively reduced by 5.6% and 2.4% for nitrate and 13.8% and 13% for total phosphorus under scenario S1 and reduced by 7.7% and 3.3% for nitrate and 18.8% and 17.4% for total phosphorus under scenario S2. Although there is some uncertainty associated with model predictions under scenarios S1 and S2, the results indicate a clear reduction in the amount of nitrate and total phosphorus lost from the sub-catchment. This result suggests that buffer strips can be introduced to reduce nitrate and total phosphorus losses over the long-term.

Alternative tillage scenarios S3 and S4 resulted in small increases in the amount of nitrate and total phosphorus lost from the sub-catchment relative to the control scenario (S0) (Fig. 6). Nitrate losses under scenarios S3 and S4 increased by 4.7% and 6.3%, respectively, and total phosphorus losses increased by 3.8% and 7.2%, respectively. The 95% prediction uncertainty range of mean annual losses ranged from 2.8 kg NO_3-N ha^{-1} yr^{-1} to 12.3 kg NO_3-N ha^{-1} yr^{-1} and 0.07 kg P ha^{-1} yr^{-1} to 0.33 kg P ha^{-1} yr^{-1} under scenario S3, and from 2.8 kg NO_3-N ha^{-1} yr^{-1} to 12.3 kg NO_3-N ha^{-1} yr^{-1} and 0.07 kg P ha^{-1} yr^{-1} to 0.34 kg P ha^{-1} yr^{-1} under scenario S4. Relative to control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range respectively increased by 5.1% and 5% for nitrate and 2.9% and 3.8% for total phosphorus under scenario S3 and increased by 6.2% and 5.0% for nitrate and 4.2% and 7.1% for total phosphorus under scenario S4. Although the 95% uncertainty ranges for losses of nitrate and total phosphorus under scenarios S3 and S4 appear to be relatively large, the upper and lower limits of those ranges depict a small but clear increase in the amount of nitrate and total phosphorus lost from the sub-catchment when alternative tillage practices are introduced. The increase in nitrate and total phosphorus losses was an unexpected result given that alternative tillage systems including conservation tillage and zero tillage have been reported to reduce sediment erosion and losses of total phosphorus and nitrogen (McDowell and McGregor, 1984; Ulén et al., 2010). Lam et al. (2011) however found that introducing alternative tillage practices within SWAT, including zero-tillage and conservation tillage, did not have a significant impact on total nitrogen and total phosphorus losses and attributed this observation to limited surface runoff and sediment erosion within the catchment (Lam et al., 2010). A number of studies have also reported an increase in the amount of dissolved phosphorus and nitrogen lost from arable fields where reduced tillage systems are implemented for successive years (McDowell and McGregor, 1984; Ulén et al., 2010). Where plant residues are left undisturbed, the incorporation of fertilisers within soils becomes limited (Ulén et al., 2010) and nutrients accumulate in topsoil (Logan et al., 1991). This practice has the potential to increase the amount of nutrients lost in surface runoff (McDowell and McGregor, 1984; Ulén et al., 2010) and may account for the small increases in nitrate and total phosphorus losses observed under scenarios S3 and S4. Periodically conducting conventional tillage within a long-term reduced tillage system is recommended by Addiscott and Thomas (2000) in order to redistribute nutrients within the soil subsurface and mitigate this risk.

Scenario S5 involved removing tile drains from the sub-catchment. This measure may not be considered practical or desirable but it is necessary to identify the important pathways of nutrient loss within the sub-catchment. Scenario S5 reduced nitrate losses by 58.9% and increased total phosphorus losses by 31.6%, relative to the control scenario (S0) (Fig. 6). The 95% prediction uncertainty ranges for mean annual losses ranged from 1.4 kg NO_3-N ha^{-1} yr^{-1} to 4.3 kg NO_3-N ha^{-1} yr^{-1} and 0.1 kg P ha^{-1} yr^{-1} to 0.4 kg P ha^{-1} yr^{-1} under scenario S5. Relative to control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range respectively reduced by 45.5% and 63.5% for nitrate and increased by 47.5% and 25.1% for total phosphorus under scenario S5. The result for nitrate indicates that subsurface drainage is a major conduit for nitrate losses from arable land to the river network within the sub-catchment. The large increase in total phosphorus losses results from an increase in surface runoff and soil erosion due to reduced subsurface drainage, and highlights the need to maintain good drainage within arable systems. The 95% confidence interval of the predicted impacts of scenario S5 on nitrate losses within the sub-catchment is also markedly smaller compared to all other scenarios, indicating a higher confidence in model predictions.

Introducing a red clover cover crop to the crop rotation scheme applied within the sub-catchment under scenario S6 reduced nitrate and total phosphorus losses by 19.6% and 1.6%, respectively (Fig. 6). Under scenario S6 the 95% prediction uncertainty range of mean annual losses ranged from 1.8 kg NO_3-N ha^{-1} yr^{-1} to 10.0 kg NO_3-N ha^{-1} yr^{-1} and 0.06 kg P ha^{-1} yr^{-1} to 0.32 kg P ha^{-1} yr^{-1} and, relative to control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range respectively reduced by 30.4% and 14.8% for nitrate and 2.7% and 0.9% for total phosphorus. In comparison, Ullrich and Volk (2009) found that introducing red clover as a cover crop within a SWAT model of the Parthe catchment in central Germany reduced nitrate losses in surface runoff by 63%, relative to a control scenario which involved conservation tillage alone. The large reduction in nitrate loss observed by our study is likely to result from the uptake of nitrate from soils by the cover crop, locking nitrate within organic plant material and preventing it from leaching from soils during wet winter months (Rubæk et al., 2011). The presence of a crop at a time of year when soils would otherwise be bare protects the soil surface and reduces the amount of nutrients lost through wind erosion and surface runoff. The root system of the cover crop also enhances the percolation of water into the soil subsurface, reducing surface runoff and erosion, further reducing nutrient losses. Following the termination of a cover crop, nutrients stored in organic plant material are slowly released to soils through the process of mineralisation. The red clover essentially acts as a ‘green manure’. The reduction in nitrate losses observed under this scenario and the slow release of nutrients ensure that less nitrogen fertiliser needs to be applied to fields, reducing fertiliser expenditure and improving soil conditions. The magnitude of the reduction in total phosphorus losses is markedly less than that observed for nitrate due to the fact that the uptake of phosphorus by plants is counteracted by the slow desorption of phosphorus from soil particles. This observation limits the potential for cover crops to reduce phosphorus losses, however it is possible to reduce losses of phosphorus through long-term phosphorus mining (Delorme et al., 2000). Mining involves the net removal of nutrients through the harvesting of cover crops, instead of incorporating the organic material of cover crops into soils as a green manure.

Although there is clear uncertainty associated with model predictions for nitrate and total phosphorus losses under each scenario (Fig. 6), the results indicate a clear, if sometimes relatively small, direction of change under each scenario. We can therefore be confident in the impacts of each mitigation option for the management of diffuse pollution, despite the degree of uncertainty that is associated with predictions.

In order to assess which mitigation options have the potential to be applied within the sub-catchment to achieve statutory water quality targets, percent exceedance curves depicting the amount of time any nitrate and total phosphorus concentration is exceeded at the sub-catchment outlet during the period from 1990 to 2009 were developed for each scenario (Fig. 7a and b). With reference to the European Drinking Water Directive, in which water is considered unfit for human consumption if it contains a nitrate concentration above 50 mg L^{-1} (equivalent to 11.3 mg NO_3-N L^{-1}), then under the control scenario (S0), the 50 mg L^{-1} water quality standard is exceeded 0.82% of the time at the sub-catchment outlet, equivalent to 60 days during the period 1990–2009 (Fig. 7a). This risk is reduced to 0.01% of the time or 1 day under scenario S5 in which tile drains are removed from the sub-catchment. Introducing a red clover cover crop to the crop rotation scheme under scenario S6 reduced the amount of time this standard was exceeded to

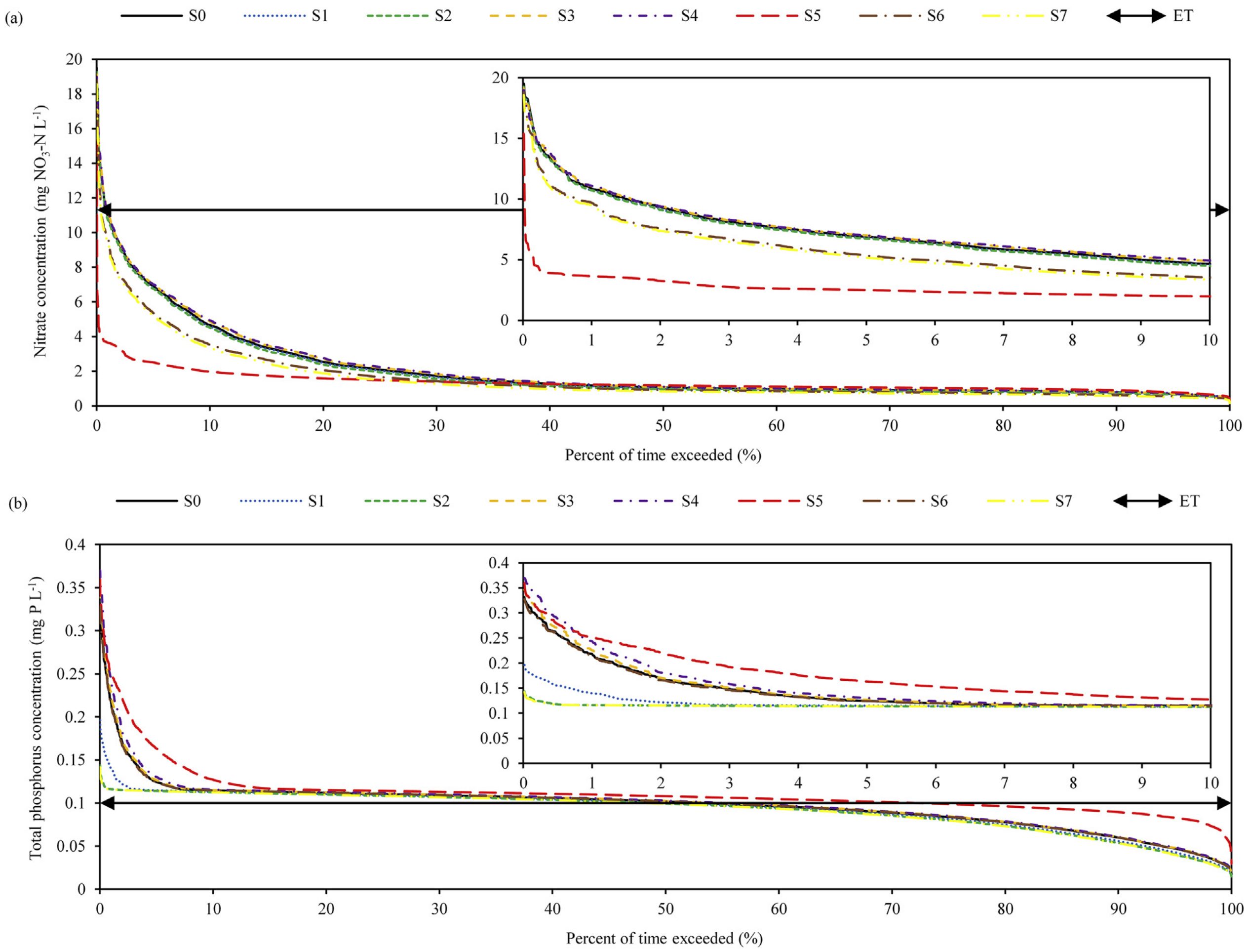

Fig. 7. Environmental Targets (ET) and percent exceedance curves for (a) nitrate concentration and (b) total phosphorus concentration as simulated at the outlet of the Blackwater sub-catchment during the period 1990–2009 under each mitigation scenario.

0.36%, equivalent to 26 days over the 20-year period 1990–2009. Under this scenario, the amount of time that the 50 mg L^{-1} standard was exceeded at the sub-catchment outlet was reduced by over 50% compared to the control scenario, benefiting aquatic ecology and water resource management. Scenarios S1-S4 had a more limited effect on the percent exceedance curves relative to the control scenario (S0) (Fig. 7a). The Diffuse Water Pollution Plan developed for the River Wensum SSSI specifies that for the river to be in a favourable condition, mean annual total phosphorus concentrations must not exceed 0.1 mg L^{-1} at the catchment outlet (Environment Agency, 2010). Under the control scenario (S0), the 0.1 mg L^{-1} target was exceeded 53% of the time at the sub-catchment outlet (Fig. 7b), with the mean annual total phosphorus concentration just below the target at 0.097 mg L^{-1}. This exceedance reduced to 51% and 49% of the time under scenarios S1 and S2, respectively, with 2 m and 6 m wide buffer strips (Fig. 7b). Under scenarios S1 and S2, mean annual total phosphorus concentrations at the sub-catchment outlet were 0.092 mg L^{-1} and 0.091 mg L^{-1}, respectively. Scenario S5, involving the removal of tile drains from arable land, increased the amount of time this target was exceeded to 72% (Fig. 7b). Under this scenario, the mean annual concentration of total phosphorus at the sub-catchment outlet equalled 0.111 mg L^{-1}, exceeding the required target. Scenarios S3, S4 and S6 had a more limited effect on the percent exceedance curves relative to the control scenario (S0) (Fig. 7b). It is clear from the scenarios considered that buffer strips represent the most effective mitigation option that can be applied within an arable catchment to reduce losses of total phosphorus.

3.2.2. *Combined effectiveness of mitigation options*

According to the model simulations, the most effective and practical mitigation options considered as part of this investigation in the Blackwater sub-catchment to reduce losses of nitrate and total phosphorus include, respectively, the introduction of a red clover cover crop to the crop-rotation applied within the sub-catchment (scenario S6) and the introduction of buffer strips of 6 m width to areas of arable land (scenario S2). In order to understand the impacts of mitigation options on long-term water quality when introduced to the sub-catchment in combination, these two mitigation options were modelled in combination under scenario S7.

The two mitigation options introduced under scenario S7 reduced nitrate and total phosphorus losses within the sub-catchment by 24.1% and 17.9%, respectively, over the period 1990–2009 (Fig. 6). In comparison, the cumulative impact of these mitigation options, when modelled individually and added together, reduced nitrate and total phosphorus losses over the same period by 24.2% and 18.6%, respectively. This result suggests that the mitigation options considered here simply combine to produce a total effect almost equal the sum of their individual effects. Under scenario S7 the 95% prediction uncertainty range of mean annual losses ranged from 1.7 kg NO_3-N ha^{-1} yr^{-1} to 9.5 kg NO_3-

N ha^{-1} yr^{-1} and 0.05 kg P ha^{-1} yr^{-1} to 0.26 kg P ha^{-1} yr^{-1} and, relative to control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range respectively reduced by 35.8% and 19% for nitrate and 19.9% and 18.5% for total phosphorus.

The 50 mg L^{-1} drinking water quality standard that applies to nitrate was exceeded 0.34% of the time at the outlet of the Blackwater sub-catchment under scenario S7 (Fig. 7a), equivalent to 25 days during the 1990–2009 period. This result compares to 0.82% of the time or 60 days under the control scenario S0, 0.75% of the time or 55 days under scenario S2 and 0.36% of the time or 26 days under scenario S6. The 0.1 mg L^{-1} water quality target that applies to total phosphorus was exceeded 48.5% of the time at the outlet of the Blackwater sub-catchment during the 1990–2009 period under scenario S7 (Fig. 7b). This result compares to 53.2% of the time under the control scenario S0, 48.6% of the time under scenario S2 and 53.8% of the time under scenario S6. These results further suggest that the combined effect of the mitigation options considered here is nearly equal to the sum of their individual impacts on water quality. Despite this finding, in practice, when choosing mitigation options, it is essential to consider their many potential impacts before introduction in the environment in order to understand the risk of pollution swapping and the potential for unintended environmental consequences (Stevens and Quinton, 2009).

4. Conclusions

Water quality models are cost-effective DSTs which can be applied to assess the quantitative impacts of a variety of mitigation options on water quality. Models must be robustly calibrated to achieve this goal, but there is often a scarcity of sufficient data to parameterise and evaluate models. High-frequency water quality monitoring has allowed the successful application of SWAT within this investigation to quantify the impacts of agricultural mitigation options on long-term water quality at a daily resolution in a lowland arable catchment in the UK. The uncertainties of the predicted impacts of each mitigation option on water quality have also been quantified and mitigation options that have the potential to be applied within arable catchments to improve water quality have been identified.

Scenario analysis found that introducing a red clover cover crop to the crop rotation scheme applied within the model reduced nitrate losses by 19.6% and total phosphorus losses by 1.6% over the long-term. This finding suggests that a cover crop can successfully be grown as a ‘green manure’, improving soil conditions, reducing expenditure on fertilisers and reducing agricultural diffuse water pollution over the long term. The prospect of mining phosphorus through the successive harvesting of cover crops is also considered, but this practice limits the potential for the cover crop to act as a green manure.

Introducing buffer strips of 2 m and 6 m width to arable land was found to be the most effective mitigation options that could be applied to reduce losses of total phosphorus, achieving reductions of 12.2% and 16.9%, respectively, although consideration must be given to the reduction in agricultural productivity that occurs under these scenarios as a result of removing areas of arable land from cultivation.

According to the findings of this investigation, the removal of subsurface tile drainage systems from areas of arable land, albeit not practical in terms of maintaining arable cultivation, represents the single most effective mitigation option that can be adopted to reduce losses of nitrate, achieving a reduction of 58.9%. This measure, however, increased total phosphorus losses by 31.6%, highlighting the need to consider multiple pollutants when evaluating the effectiveness of mitigation options to reduce agricultural diffuse water pollution.

If reductions are to be achieved in both nitrate and total phosphorus losses, the most effective combination of mitigation options that can be applied are a cover crop and buffer strips. When modelled in combination, these two mitigation options were found to have a total impact which was almost equal to the sum of their individual modelled impacts on water quality.

The alternative tillage scenarios applied within the model unexpectedly resulted in small increases in nitrate and total phosphorus losses. This result was attributed to the enrichment of nutrients within topsoil and an increased loss of nutrients in surface runoff. This observation highlights the need to conduct a detailed assessment of the potential impacts of a mitigation option prior to implementation otherwise there is a risk of introducing practices which achieve the opposite of the intended result. This example highlights the benefits provided by water quality models in aiding decision-making and catchment management.

The availability of high-frequency water quality data ensures that models can be robustly calibrated. Such techniques can impart a higher degree of confidence to model predictions and, therefore, in the predicted impacts of mitigation options on water quality. This investigation has shown that high-frequency water quality datasets can be applied within SWAT, as an example of one of the many water quality models available, to quantify the long-term impacts of agricultural mitigation options on water quality at a daily resolution and assist in the creation of more effective and reliable DSTs, leading to the development of appropriate diffuse water pollution mitigation plans. Results indicate that there is a relatively large degree of uncertainty associated with model predictions and we would recommend that impact assessments conduct a robust evaluation of prediction uncertainty to improve confidence in model predictions.

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