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Research papers

Assessing the effectiveness of riparian buffers for reducing organic nitrogen loads in the Coastal Plain of the Chesapeake Bay watershed using a watershed model

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ABSTRACT

Riparian buffers are an important conservation practice to mitigate water quality degradation in the Coastal Plain of the Chesapeake Bay watershed (CBW). Although forested and grassed riparian buffers have been implemented in this region through government programs, the impacts of riparian buffers on water quality have been rarely examined. The objective of this study was to assess the long-term effects of riparian buffers to improve water quality in the Coastal Plain of the CBW. A watershed model, Soil and Water Assessment Tool (SWAT), was employed for this study. Considering impacts of model uncertainty (i.e., equifinality) on the effectiveness of riparian buffers, we adopted all parameter sets that produced acceptable simulation results. Multiple riparian buffer implementation scenarios were developed to generate the baseline condition on total organic nitrogen (TON) loads without riparian buffers and examine variation of TON loads with areal coverage of riparian buffers. Through the calibration processes, a total of 235 acceptable parameter sets were identified and used to simulate TON loads. The simulation results indicated that riparian buffers significantly reduce TON loads. Without riparian buffers, annual TON loads from the 220 km^2 study watershed were 18 to 34 metric tons, but declined to 8 to 21 metric tons with riparian buffers. The effectiveness of riparian buffers on reducing annual TON loads increased from 17% to 45% with an increase in the extent of riparian buffer implementation. The effectiveness of riparian buffers tended to be higher during early spring than other seasons as high soil water conditions promote occurrence of surface water flow and thus TON loads. Riparian buffers were more efficient on croplands than other land use types due to high soil nutrient levels caused by fertilizer applications. The effectiveness of riparian buffers differed considerably by parameter set. Thus, efforts to consider model uncertainty are important to provide better insight into the impacts of conservation practices. This study supports ongoing riparian buffer programs for the Mid-Atlantic Coastal Plain by demonstrating the effectiveness of riparian buffers and informing implementation guidelines.

1. Introduction

The Chesapeake Bay (CB) is an important natural asset as the most productive estuary in the United States (US, CEC, 2000) as well as a Ramsar wetland site of international importance (Gardner and Davidson, 2011). The Chesapeake Bay watershed (CBW) with an area of 166,000 km^2 includes the portions of seven jurisdictions (Delaware, Maryland, New York, Pennsylvania, West Virginia, Virginia and the District of Columbia). Overall environmental conditions in the Bay have been degraded mainly by non-point source (NPS) pollutants (McCarty et al., 2008). Excessive NPS pollutant loads to the Bay cause several environmental problems, such as eutrophication and hypoxic zones, jeopardizing living organisms in the Bay (NRC, 2011). Furthermore, the high density of surface waters further exacerbates the vulnerability of this region to human activities (Kemp et al., 2005). Among various NPS sources, agricultural lands are known to be key nitrogen (N) sources.

Collaborative efforts to curb nutrient loads have been made in this region. The Chesapeake Bay Agreement between the CBW jurisdictions was initiated in 1983 and has been reconfirmed multiple times over recent decades to emphasize the protection of the Bay (CBP, 2014). The CB Total Maximum Daily Load was established to forcefully restrict permitted amounts of nutrient loads to the Bay (USEPA, 2010). To meet

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these protection regulations, agricultural conservation practices have been recommended throughout the CBW (McCarty et al., 2008). Simultaneously, the question of whether these conservation practices are effective at mitigating water quality degradation has arisen in order to efficiently achieve management goals (Santhi et al., 2006; Duriancik et al., 2008). A watershed modeling approach has been widely used since it can evaluate the effectiveness of conservation practices with fewer limitations on spatial and temporal conditions (Her et al., 2017; Jeon et al., 2018; Qi et al., 2018). Field monitoring is costly, thus modeling approaches have received substantial attention to examine conservation practice effectiveness (Shirmohammadi et al., 2006).

Winter cover crops, wetland restoration, and riparian buffers are popular conservation practices on the Coastal Plain of the CBW where agricultural land use is common (McCarty et al., 2008; Ator and Denver, 2012). Winter cover crops have been widely adopted because of their soil nutrient uptake efficiency (Hively et al., 2009). Wetlands are effective at trapping and removing nutrients (Denver et al., 2014), and riparian buffers are also efficient at reducing nutrient loads (Lowrance et al., 1997). A modeling approach has successfully demonstrated that winter cover crops are an effective management tool to reduce nutrient leaching by 90% at the watershed scale (Yeo et al., 2014; Lee et al., 2016), and their nutrient reduction functions become increasingly important under regional warming due to climate change (Lee et al., 2017a). The impacts of wetlands on controlling water quality and quantity have been widely examined at multiple scales using a modeling approach (Lee et al., 2018a, 2019; Sharifi et al., 2019; Yeo et al., 2019). Recent efforts continue to improve modeling approaches to accurately represent wetland impacts (Evenson et al., 2018; Qi et al., 2019). The necessity of riparian buffers has been emphasized, but efforts to quantify their utility have been rarely examined in this region (Lowrance et al., 1997; Wallace et al., 2018).

Hydrologic models are widely adopted as a primary tool for substantiating the role of riparian buffers on mitigating water quality degradation. Soil and Water Assessment Tool (SWAT) model has been commonly used to assess the effectiveness of filter strip. Several studies simulated SWAT to explore filter strip impacts on pollutant (sediment, total nitrogen, and total phosphorus) reduction in Georgia (Cho et al., 2010), Mississippi (Leh et al., 2018), and Oklahoma (Moriasi et al., 2011) within the United States, and China (Shi et al., 2017). In addition to SWAT, other hydrologic models have been also used for simulating riparian buffer impacts including: Hydrologic Simulation Program-Fortran (HSPF, Liu and Tong, 2011), Annualized Agricultural Non-Point Source Pollution (AnnAGNPS, Momm et al., 2014), Agricultural Policy/Environmental eXtender (APEX) and the Riparian Ecosystem Management Model (REMM) models (Williams et al., 2013). Although riparian buffers are widely explored using hydrologic models, there are few attempts focusing on model predictive uncertainty on riparian buffer function. Taylor et al. (2016) pointed out that parameter uncertainty significantly affected the effectiveness of conservation practices including riparian buffers and thus model uncertainty should be considered simultaneously.

The environmental impacts of conservation practices on water quantity and quality are commonly assessed by comparing the simulated outputs with and without conservation practices (Hashemi et al., 2016; Jeon et al., 2018; Qi et al., 2018). In practice, a single parameter set that produces the best model performance is identified through calibration. This parameter set is then applied in a simulation setting that considers implementation of conservation practice (Arnold et al., 2012). This common modeling approach presents the uncertainty problem of equifinality (i.e., different parameter sets reproduce acceptable model outputs, Beven, 2006). The non-uniqueness of hydrologic modeling parameter sets limit production of reliable and credible results for water resource management plans (Ficklin and Barnhart, 2014). A robust modeling approach should consider uncertainty to provide better insight on changes in the fate and transport of water and nutrients by implementing conservation practices.

The objective of this study was to quantify the effectiveness of riparian buffers for reducing total organic N (TON) loads within the Coastal Plain of the CBW. Although nitrate (NO_3) is the major N species in this watershed, this study focused on TON since riparian buffers are effective at mitigating nutrients transported by surface flow (e.g., TON) rather those transported by groundwater (e.g., NO_3). To take into account model parameter uncertainty, all acceptable parameter sets identified during the calibration processes were used for quantifying the effectiveness of riparian buffers for reducing TON loads. With the assumption that riparian buffers are absent in the baseline condition, the model was calibrated against both observed streamflow and TON loads. Three buffer implementation scenarios involving status quo, loss and gain in buffer areas were prepared (see Section 2.5). The calibrated models regarding multiple acceptable parameter sets were applied into the three buffer implementation scenarios and then TON loads under the baseline and implementation scenarios were compared. Specifically, we 1) compared multiple riparian buffer implementation scenarios with the baseline condition to demonstrate the effectiveness of riparian buffers for reducing TON loads in this region; 2) investigated how the effectiveness of riparian buffers varied by implementation coverage, climatic, and land use conditions; and 3) explored the impacts of model parameter uncertainty on the effectiveness of riparian buffers.

2. Materials and methods

2.1. Study area

This study was conducted in the Tuckahoe Creek Watershed (TCW), which is located in the upper region of the Choptank River watershed within the Coastal Plain of the CBW. The TCW has a drainage area of approximately 220 km^2 and drains to the USGS (#01491500) gage station (Fig. 1a) near Ruthsburg, Maryland. The Choptank River watershed has been identified as an “impaired water” by the US Environmental Protection Agency (USEPA) due to excessive exports of nutrients, sediments, and bacteria (McCarty et al., 2008). Croplands account for 54% of the TCW with the remainder of the TCW covered by forest (32.8%), pasture (8.4%), urban land (4.2%) and water bodies (0.6%, Fig. 1b). In the TCW, soils are evenly occupied by both well- (Hydrologic Soil Group – A and B%, 56%) and poorly- (Hydrologic Soil Group – C and D%, 44%) drained soils (Fig. 1c). Riparian buffers are a crucial element for improving water quality in the CBW (Lowrance et al., 1997). Furthermore, various USDA programs (e.g., the Conservation Reserve Program [CRP] and the Conservation Reserve Enhancement Program [CREP]) have been supportive for implementing forested and grassed buffers along streams. Relative to these restoration efforts, few studies have been performed to demonstrate the effectiveness of riparian buffers for mitigating water quality degradation in the Mid-Atlantic Coastal Plain.

2.2. Soil and water assessment tool

SWAT is a process-based watershed model designed to evaluate the impacts of environmental and anthropogenic changes in agricultural watersheds (Neitsch et al., 2011). In SWAT, a watershed is divided into sub-watersheds and further into hydrologic response units (HRUs) based on the unique combinations of soil, land use, and slope. All variables are simulated at individual HRU levels, and simulated outputs are aggregated at the sub-watershed and watershed levels (Neitsch et al., 2011). Water balance calculated in each HRU comprises precipitation, surface runoff, evapotranspiration, percolation, and groundwater recharge. The Soil Conservation Service (SCS) Curve Number (CN) method is used in SWAT to partition surface water into surface runoff and infiltration. Infiltrated water is removed by evapotranspiration, discharged to streams via subsurface flow, or percolated into shallow groundwater. The fate of water in shallow groundwater

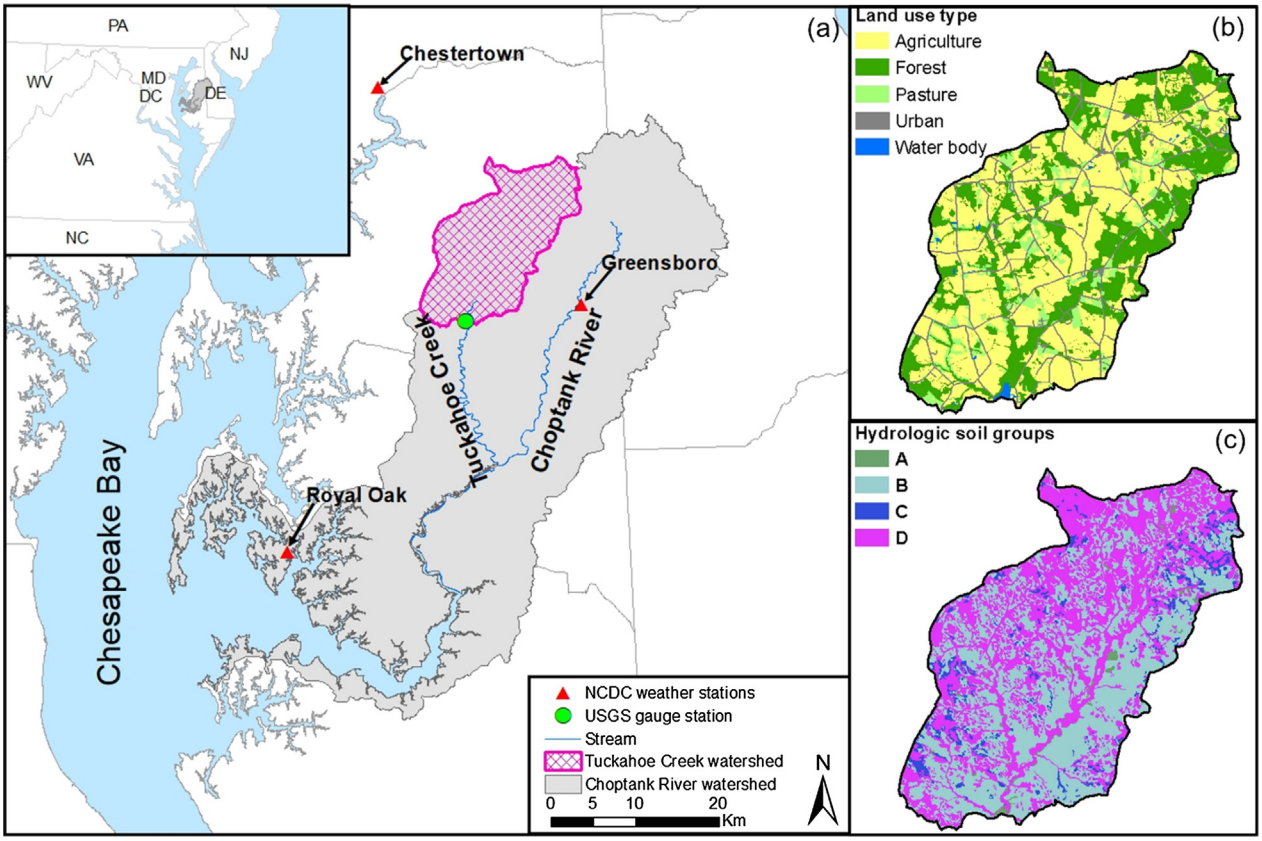

Fig. 1. Characteristics of the study area (Tuckahoe Creek Watershed): (a) location, (b) land use type, (c) hydrologic soil groups (adapted from Lee et al., 2020) Note: hydrologic soil groups (HSGs) are characterized as follows: Type A- well-drained soils with 7.6–11.4 mm·h^{-1} infiltration rate; B - moderately well-drained soils with 3.8–7.6 mm·h^{-1}; C - moderately poorly-drained soils with 1.3–3.8 mm·h^{-1}; and D – poorly-drained soils with 0–1.3 mm·h^{-1} (Neitsch et al., 2011).

varies: contribution to streams via groundwater flow, movement to the unsaturated zone (upward movement), and movement to deep groundwater (downward movement). N cycle is fully represented in SWAT with two N pools (mineral and organic N). The addition of N is simulated by fertilizer and manure applications, crop residue, fixation, and deposition. The transport of N is driven by water cycling. ON is often attached to soils and transported to streams by surface runoff. The concentration of ON is calculated as a function of N in organic pools and soil physical characteristics. The version of SWAT used in this study was SWAT-2012 (rev. 635). Please refer to Neitsch et al. (2011) for further details.

SWAT provides two methods for representing riparian buffer impacts on pollutant reduction. The first method is to modify the width of the edge of the filter strip. The model assumes that pollutants in surface runoff are attenuated by the installation of filter strips as surface runoff flows through the strips. The reduction efficiency is directly proportional to the width of the filter strip. The second method (referred to as "VFS") is to set up the vegetation filter strip (VFS) in the management operations file (.ops). This method locates VFS to trap surface runoff from upslope pollutant sources and filter it. This strip reduces the speed of overland flow, leading to deposition of pollutants. This VFS method only affects pollutant reduction. Further details about the two methods are available in Neitsch et al. (2011). This study used only VFS method as this method improves the capacity of SWAT to simulate the impacts of buffers by reflecting flow concentration (Neitsch et al., 2011). In addition, the VFS method is more appropriate compared to FILTERW regarding SWAT's semi-distributed structure (White and Arnold, 2009). To use VFS, three parameters (FILTER_RATIO: the ratio of field area to filter strip area, FILTER_CON: the fraction of the HRU which drains to the most concentrated 10% of the filters strip area, and FILTER_CH: fraction of the flow within the most concentrated 10% of the filter strip) should be defined. In this study, FILTER_RATIO, FILTER_CON, and FILTER_CH were set as 40, 0.5, and 0, respectively, according to the VFS guideline addressed in Waidler et al. (2011).

2.3. Input data

Input data for SWAT are shown in Table 1. Daily precipitation and temperature records from 2004 to 2014 were obtained from the National Oceanic Atmospheric Administration (NOAA) National Climate Data Center (NCDC) climate monitoring stations (Chestertown: USC00181750, Royal Oak: USC00187806, and Greensboro: US1MDCL0009). Daily solar radiation, relative humidity, and wind speed that are not monitored were reproduced using SWAT's built-in weather generator because of the lack of observations (Neitsch et al., 2011). Raw Digital Elevation Model (DEM) data from the Maryland Department of Natural Resources (MD-DNR) were processed in the USDA-ARS Hydrology and Remote Sensing Laboratory, Beltsville to produce a high-resolution DEM, which was used as input to SWAT. Soil data were provided by Soil Survey Geographical Database (SSURGO). This study adopted the land use map created by Lee et al. (2016) that contains detailed agricultural practices in this region (Table S1). Monthly streamflow was monitored at the watershed outlet (USGS#01491500). TON grab samples collected at the watershed outlet were available from the Chesapeake Bay Program (CBP, TUK#0181, http://data.chesapeakebay.net/WaterQuality). The TON data were converted to monthly continuous data using the USGS LOAD ESTimator (LOADEST) program (Runkel et al., 2004). This program has been employed to reproduce continuous water quality data from grab samples (Jha et al., 2007).

Table 1
List of SWAT input data (adapted from Lee et al., 2018b).

Data type	Source	Description	Year
DEM	MD-DNR	LiDAR-based 1-meter resolution	2006
Land use	USDA-NASS	Cropland Data Layer (CDL)	2008–2012
	MRLC	National Land Cover Database (NLCD)	2006
	USDA-FSA-APFO	National Agricultural Imagery Program digital Orthophoto quad imagery	1998
	US Census Bureau	TIGER road map	2010
Soils	USDA-NRCS	Soil Survey Geographical Database (SSURGO)	2012
Climate	NCDC	Daily precipitation and temperature	2004–2014
Streamflow	USGS	Daily streamflow	2006–2014
Water quality	CBP	Daily grab TON (total organic nitrogen)	2006–2011

Note: MRLC: Multi-Resolution Land Characteristics Consortium, USDA-FSA-APFO: USDA-Farm Service Agency-Aerial Photography Field Office, and TIGER: Topologically Integrated Geographic Encoding and Referencing.

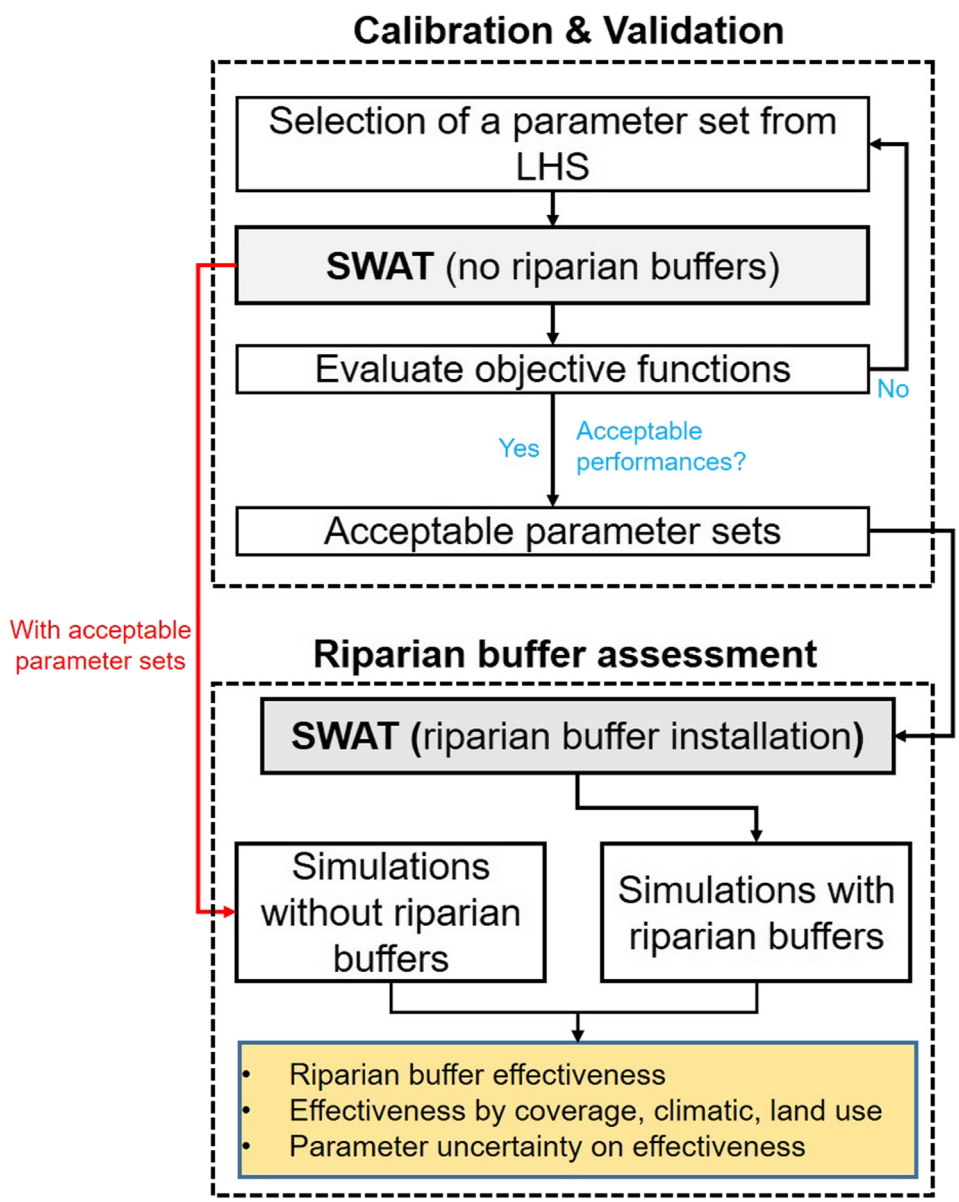

Fig. 2. Flow chart illustrating the calibration process and assessment of riparian buffer effectiveness. LHS stands for Latin-hypercube sampling.

2.4. Model calibration and validation

This study calibrated and validated SWAT at a monthly time step for 11 years from 2004 to 2014 under the baseline condition (i.e., absence of buffers): 2-year warm up (2004–2005), 5-year calibration (2006–2010), and 4-year validation (2011–2014). Since TON data are only available for a short period from 2006 to 2011, the data were not split into calibration and validation periods, and only a 6-year calibration (2006–2011) was performed. Based on previous SWAT studies, a model parameter set relevant to streamflow and TON was chosen.

Details about the parameter set used in this study are available in Table S2. 3000 different parameter sets were generated using the Latin Hypercube sampling method that divides the parameter range into sub-ranges and then selects each parameter value within each sub-range while allowing for one value for each parameter set (van Griensven and Meixner, 2003). Three statistical performance measures suggested by Moriasi et al. (2007) were considered to evaluate model performance: Nash-Sutcliffe efficiency coefficient (NSE), root mean square error - standard deviation ratio (RSR), and percent bias (P-bias). Equations for these three measures are provided in the Supplementary material (Eq. S1–3). An acceptable parameter set was identified when a simulation using the parameter set met acceptable model performance measures suggested by Moriasi et al. (2007) for both streamflow and TON loads (Table S3). We further conducted uncertainty analysis using the 95% prediction uncertainty (PPU), P- and R- factors (Singh et al., 2014). The 95 PPU was calculated at the 2.5 and 97.5 percentiles of all acceptable simulations gained from calibration procedure. The P factor indicates the ratio of observations data that belongs to 95PPU band, and the P factor ranges from 0 to 100%. As the P factor increases, the uncertainty is lowered. The R factor ranging from 0 to infinity indicates the average width of the 95PPU bands by the standard deviation of observational data (Singh et al., 2014).

2.5. Assessing environmental impacts of riparian buffers

The USDA programs (e.g., CRP and CREP) have promoted the development of riparian buffers along streams (McCarty et al., 2008). As a result of these efforts, riparian buffers have been implemented on the Coastal Plain of the CBW. In order to quantify the environmental impacts of riparian buffers established by the federal programs, the first implementation scenario (SC #1) was to set up riparian buffers on HRUs where riparian buffers were implemented via these programs. A privacy protected geospatial dataset on forested [Conservation Practice (CP) 22] and grassed (CP 21) riparian buffers was provided by the USDA-Farm Service Agency (FSA) as part of a riparian buffer assessment project (USDA-FSA, 2015a,b). The HRUs (n = 206) superimposed with the riparian buffer map were selected from the HRUs indicating croplands, forest, and pastures (n = 480) according to the conservation practice guideline (Waidler et al., 2011). Note the total number of HRUs used was 592. The baseline and first implementation scenarios were first compared to quantify the water quality benefit from riparian buffer implementation programs (Fig. 2). Then, two additional implementation scenarios with loss or gain of buffers (so-called loss and gain scenarios) were developed. The loss scenario (SC #2) was set to show the effectiveness of riparian buffers when buffer programs were not maintained. The riparian buffers were randomly removed in half of the HRUs where buffers were installed by government programs. The gain scenario (SC #3) was prepared to show the effectiveness of riparian buffers when buffers were implemented on the all croplands, forest, and pasture within the watershed. SC #2 and #3 can show the value and necessity of ongoing programs for implementing riparian buffers. The three riparian buffer implementation scenarios are summarized in Table 2.

Although TON loads were calibrated from 2006 to 2011, 9-year TON loads (2006–2014) were used to quantify the effectiveness of riparian buffers. The TON reduction efficiency of buffer implementation scenarios (SC #1–3) was computed as (Baseline − Buffer Scenario)/Baseline × 100 (%). The reduction efficiency was first compared at the annual and monthly time steps using TON loads that were exported from the watershed via the outlet. Then, the reduction efficiency for the 9-year annual average TON that moves from lands to nearby streams was computed for individual HRUs to investigate spatial variations in the effectiveness of riparian buffers.

3. Results and discussions

3.1. Model calibration and validation

A total of 235 parameter sets exhibited acceptable performance measures for monthly streamflow and TON loads. The ensemble mean of 235 acceptable simulations was plotted with corresponding observations in Fig. 3. The upper and lower limits of the 95 PPU band were reproduced by 97.5 and 2.5 percentile of 235 simulations, respectively. The 95 PPU of streamflow quantified most uncertainties as the band included the substantial portion of observational data with the P-factor values of 82 to 83% (Table 3). The simulation results of TON loads showed a smaller P-factor (60%), indicating greater uncertainty than streamflow. In contrast, the R-factor of TON loads was smaller than R-factor for streamflow, which indicated a narrower 95 PPU band.

The ensemble mean of 235 simulations well depicted observational streamflow and TON loads with “very good” and “good” performance rates, respectively, as summarized in Table 3. Several observed peak TON loads beyond the 95 PPU exist when observed streamflow was large. Since TON is delivered by water transport, fluctuations in TON loads were consistent with streamflow. SWAT tended to underestimate streamflow during heavy rain events in this region likely due to inherent model limitations (e.g., disregarding precipitation duration and intensity, Kim and Lee, 2008) and localized precipitation (Yeo et al., 2014). Thus, TON loads were also underestimated as a result of underestimated streamflow. In addition, monthly TON loads reproduced from grab samples might contain uncertainty, contributing to underestimation of TON loads. Due to these two factors, simulations likely did not capture observed peak TON loads. An extreme TON peak was observed in Aug. 2011 with the greatest daily precipitation (237.5 mm) over the period from 2006 to 2011. The transport of TON generally depends on surface runoff, therefore, a heavy rainfall event would induce substantial surface runoff and consequently high TON loads.

3.2. Riparian buffer impacts on reducing TON at the watershed scale

The 9-year average annual TON loads and reduction efficiencies under the baseline and buffer implementation scenarios were presented in Fig. 4. TON loads for individual riparian buffer implementation scenarios were simulated using the 235 acceptable parameter sets. The results showed that riparian buffers exerted a profound impact on reducing TON loads. The amount of TON loads under the baseline conditions were 18 to 34 metric tons (MT, 25 th and 75th percentiles, respectively, median value: 26 MT), while TON loads under SC #1 were 11 to 24 MT (median value: 17 MT, Fig. 4a). These results indicate that riparian buffers installed by federal programs are effective at mitigating TON loads with a reduction of 7–10 MT (median value: 9 MT) in the TCW. The corresponding reduction efficiency in SC #1 ranged from

Table 2
Summary of riparian buffer implementation scenarios.

	Description	HRUs with riparian buffers
Baseline	No riparian buffers	0
SC #1	Riparian buffer installation on the croplands, forest and pastures by the federal programs	206
SC #2	Removal of the half of riparian buffers installed in SC #1	103
SC #3	Riparian buffer installation on all croplands, forest, and pasture	480

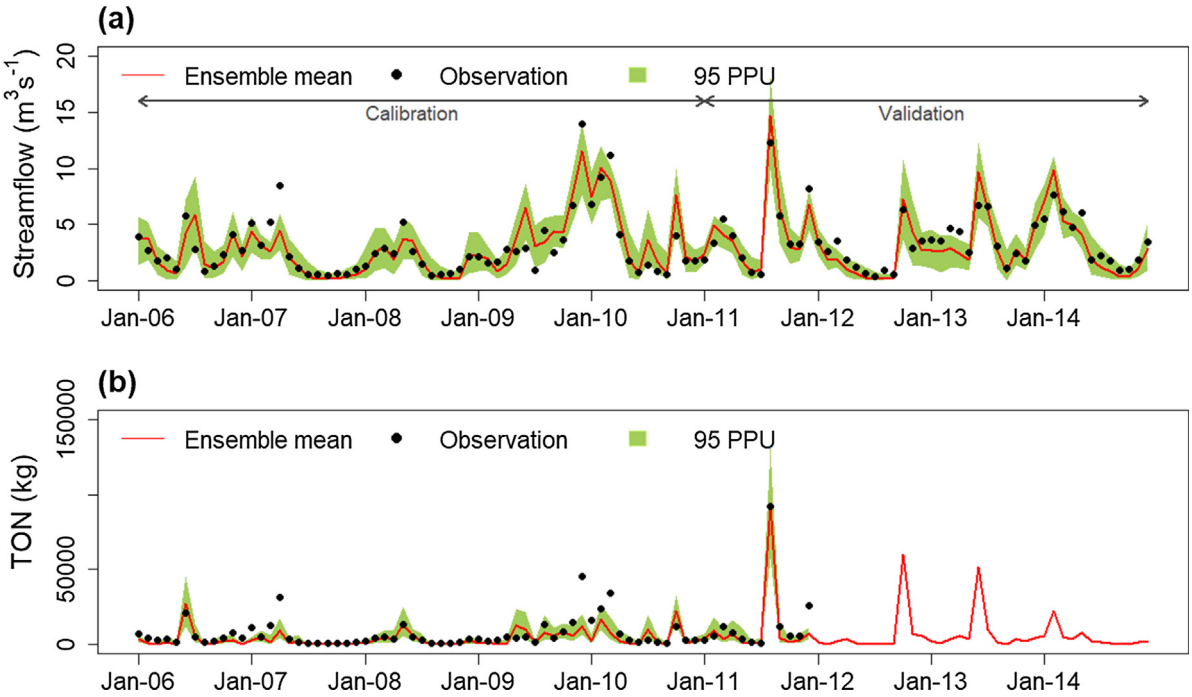

Fig. 3. Observed and simulated monthly (a) streamflow and (b) (TON) loads. TON has only a calibration period due to a lack of sufficient data for validation.

Table 3
Model performance measure for the ensemble mean and uncertainty results.

	Period	NSE	RSR	P-bias	P-factor	R-factor
Streamflow	Calibration	0.755***	0.489***	−1.8***	82%	1.127
	Validation	0.788**	0.455***	6.1***	83%	1.213
ON loads	Calibration	0.687**	0.555**	34.4**	60%	0.596

Note: Model performance was rated based on the criteria of Moriasi et al. (2007); * Satisfactory, ** Good, and *** Very Good.

20% to 44% (median value: 32%, Fig. 4b). When riparian buffers were partially eliminated and were implemented on all croplands, forest, and pasture as indicated by SC #2 and #3, TON loads were 14 to 28 MT (median value: 21 MT) and 8 to 21 MT (median value: 14 MT), respectively. The reduction efficiencies of SC #2 and #3 were 10 to 24% (median value: 17%) and 29 to 63% (median value: 45%), respectively. Relative to SC #1, SC #2 showed decreased efficiency by 20% and SC #3 showed increased efficiencies by 19%. This result can support the conclusion that riparian buffers should be properly managed and further implemented in this region to mitigate water quality degradation. In addition, the range of reduction efficiency of riparian buffers derived from 235 simulations was fairly wide. The gap in reduction efficiency between 25 th and 75th percentiles values was 24% (SC #1), 14% (SC #2), and 34% (SC #3). The gap further increased to 50% (SC #1), 28% (SC #2), and 68% (SC #3) when the efficiency was compared between more extreme lower (2.5 th) and higher (97.5 th) percentiles values (Table S4). In addition, SC #2 and #3 showed decreased efficiency by 25% and increased efficiency by 21% compared to

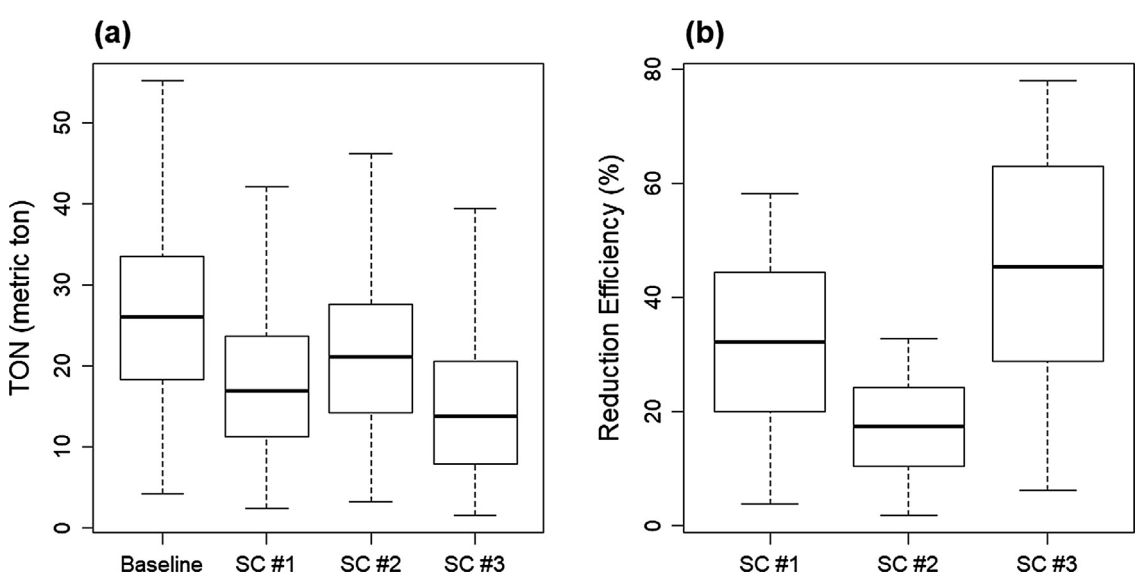

Fig. 4. The 9-year annual average TON loads (a) and reduction efficiency (b). The horizontal bold line within the box indicates the median value, and the upper and bottom limits of the box indicate 75th and 25th percentile values, respectively. The upper and lower whisker indicates the minimum and maximum values, respectively.

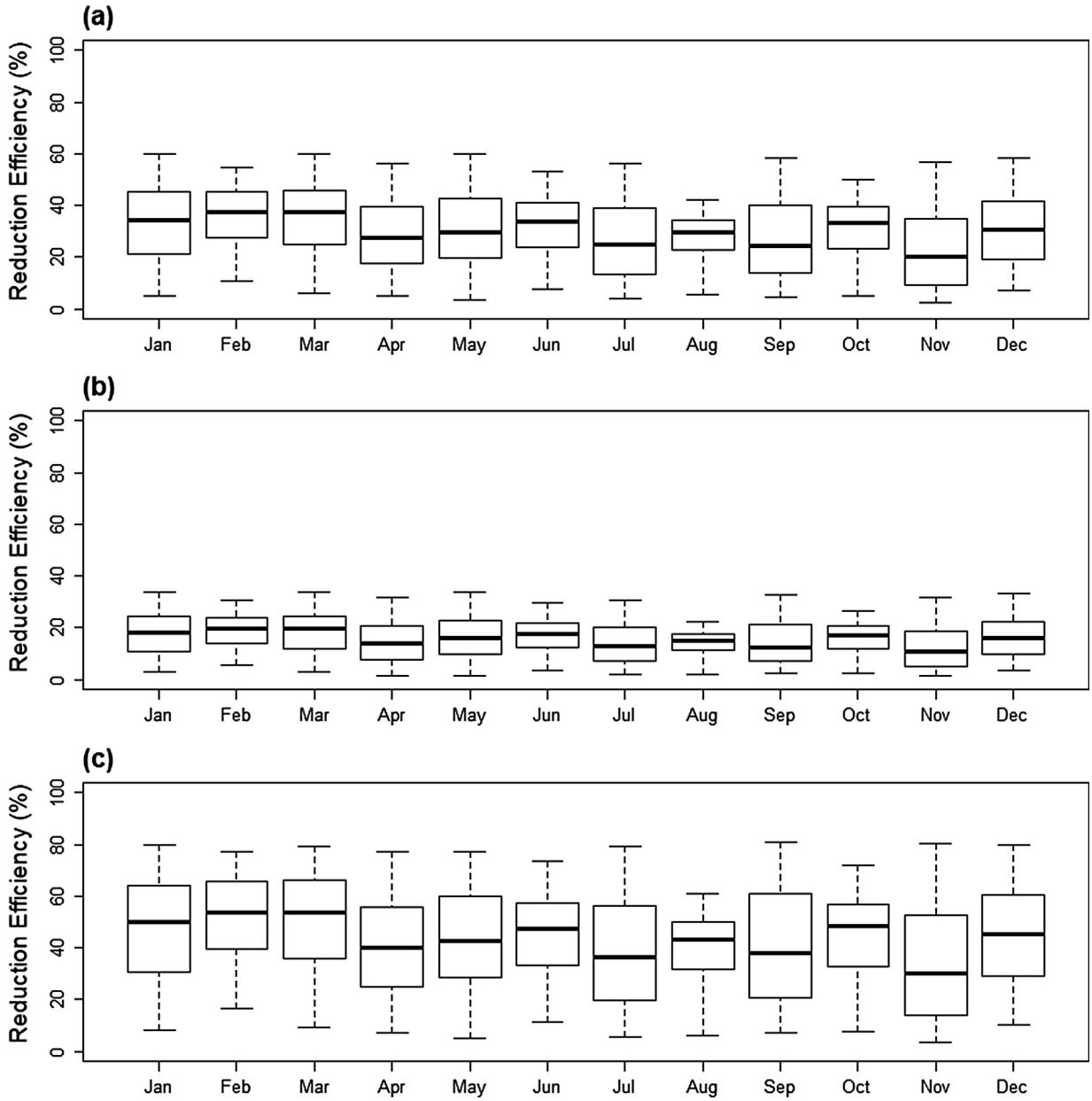

Fig. 5. Reduction efficiency of SC #1 (a), SC #2 (b), and SC #3 (c), for 9-year monthly average TON loads.

SC #1, respectively, with an increased range (2.5–97.5th percentile values) of riparian efficiency results (Table S4). This is suggestive of the parameter uncertainty in estimating the effectiveness of conservation practices if only a single parameter set is employed. Reducing errors caused by equifinality better captures physical processes and the impacts of conservation practices on water quantity and quality (Daggupati et al., 2015; Molina-Navarro et al., 2017). Thus, our results provide a broader perspective on water quality benefits of riparian buffers in this region by taking model uncertainty into account.

It is instructive to compare our results with previous studies that implemented VFS approach in SWAT. Leh et al. (2018) reported that buffer reduction efficiency for total N ranged from 1.2 to 4.9%. Their croplands only accounted for a small portion of the watershed (~6%) relative to our study site (56%) and thus buffer impacts simulated in their study were less substantial than our study. In contrast, a study by Teshager et al. (2017) tested VFS on a watershed with 78% croplands and reported an approximately 50% reduction efficiency of riparian buffers for annual nitrate loads, a greater efficiency than our study due to that study's greater proportion of croplands. Regardless of cropland proportions in a watershed, riparian buffers are effective at reducing pollutants. In particular, riparian buffers exhibited increased reduction efficiency on the area with a greater proportion of croplands, which indicates that riparian buffers are crucial for areas impaired by excessive agricultural nutrients. Our study site is listed on an "impaired" water body due to excessive pollutant loads and agriculture is the single largest pollutant source on the Coastal Plain of the CBW (McCarty et al., 2008). Riparian buffers would be an effective tool for mitigating water quality degradation in this region.

When the median values of reduction efficiency for 9-year monthly average TON loads were compared, TON loads were reduced by 20 to 37% under SC #1 relative to the baseline (Fig. 5). Reduction efficiency was slightly higher for early spring (January to March). The overall water budget is high during those months due to low ET (Lee et al., 2020), which leads to high soil water content and, in turn, a greater possibility of surface runoff to occur. Thus, the reduction efficiency of riparian buffers was high during those months when TON loads were large. The reduction efficiencies for SC #2 and #3 ranged from 13 to 20% and from 37 to 54%, respectively. Similar seasonal patterns to SC

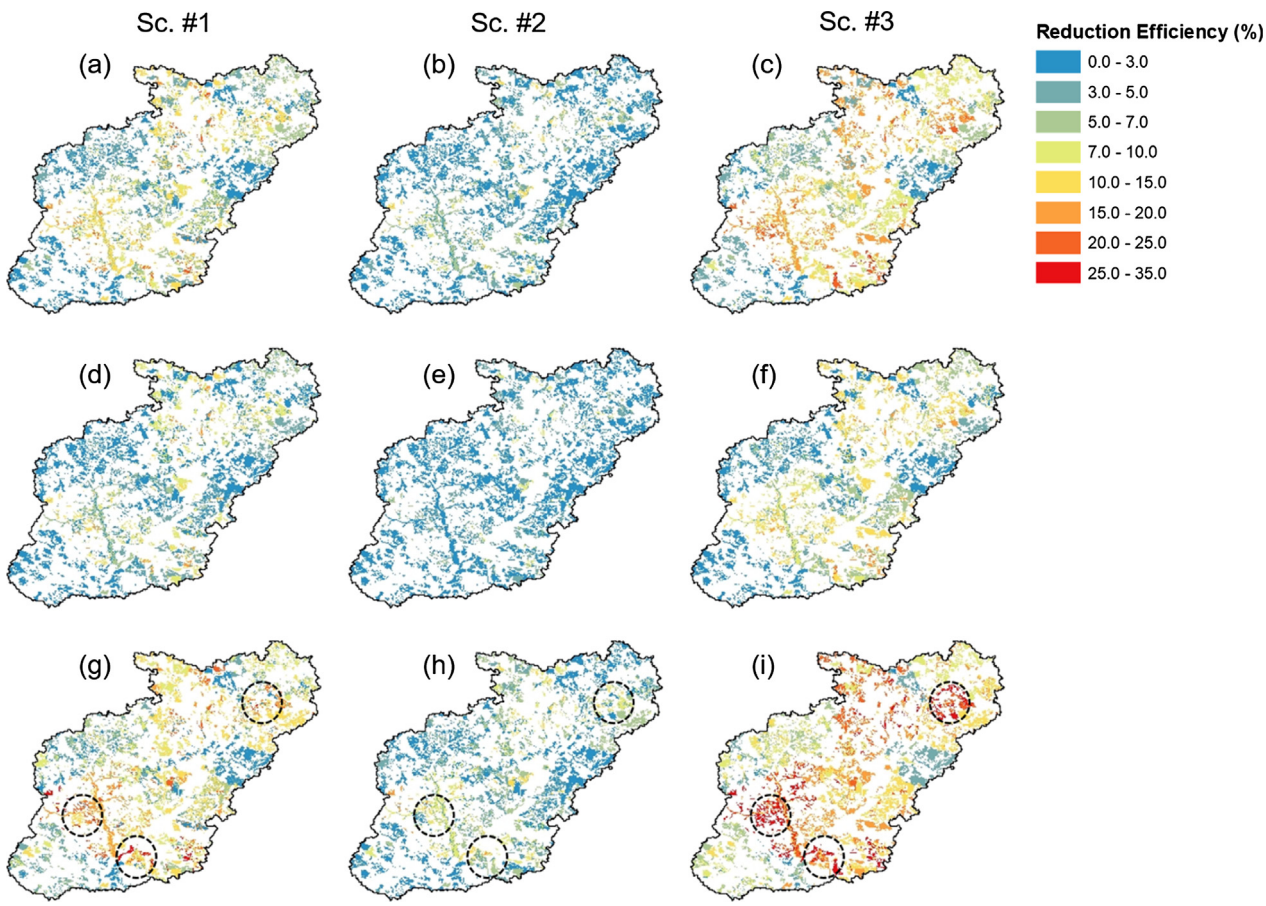

Fig. 6. Reduction efficiency of riparian buffers for 9-year annual average TON at individual HRUs. Median value: (a), (b), and (c), 25th percentile value: (d), (e), and (f), and 75th percentile value: (g), (h), and (i). Circles identify locations with notable differences in reduction efficiencies among the three buffer implementation scenarios.

#1 were observed with SC #2 exhibiting a 9 to 17% decrease in reduction efficiency and SC #3 exhibiting a 10 to 17% increase in reduction efficiency.

The monthly analysis provides information about temporal differences in delivery mechanisms of nutrients and thus emphasizes the importance of improving the ability of riparian buffers to mitigate TON loads during the early spring season via harvest of biomass on riparian buffers. Harvest of biomass (e.g., grasses and trees) is an efficient way to restore buffer storage capacity (Spinelli et al., 2006). Major summer crops are normally harvested around October in this region (Lee et al., 2016). After harvesting summer crops, harvest of biomass in riparian buffers could be employed for enhanced nutrient reduction effectiveness. When riparian buffers were implemented on all croplands, forest, and pasture (SC #3), seasonal differences in riparian buffers' efficiencies were apparent compared to SC #1. This implied that impacts of riparian buffers on reducing TON loads during early spring seasons would be considerably more effective with increases in riparian buffer areas.

3.3. Spatial variability of riparian buffer impacts

The 9-year annual average TON transported from land to nearby streams was calculated for individual HRUs. We computed the reduction efficiency of three riparian buffer implementation scenarios using 235 simulations and the median, 25th and 75 th percentile values of reduction efficiencies were mapped (Fig. 6). All HRUs were categorized according to different levels of reduction efficiency. The median values of reduction efficiencies were 0 to 25% (SC #1, Fig. 6a), 0 to 14% (SC #2, Fig. 6b), and 0 to 27% (SC #3, Fig. 6c). The numbers of HRUs with the reduction efficiency greater than 20% were 8 (SC #1), 0 (SC #2), and 34 (SC #3). The number of HRUs with the reduction efficiency less than 5% were 287 (SC #1), 476 (SC #2), and 149 (SC #3). Depending on the coverage area of buffer implementation, a number of HRUs with high or low reduction efficiency differed considerably. These comparisons illustrated that increased areas with riparian buffers can efficiently aid the achievement of water quality management goals.

It is instructive to compare the 25th and 75th percentile values for reduction efficiency among the three buffer scenarios. The 25th percentile values for reduction efficiencies showed no HRUs with the reduction efficiency greater than 20% for three implementation scenarios. In contrast, SC #1–3 included 34, 1, and 150 HRUs exceeding 20% reduction efficiency when examining the 75th percentile values. This result re-confirms the high variability in the reduction efficiency of riparian buffers depending on selection of model parameters, stressing that consideration of multiple acceptable parameter sets is essential to quantify the impacts of conservation practices using process-based hydrologic models because of model uncertainty (i.e., equifinality).

Several HRUs (highlighted with dotted circles in Fig. 6g, h, & i) showed notable differences in reduction efficiencies among the three buffer implementation scenarios. Those HRUs were frequently observed on croplands where fertilizer applications increase soil nutrient levels. Agrochemicals applied to obtain targeted crop yield are generally not fully taken up by crops in this region, and residual agrochemicals may leach into groundwater or be transported by surface runoff (Hively et al., 2009). Therefore, riparian buffers were more effective at nutrient runoff from croplands than from other land uses. This spatialized result emphasizes prioritization of riparian buffer installation for croplands with high potential of TON loads.

4. Conclusions

The effectiveness of riparian buffers for reducing TON loads in the Coastal Plain of the CBW was demonstrated using SWAT. A model simulation with a single parameter set often contains substantial model uncertainty and therefore 235 parameter sets indicating acceptable simulation results were employed in this study. Results demonstrated that riparian buffers were effective at reducing TON loads with overall reduction efficiency of approximately 45%. The reduction efficiency increased with the increasing extent of riparian buffer implementation. The reduction efficiency varied both seasonally and spatially for this region. Reduction efficiency tended to be high during early spring seasons due to an increased possibility of TON loads resulting from high soil water content that promotes the occurrence of surface flow. The reduction efficiency was more notable in croplands than other land use types, due to high soil nutrient levels from fertilizer applications. The effectiveness of riparian buffers differed by up to 30% depending on the selection of acceptable parameter sets, which implied great parameter uncertainty in simulations. Model uncertainty should be quantified through the use of multiple acceptable parameter sets or inclusion of additional calibration data (i.e., soft data) when assessing conservation practices.

The results of this study also point to effective riparian buffer implementation practices for the study site. These recommendations include: 1) increasing riparian buffer implementation to efficiently achieve water quality management goals, 2) harvest of biomass on riparian buffers after summer crop harvesting (late fall or early winter seasons) to increase nutrient reduction effectiveness of riparian buffers, and 3) prioritizing riparian buffers for croplands to target key nutrient sources. This study provides evidence for environmental benefits associated with riparian buffer programs and the value of their employment on land areas with high TON loading potential.

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.jhydrol.2020.124779.

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