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SWAT model application for evaluating agricultural conservation practice effectiveness in reducing phosphorous loss from the Western Lake Erie Basin

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ABSTRACT

Lake Erie is threatened by eutrophication and harmful algal blooms due to excess nutrient loading from agricultural sources. Agricultural conservation practices (ACPs) have been developed and implemented to reduce nutrient losses but estimating ACP effectiveness is challenging. The Soil and Water Assessment Tool (SWAT) has been used to investigate ACP effectiveness for water quality improvement. Many SWAT applications have been developed by different investigators to evaluate ACP effectiveness for reducing nutrient, particularly phosphorus (P), loading in the agriculturally-dominated Western Lake Erie Basin (WLEB). Our objective is to establish what has been achieved by past modeling research and make suggestions for future applications and improvements. We synthesized the findings of 28 SWAT modeling studies within the WLEB. Models generally performed satisfactorily against accepted criteria for streamflow and sediment, but performance for P loads, like soluble reactive P, was mostly "unsatisfactory". The "unsatisfactory" performance maybe due to imperfections and idealizations in model formulations and/or parameterization. Thus, simulations of P transport and transformation processes need improvement. In addition, model parameter selection is the key part of model set-up. Most SWAT modeling studies used default values during initial set-up, then performed calibration and validation. It was found that the calibrated P related parameter values varied widely across different studies, even within the same watershed with some values unrealistic for the study areas. The phenomena of different combinations of model parameters producing similar outputs indicates equifinality. Equifinality in the baseline model may impact results when ACPs are incorporated. Furthermore, the unrealistic values used in ACP assessment undermine the credibility of ACP effectiveness. Future model applications should try to re-examine the calibrated P parameters and make sure they are realistic for the study area as well as reduce equifinality by constraining the model with characterization of watershed conditions, better understanding of hydrologic processes, and parameter values based on real-world observations. In summary, future model applications should focus on improving P transport and transformation processes, using measured watershed characteristics for parameterization, and improving reflections of climate change, which could result in more accurate assessments of ACP effectiveness to meet targeted goals.

1. Introduction

Pollution of water bodies with excess nutrients can lead to eutrophication, hypoxic conditions, and increased occurrences of harmful and nuisance algal blooms, all of which negatively impact drinking water quality, survival of aquatic species, ecological services, and recreational uses (Haycock and Muscutt, 1995; Verhoeven et al., 2006). For coastal and marine environments, such as the Gulf of Mexico and the Chesapeake Bay, biological production is limited more by nitrogen (N), but in freshwater environments like Lake Erie, the main limiting nutrient is phosphorus (P). In particular, soluble reactive P (SRP) is of primary concern because it is the most biologically available form of P and it has been linked to increased occurrences of HNABs in Lake Erie (Stumpf et al., 2012; Michalak et al., 2013; Baker et al., 2014; Kane et al., 2014; IJC, 2014).

Furthermore, studies have found that recent P loads are dominated by nonpoint sources (Maccoux et al., 2016) and spring P loads from agricultural lands to Lake Erie directly impacts the severity of HNABs in

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the summer (Stumpf et al., 2012; IJC, 2012; Kane et al., 2014). The predominantly agricultural Maumee River Basin (MRB), one of the major river basins in the Western Lake Erie Basin (WLEB), has been found to be a major contributor to HNABs in Lake Erie due to proportionally large sediment and nutrient inputs (Richards et al., 2002; Richards et al., 2010; Stumpf et al., 2012; Obenour et al., 2014; IJC, 2014): while the MRB supplies only 5% of the water discharging to the western basin of Lake Erie, it contributes over 50% of the total P (IJC, 2014). Therefore, the 2012 Great Lakes Water Quality Agreement has revised the Lake Erie P-loading targets; The March–July P loading targets for the MRB is 186 metric tons (0.109 kg/ha) for SRP and 860 metric tons (0.506 kg/ha) for total P (TP), or a reduction of 40% compared to 2008 loads (IJC, 1978; IJC, 2014; USEPA, 2015). These load reductions are proposed to be accomplished with widespread adoption of agricultural conservation practices (ACPs) in contributing watersheds. Thus, identifying the most effective ACPs for the WLEB is of paramount importance.

Short-term monitoring programs applied with complementary hydrologic and water quality modeling have been widely implemented to evaluate the effectiveness of ACPs, including within the WLEB. The Soil and Water Assessment Tool (SWAT) (Gassman et al., 2007; Neitsch et al., 2011; Arnold et al., 2012, 2013) has been the most widely applied hydrologic model for this purpose. In evaluating the effectiveness of ACPs, the common approach is to calibrate and validate the model using available monitoring data, then alternative scenarios (e.g., different ACPs or combinations of ACPs) are simulated, and finally results are analyzed to compare nutrient loads from different scenarios simulated. However, comprehensive hydrologic and water quality models contain a number of components and their corresponding parameters must each be subjected to calibration. Many combinations of model parameters may give the same or similar model outputs, a condition known as equifinality (Beven, 2006; Brazier et al., 2000). Equifinality in the baseline model can make it difficult to identify contributing factors for final model outputs, which leads to potential uncertainty in results from applied scenarios, such as assessments of the effectiveness of ACPs (Musau et al., 2014; Her et al., 2016).

The main goal of this literature review is to synthesize the results and performance of past SWAT modeling efforts in the WLEB to understand the model's capabilities and limitations in assessing the effectiveness of ACPs. Specific objectives are: 1) to compare sensitive P related model parameters from different modeling efforts; 2) to understand how ACP performance was evaluated; and 3) to provide insights on future model applications and improvements to avoid equifinality. The results of this literature review and synthesis can be used to aid in the development of future model applications and improvements to investigate the effects of alternative scenarios on nutrient fate and transport, including ACP implementation and climate change, in the WLEB and beyond.

2. Methods and procedures

2.1. SWAT overview

The Soil and Water Assessment Tool (SWAT) (https://swat.tamu.edu/) is a distributed, process-based computational hydrologic model designed to aid in the evaluation of watershed responses to agricultural operations and management practices. Practices are evaluated through a continuous simulation of runoff and sediment and pollutant losses from watersheds (Gassman et al., 2007; Neitsch et al., 2011). The model has been applied worldwide to solve all kinds of water quantity- and quality-related problems, including assessing the effectiveness of ACPs on P losses from the WLEB. SWAT theoretical documentation (Neitsch et al., 2011) provides a detailed description of the hydrologic processes simulated within the model.

Briefly, SWAT divides a watershed into many subwatersheds, or subbasins, which are further partitioned into a series of hydrologic response units (HRUs) by setting a threshold percentage of dominant land use, soil type, and slope group. Each HRU is assumed to be homogeneous in hydrologic response and consists of homogeneous land use, soil, slope, and management practices (Gassman et al., 2007; Williams et al., 2008; Neitsch et al., 2011). Hydrologic components, soil erosion and sediment yield, and nutrient cycles are simulated for each HRU, and yields from HRUs are aggregated for subwatersheds. Runoff, sediment, and chemicals are then routed from each subwatershed through a channel network to the outlet of the simulated watershed. The model has gone through many updates and iterations, but at its core the model software directly reads and simulates the loading of water, sediment, and other constituents from defined land areas to stream reaches and the watershed outlet.

2.2. Phosphorus simulation in SWAT

The fate and transport of nutrients in a watershed depend on nutrient cycling in the soil environment (in-field) and stream channels (instream). SWAT models the P cycle within both field and stream environments. The P cycle is a dynamic feedback system of P movement and interactions between the soil and water environments. In summary, SWAT simulates six different pools of P in soils. There are three pools of inorganic (mineral) forms of P – stable, active, and solution – and three pools of organic forms of P – active organic P, stable organic P associated with humic substances, and fresh organic P associated with crop residues (Figure S2.1 in Supplemental Materials).

Phosphorus may be added into the soil by crop residues, manure, or inorganic P fertilizer applications to agricultural fields, where inorganic P fertilizer applications add to the inorganic solution P pool in the soil. Phosphorus can be removed from the soil by plant uptake, surface runoff, erosion and sediment transport, and leaching (Figures S2.1 and S2.2 in Supplemental Materials). In SWAT, these processes are controlled by parameters such as P_UPDIS, the P uptake distribution parameter, PHOSKD, the P soil partitioning coefficient, PSP, the P availability index, and PPERCO, the P percolation coefficient. These parameters are discussed more in depth later in this review. After crops are harvested and the residue is left on the ground, decomposition and mineralization of the fresh organic P pool occur in the uppermost soil layer, controlled in SWAT by CMN, the rate factor for humus mineralization of active organic nutrients. Decomposition breaks down fresh organic crop residues into simpler compounds, which are organic, plant-unavailable forms of P. Mineralization is the microbial conversion of organic, plant-unavailable P to inorganic, plant-available P (e.g., inorganic solution P, or SRP), which can be used by plants or transported from fields via surface runoff and leaching.

Plant utilization of P is estimated with a supply and demand approach. A plant's daily P demand is estimated as the difference between the actual P concentration in the plant and the optimal P concentration for plant growth, which varies with plant species and growth stage (Jones, 1983). The actual P uptake is the minimum value of the inorganic solution P content in the soil and the sum of potential P uptake and the P uptake demand not met by surface soil layers. In addition to plant usage, leaching and mass flow of water and sediments (surface runoff) may carry soluble P and organic P off of fields to surface waters. The actual amount of soluble P in surface runoff is estimated using the concentration of solution P in the top 10 mm of the soil, runoff volume, and a partitioning coefficient, which is the ratio of the soluble P concentration in the soil surface layer to the concentration of the soluble P in surface runoff. The amount of P transported with sediment is associated with sediment loss from fields, the concentration of P attached to sediment in the top 10 mm, and the P enrichment ratio, which is the ratio of the concentration of organic P transported with the sediment to the concentration in the soil surface layer.

2.3. Literature search on SWAT applications in the WLEB

For this review and synthesis, a search of the available literature was performed to gather relevant peer-reviewed research articles that applied SWAT to investigate water quality trends in the WLEB. The literature search was conducted from February to July 2020, and the following keywords were used as search inputs for Google Scholar, Web of Science, and Science Direct: "SWAT," "model," "Lake Erie," "western basin," "Maumee," "agricultural conservation practice," "water quality," "SRP," and "nutrient load." The scope of the literature search and review was limited to peer-reviewed research articles on hydrologic simulation modeling conducted using SWAT in the region of interest (WLEB) and published in English between 2000 and 2019.

A total of 28 research articles (Table S1.1 in Supplemental Materials) were found based on the criteria listed above, which modeled hydrology and water quality trends in WLEB watersheds and evaluated the effects of ACPs, land use, or climate change on water quality and quantity. For each SWAT application, where available, we collected information on: 1) input data sources and model set-up details; 2) model calibration and validation methods; 3) important model parameter values after calibration; 4) model performance measures and statistics; and 5) ACP modeling methods and effectiveness results. Information was extracted from the main article text, in-text tables and figures, and Supplemental Materials and compiled into summary tables and analyzed to gain insights on the input data and sources, calibrated parameter values, scenario results, and performance of the models applied in those SWAT modeling studies.

2.4. Watersheds where SWAT models were applied

The WLEB is defined as the collection of watersheds that drain into Lake Erie's western basin and covers over 27,000 km^2 in northwestern Ohio, eastern Indiana, and southeastern Michigan. These watersheds consist of the drainage areas for the following major rivers: the Huron, Raisin, Maumee, Portage, and Sandusky Rivers. The WLEB also includes the smaller subbasins within these larger watersheds, such as the Tiffin and St. Joseph River basins in the Maumee watershed. A majority of the land within the WLEB is agricultural row crop lands, with some major urban areas, such as the cities of Fort Wayne, IN and Toledo, OH (USDA NRCS, 2020). Climate in this region is influenced by regional dynamics as well as lake effects. The average annual temperature across the WLEB (Indiana, Ohio, and Michigan) is about 5.4 °C, and the average annual precipitation is about 924 mm (NOAA NCDC, 2020) and it increases slightly from west to east due to more lake-effect (Bosch et al., 2011).

The reviewed studies modeled one or more of the WLEB watersheds listed above or their smaller subwatersheds. A few studies also included models of the Cuyahoga or Grand River watersheds, which are not actually part of the WLEB but are instead contributing watersheds to the Central Lake Erie Basin. Fig. 1 shows the watershed areas and major rivers modeled in the reviewed research articles, as well as the locations of the United States Geological Survey (USGS) gaging stations used for SWAT model calibration and validation (Tables S1.2 and S1.3 in Supplemental Materials). Some USGS monitoring stations for major rivers, such as station number 04193500 near the outlet of the Maumee River, were used for model calibration across multiple studies.

The bedrock geology of the western basin of Lake Erie mainly consists of Devonian-age dolomite and limestone (ODNR, 2018). When Lake Erie formed from glacial advance and retreat, this bedrock was more resistant to weathering compared to the central and eastern basins, which consist of less resistant shale (ODNR, 2018). This difference in geological make-up contributed to the varying bathymetry of the basins of Lake Erie, with the western basin being shallower and therefore warmer and more biologically active, and the central and eastern basins being deeper and cooler. Part of the WLEB, namely the Maumee River Basin, was prehistorically part of the Great Black Swamp (Mitsch and Gosselink, 2007; ODNR, 2018), which has left soils in the area fertile and poorly drained (Table 1). Many of the agricultural lands in the WLEB have subsurface drainage systems installed to mitigate oversaturation and pooling due to prevailing hydrologic soil conditions, although there is no widespread data available on the extent or area percentage of subsurface drained lands.

The most common land use within the WLEB is agricultural row crops, which make up approximately 70% of the total land area (Table 2; USDA NASS, 2018). The most common agricultural land use categories in the WLEB are corn and soybean, which are often planted in a two-year annual crop rotation (ODA, 2019; USDA NASS, 2018). Generally, corn is planted in spring (April–June) and harvested in fall (September–November), and soybean is planted the following spring and harvested the following fall (ODA, 2019). In some instances, wheat is included in the rotation as a winter crop, planted in fall (September–November) and harvested the following spring (June–August), just before corn or

Table 1
Percent land area coverage for soil hydrologic groups across the WLEB (USDA NRCS, 2020). A = low runoff potential (high infiltration), B = moderately low runoff potential, C = moderately high runoff potential, D = high runoff potential (low infiltration), dual = drained/undrained condition.

Watershed	Soil hydrologic group						
	A	B	C	D	A/D	B/D	C/D
Maumee	3.0%	2.9%	5.0%	40.8%	2.9%	6.9%	38.5%
Sandusky	1.1%	3.3%	7.2%	29.9%	0.4%	9.2%	48.9%
Raisin	8.7%	11.1%	10.3%	17.3%	6.8%	8.0%	37.9%
Huron	19.5%	26.9%	14.4%	4.4%	18.0%	7.0%	9.8%
Portage	3.8%	1.8%	1.1%	13.8%	0.7%	5.3%	73.5%
Total	4.7%	5.6%	6.4%	32.7%	4.1%	7.2%	39.3%

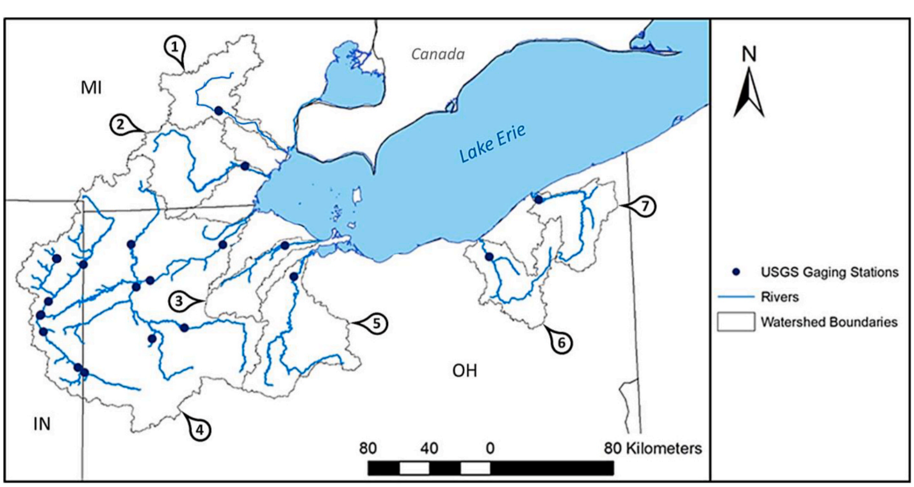

Fig. 1. Map showing the major watersheds investigated in the reviewed studies and locations of USGS gaging stations used for calibration in the models. The major river watersheds are labeled as follows: (1) Huron, (2) Raisin, (3) Portage, (4) Maumee, (5) Sandusky, (6) Cuyahoga, and (7) Grand. MI = Michigan, IN = Indiana, OH = Ohio. (Watershed boundaries and stream vectors were obtained from the USGS NHD, https://www.usgs.gov/core-science-systems/ngp/national-hydrography, and gaging station locations were obtained from the USGS NWIS site inventory, https://waterdata.usgs.gov/).

Table 2
Percent land area coverage for major land use categories across the WLEB (USDA NASS, 2018).

Watershed	Land use category								
	Soybean	Corn	Developed	Forested	Winter Wheat	Alfalfa	Woody Wetlands	Grassland/Pasture	Other
Maumee	39.2%	23.3%	11.1%	8.2%	4.6%	1.6%	2.0%	6.8%	3.1%
Sandusky	41.6%	27.3%	8.4%	10.4%	3.9%	1.1%	0.0%	4.7%	2.6%
Raisin	25.2%	19.2%	11.0%	13.6%	5.2%	3.5%	6.9%	9.9%	5.5%
Huron	5.1%	3.6%	31.9%	26.3%	1.4%	2.1%	12.8%	8.8%	8.0%
Portage	45.4%	23.0%	9.2%	6.2%	5.4%	2.3%	0.0%	3.9%	4.7%
Total	35.5%	21.7%	12.4%	10.5%	4.4%	1.8%	3.1%	6.9%	3.8%

soybean planting or after they have been inter-seeded, depending on individual farm practices (ODA, 2019).

3. Results and discussion

Objectives of SWAT model applications in the WLEB can be summarized as: 1) model evaluation to inform future studies on the applicability of SWAT for predicting tributary sediment and nutrient loads; 2) model application to assess the impact of climate change on hydrology and nutrient yield under different emission scenarios; 3) model application to present a procedure for the representation and evaluation of hydrologic and water quality impacts of ACPs; 4) model application to evaluate the effectiveness of ACPs at different implementation extents in reducing sediment and nutrient loads; 5) model application to examine how climate change will affect the effectiveness of ACPs; 6) To develop optimal cropping patterns for sustainable bioenergy production; 7) To integrate SWAT and ACP cost estimation tool to evaluate nutrient reduction effectiveness and cost effectiveness of different ACPs. Detailed objectives for each study can be found in the Supplemental Materials (Table S1.5). Regardless of the objectives of each modeling study, the primary task is to setup the model. The section next discusses model setup including model inputs (e.g. weather, digital elevation model, soil, land use and land management) and their sources as well as model parameters (e.g. curve number, the support practice factor, P uptake distribution parameter) and their selections.

3.1. SWAT model set-up

3.1.1. Model inputs and sources

Most of the SWAT applications in the WLEB used the same or similar data sources for model inputs. For example, elevation data were sourced from the USGS National Elevation Dataset and were most commonly in 30 m × 30 m resolution. In addition, soil coverage data were sourced from either the State Soil Geographic Database (STATSGO) or Soil Survey Geographic database (SSURGO) datasets from the United State Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS). Weather data were mostly sourced from nearby National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC) weather stations. Land use/land cover data came from the USGS National Land Cover Database and/or the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer datasets. A more detailed breakdown of input data sources from the reviewed SWAT modeling studies can be found in the Supplemental Materials (Table S1.4).

Monitoring data for streamflow and water quality constituents used for model calibration and validation were commonly sourced from USGS stream gaging stations (Fig. 1; Tables S1.2 and S1.3 in Supplemental Materials). Some of these USGS gaging stations also corresponded to more detailed stream monitoring data (i.e., water quality constituent concentrations) collected through the National Center for Water Quality Research (NCWQR) at Heidelberg University in Tiffin, OH (https://www.ncwqr.org). For some studies, monitoring data used in model calibration and validation came from smaller subwatershed research initiatives, state agencies, or USDA NRCS data collected as part of the Conservation Effects Assessment Project (CEAP) (https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/technical/nra/ceap/). Studies also estimated constituent loads from these stream monitoring data through software like USGS's load estimator, a Fortran program for estimation constituent loads in streams and rivers (https://water.usgs.gov/software/loadest/doc/), or Fluxmaster, a regression method to estimate long-term mean annual loads (Saad et al., 2019), for use in model calibration and validation.

3.1.2. Initial model set-up

Details on model set-up for each study can be found in the Supplemental Materials (Table S1.5), including simulation period, watershed delineation, and ACPs evaluated. Model parameter selection (model parametrization) is key during initial model set-up because proper parameter selection not only reflects how accurately the model represents a studied watershed, but also facilitates model calibration and validation. The first important group of model parameters relates to flow generation, which transports sorbed and dissolved nutrients leaving agricultural fields. The Soil Conservation Service (SCS) runoff curve number (CN), is one of the most important parameters in this group. The CN, a measure of the proportion of precipitation which runs off the ground surface, is a function of soil permeability, land use, and land management conditions (Rallison and Miller, 1982) and is adjusted according to soil moisture conditions (Arnold et al., 2013). The CNs for various agricultural and urban land use categories are listed in Section 2 of the Supplemental Materials (Tables S2.1 and S2.2, respectively).

Other important model parameters that influence overland flow and streamflow besides curve number include, but are not limited to: Manning's "n" value for the main stream channel, the surface runoff lag coefficient, the soil evaporation compensation factor, the plant uptake compensation factor, and effective hydraulic conductivity (Section 2 of Supplemental Materials). Previous studies have found through sensitivity analyses that these parameters are directly related to how well models perform in terms of simulated versus observed streamflow in the WLEB at the stream reach and whole-watershed scales.

The second important group of model parameters relates to soil erosion and sediment transport, which impact the loss of sediment-attached nutrient species. The modified Universal Soil Loss Equation (USLE), which represents expected soil erosion based on land use and slope characteristics, is used in SWAT. Multiple SWAT model parameters represent individual factors in the original USLE function: 1) the support practice, or P, factor; 2) the soil erodibility, or K, factor; and 3) the cover and management, or C, factor (Tables S2.5-S2.8 in Supplemental Materials). In SWAT, possible values for these factors can range from −1 to 1. Expected values for USLE_P for varying slopes under different management conditions and USLE_C for varying crop types are listed in the SWAT model documentation (Arnold et al., 2013).

The last important group of model parameters relates to P transformation and transport, which directly impacts P losses from agricultural fields. The model parameters, and their specifications to capture biogeochemical processes in a watershed are described in detail in the SWAT model Input/Output Documentation (Arnold et al., 2013). We summarized sensitive P parameters along with their definitions, ranges, and default values used in SWAT modeling studies that reported them

Table 3
Parameters related to P processes from SWAT modeling studies that reported them.

Reference	Watershed	P Species simulated	SWAT Model parameter	Definition	Min	Max	Initial value	Calibrated value
Cousino et al. (2015)	Maumee	TP, SRP	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.007
Culbertson et al. (2016)	Maumee	TP, SRP	P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	40.81
Daloğlu et al. (2012)	Sandusky	TP, SRP, OrgP	PHOSKD.bsn	Phosphorus soil partitioning coefficient	100	1000	175.0	292.63
			PSP.bsn	Phosphorus availability index	0.01	0.7	0.4	0.440
			P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	20.0
			PPERCO.bsn	Phosphorus percolation coefficient	10.0	17.5	10.0	5.48
Gildow et al. (2016)	Maumee	TP, SRP	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.004
			PHOSKD.bsn	Phosphorus soil partitioning coefficient	100	1000	175.0	250
			PSP.bsn	Phosphorus availability index	0.01	0.7	0.4	0.29
			P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	28
			PPERCO.bsn	Phosphorus percolation coefficient	10.0	17.5	10.0	10
			SOL_ORGP.chm	Initial organic phosphorus concentration in soil layer	–	–	–	50
			RSDCO.bsn	Residue decomposition coefficient	0.01	0.1	0.05	0.041
			ERORGP.hru	Phosphorus enrichment ratio for loading with sediment	–	–	–	1
			GWSOLP.gw	Concentration of soluble phosphorus in groundwater contribution to streamflow from subbasin	–	–	–	0.157
Her et al. 2016	St. Joseph (subbasin of Maumee)	TP	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.0042
			PHOSKD.bsn	Phosphorus soil partitioning coefficient	100	1000	175.0	1000[a]
			PSP.bsn	Phosphorus availability index	0.01	0.7	0.4	0.80
			P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	382[a]
			PPERCO.bsn	Phosphorus percolation coefficient	10.0	17.5	10.0	10.1
			RSDCO.bsn	Residue decomposition coefficient	0.01	0.1	0.05	0.1
			CMN.bsn	Rate factor for humus mineralization of active organic nutrients	0.0001	0.005	0.0003	0.0001
			SOL_SOLP(1).chm	Initial soluble phosphorus concentration in soil layer	–	–	5	11
Kalcic et al. (2019)	Maumee	TP, SRP	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.000273
			ANION_EXCL.sol	Fraction of porosity from which anions are excluded	0	1	0.5	0.1
			SOL_SOLP(1).chm	Initial soluble phosphorus concentration in soil layer	–	–	5	1[a]
Liu et al. (2019)	AXL (subbasin of Maumee)	TP, SRP	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.0015
			PHOSKD.bsn	Phosphorus soil partitioning coefficient	100	1000	175.0	128.7
			PSP.bsn	Phosphorus availability index	0.01	0.7	0.4	0.01[a]
			P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	41.2
			PPERCO.bsn	Phosphorus percolation coefficient	10.0	17.5	10.0	10.38
			CMN.bsn	Rate factor for humus mineralization of active organic nutrients	0.0001	0.005	0.0003	0.003
Mehan et al. (2019)	Matson Ditch/AXL (subbasin of Maumee)	TP, mineral (soluble) P	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.01
			PHOSKD.bsn	Phosphorus soil partitioning coefficient	100	1000	175.0	100
			PSP.bsn	Phosphorus availability index	0.01	0.7	0.4	0.7
			P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	0.5[a]
			PPERCO.bsn	Phosphorus percolation coefficient	10.0	17.5	10.0	17
			CMN.bsn	Rate factor for humus mineralization of active organic nutrients	0.0001	0.005	0.0003	0.003
Merriman et al. (2018)	Eagle Creek (subbasin of Maumee)	TP, SRP	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01	0.0001	0.003
			PHOSKD.bsn	Phosphorus soil partitioning coefficient	100	1000	175.0	112.023
			PSP.bsn	Phosphorus availability index	0.01	0.7	0.4	0.84
			P_UPDIS.bsn	Phosphorus uptake distribution parameter	0	400	20.0	200.726
			PPERCO.bsn	Phosphorus percolation coefficient	10.0	17.5	10.0	14.965
			SOL_SOLP.chm	Initial soluble phosphorus concentration in soil layer	–	–	–	20
			SOL_ORGP.chm	Initial organic phosphorus concentration in soil layer	–	–	–	100

(*continued on next page*)

Table 3 (*continued*)

Reference	Watershed	P Species simulated	SWAT Model parameter	Definition	Min	Max	Initial value	Calibrated value
			RSDCO.bsn	Residue decomposition coefficient	0.01	0.1	0.05	0.063
			CMN.bsn	Rate factor for humus mineralization of active organic nutrients	0.0001	0.005	0.0003	0.002
			ANION_EXCL.sol	Fraction of porosity from which anions are excluded	0	1	0.5	0.36

[a] Those values are not realistic.

(Table 3), however not all of the reviewed studies disclosed the model parameter values and specifications used in their model. More details on initial model settings and sensitive parameters can be found in the Supplemental Materials (Tables S1.5-S1.8. in Supplemental Materials).

3.2. Model sensitivity analysis, uncertainties, calibration and validation

Many SWAT modeling studies performed sensitivity analyses to determine sensitive parameters which directly impact streamflow (Table S1.6 in Supplemental Materials) and P losses (Tables S1.7 and S1.8 in Supplemental Materials). For example, the P percolation coefficient (PPERCO) which represents the ratio of the solution P concentration in the near soil surface to the solution P concentration in the percolate, was one of the most important parameters to P losses. Additionally, the P soil partitioning coefficient (PHOSKD), which represents the ratio of the soluble P concentration in the near soil surface to the soluble P concentration in surface runoff, is another sensitive parameter to P losses. The P partitioning coefficient reflects the mobility of solution P which occurs primarily by diffusion, and its interactions with surface runoff. Methods have been developed to determine realistic values of the P partitioning coefficient based on soil characteristics that can be found in widely used databases, i.e., STATSGO and SSURGO (Radcliffe et al., 2015; Vadas and White, 2010).

Model uncertainty is uncertainty due to imperfections and idealizations made in model formulations including simplifying assumptions, unknown boundary conditions, and the unknown effects and interactions of parameters, as well as uncertainty in the model parameterization. It is an inevitable part of watershed modeling due to the complexity and heterogeneity of the nature we model. However, assessing model uncertainty is very challenging; thus, none of the SWAT modeling studies that we reviewed on the WLEB included information and discussion on their model uncertainty.

For calibration and validation, the SWAT modeling studies followed recommended methods and software applications, including the use of SUFI2 auto-calibration in the SWAT-CUP software (https://swat.tamu.edu/software/swat-cup/), additional manual calibration, and the use of concentration and/or loading data from multiple monitoring stations where applicable. Model calibrations were performed sequentially, with streamflow first, followed by suspended sediment, and finally various nutrient species (Santhi et al., 2001). In addition to widely used statistical model performance measures (Moriasi et al., 2007, 2015), some of the reviewed studies reported secondary methods of model confirmation, such as visual evaluation of graphical data fit (Daggupati et al., 2015), calibration using other outputs such as crop yields (Xu et al., 2018) or groundwater flow (Qi and Grunwald, 2005), or the use of other spatial calibration methods instead of or in addition to the watershed outlet. We summarized calibrated model parameter values in Table 3 and Table S1.8 (Supplemental Materials), and they are further discussed in Section 3.4.

3.3. Model performance evaluation

For evaluations of model performance, simulated values were usually compared with observed values including mean annual/monthly streamflow and loads (Table S1.9 in Supplemental Materials), as well as time series comparisons. The performance of SWAT in the SWAT modeling studies was mainly determined based on Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and percent bias (PBIAS) statistical analyses. The NSE ranges from $-\infty$ to 1, with 1 representing a perfect match between simulated and observed values, and is effective in predicting seasonal peaks and temporal trends in water quantity and quality. PBIAS is better at reflecting overall watershed responses, like average flow rates, with the best value being 0%. Moriasi et al. (2007, 2015) developed corresponding descriptive model performance ratings for each of these statistics, as well as for the correlation coefficient (R^2) and RSR (the ratio of the root mean square error to the standard deviation of measured data).

The descriptive ratings developed by Moriasi et al. (2007, 2015) range from “unsatisfactory” to “very good” based on determined accepted ranges of statistical values. The calibration and validation performance for SWAT are considered acceptable when NSE and R^2 are greater than 0.50 (Moriasi et al., 2007). The SWAT model performance is “satisfactory” when NSE ranges from 0.50 to 0.65, “good” when NSE ranges from 0.65 to 0.75, and “very good” when NSE is larger than 0.75 (Moriasi et al., 2007). For hydrology, the SWAT model performance is rated as “satisfactory” when the absolute value of PBIAS ranges from 15 to 25, “good” when ranging from 10 to 15, and “very good” when it is less than 10 (Moriasi et al., 2007).

Most of the SWAT modeling studies on various WLEB watersheds performed at least at the “satisfactory” level, while some performed at the “unsatisfactory” level (Table S1.10 in Supplemental Materials) – simulated discharge and loads matched relatively well with observed values over the baseline simulation periods (Table S1.9 and Figure S1.1 in Supplemental Materials). Generally, models of watersheds dominated by agricultural land uses performed better than models of watersheds with other predominant land use categories, like urban or forested lands (e.g., Bosch et al., 2011; Keitzer et al., 2016; Yen et al., 2016). For example, in their development of SWAT models for multiple contributing watersheds of Lake Erie, Bosch et al. (2011) found that their model of the Maumee River watershed (81% agricultural) performed better for all variables (flow, sediment, total P, etc.) than the models for the Huron and Cuyahoga River watersheds (27% and 17% agricultural, respectively).

Studies also indicated that it was easier to calibrate models for variables like streamflow and sediment load compared to dissolved nutrient species, i.e., SRP, which may undergo more complex cycling and transport processes (e.g., Arabi et al., 2006; Bosch et al., 2011; Xu et al., 2018). Overall, of SWAT modeling studies that reported model calibration performance statistics, the majority of models performed at the “good” or “very good” levels for flow, and sediment, while the majority of models performed at the “unsatisfactory” or “satisfactory” levels for total P (TP), and SRP; one-quarter to one-third of the models performed unsatisfactorily for TP, and SRP (Table 4; Table S1.10 in Supplemental Materials). These performance ratings became worse for validation, with more models performing at the “unsatisfactory” level for TP, and SRP (Table 5). Since some of the reviewed studies reported performance analyses for more than one watershed, there were more NSE performance results than total reviewed studies (e.g., there were 45 values for flow calibration from 28 total studies).

Even for those models which performed satisfactorily for TP, and

Table 4
Calibration performance results from WLEB SWAT modeling studies that reported NSE for various water quantity and quality variables. This table shows the number of SWAT models that performed within a certain rating category (Moriasi et al., 2007, 2015) for each variable.

Variable	Range	Unsatisfactory NSE ≤0.50	Satisfactory 0.50 < NSE ≤0.65	Good 0.65 < NSE ≤0.75	Very Good 0.75 < NSE ≤1.00
Flow	0.31–0.95	1	4	15	25
Sediment	0.25–0.92	1	6	4	7
TP	−9.63–0.97	8	7	8	4
SRP	−38.26–0.95	4	8	0	4

Table 5
Validation performance results from reviewed WLEB modeling studies that reported NSE for various water quantity and quality variables. This table shows the number of SWAT models that performed within a certain rating category (Moriasi et al., 2007, 2015) for each variable.

Variable	Range	Unsatisfactory NSE ≤0.50	Satisfactory 0.50 < NSE ≤0.65	Good 0.65 < NSE ≤0.75	Very Good 0.75 < NSE ≤1.00
Flow	0.40–0.96	6	7	9	28
Sediment	−0.97–0.89	6	3	9	5
TP	−46.12–0.93	17	1	4	9
SRP	−182.45–0.96	7	4	3	2

SRP, model parameters related to P varied widely, which indicates equifinality. Equifinality is a phenomenon where multiple combinations of model parameter values may produce similar outputs and model performance results. More discussion on equifinality can be found in Section 3.4. Since P cycling and transformation processes are more complex, there has been an ongoing effort to improve understanding of their fate and transport, as well as the mathematical simulations of these processes. This issue is particularly pertinent for dissolved species, such as SRP, given their effects on HNABs and eutrophication in downstream water bodies, in order to accurately evaluate ACP implementation scenarios to mitigate these nutrient losses (Stumpf et al., 2012; Michalak et al., 2013; Baker et al., 2014; IJC, 2014; Kane et al., 2014).

Model performance was also influenced by the availability and frequency of monitoring data, as well as resolution of input data sources (Daggupati et al., 2015; Yen et al., 2016; Xu et al., 2018). Performance of models using climate projections can be affected by the choice of climate model ensembles and the application of bias corrections (Muenich et al., 2016; Wallace et al., 2017; Xu et al., 2018; Kalcic et al., 2019; Mehan et al., 2019). Additionally, routing of dissolved nutrient species through subsurface drainage in SWAT has been found to require further improvement to better reflect the processes that control flow through the subsurface, such as preferential flow paths in soil (Kalcic et al., 2019; Wang et al., 2020).

Even with those “satisfactory” to “very good” performance measures, which are a reflection of how closely simulated results correspond to observed data, these determinations do not necessarily indicate that the model accurately represented real-world conditions and processes (More on model parameter values used in SWAT modeling studies will be discussed in the next section). Thus, a calibration and/or validation deemed “satisfactory” for a given constituent does not mean that the model would accurately simulate the expected changes when ACPs are incorporated. Additionally, researchers have found that SWAT tends to underestimate extremely high flows and loads and overestimate extremely low flows (e.g., Gebremariam et al., 2014). This uncertainty could contribute to ongoing problems with accurate modeling of watershed nutrient fate and transport dynamics, especially since extreme weather events are projected to become more frequent with future changes in climate and have been correlated to greater nutrient loading to Lake Erie and subsequent HNAB severity (Hayhoe et al., 2010; Michalak et al., 2013; Kalcic et al., 2019).

3.4. Important model parameters and their calibrated values

This section discusses the calibrated P parameter values reported by the WLEB SWAT modeling studies (Table 3). More details on the calibrated model parameter values can be found in the Supplemental Materials (Table S1.8). The information discussed here was gathered from the text, in-text tables, and associated Supplemental Materials of the SWAT modeling studies.

Some the SWAT modeling studies reported calibrated P parameter values for their watershed models (Table 3; Fig. 2). In some cases, the calibrated parameter values did not differ very much from the default values assigned by the initial model set-up (Table 3; Supplemental Materials). For example, the P uptake distribution parameter, which controls plant uptake of P from different soil horizons. The higher value means higher percentage of P taking from surface layer. Among the seven studies that reported the calibrated P uptake distribution parameter values, five reported values ranging from 0 to 42 (default: 20.0); whereas the other two, the models developed by Her et al. (2016) and Merriman et al. (2018), had calibrated P uptake distribution parameter values of 382 for the St. Joseph River watershed and 201 for the Eagle Creek watershed, respectively (Table 3). This variation in values for the same model parameter among different SWAT modeling studies was observed for other parameters, and even within the same watershed (i.e., the Maumee River Basin). For example, Kalcic et al. (2019) reported a value of one for initial soluble P concentration in soil layer, whereas Merriman et al. (2018) reported a value of 20 – both of these studies modeled agriculturally dominated Maumee River Basin (Table 3). A value of one for the initial soluble P concentration in soil layer wouldn’t be a realistic value for any watersheds within the WLEB because studies show that there is P buildup in soils, which led increased P losses from agricultural fields in this area (Muenich et al., 2016; Williams et al., 2016; King et al., 2017).

This finding that model parameter values varied widely across modeling studies, even within the same watershed, indicates equifinality. This phenomenon reflects a high level of interaction between parameters in the model. Equifinality may interfere with a model’s reliability, particularly for alternative scenarios such as evaluations of ACP effectiveness. Even though the performance of the calibrated baseline model may be “satisfactory,” it may not be representative of real-world watershed conditions and processes. Thus, this may subsequently impact the credibility or uncertainty of model outputs for scenario comparisons because those results may have been achieved by a different combination of parameters in a flawed model and not necessarily from the scenarios being tested, especially when the evaluated ACPs directly interact with calibrated parameters.

To develop more representative models that can be reliably applied to find solutions to water quantity and quality issues, modelers should try to reduce equifinality by examining the meaning behind model parameter values and evaluating how realistic the calibrated values are for any given watershed conditions. For example, for the P availability index (PSP), possible values can range from 0.01 to 1.0, and the default initial value is 0.40, indicating that 40% of the P in the soil is available for plant uptake after fertilizer application. While Gildow et al. (2016) set their value for PSP for the Maumee River watershed to 0.29, other researchers modeling subbasins of the same watershed used very different values – Liu et al. (2019) set PSP to 0.01 for the AXL (HUC12 = 041000030603) watershed, Mehan et al. (2019) set PSP to 0.70 for the same watershed, and Merriman et al. (2018) set PSP to 0.84 for a similar subwatershed of the Maumee, the Eagle Creek watershed (Table 3). Of these values for PSP, 0.01 seems to be the least realistic for a highly agricultural but heterogeneous catchment where a large amount of P

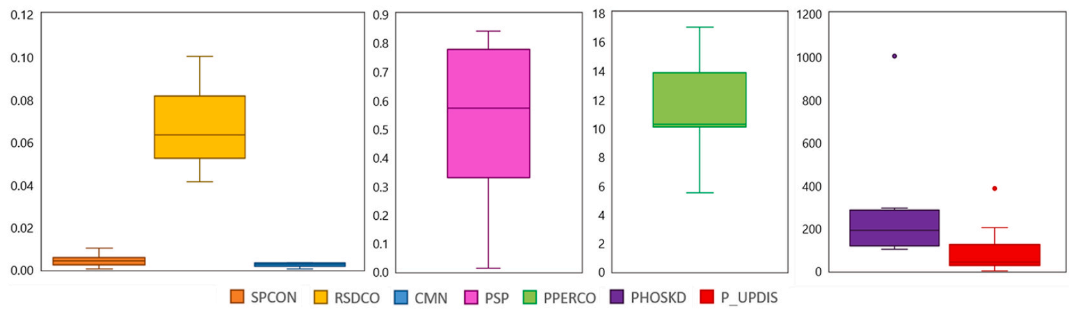

Fig. 2. Box plots showing the distribution of values for select sensitive calibrated SWAT model parameters for P reported by the SWAT modeling studies. The top line represents the 90th percentile, the top edge of the box is the 75th percentile, the middle line is the median, the bottom of the box is the 25th percentile, the bottom line is the 10th percentile, and dots represent outliers. More details, definitions, and sample sizes can be found in Table 3.

fertilizer was applied. For the Maumee, it would make sense for the value of PSP to be slightly higher, such as 0.70 or 0.84, due to influential prevailing watershed characteristics, i.e. the large proportion of agricultural row crops, widespread applications of inorganic P fertilizer to these row crops, and the existence of large pools of legacy P from past management practices. At least for PSP, this parameter can be verified with empirical data from soil P extraction assays. The process of verification for other parameters may not be as straightforward, so integration of other types of observations or sources may be required.

For the P soil partitioning coefficient, the ratio of the solution P concentration in the surface 10 mm of the soil to the concentration of the P in surface runoff, the possible model range is 100–1000, with an initial model default value of 175 in SWAT. Whereas Gildow et al. (2016) set their value at 250 for their model of the Maumee River watershed, Liu et al. (2019), Mehan et al. (2019), and Her et al. (2016)set it to 129, 100, and 1000, respectively, for nearby subwatersheds of the Maumee (Table 3). In this case, a value as high as 1000 may not be realistic for this region and would indicate that there is much more soluble P in the uppermost soil layer but very little soluble P in surface runoff. An important factor that may influence this soil partitioning parameter is the prevalence of agricultural practices that contribute to soil stratification, such as no-till and reduced till practices. A high degree of soil stratification due to no-till has the potential to redirect P, especially SRP, through subsurface drains rather than through surface runoff (Jarvie et al., 2017; Ni et al., 2020), which impact the P percolation coefficient, the ratio of the solution P concentration in the surface 10 mm of the soil to the concentration of the P in percolate, another model parameter like the P soil partitioning coefficient. Both parameters are measurable, particularly SRP in surface runoff. Based on the large amount of P loss to the Lake Erie, P soil partitioning coefficient is likely to be less than the maximum value of 1000 and may be closer to the model default of 175.

Additionally, reported calibrated values for the P uptake distribution parameter ranged from 0.5 (Mehan et al., 2019) to 28 (Gildow et al., 2016) to 41.2 (Liu et al., 2019) to 382 (Her et al., 2016) among the SWAT modeling studies that reported this parameter values (Table 3). For the P uptake distribution parameter, the possible model values can range from 0 to 400, with a default value of 20.0. This parameter controls the maximum amount of solution P removed from the soil upper layers, where it interacts with surface runoff. For the Maumee River Basin, a value as low as 0.5 is probably not realistic, where there are likely large amounts of legacy P in soil surface layers and large amounts of labile P available for plant uptake and transport via surface runoff (Muenich et al., 2016). However, the P uptake distribution parameter is also not likely to be as high as 382, as this would mean most of the P in the soil surface is available to be transported via surface runoff, whereas many agricultural fields in the region utilize subsurface drainage systems that help soils drain and redirect water that would otherwise pool in fields.

Determining model parameters such as PSP, P soil partitioning coefficient and P percolation coefficient, and P uptake distribution parameter, at a watershed scale can be very challenging. Soil testing is one way of gaining some of those values. Location, timing, and method of sampling impact the values that would be obtained from soil testing (Self and Soltanpour, 2004). However, soil testing may not be a feasible way to gain soil P values at a watershed scale because of limited resources. First, a watershed may include thousands of fields. Second, each field has different soil types and field managements. Third, P level may vary from one spot to another within a field. Consequently, obtaining accurate values that also represent the entire watershed is challenging. Therefore, uncertainty is an inevitable part of modeling. Regardless of the challenges in field estimation of model parameter values, one can rely on literature values for setting up parameter boundaries. For example, studies show that soil test P levels are usually greater than 50 mg kg^{-1} for the top 50 cm soil and are higher as it close to soil surface (King et al., 2015). Literature values show that total P in surface soils ranges from 50 to 1500 mg kg^{-1} and decreases with depth, and organic P typically varies between 15% and 90% of the total P in soils (Havlin et al., 1999). Thus, setting up one for the initial soil soluble P is not realistic.

3.5. Model application for evaluating effectiveness of ACPs

3.5.1. Overview of modeling methods

Most of the SWAT modeling studies simulated one or more ACPs, including those studies that simply documented the development of watershed models or those that evaluated the impacts of future climate change scenarios on nutrient loading. The main ACPs simulated were: cover crops, conservation tillage (no-till), filter strips, and nutrient management (adjusting fertilizer application rates) (Table S1.11 in Supplemental Materials), which are all field scale ACPs. Implementation of ACPs varied across studies, but applications commonly implemented ACPs on varying percentages of land area in the modeled watershed, targeted ACP implementation to critical source areas with high nutrient loads, or compared individual vs. combinations of ACPs in the same watershed. Other scenarios included varying levels of projected climate change severity (e.g., Bosch et al., 2014; Cousino et al., 2015; Culbertson et al., 2016) or implementation of ACPs corresponding to farmer survey input (e.g., Palm-Forster et al., 2016; Pyo et al., 2017).

Multiple studies and model documentation have discussed methods for modeling ACPs in SWAT. For example, for conservation tillage practices, many of the SWAT modeling studies used methods developed by Arabi et al. (2008), which were based on the amount of crop residue present in fields. These methods involved reducing the CN from the default value and adjusting Manning's "n" roughness coefficient based on recommended values for each residue cover percentage category (Arabi et al., 2008) for those HRUs with this practice implemented. Filter strips can be simulated by modifying the management operation file for each HRU in which the practice is implemented, which involves setting model parameter VFSCON, the fraction of total runoff from a field entering the filter strip (recommended as 0.25 to 0.75 with a default value of 0.5); and VFSRATIO, the ratio of field area to filter strip area (recommended as 40 to 60) (Waidler et al., 2011). The HRUs, which are homogeneous areas of aggregated soil, landuse and slope, are the smallest modeling units. In a given standard SWAT application, multiple potential HRUs (fields) in a subbasin are usually aggregated into a single HRU feature. In other words, the SWAT model combines multiple potential HRUs (fields) with the same landuse/landcover, soil and slope, but located at different places of a subbasin, and considers them as one HRU. Therefore, it should be noted that the model may not capture the variation of the types of actually implemented filter strips from location to location. Therefore, SWAT results on filter strips should be considered with caution. Other recommendations for modeling certain ACPs and management practices are included in the SWAT model Input/Output Documentation (Arnold et al., 2013), as well as the ArcSWAT Interface User's Guide (Winchell et al., 2013). However, it is not certain that these approaches to changing model set-up and specific parameter values to reflect individual ACPs are necessarily the best methods available, and there may be multiple ways to model the same practice.

Aside from the commonly modeled ACPs listed above, many studies also included methods of modeling subsurface drainage (Table S.12 in Supplemental Materials). While none of the SWAT modeling studies modeled subsurface drainage management as a distinct ACP, multiple studies included a description of how tile drainage was simulated, and the extent of implementation within a watershed, as part of the baseline model of existing conditions. For example, Bosch et al. (2011, 2013, 2014) simulated subsurface drainage in all of their watershed models for areas under row crops and hay with soil types C and D, as defined by the soil hydrologic group (USDA NRCS, 2020). Additionally, they set the depth to the impermeable layer at 2500 mm, the depth to subsurface drains at 1000 mm, the time to drain soil to field capacity at 24 h, and the tile drain lag time at 96 h. Similarly, Mehan et al. (2019) applied subsurface drainage in all HRUs modeled in the Matson Ditch (AXL) watershed that were planted under corn, soybean, or winter wheat and that had poorly drained to very poorly drained soils based on soil component data (USDA NRCS, 2020).

Finally, ACP effectiveness values were mainly calculated by comparing nutrient loads (alternatively, yields or concentrations) from lands with ACPs implemented to those without or with baseline management practices and expressed as a percent reduction. A resulting positive percentage indicates that the practice was effective (ACP implementation decreased nutrient loads), while a negative value indicates that the practice was not effective (ACP implementation increased nutrient loads).

3.5.2. Effectiveness of ACPs

Overall, the SWAT modeling studies recommended widespread adoption of multiple, complementary ACPs beyond what is currently in place to reduce P loading to Lake Erie, especially from the mainly agricultural WLEB (Ohio EPA, 2010, 2013; Scavia et al., 2014; IJC, 2014; USEPA, 2015). One of the advantages for modeling studies is that ACP implementation can be evaluated on the same lands over the same periods of time again and again to find the most effective ACPs or combination of ACPs for those areas. In addition, studies that investigated the impacts of different extents of ACP implementation showed that targeted implementation was more effective compared to scenarios where ACPs were randomly assigned to agricultural lands within a watershed (e.g., Arabi et al., 2006; Bosch et al., 2013; Her et al., 2017), as expected.

Results from the SWAT modeling studies showed that sediment loss reductions were more readily achieved compared to P loss reductions, especially for dissolved species like SRP. In addition, effectiveness of ACPs varied in reducing sediment and P loads (Fig. 3). Furthermore, some practices reduced loads of certain pollutants more than others (Table S1.12 in Supplemental Materials). For example, cover crops were relatively effective in reducing sediment loads, and they were more effective in reducing total P compared to its respective dissolved P. The overall mean percent effectiveness values for cover crops were 23.7% for TP, but it was just 5.2% for SRP. However, cover crop was found to increase DRP loss based on limited field studies (Carver et al., 2022; Ni et al., 2020). In addition, conservation tillage was not effective in reducing P loads but was moderately effective in reducing suspended sediment loads. The overall mean percent effectiveness for conservation tillage was 19% for suspended sediments, but the effectiveness value for SRP was negative, at −1.5%.

While concerns on P related model parameter values as well as the impacts of equifinality on ACP assessments have been enumerated in previous sections, the synthesized model results on ACP effectiveness do correspond relatively well with previous reviews and investigations of ACP effectiveness in empirical field studies (Lee et al., 2010; Tuppad et al., 2010; Jarvie et al., 2017; Christianson et al., 2018, 2021; Ni et al., 2020; Douglas-Mankin et al., 2021; Guo et al., 2021; Liu et al., 2021). For example, Jarvie et al. (2017) analyzed relationships among

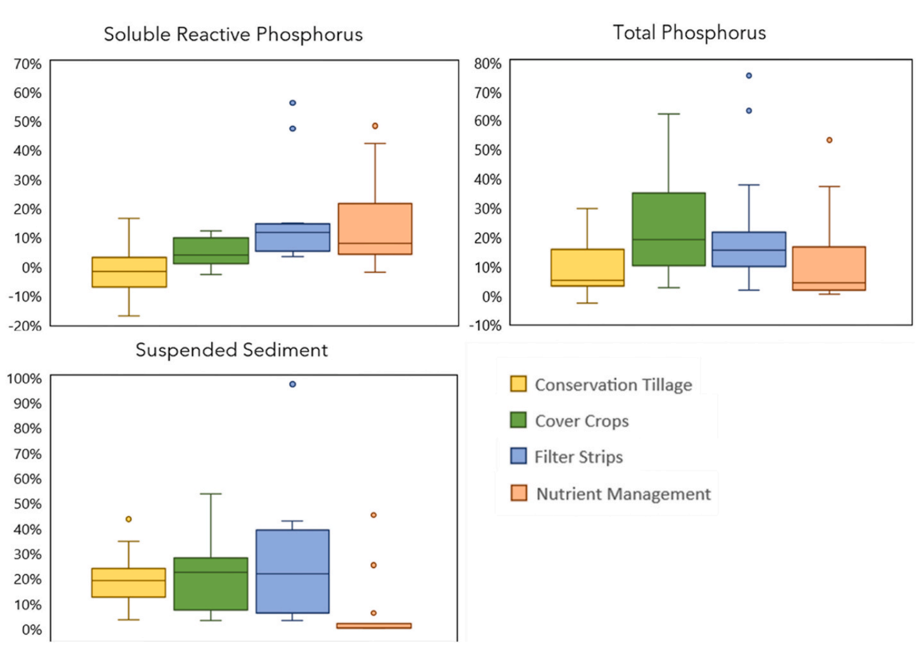

Fig. 3. Box plot showing the percent effectiveness values for the most commonly modeled ACPs in SWAT modeling studies. The top line represents the 90th percentile, the top edge of the box is the 75th percentile, the middle line is the median, the bottom of the box is the 25th percentile, the bottom line is the 10th percentile, and dots represent outliers. Conservation tillage includes no-till, mulch till, and strip-till. Cover crops include cereal rye and ryegrass. Nutrient management includes adjustments to fertilizer rate, timing, placement, and source.

real-world monitoring data and suggested that some ACPs, particularly the widespread adoption of reduced tillage or no-till, could inadvertently increase P loading – while conservation tillage may prevent sediment and its attached nutrient transport via surface runoff, it may also redirect these constituents (especially dissolved forms) through subsurface drains due to soil stratification. Additionally, Douglas-Mankin et al. (2021) found that filter strips were on average 47% effective at reducing SRP mass losses, while our review showed that filter strips were about 16% effective on average, which is probably reasonable for this area due to extensive subsurface drainage (Bhattarai et al., 2009). Furthermore, while the SWAT modeling studies seemed to underestimate ACP effectiveness overall, this may be due to the models simulating the impacts of ACP implementation at the larger watershed scale, whereas the review studies mentioned above synthesized results from field-scale experiments. In any case, this provides slightly more confidence in the synthesized results regarding ACP effectiveness evaluations despite apparent equifinality observed among individual watershed models.

Results on ACP effectiveness were also reported by modeling studies that investigated the impacts of both ACP implementation and climate change (Table S1.12 in Supplemental Materials). Under projected future climate scenarios, it was found that some ACPs are more resilient and effective in the face of increased storm intensity and temperatures compared to others. For example, Wallace et al. (2017) found that widespread implementation of combinations of ACPs was more effective in reducing overall sediment and nutrient loads under projected climate conditions compared to individual ACPs, like filter strips. Additionally, some studies found that the benefits of ACPs for nutrient load reduction could be overshadowed by the effects of climate change. Xu et al. (2018) found that ACP implementation plans that were optimized for current climate conditions were much less effective when applied under future climate scenarios. Overall, these studies concluded that widespread, adaptive implementation of combined ACPs across the WLEB would be needed to overcome excess nutrient loading both now and in the future (Michalak et al., 2013; Bosch et al., 2014; Cousino et al., 2015; Muenich et al., 2016; Culbertson et al., 2016; Wallace et al., 2017; Xu et al., 2018).

A few of the studies reviewed in this report coupled hydrologic models with cost-benefit analyses or farmer survey results to investigate the feasibility of ACP adoption in terms of the cost of ACP implementation and maintenance compared to farm revenues (e.g., Yen et al., 2016; Pyo et al., 2017; Xu et al., 2018; Liu et al., 2019). For example, Liu et al. (2019) used estimated ACP implementation costs from the USDA NRCS CEAP database as inputs in their cost-benefit optimization tool to evaluate the cost-effectiveness of different ACPs. This cost-benefit optimization tool was then coupled with a SWAT model to evaluate the overall effectiveness in terms of both nutrient reduction and costs. They found that filter strips implemented in TP/SRP critical areas were the most cost-effective in reducing both annual and spring TP/SRP losses (Liu et al., 2019).

4. Conclusions and recommendations

Results from this review showed that, while most model applications were rated "satisfactory" based on performance statistics for flow and sediment, many models were rated "unsatisfactory" for nutrients, particularly for SRP. In addition, actual model parameter values varied widely among the different SWAT modeling studies, even for the same watershed and/or for the same satisfactory results, evidently due to equifinality. In addition, some model parameter values used were not realistic (e.g. PSP of 0.01 for a highly agriculturally dominated watershed where a large amount of P fertilizer was applied), which undermines the credibility of their results on ACPs effectiveness. The equifinality, along with model parameter uncertainty, should be minimized in future model applications by constraining model parameter values based on local observations and an understanding of site characteristics. Furthermore, improvements in model development on watershed hydrologic and nutrient processes are needed to better capture nutrient transport and transformation processes to improve nutrient simulation.

In general, sediment loss reductions were more readily achieved compared to nutrient loss reductions, especially for dissolved species like SRP. Of the most commonly evaluated ACPs, cover crops and filter strips were more effective in reducing total nutrient loads, mainly due to their ability to control soil erosion and sediment transport. On the other hand, no-till was less effective, as were nutrient management and other source reduction measures. Although equifinality and parameter uncertainty are an inherent part of the modeling process, the simulated ACP effectiveness results were more conservative compared to field observations. Finally, while methods were applied to represent subsurface drainage in baseline models, none of the reviewed studies evaluated subsurface drainage management on water quality as a distinct ACP. Future SWAT applications estimating ACP effectiveness should aim to include drainage management in their analyses to establish a more complete range of results on the effectiveness of ACPs.

Credit author statement

Yongping Yuan: Conceptualization, Methodology, Investigation, Supervision, Data curation, Writing – original draft, Writing – review & editing, writing – revision, Validation, Visualization. project administration, Funding acquisition. Lydia Koropeckyj-Cox: Investigation, data collection and curation, Formal analysis, Writing – original draft, Writing – review & editing, writing – revision, Visualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.114000.

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Glossary

AcronymDefinition

ACP: Agricultural Conservation Practice
CEAP: Conservation Effects Assessment Project
HRUs: hydrologic response units
HUC: Hydrologic Unit Code
IJC: International Joint Commission
MRB: Maumee River Basin
N: Nitrogen
NASS: National Agricultural Statistics Service
NCDC: National Climatic Data Center
NO_3*-N:* Nitrate-Nitrogen
NOAA: National Oceanic and Atmospheric Administration
NRCS: Natural Resources Conservation Service
ODA: Ohio Department of Agriculture
ODNR: Ohio Department of Natural Resources
SCS: Soil Conservation Service
SRP (or DRP): Soluble/Dissolved Reactive Phosphorus
SSURGO: Soil Survey Geographic Database
STATSGO: State Soil Geographic Dataset
SWAT: Soil and Water Assessment Tool
TN: Total Nitrogen
TP: Total Phosphorus
USDA: United States Department of Agriculture
USEPA: United States Environmental Protection Agency
USGS: United States Geological Survey
USLE: Universal Soil Loss Equation
WLEB: Western Lake Erie Basin