# Evaluation of the impact of Catchment Sensitive Farming in reducing pesticide contaminants in English rivers


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# 1 ABSTRACT

This research aimed to evaluate the effectiveness of Catchment Sensitive Farming (CSF) in mitigating pesticide pollution in two English river catchments (Ancholme and Wensum) using the Soil and Water Assessment Tool (SWAT) model. SWAT was used to simulate pesticide transport from agricultural fields to rivers, considering factors like climate, soil properties, and various management practices for five commonly used herbicides: 2,4-D, Flufenacet, Bentazone, Mecoprop, and Propyzamide. The model was calibrated and validated for flow, and pesticide concentrations were simulated using regional pesticide usage data. Comparisons were made between simulated and observed pesticide levels to assess the impact of CSF. The study also investigated the potential impacts of different mitigation strategies (such as conservation tillage, no-till, strip cropping and contour cropping) on pesticide levels in rivers. While SWAT showed promise in predicting the timing of contamination events, significant discrepancies were observed between simulated and observed pesticide concentrations, highlighting the limitations of this current model implementation for accurately capturing the complex processes of pesticide fate in agricultural landscapes. Future research should focus on refining model parameters, incorporating higher-resolution spatial data for pesticide application, and exploring other mitigation strategies such as vegetative filter strips. Despite these limitations, the study provides valuable insights into the potential of SWAT for assessing the impacts of agricultural best management practices on pesticide pollution and informing future environmental management strategies.

## Declaration

I declare that this thesis is a presentation of original work and I am the sole author, under the guidance and supervision of Prof Colin Brown and Dr Martha Villamizar. Data handling and building the model was conducted in collaboration with Dr Martha Villamizar. This work has not previously been presented for a degree or other qualification at this university or elsewhere. All sources are acknowledged as references.

## Word count

10, 147 words

# 2 INTRODUCTION

## 2.1 PESTICIDES

Pest infestation is estimated to cause almost half of the losses seen in annual food production (Sharma et al., 2019) therefore pest management using a range of pesticides is required to protect crops and increase yields (Siviter et al., 2023). Synthetic pesticides have been used worldwide since the 1950s (Zhang et al., 2015; Wang et al., 2019) and their use continues to ensure food security (Zhang et al., 2015). However, continued reliance on pesticides has led to unintended negative impacts on the environment and to also pose a threat to human health (Wang et al., 2019; Sharma et al., 2019). Despite these concerns, the global pesticide market has continued to grow rapidly (Syafrudin et al., 2021).The UK has previously approved around 350 active ingredients for agricultural use in the UK (Stuart et al., 2012). The use of pesticides has increased in recent decades including in the UK with a 24% increase in the area sprayed between 2000 and 2016 (Poyntz-Wright et al., 2023). More recently between 2010 and 2018 the weight of pesticides applied continued to rise until a drop in 2020, in part due to unusual weather and cropping patterns, before use had increased back to 2010 levels in 2022 (GOV.UK, 2024). This has led to pesticides frequently being detected in groundwater at trace concentrations in the UK for a long period of time with some posing significant environmental threats (Stuart et al., 2012). Widespread pesticide contamination in UK freshwater has contributed to large losses in biodiversity, particularly before stricter water quality regulations began after the 1990s (Poyntz-Wright et al., 2023). This species loss has promoted restrictions on chemicals and the use of safer substitutes. However, even some of these substitutes have also been shown to impact non-target species (Poyntz-Wright et al., 2023; Stuart et al., 2012). This highlights the need to monitor and manage pesticide use.

There are examples of pesticides that have been banned due to their environmental concerns for water pollution. One example is Isoproturon (IPU) a selective herbicide which was previously one of the most used herbicides in Europe before its ban in 2016. Due to its mobility in soil it become one of the most frequently detected pesticides ground and surface waters above the European Union drinking water limit (Mamy et al., 2020; Hussain, 2010; Sorensen et al., 2003). There were also impacts from both IPU and its metabolites on aquatic invertebrates and its use and distribution has since been banned (Pérès et al., 1996). Metaldehyde was a commonly used slug bait in UK farming, that due to its mobility also led to contamination in rivers above limits. Regulatory assessments did not foresee its persistence in the environment, and it was not originally seen as a pollutant of concern (Keighley et al., 2021). Conventional water treatments struggle to remove metaldehyde, with the only effective removal methods being commercially unviable (Salvestrini et al., 2016). In the environment it posed risks to non-target aquatic life and was identified as a toxic pollutant (Hale et al., 2020). In 2018 metaldehyde was banned due to risks not only to aquatic life but for risks to mammals and birds (GOV.UK, 2018).The movement of Pesticides off-site beyond the area of application due to offsite movements of pesticides, in particular to surface and groundwater systems from the field through the soil continues to be of concern (Wang et al., 2019). Resulting water quality deterioration which can lead to both acute and chronic effects on aquatic species from either direct contact at the point of application or indirect exposure through residues in the water and food (Wang et al., 2019). The extent to which pesticides move from the point of application in soil can depend on the properties of the pesticide, cropping practices, irrigation strategies and weather (Agnihotri et al., 1994). The high persistence of pesticides in groundwater is of concern as they continue to enter groundwaters which supply around a third of the UKs public water supply (Syafrudin et al., 2021; Stuart et al., 2012).

Pesticide use must therefore be monitored to evaluate and manage possible impacts on human health (Kubiak-Hardiman et al., 2022; Taylor et al., 2022). Treatment of water supplies cannot always be solely relied on to remove all pesticides from raw waters, even in advanced treatment processes. For example, metaldehyde which showed recalcitrance to water treatment and went undiscovered in water systems due to a lack of an analytical method before its eventual discovery (Stuart et al., 2012). This means the monitoring and mitigation of pesticides into these water supplies are economically favoured by water utilities to prevent or reduce pesticides contamination at the source (Taylor et al., 2022). This requires determination of a pesticide's usage, persistence and leaching ability before the risk of it leaching to ground water can be assessed (Stuart et al., 2012). This assessment must also include the possible breakdown products of pesticides as pesticides can be degraded in both abiotic and biotic processes once in the environment. Pesticide metabolites are often less regulated and harder to detect, which is a concern as these metabolites are often more polar which alters their mobility in soils which can lead to higher concentrations of metabolite than the parent compound in the environment (Koskinen et al., 2001; Stuart et al., 2012).

## 2.2 FATE OF PESTICIDES

When aiming to monitor and regulate contaminants that can have either ecological or human health impacts there is also a need to understand the fate of the chemicals in environmental systems (Stuart et al., 2012). Once pesticides are applied, they can migrate through the soil into saturated and unsaturated zones of the landscape (Stuart et al., 2012). This leads to contamination of both groundwater and surface waters worldwide where groundwater is contaminated when pesticides leach from treated fields, while surface water systems accumulate pesticides as sinks from various sources (Tudi et al., 2021).

The environmental fate of pesticides occurs through multiple routes and is dependent on the properties of the compound which leads to different behaviours in the environment (Chow et al., 2020; Tudi et al., 2021). Contamination of waterways will also depend on soil condition and characteristics, the management practices used and weather variations which alter the flow path of pesticides to surface waters (Syafrudin et al., 2021; Sandin et al., 2018). This includes degradation products that can also move through the environment after being broken down by microbes which can then transport the products into soils and aquifers (Maggi et al., 2023).The breakdown of pesticides in the environment is also determined by their half-life, degradation rate ($DT_{50}$), which is the time for 50% of the pesticide to breakdown in certain conditions. Pesticides with short half-lifes may have broken down before large rain events, while those longer $DT_{50}$ values increases the window of time in which a pesticide can be picked up by runoff or leaching water.

The fate of pesticides is strongly affected by other physical and chemical characteristics of pesticides and their mobility in aqueous environments (Stuart et al., 2012). Once translocated into soils by plants or by remaining crop residue, the pesticide residues can reside in both the aqueous and solid phases of the soil, the partition between these phases will be affected by the sorption property of the pesticide. The sorption of a pesticide can determine its persistence and its ability to pollute water (Wauchope et al., 2002). Soluble pesticides can easily be carried by water molecules that allow them to leave soil layers and enter surface and ground waters (Syafrudin et al., 2021). Once dissolved in water the ability of the pesticide to leach into groundwater and waterways can be influenced by the permeability of the soil. Pesticides can also bind to soils, the levels of soil sorption is determined by their Koc, a high Koc value means the pesticide will tend to bind to soils and sediments therefore moving mostly with eroding soils or staying on site of application therefore less likely to leach into the environment (Jarvis, 2016).The amount of sorption which is also influenced by the properties of a given soil such as pH, organic matter and soil moisture (Tudi et al., 2021; Yue et al., 2017). A soil with a higher absorption capability is often found to have high organic matter while clay soils provide large surface areas for pesticides to bind to (Tudi et al., 2021). In particular pyrethroids are often found in soils as they have strong affinities to soil particles and are slow to degrade (Chow et al., 2020). Dissolved pesticides and those attached to eroded soil particles can then enter waterways through runoff from over surfaces. While similar factors impact this process, the slope of the area, rainfall and irrigation will also play a crucial role (Tudi et al., 2021). Drain flow is also an important pathway for pesticides in the environment. Water percolates through soils and enters drains which quickly channels water to ditches and rivers, particularly for low Koc pesticides this allows movement that bypasses most of the soil profile. Drain flow has therefore been highlighted as having a significant contribution to contamination waterways (Brown and van Beinum, 2009).

During the application of pesticides, they can immediately drift away from treatment sites, for example as droplets from sprayed pesticides, and carried in air currents to waterways. Particularly volatile pesticides can be carried a long distance from the point of application (Boonupara et al., 2023). Climatic conditions play a role in the quantity of pesticides moving into waterways through this route (Ramaprasad et al., 2004). This includes volatilised pesticides being deposited by rainfall and quickly returning to the surface environment including waterways (Syafrudin et al., 2021). The other factors influencing spray drift are associated with how the pesticide is initially applied. This includes the spray nozzle which will determine the droplet size altering drift. A low drift nozzle produces large, slow-moving droplets that are less likely to be carried by the wind (Nuyttens et al., 2007). The height of the 'spray boom' above the crop also has a strong influence on drift, with lower height reducing the distance for the spray to fall, meaning there is less time for the droplets to be blown off course (Fuchs, Gebler and Lorke, 2025). Wind also has major impacts on the amount of drift along with the speed the sprayer moves over the field (Desmarteau et al., 2019; (van de Zande et al., 2004).

The scenarios explained above are examples of contamination from nonpoint sources which describes the movement of contaminants from areas through watersheds and into water bodies over time (Syafrudin et al., 2021). Nonpoint source pollution can often be poorly defined as sources can diffuse over large areas (Stuart et al., 2012). However, contamination can also come from point sources where contaminants directly enter water bodies due to improper storage, disposal or misapplication (Aydinalp and Porca, 2004; Stuart et al., 2012). It is likely that contamination of water sources is more likely to result from point source rather than diffuse sources. Significant potential point sources of pollution include sprayer loading and wash down areas (Pieter et al, 2004).

## 2.3 HYDROLOGICAL PATHWAYS

The pattern of pesticide concentrations in rivers varies based on factors such as land use, hydrology, geology, and topography which create different hydrological pathways within a catchment and also influence the contamination rate and extent in rivers (Taylor et al., 2022; Burt, 2001). Catchments play a crucial role by combining all of the environmental processes of the drainage basins, and have cumulative impacts on the runoff seen at the final catchment outlet (Maggi et al., 2023).

The quality and quantity of runoff in an area will vary due to these different pathways and mechanisms of movement across the environment (Jutebring Sterte et al., 2021). In particular, land management is closely linked to water quantity and quality as it alters stock densities, fertiliser application, ploughing frequency and crop type (Weatherhead and Howden, 2009). Also, farm management methods such as underdrainage systems contribute to the ease with which pollutants can be transported from agricultural land to rivers in run-off and drainage (Sharpley and Withers, 1994).  In order to manage pollution in these rivers systems we need to understand the distinct characteristics of the pathways that cause these movements (Burt, 2001; Weatherhead and Howden, 2009).

<table>
<tr><th colspan="3">Hydrological pathways</th></tr>
<tr><td rowspan="2">Surface runoff</td><td colspan="2">- Flow of water over the soil surface<br>- More likely to occur on slopes</td></tr>
<tr><td><u>Infiltration-excess</u><br>- Rainfall exceeds infiltration capacity of the soil<br>- Causes peaks in waterflow<br>- Contributes to soil erosion<br>Storm mechanism</td><td><u>Saturation-excess</u><br>- Occurs in soils with high infiltration capacity<br>- Occurs when groundwater table is close to the surface during rainfall</td></tr>
<tr><td>Subsurface flow</td><td colspan="2">- Can be maintained even during dry periods of climatic conditions by water released from soil and bedrock<br>- Longer flow path compared to runoff</td></tr>
<tr><td>Base flow</td><td colspan="2">- Requires presence of aquifers<br>- Often considered more likely to be free from surface pollution</td></tr>
<tr><td>Flood plains</td><td colspan="2">- Conduit and barrier to water drainage into streams<br>- Links hillslopes to channels</td></tr>
<tr><td>Percolation</td><td colspan="2">- Downwards movement through soil layers<br>- Accumulates in groundwater bodies</td></tr>
</table>

*(Miller, 1977; Peters et al., 2014; Burt, 2001; Folwell et al., 2022 ; Hoang et al., 2017)*

Alongside general losses of pesticides to surface waters, some of the larger losses can come from small fractions of the agricultural areas of a catchment which are considered critical source areas (CSA). These particular areas are likely to be highly susceptible to transportation processes including both infiltration surface runoff and rapid subsurface flows to drainage systems (Sandin et al., 2018). CSAs will also occur due to having higher contaminant availability (Arbab, Collins and Conley, 2018). CSA management aims to direct resources to areas that provide the greatest benefit from remedial investment. (McDowell et al., 2024).

## **2.4 .** MONITORING

Pesticide use and contamination must be monitored to determine possible impacts on human health and the environment and to aid in mitigation efforts (Kubiak-Hardiman et al., 2022; Sandin et al., 2018). Monitoring efforts can establish the variation in pesticide occurrence and fate associated with event driven pollution and long-term trends (Taylor et al., 2022). However, the diversity of compounds involved in pesticide pollution creates a challenge for the development of effective and consistent long-term monitoring programs (Spycher et al., 2018), making accurate assessments of pesticide pollution in rivers difficult (Chow et al., 2020). There are further implications for the interpretation of the temporal trends seen in previous monitoring datasets due to hydrological effects (Chow et al., 2020).

Sampling and analytical methods have limitations that can hinder their ability to monitor pesticides. For example, spot sampling can only provide a snapshot at the time of collection which lacks the temporal resolution needed to characterise changes in pesticide levels. Increasing the resolution of spot sampling requires expensive demands for resources and specific expertise (Taylor et al., 2022).

More comprehensive methods for pesticide monitoring such as passive sampling are being used increasingly as an alternative to spot water sampling. During passive sampling freely dissolved pesticides are detected by a passive sampling device (PSD) in sampled waters. Passive sampling produces time-weighted average (TWA) concentrations (Taylor et al., 2022). However passive sampling may not be as good at capturing true total concentrations and peaks found in spot sampling (Vrana et al., 2005).In contrast, another method of using automated samplers can be programmed to collect water at certain intervals or in response to flow events, which may be useful for capturing pesticide peaks (Neumann et al., 2023). Future work may deploy a combination of passive and automated sampling to provide insights into both long term and peak pesticide levels.

Most contaminant research focusses on surface waters as they are easier to monitor and are likely to contain higher contaminant concentrations. They can also be used as an early warning for potential groundwater contamination (Stuart et al., 2012). The Chemical Monitoring Network is a long-term monitoring dataset that uses Liquid Chromatography – Mass Spectrometry (LCMS) scans to produces semi-quantitative values (µg/l) for 406 potential pesticides from sampling points at least once a week (Environment Agency, 2023).

## 2.5 CATCHMENT SENSITIVE FARMING

There is an interest in quantifying and controlling pollution in surface waters (Brown et al., 2002) as clean rivers support a wide range of services including drinking water, irrigation, industry and environment (Glavan et al., 2012). Therefore, approaches to reduce pressures from freshwater pollution are needed, including in England where only 14% of rivers are classified as 'good ecological status' within the Water Framework Directive which suggests high enough levels of pollution to likely put most taxa under pressure (Poyntz-Wright et al., 2023). Water pollution due to agricultural activities is a significant factor in the long-term degradation of rivers with negative consequences for the environment in the United Kingdom (Wang et al., 2019). Agriculture dominates the UK landscape, occupying 76% of the nation's land area (OECD, 2006). Therefore, it can have profound impacts on water environments and emphasises the need for effective measures to ensure their health (OECD, 2006).

To aid in the mitigation of these continuing impacts, and in response to ecological standards set by directives such as the Water Framework Directive (European Commission, 2023), the UK government launched the Catchment Sensitive Farming (CSF) initiative in 2006. CSF was established to identify and implement cost-effective measures that reduce the environmental impact of farming practices, aiming to reduce agricultural water pollution through targeted support and incentives for farmers (OECD, 2006). This contributes to wider UK Government objectives, such as the 25-year Environment plan, which includes reducing the levels of harmful chemicals from agriculture in the environment (DEFRA, 2018; Poyntz-Wright et al., 2023). To note, while WFD is good for setting goals of ecological targets the either good or 'bad' assessment approach has drawn criticism for its strict criteria in assessments. The "one-out-all-out principle" is thought to lead to large numbers of sites failing due only one parameter not being within acceptable limits, determining a score for an entire waterbody. It is suggested that instead we should focus on multiple parameters and present results for each separately (Carvalho et al., 2019).

CSF raises awareness of river health issues and provides farmers with the knowledge and tools to lessen their environmental impact (Thomas et al., 2020). It is a partnership effort among the Department for Environment, Food and Rural Affairs (Defra), Natural England, and the Environment Agency, and it initially targeted 40 priority catchments with known water quality problems, with a subset of 8 sites used to track organic chemicals, which mostly include pesticides. The goal is to improve the chemical and ecological status of both surface and groundwater in these high-risk areas (Collins et al., 2007). CSF's objectives align with the Water Framework Directive's requirements (Thomas et al., 2020) and with the EU Thematic Strategy for Soil, which emphasizes protecting soil to reduce diffuse pollution (Collins et al., 2007).

CSF initiative raises awareness of river health and provides farmers with the knowledge and tools to reduce their impacts on the environment (Thomas, Riley and Spees, 2020). CSF operates as a partnership between the Department for Environment, Food and Rural Affairs (Defra), Natural England (NE), and the Environment Agency (EA), which has identified 40 priority catchments of most concern. The goal is to improve the chemical and ecological status of both surface and groundwater in these high-risk areas (Collins et al., 2007). CSF's aims align with the requirements of the Water Framework Directive (WFD) (Thomas, Riley and Spees, 2020)and with other goals such as the European Thematic Strategy for Soil, which emphasises increased protection of soil resources to further reduce diffuse pollution in catchments (Collins et al., 2007).

For the successful implementation of sustainable farming practices, there is an emphasis on collaborative efforts which allow an understanding of what measures are required by learning what knowledge farmers use to guide the decisions about their current practices (Thomas, Riley and Spees, 2020). Farmers are provided with free targeted advice to encourage them to take voluntary action to reduce pollution, with a network of CSF officers across the UK that can deliver targeted support (Hankin et al., 2019; Environment Agency, 2021). Specific mitigation strategies promoted by CSF include both infrastructural improvements, such as grants for the installation of buffer strips to filter pollutants, and changes in farm management, such as limiting the use of fertilisers and pesticides or altering crop cycles to maintain the infiltration capacity of soils (Collins et al., 2007; Glavan et al., 2012).

This initiative places a strong emphasis on continual monitoring and evaluation to inform future improvements and policy development (Environment Agency, 2019). Every four years the EA is required to carry out formal evaluations of any observed improvements in environment quality due to changes in agricultural practices. Here the evaluation is made using land use and water quality modelling that incorporates losses from farms along with data on in-stream water quality at various scales (Hankin et al., 2019). The models can also account for characteristics such as climate, topography and soil type to determine input losses in an area alongside the land management practices (Withers and Lord, 2002).

Since the start of the initiative CSF has demonstrated progress in delivering water quality objectives through effective engagement with farmers and advice delivery (Environment Agency, 2019). The initiative has led to reductions in nutrient, sediment and pesticide levels in high-pressure agricultural areas, with pesticide levels in monitored catchments have seen a 34% decrease in monitored pesticide concentrations exceeding 0.1μg/l over 9 years when compared to a baseline level (Environment Agency, 2019). However, it is has been noted that despite these promising looking results it is difficult to disentangle the direct impacts of CSF interventions from other factors such as variable weather conditions or background changes in pesticide usage. This creates a critical knowledge gap in evaluating the precise effectiveness of specific conservation strategies in CSF.

## 2.6 MODELLING PESTICIDES AT CATCHMENT SCALE

One way to address the challenge of evaluating diffuse pollution interventions like CSF is through process-based modelling of pesticide fate and transport at the catchment scale (Wang et al., 2019). These models can help isolate the effects of specific land management changes from confounding factors, thereby supporting the design and assessment of mitigation strategies and identifying areas of most concerns (Brown et al., 2002). This approach is particularly useful given that improvements in water quality often take years to become apparent due to lag times, which makes it hard to directly link cause and effect using short-term monitoring data alone (Environment Agency, 2019).

Distributed hydrological models are especially valuable for these applications because they account for spatial variability in terrain, soils, and land use, which leads to uneven pollutant loading across a catchment (Weatherhead and Howden, 2009). Numerous models have been developed to simulate the fate and transport of pesticides at the catchment scale, supporting the design and evaluation of mitigation programmes such as Catchment Sensitive Farming (CSF) (Wang et al., 2019; Brown et al., 2002). The most widely used tool for this purpose is the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1993; Panagopoulos et al., 2011; Wang et al., 2019).

SWAT is an open-source model capable of continuous, long-term simulations of watershed hydrology and chemical transport (Krysanova and White, 2015). It divides a catchment into subbasins and further into Hydrologic Response Units (HRUs) which are unique combinations of land cover, soil type, and slope which represent spatial heterogeneity (Bouraoui and Grizzetti, 2008; Glavan et al., 2012). SWAT integrates a wide range of processes (physical, chemical, and biological) and can utilise Geographic Information Systems (GIS) data for inputs and results visualisation, while facilitating statistical analysis of outputs (Glavan et al., 2012). While we used SWAT for the model here there are other tools for simulating pesticide fate and transport, this includes PRZM (Pesticide Root Zone Model) (Young, 2014). These models are often developed for different applications with different focuses and environmental simplifications. This is where models like SWAT and PRZM differ, PRZM is designed for field scale applications while SWAT is designed for watershed scales (Ren et al., 2023).

Using long-term datasets in conjunction with modelling in programs like SWAT allows for more confident designation of water quality changes to particular causes (Environment Agency, 2019; Cooper and Hiscock, 2023). Baseline monitoring data can be used to calibrate models and help differentiate between changes due to management interventions and natural variability in climate or streamflow, which noted to obscure trends seen when evaluating the impact of mitigation strategies (Chow et al., 2020; Maggi et al., 2023). Another advantage of SWAT is that it requires input data (topography, land use, soil properties) that are commonly available from maps and remote sensing (Eckhardt and Arnold, 2001; Weatherhead and Howden, 2009).

Like all modelling, SWAT is dependent on interpolation and assumptions therefore any uncertainties must be understood and quantifiable (Weatherhead and Howden, 2009). A good model should be able to reach a certain level of complexity while remaining as accurate as possible (Dubus et al., 2003). To achieve accuracy the model performance can be evaluated through calibrating predictions against observed data and calculating goodness-of-fit metrics. Commonly used statistics include the coefficient of determination ($R^2$), Nash-Sutcliffe Efficiency (NSE) and Percentage Bias (PBIAS) (Glavan et al., 2012).

## 2.7 CONCLUSION

The challenges associated with pesticide use in agricultural practices are leading to contamination of environmental waters. Despite their crucial role pesticides have raised significant concerns due to their adverse effects on both human health and the environment (Sharma et al., 2019; Wang et al., 2019). Efforts to mitigate pesticide contamination have led to initiatives like CSF, which aim to reduce agricultural pollutants in rivers and promote sustainable farming practices (OECD, 2006; Environment Agency, 2019).

Through targeted interventions and farmer engagement, CSF has shown some promising results in reducing nutrient, sediment, and pesticide levels in monitored catchments (Environment Agency, 2019). However, ongoing monitoring and evaluation are essential to assess the effectiveness of CSF (Environment Agency, 2019). If we continue to model and evaluate the impacts of the program on river pollution levels by pesticides we can continue to demonstrate its effectiveness.

Modelling approaches, such as SWAT, can be used to model the fate and transport of pesticides at the catchment scale by simulating hydrological processes and land management practices which have been shown to have crucial impacts on the concentration of pesticide levels in rivers (Wang et al., 2019; Gassman et al., 2014). Using long-term datasets for the model in the time since the implantation of the programme could provide valuable insights into the impact of CSF since its implementation in a catchment (Eckhardt and Arnold, 2001; Krysanova and White, 2015). We can also utilise SWAT to identify CSAs to increase benefits of environmental protection per unit of cost. SWAT can identify area of higher pollution loads per unit area of watersheds. This can allow the targeting of specific areas for intervention (Chang et al., 2021).

## **2.8** AIMS

The aim of this work was to build catchment scale models in SWAT to determine the impact CSF has had on pesticide levels in rivers. This would be achieved by creating models of two priority catchments, with a calibrated and validated flow. Then modelling levels of commonly detected pesticides in rivers using usage data and comparing the simulated levels in rivers to observed levels to evaluate changes any changes since the implementation of CSF. This study utilised SWAT model to investigate the impact of CSF on pesticide levels in two river catchments in England: Ancholme and Wensum. These two catchments have been identified as priority sites for CSF, in particular these specific catchments were chosen based on the significant impact agricultural practices are having on rivers (Natural England et al., 2016). Ancholme is an ongoing priority area part of the CSF programme with specific focus on pressures from pesticide pollution (Natural England al., 2016). Wensum is also a catchment that is monitored for pesticide run-off from agriculture and aims to reduce pesticide run-off through advice on pesticide handling and yard management (Natural England, 2014).

The fate and transport of five commonly used herbicides were investigated, these were: 2,4-D, Flufenacet, Bentazone, Mecoprop, and Propyzamide. 2,4-D (2,4-Dichlorophenoxyacetic acid) is a widely used herbicide for weed control in various settings, including agriculture, lawns, golf courses, and parks (Aquino et al., 2007). As a selective, systemic herbicide, it primarily targets broad-leaved plants (University of Hertfordshire, 2023a). However, 2,4-D poses significant environmental concerns due to its high water solubility and low adsorption in soil. This leads to high mobility and potential for contamination of surface and groundwater, with 92% of applied 2,4-D ultimately reaching water courses (Kearns et al., 2014; Mountassif et al., 2008). Studies have shown that while concentrations in surface waters are often low in high-usage areas, higher levels can be found in soils and nearby water bodies (Islam et al., 2018). Furthermore, inadequate storage and disposal of herbicides contribute to contamination of soil, groundwater, and rivers (Islam et al., 2018). Flufenacet is a selective herbicide that is persistent in both soil and water systems (University of Hertfordshire, 2023b). Commonly it is found in high concentrations in aquatic ecosystems (Wijewardene et al., 2021) which can be of concern, posing critical risks to aquatic organisms (Álvarez et al., 2024). Bentazone is a herbicide used to protect crops from several weed species that is applied after crop emergence.  Bentazone has previously been found in many different freshwater ecosystems (Grillo-Avila et al., 2024), however it has currently been shown to be safe to non-target aquatic organisms (Queirós et al., 2022). Mecoprop is one of the most commonly used selective herbicides in the UK, used to control broad-leafed weeds particularly on winter cereals in winter and spring (Fletcher et al., 2004). Mecoprop is very mobile and leaches from soil immediately after application and during rain events (Fletcher et al., 2004). Propyzamide has often been detected in surface and groundwater monitoring and has been noted as a frequently detected contaminant (Khan and Brown, 2017). It also often has a complex pattern of in occurrence in freshwater and is found in higher concentrations than other herbicides with high application rates and has high variability during pollution events (Taylor et al., 2021).

Further to this the impact of mitigation strategies was investigated using the model to investigate the impact of changes in management practices on pesticide levels in rivers. Tillage operations are performed to prepare agricultural land for planting (Elias et al., 2018). Conventional tillage operations generally make soils more susceptible to water and wind erosion (Phillips et al., 1980). This leads to erosion of top soils and increased pollution of rivers (Elias et al., 2018). To mitigate this conservation tillage practices have been adopted, this includes conservation tillage and no-till management. The impact of cropping practices was also implemented in the model. These included strip cropping, contour cropping and conservation cropping (modelled by only using chisel ploughing). Contour cropping minimises erosions and reduces runoff by storing rainfall behind ridges. Strip cropping grows crops with different growth patterns in alternate stripes perpendicular to the contour of the slope (Gilley, 2005).

The use of SWAT modelling aims to allow us to separate the impact of CSF on pesticide contamination from other influencing factors such as changes in cropping, pesticide use, and weather conditions. By comparing modelled pesticide concentrations with observed data, this research aimed to assess the effectiveness of CSF in mitigating pesticide pollution and inform future environmental management strategies.

# 3 METHODS – THE MODEL

SWAT requires a substantial amount of input data, including meteorological data, soil maps, and land use data. Before the model can be built.

## 3.1 STUDY AREAS

The Ancholme and Wensum catchments are located in the East of England and are priority catchments for CSF, with a particular focus on mitigating pesticide runoff into rivers (Natural England, 2014; Natural England et al., 2016).

The Ancholme catchment, situated within the Humber River Basin District, is a rural area with a predominantly agricultural land use. The Ancholme catchment also designated as a drinking water protected area (Environment Agency, 2023a).The Wensum catchment encompasses the environmentally significant Pensthorpe Nature Reserve (Environment Agency, 2023b).

*Figure 1. Locations of the study areas.*

## 3.2 WATERSHED DELINEATION

Once the catchment boundaries were uploaded to SWAT the topography of the catchment was defined using a Digital Terrain Model to represent the ground surfaces of the catchments. Three-dimensional digital terrain models obtained from the Ordnance Survey Terrain grid data and was used at a resolution of 5m. A mask (shapefile) of the catchments was uploaded to the Defra data services platform to determine which 5k tiles were within the area of the catchment (DEFRA, 2025), before using then these tiles were referred to to download the correct tiles from the Ordnance Survey grid data. The tiles where the combined into one raster using the mosaic to raster function in ArcGIS pro. Using this data the watershed was delineated to define the streams and outlets in the catchment. Once SWAT had automatically defined streams and outlets using the DEM-based method the streams and outlets created were examined. The aim was to remove any outlets that seemed very close together or connected to very small streams to reduce the number of subbasins created so as to not overcomplicate the model and to reduce implying homogeneous conditions (Booij, 2005).


*Figure 2. The watersheds of both catchments Wensum and Ancholme respectively. The figure includes manually added outlets for the whole catchments.*

## 3.3 SOIL DATA

Soil data for the catchment was obtained from the national soilscapes map (LandIS, 2022). The area for each soil type within the catchment was calculated to determine their distribution. To simplify the analysis, soil types with low coverage were grouped with similar soil types. Subsequently, each group was represented by its dominant soil type for modelling.

The properties data required for each soil type for SWAT was found in data provided by the Environment Agency (HORIZON fundamentals and hydraulics). The soil associations in Ancholme were as follows: 28% Blackwood, 27% Beccles. 20% Andover, 13% Carstens, 7% Wallasea, and 5% Swaffham prior. While those in Wensum were 34% Burlingham, 19% Beccles, 19% Barrow, 15% Newport, 10% Isleham, and 3% Wick.

The most dominant soil association in Ancholme, Blackwood, is a deep permeable sandy soil, while in Wensum, Burlingham, is a deep course soil type the slowly permeable subsoils (LandIS, 2022).

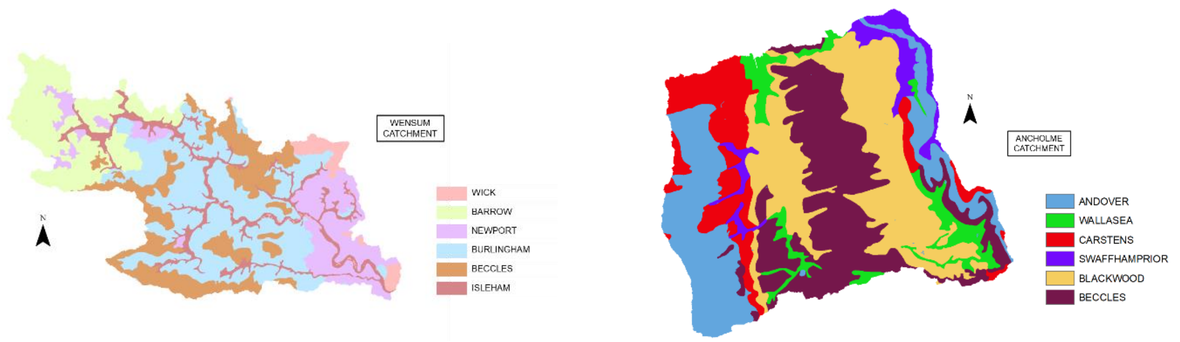



*Figure 3. Maps of the Catchments soils associations (LandIS, 2022) .*

### 3.4 LAND USE DATA

The land use data for the catchment was obtained from Centre for Ecology and Hydrology Land Cover map 2021 at a 25m resolution (UKCEH, 2021). The most dominant land use for both catchments was arable land (AGRL).

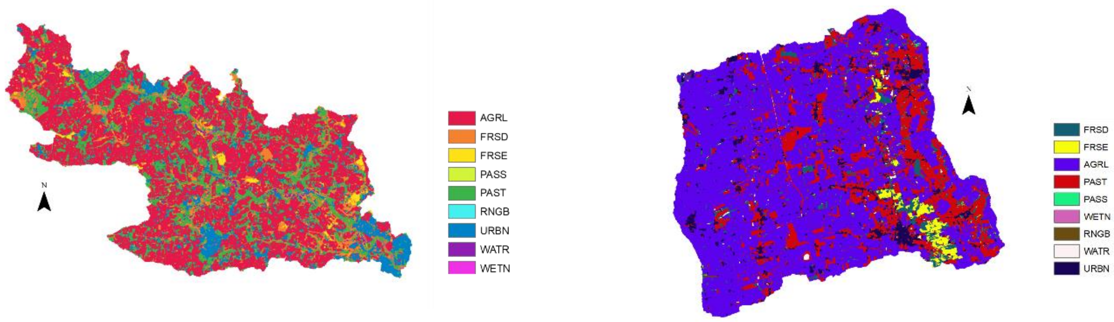



*Figure 4. Maps of the catchments Land Cover maps (UKCEH, 2021).The phrases in the key are as follows: Arable Land (AGRL), Deciduous woodland (FRSD), Coniferous woodland (FRSE), Improved grassland (PAST), Semi-natural grassland (PASS), Wetlands (WETN), Heath (RNGB), Urban (URBN) and Freshwater (WATR).*

### 3.5 PESTICIDE PROPERTIES

The properties of the pesticides used were obtained from the Pesticide Properties Database (PPDB) website (University of Hertfordshire, 2023c), where there was a range of values quoted for a variable the median value was taken. The values taken for the model include the Koc, Half-life (soil) and solubility.

| Pesticide | Soil adsorption coefficient (SKOC) | Half-life – soil (HLIFE_S) | Solubility in Water (WSOL) |
|---|---|---|---|
| Propyzamide | 548 | 51 | 9 |
| Mecoprop | 60 | 21 | 250000 |
| 2-4, D | 39 | 10 | 24300 |
| Flufenacet | 401 | 43 | 51 |
| Bentazone | 55 | 20 | 7112 |

### 3.6 CROP DATA

Crop data for the model was sourced from EA land use surveys conducted within each catchment. This data encompassed all the crop areas in agricultural land area across catchments for the years 2005, 2007, 2010, 2013, 2016, and 2019. For model simplification, similar crops were then grouped together. For instance, "winter cereals" in the model encompassed the areas covered by winter cereals, wheat, winter barley, oats, rye, and triticale. Crops with a total coverage of less than 1% across all years were excluded from the dataset.

To address data gaps in catchment-specific crop areas between the specified years, data from EA surveys covering the entire Eastern region was utilised. The year-over-year changes observed in the regional data were used to infer and estimate the corresponding changes within each catchment and the crop areas within catchments was extrapolated. Following the determination of the area for each modelled crop group in each year, potential crop rotations applicable to the model were calculated.

To estimate crop rotations in the spatial context of the model the areas of the subbasins were used to make as representative as possible estimates of the area covered by the crop for each year. Therefore if the crop covered 200ha in 2012 and the area of two subbasins in the model added up to 200ha the crop was assumed to be grown in these areas of the model for that year. Accuracy in the area covered by the crop in the model compared to the data was sacrificed to simplify crop rotations by trying to not have an individual subbasin containing different crops every year (detailed in Appendix 1 and Appendix 2).

### 3.7 HYDROLOGICAL RESPONSE UNIT DEFINITION

The HRUs were defined by grouping similar land use, soil type, and slope characteristics, this meant that each HRU was a unique combination of each of these variables and the model area was divided based on these.

### 3.8 RAINFALL AND FLOW DATA

The EA provided daily rainfall data using the subbasins from the watershed delineations of Ancholme and Wensum to give average rainfall per sub-basin. This data originated from 1km grid rainfall information. However, this would have been too high a resolution for the model, so the grid data was aggregated to the sub-basin level.

Daily flow data for the Wensum and Ancholme catchments were obtained from the National River Flow Archive (2023). For Wensum, data from Station 34004 at Costessey Mill was used (Figure 5). For the Ancholme, data from two stations had to be incorporated. While Station 29004 Bishopbridge was the most appropriate station within the catchment, it is influenced by reservoir runoff, particularly during summer months. To account for this, data from a more upstream station, Station 29009 Toft Newton, was incorporated to replace sections of the flow record potentially affected by reservoir releases (Figure 6).

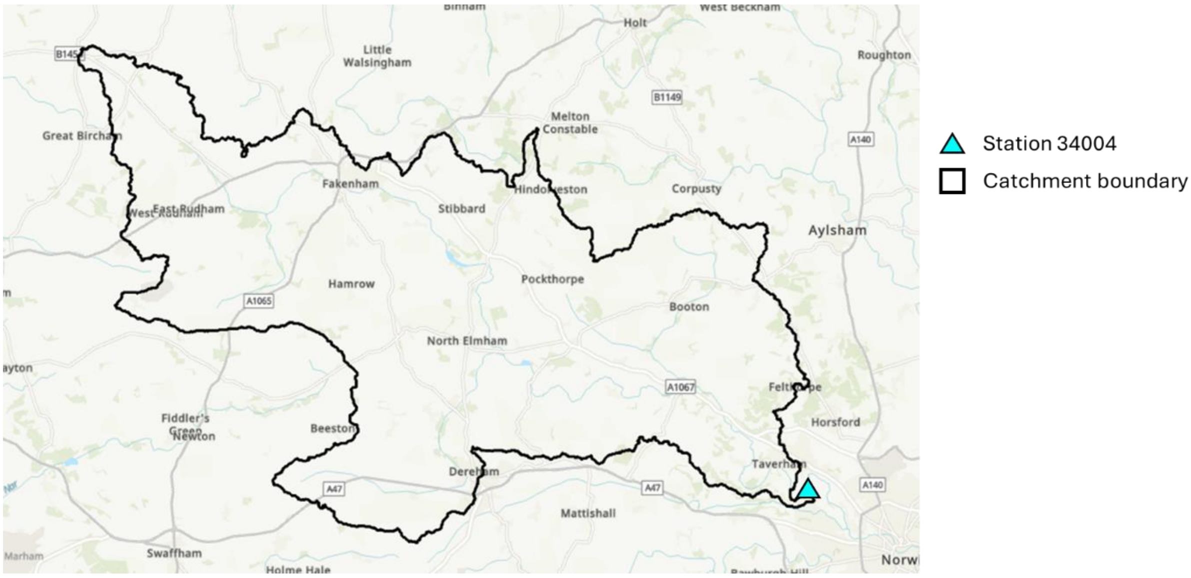



*Figure 5. Map to show location of station 34004 and catchment boundary.*

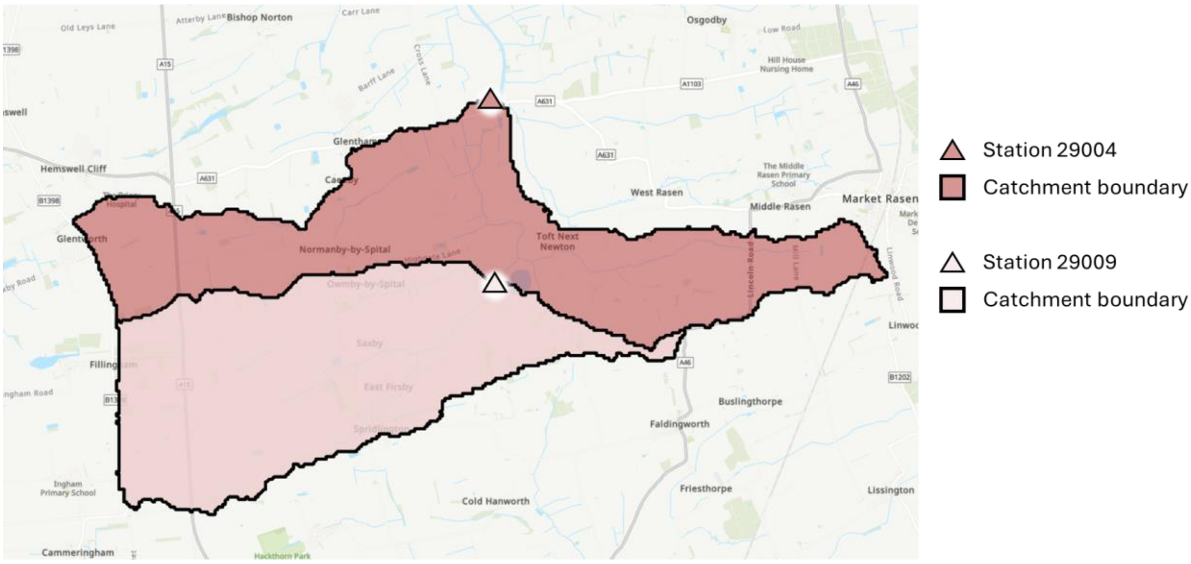



*Figure 6. Map to show locations of stations 29004 and 29009 along with their catchment boundaries.*

## 3.9 WEATHER DATA

The weather data was obtained from the Met Office Integrated Data Archive System (MIDAS) containing land surface station data including weather measurements of temperature, sunshine, radiation, and wind from stations all over the UK each at a daily resolution (Met Office, 2023). For the model, stations within or close to the catchment were identified and the data was extracted at a daily resolution for the variables: relative humidity, minimum and maximum temperature, solar radiation, and wind speed.

## 3.10 PESTICIDE DATA

The pesticide data used in the model was the expected application rates (kg/ha) of pesticides each year within the catchment. These were derived from regional pesticide usage data at a monthly resolution (FERA). The total rates were scaled down to the estimated crop areas from the estimated crop data to determine how much of the weight applied regionally was likely to have been applied in the catchment.

To compare the simulated pesticide levels expected in the catchment rivers from the model output observed data was obtained from river samples that are taken and analysed by the EA at the monitoring points in Wensum and Ancholme. At Wensum the data contained records from September 2006 to September 2023 on average every 6 days, while Ancholme had data records from August 2016 to September 2023 on average every 10 days.

### 3.11 MANAGEMENT PARAMETERS

Soils with tile drains were given the appropriate depth parameters for drainage on all arable land (Wallasea 75cm, Beccles 75cm, and Blackwood 100cm) and the time for these soils to drain from saturation to field capacity was set to 24 hours (Villamizar et al., 2020). Tillage operations between different crop years was the Moldboard Plow. Since the pesticide application data was calculated for the whole catchment the pesticide application data was added for all agricultural and for Mecoprop and 24-D the same was done with all pasture (PAST) land uses.

### 3.12 CALIBRATION AND VALIDATION

Accurate model predictions depend on proper calibration and validation using observed data. The model flow data was calibrated using the SWAT Calibration Uncertainty Procedure (SWAT-CUP) a calibration analysis tool for SWAT. Sequential Uncertainty Fitting (SUFI-2) module was used to complete a parameter sensitivity analysis and was performed for 16 parameters for both Wensum and Ancholme.

To assess model performance, a combination of goodness-of-fit metrics was used to evaluate different aspects of the simulation's accuracy. These included: $R^2$ which was used as to evaluate how well the trend of the simulated data matched the trend in the observed data, Nash-Sutcliffe Efficiency (NSE), which was used as a stricter measure of alignment between the simulated and observed values and is sensitive to both correlation and differences in magnitude and Percentage Bias (PBIAS) which shows the average tendency of the simulated flow to be larger or smaller than the observed flow. A negative value indicates model under-prediction, while a positive value indicates over-prediction (Noori et al., 2020). SWAT-CUP was run over 2000 simulations and from a selection of the simulations with the best goal value (Nash-Sutcliffe) the best simulation was selected.

*Table 1. The 15 sensitive parameters applied to SWAT-CUP.*

| # | Parameter | Data Group |
|---|---|---|
| 1 | CN2 (PAST,PASS) | mgt |
| 2 | CN2 (AGRL) | mgt |
| 3 | CN2 (FRSE,FRSD) | mgt |
| 4 | CN2 (URBN ) | mgt |
| 5 | ALPHA_BF | gw |
| 6 | GWQMN | gw |
| 7 | GW_DELAY | gw |
| 8 | GW_REVAP | gw |
| 9 | RCHRG_DP | gw |
| 10 | REVAPMN | gw |
| 11 | LAT_TTIME | hru |
| 12 | SLSOIL | hru |
| 13 | ESCO | hru |
| 14 | EPCO | hru |
| 15 | DEP_IMP | hru |

The parameters used are known to influence the hydrological processes within the catchment, from surface runoff to groundwater dynamics (van Griensven et al., 2006). This includes the initial partitioning of rainfall is primarily controlled by the SCS Curve Number (CN2), this dictates the volume of surface runoff versus infiltration. CN2 parameter was adjusted the for dominant land uses, to capture their different runoff generation characteristics and influence on peak flows. The movement and storage of water within the soil is changed by the depth down to to the impervious layer (DEP_IMP), which sets the total water storage capacity, and the lateral flow travel time (LAT_TTIME), controls the timing of lateral flow entering the stream (Neitsch et al., 2011).The dynamics of the groundwater system were represented by the groundwater delay (GW_DELAY) and the baseflow alpha factor (ALPHA_BF). GW_DELAY dictates the time lag of water in soil to enter shallow aquifers. While ALPHA_BF, the baseflow recession constant, controls groundwater flow response to changes in recharge (Singh and Saravanan, 2020).The overall catchment water balance was calibrated by the soil evaporation compensation factor (ESCO), which regulates water loss to the atmosphere, and the deep aquifer percolation fraction (RCHRG_DP), which accounts for the fraction of water which recharges to deep aquifers (Neitsch et al., 2011).

### 3.13 CHANGES TO TILLAGE PARAMETERS AND CROPPING PRACTICES

To investigate impacts of different tillage operations and cropping practices on the concentration of pesticides in rivers the following changes were applied to the model for the Wensum Catchment with Flufenacet simulated. The changes were chosen to represent how these operations will alter the variables within the catchment.

*Table 2. The parameters changed to simulate the changes of management in the model.*

| **Management** | **Changes** | |
|---|---|---|
| **Tillage** | *None* | DEPTIL = 25, EFFMIX = 0.05, CN2 = -3 |
| | *Conservation* | DEPTIL = 100, EFFMIX = 0.25, CN2 = -2 |
| **Cropping** | Strip | USLE-P = 0.3, CN2 = -5 |
| | Contour | USLE-P = 0.6, CN2 = -3 |
| | Conservation | Chisel plough only |

The shifts for tillage were simulated by altering parameters that control soil disturbance and surface runoff. Modifying the tillage depth (DEPTIL) and mixing efficiency (EFFMIX) represents a less intensive ploughing regime which reduces runoff. This was reflected by lowering the Curve Number (CN2), to reduce the surface runoff volume. For strip cropping and contour cropping the adjusted parameters were the USLE Support Practice Factor (USLE-P). USLE-P factor quantifies the ratio of soil loss with a support practice, lower USLE values show reduced soil erosion while reduced runoff was also simulated by lowering the CN2 value.

# 4 RESULTS

## 4.1 WATERSHED

Both catchments resulted in having 25 subbasins with 2282 hydrological response units in Ancholme and 2630 hydrological response units in the Wensum catchment. The arable land in Ancholme accounted for 67% of the land coverage with Wensum arable land covering 57% of the catchment. For both catchments pastures (PAST) accounted for approximately 20% of the catchments. The average annual rainfall for the Ancholme catchment was around 12500mm per year while Wensum was 16900mm per year.

Watershed parameters used in this model includes the use of the Penman/Monteith method a combination estimation method of potential evapotranspiration (PET), which uses the inputs from the weather data: relative humidity, temperature, solar radiation, and wind speed to estimate the potential evapotranspiration (PET) (Droogers and Allen, 2002).

## 4.2 CALIBRATION AND VALIDATION

The simulated hydrographs generated for Wensum and Ancholme showed a good agreement with the timing of peaks in the hydrographs. Wensum in particular indicated a strong performance in predicting flow which would be acceptable to simulate pesticide transport (Villamizar et al., 2020).

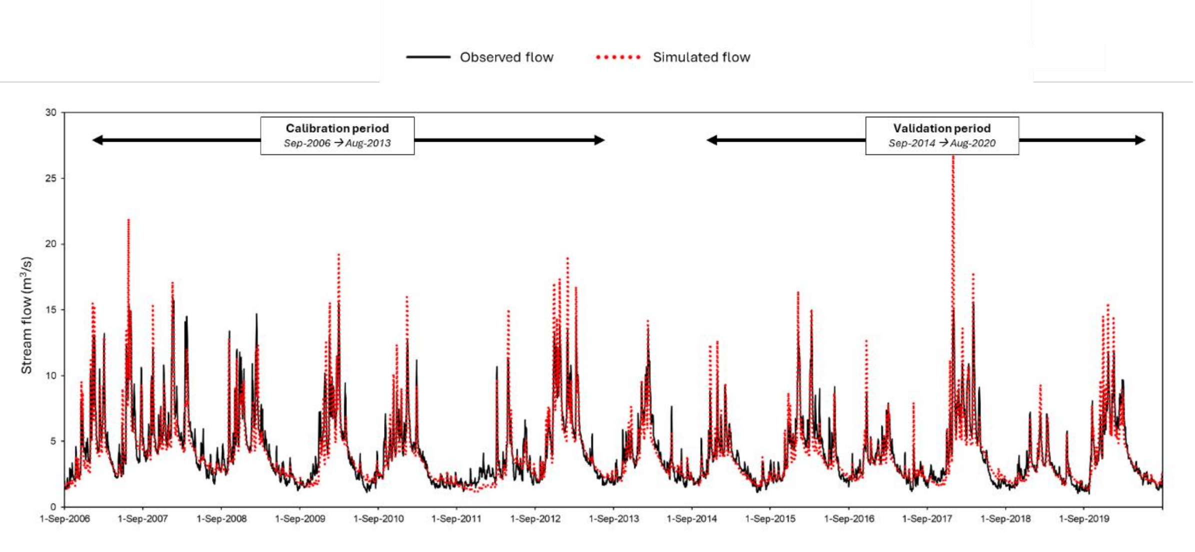



*Figure 7. The comparison of simulated and observed flow for the calibration and validation periods in the Wensum Catchment.*

For Wensum the results for the calibration period had a Nash Sutcliffe value of 0.84, suggesting a good fit during the calibration period, similar to the $R^2$ of 0.85 suggest a good fit between the simulated and observed flow. However, the PBIAS result, -2.96, suggests that the model underestimated flow compared to observed values. The validation period had a similar result with a Nash Sutcliffe of 0.81 and $R^2$ of 0.85, with only slightly less underprediction with a PBIAS value of -2.88.

*Table 3. The results from SWAT-CUP for the Wensum Catchment.*

| WENSUM | Nash Sutcliffe | $R^2$ | Percentage Bias |
|---|---|---|---|
| Calibration Period | 0.84 | 0.85 | -3.96 |
| Validation Period | 0.81 | 0.83 | -2.88 |

The performance of the Ancholme hydrograph was less reliable compared to the observed flow but a good fit was still shown between observed and simulated flow.

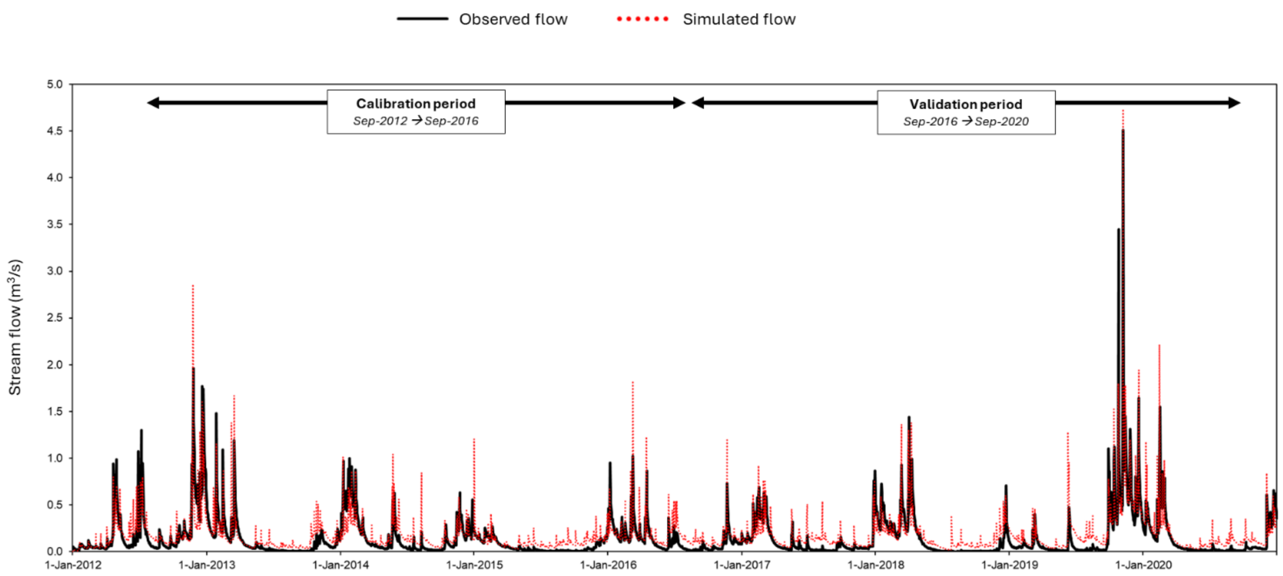



*Figure 8. The comparison of simulated and observed flow for the calibration and validation periods in the Ancholme Catchment.*

The results for the calibration period had a Nash Sutcliffe value of 0.51, suggesting only a satisfactory fit during the calibration period, similar to the $R^2$ of 0.55 suggest a less good fit between the simulated and observed flow than that observed in Wensum. The PBIAS result from Ancholme , 19.12, suggests that the model overestimated flow at a larger magnitude than Wensum underpredicted flow. The validation period had a similar result with an improved Nash Sutcliffe of 0.66 showing a good fit and $R^2$ of 0.68, with a higher value for PBIAS, 27, showing higher overprediction.

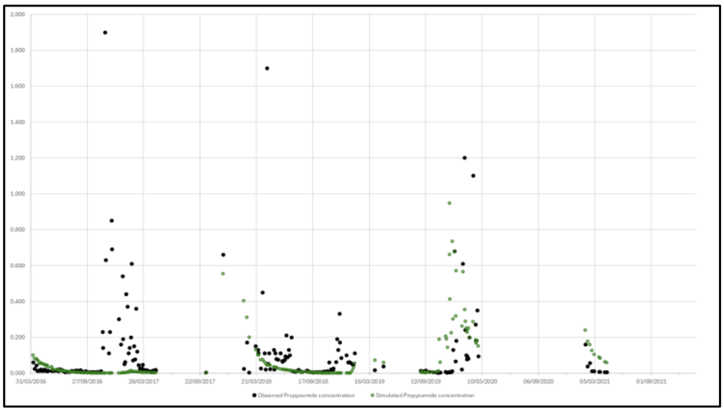
*Table 4. The results from SWAT-CUP for the Ancholme Catchment.*

| ANCHOLME | Nash Sutcliffe | $R^2$ | Percentage Bias |
|---|---|---|---|
| Calibration Period | 0.51 | 0.55 | 19.12 |
| Validation Period | 0.66 | 0.68 | 27.00 |

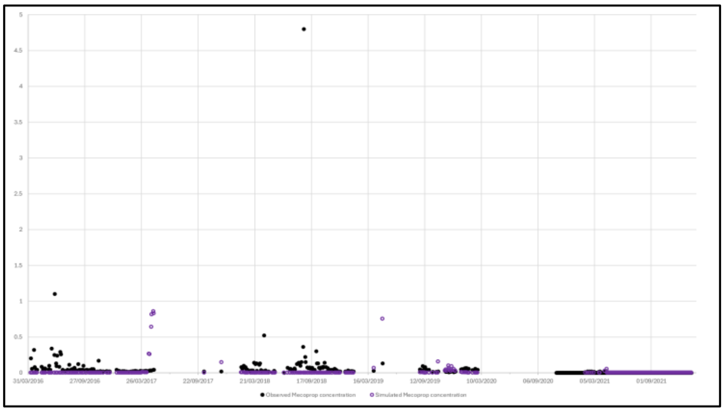
### 4.3 PESTICIDE SIMULATIONS

The pesticide concentrations simulated by SWAT for both catchment seemed to have no clear trends between the observed and simulated pesticide concentrations (Fig.7 and Fig. 9). In Ancholme the simulated pesticide concentrations were underpredicted, particularly for propyzamide, mecoprop, 2-4,D and Bentazone. However the timing of the presence of pesticides at the monitoring points was predicted well, with some increases in the modelled data matching increases in the measured data. This is particularly visible in 2019/20 for propyzamide.. The graphs in Figure 8 compared the maximum concentration of pesticide observed and simulated over yearly time periods, this more easily demonstrated the underprediction of simulated concentrations. Flufenacet was the only pesticide that significantly exceeded

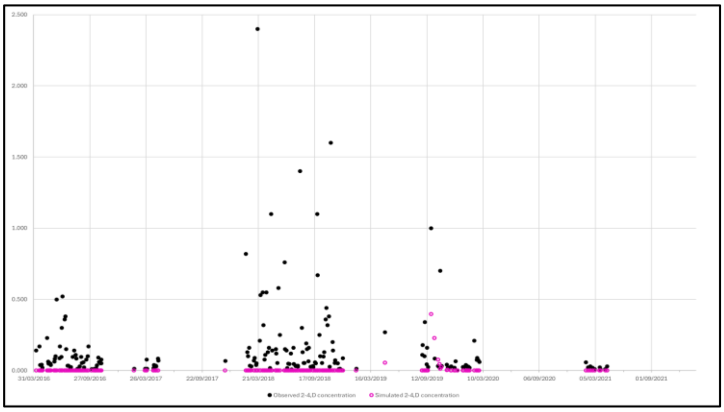
a) Propyzamide



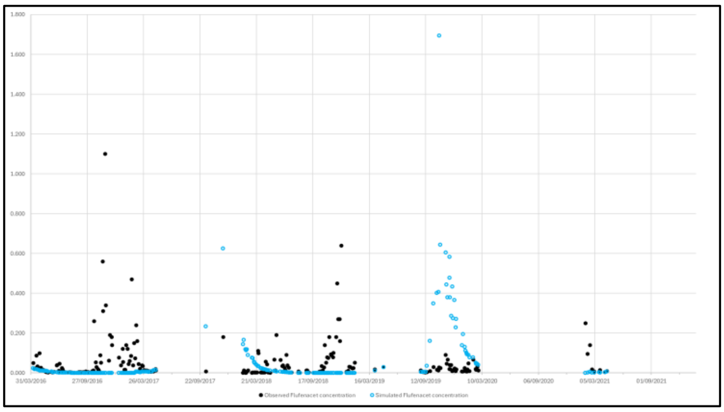
b) Mecoprop



c) 2-4,D



d) Flufenacet



e) Bentazone

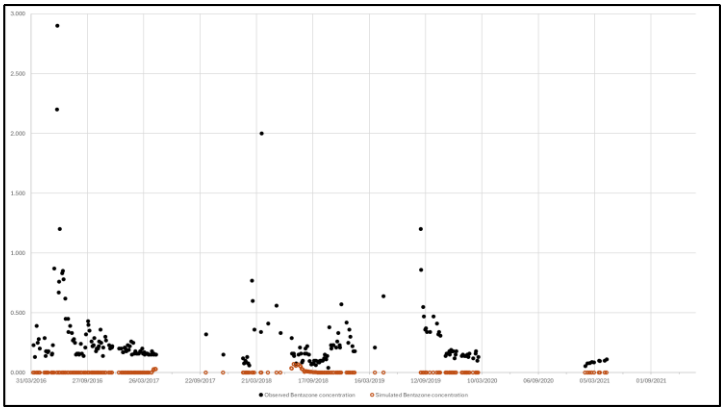


*Figure 9. The measured and simulated concentrations (µg/l) of all pesticides investigated in the Ancholme catchment.*

the observed concentrations at points across the period shown. Goodness of fit of pesticide concentrations was not performed.


*Figure 10. Graphs to demonstrate the trends between the maximum concentration from the observed and simulated data in the Ancholme catchment.*

Similarly in the Wensum catchment the simulated pesticide concentrations were underpredicted, particularly for propyzamide, 2-4,D and Bentazone while the timing of pesticides at the monitoring points was again predicted well. The timing of increases in the modelled data matched more closely to increases in the measured data for Propyzamide and Mecoprop. The graphs in Figure 10 show that Flufenacet can still exceed the observed concentrations at points across the period shown. However, in Wensum the results from mecoprop performed better in matching or exceeding the observed concentrations.

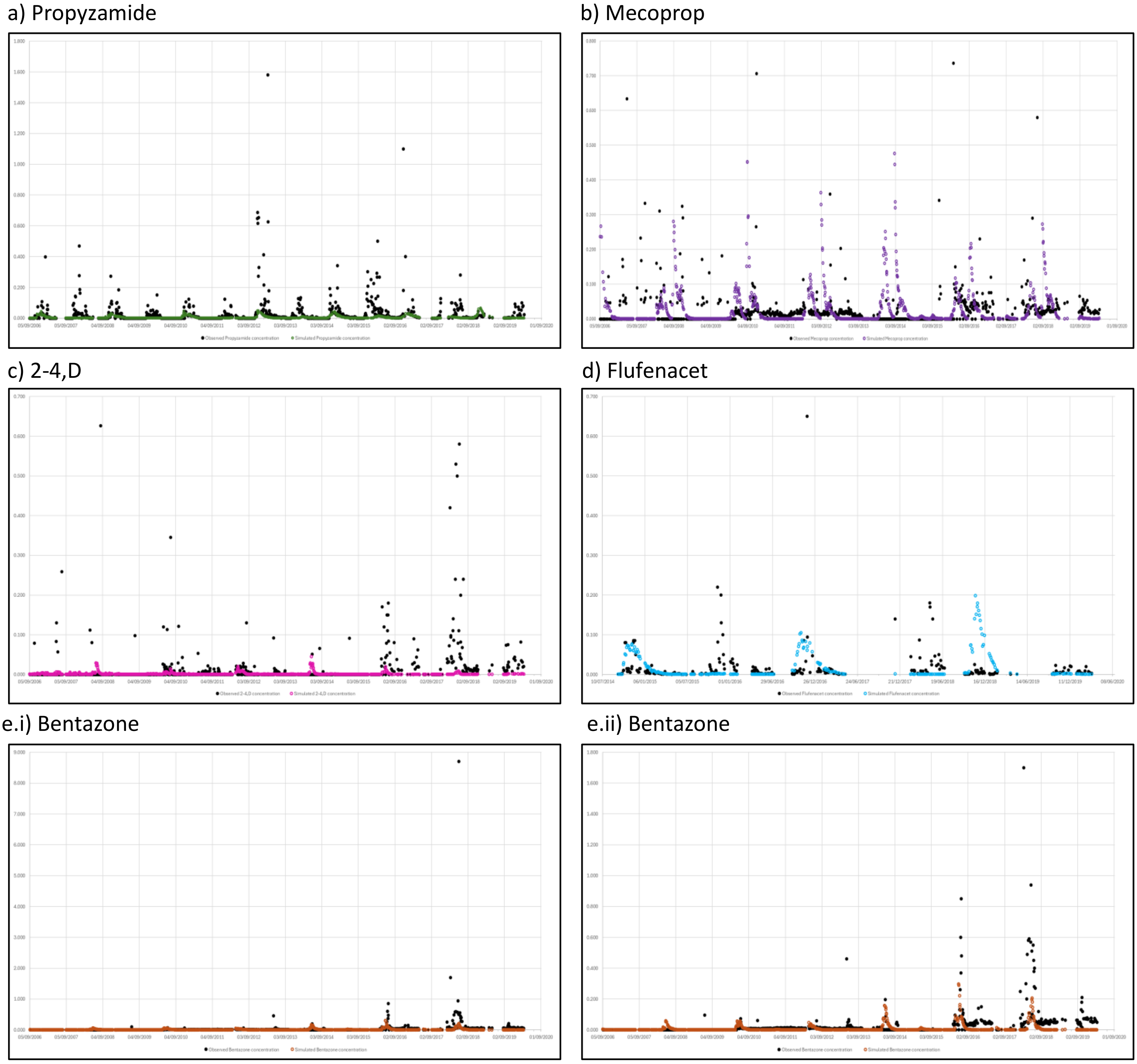



*Figure 11. The measured and simulated concentrations (µg/l) of all pesticides investigated in the Wensum catchment. e.i and e.ii both show the results for bentazone but with a reduction in the range of the y-axis.*

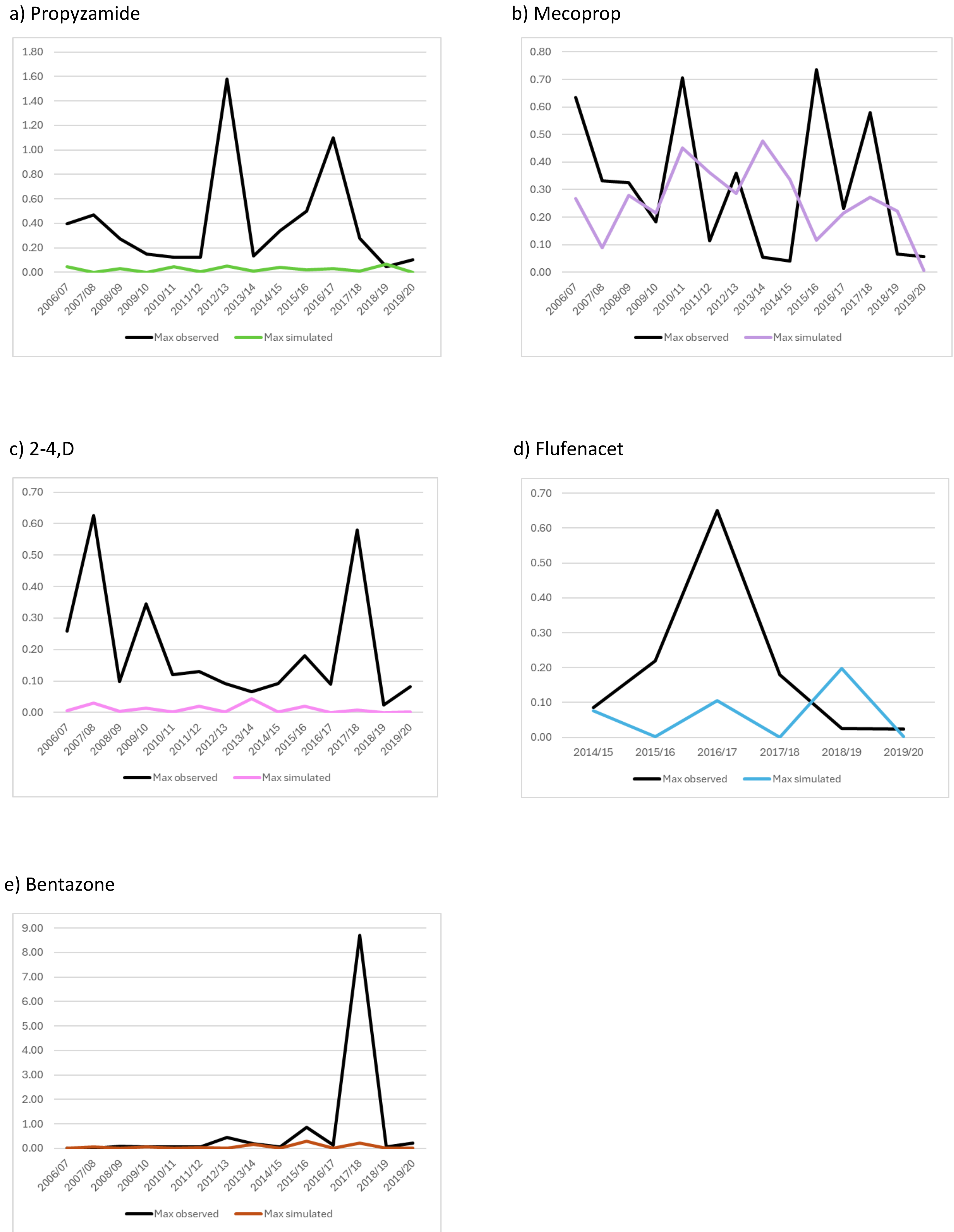
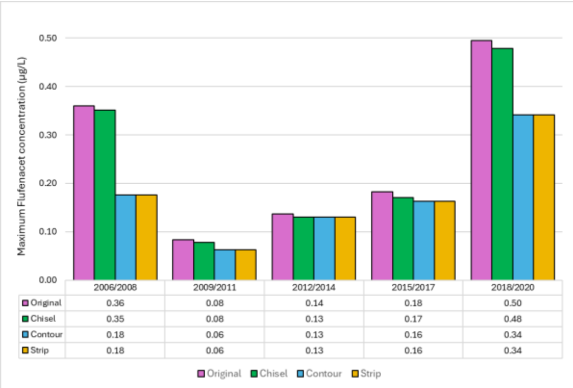



*Figure 12. Graphs to demonstrate the trends between the maximum concentration of from the observed and simulated data in the Wensum catchment.*

## 4.4 MANAGEMENT PRACTICES

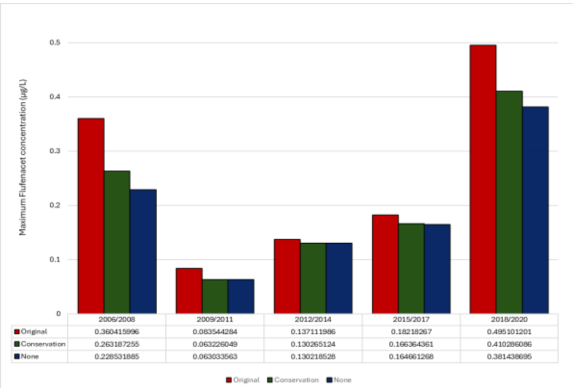
Changes to management practices in SWAT did show decreases in maximum modelled pesticide concentrations. The largest decreases were from Contour and Strip cropping strategies, however all changes from the originally modelled practices decreased the maximum concentration of flufenacet in the Wensum catchment.




| Years | Chisel | Contour | Strip |
|---|---|---|---|
| 2006/2008 | -3% | -51% | -51% |
| 2009/2011 | -7% | -26% | -26% |
| 2012/2014 | -5% | -5% | -5% |
| 2015/2017 | -6% | -10% | -10% |
| 2018/2020 | -3% | -31% | -31% |

*Figure 13. A graph to show the impact of 3 different cropping strategies on the maximum flufenacet concentration over groups of years. The table to the right shoes the percentage change in the maximum flufenacet concentration compared to the original model.*

The simulated maximum concentration of flufenacet found in the Wensum Catchment reduced across all the year groups due to new cropping practices. The largest decreases occurred in the contour and strip cropping practices with a 51% decrease in the maximum simulated concentration in 2006/2008.




| Years | Conservation | None |
|---|---|---|
| 2006/2008 | -27% | -37% |
| 2009/2011 | -24% | -25% |
| 2012/2014 | -5% | -5% |
| 2015/2017 | -9% | -10% |
| 2018/2020 | -17% | -23% |

*Figure 14. A graph to show the impact of different tillage strategies on the maximum flufenacet concentration over groups of years. The table to the right shoes the percentage change in the maximum flufenacet concentration compared to the original model.*

Similarly with changes to tillage practices there were reductions in the maximum simulated flufenacet concentration in Wensum, however these reductions were smaller with a maximum reduction of 37% with no tillage practices for 2006/2008.

# 5 DISCUSSION

Catchment Sensitive farming aligns with the goals of the EU Water Framework Directive (WFD) which has been running for over 20 years. However, despite seeing improvements in concentrations of sewage due to improvements to wastewater treatment, agricultural pollution indicators have had limited change and even a deterioration in water quality (Cooper and Hiscock, 2023). Therefore, it may have been unlikely for these models to observe any tractable differences by showing a downwards trends over out time periods. However, the observed discrepancies between simulated and measured pesticide concentrations in our study ruled out a reliable assessment of Catchment Sensitive Farming's impact on river pollution in Ancholme and Wensum. While SWAT has previously been used for pesticide transport modelling (Bannwarth et al., 2014), its application in accurately predicting pesticide loads in rivers has faced significant challenges. Previous research has reported substantial discrepancies between simulated and observed concentrations, with estimates often orders of magnitude higher or lower than actual values (Parker et al., 2007). Also, these models have previously been found to underestimate peaks in load (Noori et al., 2020), while other studies have been found to overpredict the load of river contaminants (Green and Van Griensven, 2008). This highlights the limitations of current SWAT implementations in capturing the complex processes of pesticide fate in agricultural landscapes.

Given that SWAT primarily relies on physicochemical properties of pesticides to simulate their transport (Bannwarth et al., 2014), future studies should prioritise refining and calibrating these model parameters. The physicochemical properties of the pesticides are core to how the pesticides partition and persist in the environment. For example, the soil adsorption coefficient (Koc) and the pesticide half-life in soil (DT50) may particularly influential. Koc impacts it mobility in soil meaning higher Koc values causes more pesticide to be retained in soils and less is available to run off while DT50 (half-life) determines how quickly the pesticide degrades. For example, overestimation of half-life could cause the model to simulate presences of pesticides would have already broken down. Calibrating the properties to field measurement in specific soils and climates may improve simulations. Previous studies after calibrating streamflow have calibrated pesticide properties, including the Koc and Half-life (Arnold et al., 2012), with the Koc value in particular being noted to have large impacts on the accumulated pesticide loads (Bannwarth et al., 2014). Also inclusion of more detailed information on pesticide degradation pathways, soil-pesticide interactions, and the influence of environmental factors such as temperature and soil moisture on pesticide mobility may improve model performance.

A limitation in this current model is the use of regional pesticide usage data (FERA) being placed at the scale of the hydrological response units likely introduced inaccuracies into the model. This is because regional data, after being scaled down to our catchments may not have accurately reflected the specific application rates and patterns within each unit across the catchment. Also applying uniform rates and timings across each HRU may have altered the spatial and temporal variability of when and were pesticides were applied. If sensitive areas of the model received a chemical where in reality they did not, the model will have over-predicted loads, occasionally seen in our results. Also, any hotspots of heavy use will have been diluted, causing underprediction of peaks. As a result, due to the course input data the model may have struggled to accurately simulate observed pesticide concentrations and detect fine-scale patterns. Future work using the model would be to integrate higher-resolution spatial data on pesticide application practices which could enhance the model's accuracy and predictive capabilities. The pesticide application rates, and pesticide loads should also be calibrated and validated as large changes in these values have been noted in previous attempts to calibrate them (Bannwarth et al., 2014). However, the models did demonstrate a good capacity to predict the timing of contamination events well, even some captured peaks in concentrations. The fidelity in timing indicates that the simulations of transport processes was more successful.

For hydrological response units (HRUs) in this study there were defined with a high spatial resolution, to reflect the different combinations of land-use slopes and soil types. However CSF engaging individual farmers, using actual field land parcels as modeling units my be deemed more meaningful for linking the model outputs to CSF actions (Kalcic et al., 2015). This resolution may improve the model’s future relevance to on-ground practices. However this would introduce complexity as the introduction of smaller HRUs may increase parameter uncertainty and variability in outputs.

The changes to different cropping and tillage practices in the model showed some large changes in the maximum concentration of flufenacet simulated by the model. Contour cropping and strip cropping showed the largest reductions but the differences between strip and contour cropping themselves was indistinguishable. Both these management practice have been noted as powerful strategies in improving soil health and mitigating erosion by reducing erosion by up to 60%, which will reduce the amount of runoff by pesticides (Choudhary et al., 2024). Similarly conservation tillage and no tillage operations saw large reductions in the maximum flufenacet concentration simulated. This has been noted in previous work with no increased benefits being seen between no-till management and conservation tillage and that other strategies such as vegetative buffer strips may be more effective (Elias et al., 2018).

These changes will have occurred directly due to the changes made to the parameters, particularly the Curve Numbers and the USLE-P factor. Lowering the Curve Number for contour cropping represents larger surface storage and the USLE-P represented less erosion. These changes will have reduced runoff, even for soluble and mobile pesticides, and particularly for Flufenacet which adsorbs to soil. Here I focussed on the reductions to peak concentrations of pesticides which is a particularly for ecotoxicological risk and regulatory standards (such as the EU drinking water limit of 0.1 µg/L) (Environment Agency, 2019).

Future work can consider other management changes such as the widely explored management change of the introduction of vegetative filter strips on field boundaries of fields by utilising the buffer width function, which has previously shown significantly impact runoff in the model (Lerch et al., 2017). These strips reduce non-point source pollution, by allowing vegetation to remove sediments, nutrients, and pesticides from runoff (Zhang et al., 2010). Vegetative filter strips can be defined in SWAT and these will reduce the amount of pesticides seen in run-off, but the actual value of surface run-off remains the same (Elçi, 2017). SWAT has previously been used to model the impacts of these strips, with field-scale modelling results showing how filter strips can be the most effective method of preventing pollutants reaching river systems when compared to other strategies in a calibrated model (Merriman et al., 2018).

When provided with reliable data a calibrated and validated SWAT model is considered a good tool to assess the impacts of management operations in catchments (Noori et al., 2020). HRUs in the future can be defined by real field boundaries and would aid in targeting future conservation practices at the field level, this would extend the applications of SWAT for communication to participants who may want to see how inputs and outputs correspond to fields (Kalcic et al., 2015). Furthermore, incorporating observed data on pesticide concentrations in various environmental compartments, such as soil, groundwater, and surface water, can significantly improve model calibration and validation. This continuing process of model refinement and validation is crucial for developing more robust and reliable tools for assessing the effectiveness of agricultural best management practices, such as CSF, in mitigating pesticide pollution in rivers.

With the increasing trend in the use of models to inform government decisions on diffuse pollution and management of preventative measures, catchment scale modelling can help target high risk pollution events and targeted mitigation (Collins et al., 2007). Ongoing monitoring of priority catchments will allow us to continue to quantify changes in water quality and growing our understanding of the spatial variability within catchments will provide invaluable data for these hydrological models as we continue to appreciate the many factors that influence them.

## 5.1 CONCLUSION

In conclusion, this research highlights both the potential and the challenges of modelling pesticide pollution in agricultural catchments in SWAT. When carefully calibrated and validated, it could serve as an effective tool in evaluating impacts from programs like CSF and simulate the effects of land management practices. However, here we have not been able to make conclusions on the impacts of the CSF scheme we have demonstrated its capacity to simulate pesticide movements in catchments and the impact of different landscape properties. Future studies would benefit for more fine scale data and further parameter calibrations across the model, including detailed pesticide usage data and calibration of pesticide properties. Incorporating these improvements would enhance the model’s ability to accurately quantify the benefits of programs like CSF and impacts of best management practices. By refining models and continuously comparing them against observations, we may be able to begin to discern real changes in water quality and attribute them to specific interventions from CSF by disentangling them from variables such as annual climatic conditions. This highlights the value of ongoing monitoring and modelling. Continued use of catchment scale models could help identify high risk areas (such as CSAs) and time periods for interventions. Continued long-term monitoring of priority catchments and continued refinement of models like SWAT will create reliable tools to track and predict river pollution which is critical for achieving the goals of frameworks like the WFD, as well as for protecting water resources during continually changing climates and land use pressures.

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# APPENDIX

## *appendix 1:*

*Table 5. The estimated rotations of crops in the Wensum catchment*

| SUBBASIN | AREA | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | 4483 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 24 | 3963 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 1 | 3526 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | |
| 3 | 2717 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | | WINTER CEREALS | WINTER CEREALS |
| 8 | 2065 | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY |
| 9 | 2064 | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY |
| 12 | 1875 | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE |
| 10 | 1694 | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE |
| 18 | 1645 | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET |
| 15 | 1625 | | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET |
| 4 | 1523 | SUGAR BEET | BARE FALLOW | BARE FALLOW | BARE FALLOW | | | | | | | | SUGAR BEET | | WINTER CEREALS | WINTER CEREALS | BARE FALLOW |
| 23 | 1391 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | | | | | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | | BARE FALLOW |
| 6 | 1215 | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS |
| 20 | 1198 | BARE FALLOW | | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | WINTER CEREALS |
| 16 | 1138 | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS |
| 19 | 1107 | FIELD BEANS | BARE FALLOW | BARE FALLOW | WINTER CEREALS | FIELD BEANS | FIELD BEANS | WINTER CEREALS | | SPRING BARLEY | | WINTER OILSEED RAPE | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | SPRING BARLEY |
| 2 | 999 | | | | SPRING BARLEY | SPRING BARLEY | | SPRING BARLEY | | SPRING BARLEY | SPRING BARLEY | | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY |
| 11 | 984 | | | | | SPRING BARLEY | | | | SPRING BARLEY | | | | SPRING BARLEY | SPRING BARLEY | | SPRING BARLEY |
| 21 | 982 | SUGAR BEET | FIELD BEANS | VEGATABLES AND SALAD | | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE |
| 13 | 814 | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES |
| 7 | 545 | VEGATABLES AND SALAD | VEGATABLES AND SALAD | | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD |
| 5 | 332 | VEGATABLES AND SALAD | VEGATABLES AND SALAD | BARE FALLOW | WINTER OILSEED RAPE | BARE FALLOW | WINTER CEREALS | WINTER OILSEED RAPE | | BARE FALLOW | | BARE FALLOW | | | WINTER CEREALS | VEGATABLES AND SALAD | VEGATABLES AND SALAD |
| 17 | 99 | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | POTATOES | POTATOES | POTATOES | WINTER CEREALS | BLACKCURRANTS |
| 14 | 76 | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS |
| 25 | 31 | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS | BLACKCURRANTS |

## *appendix 2:*

*Table 6. The estimated rotations of crops in the Ancholme catchment*

| SUBBASIN | AREA | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | 2904.99 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 22 | 1926.60 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | | WINTER CEREALS |
| 12 | 1886.30 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 20 | 1869.10 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 8 | 1730.87 | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 4 | 1506.33 | WINTER CEREALS | SPRING BARLEY | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS | WINTER CEREALS |
| 21 | 1393.28 | | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY |
| 25 | 1326.05 | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | | SPRING BARLEY | WINTER OILSEED RAPE |
| 16 | 1155.00 | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET | SUGAR BEET |
| 17 | 1083.59 | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER CEREALS | |
| 19 | 1078.38 | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | |
| 1 | 997.44 | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE | WINTER OILSEED RAPE |
| 11 | 992.47 | WINTER OILSEED RAPE | | | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS | FIELD BEANS |
| 10 | 973.11 | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY |
| 13 | 971.03 | SPRING BARLEY | BARE FALLOW | | BARE FALLOW | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY | SPRING BARLEY |
| 14 | 863.12 | BARE FALLOW | BARE FALLOW | BARE FALLOW | | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW | BARE FALLOW |
| 24 | 814.73 | FIELD BEANS | FIELD BEANS | FIELD BEANS | | SPRING BARLEY | | | WINTER OILSEED RAPE | WINTER OILSEED RAPE | |
| 23 | 747.14 | POTATOES | POTATOES | POTATOES | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD |
| 2 | 593.88 | VEGATABLES AND SALAD | VEGATABLES AND SALAD | VEGATABLES AND SALAD | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES | POTATOES |