PUBLIC UNIVERSITY OF NAVARRE (UPNA)
Department of Engineering

DOCTORAL THESIS

Effects of Agricultural Activities on Water Quality:
Catchment-Scale Modeling of Nutrient Pollution and Management in Cultivated Lands, Case Studies of Northern Spain and Southeastern Sweden

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Dedication

This dissertation is dedicated to my late uncle, Dr. Wilfred Ongaro, whose unwavering encouragement ignited the flames of curiosity and guided me toward the path of knowledge. His belief in my potential continues to inspire and guide me as I pursue the realms of education that he so passionately advocated. Though no longer with us, his spirit lives on as a guiding light, illuminating every step of my academic journey. This work is a testament to the seeds of inspiration he nurtured within me, and I will be eternally grateful for his guidance and love.
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Abstract

The intensification of agriculture to meet the increasing food demands and changing climate dynamics necessitates sustainable land and water resource management. This doctoral thesis examines the complex interaction between agricultural activities and water quality by exploring two agricultural-dominated watersheds in northern Spain and southeastern Sweden using the Soil Water Assessment Tool (SWAT) model. The research focuses on (i) evaluating the SWAT model’s applicability in the study areas, (ii) assessing the effects of changing from rainfed to irrigated agriculture, (iii) understanding the effects of climate change on water quantity and quality, and (iv) quantifying the efficacy of agricultural best management practices (BMPs) in minimizing nutrient export.

The transition from rainfed to irrigated agriculture in the Cidacos River watershed (480 km²) in northern Spain increased annual streamflow, nitrate load, and concentration, as well as alterations in seasonal patterns due to increased irrigation and fertilization aimed at enhancing agricultural productivity. The climate change projection analysis for this watershed showed a projected decline in streamflow and nitrates load, particularly in the long-term (2071-2100) projection scenario of RCP8.5. Comparatively, the projected decline in autumn and winter was greater than in spring and summer. These changes were attributed to the projected decreasing precipitation coupled with increasing temperatures affecting streamflow and, subsequently, the nitrate load. In Catchment C6 (33 km²) of southeastern Sweden, filter strips and sedimentation ponds emerged to be the most effective in reducing sediment and phosphorous exports, providing valuable insights for sustainable land management practices that might contribute to the preservation and revitalization of aquatic ecosystems in this region.

Overall, this dissertation emphasizes the crucial need for a comprehensive grasp of agricultural impacts on water quality. The research not only elucidates the complicated dynamics of agricultural activities and water quality by utilizing advanced hydrological modeling approaches but also provides stakeholders with practical tools to guide informed decision-making. The findings of this research provide a transformative approach toward protecting water quality, nurturing resilient ecosystems, and promoting sustainable agricultural practices in diverse geographical contexts.

Keywords: agriculture; best management practices; climate change; irrigation; nutrient pollution; SWAT model; water quality
Resumen (Abstract in Spanish)

La intensificación de la agricultura para satisfacer la creciente demanda de alimentos y la dinámica climática cambiante requiere una gestión sostenible de los recursos de la tierra y el agua. Esta tesis doctoral examina la compleja interacción entre las actividades agrícolas y la calidad del agua mediante la exploración de dos cuencas hidrográficas dominadas por la agricultura en el norte de España y el sureste de Suecia utilizando el modelo Soil Water Assessment Tool (SWAT). La investigación se centra en (i) evaluar la aplicabilidad del modelo SWAT en las áreas de estudio, (ii) evaluar los efectos del cambio de agricultura de secano a agricultura de regadío, (iii) comprender los efectos del cambio climático en la cantidad y calidad del agua, y (iv) cuantificar la eficacia de las mejores prácticas de manejo agrícola (BMP) para minimizar la exportación de nutrientes.

La transición de la agricultura de secano a la de regadío en la cuenca del río Cidacos (480 km²), en el norte de España, dio lugar a un aumento del caudal anual, de la carga de nitratos y de su concentración, así como a alteraciones en los patrones estacionales debido al aumento del riego y de la fertilización destinados a mejorar la productividad agrícola. El análisis de proyección de cambio climático para esta cuenca indicó una disminución proyectada en el flujo de agua y la carga de nitratos, particularmente en el escenario de proyección a largo plazo (2071-2100) de RCP8.5. Comparativamente, la disminución proyectada en otoño e invierno fue mayor que en primavera y verano. Estos cambios se atribuyeron a la disminución prevista de las precipitaciones, unida al aumento de las temperaturas, que afectaron al caudal de los arroyos y, por consiguiente, a la carga de nitratos. En la cuenca C6 (33 km²) del sudeste de Suecia, las franjas filtración y los estanques de sedimentación resultaron ser los más eficaces para reducir las exportaciones de sedimentos y fósforo, proporcionando información valiosa para las prácticas de gestión sostenible de la tierra que podrían contribuir a la preservación y revitalización de los ecosistemas acuáticos en esta región.

En general, esta tesis enfatiza la necesidad de obtener una comprensión integral de los impactos agrícolas en la calidad del agua. La investigación no solo esclarece la complicada dinámica que se establece entre las actividades agrícolas y la calidad del agua mediante el uso de modelización hidrológica avanzada, sino que también brinda a los agentes interesados herramientas prácticas para guiar la toma de decisiones informadas. Los hallazgos de esta investigación brindan un enfoque transformador hacia la protección...
de la calidad del agua, el fomento de ecosistemas resilientes y la promoción de prácticas agrícolas sostenibles en diversos contextos geográficos.

**Palabras clave:** agricultura; mejores prácticas de gestión; cambio climático; agricultura de regadío; contaminación por nutrientes; modelo SWAT; calidad del agua
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List of Abbreviations

95PPU 95 Percent Prediction Uncertainty
AAT All-At-a-Time
AEMET State Meteorological Agency of the Government of Spain
AdapteCCa Platform on Adaptation to Climate Change
ANLeC Average Nutrient Leaching Calculator
AnnAGNPS Annualized Agricultural Non-Point Source
BMP Best Management Practice
CAP Common Agricultural Policy
CHE Confederación Hidrográfica del Ebro (Ebro River Basin Authority)
CIMP Coupled Model Intercomparison Project
DDRMAAL Departamento de Desarrollo Rural, Medio Ambiente y Administración Local (Department of Rural Development, Environment and Local Administration)
DEM Digital Elevation Map
EU European Union
EEA European Environment Agency
EPRS European Parliamentary Research Service
ETRS European Terrestrial Reference System
FAO Food and Agricultural Organization
GAN-NIK Environmental Management of Navarra
GCM Global Climate Model
GHG Greenhouse Gas
GLUE Generalized Likelihood Uncertainty Estimation
HELCOM Helsinki Commission
HRU Hydrological Response Unit
IDENA Spatial Data Infrastructure of Navarre
INTIA Navarre Institute of Agri-Food Technologies and Infrastructures
IPCC Intergovernmental Panel on Climate Change
IUSS International Union of Soil Sciences
LULC Land Use Land Cover
<table>
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<tr>
<th>Verb</th>
<th>Description</th>
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<tr>
<td>MAPA</td>
<td>Ministerio de Agricultura, Pesca y Alimentación (Ministry of Ministry of Agriculture, Fisheries and Food)</td>
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<tr>
<td>MCMC</td>
<td>Markov Chain Monte Carlo</td>
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<tr>
<td>MUSLE</td>
<td>Modified Universal Soil Loss Equation</td>
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<tr>
<td>N</td>
<td>Nitrogen</td>
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<td>ND</td>
<td>Nitrate Directive</td>
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<td>NH₃</td>
<td>Ammonia</td>
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<tr>
<td>NLeCCS</td>
<td>Nutrient Leaching Coefficient Calculation System</td>
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<td>NO₃</td>
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<td>NOₓ</td>
<td>Nitrogen oxides</td>
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<td>NSE</td>
<td>Nash-Sutcliffe Efficiency</td>
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<tr>
<td>OAT</td>
<td>One-At-a-Time</td>
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<tr>
<td>OECD</td>
<td>Organization for Economic Co-operation and Development</td>
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<tr>
<td>P</td>
<td>Phosphorus</td>
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<tr>
<td>ParaSol</td>
<td>Parameter Solution</td>
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<tr>
<td>PBIAS</td>
<td>Percent Bias</td>
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<tr>
<td>PSO</td>
<td>Particle Swarm Optimization</td>
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<tr>
<td>R²</td>
<td>Coefficient of Determination</td>
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<td>Representative Concentration Pathway</td>
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<td>SMED</td>
<td>Swedish Environmental Emissions Data</td>
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<td>Swedish Meteorological and Hydrological Institute</td>
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<td>SNLS</td>
<td>Swedish National Land Survey</td>
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<td>Soluble P</td>
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<td>SUFI-2</td>
<td>Sequential Uncertainty Fitting, version 2</td>
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<td>SWAT</td>
<td>Soil and Water Assessment Tool</td>
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<td>SWAT-CUP</td>
<td>Soil Water Assessment Tool Calibration and Uncertainty Procedures</td>
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<tr>
<td>SWEDAC</td>
<td>Swedish Board for Accreditation and Conformity Assessment</td>
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SWEREF99  Swedish Reference Frame 1999
THERRAE  Teledetección, Hidrología, Erosión, Riegos y Análisis Estructural
         (Remote Sensing, Hydrology, Erosion, Irrigation and Structural Analysis)
TN       Total nitrogen
Total P   Total phosphorus
UNEP     United Nations Environment Programme
USDA-ARS United States Department of Agriculture's Agricultural Research Service
USLE     Universal Soil Loss Equation
UTM      Universal Transverse Mercator
WFD      Water Framework Directive
WHO      World Health Organization
WRB      World Reference Base for Soil Resources
Chapter 1:

1 General Introduction and Objectives
1.1 Background information

1.1.1 Introduction

The current agricultural practices globally have been intensified to boost crop yields and livestock production to meet increasing food demand. Unfortunately, this intensification has resulted in widespread water quality challenges. Agricultural activities significantly impact water quality, adversely affecting the environment (Sutton et al., 2011) and, in some cases, human health (WHO, 2017). The transport of fertilizers, pesticides, agrochemicals, animal waste, and soil erosion from these activities contribute substantially to pollution in surface and groundwater sources. When excess nutrients such as nitrogen (N) and phosphorus (P) enter water bodies, they cause eutrophication. Eutrophication is a process through which excessive plant and algae growth occurs. It disrupts aquatic ecosystems by depleting oxygen levels and causing harmful algal blooms (Dodds and Smith, 2016; Le Moal et al., 2019). These changes reverberate through the food chain, endangering aquatic biodiversity and ecosystem stability (Carpenter et al., 1998).

The water quality challenges from agricultural activities in Europe mirror those experienced globally, with elevated nutrient pollution potential due to agricultural intensification. The European Environment Agency (EEA) (2021) reports that agriculture is the primary source of nitrogen and phosphorus inputs to Europe’s surface waters. This has resulted in Europe’s water bodies facing eutrophication threats with negative ecological consequences. The persistent water quality challenge across several European Union (EU) member states has resulted in the search for sustainable agricultural practices under the Common Agricultural Policy (CAP) (Boezeman et al., 2020). Integrating agricultural practices that minimize nutrient export and optimize their use is critical for protecting water resources and ecosystem health.

At the regional level, countries face contrasting nutrient pollution challenges. In Spain, for instance, water quality issues from agricultural practices are exacerbated by the Mediterranean climate, characterized by water scarcity. Irrigation remains an integral aspect of crop production in this region; however, it has been reported to increase nutrient leaching and pollution in water bodies (Merchán et al., 2020). The Ebro River basin is an important agricultural area grappling with high nutrient levels, threatening the aquatic ecosystems and water supply (Isidoro and Aragüés, 2007; Ladrera et al., 2019). In more
humid countries such as Sweden, excessive nutrient enrichment has resulted in widespread hypoxia, endangering biodiversity and commercial fishing in the Baltic Sea (Conley et al., 2011). Therefore, to develop effective mitigation strategies, it’s imperative to understand the dynamics of nutrient pollution in the different regions and their associated challenges.

Similarly, climate change presents a serious challenge to water resources, necessitating the development of sustainable adaptation, mitigation, and policy intervention strategies (Krysanova et al., 2017). However, the specific impacts of climate change on water quality and its interactions with agricultural activities vary across geographical regions. Therefore, understanding the complex interplay between agricultural activities, climate change, and water quality is essential in achieving the standards outlined by regulations such as the European Water Framework Directive (European Communities, 2000). The Mediterranean region, for instance, faces a unique confluence of vulnerabilities, including geographical, climatic, and socio-economic factors, making it a focal point for climate change case studies (Vargas-Amelin and Pindado, 2014).

Agricultural best management practices (BMPs) play a pivotal role in tackling the water quality challenges associated with intensified agricultural activities. BMPs are a set of conservation practices and techniques designed to minimize the negative impacts of agriculture on water quality and the environment (Jain and Singh, 2019). They are an important component of a comprehensive strategy to protect water resources and sustain ecosystem wellbeing in the face of increasing food demand and changing environmental conditions. The adoption of BMPs not only helps protect surface and groundwater sources but also promotes sustainable agricultural practices, which are in line with Europe’s agricultural policy goals (Boezeman et al., 2020).

Moreover, mathematical and hydrological models serve as valuable tools to comprehend, evaluate, and predict the impacts of agricultural activities on water quality. These models offer a quantitative framework for understanding the complex interactions between various factors affecting water quality, such as land use, soil, climate, and hydrology. Mathematical models aid in simulating and predicting nutrient transport and management within ecosystems, which would otherwise be challenging if done experimentally due to time and resource constraints (Moges et al., 2021; Yu, 2015).
One such model used extensively in this research to assess the effects of agricultural activities on water quality is the Soil and Water Assessment Tool (SWAT) model. The SWAT model is a widely recognized hydrological model developed to simulate the impact of land management practices on water quality (Neitsch et al., 2011). The model takes into account various factors, such as soil properties, land use, climate data, agricultural management, and hydrological processes, to predict nutrient and sediment transport in watersheds. SWAT has been successfully applied in diverse geographical regions and has proven to be a valuable tool for quantifying streamflow, sediment, and nutrient export, studying climate change impacts, analyzing BMPs, and identifying vulnerable areas (Arnold et al., 2012; Neitsch et al., 2011). The SWAT model was chosen for this study due to its robustness in integrating hydrological cycle and water quality components, high spatial-temporal resolution, and ability to analyze different scenarios of interest. By integrating the insights gained from applying the SWAT model with on-the-ground agricultural practices, this research aims to provide a comprehensive understanding of the challenges posed by agricultural activities to water quality, focusing on the unique circumstances in cultivated areas of Spain and Sweden.

1.1.2 Nutrient pollution from agricultural areas

The intensification of agriculture has enhanced food production for the ever-increasing global population by utilizing modern technologies such as irrigation, farm machinery, and increased agricultural inputs, such as fertilizer and pesticides (Mateo-Sagasta et al., 2017; OECD, 2012). However, the inefficiency of these inputs, coupled with the continued expansion of agricultural areas, has resulted in increased pollutant export, soil degradation, deforestation, and many other environmental changes. According to Leip et al. (2011), only 60% of the nitrogen applied to agricultural lands is taken up by plants, with the rest being exported to water as nitrates (NO₃⁻) or emitted to the air as nitrogen oxides (NOₓ) or ammonia (NH₃). These nutrient pollutants, particularly nitrogen and phosphorus, can cause eutrophication, thereby deteriorating water quality when conveyed into water bodies through runoff. Table 1.1 provides an overview of the key agricultural pollutants, their sources, and their challenges to the receiving water bodies.
Table 1.1: Sources of agricultural water pollution (Source: Adapted from OECD (2012))

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Agricultural activities that contribute to the pollutant</th>
<th>Main pollutant-related water quality issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nutrients (N and P)</td>
<td>Agricultural production (runoff of excess nutrients, e.g., N and P from fertilizers into water bodies)</td>
<td>Causes eutrophication, which is harmful to aquatic life and human health</td>
</tr>
<tr>
<td>Sediments</td>
<td>Ineffective soil conservation practices</td>
<td>Harmful to aquatic life and water transport system due to turbidity of water</td>
</tr>
<tr>
<td>Organic matter</td>
<td>Manure application</td>
<td>Harmful to aquatic life through deoxygenation of water</td>
</tr>
<tr>
<td>Toxic contaminants</td>
<td>Application of sewage sludge on agricultural lands (heavy metals) and plant protection (pesticides)</td>
<td>Harmful to aquatic life and human health</td>
</tr>
<tr>
<td>Acid substances</td>
<td>Livestock production (ammonia volatilization)</td>
<td>Harmful to aquatic life through the acidification of water</td>
</tr>
<tr>
<td>Biological contaminants</td>
<td>Fecal sludge discharge from livestock into water</td>
<td>Pathogens, bacteria, and viruses contaminate water</td>
</tr>
<tr>
<td>Mineral salts</td>
<td>Ineffective land use practices (clearing of perennial vegetation and irrigation practices)</td>
<td>Results of salinization through activities such as irrigation</td>
</tr>
</tbody>
</table>

While agriculture is a primary contributor to the deterioration of water quality, other sources, such as natural, urban, and industrial pollution, also significantly contribute to water pollution (Farzin and Grogan, 2008; Wittmer et al., 2011). Achieving zero pollution from agricultural areas is technically impossible; however, the main challenge lies in improving production while minimizing nutrient export from cultivated lands, which can affect water quality (Galloway et al., 2008). The naturally-induced nitrogen and phosphorus loss (background/natural loss) is typically minimal compared to human-induced losses, and it's estimated at 1-2 kg ha\(^{-1}\) for nitrogen and about 0.1 kg ha\(^{-1}\) for phosphorus (Dubrovsky et al., 2010; EEA, 2005). These losses vary depending on underlying geological conditions and potential atmospheric depositions.
1.1.3 Trends of agricultural impacts on water quality

According to the European Environment Agency (EEA, 2022), nutrient concentration levels in the European environment have considerably declined over the past three decades, following a peak in the 1980s. This decline could be attributed to a drop in excessive mineral fertilization (Oger, 2022; Vigiak et al., 2023). However, these developments are insufficient to fully protect European aquatic and terrestrial ecosystems, as there are substantial regional disparities among the EU member states. Agriculture continues to be the primary source of pollution in surface and groundwater across most EU countries. About 25% of surface and groundwater stations across Europe have reported an increase in nitrate concentration between 2016 and 2019 (EEA, 2021). Some countries have reported over 50% of total nitrogen (TN) discharged into surface waters despite a general declining trend within the region. The European Environment Agency (EEA, 2020) has recommended reducing European nutrient runoff by at least 50% to address the existing challenge.

Agriculture consumes approximately 80% of the freshwater resources in the Mediterranean region, with irrigation being the primary consumer (Crovella et al., 2022; FAO, 2022). This intensive irrigation water use results in large nutrient export from agricultural areas into rivers, aquifers, and coastal zones. According to the Mediterranean Action Plan (UNEP, 2019), land-based activities such as agriculture contribute 80% of pollution to the Mediterranean Sea, creating eutrophication and endangering marine ecosystems. The agricultural water consumption in the region increased by 20% between 2000 and 2020, resulting in the over-extraction of groundwater, causing aquifers to be depleted faster than they can replenish (Duarte et al., 2021). Widespread soil erosion has been reported in the Mediterranean region, affecting an estimated 70% of agricultural land (EEA, 2021).

Over the last century, eutrophication has transformed the Baltic Sea from an oligotrophic clear-water sea into an eutrophic marine environment in the Baltic region. Approximately 75% of N load and 95% of P load is discharged into the sea directly from rivers and streams from the bordering countries (OECD, 2012). Agriculture contributes about 80% of the total diffuse load in Finland and Sweden (Helsinki Commission (HELCOM), 2009; Malmaeus and Karlsson, 2010). In Norway, agriculture contributes up to 60% of N and 45% of P loadings released in the coastal areas of the North Sea (OECD, 2012).
1.2 Problem Statement

The dynamic relationship between agricultural activities and water quality has been at the forefront of the environmental discourse, underscoring the complex interplay between human sustenance and ecosystem sustainability. In the nexus of this intricate balance, nutrient pollution from agricultural activities emerges as a formidable challenge, a subtle yet potent force that threatens the equilibrium in catchments and the vitality of ecosystems. Caught within this intricate web are not only the ecosystems that rely on clean and healthy water but also the communities that depend on these ecosystems for their livelihoods and well-being. The traditional approach of separating agricultural development and environmental conservation no longer works well to tackle these evolving challenges. In this context, catchment-scale modeling emerges as a beacon of insight, involving a multidisciplinary endeavor that combines science, technology, and policy to unravel the complexities of nutrient pollution, project its effects, and chart a path toward sustainable land use and water resource management.

This research attempts to analyze these complex interactions between agricultural activities and water resources to obtain sustainable solutions. An in-depth assessment of the environmental consequences of agricultural activities and their resultant pollution is imperative to formulating effective strategies and interventions to control and manage the pollutants. However, investigating the effects of agriculture on water quality is a complex phenomenon due to the diversity and extent of the processes and factors involved, as well as the lack of proper know-how of their relevance and measures of controlling such processes. Non-point source pollution exhibits extensive spatial and temporal variations in their occurrence, and thus, it is quite challenging to identify their sources. These pollutants are highly unpredictable due to variations in climate, land use, soil types, and other environmental factors. The complexity of the non-point source pollution pathways and contamination is not well known as it extends far beyond its sources into the ecosystem, impacting social and economic livelihoods. Central to addressing this challenge is the ability to identify the effects of these pollutions and then translate these insights into appropriate actions for mitigation. This thesis is a compilation of the research findings from exploring some of these challenges, and it proposes solutions to mitigate environmental degradation and foster a harmonious coexistence between human endeavors and the ecosystems of the Mediterranean and Baltic regions. The research
transcends the domains of data assimilation, predictive modeling, and scenario analysis to craft a narrative resulting in sustainable agricultural and water resources development.

1.3 Justification

This research aimed to contribute and lay the foundations for sustainable agricultural activities, resulting in positive social and economic impacts. It provided valuable insights into the potential impacts of nutrient pollution and proposed control measures. It contributed to a better understanding of the intensity and reality of the problems and challenges of nutrient pollution by associating them with the different land uses, management practices, climatic conditions, and edaphic factors. The research identified tools for evaluating nutrient pollution and its control measures by generating management scenarios that minimize export. This information is valuable for policy and decision-makers in planning for the future and developing effective agricultural policies and strategies. The findings from this research could provide crucial information that would contribute to the implementation of the European Communities’ Nitrate Directive (ND, Directive 91/676/EEC) and the Water Framework Directive (WFD, Directive 2000/60/EC), both of which are primarily concerned with protecting water bodies from agricultural nutrient pollution. The outcomes from this research could influence the development of robust policies that benefit farmers by enhancing crop yields while mitigating the adverse effects of nutrient pollution. These findings could also be beneficial in guiding the promotion and adoption of sustainable agricultural practices.

1.4 Objectives

1.4.1 General objective

The general objective of this research was to analyze the effects of agricultural activities on water quality through modeling nutrient pollution and management in selected agricultural-dominated catchments in northern Spain and southeastern Sweden.

1.4.2 Specific objectives

The following specific objectives were formulated to address the general objective:

i) Assessing the SWAT model’s applicability for simulating streamflow and nitrate load in the Cidacos River watershed in northern Spain (Papers 1 and 2)

ii) Evaluating the impact of changing from rainfed to irrigated agriculture in the Cidacos River watershed in northern Spain (Paper 1)
iii) Analyzing the effects of climate change on streamflow and nitrate pollution in the Cidacos River watershed in northern Spain (Paper 2)

iv) Examining the SWAT model’s applicability for simulating streamflow, sediment load, and phosphorous load in a small agricultural catchment in southeastern Sweden (Paper 3)

v) Quantifying agricultural best management practices' impacts on sediment and phosphorous export in a small catchment in southeastern Sweden (Paper 3)

1.5 Research Questions

To comprehensively address the specific objectives of this research, the following research questions were explored:

i) How does the SWAT model perform in simulating streamflow and nitrate load in an agricultural watershed under rainfed conditions in the Mediterranean region, and what parameters greatly influence the model performance in this region?

ii) How has the transition from rainfed to irrigated agriculture affected the streamflow, nitrate load, and nitrate concentration in an agricultural watershed in the Mediterranean region?

iii) What are the projected streamflow and nitrate export changes in a Mediterranean agricultural watershed under different climate change scenarios?

iv) How well does the SWAT model simulate streamflow, sediment load, and phosphorus load in an agricultural catchment in southeastern Sweden, and what parameters influence the model performance in this region?

v) How do different agricultural best management practices (BMPs) affect sediment and phosphorus export in the southeastern Sweden catchment, and what are the most effective BMPs for reducing these pollutants?

1.6 Scope and limitations of the research

This research focused on analyzing nutrient export and management from agricultural areas within the Mediterranean environment of northern Spain (Cidacos River watershed) and the Baltic environment of southeastern Sweden (Catchment C6). These two watersheds were chosen because they represent the predominant agricultural activities in their respective regions and have comprehensive, long-term hydrological and water quality data suitable for model analysis. The SWAT model version 2012 was employed as the sole hydrological modeling tool to simulate and assess the impact of agricultural...
activities on water quality. The SWAT model was evaluated to ensure its suitability for each watershed through calibration and validation before its application.

This research was limited to hydrological modeling of nutrient export and management, specifically nitrate and phosphorous loads, with no field experiments. Instead, it analyzed the long-term time series data obtained from the various agencies that collect and store them. Only nitrate export was studied in the Spanish watershed, whereas sediment and phosphorus export were studied in the Swedish catchment. All model simulations were run under rain-fed conditions. For instance, analyses were done in the Cidacos River watershed until Olite station, which was unaffected by irrigation. The data from the irrigated region was only utilized to compare the transformation from rainfed to irrigated agriculture.

For the climate change application, the focus was on the moderate (RCP4.5) and extreme (RCP8.5) climate change scenarios, despite the Intergovernmental Panel on Climate Change (IPCC) having numerous climate change scenarios and projections. Due to the complexity of the climate simulation modeling and time constraints, only an ensemble of six climate models from the Coupled Model Intercomparison Project phase 5 (CMIP5) was utilized. The availability of downscaled climate change projections data for Spain and the Navarre region influenced the CMIP5 selection. Similarly, only four most pertinent agricultural best management practices (BMPs) were analyzed in the Swedish catchment, even though numerous BMPs exist. The criteria for their selection have been elaborated in Chapter 6, section 6.2.5.

1.7 Thesis structure

This doctoral thesis followed the following structure:

The first chapter introduces the thesis by outlining the research background and presenting the state-of-the-art on how agriculture affects water quality. This chapter also articulates the central research problem, elucidating the necessity for this research, enumerating the objectives, and specifying the scope and limitations of the research.

The second chapter provides an overview of the SWAT model, including a detailed explanation of its hydrology, sediment and nutrient simulation processes, and related equations. The chapter also expounds on using SWAT-CUP for sensitivity and uncertainty analyses, calibration and validation, and model performance evaluation.
The third chapter describes the two study areas in Spain and Sweden. This includes a detailed description of the catchment factors such as climate, soil type, land use, and agricultural practices. This chapter further delves into the data acquisition and processing for model integration.

The fourth chapter evaluates the application of the SWAT model to simulate the impact of changing from rainfed to irrigated agriculture in the Cidacos River watershed on streamflow, nitrate load, and concentration. This chapter examines the SWAT model’s applicability for estimating streamflow and nitrate load in this watershed. The analysis of the change from rainfed to irrigated agriculture is based on simulating the rainfed conditions (pre-irrigation) within the irrigated zone and comparing them to the measured observations during the irrigated period (post-irrigation).

The fifth chapter utilizes the SWAT model to investigate the long-term effects of climate change on streamflow and nitrate export in the Cidacos River watershed under rainfed conditions.

The sixth chapter applies the SWAT model to quantify the impacts of four agricultural best management practices on sediment and phosphorous export from a small catchment in southeastern Sweden. The SWAT model evaluation for streamflow, sediment, and phosphorous in the study area is presented in this chapter, followed by the BMP assessment.

The seventh chapter draws together the conclusions derived from each objective, culminating in an overall conclusion. The chapter also offers the thesis’s final remarks and recommends prospective research endeavors.
Chapter 2:

2 Description of the SWAT Model and SWAT-CUP
2.1 Overview of the SWAT model

The Soil and Water Assessment Tool (SWAT) model is a freely available open-source software developed by the United States Department of Agriculture's Agricultural Research Service (USDA-ARS). It assists water resources managers, policy experts, and decision-makers in predicting and quantifying the impact of land use management on water and diffuse pollution. The model can be applied to small watersheds (catchment scale) and large basins (regional, continental, or global scale) with varying soil types, land use, and management practices (Lévesque et al., 2008).

SWAT is a data-driven, semi-distributed, continuous timescale, physical, and process-based hydrological model that simulates water, sediment, and agricultural chemicals/pollutant yields. The model simulates various watershed processes, including but not limited to surface runoff, streamflow, percolation, erosion, nutrient and pesticide load/yield and transportation, irrigation, groundwater flow, reservoir storage, channel routing, field drainage, and plant water use. (Rostamian et al., 2008). The model consists of multiple components such as weather, hydrology, erosion/sediments, soil temperature and properties, plant growth, nutrients, pesticides, land management, and channel and reservoir routing. Collectively, these components represent the various aspects of the hydrologic cycle and the processes that influence water balance in the watershed.

The SWAT model operates on a daily time step and divides the watershed's hydrology into two phases: the land phase and the routing phase. The land phase controls the amount of water, sediments, pesticides, and nutrient loadings that enter the main channel in each sub-basin, whereas the routing phase controls the movement of water and sediment through the channel network of the watershed to the outlet (Arnold et al., 2012).

SWAT adopts a two-level disaggregation scheme in which a preliminary sub-basin identification is carried out based on topographic data (Digital Elevation Map, DEM), followed by further discretization by overlaying the DEM with the land use and soil maps to form the Hydrological Response Units (HRUs). The HRU refers to a unique homogeneous combination of similar land use/land cover, soil type, and topography (elevation/slope) characteristics (Neitsch et al., 2011). The model uses the HRUs to describe the spatial heterogeneity in the watershed and represent its basic computational unit, which is assumed to be homogeneous in hydrologic response to land cover changes. Figure 2.1 summarizes the SWAT model’s input and output datasets.
2.2 Hydrology simulation in the SWAT model

The hydrologic balance in the SWAT model is simulated for each HRU using the water balance equation, as shown in Equation (2.1) (Neitsch et al., 2011).

\[
SW_t = SW_0 + \sum_{i=1}^{t} \left[ R_{\text{day}} - Q_{\text{surf}} - ET_a - W_{\text{seep}} - Q_{\text{gw}} \right]
\]  \hspace{1cm} (2.1)

Where, \(SW_t\) represents the final soil water content (mm of H\(_2\)O), \(SW_0\) represents the initial soil water content on day \(i\) (mm H\(_2\)O), \(t\) represents the time (days), \(R_{\text{day}}\) represents the amount of precipitation on day \(i\) (mm H\(_2\)O), \(Q_{\text{surf}}\) represents the amount of surface runoff on day \(i\) (mm H\(_2\)O), \(ET_a\) represents the amount of evapotranspiration on day \(i\) (mm), \(W_{\text{seep}}\) represents the amount of water entering the vadose zone on day \(i\) (mm H\(_2\)O), and \(Q_{\text{gw}}\) represents the amount of return flow on day \(i\) (mm H\(_2\)O).

The model calculates the daily soil and water temperatures in the watershed using the maximum and minimum temperature inputs. Percolation in the model is computed using a layered storage routing technique paired with a crack flow model (Chaubey et al., 2006). Potential evapotranspiration is estimated using either the Food Agricultural Organization’s (FAO) Penman-Monteith method, the Hargreaves method, or the Priestly-Taylor method (Neitsch et al., 2011). The Penman-Monteith method requires air temperature, wind speed, solar radiation, and relative humidity, the Priestly-Taylor method requires air temperature and solar radiation, while the Hargreaves method requires only air temperature. The Penman-Monteith method was adopted for this...
research since it has been widely used and proven to be very effective when using daily data (Allen, 2005). Each HRU in the watershed maintains a water balance that encompasses four storage volumes: snow, soil profile (from 0-20 m), shallow aquifer (from 2-20 m), and deep aquifer (>20 m) (Chaubey et al., 2006).

Surface runoff is the portion of precipitation that flows overland on the Earth's surface. It occurs when the amount of water on the ground exceeds the infiltration rate. The SWAT model uses the Muskingum routing method (Gill, 1978) to estimate the runoff routing through the stream channel. In the model, surface runoff can be estimated using either the Green and Ampt infiltration method (Green and Ampt, 1911) or the modified Soil Conservation Service Curve Number (SCS-CN) method (USDA, 2004). The Green and Ampt infiltration method requires sub-daily precipitation data to calculate infiltration as a function of the wetting front metric potential and effective hydraulic conductivity, whereas the SCS-CN requires daily precipitation data to calculate runoff as a function of soil permeability, antecedent moisture condition, and land use. Due to the readily available daily precipitation data, this study adopted the SCS-CN method for the surface runoff simulation, as presented in Equation (2.2).

\[ Q_{\text{surf}} = \frac{(R_{\text{day}} - I_a)^2}{(R_{\text{day}} - I_a) + S} \]  

Where, \( Q_{\text{surf}} \) represents the accumulated surface runoff or excess rainfall (mm), \( R_{\text{day}} \) represents the precipitation depth for the day (mm), \( I_a \) represents the initial abstractions (mm), including surface storage, interception, and infiltration before the runoff, and \( S \) represents the retention parameter (mm). The retention parameter (S) varies spatially due to changes in slope, land use, soil type, and management, and temporally due to changes in soil water content, and is inversely proportional to the surface runoff; that is, the higher the S value, the smaller the surface runoff and vice versa. Equation (2.3) calculates S based on the curve number (CN).

\[ S = 25.4 \left( \frac{100}{CN} - 10 \right) \]  

Generally, the initial abstraction, \( I_a \) is commonly approximated as 0.2S for small agricultural watersheds, and thus Equation (2.2) can be simplified into Equation (2.4) as follows:

\[ Q_{\text{surf}} = \frac{(R_{\text{day}} - 0.2S)^2}{(R_{\text{day}} + 0.8S)} \]
Thus, runoff only occurs when the rainfall depth for the day is less than the initial abstraction, that is, $R_{\text{day}} > I_a$

2.3 Sediment simulation in the SWAT model

The Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975) is used to estimate soil loss in the model. MUSLE estimates sediment yield using the runoff factor rather than the rainfall energy factor used by the Universal Soil Loss Equation (USLE) (Neitsch et al., 2011). MUSLE, as a result, accounts for antecedent soil moisture and estimates of sediment from a single storm event. This improves the sediment yield prediction and eliminates the need for delivery ratios because the runoff factor represents the energy utilized in the detachment and transport of sediments. Equation (2.5) shows the model's sediment yield calculation.

$$\text{Sed} = 11.8 \times (Q_{\text{surf}} \times q_s \times A_{\text{hru}})^{0.56} \times K \times C \times P \times LS \times \text{CFRG}$$ (2.5)

Where Sed represents the sediment yield or soil erosion (metric tons), $q_s$ represents the peak runoff rate ($m^3 s^{-1}$), $A_{\text{hru}}$ represents the area of the HRU (ha), $K$ represents the USLE soil erodibility factor, $C$ represents the USLE land use/cover and management factor, $P$ represents the USLE support practice factor, $LS$ represents the USLE topographic factor, and CFRG represents the USLE coarse fragment factor. CFRG is calculated as a function of the percentage of rock ($\%\text{Rock}$) in the first soil layer and can be estimated using Equation (2.6). CFRG = 1 when no rock is present in the first soil layer.

$$\text{CFRG} = \exp(-0.053 \times \%\text{Rock})$$ (2.6)

When routing, SWAT uses Manning's Equation to calculate the rate and velocity of flow. Sediment routing occurs in stream channel networks and on the land surface. The model tracks the particle size distribution of eroded sediments on the land surface and routes them through ponds, channels, and surface waterbodies (Neitsch et al., 2011). The sediment transport through the channel is controlled by both deposition and degradation operating simultaneously (Setegn et al., 2008). The maximum amount of sediment transported from a reach segment is simulated as a function of the peak channel flow rate and is calculated using Equation (2.7).

$$\text{conc}_{\text{sed, max}} = C_{\text{sp}} \left(\frac{q_s}{A_{\text{ch}}}\right)^{sp}$$ (2.7)
Where, $\text{conc}_{\text{sed,max}}$ represents the maximum sediment concentration transported or the channel carrying capacity (ton $m^{-3}$ or kg $L^{-1}$), $C_{sp}$ is an empirical coefficient defined by the user that needs to be calibrated, $q_s$ represents the peak flow rate ($m^3$ $s^{-1}$), $A_{ch}$ represents the cross-sectional flow area in the channel, and $sp$ is an exponent defined by the user, typically ranging from 1.0 to 2.0, with 1.5 being the common value.

Sediment routing in streams involves comparing the available sediment load with the estimated transport capacity of the particular stream segment (Cho et al., 2010). The sediment yield in each HRU is routed to the corresponding sub-basin channel. When the sediment load exceeds the stream transportation capacity, that is, $\text{conc}_{\text{sed},i} > \text{conc}_{\text{sed,max}}$, then deposition occurs within the channel, and the net amount of sediment deposited can be calculated using Equation (2.8).

$$\text{sed}_{\text{dep}} = (\text{conc}_{\text{sed},i} - \text{conc}_{\text{sed,max}}) \times V_{ch}$$

(2.8)

However, when the stream transportation capacity exceeds the sediment load, that is, $\text{conc}_{\text{sed,max}} > \text{conc}_{\text{sed},i}$, then degradation will occur, and the net amount of sediment re-entrained can be calculated by Equation (2.9).

$$\text{sed}_{\text{deg}} = (\text{conc}_{\text{sed,max}} - \text{conc}_{\text{sed},i}) \times V_{ch} \times K_{ch} \times C_{ch}$$

(2.9)

Where, $\text{sed}_{\text{dep}}$ and $\text{sed}_{\text{deg}}$ represents the amount of sediment deposited and re-entrained in the channel segment respectively (metric tons), $\text{conc}_{\text{sed},i}$ represents the initial sediment concentration in the reach (ton $m^{-3}$ or kg $L^{-1}$), $\text{conc}_{\text{sed,max}}$ represents the maximum sediment concentration transported by the water (ton $m^{-3}$ or kg $L^{-1}$), $V_{ch}$, represents the volume of water in the reach segment ($m^3$ of $H_2O$), $K_{ch}$ represents the channel erodibility factor and $C_{ch}$ represents the channel cover factor.

Once the deposition and degradation calculations are complete, the final amount of sediment in the channel segment is determined using Equation (2.10).

$$\text{sed}_{\text{ch}} = \text{sed}_i - \text{sed}_{\text{dep}} + \text{sed}_{\text{deg}}$$

(2.10)
segment (metric tons), \( \text{sed}_{\text{deg}} \) represents the amount of sediment re-entrained in the reach segment (metric tons).

The sediment transported out of the reach is calculated using Equation (2.11).

\[
\text{sed}_{\text{out}} = \text{sed}_{\text{ch}} \times \frac{V_{\text{out}}}{V_{\text{ch}}}
\]  

(2.11)

Where, \( \text{sed}_{\text{out}} \) represents the amount of sediment transported out of the reach (metric tons), \( \text{sed}_{\text{ch}} \) represents the amount of sediment in the reach (metric tons), \( V_{\text{out}} \) represents the volume of outflow during the time step (m\(^3\) of H\(_2\)O), and \( V_{\text{ch}} \) represents the volume of water in the reach segment (m\(^3\) of H\(_2\)O).

This method assumes that erosion is limited by the transportation capacity, thereby limiting the sediment supply from the channel erosion (Neitsch et al., 2011). In cases where sediment data is limited or continuous daily sediment data is unavailable, a sediment rating curve could be established to estimate the daily sediment concentrations and loads calibration and validation of the SWAT model (Lu and Chiang, 2019).

2.4 Nutrient simulation in the SWAT model

The SWAT model tracks nutrients dissolved in the stream and adsorbed to the sediment. The dissolved nutrients are carried with the water, while those adsorbed to sediment are deposited along the channel bed with the sediment. Excessive nutrient loading into streams and waterbodies accelerates eutrophication, polluting the water and rendering it unsuitable for human consumption. Organic and inorganic nitrogen cycles, as well as phosphorous fractions, are simulated in SWAT by dividing the nutrients in the soil into organic and inorganic parts and component pools (Figure 2.2), which can increase or decrease depending on the transformation and additions or losses occurring within each pool (Green and van Griensven, 2008).
Figure 2.2: Nitrogen and phosphorous pools and transformation processes simulated in the SWAT model (adapted from Neitsch et al. (2011)).

2.4.1 Nitrate transportation in the SWAT model

Nitrate and nitrogen movement and transformation are simulated in the model through denitrification, nitrification, mineralization, plant uptake, decay, fertilization, and volatilization processes. SWAT distinguishes three pools of organic nitrogen (active, stable, and fresh) and two pools of mineral nitrogen (ammonia and nitrates), as shown in Figure 2.2. The movement and transformation of several forms of nitrogen within the watershed are introduced into the main channel through surface runoff, lateral flow, or percolation and transported downstream with the flow (Arabi et al., 2008). The nitrate transported by water is calculated using the nitrate concentration in mobile water, as shown in Equation (2.12). This helps to obtain the mass of nitrate lost from each soil layer.

$$\text{conc}_{\text{NO}_3,\text{mobile}} = \frac{\text{NO}_3_{\text{ly}} \times \left(1 - \exp\left[-\frac{w_{\text{mobile}}}{(1 - \theta_e) \times \text{SAT}_{\text{ly}}}\right]\right)}{w_{\text{mobile}}} \quad (2.12)$$

Where $\text{conc}_{\text{NO}_3,\text{mobile}}$ represents the nitrate concentration in mobile water for a given soil layer (kg N mm$^{-1}$ H$_2$O), $\text{NO}_3_{\text{ly}}$ represents the nitrate amount in the soil layer (kg N ha$^{-1}$), $w_{\text{mobile}}$ represents the amount of mobile water in the soil layer (mm H$_2$O), $\theta_e$ represents the fraction of porosity from which anions are excluded, and $\text{SAT}_{\text{ly}}$ represents the saturated water content of the soil layer (mm H$_2$O). The amount of mobile water in the soil layer is the total amount of water lost by surface runoff, lateral flow, and percolation and is calculated using Equations (2.13) and (2.14).
\[ w_{\text{mobile}} = Q_{\text{surf}} + Q_{\text{lat,ly}} + w_{\text{perc,ly}} \] for the top 10 mm soil layer \hspace{1cm} (2.13)

\[ w_{\text{mobile}} = Q_{\text{lat,ly}} + w_{\text{perc,ly}} \] for the lower soil layers \hspace{1cm} (2.14)

Where \( Q_{\text{surf}} \), \( Q_{\text{lat,ly}} \), and \( w_{\text{perc,ly}} \) are the surface runoff generated in a given day (mm H\(_2\)O), the water discharged from the soil layer by lateral flow (mm H\(_2\)O), and water percolating the underlying soil layers (mm H\(_2\)O).

The nitrate removed in surface runoff (\( \text{NO}_3_{\text{surf}} \)), lateral flow (\( \text{NO}_3_{\text{lat,ly}} \)), and percolation (\( \text{NO}_3_{\text{perc,ly}} \)) are based on the following Equations:

\[ \text{NO}_3_{\text{surf}} = \beta_{\text{NO}_3} \times \text{conc}_{\text{NO}_3,\text{mobile}} \times Q_{\text{surf}} \] for surface runoff \hspace{1cm} (2.15)

\[ \text{NO}_3_{\text{lat,ly}} = \beta_{\text{NO}_3} \times \text{conc}_{\text{NO}_3,\text{mobile}} \times Q_{\text{lat,ly}} \] for lateral flow in the top 10 mm layer \hspace{1cm} (2.16)

\[ \text{NO}_3_{\text{lat,ly}} = \text{conc}_{\text{NO}_3,\text{mobile}} \times Q_{\text{lat,ly}} \] for lateral flow in the lower soil layers \hspace{1cm} (2.17)

\[ \text{NO}_3_{\text{perc,ly}} = \text{conc}_{\text{NO}_3,\text{mobile}} \times w_{\text{perc,ly}} \] for percolation \hspace{1cm} (2.18)

Where \( \beta_{\text{NO}_3} \) is the nitrate percolation coefficient, and the nitrate removal units are kg N ha\(^{-1}\).

The modeling of nitrates in agricultural lands using SWAT is mainly concerned with the anthropogenic pollution resulting from nonpoint and point sources of pollutant loads, such as the excessive use of pesticides and fertilizers. The impacts of nitrates and nitrogen pollutants from agricultural watersheds on the environment are based on various factors, among them the type and amount of fertilizer applied, fixation, type of crops being cultivated, crop management practices, soil characteristics, and hydro-meteorological conditions like hydrogeology and climate (Jégo et al., 2008).

2.4.2 **Phosphorous transportation in the SWAT model**

Phosphorous (P) movement in the model is tracked at the HRU level across six pools: three organic (active, stable, and fresh) and three inorganic (stable, active, and solution), as shown in Figure 2.2. The soluble inorganic (mineral) P is readily taken up by plants and is in rapid equilibrium with the active inorganic pool. However, the active inorganic pool is in slow equilibrium with the stable inorganic pool, which is relatively unavailable. On the other hand, fresh organic P is associated with crop residue and microbial mass and
can sometimes be transformed into inorganic solution or soil humus pools. The active organic pool is associated with soil humus and easily mineralizes into the inorganic pool. However, it maintains a slow equilibrium with the stable organic pool, which does not mineralize as quickly as the active pool despite also being associated with the soil humus. At the subbasin and HRU levels, the model outputs include sediment P, which is attached to the eroded sediment particles; organic P, which is found in organic matter transported from the fields; soluble P, which is the portion of phosphorus that is dissolved in the overland flow, and tile P, which is the soluble P exported through tile drains. However, when these HRU and subbasin-based P outputs are exported to the stream, they are aggregated into mineral (soluble and tile) and organic (sediment and organic) phosphorus, which sums up to the total phosphorous, as shown in Figure 2.3 (Chaubey et al., 2006).

**Figure 2.3**: Schematic diagram of phosphorus output pools aggregation at the subbasin and HRU levels and at the reach and stream levels

The movement of phosphorous in the soil is primarily through diffusion. Diffusion is the movement of ions in a soil solution over a small distance (1-2 mm) in response to a concentration gradient. The surface runoff will only partially interact with the solution P stored within the top 10 mm of the soil due to its low mobility. The amount of solution P transported in surface runoff is given by Equation (2.19).

\[
P_{surf} = \frac{P_{sol,surf} \times Q_{surf}}{\rho_b \times \text{depth}_{surf} \times k_{d,surf}}
\]

(2.19)
Where $P_{\text{surf}}$ represents the amount of soluble P lost in surface runoff (kg P ha$^{-1}$), $P_{\text{sol,surf}}$ represents the amount of P in solution in the top 10 mm soil layer (kg P ha$^{-1}$), $\rho_b$ represents the bulk density of the top 10 mm soil layer Mg m$^{-3}$), $\text{depth}_{\text{surf}}$ represents the depth of the surface layer (10 mm), $k_{d,\text{surf}}$ represents the P soil portioning coefficient (m$^3$ Mg$^{-1}$)

The organic and mineral P attached to soil particles are transported into the main channel through surface runoff. The model estimates the amount of P transported with sediment to the stream using a loading function developed by McElroy $et$ $al.$ (1976) and Williams and Hann (1978), as shown in Equation (2.20).

$$\text{sedP}_{\text{surf}} = 0.001 \times \text{conc}_{\text{sedP}} \times \frac{\text{sed}}{\text{area}_{\text{hru}}} \times \epsilon_{P,\text{Sed}}$$ \hspace{1cm} (2.20)

Where $\text{sedP}_{\text{surf}}$ represents the amount of P transported with sediment to the main channel in surface runoff (kg P ha$^{-1}$), $\text{conc}_{\text{sedP}}$ represents the concentration of P attached to sediment in the top 10 mm soil layer (g P (metric ton soil)$^{-1}$), Sed represents the sediment yield on a given day (metric tons), $\text{area}_{\text{hru}}$ represents the area of the HRU (ha), and $\epsilon_{P,\text{Sed}}$ represents the P enrichment ratio. The $\text{conc}_{\text{sedP}}$ is computed using Equation (2.21).

$$\text{conc}_{\text{sedP}} = 100 \times \left( \frac{\text{minP}_{\text{active,surf}} + \text{minP}_{\text{stable,surf}} + \text{orgP}_{\text{humic,surf}} + \text{orgP}_{\text{fresh,surf}}}{\rho_b \times \text{depth}_{\text{surf}}} \right)$$ \hspace{1cm} (2.21)

Where $\text{minP}_{\text{active,surf}}$, $\text{minP}_{\text{stable,surf}}$, $\text{orgP}_{\text{humic,surf}}$, $\text{orgP}_{\text{fresh,surf}}$ represents the amount of P in the active mineral pool, stable mineral pool, humic organic pool, and fresh organic pool in the top 10 mm soil layer (kg P ha$^{-1}$).

The enrichment ratio is the ratio of the P concentration transported with sediment to the concentration of P in the soil layer and is calculated for each storm event using Equation (2.22).

$$\epsilon_{P,\text{Sed}} = 0.78 \times \left( \text{conc}_{\text{sed,\text{surf}}} \right)^{-0.2468}$$ \hspace{1cm} (2.22)

Where $\text{conc}_{\text{sed,\text{surf}}}$ represents the concentration of sediment in surface runoff (Mg sed m$^{-3}$ H$_2$O) and is calculated using Equation (2.23).

$$\text{conc}_{\text{sed,\text{surf}}} = \frac{\text{sed}}{10 \times \text{area}_{\text{hru}} \times Q_{\text{surf}}}$$ \hspace{1cm} (2.23)
2.5 SWAT Calibration and Uncertainty Procedures (SWAT-CUP)

The SWAT-CUP (Soil Water Assessment Tool Calibration and Uncertainty Procedures) is a standalone software that provides an integrated framework for parameterization, sensitivity and uncertainty analysis, calibration, and validation of the SWAT models (Abbaspour, 2015). It comprises five calibration routines that could be used to optimize the SWAT model output files, namely: Sequential Uncertainty Fitting, version 2 (SUFI-2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov Chain Monte Carlo (MCMC) procedures. Figure 2.4 illustrates the linkage between the SWAT model and SWAT-CUP. The multi-site SUFI-2, a semi-automated inverse modeling routine procedure of SWATCUP, was adopted in this study since it is the most extensively used routine for the SWAT model calibration. The SUFI-2 procedure is an iterative optimization algorithm that combines parameter calibration and stochastic analysis of model outputs (Faramarzi et al., 2009). The SUFI-2 algorithm consists of several crucial steps in achieving effective model calibration, sensitivity, and uncertainty estimation.

![Diagram](image)

**Figure 2.4:** Schematic linkage between the SWAT model and SWAT-CUP's five optimization algorithms (adapted from Abbaspour, (2015)).
2.5.1 Sensitivity analysis in SWAT-CUP

The sensitivity analysis identifies the parameters that have the most influence on the model outputs. It streamlines the calibration process by eliminating those deemed as not sensitive, allowing prioritization of efforts and resources toward calibrating the most influential parameters, thereby improving the model performance. The SUFI-2 algorithm offers two types of sensitivity analysis: one-at-a-time (OAT) or local sensitivity analysis and the all-at-a-time (AAT) or global sensitivity analysis. In the local sensitivity analysis, one parameter is changed while keeping all others constant and observing its effect on the model outputs and objective function. This method requires only a few iterations (3-5), therefore straightforward and quick; however, the parameter sensitivity depends on the accuracy of the other fixed parameters. In contrast, the global sensitivity analysis involves simultaneous changes in all the parameters, necessitating a larger number of runs (usually 500 to 1000 or more) to observe the influence of each parameter on the model outputs and objective function. This method is known to produce more reliable results, although the selection of parameter ranges and the number of runs could affect the relative sensitivity of the parameters.

The global sensitivity in SWAT-CUP uses multiple regression, as illustrated in Equation (2.24) to quantify the sensitivity of each parameter (Abbaspour et al., 2018).

\[ g = \alpha + \sum_{i=1}^{n} \beta_i b_i \]  

(2.24)

Where \( g \) represents the objective function value, \( \alpha \) represents the regression constant, \( \beta_i \) represents the co-efficient of the parameter, and \( b_i \) represents the relative significance of each parameter determined using a t-test and assessed by t-stat and p-value. The smaller the p-value, the more sensitive the parameter was, and vice versa. The best combination for the most sensitive parameter is a very small p-value and a large t-stat value (absolute). Parameters with p-values less than 0.05 (p-value < 0.05) are considered to be highly sensitive.

The sensitivity analysis in SWAT-CUP is based on the Latin Hypercube sampling for parameter space exploration (Zhao et al., 2018). Latin Hypercube sampling is preferable to random sampling since it allows for more efficient and effective sampling. It maximizes the diversity of parameter combinations while ensuring adequate parameter space coverage. The Latin Hypercube sampling procedure divides the parameter ranges into multiple intervals (usually 100) to generate equally probable parameter values within.
each interval in a process known as stratification. The algorithm then randomly selects a single parameter value from each interval to form a Latin Hypercube sample set. The selected set of parameter values represents one combination of the parameters for executing the SWAT model. This process is repeated iteratively to generate numerous Latin Hypercube sample sets. The generated parameter sets are used to run the SWAT model multiple times, and the SUFI-2 algorithm calculates the objective function for each model run.

2.5.2 Uncertainty analysis in SWAT-CUP

The propagation of all model parameter input uncertainties to the model output is quantified using the 95 percent prediction uncertainty (95PPU). The 95PPU is a statistical indicator derived from Latin Hypercube sampling that provides a measure of confidence in the SWAT model's predictions at the 2.5% and 97.5% levels of the cumulative distribution of output variables (Abbaspour, 2015; Abbaspour et al., 2015, 2018). The 95PPU accounts for various uncertainties in the model, including conceptual model simplifications, unaccounted processes, unknown parameter effects and interactions, input data quality, etc., and is quantified using the p-factor and r-factor. The p-factor represents the percentage of observed data bracketed within the 95PPU band, whereas the r-factor is the thickness of the 95PPU band calculated using Equation (2.25) as the ratio of the average distance between the 95PPU band and the standard deviation of the observed data (Abbaspour et al., 2004; Abbaspour et al., 2018). Satisfactory calibration was achieved when at least 50% of the observed data fell within the 95PPU band (p-factor $> 0.5$).

$$r - \text{factor}_j = \frac{1}{n_j} \sum_{t_i=1}^{n_j} \left( \frac{x_{t_i 0.025}^{\text{sim}} - x_{t_i 0.975}^{\text{sim}}}{\sigma_{\text{obs}_j}} \right)$$

(2.25)

Where $x_{t_i 0.025}^{\text{sim}}$ and $x_{t_i 0.975}^{\text{sim}}$ represents upper and lower bounds of the 95PPU at t timestep and i simulations; $n_j$ represents the number of data points, and $\sigma_{\text{obs}_j}$ represents the standard deviation of the jth observed variable.

2.5.3 Calibration and validation in SWAT-CUP

Calibration aims to minimize the difference between model simulations and observations through the optimization (minimization or maximization) of an objective function, as shown in Equations 2.26 and 2.27:
Min: \[ g(\theta) = \sum_{j=1}^{v} [w_j \sum_{i=1}^{n_j} (x_{\text{obs}} - x_{\text{sim}})_i^2] \] (2.26)

or,

Max: \[ g(\theta) = \sum_{j=1}^{v} w_j \left( 1 - \frac{\sum_{i=1}^{n_j} (x_{\text{obs}} - x_{\text{sim}})_i^2}{\sum_{i=1}^{n_j} (x_{\text{obs}} - \bar{x}_{\text{sim}})_i^2} \right) \] (2.27)

Where \( g \) represents the objective function, \( \theta \) represents a vector of the model parameters, \( x_{\text{obs}} \) represents an observed variable, \( x_{\text{sim}} \) represents the corresponding simulated variable, \( \bar{x}_{\text{sim}} \) represent the mean of the simulated variable, \( v \) represents the number of measured variables used to calibrate the model, \( w_j \) represents the weight of the \( j \)th variable, and \( n_j \) represents the number of measured observations in the \( j \)th variable.

The objective function assesses the goodness of fit between the simulated model outputs and the observed data. SWAT-CUP facilitates understanding model performance and identifies optimal parameter values by comparing the model outputs against the observed data using different parameter sets, leading to better model calibration. SWAT-CUP achieves this by applying statistical and optimization techniques to rank and optimize the parameter sets based on objective function values. The algorithm updates parameter distributions during the iterative process using Bayesian concepts and feedback techniques (Abbaspour, 2015). This updating process helps improve the parameter distributions' precision, thus reducing the uncertainty associated with the model predictions.

Validation is used to build confidence in the calibrated parameters. It involves applying the calibrated parameter ranges to an independent set of measured observations without any alterations. In the validation process, a single iteration with the same number of simulation runs as in the last calibration is performed, and the results are quantified using the p-factor, r-factor, and objective function values. The data used in the validation period must adhere to physical conditions similar to the calibration period, such as climate and land use. Furthermore, the average variance in data during calibration and validation periods should be more or less the same.

2.6 SWAT model performance evaluation

The model performance was evaluated using various widely recognized statistical techniques. Moriasi et al. (2007) recommend the following quantitative statistical
techniques for evaluating the SWAT model performance: Coefficient of Determination ($R^2$), Nash-Sutcliffe efficiency (NSE), and percent bias (PBIAS).

The *coefficient of determination* ($R^2$) is the correlation between the observed and simulated values. It calculates the probability of the simulated values matching the observed data. It estimates the number of data points that fall within the results of the best-fit line created by the regression equation. The higher the coefficient of determination, the greater the proportion of points the line passes through when the data points and line are plotted, with a value of 1 indicating perfect correlation. Values of 1 or 0 would indicate that the regression line represents all or none of the data. A greater coefficient indicates better goodness of fit for the observations. However, it's important to note that $R^2$ is oversensitive to high extreme values (Krause *et al.*), 2005) and insensitive to additive and proportional differences between model predictions and measured data (Legates and McCabe, 1999). $R^2$ is calculated using Equation (2.28), using the same symbols as the previous equations.

$$R^2 = \frac{\sum_{i=1}^{n}(x_{obs}-\bar{x}_{obs})\times(x_{sim}-\bar{x}_{sim})^2}{\sum(x_{obs}-\bar{x}_{obs})^2\times\sum(x_{sim}-\bar{x}_{sim})^2} \quad (2.28)$$

The *Nash-Sutcliffe Efficiency* (NSE) (Nash and Sutcliffe, 1970) is a normalized statistic that determines the relative magnitude of the residual variance compared to the observed or measured data variance. It measures how well a model predicts observed data compared to the average observed value. The NSE value ranges from $-\infty$ to 1, with 1 indicating a perfect match between the model's predictions and the observed data. Values closer to 1 signify better model performance, while negative values suggest the model performs worse than a simple average. NSE is good for continuous long-term simulations and can be used to determine how effectively the model simulates trends for a given output response (Moriasi *et al.*, 2015). However, it does not indicate whether the model underestimates or overestimates the observations; therefore, it cannot be utilized for single-event simulations. Due to the squared differences, NSE is sensitive to extreme values (Krause *et al.*, 2005). NSE is calculated using Equation (2.29), using the same symbols as the previous equations.

$$\text{NSE} = 1 - \left(\frac{\sum_{i=1}^{n}(x_{obs} - x_{sim})^2}{\sum_{i=1}^{n}(x_{obs} - \bar{x}_{obs})^2}\right) \quad (2.29)$$
**Percent Bias (PBIAS)** is the deviation of the results from the observations expressed as a percentage. It measures the average tendency of the simulated data to be larger or smaller than the observed data. An ideal model should have a PBIAS of 0. However, models tend to have either a positive or negative PBIAS, implying either an underestimation or an overestimation of the observations. However, PBIAS cannot be utilized for single-event simulations to identify variations in magnitude and timing for the output response because it only provides the average magnitudes. Additionally, it does not indicate how well a model simulates residual variations and trends for a given output response. PBIAS is calculated using Equation (2.30), using the same symbols as the previous equations.

\[
PBIAS = \left[ \frac{\sum_{i=1}^{n}(x_{\text{obs}} - x_{\text{sim}}) \times 100}{\sum_{i=1}^{n}x_{\text{obs}}} \right]
\]

(2.30)

Table 2.1 summaries the model performance evaluation criteria for the selected statistical performance techniques based on Moriasi *et al.* (2015). These indices served as the benchmark for evaluating the model's accuracy and reliability in replicating the observed data.

**Table 2.1:** The SWAT model performance evaluation criteria for recommended statistical performance measures at the catchment scale.

<table>
<thead>
<tr>
<th>Performance metrics</th>
<th>Range</th>
<th>Optimal value</th>
<th>Output variable</th>
<th>Performance evaluation criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Minimum threshold</td>
<td>Very Good</td>
</tr>
<tr>
<td>R²</td>
<td>0 – 1</td>
<td>1</td>
<td>Streamflow</td>
<td>≥ 0.60</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sediment</td>
<td>≥ 0.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Nitrate</td>
<td>≥ 0.30</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Phosphorous</td>
<td>≥ 0.40</td>
</tr>
<tr>
<td>NSE</td>
<td>-∞ – 1</td>
<td>1</td>
<td>Streamflow</td>
<td>≥ 0.50</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sediment</td>
<td>≥ 0.45</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Nitrate</td>
<td>≥ 0.35</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Phosphorous</td>
<td>≥ 0.35</td>
</tr>
<tr>
<td>PBIAS</td>
<td>-∞ – ∞</td>
<td>0</td>
<td>Streamflow</td>
<td>≤ ±25%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sediment</td>
<td>≤ ±55%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Nitrate</td>
<td>≤ ±70%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Phosphorous</td>
<td>≤ ±70%</td>
</tr>
</tbody>
</table>
Chapter 3:

3 Description of the Study Areas and Data Acquisition
3.1 Introduction

The dissertation focused on two agricultural-dominated watersheds, namely the Cidacos River watershed in northern Spain and the Swedish Environmental Monitoring Program’s Catchment C6 in southeastern Sweden. These watersheds were carefully selected because of their contrasting geographical, climatic, agricultural, and water quality challenges in Europe. They represent the prevalent agricultural practices in their regions, providing valuable insights into the complexities and challenges of water management and ecological sustainability in such contexts. The two study areas exemplify agricultural landscapes with unique climatic, geographical, and socioeconomic characteristics. This chapter aims to provide detailed descriptions of these two study areas, contextualizing their geographical locations, climatic conditions, land uses, soil characteristics, and hydrological and ecological attributes. The chapter further elucidates the primary data used in the studies and their acquisition techniques.

3.2 Description of the Cidacos River watershed (Spain)

The Cidacos River is one of the tributaries of the Aragón River, a tributary of the Ebro River. It is located approximately 15 km south of Pamplona, the capital of the Chartered Community of Navarre in Spain, at latitudes 42° 69' and 42° 34' north and longitudes 1° 72' and 1° 47' west. The Cidacos River drains a watershed area of 477 km² and runs north-south, with an approximate length of 44 km and width of 15 km in its widest section (Figure 3.1). The watershed's headwater is somewhat mountainous in the north, with high altitudes of slightly over 1000 m above sea level, but then crosses down to slightly uneven to low terrain of approximately 300 m above sea level in the south at the river's mouth in Traibuenas, where it joins the Aragón River. The watershed's climate is humid to dry, temperate, mild Mediterranean, with cold winters (monthly average: 4.7 °C to 5.4 °C in January) and warm summers (monthly average: 21.2 °C to 23.7 °C in August) that vary spatially from North to South. The annual average temperature ranges from 12.2 °C to 14.2 °C (north to south). The watershed receives annual precipitation from 800 mm in the north to 400 mm in the south, characterized by strong inter-annual variability and high summer aridity. The wettest months are April and May (Merchán et al., 2020). The annual evapotranspiration rate is approximately 1150 mm year⁻¹, with nearly 76% occurring between April and September (Merchán et al., 2020).
Figure 3.1: The Cidacos River watershed location, elevation map, and measuring stations.

Agriculture is the watershed's predominant land use (Table 3.1, Figure 3.2a), accounting for 53% of the total area. Other major land uses in the watershed include forests (25%) and pasture and bushlands (17%). The remaining 5% comprises urban, residential areas, built-up land, bare land, and water bodies. Rainfed agriculture covers 176 km$^2$ (37% of the total area and 70% of cultivated land) and is primarily in the watershed's upper reaches until Olite town. Irrigated land, on the other hand, covers 77 km$^2$ (16% of the total area and 30% of the cultivated land) and is mainly in the watershed's lower reaches. Table 3.1 shows the proportions of the land use land cover (LULC) classes in the watershed.
Table 3.1: Land use land cover (LULC) classes and their proportions in the Cidacos River watershed

<table>
<thead>
<tr>
<th>Land Use</th>
<th>Land Use Class</th>
<th>SWAT Code</th>
<th>Area covered (km²)</th>
<th>Percentage of watershed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture*</td>
<td>Corn</td>
<td>CORN</td>
<td>67.88</td>
<td>14.23</td>
</tr>
<tr>
<td>(53.15%)</td>
<td>Wheat</td>
<td>WWHT</td>
<td>77.30</td>
<td>16.20</td>
</tr>
<tr>
<td></td>
<td>Winter Barley</td>
<td>WBAR</td>
<td>51.30</td>
<td>10.75</td>
</tr>
<tr>
<td></td>
<td>Tomatoes</td>
<td>TOMA</td>
<td>20.53</td>
<td>4.30</td>
</tr>
<tr>
<td></td>
<td>Potatoes</td>
<td>POTA</td>
<td>9.58</td>
<td>2.01</td>
</tr>
<tr>
<td></td>
<td>Orchard and Vineyards</td>
<td>ORCD</td>
<td>26.21</td>
<td>5.49</td>
</tr>
<tr>
<td></td>
<td>Asparagus</td>
<td>ASPR</td>
<td>0.71</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>Apple</td>
<td>APPL</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Forest</td>
<td>Deciduous Forest</td>
<td>FRSD</td>
<td>3.53</td>
<td>0.74</td>
</tr>
<tr>
<td>(25.06%)</td>
<td>Evergreen Forest</td>
<td>FRSE</td>
<td>10.09</td>
<td>2.11</td>
</tr>
<tr>
<td></td>
<td>Mixed Forest</td>
<td>FRST</td>
<td>20.51</td>
<td>4.30</td>
</tr>
<tr>
<td></td>
<td>Oak Tree</td>
<td>OAK</td>
<td>50.97</td>
<td>10.69</td>
</tr>
<tr>
<td></td>
<td>Pine Tree</td>
<td>PINE</td>
<td>34.46</td>
<td>7.22</td>
</tr>
<tr>
<td>Pasture/Bushes</td>
<td>Pasture</td>
<td>PAST</td>
<td>6.67</td>
<td>1.40</td>
</tr>
<tr>
<td>(16.92%)</td>
<td>Shrubland/brushes</td>
<td>RNGB</td>
<td>73.03</td>
<td>15.31</td>
</tr>
<tr>
<td></td>
<td>Grassland/Herbaceous</td>
<td>RNGE</td>
<td>0.99</td>
<td>0.21</td>
</tr>
<tr>
<td>Urban, Residential and built-up land</td>
<td>Urban Transportation</td>
<td>UTRN</td>
<td>6.32</td>
<td>1.32</td>
</tr>
<tr>
<td>(2.55%)</td>
<td>Urban Commercial</td>
<td>UCOM</td>
<td>0.74</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Urban Medium Density</td>
<td>URML</td>
<td>2.39</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>Urban Industrial</td>
<td>UIDU</td>
<td>1.90</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>Urban Institutional</td>
<td>UINS</td>
<td>0.82</td>
<td>0.17</td>
</tr>
<tr>
<td>Bare land (1.50%)</td>
<td>Bare land</td>
<td>BARR</td>
<td>7.16</td>
<td>1.50</td>
</tr>
<tr>
<td>Water</td>
<td>Water</td>
<td>WATR</td>
<td>2.41</td>
<td>0.51</td>
</tr>
<tr>
<td>(0.83%)</td>
<td>Non-forested Wetland</td>
<td>WETN</td>
<td>1.04</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>Herbaceous Wetlands</td>
<td>WETF</td>
<td>0.46</td>
<td>0.10</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td></td>
<td>477.03</td>
<td>100</td>
</tr>
</tbody>
</table>

*Agriculture land use encompasses rainfed (37%) and irrigated (16%) croplands.

The irrigated area gets its water from the Navarre Canal, which flows from the Itoíz Reservoir on the Irati River, about 70 km north of the study area (INTIA, 2021). The conversion from rainfed cultivation to irrigation within the study area has been gradual, with most changes occurring between 2009 and 2012 (Figure 3.3). By 2013, approximately 90% of the current irrigated area had been converted from rainfed to irrigation. The main irrigation method used in the study area is pressurized (sprinkler)
(71%) with buried fixed sprinkler systems. Drip irrigation (20.3%) and pivot/canon irrigation (8.5%) are two other types of irrigation used in the area (INTIA, 2021).

Figure 3.2: The Cidacos River watershed (a) land use land cover map and (b) soil type map (FAO-WRB classification).

Figure 3.3: Cumulative annual percentage of the irrigated area converted from rainfed agriculture in the Cidacos River watershed from 2006 to 2020.

The main crops grown in the watershed are rainfed winter cereals (wheat and barley) and vineyards (orchards). Corn, tomatoes, and potatoes are among the crops grown in the irrigated area. The average annual fertilizer application rates range from 80 to 130 kg N
ha\(^{-1}\) for winter cereals and 40 to 50 kg N ha\(^{-1}\) for vineyards. Crop diversity is greater in the irrigated area than in the rain-fed zone. Consequently, fertilizer applications have increased to meet the increased production expectations. The annual average fertilization rates in the irrigated region are 260 to 300 kg N ha\(^{-1}\) for corn and 120 to 200 kg N ha\(^{-1}\) for tomatoes and potatoes. Table 3.2 summarizes the annual agricultural management practices in the Cidacos River watershed, including cropping cycles, tillage, fertilization, irrigation water consumption, and crop yield for the most common crops.

**Table 3.2:** Average annual agricultural practices and yield in the Cidacos River watershed

<table>
<thead>
<tr>
<th>Crop type</th>
<th>Cropping cycle</th>
<th>Tillage date</th>
<th>Fertilization date</th>
<th>Fertilization (N kg ha(^{-1}) yr(^{-1}))</th>
<th>Type of fertilizer applied*</th>
<th>Irrig. water consumption (mm ha(^{-1}) yr(^{-1}))</th>
<th>Annual crop yield (100 kg ha(^{-1}) yr(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td>01 Nov - 01 Jul</td>
<td>01 Oct</td>
<td>01 Oct</td>
<td>40</td>
<td>9-23-30</td>
<td>Rainfed</td>
<td>&gt; 50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>01 Jan</td>
<td></td>
<td>60</td>
<td>Urea + Ammonium sulfate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Winter barley</td>
<td>01 Nov - 01 Jul</td>
<td>01 Oct</td>
<td>01 Oct</td>
<td>40</td>
<td>9-23-30</td>
<td>Rainfed</td>
<td>&gt; 50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>01 Jan</td>
<td></td>
<td>60</td>
<td>Urea + Ammonium sulfate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corn</td>
<td>01 May - 01 Nov</td>
<td>01 Apr</td>
<td>15 Apr</td>
<td>40</td>
<td>9-23-30</td>
<td></td>
<td>700 – 800</td>
</tr>
<tr>
<td></td>
<td></td>
<td>15 Jun</td>
<td></td>
<td>260</td>
<td>Urea</td>
<td></td>
<td>90 – 110</td>
</tr>
<tr>
<td>Tomato</td>
<td>10 May - 15 Sept</td>
<td>01 Apr</td>
<td>15 Apr</td>
<td>60</td>
<td>9-23-30</td>
<td></td>
<td>550 – 650</td>
</tr>
<tr>
<td></td>
<td></td>
<td>15 Jun</td>
<td></td>
<td>120</td>
<td>8-4-10</td>
<td></td>
<td>500 – 550</td>
</tr>
<tr>
<td>Potato</td>
<td>01 May - 15 Sept</td>
<td>01 Apr</td>
<td>15 Apr</td>
<td>60</td>
<td>9-23-30</td>
<td></td>
<td>500 – 600</td>
</tr>
<tr>
<td></td>
<td></td>
<td>15 Jun</td>
<td></td>
<td>120</td>
<td>NAC 27%</td>
<td></td>
<td>250 – 400</td>
</tr>
</tbody>
</table>

*9-23-30 contains 9% nitrogen (N), 23% phosphorous (P), and 30% potassium (K) (typically used for plants with high P and K requirements); Urea + ammonium sulfate fertilizer has a nitrogen content of 38% and a sulfate content of 18.75%; urea has a nitrogen content of 46%; 8-4-10 is composed of 8% nitrogen, 4% phosphorous, and 10% potassium (commonly used as a top dressing in crops that require an additional boost of N and K, and in soils with minor P deficiencies); NAC 27% is composed of calcium ammonium nitrate, which contains 27% nitrogen.

The most abundant soil textures in the watershed are loam and clay-loam, which are found in most agricultural areas, while loamy-sand and sandy-loam soils are found on eroded hillslopes. Red clay soils dominate the watershed with sandstone and mudstones. According to the FAO classification system (IUSS Working Group WRB, 2015), the
watershed's predominant soil types (Table 3.3, Figure 3.2b) are Haplic Calciols soils (51.6%), Fluvic Camisols soils (26.1%) which are mostly found along the river network path, and Alaric Regosols (18%). Haplic Phaeozem (1.7%), Calcic Castanea's (1.6%), Fluvic Phaeozem (0.4%), Eutric Fluvisols (0.3%), and Dystric Cambisols (0.2%) are among the other soils found in the watershed.

**Table 3.3**: Soil distribution in the Cidacos River watershed

<table>
<thead>
<tr>
<th>USDA soil name</th>
<th>FAO soil name</th>
<th>FAO symbol</th>
<th>Area (km²)</th>
<th>Percent (%)</th>
<th>Soil texture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Typic Calcierepts</td>
<td>Haplic Calciols</td>
<td>CLh</td>
<td>246.31</td>
<td>51.63</td>
<td>Loam</td>
</tr>
<tr>
<td>Typic/Fluventic</td>
<td>Fluvic Cambisols</td>
<td>CMf</td>
<td>124.49</td>
<td>26.10</td>
<td>Clay-Loam</td>
</tr>
<tr>
<td>Haploxerepts</td>
<td>Calcaric Regosols</td>
<td>RGc</td>
<td>85.98</td>
<td>18.02</td>
<td>Loamy-Sand</td>
</tr>
<tr>
<td>Typic/Lithic Xerorthents, Udorhent</td>
<td>Haplic Phaeozem</td>
<td>PHh</td>
<td>8.19</td>
<td>1.72</td>
<td>Clay-Loam</td>
</tr>
<tr>
<td>Lithic-Ruptic Haplustolls</td>
<td>Calcic Kastanozems</td>
<td>KSk</td>
<td>7.47</td>
<td>1.56</td>
<td>Loam</td>
</tr>
<tr>
<td>Typic calcixeroll</td>
<td>Fluvic Phaeozem</td>
<td>PHf</td>
<td>1.93</td>
<td>0.41</td>
<td>Loam</td>
</tr>
<tr>
<td>Fluventic Haploxerolls</td>
<td>Eutric Fluvisols</td>
<td>FLe</td>
<td>1.58</td>
<td>0.33</td>
<td>Clay-Loam</td>
</tr>
<tr>
<td>Typic Xerofluvent</td>
<td>Dystric Cambisols</td>
<td>CMD</td>
<td>1.08</td>
<td>0.23</td>
<td>Sandy-Loam</td>
</tr>
</tbody>
</table>

### 3.3 Description of Catchment C6 (Sweden)

The study area, Catchment C6 (Figure 3.4), is an agricultural catchment in southeastern Sweden within the Lake Malaren basin of Uppsala County. It is one of the small Swedish agricultural monitoring catchments located in leaching region 6. Leaching regions (Figure 3.4a) are sub-divisions of agricultural production areas in Sweden that are relatively homogeneous in terms of climate and farming (Kyllmar et al., 2006). These agricultural monitoring catchments have been designated as the main agricultural areas for intensive water quality monitoring since 1990 under the Swedish Environmental Monitoring Program (Kyllmar et al., 2014).
Crop production within the monitored catchments is generally more intensive than in the wider region. Catchment C6 covers 3298 ha (33 km²) and is characterized by high levels of phosphorous load and sediment (suspended solids) exportation in comparison to the other catchments (Kyllmar et al., 2014). The long-term average total phosphorous export from the study area (0.50 kg P ha⁻¹ yr⁻¹) is higher than the average of all agricultural monitoring areas combined (0.43 kg P ha⁻¹ yr⁻¹), with the agricultural calendar year of 2021/2022 recording the highest total phosphorous load (0.65 kg P ha⁻¹ yr⁻¹) among the monitored catchments (Linefur et al., 2022). On the contrary, nitrogen losses from the catchment (6.3 kg N ha⁻¹ yr⁻¹) are very low, ranking among the least in the monitored catchments (Linefur et al., 2022). Table 3.4 details the total nitrogen and total phosphorous exported from the various agricultural monitoring catchments in Sweden.
**Table 3.4:** The average annual total nitrate (Total N) load and total phosphorous (Total P) load in different agricultural monitoring catchments in Sweden from 2005-2020 (source: Linefur et al., 2022).

<table>
<thead>
<tr>
<th>Catchment ID</th>
<th>Area (km²)</th>
<th>Long-term averages (kg ha⁻¹ yr⁻¹)</th>
<th>Values for 2020/2021 (kg ha⁻¹ yr⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Tot-N load</td>
<td>Tot-P load</td>
</tr>
<tr>
<td>C6</td>
<td>33</td>
<td>6.3</td>
<td>0.50</td>
</tr>
<tr>
<td>E21</td>
<td>16.3</td>
<td>15.2</td>
<td>0.08</td>
</tr>
<tr>
<td>E23</td>
<td>7.4</td>
<td>7.4</td>
<td>0.39</td>
</tr>
<tr>
<td>E24</td>
<td>6.3</td>
<td>6.6</td>
<td>0.55</td>
</tr>
<tr>
<td>F26</td>
<td>1.8</td>
<td>15.8</td>
<td>0.52</td>
</tr>
<tr>
<td>H29</td>
<td>7.2</td>
<td>11.9</td>
<td>0.15</td>
</tr>
<tr>
<td>I28</td>
<td>4.8</td>
<td>16.3</td>
<td>0.33</td>
</tr>
<tr>
<td>K31</td>
<td>7.7</td>
<td>7.0</td>
<td>0.16</td>
</tr>
<tr>
<td>K32</td>
<td>8.6</td>
<td>15.2</td>
<td>0.28</td>
</tr>
<tr>
<td>M36</td>
<td>7.9</td>
<td>16.9</td>
<td>0.58</td>
</tr>
<tr>
<td>M39</td>
<td>6.8</td>
<td>33.1</td>
<td>0.41</td>
</tr>
<tr>
<td>M42</td>
<td>8.2</td>
<td>26.6</td>
<td>0.43</td>
</tr>
<tr>
<td>N34</td>
<td>13.9</td>
<td>32.7</td>
<td>0.41</td>
</tr>
<tr>
<td>O14</td>
<td>10.2</td>
<td>13.1</td>
<td>0.56</td>
</tr>
<tr>
<td>O17</td>
<td>9.7</td>
<td>12.8</td>
<td>0.20</td>
</tr>
<tr>
<td>O18</td>
<td>7.7</td>
<td>15.1</td>
<td>1.64</td>
</tr>
<tr>
<td>S13</td>
<td>35.2</td>
<td>8.5</td>
<td>0.32</td>
</tr>
<tr>
<td>U8</td>
<td>5.7</td>
<td>6.7</td>
<td>0.54</td>
</tr>
<tr>
<td>X2</td>
<td>32.8</td>
<td>4.1</td>
<td>0.20</td>
</tr>
</tbody>
</table>

The catchment receives an average of 550 mm of precipitation annually, has an annual average temperature of 5.5 °C (ranging from -21°C to 28°C), and a potential evapotranspiration rate of 400 to 500 mm. Most of the arable land is artificially drained through subsurface tile drains at an average depth of 1 meter. Runoff on the soil occasionally occurs during snowmelt or intensive rainfall events. The average annual flow at the stream outlet is estimated to be 220 mm.

Agriculture is the predominant land use in the catchment, accounting for nearly 60% of the total area, while forest land accounts for slightly more than 30% (Figure 3.4b). The main crops cultivated in the arable land are cereals (winter wheat and spring barley). Other crops commonly cultivated in the catchment are oilseed rape, oats, rye, and some leguminous plants (beans and peas). The catchment has a heavy soil texture primarily
composed of postglacial clay soils with silty clay soil, mainly the arable land surface, while clay loam and silty clay loam soils dominate the forested areas (Figure 3.4c).

The catchment receives nitrogen and phosphorous primarily from mineral fertilizers, with an average annual supply of 120 kg N ha\(^{-1}\) (ranging from 100 to 150 kg N ha\(^{-1}\)) and 12 kg P ha\(^{-1}\) (ranging from 7 to 21 kg P ha\(^{-1}\)), respectively (Swedish Environmental Emissions Data (SMED), 2019). Only a tiny portion of the cultivated land (≤5%) is organically farmed with stable manure. The annual average mineral phosphorous fertilization rates for the dominant crops are 21 kg P ha\(^{-1}\) yr\(^{-1}\) for winter wheat and 14 kg P ha\(^{-1}\) yr\(^{-1}\) for spring barley. The Swedish authorities have set a phosphorous threshold of a maximum of 22 kg P ha\(^{-1}\) yr\(^{-1}\) on average over five years. The annual average nitrogen fixation by leguminous crops is 100 kg N ha\(^{-1}\) yr\(^{-1}\). Table 3.5 summarizes the average mineral fertilization rates and crop yields for the commonly cultivated crops in the catchment.

**Table 3.5:** Average annual agricultural practices and yield in Catchment C6

<table>
<thead>
<tr>
<th>Crop type</th>
<th>Cropping cycle</th>
<th>Date of Tillage</th>
<th>Annual mineral fertilization</th>
<th>Annual Crop yield</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>N (kg ha(^{-1}))</td>
<td>P (kg ha(^{-1}))</td>
</tr>
<tr>
<td>Spring Barley</td>
<td>30 Apr – 20 Aug</td>
<td>14 Oct</td>
<td>95</td>
<td>14</td>
</tr>
<tr>
<td>Winter Wheat</td>
<td>11 Sep – 27 Aug</td>
<td>03 Sep</td>
<td>153</td>
<td>21</td>
</tr>
<tr>
<td>Oats</td>
<td>30 Apr – 20 Aug</td>
<td>06 Oct</td>
<td>75</td>
<td>13</td>
</tr>
<tr>
<td>Spring Wheat</td>
<td>30 Apr – 30 Aug</td>
<td>06 Oct</td>
<td>114</td>
<td>14</td>
</tr>
<tr>
<td>Grain Legumes</td>
<td>13 May – 30 Aug</td>
<td>06 Oct</td>
<td>-</td>
<td>20</td>
</tr>
<tr>
<td>Rape</td>
<td>05 Sep – 06 Aug</td>
<td>02 Sep</td>
<td>162</td>
<td>17</td>
</tr>
<tr>
<td>Rye</td>
<td>11 Sep – 16 Aug</td>
<td>02 Sep</td>
<td>98</td>
<td>17</td>
</tr>
</tbody>
</table>

### 3.4 Data acquisition in the Cidacos River watershed

The data used for the research in the Cidacos River watershed were primarily obtained from the Government of Navarre agencies and websites, as shown in Table 3.6. The climate data were obtained at a daily time-step from 25 weather stations (both manual and automatic) located within and near the watershed from 1990 to 2020 (Figure 3.5). The selected stations represented the spatial heterogeneity of the watershed's climate. The meteorological data included daily data of precipitation (mm), maximum and minimum daily temperatures (°C), solar radiation (MJ m\(^{-2}\) s\(^{-2}\)), wind speed (m s\(^{-1}\)), and relative humidity (%) data. The agricultural management information (Table 3.1), which included planting and harvesting dates, the average annual fertilizer application rates, and the main crops cultivated in the watershed, were obtained from INTIA’s technical team and...
extension advisors who conduct field interviews in consultation with key informants such as farmers within the watershed. The monthly observed streamflow data and nitrate loads from 2000-2020 were used for the model evaluation. The data used were obtained from the Olite gauging station since it was the only station in the watershed with consistent and extensive long-term data of observed discharge and nitrate concentration data. This station has been operational since 1988 and covers the watershed area under rainfed agriculture. The contribution of nitrate pollution from point sources in the study area is negligible, accounting for only about 1.5% of the nitrate loads (Merchán et al., 2020); thus, it was not considered in the modeling.

**Table 3.6:** The SWAT model input data requirement and their sources

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Resolution*</th>
<th>Source**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography map</td>
<td>25m, ETRS89 UTM Zone 30N projection</td>
<td>IDENA portal for Digital Elevation Map (DEM) data</td>
</tr>
<tr>
<td>Land use map</td>
<td>25m, 2019 LULC map</td>
<td>IDENA portal for Land Use/Cover data</td>
</tr>
<tr>
<td>Soil type map</td>
<td>1:25000</td>
<td>IDENA portal, Soil type data</td>
</tr>
<tr>
<td>Meteorological</td>
<td>Daily (1990-2020)</td>
<td>Meteorology and climatology portal</td>
</tr>
<tr>
<td>Water quality</td>
<td>Monthly (2000-2020)</td>
<td>GAN-NIK and INTIA</td>
</tr>
<tr>
<td>Agricultural management</td>
<td>Annual</td>
<td>Consultation with the farmers and key stakeholders (INTIA)</td>
</tr>
<tr>
<td>Irrigation</td>
<td>Monthly (2017-2020)</td>
<td>INTIA and Aguacanal reports</td>
</tr>
<tr>
<td>Climate change</td>
<td>Daily (1961-2100)</td>
<td>Spanish climate change portals of AdapteCCa and AEMET</td>
</tr>
</tbody>
</table>

*ETRS89 UTM Zone 30N projection refers to a coordinate reference system of the Universal Transverse Mercator (UTM) projection based on the European Terrestrial Reference System 1989 (ETRS89) datum.

**IDENA is the government portal for spatial data and infrastructure in Navarre; meteorology portal is the government website with data from all the weather stations in Navarre; Water in Navarra portal is the government website for all river discharge data in Navarre; INTIA is the government agency for agri-food technologies and infrastructure in charge of agriculture and irrigation in Navarre; GAN-NIK is the government agency in charge of environmental management in Navarre; Aguacanal is the company in charge of the Navarre Canal’s irrigable zone first phase; AdapteCCa refers to the Platform on Adaptation to Climate Change in Spain that contains statistically downscaled climate data for the whole of Spain; AEMET is the Spanish government national meteorological agency.
Figure 3.5: Meteorological data stations (left side) in the Cidacos River watershed, with their data length (start to end dates) between 1990 to 2020, and missing data count for each station (right side)

3.5 Data acquisition in the Catchment C6

The data used in the analysis of Catchment C6 were sourced from various Swedish government agencies' websites and portals, as shown in Table 3.7. The geospatial data, such as topography, land use (Figure 3.4b), and soil texture (Figure 3.4c) maps, were obtained from the Swedish National Land Survey portal. These data were initially preprocessed in QGIS to reclassify into the appropriate SWAT format prior to utilization in the model. The meteorological data (1990-2020), which includes precipitation, temperature (maximum and minimum), relative humidity, wind velocity, and solar radiation, was obtained at a daily time-step from the Swedish Meteorological and Hydrological Institute (SMHI) website. The data were obtained from a weather station located in Enkoping, which is about 2 km away from the catchment in the southwest. The agricultural management information (Table 3.3) from leaching region 6 obtained through
annual interviews with the farmers was used for the study. The observations (2005-2020) for streamflow, sediments, and phosphorous load were obtained from the water quality database of the Swedish environmental monitoring program. This program has been at the forefront of collecting water quality data in the catchment and other agricultural monitoring areas since the 1990s.

Table 3.7: The resolution and sources of the data used in this study.

<table>
<thead>
<tr>
<th>Data type</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
<th>Period</th>
<th>Source*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography map</td>
<td>-</td>
<td>5m × 5m</td>
<td>-</td>
<td>SNLS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SWEREF99 TM**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land use map</td>
<td>-</td>
<td>5m × 5m</td>
<td>2021</td>
<td>SNLS</td>
</tr>
<tr>
<td>Soil map</td>
<td>-</td>
<td>1:50000</td>
<td>-</td>
<td>SNLS</td>
</tr>
<tr>
<td>Meteorological</td>
<td>Daily</td>
<td>Enköping station</td>
<td>1990-2020</td>
<td>SMHI</td>
</tr>
<tr>
<td>Streamflow</td>
<td>Daily</td>
<td>C6 outlet</td>
<td>2000-2020</td>
<td>SEPA</td>
</tr>
<tr>
<td>Sediment</td>
<td>Biweekly</td>
<td>C6 outlet</td>
<td>2004-2020</td>
<td>SEPA</td>
</tr>
<tr>
<td>Phosphorous</td>
<td>Biweekly</td>
<td>C6 outlet</td>
<td>2004-2020</td>
<td>SEPA</td>
</tr>
<tr>
<td>Agricultural</td>
<td>Annual</td>
<td>Leaching region 6</td>
<td>2016-2020</td>
<td>SEPA</td>
</tr>
<tr>
<td>management</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* SNLS is the Swedish National Land Survey; SMHI is the Swedish Meteorological and Hydrological Institute; and SEPA is the Swedish Environmental Protection Agency

** SWEREF99 TM refers to the Swedish Reference Frame 1999, the coordinate reference system used in Sweden for mapping and surveying purposes.

The streamflow at the catchment's outlet is continuously measured using a standard V-notch weir. A weight gauge, displacement body, and data logger are used to measure the water level. Heating equipment is used to prevent the measuring section from freezing during winter. The data loggers automatically retrieve data, which can be collected daily through a cellular phone network or manually by visiting the station regularly. The data is checked for any errors, such as interrupted recording and abnormal changes in water levels, which must be corrected before entering the information into the database. Weather data, expert knowledge, and data from nearby stations are used for the correction.

Water quality at the catchment outlet has been monitored since 1993. The water quality data used in this study were collected using flow-proportional (automatic) sampling techniques. In this method, water samples are collected and stored in 10-liter glass bottles, from which a composite sample is taken after shaking biweekly, and the bottle is emptied. The sampling intensity is flow-dependent, with more sub-samples collected during high
flows. Time-proportional sampling is used during low flows, with two sub-samples per day. The comprehensive sampling protocol is described in Kyllmar et al. (2014).

The water samples were analyzed according to the Swedish Standard methods in a water laboratory accredited by the Swedish Board for Accreditation and Conformity Assessment (SWEDAC) (Kyllmar et al., 2014). Several water quality parameters were tested in the lab, but only those related to sediment and phosphorous were of interest to this study. The total phosphorous (Total P) was measured directly from unfiltered water samples, while the soluble phosphorous (Soluble P) was measured after filtration at 0.2µm to avoid the influence of particle-bound phosphorus. The nutrient loads were computed as the product of the daily streamflow and corresponding concentrations, then summarized into monthly averages for the model evaluation.
Chapter 4:

4 Evaluation of the Impact of Changing from Rainfed to Irrigated Agriculture in the Cidacos River Watershed

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4.1 Introduction

Agricultural intensification and increased demand for high-value food production because of market liberalization and population growth have put a lot of pressure on the available water resources and the environment. Agriculture is the largest global freshwater consumer, accounting for more than 70% of the global freshwater resources withdrawals (FAO, 2017b; World Bank, 2020) and nearly 90% consumptive water use (Siebert et al., 2010). Irrigation accounts for more than 70% of the agricultural water demand (Zeng and Cai, 2014). In the 50 years from 1965 to 2015, the global area under irrigation farming more than doubled (Mateo-Sagasta et al., 2018). The need for more agricultural production, combined with the effects of climate change, pollution, population growth, and water conflicts, is expected to drive up the demand for irrigation even further (World Bank, 2020). On average, irrigated agricultural productivity per unit of land is more than double that of rainfed cultivation, resulting in increased production intensity and crop diversification (World Bank, 2020). In Spain, irrigation, which covers only 16% of the agricultural land, contributes more than 50% of total agricultural output, six times more than rainfed areas (MAPA, 2021). Over the ten years between 2003 and 2013, the irrigated area in Europe increased by 13.4%. In Spain, the increase was approximately 16% between 2007 and 2017 (MAPA, 2021). Most of the irrigable areas in Europe are mainly found within the Mediterranean region, with Italy and Spain having the largest share of irrigated agricultural lands (EPRS, 2019).

Spain's agricultural activities have relied on rainfed and irrigated cultivation, focusing more on irrigation in recent years. According to the Heinrich Böll Foundation (2019), rainfed agricultural lands in Spain's dry Mediterranean areas have decreased by 23% over the last 30 years, mainly due to low productivity and inadequate support from the Common Agricultural Policy (CAP). However, the Spanish Ministry of Agriculture reported an increase in irrigated acreage of more than 400,000 ha (which accounted for 16.2% of the irrigated land) over the past decade as of 2018 (MAPA, 2021). Navarre, located in Northern Spain and mainly in the Mediterranean region, has experienced a relatively rapid expansion of irrigated lands. The irrigated area in Navarre increased by around 25% between 2000 and 2020, with more pressurized irrigation systems installed in recent years (DDRMAAL, 2021). Irrigation expansion in the Navarre region was accelerated by establishing the “Canal de Navarra” project to convert 59,160 ha into irrigation. Approximately 40% (22,363 ha) of the proposed land has been converted into
irrigation within the project's first phase, with the remainder being transformed in the second phase (Government of Navarre, 2022). The lower reaches of our study area, the Cidacos River watershed, is part of the area converted from rainfed cultivation to irrigation under the project’s first phase, with approximately 7,700 ha of its total cultivated area converted to irrigation.

Previous studies have shown that the conversion from rainfed to irrigated agriculture affects water quality by increasing its salinity (Duncan et al., 2008; Pulido-Bosch et al., 2018) and nitrate pollution (Merchán et al., 2020; Muñoz-Carpena et al., 2002; Stamatis et al., 2011). Nitrate pollution leads to eutrophication, which endangers water quality for human consumption and the environment (Sutton et al., 2011; WHO, 2017). Although factors such as cultivation, livestock farming, aquaculture, and so on may contribute to an increase in nitrate pollution in agricultural areas (Casali et al., 2008; Mateo-Sagasta et al., 2018; Menció et al., 2016), the introduction of irrigation through agricultural intensification would result in higher nitrate loads and yields in such areas. In Spain, for example, flood-irrigated areas have reported nitrate yield values exceeding 100 N kg ha⁻¹ yr⁻¹ (Barros et al., 2012; García-Garizábal et al., 2012); pressurized irrigation systems have reported values ranging from 20 to 70 N kg ha⁻¹ yr⁻¹ (Andrés and Cuchí, 2014a; Cavero et al., 2003; Merchán et al., 2015, 2018, 2020); and rainfed agricultural areas tend to report lower nitrate levels with values ranging from 16 to 37 N kg ha⁻¹ yr⁻¹ (Casali et al., 2008; Merchán et al., 2018, 2020). Other European countries, such as Sweden and Estonia, have also recorded lower nitrate yields in rainfed areas, ranging from 6 to 32 N kg ha⁻¹ yr⁻¹ and 10 to 40 N kg ha⁻¹ yr⁻¹, respectively (Iital et al., 2014; Kyllmar et al., 2014). Irrigation is generally implemented in arid and semi-arid environments where the nitrate load under rain-fed agriculture is usually lower. Hence, a change from rainfed to irrigated agriculture in these areas is likely to increase the nitrate load export from a watershed; thus, estimating their quantities is essential to determine the potential impacts.

The introduction of irrigation also affects the hydrology of the irrigated areas. This includes the surface and groundwater by increasing the flows and recharging the groundwater aquifer, particularly when irrigation water is obtained outside the watershed (Zeng and Cai, 2014).

There has been limited research comparing the hydrological behavior and quality of return flows in agricultural areas before and after irrigation implementation. However, such information is important because shifting from rainfed to irrigated agriculture can
change the water regime and increase the concentrations and exports of agrochemicals, which are very harmful to the environment. This study expands on the baseline study by Merchán et al. (2020), which found an increase in the salt and nitrate concentrations in the Cidacos River’s lower reaches, where irrigation has been implemented for the past decade. However, no information was provided about the impact of irrigation on streamflow and nitrate exportation. This was primarily due to the lack of observed streamflow data before the irrigation period (streamflow measurement in the irrigated section began in June 2017), making it impossible to understand the streamflow patterns before this period and calculate the nitrate export. This analysis is essential in the current context of the increasing scarcity of water resources and growing concern about the contamination of aquifers and surface waters with nitrates and other substances, mainly from agriculture. Furthermore, even when there are relatively long data series of the behavior before and after irrigation, the comparison is not entirely accurate because the response of the rainfed period is not compared to that of the same period and climatic conditions in irrigation. The latter can only be possible by simulating the rainfed scenario and comparing it with the same period after irrigation.

Therefore, this study aimed to use the Soil Water Assessment Tool (SWAT) model to simulate and understand the behavior of the Cidacos River in the irrigated area from mid-2017 to 2020 before irrigation implementation and then compare those simulated results (rainfed condition) with the measured values (post-irrigation). The findings from this study contribute critical information to the implementation of the European Communities’ Nitrate Directive (ND, Directive 91/676/EEC) and the Water Framework Directive (WFD, Directive 2000/60/EC), both of which are concerned with protecting water bodies against nitrate pollution from agricultural areas (European Communities, 1991, 2000).

4.2 Materials and methods

4.2.1 Study area description
The study was carried out in the Cidacos River watershed in Navarre, located in northern Spain. Refer to Chapter 3, section 3.1. for the detailed description of the study area.

4.2.2 Data acquisition
Refer to Chapter 3, section 3.3. for the Cidacos River watershed’s data collection and processing information.
4.2.3 Model description

Refer to Chapter 2 for a detailed overview of the SWAT model, including hydrology and nitrate load simulation, and model evaluation criteria.

4.2.4 The model setup and run

The model set-up was preceded by preparing and processing the necessary spatial datasets such as DEM, soil and land use grid maps, and discharge outlet points on the QGIS 3.18 interface. The model was set up in the QSWAT3 1.1.1 interface by performing watershed delineation, HRU creation, input editing, and running the SWAT model. The watershed was delineated using the DEM and the Cidacos River shapefile until the outlet at Traibuenas. Discretization was done using a minimum area threshold of 10 km² required to create streams, resulting in a watershed area of 477.02 km² with 23 sub-watersheds. A slope elevation band of 0-5%, 5-10%, and 10% and above was provided to the model. The watershed’s overall elevation ranged from 315 m to 1150 m, with an average elevation of 560 m. By overlaying the LULC and soil grid maps and using a 5% threshold for land uses, soil type, and slope values, 1404 HRUs were generated. This threshold was chosen to eliminate minor land uses, soils, and slopes in each sub-watershed, facilitating model processing by improving its performance, speed, and efficiency. Using the SWAT editor, the weather data and agricultural management information were added to the model. Figure 4.1 shows the flow diagram for the SWAT model simulation of changing from rainfed to irrigated agriculture in this study.
**Figure 4.1:** Flow diagram for the SWAT model simulation of changing from rainfed to irrigated agriculture in the lower reaches of the Cidacos River watershed

### 4.2.5 Sensitivity analysis, calibration, and validation

The SWAT Calibration and Uncertainty Procedures (SWATCUP) version 5.1.6, a standalone software, was used to perform sensitivity analysis, calibration, and validation of the model. The multi-site Sequential Uncertainty Fitting, version 2 (SUFI-2), a semi-automated inverse modeling routine procedure of SWATCUP, was used in this study. The model was run 500 times for each iteration, and the parameter sensitivity was determined by performing a global sensitivity analysis in which all parameters changed simultaneously. Multiple regression computations were used to identify the most sensitive parameters. The Latin hypercube-generated parameters are regressed against the objective function values in this system (Abbaspour, 2015). The t-test was used to determine the relative significance of each parameter.

The p-values and t-stat indices were used to assess the sensitivity of the parameters. The parameter was more sensitive when the p-value was lower, and vice versa. The best combination for obtaining the most sensitive parameter is a very small p-value and a large
t-value (absolute). Parameters that had p-values less than 0.05 were deemed highly sensitive. The parameter sensitivity was ranked using the t-stat index and the p-value to identify the most sensitive parameters that had the greatest impact on the model outputs (Arnold et al., 2012). Larger parameter uncertainties were initially assumed to ensure that most observed data fell within the 95 Percent Prediction Uncertainty (95PPU) band (Abbaspour et al., 2018). 95PPU accounts for all the uncertainties within the model combined. The parameter ranges were adjusted after every iteration run during the calibration phase until most of the observed data were bracketed in the 95PPU band. The model was deemed satisfactory when more than 50% of the observed flow data were bracketed within the 95PPU.

The model was run from 1990 to 2020, with the first ten years (1990-1999) serving as the warm-up period to allow the model to reach an optimal state before reading the outputs. The model was then evaluated over the remaining period (2000-2020), which was divided into calibration (2000-2010) and validation (2011-2020) phases. The streamflow parameters were first satisfactorily calibrated and fixed before calibrating the nitrate parameters. The calibration parameters were chosen from the abundant existing literature on streamflow and nitrate calibration using the SWAT model in the Mediterranean region (Abbaspour, 2015; Abbaspour et al., 2015, 2018; Kamali et al., 2017; Kouchi et al., 2017; Rouholahnejad et al., 2014). To change the parameter values in SWAT, three methods (parameter qualifiers) are used: "R" which refers to a relative change of the specified parameter that increases or decreases the existing SWAT parameter value by multiplying it by \((1 + \text{fitted value})\) to obtain the new parameter value; "V" which refers to value change or replacement which means that the initial SWAT parameter value is to be directly replaced by the fitted value; and "A" which refers to addition and means that the fitted value is added to the initial SWAT parameter value. After the sensitivity analysis, the final streamflow and nitrate load calibration parameters were chosen.

The model results were presented graphically on the hydrograph plots for the simulated and observed values during the calibration and validation periods. The model's performance was evaluated using the statistical performance indicator techniques discussed in Chapter 2, section 2.6.
4.2.6 Irrigation impact assessment

The impact of the change from rainfed to irrigated agriculture for the watershed was assessed at the outlet in Traibuenas using an irrigation impact index (Equation 4.1) that was established by calculating the ratio of the change (in streamflow, nitrate load, and nitrate concentration) in the post-irrigation (observed/irrigated) and pre-irrigation (simulated/rainfed) for the downstream and upstream sections located at Traibuenas and Olite, respectively to the area converted to irrigation as follows:

$$III_i = \frac{\Delta Post_{(ds-us)} - \Delta Pre_{(ds-us)}}{\Delta IA}$$

(4.1)

Where $III_i$ represents the irrigation impact indices for streamflow ($m^3 ha^{-1}$), nitrate load ($kg ha^{-1}$), and nitrate concentration ($mg L^{-1} ha^{-1}$) for the period considered; $\Delta Post_{(ds-us)}$ represents the change in the post-irrigation values between downstream (Traibuenas) and upstream (Olite) sections for each of the variables; $\Delta Pre_{(ds-us)}$ represents the change in the pre-irrigation values between downstream (Traibuenas) and upstream (Olite) sections for each variable; $\Delta IA$ is the change in the irrigated area in hectares.

These indices helped calculate the annual rate of change per unit area, which could be used to estimate similar changes in the watershed as well as compare different watersheds. The variation was computed as the percentage of the average annual change for each variable at the watershed outlet.

4.3 Results and discussion

4.3.1 Model evaluation

4.3.1.1 Parameterization and sensitivity analysis

The most influential parameters for the model’s calibration and validation were identified using a global sensitivity analysis. The curve number, soil evaporation factor, and groundwater delay time were the most sensitive streamflow calibration parameters, while the denitrification factor and nitrate percolation coefficient were the most sensitive nitrate calibration parameters. Table 4.1 shows the ranges of selected sensitive parameters during streamflow and nitrate load calibration. All other parameters used for the model simulation in this study area are listed in Table A 1 in Appendix II. The curve number is an important parameter for the watershed’s hydrology because it directly influences the surface runoff and infiltration rate. Since the initial model underestimated the baseflow
and overestimated runoff, the default curve number parameter values in each HRU were reduced by 12%, resulting in slightly reduced surface runoff and increased infiltration. The evaporation factor was sensitive because agricultural areas in the Mediterranean regions have high evapotranspiration rates. The model's evaporation generation capacity increased by lowering the default parameter value, thus appropriately representing the watershed's evaporative demand (Niraula et al., 2015). Similar sensitivity analysis findings have been obtained by other researchers in the Mediterranean catchments (Ficklin et al., 2012; Molina-Navarro et al., 2014, 2016; Niraula et al., 2015).

**Table 4.1:** Selected sensitive streamflow and nitrate load parameters used for the SWAT model simulation in the Cidacos River watershed.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Change Method*</th>
<th>Parameter adjustment values</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN2.mgt</td>
<td>Initial SCS runoff CN number for moisture condition II</td>
<td>R</td>
<td>Min. value</td>
</tr>
<tr>
<td>ESCO.hru</td>
<td>Soil Evaporation compensation factor</td>
<td>R</td>
<td>-0.40</td>
</tr>
<tr>
<td>GW_DELAY.gw</td>
<td>Groundwater delays (days)</td>
<td>V</td>
<td>20</td>
</tr>
<tr>
<td>CDN.bsn</td>
<td>Denitrification exponential rate coefficient</td>
<td>V</td>
<td>0</td>
</tr>
<tr>
<td>NPERCO</td>
<td>Nitrate Percolation coefficient</td>
<td>V</td>
<td>0.01</td>
</tr>
<tr>
<td>FIXCO.bsn</td>
<td>Nitrogen fixation coefficient</td>
<td>V</td>
<td>0.45</td>
</tr>
</tbody>
</table>

*R is a relative change method that multiplies the existing value with (1+fitted value), whereas V replaces the existing value with the fitted value.

The greatest influence on nitrate load was the amount of fertilizer lost to denitrification. Denitrification losses are higher in areas with high moisture content than in dry regions; thus, its parameter value was set very low due to the watershed’s Mediterranean climatic conditions. The nitrate percolation parameter governs how much nitrate is removed by surface runoff relative to the amount percolated. Typically, the default value ranges from 0.01 to 1; a lower value closer to 0 means that all of the nitrate is percolated and not in the surface runoff, while a percolation coefficient of 1 indicates that the surface runoff has the same nitrate content as percolation (Arnold et al., 2012). Because of the high nitrate concentration levels in the groundwater measurements, which indicate a high watershed nitrate percolation rate, this parameter was set relatively low in the model. The nitrogen fixation parameter regulates the amount of additional nitrogen provided to the plant to meet the legume demand when insufficient nitrate is in the root zone (Neitsch et
al., 2011). The greater the nitrogen fixation value, the more fixed the nitrogen demand, and vice versa.

4.3.1.2 Streamflow Calibration and validation

The maximum and minimum parameter values were used to account for the uncertainty for each parameter, with the fitted value providing the best simulation. The 95PPU was used to quantify model uncertainties, such as those related to parameters, input data, and structure. During the calibration and validation periods, the 95PPU results were represented by p-factor (0.56 and 0.65) and r-factor (0.70 and 0.67) values, respectively. These uncertainties may result in overestimation or underestimation by the model, often due to the model not fully capturing all the hydrologic components in the watershed because of the model's conceptual simplifications (Ficklin et al., 2013; Meaurio et al., 2015; Rostamian et al., 2008; Tolson and Shoemaker, 2007).

The model produced good results for streamflow prediction during calibration and validation, reproducing most of the observed discharge and its tendency over time (Figure 4.2). The NSE values (0.82 and 0.83) and $R^2$ (0.83 and 0.84) during calibration and validation periods indicate a strong relationship between the observed and simulated values, indicating a 'good' fit. The negative PBIAS values (-8.7% and -5.6%) showed a slight but reasonable overestimation of the average flows by the model during the simulation periods. The RSR value of 0.42 was satisfactory because it was below the recommended threshold of less than 0.7, indicating a good model performance. The results of the four statistical performance indicators deemed the model to be 'very good' and capable of simulating monthly streamflow in the study area as per the recommendations of Moriasi et al. (2007). The validation period resulted in better model performance compared to the calibration period. This could be due to improved input data, such as precipitation and land use during the validation period. The validation period's input data was more accurate, such as precipitation with few to no missing gaps and using the most recent land use map from 2019. However, there were a few meteorological data inconsistencies before 2004, particularly for the automatic stations, as most were only operational after March 2004.
Figure 4.2: Observed (dotted blue line) and simulated (solid red line) monthly discharge hydrographs and precipitation (grey bars) during the calibration (2000-2010) and validation (2011-2020) periods at the Olite gauging station in the Cidacos River

4.3.1.3 Nitrate load calibration and validation

The nitrate load parameters were calibrated after successfully calibrating and fixing the streamflow parameters. Comparisons between the observed and simulated monthly nitrate loads hydrographs (Figure 4.3) indicated a good model performance. The uncertainties in nitrate load simulation were accounted for using the 95PPU represented by the p-factor (0.72 and 0.63) and r-factor (0.92 and 0.98) during calibration and validation periods, respectively. Some of the model weaknesses could have resulted from errors in the input data. These include estimations of missing precipitation data used to generate the discharge (Bothisias et al., 2014); insufficient observed nitrate load data available since the concentration data were obtained from a highly scattered sampling frequency (in most cases collected only once per month at random dates and with several months having missing data) (Epelde et al., 2015); and information related to the agricultural management operations and practices such as fertilizer application or planting and harvesting dates (Zettam et al., 2020). The model simulation results were in good agreement with the observed data, indicating good accountability of the model's various agricultural inputs. The model's statistical performance was adequate, with acceptable NSE values (0.71 and 0.68) and R² values (0.72 and 0.79) during the calibration and
validation periods, respectively. The PBIAS results show that the model underestimates the nitrate loads by -9.2% and -7% during the calibration and validation periods, respectively. These results are within the acceptable thresholds recommended by Moriasi et al. (2007), indicating a good model performance.

Figure 4.3: Plot of observed (dotted green line) and simulated (solid red line) monthly nitrate load and measured streamflow (blue bars) during calibration and validation periods at the Olite gauging station in the Cidacos River

The inter-annual and seasonal variability of nitrate load was very high throughout the simulation period. Loads were higher in wetter years than in dry years, and vice versa. Nitrate loads in the watershed increased from mid-autumn and peaked during winter when precipitation was abundant, and thus streamflow, but gradually decreased from spring to summer, when precipitation was scarce. This could be attributed to increased streamflow and, to some extent, the nitrogen fertilizer application on agricultural fields because the planting season begins in October/November, increasing soil nitrogen levels, nitrate concentration, and, subsequently, nitrate loads in the watershed. Because nitrate load is a function of discharge used to transport it downstream, higher precipitation in the watershed during the winter and spring months will inevitably increase nitrate load exportation in the river. However, less nitrate load is exported during the summer, when precipitation is scarce, resulting in limited streamflow; in addition, there are almost no agricultural activities in the watershed's upper reaches, which rely primarily on rain-fed
farming. These results are consistent with those obtained by Lam et al. (2009) when modeling agricultural catchments in Europe, where they reported that these patterns could be attributed to higher nitrogen concentrations in the winter due to nitrogen mobilization in the watershed and a lack of plant uptake, resulting in the accumulation of leachable nitrates and thus an increase in nitrogen concentration in streamflow during winter. Similar findings have also been reported by Donmez et al. (2020), who inferred that an increase in fertilization would lead to an increase in the amount of nitrate in the soil, which would be directly related to plant growth and agricultural production and management. According to Abbaspour et al. (2015), nitrate dynamics in agricultural watersheds are governed mainly by the fate and transportation of fertilizer in the soil, the rate of organic matter decomposition, and the prevailing climate.

4.3.2 Irrigation dynamics in the watershed

The conversion of agricultural land from rainfed to irrigation in the study area began in late 2006, with nearly 70% of the changes occurring between 2009 and 2012 (Figure 3.3). By 2020, at least 16% of the watershed had been converted into irrigated land. This study evaluated the conversion from rainfed to irrigation using the available data (mid-2017 to 2020). The seasonal irrigation patterns show that in winter, irrigation is minimal (only 1%), while in the summer, irrigation water applications are high (57%) (Figure 4.4). Irrigation was mostly done during periods of low precipitation, especially from July to September (Figure 4.4a). Similar seasonal irrigation patterns have been observed in other semi-arid irrigated watersheds within the Ebro basin (Andrés and Cuchí, 2014b; García-Garizábal et al., 2011, 2017; Merchán et al., 2015) and around the world (Scott et al., 2011).
Figure 4.4: (a) Monthly average precipitation, irrigation, and streamflow distribution at the watershed outlet in Traibuenas from mid-2017 to 2020, (b) seasonal precipitation and irrigation distribution pattern, and (c) the percentage of irrigation water applied each season.

According to the INTIA reports (INTIA, 2019, 2020, 2021), the average water inflow into the irrigated section of the watershed was 51% precipitation, 31% river inflow from the Olite gauging station, and 17% irrigation water from the Navarre canal. In 2020, evapotranspiration accounted for 33.5% of output, groundwater storage accounted for 3.5%, and the outflow at the Traibuenas gauging station accounted for 42%. The irrigation performance efficiency in the study area was relatively high (84.6%), indicating a well-managed irrigation system. However, there is a spatial variation, with some irrigated plots having lower efficiencies than others, which are compensated for by the higher ones. The irrigation efficiency value was slightly higher than the figures reported by other researchers in the Ebro basin, such as 76% (Andrés and Cuchi, 2014b) and 72% (Skhiri and Dechmi, 2012) in watersheds with predominantly sprinkler irrigation.

4.3.3 Observed nitrate concentration dynamics

Nitrate concentrations at the watershed outlet in Traibuenas have been monitored since 2000. The average annual nitrate concentration distribution pattern from 2000 to 2020 is depicted in Figure 4.5. During the pre-irrigation period (2000-2008), the average nitrate

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concentration at the Traibuenas gauging station was 27.72 mg L\(^{-1}\) (median value of 27.49 mg L\(^{-1}\); interquartile range (IQR): 34.77 mg L\(^{-1}\) to 23.77 mg L\(^{-1}\)) with maximum and minimum concentrations of 57.20 mg L\(^{-1}\) and 4 mg L\(^{-1}\), respectively. The monthly median values ranged from 45.64 mg L\(^{-1}\) in January to 11.33 mg L\(^{-1}\) in September. For the pre-irrigation period, 80 nitrate concentration samples were analyzed, with only 6.3% (5 samples) exceeding the 50 mg L\(^{-1}\) threshold recommended by Nitrate Directives and 45% (36 samples) falling below the 25 mg L\(^{-1}\) for unaffected waters. The nitrate concentration varied between the years, with the lowest value recorded in 2002 due to a severe drought, resulting in limited cultivation, and the highest in 2007 due to abundant precipitation and, thus, increased cultivation. The seasonal cycles were not consistent for all the years during the pre-irrigation period, with high nitrate concentrations in winter and spring and low concentrations in summer and autumn. The temporal fluctuation in nitrate concentration before the irrigation implementation was in tandem with the precipitation distribution pattern for each season in a specific year. These findings are consistent with those made by Orellana-Macias et al. (2020) in a study of nitrate vulnerable zones evolution in the north-east of Spain and Hernández-García et al. (2020) in a small rainfed experimental watershed in Navarre, where they both observed an increase in nitrate concentration during the years with more precipitation compared to years with less due to increased cultivation and subsequent crop fertilization. The nitrate concentration substantially declined during the transition period (2009 to 2012) because this was the period when the irrigation infrastructure was being constructed; thus, most of the agricultural land was left uncultivated except for the upstream area, which was unaffected by this development.
Figure 4.5: The average annual nitrate concentration distribution pattern at the watershed outlet in Traibuenas before and after irrigation implementation from 2000 to 2020.

During the post-irrigation period (2013 to 2020), 71 nitrate concentration samples were analyzed. The nitrate concentration in the post-irrigation period was twice as high as in the pre-irrigation period (Figure 4.5), with a mean of 53.14 mg L\(^{-1}\) (median value of 54.99 mg L\(^{-1}\); IQR: 57.95 mg L\(^{-1}\) to 47.83 mg L\(^{-1}\)) and maximum and minimum concentrations of 97.10 mg L\(^{-1}\) and 16.04 mg L\(^{-1}\), respectively. The monthly median concentration values ranged from 73.70 mg L\(^{-1}\) in September to 31.9 mg L\(^{-1}\) in March. Hernández-García et al. (2020) found similar results when comparing the nitrate concentration levels in rainfed and irrigated experimental watersheds in Navarre, with the findings indicating a threefold higher nitrate concentration in the irrigated watershed than in the rainfed one. The collected samples exceeded the recommended Nitrate Directive threshold of 50 mg L\(^{-1}\) in 56.3% (40 samples), indicating that the river was contaminated with nitrate, while only 2.8% (2 samples) fell below the 25 mg L\(^{-1}\) level (unaffected waters). The nitrate concentration was significantly higher (p < 0.01) during the post-irrigation period than during the pre-irrigation period from May to December. Following the irrigation implementation, the seasonal cycle of nitrate concentrations was substantially altered; the peak concentration shifted from January-February to August-September, and the lowest concentration shifted from September-October to March-April.

The nitrate concentration patterns in the watershed may be related to the cropping practices before and after irrigation. Before irrigation, the main crops grown in the
watershed were mostly rainfed winter cereals (wheat and barley), which required less nitrate fertilization. However, following the implementation of irrigation, high-value crops such as tomatoes and corn, which require more fertilization, were introduced into the watershed, increasing nitrate concentration levels, particularly during the summer and autumn. Lower nitrate concentration and export levels from rainfed cultivated areas in Navarre have also been reported by other studies (Casalí et al., 2008; Hernández-García et al., 2020; Lassaletta et al., 2010). During the pre-irrigation period, cultivation was mostly done during the winter and spring when there was enough precipitation. However, this decreased during the summer and autumn when productivity was low due to a lack of precipitation, resulting in lower nitrate concentration. Hernández-García et al. (2020) obtained similar seasonal patterns during rainfed conditions in their studies of small experimental watersheds within Navarre with similar characteristics to the Cidacos River watershed. The post-irrigation phase, however, sees year-round cultivation with irrigation supporting farming during the summer and autumn, a period when productivity was previously low.

4.3.4 Variations in streamflow and nitrate (load and concentration) due to irrigation

The irrigation impact index and the average annual variation after irrigation implementation showed a positive response in streamflow, nitrate load, and nitrate concentration. The annual irrigation impact index per unit irrigated area (Equation 4.1) shows that irrigation increased the streamflow (952.33 m$^3$ ha$^{-1}$, +18.8%), nitrate load (68.17 kg ha$^{-1}$, +62.3%), and nitrate concentration (0.89 mg L$^{-1}$ ha$^{-1}$, +79%) at the watershed outlet (Figure 4.6). These findings are comparable to those obtained by Merchán et al. (2013), who reported an increase of streamflow, nitrate load, and nitrate concentration by 23%, 27%, and 8%, respectively, in the Lerma catchment within the Ebro basin in Spain after irrigation implementation. However, the variation in exported nitrate load and concentration was slightly higher in this study than in Merchán et al. (2013) because the Lerma catchment had higher nitrogen concentration levels before irrigation implementation than the Cidacos River watershed due to different fertilization management practices. Similar annual nitrate exportation rates after irrigation implementation have been reported in Monegros within the Ebro basin at 49 kg ha$^{-1}$ (Cavero et al., 2003) and in La Violada irrigation district in north-east Spain at 66 kg ha$^{-1}$ (Barros et al., 2012). Likewise, the reported increases in nitrate concentration values after irrigation of 0.7 to 0.8 mg L$^{-1}$ ha$^{-1}$ in the middle Ebro River basin (Causapé et al.,
2004) and 0.91 mg L\(^{-1}\) ha\(^{-1}\) in the Arba River basin (CHE, 2006) are in close agreement with our findings.

**Figure 4.6:** Comparison of average annual changes in (a) streamflow, (b) nitrate load, and (c) nitrate concentration before and after irrigation at Olite and Traibuenas stations from mid-2017 to 2020

The increased streamflow in the post-irrigation period was consistent with the addition of irrigation water from outside the watershed via the Navarre canal. The irrigation impact on streamflow was more pronounced in the summer and autumn compared to winter and spring, resulting in changes in the watershed’s hydrological behavior (Figure 4.7). More research into the effects of these changes on flora and fauna is needed in the future to understand their impacts.
Figure 4.7: Seasonal comparison of (a) pre-irrigation and post-irrigation results and (b) the percentage changes after irrigation implementation for streamflow, nitrate load, and concentration at the Traibuenas gauging stations from mid-2017 to 2020.

The changes in nitrate (load and concentration) in the post-irrigation period were attributed to increased nitrogen fertilizer application resulting from cultivating high-value crops (with high nitrogen fertilizer demand) to boost productivity due to irrigation. Furthermore, the introduction of irrigation has resulted in a shift in cropping cycles because crops can now receive water throughout the year, with rainfall primarily supporting agriculture in the winter and spring and irrigation in the summer and autumn. The concentration and exported nitrate were comparatively higher in the summer and autumn (from May to October) due to nitrate mobilization resulting from irrigation, increased fertilizer application during that period, and low streamflow despite the irrigation water contributions. The highest nitrate concentration in the post-irrigation period was observed from August to October, which could be influenced by the top-dressing fertilization (Causapé et al., 2004; Merchán et al., 2013, 2015).
The increase in exported nitrate load during the summer was very high (243%) due to increases in both streamflow (70%) and nitrate concentration (124%) in the same period (Figure 4.7). The exported nitrate load is directly influenced by streamflow and nitrate concentration, whereby a slight increase in streamflow produces a greater change in the exported nitrate load than a slight increase in the nitrate concentration. This effect of increased flow on the exported nitrate loads has been reported in other studies in irrigated areas (Barros et al., 2012; Merchán et al., 2013). Given the importance of nitrate exportation, some studies (Arauzo et al., 2011; Causapé et al., 2004; Merchán et al., 2013, 2015) have proposed its adoption in agricultural management decisions for nitrogen impact assessment rather than relying solely on the Nitrate Directive’s nitrate concentration thresholds.

4.4 Conclusion

The main findings and conclusions of this chapter are provided in Chapter 7, sections 7.1 and 7.2.
Chapter 5:

5 Effects of Climate Change on Streamflow and Nitrate Pollution in the Cidacos River Watershed


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5.1 Introduction

Agriculture is one of the most important sectors of any regional or national economy globally. It is the primary source of livelihood and the backbone of most nations' economic systems, with more than 60% of the world population directly dependent on it (FAO, 2017a). However, agricultural intensification puts great pressure on available water resources and the environment, potentially causing damage. These damages could range from soil erosion, which is much more common in agricultural environments than in other soil uses (Garcia-Ruiz et al., 2015; Almagro et al., 2016; Boardman and Poesen, 2006), to water quality degradation caused by non-point source pollution (Chahor et al., 2014; Giménez et al., 2012; Merchán et al., 2018; Sutton et al., 2011). Studies conducted within the Navarra region of northern Spain have identified considerable nitrate and phosphate concentrations in streams in cereal crop areas, where the recommended thresholds are often exceeded, albeit with seasonal and annual variability (Casali et al., 2008; Hernández-Garcia et al., 2020; Merchán et al., 2019).

The Cidacos River watershed in the Navarre region has diverse land uses, with rainfed agriculture predominating. The watershed holds decades' worth of nitrate concentration, discharge, and meteorological data collected by the Government of Navarra at various stations, hence making it ideal for conducting investigations on agricultural activities’ impact on the quality and quantity of water resources in the area. Some of the challenges associated with agricultural practices in the study area are nitrate pollution in surface waters, as evidenced by high nitrate concentration levels in the Cidacos River (Merchán et al., 2020), and anticipated climate change effects due to projected changes in temperature and precipitation affecting the cropping system (Funes et al., 2016; Trnka et al., 2011).

Climate change impacts on water resources can be quantified by using various Global or Regional Climate Models (GCMs or RCMs) and future radiative forcing scenarios, known as Representative Concentration Pathways (RCPs), to establish appropriate adaptation measures and policy interventions (Krysanova et al., 2017). The Mediterranean region, particularly Spain, is considered to be highly vulnerable to the effects of climate change due to its geographical location and the imbalance between the available water resources and the current demands (Vargas-Amelin and Pindado, 2014). Furthermore, most climate change model projections for Spain indicate an increase in temperature and a decrease in precipitation by the end of the 21st Century (Candela et al.,
Climate change is expected to affect all aspects of the environment, compounding agricultural effects on streamflow and nitrate exportation (Arora, 2019). For instance, a change in streamflow due to projected temperature and precipitation changes would result in extreme events such as droughts or floods. These events would, in turn, influence the nitrate dynamics in the watershed by changing the exported nitrates loads and concentration accumulated in the soils and water. Therefore, it is important to investigate the potential effects of climate change on streamflow and nitrate dynamics, as they would impair the current hydrological conditions and hinder the achievement of nitrate standards as stipulated by the European Water Framework Directive (European Communities, 2000).

Nitrate pollution is a global concern that affects water quality by making it unsafe for human consumption (WHO, 2017) and increasing eutrophication (Sutton et al., 2011). Nitrate pollution contributors in a watershed could include agriculture, livestock, and aquaculture (Casali et al., 2008; Mateo-Sagasta et al., 2018; Menció et al., 2016). Whilst some level of nitrate exportation is inevitable in agricultural areas, improved management practices could limit its effect on streams (Beaudoin et al., 2005; Boithias et al., 2014; Cameron et al., 2013). To address the nitrate pollution challenge, the European Commission has established policy legislations such as the Nitrate Directive (ND, Directive 91/676/EEC) and the European Water Framework Directive (WFD, Directive 2000/60/EEC) to protect water bodies from agricultural nitrate pollution, with a nitrate concentration threshold of 50 mg L\(^{-1}\) for European rivers (European Communities, 1991). However, more research is needed to understand the spatial and temporal interactions of water quality variables and quantify the loads to assess their climate change impacts.

Mathematical models are fundamental tools for hydrological and environmental planning, with their greatest potential being the ability to generate scenarios in the face of voluntary or imposed changes in land use or management. The Soil Water Assessment Tool (SWAT) model is one of the best available tools for simulating the response of agricultural (or non-agricultural) watersheds to water quality. The SWAT model has been widely used by water resources experts to understand the characteristics of a watershed and predict its hydrological response to external (climate) and internal (water management, land management, etc.) drivers and their impacts. The SWAT model has been applied in the Mediterranean region and particularly Spain for streamflow analysis (Harraki et al., 2021;
Jimeno-Sáez et al., 2018; Meaurio et al., 2015) and water quality assessment of nitrogen and nitrates (Epelde et al., 2015; Zabaleta et al., 2014; Zettam et al., 2020). The majority of nitrate studies conducted by the SWAT model focus on how to reduce nitrate pollution through land use changes (Ferrant et al., 2011; Wang et al., 2008), as well as regulating fertilizer application rates and other management practices like tillage (Boithias et al., 2014; Cerro et al., 2014; Ferrant et al., 2011; R. Liu et al., 2013). Despite several studies on streamflow and hydrological response to climate change, there has been very little research on the effects of climate change on water quality (Ficklin et al., 2010; Luz Rodríguez-Blanco et al., 2019; Martinková et al., 2011; Molina-Navarro et al., 2014). Moreover, there are no long-term climate change assessments of the effects of agricultural activities on streamflow and water quality in the Navarre region.

This study aimed to evaluate the SWAT model's applicability for climate change prediction of streamflow and nitrate load in a rainfed agricultural Mediterranean watershed in northern Spain. The model was first evaluated for its capacity to simulate streamflow and nitrate export under rainfed agricultural conditions in the upper reaches of the Cidacos River watershed and then used to assess the climate change impacts by comparing future projections to the historical baseline under two emission scenarios (RCP4.5 and RCP8.5). The findings from this study could provide valuable information on climate change adaptation and mitigation measures in the future and deepen the knowledge of nitrate exportation and pollution in the study area.

5.2 Materials and methods

5.2.1 Study area description

The study was carried out in the Cidacos River watershed in Navarre, located in northern Spain. Refer to Chapter 3, section 3.1. for the detailed description of the study area.

5.2.2 Data acquisition

Refer to Chapter 3, section 3.3. for the Cidacos River watershed’s data collection and processing information.

5.2.3 Model description

Refer to Chapter 2 for a detailed overview of the SWAT model, including hydrology and nitrate load simulation, and model evaluation criteria.
5.2.4 The model set-up and run

Refer to Chapter 4, section 4.2.4, where the model setup for this study has been discussed. Figure 5.1 illustrates the SWAT model climate change simulation flow diagram for the Cidacos River Watershed.

![Flow diagram of the SWAT model simulation of climate change in the Cidacos River watershed](image)

**Figure 5.1:** Flow diagram of the SWAT model simulation of climate change in the Cidacos River watershed

5.2.5 Sensitivity analysis, calibration, and validation

Refer to Chapter 4, section 4.2.5, where the sensitivity analysis, calibration, and validation of this study have been discussed.

5.2.6 Climate change scenario development

The climate change impact in the study area was analyzed using an ensemble of six Global Climate Models (ACCESS1-0, BCC-CSM1-1, CMCC-CM, GDFL-ESM2G, IPSL-CM5A-LR, and MPI-ESM-MR) from bias-corrected Coupled Model Intercomparison Project (CMIP) climate forcing data statistically downscaled on a 5 km grid for the
Navarre region for historical and future data of RCP4.5 and RCP8.5 emission scenarios. This data was developed by the Spanish National Agency for Meteorology (AEMET) and was downloaded from the Platform on Adaptation to Climate Change in Spain (AdapteCCa) portal (AdapteCCa, 2021). These two projected radiative forcing scenarios represent the potential moderate (RCP4.5) and more aggressive (RCP8.5) climate change impact scenarios, with RCP4.5 assuming that greenhouse gas emissions will be gradually reduced in the coming years to achieve stability by 2100 and RCP8.5 assuming that greenhouse gas (GHG) emissions will continue to rise at current levels throughout the 21st century (IPCC 2014). Only the precipitation and temperature (maximum and minimum) datasets were used for the climate change simulation.

The calibrated SWAT model was used to simulate projected streamflow and nitrate load trends using climate change data (precipitation and temperature) as inputs while assuming all other variables to be constant. Crop heat units were used in the simulation to assign agricultural management operations such as planting, harvesting, and fertilization periods automatically. The simulation was run for each GCM from 1971-2000 for historical reference and 2011-2100 for the RCP4.5 and RCP8.5 future projection scenarios. In total, 18 simulations with six historical and 12 future projections were run (6 for each emission scenario). The future projection scenarios of streamflow and nitrate export were analyzed for three distinct periods categorized into short-term (2011-2040), medium-term (2041-2070), and long-term (2071-2100) by comparing each model to its historical period (1971-2000). Finally, the models' results were combined and averaged to obtain an ensemble for the climate change analysis.

5.3 Results and discussions
5.3.1 Model evaluation

Refer to Chapter 4, section 4.3, where the model evaluation for this study has been exhaustively discussed, including parameterization and sensitivity analysis results, as well as calibration and validation results of streamflow and nitrate load.

5.3.2 Climate change impact analysis
5.3.2.1 Projected precipitation and temperature

Analysis of the future climate projection compared to the historical reference depicts a general decrease in precipitation and an increase in temperature. Figure 5.2 illustrates the
percent decrease in mean annual precipitation and increase in average temperature for all six climate models under RCP4.5 and RCP8.5 emission scenarios over the three projected periods relative to the historical period. The average decline in precipitation in the short-, medium-, and long-term projections were -3.5%, -6.9%, and -7.6% for RCP4.5, and -3.1%, -7.9%, and -14.8% for RCP8.5, respectively. The average temperature projections, on the other hand, increased progressively over the three periods, by 1.2 °C, 1.9 °C, and 2.2 °C for RCP4.5, and 1.4 °C, 2.0 °C, and 4.3 °C for RCP8.5. The projected precipitation data varied more among the selected models than the projected temperature, which was closely comparable across the models. These projections are similar to those reported by the European Environment Agency (EEA) (2017) for the Mediterranean region, indicating a significant increase in warming of 2 °C to 5°C from the 2050s to the end of the 21st century, while the mean annual precipitation could decrease by -5% to -15%, and in the worst case scenario, up to -25%, with an acceleration expected at the end of the century. Furthermore, winter and autumn project a higher decrease in precipitation than summer and spring, while summer temperature increases are greater than winter. Projected precipitation decline and temperature increase over the three time periods of 2040, 2070, and 2100 have also been reported for other studies within the Mediterranean region (Abd-Elmabod et al., 2020; Al-Mukhtar and Qasim, 2019; Fonseca and Santos, 2019). These projected climate changes are expected to alter the watershed’s hydrological cycle by increasing the air temperature and, thus, evapotranspiration. A warmer atmosphere is expected to hold more water vapor, causing precipitation concentrations to rise, resulting in more frequent and intense extreme events (Abd-Elmabod et al., 2020; Navarra and Tubiana, 2013). However, greater losses in open surface waters and soils are also expected with the projected high evapotranspiration rates.
5.3.2.2 Effects of climate change on streamflow

The simulated climate change projections showed a declining effect on streamflow for both emission scenarios over all the projected periods analyzed with high interannual fluctuations (Figure 5.3). The average annual streamflow decreased by -11.5%, -27.4%, and -28.5% for RCP4.5 and -8.5%, -27.5%, and -52.4% for RCP8.5 during the short-, medium-, and long-term future climate projections, respectively, compared to the historical reference period. This decline was mainly attributed to the projected decrease in precipitation and increasing temperatures for all the climate models used in the study (Figure 5.2), leading to a rise in the watershed’s evapotranspiration. Higher evapotranspiration rates and lower precipitation would result in declining discharge unless there is a significant shift in the seasonal pattern with more precipitation occurring during colder seasons (Anand and Oinam, 2019; Molina-Navarro et al., 2014, 2016).
Figure 5.3: Average annual streamflow evolution over historical (1971-2000), short-term (2011-2040), medium-term (2041-2070), and long-term (2071-2100) periods under RCP4.5 and RCP8.5 climate change projections.

The long-term climate projection had the highest streamflow reductions for RCP4.5 (-28.5%) and RCP8.5 (-52.4%). The considerable streamflow reduction in RCP8.5 long-term projection compared to RCP4.5 was due to the continuous increase in temperature and decreasing precipitation caused by the lack of climate change mitigation measures to reduce the GHG emissions for this scenario. However, for RCP4.5, some mitigation measures to reduce GHG emissions are expected to be implemented gradually from the mid-term projection onwards. The RCP4.5 long-term projection showed greater extreme streamflow occurrences than the RCP8.5, which could be attributed to variations in precipitation and temperature intensity, timing, and frequency. This could potentially result in more frequent and severe floods and streamflow under RCP4.5, as well as drought and drier conditions under the RCP8.5 scenario, lowering the streamflow.

The projected long-term streamflow reductions were slightly higher in summer and autumn than in winter and spring for both emission scenarios (Figure 5.4a). The long-term projection showed the greatest decrease, with a -66.4% (RCP8.5) and -42.0% (RCP4.5) reduction in streamflow during autumn. The declining patterns of the seasonal projections correspond to changes in precipitation and temperature. These findings are consistent with other studies in the Mediterranean climate that have found that annual streamflow in a watershed or on a regional scale is extremely sensitive to changes in
precipitation, such that a slight decrease in precipitation in regions with high temperatures and consequently higher evapotranspiration rates would likely result in a significant reduction in runoff (Ficklin et al., 2013; Molina-Navarro et al., 2014, 2016). The results, especially the RCP8.5 long-term projection, have very strong implications for the water available in the river by the end of the century if the current global warming trends continue. A decline of more than 50% of the currently available streamflow would seriously affect the available water resources for the aquatic ecosystem, domestic consumption, and agricultural use.

Figure 5.4: Seasonal percent changes in projected future (a) streamflow and (b) nitrate load over the short-, medium-, and long-term periods under RCP4.5 and RCP8.5 emission scenarios relative to the historical reference.

5.3.2.3 Effects of climate change on nitrate load

The simulated future annual nitrate load decreased by -21.7%, -17.7%, and -12.8% for RCP4.5 and -20.5%, -16.6%, and -43.6% for RCP 8.5 in the short-, medium-, and long-projections, respectively, compared to the historical reference period with very high interannual variability (Figure 5.5). The short-term and medium-term nitrate load projections under RCP4.5 and RCP8.5 were quite similar. However, there was a considerable difference in the long-term projection, with RCP8.5 experiencing the greatest decline of -43.6% compared to -12.8 for RCP4.5. The decrease in projected nitrate load was primarily due to the reduction in projected streamflow. The statistical
The relationship between streamflow and nitrate load showed a good correlation (p-value < 0.05) for RCP4.5 and RCP8.5 over the entire future projection period. This relationship indicates that streamflow, mainly driven by precipitation and temperature, would play an essential and critical role in determining the future nitrate export since it is the primary driving mechanism. However, the relationship between streamflow and nitrate load is not always linear despite streamflow having the greatest influence. Other factors that could play a critical role in determining the sources, amounts, mobilization, and transport pathways of nitrate in an agricultural watershed include precipitation amount and intensity, land cover type and practices, fertilization quantity and type, as well as cropping pattern and schedule (Boithias et al., 2014; Cameron et al., 2013; Parajuli and Risal, 2021). Additionally, the presence of buffer zones and riparian vegetation could help minimize nitrate mobilization and transport to surface waterways (Beaudoin et al., 2005). These results are consistent with other studies within the Mediterranean region (Molina-Navarro et al., 2014) and the Iberian Peninsula (Carvalho-Santos et al., 2016) that have reported a decrease in nitrogen exportation due to the reduced streamflow. Mander et al. (2000) also found that reducing surface water runoff considerably reduced nitrate load exportation in cultivated areas.

**Figure 5.5:** Average annual nitrate load evolution over historical (1971-2000), short-term (2011-2040), medium-term (2041-2070), and long-term (2071-2100) periods under RCP4.5 and RCP8.5 climate change projections.
The magnitude and frequency of nitrate load occurrence were greater in the long-term projection scenario of RCP4.5 than in RCP8.5, similar to the streamflow results. This pattern could be due to the timing of agricultural management operations, such as fertilization, which could have coincided with heavy rainfall as well as more available water to transport the nitrates. The increase in frequency and severity of extreme precipitation events under RCP4.5 after the 2070s in the Mediterranean region have been reported to result in increased streamflow and nitrate export (Almeida et al., 2022; Barredo et al., 2017; Giorgi and Lionello, 2008; Todaro et al., 2022).

Nitrate load decreased in all seasons and projected periods for both emission scenarios, with the greatest decrease occurring in summer for the RCP8.5 long-term projection (-50.2%) and autumn for the RCP4.5 medium-term projection (-22.6%) (Figure 5.4b). This could be due to higher streamflow reduction and the aforementioned factors during the same period. However, the nitrate concentration is projected to rise by 4.1%, 34.8%, and 45.1% for RCP4.5 and 5.2%, 36.8%, 54.1% for RCP 8.5 in the short-, medium-, and long-term projections, respectively due to the faster streamflow decline than the nitrate exportation rate (Figure 5.6). This would result in the accumulation of more nitrates in the riverbed and soil, resulting in soil and groundwater pollution. Carvalho-Santos et al. (2016) observed an increasing trend in future nitrate concentration despite the declining nitrate loads attributed to declining streamflow. The projected increase in nitrate concentration at the end of the century will be of great concern as the current figures within the watershed already indicate a higher nitrate concentration. Findings by Merchán et al. (2020) have categorized the watershed as a "Nitrate Vulnerable Zone"; hence, any increase in concentration is likely to exacerbate the problem further. Furthermore, increased nitrate concentration would increase eutrophication in the river, thus enhancing algae bloom and consequently degrading the water quality and resulting in higher water treatment costs (Tong et al., 2012).
Figure 5.6: Projected evolution of the average annual nitrate concentration in the Cidacos River watershed over historical (1971-2000), short-term (2011-2040), medium-term (2041-2070), and long-term (2071-2100) periods under RCP4.5 and RCP8.5 climate change scenarios

5.3.2.4 Effect of climate change on agriculture

Projected climate change is expected to heavily impact agricultural activities through changes in phenology and cropping cycle (Funes et al., 2016; Trnka et al., 2011), as well as higher water demands due to increased evapotranspiration (Saadi et al., 2015; Valverde et al., 2015). Consequently, crop yields are expected to decline, especially under the RCP8.5 long-term projection with no adaptation measures (Feyen et al., 2020), in addition to higher inter-annual variability and decreased production resilience (Zampieri et al., 2020). Reduced streamflow would greatly affect irrigation, particularly for corn and tomatoes grown in the study area, which relies heavily on irrigation. Extreme warming, as projected in the medium and long term, will shorten the growing seasons for most crops. According to Mougou et al. (2011), a temperature increase of 2.5 °C to 4 °C would shorten the growing period of wheat in the Mediterranean region by 16 to 30 days. Recurrent drought events could result in heavy agricultural losses of more than -50% in irrigated areas and -15% in rain-fed cereal production (Mougou et al., 2011). Other negative climate change impacts on agriculture in the region include the emergence of new and re-emerging crop pests and diseases, which would increase production losses, as well as increased wildfire incidences caused by the projected extreme weather. These
factors would result in food insecurity and increased economic losses in the region and should thus be mitigated to limit the potential negative consequences.

5.3.2.5 Climate change adaptation and mitigation measures

Based on this study’s findings, it’s evident that climate change would negatively affect the agricultural areas in northern Spain and the Mediterranean region since water resources will be under great pressure and nitrate pollution of surface and groundwater will increase. As a result, robust agricultural policies, regulatory frameworks, and legislation aimed at climate change adaptation and mitigation would be required to minimize the potential negative impacts. The projected water scarcity and increased drought events would limit irrigation-based adaptation actions. However, agricultural management practices such as crop distribution, schedules, diversification, and rotation would be central to the adaptation strategy at the farm scale. Land use change by introducing drought-resistant crops could also improve climate change resilience. An effective adaptation and mitigation strategy would prioritize the following actions: (i) farming practices, which would include crop diversification, changing crop type and land use, and adjusting rotation patterns; (ii) water management practices, which would emphasize the need for technological development and innovation for crops and agricultural practices such as precision agriculture and modifying irrigation; (iii) farm management practices that focus on diversifying income sources, such as the government establishing programs to ensure agricultural subsidies, the provision of insurance to farmers to stabilize their income, and agricultural financial assistance; (iv) agricultural management practices that focus on optimal nitrogen fertilization, the use of organic fertilizers, and soil health improvement. Nitrogen surplus in the soil can be reduced through efficient application according to the soil nitrogen availability and potential crop yield. Combining these adaptation and mitigation strategies would improve the potential for increasing or at least maintaining crop yield.

5.4 Conclusion

The main findings and conclusions of this chapter are provided in Chapter 7, section 7.3.
Chapter 6:

6 Quantification of Agricultural Best Management Practices Impacts on Sediment and Phosphorous Export in a Small Catchment in Southeastern Sweden

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6.1 Introduction

Agricultural nutrient pollution is one of the leading sources of nonpoint source pollution in freshwater systems, especially in regions where the intensification of agriculture has led to increased nutrient inputs, affecting more than half of the global freshwater systems (Grizzetti et al., 2021; Mateo-Sagasta et al., 2018; Xia et al., 2020). The runoff from agricultural areas transports suspended sediments and excess nutrients from fertilizers and manure into water bodies. These pollutants endanger the quality of water resources and could have far-reaching consequences for aquatic ecosystems and human health (Oduor et al., 2023; Sutton et al., 2011). Almost 40% of the European Union region's water bodies, such as lakes, rivers, and coastal areas, have been affected by pollution from agricultural areas (Mateo-Sagasta et al., 2017; UN Water, 2015). Most European countries have enacted regulations to reduce nutrient pollution to address this issue, such as limiting nutrient discharges from point sources and implementing best management practices (BMPs) in agricultural areas. Efforts to improve water quality monitoring and data collection have also increased in the past few years to enhance informed decision-making (European Environment Agency (EEA), 2022).

The over-application of fertilizers, manure, and other agricultural inputs can result in the excess accumulation of nutrients in soils, which can then be transported to freshwater systems through runoff and leaching. Excessive phosphorous loading in freshwater systems can lead to eutrophication, which can have severe ecological and economic impacts (Carpenter et al., 1998; Sánchez-Colón and Schaffner, 2021). Similarly, intensive cultivation practices like tillage and plowing have contributed to soil erosion, which increases sediment export. Sediments can affect freshwater ecosystems by reducing light penetration through increased turbidity, burying benthic habitats, and transporting pollutants adhered to soil particles (Meyer et al., 2015).

The concentration of nutrients in runoff and drainage water from cultivated areas depends on numerous complex, interrelated factors, including previous agricultural management practices, land use and cover, soil type and characteristics, amount and intensity of precipitation, drainage system, topography, and many others (Ulén and Fölster, 2007). To mitigate the negative impacts of nutrient exportation from agricultural areas, Sweden has put in place various measures, such as regulating fertilizer by setting limits on the amounts of nitrogen and phosphorous fertilization based on soil type and crop needs, managing livestock farming to reduce nutrient runoff from manure, encouraging the growth of cover
crops, establishing buffer zones (filter strips), and restoring wetland to reduce nutrient and sediment runoff into waterways (Kyllmar et al., 2023; Mårtensson et al., 2023). Despite implementing some of these measures, their effectiveness is not well known. Therefore, there is still a need to evaluate and identify the BMPs that could help reduce sediment and phosphorous exports from cultivated areas.

BMPs are land management practices designed to reduce nutrient inputs to soils, prevent soil erosion, and improve water quality. BMPs have been identified to minimize sediment and nutrient pollution from agricultural activities. Previous studies have shown that BMPs, such as reduced tillage, buffer strips, regulated fertilization, etc., can effectively reduce sediment and phosphorous export from agricultural systems (Arabi et al., 2006; Sharpley et al., 2006; Sharpley et al., 2015). However, the effectiveness of these BMPs varies depending on soil type, climate, land use, and the specific BMP implemented. The effectiveness of BMPs can also be influenced by changes in management practices over time, such that if a farmer stops implementing a particular BMP, sediment and phosphorous export may increase again. In spite of these challenges, studies have shown that BMPs can effectively reduce sediment and phosphorous export if properly implemented and managed (Bracmort et al., 2006; Gitau et al., 2008; Liu et al., 2017).

Modeling approaches have been widely used to evaluate the impact of BMPs on nutrient export from agricultural systems. Models enable the examination of scenarios that are not easily studied through direct experimentation, saving time and resources (Moges et al., 2021; Yu, 2015). One widely used model for this purpose is the Soil and Water Assessment Tool (SWAT) model, which has been extensively applied on catchment and regional scales to understand the dynamics of land use and management practices on water quality (Arnold et al., 2012). The SWAT model provides a comprehensive framework for understanding and quantifying the impact of various factors on sediment and nutrient transport, including phosphorus, by modeling the complex interactions between land use, climate, soil, and surface and groundwater (Neitsch et al., 2011). Its applicability and reliability have been demonstrated in numerous studies worldwide, making it an ideal choice for adoption in this study.

In Sweden, most SWAT modeling applications are focused on climate change (e.g., Grusson et al., 2021; Jiménez-Navarro et al., 2023, 2021, etc.), hydrology and water quality (e.g., Bekarias et al., 2005; Exbrayat et al., 2010, etc.), and land use management (e.g., Ekstrand et al., 2010; Thodsen et al., 2017, etc.), however, its application for BMPs
analyses are limited or absent. Nevertheless, other models have been adopted to estimate the potential nutrient reduction of selected BMPs. For instance, Arheimer et al. (2005) used the HBV-NP model to assess the cost-effectiveness of implementing different cover crop scenarios, constructed wetlands, and buffer strips in the Ronnea catchment in southern Sweden. Similarly, Mårtensson et al. (2023) employed the Nutrient Leaching Coefficient Calculation System (NLeCCS) and the Average Nutrient Leaching Calculator (ANLeC) models to estimate nutrient leakage in the current study area and its entire leaching region by considering different crop combinations, variations in cultivation practices, cover crops, and buffer zones.

The main objective of this study was to use the SWAT model to quantify the effectiveness of selected agricultural BMPs (filter strips, sedimentation ponds, grassed waterways, and no-tillage) in reducing sediment and phosphorus export from a small agricultural catchment in southeastern Sweden. This objective was accomplished by carrying out the following two specific objectives: (i) calibrating and validating the SWAT model for streamflow, sediment, and phosphorous load in the study area and then (ii) using the calibrated model to simulate different BMP scenarios and assessing their effectiveness in reducing sediment and phosphorous export relative to the baseline scenario.

6.2 Materials and Methods

6.2.1 Study area description

The study was carried out in Catchment C6, located in southeastern Sweden. Refer to Chapter 3, section 3.2, for the detailed study area description.

6.2.2 Data acquisition

Refer to Chapter 3, section 3.4, for Catchment C6’s data collection and processing information.

6.2.3 Model description

Refer to Chapter 2 for a detailed overview of the SWAT model, including hydrology, sediment load, and phosphorous load simulation and model evaluation criteria.

6.2.4 The model set-up, calibration, and validation

The model was set up using QSWAT3 (version 1.1.1) within the QGIS 3.16 interphase. The catchment was delineated into 34 subbasins using the digital elevation model (DEM)
and the stream shapefile, with the catchment outlet point assigned. The catchment elevation ranged from 10 – 58 m above sea level (a.s.l) with a mean elevation of 27 m a.s.l. (standard deviation ±8.54 m). The DEM was overlaid with land use and soil data to generate 349 HRUs, which served as the model's primary simulation units. The meteorological data and agricultural management information were updated in the SWAT editor before running the model on a daily time-step from 1990 to 2020. The first ten years of the model run were used as a warm-up period for the model initialization. The model outputs for hydrology, sediment transport, and phosphorous export were extracted monthly from 2005 to 2020. These outputs were compared to observations for calibration (2005 – 2012) and validation (2013 – 2020) using the SWAT Calibration and Uncertainty Programs (SWAT-CUP) software. Figure 6.1 illustrates the flow diagram of the SWAT model simulation of agricultural BMPs in the study area.

The model calibration was done using the Sequential Uncertainty Fitting, version 2 (SUFI-2) algorithm of the SWAT-CUP (Abbaspour, 2015). The details of the SWAT-CUP parameterization, sensitivity and uncertainty analyses, calibration, validation, and performance evaluation are already discussed in Chapter 2, sections 2.5 and 2.6. The parameters controlling hydrology processes, sediment, and phosphorous export were selected by reviewing the existing literature on the SWAT model's application in similar catchments. The initial parameter uncertainty ranges were assigned based on the absolute SWAT parameter limits provided in SWAT-CUP. A global sensitivity analysis was conducted through an initial 500 model runs to determine the most sensitive parameters. The most sensitive parameters for each variable are discussed further in section 6.3.1 of the results.
Figure 6.1: Flow diagram for the SWAT model simulation of agricultural BMPs in Catchment C6

6.2.5 Agricultural BMPs scenario representation

The calibrated SWAT model was used to quantify the sediment and phosphorous export for the various BMP scenarios. The BMPs were selected based on the available literature (Arabi et al., 2006, 2008; Bracmort et al., 2006) and local agricultural management information (Mårtensson et al., 2023). The choice of the BMPs was based on factors such as practicality, ease of adoption and acceptance by the farmers, the viability of implementation, and potential effectiveness in reducing sediment and phosphorous. The calibrated model representing the existing land use and management practices in the catchment was used as the baseline scenario (no BMP implementation). The analyzed scenarios included the implementation of filter strips, sedimentation ponds, grassed
waterways, and conservation tillage practices. The modified SWAT model parameters for each BMP scenario implementation are shown in Table 6.1. The statistical significance of the average annual values of each BMP scenario was assessed using the Wilcoxon–Mann–Whitney Rank-Sum test (Helsel et al., 2020). A BMP scenario was considered statistically significant when the p-value was less than 5% (p-value < 0.05). The efficacy of the BMPs in minimizing sediment and phosphorous export from the catchment was determined by comparing the averages of each implemented BMP scenario to the baseline scenario.

**Table 6.1**: Modified SWAT model parameters for the BMPs scenarios implementation.

<table>
<thead>
<tr>
<th>BMP scenario</th>
<th>Modified SWAT parameter</th>
<th>Parameter*</th>
<th>Baseline value (No BMP)</th>
<th>Adjustment value (With BMP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter strip</td>
<td>FILTERW.mgt</td>
<td>0</td>
<td>7.5 (m)</td>
<td></td>
</tr>
<tr>
<td>Sedimentation ponds</td>
<td>PND_FR.pnd</td>
<td>0</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PND_PSA.pnd</td>
<td>5</td>
<td>500 (ha)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PND_PVOL.pnd</td>
<td>25</td>
<td>50 ($10^4$ m$^3$ H$_2$O)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PND_K.pnd</td>
<td>0</td>
<td>0.05 (mm hr$^{-1}$)</td>
<td></td>
</tr>
<tr>
<td>Grressed waterway</td>
<td>CH_COV1.rte</td>
<td>0.25</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CH_COV2.rte</td>
<td>0.2</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CH_N2.rte</td>
<td>0.25</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>No-tillage (Zero till)</td>
<td>CN2.mgt</td>
<td>Varies**</td>
<td>-10%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EFFMIX.till.dat</td>
<td>0.95</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DEPTIL.till.dat</td>
<td>150</td>
<td>25 (mm)</td>
<td></td>
</tr>
</tbody>
</table>

* The parameter descriptions are in the text.
** The CN2 parameter value varies for each HRU depending on land use, soil permeability, and antecedent soil moisture conditions. These values ranged from 55 to 72 in the catchment.

*Filter strips*, also known as buffer zones, are vegetation (such as trees, shrubs, and grass) planted along the edges of fields to trap sediment and nutrient pollutants that might be carried into nearby waterways. Filter strips are particularly effective in areas where cultivated fields are adjacent to streams or other water bodies. According to Mårtensson et al. (2023), filter strips are assumed to be installed along the edges of all fields and that all the fields in the catchment were connected to a watercourse. The primary purpose of filter strips is to reduce the amount of suspended sediments and dissolved contaminants in runoff water (Tuppad et al., 2010). The effectiveness of filter strips in contaminant removal, also known as trapping efficiency ($\text{Trap}_{\text{eff}}$) is dependent on the filter strip width (FILTERW) and is determined using Equation (2) (Arabi et al., 2008).
\[ \text{Trap}_{\text{eff}} = 0.367 \times \text{FILTERW}^{0.2967} \] 

According to Dosskey et al. (2008), a properly installed filter strip can effectively retain up to 90% of nutrients and sediment. In the SWAT model, the sediment and nutrient reduction rate across the filter strip is quantified as a function of the average filter strip width and the volume of water from the reach. Filter strip was implemented in the model by modifying the filter strip width (FILTERW) parameters by varying its value from 5 to 10 meters compared to the default without a filter. This range was based on the recommended buffer zone size of between 6 meters and 18 meters for all soil types permitted under the current Swedish regulations (Mårtensson et al., 2023). The sediment and phosphorus reduction rates were then determined for each filter width over the entire range, and the width with the highest reduction was considered the most effective.

Sedimentation ponds, also known as detention ponds or constructed wetlands, are shallow basins with a large surface area typically lined with vegetation designed to trap and reduce or remove sediments and agricultural pollutants from runoff by allowing them to deposit and settle at the bottom of the pond. The settled sediments can then be periodically removed from the pond by dredging or excavation and disposed of properly. Sedimentation and biological processes help to remove and reduce suspended sediments and nutrients in the pond. Nutrient retention occurs in the pond via sorption, precipitation, and incorporation (Waidler et al., 2009). The ponds can also help reduce floods by temporarily storing excess water during heavy rain. Sedimentation ponds were implemented in the SWAT model by adding pond parameters which included the fraction of subbasin area that drains into the ponds (PND_FR), the total surface area of the ponds when filled to the principal spillway (PND_PSA), volume of water needed to fill the ponds (PND_PVOL), and the hydraulic conductivity through the bottom of the pond (PND_K). The selected parameter ranges were based on the absolute SWAT parameter value range in SWAT-CUP (Abbaspour, 2015).

Grassed waterways are typically broad, shallow watercourses vegetated (with grass) to reduce the flow velocity and trap sediments and pollutants. Unlike filter strips, grassed waterways are usually installed in the drainage pathway (Evrard et al., 2007). Grassed waterways can withstand higher in-channel velocities than bare channels since vegetation retards the flow velocity and protects the soil. Grassed waterways were implemented in the SWAT model by modifying the channel parameters such as the channel's Manning's
coefficient of roughness (CH_N2), channel erodibility factor (CH_COV1), and channel cover factor (CH_COV2) as recommended by Bracmort et al. (2006) and Kaini et al. (2012). The default values for CH_COV1 and CH_COV2 were adjusted to 0.001, while the CH_N2 value was increased by 50% of its original value to represent a fully protected vegetative cover (Arabi et al., 2008; Kaini et al., 2012). It's worth noting that the 0.001 value chosen was an arbitrary, very small number close to zero to prevent the model from using the default values when set to 0. Other grass waterway design parameters found in the management operations file included depth (GWATD), width (GWATW), length (GWATL), and slope (GWATS), which all remained set to the model's default values as provided in the SWAT documentation (Arnold et al., 2012).

No-tillage (zero tillage) was only applied to arable land comprising about 60% of the total catchment area. The no-tillage practice involves leaving the soil undisturbed, and crop residue is maintained on the soil after harvest. No-tillage is one of the conservation tillage practices. Melero et al. (2009) describe conservation tillage as any tillage and planting practice that maintains at least 30% of the soil surface covered by residues after planting. In the SWAT model, tillage operations differ based on their mixing efficiencies (EFFMIX), which indicate the fraction of materials (such as residue, nutrients, pesticides, bacteria, etc.) distributed within the mixed soil depth (DEPTIL) of each soil layer. The SWAT model's tillage database provides information on mixing efficiencies and tillage depths for over 100 tillage practices, which maybe be specified in the model using their unique tillage identifiers (TILL_ID). The no-tillage scenario was implemented in the model using TILL_ID = 4. The parameter values for EFFMIX and DEPTIL are set at 0.05 and 25 mm, respectively. It is also recommended to reduce the curve number (CN2) parameter value by 2–3 units up to a maximum of 10% from the calibrated value when implementing tillage BMPs (Tuppad et al., 2010). CN was thus reduced by -10% to achieve the most optimal results.

6.3 Results and discussion

6.3.1 Model evaluation

6.3.1.1 Parameterization and sensitivity analysis

The sensitivity analysis was performed through a global sensitivity test of various selected initial parameters for streamflow, sediment, and phosphorous load. Streamflow parameters were analyzed and calibrated first, then sediments load parameters, and
finally, phosphorous parameters. Several studies (e.g., Abbaspour, 2015; Abbaspour et al., 2018, 2015; Arnold et al., 2012b; Yuan and Koropeckyj-Cox, 2022) have recommended the sequential calibration of streamflow, followed by sediments, and finally nutrients due to the interdependencies between the constituent variables as well as shared transportation processes. Table 6.2 presents the five most sensitive parameters for each variable. All other parameters used for the model simulation in this study area are listed in Table A 2 in Appendix II.

**Table 6.2**: Selected most sensitive SWAT parameters and adjusted values for streamflow, sediment load, and phosphorous load simulation in Catchment C6.

<table>
<thead>
<tr>
<th>SWAT input parameter*</th>
<th>Parameter description</th>
<th>Units</th>
<th>Parameter adjustment value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Default</td>
<td>Min</td>
</tr>
<tr>
<td>Hydrology parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>v__SFTMP.bsn</td>
<td>Snowfall temperature</td>
<td>°C</td>
<td>1</td>
</tr>
<tr>
<td>v__SMTMP.bsn</td>
<td>Snowmelt base temperature</td>
<td>°C</td>
<td>0.5</td>
</tr>
<tr>
<td>V__GW_DELAY.gw</td>
<td>Groundwater delay</td>
<td>days</td>
<td>31</td>
</tr>
<tr>
<td>r__SOL_AWC.sol</td>
<td>Available water capacity of the soil layer</td>
<td>mm H₂O/mm soil</td>
<td>-</td>
</tr>
<tr>
<td>r__CN2.mgt</td>
<td>Initial SCS runoff curve number for moisture condition II</td>
<td>-</td>
<td>35-98</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sediment load parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>v__CH_N2.rte</td>
<td>Manning's &quot;n&quot; value for the main channel</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>v__CH_K2.rte</td>
<td>Effective hydraulic conductivity in the main channel</td>
<td>mm hr⁻¹</td>
<td>-</td>
</tr>
<tr>
<td>v__LAT_SED.hru</td>
<td>Sediment concentration in lateral and groundwater flow</td>
<td>mg L⁻¹</td>
<td>0</td>
</tr>
<tr>
<td>v__SPCON.bsn</td>
<td>Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing</td>
<td>-</td>
<td>0.001</td>
</tr>
<tr>
<td>v__PRF_BSN.bsn</td>
<td>Peak rate adjustment of sediment routing in the main channel</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phosphorous load parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>v__PSP.bsn</td>
<td>Phosphorous availability index</td>
<td>-</td>
<td>0.40</td>
</tr>
<tr>
<td>v__P_UPDIS.bsn</td>
<td>Phosphorous uptake distribution parameter</td>
<td>-</td>
<td>20</td>
</tr>
<tr>
<td>v__PHOSKD.bsn</td>
<td>Phosphorous soil partitioning coefficient</td>
<td>m³ Mg⁻¹</td>
<td>175</td>
</tr>
<tr>
<td>v__PPERCO.bsn</td>
<td>Phosphorous percolation coefficient</td>
<td>10 m³ Mg⁻¹</td>
<td>10</td>
</tr>
<tr>
<td>v__RS5.swq</td>
<td>Organic P settling rate in the reach at 20 °C</td>
<td>day⁻¹</td>
<td>0.05</td>
</tr>
</tbody>
</table>
**v** represents a parameter change by replacing the existing value with the fitted value, whereas "r" represents a relative change by varying the existing value with the fitted value. Generally, the replacement method is used for basin-wide parameters, whereas the relative change method is adopted for variations in HRU-specific parameters.

Parameters influencing snow, baseflow (or groundwater), soil properties, and land use management were highly sensitive to streamflow (Table 6.2). This region experiences heavy snowfall and accumulation during winter; thus, their dynamics (snowfall and melt) play a pivotal role in the catchment's hydrological processes. The timing, magnitude, and rate of snowfall and snowmelt strongly influence runoff and, consequently, streamflow. The catchment water balance indicated a prevalent baseflow of approximately 90% of the surface runoff in the catchment, thus the sensitivity of groundwater parameters. This was attributed to tile drainage, simulated in the model as lateral flow (Neitsch et al., 2011), and the drainage of surface runoff into baseflow. Variations in the catchment's soil characteristics and land use patterns were captured using the soil and land management parameters such as the available water, soil water capacity, and curve number. The most sensitive sediment parameters included those that influence channel transportation and re-entrainment capacity (CH_N2, CH_K2, SPCON, PRF) and sediment concentration in the baseflow (LAT_SED). These results are comparable to those obtained by Abbaspour et al. (2007) and Arabi et al. (2008), highlighting the relevance of these parameters in sediment computations.

The phosphorus load simulation in the model used various default parameters. The most sensitive phosphorous load parameters are presented in Table 6.2. The phosphorous availability index (PSP) of 0.5, which is close to the default value of 0.4, indicated that 50% of the phosphorous in the soil was available for plant uptake. Yuan and Koropeckyj-Cox (2022) reported a wide range of PSP parameter values, with higher values observed in agricultural areas with intensive inorganic phosphorous fertilizer application and substantial pools of legacy phosphorous from prior management practices. The phosphorous uptake distribution factor (P-UDIS) has consistently emerged as a sensitive parameter in most SWAT phosphorous load simulation studies (Abbaspour et al., 2007; Y. Liu et al., 2019; Yuan and Koropeckyj-Cox, 2022). This parameter controls the amount of phosphorous taken up by plants across different soil layers. A higher value implies that most phosphorous is taken up from the upper or surface soil layers (top 10 mm), whereas a lower value indicates that phosphorous is mostly taken up from the deeper soil layers.
The PHOSKD and PPERCO parameters govern the soluble P movement through the soil, while the RS5 parameter is responsible for the organic P settling.

6.3.1.2 Model calibration and validation

The magnitude and temporal dynamics of the SWAT model simulations at monthly time-step replicated most of the streamflow, sediment load, and total P load observations during calibration and validation periods (Figure 6.2). The model accurately captured the catchment's hydrological behavior well at low and peak flows. The sediment and total P loads were also reasonably simulated despite the slight underestimation of a few peaks, which may be attributed to process simplifications in the SWAT model, such as the simplification of the soil loss equation adopted by the model (Abbaspour et al., 2007; Pandey et al., 2021; Tolson and Shoemaker, 2007). However, the 95PPU was used to quantify all these uncertainties associated with the simulations. Notably, the 95PPU band bracketed 79% of streamflow observations, 63% of sediment load observations, and 53% of the total P load observations on average, indicating satisfactory model performance given the inherent uncertainties. These results could be attributed to the detailed, high-resolution input data and the model's ability to capture the dominant processes in the catchment very well.

Figure 6.2: Comparison of average monthly simulated (red lines) and observed (grey lines) (a) streamflow, (b) sediment load, and (c) phosphorous load at the catchment outlet
during the calibration and validation period. Observed total monthly precipitation (grey bars) is displayed alongside the streamflow hydrograph.

The statistical performance indicators for the best simulations yielded satisfactory results during calibration and validation periods (Table 6.3). Streamflow simulation exhibited "very good" model performance during calibration/validation periods (NSE = 0.80/0.84). Similarly, sediment load (NSE = 0.67/0.69) and total P load (NSE = 0.61/0.62) demonstrated reasonably good performance. Moriasi et al. (2015) recommended that "very good or excellent" model variation performance is achieved when PBIAS is less than ±5% for streamflow, ±10% for sediment load, and ±15% for nutrients. A comparison of average monthly streamflow observation and simulation showed relatively minimal variation (PBIAS < ±5%), indicating excellent performance. A positive PBIAS value indicates that the observations were greater than the simulations, implying that the model underestimated the observations, whereas a negative PBIAS indicates that the observations were less than the simulations, implying that the model overestimated the observations. The performance of sediment load and total P load were also reasonably good despite some slight underestimation but still within the recommended threshold. Based on these findings, the model can be considered good and capable of replicating the catchment dynamics with reasonable certainty, making it suitable for adoption in other applications.

Table 6.3: SWAT model performance statistical indicator metrics for catchment C6.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Performance indicator</th>
<th>Threshold</th>
<th>Calibration</th>
<th>Validation</th>
<th>Model performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Streamflow</td>
<td>NSE</td>
<td>&gt; 0.5</td>
<td>0.80</td>
<td>0.84</td>
<td>Very good</td>
</tr>
<tr>
<td></td>
<td>R²</td>
<td>&gt; 0.5</td>
<td>0.82</td>
<td>0.85</td>
<td>Very good</td>
</tr>
<tr>
<td></td>
<td>PBIAS</td>
<td>±25%</td>
<td>-2.5%</td>
<td>+4.9%</td>
<td>Very good</td>
</tr>
<tr>
<td>Sediment load</td>
<td>NSE</td>
<td>&gt; 0.5</td>
<td>0.67</td>
<td>0.69</td>
<td>Good</td>
</tr>
<tr>
<td></td>
<td>R²</td>
<td>&gt; 0.5</td>
<td>0.72</td>
<td>0.64</td>
<td>Good</td>
</tr>
<tr>
<td></td>
<td>PBIAS</td>
<td>±55%</td>
<td>+14.5%</td>
<td>+21.8%</td>
<td>Good</td>
</tr>
<tr>
<td>Total phosphorous</td>
<td>NSE</td>
<td>&gt; 0.5</td>
<td>0.61</td>
<td>0.62</td>
<td>Good</td>
</tr>
<tr>
<td></td>
<td>R²</td>
<td>&gt; 0.5</td>
<td>0.64</td>
<td>0.71</td>
<td>Good</td>
</tr>
<tr>
<td></td>
<td>PBIAS</td>
<td>±70%</td>
<td>+26.3%</td>
<td>+18%</td>
<td>Good</td>
</tr>
</tbody>
</table>

*These thresholds are the minimum performance requirement beyond which the model would be deemed unsuitable.
6.3.2 Effect of BMP implementation

The catchment’s BMP scenarios had varying effects on streamflow, sediment load, and phosphorous (soluble P and total P) load. The impact of BMP implementation on streamflow was negligible (Table 6.4, Figure 6.3), with no change, except for a −10.8% reduction in streamflow when the sedimentation pond was implemented. Sedimentation ponds are designed to capture and temporarily retain sediment-laden runoff, resulting in a reduced volume of water flowing into the stream and subsequently decreasing the streamflow. Additionally, the extended runoff flow path through sedimentation ponds allows for infiltration and evaporation, thus further contributing to streamflow reduction. However, this retention is temporary, hence the slight decline. Other studies have also reported insignificant to no impact on streamflow due to the implementation of structural BMPs such as filter strips, wetlands, reduced tillage (Motsinger et al., 2016), as well as grassed waterways and filter strips (Bracmort et al., 2006). For sediment, soluble P, and total P loads, only filter strip and sedimentation pond scenarios were statistically significant (p < 0.05) relative to the baseline scenario (Table 6.4, Figure 6.3).

Table 6.4: P-values from the Wilcoxon–Mann–Whitney Rank-Sum statistical significance test of average annual values for the BMP scenarios relative to the baseline. A P-value < 0.05 is considered statistically significant.

<table>
<thead>
<tr>
<th>BMP Scenario</th>
<th>Streamflow</th>
<th>Sediment load</th>
<th>Soluble P load</th>
<th>Total P load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter strip (7.5 m)</td>
<td>1</td>
<td>0.003</td>
<td>&lt; 0.001</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Sedimentation pond</td>
<td>0.202</td>
<td>0.002</td>
<td>0.021</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Grassed waterway</td>
<td>0.980</td>
<td>0.161</td>
<td>0.654</td>
<td>0.601</td>
</tr>
<tr>
<td>No-Tillage</td>
<td>1</td>
<td>0.723</td>
<td>0.211</td>
<td>0.921</td>
</tr>
</tbody>
</table>
Figure 6.3: Comparative boxplots for annual average (a) streamflow, (b) sediment load, (c) soluble phosphorus load, and (d) total phosphorus load for the baseline scenario (BS) and the various BMPs (filter strip (FS), sedimentation ponds (SP), grassed waterways (GWW), and no-tillage (NT)) implemented on the study area.

The implemented agricultural BMPs reduced sediment and phosphorous loads in the catchment, with varying degrees of reduction for each BMP compared to the baseline, as illustrated in Figure 6.4. Specifically, the average annual sediment load was reduced by 103 kg ha\(^{-1}\) year\(^{-1}\) (−32%) in the filter strip scenario, 111 kg ha\(^{-1}\) year\(^{-1}\) (−35%) in the sedimentation pond scenario, 44 kg ha\(^{-1}\) year\(^{-1}\) (−14%) in the grassed waterways scenario, and 4 kg ha\(^{-1}\) year\(^{-1}\) (−1.3%) in the no-tillage scenario. Figure 6.4 shows variations in the reductions for soluble P and total P loads across different scenarios, except for the filter strip scenario, where they were relatively equal. Soluble P load reduced by 0.073 kg P ha\(^{-1}\) year\(^{-1}\) (−67%) in filter strip scenario, 0.040 kg P ha\(^{-1}\) year\(^{-1}\) (−36%) in the sedimentation pond scenario, and 0.018 kg P ha\(^{-1}\) year\(^{-1}\) (−17%) in the no-tillage scenario. However, the implementation of grassed waterways resulted in a slight increase in soluble P by 0.005 kg P ha\(^{-1}\) year\(^{-1}\) (+4%). The total P load followed a similar pattern to the sediment load, with reductions of 0.320 kg P ha\(^{-1}\) year\(^{-1}\) (−67%) in the filter strip scenario, 0.241 kg P ha\(^{-1}\) year\(^{-1}\) (−50%) in the sedimentation pond scenario, 0.026 kg P ha\(^{-1}\) year\(^{-1}\)
(−5%) in grassed waterway scenario, and slight reduction of 0.001 kg P ha⁻¹ year⁻¹ (−0.2%) in no-tillage scenario.

Figure 6.4: Summary of the variation in average annual sediment, soluble phosphorus, and total phosphorus export in the catchment for each BMP scenario relative to the baseline.

The findings indicate that filter strips and sedimentation ponds effectively reduce sediment and phosphorous loads at the catchment outlet, with filter strips being the most effective for reducing phosphorous load and sedimentation ponds effectively reducing sediment load. The catchment's phosphorus (total P and soluble P) load reduction is consistent with the sediment load reduction, though the phosphorous load reduction rate is slightly higher. This could be attributed to the strong relationship between sediment and total phosphorous loads, with R² values of 0.96 for observed monthly loads and 0.92 for observed annual loads, explaining the effectiveness of sediment control measures such as filter strips and sedimentation ponds in reducing nutrient losses. Venishetty and Parajuli (2022) observed a similar sediment-phosphorous load relationship for simulation in two agriculture-dominated catchments, where a slight reduction in sediment load by −8% and −15% as a result of filter strip BMP implementation resulted in −33% and −66% reduction.
in total P load. Based on these findings, sediment transport could be regarded as the catchment's primary driver of phosphorous export.

The effectiveness of filter strips in reducing sediment and phosphorous export increased with increasing filter strip width, as illustrated in Figure 6.5. The sediment and phosphorous loads were reduced by approximately −25% and −55%, respectively, for the 5 m filter strip width and −30% and −75% for the 10 m filter strip width. The reduction in soluble P and total P was virtually the same, with a mere 1–3% difference that may be considered negligible. Optimal performance was observed with an 8 m filter width, resulting in nearly −40% and −70% reduction in sediment and phosphorus loads, respectively. The effectiveness of filter strips in reducing sediment and nutrient export has been reported in various studies. For instance, Mekonnen et al. (2017) reported −15% and −39% reductions in sediment load when 5 m and 30 m filter strip widths were implemented in the snow-dominated Assiniboine River watershed in Canada. The study also found total P reductions of −27% and −60% for the same filter strip widths. Similarly, Syversen (2005) observed a −60% to −89% reduction in total P load for 5 m and 10 m buffer zones on slopes greater than 10% in a study of the effects of buffer zones in the Nordic climate. These findings are consistent with our results, reaffirming the vital role of filter strips in mitigating sediment and nutrient loss in cold regions. Sediment load reduction by filter strips can be attributed to reduced runoff transportation capacity, which facilitates deposition, and dense vegetation, which facilitates sediment entrapment (Akan and Atabay, 2017).
Figure 6.5: Effect of filter strip width variation (from 5 m to 10 m) on the average annual sediment, soluble phosphorus, and total phosphorus reduction.

Sedimentation ponds reduced sediment, soluble P, and total P loads by −35%, −36%, and −50%, respectively. However, these reduction rates were lower compared to some previous findings of −58% (Zhang and Zhang, 2011), −54% (Fiener et al., 2005), and −80% (Markle et al., 2011). The observed different reduction rates could be attributed to various factors, including the size and location of the ponds within the catchment, soil type, and agricultural management practices in the specific catchments, among many others. The flow retention time in the sedimentation pond also plays a crucial role in sediment and nutrient reduction, with shorter durations hindering the adsorption of dissolved and fine particles (Budd et al., 2009; Fiener et al., 2005). It's important to note that if sedimentation ponds are not well maintained and emptied of the settled material, they could become a potential source of legacy phosphorous (Engebretsen et al., 2019).
The effectiveness of grassed waterways and no-tillage in sediment and nutrient removal was not statistically significant (Table 6.4). Grassed waterways reduced sediment and total P loads by −14% and −5%, respectively, but increased soluble P by +4%. Grassed waterways are designed to slow flow velocity and retain sediment-laden runoff, allowing sediments to settle and reducing load. They primarily target sediment and nutrients from surface runoff and may not effectively capture the subsurface pathways such as tile drains, which are common in the study area, hence the observed limited effectiveness. The decrease in sediment load subsequently reduced the total P load since the sediment-bound particulate P (organic P) load was settled with the sediment. However, the total P reduction was minimal due to the concurrent increase in soluble P load, although the particulate P is much greater than soluble P. The slight increase in soluble P could be attributed to potential phosphorus release via desorption since grasses may uptake nutrients and release them into the water as they decompose (Fiener and Auerswald, 2009). According to Jarvie et al. (2017), the increase in soluble P despite declining total P resulting from grassed waterways could be due to the gradual accumulation of legacy phosphorous that can be readily mobilized as well as the presence of tile drainage, facilitating rapid and direct runoff transmission into the stream network.

No-tillage, on the other hand, reduced soluble P by −17% but had a minimal effect on sediment and total P loads, reducing them by only −1.3% and −0.2%, respectively. The negligible effect of no-tillage on sediment and total phosphorous could be attributed to the prevalent subsurface flow in the catchment. No-tillage has been shown to be generally more effective in reducing sediment and nutrient transport in surface runoff but less effective in subsurface flows (Koskiaho et al., 2002; Sun et al., 2015; Tiessen et al., 2010). A review of no-tillage practice on phosphorous loss control in the Scandinavian region by Ulén et al. (2010) showed greater soluble P losses than total P resulting from shallow tillage, which was attributed to phosphorous accumulation in the non-inverted topsoil. Furthermore, no-tillage has been reported to promote the stratification of soil phosphorous, resulting in differential effects on soluble P and total P (Jarvie et al., 2017; Sharpley et al., 2015; Smith et al., 2015). It preserves the soil's natural structure and reduces soil disturbance during planting while retaining crop residue, which enhances nutrient retention in the soil, thereby reducing soluble P export (Bogunovic et al., 2018).
6.4 Conclusion

The main findings and conclusions of this chapter are provided in Chapter 7, sections 7.1 and 7.4.
Chapter 7:

7 General Conclusion and Recommendations
This chapter summarizes the key findings and conclusions from this dissertation and suggests some future research prospects.

7.1 Conclusion on the SWAT model application in northern Spain and southeastern Sweden

The application of the SWAT model in this research demonstrated its robust capabilities in analyzing the effects of agricultural activities and climate change on water quality at the catchment scale in cultivated lands of northern Spain and southeastern Sweden, with diverse hydrological, climatic, and geographical contexts. In the Cidacos River watershed of northern Spain, the SWAT model’s statistical evaluation results during calibration (2000-2010) and validation (2011-2020) periods exhibited good performances with high NSE values of 0.82 and 0.83 for streamflow and 0.71 and 0.68 for nitrate load, indicating its suitability for adoption in the area. The statistical evaluation results during calibration (2005-2012) and validation (2013-2020) periods in the C6 catchment were deemed satisfactory with NSE values of 0.80 and 0.84 for streamflow, 0.67 and 0.69 for sediment load, and 0.61 and 0.62 for total phosphorous load.

These findings highlight the SWAT model's potential as a valuable decision-support tool for watershed management and policy development. The model's ability to reproduce the magnitude and temporal dynamics of the observed data despite the inherent uncertainties demonstrates its capacity to comprehend the complex dynamics between agricultural activities and water quality. These findings demonstrate the SWAT model’s potential in guiding sustainable land use practices, optimizing fertilizer application strategies, and designing effective land and water conservation measures. Furthermore, the results emphasize the importance of employing modeling approaches to support evidence-based water resource management and environmental protection strategies in cultivated regions, ultimately enhancing agricultural sustainability.

7.2 Conclusion on the evaluation of the impact of changing from rainfed to irrigated agriculture in the Cidacos River watershed in northern Spain

This study examined the impact of changing from rainfed to irrigated agriculture on streamflow, nitrate load, and nitrate concentration in a Mediterranean watershed in northern Spain by simulating the rainfed conditions using the SWAT model and compared them to the current post-irrigation period. The results indicate a significant increase in the annual streamflow, nitrate load, and concentration at the watershed outlet in the post-
irrigation period. Higher irrigation impact was observed during summer and autumn when irrigation peaked than in winter and spring. The increase in streamflow was explained by additional water from irrigation, whereas the increase in nitrate export and concentration was attributed to increased fertilization from the cultivation of high nitrogen-consuming crops and more available water to mobilize nitrates. The implementation of irrigation and subsequent agricultural intensification resulted in changing cropping patterns and doubling nitrate concentrations at the outlet, exceeding the Nitrate Directive thresholds recommended by the European Commission. Therefore, nitrate minimization practices such as efficient nitrogen fertilizer application and creating nitrogen buffer zones along the river’s riparian zone should be considered to control nitrate exportation and pollution from cultivated lands into the river. Despite this study’s valuable and significant findings, more data are needed to further analyze and assess the impact of irrigation, especially during summer and autumn, which was modified following irrigation. The methodology and findings from this study can be applied to other areas with similar conditions, allowing a more comprehensive assessment of the effect of changing from rainfed to irrigated agriculture on streamflow and nitrate pollution. These findings could assist farmers, water experts, and policy/decision makers in improving water resources management at the watershed level and be useful in guiding the development of new irrigation systems, thereby improving sustainable agriculture.

7.3 Conclusion on the effects of climate change on streamflow and nitrate pollution in the Cidacos River watershed in northern Spain

The effect of climate change on water resources and nitrate export is of major concern in the Mediterranean region and northern Spain due to its arid and semi-arid climatic conditions. This study evaluated the adoption of the SWAT model for simulating current and future streamflow and nitrate loads under rainfed conditions in a Mediterranean agricultural area in northern Spain. The projected decline in precipitation and rise in temperature negatively impact both the streamflow and nitrate export on spatial and temporal scales. Reduced streamflow would reduce available water resources for agricultural and domestic use, resulting in lower agricultural yield, limited productivity, and conflicts over scarce water resources. Although the projected nitrate load would also decrease due to declining streamflow, the nitrate concentration levels are expected to rise due to the faster streamflow reduction rate than the nitrate load exportation rate, resulting
in nitrate pollution by accumulation in the soil and riverbed as well as groundwater pollution through percolation.

This study's findings could help understand the scope of the climate change problem in northern Spain and develop appropriate adaptation and mitigation measures to help minimize the expected adverse effects. These measures could include more sustainable water resource management and better land management policies such as efficient nitrogen fertilization. These initiatives would be critical to adhere to the European Union’s nitrate policies and legislation, as outlined in the Water Framework Directive and the Nitrate Directive. Despite this study’s valuable findings, further research using various climate models, ensembles, and other emission scenarios is needed to evaluate these impacts fully. More research could be done to help understand the scope and magnitude of the uncertainties by combining future climate, projected land uses, and population changes.

7.4 Conclusion on quantifying agricultural best management practices impacts on sediment and phosphorous export in Catchment C6 in southeastern Sweden.

This study used the SWAT model to analyze the effectiveness of four BMPs (filter strip, sedimentation ponds, grassed waterways, and no-tillage) in reducing sediment and phosphorous export in a small agricultural intensive catchment in Sweden. Filter strips and sedimentation ponds effectively reduced sediment and phosphorous export. Filter strips were more effective in minimizing phosphorous losses, whereas sedimentation ponds were quite effective in minimizing sediment losses. Grassed waterways and no-tillage were less effective in pollutant reduction, with a slight increment in soluble P observed for grassed waterways. These results provide valuable insights for agricultural water management not only in the study area but also in Sweden and other regions globally facing similar water quality issues from agricultural activities.

The findings from this study contribute to the ongoing efforts to mitigate sediment and nutrient pollution in Swedish agricultural areas, thereby supporting the conservation and restoration of aquatic ecosystems. These results are instrumental in attaining the Swedish Environmental Protection Agency’s targets of lowering sediment and nutrient levels in watercourses and contributing to achieving the European Water Framework Directives' goal of "good ecological status" by 2027 and ultimately zero eutrophication someday. However, further research is necessary using field experiments and other water quality
models in the catchment to corroborate these findings and enhance the efficacy of BMPs in water quality management and pollution reduction. Researchers around the world could adopt this study’s methodology and results as a reference for similar studies in different regions. By sharing results and experiences, countries facing similar environmental challenges can work together to develop best practices and solutions. This research contributes to the knowledge base and guides decision-making processes for sustainable agriculture and water resource management at the local, national, regional, and international levels.

7.5 Final remarks

This research has contributed to the body of knowledge on sustainable agricultural practices and water resource management by demonstrating the SWAT model’s applicability in diverse geographical and climatic conditions. The findings have the potential to inform evidence-based decision-making, policy formulation, and agricultural practices not only in the studied regions but also in other similar areas globally facing similar challenges.

The research has emphasized the necessity for effective nutrient management practices, particularly in irrigated areas of northern Spain and the Mediterranean region at large, to help reduce nitrate pollution and adhere to the recommended water quality standards. There is an urgent need to address the looming climate change-related concerns by implementing adaptative strategies, such as optimized water resource management and efficient nitrogen fertilization, to mitigate the potential negative climate change effects on water availability and quality. This research has reaffirmed the importance of agricultural conservation measures in minimizing sediment and nutrient export to enhance agricultural sustainability.

The application of the SWAT model in the case studies has produced valuable insights into the complex interactions between agricultural activities and water quality, thereby offering practical guidance for sustainable land and water resources management. The research findings could be useful to farmers, decision- and policy-makers, as well as researchers aiming to enhance agricultural sustainability and protect water resources.

Furthermore, this research recommends the continued exploration into other BMPs and their combinations besides those examined in this study to further understand their effectiveness. Future research is also recommended into the scenarios of water use or
demand and the integration of holistic strategies to ensure a harmonious balance between agricultural productivity and environmental management.
References


Intergovernmental Panel on Climate Change (IPCC). (2014). *Climate change impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Working Group*


Sharpley, Andrew N., Bergström, L., Aronsson, H., Bechmann, M., Bolster, C. H.,


Appendices
Appendix I: Publications

Publications in peer-reviewed journals


Presentations at international conferences


Presentations at workshops and seminars


### Appendix II: SWAT Model Input Parameters

**Table A1**: The SWAT model input parameters and adjusted values for streamflow and nitrate load simulation in the Cidacos River watershed in Spain

<table>
<thead>
<tr>
<th>SWAT input parameter</th>
<th>Parameter description</th>
<th>Units</th>
<th>Parameter adjustment value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Default</td>
</tr>
<tr>
<td>v__ALPHA_BF.gw</td>
<td>Baseflow alpha factor</td>
<td>day(^{-1})</td>
<td>0.048</td>
</tr>
<tr>
<td>v__GW_REVAP.gw</td>
<td>Groundwater &quot;revap&quot; coefficient.</td>
<td>-</td>
<td>0.02</td>
</tr>
<tr>
<td>v__GW_DELAY.gw</td>
<td>Groundwater delay</td>
<td>days</td>
<td>31</td>
</tr>
<tr>
<td>v__REVAPMN.gw</td>
<td>Threshold depth of water in the shallow aquifer for &quot;revap&quot; to occur</td>
<td>mm H(_2)O</td>
<td>1</td>
</tr>
<tr>
<td>v__GWQMN.gw</td>
<td>Threshold depth of water in the shallow aquifer required for return flow to occur</td>
<td>mm H(_2)O</td>
<td>1000</td>
</tr>
<tr>
<td>r__SOL_AWC.sol</td>
<td>Available water capacity of the soil layer</td>
<td>mm H(_2)O/ mm soil</td>
<td>-</td>
</tr>
<tr>
<td>r__SOL_BD.sol</td>
<td>Moist bulk density</td>
<td>mm H(_2)O/ mm soil</td>
<td>-</td>
</tr>
<tr>
<td>r__SOL_K.sol</td>
<td>Saturated hydraulic conductivity</td>
<td>mm H(_2)O/ mm soil</td>
<td>-</td>
</tr>
<tr>
<td>r__CN2.mgt</td>
<td>Initial SCS runoff curve number for moisture condition II</td>
<td>-</td>
<td>35-98</td>
</tr>
<tr>
<td>r__ESCO.hru</td>
<td>Soil evaporation compensation factor</td>
<td>-</td>
<td>0.95</td>
</tr>
<tr>
<td>r__OV_N.hru</td>
<td>Manning's &quot;n&quot; value for overland flow</td>
<td>-</td>
<td>0.14</td>
</tr>
</tbody>
</table>

---

*Hydrology parameters*
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Units</th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>v__EPCO.bsn</td>
<td>Plant uptake compensation factor</td>
<td>-</td>
<td>-</td>
<td>0.1</td>
<td>0.95</td>
<td>0.74</td>
</tr>
<tr>
<td>v__LAT_ORGN.gw</td>
<td>Organic N in the baseflow</td>
<td>mg L(^{-1})</td>
<td>0</td>
<td>10</td>
<td>31</td>
<td>16</td>
</tr>
<tr>
<td>r__SHALLST_N.gw</td>
<td>Concentration of nitrate in groundwater contribution to streamflow from subbasin</td>
<td>mg L(^{-1})</td>
<td>0</td>
<td>-28%</td>
<td>45%</td>
<td>-20%</td>
</tr>
<tr>
<td>r__ANION_EXCL.sol</td>
<td>Fraction of porosity from which anions are excluded</td>
<td>-</td>
<td>0.5</td>
<td>-15%</td>
<td>53%</td>
<td>-5%</td>
</tr>
<tr>
<td>v__ERORGN.hru</td>
<td>Organic N enrichment ratio</td>
<td>-</td>
<td>0</td>
<td>1.05</td>
<td>3.15</td>
<td>1.85</td>
</tr>
<tr>
<td>r__SOLN_CON.hru</td>
<td>Soluble nitrogen concentration in runoff</td>
<td>mg L(^{-1})</td>
<td>0</td>
<td>-5%</td>
<td>80%</td>
<td>9.5%</td>
</tr>
<tr>
<td>v__N_UPDIS.bsn</td>
<td>Nitrogen uptake distribution parameter</td>
<td>-</td>
<td>20</td>
<td>12.3</td>
<td>37.2</td>
<td>34.1</td>
</tr>
<tr>
<td>v__RCN.bsn</td>
<td>Concentration of nitrogen in precipitation</td>
<td>mg L(^{-1})</td>
<td>1</td>
<td>1.25</td>
<td>3.75</td>
<td>2.85</td>
</tr>
<tr>
<td>v__NPERCO.bsn</td>
<td>Nitrogen percolation coefficient</td>
<td>-</td>
<td>0.2</td>
<td>0.01</td>
<td>0.6</td>
<td>0.05</td>
</tr>
<tr>
<td>v__CMN.bsn</td>
<td>Rate factor for humus mineralization of active organic nutrients (N and P)</td>
<td>-</td>
<td>0.0003</td>
<td>0.001</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>v__CDN.bsn</td>
<td>Denitrification exponential rate coefficient</td>
<td>-</td>
<td>1.4</td>
<td>0</td>
<td>0.162</td>
<td>0.04</td>
</tr>
<tr>
<td>v__SDNCO.bsn</td>
<td>Denitrification threshold water content</td>
<td>-</td>
<td>1.1</td>
<td>0.35</td>
<td>1.1</td>
<td>0.75</td>
</tr>
<tr>
<td>v__FIXCO.bsn</td>
<td>Nitrogen fixation coefficient</td>
<td>-</td>
<td>0</td>
<td>0.45</td>
<td>1.4</td>
<td>1.16</td>
</tr>
<tr>
<td>v__BC3_BSN.bsn</td>
<td>Rate constant for hydrolysis of organic nitrogen to ammonia</td>
<td>day(^{-1})</td>
<td>0.21</td>
<td>0.11</td>
<td>0.31</td>
<td>0.24</td>
</tr>
<tr>
<td>r__SOL_NO3.chm</td>
<td>Initial NO3 concentration in the soil layer</td>
<td>mg kg(^{-1})</td>
<td>-</td>
<td>-18%</td>
<td>45%</td>
<td>15.1%</td>
</tr>
</tbody>
</table>
Table A 2: The SWAT model input parameters and adjusted values for streamflow, sediment load, and total phosphorous load simulation in the Catchment C6 in southeastern Sweden.

<table>
<thead>
<tr>
<th>SWAT input parameter</th>
<th>Parameter description</th>
<th>Units</th>
<th>Parameter adjustment value</th>
</tr>
</thead>
<tbody>
<tr>
<td>v__SFTMP.bsn</td>
<td>Snowfall temperature</td>
<td>°C</td>
<td>Default: 1, Min: -5, Max: 5, Best fit: -2.5</td>
</tr>
<tr>
<td>v__SMTMP.bsn</td>
<td>Snowmelt base temperature</td>
<td>°C</td>
<td>Default: 0.5, Min: 0, Max: 5, Best fit: 4.5</td>
</tr>
<tr>
<td>v__SMFMX.bsn</td>
<td>Maximum melt rate for snow during the year (on 21 Jun)</td>
<td>mm H2O/ °C-day</td>
<td>Default: 4.5, Min: 5, Max: 2.5</td>
</tr>
<tr>
<td>v__SMFMN.bsn</td>
<td>Minimum melt rate for snow during the year (on 21 Dec)</td>
<td>mm H2O/ °C-day</td>
<td>Default: 4.5, Min: 0, Max: 1.8</td>
</tr>
<tr>
<td>v__TIMP.bsn</td>
<td>Snowpack temperature lag factor</td>
<td>-</td>
<td>Default: 1, Min: 0.01, Max: 1, Best fit: 0.5</td>
</tr>
<tr>
<td>v__SURLAG.bsn</td>
<td>Surface runoff lag coefficient</td>
<td>-</td>
<td>Default: 4, Min: 1, Max: 10, Best fit: 5.722</td>
</tr>
<tr>
<td>v__ALPHA_BF.gw</td>
<td>Baseflow alpha factor</td>
<td>day⁻¹</td>
<td>Default: 0.048, Min: 0.01, Max: 1, Best fit: 0.85</td>
</tr>
<tr>
<td>v__GW_REVAP.gw</td>
<td>Groundwater &quot;revap&quot; coefficient</td>
<td>-</td>
<td>Default: 0.02, Min: 0.02, Max: 0.2, Best fit: 0.075</td>
</tr>
<tr>
<td>v__GW_DELAY .gw</td>
<td>Groundwater delay</td>
<td>days</td>
<td>Default: 31, Min: 0, Max: 17.5, Best fit: 3.5</td>
</tr>
<tr>
<td>v__REVAPMN.gw</td>
<td>Threshold depth of water in the shallow aquifer for &quot;revap&quot; to occur</td>
<td>mm H2O</td>
<td>Default: 1, Min: 17, Max: 55, Best fit: 45</td>
</tr>
<tr>
<td>v__GWQMN.gw</td>
<td>Threshold depth of water in the shallow aquifer required for return flow to occur</td>
<td>mm H2O</td>
<td>Default: 1000, Min: 2.5, Max: 10, Best fit: 5.1</td>
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<tr>
<td>v__RCHRG_DP.gw</td>
<td>Deep aquifer percolation fraction</td>
<td>-</td>
<td>Default: 0.05, Min: 0, Max: 1, Best fit: 0.2</td>
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<tr>
<td>r__SOL_AWC.sol</td>
<td>Available water capacity of the soil layer</td>
<td>mm H2O/ mm soil</td>
<td>Default: -80%, Min: 10%, Max: -40%</td>
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<tr>
<td>r__CN2.mgt</td>
<td>Initial SCS runoff curve number for moisture condition II</td>
<td>-</td>
<td>Default: 35-98, Min: -20%, Max: 0, Best fit: -12%</td>
</tr>
<tr>
<td>Parameter</td>
<td>Description</td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>---------------------------</td>
<td>------------------------------------------------------------------------------</td>
<td>---------</td>
<td>---------</td>
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<tr>
<td><strong>Soil evaporation</strong></td>
<td>Compensation factor</td>
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<td><strong>Manning's &quot;n&quot; value</strong></td>
<td>Overland flow</td>
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<td>-90%</td>
</tr>
<tr>
<td><strong>Maximum canopy storage</strong></td>
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<td><strong>Manning's &quot;n&quot; value</strong></td>
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<tr>
<td><strong>Effective hydraulic conductivity</strong></td>
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<td><strong>Baseflow alpha factor</strong></td>
<td>Bank storage</td>
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<td><strong>USLE equation</strong></td>
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<td><strong>Sediment concentration</strong></td>
<td>Lateral and groundwater flow</td>
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<tr>
<td><strong>Linear parameter</strong></td>
<td>Calculating the maximum amount of sediment that can be re-entrained</td>
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<td><strong>Exponent parameter</strong></td>
<td>Calculating sediment re-entrained in channel sediment routing</td>
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<td><strong>Peak rate adjustment</strong></td>
<td>for sediment routing in the subbasin (tributary channels)</td>
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</tr>
<tr>
<td><strong>Peak rate adjustment</strong></td>
<td>for sediment routing in the main channel</td>
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<td>1</td>
</tr>
<tr>
<td><strong>Organic P in baseflow</strong></td>
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</tr>
<tr>
<td><strong>Fraction of porosity</strong></td>
<td>From which anions are excluded</td>
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<td>0.5</td>
</tr>
<tr>
<td><strong>Phosphorous enrichment ratio</strong></td>
<td>Loading without sediment</td>
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</tr>
<tr>
<td><strong>Phosphorous availability index</strong></td>
<td></td>
<td></td>
<td>0.40</td>
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<tr>
<td>v__P_UPDIS.bsn</td>
<td>Phosphorous uptake distribution parameter</td>
<td>-</td>
<td>20</td>
</tr>
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<td>------------------------</td>
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<tr>
<td>v__PHOSKD.bsn</td>
<td>Phosphorous soil partitioning coefficient</td>
<td>m³ Mg⁻¹</td>
<td>175</td>
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<td>v__PPERCO.bsn</td>
<td>Phosphorous percolation coefficient</td>
<td>10 m³ Mg⁻¹</td>
<td>10</td>
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<tr>
<td>v__CMN.bsn</td>
<td>Rate factor for humus mineralization of active organic nutrients</td>
<td>-</td>
<td>0.003</td>
</tr>
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<td></td>
<td>(N and P)</td>
<td></td>
<td></td>
</tr>
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<td>v__BC4_BSN.bsn</td>
<td>The rate constant for the decay of organic P to dissolved P</td>
<td>day⁻¹</td>
<td>0.35</td>
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<tr>
<td>v__RS5.swq</td>
<td>Organic P settling rate in the reach at 20 °C</td>
<td>day⁻¹</td>
<td>0.05</td>
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