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Quantification of agricultural best management practices impacts on sediment and phosphorous export in a small catchment in southeastern Sweden

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ABSTRACT

Agricultural activities contribute to water pollution through sediments and nutrient export, negatively affecting water quality and aquatic ecosystems. However, implementing best management practices (BMPs) could help control sediments and nutrient losses from agricultural catchments. This study used the Soil Water Assessment Tool (SWAT) model to assess the effectiveness of four BMPs in reducing sediment and phosphorus export in a small agricultural catchment (33 km^2) in southeastern Sweden. The SWAT model was first evaluated for its ability to simulate streamflow, sediment load, and total phosphorous load from 2005 to 2020. Then, the calibrated parameters were used to simulate the agricultural BMP scenarios by modifying relevant parameters. The model performed satisfactorily during calibration and validation for streamflow (NSE = 0.80/0.84), sediment load (NSE = 0.67/0.69), and total phosphorous load (NSE = 0.61/0.62), indicating its suitability for this study. The results demonstrate varying effects of BMP implementation on sediment and phosphorus (soluble and total) export, with no significant change in streamflow. Filter strips were highly effective in reducing sediment (−32%), soluble phosphorus (−67%), and total phosphorous (−66%) exports, followed by sedimentation ponds with −35%, −36%, and −50% reductions, respectively. Grassed waterways and no-tillage were less impactful on pollutant reduction, with grassed waterways showing a slight increase (+4%) in soluble phosphorus and no-tillage having a minimal effect on sediment (−1.3%) and total phosphorus (−0.2%) export. These findings contribute to the ongoing efforts to mitigate sediment and nutrient pollution in Swedish agricultural areas, thereby supporting the conservation and restoration of aquatic ecosystems, and enhancing sustainable agricultural practices.

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

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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., 2015, 2006). 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 examining 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., 2012b). 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 assess their effectiveness in reducing sediment and phosphorous export relative to the baseline scenario.

2. Methodology

2.1. Catchment area description

The study area, Catchment C6 (Fig. 1), 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 (Fig. 1a) are subdivisions 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., 2014b).

Crop production within the monitored catchments is generally more intensive than in the wider region. Catchment C6 covers 3298 ha (33 km^2) and is characterized by high levels of phosphorous load and sediment (suspended solids) exportation in comparison to the other catchments (Kyllmar et al., 2014b). 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 S1 of the supplementary materials details the total nitrogen and total phosphorous exported from the various agricultural monitoring catchments in Sweden.

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 400–500 mm (Swedish Meteorological and Hydrological Institute (SMHI), 2022). Most of the arable land is artificially drained through subsurface tile drains at an average depth of 1 m. 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 (Linefur et al., 2022).

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% (Fig. 1b). The main crops cultivated in the arable land are cereals (winter wheat and spring barley) (Kyllmar et al., 2014a). Other crops commonly cultivated in the catchment are oilseed rape, oats, rye, and some leguminous plants (beans and peas). The

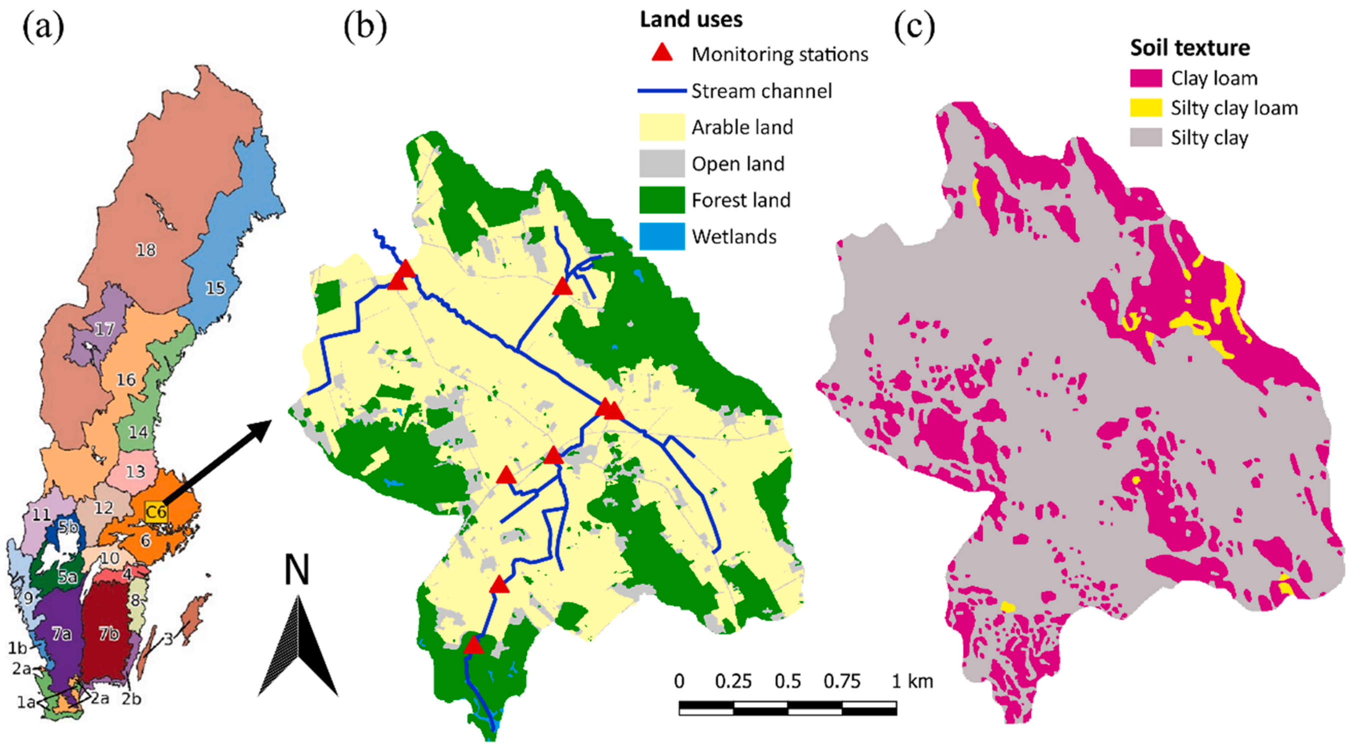

Fig. 1. (a) Location of the catchment C6 location within Sweden and in the leaching region 6, (b) land use, and (c) soil maps of the catchment C6.

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 (Fig. 1c).

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 (Linefur et al., 2022). Only a tiny portion of the cultivated land ($\leq$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 (Linefur et al., 2022). The Swedish authorities have set a phosphorous threshold of a maximum of 22 kg P ha^{-1} yr^{-1} on average over five years (Djodjic et al., 2023). The average mineral fertilization rates and crop yields for the commonly cultivated crops in the catchment are provided in Table S2 of the supplementary materials.

2.2. Data acquisition and analysis

The data used in this study were sourced from various Swedish government agencies' websites and portals, as shown in Table 1. The geospatial data, such as topography, land use (Fig. 1b), and soil texture (Fig. 1c) 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 from leaching region 6 obtained through annual interviews with the farmers was used for the study. Table S2 of the supplementary material details the agricultural management data used. 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 1990 s

Table 1
The resolution and sources of the data used in this study.

Data type	Temporal resolution	Spatial resolution	Period	Source *
Topography map	-	5 m × 5 m, SWEREF99 TM	-	SNLS
Land use map	-	5 m × 5 m	2021	SNLS
Soil map	-	1:50000	-	SNLS
Meteorological	Daily	Enköping station	1990–2020	SMHI
Streamflow	Daily	C6 outlet	2000–2020	SEPA
Sediment	Biweekly	C6 outlet	2004–2020	SEPA
Phosphorous	Biweekly	C6 outlet	2004–2020	SEPA
Agricultural Management	Annual	C6 catchment	2016–2020	SEPA

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

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 (Kyllmar et al., 2014b).

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., 2014b). 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 (Tot-P) was measured directly from unfiltered water samples, while the soluble phosphorous (Sol-P) was measured after filtration at 0.2 μm 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.

2.3. SWAT model description

The SWAT model is an open-source hydrological model that simulates water quantity and quality processes developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS). The model is widely used by researchers, experts, managers, and decision-makers in water resources and agriculture to evaluate the impacts of land use or land cover changes, climate change, and management practices on water quantity and quality at regional and catchment levels. The SWAT model is a continuous time scale, semi-distributed, physically, and process-based model that simulates hydrology, erosion, sediment, and nutrient transport at various spatial and temporal scales (Arnold et al., 2012b). The SWAT simulation process divides the catchment's hydrology into land and routing phases. The land phase controls the amount of water, sediments, pesticides, and nutrients loadings that enter the main channel in each sub-basin, whereas the water/routing phase controls water and sediment movement through the channel network of the catchment to the outlet (Arnold et al., 2012a). The model uses a two-level disaggregation approach in which a preliminary subbasin identification is done using the topographic data from the Digital Elevation Map (DEM), followed by further discretization into Hydrological Response Units (HRUs) by overlaying the DEM with the land use and soil maps. HRUs are small areas of unique homogeneous combinations of similar land use/land cover, soil type, and topographic characteristics. The HRUs represent the basic computational unit of the model, which assumes they have uniform hydrologic responses to land cover changes (Neitsch et al., 2011).

The SWAT model simulates runoff (surface and subsurface) using the modified Soil Conservation Service Curve Number (SCS-CN) method (USDA, 2004). This method estimates the amount of precipitation that would result in direct runoff based on the soil infiltration capacity, antecedent soil moisture conditions, and land use/cover characteristics (Neitsch et al., 2011). The model simulates the hydrological cycle using the water balance equation (Neitsch et al., 2011). The runoff for each HRU is simulated separately and then routed using the Muskingum routing method (Gill, 1978) to estimate the total runoff in the stream channel. The potential evapotranspiration in the catchment is estimated using the Food and Agricultural Organization's (FAO) Penman-Monteith method (Allen et al., 1998).

The SWAT model estimates sediment loading using the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975). MUSLE helps simulate soil erosion at the HRUs level by considering various factors such as slope, soil erodibility, and vegetation cover. Manning's Equation calculates the flow rate and velocity when routing sediment in the model. 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 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. Phosphorous movement in the model is tracked at the HRU level across six pools: three organic and three inorganic (Neitsch et al., 2011). The inorganic (mineral) pool comprises solution, active, and stable phosphorus pools. The soluble inorganic phosphorus 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, the organic pool comprises fresh, active, and stable phosphorus pools. Fresh organic phosphorus 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 inorganic pool, although it maintains a slow equilibrium with the stable organic pool, which does not mineralize quickly as the active pool despite also being associated with the soil humus. At the subbasin and HRU levels, the model outputs include sediment phosphorus, which is attached to the eroded sediment particles, organic phosphorous, which is found in organic matter transported from the fields, soluble phosphorous, which is the portion of phosphorus that is dissolved in the overland flow, and tile phosphorous, which is the soluble phosphorus exported through tile drains. However, when these HRU and subbasin-based phosphorus outputs are exported to the stream, they are aggregated into mineral (soluble and tile) and organic (sediment and organic) phosphorus, as shown in Fig. S1 of the supplementary material (Chaubey et al., 2006). The sum of the mineral and organic phosphorous pools is the total phosphorous.

2.4. SWAT 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 to 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 10 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.

The model calibration was done using the Sequential Uncertainty Fitting, version 2 (SUFI-2) algorithm of the SWAT-CUP (Abbaspour, 2015). The SWAT-CUP manual provides detailed step-by-step procedures for parameterization, sensitivity and uncertainty analyses, calibration, validation, performance evaluation, and the relevant equations involved. 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. Table S3 in the supplementary materials details all the parameters used for the model calibration. The most sensitive parameters for each variable are discussed further in Section 3.1 of the results.

The model calibration process involved iteratively adjusting the parameter ranges for the sensitive parameters in each iteration (with

500 runs) until most of the observed data were bracketed within the 95% Prediction Uncertainty (95PPU) band. 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., 2018, 2015). 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 Eq. (1) as the ratio of the average distance between the 95PPU band and the standard deviation of the observed data (Abbaspour et al., 2018, 2004). Satisfactory calibration was achieved when at least 50% of the observed data fell within the 95PPU band (p-factor > 0.5).

$$r-\text{factor}_j = \frac{\frac{1}{n_j}\sum_{t_{i=1}}^{n_j}\left(x_{sim}^{t_i,97.5\%} - x_{sim}^{t_i,2.5\%}\right)}{\sigma_{obs_j}} \quad (1)$$

Where $x_{sim}^{t_i,97.5\%}$ and $x_{sim}^{t_i,2.5\%}$ are upper and lower bounds of the 95PPU at t time-step and i simulations; n_j is the number of data points, and σ_{obs_j} is the standard deviation of the jth observed variable.

The model performance was evaluated using various widely recognized objective functions, such as the Nash-Sutcliffe efficiency (NSE), the coefficient of determination (R^2), the ratio of the root-mean-square error to the standard deviation of observed data (RSR), and the percent bias (PBIAS). A good model performance is obtained when NSE and R^2 are maximized (ideal value is 1) while RSR and PBIAS are minimized (ideal value is 0). The following threshold values are suggested (Abbaspour et al., 2018; Arnold et al., 2012b; Moriasi et al., 2007) for satisfactory model performance metrics: NSE >0.5, $R^2 > 0.5$, RSR ≤ 0.7, and PBIAS $\pm$25% for streamflow, PBIAS $\pm$55% for sediment, and PBIAS $\pm$70% for nutrients (Nitrates and Phosphates). Additionally, the model can be classified as "good" when the NSE is between 0.7 and 0.8 and "very good" when NSE is greater than 0.8. These indices served as the benchmark for evaluating the model's accuracy and reliability in replicating the observed data.

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., 2008, 2006; 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 2. 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.

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 ($Trap_{eff}$) is dependent on the filter strip width (FILTERW) and is determined using Eq. (2) (Arabi et al., 2008).

$$Trap_{eff} = 0.367 \times FILTERW^{0.2967} \quad (2)$$

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 m compared to the default without a filter. This range was based on the recommended buffer zone size of between 6 m and 18 m for all soil types permitted under the current Swedish regulations (Mårtensson et al., 2023). The sediment and phosphorus reduction rate 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

Table 2
Modified SWAT model parameters for the BMPs scenarios implementation.

BMP scenario	Modified SWAT parameter		
	Parameter*	Baseline value (No BMP)	Adjustment value (With BMP)
Filter strip	FILTERW.mgt	0	7.5 (m)
Sedimentation ponds	PND_FR.pnd	0	0.5
	PND_PSA.pnd	5	500 (ha)
	PND_PVOL.pnd	25	50 (10^4 m^3 H2O)
	PND_K.pnd	0	0.05 (mm hr^{-1})
Grassed waterway	CH_COV1.rte	0.25	0.001
	CH_COV2.rte	0.2	0.001
	CH_N2.rte	0.25	0.40
No-tillage (Zero till)	CN2.mgt	Varies* *	-10%
	EFFMIX.till.dat	0.95	0.05
	DEPTIL.till.dat	150	25 (mm)

* *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.

* The parameter descriptions are in the text.

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., 2012a).

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. 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.

3. Results and discussion

3.1. Model Evaluation

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 3 presents the five most sensitive parameters for each variable. All other parameters used for the calibration are in Table S3 of the supplementary material.

Parameters influencing snow, baseflow (or groundwater), soil properties, and land use management were highly sensitive to streamflow (Table 3). 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

Table 3
Selected most sensitive SWAT parameters and adjusted values for streamflow, sediment load, and phosphorous load calibration.

SWAT input parameter*	Parameter description	Units	Parameter adjustment value			
			Default	Min	Max	Fitted
Hydrology parameters						
v_SFTMP.bsn	Snowfall temperature	°C	1	-5	5	-2.5
v_SMTMP.bsn	Snowmelt base temperature	°C	0.5	0	5	4.5
v_GW_DELAY.gw	Groundwater delay	days	31	0	17.5	3.5
r_SOL_AWC.sol	Available water capacity of the soil layer	mm H_2O/ mm soil	-	-80%	10%	-40%
r_CN2.mgt	Initial SCS runoff curve number for moisture condition II	-	35–98	-20%	-5%	-12%
Sediment load parameters						
v_CH_N2.rte	Manning's "n" value for the main channel	-	-	0.01	0.3	0.25
v_CH_K2.rte	Effective hydraulic conductivity in the main channel	mm hr^{-1}	-	40	110	65
v_LAT_SED.hru	Sediment concentration in lateral and groundwater flow	mg L^{-1}	0	0	50	27.65
v_SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	-	0.001	0.001	0.01	0.005
v_PRF_BSN.bsn	Peak rate adjustment of sediment routing in the main channel	-	1	0	2	1.122
Phosphorous load parameters						
v_PSP.bsn	Phosphorous availability index	-	0.40	0.1	0.7	0.5
v_P_UPDIS.bsn	Phosphorous uptake distribution parameter	-	20	0	100	53.3
v_PHOSKD.bsn	Phosphorous soil partitioning coefficient	m^3 Mg^{-1}	175	100	200	146.3
v_PPERCO.bsn	Phosphorous percolation coefficient	10 m^3 Mg^{-1}	10	10	17.5	17.45
v_RS5.swq	Organic P settling rate in the reach at 20 °C	day^{-1}	0.05	0.001	0.5	0.095

[*] " 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.

presented in Table 3. 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; 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.

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 (Fig. 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.

The statistical performance indicators for the best simulations yielded satisfactory results during calibration and validation periods (Table 4). 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.

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 5, Fig. 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

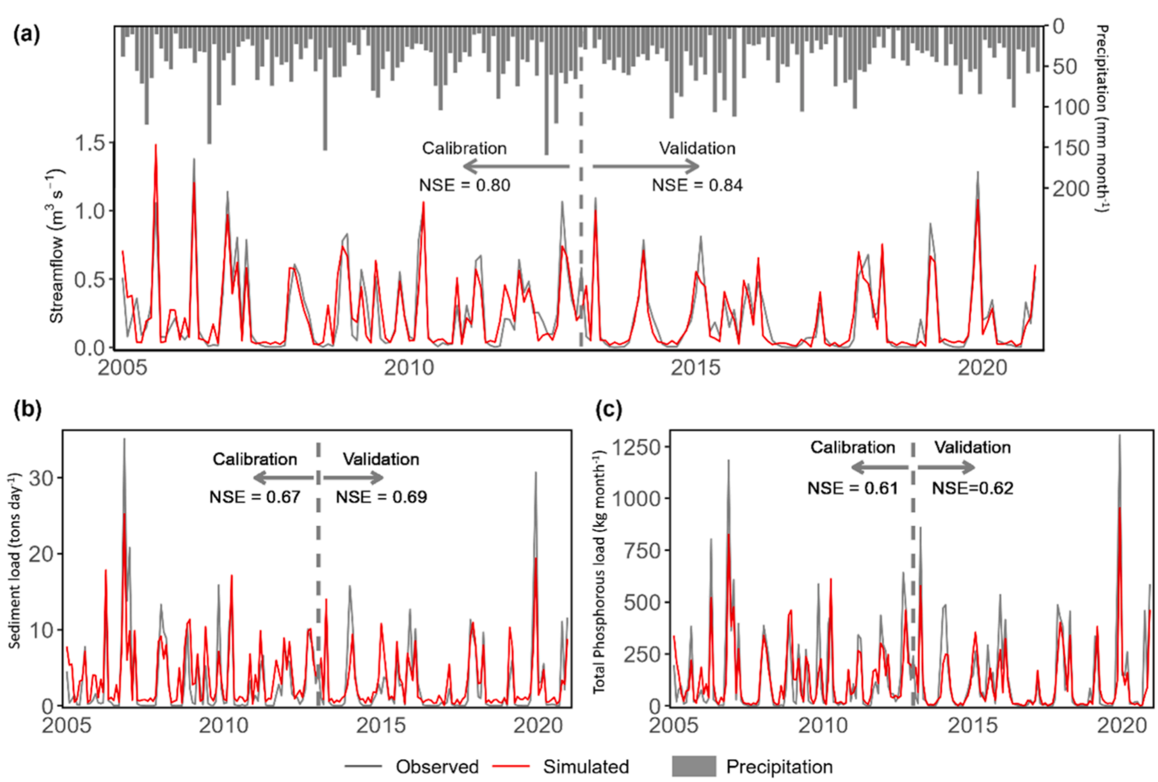

Fig. 2. Comparison of average monthly simulated (red lines) and observed (grey lines) (a) streamflow, (b) sediment load, and (c) phosphorous load at the catchment outlet during the calibration and validation period. Observed total monthly precipitation (grey bars) is displayed alongside the streamflow hydrograph.

Table 4
SWAT model performance statistical indicator metrics for catchment C6.

Variable	Performance indicator	Threshold*	Calibration	Validation	Model performance
Streamflow	NSE	>0.5	0.80	0.84	Very good
	R2	>0.5	0.82	0.85	Very good
	RSR	≤0.7	0.42	0.47	Satisfactory
	PBIAS	±25%	-2.5%	+4.9%	Very good
Sediment load	NSE	>0.5	0.67	0.69	Good
	R2	>0.5	0.72	0.64	Good
	RSR	≤0.7	0.55	0.56	Satisfactory
	PBIAS	±55%	+14.5%	+21.8%	Good
Total phosphorous load	NSE	>0.5	0.61	0.62	Good
	R2	>0.5	0.64	0.71	Good
	RSR	≤0.7	0.61	0.63	Satisfactory
	PBIAS	±70%	+26.3%	+18%	Good

* These thresholds are the minimum performance requirement beyond which the model would be deemed unsatisfactory.

Table 5
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.

BMP Scenario	Streamflow	Sediment load	Soluble P load	Total P load
Filter strip (7.5 m)	1	0.003	<0.001	<0.001
Sedimentation pond	0.202	0.002	0.021	<0.001
Grassed waterway	0.980	0.161	0.654	0.601
No-Tillage	1	0.723	0.211	0.921

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 5, Fig. 3).

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 Fig. 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. Fig. 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

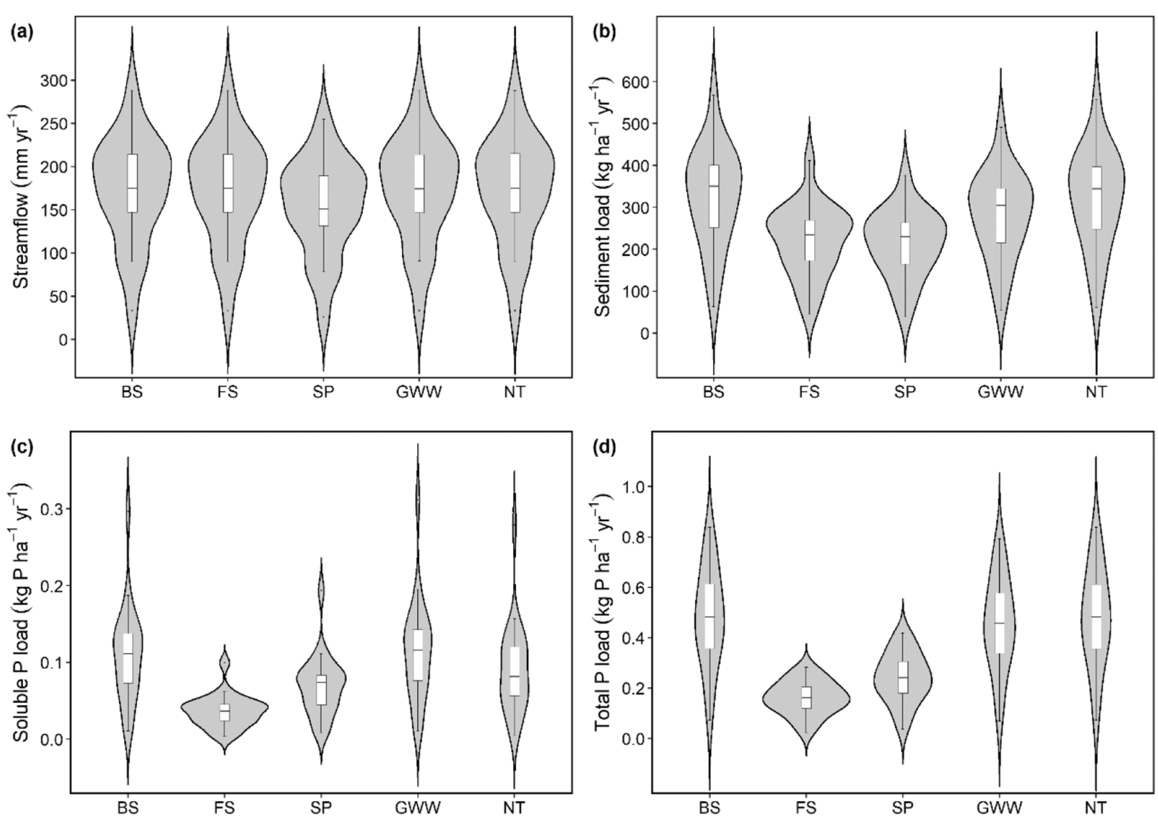

Fig. 3. Comparative boxplots for annual average (a) streamflow, (b) sediment load, (c) soluble phosphorus load, and (d) total phosphorus load for the baseline scenario (BS) and the various BMPs (filter strip (FS), sedimentation ponds (SP), grassed waterways (GWW), and no-tillage (NT)) implemented on the study area.

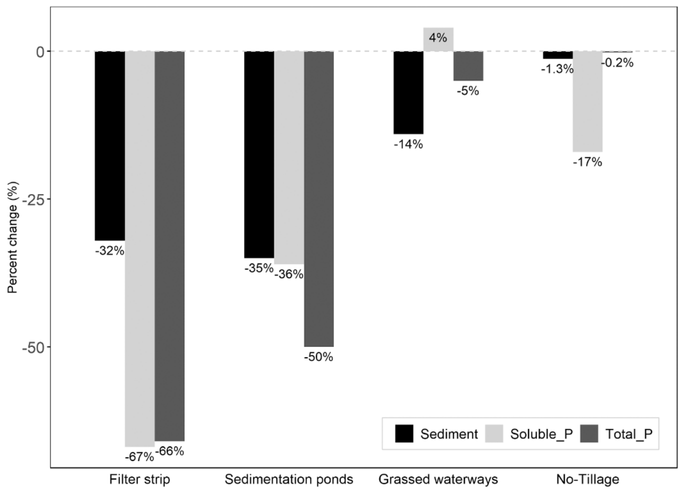

Fig. 4. Summary of the variation in average annual sediment, soluble phosphorus, and total phosphorus export in the catchment for each BMP scenario relative to the baseline.

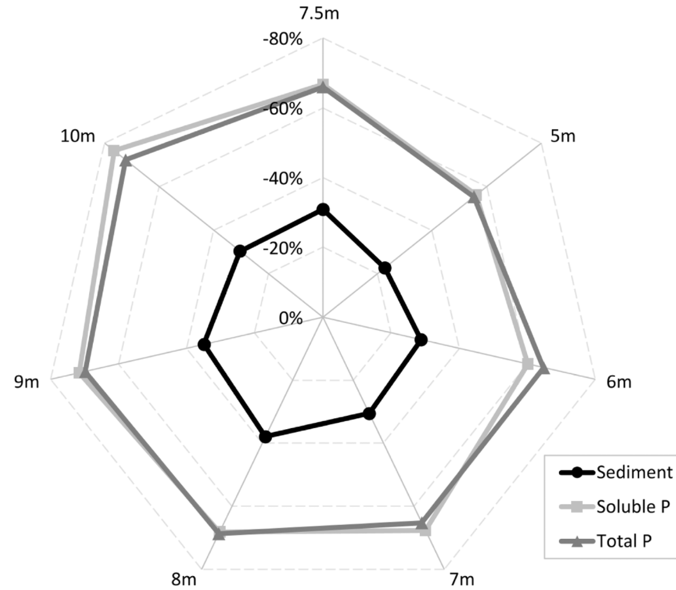

Fig. 5. Effect of filter strip width variation (from 5 m to 10 m) on the average annual sediment, soluble phosphorus, and total phosphorus reduction.

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.

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 R^2 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 Fig. 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).

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 5). 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).

4. Conclusion

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. The model performed satisfactorily for streamflow, sediment, and total phosphorous, indicating its suitability for this study. 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 as well as contributing to the achievement of 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.

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CRediT authorship contribution statement

Brian Omondi Oduor: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - original draft, Writing – review & editing. **Miguel Ángel Campo-Bescós:** Conceptualization, Project administration, Resources, Funding acquisition, Supervision, Writing – review & editing. **Noemí Lana-Renault:** Supervision, Funding acquisition, Writing – review & editing. **Katarina Kyllmar:** Conceptualization, Resources, Supervision, Writing – review & editing. **Kristina Mårtensson:** Resources, Supervision, Writing – review & editing. **Javier Casalí:** Conceptualization, Project administration, Resources, Funding acquisition, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2023.108595.

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