Modelling the Impacts of Catchment Mitigation Measures on Water Quality

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ABSTRACT

Diffuse nutrient and pesticide pollution is a major global and growing pressure on water quality and poses risks to aquatic ecosystems, human health and water resources. Due to threats to water quality, the costs of water treatment and the recalcitrance of some pollutants to traditional water treatment techniques, there is increased focus on the potential to mitigate agricultural diffuse water pollution through catchment management. Water quality models have the potential to be applied as decision support tools to identify mitigation measures that can reduce agricultural diffuse water pollution but, to date, insufficient consideration has been given to the uncertainties of water quality model predictions and the impacts of farm-based mitigation measures on multiple pollutants and at a daily temporal resolution. To address these shortcomings, and the need to identify mitigation measures that can reduce agricultural diffuse water pollution, the Soil and Water Assessment Tool model was applied to identify the impacts of farm-based mitigation measures on diffuse nitrate, total phosphorus and metaldehyde pollution at a daily time-step within the River Wensum catchment in the East of England. Prohibiting metaldehyde application in areas where the slope exceeded 2% was the most effective option to mitigate diffuse metaldehyde pollution, whilst introducing a red clover cover crop reduced nitrate losses by 19.6% and implementing buffer strips of 6 m width reduced total phosphorus losses by 16.9%. Results also highlighted the need to consider the impacts on multiple pollutants and the degree of uncertainty associated with model predictions when evaluating the effectiveness of mitigation measures. According to model predictions, a catchment management based approach does have the potential to reduce agricultural diffuse water pollution, the risk of water quality non-compliance and the subsequent need for raw water treatment. Overall, this thesis contributes to the development of effective strategies to mitigate agricultural diffuse water pollution.

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CREAMS	Chemicals, Runoff and Erosion from Agricultural Management Systems
CSF	Catchment Sensitive Farming
Defra	Department for Environment, Food and Rural Affairs
DEM	Digital Elevation Model
DST	Decision Support Tool
DTC	Demonstration Test Catchment
DTM	Digital Terrain Model
DWPA	Drinking Water Protected Area
EEA	European Environment Agency
EPA	Environmental Protection Agency
EPIC	Environmental Policy Integrated Climate
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
FARMSCOPER	Farm Scale Optimisation of Pollutant Emission Reductions
GAC	Granular Activated Carbon
GLEAMS	Groundwater Loading Effects of Agricultural Management Systems
GLUE	Generalised Likelihood Uncertainty Estimation
HRU	Hydrologic Response Unit
HSPF	Hydrological Simulation Program – FORTRAN
HYPE	Hydrological Predictions for the Environment
IFA	International Fertilizer Association
LCM2007	Land Cover Map 2007
MCMC	Markov Chain Monte Carlo
MIDAS	Met Office Integrated Data Archive System

MME	Multiple-Model Ensemble
MUSLE	Modified Universal Soil Loss Equation
NATMAP	National Soil Map
NSE	Nash-Sutcliffe Efficiency
NSI	National Soils Inventory
ParaSol	Parameter Solution
PBIAS	Percent Bias
PoMs	Programmes of Measures
PSO	Particle Swarm Optimisation
RBMP	River Basin Management Plan
RMSE	Root Mean Square Error
ROTO	Rooting Outputs to Outlet
RSR	The Ratio of the Root Mean Square Error to the Standard Deviation of the Measured data
S0	Control Scenario
S1	Scenario 1
S2	Scenario 2
S3	Scenario 3
S4	Scenario 4
S5	Scenario 5
S6	Scenario 6
S7	Scenario 7
SAC	Special Area of Conservation
SDG	Sustainable Development Goal
SSSI	Site of Special Scientific Interest
STDEV	Standard Deviation
SUFI-2	Sequential Uncertainty Fitting version 2

SWAT	Soil and Water Assessment Tool
SWAT-CUP	Soil and Water Assessment Tool Calibration and Uncertainty Program
SWRRB	Simulator for Water Resources in Rural Basins
USLE	Universal Soil Loss Equation
UV	Ultraviolet
WFD	Water Framework Directive
WTW	Water Treatment Works

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1 INTRODUCTION

Global agricultural production increased by more than threefold during the 53-year period from 1961-2013 (Food and Agriculture Organization of the United Nations [FAO], 2016). This increase in production may partially be attributed to a 10.6% increase in the total global land area under agricultural land use (FAO, 2016), but it is largely a result of the intensification of agriculture that occurred under the so-called Green Revolution, which saw an increase in irrigation, fertiliser and pesticide use, the mechanisation of agriculture and the development of higher yield crop cultivars (Matson et al., 1997). These developments led to a tremendous increase in agricultural yields (FAO, 2016), but it came at a high cost to the environment (Carpenter et al., 1998; Foley et al., 2005).

Some of the concerns over continued agricultural expansion relate to habitat loss (Pimm and Raven, 2000), the negative impact on biodiversity (Fahrig, 2003), and the link it has to species extinction (Sala et al., 2000). It is also known that inputs of nitrogen and phosphorus as fertiliser to agricultural land often exceed the amount that is extracted by crops, creating a surplus of nutrients within agricultural land that may then be transferred to water bodies (Carpenter et al., 1998). Agriculture is one of the main sources of nitrogen and phosphorus in surface waters (Kronvang et al., 2009), and their oversupply can result in eutrophication, impairing the health of ecosystems (Carpenter et al., 1998). Nutrient enrichment in surface waters can also have negative implications for the supply of water and human health (Withers and Lord, 2002). Pesticides that are applied to agricultural land have also been detected within water bodies, and there is increased concern over their potential impacts on non-target species, water quality and human health (Carter, 2000; Stuart et al. 2012).

Agricultural diffuse water pollution is one of the main pressures on water resources and threats to biodiversity (Vörösmarty et al., 2010). Trends suggest that agricultural expansion and intensification will exacerbate those pressures in the coming decades (Tilman et al., 2001), and, unless agricultural practices are adapted, diffuse pollution from agriculture is expected to continue to increase (Carpenter et al., 1998). Given this threat, 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 the European Union (EU) (Council of the European Union, 1991; 2000), and the Clean Water Act in the United States (United States Congress, 2002). Human population growth is also expected to create unprecedented demand for food and water in the future (Vörösmarty et al., 2000; Alexandratos and Bruinsma, 2012). Due to the current and projected future global pressures on water resources, there is an increasing need to develop mitigation techniques that have the potential to reduce agricultural diffuse water pollution and improve water quality.

1.1 Catchment Modelling

Water quality models are one example of numerous types of mathematical model which have been applied in many fields of research from engineering to the natural sciences and social sciences. Such models are mathematical expressions of real world phenomena and are often required because there are gaps in the understanding of how a real world system functions and how it responds to changes (Beven, 2012). They may for example, be applied to model catchment systems, physical laws, weather, climate and ecosystems. When monitoring hydrological systems, models are often helpful because limited resources may constrain the scale of experiments, what can be measured in-field, and the spatial and temporal scale of those measurements (Beven, 2012). To assess how a catchment system may respond to a future change (e.g. the introduction of a mitigation measure, land use change or climate change), we must also be able to extrapolate from the observations that are available, to these new conditions and water quality models can assist this extrapolation through prediction. Water quality models therefore have the potential to provide cost-effective and timely evidence of the impacts of mitigation measures on water quality at a scale that is often unfeasible for in-field investigations. As a result, such models have been increasingly applied as Decision Support Tools (DSTs) to investigate the impacts of mitigation measures on agricultural diffuse water pollution, to assist policy development and to improve the decisions that are made through the provision of knowledge (Collins and McGonigle, 2008). In doing so, water quality models can assist the development of effective mitigation techniques and can aid the development of appropriate catchment management plans to improve water quality. This thesis is situated in the area of research that endeavours to examine diffuse agricultural pollution mitigation measures through the application of catchment-scale water quality models.

Catchment-scale water quality models have been applied to investigate the pressures from agriculture on water resources and to assess which measures have the potential to mitigate those impacts, but to date, a lack of research into the uncertainties of catchment model predictions has left a gap in knowledge. It would be intriguing to know the uncertainties of model predictions, not least because it would inform the degree of confidence that can be attached to those predictions. Quantifying this uncertainty will allow catchment models to become more effective and reliable DSTs. In particular, to date, there has not been sufficient research to investigate the impacts of catchment-based diffuse agricultural pollution mitigation measures on multiple pollutants and at a daily temporal resolution. An investigation into these issues is therefore merited.

Since 2010 the River Wensum catchment, located in Eastern England, 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 measures whilst maintaining agricultural productivity (Wensum Alliance, 2014). For the purposes of the Wensum DTC project, the Blackwater sub-catchment has been selected as a pilot area where the effects of changes in agricultural management practices will be investigated, and is considered to be representative of the wider 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. Due to an abundance of available water quality data collected as part of this wider research project, the River Wensum catchment has been selected as an appropriate site to conduct an investigation to model the impacts of agricultural mitigation measures on water quality.

1.2 Aim and Scope

Within the wider context described above, the overarching aim of this study is to model the impacts of agricultural mitigation measures on surface water quality and assess the uncertainties of catchment-scale water quality model predictions within the River Wensum catchment.

The specific objectives of this study are the following:

1. Compile and process the datasets required to develop and apply a catchment-scale water quality model of the study area.
2. Develop a catchment-scale water quality model of the study area.
3. Identify catchment measures that have the potential to mitigate diffuse water pollution from agriculture.
4. Apply the water quality model to generate predictions that can be used to identify the effects of mitigation measures on surface water quality in the study area at a daily time-step.
5. Estimate the uncertainties of model predictions.

The scope of the research is limited to modelling the impacts of agricultural mitigation measures on nitrate, total phosphorus and metaldehyde within the River Wensum catchment. The focus on agricultural mitigation measures is justified because agriculture is the largest source of nitrogen pollution and, although point sources are still the principal source of phosphorus pollution in some parts of the world, agriculture is a large and increasingly important source (Carpenter et al., 1998; European Environment Agency [EEA], 2005; White and Hammond, 2007). The River Wensum catchment is selected as the test catchment for the research due to an abundance of data and the presence of a responsive community of stakeholders. Nitrate, total phosphorus and metaldehyde are the water quality parameters chosen because of the focus of environmental and drinking water supply legislation on nutrients and pesticides in water. These limits to the scope of the research are necessary so that the research can focus on the key issues affecting surface water quality.

1.3 Significance of the Study

One of the intended practical outcomes of this study is to identify which mitigation measures have the potential to be applied within agricultural systems to reduce agricultural diffuse water pollution and improve water quality. Secondly, it is intended that the development of such knowledge will lead to practical solutions to the problem of agricultural diffuse water pollution and assist the development of sustainable agricultural practices. On a theoretical basis, the third intended outcome is to demonstrate the novel use of a technique to assess the uncertainties of model predictions. Such a consideration of model prediction uncertainty is rarely conducted and is intended to inform the degree of confidence that can be attached to model predictions, improving the reliability and effectiveness of catchment-scale water quality models as DSTs and enabling better-informed management and policy decisions to be made. Fourthly, catchment-scale water quality models are infrequently applied at a daily temporal resolution, often because of insufficient data. Given their limited application at a daily resolution and the deficit in knowledge that this creates, another point of concern for this study is to model pollutants at a daily resolution and to assess the impacts of agricultural mitigation measures on daily water quality. Fifthly, modelling studies often consider the impacts of mitigation measures on a single pollutant in isolation from others but a measure that reduces the losses of one pollutant could exacerbate losses of others. To develop a better understanding of the risk of pollution swapping, this study considers the impacts of mitigation measures on multiple pollutants.

1.4 Structure of the Thesis

This thesis contains six further chapters. In Chapter 2, to establish this study within the context of the wider research area, a critical review of historical research, current theory, legislation and practice that relates to surface water quality, catchment management, and catchment-scale water quality modelling is provided. From this review, gaps in knowledge are established and areas that require further research are identified. A review of the key aspects of 10 hydrological models is also provided and the Soil and Water Assessment Tool (SWAT) model and SWAT Calibration and Uncertainty Program (SWAT-CUP) are described in more detail. Chapter 3 characterises the Wensum catchment and describes the datasets that were used within this study. In Chapter 4, the methodology used to set-up and operate the SWAT water quality models of the River Wensum catchment and Blackwater sub-catchment is described. The methodology used to perform model calibration and validation within SWAT-CUP is also described and the performance of the models are evaluated. In Chapters 5 and 6, agricultural mitigation measures are identified and the results of model predictions of the effects of those measures on nitrate, total phosphorus and metaldehyde are presented and discussed.

Chapter 7 details conclusions, a summary of the research and findings and suggests potential areas of future research.

2 LITERATURE REVIEW

2.1 Introduction

Water is vital for life, but this essential resource is increasingly threatened due to population growth and the increased demand for water for domestic and industrial purposes (Carr and Neary, 2008). The abstraction of water for domestic activities, industry, agriculture, mining and hydroelectric energy generation, can cause a deterioration in water quality and a reduction in water quantity that not only threatens ecosystems but also the availability of water that is safe for human use. The Sustainable Development Goals (SDGs) recognise the importance of providing safe, secure and sustainable water supplies and ending hunger, ensuring food security whilst also promoting sustainable agriculture (United Nations, 2015a). Reconciling the need to provide safe and secure water whilst also ending hunger and ensuring food security will be a difficult task because agriculture is often one of the drivers of water quality degradation (Ongley, 1996), and so these goals will require new approaches to agriculture and food production if they are to be achieved. In the above context, this thesis contributes to achieving the SDGs through the development of improved catchment management practices to develop the sustainable form of agriculture envisaged by the SDGs.

During the 20th Century, the global human population more than trebled from 1.65 billion to 6 billion (United Nations, 1999). By 2015, the global population had reached 7.3 billion and is now expected to grow to 8.5 billion in 2030, 9.7 billion in 2050 and 11.2 billion in 2100 (United Nations, 2015b). Such rapid human population growth will create unprecedented demand for food and water (Vörösmarty et al., 2000; Alexandratos and Bruinsma, 2012). For example, to meet the demands of the projected world population in 2050, it is estimated that cereal production will need to increase by 46%, meat production by 76% and production of oil crops by 89% (Alexandratos and Bruinsma, 2012). In order to meet the growth in food demand that results from a growing population we must either convert large areas of land for use within agriculture or increase agricultural productivity (i.e. improve crop yields). Since 1700, the total land surface area under agricultural use has increased more than 4.5-fold and is projected to continue to grow (Meyer and Turner, 1992; Tilman et al., 2001). Alexandratos and Bruinsma (2012) predict that, relative to the level in 2007, the total land surface area under agricultural use in 2050 will have increased by 4.2%. Such increases are not sustainable over the long term due to the impacts of agricultural expansion on the environment, which include habitat and biodiversity loss and species extinction (Pimm and Raven, 2000; Sala et al., 2000; Fahrig, 2003). If there is to be any long-term and sustainable solution to problem of providing food for an unprecedented and growing world population, it is to increase crop yields whilst also minimising the environmental impacts of the intensification of agriculture that such a policy would require (Tilman et al., 2011).

So far, agricultural production has managed to increase at a rate greater than the rate of growth of the global population and has reduced malnourishment (FAO, 2016). During the 53-year period from 1961-2013, global agricultural production increased more than 3-fold, whilst the global population only increased 2.3-fold from 3.08 billion to 7.18 billion (FAO, 2016). This incredible human achievement may partially be attributed to a 10.6% increase in the total land surface area under agricultural use, but it occurred mainly as a result of the intensification of agriculture on land that was already subject to agricultural use (Matson et al., 1997; FAO, 2016). This increase in production occurred during the so-called Green Revolution which started in the 1960s and saw the development of higher yield crop cultivars, an increase in irrigation, fertiliser and pesticide use, increased cropping intensities and the mechanisation of agriculture (Matson, 1997). The long-term increase in crop yields that resulted from these developments is self-evident in the positive trend observed for wheat, rice and maize yields on a worldwide basis from 1961-2013 (Figure 2.1).

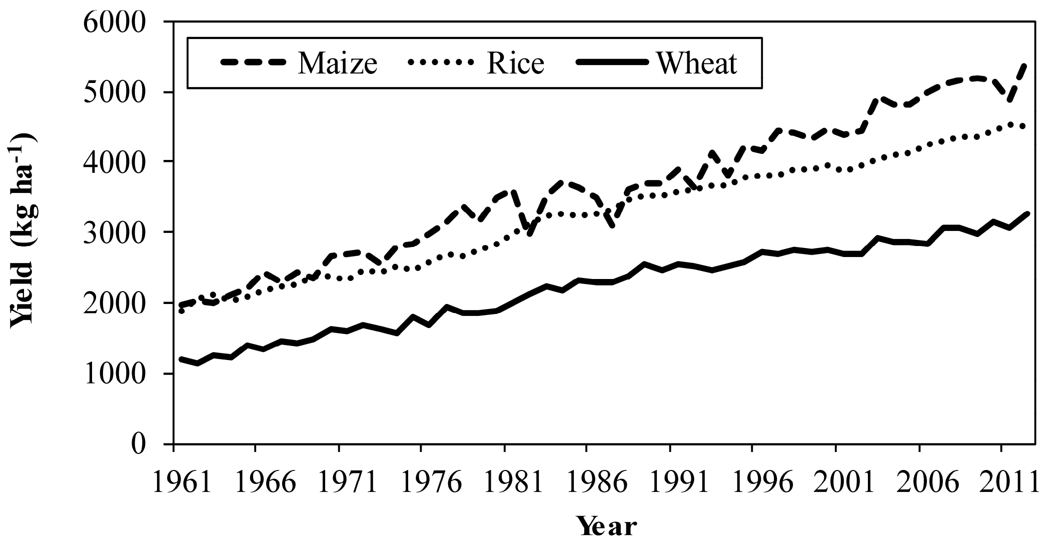

Figure 2.1: World wheat, rice and maize yields from 1961-2013 (FAO, 2016).

One of the main factors behind the increase in agricultural production and yields witnessed between 1961-2013 was an improved ability to overcome the constraints on crop growth in agricultural systems, which, in natural ecosystems, is often limited by the availability of nutrients and water. (Matson et al., 1997). This is evident in the 9.3-fold and 3.7-fold increase in nitrogen and phosphate fertiliser consumption, respectively, that occurred during the same period (Figure 2.2) (International Fertilizer Association [IFA], 2016). Another development that increased crop production and yields involved the improved ability to manage crop pests through increased use of pesticides (Ridgway et al., 1978). It is difficult to obtain data for actual global pesticide consumption in terms of the mass consumed but if we consider global trade values to be a proxy for pesticide consumption, in terms of import values, the size of the global pesticide industry increased more than 124-fold from 1961-2013 (Figure 2.3) (FAO, 2016).

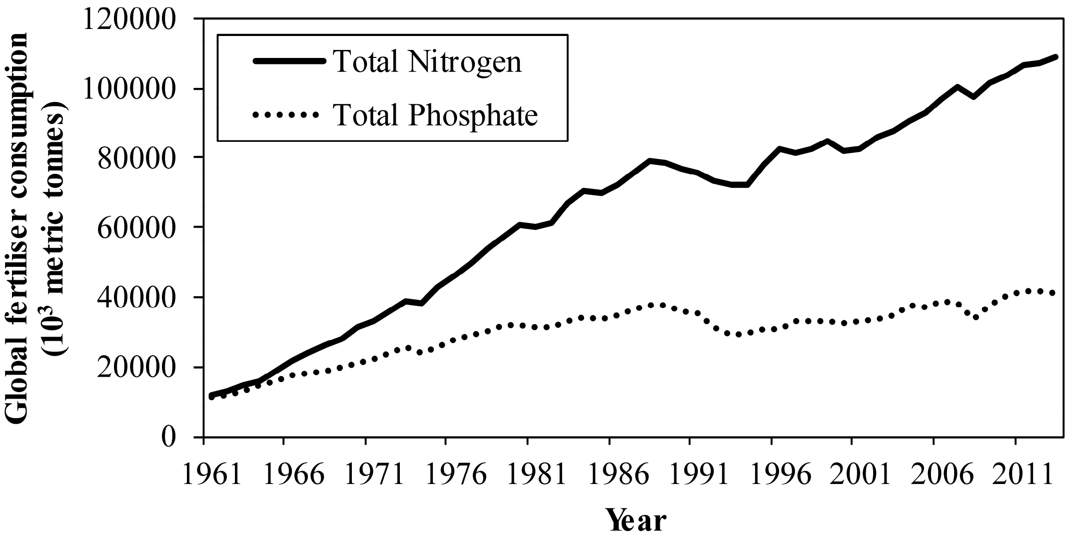

Figure 2.2: World nitrogen and phosphate fertiliser consumption from 1961-2013 (IFA, 2016).

Such increases in agricultural production and crop yields have improved food security but there are now concerns about the environmental impacts of the intensification of agriculture and whether it is sustainable over the long term (Matson et al., 1997). For example, the intensification of agriculture can lead to increased soil erosion, reductions in soil fertility and biodiversity, increased pollution of surface water and groundwater, eutrophication and increased greenhouse gas emissions (Matson et al., 1997). Whilst concerns about the environmental impacts of the intensification of agriculture are growing, so are the concerns about the ability of the world to feed a rapidly growing global population. At the same time as this, 10.8% of the global population is still malnourished (FAO, 2016). Given these needs, the potential for agricultural intensification to meet this growth in the demand for food is subject to ongoing research and development (Tilman et al., 2011). Reconciling the need to provide an increased amount of food for a growing human population whilst also protecting the environment is a very challenging prospect for the 21st Century and it is essential that new strategies are developed to ensure that agriculture can sustainably intensify in the future to meet these requirements.

The effects of agricultural expansion to meet growing food demand, as well as the agricultural intensification that has been achieved through the increased use of fertilisers and pesticides, have also compromised global water quality (Matson et al., 1997; Bennett et al., 2001). It is essential to ensure that water quality meets a sufficient standard if we are to maintain safe drinking water supplies and to ensure that water is suitable for use in industry, leisure and agriculture. Due to the increasing use of fertilisers and pesticides and the rapid degradation in water quality, there is an urgent need to mitigate the impacts of agriculture on water quality. In this regard, this study makes a valuable contribution to the development of effective strategies for the mitigation of agricultural diffuse water pollution and its findings are transferable to other catchments.

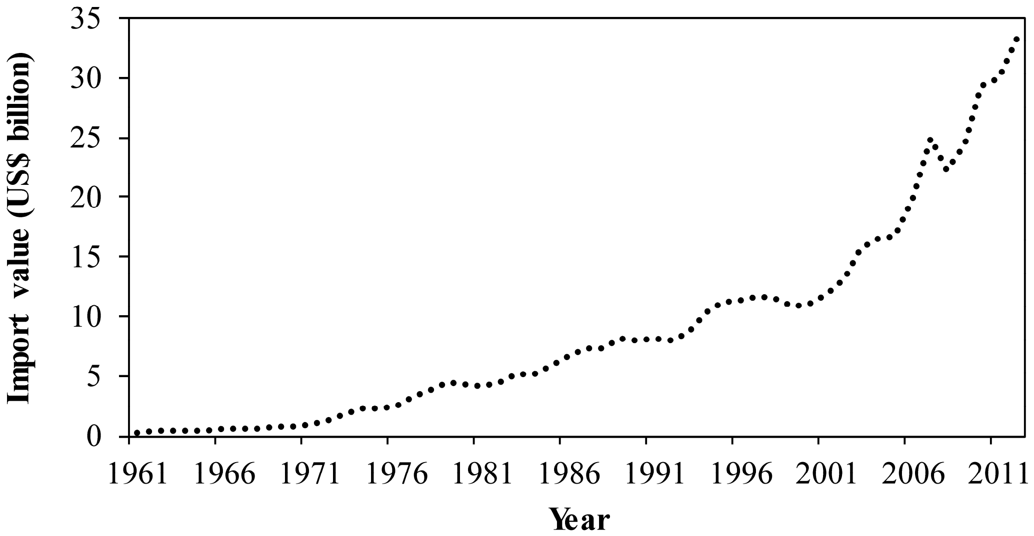

Figure 2.3: World pesticide import trade value from 1961-2013 (FAO, 2016).

2.2 Water Quality Stressors

Globally, the pressures on water resources are increasing and water quality is becoming increasingly degraded, damaging ecosystems, threatening human health, reducing quantities of safe and usable water, negatively impacting on livelihoods, creating economic costs to societies and inhibiting potential development (Palaniappan et al., 2010). There are a large number of stressors on water resources but the main human activities that affect water quality include agriculture, industry, water provision systems, human waste disposal, population growth, urbanisation and development (Palaniappan et al., 2010). The pressures on water resources are also expected to be exacerbated in the future as the global population grows, countries develop and industry and agriculture expand (Carr and Neary, 2008). Climate change also threatens to have a diverse range of impacts on freshwater resources and water quality and poses a number of risks to drinking water supplies (Jiménez-Cisneros et al., 2014). Meanwhile, it is estimated that humankind already collectively appropriates more than half of the world's accessible fresh surface water resources and this is expected to increase in the future (Postel et al., 1996). The effects of poor water quality also disproportionately impact vulnerable communities, including the poor and children, who are least able to adapt to change (Palaniappan et al., 2010).

2.2.1 Sources of Pollution

It is clear from the above that there are a large number of sources of pollution that can have an impact on water quality. To identify the sources of pollution that are most important, it will be helpful to first classify the types of pollution that there are. One particularly useful system used to identify the origins of a pollutant involves classifying pollutants based on their source. Using this system, pollution can be described as originating from either point or diffuse sources. Point source pollution, as defined in the United States Clean Water Act, is *"…any discernible, confined and discrete conveyance, including but not limited to any pipe, ditch, channel, tunnel, conduit, well, discrete fissure, container, rolling stock, concentrated animal feeding operation, or vessel or other floating craft, from which pollutants are or may be discharged. This term does not include agricultural storm-water discharges and return flows from irrigated agriculture."* (United States Congress, 2002). Point source pollution originates from a discrete source and may include for example, leaking septic tanks, chemical spills and discharges from wastewater treatment works. Diffuse pollution, sometimes referred to as non-point source pollution, is non-discrete and originates over a wide area.

Examples of diffuse pollution include pollutants contained in runoff from agricultural land or urban areas, discharges from agricultural tiles drains and atmospheric deposition. Discharges of point source pollution such as those from wastewater treatment works are often continuous over time and may be easily monitored and regulated through a sampling regime (Carpenter et al., 1998). Due to their discrete nature, pollution from point sources can also often be treated at source and are therefore relatively simple to control. For example, a leaking septic tank may be replaced, discharges of wastewater by industry may be controlled through a permit system, wastewater treatment works can install technologies to clean water and measures can be taken to reduce the future likelihood of chemical spills. Diffuse pollution is often non-continuous in time and may, for example, be related to agricultural activities, rainfall events, wildfires or construction (Carpenter et al., 1998). Diffuse pollution often originates over large areas and may be transported to bodies of water via surface or subsurface routes or the atmosphere. Due to the nature of diffuse pollution, it is more difficult to control but it may potentially be regulated through a system of land management and controls on atmospheric emissions. With the development of improved wastewater treatment techniques and the removal of phosphate salts from detergents, point source pollution has been reduced and water quality has improved (Taylor and Pionke, 1999). This is not to say that point source pollution is no longer a concern, because it is still an important source of pollution in some countries and it may increase in the future as the global population grows, but the relative importance of diffuse pollution has increased, and in some countries it is now the primary source of water pollution (Carpenter et al., 1998).

Agriculture is a major source of diffuse pollution and is an important global pressure on surface water and groundwater quality (Carpenter et al., 1998; Vörösmarty et al., 2010; EEA, 2012; Solheim et al., 2012). In the EU, diffuse pollution is a pressure in 45% of surface water bodies whilst point source pollution is a pressure in only 16% of surface water bodies (EEA, 2016a). It is also the most frequent pressure on water quality in surface water bodies observed within the EU as a whole (EEA, 2016a). For example, nutrient enrichment that results in-part from agricultural diffuse water pollution is a pressure in 52% and 56% of surface water bodies in the UK and Germany, respectively (EEA, 2016b). In the United States, diffuse pollution from agriculture is also the primary cause of water quality impairment in streams and the third most frequent cause of water quality impairment in lakes, ponds and reservoirs (Environmental Protection Agency [EPA], 2009). Diffuse pollution is by far the largest source of nitrogen and phosphorus in surface waters in the United States, contributing 82% and 84% of total nitrogen and phosphorus loads, respectively (Figure 2.4) (Carpenter et al., 1998). Of this diffuse pollution, cropland is the largest source and is responsible for 48% of total nitrogen loads and 37% of the total phosphorus loads within surface waters (Figure 2.5 and Figure 2.6) (Carpenter et al., 1998).

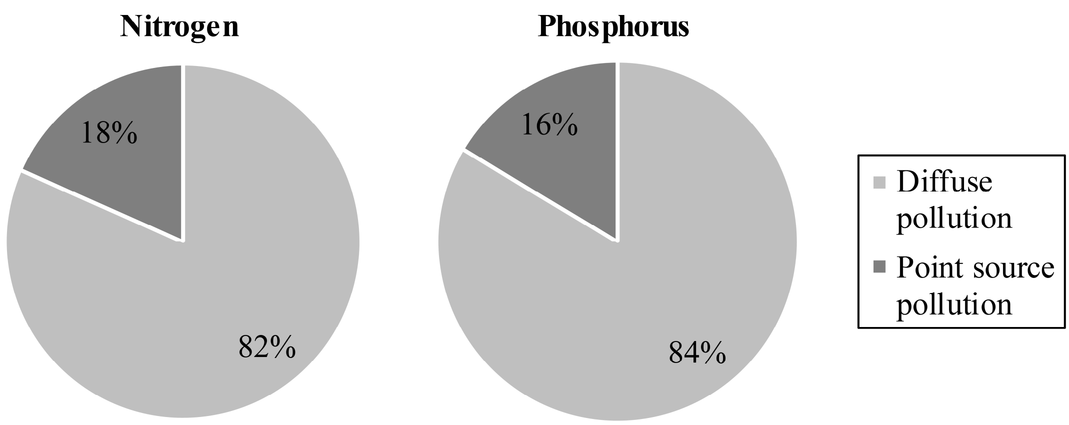

Figure 2.4: Diffuse and point source apportionment for total nitrogen and phosphorus loads in surface waters in the United States (Carpenter et al., 1998).

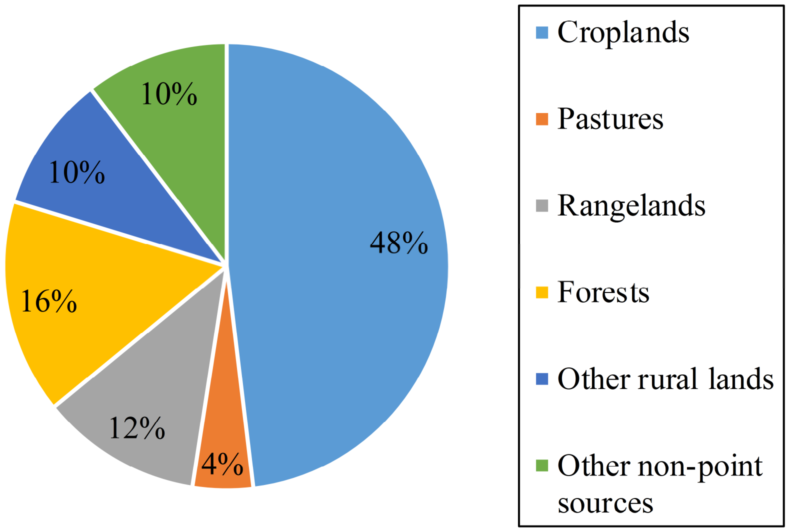

Figure 2.5: Source apportionment for diffuse nitrogen loads in surface waters in the United States (Carpenter et al., 1998).

Despite the improvements in water quality that have resulted from a reduction in point source pollution, there are still a large number of issues that affect water quality including eutrophication, contamination by pesticides and heavy metals and the siltation of river channels (Haygarth and Jarvis, 2002). Increased attention is therefore now being directed at diffuse pollution and the role that agriculture plays. This thesis therefore focuses on diffuse pollution from agriculture.

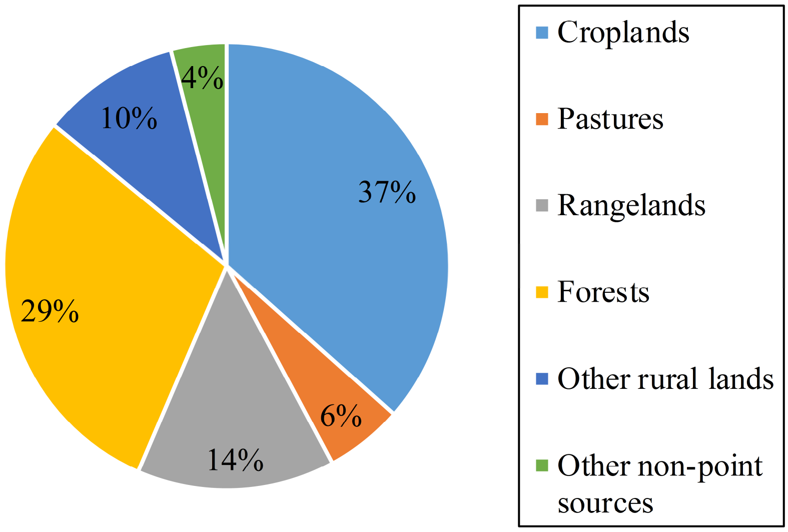

Figure 2.6: Source apportionment for diffuse total phosphorus loads in surface waters in the United States (Carpenter et al., 1998).

2.2.2 Diffuse Nutrient Pollution and Catchment Management as a Solution

As mentioned in Section 2.2.1, diffuse pollution from agriculture is a major concern for water quality. This section focuses on diffuse nutrient pollution from agriculture and the role of catchment management as a potential solution to mitigate this problem. The content of this section has been published in the *Journal of Environmental Management* (Taylor et al., 2016).

Agricultural diffuse water pollution remains a notable global pressure on surface water and groundwater quality (Carpenter et al., 1998; Vörösmarty et al., 2010; EEA, 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 WFD in Europe (Council of the European Union, 1991; 2000), and the Clean Water Act in the United States (United States Congress, 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 (EEA, 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 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 (EEA 2005; Kronvang et al., 2009). In the 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 (EEA, 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 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).

2.2.3 Diffuse Pesticide Pollution and Catchment Management as a Solution

This section focuses on diffuse pesticide pollution from agriculture and the role of catchment management as a potential solution to mitigate this problem.

Pesticides are used to control pests in agriculture, forestry, for disease control (i.e. malaria) and in the public, private, commercial and industrial sectors but their predominant use is in agriculture (Falconer, 1998). Pesticides include but are not limited to insecticides, herbicides, rodenticides, fungicides and molluscicides and their use has substantially increased since the 1940s (Gevao and Jones, 2002). Some pesticides are non-selective in the species they target and once applied, they may enter water and impact on non-target aquatic species and other organisms including Man (Carter, 2000; Aktar et al., 2009). Metaldehyde is a molluscicide that is applied to arable land to control populations of terrestrial gastropods (i.e. slugs and snails) which have the potential to damage crops (Bailey, 2002). The molluscicidal properties of metaldehyde were discovered in 1934 (Uneke, 2007), and it has since become one of the most widely-used chemical gastropod controls (Bailey, 2002). In the UK it is the most commonly used molluscicide, accounting for 84% of molluscicide use by area treated (Garthwaite et al., 2015), and is generally applied as a bran, wheat or barley-based pellet in formulations of 2-8% metaldehyde (Bailey, 2002). It is soluble in water and highly-mobile in soils (European Food Safety Authority, 2010), and under aerobic conditions it has a soil half-life of approximately two months (EPA, 2006). The stable and mobile nature of metaldehyde allows it to enter surface waters via surface and subsurface routes from point and diffuse sources, including by accidental spillage, incorrect disposal, surface runoff, leaching and drain-flow (Carter, 2000). Metaldehyde is a toxic compound that has the potential to cause harm to humans, other mammals, birds, fish and other aquatic organisms (World Health Organization, 1996), and Stuart et al. (2012) suggested that acetaldehyde, the main metabolite of metaldehyde, is one of the greatest risks to drinking water supplies from pesticides.

To protect human health, the EU Drinking Water Directive has set a maximum permissible concentration of 0.1 µg L^{-1} for any single pesticide in drinking water (Council of the European Union, 1998). Metaldehyde has however been found to be present in surface waters at relatively high concentrations. In northern France for example, Lazartiques et al. (2012) monitored water quality within multiple barrage ponds involved in farming fish and found that metaldehyde concentrations regularly exceeded the 0.1 µg L^{-1} limit, recording a peak concentration of 6.98 µg L^{-1}. For the Ouse catchment in Yorkshire, England, Kay and Grayson (2014) presented surface water quality data recorded between April 2008 and August 2011 at 21 monitoring sites along the river network and nine Water Treatment Works (WTW), and found a seasonal pattern in metaldehyde concentrations which peaked between October and December. This period coincides with the time during which metaldehyde is generally applied. Peak concentrations exceeded the 0.1 µg L^{-1} limit at many sites within the catchment, including the intakes of WTW, and generally ranged between 0.4-0.6 µg L^{-1}, with a maximum concentration of 2.7 µg L^{-1} recorded on one occasion. For humans, the acceptable daily intake for metaldehyde is 20 µg kg^{-1} day^{-1} (European Food Safety Authority, 2010) which would suggest that, according to the available data, there is no immediate health risk to humans. Nevertheless, where drinking water exceeds the 0.1 µg L^{-1} limit, dilution or removal is required.

Traditional water treatment techniques, including Granular Activated Carbon (GAC) filtration, ultraviolet (UV) irradiation and ozonation are effective treatment solutions for the majority of pesticides but metaldehyde is polar and hydrophilic and displays a low affinity with GAC, and is not readily oxidised (Cooper, 2011; Autin et al., 2012; Tao and Fletcher, 2013; Busquets et al., 2014). It is therefore not effectively removed by such techniques. For example, Kay and Grayson (2014) found that there was no statistically significant difference between metaldehyde concentrations recorded at the intakes and outlets of WTW. There are therefore difficulties in reducing metaldehyde concentrations below the drinking water quality standard, creating a risk of non-compliance (Cooper, 2011). Metaldehyde concentrations in drinking water may potentially be controlled by blending surface water with groundwater that does not contain metaldehyde and through a system of abstraction management by selectively switching-off WTW intakes during periods of elevated in-stream metaldehyde concentration, but the most sustainable solution to protecting water resources is to mitigate the potential for metaldehyde to enter watercourses at the point of origin. Changing catchment management practices to mitigate this risk has therefore received increased attention as a potential solution (Cooper, 2011; Kay and Grayson, 2014). For example, the Metaldehyde Stewardship Group in the UK is an industry-led organisation which promotes best practice for metaldehyde use and aims to minimise the environmental impact of metaldehyde and to protect water bodies (Metaldehyde Stewardship Group, 2016a). This represents a shift in perceived responsibility and focus, with an emphasis on addressing the source of pollution rather than the ‘end-of-pipe’ strategy of water treatment.

Within the UK, water companies that are at risk of exceeding the drinking water quality limit of 0.1 μg L^{-1} that applies to metaldehyde are given so-called Undertakings to ensure water quality compliance (Drinking Water Inspectorate, 2016). For example, Anglian Water Services Ltd has been given an Undertaking to assess and address the risk of non-compliance for metaldehyde for water abstracted from surface water catchments and is required to implement catchment-based measures (Drinking Water Inspectorate, 2014). In response to this and as a fundamental part of its catchment strategy under UK water industry regulations, Anglian Water Services Ltd launched the ‘Slug it Out’ campaign which is comprised of a trial project that provides a financial incentive to farmers to not use metaldehyde and encourages the use of ferric phosphate as an alternative solution (Anglian Water Services Ltd, 2016). A team of catchment advisors has also been set-up to engage agronomists and farmers in a discussion about practical solutions to the problem. There is a scarcity of information on the impacts of mitigation measures on diffuse metaldehyde pollution and a study which investigates the risk of non-compliance for metaldehyde and the impacts of mitigation measures at a daily time-step is therefore merited. The Wensum catchment is one of the drinking water catchments managed by Anglian Water Services Ltd that is subject to the Undertaking for metaldehyde. It has been selected as an appropriate area for this investigation due to the availability of data and a responsive community of stakeholders.

2.3 Hydrological Models

Hydrological models with water quality modelling components have the potential to provide cost-effective and timely evidence of the impacts of changes to management practices on diffuse pollution at a scale that is often unfeasible for in-field investigations. Such models are increasingly applied as DSTs to provide evidence to develop agricultural diffuse water pollution management policy (Collins and McGonigle, 2008), but studies rarely consider the uncertainties of model predictions and this uncertainty can sometimes be quite large (Stow et al., 2007). Conducting uncertainty assessments to capture this uncertainty would allow models to provide an estimate of the uncertainties of the impacts of mitigation measures on agricultural diffuse water pollution. By providing this knowledge, better-informed decisions could be made, and the effectiveness and reliability of models as DSTs to assist catchment management and policy development could be improved. Catchment models are also infrequently applied at a daily resolution often because there is not sufficient data to apply models at such a high temporal resolution (Gassman et al., 2007). Studies more frequently apply models at longer time-steps (i.e. monthly or yearly), but it remains important to apply models at a daily temporal resolution to develop a better understanding of the dynamics of pollutant losses, how frequently water standards are exceeded and the effectiveness of mitigation measures. Modelling studies which seek to examine the impacts of mitigation measures on water quality also often consider single pollutants (e.g. Schilling and Wolter, 2009; Betrie et al., 2011), but each measure that is introduced may have impacts on other pollutants that are not considered in the analysis. For example, a measure aimed at reducing the losses of one pollutant may exacerbate the losses of others (Heathwaite et al., 2000). This phenomenon is known as pollution swapping and although it is concept that is widely understood, it is an area of research that has received little attention (Stevens and Quinton, 2009). There is therefore a need to model the impacts of mitigation measures on multiple pollutants to develop a better understanding of the impacts of measures on a variety of pollutants and to mitigate the risk of introducing measures that lead to unforeseen increased losses of other pollutants. There clearly remain a number of gaps in knowledge and major shortcomings in the approaches used in the application of models to investigate the impacts of mitigation measures on diffuse water pollution. There is therefore a clear need for further research in this area. To identify the hydrological models that may be suitable for application within this investigation to address these shortcomings and gaps in knowledge, the types of hydrological models that are available to be applied and their characteristics must first be outlined.

Model may be classified as lumped, semi-lumped, semi-distributed or fully-distributed depending on their spatial configuration (Beven, 2012). Lumped models treat a catchment as one homogeneous unit with parameters, such as slope, that are a spatial average for the whole area and can only yield predictions for the catchment as a whole unit. Semi-lumped models discretize a catchment into sub-catchments whilst semi-distributed models discretise a catchment into zones based on topographic characteristics (i.e. slope or elevation), soil type and land use and are capable of generating predictions for each of these zones. Fully-distributed models discretise a catchment into grid-based units and are capable of making predictions for each unit throughout the grid-space. One advantage that semi-distributed and fully-distributed models have over lumped models is that they can spatially distribute changes in land use and management practices throughout the model area, whereas lumped models cannot. Due to the level of detail that is required to adequately model and reflect 'real-world' land use and land management practices, lumped models are not considered to be appropriate for the purposes of this investigation.

Models may also be classified as either physically-based, semi-physically based, conceptual or empirical depending on the extent to which physical processes are simulated within the model (Devia et al., 2015). The advantages and disadvantages of each of these model types are reviewed in detail by Wong and Koh (2008).

Empirical models, sometimes referred to as black-box models, are derived from the mathematical relationships between input and output times series and are not based on an explicit consideration of the physical processes of a catchment system (Devia et al., 2015). For example, an empirical model of a catchment may relate precipitation (i.e. the input) to river discharge (i.e. the output) without any explicit consideration of the relevant physical processes that occur within a catchment and affect this relationship. An example of an empirical model is the Runoff Curve Number method which is used to predict surface runoff from rainfall (Cronshey et al., 1986). The advantages of empirical models include that they can be developed and applied without much difficulty and are computationally efficient (de Vos and Rientjes, 2005). They also have the power to derive relationships between inputs and outputs without the need the need to consider physical processes and can be developed overtime to compensate for changes in a system (American Society of Civil Engineers, 2000). Some of the disadvantages of empirical models are that they are only valid when applied within the boundaries of the observed data with which they were calibrated and they may not be generalised to other sites or under alternative scenarios within the same system (de Vos and Rientjes, 2005). Because empirical models do not represent the physical processes of a catchment system, it is also difficult to attach any physical meaning to outputs, which can limit the ability of such models to provide insights into important processes within a catchment. Although empirical models have good predictive power they lack explanatory power and due to these reasons, they are not considered to be suitable for the purposes of this investigation (Devia et al., 2015).

Conceptual models, sometimes referred to as grey-box models, use simplified equations that have a physical basis to define physical processes and are considered to be an intermediate class that sits between empirical and physically-based models (Devia et al., 2015). Some model parameters are derived through direct measurement but others have no physical meaning and must be derived through calibration. Examples of conceptual models include HBV (Lindström et al., 1997) and TOPMODEL (Beven et al., 1984). The advantages of conceptual models are that they are less data intensive than physically-based models and because they are less complex than physically-based models they are also more computationally efficient (Lee et al., 2005). But because some parameters of conceptual models are not physically-based their ability to predict the impacts of changes in land use and management within a catchment is inhibited (He et al., 2011a). For this reason, it is also difficult to extend the findings from the conceptual model of one experimental catchment to other unmodelled locations (He et al., 2011b). Regionalisation techniques can be used to relate model parameters to catchment characteristics and under these circumstances conceptual models may be applied to conduct impact studies (He et al., 2011a; 2011b), however, for the reasons identified above, conceptual models are not considered to be suitable for the purposes of this investigation.

Within physically-based models, sometimes referred to as white-box models, physical processes are defined and governed by mathematical expressions that are based on real-world physical laws (Devia et al., 2015). Model parameters have a physical meaning and can be determined from direct in-field measurement. An example of a physically-based model is MIKE-SHE (DHI, 2016a). Although most components of the model are physically-based, SWAT is classified as a semi-physically based model because some components are conceptual or empirical (Arnold et al., 1998; Abbaspour et al., 2007). Physically-based models are data intensive and require a relatively large number of datasets with a high degree of spatial detail to define model parameters (de Vos and Rientjes, 2005). Due to their complexity, they are less computationally efficient than empirical or conceptual models, but the structure of physically-based models allows them to overcome a lot of the deficiencies that these two other model types possess (Abbott et al., 1986). For example, physically-based models are often spatially distributed (i.e. semi-distributed or grid-based) which allows them to model spatial changes in land use and management practices, thereby also allowing users to interpret the effects of these changes. Because they are often spatially distributed, they are also useful in investigations that require a high-degree of spatial detail. Because parameters within physically-based models also have a physical basis, it is also possible to interpret the physical consequences of changes in parameter values (Devia et al., 2015. Due to their structure, the findings derived from physically-based models can also be more easily extended to other catchment systems. Because of these advantages, and the deficiencies associated with other model types, physically-based and semi-physically based models are considered to be the most suitable types of model to apply within this investigation.

The key aspects of a total number of 10 hydrological models which includes SWAT, DAYCENT, INCA, DNDC, MODFLOW, PHREEQC, Hydrological Predictions for the Environment (HYPE), HydroGeoSphere, Hydrological Simulation Program - FORTRAN (HSPF) and MIKE SHE reviewed as part of the process to identify a suitable model to apply for the purposes of this investigation are summarised in Table 2.1 to Table 2.10.

Table 2.1: A summary of the key aspects of the Soil and Water Assessment Tool (SWAT) hydrological model.

Model name	SWAT
Type	Semi-physically based, semi-distributed model
Applications	Modelling impacts of changes in land use and management practices; pollutant loss studies; climate change impacts; hydrologic assessments; best management practices analysis.
Inputs	*Site specific data*: Digital elevation model; soil map and soil properties; land cover map; land management practices (e.g. crop types grown; fertiliser and pesticide application amount and timing; irrigation practices; cultivation and harvesting dates; residue management and tillage practices); point sources. *Meteorological data*: Daily values for precipitation; minimum and maximum air temperature; solar radiation; relative humidity; wind speed.
Outputs	Discharge; surface runoff; groundwater flow; lateral flow; drain flow; actual evapotranspiration; soil and aquifer water storage; nutrient, sediment and pesticide load; crop yield.
Developer	United States Department of Agriculture Agricultural Research Service and Texas A&M AgriLife Research
Website	http://swat.tamu.edu/
Language	Fortran
Availability	Free access
Notable references	Arnold et al. (2012) *Describes the model and a methodology for model calibration and validation.* Neitsch et al. (2011) *Describes the processes modelled by SWAT and the equations used to define those processes.* Arnold et al. (2014) *Details the input requirements and outputs of the model.* Gassman et al. (2007) *Describes the history of SWAT, its structure and previous applications.*

Table 2.2: A summary of the key aspects of the DAYCENT hydrological model.

Model	DAYCENT
Type	Physically-based, lumped model
Applications	Modelling the impacts of climate change and management practices on N-gas and CO_2 emissions from soils, nitrate leaching and crop yields; best management practices analysis; agricultural sustainability analysis; investigations into soil system dynamics.
Inputs	*Site specific data:* Soil map; soil properties (e.g. texture; depth; field capacity; wilting point; bulk density; clay, silt and organic carbon content; saturated hydraulic conductivity); land cover map; land management practices (e.g. crop types grown; fertiliser application amounts and timing; tillage types and timing; irrigation practices; cultivation and harvesting dates). *Meteorological data* Daily values for precipitation; minimum and maximum air temperature; solar radiation; relative humidity; wind speed.
Outputs	Crop yield; N-gas flux (N_2O, NO_x, N2), CH_4 and CO_2 flux from soils for each layer; soil temperature; soil water content; soil ammonium and nitrate content; nitrate leached; carbon and nitrogen content of plants; actual evapotranspiration; soil organic carbon content; water balance.
Developer	Professor William Parton (Natural Resource Ecology Laboratory, Colorado State University)
Website	http://www.nrel.colostate.edu/projects/daycent-home.html
Language	C++
Availability	Access by request (century@nrel.colostate.edu)
Notable references	Parton et al. (1998) *Describes the DAYCENT model and tests the ability of the model to simulate soil water content and temperature.* Parton et al. (2001) *Describes the N-gas sub-model of DAYCENT and tests the ability of the model to simulate NO_x and N_2O emissions from soils.* Del Grosso et al. (2005) *Applied DAYCENT to test the impacts of agricultural practices on N_2O emissions, nitrate leaching and crop yields.*

Table 2.3: A summary of the key aspects of the INCA hydrological model.

Model	INCA (N, P, C and Sed model variants)
Type	Physically-based, semi-distributed model
Applications	Modelling the impacts of climate change and changes in land use; catchment management; climate change impact assessments.
Inputs	*Site specific data:* Digital elevation model; land cover map; land management practices (e.g. fertiliser application amount and timing) hydrologically effective rainfall; soil moisture deficit; point source discharges; river network map; nitrogen deposition rate. For each land cover type: denitrification rate; nitrogen fixation rate; plant nitrate uptake rate; ammonium nitrification, mineralisation and immobilisation rate; plant ammonium uptake rate; plant growing seasons. *Meteorological data:* Daily values for precipitation and air temperature.
Outputs	Daily discharge; in-stream concentrations of nitrate, ammonium, suspended sediment; total phosphorus; soluble reactive phosphorus and chlorophyll-a; macrophyte and epiphyte biomass at in-stream sites; organic and inorganic phosphorus concentration in soil water, groundwater and surface runoff; daily N and P fluxes from and to all storage pools for each land use type; soil temperature; ammonium and nitrate concentration in groundwater and soil water.
Developer	Prof. Andrew Wade and Prof. Paul Whitehead (University of Reading)
Website	http://www.reading.ac.uk/geographyandenvironmentalscience/research/INCA/
Language	Matlab
Availability	Access by request (a.j.wade@reading.ac.uk)
Notable references	Whitehead et al. (1998a) *Provides a description of the model structure and equations of the original INCA-N model.* Whitehead et al. (1998b) *Applied INCA-N to test model performance in simulating discharge, and concentrations of nitrate and ammonium and investigated the impacts of land use change.* Wade et al. (2002a) *Provides a description of a new version of the INCA-N model and compares the performance of the newer version against the performance of the original model in simulating discharge and nitrate concentration.* Wade et al. (2002b) *Provides a description of the model structure and equations of the INCA-P model.*

Table 2.4: A summary of the key aspects of the DNDC hydrological model.

Model	DNDC
Type	Physically-based, lumped (in site mode) or fully-distributed (in regional mode) model
Applications	Developing predictions for soil biogeochemistry, gaseous emissions from soils, crop development and modelling the impacts of changes in climate, land use and land management practices.
Inputs	*Site specific data:* Soil input data: land use; soil type; bulk density; pH; field capacity; wilting point; hydraulic conductivity; porosity; organic carbon content; nitrate and ammonium concentration at soil surface; slope of land surface; soil salinity index. Land use practices: crop types and rotation; cultivation and harvesting dates; tillage practices (frequency, timing and method); fertiliser practices (frequency, timing, type, rate and depth); irrigation (frequency, timing; method and amount); grazing and grass cutting events; residue management. Additional data: Runoff curve number; Manning's roughness coefficients for soil and river channel; channel slope and length. *Meteorological data:* Daily values for precipitation; mean or minimum and maximum air temperature; solar radiation; relative humidity; wind speed.
Outputs	Water balance; emissions of carbon dioxide, methane and nitrous oxide from soil; soil carbon budget; soil nitrogen budget; crop development and yield.; carbon, nitrogen and phosphorus pools in soils; influx (including source) of carbon, nitrogen and phosphorus to soil; efflux (including flux pathway) of carbon, nitrogen and phosphorus from soils.
Developer	The late Changsheng Li (Institute for the Study of Earth, Oceans and Space, University of New Hampshire)
Website	http://www.dndc.sr.unh.edu/
Language	C++
Availability	Free access
Notable references	Li et al. (1992a) *Describes the structure of the model, model inputs and sensitivity.* Li et al. (1992b) *Describes a number of previous applications of the model to demonstrate its successful performance.* Institute for the Study of Earth, Oceans and Space (2012) *Provides a methodology on how to operate the model and describes model input requirements and outputs.* Gilhespy et al. (2014) *Reviews the history of the model, different versions that have been developed and discusses its strengths and weaknesses.*

Table 2.5: A summary of the key aspects of the MODFLOW hydrological model.

Model	MODFLOW (including the MODPATH and MOC3D extensions)
Type	Physically-based, fully-distributed model
Applications	Groundwater resource management; contaminant transport investigations; climate change impact assessments; chemical transport.
Inputs	*Site specific data:* Digital elevation model; channel geometry; initial hydraulic conditions; geological layers and their properties (e.g. spatial extent, upper and lower depth, hydraulic conductivity, specific storage); point sources and extractions. *Meteorological data:* Precipitation; evapotranspiration.
Outputs	Hydraulic head evolution; surface runoff; lateral flow; groundwater flow; groundwater budget and particle path lines; river stage.
Developer	United States Geological Survey
Website	http://water.usgs.gov/ogw/modflow/
Language	Fortran 90 and C
Availability	Free access
Notable references	Harbaugh (2005) *Describes the concepts, model equations of MODFLOW-2005 and provides user input instructions.* McDonald and Harbaugh (2003) *Summarise the history and development of MODFLOW.*

Table 2.6: A summary of the key aspects of the PHREEQC hydrological model.

Model	PHREEQC
Type	Physically-based, lumped model
Applications	Modelling of chemicals in solution, chemical transport, surface water and groundwater management.
Inputs	Temperature; pH; chemical concentrations; valence states of chemicals; density of solution.
Outputs	Chemical diffusion and transport; chemical composition of a solution (reactions modelled include: mineral dissolution, mineral precipitation, cation exchange, surface complexation, gas exchange, evaporation); changes in hydrological conditions (temperature, pH and redox state); a breakdown of the geochemical reactions that account for the changes in the chemical composition of a solution over time.
Developer	David Parkhurst (United States Geological Survey)
Website	http://wwwbrr.cr.usgs.gov/projects/GWC_coupled/phreeqc/
Language	C++
Availability	Free access
Notable references	Parkhurst and Appelo (2013) *The user guide for PHREEQC which also provides example applications.*

Table 2.7: A summary of the key aspects of the Hydrological Predictions for the Environment (HYPE) hydrological model.

Model	HYPE
Type	Physically-based, semi-distributed model
Applications	Modelling the impacts of land use and management practices on water quality; best management practice analysis; water resources and catchment management; climate change impact assessments; pollutant loss studies.
Inputs	*Site specific data:* Digital elevation model; river network map; land cover; land management practices (e.g. crop types; tile drain depths; fertiliser application timing and amount; cultivation and harvesting dates; residue management) soil map and soil properties (e.g. initial nutrient content); point sources. *Meteorological data:* Precipitation; air temperature; relative humidity; fraction of precipitation that is snowfall; minimum air temperature; maximum air temperature; wind speed; solar radiation.
Outputs	Flow rate; nitrogen and phosphorus concentration and load; water balance; groundwater flow; surface runoff.
Developer	Swedish Meteorological and Hydrological Institute
Website	http://hypecode.smhi.se/
Language	Fortran 95
Availability	Free access
Notable references	Strömqvist et al. (2012) *Describes the application of HYPE to model the whole of Sweden.* Arheimer et al. (2012) *Describes the application of HYPE to the Baltic region to model the impacts of future climate change and mitigation measures on nutrient loads and water volumes that enter the Baltic Sea.*

Table 2.8: A summary of the key aspects of the HydroGeoSphere hydrological model.

Model	HydroGeoSphere
Type	Physically-based, fully-distributed model
Applications	Modelling impacts of climate change, land use, and management practices on catchment hydrology and water quality; flood risk assessments; catchment and water resource management; pollutant loss studies.
Inputs	*Site specific data:* Digital elevation model; land use map; soil map; soil properties (e.g. profile, porosity and permeability); geological layers and their properties (e.g. spatial extent, upper and lower depth, hydraulic conductivity, storavity; residual saturation and specific storage) crop types and vegetation properties (e.g. leaf area index and root depth) Manning's roughness coefficient for land surface; point sources. *Meteorological data:* Precipitation; air temperature; potential evapotranspiration.
Outputs	Discharge; overland flow; unsaturated zone flow; groundwater flow; water balance; hydraulic head; water quality (e.g. concentrations of nutrients and other contaminants).
Developer	Aquanty
Website	http://www.aquanty.com/hydrogeosphere/
Language	Fortran 95
Availability	Licensed access
Notable references	Brunner and Simmons (2012) *Reviews HydroGeoSphere and its capabilities.* Aquanty (2016) *Describes the processes modelled within HydroGeoSphere and the equations which govern those processes.* Goderniaux et al. (2009) *Describes the application* of *HydroGeoSphere to model the impacts of climate change on groundwater reserves.*

Table 2.9: A summary of the key aspects of the Hydrological Simulation Program - FORTRAN (HSPF) hydrological model.

Model	HSPF
Type	Physically-based, semi-distributed model
Applications	Modelling impacts of changes in land use and management practices; climate change impacts; pollutant loss studies; best management practices analysis; hydrological assessments; catchment management and planning.
Inputs	*Site specific data:* Digital elevation model; river network geometry; soil map and soil properties; land cover map; land management practices (e.g. crop types grown, fertiliser and pesticide application amount and timing; cultivation and harvesting dates and tillage practices); point sources. *Meteorological data:* Hourly values for precipitation; air temperature; dew point temperature; wind speed; solar radiation; potential evapotranspiration; relative humidity; cloud cover.
Outputs	Water balance; discharge; surface runoff; soil moisture content; interflow; baseflow; evapotranspiration; groundwater recharge; nutrient (e.g. ammonium, nitrate, organic nitrogen, orthophosphate and organic phosphorus), sediment and pesticide load and concentration; pH; dissolved oxygen; biological oxygen demand; zooplankton; phytoplankton; faecal coliforms.
Developer	United States Environmental Protection Agency
Website	https://www.epa.gov/exposure-assessment-models/hspf
Language	Fortran 77
Availability	Free access
Notable references	Bicknell et al. (1997) *The user manual for HSPF.* Donigian et al. (1984) *A guide which describes the entire application process for HSPF.* Singh et al. (2005) *An intercomparison study which describes the application of HSPF and SWAT to simulate streamflow in a test catchment.*

Table 2.10: A summary of the key aspects of the fully-integrated MIKE SHE hydrological model.

Model	MIKE SHE
Type	Physically-based, fully-distributed model
Applications	Catchment management and planning; water supply management; assessing the impacts of land use, climate change and agriculture; water quality remediation; pollutant loss studies.
Inputs	*Site specific data*: Digital elevation model; geological layers and their properties (i.e. spatial extent, upper and lower depth, horizontal and vertical hydraulic conductivity, specific yield and specific storage); depth of tile drains; time to drain soils to field capacity; river network map; river cross-sections; Manning's M values for land surface (this is the inverse of Manning's n); land cover map; crop types and rotation (i.e. cultivation and harvesting dates and irrigation practices); vegetation properties (i.e. leaf area index, root depth and crop coefficient over time); soil map; soil properties (i.e. profile; saturated moisture content; effective saturation moisture content; field capacity; wilting point; residual moisture content; hydraulic conductivity; bulk density). *Meteorological data*: Precipitation; potential evapotranspiration.
Outputs	Overland flow; river flow; unsaturated zone flow; groundwater flow; actual evapotranspiration; water quality (e.g. nutrient, sediment and pesticide loads and concentrations); water balance.
Developer	MIKE Powered by DHI
Website	https://www.mikepoweredbydhi.com/
Language	Fortran
Availability	Licensed access
Notable references	DHI (2016b) *Describes the step-by-step methodology to be used when constructing a fully-integrated MIKE SHE model.* DHI (2016a) *The user guide for MIKE SHE which describes the history of the model, model structure, input requirements and outputs.* DHI (2016c) *The reference guide for MIKE SHE which describes the processes that are modelled and the equations used to govern those processes.*

The model that is to be selected for use within this investigation should meet the following criteria. It should:

1. Simulate the key hydrological and pollutant processes relevant to the River Wensum catchment and Blackwater sub-catchment.
2. Be capable of modelling the impacts of mitigation measures on nitrate, total phosphorus and metaldehyde.

3. Provide outputs at the required spatial and temporal scales (i.e. at the catchment and sub-catchment scales and at a daily time-step).
4. Be computationally efficient.
5. Have data requirements that can be met by this study.
6. Be able to simulate spatially varying crop rotations.

SWAT simulates all of the key hydrological and pollutant processes found within catchments, including the River Wensum catchment and Blackwater sub-catchment (Neitsch et al., 2011). For example, the hydrological processes simulated by the model include precipitation, evapotranspiration, infiltration, surface runoff, lateral flow, groundwater return flow, water routing and transmission losses in streams (see section 2.4.1 for a detailed description of the processes simulated within SWAT) (Neitsch et al., 2011). The pollutant processes simulated by the model include sediment erosion, the nitrogen and phosphorus cycles and pesticide fate and transport (Neitsch et al., 2011). Unlike other models, it is explicitly designed to simulate the impacts of mitigation measures on nutrients and pesticides within catchments (Arnold et al., 2012), and it can simulate the effects of these measures on nitrate, total phosphorus and metaldehyde (Neitsch et al., 2011). SWAT can also provide outputs at the catchment and sub-catchment scales and at a daily time-step (Arnold et al., 2014). The model is also considered to be computationally efficient (Neitsch et al., 2011), allowing to simulations to be conducted in a timely manner. The data requirements of SWAT, which includes land use, soil, topographic, meteorological and management datasets, can also be feasibly met by this study (Arnold et al., 2014). Finally, the model can also simulate spatially varying crop rotations (Neitsch et al., 2011). SWAT is considered to meet the criteria defined above, thereby justifying its selection for application within this investigation.

SWAT is also an open source model that is freely available, is subject to ongoing development, is widely used, provides considerable user support and is relatively user-friendly. Given these advantages, the properties of the model and the potential applications that SWAT lends itself to, it is considered to be highly suitable for application within this study to assess the impacts of catchment mitigation measures on water quality and the model is discussed in more detail in Section 2.4.

2.4 The Soil and Water Assessment Tool (SWAT)

The SWAT model is jointly developed by the United States Department of Agriculture Agricultural Research Service and Texas A&M AgriLife Research and is the product of over 40 years of research (Gassman et al., 2007). According to Williams et al. (2008), the model was developed as a successor to the Simulator for Water Resources in Rural Basins (SWRRB) model (Williams et al., 1985), and the Routing Outputs to Outlet (ROTO) model (Arnold et al., 1995). The SWAT model in its current form includes components from a number of other models (Figure 2.7). The hydrology, crop-growth and pesticide transport components of the SWAT model are derived from the field-scale models referred to as the Chemicals, Runoff and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980), the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1984) and the Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), respectively (Arnold et al., 2012). These three sub-models, a groundwater sub-model, a weather generator and a sediment routing sub-model were first integrated into the SWRRB model to simulate the effects of management practices on hydrology and sediment yields at the catchment scale (Williams et al., 1985). ROTO was developed to overcome the spatial limitations of SWRRB and to assess the downstream impacts of management practices in larger catchments (Arnold et al., 1995). ROTO was initially developed as a separate model to be run alongside SWRRB to route outputs further downstream within a catchment, thereby increasing the number of sub-catchments that could be analysed within SWRRB which until this point was limited to ten sub-catchments (Gassman et al., 2007). This approach was considered to be quite cumbersome in practice, and to overcome these difficulties the SWRRB and ROTO models were merged into what became the first SWAT model. Since the model’s creation, SWAT has been subject to continued development and expansion, and now incorporates the in-stream kinetic routines of the QUAL2E water quality model (Brown and Barnwell, 1987) and improved carbon cycling routines based on those from the CFARM model (Kemanian et al., 2011). The model is also now able to account for changes in agricultural management practices and land use over time (Arnold et al., 2012). An ArcGIS SWAT interface (ArcSWAT) has also been developed to pre-process model inputs and to execute simulations within SWAT (Olivera et al., 2006). A description of the SWAT model, the processes simulated by the model, key model features and previous and potential applications are provided for reference in the sections that follow.

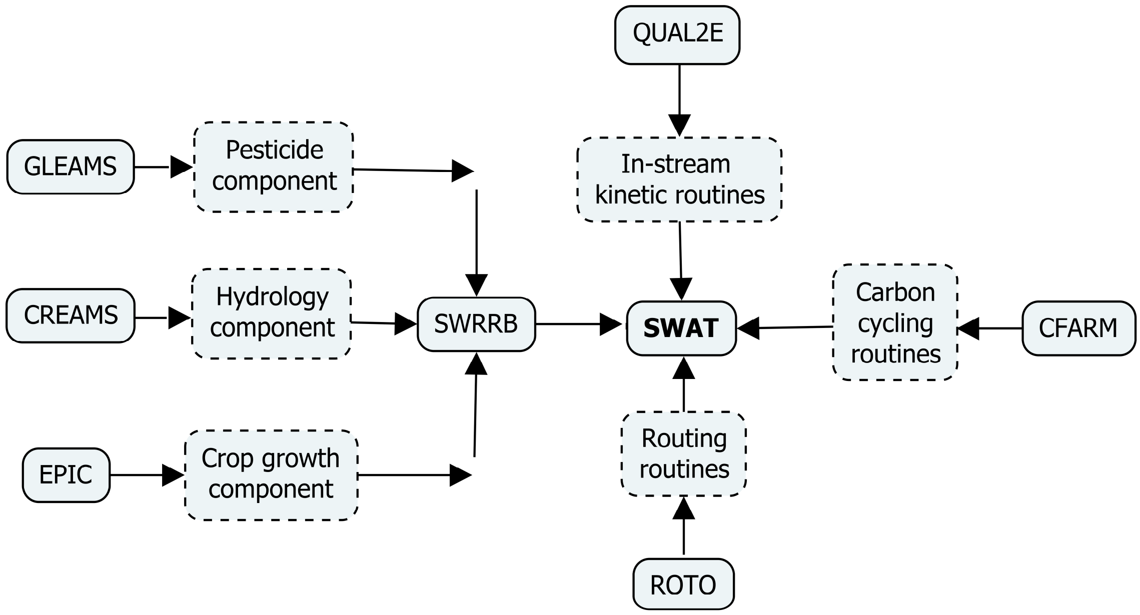

Figure 2.7: Schematic diagram of SWAT model components and development history. Adapted from Gassman et al. (2007) and Arnold et al. (2012).

2.4.1 Model Description

SWAT is a semi-distributed, semi-physically based, continuous time-step model that is designed to simulate the impacts of management practices on surface water, groundwater, nutrients, sediments and pesticides at the catchment scale (Arnold et al., 2012). The model operates at a daily time-step, is computationally efficient and enables users to simulate the impacts of variations in management practices and land use over long time-periods (Neitsch et al., 2011). The model requires information on land use, topography, soils, management practices and weather for the catchment where it is to be applied. Within SWAT, a catchment is divided into sub-catchments which are sub-divided into Hydrologic Response Units (HRUs) that consist of unique combinations of homogeneous types of land use, soil and slope characteristics (Arnold et al., 2012). Each HRU represents a percentage of the sub-catchment area and is not modelled contiguously in space. As an alternative to the HRU approach, users may choose to only divide the catchment into sub-catchments which reflect the single most dominant land use, soil type and slope category within each sub-catchment (Gassman et al., 2007). The major processes modelled within SWAT include climate, hydrology, plant growth, sediment erosion, nutrient cycling and transport, pesticide fate and transport and management practices (Neitsch et al., 2011).

The hydrologic cycle as modelled within SWAT is based on the water balance equation as defined by Equation 1 and outlined by Neitsch et al. (2011):

$$SW_t = SW_0 + \sum_{i=I}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \quad (1)$$

Where:

SW_t is the final soil water content day i (mm H_2O)

SW_0 is the initial soil water content on day i (mm H_2O)

t is the time (days)

R_{day} is the amount of precipitation on day i (mm H_2O)

Q_{surf} is the amount of surface runoff on day i (mm H_2O)

E_a is the amount of evapotranspiration on day i (mm H_2O)

w_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O)

Q_{gw} is the amount of return flow on day i (mm H_2O)

The hydrologic cycle is also the primary driver of the other processes simulated within the model because it impacts on plant growth and nutrient, sediment and pesticide transport (Arnold et al., 2012).

Hydrological processes within SWAT are split into two phases: (i) the land-based phase; and (ii) the channel-based phase (Neitsch et al. 2011). The former determines the amount of water, sediment, nutrients and pesticides that enter the stream network. The latter routes water, sediment nutrients and pesticides through the stream network within the catchment.

The hydrologic cycle within a catchment is driven and controlled by the local climate (Arnold et al., 2012). This is also the case within SWAT. The meteorological inputs that are therefore 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 the required daily meteorological inputs from long-term (i.e. preferably 20 years or more) monthly climate statistics from local weather stations (Arnold et al., 2012). SWAT uses the mean daily temperature values to estimate whether precipitation should be classified as either snow or rain (Gassman et al., 2007). Daily soil temperature is also calculated due to the impact it has on water movement and residue decay (Arnold et al., 2012). The hydrological processes modelled within SWAT include canopy storage, infiltration, redistribution of water throughout the soil profile, evapotranspiration, lateral flow, surface runoff, ponds, tributaries, transmission losses in streams, and return flow (Neitsch et al., 2011).

The volume of surface runoff within the model is calculated using a modified version of the Soil Conservation Service Runoff Curve Number method (Neitsch et al., 2011). The rate of infiltration of water from the surface into soils is determined by the hydraulic conductivity and the initial water content of soils. Percolation is calculated for each layer of soil within the model and occurs when the water content of one layer exceeds field capacity and the soil layer below is unsaturated (Neitsch et al., 2011). The rate of flow is determined by the hydraulic conductivity of the soil layer. A kinematic storage model developed by Sloan et al. (1983) and outlined by Sloan and Moore (1984) is used to simulate lateral flow within the subsurface and takes account of variations in slope and the hydraulic conductivity and water content of soils (Neitsch et al., 2011). The model also incorporates routines to simulate tile drainage. By default, potential evapotranspiration within the model is calculated using the Penman-Monteith method (Monteith, 1965; Allen et al., 1998), but there is the option to use either the Priestley-Taylor method (Priestley and Taylor, 1972) or the Hargreaves method instead (Hargreaves and Samani, 1985). After potential evapotranspiration has been calculated, SWAT then calculates actual evapotranspiration (Neitsch et al., 2011). Any rainfall that has been intercepted by the plant canopy is first evaporated. Transpiration by plants and evaporation from soils is then calculated using the method described by Ritchie (1972) and outlined by Neitsch et al. (2011). Water that percolates below the soil profile within SWAT becomes groundwater recharge and is partitioned between a deep and shallow aquifer. Water that enters the deep aquifer is considered to contribute groundwater return flow to streams outside of the catchment and is lost from the model. Water that enters the shallow aquifer contributes return flow (also known as baseflow) to streams within the modelled catchment. SWAT incorporates a simplified version of the plant growth sub-model from the EPIC model and is applied to assess nutrient and water removal by plants from soils, plant biomass and yield and transpiration (Williams et al., 1984). The model uses the accumulating heat unit approach to simulate plant development (Neitsch et al., 2011). Under non-optimal conditions, plant growth may be constrained by insufficient nutrient and water availability and temperature stress. Sediment erosion is calculated using the Modified Universal Soil Loss Equation (MUSLE) (Smith et al., 1984; Neitsch et al., 2011). The nitrogen and phosphorus cycles are modelled within SWAT to simulate the movement and transformation of nitrogen and phosphorus within the environment (Neitsch et al., 2011). Pesticide fate and transport is also modelled within SWAT which accounts for volatilisation, leaching, decay and transportation in surface runoff (in solution and when attached to eroded sediment). SWAT is also able to simulate the management practices that occur within a catchment including irrigation, nutrient and pesticide application, tillage and a variety of mitigation practices including buffer strips and reduced tillage (Gassman et al., 2007). Once SWAT has determined the amount of water, sediment, nutrients and pesticides that is transported from land to the river network, they are routed downstream. The in-stream processes modelled by SWAT include biodegradation, transformation, deposition, resuspension, volatilisation and diffusion (Neitsch et al., 2011). The SWAT model simulates all of the key physical processes found within the Wensum catchment and so it is considered to a suitable model to apply within this investigation.

Neitsch et al. (2011) provides a detailed review of the physical processes modelled within SWAT, the theory behind the model and the equations applied within the model to simulate physical processes. Input variables define physical properties within the model and parameters are used to define which management practices are performed. Arnold et al. (2014) provides a detailed overview of the model input requirements and outputs. Arnold et al. (2012) also present an overview of the 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).

2.4.2 Model Applications

The acceptance of SWAT as a robust catchment modelling tool is evidenced by the hundreds of SWAT related peer-reviewed articles that have been published within scientific journals (Gassman et al., 2007). SWAT has been applied to conduct hydrology and water quality assessments, sensitivity analyses, pollutant loss studies and to assess climate change impacts, management practice impacts, land use impacts and calibration techniques (Gassman et al., 2007). For reference, Gassman et al. (2007) provide a detailed summary of over 250 previous applications relating to SWAT and Krysanova and Arnold

(2008), Douglas-Mankin et al. (2010) and Tuppad et al. (2011) review the historical development and applications of the model.

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 SWAT for assessing the impacts of mitigation measures 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 also been widely and successfully applied to assess the impacts of agricultural mitigation measures on water quality (e.g. Santhi et al., 2006; Hu et al., 2007; Gevaert et al., 2008; 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 measures that have been modelled include buffer strips, nutrient management plans, alternative tillage practices and techniques, alternative crop rotations and changes in land use. Shepherd et al. (1999) evaluated the suitability of 14 different models to simulate diffuse nutrient losses to watercourses in eastern England in the UK and found that SWAT was the most suitable model for this task. Due to the widespread acceptance of SWAT as a robust tool to assess the impacts of catchment management practices on water quality, it is considered to be suitable for this aspect of this research project.

For a model to be applied with confidence, it is important to assess the ability of the model to simulate the variables of interest (e.g. flow rate or nitrate concentration) and to conclude whether it can do so with a sufficient degree of accuracy. There is no standard or universally accepted metric applied to assess model performance but Moriasi et al. (2007) suggest that models should achieve a Nash-Sutcliffe Efficiency (NSE) coefficient of greater than 0.5 for flow, sediment, 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.

A review of the literature has shown the SWAT is suitable for application to assess the impacts of catchment mitigation measures on water quality and that it is considered to be an appropriate DST for assisting authorities in managing catchments to achieve statutory water quality targets. It is therefore judged that SWAT is highly suitable for application within this study. For this reason, and those described in Section 2.3, it has been selected as the water quality model to be applied for the purposes of this research.

2.4.3 The Swat Calibration and Uncertainty Program (SWAT-CUP)

SWAT-CUP is a computer program that can be applied to SWAT models to conduct semi-automated calibration, validation, sensitivity analysis and uncertainty analysis, although a manual approach can also be used within the program to calibrate models (Abbaspour, 2015; Abbaspour et al., 2015). SWAT-CUP incorporates five optimisation algorithms that can be used to optimise model parameters including Sequential Uncertainty Fitting version 2 (SUFI-2) (Abbaspour et al., 2004; 2007), Generalised Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992); Particle Swarm Optimisation (PSO) (Kennedy and Eberhart, 1995), Parameter Solution (ParaSol) (van Griensven and Meixner, 2006) and Markov Chain Monte Carlo (MCMC) (Vrugt et al., 2003). Relative to manual techniques, the semi-automated nature of SWAT-CUP provides an efficient mechanism to conduct model calibration, validation, sensitivity analysis and uncertainty analysis. Due to the advantages that SWAT-CUP provides over a manual approach, it has been selected as the program that will be applied within this study to undertake these tasks.

SWAT-CUP incorporates a parallel processing module that allows multiple SWAT model simulations to be run in parallel (i.e. concurrently) when using the SUFI-2 algorithm (Abbaspour, 2015). The parallelised approach is more computationally efficient than the non-parallelised approach which runs one simulation at a time, reducing the amount of time it takes to conduct model sensitivity analysis, calibration, validation and scenario analysis (Rouholahnejad et al., 2012). At present, the parallel processing module within SWAT-CUP supports the parallelisation of SUFI-2 but none of the other optimisation algorithms. The robustness of SUFI-2 as an algorithm for the optimisation of hydrological model parameters and its suitability for performing model calibration, validation and sensitivity analysis has been demonstrated in the examples of Abbaspour et al. (2007), Yang et al. (2008) and Faramarzi et al. (2009). For these reasons, and the increased computational efficiency that the parallelised version of SUFI-2 allows over the other optimisation algorithms, it has been chosen as the optimisation algorithm that will be applied within SWAT-CUP for this study.

Within SUFI-2, the values of model parameters are considered to be uncertain (Abbaspour et al., 2007), and this parameter uncertainty propagates uncertainties in model predictions. SUFI-2 is based on the concept of equifinality which proposes that multiple parameter sets provide predictions that are acceptable (Beven, 1993; Beven and Freer, 2001; Beven, 2006). Arguing in favour of the concept of equifinality and the non-uniqueness of parameter sets, Beven and Freer (2001) suggest that practitioners should search for those parameter sets that provide an adequate representation of a system rather than a single 'optimum' parameter set. These parameter sets are described as behavioural (i.e. they provide predictions that are an acceptable fit to observations). Numerous performance criteria have been used to assess whether a parameter set is behavioural or non-behavioural but one commonly applied is whether the predictions developed from a particular parameter set achieve an NSE value of greater than 0.5. Based on this criterion, if a parameter set achieves an NSE greater than 0.5 it is considered to be behavioural. It is difficult to reject one behavioural parameter set in favour of another that achieves a superior performance according to the performance criterion applied given that the performance of a parameter set may be dependent on the calibration and validation time periods used to assess performance (Beven, 2006). A parameter set might perform differently if a different time period is used. Since each of the behavioural parameters provide predictions that are considered to be acceptable, they may also be applied to provide an assessment of prediction uncertainty (Beven, 1993). The objective of the SUFI-2 algorithm is to identify the optimum range of values for each parameter which can be applied to identify those solutions that are behavioural. This approach yields multiple predictions that are acceptable and provides a means to assess model prediction uncertainty. A brief step-by-step overview of the SUFI-2 algorithm is provided below but for a more detailed description of the conceptual basis of SUFI-2 and a description of the algorithm see Abbaspour et al. (2004) and Abbaspour et al. (2007) which provide the basis of the description below.

Stage 1: A suitable objective function must first be selected and will be used later in the process to provide a statistical assessment of the performance of the model in simulating the variables of interest (e.g. flow rate). Example objective functions that may be used include the NSE coefficient or percent bias (PBIAS).

Stage 2: A physically realistic uncertainty range must be defined for the value of each parameter that is to be optimised. The value of a parameter is considered to be uniformly distributed within this range, as defined by the minimum and maximum values.

Stage 3: A sensitivity analysis should be conducted to identify those parameters that model outputs are sensitive to and, therefore, the parameters that should be included in model calibration.

Stage 4: Initial global uncertainty ranges are defined for each parameter and Latin Hypercube sampling (McKay et al., 1979) is conducted to generate n parameter sets, where n equals the number of simulations to be performed. Abbaspour et al. (2007) recommends that between 500-1000 simulations are performed during this first iteration and each iteration that follows. A total of n simulations are then performed and the model outputs for variables of interest (e.g. flow rate) are saved.

Stage 5: To assess the performance of the model in simulating the variables of interest (e.g. flow rate) the objective function (e.g. the NSE coefficient) is calculated for each simulation.

Stage 6: A number of measures are calculated, including the 95% confidence interval of each parameter, to identify improved parameter ranges that may be used in future iterations.

Stage 7: Next, the 95% prediction uncertainty range is calculated for each variable of interest (e.g. flow rate) at each time-step. The 95% uncertainty range equates to simulations that are contained between the 2.5th and 97.5th percentiles. The goodness of fit of the model is assessed by calculating: (i) the proportion of observations that are bracketed by the 95% uncertainty range and; (ii) the d-factor, which is the ratio of the mean distance between the upper and lower 95% uncertainty range to the standard deviation of the measured data (a measure of the degree of uncertainty). The performance of the model in simulating the variables of interest (i.e. flow rate) can also be assessed from the values achieved for the objective function.

Under an ideal scenario, 100% of observations would be bracketed by the uncertainty band and the d-factor would be minimal. In practice, a balance must be achieved to maximise the proportion of observations bracketed by the 95% uncertainty range, whilst minimising the degree of uncertainty in predictions and maximising model performance according to the objective function. When it is judged that the model is sufficiently calibrated according to the criteria defined above, the process is finished. If the model is not deemed to be sufficiently calibrated, **Stage 8** is performed.

Stage 8: Uncertainty ranges tend to be quite large during the first iteration and additional iterations generally need to be performed. Using those estimates derived in **Stage 6**, parameter ranges are updated and a subsequent iteration beginning at **Stage 4** is performed.

The first stage in the process of performing model calibration and validation within SWAT-CUP is to identify the model parameters that should be included to accurately simulate the variables of interest. For example, parameters that affect baseflow and surface runoff within SWAT are important for determining flow rate within a river and so should be included when calibrating flow rates within the model. The parameters that are important can usually be identified from literature, although expert judgement may also be used. Care should be taken to ensure that the ranges assigned to parameter values remain within a physically realistic uncertainty range (Arnold et al., 2012). Next, using those parameters selected, a sensitivity analysis should be conducted to identify the parameters that model outputs are sensitive to. Sensitivity analysis involves calculating the rate of change in a variable (i.e. flow rate) compared to changes in parameter values (Arnold et al., 2012). Only those parameters that model outputs are sensitive to should be included calibration. Next, model calibration is performed to optimise parameter ranges to improve the goodness of fit between model predictions and observations. When completed, the performance of the model in simulating variables of interest (e.g. flow rate or nitrate concentration) can be assessed and a judgement can be made regarding whether the model performs satisfactorily. If model performance is considered to be satisfactory, validation of the model parameter sets obtained from calibration can then be performed during a period of time that is independent from the calibration time period. The purpose of validation is to examine if the parameter sets obtained from calibration also perform satisfactorily during an independent time period. If the model performs satisfactorily during calibration and validation it can be applied to conduct impact assessments.

2.5 Chapter Summary

In this chapter, a review was carried out to establish this study within the context of research that relates to surface water quality, catchment management, agriculture, environmental policy and catchment-scale water quality modelling. The importance of providing safe and sustainable water supplies whilst also increasing agricultural production to meet the needs of a growing global population was discussed and it was recognised that reconciling these two needs will be a difficult challenge because agriculture is often one of the drivers of water quality degradation. The potential for agricultural intensification to meet the growth in demand for food was discussed and the environmental impacts of intensification were identified. It was considered that new strategies will need to be developed to ensure that agriculture can sustainably intensify to meet food demand, whilst also minimising the impacts on the environment and ensuring the supply of safe water. It was also recognised that there is an urgent need to mitigate the impacts of agriculture on water quality due to the increasing amounts of fertilisers and pesticides used in agriculture and the rapid degradation in water quality.

The current state of water quality was assessed and the main stressors on water resources and the effects of poor water quality were identified. The types and sources of water pollution were described and the relative importance and difficulties of controlling diffuse and point source pollution were discussed. Diffuse pollution from agriculture was identified as a major global pressure on surface water and groundwater quality. The role of catchment management as a potential solution that can be used to mitigate agricultural diffuse water pollution and the potential for catchment-scale water quality models to be applied as DSTs to identify effective mitigation measures was also highlighted.

The types of models available for application were described in detail and the key aspects of 10 different models were reviewed as part of a process to identify the most suitable model to apply within this study. As a result of this review, the SWAT model was identified as highly suitable for application to assess the impacts of mitigation measures on pollutant losses and water quality and was selected as the model to be applied for the purposes of this research. Because the model is semi-physically based, its findings are also transferable to other similar catchments. The history of SWAT, the processes simulated within the model and the model structure were described in detail and the previous and potential applications of SWAT were discussed. The program SWAT-CUP, which can be applied to SWAT models to conduct semi-automated calibration, validation, sensitivity analysis and uncertainty analysis, was also described in detail and an overview of the SUFI-2 optimisation algorithm was provided.

From the review in this chapter, a number of gaps in knowledge and major shortcomings in earlier work were identified which provided the motivation for the aims identified in Chapter 1. Firstly, a clear need to develop mitigation measures that can be adopted to mitigate agricultural diffuse water pollution, improve water quality and assist the development of sustainable agricultural practices was identified. Secondly, it was identified that modelling studies rarely consider the uncertainties of predictions and that additional research to provide estimates of the uncertainties of the predicted impacts of mitigation measures on diffuse water pollution is therefore required. Conducting uncertainty analyses will inform the degree of confidence that can be attached to model predictions, improve the reliability of models as DSTs and allow better-informed policy decisions to be made. Thirdly, it was established that there is a need to undertake additional research to investigate the impacts of mitigation measures on pollutants at a daily resolution to develop a better understanding of how frequently water quality standards are exceeded, the effectiveness of measures and the dynamics of pollutant losses. Fourthly, it was found that additional research to model the impacts of mitigation measures on multiple pollutants needs to be performed to develop a better understanding the impacts of measures on various pollutants and to mitigate the risk of introducing measures that exacerbate losses of other pollutants. Fifthly, the recalcitrance of metaldehyde to traditional water techniques, a lack of research into the impacts of catchment mitigation measures on metaldehyde and the subsequent need for a study to investigate potential solutions was also noted.

3 STUDY AREA AND DATA

3.1 The River Wensum Catchment

The River Wensum catchment has been selected as the study area to investigate the impacts of agricultural mitigation measures on diffuse metaldehyde pollution (see Chapter 6).

The River Wensum is a shallow-gradient, naturally-enriched, groundwater-dominated, lowland calcareous river located in Norfolk, England and drains a total catchment area of 675 km^2 (Sear et al., 2006) (Figure 3.1). The source of the river is located on Colkirk Heath, near South Raynham (52° 47′ 4.06″ N, 0° 52′ 44.26″ E) in North Norfolk at a height of 75 m above sea level and flows in a south-easterly direction for a distance of 78 km until it merges with the River Yare in the city of Norwich.

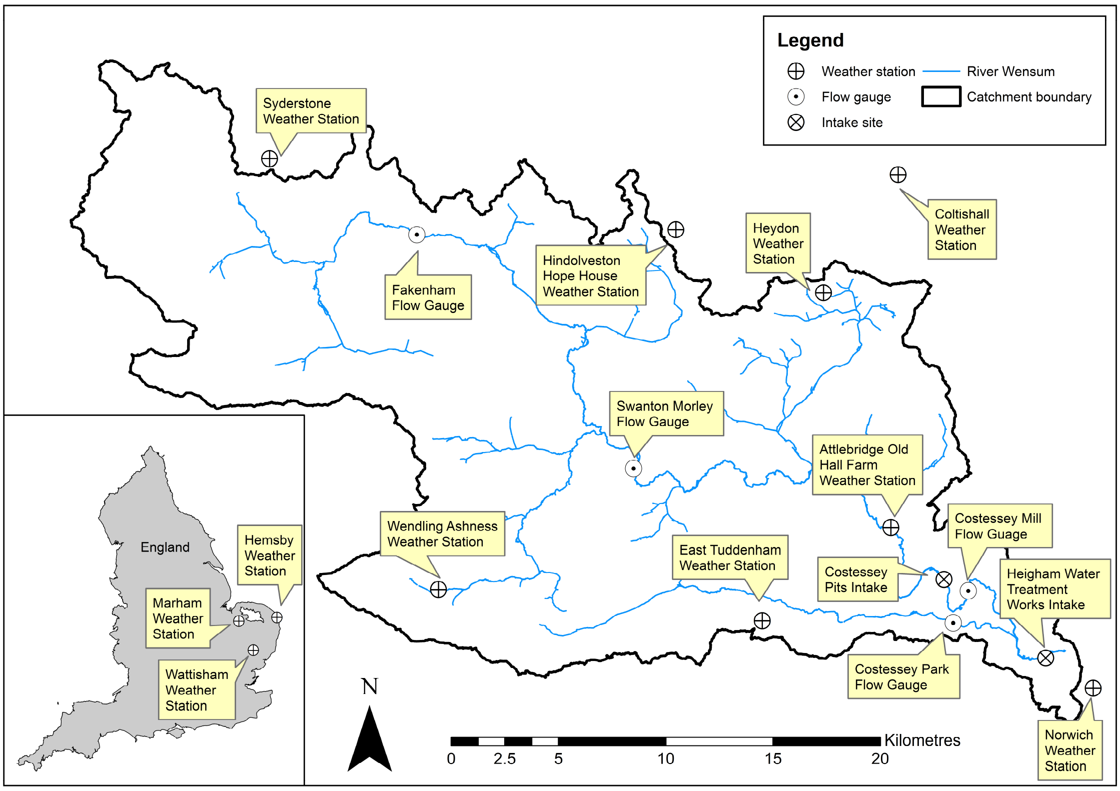

Figure 3.1: A map of the location of the River Wensum catchment, nearby weather stations, flow gauges and the intake sites where water is abstracted from the river for use within the public water supply.

In recognition of the status of the River Wensum as one of the best whole-river examples of its type, a 71 km stretch from the source of the river to a downstream site at Hellesdon Mill (52° 37′ 18.26″ N, 1° 19′ 24.26″ E) was designated as a Site of Special Scientific Interest (SSSI) in 1993, incorporating an area of 393.31 ha, and is intended to enhance or conserve features of importance within the site (Natural England, 1993). Reasons cited for this designation include the presence of a high-diversity of species, including over 100 different plant species, as well as a diverse population of invertebrates and fish, within a traditionally-managed and relatively pristine lowland corridor. In further recognition of the presence of important fauna and flora, an area of 306.79 hectares along the River Wensum was also designated as a Special Area of Conservation (SAC) in 2005 under the EU Habitats Directive (Council of the European Union, 1992; English Nature, 2005; Joint Nature Conservation Committee, 2015; 2016). Within the SAC, a favourable conservation status must be maintained or restored for populations of white clawed crayfish (Austropotamobius pallipes), European bullhead (Cottus gobio), brook lamprey (Lampetra planeri), Desmoulin's whorl snail (Vertigo moulinsiana) and for watercourses which host Ranunculion fluitantis and Callitricho-Batrachion vegetation (Joint Nature Conservation Committee, 2016). A favourable conservation status as defined within the EU Habitats Directive is essentially a status at which the target of interest is not in decline and its long-term abundance and distribution is not threatened (Council of the European Union, 1992).

Despite these goals, the most recent condition assessment carried out in 2010 found that, of the protected habitats contained within the SSSI, 11.05% are in a favourable condition, 47.70% are in an unfavourable but recovering condition and 41.25% are in an unfavourable and unchanging condition (Natural England, 2016). Reasons cited for unfavourable conditions include agricultural diffuse water pollution, siltation of river channels, the presence of invasive freshwater species, water pollution from discharges into the river network (including discharges from sewage treatment works), water abstraction, unsuitable water levels and the presence of unsuitable dams, weirs and other structures (Natural England, 2015a). Indeed, to safeguard water resources from potential risks to drinking water quality, the entirety of the catchment is designated as a Drinking Water Protected Area (DWPA) (Environment Agency, 2009).

Prior to anthropogenic modification, the River Wensum existed as a mixed single-thread sinuous and anastomosing river surrounded by floodplains which hosted a patchwork of marshland and woodland (Sear et al., 2006). Most of the floodplains were cleared approximately 4500 years ago for use within agriculture and the establishment of settlements and by medieval times, the structure of river had been modified to the form it takes today. Impoundment of the river by mill-structures started approximately 900 years ago and peaked just before the Industrial Revolution (circa 1760) and has had a major effect on the hydrology and ecology of the river. Despite these changes, the river environment that is present today is considered to be of great ecological and cultural importance and its preservation is dependent on the implementation of effective management strategies to mitigate or remove the pressures and threats that it currently faces.

3.1.1 Geology and Hydrogeology

The entire catchment is underlain by Cretaceous Chalk bedrock deposits that formed under warm and shallow marine conditions between 66 to 100 million years ago (Figure 3.2) (Sear et al., 2006; British Geological Survey, 2016a). The Chalk dips in a north-easterly direction at a shallow angle of less than 1° and is composed of a well-fissured and fine-grained limestone that forms a major aquifer used to meet a large proportion of water demand in eastern England (Hiscock, 1993; Hiscock et al., 1996; Sear et al 2006; Allen et al., 1997). The Chalk is mostly composed of coccoliths, the calcium carbonate plates that combine to form the shells of a type of phytoplankton known as coccolithophores (Stanley et al., 2005). At some sites in the east of the catchment, the Chalk is overlain by the Wroxham Crag Formation (Lewis, 2014). The Wroxham Crag Formation is primarily composed of sand and gravel, although clay and silt beds and laminae are present in the upper profile of the formation (Rose et al., 2001; Rose et al., 2002). The bedrock geology is unconformably overlain by a complex sequence of superficial deposits of Quaternary origin which include tills, glaciofluvial and glaciolacustrine sands and gravels that were deposited during the Pleistocene and alluvium, river terrace depots, wind-blown sand and peat deposited during the Holocene (Figure 3.3) (Sear et al., 2006; Lewis, 2014).

The aquifers within the catchment consist of the alluvium, river terrace deposits, glaciolacustrine and glaciofluvial sands and gravels, the Wroxham Crag Formation and the Chalk (Lewis, 2014). These layers are intersected by different tills of low permeability, creating a complex network of aquifers. The aquifer system as a whole is estimated to have a mean transmissivity of 685 m^2 day^{-1} and a mean storage coefficient of 0.064 (Toynton, 1983).

Several sources contribute to streamflow within the study area including surface runoff, lateral flow, drain flow and groundwater return flow, which is the principal source. The river has baseflow indexes of 0.82, 0.75, 0.75 and 0.64 at the flow gauges located at Fakenham, Swanton Morley, Costessey Mill and Costessey Park, respectively (Figure 3.1) (National River Flow Archive, 2016a,b,c,d). In the north-west of the catchment where chalk bedrock is located close to the surface, river flow is largely derived from groundwater flow from the underlying chalk aquifer (Sear et al., 2006). In a south-easterly direction along the river, the depth of superficial deposits increases and the contribution to river flow by surface water also increases.

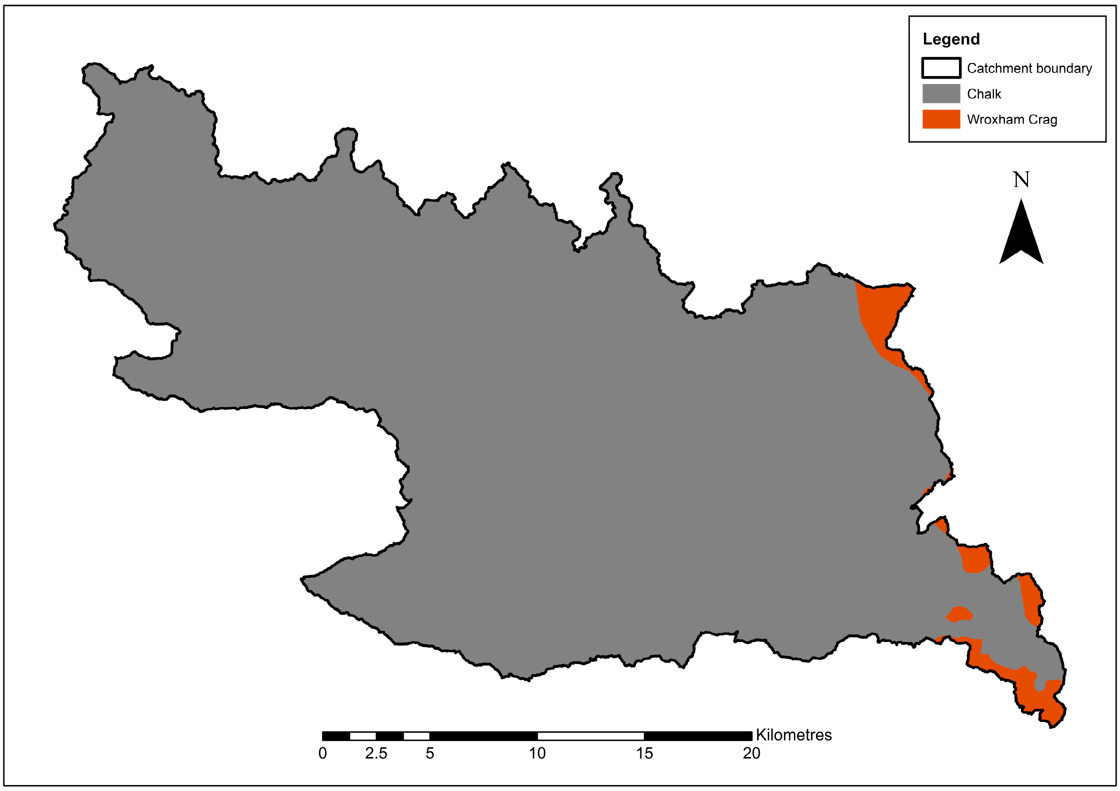

Figure 3.2: The bedrock geology of the River Wensum catchment. Based upon DiGMapGB-625, with the permission of the British Geological Survey (British Geological Survey, 2016b).

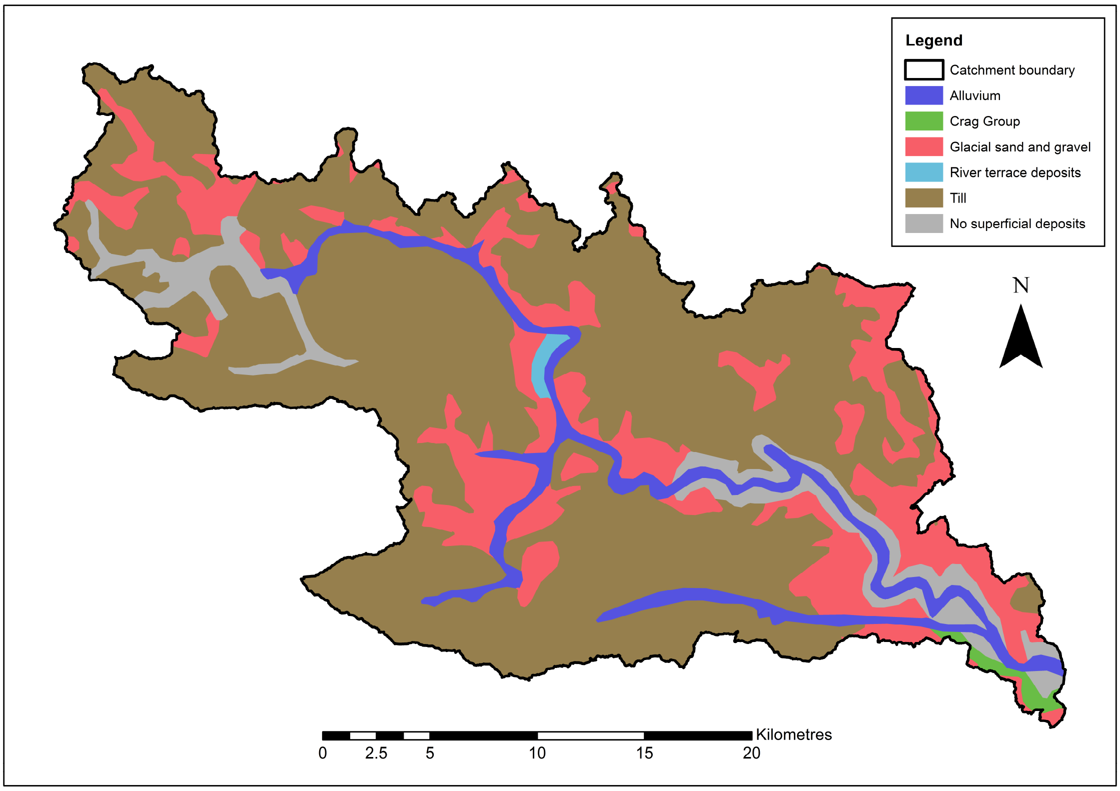

Figure 3.3: The superficial geology of the River Wensum catchment. Based upon DiGMapGB-625, with the permission of the British Geological Survey (British Geological Survey, 2016b).

3.1.2 Topography

According to the NEXTMap British Digital Terrain Model Dataset, which has a resolution of 5 m, the catchment reaches a maximum elevation of 102.7 m above sea level in the upper reaches of the north of the catchment at Swanton Novers (52° 51′ 1.98″ N, 1° 0′ 0.36″ E) and falls to a few centimetres above sea level at the confluence of the River Wensum with the River Yare to the south-east of Norwich (Figure 3.4) (Intermap Technologies, 2007). The terrain of the catchment is relatively flat, with 90% of the area having a slope of 5% or less (Figure 3.5). The main river channel slopes in a south-easterly direction and experiences a fall of 75 metres over the 78 km length of the river channel, representing an average gradient of 0.96 m km^{-1} (Sear et al., 2006). The River Wensum valley and the principal tributaries of the main river form the most distinct topographical features that are present within the catchment. At certain sites the river and its tributaries have eroded down through superficial deposits into the underlying chalk bedrock. There are also a number of dry valleys above the headwaters in the north-west of the catchment that formed under periglacial conditions.

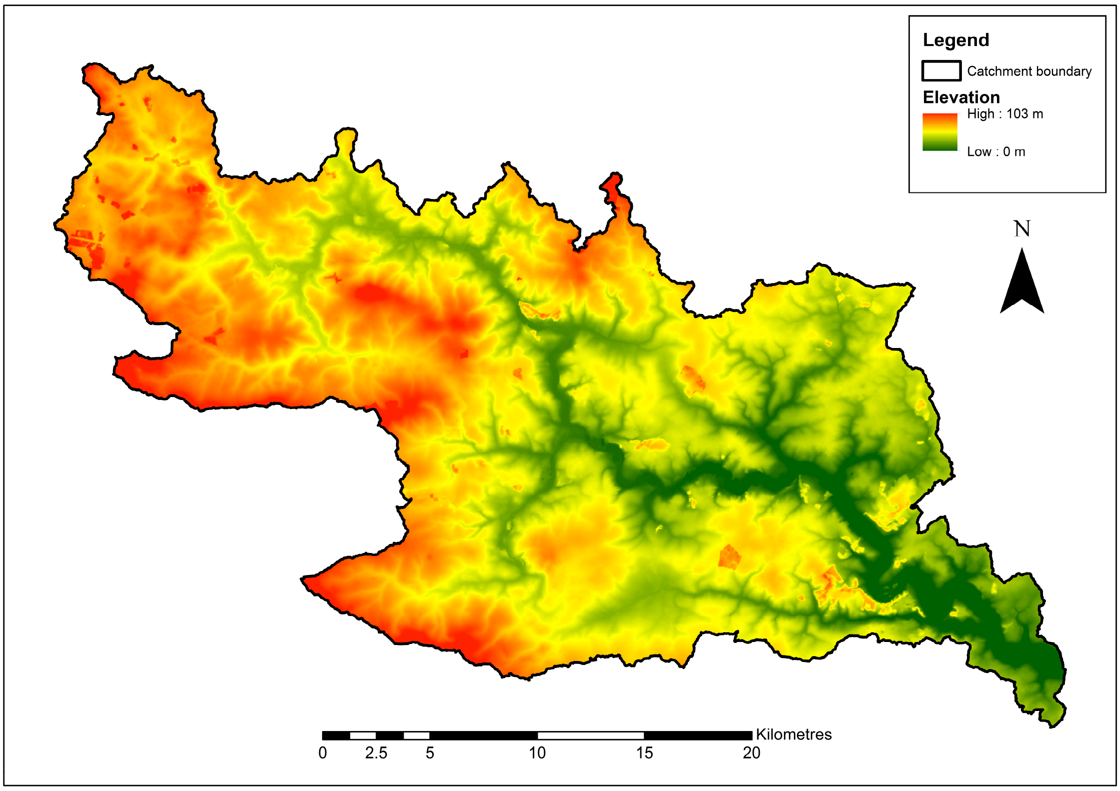

Figure 3.4: The digital elevation model of the River Wensum catchment. Map derived from Intermap Technologies (2007).

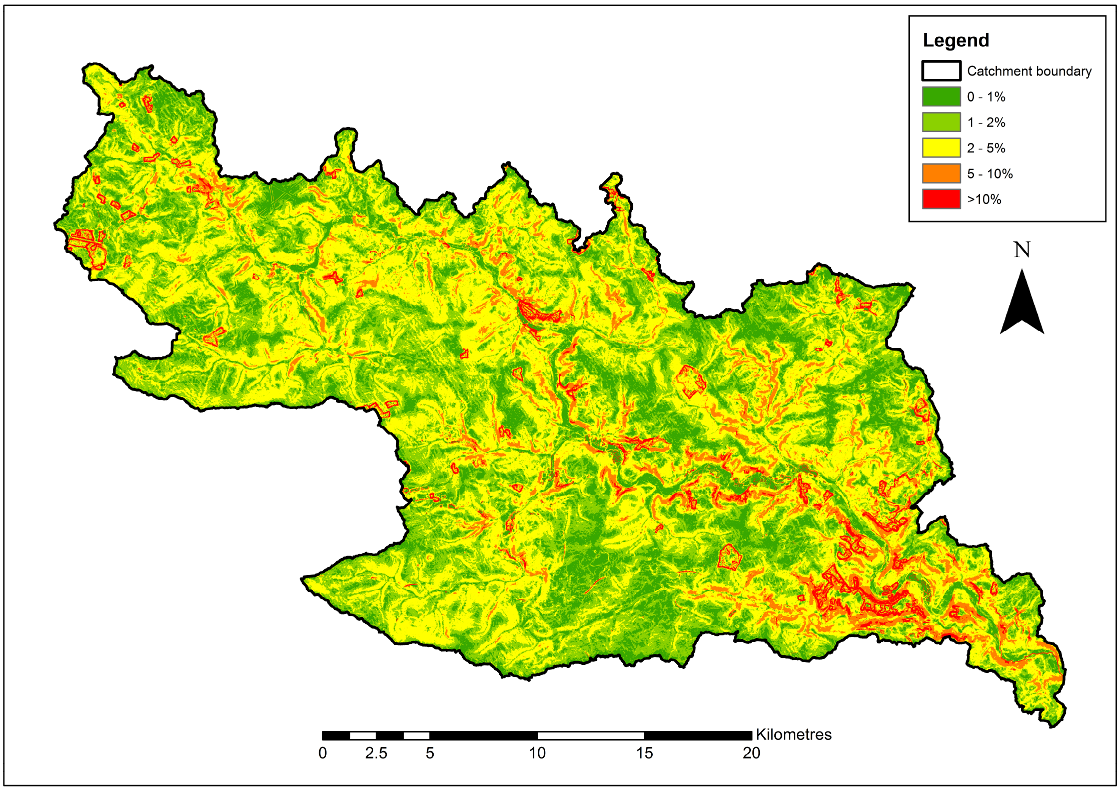

Figure 3.5: The slope of the River Wensum catchment. Map derived from Intermap Technologies (2007).

3.1.3 Data Description

3.1.3.1 Land Cover

The topographic characteristics of the River Wensum catchment make it highly-suitable for use in agriculture. As such, according to 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), land cover within the catchment is largely arable (Figure 3.6). Of the total catchment area, 62% is used in agriculture for growing crops, 18.9% is grazing pasture, 7.3% is broadleaf woodland, 4.4% is other grassland 4.2%, forms suburban settlements, 1.4% is coniferous woodland, 1.4% forms urban settlements and 0.5% is freshwater. Although the catchment is predominantly rural there are a number of main urban centres including the city of Norwich which has a population of 132,000 and the towns of Dereham and Fakenham which have populations of 19,000 and 8,000, respectively (Office for National Statistics, 2016).

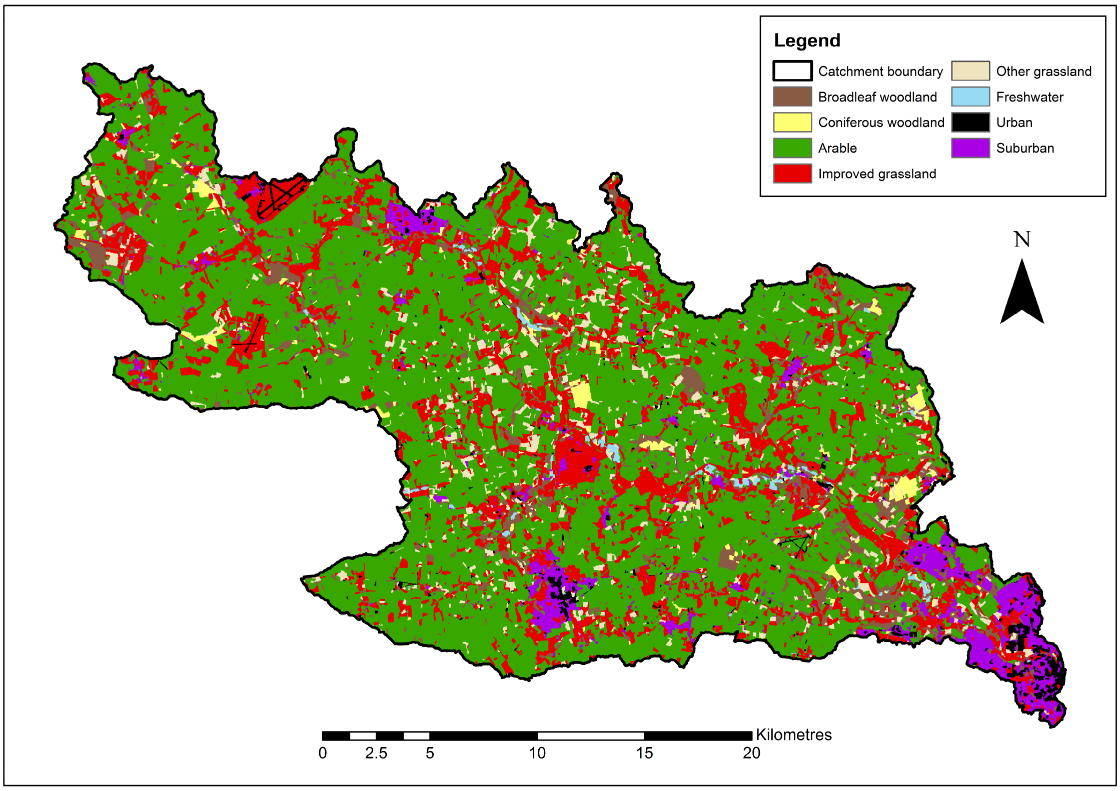

Figure 3.6: A map of the land cover of the River Wensum catchment. Based upon LCM2007 © NERC (CEH) 2011. Contains Ordnance Survey data © Crown Copyright 2007. © third party licensors.

3.1.3.2 Soils

According to the National Soil Map (NATMAP) vector dataset which displays the spatial occurrence of 300 distinct Soil Associations across England and Wales, 12 different Soil Associations are present within the River Wensum catchment (Figure 3.7) (Cranfield University, 2016a). Four of the Soil Associations (Burlingham 1, Burlingham 3, Wick 2 and Wick 3) are loamy soils (37.52% of the catchment), three (Isleham 2, Newport 3 and Newport 4) are primarily sandy soils (23.54% of the catchment), four others (Barrow, Beccles 1, Beccles 2 and Gresham) are loamy over clayey soils (37.7% of the catchment) and one (Adventurers 2) is composed of peat (1.24% of the catchment) (Figure 3.8) (Cranfield University, 2016b). Each Soil Association is composed of multiple Soil Series which possess distinct properties and is named after the Soil Series that is present in the greatest proportion. For example, Burlingham 1, is predominantly composed of the Burlingham Soil Series, but the Wighill, Wick and Newport Soil Series are also present in smaller proportions (Cranfield University, 2016c). The properties of each of the Soil Associations were derived from the HORIZON Hydraulics, HORIZON Fundamentals, SOILSERIES Agronomy, LandIS Soils Guide and National Soils Inventory (NSI) Profile datasets (Cranfield University, 2016b,d,e).

The headwaters of the catchment are dominated by the Barrow Soil Association which is mainly composed of well-drained deep loamy over clayey soils (Cranfield University, 2016f). Along the main river valley and tributaries, soils are predominantly from Isleham 2 Soil Association which are deep sandy and peaty soils that are seasonally waterlogged due to interaction with groundwater (Cranfield University, 2016g). These soils are considered to be at risk of wind erosion and flooding during the winter months. The soils present in the mid-section of the catchment are primarily from the Burlingham 1 Soil Association and are primarily deep loamy soils that are slowly permeable and slightly prone to seasonal waterlogging (Cranfield University, 2016c). The lower section of the catchment is dominated by soils from the Newport 4 Soil Association which is a deep sandy soil that is well-drained and susceptible to wind erosion (Cranfield University, 2016h).

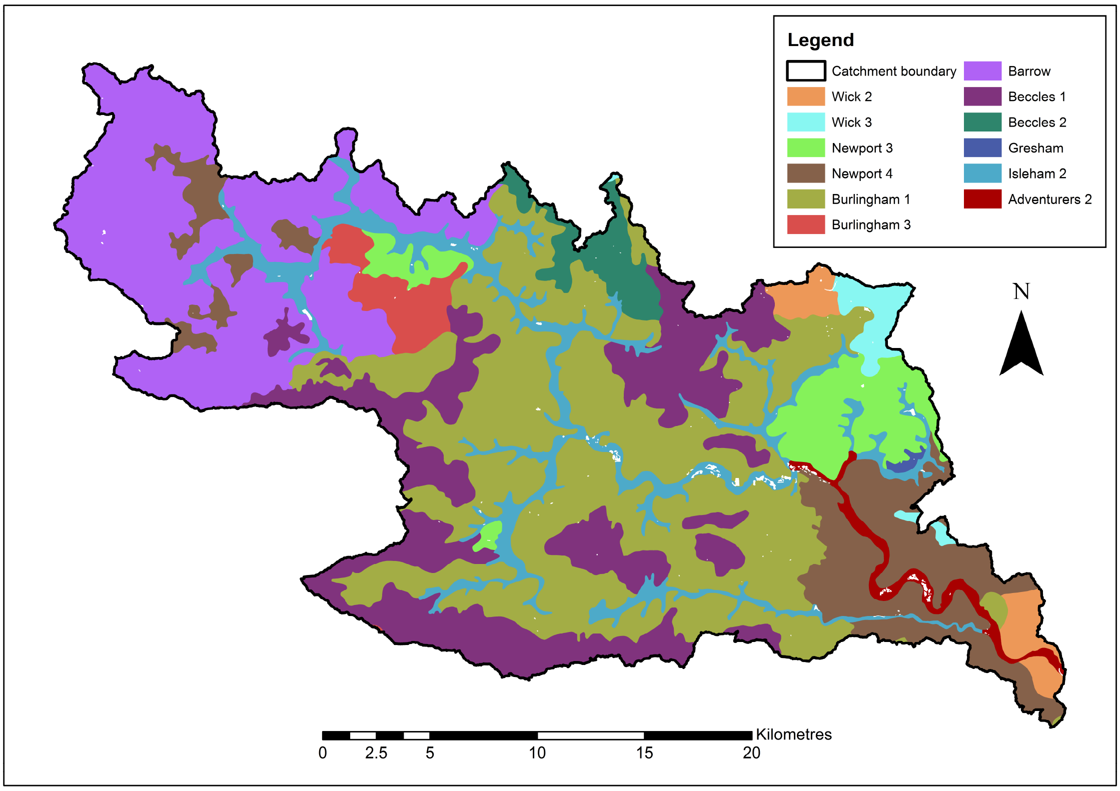

Figure 3.7: A map of the National Soil Map of England and Wales (NATMAP) soil types of the River Wensum catchment. Map derived from Soils Data © Cranfield University (NSRI) and the Controller of Her Majesty's Stationary Office [2016].

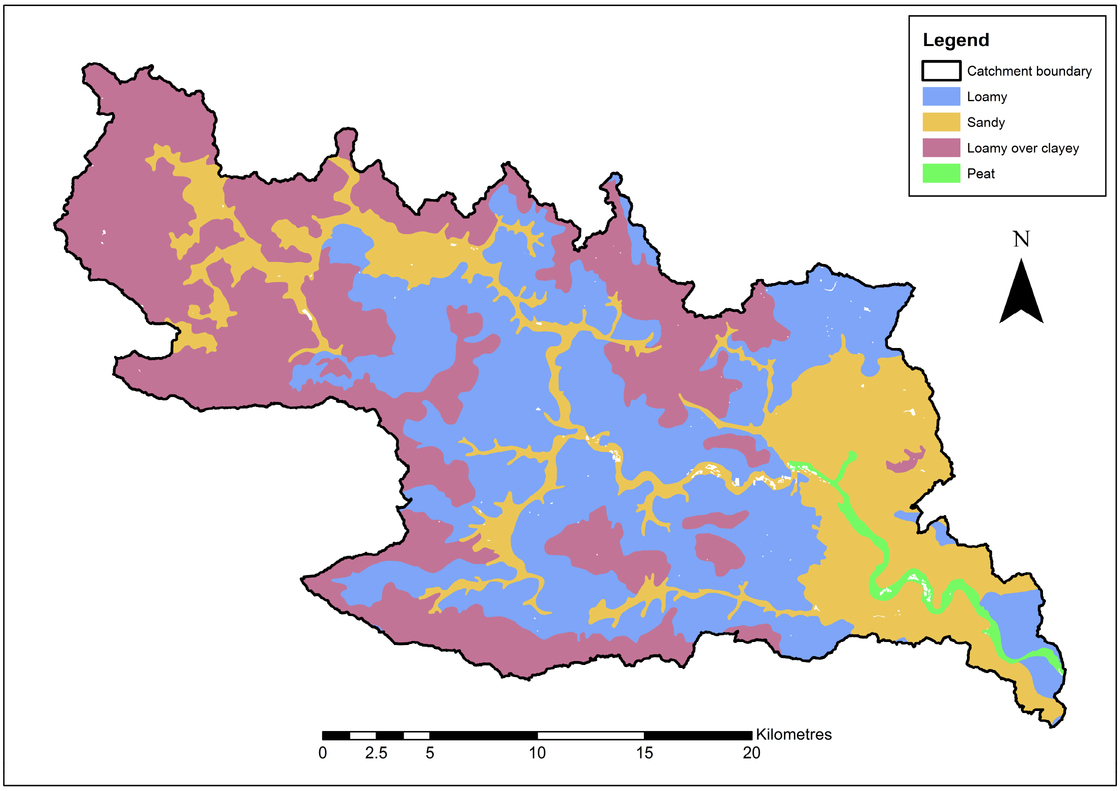

Figure 3.8: A map of the general soil types of the River Wensum catchment. Map derived from Soils Data © Cranfield University (NSRI) and the Controller of Her Majesty's Stationary Office [2016].

3.1.3.3 Agriculture

Data from the Agricultural Census conducted by Department for Environment, Food and Rural Affairs (Defra) (2016a) and held by EDINA at Edinburgh University Data Library (EDINA, 2014) was obtained for the River Wensum catchment for the period 1993-2010 in a 2 km grid square format. According to this data, wheat, oilseed rape, barley and sugar beet were the crops most commonly grown within the catchment during 1993-2010 (Figure 3.9). Based on expert agronomic advice, the crop rotation applied within the model, listed in order of cultivation, consisted of winter wheat, winter barley, winter oilseed rape, winter wheat and sugar beet (Table 3.1). The rotation was initiated at different starting points within the scheme based on crop-type, and was distributed randomly within the model because actual crop distributions within the catchment were unknown. Fertiliser application rates were determined from the Defra RB209 Fertiliser Manual (Defra, 2010a). Pesticide application rates were determined from UK Annual Pesticide Surveys for the period 2004-2014 (Garthwaite et al., 2005; 2007; 2010; 2011; 2013; 2015). The pesticide was applied to all cropped areas within the model. In order to account for the fact that not all areas of each crop type were always treated with metaldehyde according to real-world data, the pesticide application rates applied within the model were multiplied by the percentage of the total area of crop grown that were treated with metaldehyde (Table 3.2). The timing of pesticide application was based on agronomic advice. The timings of tillage, cultivation, fertiliser application and harvest were determined for sugar beet from British Sugar (2010), and for all other crop types from UK Agriculture (2014).

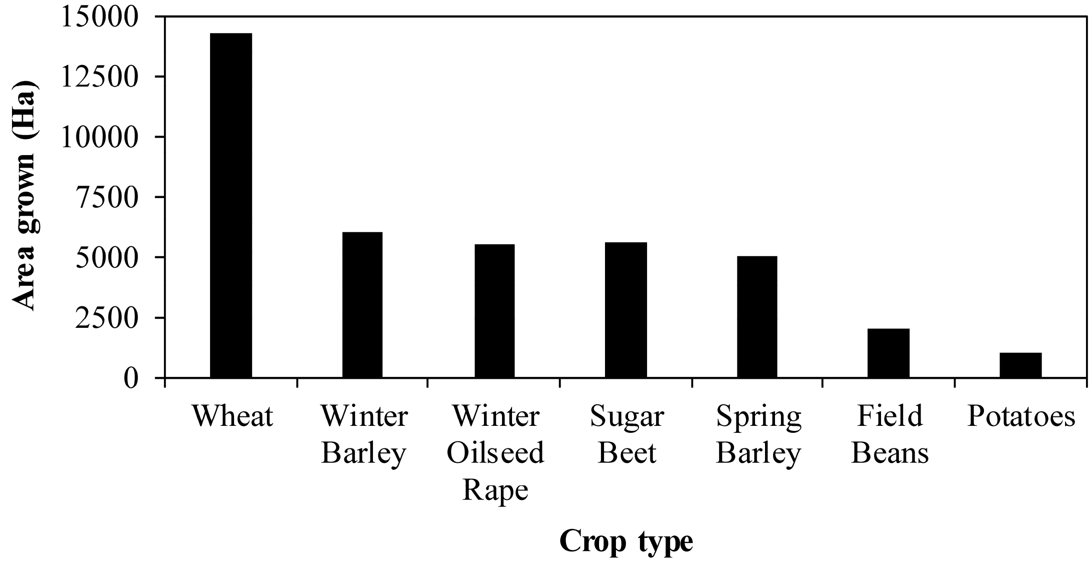

Figure 3.9: The area of each crop type most frequently grown within the River Wensum catchment according to the 2010 Agricultural Census conducted by the Department for Environment, Food and Rural Affairs (Defra, 2016a; EDINA, 2014).

Table 3.1: The crop-rotation scheme and management operations applied within the SWAT model of the Wensum catchment.

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

Table 3.2: The rates of metaldehyde application applied to each crop type within the SWAT model of the Wensum catchment as determined from UK Annual Pesticide Surveys for 2004-2014 (Garthwaite et al., 2005; 2007; 2010; 2011; 2013; 2015). The numbers enclosed in brackets are the percentage of the total area of each crop grown that were treated with metaldehyde. A percentage greater than 100 indicates that the area has been treated more than once.

Year	Application rate for wheat (kg ha^{-1})	Application rate for barley (kg ha^{-1})	Application rate for oilseed rape (kg ha^{-1})	Application rate for sugar beet (kg ha^{-1})
2004	0.374 (13.3)	0.338 (2.40)	0.234 (92.66)	0.152 (0.86)
2005	0.363 (18.82)	0.285 (2.45)	0.116 (164.34)	0.288 (0.9)
2006	0.344 (28.91)	0.284 (7.25)	0.214 (125.51)	0.425 (0.94)
2007	0.325 (39)	0.284 (12.05)	0.312 (86.69)	0.409 (1.88)
2008	0.264 (28.86)	0.263 (8.21)	0.271 (68.41)	0.392 (2.81)
2009	0.202 (18.71)	0.241 (4.38)	0.229 (50.14)	0.371 (2.91)
2010	0.179 (15.19)	0.182 (3.39)	0.196 (47.63)	0.350 (3.01)
2011	0.156 (11.68)	0.123 (2.40)	0.163 (45.12)	0.261 (2.70)
2012	0.142 (15.31)	0.124 (3.09)	0.140 (56.68)	0.171 (2.38)
2013	0.127 (18.94)	0.124 (3.78)	0.117 (68.25)	0.162 (2.54)
2014	0.127 (18.94)	0.124 (3.78)	0.117 (68.25)	0.152 (2.69)
2015	0.127 (18.94)	0.124 (3.78)	0.117 (68.25)	0.152 (2.69)

3.1.3.4 Meteorological Data and Climate

Observations of meteorological variables recorded for the period 1 January 1980 to 31 October 2015 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). Daily observations of mean wind speed, sunshine hours, minimum and maximum air temperature and mean relative humidity were obtained from the UK MIDAS weather station located at Marham (Station ID: 409), which is sited approximately 15 km to the east of the Wensum catchment. The Angstrom formula, outlined by Allen et al. (1998), was used to calculate an estimate of solar radiation from observations of daily sunshine hours and is defined by Equation 2.

$$\text{Solar radiation } (R_s) = \left(a_s + b_s \frac{n}{N}\right) R_a \qquad (2)$$

Where:

R_s	is solar or shortwave radiation (MJ m^{-2} day^{-1})
n	is the actual duration of sunshine (hour)
N	is the maximum possible duration of sunshine or daylight hours (hour)
$\frac{n}{N}$	is the relative sunshine duration (dimensionless)
R_a	is extraterrestrial radiation (MJ m^{-2} day^{-1})
a_s	is the regression constant which expresses the fraction of extraterrestrial radiation reaching Earth on overcast days ($n = 0$)
$a_s + b_s$	is the fraction of extraterrestrial radiation reaching Earth on clear days ($n = N$)

The Angstrom values, a_s and b_s, vary because they are dependent on atmospheric conditions (i.e. humidity and dustiness) and solar declination (i.e. the time of year and latitude of the site) (Allen et al., 1998). Allen et al. (1998) recommend that at a site where no calibration has been performed to improve estimates of a_s and b_s, the values $a_s = 0.25$ and $b_s = 0.5$ should be used.

Where no record of sunshine hours exists within the Marham record, observations recorded at the weather stations located at Coltishall (Station ID: 429), Norwich Weather Centre (Station ID: 408), Hemsby (Station ID: 433) and Wattisham (Station ID: 440) were used to interpolate missing data using the nearest neighbour technique. Observations of precipitation were obtained from the MIDAS weather stations located at Attlebridge: Old Hall Farm (Station ID: 4812), East Tuddenham (Station ID: 4817), Heydon (Station ID: 4807), Hindolveston: Hope House (Station ID: 4886), Syderstone (Station ID: 4710) and Wendling: Ashness (Station ID: 4793). Where observations of precipitation were missing from the records from the weather stations listed above, the missing data was interpolated from the weather stations listed in Table 3.3 using the nearest neighbour technique.

The River Wensum catchment has a temperate maritime climate and, according to data from the MIDAS weather station located at Heydon (Station ID: 4807), had a mean annual rainfall of 714 mm and an annual rainfall range of 542.6-878.8 mm during 1981-2010 (Met Office, 2012). It is clear that the catchment is characterised by a relatively low annual amount of rainfall when compared to England as a whole, which experienced a mean annual rainfall of 855 mm during 1981-2010 (Figure 3.10) (Met Office, 2016). Mean monthly precipitation within the catchment was lowest in February (45.1 mm) and highest in October (74.6 mm) (Figure 3.10). Rainfall within the catchment is unevenly distributed on a monthly basis throughout the course of a year, with the wettest season occurring on average during the Autumn months from September to November, experiencing a mean rainfall total of 209.4 mm (29.3% of the mean annual total) during 1981-2010 (Figure 3.10). On an average basis spring witnesses the least amount of rainfall, experiencing a mean rainfall total of 147.7 mm (20.7% of the mean annual total) during 1981-2010 (Figure 3.10). Due to the relatively flat topography of the catchment, the topographic features that are present have relatively little impact on the rainfall regime within the catchment.

Table 3.3: The UK MIDAS weather stations used to interpolate precipitation data missing from the primary weather station using the nearest neighbour technique. The weather stations are listed in order of their proximity to the primary weather station.

Primary MIDAS Weather Station	Weather Stations used to Interpolate Data
Attlebridge: Old Hall Farm (Station ID: 4812)	Costessey (Station ID: 423), Hevingham (Station ID: 4904), East Tuddenham (Station ID: 4817), Heathersett Tower (Station ID: 30465)
East Tuddenham (Station ID: 4817)	Runhall: Beech House Farm (Station ID: 4755), Attlebridge: Old Hall Farm (Station ID: 4812), Heathersett Tower (Station ID: 30465)
Heydon (Station ID: 4807)	Mannington Hall (MIDAS Station ID: 24219)
Hindolveston: Hope House (Station ID: 4886)	Melton Constable (Station ID: 4732), Heydon (Station ID: 4807)
Syderstone (Station ID: 4710)	Fakenham: Dunton Hall (Station ID: 56084), North Creake (Station ID: 4712),
Wendling: Ashness (Station ID: 4793)	East Dereham (Station ID: 30462), North Elmham: Tower Hill (Station ID: 4790)

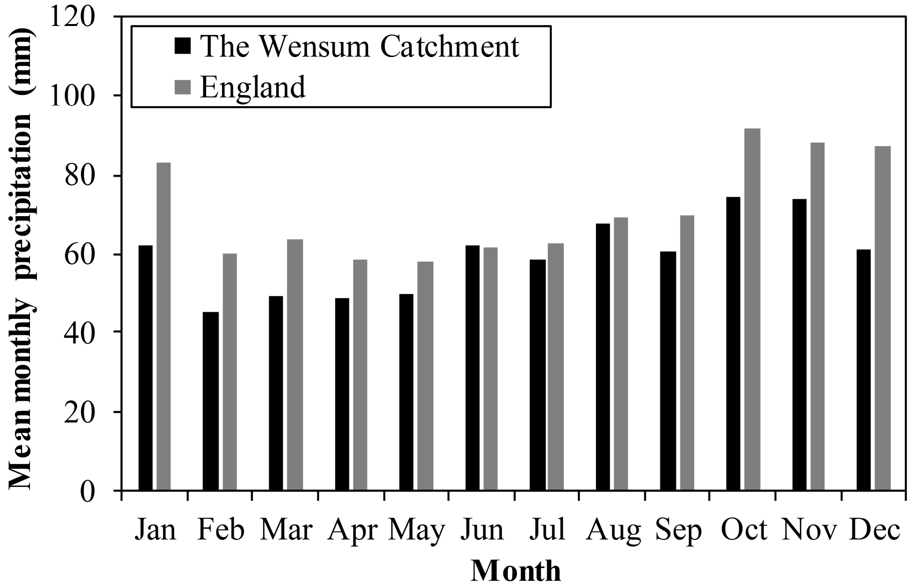

Figure 3.10: Mean total monthly precipitation for the River Wensum catchment and England as a whole during 1981-2010 (Met Office, 2012; Met Office, 2016). Precipitation data for the River Wensum catchment was obtained from the UK MIDAS Weather Station located at Heydon (Station ID: 4807) (Met Office, 2012).

According to data from the nearby MIDAS weather station located at Marham (Station ID: 409), monthly mean maximum daily air temperature within the catchment ranged from 6.8°C in January to 22.1°C in July during 1981-2010 (Figure 3.11). Monthly mean minimum daily air temperature within the catchment during the same period ranged from 1.0 °C in February to 12.1 °C in July (Figure 3.11). This is fairly typical when compared to England as a whole (Figure 3.11) (Met Office, 2016). Mean monthly sunshine hours within the catchment are also fairly typical when compared to England as a whole (Figure 3.12). Mean monthly sunshine hours were lowest in December (51.5 hours) and highest in July (206 hours) (Figure 3.12).

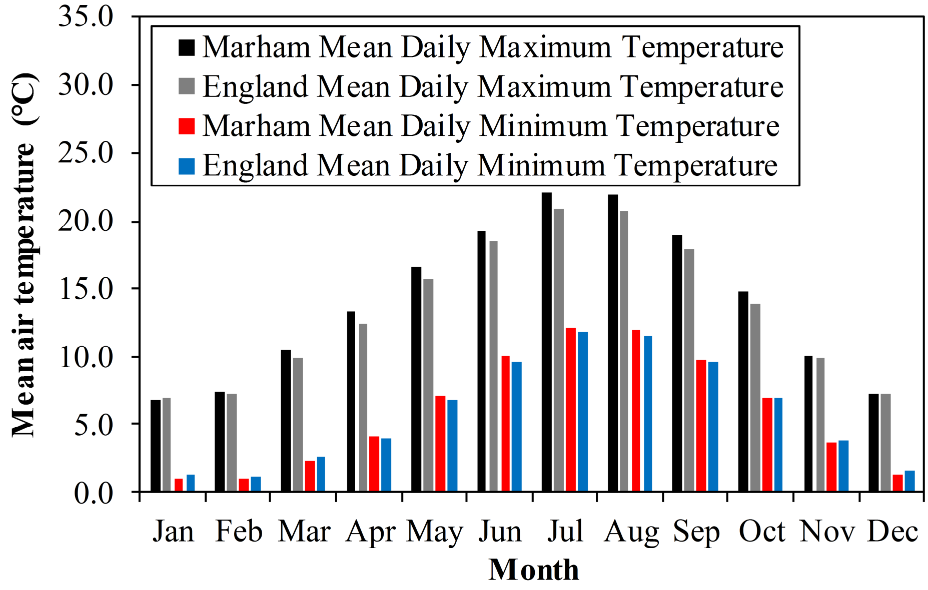

Figure 3.11: Monthly mean maximum and minimum air temperatures at the UK MIDAS weather station located at Marham (Station ID: 409) and for England as a whole during 1981-2010 (Met Office, 2012; Met Office, 2016).

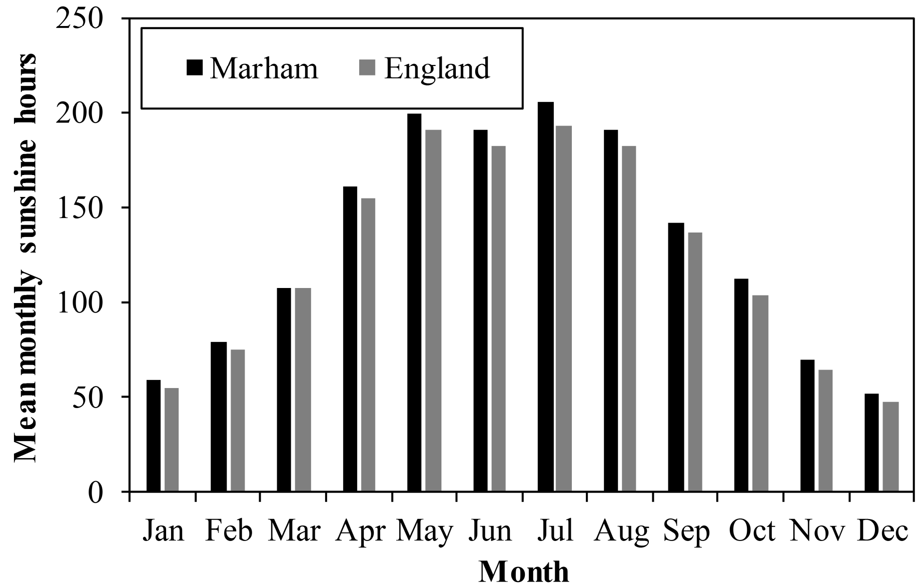

Figure 3.12: Mean total monthly sunshine hours at the UK MIDAS weather station located at Marham (Station ID: 409) and for England as a whole during 1981-2010 (Met Office, 2012; Met Office, 2016).

3.1.3.5 Flow and Metaldehyde Data

Daily mean discharge data were obtained from four gauges for the period 1 January 2008 to 31 October 2015 from the National River Flow Archive (2015) (see Figure 3.1 for names and locations). Flow statistics for the four flow gauges located within the catchment are provided for reference in Table 3.4. When compared, the 95% exceedance (Q95) and 10% exceedance (Q10) statistics can be used as a measure of the degree of variability of the flow rate within the river (National River Flow Archive, 2016e).

Table 3.4: Flow statistics for the four flow gauges within the River Wensum catchment located at Fakenham, Swanton Morley, Costessey Mill and Costessey Park (National River Flow Archive, 2016a,b,c,d). Q95, Q70, Q50 and Q10 denote the flow rate that is exceeded 95%, 70%, 50% and 10% of the time, respectively.

Statistic	Fakenham	Swanton Morley	Costessey Mill	Costessey Park
Record duration	1966-2015	1969-2015	1960-2015	1961-2015
Mean flow rate (m^3 s^{-1})	0.867	2.739	4.074	0.35
95% exceedance (Q95) (m^3 s^{-1})	0.242	0.936	1.34	0.079
70% exceedance (Q70) (m^3 s^{-1})	0.493	1.52	2.349	0.162
50% exceedance (Q50) (m^3 s^{-1})	0.69	2.14	3.228	0.237
10% exceedance (Q10) (m^3 s^{-1})	1.65	5.05	7.46	0.693

Anglian Water Services Ltd provided observations of metaldehyde concentration for two sites where surface water is licensed for abstraction from the river for the purpose of drinking water supply (Figure 3.1). During the period 1 January 2008 to 31 October 2015, 378 and 398 grab samples were collected at the Costessey Pits and Heigham WTW intakes, respectively. According to the grab samples, the mean metaldehyde concentration at the Costessey Pits and Heigham WTW intakes during the period 1 January 2008 to 31 October 2015 was 0.046 µg L^{-1} and 0.055 µg L^{-1}, respectively. During this period, the maximum metaldehyde concentration recorded was 1.23 µg L^{-1} at the Costessey Pits intake and 1.64 µg L^{-1} at the Heigham WTW intake. To estimate flow at the two intake sites, it was necessary to apply a correction factor to observations of flow from the nearest gauges to take account of the increase or decrease in the catchment area that contributes to flow at these sites. To estimate flow at the Costessey Pits intake, observations of flow recorded at Costessey Mill were reduced by 0.06%. To estimate flow at the Heigham WTW intake, the sum of observations of flow recorded at Costessey Mill and Costessey Park was increased by 3.6%. In combination with the grab sample observations of metaldehyde concentration, the estimates of flow determined for the Costessey Mill and Heigham WTW intake sites were used to estimate daily metaldehyde load at those two locations.

3.2 The Blackwater Sub-catchment

The Blackwater sub-catchment has been selected as the study area to investigate the impacts of agricultural mitigation measures on diffuse nutrient pollution from agriculture (see Chapter 5).

The Blackwater sub-catchment, which is located in the north-eastern section of the River Wensum catchment, drains an area of 19.6 km^2 and has been intensively monitored as part of the Wensum DTC project (Figure 3.13).

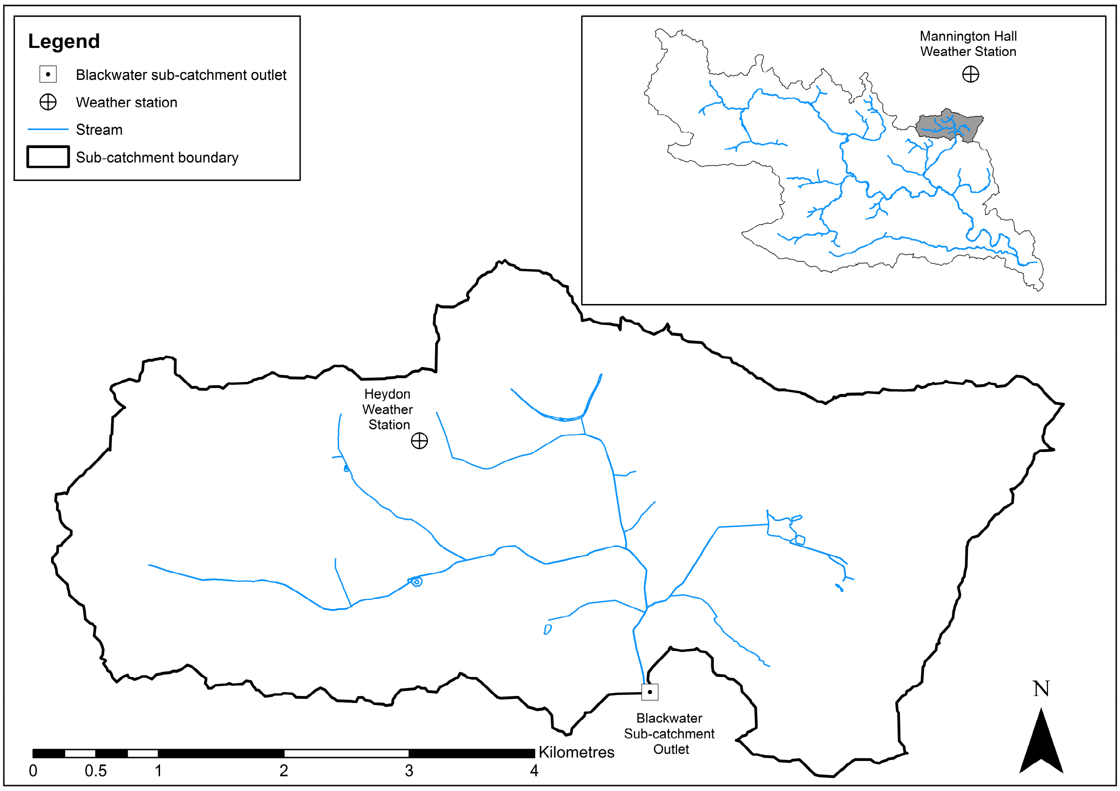

Figure 3.13: A map of the location of the Blackwater sub-catchment in relation to the River Wensum catchment, nearby weather stations and the outlet of the sub-catchment.

3.2.1 Geology and Hydrogeology

The entirety of the Blackwater sub-catchment is underlain at a depth of approximately 20 m by Cretaceous Chalk bedrock deposits that are also present over the entire extent of the rest of the River Wensum catchment (Figure 3.14) (Lewis, 2014). In the east of the sub-catchment, the Chalk is overlain by the Wroxham Crag formation (16-22 m depth) (Lewis, 2014). As is the case for the rest of the River Wensum catchment, the bedrock of the Blackwater sub-catchment is also unconformably overlain by a complex sequence of superficial deposits of Quaternary origin (Figure 3.15) (Lewis, 2014). The superficial geology of the sub-catchment includes Holocene wind-blown sand, alluvium, river terrace deposits and Pleistocene tills (i.e. the Weybourne Town Till, Bacton Green Till, Walcott Till, Lowestoft Till and Happisburgh Till Members) and glaciofluvial and glaciolacustrine sands, gravels and silts of the Briton's Lane (0.2-7 m depth), Sheringham Cliffs (0.2-12 m depth), Lowestoft (8-16 m depth) and Happisburgh Formations (12-17 m depth) (Lewis, 2014). The western and central sections of the sub-catchment are dominated by low permeability tills whilst the eastern section of the catchment is dominated by more freely-draining glacial sand and gravels (Figure 3.15).

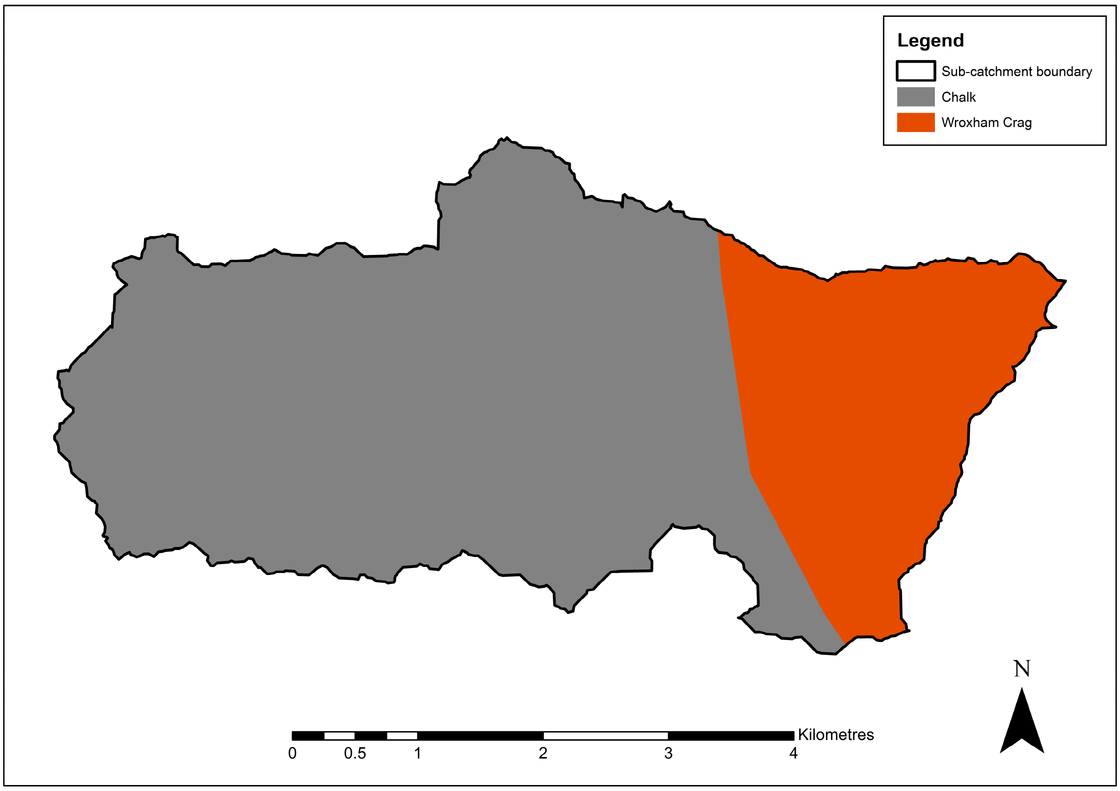

Figure 3.14: The bedrock geology of the Blackwater sub-catchment. Based upon DiGMapGB-625, with the permission of the British Geological Survey (British Geological Survey, 2016b).

Stream flow within the Blackwater sub-catchment is derived from groundwater return flow, lateral flow in the soil zone, surface runoff and contributions from an extensive tile drain network which is situated at depths between 1-1.55 m (Howson, 2012; Outram et al., 2016). Streamflow within the sub-catchment is sustained by baseflow during periods of low rainfall. The sub-catchment has a baseflow index of 0.80, which is similar to that of the River Wensum catchment as a whole (Robson and Reed, 1999).

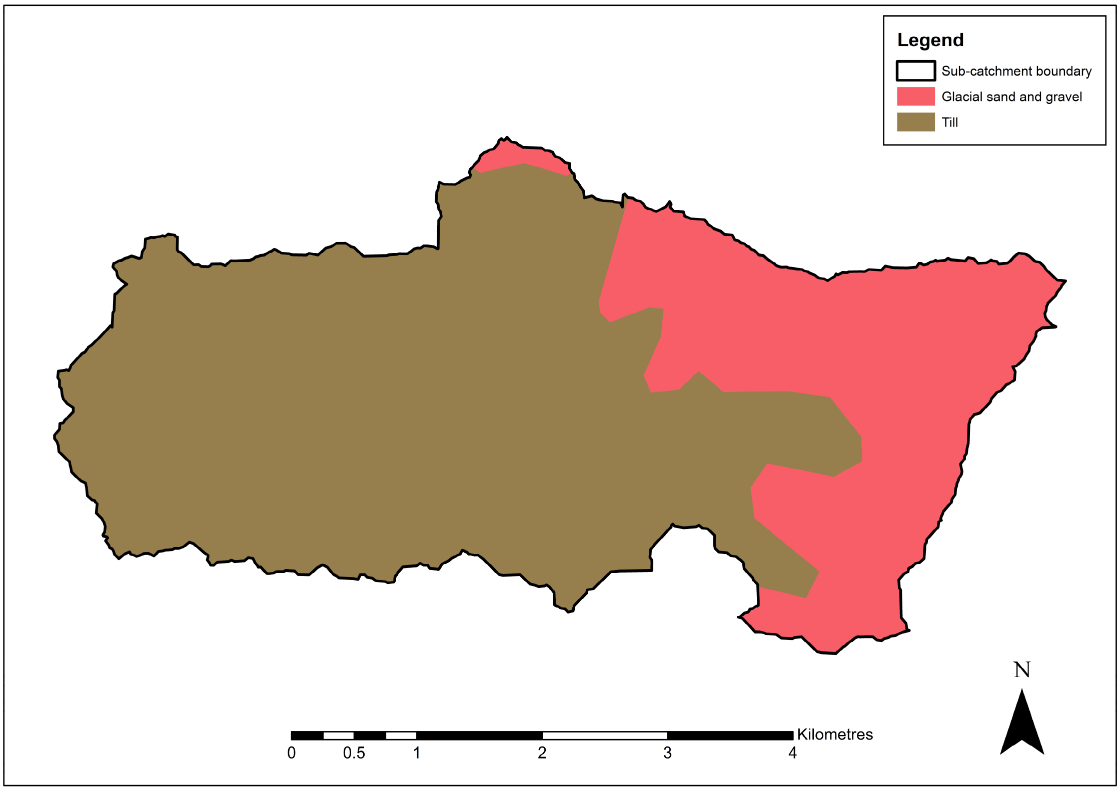

Figure 3.15: The superficial geology of the Blackwater sub-catchment. Based upon DiGMapGB-625, with the permission of the British Geological Survey (British Geological Survey, 2016b).

3.2.2 Topography

According to the NEXTMap British Digital Terrain Model Dataset, the topography of the sub-catchment is relatively subdued, with elevation ranging between 28-70m above sea level (Figure 3.16), and 95% of the sub-catchment area having a slope of 5% or less (Figure 3.17) (Intermap Technologies, 2007).

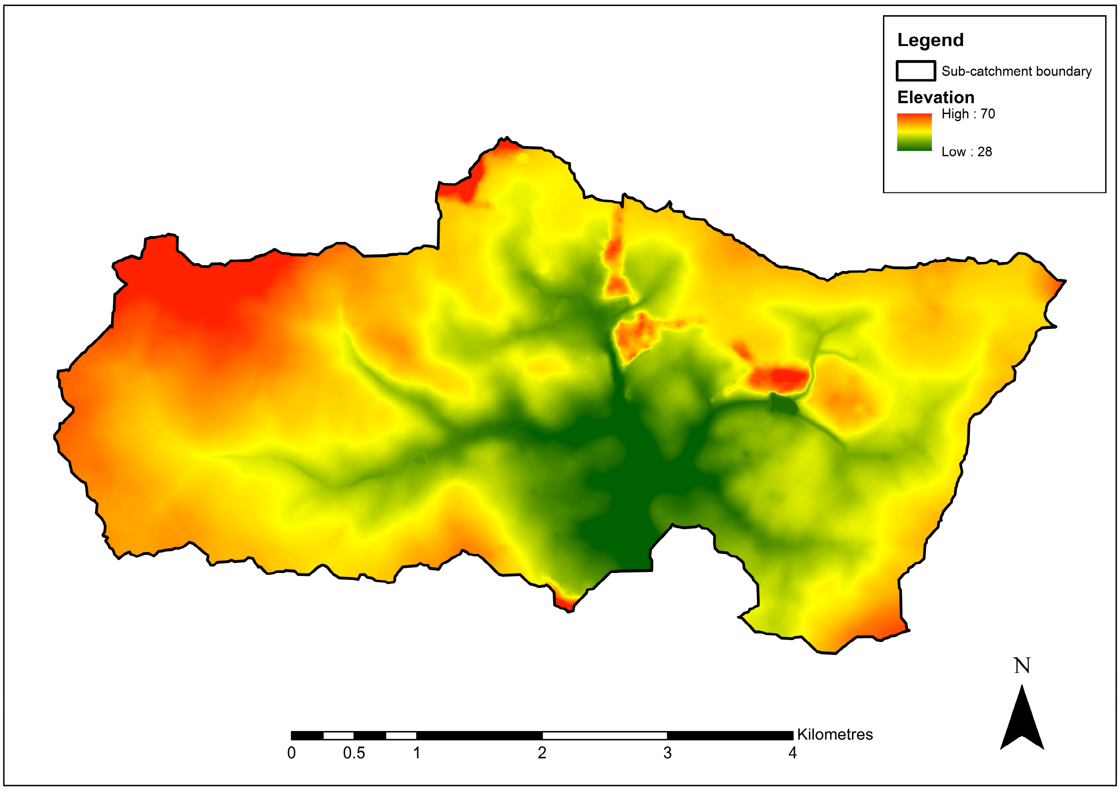

Figure 3.16: The digital elevation model of the Blackwater sub-catchment. Map derived from Intermap Technologies (2007).

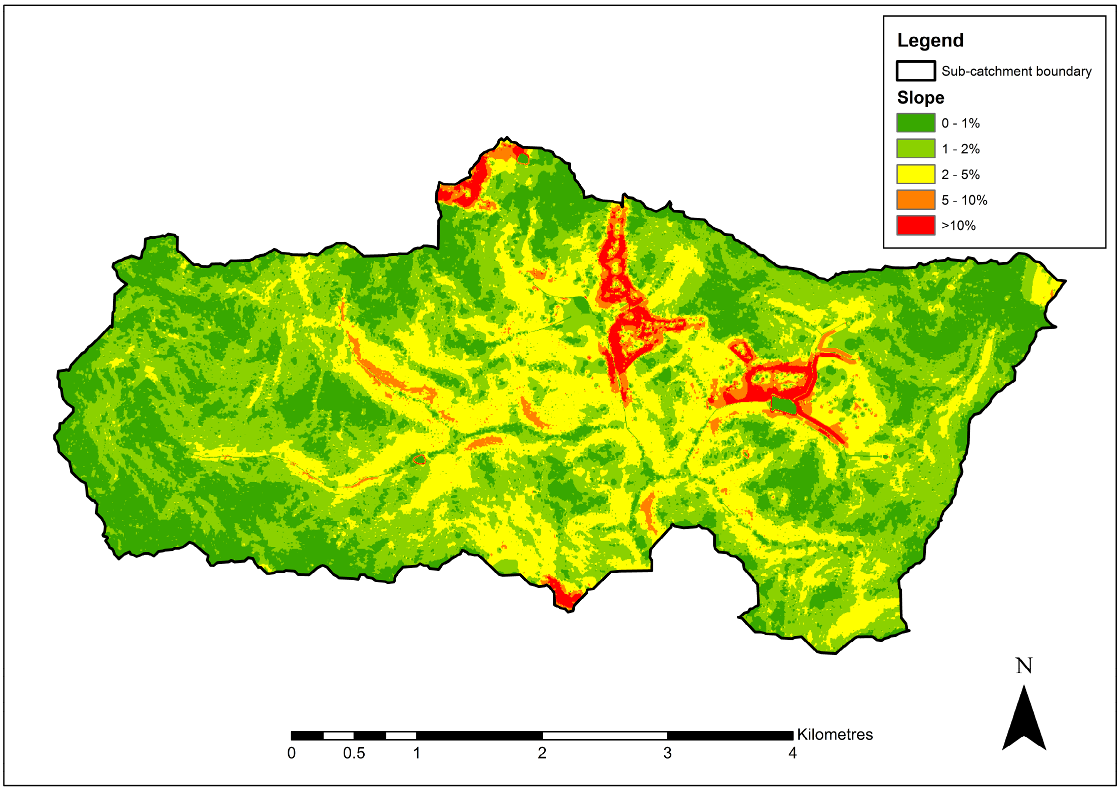

Figure 3.17: The slope of the Blackwater sub-catchment. Map derived from Intermap Technologies (2007).

3.2.3 Data Description

3.2.3.1 Land Cover

According to the LCM2007 raster dataset, land cover within the Blackwater sub-catchment is largely arable with 86.05% of the land area utilised for agricultural purposes (Figure 3.18) (Morton et al., 2011). The dominance of the arable farming industry within the sub-catchment is reflected by the fact that 74.2% of the land area is utilised for growing crops, 11.8% as grazing pasture, 9.2% is broadleaf woodland, 2.2% is other grassland, 1.5% is coniferous woodland, 0.5% forms suburban settlements, 0.3% is freshwater and 0.3% forms urban settlements.

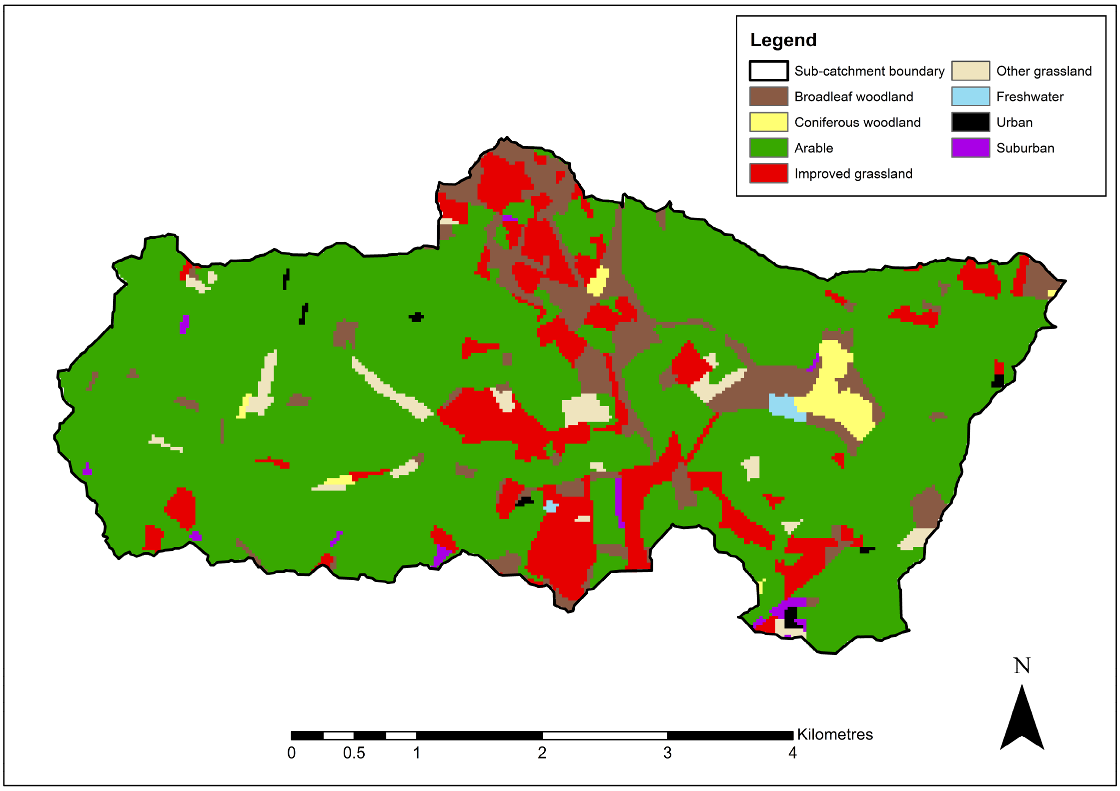

Figure 3.18: A map of the land cover of the Blackwater sub-catchment. Based upon LCM2007 © NERC (CEH) 2011. Contains Ordnance Survey data © Crown Copyright 2007. © third party licensors.

3.2.3.2 Soils

According to the NATMAP vector dataset, five different Soil Associations are present within the Blackwater sub-catchment (Figure 3.19) (Cranfield University, 2016a). 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 primarily composed of sandy soils (Figure 3.20) (Cranfield University, 2016b). The north of the sub-catchment and east of the sub-catchment are dominated by the Wick 2 and Wick 3 Soil Associations, respectively, which are deep loamy soils that are coarse and well-drained but are at risk of erosion by surface runoff (Cranfield University, 2016i,j). Soils in the west of the sub-catchment are predominantly from the Beccles 1 Soil Association which are loamy over clayey soils that are slowly permeable and prone to seasonal waterlogging (Cranfield University, 2016k). The south of the sub-catchment is dominated by the deep loamy soils of the Burlingham 1 Soil Association (Cranfield University, 2016c), but a small area of the deep sandy soils of the Isleham 2 Soil Association is also present at a site near to the location of the outlet of the Blackwater sub-catchment (Cranfield University, 2016g).

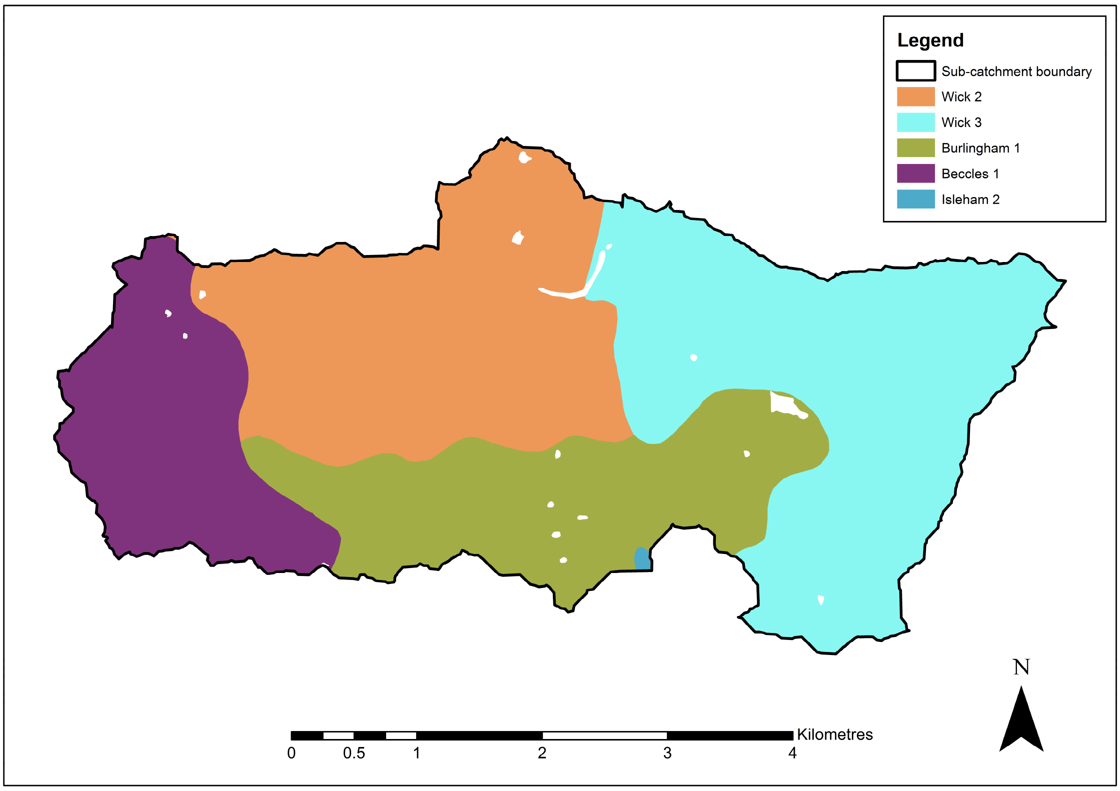

Figure 3.19: A map of the National Soil Map of England and Wales (NATMAP) soil types of the Blackwater sub-catchment. Map derived from Soils Data © Cranfield University (NSRI) and the Controller of Her Majesty's Stationary Office [2016].

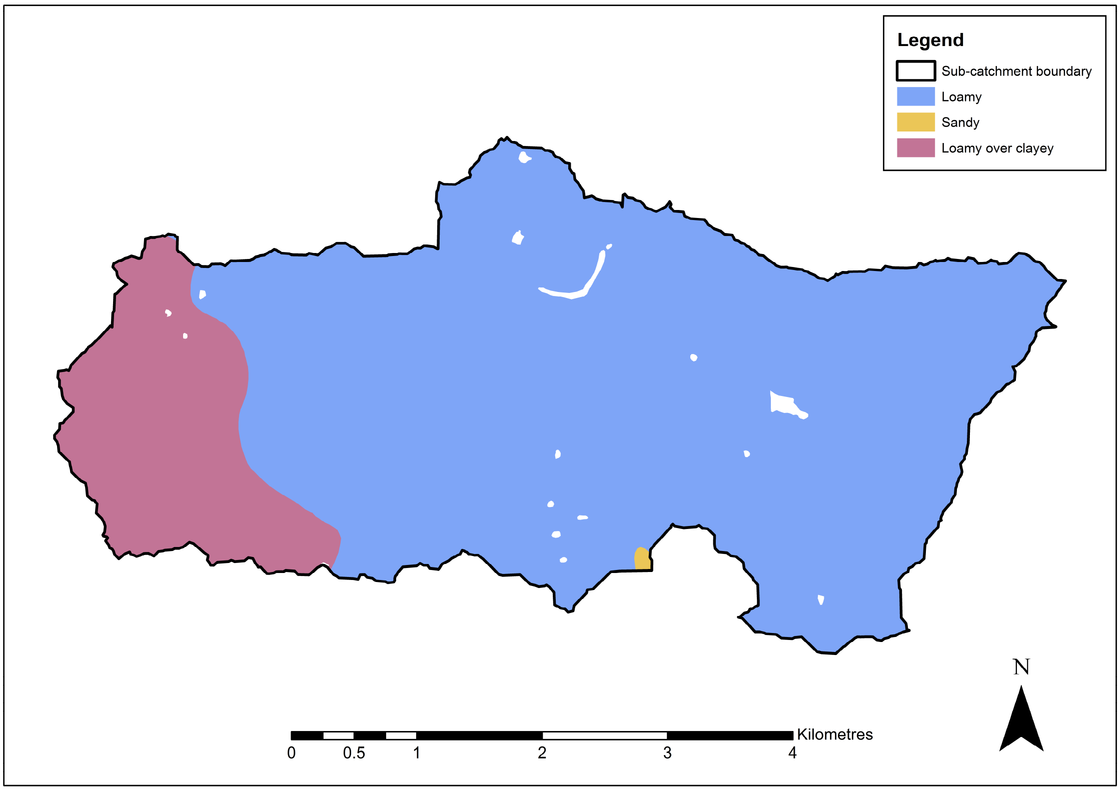

Figure 3.20: A map of the general soil types of the Blackwater sub-catchment. Map derived from Soils Data © Cranfield University (NSRI) and the Controller of Her Majesty's Stationary Office [2016].

3.2.3.3 Agriculture

Data from the Agricultural Census conducted by Defra (2016a) and held by EDINA at Edinburgh University Data Library (EDINA, 2014) was obtained for the Blackwater sub-catchment for the period 1993-2010 in a 2 km grid square format. This data was used to identify those crops commonly grown within the sub-catchment (Figure 3.21) and to identify an appropriate crop rotation plan to implement within the SWAT model of the sub-catchment (Defra, 2016a; EDINA, 2014). Based on this analysis, it was found that the crops most commonly grown within the sub-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 3.5). 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 crop types except sugar beet where the source used was British Sugar (2010).

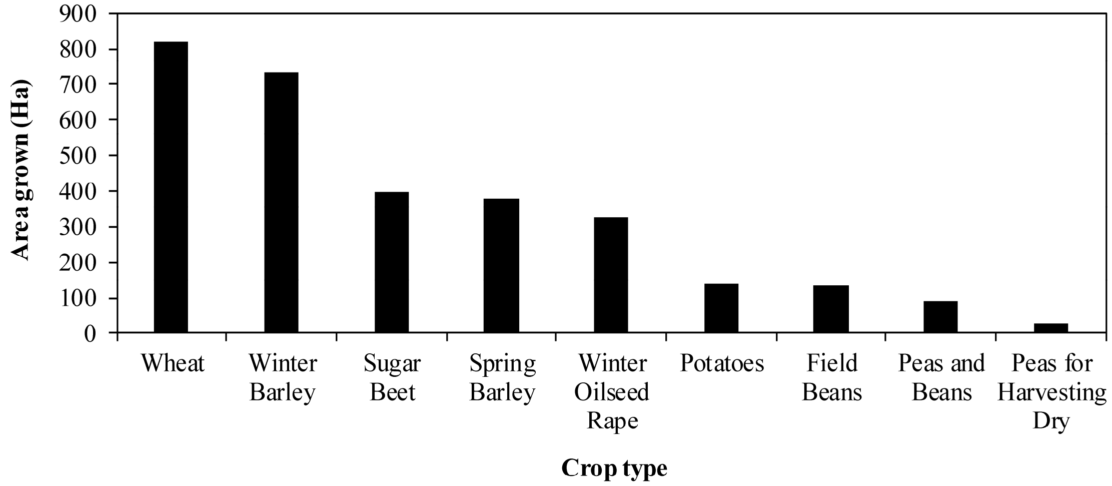

Figure 3.21: The area of each crop type grown within the Blackwater sub-catchment according to the 2010 Agricultural Census conducted by the Department for Environment, Food and Rural Affairs (Defra, 2016a; EDINA, 2014).

As part of the Wensum DTC project, a variety of agricultural mitigation measures have been introduced on the Salle Estate to assess the impacts of mitigation options on agricultural diffuse water pollution and water quality within the Blackwater sub-catchment (Lovett et al., 2015). The mitigation measures that have been tested include the introduction of an oilseed radish 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 and direct drilling to establish autumn and spring-sown crops, with the intention of reducing sediment and nutrient loss in surface runoff, have also been introduced as additional mitigation measures in some pilot areas of the sub-catchment.

Table 3.5: The seven-year crop-rotation scheme and management operations applied within the SWAT model of the Blackwater sub-catchment.

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

3.2.3.4 Meteorological Data and Climate

Observations of meteorological variables recorded for the period 1 January 1980 to 31 October 2015 were obtained from UK MIDAS Land and Marine Surface Stations Data for application within the model (Met Office, 2012). Observations of daily minimum and maximum temperature, sunshine hours, wind speed and relative humidity were obtained from the UK MIDAS weather station located at Marham (Station ID: 409), which is sited approximately 40 km to the south-west of the Blackwater sub-catchment. The Angstrom formula (see Equation 2 in Section 3.1.3.4) was used to calculate an estimate of solar radiation from observations of daily sunshine hours. Where observations of daily sunshine hours were missing from the Marham record, observations recorded at the nearby MIDAS weather stations located at Coltishall (Station ID: 429), Norwich Weather Centre (Station ID: 408), Hemsby (Station ID: 433) and Wattisham (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 (Station ID: 4807) (Figure 3.13). Where observations of precipitation were 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.

For a description of the climate of the Blackwater sub-catchment please refer to Section 3.1.3.4.

3.2.3.5 Flow and Nutrients Data

As part of the Wensum DTC project, 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-minute intervals at the outlet of the Blackwater sub-catchment using automated bankside monitoring equipment since April 2011 (Figure 3.13). Stream temperature, pH, electrical conductivity, turbidity, dissolved oxygen, chlorophyll, ammonium, nitrate, and total reactive phosphorus have also been monitored as part of this work. 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 research.

Between December 2011 to February 2014 flow gauging using an electromagnetic open channel flow meter was conducted on 16 occasions during high, moderate and low flow events. These measurements, in combination with observations of river stage from the pressure transducers, were used to develop a power-law stage-discharge rating curve (Figure 3.22). This is an often used technique for deriving discharge time-series from stage measurements (Reitan and Petersen-Øverleir, 2009). This rating curve 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 of discharge, nitrate and total phosphorus load were applied within this research 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.

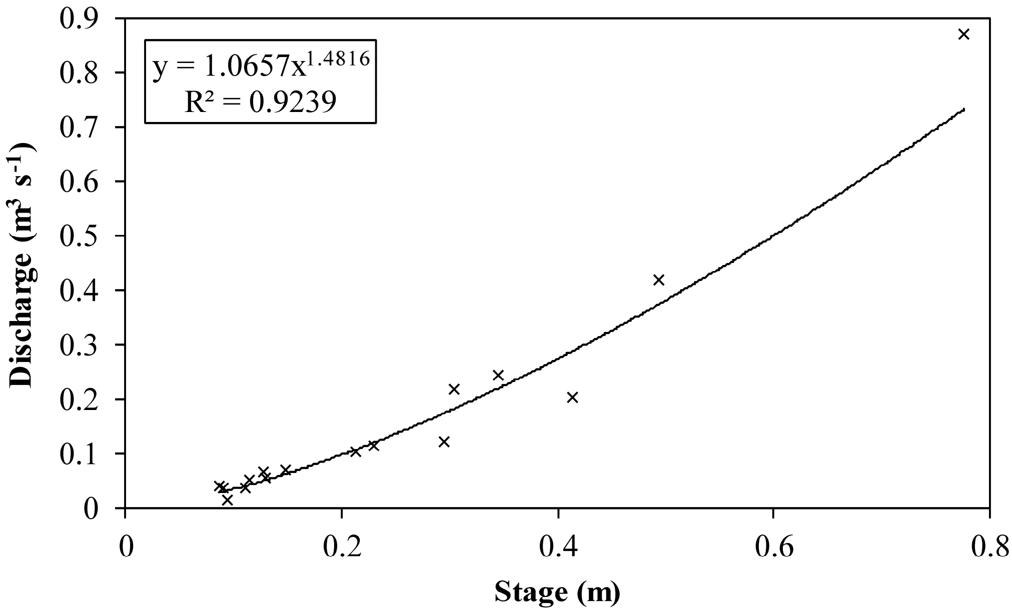

Figure 3.22: Power-law stage-discharge rating curve depicting the relationship between stage and discharge at the outlet of the Blackwater sub-catchment according to 16 flow gauging measurements taken during December 2011 - February 2014.

Statistics for discharge, nitrate and total phosphorus concentration that were recorded at the outlet of the Blackwater sub-catchment by the automated bankside monitoring equipment from 1 December 2011 to 30 June 2014 are provided for reference in Table 3.6.

Table 3.6: Statistics for discharge, nitrate and total phosphorus concentration at the outlet of the Blackwater sub-catchment for the period 1 December 2011 to 30 June 2014. Q95, Q70, Q50 and Q10 denote the flow rate or concentration that was exceeded 95%, 70%, 50% and 10% of the time, respectively.

Statistic	Discharge ($m^3 s^{-1}$)	Nitrate Concentration (mg NO_3-N L^{-1})	Total Phosphorus Concentration (mg P L^{-1})
Mean	0.112	6.15	0.089
95% exceedance (Q95)	0.021	3.88	0.052
70% exceedance (Q70)	0.048	5.34	0.069
50% exceedance (Q50)	0.071	5.95	0.083
10% exceedance (Q10)	0.238	8.57	0.118

3.3 Chapter Summary

In this chapter, the characteristics of the River Wensum catchment and the Blackwater sub-catchment were described. The Wensum catchment was identified as being of great ecological and cultural importance and suffers from various pressures including agricultural diffuse water pollution. It was recognised that there exists a specific need within the River Wensum catchment to identify mitigation measures that can be introduced to reduce agricultural diffuse water pollution. The datasets applied within this study to develop SWAT models of the Wensum and Blackwater sub-catchment were also described prior to their application within SWAT which is described in the next chapter.

4 SWAT MODEL SET-UP AND CALIBRATION AND VALIDATION

The content of Section 4.2 of this chapter have been published in the *Journal of Environmental Management* (Taylor et al., 2016).

4.1 Model Build Process for the Wensum and Blackwater Sub-catchment SWAT Models

Version 2012.10.0.14 of ArcSWAT, the ArcGIS interface developed to pre-process model inputs and to execute simulations within SWAT, was used to build the SWAT models applied in this study (Texas A&M University, 2015). The datasets applied and the methodology adopted to build the SWAT models of the Wensum and Blackwater sub-catchments are described below. The methodology applied in this study is the standard recommended practice to build a SWAT model which is available for reference in Winchell et al. (2013).

4.1.1 Data Requirements

The spatial datasets required to set-up and run a SWAT model include: (i) a topographic map (i.e. either a Digital Elevation Model (DEM) or a Digital Terrain Model (DTM)); (ii) a land cover map and (iii) a soil map and soil properties dataset. The temporal datasets required include: (i) daily meteorological data (i.e. precipitation, minimum and maximum air temperature, mean wind speed, mean relative humidity and daily sunshine hours) and (ii) agricultural practices (e.g. fertiliser and pesticide types, application amount and timing; crop rotations; cultivation and harvesting dates; irrigation practices; tillage practices and timing; tile drain locations and depths) (Winchell et al., 2013). The datasets required for model calibration and validation for this specific study include observations of discharge, nitrate, total phosphorus and metaldehyde concentration and load.

4.1.2 Catchment Delineation

The first stage of setting-up a SWAT model within ArcSWAT is to perform catchment delineation (Winchell et al., 2013). This is an automated process that requires users to specify and input a DEM or DTM of the area that is to be modelled. The NEXTMap British Digital Terrain Model Dataset (see Sections 3.1.2 and 3.2.2) was applied within this study to perform delineation within the SWAT models of the Wensum and Blackwater sub-catchment (Intermap Technologies, 2007). Once delineation has been completed, the catchment boundary, sub-catchments, river network, river outlet locations (i.e. points of confluence with other rivers) and monitoring sites will have all been defined within the model. To automatically delineate the river network that is present, the model suggests a value for the minimum upstream drainage area that is required before a stream is formed and modelled within SWAT (Winchell et al., 2013). In practice, users can adjust this area but this study used the values recommended by the model. One stream alone is modelled within each sub-catchment within SWAT and so this threshold area also determines the number of sub-catchments that will be represented within the model and the level of detail of the stream network modelled. This output was compared to the stream network actually present within the River Wensum catchment to ensure that the stream networks, as simulated within the SWAT models of the Wensum and Blackwater sub-catchment, are represented appropriately.

To extract data for river discharge and in-stream nitrate, total phosphorus and metaldehyde load and to assist model calibration, validation and scenario analysis, the locations of gauging stations and water quality sampling sites were defined as monitoring sites within the models of the Wensum and Blackwater sub-catchment. The locations of each of these sites is provided in Table 4.1.

Table 4.1: The coordinates of the locations of flow gauges and water quality sampling sites used in this investigation.

Site	Variables Monitored	Coordinates (latitude, longitude)
Fakenham	Discharge	52.827049, 0.84688978
Swanton Morley	Discharge	52.72551, 0.98986661
Costessey Mill	Discharge	52.668306, 1.216729
Costessey Park	Discharge	52.655123, 1.2054081
Costessey Pits intake	Metaldehyde concentration	52.673515, 1.2003934
Heigham water treatment works intake	Metaldehyde concentration	52.638763, 1.2679429
Blackwater sub-catchment outlet	Discharge, nitrate concentration, total phosphorus concentration	52.777101, 1.1495666

A total number of 35 and 29 sub-catchments were delineated within the SWAT models of the Wensum and Blackwater sub-catchment, respectively (Figure 4.1 and Figure 4.2). When defining the number of sub-catchments to be modelled within SWAT, a compromise must be reached between the level of detailed to be modelled and the computational efficiency of the model (i.e. the time it takes to run simulations). The above configurations were considered to be an appropriate compromise between these two factors.

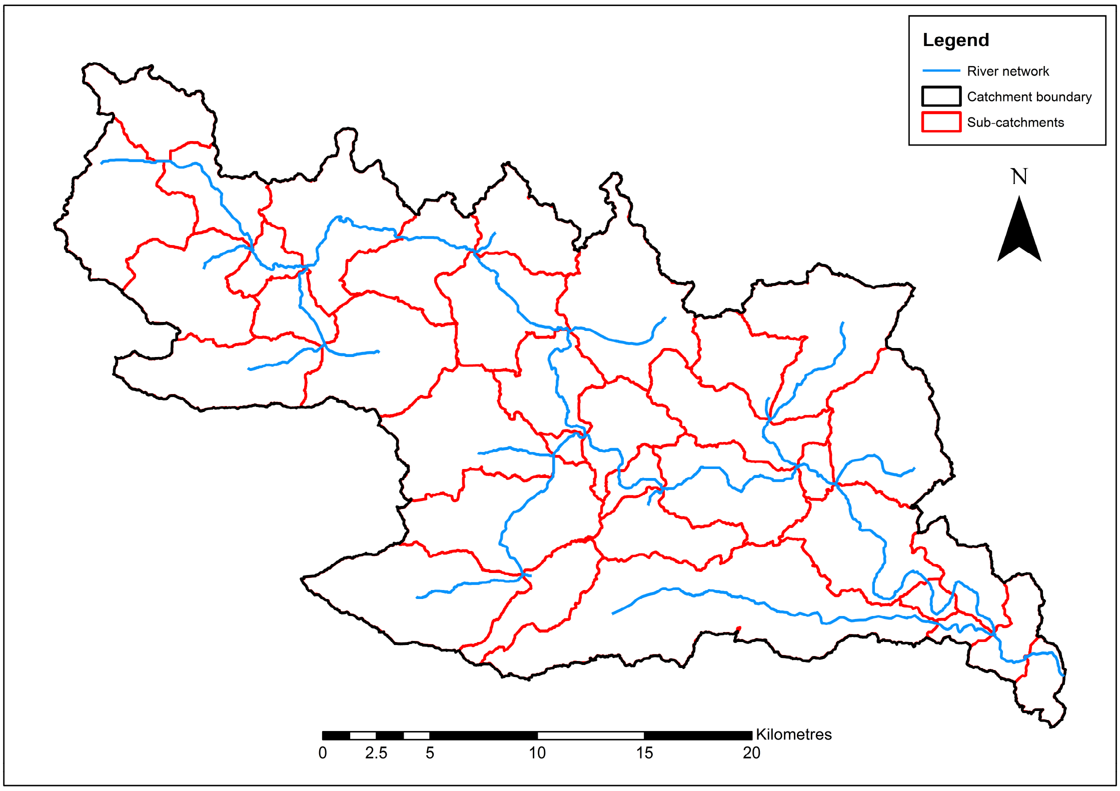

Figure 4.1: The sub-catchments and stream network delineated within the SWAT model of the Wensum catchment.

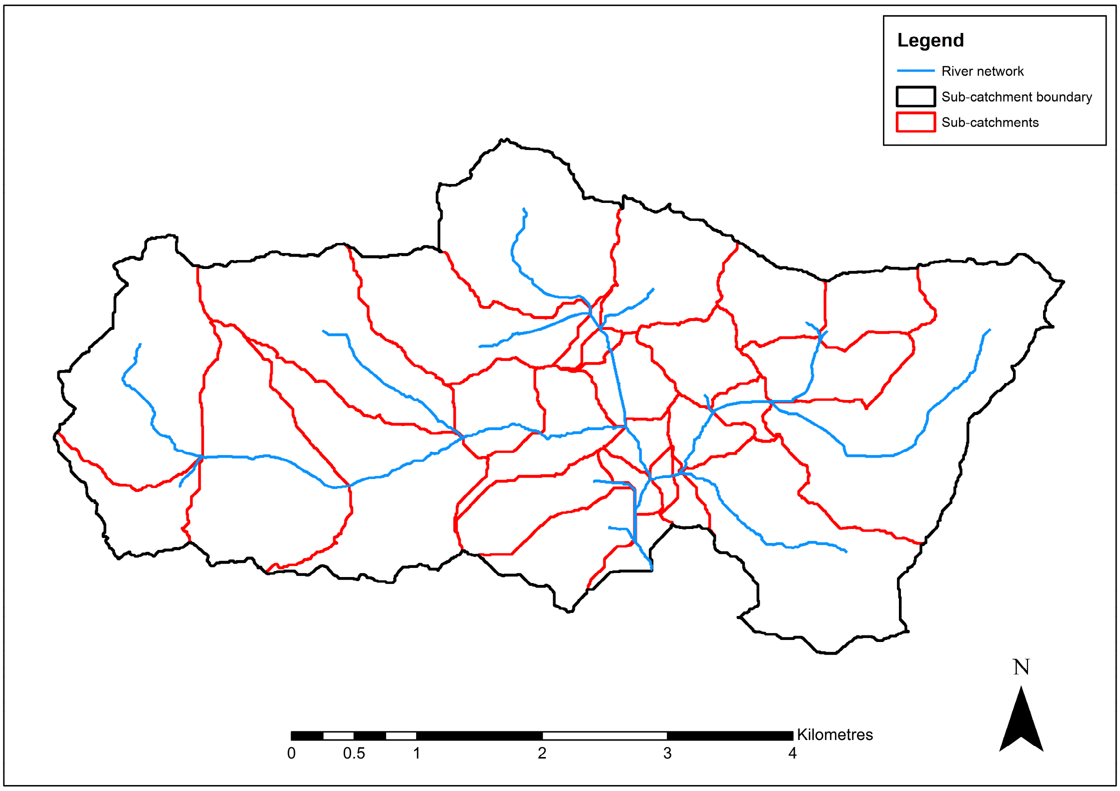

Figure 4.2: The sub-catchments and stream network delineated within the SWAT model of the Blackwater sub-catchment.

4.1.3 Hydrologic Response Unit Definition

Once catchment delineation has been performed within ArcSWAT the next step is to define the HRUs that are present within each sub-catchment (Winchell et al., 2013). Within SWAT, HRUs divide each sub-catchment into unique combinations of land use, soil and slope classes. Although they might not form one contiguous area within a sub-catchment, those areas that possess the same combinations of land use, soil and slope classes within a sub-catchment are lumped together to form a HRU. To complete this task within ArcSWAT the land cover, soil and slope datasets of the modelled area must first be defined.

The LCM2007 raster dataset, which has a resolution of 25 meters, was used to define land use within the models of the Wensum and Blackwater sub-catchment (see Sections 3.1.3.1 and 3.2.3.1) (Morton et al., 2011). The land cover classes of the LCM2007 dataset were reclassified to the corresponding SWAT land cover classes within ArcSWAT as identified in Table 4.2.

Table 4.2: The Land Cover Map 2007 (LCM2007) dataset land cover classes and the corresponding SWAT land cover classes which they were reclassified to.

LCM2007 Land Cover Class	SWAT Land Cover Class
Broadleaf woodland	Deciduous forest
Coniferous woodland	Evergreen forest
Arable	Agricultural land
Improved grassland	Pasture
Other grassland	Range grasses
Freshwater	Water
Urban	Urban high-density
Suburban	Urban medium-density

The NATMAP vector dataset was used to define soil types within the models of the Wensum and Blackwater sub-catchment (see Sections 3.1.3.2 and 3.2.3.2) (Cranfield University, 2016a). The properties of the Soil Associations of the NATMAP dataset are not included in the SWAT soil database and so the values of these properties for each Soil Series were manually added to the model database. At present, the SWAT soil database can only account for the properties of the predominant Soil Series of each Soil Association. The properties required by SWAT for each soil layer and the corresponding soil property derived from the HORIZON Hydraulics, HORIZON Fundamentals, SOILSERIES Agronomy, LandIS Soils Guide and NSI Profile datasets used within the models are listed in Table 4.3 (Cranfield University, 2016b,d,e).

Table 4.3: The properties required by SWAT for each layer of each soil type and the corresponding properties provided as input and their sources.

SWAT Soil Property	Dataset Property	Source
Depth from soil surface to bottom of soil layer (mm)	LOWER_DEPTH	HORIZON Fundamentals [a]
Moist bulk density (g cm^{-3})	BULK_DENSITY	HORIZON Hydraulics [a]
Available water capacity	Calculated from THV5 (percentage water content at field capacity) and THV1500 (percentage water content at wilting point)	HORIZON Hydraulics [a]
Saturated hydraulic conductivity (mm hr^{-1})	KSAT_SUBVERT	HORIZON Hydraulics [a]
Sand content (%)	SAND_TOTAL	HORIZON Fundamentals [a]
Silt content (%)	SILT	HORIZON Fundamentals [a]
Clay content (%)	CLAY	HORIZON Fundamentals [a]
Organic carbon content (%)	OC	HORIZON Fundamentals [a]
Rock fragment content (%)		LandIS Soils Guide [b]
Maximum rooting depth in the soil profile (mm)	DROCK	SOILSERIES Agronomy [a]
Fraction of porosity from which anions are excluded	SWAT default value used (= 0.5)	
Moist soil albedo	Calculated from MATRIX_COLOUR	National Soils Inventory Profiles [c]
Universal Soil Loss Equation soil erodibility (K) factor	Calculated from SAND_TOTAL, SILT, CLAY and OC	HORIZON Fundamentals [a]

[a] Cranfield University (2016d); [b] Cranfield University (2016b); [c] Cranfield University (2016e).

The available water capacity was calculated from the fraction of water content present at field capacity (THV5) and the fraction of water content present at the wilting point (THV1500) using Equation 3 as defined by Arnold et al. (2014):

$$AWC = FC - WP \qquad (3)$$

Where: AWC is the available water capacity of the soil layer

FC is the fraction of water content present at field capacity

WP is the fraction of water content present at the wilting point

The moist soil albedo defines the fraction of incident solar radiation that is reflected by the soil surface and is a function of the soil colour. It was calculated using Equation 4 as defined by Natural Resources Conservation Service (2016):

$$Soil\ Albedo = (0.069 \times colour\ value) - 0.114 \qquad (4)$$

The Universal Soil Loss Equation (USLE) soil erodibility (K) factor describes the erodibility of soils and was calculated using Equation 5 as defined by Neitsch et al. (2011):

$$K_{USLE} = f_{csand} \times f_{cl-si} \times f_{orgc} \times f_{hisand} \qquad (5)$$

Where: f_{csand} is a factor that reduces the erodibility of soils with high coarse sand content and increases the erodibility of soils with low sand content.

f_{cl-si} is a factor that reduces the erodbility of soils with high clay to silt ratios.

f_{orgc} is a factor that reduces the erodibility of soils with high organic carbon content.

f_{hisand} is a factor that reduces the erodibility of soils with very high sand content.

These factors are calculated using Equations 6 to 9 as defined by Neitsch et al. (2011).

$$f_{csand} = \left(0.2 + 0.3 \times exp\left[-0.256 \times m_s \times \left(1 - \frac{m_{silt}}{100}\right)\right]\right) \qquad (6)$$

$$f_{cl-si} = \left(\frac{m_{silt}}{m_c + m_{silt}}\right)^{0.3} \qquad (7)$$

$$f_{orgc} = \left(1 - \frac{0.25 \times orgC}{orgC + exp[3.72 - 2.95 \times orgC]}\right) \qquad (8)$$

$$f_{hisand} = \left(1 - \frac{0.7\left(1 - \frac{m_s}{100}\right)}{\left(1 - \frac{m_s}{100} + exp\left[-5.51 + 22.9\left(1 - \frac{m_s}{100}\right)\right]\right)}\right) \qquad (9)$$

Where: m_s is the sand content (%) (0.05-2mm sized particles)

m_{silt} is the silt content (%) (0.002-0.05 sized particles)

m_c is the clay content (%) (< 0.002 mm sized particles)

$orgC$ is the organic carbon content (%)

HRU definition in ArcSWAT also involves dividing the modelled area into slope classes (Winchell et al., 2013). ArcSWAT automatically derived a map of slope within the modelled area from the DTM during catchment delineation. The next step in HRU definition involved applying this map to categorise slope within the modelled area. A maximum of 5 slope categories can be used to define slope classes within SWAT. The slope classes used within the SWAT models of the Wensum and Blackwater sub-catchment were defined as 0-1%, 1-2%, 2-5%, 5-10% and >10%. The ranges selected were considered to be appropriate due to the relatively subdued topography of the Wensum catchment.

After classifying land use, soil and slope within ArcSWAT the distribution of HRUs within the modelled areas were defined (Winchell et al., 2013). Users can define either one HRU per sub-catchment based on either the dominant HRU or the dominant land use, soil and slope class present within the sub-catchment, or to define multiple HRUs for each sub-catchment. In order to reflect land use, soil and slope classes more accurately, multiple HRUs were defined within the models of the Wensum and Blackwater sub-catchment. Users can specify thresholds to eliminate minor land use, soil and slope classes from each sub-catchment and to determine the land use, soil and slope classes to be modelled within HRUs. If a land use, soil or slope class is present at a level below this threshold they are eliminated from the sub-catchment. Thresholds of 20%, 10% and 20% were applied to land use, soil and slope class, respectively, to define the HRUs within each sub-catchment for both models. These are the default recommended thresholds and are considered to offer a sufficient level of detail for most applications (Winchell et al., 2013). Lower thresholds can be used to represent land use, soil and slope classes in more detail but a greater level of detail reduces the computational efficiency of simulations (i.e. it takes longer to run simulations). In practice, a compromise must be reached between the level of detail simulated and the computational efficiency of simulations.

4.1.4 Weather Station Definition and Meteorological Input Data

After HRUs have been defined the next step is to define weather station locations and to import meteorological datasets. The meteorological datasets required by SWAT are daily observations of precipitation, maximum and minimum temperature, mean relative humidity, solar radiation and mean wind speed (Arnold et al., 2014). The sources of the meteorological datasets applied within the SWAT models of the Wensum and Blackwater sub-catchment are described in Sections 3.1.3.4 and 3.2.3.4. The locations of each of the weather stations applied and the observations used are provided in Table 4.4.

Table 4.4: The locations of the UK Met Office Integrated Data Archive System (MIDAS) weather stations and the meteorological observations applied within the SWAT models of the Wensum and Blackwater sub-catchment.

MIDAS Weather Station	Observation	Coordinates (latitude, longitude)
Marham (Station ID: 409)	Maximum temperature, minimum temperature, mean relative humidity, solar radiation, mean wind speed	52.651, 0.56772
Attlebridge: Old Hall Farm (Station ID: 4812)	Precipitation	52.6962, 1.1654
East Tuddenham (Station ID: 4817)	Precipitation	52.6595, 1.07405
Heydon (Station ID: 4807)	Precipitation	52.7957, 1.12606
Hindolveston: Hope House (Station ID: 4886)	Precipitation	52.8247, 1.02592
Syderstone (Station ID: 4710)	Precipitation	52.8612, 0.74711
Wendling: Ashness (Station ID: 4793)	Precipitation	52.6782, 0.85209

For each meteorological data type loaded into the model (e.g. precipitation, mean wind speed etc.), SWAT assigns each sub-catchment to the nearest weather station. On occasions when no observations were available, the built-in SWAT weather generator was used to generate estimates of the required meteorological inputs. The SWAT weather generator is described in detail in Neitsch et al. (2011) and generates estimates of meteorological variables from long-term (i.e. ideally 20 years or more) monthly climate statistics from each weather station. The mean monthly climate statistics required by the SWAT weather generator, the weather stations whose datasets those statistics were derived from and the period of time covered by the record that was used are listed in Table 4.5. Each of the statistics are defined in Arnold et al. (2014). The program pcpSTAT was used to calculate the statistical parameters required by the SWAT weather generator for precipitation (Liersch, 2003).

Once the weather stations have been defined and the meteorological datasets to be used have been imported into the model, the model databases and input files are automatically written within ArcSWAT.

Table 4.5: The mean monthly climate statistics required by the SWAT weather generator, the UK Met Office Integrated Data Archive System (MIDAS) weather stations whose datasets those statistics were derived from and the period of time those datasets covered.

Monthly Climate Statistics	MIDAS Weather Station(s)	Period of Record
Mean daily maximum air temperature; mean daily minimum air temperature; standard deviation of daily maximum air temperature; standard deviation of daily minimum air temperature; mean daily solar radiation; mean daily relative humidity; mean daily wind speed	Marham (Station ID: 409)	The years: 1980-2014
Mean monthly precipitation total; standard deviation of daily precipitation; skew coefficient of daily precipitation; probability of a wet day following a dry day; probability of a wet day following a wet day; mean number of wet days; maximum half-hourly rainfall	Attlebridge: Old Hall Farm (Station ID: 4812), East Tuddenham (Station ID: 4817), Heydon (Station ID: 4807), Hindolveston: Hope House (Station ID: 4886), Syderstone (Station ID: 4710), Wendling: Ashness (Station ID: 4793)	The years: 1981-2010 for all weather stations except Heydon (Station ID: 4807) where the record covered 1980-2014.

4.1.5 Modifying SWAT Inputs to Represent Agricultural Practices

After creating the model databases and input files which contain the default model settings, the input files of the SWAT models were edited to represent agricultural practices within the Wensum and Blackwater sub-catchment. This is an important step because, to assess the impacts of agricultural mitigation measures on water quality, the models should reflect agricultural practices within the catchment. SWAT can represent detailed management operations at the HRU level including the crop types grown, cultivation and harvesting dates, the type, rate and timing of pesticide and fertiliser application, tillage types and timing and irrigation practices (Winchell et al., 2013). The crop rotations, tillage practices, fertiliser practices, pesticide practices and cultivation and harvesting dates applied within the models of the Wensum and Blackwater sub-catchment are described in detail in Sections 3.1.3.3 and 3.2.3.3.

Tile drains were also applied on all areas of arable land within the models of the Wensum and Blackwater sub-catchment except on arable sites where well-drained sandy soils were present. In practice, this meant that tile drains were not implemented on arable land where the Isleham 2, Newport 3 and Newport 4 Soil Associations are located. These sandy soils freely drain and were considered to not require the assistance of tile drains to remove excess soil water and so it was deemed that tile drains were not likely to be present in these areas (Cranfield University, 2016g,h,l). The initial values of the SWAT model parameters used to define the properties of tile drains within the models of the Wensum and Blackwater sub-catchment were determined from the literature and are described in Table 4.6. The value for the tile drain lag time parameter (GDRAIN) was based on expert judgement and was determined from in-field experience.

Table 4.6: The SWAT model parameters used to define the properties of tile drains within the models of the Wensum and Blackwater sub-catchment and their respective values.

SWAT Tile Drain Parameter	Description	Value
DDRAIN	Depth to tile drain from surface (mm)	1000 [a]
TDRAIN	Time it takes to drain soils to field capacity (hours)	48 [b]
GDRAIN	Tile drain lag time (i.e. the time it takes to transfer water to the exit of tile drains after entering) (hours)	12

[a] Outram et al. (2016); [b] Arnold et al. (2014).

A system of automatic irrigation was applied within the models of the Wensum and Blackwater sub-catchment. The automated irrigation system applied within SWAT is triggered when the plant water demand stress threshold, defined as the fraction of potential plant growth due to water stress, is below a user-defined value (Arnold et al., 2014). On each day when the plant water stress is below this threshold value, the model automatically applies water up to a user-specified amount. Within SWAT, irrigation water first fills the top soil layer to field capacity and continues working downwards until all soil layers are filled to field capacity or the whole water amount has been applied (Arnold et al., 2014). The parameters used to define this system of automatic irrigation within the models of the Wensum and Blackwater sub-catchment were determined from the literature and are described in Table 4.7. This final step concludes the model set-up process within ArcSWAT and model sensitivity analysis, calibration and validation can now be performed within SWAT-CUP.

Table 4.7: The SWAT model parameters that control and define automatic irrigations practices within the models of the Wensum and Blackwater sub-catchment.

SWAT Automatic Irrigation Parameter	Description	Value
AUTO_WSTRS	The plant water stress threshold that triggers automatic irrigation	0.95 [a]
IRR_EFF	The irrigation efficiency factor which accounts for conveyance and evaporative loss	0.90 [b]
IRR_MX	Maximum depth of irrigation water applied (mm)	25

[a] Arnold et al. (2014); [b] Schneider (2000).

4.2 Blackwater Sub-catchment Nutrients Model

4.2.1 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 SWAT-CUP version 5.1.6.2 (Abbaspour, 2015). 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 4.8). 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.

Table 4.8: 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 - 0.2[a]	-0.035 - 0.087 [a]
CN2 AGRL	Runoff curve number for agricultural land	-0.2 - 0.2[a]	-0.15 - -0.05 [a]
CN2 FRSD	Runoff curve number for deciduous forest	-0.2 - 0.2[a]	-0.13 - 0.093 [a]
CN2 PAST	Runoff curve number for pasture land	-0.2 - 0.2[a]	-0.23 - -0.082 [a]
SOL_AWC	Available water capacity of soil layer (mm H_2O/mm soil)	-0.2 - 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 - 0.2[a]	-0.041 - 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 - 0.2[a]	-0.25 - -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.

4.2.2 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, percent 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.

4.2.2.1 Nash-Sutcliffe Efficiency Coefficient

The Nash-Sutcliffe Efficiency (NSE) coefficient proposed by Nash and Sutcliffe (1970) is defined by Equation 10.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - \overline{Y^{obs}})^2} \qquad (10)$$

Where:

n is the total number of observations

Y_i^{obs} is the value of the observed variable at the i^th time-step

Y_i^{sim} is the value of the simulated variable at the i^th time-step

$\overline{Y^{obs}}$ 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 -∞ 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.

4.2.2.2 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 11. 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.

$$\text{PBIAS} = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right) * 100}{\sum_{i=1}^{n}(Y_i^{obs})} \qquad (11)$$

4.2.2.3 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 12 (Moriasi et al., 2007).

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\mathrm{STDEV_{obs}}} = \frac{\left[\sqrt{\sum_{i=1}^{n}(Y_i^{obs}-Y_i^{sim})^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}(Y_i^{obs}-\overline{Y^{obs}})^2}\right]} \qquad (12)$$

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.

4.2.2.4 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.

4.2.3 Calibration and Validation

Sensitivity analysis identified that the parameters listed in Table 4.8 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 4.8.

4.2.3.1 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 Figure 4.3 and Figure 4.4. 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 4.9). 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 4.9). 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.

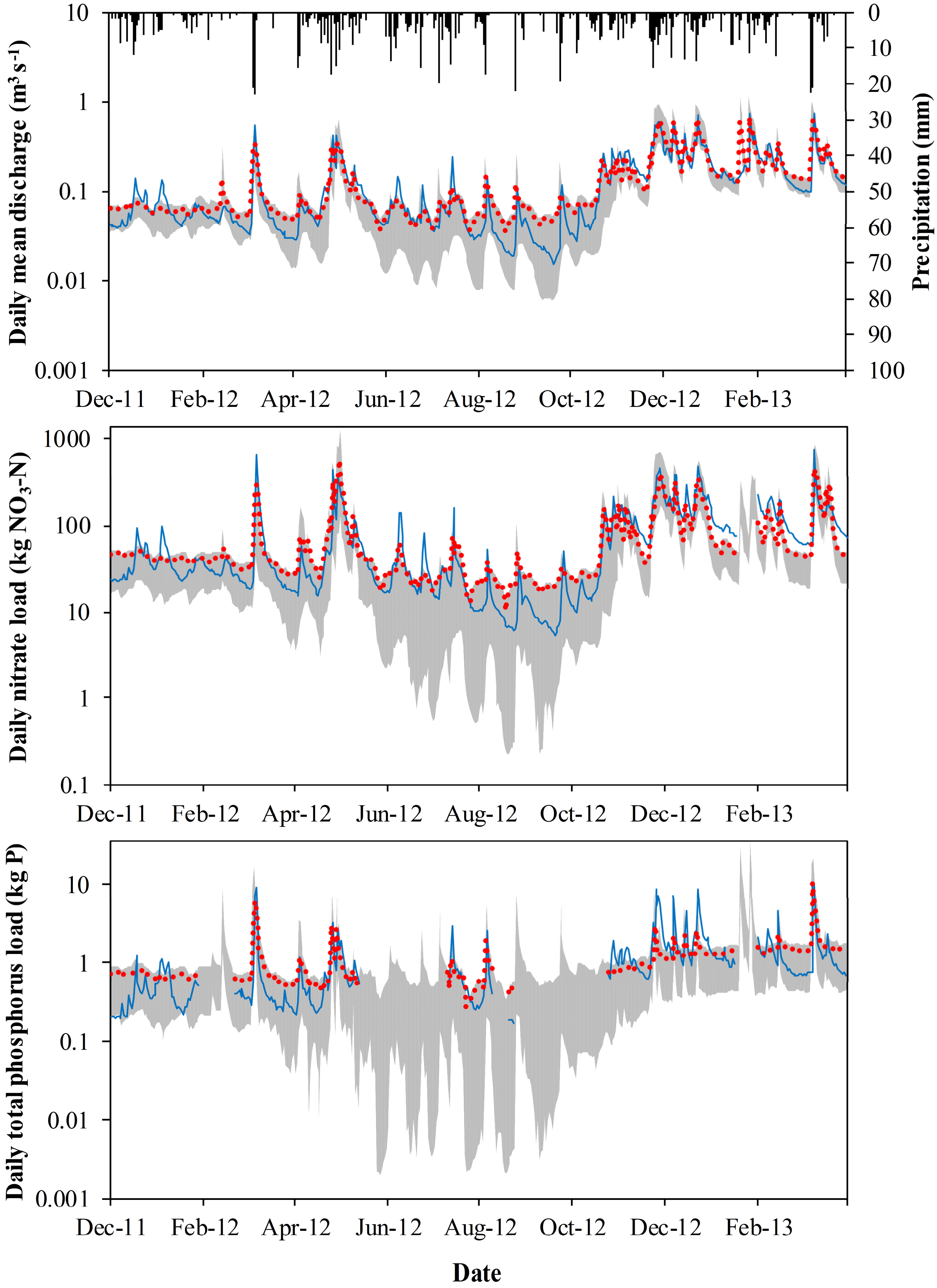

Figure 4.3: Observed (solid line) and the best simulated (dotted line) daily mean discharge, nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment during the calibration time period (1 December 2011 – 31 March 2013). The 95% confidence interval is represented by the hatched area and the daily rainfall amount recorded at Heydon weather station is plotted in the top panel for reference.

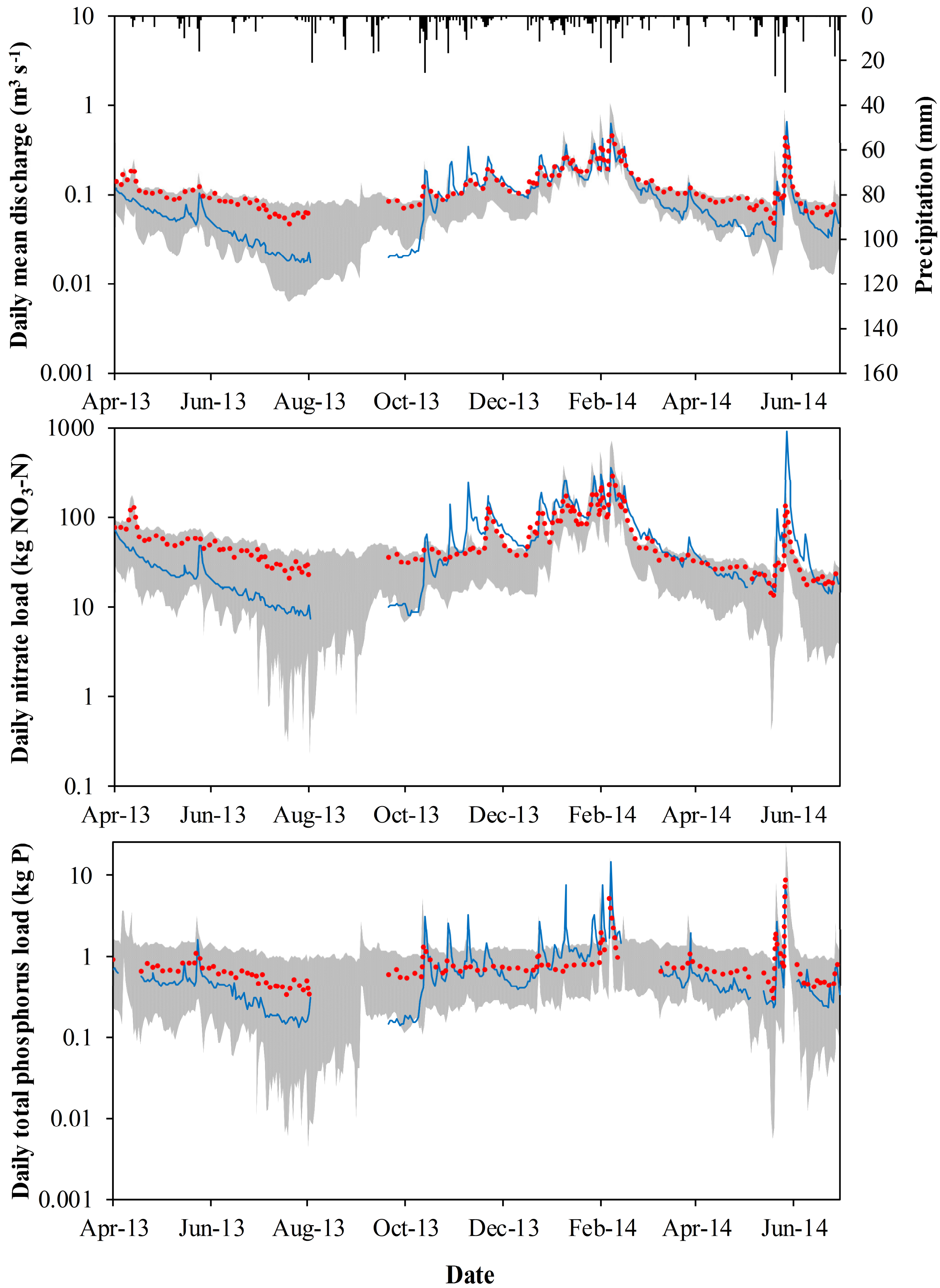

Figure 4.4: Observed (solid line) and the best simulated (dotted line) daily mean discharge, nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment during the validation time period (1 April 2013 – 30 June 2014). The 95% confidence interval is represented by the hatched area and the daily rainfall amount recorded at Heydon weather station is plotted in the top panel for reference.

Table 4.9: 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

4.2.3.2 Baseflow Simulation

To further evaluate model performance, the baseflow index modelled at the outlet of the Blackwater sub-catchment during the calibration and validation periods was compared to the value of 0.80 reported for the sub-catchment by Robson and Reed (1999). According to model predictions, the baseflow index at the outlet of the Blackwater sub-catchment during the calibration and validation periods was 0.58 and 0.65, respectively (Table 4.10). These values are less than the value of 0.80 reported by Robson and Reed (1999), suggesting that the baseflow index during the calibration and validation periods was different to that when reported by Robson and Reed (1999), or that the model underestimates baseflow within the sub-catchment, but a visual evaluation of Figure 4.3 and Figure 4.4 indicates that the model performs reasonably well in simulating baseflow during the calibration and validation periods.

Table 4.10: Modelled total flow, baseflow and baseflow index 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.

Period	Total flow (mm)	Baseflow (mm)	Baseflow index
Calibration (1 December 2011 – 31 March 2013)	437	255	0.58
Validation (1 April 2013 – 30 June 2014)	324	211	0.65

4.2.3.3 Nitrate Simulation

The model performance in simulating daily nitrate loads during the calibration and validation time periods is shown in Figure 4.3 and Figure 4.4, 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 4.9). 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 4.9). When evaluated at a daily time-step however, there is a notable decline in model performance during the validation period.

A visual inspection of Figure 4.4 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 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 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 4.9). 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.

4.2.3.4 Total Phosphorus Simulation

The model performance in simulating daily total phosphorus loads during the calibration and validation time periods can be observed in Figure 4.3 and Figure 4.4, 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 (Figure 4.5). 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 4.9). 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 percent bias values achieved during the calibration and validation time periods indicate that the model simulates overall total phosphorus loads with reasonable accuracy (Table 4.9). When evaluated at a monthly time-step, the model performance in simulating total phosphorus loads does achieve the satisfactory performance criteria (Table 4.9). 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.

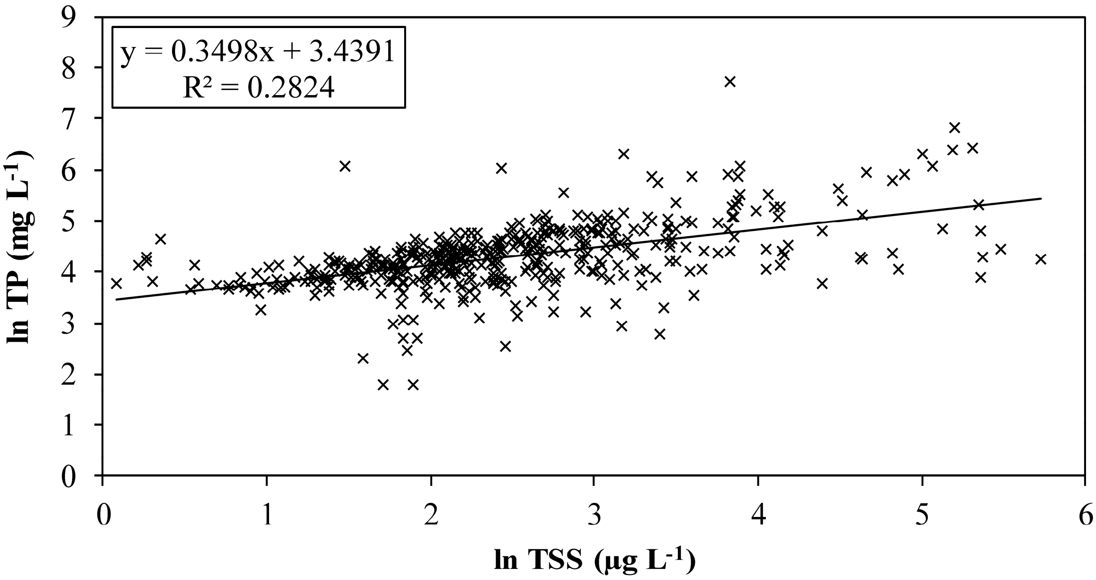

Figure 4.5: Log-log regression model of the relationship between the concentration of total suspended solids (TSS) and the concentration of total phosphorus (TP) at the outlet of the Blackwater sub-catchment according to stream water samples collected during 1 October 2010 – 31 March 2015.

4.2.3.5 Crop Yield Simulation

As an additional test of model performance, the crop yields simulated by the Blackwater model were compared to mean yields recorded by all farms up to the outlet of the Blackwater sub-catchment (Figure 3.13), and to mean yields recorded for eastern England (Table 4.11). Because no crops were harvested during the periods of the years 2011 and 2013 that were included in the calibration period, crop yields simulated during calibration were compared to crop yields observed during 2012. During the calibration period from 1 December 2011 – 31 March 2013, crop yields simulated by the model compared favourably with observations for the Blackwater sub-catchment and eastern England (Table 4.11). According to observations for the Blackwater sub-catchment, the model underestimated spring barley, sugar beet, winter oilseed rape and winter wheat yields by 11.8%, 10.1%, 7.1% and 19.1%, respectively, and overestimated spring bean and winter barley yields by 6.8% and 22.5%, respectively. When compared to observations for eastern England, the model overestimated spring barley, winter barley and winter oilseed rape yields by 5.2%, 22.5% and 11.9%, respectively, whilst the model underestimated winter wheat yields by 3.6%. Because no crops were harvested during the period of the year 2014 included in the validation period, crop yields simulated during validation were compared to crop yields observed during 2013. Model predictions of crop yield during the validation period from 1 April 2013 – 30 June 2014 also compare favourably with observations for the Blackwater sub-catchment and eastern England (Table 4.11). According to observations for the Blackwater sub-catchment, the model overestimated spring barley, sugar beet and winter barley yields by 20.1%, 9.7% and 18.1%, respectively, and underestimated spring bean, winter oilseed rape and winter wheat yields by 5.3%, 6.5% and 14.6%, respectively. When compared to observations for eastern England, the model overestimated spring barley, winter barley and winter oilseed raped yields by 20.3%, 7.6% and 27.9%, respectively, and underestimated winter wheat yields by 14.1%. These results compare favourably with those achieved by previous studies (Srinivasan et al., 2010; Nair et al., 2011; Baffaut et al., 2015), indicating that the model can perform well in simulating crop yields without calibration. For the purposes of this study, it is considered the model performs satisfactorily in simulating crop yields. Factors that may account for the apparent differences between observed and predicted crop yields include that SWAT does not currently account for the impacts of weeds and pests on crop growth (Neitsch et al., 2011). There may also be differences between modelled and actual agricultural management practices and responses to extreme events which affect crop growth and yield (Srinivasan et al., 2010; Mittelstet et al., 2015). A better model performance in simulating crop yields may result if crop parameters are calibrated within SWAT (Nair et al., 2011).

Table 4.11: Simulated and mean observed crop yields for the Blackwater sub-catchment and mean observed yields for eastern England during the calibration (1 December 2011 – 31 March 2013) and validation (1 April 2013 – 30 June 2014) periods, respectively. Data for eastern England is from Defra (2016b). Data for the Blackwater sub-catchment is for all farms up to the outlet of the sub-catchment and is from Wensum Alliance (2017). The numbers enclosed in brackets are the percentage difference between the simulated and observed yields.

Crop	Simulated yield (tonnes ha^{-1})	Blackwater sub-catchment mean observed yield (tonnes ha^{-1})	Eastern England mean observed yield (tonnes ha^{-1})
Calibration:			
Spring barley	5.99	6.79 (-11.8)	5.69 (5.2)
Spring beans	2.59	2.43 (6.8)	N/A
Sugar beet	57.60	64.09 (-10.1)	N/A
Winter barley	8.41	6.87 (22.5)	6.87 (22.5)
Winter oilseed rape	4.09	4.41 (-7.1)	3.66 (11.9)
Winter wheat	7.01	8.67 (-19.1)	7.27 (-3.6)
Validation:			
Spring barley	6.93	5.77 (20.1)	5.77 (20.3)
Spring beans	4.15	4.38 (-5.3)	N/A
Sugar beet	73.91	67.39 (9.7)	N/A
Winter barley	6.97	5.90 (18.1)	6.48 (7.6)
Winter oilseed rape	4.30	4.60 (-6.5)	3.36 (27.9)
Winter wheat	6.76	7.91 (-14.6)	7.87 (-14.1)

4.3 Wensum Catchment Metaldehyde Model

4.3.1 Model Calibration

The SUFI-2 optimisation algorithm was applied within Version 5.1.6.2 of SWAT-CUP to perform sensitivity analysis and calibration (Abbaspour et al., 2004). A sensitivity analysis consisting of 500 simulations was conducted to identify the parameters that the model outputs of discharge and metaldehyde load are sensitive to. The model was calibrated at a daily time-step against observations of discharge and metaldehyde load recorded during the period from 1 January 2008 to 31 October 2015. A preceding warm-up period of four years was applied to allow the model to reach a steady-state. The limited availability of metaldehyde data precluded the opportunity to conduct a split-time calibration and validation for the model. The performance of the model was evaluated against statistical measures including the NSE coefficient, PBIAS and RSR. These objective functions are described in Section 4.2.2 and are the statistical measures recommended for use in model evaluation and reviewed in detail by Moriasi et al. (2007). SWAT does not provide pesticide concentration as an output and so metaldehyde concentration had to be calculated from model predictions of discharge and metaldehyde load at the Costessey Pits and Heigham WTW intake sites.

4.3.2 SWAT Metaldehyde Parameters

SWAT includes parameters which define the physical and chemical properties of pesticides and control their transport and fate within the model (Arnold et al., 2014). Metaldehyde is not included in the SWAT pesticide database and so the values of these properties for metaldehyde (see Table 4.12) were determined from the literature and were manually added to the model database.

Table 4.12: The physical and chemical properties of metaldehyde and associated SWAT model parameters.

Parameter	Description	Value
SKOC	Soil adsorption coefficient normalised for soil organic carbon content (mL g^{-1})	240[a]
WOF	Wash-off fraction	0.6[b]
HLIFE_F	Half-life of metaldehyde on foliage (days)	35[c]
HLIFE_S	Half-life of metaldehyde in soil (days)	60[c]
AP_EF	Application efficiency for metaldehyde	0.75[d]
WSOL	Solubility of metaldehyde in water (mg L^{-1})	220[a]

[a] Tomlin (2006); [b] Willis et al. (1980); [c] EPA (2006); [d] Arnold et al. (2014).

Sensitivity analysis found that model outputs for discharge and metaldehyde load were sensitive to 29 parameters (Table 4.13). Six iterations of 500 simulations were conducted to calibrate the model against observations of discharge and metaldehyde load at a daily time-step during the period 1 January 2008 to 31 October 2015.

Table 4.13: The sensitive model parameters and the initial and final calibrated ranges.

Parameter	Description	Initial range	Final range
ALPHA_BF	Baseflow recession constant (day^{-1})	0 - 1	0.30 - 0.38
GW_DELAY	Groundwater delay time (days)	0 - 500	270 - 400
CH_N2	Manning's roughness coefficient for the main channel	0 - 0.3	0.21 - 0.24
CH_K2	Hydraulic conductivity of main channel alluvium (mm hr^{-1})	0 - 100	20 - 31
ALPHA_BNK	Baseflow recession constant for bank storage (day^{-1})	0 - 1	0.098 - 0.27
GW_REVAP	Groundwater evaporation coefficient	0.02 - 0.2	0.030 - 0.14
SURLAG	Surface runoff lag coefficient	1 - 24	1 - 4.7
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	250 - 300
RCHRG_DP	Deep aquifer percolation fraction	0 – 0.1	0.067 - 0.078
OV_N	Manning's roughness coefficient for overland flow	-0.2 to 0.2[a]	0.056 - 0.21[a]
CN2 AGRL	Runoff curve number for agricultural land	-0.2 to 0.2[a]	-0.025 to 0.0055[a]
CN2 FRSD	Runoff curve number for deciduous forest	-0.2 to 0.2[a]	0.085 - 0.15[a]
CN2 PAST	Runoff curve number for pasture land	-0.2 to 0.2[a]	0.098 - 0.21[a]
SOL_Z	Depth from soil surface to the bottom of soil layer (mm)	-0.2 to 0.2[a]	-0.38 to -0.32[a]
SOL_K	Saturated hydraulic conductivity of soil layer (mm hr^{-1})	-0.2 to 0.2[a]	0.19 - 0.33[a]
GDRAIN	Tile drain lag time (hours)	0 - 100	18 - 31
TDRAIN	Time to drain soil to field capacity (hours)	0 - 72	57 - 72
ESCO	Soil evaporation compensation factor	0 - 1	0.76 - 0.90[a]
SKOC	Soil adsorption coefficient normalised for organic carbon content (mL g^{-1})	-0.2 to 0.2[a]	0.34 - 0.42[a]
WOF	Metaldehyde wash-off fraction	-0.2 to 0.2[a]	-0.17 to -0.10[a]
HLIFE_F	Half-life of metaldehyde on foliage (days)	-0.2 to 0.2[a]	-0.23 to -0.16[a]
HLIFE_S	Half-life of metaldehyde in soils (days)	-0.2 to 0.2[a]	-0.11 to -0.057[a]
AP_EF	Application efficiency for metaldehyde	0.9 - 1	0.90 - 0.93
CHPST_REA	Reaction coefficient in reach for metaldehyde (day^{-1})	-0.2 to 0.2[a]	-0.083 to -0.016[a]
CHPST_KOC	Partition coefficient between water and sediment in reach for metaldehyde (m^3 g^{-1})	-0.2 to 0.2[a]	-0.13 to -0.051[a]
CHPST_RSP	Resuspension velocity for metaldehyde sorbed to sediment (m day^{-1})	-0.2 to 0.2[a]	-0.15 to -0.10[a]
CHPST_MIX	Mixing velocity for metaldehyde in reach (m day^{-1})	-0.2 to 0.2[a]	-0.058 to -0.017[a]
SEDPST_BRY	Metaldehyde burial velocity in bed sediment (m day^{-1})	-0.2 to 0.2[a]	-0.37 to -0.26[a]
PERCOP	Pesticide percolation coefficient	-0.2 to 0.2[a]	-0.30 to -0.15[a]

[a] A relative change where the initial parameter value has been multiplied by 1 plus a number from within the defined range.

4.3.3 Calibration

4.3.3.1 Discharge Simulation

A visual examination of the observed and simulated hydrographs at each of the four flow gauges during the calibration period indicates that the model has a tendency to underestimate peak discharges, but the timings of those peaks and the recession curves compare favourably (Figure 4.6). When evaluated at a daily time-step, the model achieved NSE, PBIAS and RSR values which indicate that the model achieved a good overall fit to the observed hydrograph at each flow gauge (Table 4.14). The PBIAS values show that, for discharge, the model has an overestimation bias of -10.2% at the Fakenham gauge, and underestimation biases of 8.3%, 12% and 2.8% at the Swanton Morley, Costessey Mill and Costessey Park gauges, respectively. The RSR values indicate that the model achieves a relatively low residual error for discharge at each gauge. The statistical performance of the model compares favourably with previous studies (Moriasi et al., 2007), and can be considered to perform satisfactorily in simulating discharge within the catchment at a daily time-step during the calibration period.

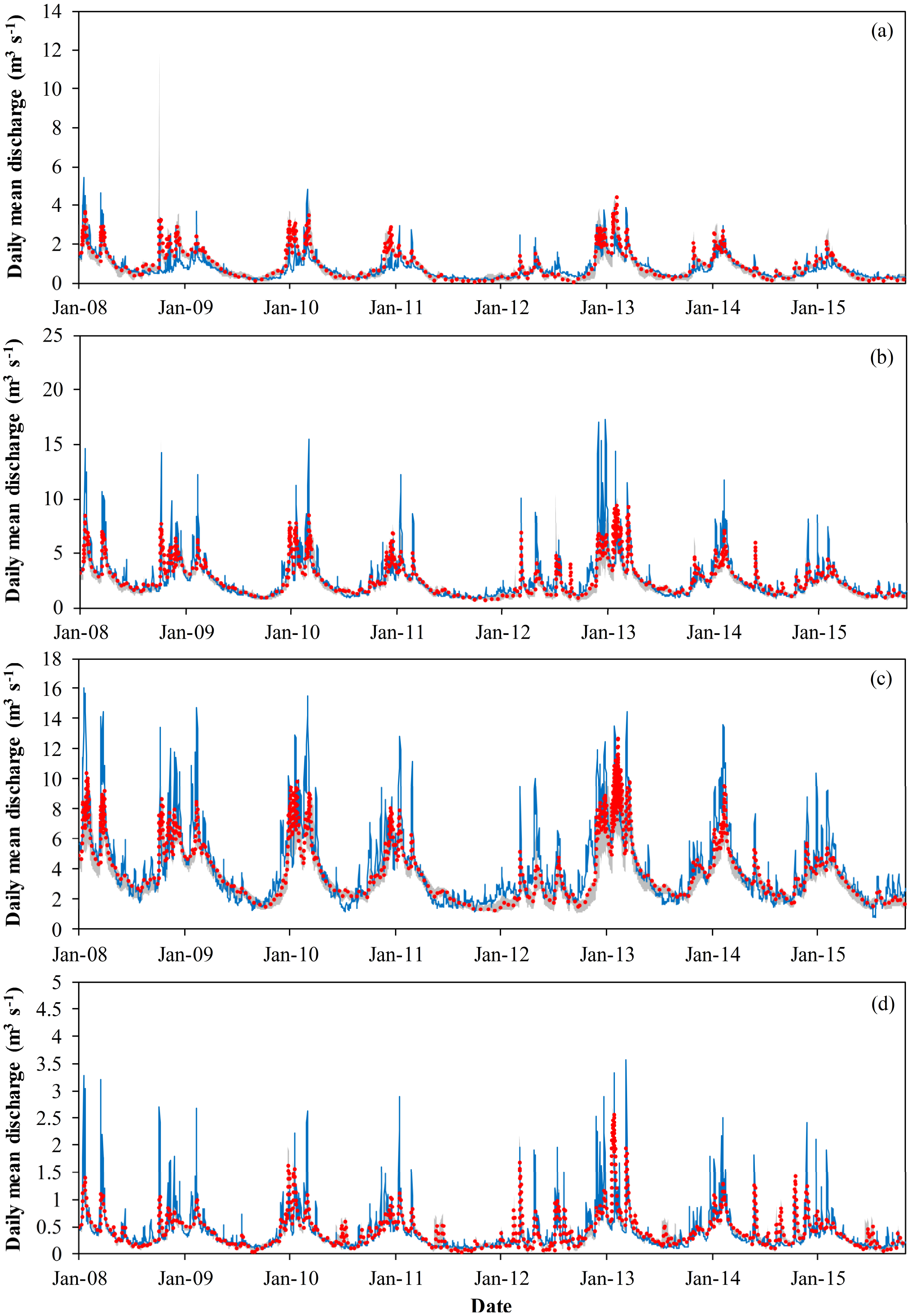

Figure 4.6: Hydrographs depicting observed (solid line) and best simulated (dotted line) daily mean discharge for the flow gauges located at (a) Fakenham, (b) Swanton Morley, (c) Costessey Mill and (d) Costessey Park during the calibration period (1 January 2008 - 31 October 2015). The 95% confidence interval is depicted by the hatched area.

Table 4.14: The statistical performance of the model in simulating mean discharge, metaldehyde load and metaldehyde concentration at a daily time-step during the calibration period from 1 January 2008 to 31 October 2015, as measured by the Nash-Sutcliffe Efficiency (NSE) coefficient, percent bias (PBIAS) and ratio of the root-mean square error to the standard deviation of measured data (RSR). A positive PBIAS indicates a tendency of the model to underestimate a variable, whilst a negative PBIAS indicates a tendency to overestimate a variable.

Variable	NSE	PBIAS (%)	RSR
Fakenham:			
Discharge	0.52	-10.2	0.70
Swanton Morley:			
Discharge	0.68	8.3	0.56
Costessey Mill:			
Discharge	0.67	12.0	0.58
Costessey Park:			
Discharge	0.57	2.8	0.66
Costessey Pits:			
Metaldehyde load	0.50	-1.1	0.71
Metaldehyde concentration	-0.54	-46.6	1.24
Heigham WTW:			
Metaldehyde load	0.44	28.8	0.75
Metaldehyde concentration	0.11	-12.8	0.94

4.3.3.2 Baseflow Simulation

To further evaluate model performance, the modelled baseflow indexes at the four flow gauging stations within the catchment during the calibration period were compared to published values. According to model predictions, the baseflow indexes at the flow gauges located at Fakenham, Swanton Morley, Costessey Mill and Costessey Park were 0.56, 0.58, 0.61 and 0.56, respectively, during the calibration period from 1 January 2008 – 31 October 2015 (Table 4.15). These values are relatively lower than the observed baseflow indexes for each gauge which have been calculated from long-term measurements collected from 1966, 1969, 1960 and 1961 to 2015 at the gauges located at Fakenham, Swanton Morley, Costessey Mill and Costessey Park, respectively

(National River Flow Archive, 2016a,b,c,d). This result suggests that either the baseflow index at each site was lower than the long-term observed baseflow index during the calibration period or that the model under predicts baseflow at each flow gauge within the catchment, but a visual evaluation of Figure 4.6 indicates that the model performs reasonably well in simulating baseflow.

Table 4.15: Modelled total flow, baseflow and baseflow index at the flow gauges located within the River Wensum catchment during the calibration period (1 January 2008 – 31 October 2015) and the long-term measured baseflow indexes.

Flow gauge	Total flow (mm)	Baseflow (mm)	Modelled baseflow index	Measured baseflow index
Fakenham	1200	675	0.56	0.82 [a]
Swanton Morley	1481	861	0.58	0.75 [b]
Costessey Mill	1546	937	0.61	0.75 [c]
Costessey Park	1426	793	0.56	0.64 [d]

[a] National River Flow Archive (2016a), [b] National River Flow Archive (2016b), [c] National River Flow Archive (2016c), [d] National River Flow Archive (2016d).

4.3.3.3 Metaldehyde Simulation

A visual analysis of observed and simulated metaldehyde concentrations at both intake sites indicates a seasonal pattern in metaldehyde loss and concentration, which regularly peaks during the period from September to January (Figure 4.7). The catchment is clearly at an increased risk of exceeding the 0.1 μg L^{-1} limit during this period, which coincides with the time when metaldehyde was applied within the model and is generally applied within the catchment. This problematic period was also recognised by Kay and Grayson (2013).

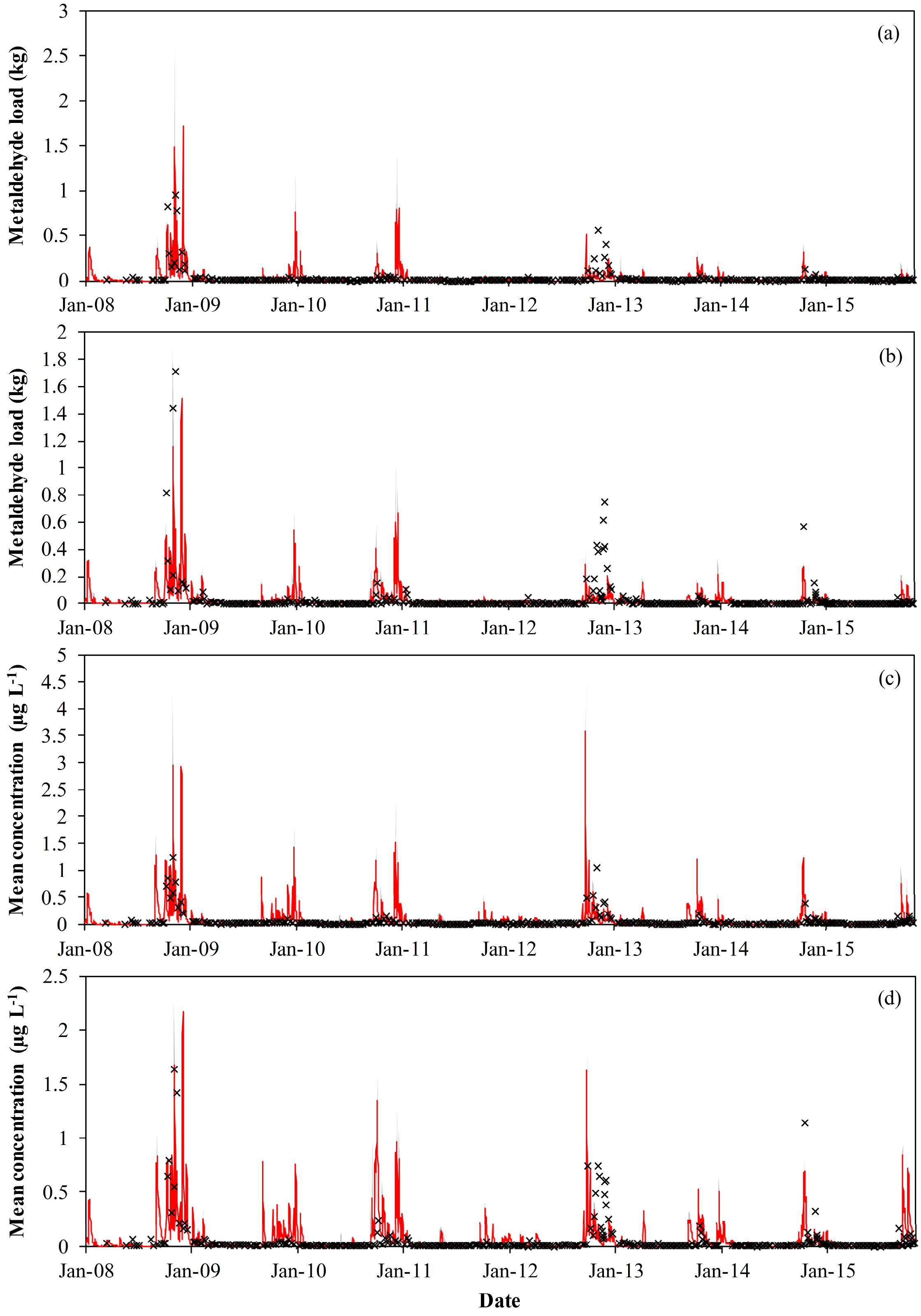

Figure 4.7: Observed (crosses) and best simulated (solid line) daily metaldehyde load for the intakes at (a) Costessey Pits and (b) Heigham WTW and mean metaldehyde concentration for the intakes at (c) Costessey Pits and (d) Heigham WTW during the calibration period (1 January 2008 – 31 October 2015). The 95% confidence interval is depicted by the hatched area.

When evaluated at a daily time-step, the model achieved NSE, PBIAS and RSR values for metaldehyde load during the calibration period that indicate a mixed performance (Table 4.14). There are a number of quality limitations associated with the observed metaldehyde data used within this study that must be considered when evaluating the performance of the model. Firstly, observations of metaldehyde concentration and estimates of load were determined from grab samples collected at one instant in time. Ideally, the observed metaldehyde concentration should equal the mean daily in-stream value, but the grab sample measurements may not capture the mean metaldehyde concentration of a day, depending on the timing of sample collection and rainfall events. Secondly, the grab sample record only contains observations for 13.6% and 14.3% of days during the calibration period at the Costessey Pits and Heigham WTW intakes, respectively. These factors may limit the calibration performance of the model. Despite these limitations, the NSE values indicate that the model achieved a relatively good fit of the observed metaldehyde load at both intake sites. The PBIAS values of -1.1% and 28.8% achieved for metaldehyde load at the Costessey Pits and Heigham WTW intakes, respectively, indicate that the model almost matches observations at the Costessey Pits intake, whilst possessing a moderate bias to underestimate metaldehyde load at the Heigham WTW intake. Given the factors that limit the quality of observations, the model achieves RSR values for metaldehyde load which indicate relatively low levels of residual error.

The statistical measures of performance indicate that the model also achieved a mixed performance in simulating metaldehyde concentration at the two intake sites (Table 4.14). Moriasi et al. (2007) recommend that performance criteria should be relaxed when using observations that possess a large uncertainty to assess model performance. Given the limitations associated with the observations of metaldehyde concentration applied within this study, it would be unfair to dismiss the performance of the model in simulating metaldehyde concentration at a daily time-step as inadequate based on the performance statistics alone. The statistics are perhaps more a reflection of the limitations of the data rather than the performance of the model itself. A visual evaluation of observed and simulated metaldehyde concentrations at both intakes indicates a more skilful performance than is suggested by the statistical measures (Figure 4.7). The magnitudes of peak events were overestimated or underestimated on a number of occasions but the timings of peaks and recession curves compare favourably with observations. Some events were not reproduced in the observed record and on a number of occasions during

October to November 2012, the magnitude of some observed peak events were not reproduced by the model. This is not unexpected given the uncertainties associated with data from the observed record. If these uncertainties are taken into account, both the visual evaluation and statistical performance indicate that the model possesses sufficient skill to predict discharge, metaldehyde concentration and load. The model can therefore be applied to assess the risk of non-compliance for metaldehyde and to quantify the impacts of mitigation options on diffuse metaldehyde pollution.

4.3.3.4 Crop Yield Simulation

As an additional test of model performance, the crop yields simulated by the Wensum model were compared to mean yields recorded by all farms up to the outlet of the Blackwater sub-catchment (Figure 3.13) during the period 2011-2014, and to mean yields recorded during the period 2008-2015 for eastern England (Table 4.16). During the calibration period from 1 January 2008 – 31 October 2015, crop yields simulated by the model compared favourably with observations for the Blackwater sub-catchment and eastern England (Table 4.16). According to observations for the Blackwater sub-catchment, the model underestimated sugar beet yields by 5%. It is important to consider that the Blackwater is only 2.9% of total area of the Wensum catchment and so a difference in yields can reasonably be expected. When compared to observations recorded for the Blackwater sub-catchment and eastern England respectively, winter barley yields were overestimated by 17.8% and 15.2%, winter oilseed rape yields were overestimated by 2.6% and 14.9% and winter wheat yields were underestimated by 15.1% and 6.7%. These results compare favourably with those achieved by previous studies (Srinivasan et al., 2010; Nair et al., 2011; Baffaut et al., 2015), indicating that the model can perform well in simulating crop yields without calibration. Based on the above analysis, it is considered that the model performs satisfactorily in simulating crop yields. The factors which may account for the apparent differences between observed and predicted crop yields are described in Section 4.2.3.5 and also apply here.

Table 4.16: Crop yields simulated by the model of the River Wensum catchment and mean observed crop yields for the Blackwater sub-catchment and eastern England during the calibration period (1 January 2008 – 31 October 2015). Data for eastern England is from Defra (2016b). Data for the Blackwater sub-catchment is for all farms up to the outlet of the sub-catchment and is from Wensum Alliance (2017) The numbers enclosed in brackets are the percentage difference between the simulated and observed yields.

Crop	Simulated yield (tonnes ha^{-1})	Blackwater sub-catchment mean observed yield (tonnes ha^{-1})	Eastern England mean observed yield (tonnes ha^{-1})
Sugar beet	70.11	73.81 (-5.0)	N/A
Winter barley	7.37	6.25 (17.8)	6.4 (15.2)
Winter oilseed rape	4.11	4.00 (2.6)	3.58 (14.9)
Winter wheat	7.48	8.81 (-15.1)	8.02 (-6.7)

4.4 Use of Automatic Irrigation in the Models

Although a system of automatic irrigation was implemented within the models of the River Wensum catchment and Blackwater sub-catchment, it was recognised post-development that it is unrealistic to assume that all crop types are irrigated, when only high-value crops, such as potatoes and fruit, are likely to be irrigated (Watts et al., 2015). Although sugar beet does receive some irrigation, less than 5% of the crop is irrigated (British Sugar and NFU Sugar, 2011). Because this unrealistic assumption was included in both models, it is important to determine how much irrigation water was applied within the models and to identify the implications of this for the findings of this investigation.

It was found that no irrigation water was applied within the model of Blackwater sub-catchment during the calibration period from 1 December 2011 – 31 March 2013. As such, the system of automatic irrigation did not have any impact on model parameterisation and model behaviour during model calibration. The absence of irrigation water also indicates that the crops grown within the model did not experience water stress during this period. During the validation period from 1 April 2013 – 30 June 2014, 10.8 mm of irrigation water was applied to cropland within the Blackwater sub-catchment (equivalent to 8.48 mm per annum during the validation period). A total of 831.5 mm of precipitation occurred during the validation period, and so the irrigation water represents an addition of 1.3% of water to the water budget of the model during validation. Although this irrigation water is not likely to have been present, it is not considered to have had a major impact on model results due to the relatively small volume applied. Nevertheless, it is important to consider the implications of the automatic irrigation assumption on crop growth, soil water content, soil hydrological behaviour and pollutant mobilisation and transport. For example, wetter soils due to irrigation during periods of plant water stress may have resulted in increased crop growth and an increase in the uptake of nutrients from soils by crops than would otherwise have occurred, potentially reducing the amount of nutrients available to be lost in rainfall events. Wetter soils due to irrigation may have also resulted in increased nutrient losses from soils through increased leaching and the increased susceptibility of soils to nutrient loss in surface runoff.

Within the model of the Wensum catchment, it was found that 264.79 mm of irrigation water was applied to cropland during the calibration period from 1 January 2008 – 31 October 2015 (equivalent to 33.78 mm per annum during the calibration period). A total of 5494.7 mm of precipitation occurred during the same period, and so the irrigation water represents an addition of 4.82% of water to the water budget of the model during calibration. Although this is more irrigation water than was applied within the Blackwater model during validation, it is still a relatively small amount. The potential effects of the irrigation water on nutrient losses described above also apply here, potentially increasing losses of metaldehyde through leaching and surface runoff.

It is important to also consider the potential effects of the irrigation assumption on the apparent relative effectiveness of mitigation measures. For example, wetter soils may have increased the incidence and severity of surface runoff events within the Wensum and Blackwater models, potentially increasing the apparent relative effectiveness of buffer strips, the introduction of a red clover cover crop, a system of no metaldehyde application to arable land that has a slope of >2% or where clay soils are present, whilst exacerbating losses due to the use of reduced tillage techniques and the removal of tile drains. It is possible that the increased uptake of nutrients by plants may counteract this effect to some degree for nitrate and total phosphorus.

4.5 Chapter Summary

In this chapter, the methodology used to build the SWAT models of the Wensum and Blackwater sub-catchment was described. The temporal and spatial datasets used within the models and the agricultural practices simulated were also described. Sensitivity analysis, calibration and validation were conducted at a daily time-step for the SWAT model of the Blackwater sub-catchment for discharge, nitrate and total phosphorus load. Sensitivity analysis and calibration were also performed for the SWAT model of the Wensum catchment for discharge and metaldehyde load. It was found that there was at an increased risk of exceeding the 0.1 $\mu g\ L^{-1}$ limit for metaldehyde at the Costessey Pits and Heigham WTW intake sites each year during the period from September to January. The parameters included in model calibration and their initial and final calibrated ranges were identified. The objective functions NSE, PBIAS and RSR used to evaluate model performance were defined and were applied to provide a statistical assessment of the performance of both models in simulating the variables of interest. The model of the Blackwater sub-catchment was considered to perform satisfactorily in simulating discharge and nitrate and total phosphorus load at a daily time-step and the model of the Wensum catchment was considered to perform satisfactorily in simulating discharge, metaldehyde load and concentration. The satisfactory performance of the models suggests that they can be applied with confidence to assess the impacts of agricultural mitigation measures on water quality.

5 IMPACTS OF MITIGATION MEASURES ON NUTRIENT CONCENTRATIONS

The content from Sections 5.1 to 5.2.1.2 of this chapter have been published in the *Journal of Environmental Management* (Taylor et al., 2016).

5.1 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; 2016). 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 5.1).

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, and pulverises soils into a finer material, removing air pockets and preparing the seedbed for cultivation (see Table 5.2). 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.

Table 5.1: 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

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, 2013). 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 5.2. 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.

Table 5.2: 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

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 1986-1989. The period from 1990-2009 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.

5.2 Results and Discussion

5.2.1 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.

5.2.1.1 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) (Figure 5.1a). 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) (Figure 5.1b). 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 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 (Figure 5.1). 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) (Figure 5.1). 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) (Figure 5.1). 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.

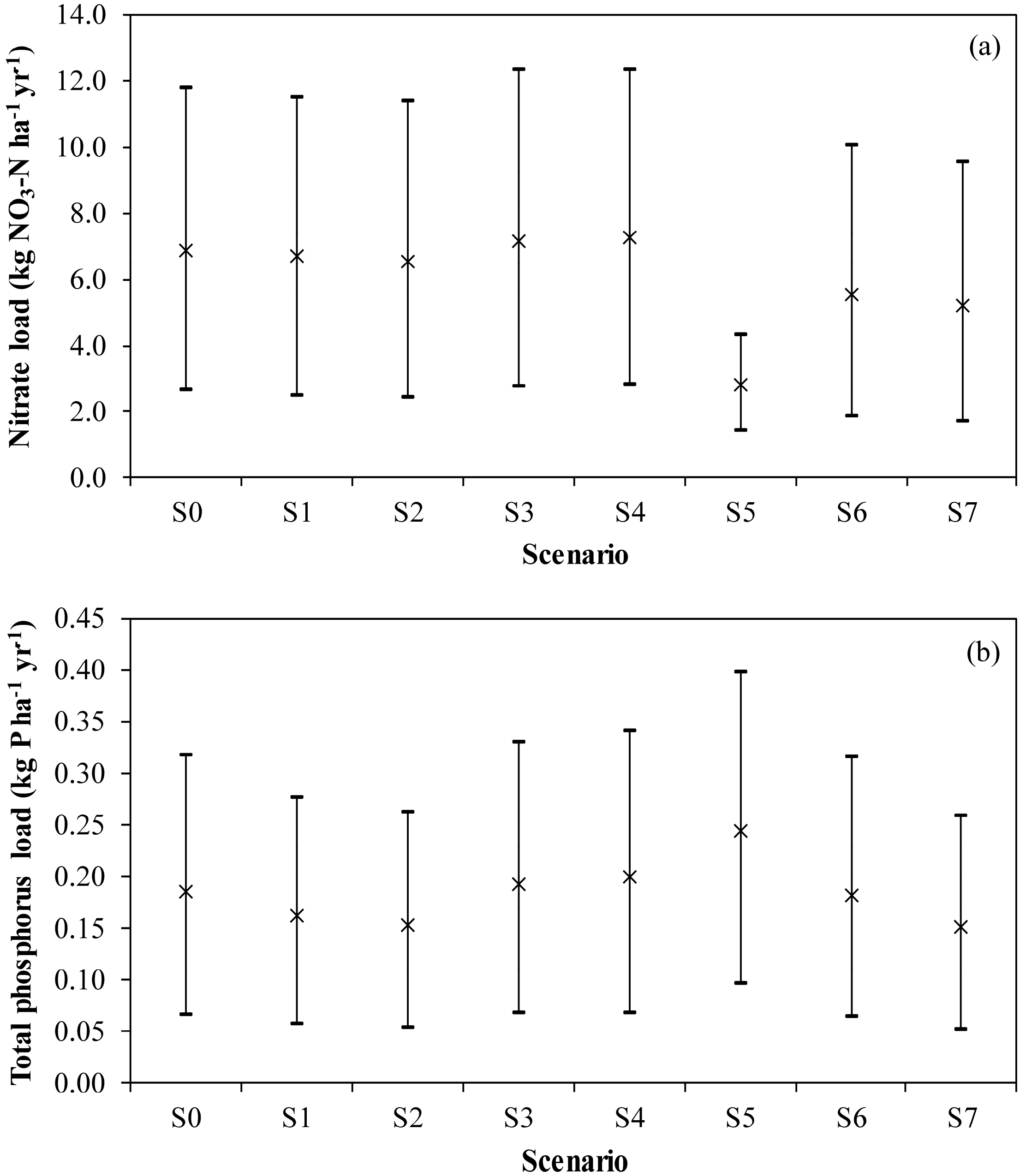

Figure 5.1: (a) The mean annual nitrate load and (b) the mean annual total phosphorus load exported from the Blackwater sub-catchment during the period 1990-2009 under each mitigation scenario. The upper and lower bounds of the 95% prediction uncertainty range are also shown at the end of each line. The '×' represents the mean value of each scenario.

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 (Figure 5.1). 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 (Figure 5.1), 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 1990-2009 were developed for each scenario (Figure 5.2). 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 (Figure 5.2a). 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 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) (Figure 5.2a). 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 (Figure 5.2b), 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 (Figure 5.2b). 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% (Figure 5.2b). 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) (Figure 5.2b). 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.

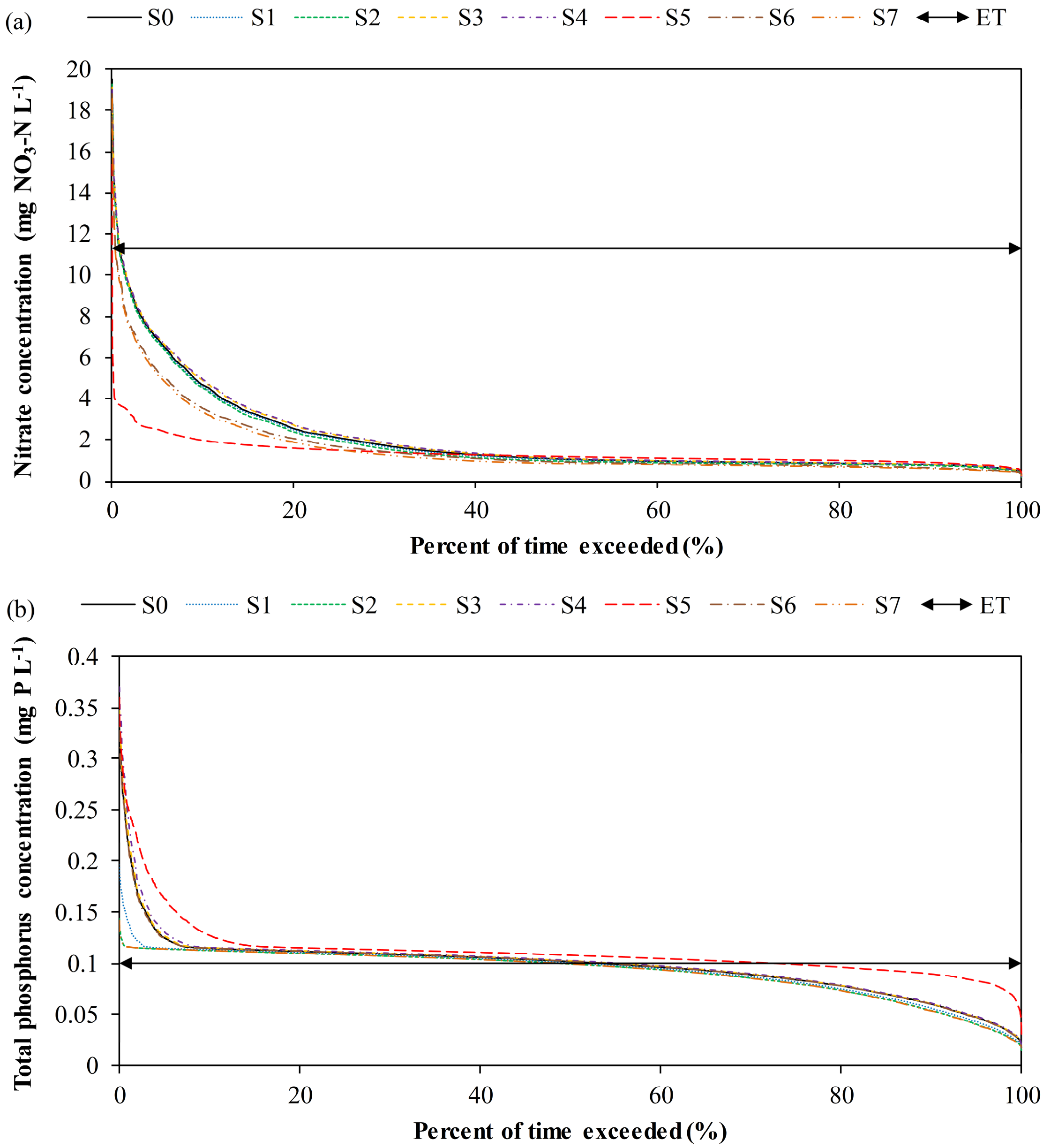

Figure 5.2: Environmental Targets (ET) and percent exceedance curves for (a) nitrate concentration and (b) total phosphorus concentration as simulated at the outlet of the Blackwater sub-catchment during the period 1990-2009 under each mitigation scenario.

5.2.1.2 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 (Figure 5.1). 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 (Figure 5.2a), 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 (Figure 5.2b). 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).

5.2.1.3 Implications for Catchment Management

The evidence from this study may be used to influence future agri-environmental policy, develop improved agricultural practices to reduce diffuse pollution from agriculture and to increase the uptake of mitigation measures. From a catchment management perspective, Catchment Change Network (2012) identified barriers that need to be overcome to effectively address the problem of diffuse pollution from agriculture. Solutions to the barriers identified include:

1. Improved availability of and access to data concerning water quality, pollution sources and management practices.
2. Increased provision of education and access to research and case studies to raise awareness.
3. Policy changes to support long-term responsible catchment management (i.e. increased emphasis within funding schemes for actions taken to improve water quality).
4. Development of integrated farm plans which align economic and environmental interests.

The results of this investigation may be used to partially address each of the barriers identified above. For example, the results may be shared with stakeholders, improving the availability of surface water quality data. The mitigation measures considered by this investigation also increase the evidence base of the impacts of individual and combined measures and the results of this investigation may be used as examples to assist farmers in developing appropriate mitigation schemes. The findings of this study may also be used to assist policy development and to engage with farmers about the commercial benefits of adopting mitigation measures that reduce agricultural water pollution, such as reductions in fertiliser loss and expenditure, assisting the development of farm plans which align economic and environmental goals.

The Catchment Sensitive Farming (CSF) project aims to reduce agricultural water pollution by providing farmers with training and advice to adopt practices to minimise the impacts of agriculture on water quality (Natural England, 2017). The results of this study are therefore relevant to the CSF project, and may be used by CSF officers to advise farmers and land managers on practices that can be adopted to mitigate agricultural diffuse water pollution. The overlapping 95% confidence intervals observed under each mitigation scenario indicate that there is a relatively large degree of uncertainty associated with model predictions and suggest that the potential impacts of measures, should they be introduced, are very uncertain (Figure 5.1). This uncertainty creates difficulties for policy makers, farmers, farm advisers, CSF officers and other stakeholders when developing catchment management strategies to mitigate agricultural diffuse water pollution because it complicates any assessment of the benefits of mitigation measures.

This may create reluctance amongst stakeholders to incentivise and introduce measures and act as a barrier to the implementation of catchment management strategies to reduce agricultural diffuse water pollution. Thus, uncertainty creates a challenge to the development of strategies to mitigate agricultural diffuse water pollution and although it may appear to be an appealing option, waiting for the uncertainties to be reduced does not represent a solution to the problem we seek to address. A more pragmatic approach to the problem of agricultural diffuse water pollution involves quantifying and working within the scope of the uncertainties, presenting them to allow people to develop a better understanding of the potential impacts of introducing mitigation measures on water quality, whilst also working to constrain the uncertainties. Providing uncertainty assessments whilst also presenting a clear explanation of the potential benefits of a measure should help to create realistic expectations of the impacts of measures and may encourage the uptake of effective solutions. It is hoped that identifying a range of potential outcomes will reduce the likelihood that stakeholder confidence is undermined if a particular impact is not achieved, compared to if a singular prediction was provided by a deterministic assessment, assisting the creation of trust and the development of fruitful working partnerships between experts and stakeholders.

5.3 Chapter Summary

In this chapter, the agricultural mitigation measures applied within the SWAT model of the Blackwater sub-catchment were identified and the effects of those measures on nitrate and total phosphorus loads and concentrations were presented and discussed. Introducing a red clover cover crop was found to reduce nitrate and total phosphorus losses by 19.6% and 1.6%, respectively, and suggests that red clover can be successfully grown as a green manure, reducing fertiliser expenditure and agricultural diffuse water pollution over the long term. Buffer strips of 2 m and 6 m width on arable land reduced total phosphorus losses by 12.2% and 16.9%, respectively, and were the mitigation measures most effective at reducing total phosphorus losses within the sub-catchment. Removing tile drains from arable land was the measure most effective at reducing losses of nitrate and reduced nitrate losses by 58.9%. This measure also increased losses of total phosphorus by 31.6%. This result highlights the importance of modelling the impacts of mitigation measures on multiple pollutants to mitigate the risk of introducing measures that exacerbate losses of other pollutants. Conservation tillage and no-tillage resulted in small increases in nitrate and total phosphorus losses, highlighting the importance of assessing the potential impacts of mitigation measures prior to their introduction. The most effective combination of measures that can be introduced to reduce losses of nitrate and total phosphorus are a red clover cover crop and buffer strips. According to the results, the prediction uncertainties indicate that there can be a relatively large degree of uncertainty associated with model predictions. This result highlights the need to conduct robust uncertainty analyses when evaluating the effectiveness of mitigation measures on diffuse nitrate and total phosphorus pollution to develop a better understanding of the potential impacts of mitigation measures. Although no mitigation measure resulted in nil-exceedance of the drinking water quality standard that applies to nitrate, it was found that mitigation measures can reduce diffuse nitrate pollution and the proportion of time that this limit was exceeded. Although the target for mean annual total phosphorus concentration was not exceeded under all scenarios except scenario S5, the proportion of days in which this target was exceeded was also successfully reduced by mitigation measures.

6 Impacts of Mitigation Measures on Metaldehyde Concentrations

6.1 Mitigation Scenarios

The satisfactory performance of the Wensum SWAT model in simulating discharge, metaldehyde load and concentration suggests that the model can be applied with confidence to assess the impacts of agricultural mitigation measures on metaldehyde load and concentration within the River Wensum catchment.

A number of mitigation scenarios were developed in consultation with stakeholders and experts (Table 6.1). The control scenario (S0) represents a best estimate of current conditions and practices and was applied as the baseline scenario to which the other mitigation scenarios were compared. Scenario S0 includes buffer strips of 2 m width on arable land. This practice is compulsory under cross-compliance rules to qualify for the Basic Payment Scheme and is therefore considered to be widely practiced (Defra, 2015). Scenario S1 involves the introduction of buffer strips of 6 m width to arable land. This is a voluntary practice under the Countryside Stewardship scheme which provides a financial incentive for farmers to introduce measures which benefit the environment (Natural England, 2015b). Under scenario S2, the maximum application rate of metaldehyde to all areas of arable land was limited to 0.16 kg ha^{-1}. This is a practice that may be recommended in the UK for the additional protection of water and is one of the guidelines issued by the Metaldehyde Stewardship Group (Metaldehyde Stewardship Group, 2016b). Scenarios S3 and S4 are more targeted approaches to mitigation and involve the introduction of mitigation practices to areas considered to be at a high risk of metaldehyde loss due to their potential susceptibility to surface runoff. Under scenario S3, no metaldehyde was applied to areas of arable land where the slope exceeds 2%. This represents 42.4% of the catchment within the SWAT model. Under scenario S4, no metaldehyde was applied to areas of arable land where clay soils are present, representing 39.1% of the catchment area within the model.

Table 6.1: The mitigation measures scenarios applied within the SWAT model of the Wensum catchment.

Scenario Number	Description
S0	The baseline scenario which reflects current conditions and practices
S1	Establishment of buffer strips of 6 m width on arable land
S2	Maximum metaldehyde application rate of 0.16 kg ha^{-1} on arable land
S3	No applications of metaldehyde to arable land that has a slope of >2%
S4	No applications of metaldehyde to arable land where clay soils are present

Each scenario was run 500 times at a daily time-step during the period 1 January 2008 to 31 October 2015 to determine the impacts of each mitigation measure on metaldehyde pollution and to capture the uncertainty of predictions. This relatively long-period of time is considered to reflect a typical range of climatological conditions.

6.2 Results and Discussion

6.2.1 Mitigation Scenario Impacts

According to predictions at the Costessey Pits and Heigham WTW intake sites, buffer strips of 6 m width under scenario S1 achieved moderate reductions in the amount of metaldehyde lost from arable land within the Wensum catchment relative to the control scenario (S0) (Figure 6.1). According to the mean prediction that was derived from the 500 model simulations performed under scenario S1, buffer strips of 6 m width reduced monthly metaldehyde losses per hectare of arable land that contributes to each site by 20% and 19.4% at the Costessey Pits and Heigham WTW intake sites, respectively. The reductions predicted are likely to result from a reduction in the amount of metaldehyde lost in surface runoff due to a widening of buffer strips from 2 m width under the control scenario to 6 m width under scenario S1. Although no specific data is available for the effectiveness of buffer strips at reducing metaldehyde losses, it is possible to compare the results of this study with studies that investigated the effectiveness of buffer strips on other pesticides. For example, Arora et al. (1996) found that for buffer strips of 20.12 m width, retention rates for the herbicides atrazine, metolachlor, and cyanazine ranged from 11-100%, 16-100% and 8-100%, respectively, for six runoff events during the years

1993-1994. The large range in retention rates was attributed to variations in the runoff generated by each storm event and variations in infiltration within the buffer zone during each event. The key factor in determining retention rates was identified as the amount of infiltration of surface runoff that occurred in the buffer zone which is dependent on soil moisture conditions. Gevaert et al. (2008) introduced buffer strips of 5 m width to arable land within a SWAT model of the Nil catchment in Belgium and found that total losses of atrazine reduced by 11.67%. Reichenberger et al. (2007) conducted a review of 14 studies which examined the effectiveness of buffer strips on pesticide losses and found that their effectiveness varied considerably, depending on the width of the buffer strip, the amount and rate of runoff generated by each storm event, soil properties, soil moisture conditions and the amount of infiltration that occurred in the buffer zone. Pesticides strongly adsorbed to sediment are also likely to be more easily removed from surface runoff by buffer strips (Zhang et al., 2010). As evidenced by our study, and the findings of others, it is clear that buffer strips can be effective at reducing metaldehyde losses but their effectiveness varies, depending on local conditions, the width of the buffer and the nature of storm events. For monthly metaldehyde losses, the 95% prediction uncertainty range within which 95% of the 500 model predictions fell ranged from 6.87×10^{-6} kg ha^{-1} month^{-1} to 1.60×10^{-5} kg ha^{-1} month^{-1} and 5.93×10^{-6} kg ha^{-1} month^{-1} to 1.38×10^{-5} kg ha^{-1} month^{-1} at the Costessey Pits and Heigham WTW intakes, respectively, under scenario S1 (Figure 6.1). Relative to the control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range reduced by 16.6% and 23% at the Costessey Pits intake site, and 16.9% and 22.7% at the Heigham WTW intake, respectively. Although there is some uncertainty in model predictions under scenario S1, the results indicate a clear reduction in the amount of metaldehyde lost from arable land within the Wensum catchment and suggest that buffer strips can be introduced to reduce metaldehyde losses over the long term.

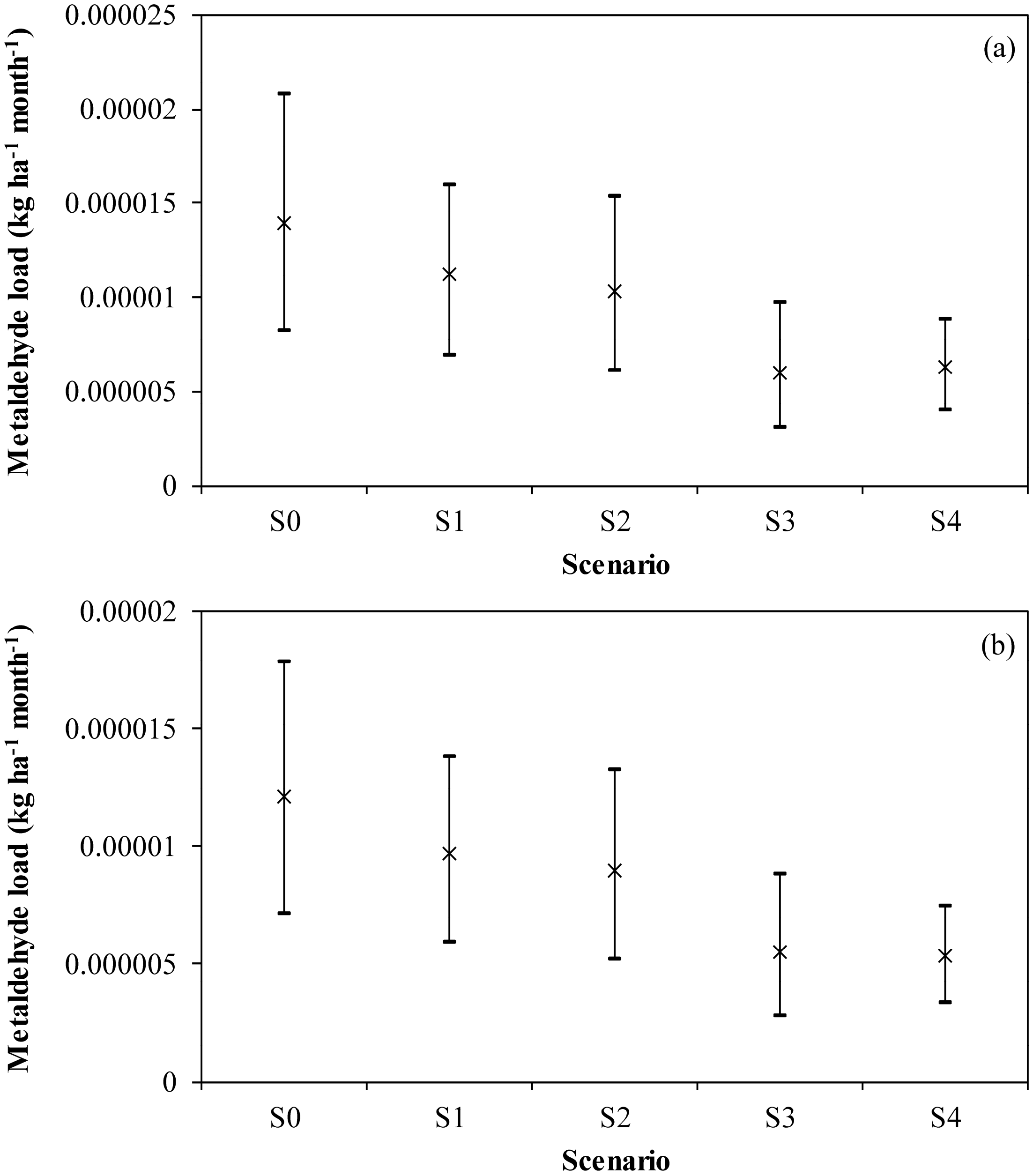

Figure 6.1: The monthly metaldehyde load per hectare of arable land at the (a) Costessey Pits and (b) Heigham water treatment works intake sites during the period 1 January 2008 – 31 October 2015 under each mitigation scenario. The upper and lower bounds of the 95% prediction uncertainty range are also shown at the end of each line. The '×' represents the mean prediction that was derived from the 500 model simulations conducted for each scenario.

Limiting metaldehyde applications to a maximum rate of 0.16 kg ha^{-1} on all areas of arable land under scenario S2 also resulted in moderate reductions in the amount of metaldehyde lost relative to the control scenario S0, and was slightly more effective than scenario S1 (Figure 6.1). According to the mean prediction that was derived from the 500 model simulations performed under scenario S2, monthly metaldehyde losses per hectare of arable land that contributes to each site reduced by 26.1% and 25.9% at the Costessey Pits and Heigham WTW intake sites, respectively. Under scenario S2, the 95% prediction uncertainty range of monthly metaldehyde losses ranged from 6.05×10^{-6} kg ha^{-1} month^{-1} to 1.53×10^{-5} kg ha^{-1} month^{-1} and 5.21×10^{-6} kg ha^{-1} month^{-1} to 1.32×10^{-5} kg ha^{-1} month^{-1} at the Costessey Pits and Heigham WTW intakes, respectively. Relative to the control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range reduced by 26.6% and 26.1% at the Costessey Pits intake site, and by 27.0% and 25.6% at the Heigham WTW intake, respectively. The reductions in metaldehyde losses predicted under this scenario are to be expected given that 19.1% less metaldehyde has been applied to arable land which also means that there is less metaldehyde available to be lost within the catchment. Nevertheless, these results do suggest that limiting metaldehyde application rates to 0.16 kg ha^{-1} on areas of arable land can be an effective mitigation measure to reduce metaldehyde losses. It is, however, important to remember that, although the application rate for metaldehyde should not be greater than is necessary to effectively control the impacts of slugs and snails, metaldehyde application rates can only realistically be reduced to a level where metaldehyde still sufficiently controls their impacts (Bereswill et al., 2014).

Prohibiting metaldehyde application on areas of arable land where the slope exceeds 2% under scenario S3 achieved relatively large reductions in the amount of metaldehyde lost from arable land when compared to the control scenario S0 (Figure 6.1). According to the mean prediction that was derived from the 500 model simulations performed under scenario S3, monthly metaldehyde losses per hectare of arable land that contributes to each site reduced by 57.1% and 54.4% at the Costessey Pits and Heigham WTW intake sites, respectively. Under scenario S3, the 95% prediction uncertainty range of monthly metaldehyde losses ranged from 3.05×10^{-6} kg ha^{-1} month^{-1} to 9.69×10^{-6} kg ha^{-1} month^{-1} and 2.82×10^{-6} kg ha^{-1} month^{-1} to 8.85×10^{-6} kg ha^{-1} month^{-1} at the Costessey Pits and Heigham WTW intakes, respectively. Relative to the control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range reduced by 63.0% and 53.2% at the Costessey Pits intake site, and by 60.5% and 50.3% at the Heigham WTW intake, respectively, under scenario S3. Under this scenario, the amount of metaldehyde applied within the model was reduced by 50.4%. The reductions in losses of metaldehyde achieved under this scenario cannot be accounted for by the reduction in the amount of metaldehyde applied alone. Within the model, areas with a slope greater than 2% account for 53% of arable land up to the Costessey Pits intake and 50.6% of arable land up to the Heigham WTW intake but, according to the mean prediction derived from the 500 simulations performed under scenario S3, they account for 57.1% and 54.4% of metaldehyde losses, respectively. This finding suggests that areas with a slope of greater than 2% are at a higher risk of metaldehyde loss than areas of arable land where slopes are more shallow. According to Bereswill et al. (2014), areas where the slope of fields equals or exceeds 2% are at a relatively higher risk of surface runoff and the loss of pesticides in surface runoff compared to areas with slopes that are more shallow. Prohibiting metaldehyde application on these higher risk zones reduces the potential for metaldehyde to be lost in surface runoff, which may account for the reduction in metaldehyde lost under scenario S3.

Prohibiting metaldehyde application on areas of arable land where clay soils are present under scenario S4 also resulted in relatively large reductions in metaldehyde losses when compared to the control scenario S0 (Figure 6.1). According to the mean prediction that was derived from the 500 model simulations performed under scenario S4, monthly metaldehyde losses per hectare of arable land that contributes to each site reduced by 55.1% and 55.6% at the Costessey Pits and Heigham WTW intake sites, respectively. Under scenario S4, the 95% prediction range of monthly metaldehyde losses ranged from 4.00×10^{-6} kg ha^{-1} month^{-1} to 8.77×10^{-6} kg ha^{-1} month^{-1} and 3.38×10^{-6} kg ha^{-1} month^{-1} to 7.44×10^{-6} kg ha^{-1} month^{-1} at the Costessey Pits and Heigham WTW intakes, respectively. The 95% uncertainty range for metaldehyde losses observed under scenario S4 is more narrow than for all other scenarios. Relative to the control scenario S0, the lower and upper bounds of the 95% prediction uncertainty range reduced by 51.5% and 57.7% at the Costessey Pits intake site, and by 52.6% and 58.3% at the Heigham WTW intake, respectively. Under this scenario, the amount of metaldehyde applied to arable land was reduced by 49.1% and so, as was also recognised for scenario S3, the reductions in metaldehyde losses observed under this scenario cannot only be accounted for by a reduction in metaldehyde application. Within the model, areas with clay soil account for 48.7% of arable land up to the Costessey Pits intake and 46.6% of arable land up to the Heigham WTW intake but, according to the mean prediction derived from the 500 model simulations performed under scenario S3, they account for 55.1% and 55.6% of metaldehyde losses, respectively. This finding suggests that areas with clay soils are at a greater risk of metaldehyde loss than areas of arable land where other soil types are present. According to Cronshey et al. (1986), clay soils possess very low infiltration rates and are at a higher risk of runoff than other soil types. Prohibiting metaldehyde application on these higher risk soil types reduces the potential for metaldehyde to be lost from arable land in surface runoff and may account for the reduction in metaldehyde lost under this scenario.

Although there is a relatively large degree of uncertainty associated with model predictions, according to the mean prediction that was derived from the 500 model simulations performed for each scenario and the upper and lower bounds of the 95% uncertainty range, there is a clear reduction in metaldehyde losses under each scenario (Figure 6.1). The degree of uncertainty identified in Figure 6.1 highlights the importance of considering prediction uncertainty when evaluating the effectiveness of mitigation measures on pollutants. By assessing this uncertainty, it is possible to develop a better understanding of the potential effectiveness of mitigation measures, which also allows better-informed management and policy decisions to be made.

To assess the risk of exceeding the 0.1 $\mu g\ L^{-1}$ limit that applies to metaldehyde under each scenario and to identify which mitigation measures have the potential to mitigate the risk that this limit will be exceeded, percent exceedance curves which depict the proportion of time any metaldehyde concentration was exceeded at the Costessey Pits and Heigham WTW intakes during the period 1 January 2008 to 31 October 2015 were developed (Figure 6.2). The percent exceedance curves were developed from the mean prediction that was derived from the 500 model simulations conducted for each scenario. Under the baseline scenario (S0), metaldehyde concentrations exceeded the 0.1 $\mu g\ L^{-1}$ limit 15.3% and 15.0% of the time at the Costessey Pits and Heigham WTW intake sites, respectively, and is equivalent to 439 and 431 days during the period 1 January 2008 to 31 October 2015 (Table 6.2). Under this scenario, maximum metaldehyde concentrations of 3.92 $\mu g\ L^{-1}$ and 2.09 $\mu g\ L^{-1}$ were recorded at the Costessey Pits and Heigham WTW intakes, respectively.

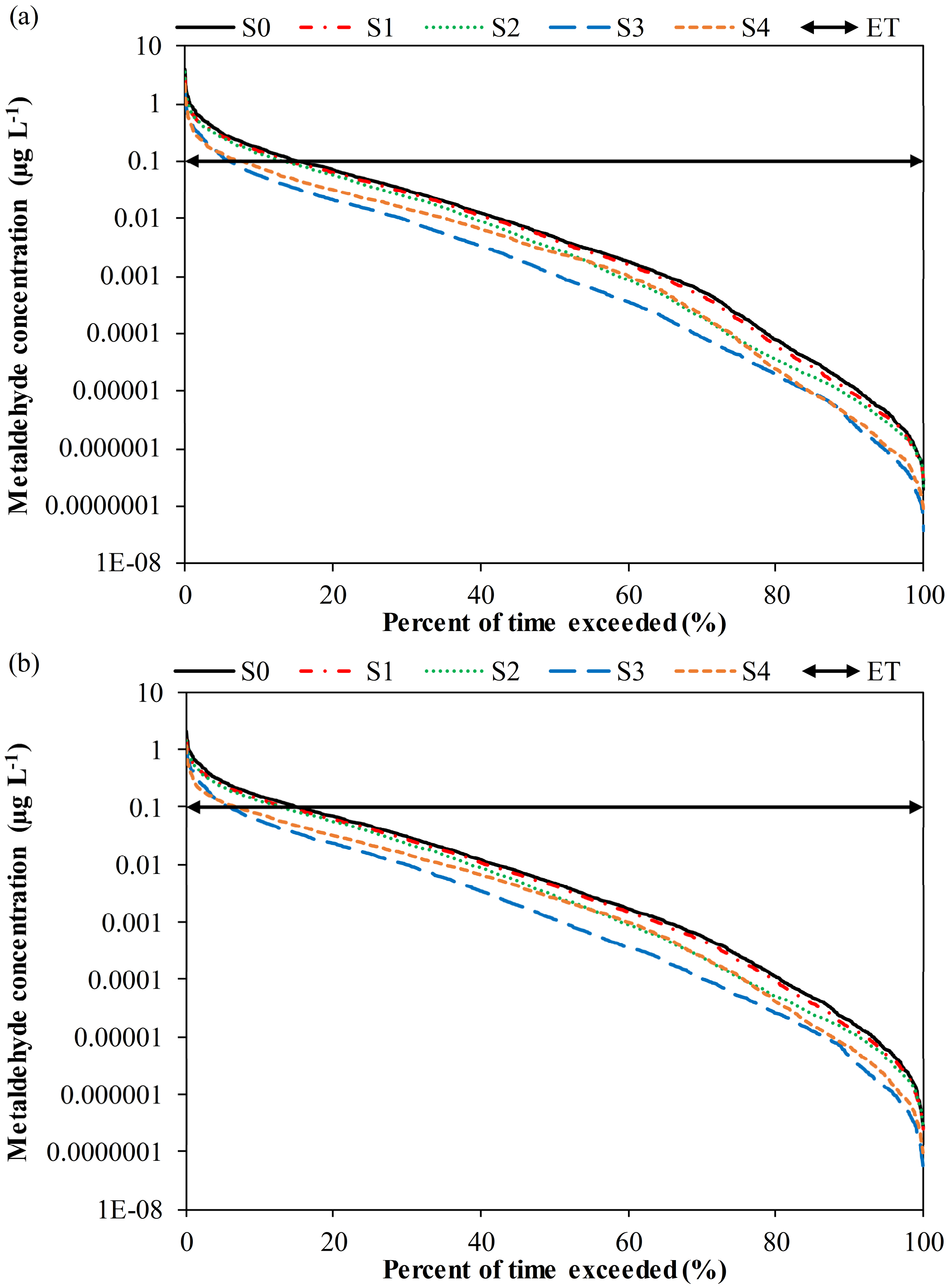

Figure 6.2: The Environmental Target (ET) for metaldehyde and percent exceedance curves for the intakes at (a) Costessey Pits and (b) Heigham WTW under each mitigation scenario during the period 1 January 2008 – 31 October 2015.

No scenario resulted in nil-exceedance of the 0.1 µg L^{-1} limit at the Costessey Pits and Heigham WTW intakes but scenario S3 was found to be the most effective mitigation option, in terms of its ability to reduce the number of days this limit was exceeded and the maximum concentration that occurred. Under scenario S3, the percent of time the 0.1 μg L^{-1} limit was exceeded was reduced to 6% and 5.9% at the Costessey Pits and Heigham WTW intake sites, respectively (Table 6.2). This result is equivalent to 172 and 170 days at each site during the period 1 January 2008 to 31 October 2015 and, when compared to the control scenario, represents a reduction of 60.8% and 60.5%. Under scenario S3, the maximum metaldehyde concentration recorded at the Costessey Pits and Heigham WTW intakes was reduced to 1.75 μg L^{-1} and 1.02 μg L^{-1}, respectively, equivalent to a reduction of 55.2% and 51.1% at each site. Scenario S3 prohibits metaldehyde application on areas of arable land where the slope exceeds 2%. Gentle slopes or flat land allows water to penetrate into the soil and increase runoff concentration times, thereby reducing the potential for metaldehyde appearance in quick overland flow (Bereswill et al., 2014).

Table 6.2: The percent of time metaldehyde concentrations exceeded 0.1 μg L^{-1} and the maximum metaldehyde concentration recorded at the Costessey Pits and Heigham WTW intake sites under each mitigation scenario during the period 1 January 2008 to 31 October 2015.

Intake Site	S0	S1	S2	S3	S4
Costessey Pits					
Percent exceedance (%)	15.3	14	13.2	6	7.7
Relative change in exceedance (%)	-	-8.9	-14.1	-60.8	-49.9
Maximum concentration (μg L^{-1})	3.92	2.74	3.53	1.75	2.15
Relative change in maximum concentration (%)	-	-30.1	-10	-55.2	-45.2
Heigham WTW					
Percent exceedance (%)	15	13.6	12.8	5.9	6.9
Relative change in exceedance (%)	-	-9.8	-15.1	-60.5	-54.2
Maximum concentration (μg L^{-1})	2.09	1.47	1.43	1.02	1.15
Relative change in maximum concentration (%)	-	-29.8	-31.5	-51.1	-44.9

Scenario S4 was found to be the second most effective mitigation option, in terms of its ability to reduce the number of days the 0.1 μg L^{-1} limit was exceeded and the maximum concentration that occurred, and prohibited the application of metaldehyde to arable land where clay soils are present. Under scenario S4, the percent of time the 0.1 μg L^{-1} limit was exceeded was reduced to 7.7% and 6.9% at the Costessey Pits and Heigham WTW intake sites, respectively. This result is equivalent to 220 and 197 days at each site and, when compared to the control scenario, represents a reduction of 49.9% and 54.2%. Under scenario S4, the maximum metaldehyde concentration recorded at the Costessey Pits and Heigham WTW intakes was reduced to 2.15 μg L^{-1} and 1.15 μg L^{-1}, respectively, equivalent to a reduction of 45.2% and 44.9% at each site. Metaldehyde is weakly adsorbed by clay soils (European Food Safety Authority, 2010), and clay soils are relatively less permeable and more susceptible to surface runoff than other soil types (Cronshey et al., 1986). Metaldehyde can therefore be quickly flushed into river courses in areas with clay soils.

According to model predictions, areas of arable land with a slope of greater than 2% and areas of arable land where clay soils are present are at a relatively higher risk of metaldehyde loss. The results of this study suggests that the most effective approach to reduce metaldehyde concentrations at raw water intake sites involves targeting areas that are at a relative high risk of metaldehyde loss. The susceptibility of an area to such losses can be identified from the characteristics of a site, including soil composition and topography.

Scenario S1 was the least effective mitigation option, in terms of reducing the number of days the 0.1 μg L^{-1} limit was exceeded, and involved the introduction of buffer strips of 6 m width to all areas of arable land. Nevertheless, it reduced the percent of time that the 0.1 μg L^{-1} limit was exceeded to 14% and 13.6% at the Costessey Pits and Heigham WTW intakes, respectively (Table 6.2). This result is equivalent to 400 and 388 days at each site and, when compared to the control scenario, represents a reduction of 8.9% and 9.8%. Under scenario S1, the maximum metaldehyde concentration recorded at the Costessey Pits and Heigham WTW intakes was reduced to 2.74 μg L^{-1} and 1.47 μg L^{-1}, respectively, equivalent to a reduction of 30.1% and 29.8% at each site. These are notable reductions and this practice is the only one considered for which farmers are able to receive financial payments to compensate the loss of land from arable production.

Limiting the maximum application rate of metaldehyde to 0.16 kg ha^{-1} on arable land under scenario S2 reduced the percent of time that the 0.1 μg L^{-1} limit was exceeded to 13.2% and 12.8% at the Costessey Pits and Heigham WTW intakes, respectively (Table 6.2). This result is equivalent to 377 and 365 days at each site and, when compared to the control scenario, represents a reduction of 14.1% and 15.1%. Under scenario S2, the maximum metaldehyde concentration recorded at the Costessey Pits and Heigham WTW intakes was reduced to 3.53 μg L^{-1} and 1.43 μg L^{-1}, respectively, equivalent to a reduction of 10% and 31.5% at each site. It is important to note an apparent downward trend in the amount of metaldehyde that has been applied to each of the four crop types considered within this investigation over time in the UK (Table 3.2). This trend suggests that either the need for metaldehyde use has reduced in recent years, or that farmers have recognised the risks of metaldehyde loss and the potential regulatory consequences that may result, such as a ban on metaldehyde use, and are self-regulating, reducing the amount they apply to arable land.

6.3 Chapter Summary

In this chapter, the agricultural mitigation measures applied within the SWAT model of the Wensum catchment were described and the effects of those measures on metaldehyde load and concentration at the Costessey Pits and Heigham WTW intake sites were presented and discussed. Introducing buffer strips of 6 m width to arable land reduced metaldehyde losses by 20% at the Costessey Pits intake and by 19.4% at the Heigham WTW intake. These are notable reductions in metaldehyde loss and, out of those considered, this is the only measure for which farmers are able to receive financial compensation. Limiting metaldehyde application rates to 0.16 kg ha^{-1} reduced metaldehyde losses by 26.1% and 25.9% at the Costessey Pits and Heigham WTW intake sites, respectively. Although this measure is effective at reducing metaldehyde loss, care must be taken to avoid the risk that metaldehyde application rates are reduced to a level where they are no longer sufficient to effectively control the impacts of molluscs on crops. At the Costessey Pits and Heigham WTW intakes respectively, prohibiting metaldehyde application on areas of arable land where the slope exceeds 2% reduced metaldehyde losses by 57.1% and 54.4%, whilst prohibiting metaldehyde application on areas of arable land where clay soils are present reduced metaldehyde losses by 55.1% and 55.6%. Prohibiting metaldehyde application on areas of arable land where the slope exceeds 2% was found to be the most effective measure at reducing peak metaldehyde concentrations and the percent of time that the 0.1 µg L^{-1} limit was exceeded. Model predictions suggested that areas of arable land where clay soils are present and areas of arable land with a slope of greater than 2% are at a relatively higher risk of metaldehyde loss than other zones. The results also suggested that targeting these areas may be an effective approach to reduce metaldehyde losses from arable land and concentrations at raw water intake sites. The degree of uncertainty associated with model predictions highlighted the importance of conducting an uncertainty assessment when evaluating the impacts of a mitigation measure on diffuse metaldehyde pollution to develop a better understanding of the potential effectiveness of mitigation measures. Although no mitigation measure resulted in nil-exceedance at the intake sites of the 0.1 μg L^{-1} limit that applies to metaldehyde in drinking water, results showed that catchment mitigation measures can reduce diffuse metaldehyde pollution and the proportion of time that this limit is exceeded. The results also suggest that a catchment management based approach can reduce the need for raw water treatment for metaldehyde and, therefore, the total cost associated with such treatment.

7 Summary and Conclusions

7.1 Research Developments

The stated aim of this thesis as defined in Chapter 1 was to model the impacts of agricultural mitigation measures on surface water quality and assess the uncertainties of catchment-scale water quality model predictions within the River Wensum catchment. Due to threats to water quality, the costs of water treatment and the recalcitrance of some pollutants to traditional water treatment techniques, there has been increased focus on the potential to mitigate agricultural diffuse water pollution through catchment management. Water quality models have the potential to be applied as DSTs to identify mitigation measures that can be introduced to reduce agricultural diffuse water pollution and improve water quality. One advantage of such models is that they can provide cost-effective and timely evidence of the impacts of mitigation measures at a scale that is often unfeasible for in-field investigations but there remain gaps in knowledge and major shortcomings in the approaches used which provided the motivation for the work contained herein. The main shortcomings in the approaches used and developments made in this thesis to address them are discussed below.

7.1.1 The Temporal Resolution at Which Pollutants and Mitigation Measures Impacts Are Modelled

Deficiency: Catchment-scale water quality models are infrequently applied at a daily time-step, often because there is insufficient data to apply models at such a high temporal resolution, but this creates a deficit in knowledge. Major pollutant losses from agricultural land are often event-based and occur over short periods of time (i.e. hours to days). If models are applied at longer time-steps (i.e. weekly, monthly or yearly), the details of such event-based responses can be lost. For example, nitrate, total phosphorus and metaldehyde concentrations may exceed water quality standards when simulated at a daily resolution but these occurrences of water quality non-compliance may be lost due to the effect of averaging when simulating longer time-steps. This is important because water quality standards are established to protect aquatic ecosystems and human health and to ensure that water remains fit for use in industry and for leisure purposes. If events of water quality exceedance are not flagged, damage can occur and it might not be recognised that action needs to be taken to address the issue. To sufficiently and confidently determine the effectiveness of mitigation measures on water quality, it is also important to understand their impacts on water quality at a daily time-step for this very reason. Understanding how catchments and pollutants respond to storm events over such short time-scales can therefore yield information that may be useful to the catchment manager who seeks to mitigate pollutant losses. Where raw water is abstracted from water bodies to supply drinking water it is also advantageous to know how quickly a catchment system responds to a storm event and how soon after such events pollutants are observed in water. For example, in the case of the river water abstraction sites within the Wensum catchment it would be useful for water resource managers to know how soon after storm events a metaldehyde response occurs at the intake sites, or when problematic periods occur throughout the year when metaldehyde concentrations regularly exceed drinking water quality standards so that they know when to switch-off the water treatment work intakes. This information can only really be supplied in a useful form if the response is understood at least at a daily temporal resolution.

Development: To address these shortcomings and to provide this information, SWAT models of the Wensum and Blackwater sub-catchment were developed and high-temporal resolution datasets were used to perform model calibration and validation at a daily time-step for discharge, nitrate, total phosphorus and metaldehyde. The models developed were applied to identify the at-risk periods within the catchment for metaldehyde and to identify the impacts of agricultural mitigation measures on pollutant losses and water quality at a daily resolution. As a result, we now better understand the dynamics of pollutant responses within the River Wensum catchment, how frequently water quality standards are exceeded, the risk of non-compliance and how effective potential agricultural mitigation measures may be at mitigating pollutant losses. Such a development improves the reliability and effectiveness of water quality models as DSTs to aid decision making and catchment management.

7.1.2 Modelling the Impacts of Mitigation Measures on Multiple Pollutants

Deficiency: Within studies which seek to examine the impacts of mitigation measures on water quality, pollutants are often considered in isolation. For example, some studies may evaluate the impacts of mitigation measures on nitrate alone. This may be justified in the sense that data is only available for nitrate or that the researchers are only interested in nitrate as a pollutant and not others but this doesn’t match with the reality of the impacts of mitigation measures because, when they are introduced, they may have impacts on multiple pollutants within a catchment system. It is therefore important to consider the impacts of mitigation measures on multiple pollutants. For example, introducing a mitigation measure that reduces nitrate losses might in-turn exacerbate losses of sediment and total phosphorus but how would the catchment modeller or catchment manager be aware of this risk unless multiple pollutants are considered within assessments? This phenomenon is known as pollution swapping and is an area of research that has received relatively little attention.

Development: To address this deficiency and to mitigate the risk of pollution swapping, this thesis modelled the impacts of agricultural mitigation measures on both nitrate and total phosphorus within the River Wensum catchment. The impacts of buffer strips on metaldehyde were also considered. Results highlighted the need to consider the impacts of mitigation measures on multiple pollutants to avoid the risk of pollution swapping. For example, although removing tile drains from the Blackwater sub-catchment reduced nitrate losses, this measure also exacerbated losses of total phosphorus. As a result of this research, we now have a better understanding of the impacts of a number of measures on multiple pollutants including nitrogen and phosphorus, reducing the risk that unforeseen increased losses of other pollutants may occur as a result of the introduction of a measure.

7.1.3 Uncertainty in Model Predictions

Deficiency: Models are often applied in a deterministic manner during calibration, validation and when evaluating the impacts of mitigation measures on pollutant losses and water quality. This approach rejects the concept of equifinality which posits that multiple parameter sets may provide acceptable model predictions in favour of searching for an optimum parameter set and does not treat parameter values as uncertain (Beven, 1993). It assumes that the optimum parameter set obtained from calibration is the ‘best’ representation of a system and that it therefore yields the best model performance and predictions and applies this single parameter set to assess the impacts of mitigation measures on pollutant losses and water quality. This deterministic approach gives no consideration to the uncertainty of model parameters and predictions. Although model and prediction uncertainty can be quite large, this uncertainty is rarely considered or assessed by studies.

Development: To address this deficiency, SWAT was applied with a probabilistic approach by considering parameter values to be uncertain and allowing them to vary within a calibrated range. This allowed the model to account for uncertainties in parameter values and to provide an estimate of the uncertainties of the impacts of agricultural mitigation measures on pollutant loads in model predictions. By adopting this method, the results obtained captured the potential uncertainty of model predictions and allowed an estimate of this uncertainty to be provided. Results highlighted the importance of considering prediction uncertainty when evaluating the impacts of mitigation measures on pollutants. Quantifying and capturing this uncertainty allows a better understanding of the potential effectiveness of mitigation measures to be developed. This approach allows better-informed management and policy decisions to be made and has allowed the model to become a more effective and reliable decision support tool to assist catchment management and policy development, and it is an approach that should be recommended and adopted. As a result of this approach, we can have more confidence in the model predictions that have been developed and the results that were obtained by this study compared to if a deterministic approach had been used because the latter fails to capture a range of possibilities.

7.1.4 Management of the River Wensum Catchment and Scaling Up

Deficiency: Due to the impacts of agriculture on water quality and the recalcitrance of some agricultural pollutants to traditional water treatment techniques, there exists a need to identify mitigation measures that have the potential to reduce agricultural diffuse water pollution at the point of origin, to improve water quality and to ensure that the necessary water quality standards can be met. Metaldehyde is not effectively removed from water by traditional treatment techniques but there is a lack of information on the effectiveness of measures to mitigate diffuse metaldehyde pollution. The need for a study to investigate potential solutions was therefore noted. Reconciling the need to provide safe water whilst also ending hunger as the world human population grows also requires the development of improved agricultural practices to minimise the impacts of agriculture on water quality. Due to the cultural and ecological importance of the River Wensum and the need to preserve it that arises from this importance, there also exists a specific need to identify effective management strategies to mitigate or remove the pressure that it currently faces from agricultural diffuse water pollution.

Development: The application of SWAT within this study has shown that by managing agricultural practices within a catchment, it is possible to reduce agricultural diffuse water pollution and improve water quality. By mitigating the potential for agricultural pollutants to enter watercourses at their point of origin (i.e. in-field), this study has also developed effective and practical solutions to the problem of agricultural diffuse water pollution and the problems it creates. The solutions developed by this study also have the potential to form a management strategy that can be implemented within the River Wensum catchment to mitigate agricultural diffuse water pollution, to minimise the pressure that it currently exerts on the river system and to help preserve this ecological and culturally important river. Because SWAT is a semi-physically based model, as opposed to an empirical or conceptual model, the findings of this study are also transferable to other similar catchments and can also assist in their management to reduce agricultural diffuse water pollution further increasing the scope and impact of the work conducted herein.

7.2 Research Summary and Findings

Water quality models are cost-effective DSTs which can be applied to assess the quantitative impacts of a variety of mitigation measures 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 study to investigate the long-term impacts of agricultural mitigation measures on surface water quality in a lowland arable catchment in the UK. This study has improved upon earlier work by adopting a more sophisticated approach to model calibration and validation and scenario analysis and applied SWAT within the River Wensum catchment at a daily time-step to: (i) identify the frequency and duration that metaldehyde concentrations exceed the 0.1 $\mu g\ L^{-1}$ water quality standard at public water supply intake sites; (ii) provide an assessment of the at-risk periods for metaldehyde within the catchment; (iii) identify the impacts of mitigation measures on diffuse nitrate, total phosphorus and metaldehyde pollution from agriculture and; (iv) identify mitigation measures that have the potential to be introduced within catchments to reduce agricultural diffuse water pollution and improve water quality.

Scenario analysis found that introducing buffer strips of 6 m width to arable land reduced metaldehyde loads by 20% at the Costessey Pits intake and by 19.4% at the Heigham WTW intake. These reductions were attributed to a reduction in the amount of metaldehyde lost in surface runoff. Limiting metaldehyde application rates to a maximum of 0.16 kg ha^{-1} on all areas of arable land reduced metaldehyde loads by 26.1% and 25.9% at the Costessey Pits and Heigham WTW intake sites, respectively. Although results suggest that reducing metaldehyde application rates can be an effective measure to reduce metaldehyde losses, it is important to remember that application rates can only realistically be reduced to a level where metaldehyde is still effective at controlling the impacts of slugs and snails.

At the Costessey Pits and Heigham WTW intake sites, respectively, prohibiting metaldehyde application on areas of arable land where the slope exceeds 2% reduced metaldehyde loads by 57.1% and 54.4%, whilst prohibiting metaldehyde application on areas of arable land where clay soils are present reduced metaldehyde loads by 55.1% and 55.6%. Results suggested that these areas of arable land are at a relatively higher risk of metaldehyde loss than other zones and that targeting these areas may be an effective approach for mitigating metaldehyde loss. The development of a conceptual catchment model allowed this study to identify and target areas that are considered to be at a relatively high risk of metaldehyde loss and it is recommended that such a conceptual understanding is developed for each location where metaldehyde poses a problem.

It was found that the catchment was at an increased risk of exceeding the 0.1 µg L^{-1} limit for metaldehyde at the Costessey Pits and Heigham WTW intake sites each year during the period from September to January. Prohibiting metaldehyde application on areas of arable land where the slope exceeds 2% was the measure most effective at reducing peak metaldehyde concentrations and the percent of time the 0.1 µg L^{-1} limit was exceeded. Although no mitigation measure resulted in nil-exceedance of the 0.1 µg L^{-1} limit for metaldehyde at the public water supply intake sites, it was found that farm-based measures can reduce diffuse metaldehyde pollution and reduce the risk of water quality non-compliance. It was also found that a catchment management based approach to diffuse pollution control for metaldehyde does have the potential to reduce the need for raw water treatment and, as a result, also has the potential to reduce the associated costs of treatment.

Scenario analysis found that introducing a red clover cover crop to the crop rotation scheme applied within the SWAT model of the Blackwater sub-catchment reduced nitrate losses by 19.6% and total phosphorus losses by 1.6% over the long term. This finding suggests that a red clover 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 possibility 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 were found to be the most effective mitigation measures that could be adopted 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 production, represents the single most effective mitigation measure 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 potential effectiveness of mitigation measures at reducing agricultural diffuse water pollution.

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

The alternative tillage scenarios applied within the SWAT model of the Blackwater sub-catchment 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 measure 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 uncertainties of the predicted impacts of mitigation measures on diffuse agricultural nitrate, total phosphorus and metaldehyde pollution were also quantified. Results indicate that there can be a relatively large degree of uncertainty associated with model predictions and it is recommended that future impact assessments conduct a robust evaluation of prediction uncertainty to develop a better understanding of the potential impacts of mitigation measures and to improve confidence in model predictions.

The availability of high-frequency water quality data ensures that models can be robustly calibrated and tested. By modelling water quality at a daily time-step, considering the impacts of mitigation measures on multiple pollutants, as well as accounting for the uncertainties in model parameters and predictions it is possible to impart a higher degree of confidence to model predictions and, therefore, in the predicted impacts of mitigation measures on water quality. This study has shown that high-frequency water quality datasets can be applied within SWAT, as an advanced example of the many water quality models available, to quantify the long-term impacts of agricultural mitigation measures on water quality at a daily resolution to assist the creation of more effective and reliable DSTs, leading to the development of appropriate diffuse water pollution mitigation plans.

7.3 Further Research

Whilst the improvements to the modelling of catchment mitigation measures on water quality presented in this thesis and the new knowledge gained as a result represent considerable developments over earlier work, there remains room to further enhance and advance catchment modelling research. Beneficial areas of further research include:

Application of a Multiple-Model Ensemble (MME) modelling approach: Future studies could adopt a MME approach to assess the impacts of changes in management practices or other environmental changes on water quality. This approach would involve combining single model predictions into multiple-model ensembles to identify the effects of model structure on predictions and could be applied to evaluate the performance of the multiple-model ensembles relative to single model predictions. MMEs have been found to improve on the overall performance of individual models in simulating hydrology and water quality (Viney et al., 2009; Exbrayat et al., 2010; Exbrayat et al., 2011). This technique would improve understanding of the uncertainty associated with single-model and multiple-model predictions and would improve confidence in the predicted impacts of a change in the environment (e.g. changes in land use, management practices or climate). This is a relatively novel approach to water quality modelling but has received some interest as indicated by the examples of Bormann et al. (2009), Breuer et al. (2009), Huisman et al. (2009), Viney et al. (2009), Exbrayat et al. (2010) and Exbrayat et al. (2011).

Climate change impact assessment: The application of meteorological datasets from the latest climate change scenario projections, such as those from the EURO-CORDEX project (Jacob et al., 2014; EURO-CORDEX, 2016), within SWAT to assess the impacts of predicted future changes in climate on water quality. An ensemble of climate change scenarios should be considered to account for the potential uncertainty in future climate projections. This assessment would allow an estimate to be made of the potential impacts of climate change on water quality. The model developed could also be applied to examine the effectiveness of catchment measures to mitigate the predicted impacts on water quality. This new knowledge could be applied to develop an effective management strategy to minimise the impacts of future climate change on water quality within catchments.

Mitigation measure cost-benefit analysis: A cost-benefit analysis could be conducted to assess the costs or savings that each agricultural mitigation measure would incur on land managers and to assess the relative cost-effectiveness of each measure at reducing diffuse water pollution. This is similar to the approach adopted within the spreadsheet-based FARMSCOPER model (Zhang et al., 2012; ADAS, 2016), and could be conducted to ensure that the optimum combination of mitigation measures is adopted to provide the greatest net-benefit to water quality whilst minimising costs. Incorporating such an analysis into mitigation assessments and any catchment management plans that are developed as a result could improve the viability of future plans.

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9 APPENDICES

Appendix 1 Published Articles

Modelling the Impacts of Agricultural Management Practices on River Water Quality in Eastern England

Reference

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Title Page

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Highlights

- Water quality models can help the development of diffuse pollution mitigation plans.
- Multiple pollutants must be considered when assessing mitigation option impacts.
- Cover crops can reduce agricultural diffuse water pollution over the long term.
- Reduced tillage strategies can potentially increase nutrient losses.
- Prediction uncertainty needs to be considered during impact assessment.

Abstract

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.

Keywords
Catchment management; Catchment modelling; Diffuse water pollution; Mitigation scenarios; SWAT; Water quality.

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 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 (Figure 9.1), 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-minute 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.

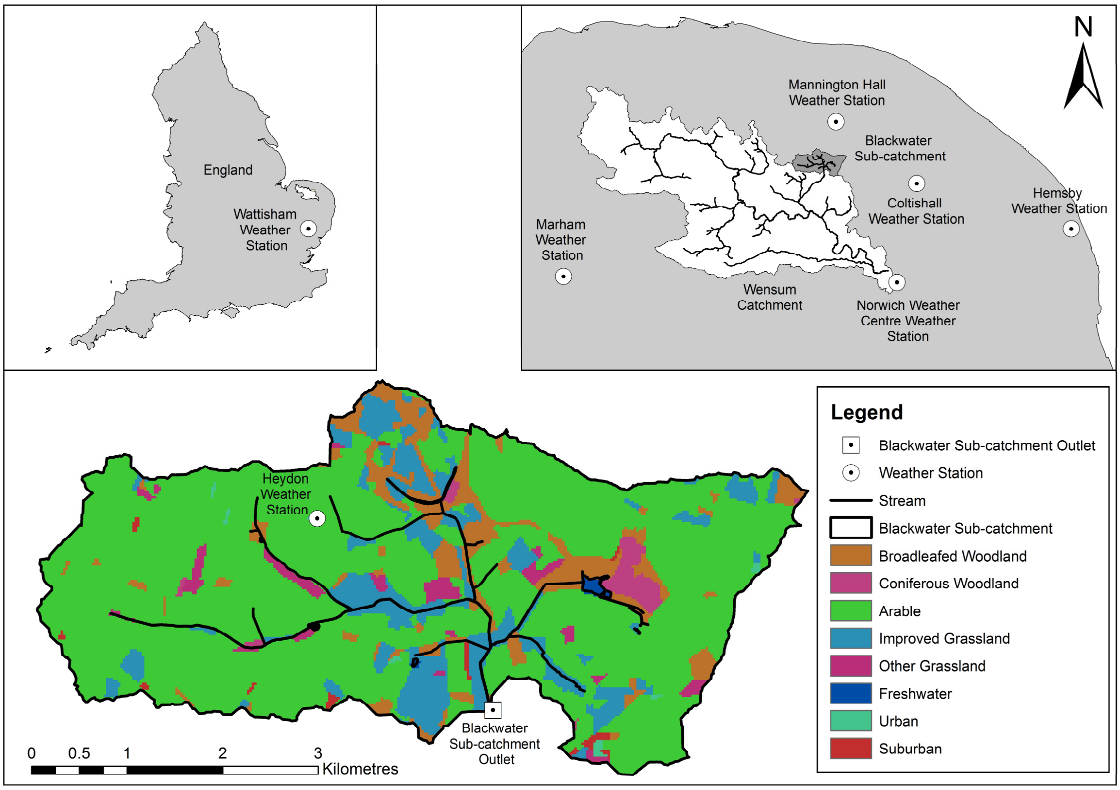

Figure 9.1: A map of the location and land cover of the Blackwater sub-catchment in relation to the River Wensum catchment within England. The locations of the weather stations used in this investigation and the outlet of the sub-catchment are also shown. Based upon LCM2007 © NERC (CEH) 2011. Contains Ordnance Survey data © Crown Copyright 2007. © third party licensors.

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 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 (Figure 9.1). 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 28-70 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-minute 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 (Figure 9.2) 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 9.1). 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).

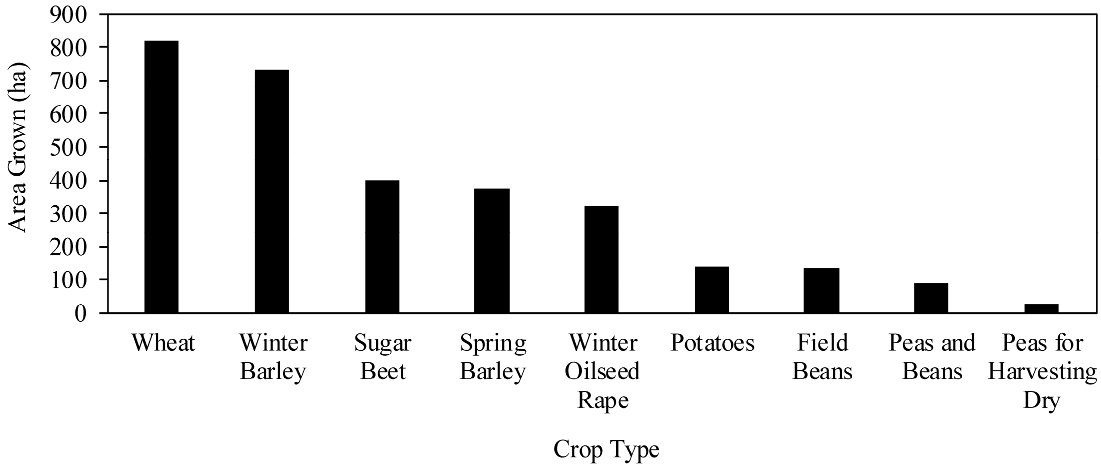

Figure 9.2: The area of each crop type grown within the Blackwater sub-catchment according to the 2010 Agricultural Census conducted by the Department for Environment, Food and Rural Affairs (Defra, 2016; EDINA, 2014).

Table 9.1: 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

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 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) (Figure 9.1). 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-minute intervals at the outlet of the Blackwater sub-catchment since April 2011 (Figure 9.1). 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 (Intermap 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 9.2). 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.

Table 9.2: 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 - 0.2[a]	-0.035 - 0.087 [a]
CN2 AGRL	Runoff curve number for agricultural land	-0.2 - 0.2[a]	-0.15 - -0.05 [a]
CN2 FRSD	Runoff curve number for deciduous forest	-0.2 - 0.2[a]	-0.13 - 0.093 [a]
CN2 PAST	Runoff curve number for pasture land	-0.2 - 0.2[a]	-0.23 - -0.082 [a]
SOL_AWC	Available water capacity of soil layer (mm H_2O/mm soil)	-0.2 - 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 - 0.2[a]	-0.041 - 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 - 0.2[a]	-0.25 - -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.

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.

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

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 -∞ 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.

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

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).

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

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 9.3).

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, and pulverises soils into a finer material, removing air pockets and preparing the seedbed for cultivation (see Table 9.4). 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.

Table 9.3: 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

Table 9.4: 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

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 9.4. 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 1986-1989. The period from 1990-2009 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 9.2 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 9.2.

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 Figure 9.3 and Figure 9.4. 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 9.5). 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 9.5). 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.

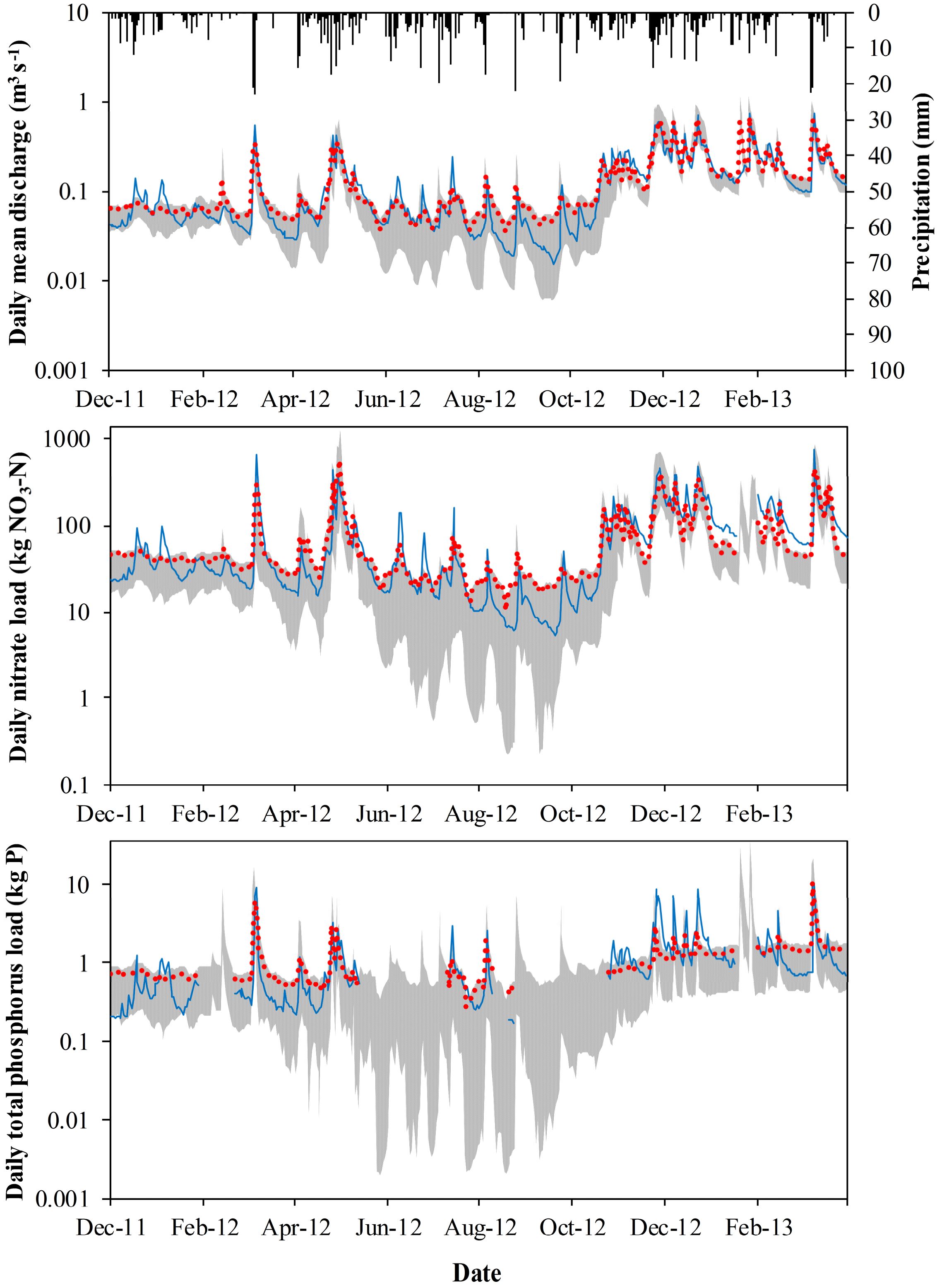

Figure 9.3: Observed (solid line) and the best simulated (dotted line) daily mean discharge, nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment during the calibration time period (1 December 2011 – 31 March 2013). The 95% confidence interval is represented by the hatched area and the daily rainfall amount recorded at Heydon weather station is plotted in the top panel for reference.

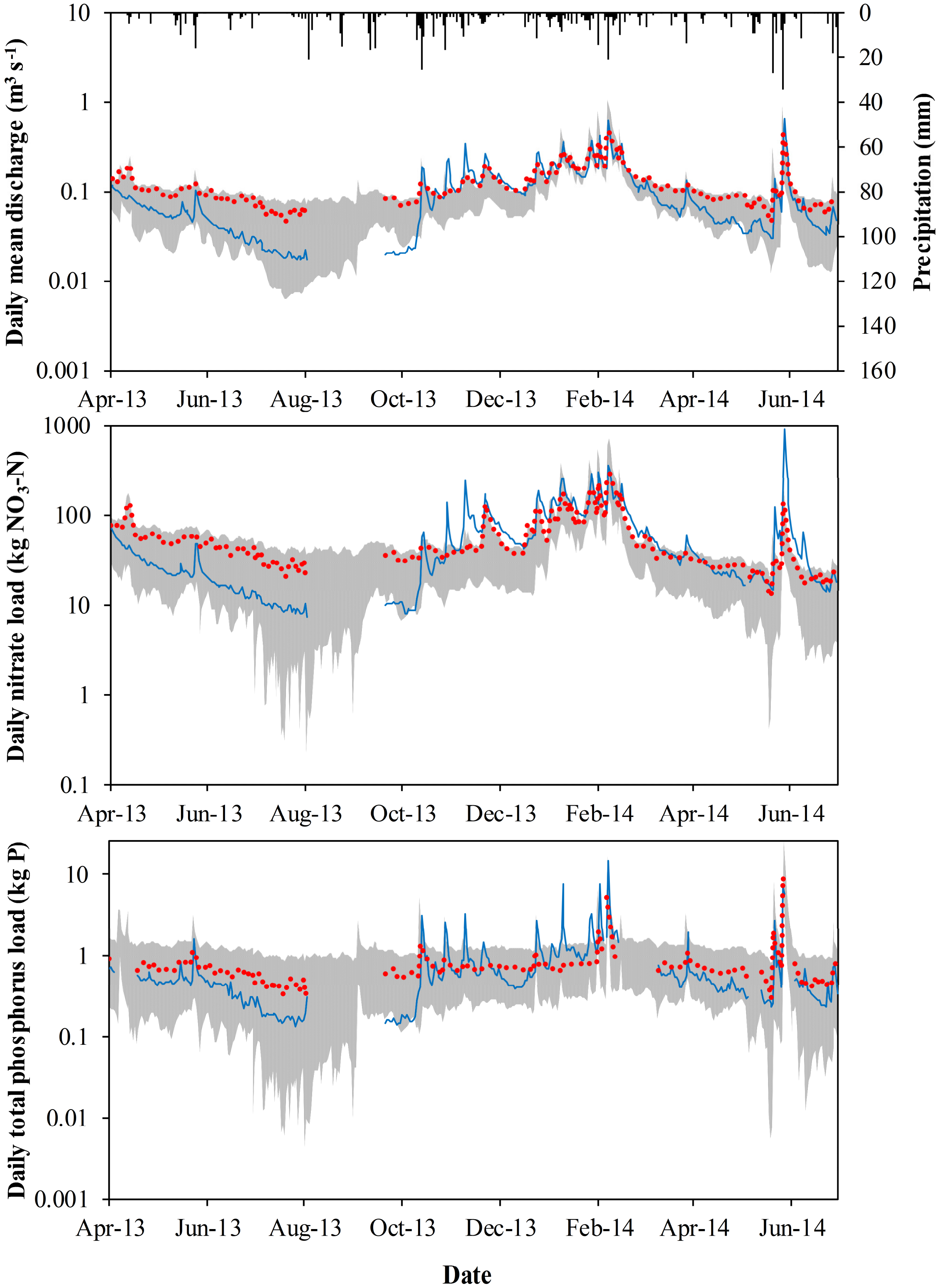

Figure 9.4: Observed (solid line) and the best simulated (dotted line) daily mean discharge, nitrate and total phosphorus loads recorded at the outlet of the Blackwater sub-catchment during the validation time period (1 April 2013 – 30 June 2014). The 95% confidence interval is represented by the hatched area and the daily rainfall amount recorded at Heydon weather station is plotted in the top panel for reference.

Table 9.5: 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

3.1.2 Nitrate simulation

The model performance in simulating daily nitrate loads during the calibration and validation time periods is shown in Figure 9.3 and Figure 9.4, 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 9.5). 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 9.5). When evaluated at a daily time-step however, there is a notable decline in model performance during the validation period.

A visual inspection of Figure 9.4 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 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 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 9.5). 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 Figure 9.3 and Figure 9.4, 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 (Figure 9.5). 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.

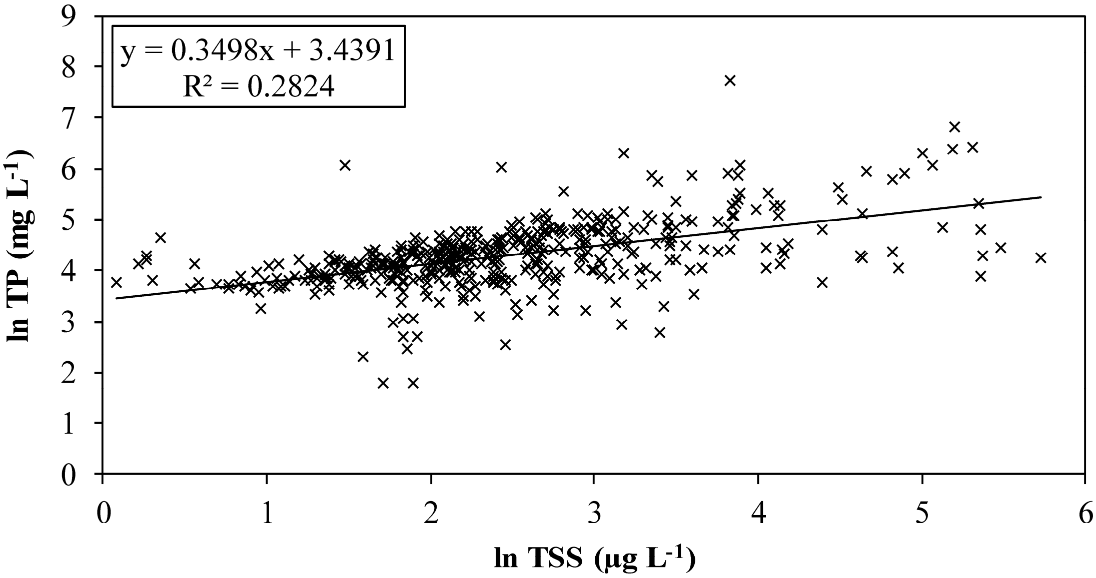

Figure 9.5: Log-log regression model of the relationship between the concentration of total suspended solids (TSS) and the concentration of total phosphorus (TP) at the outlet of the Blackwater sub-catchment according to stream water samples collected during 1 October 2010 – 31 March 2015.

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 9.5). 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 9.5). When evaluated at a monthly time-step, the model performance in simulating total phosphorus loads does achieve the satisfactory performance criteria (Table 9.5). 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) (Figure 9.6a). 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) (Figure 9.6b). 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 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 (Figure 9.6). 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.

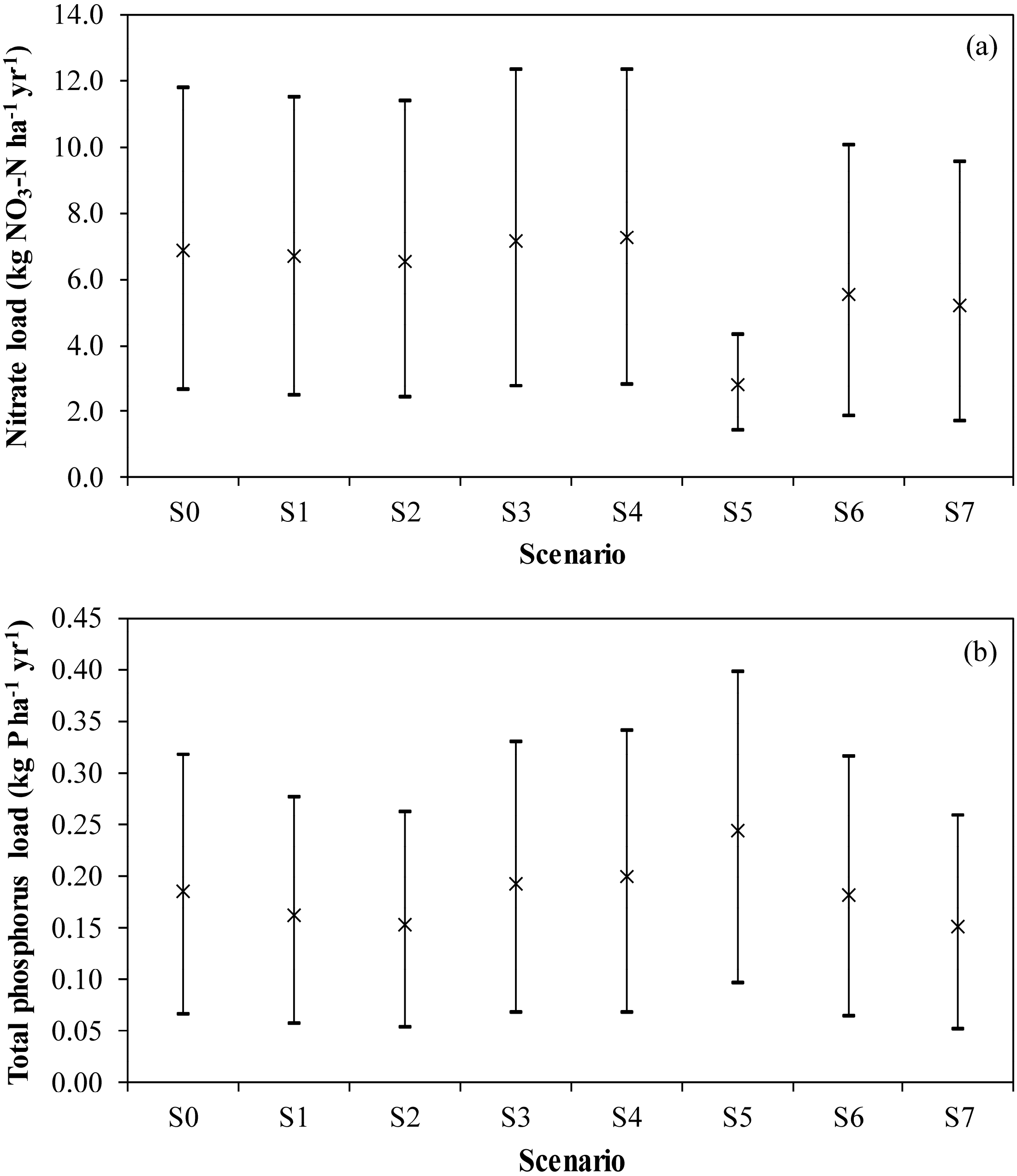

Figure 9.6: (a) The mean annual nitrate load and (b) the mean annual total phosphorus load exported from the Blackwater sub-catchment during the period 1990-2009 under each mitigation scenario. The upper and lower bounds of the 95% prediction uncertainty range are also shown at the end of each line. The '×' represents the mean value of each scenario.

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) (Figure 9.6). 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) (Figure 9.6). 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 (Figure 9.6). 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 (Figure 9.6), 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 1990-2009 were developed for each scenario (Figure 9.7a and Figure 9.7b). 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 (Figure 9.7a). 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 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) (Figure 9.7a). 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 (Figure 9.7b), 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 (Figure

9.7b). 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% (Figure 9.7b). 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) (Figure 9.7b). 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.

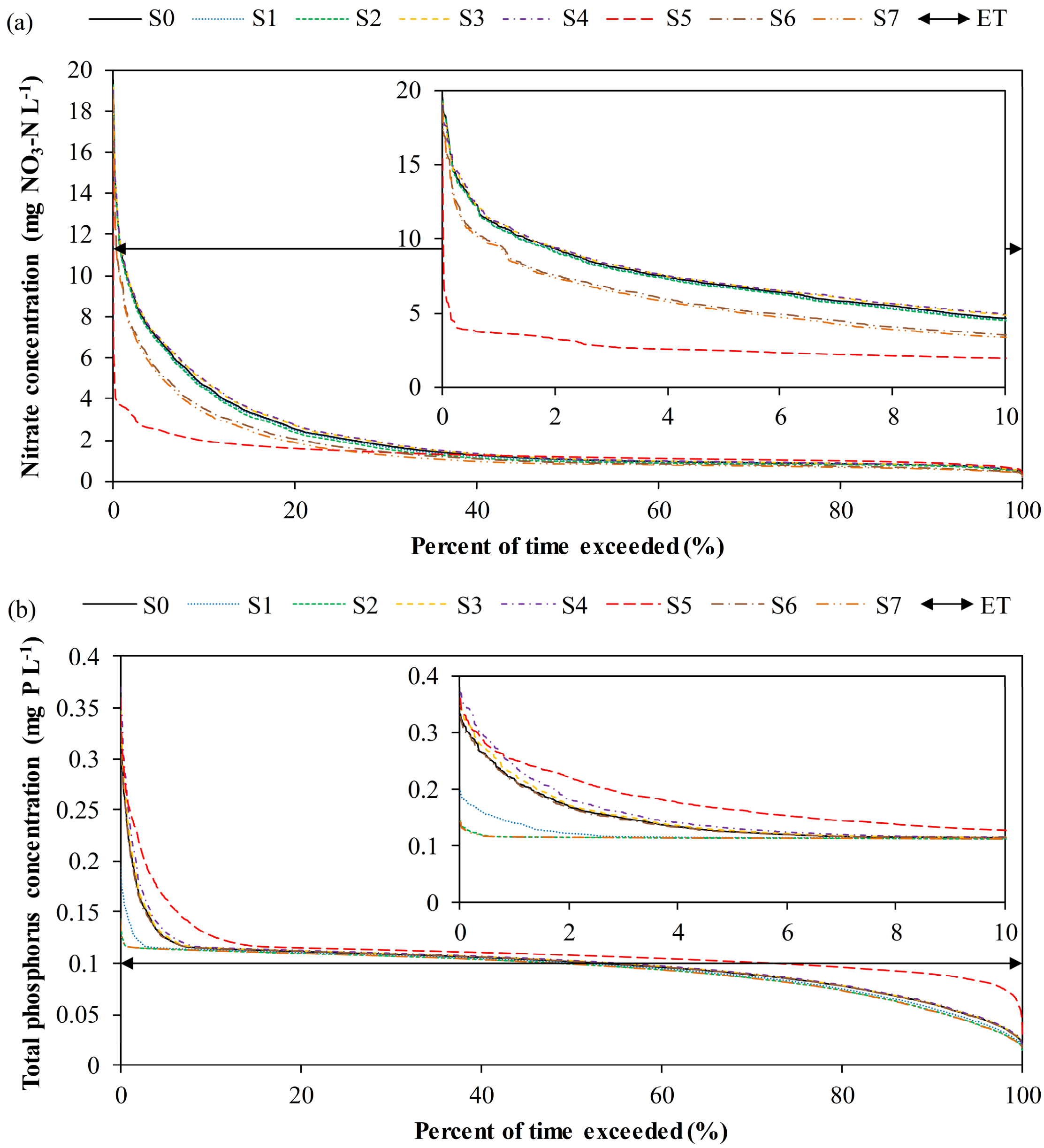

Figure 9.7: Environmental Targets (ET) and percent exceedance curves for (a) nitrate concentration and (b) total phosphorus concentration as simulated at the outlet of the Blackwater sub-catchment during the period 1990-2009 under each mitigation scenario.

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 (Figure 9.6). 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 (Figure 9.7a), 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 (Figure 9.7b). 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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