AMERICAN UNIVERSITY OF BEIRUT

A REVIEW OF THE USE OF THE SOIL AND WATER ASSESSMENT TOOL (SWAT) TO MODEL NUTRIENT LOADING IN THE FACE OF CLIMATE CHANGE

by
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ABSTRACT

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Title: A Review of the Use of the Soil and Water Assessment Tool (SWAT) to Model Nutrient Loading in the Face of Climate Change

As global climate patterns continue to evolve, the complex relation between land use, hydrology, and nutrient dynamics in watersheds becomes increasingly complex. The Soil and Water Assessment Tool (SWAT) has emerged as a robust tool for simulating the impacts of land management practices, climate variability, and changing environmental conditions on water resources. This thesis offers a comprehensive literature review of the application of SWAT in modeling nutrient loading, with a particular focus on addressing the challenges posed by climate change. It provides an insights into the strengths and limitations of SWAT, shedding light on its ability to capture the intricate relationships between climate, land use, and nutrient cycling. The review encompassed examining recent advancements and methodologies employed in utilizing SWAT to assess nutrient dynamics within diverse landscapes. Special attention was given to the tool's ability to predict nutrient transport, transformations, and loading under various climate change. The results of this work revealed weaknesses in the model's ability to simulate nutrient transport in cold and mountainous regions. Moreover, it revealed a skew in the geographical extent where the model has been applied. Integration of future climate data projections was found to vary significantly between studies in terms of the spatio-temporal scale, GCM models adopted, and the use of ensemble estimates. This work helps policymakers identify the existing limitations of SWAT, while proposing future developments needed to improve its use as an effective predictive tool for assessing future water quality impairments in the face of a changing climate.

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CHAPTER 1

INTRODUCTION

Watershed managers worldwide are pressed to expand their understanding of how the future impacts of climate change will impact watersheds (Kim et al., 2020). Projected changes in the climatic regimes will alter the watersheds' natural processes and have long-term implications on the economic and ecological services they provide (Marshall & Randhir, 2008). Although the earth's climate is dynamic and variable, anthropogenic activities (e.g., urbanization, population growth, fossil fuel burning, agriculture production, and deforestation) have accelerated the release of greenhouse gases (such as carbon dioxide, methane, nitrous oxide, ozone, etc.) into the earth's atmosphere, thereby trapping heat and accelerating the warming of the global mean temperature and changing the hydrological cycle (USEPA, 2004). The Inter-governmental Panel on Climate Change (IPCC) reported that sea levels rose by approximately 15 to 20 cm over the last century and surface temperatures increased by 0.45-0.6 degrees Celsius (Marshall & Randhir, 2008). Moreover, the IPCC's Fifth Assessment Report (AR5) projected that future temperatures may increase by 3.7 degrees Celsius by 2100 (Kim et al., 2020). Future projections indicate that many areas will experience increases in water stress and/or extreme odds. Martel et al. (2021) reported that based on data compiled from fifty-eight (58) research studies rainfall extreme events in many areas are expected to increase in severity. For example, the probability associated with the current 20-year daily rainfall event was projected to become 3 to 4 times higher, while the probability of a 100-year daily rainfall event will become between 4 to 5 times higher. The projected changes in precipitation and temperature will also play a significant role in altering soil moisture, which has a direct impact on weather forecasting, drought monitoring, and hydrological modeling (Yunqian Wang et al., 2019). Seager et al. (2012) reported that climate change will cause the annual mean soil moisture to drop by around 5% in the near future (2021 – 2040) in California, Nevada, the Colorado River headwater, and Texas.

The increasing global temperatures along with changes in other climatic forcings will inevitably impact the hydrologic processes at the watershed level. Such impacts will not only affect the hydrology but may lead to the impairment of water systems due to water quality degradation resulting from changes to surface runoff, sediment loading, nutrient loading, nutrient transformation, and transport processes (Me et al., 2018). Brown et al. (2007) concluded irreversible consequences to the hydrologic regimes, flow velocity, water levels, hydraulic characteristics, and habitat availability. Furthermore, Lane et al. (2007) affirmed that extreme rainfall events and flooding caused by climatic changes could increase loads of suspended solids, sediment yields, nutrient loadings, and other chemical/biological pollutants (Whitehead et al., 2009).

While these nutrients (namely nitrogen and phosphorous) are essential for the growth and development of organisms, their availability in excessive levels within the hydrologic systems will render waterbodies eutrophic and unable to meet their designated uses (Molina-Navarro et al., 2014). For example, high nutrient levels can lead to the excessive growth of algae, the degradation of aquatic ecosystems, the depletion of oxygen levels in the receiving water, and the formation of cyanotoxins; all of which can lead to mass aquatic deaths and bring about negative socio-economic impacts (Figure 1) (SACEP, 2014).

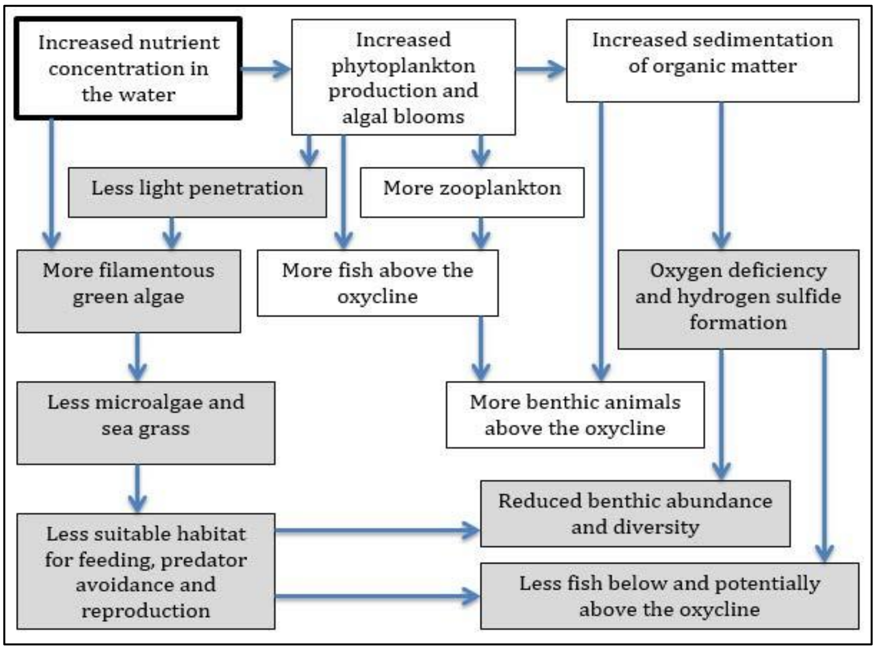

Figure 1 Illustrative schematic showing the impacts of excessive nutrient loading (pollution) on waterbodies (Ariel L. Salas & Kumaran Subburayalu, 2019)

Changes in temperature and precipitation can increase nutrient loading to hydrologic systems. Whitehead et al. (2009) showed that an increase in temperature decreased summer flows, which sequentially diminished the ability to dilute nutrient loads. Meanwhile, increased extreme precipitation/rainfall events are expected to favor increased surface runoff and erosion and thus may amplify the nutrient loads reaching the aquatic system (Jeppesen et al., 2009). Although there is a consensus that climate change will have an impact on surface water quality, the magnitude of its effects on runoff, nutrient loading, nutrient transport, etc. is still less understood given the lack of quantitative results (Verma et al., 2015). There is thus a need to properly quantify and assess the impacts of climate change on water quantity and quality.

Scientists and researchers have developed hydrological and water quality models that can be coupled with climatic models and/or with climate data (Verma et al., 2015). These models are used to assess the linkages between climate parameters (such as precipitation, temperature, relative humidity, etc.), anthropogenic activities, and water resources (Verma et al., 2015). They have been used to simulate and predict the changes in hydrological processes, including but not limited to infiltration, evapotranspiration, recharge, percolation, surface flow, and subsurface flow (C. Baffaut, 2015), snow accumulation, and snowmelt along with other complementary processes (Shrestha et al., 2012). These models are often run with a variety of climatic scenarios that are derived directly from the outputs of General Circulation Models (GCMs) (X. Wang et al., 2018). To simulate the present climate and predict future climatic changes, climate models, such as the General Circulation Model (GCM) and Regional Climate Model (RCM) have been developed. It is worth noting that a 20-to-25-year period is most suitable for climate change studies to explore the potential responses in the future due to climate change relative to a baseline period (historical period) (Kujawa et al., 2020; Wang & Kalin, 2018).

GCMs are considered the primary tool for understating how the global climate systems behave over the coming centuries. They have a considerable coarse resolution (typically ranging between 150 to 300 km) and so are only able to provide relevant information on large spatial scales. While RCMs focus more on specific areas and have much finer resolutions, usually about a few kilometers. Hence, the latter is considered much closer to the scale of real-world observations about land cover, soil types, and topography.

Given that GCMs' output data are too coarse to be directly used in hydrological modeling, it would be problematic to predict variations in weather variables such as frequencies, topography, persistence, local variance, etc. Hence, the data output is often downscaled to use them with hydrological models. Downscaling plays a crucial role in narrowing down the spatial and temporal resolution gap between GCM and hydrological models (i.e., SWAT) at a local scale (Chokkavarapu & Mandla, 2019; Hausfather, 2018). Hence, different methods have been developed to downscale the output data from GCM models to "fit" with hydrological data and other variables. Figure 2 shows how a water quality model can be coupled with future climatic data as well as other input data related to topography, soil use, land use, etc.

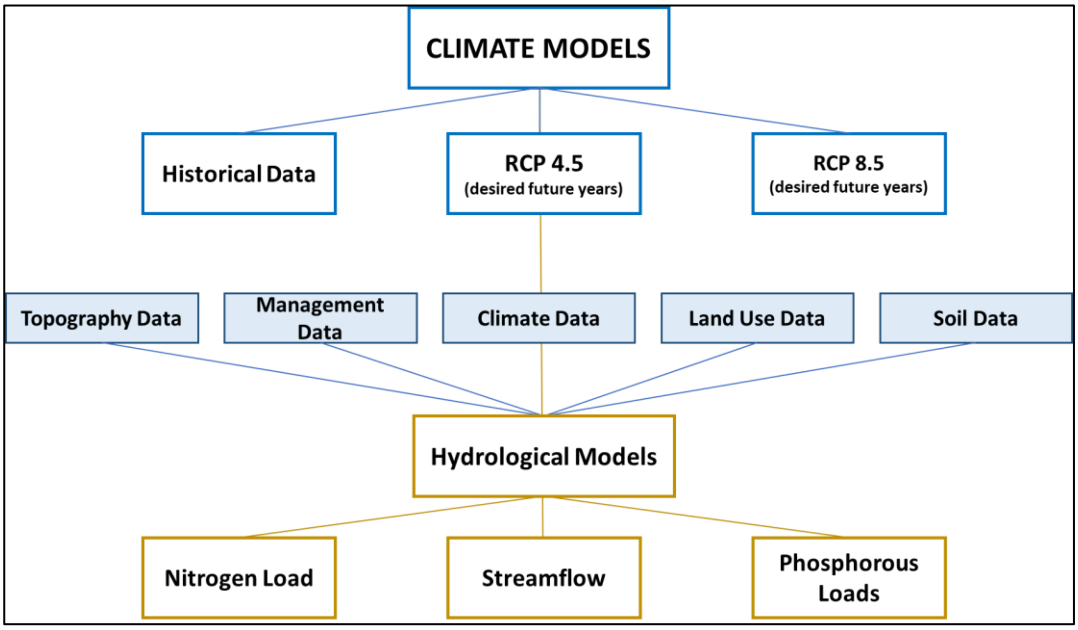

Figure 2 Schematic Flow Diagram of a typical coupled hydrological and climate simulation model. Adapted from (Nguyen et al., 2019)

Numerous water quality models have been developed to predict the changes in the hydrological processes and the associated water quality. Burigato Costa et al. (2019) identified seven of the most used models; these include the Water Quality Analysis Simulation Program (WASP), Spatially Referenced Regression on Watershed Attributes (SPARROW), CE-QUAL-W2, Environmental Fluid Dynamics Code (EFDC), Soil and Water Assessment Tool (SWAT), QUALS, and AQUATOX. Globally, the SWAT model is the most extensively applied water quality model. Figure 3 shows how the use of water quality models has increased over the past 20 years (1997 – 2017), with SWAT being the most used water quality model (Burigato Costa et al., 2019).

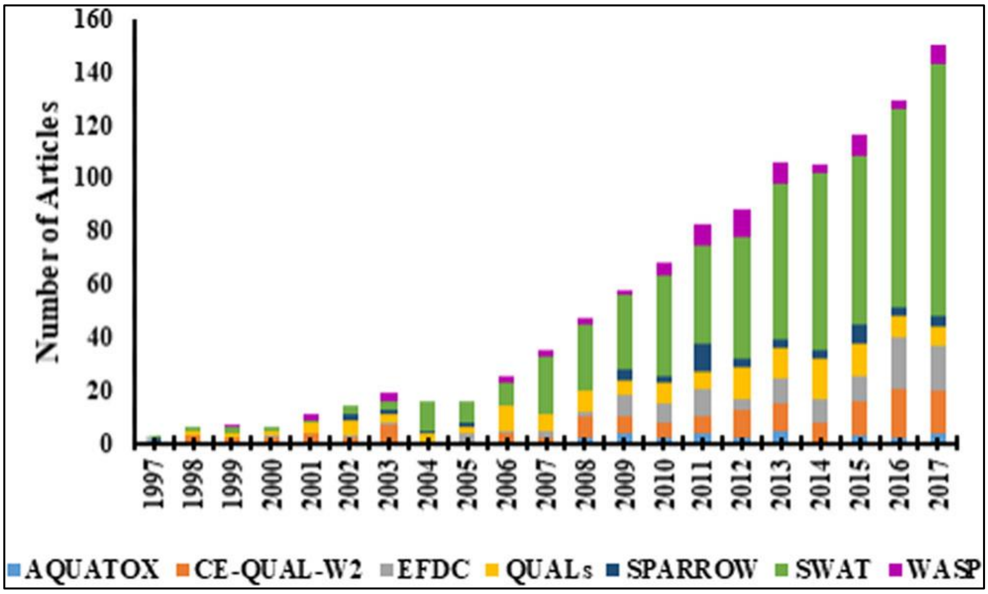

Figure 3 Application of models to water quality over a period of 20 years (1997 - 2017) (Burigato Costa et al., 2019)

Some of the main strengths of SWAT include its ability: 1) to model watersheds with limited monitoring data, 2) to integrate with GIS platforms, 3) to make use of built-in model calibration routines, and 3) to perform long-term simulations (Neitsch et al., 2012b; Verma et al., 2015). Another major advantage of SWAT is its ability to quantify and model the impacts of climatic, land use/landcover, policy/management, and hydrological changes on water quality (Li et al., 2011).

SWAT has been extensively used to model the movement and transportation of nutrients (specifically nitrogen and phosphorous), pesticides, and sediments in aquatic systems (Arnold et al., 2012; Arnold, 2012). With regard to its use to estimate nutrient movement and transportation, SWAT has been successfully and extensively applied to modeling Nitrogen (N) and Phosphorous (P) loading, in their various forms (Almeida et al., 2018).

This work will review previous studies that have attempted to assess the impacts of climate change on water quality using the SWAT model, with an emphasis on studies that have looked at nutrient loading. This study thus aims to examine, summarize, and synthesize the major assumptions, data sources, results, and limitations that have been outlined and discussed in the surveyed studies. Additionally, this work will identify the main research gaps and outline how best to use the SWAT model to assess the impacts of climate change variability on nutrient loading at the watershed level.

To the best of our knowledge, no review has been conducted to study the use of the SWAT model when it comes to assessing the effects of future climate change on nutrient loading and water quality at the watershed level. This work thus provides a comprehensive review that summarizes what has been typically used about input data sources, scenario development, and model setup. We also discuss the existing assumptions and limitations of the different SWAT applications that have attempted to predict future nutrient loading at the watershed level. Finally, we provide recommendations on how future SWAT-related studies should assess the impacts of climate change on nutrient loading at the watershed level. This work will help policymakers to identify the existing limitations of SWAT, while also highlighting to water quality modelers the future developments needed within the SWAT modeling environment to improve its use as a predictive tool for assessing water quality impairments in the face of a changing climate.

CHAPTER 2

SOIL AND WATER ASSESSMENT TOOL (SWAT)

2.1 The SWAT Model

Eco-hydrological and water quality models have gained increased interest over the past few decades and have been used to evaluate the impacts of climate, land use, and land management practices on the quantity and quality of water resources (D. N. Moriasi, 2015). SWAT was developed by the US Department of Agriculture to simulate the generation and/or transport of runoff, sediment, and nutrients in ungauged watersheds (Ba et al., 2020). It is a continuous distributed model that operates on a daily or more frequent (smaller) time step (Records et al., 2014). The model characterizes the large-scale spatial variability in soil, land use, and management practices by discretizing the watershed into sub-units (or sub-basins) using a two (2) step approach:

Step 1 comprises a topographic discretization that divides the watershed into sub-basins that serve as the basis for determining the routing structure of water and pollutants (nutrients) through the watershed.

Step 2 further divides each sub-basin (sub-unit/sub-watershed) into one or several homogenous Hydrological Response Units (HRUs) obtained by overlying the soil, land use, and land management maps.

The response of each HRU in terms of water, sediment, and nutrient losses is grouped at the sub-basin level and routed to the watershed outlet through the channel network (Bouraoui et al., 2004). It is worth noting that predicted flows are based on the water balance equation applied to the soil profile. SWAT thus accounts for precipitation, infiltration, surface runoff, evapotranspiration, lateral flow, and percolation (Čerkasova et al., 2021; Tong et al., 2007). The hydrologic cycle simulated by SWAT is based on the following water balance equation:

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

Where $\mathrm{SW_t}$ – final soil water content (mm H_2O);

$\mathrm{SW_0}$ – initial soil water content on the day i (mm H_2O);

t – time (days);

$\mathrm{R_{day}}$ – the amount of precipitation on the day i (mm H_2O);

$\mathrm{Q_{surf}}$ – the amount of surface runoff on the day i (mm H_2O);

$\mathrm{E_a}$ – the amount of evapotranspiration on the day i (mm H_2O);

$\mathrm{w_{seep}}$ – the amount of water entering the vadose zone from the soil profile on the day i (mm H_2O);

$\mathrm{Q_{gw}}$ – the amount of return flow on the day i (mm H_2O);

The impacts of climate change on the watershed ecosystems and hydrologic processes are complex due to a range of components involved in the system. One of them is related to water quality and more specifically nutrient loading. In the SWAT modeling approach, nutrients (N and P) are described in terms of their different chemical forms and their respective sources (Ariel L. Salas & Kumaran Subburayalu, 2019). SWAT simulates the movement and transformation of nutrients (mainly N and P) in the watershed by accounting for mineralization, immobilization, denitrification, volatilization, plant uptake for N and mineralization, immobilization, and plant uptake for P (Bouraoui et al., 2004).

Phosphorus is an essential plant macronutrient often not present in sufficient available forms in the soil for optimum crop growth requirements. P is added to the soil as fertilizer, manure, and/or as crop residue application. On the other hand, plant uptake and erosion are the two main processes for removing them from the soil (Trang et al., 2017). P combines with other ions in the soil to form insoluble compounds that can precipitate out of the solution. This characteristic allows P to be transported primarily by surface runoff. Soluble forms of P that are plant available are the inorganic forms known as orthophosphates (H_2PO^{4-}or HPO_4^{2-}). These forms are mobile and can be transported by diffusion or by surface water flow into field drains, but they are easily adsorbed to clay particles or immobilized by organic matter and therefore are limited to the upper soil layers (Trang et al., 2017). SWAT models six different pools of P in the soil; three pools are associated with the inorganic forms of P (solution, active, and stable), and the other three with the organic P forms (Mehdi et al., 2015). Organic P is associated with humus, insoluble forms of mineral P, and plant-available P in the soil solution. Phosphorus is transformed into organic P by algae's death. The organic P can then be mineralized to soluble phosphorus. This process is impacted by temperature (Li et al., 2011).

Nitrogen is an important nutrient. Its cycle is complex and includes the water, atmosphere, and soil. Nitrogen can be found in five forms namely, ammonium ($NH4^+$), nitrate (NO_3^-), fresh organic nitrogen, active organic nitrogen, and stable organic Nitrogen. Several processes take part in the nitrogen cycle. These include mineralization, decomposition, nitrification, ammonia volatilization, and denitrification (Li et al., 2011). The SWAT model has three major forms of nitrogen that it models in mineral soils: (1) the organic pool associated with humus, (2) a plant-available pool in the soil solution, and (3) an insoluble inorganic component. There are five main pools associated with these nitrogen forms: two inorganic pools ($NH4^+$ and NO_3^-) and three organic pools (fresh plant residue, stable humic substances, and active humic substances) (Neitsch et al., 2012a).

Most of the total nitrogen (TN) consists of nitrate with small proportions of nitrite and ammonium (Bouraoui, 2002). The dissolved forms of nitrogen (nitrate) are more related to the seasonality of streamflow and input from management practices within the watershed and therefore less influenced by changes in the number of large streamflow events (Ahmadi et al., 2014). Nitrogen may be removed from an HRU via plant assimilation, leaching, denitrification, volatilization, runoff, and soil erosion (Bouraoui et al., 2004).

2.2 Model source code

The SWAT model uses different source codes, such as SWAT versions 2000/2005/2009/2012, SWAT-CUP, SWAT-HS, and ArcGIS SWAT (or ArcSWAT). These SWAT source codes are constantly updated (Yinping Wang et al., 2019). Extensive documentation (such as a user’s manual describing model input and output, and theoretical documents describing different equations) related to the different SWAT versions can be accessed at the SWAT website (http://swatmodel.tamu.edu). The different SWAT versions along with the main features of each, which have been used in the peer-reviewed articles that relate to nutrient modeling and/or climate simulations, are summarized in Table 1.

Table 1 Different SWAT versions

SWAT version	Nutrient modeling features	Climate change modeling features	References
SWAT Versions 2000-2005			
SWAT version 2000	Discharge, sediment, inorganic nitrogen, inorganic phosphorous	Temperature	(Li et al., 2011; Tong et al., 2007)
SWAT version 2005	NO3-N, TN, TP, suspended solids	Temperature and precipitation projection	(Jha et al., 2013; Johnson et al., 2015),
SWAT version 2009	sediment and nutrients (TP and TN)	air temperature and precipitation	(Van Liew, 2012)
SWAT version 2012 Rev. 627/635/645/654/664	TP, TN, DRP	Temperature and precipitation projection	(Kujawa et al., 2020)
SWAT version 2012 integrated with Python	TP, PO4-P, NO2-N, NO3-N, NH4-N, TN	Temperature and precipitation projection	(Bučienė et al., 2019)
SWAT version 2012 Rev. 666	Flow, TN, TP, Soluble P	Temperature and precipitation projection	(Mehan et al., 2019)
SWAT version 2012 Rev. 635	TP, TN, DRP	Temperature and precipitation projection	(Miralha et al., 2021)
SWAT version 2012	Flow, sediment, nutrient (TN and TP)	air temperature and precipitation	(Thang et al., 2018; X. Wang et al., 2018)
ArcSWAT			
version 2012 (2012)	N and P are divided into different forms for cyclic conversion when simulating the TN and TP in the watershed	Temperature and precipitation projection	(Bi et al., 2018)
version 2012.10.13 (2012)	Flow rates and nutrient loading in streams (NO3- and SRP loadings)	Temperature and precipitation projection	(Coppens et al., 2020)

SWAT version	Nutrient modeling features	Climate change modeling features	References
version 2012 embedded in ArcGIS 10.2 software (2012)	streamflow parameters, sediment parameters, TN parameters, TP parameters	Temperature, precipitation, relative humidity, wind speed	(Li & Kim, 2019)
version 510 run on ArcGIS 9.3.1 (2009)	streamflow. NO3-N, and TP loads	Temperature and precipitation projection	(Mehdi et al., 2015; Mehdi et al., 2016)
version 2012 rev. 637	Different species of Nitrogen and Phosphorous	impacts of climate change (precipitation and temperature) and land management practices (ex. Urbanization) on water quality	(Nguyen et al., 2019)
version 2012 embedded in ArcGIS 10.3 (2012)	TSS, NO3-N, PO4 3-	Temperature and precipitation projection	(Pinheiro et al., 2019)
version 2012.10.21 embedded in ArcGIS-Arcview extension and graphical user interface for SWAT	sediments, nitrate nitrogen, total nitrogen, mineral phosphorous, dissolved oxygen	-	(Pulighe et al., 2019)
ArcSwAT interface for SWAT2005	Total Nitrogen and Total Phosphorous	precipitation, temperature, solar radiation, wind speed, relative humidity	(Shrestha et al., 2012)
Version 2.3.4 (2015)	flow, suspended solids, TP loads, Nitrate-N loads	Temperature and precipitation projection	(Verma et al., 2015)
ArcSwAT 2.0 interface for	total suspended solids, total nitrogen, and total phosphorous	-	(Ye & Grimm, 2013)

SWAT version	Nutrient modeling features	Climate change modeling features	References
SWAT2005 (2008)			
SWAT-LAB	daily flow, monthly flow, sediment, Total Nitrogen, and Total Phosphorous (high-resolution model where data availability is limited.	Precipitation	(Čerkasova et al., 2018, 2019, 2021)
SWAT-CUP			
version 2012	TP, PO4-P, NO2-N, NO3-N, NH4-N, TN	Temperature and precipitation projection	(Bučienė et al., 2019)
-	sediments and TN loads	precipitation, max., and min. temperatures, solar radiation, wind speed, relative humidity	(Jisun, 2013)
-	Total Nitrogen and Total Phosphorous	precipitation, temperature, snow melt, evapotranspiration, soil water	(Marcinkowski et al., 2017)
version 5.1.6.2	TP loads	Temperature, precipitation, evaporation	(Nazari-Sharabian et al., 2019)
-	TN and TP loading change	Temperature change and rainfall change	(Trang et al., 2017)
version 2007	TN and TP loading	temperature and precipitation	(Yan et al., 2019)
SWAT-HS	**suspended solids, streamflow, nitrate, dissolved phosphorous, TN**	**air temperature, precipitation, relative humidity, and solar radiation**	**(Mukundan et al., 2020)**

Amongst the peer-reviewed studies, different versions of SWAT were used. For example, SWAT version 2012 was supported with an automated system on Python. Moreover, SWAT versions 2000/2005/2009/2012 used an interface supported by ArcGIS with different model versions each having its code to represent different hydrological models (Jha et al., 2013; Johnson et al., 2015; Khoi et al., 2022; Li et al., 2011).

Tong et al. (2007) ran the SWAT model (version 2000) using a SWAT extension interface known as the Better Assessment Science Integrating Point and Non-Point Sources (BASIN). This version provides all relevant input data needed by SWAT to carry out the simulation. It also provides an environmental analysis system for watershed and water quality studies. This version was able to project/model future climatic changes related to temperatures (Li et al., 2011). Meanwhile, Version 2005 included updated data inputs, calibration efforts, and additional climatic change projection parameters (i.e., precipitation) (Jha et al., 2013).

SWAT version 2009 used by (Van Liew, 2012) enables modeling the transfer and internal cycling of the major forms of N and P. Different revisions of version 2012 are available. For example, rev. 666 was used to estimate the amount of P available for subsurface drain transport (Mehan et al., 2019), whereas rev. 635 included modification on the movement of soluble P through subsurface tile drains (Miralha et al., 2021). Another revision of SWAT2012 integrated Python to determine the causal relationship of changes in the concentration of N and P compounds in the Akmena Dane River and Ekete Rier, Lithuania (Bučienė et al., 2019). Meanwhile, Kujawa et al. (2020), used 5 different versions of SWAT (SWAT 2012 rev. 627/635/645/654/664) and compared their outputs.

Different versions of ArcSWAT have been used. ArcSWAT primarily permits the construction of model inputs from digital maps using GIS (Ye & Grimm, 2013). It is also considered an interface that helps you set up the model. It was used across 11 studies (Bi et al., 2018; Coppens et al., 2020; Li & Kim, 2019; Mehdi et al., 2015; Mehdi et al., 2016; Nguyen et al., 2019; Pinheiro et al., 2019; Pulighe et al., 2019; Shrestha et al., 2012; Verma et al., 2015; Ye & Grimm, 2013).

SWAT-LAB, another model version, was used in different studies (Čerkasova et al., 2018, 2019, 2021). It capitalizes on the benefits of the script-based input generator and the system flexibility in terms of automatic data generation (which is a unique feature among the different SWAT source codes) and helps create high-resolution hydrological and water quality models. It also supports different types of model discretization (sub-basin, hillslope, or grid) to overcome the difficulties related to inconsistent data structure and availability, nutrient emission-based data availability on administrative-level boundaries rather than sub-watersheds, inflexible and unpractical standard GIS-only tool functionality (Čerkasova et al., 2021).

SWATCUP is an interface developed for the SWAT model. It is used to conduct calibration/validation/uncertainty and sensitivity analysis of SWAT models. It has been used across different studies to carry out the needed calibration/uncertainty and sensitivity analysis (Bučienė et al., 2019; Jisun, 2013; Marcinkowski et al., 2017; Mehan et al., 2019; Mukundan et al., 2020; Nazari-Sharabian et al., 2019; Pinheiro et al., 2019; Thang et al., 2018; Trang et al., 2017; Y. Wang et al., 2018; Yan et al., 2019).

Lastly, SWAT-HS represented a modified version of the SWAT model that is capable of simulating saturation excess runoff. Mukundan et al. (2020) used this model for the Cannonsville Reservoir Watershed, New York, USA. The model is also set up to model streamflow and nutrient loading (P loading).

2.3 SWAT input data

The SWAT model requires two main types of input data (Li et al., 2011). The first set is a set of spatial data, which includes the topography data derived from a digital elevation map (DEM), soil maps (showing soil types and properties thus generating a soil database for future reference), and the land use or land cover maps (showing the different land uses in the selected study area such as agricultural, urban, etc.) (Li & Kim, 2019; Li et al., 2011; Verma et al., 2015; Zhang et al., 2012). It is worth noting that several studies conducted in the early 2000s used topographical data and DEMs with a resolution of 30 x 30 m (Čerkasova et al., 2019). More recent applications use 10 m resolutions (Bi et al., 2018; Jisun, 2013; Kujawa et al., 2020; Mehan et al., 2019; Mukundan et al., 2020; Nguyen et al., 2019; Pulighe et al., 2019; Tong et al., 2007; Van Liew, 2012), with a few applications attempt ting to work with even a finer resolution (e.g. Čerkasova et al. (2019) who used a 5m resolution).

The second set of data is referred to as property data (Li et al., 2011); they include hydrological data (including different hydrological processes such as flow, surface runoff, and evapotranspiration), water quality or point source discharge data (such as sediment yield, concentrations of TN and TP or nutrient loading, etc.), climate/meteorological data (related to solar radiation, relative humidity, wind speed, precipitation, and temperature), soil data information (type and properties), and land management practices (fertilizer application, tillage crop, planting, harvesting, manure applications) (Verma et al., 2015). Property data plays an important role in enhancing the quality of simulation and controlling water quality processes (Li & Kim, 2019). It is worth noting that the above input data are obtained from different sources such as governmental databases as well as public open-access databases. In some cases, climatic input data could be generated using the built-in weather generator in SWAT (Čerkasova et al., 2019, 2021; Jha et al., 2013; Lee et al., 2018; Molina-Navarro et al., 2014; Mukundan et al., 2020; Nazari-Sharabian et al., 2019; X. Wang et al., 2018).]

2.4 SWAT outputs

SWAT generates a range of outputs, including hydrological outputs such as surface runoff, groundwater recharge, streamflow, and sediment yield, as well as water quality outputs such as total nitrogen, total phosphorus, and sediment load. These outputs are generated for various spatial and temporal resolutions, depending on the specific research question or management application. For example, runoff and water quality can be simulated at daily, monthly, or annual time steps, while streamflow and sediment yield can be simulated at monthly or annual time steps. Spatial resolution can range from small sub-watersheds to large river basins, depending on the modeling needs and data availability.

2.5 SWAT calibration and validation

An extensive array of statistical indices have been used to evaluate SWAT models. Arnold (2012) mentioned 20 potential statistical tests that can be used for that purpose, including coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), root mean square error (RMSE), t-tests, non-parametric function tests, objective function, etc. D. N. Moriasi (2015) described different final performance evaluation criteria for recommended statistical performance measures (mainly R^2, NSE, and PBIAS) to judge the success of SWAT (and other watershed and field scale models) results. The table below shows the ranges of performance evaluation criteria recommended for assessing the performance of the models as suggested by D. N. Moriasi (2015).

Table 2 Ranges of performance evaluation criteria for recommended statistical performance measures (D. N. Moriasi, 2015)

Measure	Output Response	Performance Evaluation Criteria			
		Very Good	**Good**	**Satisfactory**	**Not Satisfactory**
R2	Flow	R2> 0.85	0.75<R2<0.85	0.60<R2<0.75	R2<0.60
	Sediment	R2> 0.80	0.65<R2<0.80	0.40<R2<0.65	R2<0.40
	N/P	R2> 0.70	0.60<R2<0.70	0.30<R2<0.60	R2<0.30
NSE	Flow	NSE>0.80	0.70<NSE<0.80	0.50<NSE<0.70	NSE<0.50
	Sediment	NSE>0.80	0.70<NSE<0.80	0.45<NSE<0.70	NSE<0.45
	N/P	NSE>0.65	0.50<NSE<0.65	0.35<NSE<0.50	NSE<0.35
PBIAS	Flow	PBIAS<±5	±5<PBIAS<±10	±10<PBIAS<±15	PBIAS>±15
	Sediment	PBIAS<±10	±10<PBIAS<±15	±15<PBIAS<±20	PBIAS>±20
	N/P	PBIAS<±15	±15<PBIAS<±20	±20<PBIAS<±30	PBIAS>±30

Parameter sensitivity analysis is often the first step conducted before proceeding with the calibration and validation processes of the SWAT model. This step provides insights as to which parameters contribute most to the output variance due to changes in input variables (Li et al., 2011) along with its significance in model development and evaluation (Verma et al., 2015). It is a necessary step to determine the key parameters required for calibration. The parameter sensitivity analysis is an available tool/function included in different SWAT versions. One method commonly used in many studies is the Latin Hypercube on-factor-at-a-time (LH-OAT) method (Jordan et al., 2014; Li et al., 2011; Thang et al., 2018).

CHAPTER 3

RESEARCH METHODOLOGY

The scope of the work will consist of a series of interrelated activities. First, a comprehensive literature review will be conducted. The review will provide general information about the SWAT hydrological model, its capabilities, history, objectives, and its applications worldwide. Additionally, the study will shed light on the approaches adopted to couple the SWAT model with climate change models/data and how these couplings have evolved. Furthermore, the review will specifically focus on reviewing the studies that used the SWAT model to assess the impacts of future climate change on nutrient loading at the watershed level. Finally, the review discusses the existing limitations and proposes a set of recommendations to improve the capabilities of SWAT to assess nutrient pollution as a function of a changing climate.

3.1 Literature review

A mixed qualitative and quantitative research approach was adopted to identify and review the existing literature associated with the modeling of nutrient loading and water quality impairments at the watershed level using the SWAT model, while accounting for future climatic predictions. The review process explored the limitations of past applications and identified areas of need of further development. This process involved the collection, analysis, and synthesis of the existing literature and the generation of relevant visual summaries (statistics and graphic representations). Figure 4 summarizes the adopted research methodology for the literature review.

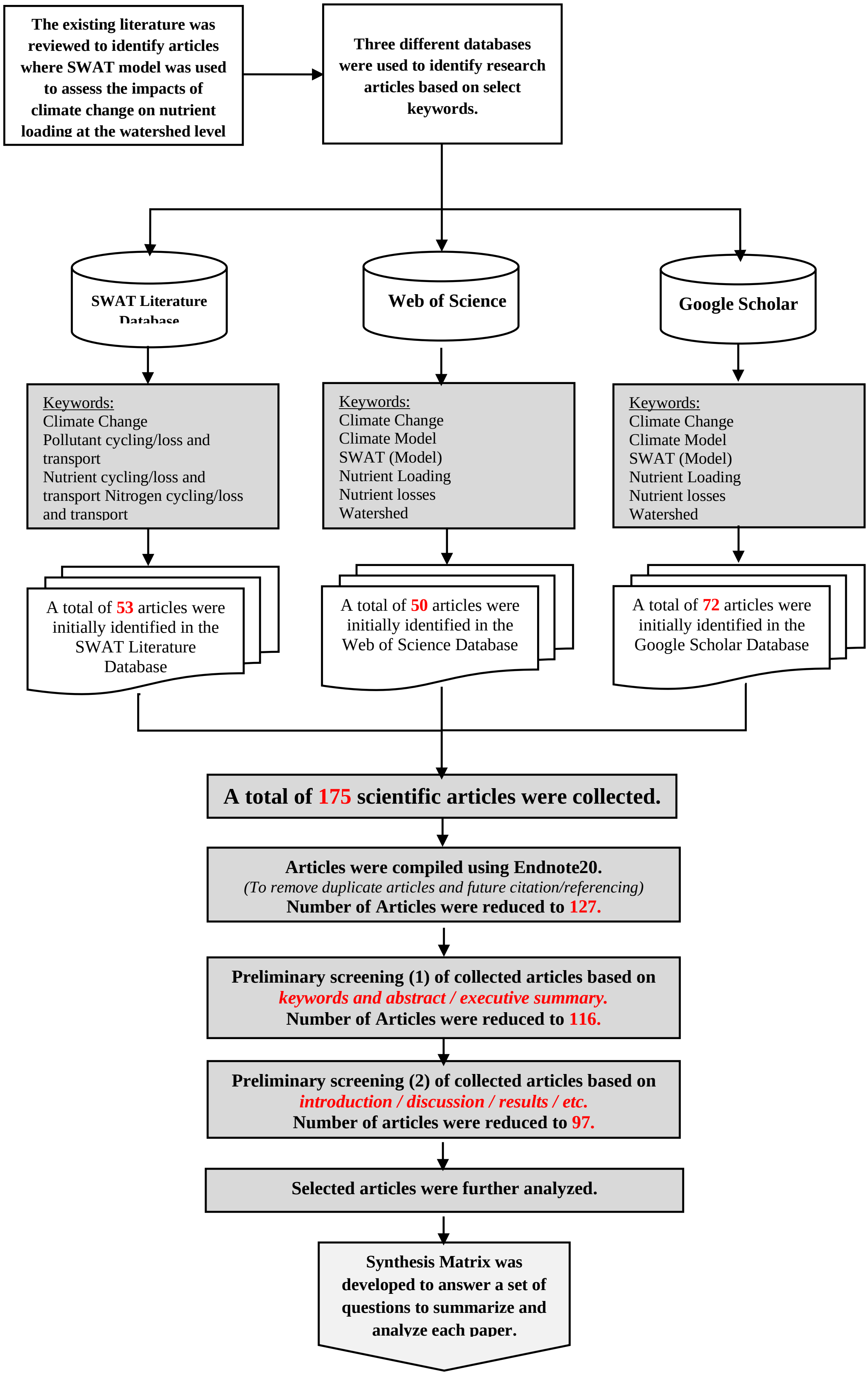

Figure 4 Research methodology to develop the synthesis matrix.

As a first step, it was essential to define the research scope and objective(s) related to the application of the SWAT model in modeling nutrient loading in the face of climate change (under different future climatic scenarios) at the watershed level. This was done by determining inclusion/exclusion criteria mainly related to publication date, study of design and geographical focus before the comprehensive search strategy.

To meet our main research objectives, we developed a comprehensive search strategy by identifying relevant electronic databases based on the research scope. We limited our search to three main knowledge databases that included the SWAT Literature Database, the Web of Science (WoS) Database, and the Google Scholar Database. These three resources were checked for research articles that used the SWAT model to assess the impacts of future climate change on nutrient loading at the watershed level. Moreover, suitable exclusion criteria (discussed in the below paragraphs) were applied to ensure the selection of high-quality and relevant literature. The selection process aimed to guarantee that the chosen articles were methodologically sound, contributed to the research topic/question(s), and provided a robust foundation for the theoretical framework and analysis for this paper. A tailored set of keywords and synonyms were generated using controlled vocabulary when applicable.

The SWAT Literature Database was first used, as this database records all peer-reviewed scientific papers that have been published and that have used the SWAT model. Based on the SWAT literature database, there was a total of 5,208 journal papers published since its development (as of August 2022). Studies published before 2000 were excluded from this study to capture the most recent advancements in the SWAT model.

To filter through these papers, keywords such as **climate change**, **climate models**, **nutrient loading**, and **nutrient transportation** were considered. Four searches were conducted in the SWAT Literature Database using the following search options:

- The first search used the terms **climate change and pollutant cycling/loss and transport**. The search returned **33** journal papers.
- The second search used the terms **climate change and nutrient cycling/loss and transport.** The search returned **10** journal papers.
- The third search used the terms **climate change and nitrogen cycling/loss and transport.** The search found **7** journal papers.
- The fourth search used the **terms climate change and phosphorous cycling/loss and transport.** The search found **3** journal papers.

Collectively, the four searches identified **53** relevant and unique articles. A similar search strategy was adopted with the Web of Science and Google Scholar. For the Web of Science database, an advanced search was used with the following keywords selected to narrow down our search and specifically focus on the research topic. The keywords were **"climate change"**, **"climate model"**, **"SWAT model", "nutrient loading"**, **"nutrient losses"** and **"watershed"**. This search returned **50** relevant articles based on the keyword selection.

As shown in Figure 5, the number of studies has been increasing over time, especially after 2015. As can be seen in Figure 6, most of the published articles (~40%) were conducted in the United States of America (USA), followed by studies in the People's Republic of China (PRC) (~30%), and Iran / Italy (~4% each).

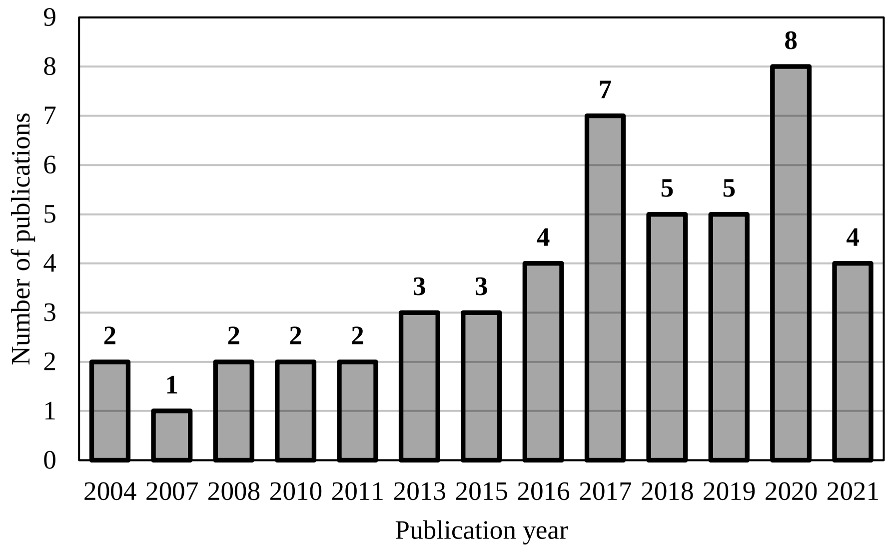

Figure 5 Web of Science (WoS) number of publications related to the SWAT model based on the keyword search by year.

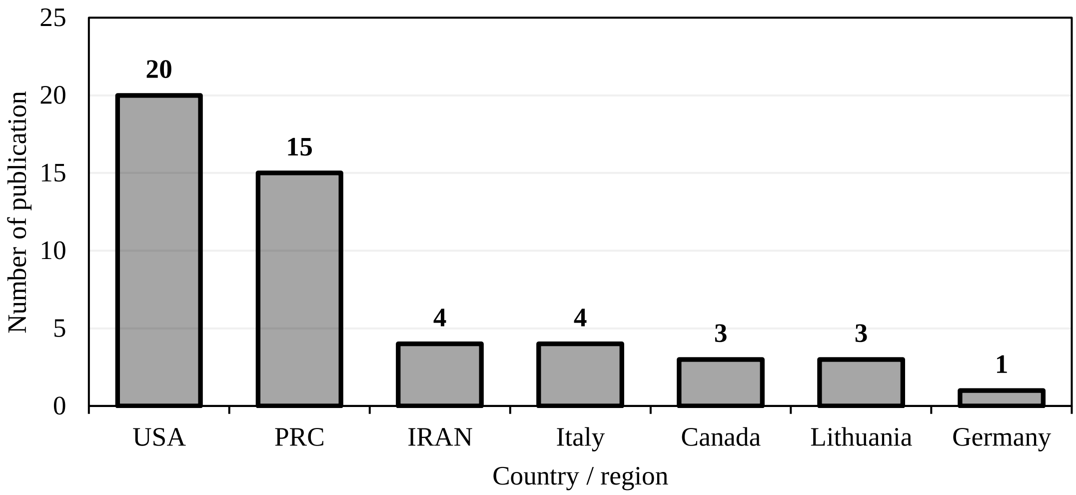

Figure 6 Number of filtered Web of Science (WoS) publications by country/region.

A similar approach was adopted with Google Scholar Database. In the advanced search criteria, we searched for and opted to select published articles starting from the year 2000. We then refined our search method using the same main keywords used in our Web of Science search method, **“climate change”**, **“climate model”**, **“SWAT**

model", "nutrient loading", **"nutrient losses"**, and **"watershed"**. The search returned **72** journals.

Across the three databases, a total of **175** articles were identified (**SWAT Database = 53, Web of Science = 50, and Google Scholar = 72)**. Given that several of the articles identified from these searches may be duplicated, we compiled them under one main reference file using EndNote20. Duplicate studies were identified and deleted. Accordingly, the number of research articles was reduced to **127**.

Each of the selected **127** articles was then assessed individually to assess its relevance regarding the study objectives. The method of identifying relevance was mainly based on establishing a systematic screening process. The screening process involved focusing on the research papers' titles, identifying specific key terms/keywords (such as climate change, climate models, nutrient loading, SWAT model, water quality, watershed, and waterbodies (lakes, rivers, etc.), and reviewing the abstract and/or executive summary. Finding most or all these terms indicated that the article/publication was worth reading in detail. This process was the first filter (Preliminary Screening 1) that was used to further refine the initial selection process. Accordingly, the number of research articles was further reduced to **116.** Appendix 1 lists the studies that were removed during the 1st preliminary screening.

The remaining **116** articles were further examined for relevance by going through their introduction, methodology, discussion, results, and conclusion sections. This process was the second filter method (Preliminary Screening 2) and was used to further refine the selection process. A total of 19 papers were found to be irrelevant and were excluded. This step resulted in retaining a total of **97 articles.** Appendix 2 lists the studies that were removed during the 2nd preliminary screening. The table below shows the final count of articles that were deemed relevant and were included in the review.

Table 3 Number of significant references uploaded to EndNote based on the selected Databases.

Research database	**Number of references**
SWAT literature database	24
Web of Science (WoS)	33
Google Scholar	40
Total number of references	**97**

Some of the peer-reviewed articles were excluded due to several factors (such as incomplete sets of data, lack of a particular level of evidence, etc.). Articles were excluded if they reported only on the impacts of climate change on nutrient loading by assessing historical climate data. Additionally, some articles were excluded since they only addressed the issue of climate change without focusing on its impact on nutrient loadings. For example, some papers did not specify the hydrological model (SWAT) or used different hydrological models (Li et al., 2020) or climate models (Burigato Costa et al., 2019; Neumann et al., 2021) or did not specify the type and future projection periods, or did not focus on nutrient modeling (N and P).

Ultimately, we ended up with 88 significant articles that were examined and analyzed in detail. The 9 articles which were excluded due to the above-mentioned reasons are as follows (Table 4).

Table 4 Excluded Reference after final review.

Ref. No	Reference
1	Cousino, L. K., et al. (2015). "Modeling the effects of climate change on water, sediment, and nutrient yields from the Maumee River watershed." Journal of Hydrology: Regional Studies 4: 762-775.
2	Cui, T., et al. (2021). "Evaluation of Temperature and Precipitation Simulations in CMIP6 Models Over the Tibetan Plateau." Earth and Space Science 8(7).
3	Fan, M. and H. Shibata (2015). "Simulation of watershed hydrology and stream water quality under land use and climate change scenarios in Teshio River watershed, northern Japan." Ecological Indicators 50: 79-89.
4	Gabriel, M., et al. (2018). "Modeling the combined effects of changing land cover, climate, and atmospheric deposition on nitrogen transport in the Neuse River Basin." J Hydrol Reg Stud 18: 68-79
5	Gaudet, M. M. a. B. (2017). "'SRES' Scenarios and 'RCP' Pathways." From Meteorology to Mitigation: Understanding Global Warming.
6	Gunn, K. M., et al. (2021). "Integrating Daily CO2 Concentrations in SWAT-VSA to Examine Climate Change Impacts on Hydrology in a Karst Watershed." Transactions of the ASABE 64(4): 1303-1318.
7	James, T. S., et al. (2014). "Relative Sea-level projections in Canada and the Adjacent Mainland United States." Geological Survey of Canada.
8	Jayakody, P., et al. (2014). "Impacts of climate variability on water quality with best management practices in sub-tropical climate of USA." Hydrological Processes 28(23): 5776-5790.
9	Meehl, G. A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, and A. J. W. a. Z.-C. Z. I.G. Watterson (2007). "Global Climate Projections." The Physical Science Basis.Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

3.2 Assessment of recent literature

The final remaining research articles (88) were assessed individually based on a unified set of questions. For that reason, a standardized data extraction form (Synthesis Matrix Questionnaire) was developed to systematically extract relevant information for each study, which showed different questions categorized into 4 main sections that included:

1) SWAT model application
2) Climate models and SWAT integration
3) Nutrients
4) Challenges and future recommendations

The synthesis matrix questionnaire is represented in (Table 5).

3.2.1 SWAT model application

Given the different versions of the SWAT model, this section aimed to identify the different source codes (such as ArcSWAT, SWAT2005, etc.) and the types of hydrological/instream processes (such as infiltration ET, and snow dynamics) used in each study. Additionally, the type of input data files used to carry out model simulations on nutrient loading was examined (mainly relating to topography 'DEM', soil type, land use data, meteorological data, hydrology, and water quality). Additional relevant data layers were assessed if they impact the transport of nutrients (examples include, fertilizer application, point and non-point source data). The inclusion of management practices (tiling, contouring, fertilizer timing, and amount) was also reviewed. Finally, the calibration and validation processes used were identified in terms of the model performance metrics (such as R^2, NSE, and PBIAS), the duration/periods adopted, and the parameters considered.

3.2.2 Climate models and SWAT integration

Climate models are used to understand the impacts of climate change on complex earth systems and to draw conclusions on past and future climate systems. Our inquiries focused on understanding which climatic parameters from the climate models were used in SWAT (such as precipitation and temperature). We also looked at the type of climate models (statistical, RCM, or GCM) used, and whether such climate models required further downscaling to improve the accuracy of climate change projections and impact assessments at local scales. After identifying the climate models and using the ideal downscaling method, we reported on the emission scenarios (Special Report on Emissions Scenarios - SRES vs. Representative Concentration Pathways - RCP) analyzed by each paper.

3.2.3 Nutrients and Flow

The questions proposed in this section mainly focus on the types of nutrients (Nitrogen and Phosphorous and their different forms) that were accounted for in the model. Moreover, it identifies whether nutrient loadings were allowed to change over time or if they were held constant (by modifying the land management practices such as fertilizer application rates, and land use land changes at the watershed area) as this can help to project and predict the impact on water quality and identify management strategies for reducing nutrient pollution in a watershed area. This section also looks at the nutrient processes that were used for the transformation between different types of nutrients, such as organic and inorganic, and how those were affected by changes in climate. Similarly, we look at how future flows were predicted and how the forcing functions were modeled over time and space.

3.2.4 Challenges and Future Recommendations

The integrated application of SWAT with climate models often reveals new research opportunities and identifies weaknesses and challenges regarding our understanding of the scale of this change or the data requirements needed to make such predictions. Consequently, limitations related to the development of SWAT and the adopted climate models were recorded, along with proposed future research development needs.

Table 5 Synthesis Matrix Questionnaire used for each paper.

Description
1. SWAT • What model source code was used? • Did the model account for hydrological/instream processes (such as infiltration, ET, and snow dynamics)? • What were the input data files used and at what spatial and temporal resolution? • Were the land use/land cover as well as management practices assumed to be dynamic or static over time? • Was the model calibrated and validated? What model parameters were considered for calibration/validation? What methods were used/developed for the calibration and validation phases? How long were the time series used in the calibration/validation? What parameters were used in the calibration and validation process? • What methods were used to assess model performance (R2, NSE, PBIAS)? • Was a sensitivity analysis conducted? • Were model parameters allowed to change over time? And if so, which? • At what spatial and temporal level was the calibration conducted?
2. Climate data and SWAT integration • What future climate data were used with the SWAT application (e.g., temperature, precipitation, snow, etc.)?

• What was the spatiotemporal resolution of the climatic data used? • What emission scenarios were considered (SRES vs. RCP)? What type of climate models/scenarios were used (GCM, RCM, others) to generate future climate data? • Was the climatic data downscaled and if so what type of downscaling methods were used? • Did the study use an ensemble of climate models or single climate models?
3. Nutrients and flow • Which hydrological variables were modeled? • Which nutrients were modeled and in which form? • Was nutrient loading (N and P) allowed to change over time? If so how? • Was nutrient processing and transformation allowed to change over time?
4. Challenges and future recommendations • What were the limitations of the study? • What were the identified future research development needs?

It should be noted that our research methodology opted for a modified approach rather than using a particular research methodology such as the PRISMA methodology. The latter is a well-established and rigorous framework to guide the systematic review and meta-analysis process in healthcare and medical research. However, it is also applicable to reports of systematic reviews evaluating other non-health-related interventions (Alina Trifu & 2022).

CHAPTER 4

RESULTS AND DISCUSSION

4.1 SWAT Model Application

Of the combined 97 peer-reviewed publications retrieved from the 3 selected databases, 88 were found to be significant. Table 6 provides a detailed summary of those. The studies covered 57 different watersheds across different regions of the world. We found that most of the SWAT applications that assessed the impacts of climate change on nutrient loading were conducted in the US and China, with 18 and 8 published studies since 2000, respectively.

Table 6 List of peer-reviewed publications that used SWAT as a tool for modeling the future impacts of climate change on nutrient loading at the watershed level.

Country/Region	Watershed Name	Watershed Area	Reference
United States	Upper Mississippi River Basin	492,000 km^2	• (Jha et al., 2013)
Vietnam, Cambodia, and Lao PDR	3S River Basin (Sekong, Sesan and Srepok)	78,650 km^2	(Khoi et al., 2022; Trang et al., 2017)
China	Launhe River Basin	44,750 km^2	(Bi et al., 2018)
China	Lower Kaidu River Basin	43,890 km^2	(Ba et al., 2020)
United States	Connecticut River Watershed	28,500 km^2	(Marshall & Randhir, 2008)
United States	Maumee River	21,538 km^2	(Kujawa et al., 2020; Miralha et al., 2021; Verma et al., 2015)
United States	St. Croix River Basin	20,000 km^2	(Yang et al., 2019)

Country/Region	Watershed Name	Watershed Area	Reference
United States	Western Lake Erie Basin, Maumee River	17,100 km^2	(Cousino et al., 2015)
United States	Western Lake Erie Basin, Maumee River	17,000 km^2	(Kalcic et al., 2019)
United States	Maumee River Basin	16,200 km^2	(Andreas M. Culbertson, 2016)
China	Miyun Reservoir Watershed	15,400 km^2 – 15,788 km^2	(Feng & Shen, 2021; Wang et al., 2018)
Canada	Upper Assiniboine Catchment	13,500 km^2	(Shrestha et al., 2012)
China	Liao River basin, the Zhaosutai River basin, and the Tiaozi River basin	11,283 km^2	(Wang et al., 2018)
Belarus, Lithuania, Poland, Russia, Latvia	Nemunas River Basin	9,7928 km^2	(Čerkasova et al., 2018, 2021)
Portugal	Sorraia River Basin	7,730 km^2	(Almeida et al., 2018)
Vietnam	Dong Nai River Basin	7,500 km^2	(Thang et al., 2018)
United States	Great Miami and Little Miami Watersheds	7,078 km^2	(Ariel L. Salas & Kumaran Subburayalu, 2019)
South Korea	Mountainous watershed	6,640 km^2	(Kim et al., 2014)
China	Xin'anjiang Catchment	6,260 km^2	(Zhai & Zhang, 2018)
China (Hong Kong)	Ru River Basin	5,803 km^2	(Yang et al., 2018)
China	Lower Pearl River Basin	5,092 km^2	(Li et al., 2011)
China	Shitoukoumen Reservoir Catchment	4,944 km^2	(Zhang et al., 2012)

Country/Region	Watershed Name	Watershed Area	Reference
United States	Little Miami River Watershed	4,498 km^2	(Tong et al., 2007)
Poland	Upper Narew and Barycz Catchments	4,231 km^2 5,522 km^2	(Marcinkowski et al., 2017)
United States	Sprague River Watershed	4,000 km^2	(Records et al., 2014)
Canada	South Nation River	3,858 km^2	(El-Khoury et al., 2015)
Denmark	Funen Island Catchment	3,528 km^2	(Trolle et al., 2015)
United Kingdom	Yorkshire Ouse Catchment	3,500 km^2	(Bouraoui, 2002)
United States	Sandusky River Watershed	3,458 km^2	(Xu et al., 2018)
South Korea	Saemangeum River Basin	3,367 km^2	(Kim et al., 2020; Li & Kim, 2019)
Lithuania	Minijia River Basin	3,097 km^2	(Čerkasova et al., 2019; Povilaitis et al., 2018)
Japan	Teshio River Catchment	2,908 km^2	(Fan & Shibata, 2015)
Japan	Asahi River Watershed	1,810 km^2	(Shimizu, 2011)
Finland	Vantaanjoki watershed	1,682 km^2	(Bouraoui et al., 2004)
United States	Shell Creek Watershed	1,214 km^2	(Van Liew, 2012)
United States	Cannonsville Reservoir Watershed	1,178 km^2	(Mukundan et al., 2020)
Germany	Almuhl River Basin	980 km^2	(Mehdi, Ludwig, et al., 2015; Mehdi et al., 2016)
Azerbaijan	Mahabad Dam Watershed	808 km^2	(Nazari-Sharabian et al., 2019)
South Korea	Youngsan River Basin	646 km^2	(Jisun, 2013)

Country/Region	Watershed Name	Watershed Area	Reference
Canada	Pike River Watershed	630 km^2	(Gombault et al., 2015)
Canada	Pike River Watershed	629 km^2	(Mehdi, Lehner, et al., 2015)
Lithuania	Akemnta-Dane River Catchment	594 km^2	(Bučienė et al., 2019)
United States	Sycamore Creek (Verde River)	505 km^2	(Ye & Grimm, 2013)
Poland	Reda River Catchment	482 km^2	(Piniewski et al., 2014)
Australia	Onkaparinga River Catchment	317 km^2	(Shrestha et al., 2017)
United States	Tuckhose Creek Watershed and Greensboro Watershed	220 km^2 290 km^2	(Lee et al., 2018)
United States	Eagle Creek Watershed	248 km^2	(Ahmadi et al., 2014)
Australia	Torrens Catchment	200 km^2	(Nguyen et al., 2019)
Italy	Zero River Basin / Catchment	140 km^2	(Pesce et al., 2018; Sperotto et al., 2019)
Italy	Sulcis River Catchment	77 km^2	(Pulighe et al., 2019)
Spain	Ompolveda River Catchment	88 km^2	(Molina-Navarro et al., 2014)
New Zealand	Lake Rotorua Catchment	80.8 km^2	(Me et al., 2018)
United States	Mason Ditch Watershed	46 km^2	(Mehan et al., 2019)
Brazil	Concordia Catchment	30 km^2	(Pinheiro et al., 2019)
Slovenia	Reka River Catchment	30 km^2	(Glavan et al., 2015)
Turkey	Mogan Lake Catchment	8 km^2	(Coppens et al., 2020)
United States	Wolf Bay Watershed	-	(Wang & Kalin, 2018)

Regarding the size of the watersheds studied, we found that they varied significantly (Figure 7). As can be seen, watersheds smaller than 1,000 km^2 represented 24.56% of all studies. Similarly, watersheds between 100 and 5,000 km^2 in size accounted for a quarter of all the studies (24.56%). Watersheds between 5,001 – 10,000 km^2 represented 14.04% of all studies, while those conducted on large watersheds (10,0001 – 100,000 km^2) represented 22.81%. Only 1.75% and 12.28% of the studies were conducted on watersheds that were either greater than 100,000 km^2 or smaller than 100 km^2, respectively.

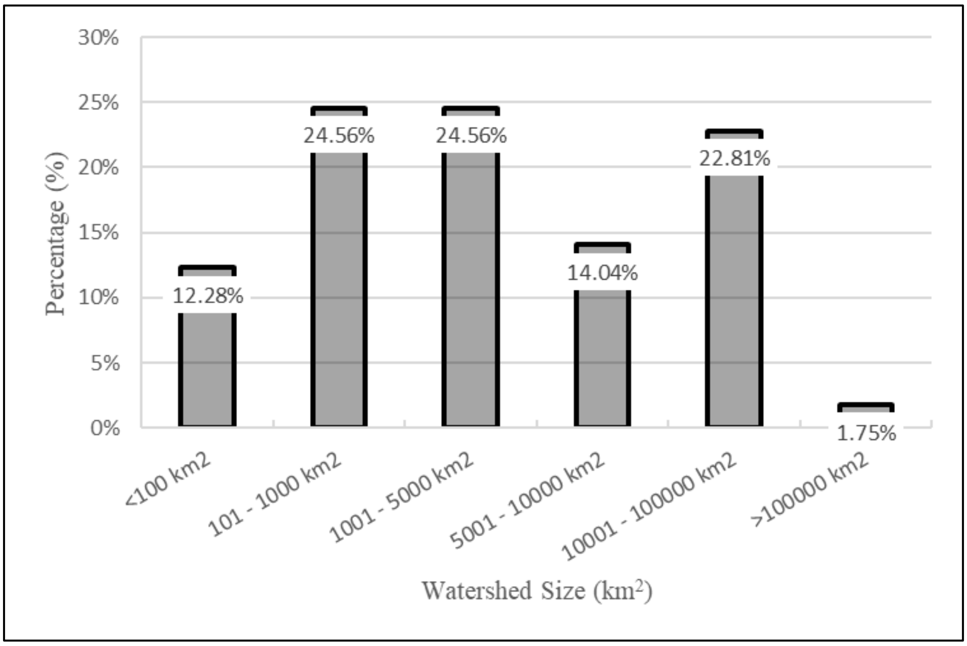

Figure 7 SWAT topic-related publications based on watershed size (km^2)

Overall while the number of SWAT publications has increased dramatically since 2009, SWAT assessment of future climate change impacts on nutrient loadings at the watershed level started to increase in 2018. As illustrated in Figure 8, the number of articles published in 2018 was almost 5 times greater than those published in the preceding year (i.e., 2017). Tan et al. (2020) reported that this might be due to the increase in extreme weather events occurrences around the world over the past few years.

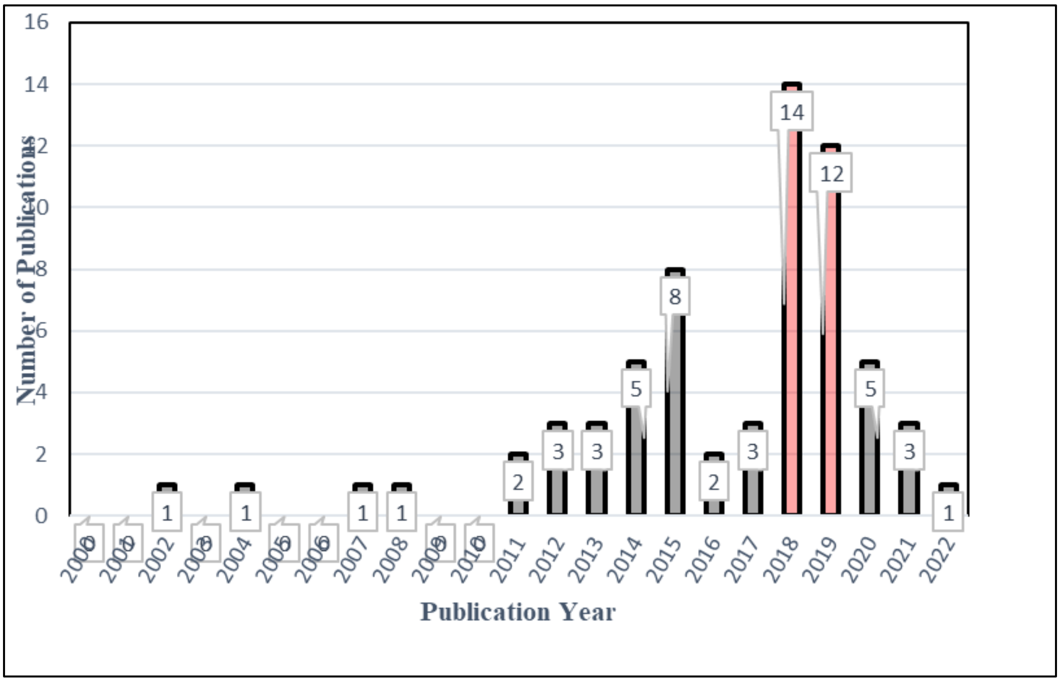

Figure 8 SWAT topic-related publications based on publication year (2000-2022)

4.1.1 SWAT Model Input Data Files

As mentioned in section 2.3 (SWAT input data), the SWAT model operates on various input data files that describe the hydrological and physical characteristics of the watershed being studied. The adopted spatial and temporal resolution of these input data can significantly affect the accuracy and detail of the simulation results. Moreover, it is worth noting that the spatial and temporal resolutions can vary based on the available data sources, the specific aims of the modeling study, and the size of the watershed being simulated. Finer spatial and temporal resolutions generally lead to more detailed and accurate simulations if the needed data are available. The below table, Table 7 represents the different SWAT input data files used in each study. These include digital elevation models (DEM), soil properties, meteorological data (such as precipitation, and temperature), farm management, hydrological data, and water quality monitoring data. It also demonstrates the different values (along with the spatio-temporal information) of the input data files used across the different studies.

Table 7 Values of SWAT model input data files

Reference	Digital Elevation Model (DEM)	Soil properties/data	Meteorological Data (precipitation, temperature, etc.)	Hydrological Data	Water Quality Monitoring Data
(Ahmadi et al., 2014)	30m	County-based soil data from the US Soil Survey Geographic Database	Precipitation Temperature	Daily Streamflow	NO3-
(Ariel L. Salas & Kumaran Subburayalu, 2019)	10m	No data available	Precipitation Temperature	No data available	No data available
(Ba et al., 2020)	90m	1:1,000,000	Daily Precipitation and Temperature	Daily streamflow	TP and TN
(Bi et al., 2018)	No data available	1:1,000,000	Daily Precipitation and Temperature	Monthly flow data	TP and TN
(Bouraoui, 2002)	50m	Gridded-type map	No data available	No data available	No data available
(Bouraoui et al., 2004)	25m x 25m	1:1,000,000	No data available	No data available	No data available

Reference	Digital Elevation Model (DEM)	Soil properties/data	Meteorological Data (precipitation, temperature, etc.)	Hydrological Data	Water Quality Monitoring Data
(Čerkasova et al., 2018)	35m x 35m	1:10 000	Precipitation and Temperature	Monthly flow data	TP and TN
(Čerkasova et al., 2019)	35m x 35m	1:10 000	Precipitation and Temperature	Daily Flow	TP and TN
(Coppens et al., 2020)	30m	Used, no data available	Daily precipitation, wind speed, max. and min temperature, solar radiation, and relative humidity	Daily Flow	NO3 and SRP
(Cousino et al., 2015)	30m	Used, no data available	Daily precipitation and temperature	No data available	No data available
(Cui et al., 2021)	90m	no data available	Daily precipitation and temperature	No data available	TP
(El-Khoury et al., 2015)	90m	no data available	Daily precipitation, wind speed, max. and min temperature, solar radiation, and relative humidity	No data available	NO3-, NO2. N, P
(Feng & Shen, 2021)	30m	1:10,000,000	precipitation and temperature	Daily streamflow	
(Glavan et al., 2015)	25m	1:25,000	‘	Daily flow	NO3-, TP

Reference	Digital Elevation Model (DEM)	Soil properties/data	Meteorological Data (precipitation, temperature, etc.)	Hydrological Data	Water Quality Monitoring Data
(Jisun, 2013)	10m	1:25,000	Precipitation, air temperature (max., min.), solar radiation, wind speed, relative humidity	Daily streamflow	Sediment and TN
(Khoi et al., 2022)	250m	10km	Daily Rainfall and max./min. temp.	Daily Discharge	TSS and TN
(Li et al., 2018)	1:1,000,000	no data available	Precipitation, air temperature (max., min.), relative humidity, wind speed	Daily streamflow	TN and TP
(Li et al., 2011)	1:250 000	1:1 000 000	Precipitation, air temperature (max., min.), relative humidity, wind speed	Yearly and Monthly Discharge	Yearly Nutrient load (TP and TN)
(Mehdi et al., 2015)	50m	no data available	Precipitation, air temperature (max., min.), relative humidity, wind speed, cloud cover, hours of sunshine	Daily Flow	

Reference	Digital Elevation Model (DEM)	Soil properties/data	Meteorological Data (precipitation, temperature, etc.)	Hydrological Data	Water Quality Monitoring Data
(Mukundan et al., 2020)	10m	no data available	Precipitation and air temperature	No data available	NH4 / NO3-
(Nguyen et al., 2019)	10m	10m	Daily precipitation, temperature, solar radiation, relative humidity	Daily Streamflow	Monthly TP and TN
(Pesce et al., 2018)	5m	500m x 500m	Daily precipitation, temperature	Daily Streamflow	Nitrate and ammonia
(Pulighe et al., 2019)	10m	1:50,000	precipitation, temperature, solar radiation, relative humidity	Monthly Discharge	SS, NO3-, TN, TP
(Shimizu, 2011)	50m	1:200,000	precipitation, temperature	Monthly Discharge	SS, TP, TN
(Shrestha et al., 2017)	30m	no data available	no data available	Monthly flow	TP and TN
(Shrestha et al., 2012)	90m	1:1 000 000	precipitation, temperature	No data available	TP and TN
(Thang et al., 2018)	90m	1km	precipitation, temperature, solar radiation, relative humidity	Daily Streamflow	TP and TN
(Trang et al., 2017)	250m	no data available	precipitation, temperature, solar radiation, relative	Daily Discharge	NO3_, NH4+, P

Reference	Digital Elevation Model (DEM)	Soil properties/data	Meteorological Data (precipitation, temperature, etc.)	Hydrological Data	Water Quality Monitoring Data
			humidity, wind speed		
(Verma et al., 2015)	30m	90m x 90m	Daily precipitation and temperature	Daily flow	TSS< NO3-, NH4+
(X. Wang et al., 2018)	30m	1:1 000 000	precipitation, temperature, solar radiation, relative humidity, wind speed	Monthly streamflow	TN and TP
(Y. Wang et al., 2018)	90m	no data available	Daily precipitation, temperature, solar radiation, relative humidity, wind speed	Streamflow	TN and TP
(Yan et al., 2019)	90m	1:1 000 000	Daily precipitation, temperature, solar radiation, relative humidity, wind speed	Monthly streamflow	TN
(Yang et al., 2019)	90m x 90m	no data available	Daily precipitation, max., and min., temperature, solar radiation, relative humidity, wind speed	no data available	Sediment and Non-Point Source Pollution (NPS)

The spatial resolution of the DEMs across the studies varied from 5 m (highest resolution) up to 250 m (lowest resolution). The higher the DEM resolution, the greater the preservation of the topographical land/watershed features. For example, Pesce et al. (2018) used a DEM of 5m spatial resolution to study the impact of climate change on nutrient loads in the Zero River Basin (ZRB) in Venice Italy. While (Khoi et al., 2022); Trang et al. (2017) opted for a DEM with a spatial resolution of 250 m for the 3S (Sesan, Sekong, and Srepok) River Basin in Laos, Vietnam, and Cambodia. The most commonly used DEM was at the 30 m spatial resolution, with 25% of studies using it. On another note, the most common hydrological data used across the studies was flow; yet it was used at different time steps. Most studies worked with daily flows. It is worth noting that hydrological data play an important role in the SWAT model, as they are essential for accurately representing the hydrological processes within the watershed (Jayakody et al., 2014).

4.1.2 SWAT Hydrological/Instream Process

The SWAT model simulates various hydrological processes within a watershed. Many studies have accounted for different instream hydrological processes such as infiltration, evapotranspiration, and potential evapotranspiration (PET). Kim et al. (2020) simulated changes in the PET for the future period (2050s - 2090s), which they predicted would increase in a similar fashion to streamflow. They estimated that the percent increase in streamflow in the Saemangeum River Basin in South Korea would range between 26.5% and 51.8%, while PET would increase between 5.1 and 11.4%. Marshall and Randhir (2008) assumed that the annual PET rate would increase by 19%

and 3% under a warming high (WH) and warming low (WL) scenarios, respectively when they studied the Connecticut River basin in Central New England, USA. Additionally, evapotranspiration rates were simulated to change under both climate scenarios as a result of temperature changes. Cousino et al. (2015) assumed PET and ET rates would increase under all climate scenarios when they assessed the Maumee River watershed in the USA. PET values were expected to increase on average by 10% and 17% for 2046–2065 and 2080–2099, respectively. Increases in ET were more extreme, with an average rise of 28% for 2046–2065 and 46% for 2080–2099. These increases in ET were predicted to lead to decreases in the total water available for runoff. Marcinkowski et al. (2017) showed that ET was projected to increase by 2.6 to 6.8% in the Upper Narew (NE Poland) and the Barycz (SW Poland) catchments for the future periods of 2021-2050 and 2071-2100 under RCP 4.5, by the projected temperature increase. Kalcic et al. (2019) projected an increase between 1-11% in precipitation accompanied by a 24-50% decrease in snowfall and a 7-12% increase in evapotranspiration for the river basins in Western Lake Erie, USA.

4.1.3 Sensitivity Analysis

One of the first steps in the calibration and validation process in SWAT is the determination of the most sensitive parameters for a given area, this can be done by using sensitivity analysis. It is a method used for determining the rate of change in model output concerning changes in model input parameters (Arnold, 2012). In brief, it evaluates how different parameters influence a predicted output. Sensitivity analysis plays an integral part in model development and engages analytical examination of input parameters to aid in model validation and provide guidance for future research

(Khairi Khalida, 2016). Table 8 shows the assessed and most sensitive model parameters that were reported in each study along with how the sensitivity analysis was implemented and interpreted.

Most of the studies assessed the sensitivity of the SWAT model by looking at how the hydrological changes affected runoff, infiltration, percolation, subsurface flow, streamflow, and nutrient concentrations. The water quantity parameter that was often cited as having the highest sensitivity was the CN2, which is the initial SCS runoff curve number for moisture content. It was identified as a sensitive variable in a total of 23 studies (Pesce et al., 2018; Shrestha et al., 2012; Verma et al., 2015; Zhang et al., 2012). As for the water quality parameters, 83% of the studies showed that the most sensitive parameters were related to flow, TN, TP, and suspended sediments.

Table 8 Sensitivity analysis methods and assessed sensitive parameters.

Reference	Sensitivity analysis method	Number of assessed parameters	Most sensitive parameters	Decision based on changes in which parameter
(Ba et al., 2020)	Sequential Uncertainty Fitting Ver. 2 (SUIF-2)	27 Parameters	10 parameters **LAT_TTIME** Lateral flow travel time **NPERCO** Nitrogen percolation coefficient **ALPHA_BF** Baseflow alpha factor **GW_REVAP** Groundwater evaporation coefficient **GW_DELAY** Groundwater delay **ESCO** Soil evaporation compensation factor **BIOMIX** Biological mixing efficiency **USLE_P USLE** equation support practice **BC1** The rate constant for biological oxidation of NH3	Impact on streamflow and water quality calculations
(Bouraoui et al., 2004)	Monte-Carlo Sensitivity Analysis Method	No data mentioned	Curve Number Topsoil Saturated hydraulic conductivity	No data mentioned

Reference	Sensitivity analysis method	Number of assessed parameters	Most sensitive parameters	Decision based on changes in which parameter
			Available water capacity Groundwater recession coefficient groundwater-root zone evaporation coefficient	
(Bučienė et al., 2019)	Particle Swarm Optimization (PSO) SWAT CUP Program	No data mentioned	No data mentioned	No data mentioned
(Coppens et al., 2020)	Sequential Uncertainty Fitting (SUIF-2) Global Sensitivity Analysis	No data mentioned	32 parameters related to flow rate or nutrient loading	No data mentioned
(Glavan et al., 2015)		No data mentioned	Flow Sediment Nitrate-nitrogen TP	No data mentioned
(Jordan et al., 2014)	Automatic Sensitivity Analysis	No data mentioned	13 parameters related to flow and TSS	No data mentioned
(Laursen & Hanief, 2017)	one-on-one sensitivity analysis testing	No data mentioned	Snowfall temperature Snowmelt base temperature Melt factor for snow on Jun. Melt factor for snow in December. Surface runoff lag coefficient	No data mentioned

Reference	Sensitivity analysis method	Number of assessed parameters	Most sensitive parameters	Decision based on changes in which parameter
			Plant uptake compensation factor Baseflow alpha factor in bank storage Groundwater delay Maximum canopy storage SCS runoff curve number Soil bulk density Soil evaporation compensation Saturated hydraulic conductivity	
(Li et al., 2018)	Sequential Uncertainty Fitting (SUIF-2) Global Sensitivity Analysis using the Latin hypercube one-factor-at-a-time. (LH-OAT) sampling method	No data mentioned	15 runoff and 13 water quality parameters	No data mentioned
	Sequential Uncertainty Fitting (SUIF-2) Global Sensitivity Analysis using the	No data mentioned	6 hydrologic parameters (in hypercube one-factor-at-a-time type of sensitivity analysis result is 6 of	These sensitive parameters were found to considerably influence the stream discharge of the watershed

Reference	Sensitivity analysis method	Number of assessed parameters	Most sensitive parameters	Decision based on changes in which parameter
	Latin hypercube one-factor-at-a-time. (LH-OAT) sampling method		the 14 hydrologic parameters (CN2, SOL_AWC, SOL_K, ALPHA)	
(Li et al., 2011)	Latin Hypercube-One-At-a-Time (LH-OAT) method	No data mentioned	Discharge, sediment, inorganic nitrogen and phosphorous	No data mentioned
(Me et al., 2018)	Latin Hypercube-One-At-a-Time (LH-OAT) method	No data mentioned	Q, SS, ORGP, DRP, ORGN, NH4–N, and NO3–N	No data mentioned
(Nazari-Sharabian et al., 2019)	SWAT-CUP program	No data mentioned	Streamflow parameters	t-stat values and p-values were used to measure the sensitivities of parameters
(Nguyen et al., 2019)	Sequential Uncertainty Fitting (SUIF-2) Global sensitivity analysis	No data mentioned	No data mentioned	No data mentioned
(Pinheiro et al., 2019)	SWAT-CUP Program Automatic Sensitivity Analysis using SUFI-2	No data mentioned	No data mentioned	t-stat values and p-values
(Pulighe et al., 2019)	SWAT-CUP sensitivity analysis and	No data mentioned	27 parameters related Waterflow	No data mentioned

Reference	Sensitivity analysis method	Number of assessed parameters	Most sensitive parameters	Decision based on changes in which parameter
	manual trial-and-error procedure		Sediment Nitrate TN Phosphorous DO	
(Shimizu, 2011)	Latin Hypercube-One-At-a-Time (LH-OAT) method	No data mentioned	Phosphorous Discharge Support Practice Factor (USLE_P)	No data mentioned
(Shrestha et al., 2013)	SWAT-CUP Program Automatic Sensitivity Analysis using SUFI-2	No data mentioned	No data mentioned	No data mentioned
(Thang et al., 2018)	Latin Hypercube-One-At-a-Time (LH-OAT) method	No data mentioned	Hydrology sediment and nutrient processes (nitrogen and phosphorus) Manning's value for main channel (CH_CN2), the curve number (CN2), the saturated hydraulic conductivity (SOL_K), the groundwater 'delay' time (GW_DELAY), and the groundwater 'revamp' coefficient	No data mentioned

Reference	Sensitivity analysis method	Number of assessed parameters	Most sensitive parameters	Decision based on changes in which parameter
			(GW_REVAP)	
(Verma et al., 2015)	Sensitivity Analysis Tol in the ArcSWAT interface	No data mentioned	13 parameters related to flow	No data mentioned
(Y. Wang et al., 2018)	SWAT-CUP Program Automatic Sensitivity Analysis using SUFI-2	No data mentioned	five snowmelt parameters SFTMP, SMTMP, SMFMX, SMFMN, and TIMP	No data mentioned
(Yan et al., 2019)	SWAT-CUP Program Automatic Sensitivity Analysis using SUFI-2	No data mentioned	Hydrology, nitrogen, nitrate	No data mentioned
(Zhang et al., 2012)	No data mentioned	No data mentioned	CN2 (curve number), soil evaporation compensation factor, soil available water capacity, and base flow alpha factor	No data mentioned

4.1.4 Model Performance

The performance of the SWAT model can be assessed by comparing its simulated values with observed data. Various statistical measures, such as R^2, Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS) can be used to evaluate the model's goodness of fit. R^2 mainly describes the degree of collinearity between measured and simulated data, its value ranges between 0 and 1, where 0 indicates no correlation and 1 represents perfect correlation. Whereas NSE is used to provide a measure of how well the simulated output matches the observed data, its value ranges between $-\infty$ and 1 where the value of 1 describes a perfect fit between the simulated and the observed. Likewise, PBIAS is used to assess the accuracy of the model by quantifying the systematic errors or deviations it introduces when estimating a quantity or making predictions. Table 9 provides a summary of the model performance metrics that were used across several studies as well as their reported values.

Table 9 Model performance values across the selected studies

Reference	Model performance parameter (Flow/Discharge)			Model performance parameter (Nutrient N/P forms)			Time step value	
	R^2	NSE	PBIAS	R^2	NSE	PBIAS	Daily	Monthly
(Pesce et al., 2018)	0.2	0.61	-	NO3- 0.8 NH4+ 0.59	NO3- 0.6 NH4+ 0.51	NA	Y	
(Shrestha et al., 2012)	0.7	0.7	-	TN 0.95 TP 0.89	TN 0.95 TP 0.7	NA		Y
(Zhang et al., 2012)	-	-	-	TN 0.27 TP 0.68	-	-	Y	
(Khoi et al., 2022)	-	0.53-0.89	-30 to 33%	-	TN 0.53-0.94	-12% to 18%		Y
(Molina-Navarro et al., 2014)	0.6	0.44	13.4%	NO3- 0.66 TP 0.80	NO3- 0.51 TP 0.57	NO3- 45.2% TP 38%		Y
(X. Wang et al., 2018)	-	0.75	-	TN and TP 0.75	TN and TP 0.75	-		Y
(Bi et al., 2018)	0.95	0.95	-	TN 0.64 TP 0.79	TN 0.58 TP 0.0.74	-		Y
(Thang et al., 2018)	0.76-0.89	0.67-0.87	-	TN 0.55 TP0.64	TN 0.49 TP 0.54	-		Y

The most reported and used model performance indices were NSE (51.7%) and R^2 (41.37%). It is worth noting that nutrient loads in the SWAT model are closely linked with the performance of flow. Several studies (Bi et al., 2018; Thang et al., 2018) reported low skill for nutrients but a high skill for flow simulations. The selected model parameters were adjusted to improve agreement between the simulated and the observed data. On the other hand, other studies (Molina-Navarro et al., 2014; Pesce et al., 2018) have reported a high skill for nutrients but a low skill for flow. Experiencing variations in model performance for nutrient and flow simulations in the SWAT model is attributed to different reasons, such as insufficient data quality, which in turn should be accurate and representative of the studied watershed. Additionally, model calibration and validation processes play pivotal roles in for achieving accurate simulations. (Lee et al., 2018). Other studies (Khoi et al., 2022; X. Wang et al., 2018) have reported flow and nutrient skills similarly.

Shrestha et al. (2012) reported that the SWAT model predicted flows with a high skill (R^2 = NSE = 0.7) with similar predictions for nutrients (TN: R^2 = NSE = 0.95 and TP: between 0.7 and 0.89). However, they attributed the difficulties in reproducing the observed nutrient loads to uncertainties with model parameter selection, missing or low-quality input data, and limitations with the process algorithm (e.g., SWAT doesn't account for frozen soil process, which can strongly affect the magnitude and rate of runoff and related nutrient transport).

Thang et al. (2018) showed that while the simulated streamflow followed the trend of the observed streamflow, it could not capture well the observed high flow. They attributed this to the uneven rain gauge distribution (as there was only one rain gauge station located in one area of the Dong Nair River Basin).

4.1.5 Land use/land cover and management practices

Given that the main objective of the targeted studies was to assess the future impacts of climate change on nutrient loading at the watershed level, many of them held the non-climatic factors, such as land use/land cover (LULC), as well as management practices constant over time. Pesce et al. (2018) for example, kept the land-use/land cover, management practices (tilling, fertilizer timing and amount), and anthropogenic emissions (i.e., WWTP, industrial discharges) in the Zero river basin, Italy unchanged when assessing the impacts of climate change on their study region. Similar assumptions were considered by Kujawa et al. (2020) in the Maumee River basin located in parts of Michigan, Indiana, and Ohio, USA during the selected future projected mid-century period 2046-2065. Marcinkowski et al. (2017) held these factors constant in the Upper Narew (Northeast Poland) catchment and Barycz (Southwest Poland) catchment for the near (2021-2050) and far (2071-2100) futures. Shrestha et al. (2012) also did not account for changes to non-climatic factors, such as land use, crop type, and fertilizer application when they assessed the Upper Assiniboine Catchment, Canada during the future period (2041-2070). Similarly, Yan et al. (2019) for the Miyun Reservoir Basin (MRB), China had crop management practices and fertilizer application unchanged over their future assessment periods 2021-2035 and 2051-2065.

Interestingly, several studies allowed the management practices and land use and land cover to be dynamic over time along with changes in climate by using the land use change method implemented in SWAT. Molina-Navarro et al. (2014) developed different future land use management scenarios that included land use change (e.g., change land from forests to agricultural land), modification of fertilizer application rates, change in crop types (replacement of winter barely by sunflower which requires less fertilizer application), changes in crop rotation (plantation of winter barely for 3 years and the 1-year growing peas) in their study on the Ompólveda River catchment river basin, in central Spain. Similarly, Almeida et al. (2018) developed a combination of societal (shared socio-economic pathways (SSPs)) and climate scenarios (RCPs), whereby each of the SSPs describes a varying socio-economic pathway coupled with a climate change scenario and integrated into the SWAT model. Bi et al. (2018) developed different land use change scenarios, which have different impacts on water quality, underlying surface properties, and other hydrological and nutrient processes.

4.2 Climate Models and SWAT Integration

4.2.1 GCMs and RCMs

The responses of water quality to climate change are complex and controlled by a variety of factors. Warmer temperatures can lead to increased loads of some nutrients in water bodies (e.g., nitrate) (Ahmadi et al., 2014), while also reducing loads of other constituents (e.g., organic nitrogen and phosphorus) through accelerated decomposition and mineralization, as well as altering the timing and magnitude of low and high flows (Coppens et al., 2020). Additionally, changes in the frequency and intensity of precipitation brought about by climate change can result in increased nutrient fluxes via greater stream discharge and accelerated surface runoff and erosion of highland soils. It is also worth noting that in climate change, precipitation and temperature are the two dominant factors impacting streamflow and non-point source pollution loads, where precipitation has the greatest influence on streamflow and sediment loads, while temperatures influence nitrogen (N) and Phosphorous (P) concentrations and their transport in surface waters (Li & Kim, 2019). As temperatures increase, nutrient biogeochemical reaction rates generally increase, thus affecting the availability and cycling of nutrients in water systems (such as the rates of nitrification, mineralization, and denitrification). For instance, warmer temperatures increase decomposition and mineralization of organic nutrients forms in soils, hence making them available for transport to adjacent waterbodies (Shrestha et al., 2012). Different peer-reviewed articles have explored the future impacts of climate change on nutrient loading by running SWAT simulations (Shrestha et al., 2012).

Of the studies assessed, 61% directly used weather data from GCM without relying on downscaling techniques. Based on the selected peer-reviewed articles, the three most used GCM models were the GFDL-ESM2M (developed by Geophysical Fluid Dynamics Laboratory Earth System models – United States of America), IPSL-CM (developed by Institut Pierre Simon Laplace Climate Models – France) and HadGEM (developed by Hadley Centre Global Environmental Model – United Kingdom). Around 18% of the studies used statistical downscaled data. We also found that 6% of the studies directly used data from Regional Climate models (RCMs) to run their SWAT models. The remaining 15% either did not use climate models but rather developed future scenarios by assuming a certain rate of change in temperature or precipitation over time (Jisun, 2013; Li et al., 2011; Marshall & Randhir, 2008; Me et al., 2018; Molina-Navarro et al., 2018; Nazari-Sharabian et al., 2019). For example, Li et al. (2011) based their predictions on the IPCC estimates that temperatures in China will rise by 1.4 degrees Celsius by 2050 and by 2-3 degrees Celsius by the end of the 21st century. Marshall and Randhir (2008) developed 2 scenarios, which they named the warming high and the warming low scenarios. Though GCMs are widely used to make climate predictions and are more commonly used worldwide, especially for hydrological models, Nazari-Sharabian et al. (2019), opted to use Earth System Models (ESMs) as they tend to reach far beyond GCMs and simulate all relevant aspects of the earth's system (physical, chemical, and biological processes). Additionally, ESMs can be used to study climate variability at different timescales, account for interactions between the ocean and atmosphere, and carbon-climate feedback. The percent distribution of climate models/data sources used in the reviewed SWAT studies is summarized in Figure 9.

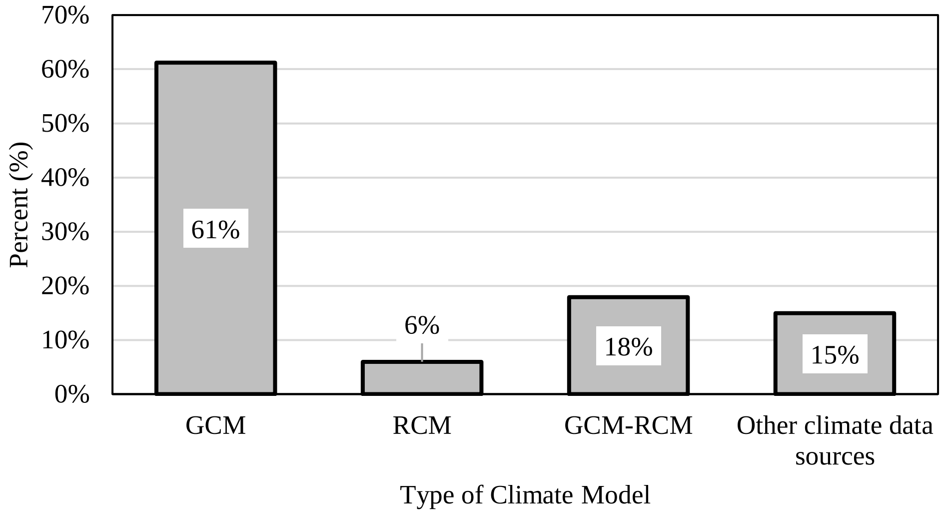

Figure 9 Percentage distribution of climate models used among the selected studies.

For the studies that used climate models, different statistical downscaling techniques were used; the most common methods of downscaling are listed in Table 10.

Table 10 Common downscaling methods used.

Downscaling Techniques	Description	GCM	Parameter downscaled	Resolution	Period	References
None		CCSM4 CMCC–CM CMCC–CMS CNRM–CM5 FGOALS_S2 IPSL–CM5A–MR MIROC5 MPI–ESM–MR MRI–CGCM3 NorESM1–M		N $1.25° \times 0.94°$ $0.75° \times 0.75°$ $1.88° \times 1.86°$ $1.41° \times 1.40°$ $2.81° \times 1.66°$ $2.50° \times 1.27°$ $1.41° \times 1.40°$ $1.88° \times 1.86°$ $1.13° \times 1.12°$ $2.50° \times 1.89°$	Monthly	Kim et al., 2020
		BCC-CSM1-1 CanESM2 GFDL-ESM2G HadGEM2-CC INM-CM4 MIROC-ESM	Precipitation Min. and Max. Temperatures Relative Humidity Wind speed solar radiation		Daily	Li et al., 2020
Delta Change / Factor Method	Modifies the observed historical time series by adding the difference	BCCR-RCM2.0 CCCMA_CGCM3.1 CNRM_CM3 CSIRO_MK3.0 GFDL-CM2.0	Precipitation Temperature		Monthly	(Jha et al., 2013; Lee et al., 2018; Thang et al.,

Downscaling Techniques	Description	GCM	Parameter downscaled	Resolution	Period	References
	between the future and the baseline periods as simulated by a GCM. It has been widely used due to its simplicity which enables the rapid generation of a wide range of plausible climate scenarios from a group of GCMs	GFDL-CM2.1 MIROC3.2_MEDRES MIUB_ECHO_G MPI_ECHAM5 MRICGCM2.3.2A				2018; Verma et al., 2015)
		BCC-CSM1-1.1 CCSM4.1 GFDL-ESM2G.1 IPSL_CM5A-1. R.1 MIROC_ESM-CHEM.1	Precipitation Temperature CO2 concentrations		Monthly	Lee et al., 2018
		CanESM2 CNRM-CM5 HadGEM2-AO IPSL-CM5A-LR MPI-ESM-MR	Precipitation Temperature		--	Thang et al., 2018
		CGCM3 GFDL-CM2 HadCM3	Precipitation Temperature	12×12 km^2	Monthly	Verma et al., 2015
Bilinear Interpolation Method	Used to interpolate GCMs grid point data to precipitation and temperature observation stations in the studied watershed	ACCESS1.3 HadGEM-ES	Precipitation Temperature	30×30 m^2	--	(Feng & Shen, 2021)

Downscaling Techniques	Description	GCM	Parameter downscaled	Resolution	Period	References
Multivariate Adaptive Constructed Analog (MACA)	Used to improve the coarse resolution of GCMs to a higher spatial resolution that captures different observed patterns of meteorological data and simulated changes in climate models. It is favored over the other downscaling methods as it has direct daily interpolate bias correction in regions of complex terrain due to its use of a historical library of observations and multivariate approach.	20 GCMs	air temperature, precipitation, relative humidity, and solar radiation	4 km grid		(Mukundan et al., 2020)

Downscaling Techniques	Description	GCM	Parameter downscaled	Resolution	Period	References
Nonhomogeneous Hidden Markov Model (NHMM)		CanESM2 CNRM-CM5 GFDL-ESM2M IPL-CM5B-LR MIROC5 MRICGM3	daily rainfall Temperature		Daily	(Nguyen et al., 2019; Shrestha et al., 2017)
		CanESM2 CNRM-CM5 GFDL-ESM2M IPSL-CM5B-LR MIROC5 MRI-CGCM3	daily rainfall		Daily	Shrestha et al., 2017
Coefficient adjustment method	involves producing the projected daily series of climate data (mainly precipitation and temperature) under different scenarios of the selected GCMs, rather than directly using the daily outputs generated by GCMs.	21 GCMs	Precipitation Temperature	1° lat/long	Daily	(Zhai & Zhang, 2018)

Interestingly, most of the studies (79%) conducted did not use an ensemble of climate models but instead used individual GCM/RCMs (Figure 10). Those that used ensemble models are summarized in Table 11.

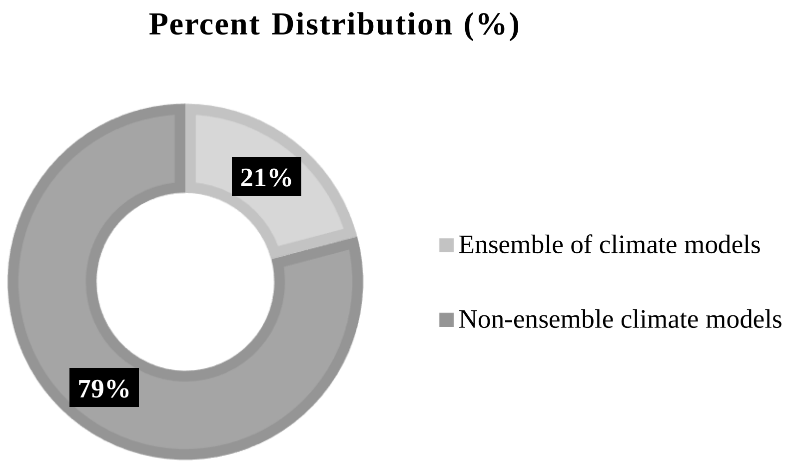

Figure 10 Usage of ensemble and non-ensemble climate models percent distribution

Table 11 Climate models used in the SWAT studies

Reference	Country / Region	Evaluated Parameters	Climate Model	Ensemble?
			GCM / RCM	
(Ahmadi et al., 2014)	United States	Precipitation Min. and Max. Temperatures	16 GCMs	Non-Ensemble
(Almeida et al., 2018)	Portugal	Precipitation Surface air temperatures	2 GCMs GFDL-ESM2M IPSL-CM5A-LR	Non-Ensemble
(Andreas M. Culbertson, 2016)	United States	Precipitation Daily min. and max. temperatures Other meteorological parameters were simulated by the SWAT weather generator	15 GCMs	Ensemble
(Ba et al., 2020)	China	--	3 GCMs HadGEM3-RA RegCM4 SUN-MM5	Non-Ensemble
(Bi et al., 2018)	China	--	Y. 5 GCMs GFDL-ESM2M HADGEM2-ES IPSL-CM5A-LR MIROC-ESM-CHEM NORESM1-M	Non-Ensemble
(Bouraoui, 2002)	United Kingdom	Precipitation Temperature	4 GCMs CSIRO-Mk2 ECHAM4 CGCM1 HadCM2	Non-Ensemble
(Čerkasova et al., 2018; 2021)	Belarus, Lithuania, Poland, Russia, Latvia	Precipitation Daily min. and max. temperature values CO2 concentration change	5 GCMs GFDL-ESM2M HadGEM2-ES IPSL-CM5ALR MIROC NorESM1-M	Ensemble

Reference	Country / Region	Evaluated Parameters	Climate Model	Ensemble?
			GCM / RCM	
(Čerkasova et al., 2019)	Lithuania	Precipitation Temperature	1 GCM HadGEM2-ES	Non-Ensemble
(Coppens et al., 2020)	Turkey	Precipitation Temperature	1 GCM MPI-ESM-MR(MPI)	Non-Ensemble
(Cousino et al., 2015)	United States	Daily Precipitation Daily Temperature	2 GCMs	Non-Ensemble
(Fan & Shibata, 2015)	Japan	Precipitation Temperature	1 GCM	Non-Ensemble
(Feng & Shen, 2021)	China	Precipitation Temperature	2 GCMs ACCESS1.3 HadGEM-ES	Non-Ensemble
(Glavan et al., 2015)	Slovenia	--	4 RCMs nested with 2 GCMs	Non-Ensemble
(Gombault et al., 2015)	Canada	--	CGCM3-ARP	Non-Ensemble
(Jha et al., 2013)	United States	Daily Precipitation Daily min and max.Temperature	10 GCMs BCCR-RCM2.0 CCCMA_CGCM3.1 CNRM_CM3 CSIRO_MK3.0 GFDL-CM2.0 GFDL-CM2.1 MIROC3.2_MEDRES MIUB_ECHO_G MPI_ECHAM5 MRICGCM2.3.2A	Non-Ensemble
(Jisun, 2013)	South Korea		No data available	Ensemble
(Kalcic et al., 2019)	United States	Precipitation Temperature	A 5-member ensemble of climate models was used in this study 1 global model from the CMIP5 - CESMI-CAMS 2 regional dynamically	Non-Ensemble

Reference	Country / Region	Evaluated Parameters	Climate Model	Ensemble?
			GCM / RCM	
			downscaled models - CRCM-CGCM3 & RCM3-GFDL from CMIP3 2 regional models dynamically downscaled from CMIP5 - RCM4-GFDl & RCM4-HadGEM	
(Khoi et al., 2022; Trang et al., 2017)	Vietnam, Cambodia , and Lao PDR	Rainfall Temperature	5 GCMs CanESM2 CNRM-CM5 HadGEM2-A0 IPSL-CM5A-LR MPI-ESM-MR	Non-Ensemble
(Kim et al., 2020)	South Korea		10 GCMs	Non-Ensemble
(Li & Kim, 2019)	South Korea	PrecipitationMin. and Max. Temperatures Relative Humidity Wind speed solar radiation	6 GCMBCC-CSM1-1CanESM2GFDL-ESM2GHadGEM2-CCINM-CM4MIROC-ESM	Non-Ensemble
(Kim et al., 2014)	South Korea			Non-Ensemble
(Kujawa et al., 2020)	United States	Precipitation Temperature	6 GCMs CanESM2 CSIRO_r6 CSIRO_r4 CSIRO_r10 MPI-ESM NorESM	Non-Ensemble
Miralha et al., 2021	Germany	Precipitation Min. and Max. Temperatures	4 GCMs CCSM4 MPI-ESM-MR (i.e. MPI) CNRM-CM5 (i.e. CNRM) IPSL-CM5A-MR (IPSL)	Non-Ensemble

Reference	Country / Region	Evaluated Parameters	Climate Model	Ensemble?
			GCM / RCM	
(Verma et al., 2015)	United States	Monthly Precipitation Temperature	3 GCM CGCM3 GFDL-CM2 HadCM3	**Ensemble**
(Lee et al., 2018)	United States	Precipitation Temperature CO2 concentrations	5 GCMs BCC-CSM1-1.1 CCSM4.1 GFDL-ESM2G.1 IPSL_CM5A-1.R.1 MIROC_ESM-CHEM.1	Non-Ensemble
(Li et al., 2011) check dates	China		No data available	No data available
(Marcinkowski et al., 2017)	Poland	Daily Precipitation Temperature	8 GCM-RCM runs provided with EURO-CORDEX experiment	Non-Ensemble
(Marshall & Randhir, 2008)	United States	Daily Precipitation Temperature	No data available	No data available
(Me et al., 2018)	New Zealand	Precipitation Temperature	No data available	No data available
(Mehan et al., 2019)	United States		9 GCMs bcc_csm1_1 CCSM4 GFDL_ESM2G GFDL_ESM2M IPSL_CM5ALR IPSL_CM5AMR MIROCESM MIROCESMCHEM NorESM1M	Non-Ensemble
(Mehdi, Lehner, et al., 2015)	Canada		RCM piloted by GCM 3 Scenarios CC1 CRCM4.1.1 with CGCM3-4 CC2 CRCM4.2.3 with CGCM3-5	Non-Ensemble

Reference	Country / Region	Evaluated Parameters	Climate Model GCM / RCM	Ensemble?
			CC3 CRCM4.2.3 with ECHAM5	
(Mehdi, Ludwig, et al., 2015; Mehdi et al., 2016)	Germany		Each RCM simulation was driven by a coupled general circulation model (GCM) CRC-CGC-45k RAC-ECM-MB1-50k RAC-ECM-MB2-50k RAC-ECM-MB3-50k RCA-BCM-50k RCA-ECM-50k RCA-HCM-50k	Ensemble
(Molina-Navarro et al., 2014)	Spain	Monthly Average of Rainfall Daily Min. and Max Temperatures	No data available	No data available
(Mukundan et al., 2020)	United States		20 GCMs	Non-Ensemble
(Nazari-Sharabian et al., 2019)	Azerbaijan	Daily Climate Predictions	No data available	No data available
(Nguyen et al., 2019)	Australia	Rainfall Temperature	6 GCM CanESM2 CNRM-CM5 GFDL-ESM2M IPL-CM5B-LR MIROC5 MRICGM3	Ensemble
(Pesce et al., 2018; Sperotto et al., 2019)	Italy	Precipitation Min. and Max Temperatures	General Circulation Model/ Regional Climate Model (GCM/RCM) nested simulations available with the highest spatial resolution were	Non-Ensemble

Reference	Country / Region	Evaluated Parameters	Climate Model GCM / RCM	Ensemble?
			selected 0.75x0.75 degree, Coupling GCM CMCC-CM with RCM COSMO-CLM	
(Pinheiro et al., 2019)	Brazil		No data available	Non-Ensemble
(Piniewski et al., 2014)	Poland	Precipitation Temperature CO2 Concentrations (But also CO2 concentration was considered to better represent the future climate conditions)	1 RCM RCA3 coupled with GCM ECHAM5	Ensemble
(Records et al., 2014)	United States	Precipitation Temperature	3 GCMs INMCM4 MIROC5 CanESM2	Non-Ensemble
(Shrestha et al., 2017)	Australia		6 GCM CanESM2 CNRM-CM5 GFDL-ESM2M IPSL-CM5B-LR MIROC5 MRI-CGCM3	Ensemble
(Shrestha et al., 2012)	Canada	Daily Precipitation Min. and Max. Temperature	CRCM HRM3 RCM3	Ensemble
(Thang et al., 2018)	Vietnam	Precipitation Temperature	5 GCMs: CanESM2 CNRM-CM5 HadGEM2-AO IPSL-CM5A-LR MPI-ESM-MR	Non-Ensemble
(Tong et al., 2007)	United States		No data available	No data available

Reference	Country / Region	Evaluated Parameters	Climate Model GCM / RCM	Ensemble?
(Trolle et al., 2015)	Denmark	Precipitation Air Temperature (precipitation for quantifying water and nutrient runoff), which are the main drivers of change in hydrology and nutrient dynamics	No data available	Ensemble
(Van Liew, 2012)	United States	Monthly Temperature Precipitation		Non-Ensemble
(Wang & Kalin, 2018)	United States	Precipitation Temperature	4 GCMs GFD-CM2-0 GISS-model-e-r NCAR-CCSM3-0 UKMO-HadCM3	Non-Ensemble
(Wang et al., 2018)	China	Daily Precipitation Min. and Max. Temperature	1 GCM HadCM3	Non-Ensemble
(Xu et al., 2018)	United States		1 GCM CESM1	Non-Ensemble
(Yang et al., 2019)	United States	Daily Precipitation Daily Temperature	4 GCM ESM2M HadGEM-ES IPSL-CM5A-LR MIROC-ESM-CHEM	Non-Ensemble
(Yang et al., 2018)	China (Hong Kong)		16 GCMs	Non-Ensemble
(Ye & Grimm, 2013)	United States	Precipitation Min. and Max Temperatures	1 GCM. CGCM2	Non-Ensemble
(Zhai & Zhang, 2018)	China	Precipitation Temperature	21 GCMs	Non-Ensemble
(Zhang et al., 2012)	China		1 GCM HadCM3	Non-Ensemble

4.2.2 Climate Change Scenarios

It is worth noting that many of the studies used a range of SRES scenarios, i.e., using A1B, B1, B2, and A2 in the same study. The most applied SRES scenarios were the A2 (used in 13 studies), A1B (used in 9 studies), B1 (used in 6 studies), followed by B2 (used in 2 studies). As for the updated set of emission scenarios (i.e., RCP), the most utilized were RCP 4.5 (applied in 26 studies) and RCP 8.5 (applied in 33 studies). The following table lists the different emissions scenarios used (RCP and SRES) in each study while also showing the future projected study periods.

Table 12 Climate Emission Scenarios (SRES vs. RCP)

Reference	**Emission Scenario**								**Studied Period(s)**
	SRES				**RCP**				
	A2	**B1**	**B2**	**A1B**	**2.6**	**4.5**	**6**	**8.5**	
(Ahmadi et al., 2014)	Y	Y		Y					Mid-Century 2045 - 2064 Late Century 2080-2099
(Almeida et al., 2018)						Y		Y	Early Century 2025-2034 (2030s) Mid-Century 2055 - 2064 (2060s)
(Andreas M. Culbertson, 2016)						Y		Y	Near Century 2010-2039 Mid-Century 2040-2069 Late-Century 2070-2099
(Ba et al., 2020)						Y		Y	Future Period 2040-2044
(Bi et al., 2018)					Y	Y		Y	Future Period till 2050
(Bouraoui, 2002)									4 Transient scenarios of 30 years centered on the year 2050 were selected 2020 (1 GCM) 2050 (4 GCMs) 2080 (1 GCM) % change scenarios for

Reference	Emission Scenario								Studied Period(s)
	SRES				RCP				
	A2	B1	B2	A1B	2.6	4.5	6	8.5	
									precipitation and temperature were considered for each period
(Čerkasova et al., 2018; 2021)						Y		Y	Near Term Period up to 2050 Long Term Period up to 2100
(Čerkasova et al., 2019)						Y		Y	Near Term Period 2020-2050 Long-Term Period 2051-2099
(Coppens et al., 2020)						Y		Y	Future Period 2020-2090
(Cousino et al., 2015)					Y	Y	Y	Y	Near Future Period 2046-2065 Late Future Period 2080-2099
(Fan & Shibata, 2015)		Y							Short Term Period 2010-2039 Mid-Term 2040-2069 Long Term 2070-2099
(Feng & Shen, 2021)						Y		Y	Near Period 2020-2042 Future Period 2060-2082
(Glavan et al., 2015)				Y					Early Period 2001-2030 (2030s) Mid-Period 2031-2060 (2060s) Later Period 2061-2090 (2090s)
(Gombault et al., 2015)	Y								Future Period 2041-2070
(Jha et al., 2013)				Y					Mid-century period 2045-2065
(Jisun, 2013)						Y		Y	Mid-Century Period 2020-2069
(Kalcic et al., 2019)	Y							Y	Future Mid-Century Period 2046-2065
(Khoi et al., 2022; Trang et al., 2017)						Y		Y	Early Period 2030s Mid Period 2060s Late Period 2090s
(Kim et al., 2020)								Y	

Reference	Emission Scenario								Studied Period(s)
	SRES				RCP				
	A2	B1	B2	A1B	2.6	4.5	6	8.5	
(Li & Kim, 2019)						Y		Y	First Period: - 2019-2059Second Period - 2060-2099
(Kim et al., 2014)	Y	Y		Y		Y		Y	Early Period 2020-2059 (2040s) Late Period 2060-2099 (2080s)
(Kujawa et al., 2020)								Y	Future Mid-Century Period 2046-2065 A 20-year time window is appropriate for climate change studies based on the revised climate period from the World Meteorological Organization
Miralha et al., 2021								Y	Future Period 2046-2065
(Verma et al., 2015)				Y					Mid-Century Period 2045-2055 Far-Century Period 2089-2099
(Lee et al., 2018)								Y	Future Period 2083-2098
(Li et al., 2011) check dates									
(Marcinkowski et al., 2017)						Y			Near Future Period 2021-2050 Far Future Period 2071-2100
(Marshall & Randhir, 2008)	Y								Future Period 2060-2100
(Me et al., 2018)								Y	
(Mehan et al., 2019)	Y					Y		Y	Mid-Century Period 2020-2069 Far Century Period 2070-2099

Reference	Emission Scenario								Studied Period(s)
	SRES				RCP				
	A2	B1	B2	A1B	2.6	4.5	6	8.5	
(Mehdi, Lehner, et al., 2015)	Y								Future Period 2041-2070
(Mehdi, Ludwig, et al., 2015; Mehdi et al., 2016)	Y			Y					Future Period 2041-2070
(Molina-Navarro et al., 2014)	Y	Y		Y					Near Future Period 2046-2065 Far Future Period 2081-2100
(Mukundan et al., 2020)								Y	Mid-Century Period 2051-2060
(Nazari-Sharabian et al., 2019)						Y		Y	Future Period 2020-2050
(Nguyen et al., 2019)						Y		Y	Future Scenario 2021-2050
(Pesce et al., 2018; Sperotto et al., 2019)						Y		Y	Mid-term period 2041-2070 long term period 2071-2100
(Pinheiro et al., 2019)						Y		Y	
(Piniewski et al., 2014)				Y					Future Period 2035-2064
(Records et al., 2014)						Y		Y	Future Period 2040s
(Shrestha et al., 2017)						Y		Y	Future Period 2046-2070
(Shrestha et al., 2012)	Y								Future Period 2041-2070
(Thang et al., 2018)						Y		Y	Near Future Period 2015-2040 (2020s) Mid-Furure Period 2045-2070 (2050s) Far Future Period 2075-2100 (2080s)
(Tong et al., 2007)									
(Trolle et al., 2015)									Future Period 2071-2099

Reference	**Emission Scenario**								**Studied Period(s)**
	SRES				**RCP**				
	A2	**B1**	**B2**	**A1B**	**2.6**	**4.5**	**6**	**8.5**	
(Van Liew, 2012)	Y	Y		Y					Future Period 2040-2059
(Wang & Kalin, 2018)	Y	Y		Y					Period 2016-2040 25 years is a good period long enough to explore the potential responses in the future due to climate change relative to a baseline period.
(Wang et al., 2018)						Y		Y	2021-2040 (2020s) 2041-2070 (2050s) 2071-2100 (2080s)
(Wang et al., 2018)		Y	Y						Near Future Period 2021-2050
(Xu et al., 2018)	Y							Y	Future Period 2042 - 2065
(Yang et al., 2019)						Y		Y	Future Period 2020-2099
(Yang et al., 2018)						Y		Y	Mid Centrury Period 2040-2060 Late Century Period 2070-2090
(Ye & Grimm, 2013)			Y						Future Period 1991-2100
(Zhai & Zhang, 2018)					Y	Y		Y	2021-2030 (2020s) 2031-2040 (2030s)
(Zhang et al., 2012)	Y								2010-2039 (2020s) 2040-2069 (2050s) 2070-2099 (2080s)

Even though the RCP scenarios represent a profoundly different approach to examining future climate than what was considered in the previous scenarios (SRES), there are similarities between some RCP and SRES scenarios in terms of median temperature increase by 2100 (James et al., 2014), as illustrated in Table 13.

Table 13 Comparison between RCP and SRES Scenarios

RCP Scenario	**(Equivalent) SRES**
RCP 2.6	None
RCP 4.5	SRES B1
RCP 6.0	SRES B2
RCP 8.5	SREs A1F1/A1B

The choice of climate scenarios, particularly between SRES and RCP, reflects advancements in climate science and a desire for more realistic and policy-relevant projections. The SRES scenarios provided a range of potential future emissions based on different socioeconomic storylines. However, they became outdated as the understanding of climate science and the complexities of human activities influencing climate evolved. The RCPs on the other hand address these shortcomings by focusing on specific radiative forcing pathways and considering a broader range of potential future climates. RCPs offer a more robust framework for integrating emission scenarios with climate modeling, allowing for a more comprehensive exploration of climate change impacts. Moreover, RCPs align with the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report, providing a standardized and globally accepted set of scenarios that facilitates consistency and comparability across studies. The RCPs, ranging from low to high radiative forcing (RCP 2.6, 4.5, 6, & 8.5), allow researchers, policymakers, and stakeholders to assess a spectrum of potential climate futures, enhancing the relevance and applicability of climate projections for a wide array of applications. Consequently, this was evident in the peer-reviewed articles chosen.

4.2.3 Other Climate Variables

Other climate variables (such as windspeed, relative humidity, solar radiation, etc.) were generated using the automated SWAT weather generator. This feature is used to simulate future weather conditions based on historical/observed weather data and statistical patterns collected from weather gauge stations. It is also worth noting that they do not predict weather with high precision but generate synthetic weather sequences that can be used for various purposes (impact of different climate scenarios on waterbodies). For example, Kujawa et al. (2020) and Miralha et al. (2021) used the automated weather generator to predict different climatic variables (such as windspeed, relative humidity, and solar radiation) for the mid-future century time period 2046 to 2065. Others such as (Lee et al., 2018; Thang et al., 2018; Verma et al., 2015) also used the weather generator to model the above-mentioned climate variables (windspeed, relative humidity, solar radiation) for different future periods (far-future century period 2070-2100).

For watersheds that are affected by snow, it is important to note how the SWAT applications accounted for future changes in snow (snow accumulation, snowmelt, snow dynamics, etc.). Gombault et al. (2015), used a modified version of SWAT 2005 to simulate hydrological process and NPS pollution changes in the Pike River watershed in Southern Quebec, Canada. It was evident in that study that the SWAT model had certain limitations in simulating snowmelt or snowfall at extremely low temperatures (zero degrees Celsius) during the future projection period (2041-2070), which caused overestimation or underestimation of several parameters such as sediment and TP loads. Kim et al. (2014) assessed the impacts of potential climate change on snowmelt and how that affected non-point source pollution loads reaching a stream in a South Korean watershed. They used the Terra MODIS NDSI (Moderate Resolution Imaging Spectroradiometer Normalized Difference Snow Index - a remote sensing index specifically designed for snow cover detection) to obtain the snow cover area in the studied watershed and determined the snow depletion parameters using an 11-year data historical period (2000-2010) for future projection. To conduct future projections, the SWAT model was set up using the different observed historical input data (such as inflow, sediment, TN, TP, etc.), meteorological data (precipitation and temperature), snow depth data (which are necessary to determine the snow depletion parameters for the watershed) as per the below equation.

$$snocov = SNO/SNO100 \times (SNO/SNO100) + \exp\left(cov1 - cov2 \times SNO/SNO100\right)^{-1};$$

Accordingly, the SWAT snowmelts parameters and TERRA MODIS images were linked to obtain the snow cover area and the snow depth distribution (SDD), which were then used to project snow dynamics for future periods (2040s and 2080s). Shrestha et al. (2012) used SWAT version 2005, which is equipped with a temperature-index modeling approach, to estimate snow accumulation and melt in the upper Assiniboine catchment, located in the Lake Winnipeg watershed, Canada.

4.3 Nutrients and flow

4.3.1 Changes in Flow/Streamflow/Discharge

Changes in temperature and precipitation play important roles in nutrient mineralization, immobilization, and emission to the atmosphere. In addition, such climatic changes regulate nutrient export by affecting water availability for nutrient delivery from land to rivers, and nutrient phase change along the transport pathways

(Yang et al., 2019). An important transport pathway for nutrient and sediment export is via discharge or streamflow (Miralha et al., 2021). Around 49% of the reviewed studies reported an increase in flow due to increased seasonal precipitation (Andreas M. Culbertson, 2016; Čerkasova et al., 2018; Lee et al., 2018; Shrestha et al., 2012; Thang et al., 2018; Tong et al., 2007; Trang et al., 2017; Trolle et al., 2015; Yan et al., 2019; Yang et al., 2019). The range of projected increase varied from as low as 1% up to 100%. The lowest projected increase was reported in the 3SRB River Basin of the Lower Mekong Basin, Thailand, where minor changes in rainfall and temperature were expected to increase future flows by 1% under RCP 8.5 by the mid-century future period (2040s) (Khoi et al., 2022). On the other hand, the highest future projected increase in flow was reported in the St. Croix River basin, USA where it was expected to increase between 60% to 100% by the last 2 decades of the 21st century (the 2080s-2090s) under RCP 8.5 (Yang et al., 2019).

On the other hand, almost 40% of the studies projected a decrease in future flows, which was attributed to a decrease in precipitation and an increase in both evapotranspiration and temperature (Almeida et al., 2018; Molina-Navarro et al., 2014; Nazari-Sharabian et al., 2019; Nguyen et al., 2019; Y. Wang et al., 2018; Ye & Grimm, 2013). The range of decrease recorded among the selected studies varied between 1.8% to 60%. The lowest recorded decrease in flow was reported by Nguyen et al. (2019) in the Mediterranean Torrens Catchment, South Australia as a result of a decrease in precipitation and an increase in temperature during the future projected period (2021-2050) under both RCP 4.5 and 8.5. The highest projected reduction in flow was 60% reported by Coppens et al. (2020) during the future projected period (2060-2080) under RCP 8.5 in Lake Mogan, near Ankara, Turkey also due to the temperature increases and decreases in precipitation. Likewise, Ye and Grimm (2013) reported a decrease in flow in the Sycamore Creek (a tributary of the Verde River, Phoenix, Arizona) by 31% for the 2011-2040 period, by 47% for the 2041-2070 period, and 56% for the 2071-2100 period, under SRES ‘B2’ as a result of increased temperature and decreased precipitation. They also presumed that other hydrological processes such as lateral flow, soil water, and groundwater recharge were also projected to decrease.

Other studies (11%) reported no clear trends (increase/decrease) in future projected river flows. For example, Zhang et al. (2012) reported a variable increase/decrease in flow trend in the Shitoukoumen Reservoir Basin, China (2010-2022 upward trend, 2022-2040 downward trend, 2040-2062 sharp increase, 2062-2078 slow declining trend, 2082-2088 sharp upward and downward trends, 2088-2099 increasing trend) under SRES ‘A2’. Čerkasova et al. (2021) and Pinheiro et al. (2019) reported no projected trends under different emissions scenarios (RCP 4.5 and 8.5) during the studied future periods due to the high variability of historical/observed data.

4.3.2 Changes to Phosphorous

The highest projected increase in phosphorus concentrations was reported by (Almeida et al., 2018). They expected that TP levels would increase by 200% and 500%, respectively, during the future period 2060 (defined as a 10-year average from 2055 to 2064) under the different emission storylines (RCP 4.5 and RCP 8.5). This increase was a result of projected increases in the use of fertilizers and a decrease in water availability in the river (as the precipitation during the projected period was expected to decrease).

(Čerkasova et al., 2018, 2021) simulated the TP and TN loadings under emission scenarios RCP 4.5 and 8.5, using the SWAT model in a large-scale watershed (Nemunas River Basin) shared among several countries Belarus, Lithuania, Poland, Russia, and Latvia. The study projected a significant increase in TP (62%) (under RCP 4.5) and TN (32%) (under RCP 8.5) concentrations in the fall, winter, and spring months (October to April), and then a reduction in loads for the summer period for the long-term future projected period (2100). The increase in TP was primarily associated with the projected increase in sediment loads during the simulation period, which was reported as the main source of particle-bound phosphorous (Čerkasova et al., 2018).

Another study by Trang et al. (2017) showed that TP annual yield was predicted to increase for all future periods (the 2030s,2060s, and 2090s) with the highest recorded in the 2090s during the wet season under emission scenarios RCP 4.5 and 8.5. This increase was directly associated with the increase in river discharge because of increased precipitation in the 3S River Basin (Sekong, Sesan, and Srepok Rivers) (Trang et al., 2017). This was also the case as reported by X. Wang et al. (2018), who projected an increase in TP loading under emissions scenarios A2 (2%) and B2 (6%) as a result of increased precipitation, rainfall intensity, and soil erodibility in the Liao River basin, China during the near future projected period 2021-2050. This was also reported by Molina-Navarro et al. (2014) who studied changes to TP loading in the catchment of the Ompólveda River in Spain under different climate change scenarios. They found that the TP export showed a strong statistical relationship with the amount of direct runoff and TP concentrations, implying that soil erosion caused by increased runoff events was one of the main sources of TP. Yang et al. (2019) reported that projected climate conditions would generally result in increasing nutrient export (in specific TP) in the St. Croix River Basin (SCRB), USA during the period 2020-2099 under RCP 4.5 by 18% and RCP 8.5 by 35.7%. (Kim et al., 2014) studied the impacts on nutrient loads during snowmelt periods. They reported an 115% increase under scenario RCP 4.5 and a 110.8% increase under scenario 8.5. In conclusion, TP loads during the snowmelt period under RCP scenarios (4.5 and 8.5) showed a greater increase in annual total loads as compared to the SRES scenarios (A1B, B1, A2) which showed an overall decrease in loads. The reasoning behind this was due to the big differences in precipitation during the snowmelt period between the SRES and RCP scenarios.

On the other hand, other studies reported a projected decrease in TP loadings. Shrestha et al. (2017) estimate a 20% decrease in annual TP loads, with an overall decrease across all seasons, with spring experiencing the highest decline, with a 44.9% drop under emission scenario RCP 8.5 during the future studied period (2046-2070). The decrease in TP loads was a result of a decrease in precipitation (9.7% decrease), flow (up to a 20.5% decrease), and sediment yields. Y. Wang et al. (2018) also reported that TP would decrease in the future due to climate change. They reported that reductions were largest under RCP 8.5 as compared to RCP 4.5 in the Liao River, Northeastern China. The opposite was reported by Čerkasova et al. (2019) in the Mnija River, Lithuania, as their results indicated a 35% decrease in TP loading under RCP 4.5 and a 28% decrease under RCP 8.5 for the period between 2051-2099. (Coppens et al., 2020), reported that SRP was predicted to decline by 11% across most emissions scenarios. The decrease in SRP loading was more associated with changes in the lateral groundwater flows rather than to the changes in surface runoff.

Several studies recorded no significant changes in TP or fluctuations during the future projected period. For example, (Zhang et al., 2012) reported a fluctuating upward trend for the simulated period between 2042 2048 and a downward trend for the 2070-2078 period. Bi et al. (2018) projected that there would be no future incidence of TP pollution under RCP 2.6 and 8.5.

Several articles (Bi et al., 2018; Gombault et al., 2015; Jisun, 2013; Marcinkowski et al., 2017; Shrestha et al., 2017; Thang et al., 2018; Y. Wang et al., 2018) showed that the incidence of TP pollution indicates a positive correlation with precipitation change and runoff/streamflow and a negative correlation with temperature. This will impact surface runoff and consequently soil erosion, transportation of the bulk of sediment-attached particles, and nutrient transport. The higher the increase in precipitation, especially during winter and flood seasons, the higher the quantity of surface and total runoff, resulting in the transport of a greater number of sediments, TP, and TN from the land into water courses (Gombault et al., 2015).

4.3.3 Changes to Nitrogen

X. Wang et al. (2018) reported an annual 6% to 10% increase in TN load under SRES scenarios A2 and B2, respectively, in the Liao River Basin for the future studied projected period (2021-2050). It was shown that TN was mainly controlled by the amount of streamflow and capacity of soil infiltration. Marcinkowski et al. (2017) projected an increase of 35% and 45% in TN loading in the Baric and Upper Narew Catchments, Poland, respectively in the far future period (2071-2100) using RCP 4.5. Similarly, Gombault et al. (2015) projected a TN increase of 24-34% for the future projected period (2041-2070); yet they reported considerable increases in certain months. Shrestha et al. (2012) showed an overall increase in TN loading over the future period (2041-2070). Whereby TN load was expected to increase between 10 and 50%, depending on the RCM. Noting that fertilizer inputs were held constant, they concluded that these increases resulted from enhanced decomposition and mineralization of biomass.

Kim et al. (2014), projected future climate change using different emissions scenarios (SRES and RCP) for two different future periods (the 2040s and 2080s). Running the models under SRES emissions scenarios A1B, A2, and B1 showed that future monthly TN values would experience a big increase during the month of April as compared to baseline records; yet an overall annual decrease in TN loading ranging between 1% to 8.9% during the 2040s period and 0.5% to 11.6% during the 2080s period. They reported that under scenarios RCP 4.5 and 8.5 TN loadings were projected to increase by 63.6% and 69.6%, respectively during the 2080s period. Meanwhile, oth Khoi et al. (2022) and Yan et al. (2019) showed an increase in TN loads of 11.35% and 14%-26.9% based on the emission scenarios used (RCP 4.5 and 8.5). Though, Khoi et al. (2022) projected a declining trend in precipitation ranging between 28-34% during the future studied period (2020-2099). The variations in TN load projections were attributed to the projected changes in streamflow. It is worth noting that the highest increase in TN loads was also observed in the months witnessing increased precipitation or during the flood season (June through September). Yan et al. (2019) showed the largest increase in TN loading during the month of July under RCP 4.5 and 8.5. The seasonal variation in the TN loading was consistent with projected seasonal changes in streamflow. The strongest increase in the TN loading would occur in the flood season between June and September. Lee et al. (2018) justified that their future projected 66%

increase in annual nitrate loads in Tuckhose Creek Watershed (TCW) and 56% increase for Greensboro Watershed (GW), Maryland, USA were not solely a result of the increase associated with the change in rate of precipitation but also due to significant export of nitrate from fertilization application. Mukundan et al. (2020) and Marshall and Randhir (2008) carried out a SWAT simulation using future climate change scenarios RCP 4.5 and SRES A2, respectively. Future projections showed an increase in the loading of particulate forms of N due to an increase in the frequency and magnitude of large storm events that carry sediments and particulate forms of nitrogen. Runoff from rainfall and snowmelt events is known to drive nitrate transport processes. NO3-loading was mostly determined by runoff and therefore more linked with changes in precipitation than with temperature changes (Kim et al., 2020). On the other hand, Li et al. (2011) attributed the increase of the inorganic form of nitrogen to temperature increase, whereby a 3-degree (C) increase resulted in a 40% increase in load. In their study, the increase in inorganic nitrogen was greater than that of sediment and discharge, which indicates that inorganic nitrogen was more sensitive to temperature change as compared to the other parameters. It was also mentioned that with an expected temperature increase, an increase in microbial activity was expected to accelerate decomposition and enhance nutrient transformation from organic to inorganic forms (Li et al., 2011). Tong et al. (2007) reached the conclusions and showed that in almost all species of nitrogen (including NH4+), the average daily concentration increased under future projections as the degree of dryness increased, thus attributing the increase of NH4+ to an increase in temperature. The driest scenario (using emission scenario RCP 8.5) produced the highest average daily concentration, this indicates that the pollutant is likely to become more concentrated as the runoff volume decreases. Me et al. (2018) reported an increase of 14.4% because of a 2.7-degree Celsius increase in temperature.

Verma et al. (2015) projected that changes in nitrate loads were similar to the changes projected in average monthly flows, as there was a rise in nitrate loads during winter and spring months (high flows/discharge) for both future periods (2045-2055 and 2089-2099 by 17% and 28% respectively) and a decrease in summer months (low flows/discharge) during the same future periods (by 43% and 33%). A similar trend was observed in (Coppens et al., 2020), whereby NO3-loading was projected to decrease by 45% due to the decrease in precipitation, reduction in the runoff, and groundwater flow. The nitrate loadings in the Upper Mississippi River Basin (Jha et al., 2013) showed large variations in nitrate loading trends as the Iowa sub-watersheds were expected to show decreasing trends throughout the course of the future periods whereas the Illinois sub-watersheds showed an increasing trend. This variation between the sub-watersheds was due to the different environmental characteristics of each.

In general, the trends of sediment yield, TN, and TP loads occur in the same direction as the trend of streamflow (Thang et al., 2018). Overall, the above results indicate that future TN and TP loadings will change with the timing and magnitude of runoff. Changes in TN and TP (or nutrient transport regime) are attributed to changes in climatic variables (Shrestha et al., 2012).

4.4 Limitations and Future Framework

4.4.1 Limitations in the SWAT model

SWAT is a widely used water quality model dealing with many aspects related to water cycle simulation, but it still has limitations. A common limitation of the SWAT model is related to its limited ability for simulating and predicting snowmelt runoff. SWAT is equipped with a simplified snowmelt module that uses a degree-day method, which relies on temperature indices, mainly snowpack temperature and air temperature on snowmelt. This in turn does not allow the model to capture the spatial and temporal variability of snow accumulation and snow melting in mountainous regions accurately. Additionally, this method may not fully account for the impact of other meteorological factors such as solar radiation. Solar radiation according to (Ariel L. Salas & Kumaran Subburayalu, 2019) is one of the main energy sources of snow melting and is expected to be more influential as compared to temperature, given that part of the solar radiation energy is used to warm the snow up and the rest to melt the snow (Meriö, 2015).

The SWAT model has also been shown to have limited capabilities to predict flows and subsequently nutrient loads in cold regions, with frozen ground. Shrestha et al. (2012) showed poor correspondence between measurements and model-predicted nutrient response for cold regions/environments. They also showed the lack of SWAT to capture intra-seasonal variations in nutrient responses due to the lack of an appropriate process algorithm in SWAT for dealing with frozen ground. Their study suggested that new source codes should be written to better deal with frozen ground/soils so that the SWAT model can be more effectively employed in such regions. A study by Gombault et al. (2015) also reported that SWAT’s limitations to properly simulate snowmelt or snowfall at temperatures close to 0 degrees Celsius generally led to overestimating sediment and TP loads during the snowmelt season.

Another major limitation that has been commonly cited among the reviewed articles is related to the coarse spatial and temporal scales of the data often used to calibrate the model. In terms of spatial scale limitations, it was shown by Li et al. (2011) and Trang et al. (2017) that adopting a relatively coarse spatial resolution (DEM 250 m) will often lead to an inaccurate representation of the fine-scale hydrological processes. Another limitation associated with the adopted spatial scale was highlighted by (Wang & Kalin, 2018); they showed that the assumption of homogeneity for sub-watersheds in terms of soil properties, land use, and climate does not accurately represent the actual variability observed within smaller sub-watersheds. This assumption may not hold in highly heterogenous landscapes. In terms of temporal scale limitations, the SWAT model mainly uses a daily time step when making predictions. This scale may not capture the short-term, high-intensity events (e.g., flash floods) or rapid changes in land use and management practices that may be occurring at a finer timestep. This limitation is particularly important when simulating the impacts of climate variability, extreme weather events, or certain land management practices that occur on shorter time scales (such as hourly or sub-daily scales) (James et al., 2014).

Another major limitation of SWAT studies is their assumption that land use and management practices remain constant over the entire simulation period. Changes in land use or management practices within the simulation period may not be well captured, limiting the model's ability to assess the impact of dynamic changes (Martel et al., 2021).

Another source of limitations is the limited capability of SWAT to integrate with future climate models. Almost all studies only considered future changes in temperature and precipitation and neglected changes to other meteorological parameters (such as relative humidity, wind speed, and solar radiation) that can affect estimates of flow and water quality (Coppens et al., 2020; Pesce et al., 2018). Additionally, SWAT models do not account for the uncertainties associated with the downscaling techniques. The performance of the available downscaling methods varies greatly and unfortunately, that uncertainty is never accounted for in SWAT. Jha et al. (2013) showed that uncertainty arises from climate model simulations, as current climate models provide inconsistent projections. Similarly, (Mukundan et al., 2020; Swain, 2017; Yan et al., 2019; Ye & Grimm, 2013) identified several distinct uncertainties in climate models stemming from internal variability (related to structural and parameter uncertainty), scenario uncertainty, poor quality of input data, insufficient knowledge of the modeler regarding various process that can be incorporated by the model, and exclusion of some important hydrological processes from the model that might have critical effects on climate change. Equally important is the limited use of ensemble future climate estimates when working with SWAT. Moreover, the dependence on GCMs is another limitation. While GCMs are valuable tools for understanding global and regional climate trends, they cannot often capture microclimates properly. Microclimates can exhibit rapid changes on much shorter time scales, ranging from minutes to hours. GCMs might not capture the rapid fluctuations in local weather conditions, making them less suitable for studying short-term events or phenomena.

Another limitation which was evident among the peer-reviewed articles was the lack of representation of certain locations, such as the Middle East and Sub-Saharan

Africa. These regions often present unique complexities in terms of topography, land cover, and climate processes that are challenging to capture accurately in global and regional-scale models. The Middle East, for example, exhibits intricate interactions between large bodies of water, arid deserts, and complex mountainous terrains, making it difficult to represent these features adequately at the coarse resolution of many climate models (Neumann et al., 2021). Additionally, limited data availability, especially for historical observations and local climate processes, further hinders the development of accurate models for these regions. The lack of comprehensive representation in these areas underscores the need for increased research focus, data collection, and model refinement to better address the specific climatic challenges and vulnerabilities faced by the populations in such areas.

4.4.2 Additional Research

Though substantial improvements have been witnessed over the recent years in terms of linking hydrological models with climate models, there are several gaps to the best of our knowledge that follow from our findings and would benefit from further research. As such additional research is needed to be considered, such as:

1. Allowing SWAT to account for temporally variable land management practices and land use/land cover changes (during the future projected period) over time. Moreover, there is a need to couple these changes with different climatic forcings. Changes in land use/land cover may alter the values of many important meteorological and hydrological processes/parameters (Ahmadi et al., 2014; Y. Wang et al., 2018).

2. Accounting for farm-scale changes in the SWAT model enhances its accuracy and utility for studying the impact of climate change on nutrient loadings. Since farms are considered a primary source of nutrient inputs to watersheds, incorporating such changes in the SWAT model allows for an enhanced spatial resolution, thus enabling the model to capture different variations in land use, management practices, and nutrient application rates. Farm changes are directly linked to land use changes (mentioned above – point no. 1). Future work should focus on providing data at the farm level.
3. Incorporating heavily irrigated lands and modeling the formation of water gullies at the farm level in the SWAT model. Such improvements can help assess how climate change influences nutrient transport and runoff, particularly during intense storms. This improvement can provide information for adaptive management strategies. Moreover, this can allow for a better understanding of how changes in land use, irrigation practices, and gully erosion influence water quality.
4. Yang et al. (2019) and Kalcic et al. (2019) suggest that future SWAT studies also need to evaluate how future population growth and urbanization would further affect nutrient export to better understand future changes in water quality. This will help in the development of local water quality improvement policies or zoning restrictions and regulations.
5. There is a need to improve the SWAT model by allowing for a better blending of process- and data-based approaches. The development of a hybrid SWAT model can potentially give robust solutions when dealing with large watersheds with limited data. Examples of such hybrid models include the incorporation of

SWAT with artificial neural networks (ANN). The usefulness of this approach has been shown by Noori et al, (2020).

6. Improved understanding and representation of different regions such as the Middle East and Africa since they are expected to face some of the most significant changes in future climate and are a major source of nutrient pollution.

APPENDIX

APPENDIX 1

1	Bučienė, et al. (2019). "Changes in Nutrient Concentrations of Two Streams in Western Lithuania with Focus on Shrinkage of Agriculture and Effect of Climate, Drainage Runoff and Soil Factors." Water 11(8).
2	Burigato Costa, C., et al. (2019). "Applicability of water quality models around the world review." Environ Sci Pollut Res Int 26(36): 36141-36162.
3	Kim, S. B., et al. (2014). "Assessment of future climate change impacts on snowmelt and stream water quality for a mountainous high-elevation watershed using SWAT." Paddy and Water Environment 13(4): 557-569.
4	Krysanova, V. and R. Srinivasan (2014). "Assessment of climate and land use change impacts with SWAT." Regional Environmental Change 15(3): 431-434.
5	Li, X., et al. (2020). "A scientometric review of the research on the impacts of climate change on water quality during 1998-2018." Environ Sci Pollut Res Int 27(13): 14322-14341.
6	Marshall, E. and T. Randhir (2008). "Effect of climate change on watershed system: a regional analysis." Climatic Change 89(3-4): 263-280.
7	Neitsch, S. L., et al. (2012). "Soil and water assessment tool theoretical documentation version 2012." Texas Water Resources Institute.
8	Neumann, A., et al. (2021). "A review of the current state of process-based and data-driven modeling: guidelines for Lake Erie managers and watershed modellers." Environmental Reviews 29(4): 443-490.
9	Swain, S. (2017). "Hydrological Modeling through Soil and Water Assessment Toolin a Climate Change Perspective A Brief Review." 2017 2nd International Conference for Convergence in Technology (I2CT): pp. 358-361.
10	Tan, M. L., et al. (2020). "A review of SWAT applications, performance and future needs for simulation of hydro-climatic extremes." Advances in Water Resources 143.
11	Yamini Priya, R. and R. Manjula (2021). "A review for comparing SWAT and SWAT coupled models and its applications." Materials Today: Proceedings 45: 7190-7194.

APPENDIX 2

1	C. Baffaut, S. M. D., M. D. Smolen, M. A. Youssef, J. V. Bonta, M. L. Chu, J. A. Guzman, V. S. Shedekar, M. K. Jha, J. G. Arnold (2015). "Hydrologic and Water Quality Modeling: Spatial and Temporal Considerations." Transactions of the ASABE 58(6): 1661-1680.
2	Chokkavarapu, N. and V. R. Mandla (2019). "Comparative study of GCMs, RCMs, downscaling and hydrological models: a review toward future climate change impact estimation." SN Applied Sciences 1(12).
3	Cui, T., et al. (2021). "Evaluation of Temperature and Precipitation Simulations in CMIP6 Models Over the Tibetan Plateau." Earth and Space Science 8(7).
4	Gaudet, M. M. a. B. (2017). "'SRES' Scenarios and 'RCP' Pathways." From Meteorology to Mitigation: Understanding Global Warming.
5	Gunn, K. M., et al. (2021). "Integrating Daily CO2 Concentrations in SWAT-VSA to Examine Climate Change Impacts on Hydrology in a Karst Watershed." Transactions of the ASABE 64(4): 1303-1318.
6	Hausfather, R. M. a. Z. (2018, 2018). "Climate Modelling: How do climate models work? ." Carbon Brief, Clear on Climate. Retrieved 28/08/2022, 2022.
7	IPCC (2000). "IPCC Special Report Emissions Scenarios: Summary for Policy Makers." 27.
8	James, T. S., et al. (2014). "Relative Sea-level projections in Canada and the Adjacent Mainland United States." Geological Survey of Canada.
9	Lane, S. N., et al. (2007). "Interactions between sediment delivery, channel change, climate change and flood risk in a temperate upland environment." Earth Surface Processes and Landforms 32(3): 429-446.
10	Martel, J.-L., et al. (2021). "Climate Change and Rainfall Intensity–Duration–Frequency Curves: Overview of Science and Guidelines for Adaptation." Journal of Hydrologic Engineering 26(10).
11	Meehl, G. A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, and A. J. W. a. Z.-C. Z. I.G. Watterson (2007). "Global Climate Projections." The Physical Science Basis.
12	Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.
13	Office, M. (2018). "UKCP Guidance: Representative Concentration Pathways." Environment Agency.
14	SACEP, S. A. C.-o. E. P. (2014). "Nutrient Loading and Eutrophication of Coastal Waters of the South Asian Seas - A Scoping Study."
14	Seager, R., et al. (2012). "Projections of declining surface-water availability for the southwestern United States." Nature Climate Change 3(5): 482-486.
16	Wang, Y., et al. (2019). "Quantifying the Effects of Climate and Vegetation on Soil Moisture in an Arid Area, China." Water 11(4).
17	Wayne, G. (2013). "The Beginner's Guide to Representative Concentration Pathways." Skeptical Science 1(1): 25.

18	Wilcke, R. A. I. and L. Bärring (2016). "Selecting regional climate scenarios for impact modelling studies." Environmental Modelling & Software 78: 191-201.
19	Zak, R. J. N. D. R. (2011). "Ecological Lessons from Free-Air CO_2 Enrichment (FACE) Experiments." Annual Review of Ecology, Evolution, and Systematics 42: 181-203.

REFERENCES

Ahmadi, M., Records, R., & Arabi, M. (2014). Impact of climate change on diffuse pollutant fluxes at the watershed scale. *Hydrological Processes*, *28*(4), 1962-1972. https://doi.org/10.1002/hyp.9723

Alina Trifu, E. S., Daniel Onuț Badea, Eugenia Bulboacă, Vergilică Haralambie, & (2022). Applying the PRISMA method for obtaining systematic reviews of occupational safety issues in literature search. *MATEC Web of Conferences*, *354*, 8. https://doi.org/https://doi.org/10.1051/matecconf/202235400052

Almeida, C., Ramos, T., Segurado, P., Branco, P., Neves, R., & Proença de Oliveira, R. (2018). Water Quantity and Quality under Future Climate and Societal Scenarios: A Basin-Wide Approach Applied to the Sorraia River, Portugal. *Water*, *10*(9). https://doi.org/10.3390/w10091186

Andreas M. Culbertson, J. F. M., Noel Aloysius, Stuart A. Ludsin. (2016). Anticipated impacts of climate change on 21st century Maumee River discharge and nutrient loads. *Journal of Great Lakes Research*, *42*(6), 1332-1342. https://doi.org/doi.org/10.1016/j.jglr.2016.08.008.

Ariel L. Salas, E., & Kumaran Subburayalu, S. (2019). Implications of climate change on nutrient pollution: a look into the nitrogen and phosphorus loadings in the Great Miami and Little Miami watersheds in Ohio. *AIMS Environmental Science*, *6*(3), 186-221. https://doi.org/10.3934/environsci.2019.3.186

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Van Griensven, A., Van Liew, M. W., Kannan, N., & Jha, M. K. (2012). SWAT: Model Use, Calibration, and Validation. *Transactions of the ASABE*, *55*(4), 1491-1508.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Van Griensven, A., Van Liew, M. W., Kannan, N., & Jha, M. K. (2012). SWAT: Model Use, Calibration, and Validation. *Transactions of the ASABE*, *55*(4), 1491-1508.

Ba, W., Du, P., Liu, T., Bao, A., Chen, X., Liu, J., & Qin, C. (2020). Impacts of climate change and agricultural activities on water quality in the Lower Kaidu River Basin, China. *Journal of Geographical Sciences*, *30*(1), 164-176. https://doi.org/10.1007/s11442-020-1721-z

Bi, W., Weng, B., Yuan, Z., Ye, M., Zhang, C., Zhao, Y., Yan, D., & Xu, T. (2018). Evolution Characteristics of Surface Water Quality Due to Climate Change and LUCC under Scenario Simulations: A Case Study in the Luanhe River Basin. *Int J Environ Res Public Health*, *15*(8). https://doi.org/10.3390/ijerph15081724

Bouraoui, F., Galbiati, L., and Bidoglio, G. (2002). Climate change impacts on nutrient loads in the Yorkshire Ouse catchment (UK). *Hydrol. Earth Syst. Sci.*, *6*, 197–209. https://doi.org/https://doi.org/10.5194/hess-6-197-2002

Bouraoui, F., Grizzetti, B., Granlund, K., Rekolainen, S., & Bidoglio, G. (2004). Impact of climate change on the water cycle and nutrient losses in a Finnish catchment. *Climatic Change*, *66*(1-2), 109-126. https://doi.org/10.1023/B:CLIM.0000043147.09365.e3

Brown, L. E., Hannah, D. M., & Milner, A. M. (2007). Vulnerability of alpine stream biodiversity to shrinking glaciers and snowpacks. *Global Change Biology*, *13*(5), 958-966. https://doi.org/10.1111/j.1365-2486.2007.01341.x

Bučienė, Povilaitis, Langas, Bučas, Petkuvienė, Vaičiūtė, & Gužys. (2019). Changes in Nutrient Concentrations of Two Streams in Western Lithuania with Focus on Shrinkage of Agriculture and Effect of Climate, Drainage Runoff and Soil Factors. *Water*, *11*(8). https://doi.org/10.3390/w11081590

Burigato Costa, C., da Silva Marques, L., Almeida, A. K., Leite, I. R., & de Almeida, I. K. (2019). Applicability of water quality models around the world-a review. *Environ Sci Pollut Res Int*, *26*(36), 36141-36162. https://doi.org/10.1007/s11356-019-06637-2

C. Baffaut, S. M. D., M. D. Smolen, M. A. Youssef, J. V. Bonta, M. L. Chu, J. A. Guzman, V. S. Shedekar, M. K. Jha, J. G. Arnold (2015). Hydrologic and Water Quality Modeling: Spatial and Temporal Considerations. *Transactions of the ASABE*, *58*(6), 1661-1680. https://doi.org/10.13031/trans.58.10714

Čerkasova, N., Umgiesser, G., & Ertürk, A. (2018). Development of a hydrology and water quality model for a large transboundary river watershed to investigate the impacts of climate change – A SWAT application. *Ecological Engineering*, *124*, 99-115. https://doi.org/10.1016/j.ecoleng.2018.09.025

Čerkasova, N., Umgiesser, G., & Ertürk, A. (2019). Assessing Climate Change Impacts on Streamflow, Sediment and Nutrient Loadings of the Minija River (Lithuania): A Hillslope Watershed Discretization Application with High-Resolution Spatial Inputs. *Water*, *11*(4). https://doi.org/10.3390/w11040676

Čerkasova, N., Umgiesser, G., & Ertürk, A. (2021). Modelling framework for flow, sediments and nutrient loads in a large transboundary river watershed: A climate change impact assessment of the Nemunas River watershed. *Journal of Hydrology*, *598*. https://doi.org/10.1016/j.jhydrol.2021.126422

Chokkavarapu, N., & Mandla, V. R. (2019). Comparative study of GCMs, RCMs, downscaling and hydrological models: a review toward future climate change impact estimation. *SN Applied Sciences*, *1*(12). https://doi.org/10.1007/s42452-019-1764-x

Coppens, J., Trolle, D., Jeppesen, E., & Beklioğlu, M. (2020). The impact of climate change on a Mediterranean shallow lake: insights based on catchment and lake modelling. *Regional Environmental Change*, *20*(2). https://doi.org/10.1007/s10113-020-01641-6

Cousino, L. K., Becker, R. H., & Zmijewski, K. A. (2015). Modeling the effects of climate change on water, sediment, and nutrient yields from the Maumee River watershed. *Journal of Hydrology: Regional Studies*, *4*, 762-775. https://doi.org/10.1016/j.ejrh.2015.06.017

Cui, T., Li, C., & Tian, F. (2021). Evaluation of Temperature and Precipitation Simulations in CMIP6 Models Over the Tibetan Plateau. *Earth and Space Science*, *8*(7). https://doi.org/10.1029/2020ea001620

D. N. Moriasi, M. W. G., N. Pai, P. Daggupati (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763-1785. https://doi.org/10.13031/trans.58.10715

El-Khoury, A., Seidou, O., Lapen, D. R., Que, Z., Mohammadian, M., Sunohara, M., & Bahram, D. (2015). Combined impacts of future climate and land use changes on discharge, nitrogen and phosphorus loads for a Canadian river basin. *J Environ Manage*, *151*, 76-86. https://doi.org/10.1016/j.jenvman.2014.12.012

Feng, M., & Shen, Z. (2021). Assessment of the Impacts of Land Use Change on Non-Point Source Loading under Future Climate Scenarios Using the SWAT Model. *Water*, *13*(6). https://doi.org/10.3390/w13060874

Glavan, M., Ceglar, A., & Pintar, M. (2015). Assessing the impacts of climate change on water quantity and quality modelling in small Slovenian Mediterranean catchment – lesson for policy and decision makers. *Hydrological Processes*, *29*(14), 3124-3144. https://doi.org/https://doi.org/10.1002/hyp.10429

Gombault, C., Madramootoo, C. A., Michaud, A. R., Beaudin, I., Sottile, M. F., Chikhaoui, M., & Ngwa, F. F. (2015). Impacts of climate change on nutrient losses from the Pike River watershed of southern Québec. *Canadian Journal of Soil Science*, *95*(4), 337-358. https://doi.org/10.4141/cjss-2014-012

Hausfather, R. M. a. Z. (2018, 2018). *Climate Modelling: How do climate models work?* . Retrieved 28/08/2022 from

James, T. S., Henton, J. A., Leonard, L., Darlington, A., Forbes, D. L., & Craymer, M. (2014). Relative Sea-level projections in Canada and the Adjacent Mainland United States. *Geological Survey of Canada*. https://doi.org/10.4095/295574

Jayakody, P., Parajuli, P. B., & Cathcart, T. P. (2014). Impacts of climate variability on water quality with best management practices in sub-tropical climate of USA. *Hydrological Processes*, *28*(23), 5776-5790. https://doi.org/10.1002/hyp.10088

Jeppesen, E., Kronvang, B., Meerhoff, M., Sondergaard, M., Hansen, K. M., Andersen, H. E., Lauridsen, T. L., Liboriussen, L., Beklioglu, M., Ozen, A., & Olesen, J. E. (2009). Climate change effects on runoff, catchment phosphorus loading and lake ecological state, and potential adaptations. *J Environ Qual*, *38*(5), 1930-1941. https://doi.org/10.2134/jeq2008.0113

Jha, M. K., Gassman, P. W., & Panagopoulos, Y. (2013). Regional changes in nitrate loadings in the Upper Mississippi River Basin under predicted mid-century climate. *Regional Environmental Change*, *15*(3), 449-460. https://doi.org/10.1007/s10113-013-0539-y

Jisun, C. S., Park & Yeon, Yeu & Hong-Joo, Yoon & Chuluong, Choi & Jinsoo, Kim. (2013). Impacts of climate change under IPCC RCP scenarios on streamflow and water quality in the Youngsan Basin, South Korea. *Disaster Advances*, *6*, 34-141.

Johnson, T., Butcher, J., Deb, D., Faizullabhoy, M., Hummel, P., Kittle, J., McGinnis, S., Mearns, L. O., Nover, D., Parker, A., Sarkar, S., Srinivasan, R., Tuppad, P., Warren, M., Weaver, C., & Witt, J. (2015). Modeling Streamflow and Water Quality Sensitivity to Climate Change and Urban Development in 20 U.S. Watersheds. *JAWRA Journal of the American Water Resources Association*, *51*(5), 1321-1341. https://doi.org/10.1111/1752-1688.12308

Jordan, Y. C., Ghulam, A., & Hartling, S. (2014). Traits of surface water pollution under climate and land use changes: A remote sensing and hydrological modeling approach. *Earth-Science Reviews*, *128*, 181-195. https://doi.org/10.1016/j.earscirev.2013.11.005

Kalcic, M. M., Muenich, R. L., Basile, S., Steiner, A. L., Kirchhoff, C., & Scavia, D. (2019). Climate Change and Nutrient Loading in the Western Lake Erie Basin: Warming Can Counteract a Wetter Future. *Environ Sci Technol*, *53*(13), 7543-7550. https://doi.org/10.1021/acs.est.9b01274

Khairi Khalida, M. F. A., Nor Faiza Abd Rahmanc, Muhamad Radzali Mispand, Siti Humaira Harone, Zulhafizal Othmana, Mohd Fairuz Bachoka. (2016).

Sensitivity analysis in watershed model using SUFI-2 algorithm *Procedia Engineering 162*, 441 – 447 https://doi.org/doi: 10.1016/j.proeng.2016.11.086
Khoi, D. N., Loi, P. T., Trang, N. T. T., Vuong, N. D., Fang, S., & Nhi, P. T. T. (2022). The effects of climate variability and land-use change on streamflow and nutrient loadings in the Sesan, Sekong, and Srepok (3S) River Basin of the Lower Mekong Basin. *Environ Sci Pollut Res Int*, *29*(5), 7117-7126. https://doi.org/10.1007/s11356-021-16235-w
Kim, D.-H., Jang, T., & Hwang, S. (2020). Evaluating impacts of climate change on hydrology and total nitrogen loads using coupled APEX-paddy and SWAT models. *Paddy and Water Environment*, *18*(3), 515-529. https://doi.org/10.1007/s10333-020-00798-4
Kim, S. B., Shin, H. J., Park, M., & Kim, S. J. (2014). Assessment of future climate change impacts on snowmelt and stream water quality for a mountainous high-elevation watershed using SWAT. *Paddy and Water Environment*, *13*(4), 557-569. https://doi.org/10.1007/s10333-014-0471-x
Kujawa, H., Kalcic, M., Martin, J., Aloysius, N., Apostel, A., Kast, J., Murumkar, A., Evenson, G., Becker, R., Boles, C., Confesor, R., Dagnew, A., Guo, T., Logsdon Muenich, R., Redder, T., Scavia, D., & Wang, Y. C. (2020). The hydrologic model as a source of nutrient loading uncertainty in a future climate. *Sci Total Environ*, *724*, 138004. https://doi.org/10.1016/j.scitotenv.2020.138004
Lane, S. N., Tayefi, V., Reid, S. C., Yu, D., & Hardy, R. J. (2007). Interactions between sediment delivery, channel change, climate change and flood risk in a temperate upland environment. *Earth Surface Processes and Landforms*, *32*(3), 429-446. https://doi.org/10.1002/esp.1404
Laursen, A. E., & Hanief, A. (2017). SWAT modeling of hydrology, sediment and nutrients from the Grand River, Ontario. *Water Quality Research Journal*, *52*(4), 243-257. https://doi.org/10.2166/wqrj.2017.014
Lee, S., Yeo, I.-Y., Sadeghi, A. M., McCarty, G. W., Hively, W. D., Lang, M. W., & Sharifi, A. (2018). Comparative analyses of hydrological responses of two adjacent watersheds to climate variability and change using the SWAT model. *Hydrology and Earth System Sciences*, *22*(1), 689-708. https://doi.org/10.5194/hess-22-689-2018
Li, C., Zhang, Y., Kharel, G., & Zou, C. B. (2018). Impact of Climate Variability and Landscape Patterns on Water Budget and Nutrient Loads in a Peri-urban Watershed: A Coupled Analysis Using Process-based Hydrological Model and Landscape Indices. *Environ Manage*, *61*(6), 954-967. https://doi.org/10.1007/s00267-018-1019-4
Li, T., & Kim, G. (2019). Impacts of Climate Change Scenarios on Non-Point Source Pollution in the Saemangeum Watershed, South Korea. *Water*, *11*(10). https://doi.org/10.3390/w11101982
Li, X., Li, Y., & Li, G. (2020). A scientometric review of the research on the impacts of climate change on water quality during 1998-2018. *Environ Sci Pollut Res Int*, *27*(13), 14322-14341. https://doi.org/10.1007/s11356-020-08176-7
Li, Y., Chen, B.-M., Wang, Z.-G., & Peng, S.-L. (2011). Effects of temperature change on water discharge, and sediment and nutrient loading in the lower Pearl River basin based on SWAT modelling. *Hydrological Sciences Journal*, *56*(1), 68-83. https://doi.org/10.1080/02626667.2010.538396

Marcinkowski, P., Piniewski, M., Kardel, I., Szcześniak, M., Benestad, R., Srinivasan, R., Ignar, S., & Okruszko, T. (2017). Effect of Climate Change on Hydrology, Sediment and Nutrient Losses in Two Lowland Catchments in Poland. *Water*, *9*(3). https://doi.org/10.3390/w9030156

Marshall, E., & Randhir, T. (2008). Effect of climate change on watershed system: a regional analysis. *Climatic Change*, *89*(3-4), 263-280. https://doi.org/10.1007/s10584-007-9389-2

Martel, J.-L., Brissette, F. P., Lucas-Picher, P., Troin, M., & Arsenault, R. (2021). Climate Change and Rainfall Intensity–Duration–Frequency Curves: Overview of Science and Guidelines for Adaptation. *Journal of Hydrologic Engineering*, *26*(10). https://doi.org/10.1061/(asce)he.1943-5584.0002122

Me, W., Hamilton, D. P., McBride, C. G., Abell, J. M., & Hicks, B. J. (2018). Modelling hydrology and water quality in a mixed land use catchment and eutrophic lake: Effects of nutrient load reductions and climate change. *Environmental Modelling & Software*, *109*, 114-133. https://doi.org/10.1016/j.envsoft.2018.08.001

Mehan, S., Aggarwal, R., Gitau, M. W., Flanagan, D. C., Wallace, C. W., & Frankenberger, J. R. (2019). Assessment of hydrology and nutrient losses in a changing climate in a subsurface-drained watershed. *Sci Total Environ*, *688*, 1236-1251. https://doi.org/10.1016/j.scitotenv.2019.06.314

Mehdi, B., Ludwig, R., & Lehner, B. (2015). Evaluating the impacts of climate change and crop land use change on streamflow, nitrates and phosphorus: A modeling study in Bavaria. *Journal of Hydrology: Regional Studies*, *4*, 60-90. https://doi.org/10.1016/j.ejrh.2015.04.009

Mehdi, B., Ludwig, R., & Lehner, B. (2016). Simulated future changes of extreme nutrient loads in a mesoscale agricultural watershed in Bavaria / Simulierte zukünftige Änderungen der Extremwerte für Nährstofffrachten in einem mesoskaligen landwirtschaftlichen Einzugsgebiet in Bayern. *Die Bodenkultur: Journal of Land Management, Food and Environment*, *67*(2), 77-90. https://doi.org/10.1515/boku-2016-0008

Meriö, L.-J. (2015). *The measurement and modeling of snowmelt in subarctic site using low cost temperature loggers* University of Oulu]. Sweden.

Miralha, L., Muenich, R. L., Scavia, D., Wells, K., Steiner, A. L., Kalcic, M., Apostel, A., Basile, S., & Kirchhoff, C. J. (2021). Bias correction of climate model outputs influences watershed model nutrient load predictions. *Sci Total Environ*, *759*, 143039. https://doi.org/10.1016/j.scitotenv.2020.143039

Molina-Navarro, E., Andersen, H. E., Nielsen, A., Thodsen, H., & Trolle, D. (2018). Quantifying the combined effects of land use and climate changes on stream flow and nutrient loads: A modelling approach in the Odense Fjord catchment (Denmark). *Sci Total Environ*, *621*, 253-264. https://doi.org/10.1016/j.scitotenv.2017.11.251

Molina-Navarro, E., Trolle, D., Martínez-Pérez, S., Sastre-Merlín, A., & Jeppesen, E. (2014). Hydrological and water quality impact assessment of a Mediterranean limno-reservoir under climate change and land use management scenarios. *Journal of Hydrology*, *509*, 354-366. https://doi.org/10.1016/j.jhydrol.2013.11.053

Mukundan, R., Hoang, L., Gelda, R. K., Yeo, M.-H., & Owens, E. M. (2020). Climate change impact on nutrient loading in a water supply watershed. *Journal of Hydrology*, *586*. https://doi.org/10.1016/j.jhydrol.2020.124868

Nazari-Sharabian, M., Taheriyoun, M., Ahmad, S., Karakouzian, M., & Ahmadi, A. (2019). Water Quality Modeling of Mahabad Dam Watershed–Reservoir System under Climate Change Conditions, Using SWAT and System Dynamics. *Water*, *11*(2). https://doi.org/10.3390/w11020394

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R., & King, K. W. (2012a). Soil and water assessment tool theoretical documentation version 2012. *Texas Water Resources Institute*.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R., & King, K. W. (2012b). Soil and water
assessment tool theoretical documentation version 2012. *Texas Water Resources Institute*.

Neumann, A., Dong, F., Shimoda, Y., Arnillas, C. A., Javed, A., Yang, C., Zamaria, S., Mandal, S., Wellen, C., Paredes, D., Feisthauer, N., Blukacz-Richards, E. A., Yerubandi, R. R., & Arhonditsis, G. B. (2021). A review of the current state of process-based and data-driven modelling: guidelines for Lake Erie managers and watershed modellers. *Environmental Reviews*, *29*(4), 443-490. https://doi.org/10.1139/er-2020-0070

Nguyen, H. H., Recknagel, F., & Meyer, W. (2019). Effects of projected urbanization and climate change on flow and nutrient loads of a Mediterranean catchment in South Australia. *Ecohydrology & Hydrobiology*, *19*(2), 279-288. https://doi.org/10.1016/j.ecohyd.2018.10.001

Pesce, M., Critto, A., Torresan, S., Giubilato, E., Santini, M., Zirino, A., Ouyang, W., & Marcomini, A. (2018). Modelling climate change impacts on nutrients and primary production in coastal waters. *Sci Total Environ*, *628-629*, 919-937. https://doi.org/10.1016/j.scitotenv.2018.02.131

Pinheiro, A., Kaufmann, V., Piazza, G. A., & Campo, C. G. C. (2019). Scenarios from the Eta Model on quality and hydrological quantity in the Atlantic Forest, Southern Brazil. *Rbrh*, *24*. https://doi.org/10.1590/2318-0331.241920180189

Pulighe, G., Bonati, G., Colangeli, M., Traverso, L., Lupia, F., Altobelli, F., Dalla Marta, A., & Napoli, M. (2019). Predicting Streamflow and Nutrient Loadings in a Semi-Arid Mediterranean Watershed with Ephemeral Streams Using the SWAT Model. *Agronomy*, *10*(1). https://doi.org/10.3390/agronomy10010002

Records, R. M., Arabi, M., Fassnacht, S. R., Duffy, W. G., Ahmadi, M., & Hegewisch, K. C. (2014). Climate change and wetland loss impacts on a western river's water quality. *Hydrology and Earth System Sciences*, *18*(11), 4509-4527. https://doi.org/10.5194/hess-18-4509-2014

SACEP, S. A. C.-o. E. P. (2014). Nutrient Loading and Eutrophication of Coastal Waters of the South Asian Seas - A Scoping Study.

Seager, R., Ting, M., Li, C., Naik, N., Cook, B., Nakamura, J., & Liu, H. (2012). Projections of declining surface-water availability for the southwestern United States. *Nature Climate Change*, *3*(5), 482-486. https://doi.org/10.1038/nclimate1787

Shimizu, Y. O., Shin-Ichi & Saito, Mitsuyo. (2011). Effect of Climate Change on Nutrient Discharge to Coastal area, Western Japan. *IAHS-AISH Publication*.

Shrestha, B., Babel, M. S., Maskey, S., van Griensven, A., Uhlenbrook, S., Green, A., & Akkharath, I. (2013). Impact of climate change on sediment yield in the Mekong River basin: a case study of the Nam Ou basin, Lao PDR. *Hydrology and Earth System Sciences*, *17*(1), 1-20. https://doi.org/10.5194/hess-17-1-2013

Shrestha, M. K., Recknagel, F., Frizenschaf, J., & Meyer, W. (2017). Future climate and land uses effects on flow and nutrient loads of a Mediterranean catchment in South Australia. *Sci Total Environ*, *590-591*, 186-193. https://doi.org/10.1016/j.scitotenv.2017.02.197

Shrestha, R. R., Dibike, Y. B., & Prowse, T. D. (2012). Modeling Climate Change Impacts on Hydrology and Nutrient Loading in the Upper Assiniboine Catchment. *JAWRA Journal of the American Water Resources Association*, *48*(1), 74-89. https://doi.org/10.1111/j.1752-1688.2011.00592.x

Swain, S. (2017). Hydrological Modeling through Soil and Water
Assessment Toolin a Climate Change Perspective A Brief Review. *2017 2nd International Conference for Convergence in Technology (I2CT)*, pp. 358-361. https://doi.org/doi: 10.1109/I2CT.2017.8226151

Tan, M. L., Gassman, P. W., Yang, X., & Haywood, J. (2020). A review of SWAT applications, performance and future needs for simulation of hydro-climatic extremes. *Advances in Water Resources*, *143*. https://doi.org/10.1016/j.advwatres.2020.103662

Thang, L. V., Khoi, D. N., & Phi, H. L. (2018). Impact of climate change on streamflow and water quality in the upper Dong Nai river basin, Vietnam. *La Houille Blanche*, *104*(1), 70-79. https://doi.org/10.1051/lhb/2018010

Tong, S. T. Y., Liu, A. J., & Goodrich, J. A. (2007). Climate Change Impacts on Nutrient and Sediment Loads in a Midwestern Agricultural Watershed. *Journal of Environmental Informatics*, *9*(1), 18-28. https://doi.org/10.3808/jei.200700084

Trang, N. T. T., Shrestha, S., Shrestha, M., Datta, A., & Kawasaki, A. (2017). Evaluating the impacts of climate and land-use change on the hydrology and nutrient yield in a transboundary river basin: A case study in the 3S River Basin (Sekong, Sesan, and Srepok). *Sci Total Environ*, *576*, 586-598. https://doi.org/10.1016/j.scitotenv.2016.10.138

Trolle, D., Nielsen, A., Rolighed, J., Thodsen, H., Andersen, H. E., Karlsson, I. B., Refsgaard, J. C., Olesen, J. E., Bolding, K., Kronvang, B., Søndergaard, M., & Jeppesen, E. (2015). Projecting the future ecological state of lakes in Denmark in a 6 degree warming scenario. *Climate Research*, *64*(1), 55-72. https://doi.org/10.3354/cr01278

Van Liew, M. F., Song & Pathak, Tapan. (2012). Climate change impacts on streamflow, water quality, and best management practices for the Shell and Logan Creek Watersheds in Nebraska, USA. *International Journal of Agricultural and Biological Engineering*, *5*. https://doi.org/10.3965/j.ijabe.20120501.003

Verma, S., Bhattarai, R., Bosch, N. S., Cooke, R. C., Kalita, P. K., & Markus, M. (2015). Climate Change Impacts on Flow, Sediment and Nutrient Export in a Great Lakes Watershed Using SWAT. *CLEAN - Soil, Air, Water*, *43*(11), 1464-1474. https://doi.org/10.1002/clen.201400724

Wang, R., & Kalin, L. (2018). Combined and synergistic effects of climate change and urbanization on water quality in the Wolf Bay watershed, southern Alabama. *J Environ Sci (China)*, *64*, 107-121. https://doi.org/10.1016/j.jes.2016.11.021

Wang, X., Li, Z., & Li, M. (2018). Impacts of climate change on stream flow and water quality in a drinking water source area, Northern China. *Environmental Earth Sciences*, *77*(11). https://doi.org/10.1007/s12665-018-7581-5

Wang, Y., Bian, J., Zhao, Y., Tang, J., & Jia, Z. (2018). Assessment of future climate change impacts on nonpoint source pollution in snowmelt period for a cold area using SWAT. *Sci Rep*, *8*(1), 2402. https://doi.org/10.1038/s41598-018-20818-y

Wang, Y., Jiang, R., Xie, J., Zhao, Y., Yan, D., & Yang, S. (2019). Soil and Water Assessment Tool (SWAT) Model: A Systemic Review. *Journal of Coastal Research*, *93*(sp1). https://doi.org/10.2112/si93-004.1

Wang, Y., Yang, J., Chen, Y., Fang, G., Duan, W., Li, Y., & De Maeyer, P. (2019). Quantifying the Effects of Climate and Vegetation on Soil Moisture in an Arid Area, China. *Water*, *11*(4). https://doi.org/10.3390/w11040767

Whitehead, P. G., Wilby, R. L., Battarbee, R. W., Kernan, M., & Wade, A. J. (2009). A review of the potential impacts of climate change on surface water quality. *Hydrological Sciences Journal*, *54*(1), 101-123. https://doi.org/10.1623/hysj.54.1.101

Yan, T., Bai, J., Arsenio, T., Liu, J., & Shen, Z. (2019). Future climate change impacts on streamflow and nitrogen exports based on CMIP5 projection in the Miyun Reservoir Basin, China. *Ecohydrology & Hydrobiology*, *19*(2), 266-278. https://doi.org/10.1016/j.ecohyd.2018.09.001

Yang, Q., Zhang, X., Almendinger, J. E., Huang, M., Chen, X., Leng, G., Zhou, Y., Zhao, K., Asrar, G. R., & Li, X. (2019). Climate change will pose challenges to water quality management in the st. Croix River basin. *Environ Pollut*, *251*, 302-311. https://doi.org/10.1016/j.envpol.2019.04.129

Ye, L., & Grimm, N. B. (2013). Modelling potential impacts of climate change on water and nitrate export from a mid-sized, semiarid watershed in the US Southwest. *Climatic Change*, *120*(1-2), 419-431. https://doi.org/10.1007/s10584-013-0827-z

Zhai, X., & Zhang, Y. (2018). Impact assessment of projected climate change on diffuse phosphorous loss in Xin'anjiang catchment, China. *Environ Sci Pollut Res Int*, *25*(5), 4570-4583. https://doi.org/10.1007/s11356-017-0790-8

Zhang, L., Lu, W., An, Y., Li, D., & Gong, L. (2012). Response of non-point source pollutant loads to climate change in the Shitoukoumen reservoir catchment. *Environ Monit Assess*, *184*(1), 581-594. https://doi.org/10.1007/s10661-011-2353-7