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Assessing land use change impact on stream discharge and stream water quality in an agricultural watershed

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ABSTRACT

Land use and land cover (LULC) change impacts on hydrology and water quality are of critical importance in regions where water quality is degraded. One such location is the Mississippi Delta in the United States, where widespread agriculture across the landscape is a major contributing source to sediment- and nutrient-heavy runoff. To address how the landscape has changed in the recent past and consider how it may continue to change in the future, we analyzed the temporal and spatial variability of the LULC changes (e.g. forest, cropland, corn and soybean) in the Big Sunflower River Watershed. We applied these LULC changes in the Soil and Water Assessment Tool (SWAT) model to demonstrate the impacts on stream discharge, total suspended sediments (TSS) concentrations, total nitrogen (TN), and total phosphorus (TP) yields. Model performance was considered satisfactory to good (R^2 = 0.46–0.88, NSE = 0.34–0.64) for all simulated water quantity and water quality parameters. TSS concentrations increased 1.9%, while TN and TP yields increased by 12.7%, and 10.2%, respectively as the area of the cropland increased. Stream discharge was unchanged. Moreover, TN yield increased as the percentage of land occupied by cornfields increased while TP yield increased as the percentage of land occupied by soybean increased, due to differences in crop management practices such as fertilization and tillage.

1. Introduction

Rapid conversion of natural bottomland hardwood forests to agriculture throughout the 1900 s has resulted in widespread LULC changes across the Lower Mississippi Alluvial Valley in the United States. Changes such as these in LULC can alter runoff regimes (Howe et al., 1967; Jayakody et al., 2014; Onstad and Jamieson, 1970) leading to changes in the erosion and transport of sediments (Wang et al., 2016; Nelson and Booth, 2002; Ursic and Dendy, 1963) and nutrients (Lacher et al., 2019). As a consequence, the chronic hypoxic zone in the Gulf of Mexico fed by excess nutrients from agricultural runoff, has increased in tandem with the increase of agriculture in the Lower Mississippi Alluvial Valley (Turner et al., 2007). At the small scale, conversion from croplands to forests and grasslands resulted in a 283% decrease in stream nitrate as a fertilizer applications ceased (Schilling and Spooner, 2006).

Modeling frameworks such as the Conversion of Land Use and its Effects (CLUE) is a powerful tool that can integrate both current and projected future conditions by combining user-defined trends based on target land cover change area and probability change to simulate future land cover change (Verburg et al., 2002; Zare et al., 2017). In addition to CLUE, stochastic methods such as Markov chains have been applied to project land use change (Bell, 1974; Britz et al., 2011; Guan et al., 2011). However, there is a research gap to simulate LULC change in large agricultural watersheds where LULC change could happen frequently among LULCs due to annual changes in crop rotations.

Even within agricultural land uses, the response of water quantity and water quality can vary due to differences in crop physiology and management needs. For example, the amount of crop residue remaining in the field after harvest, is determined by tillage type and crop yield and has impacts on surface runoff and soil water infiltration (Dickey et al., 1985; Kaspar et al., 2001; Larson et al., 1978). In a comparison between soybean and corn, soybean fields were more prone to erosion because

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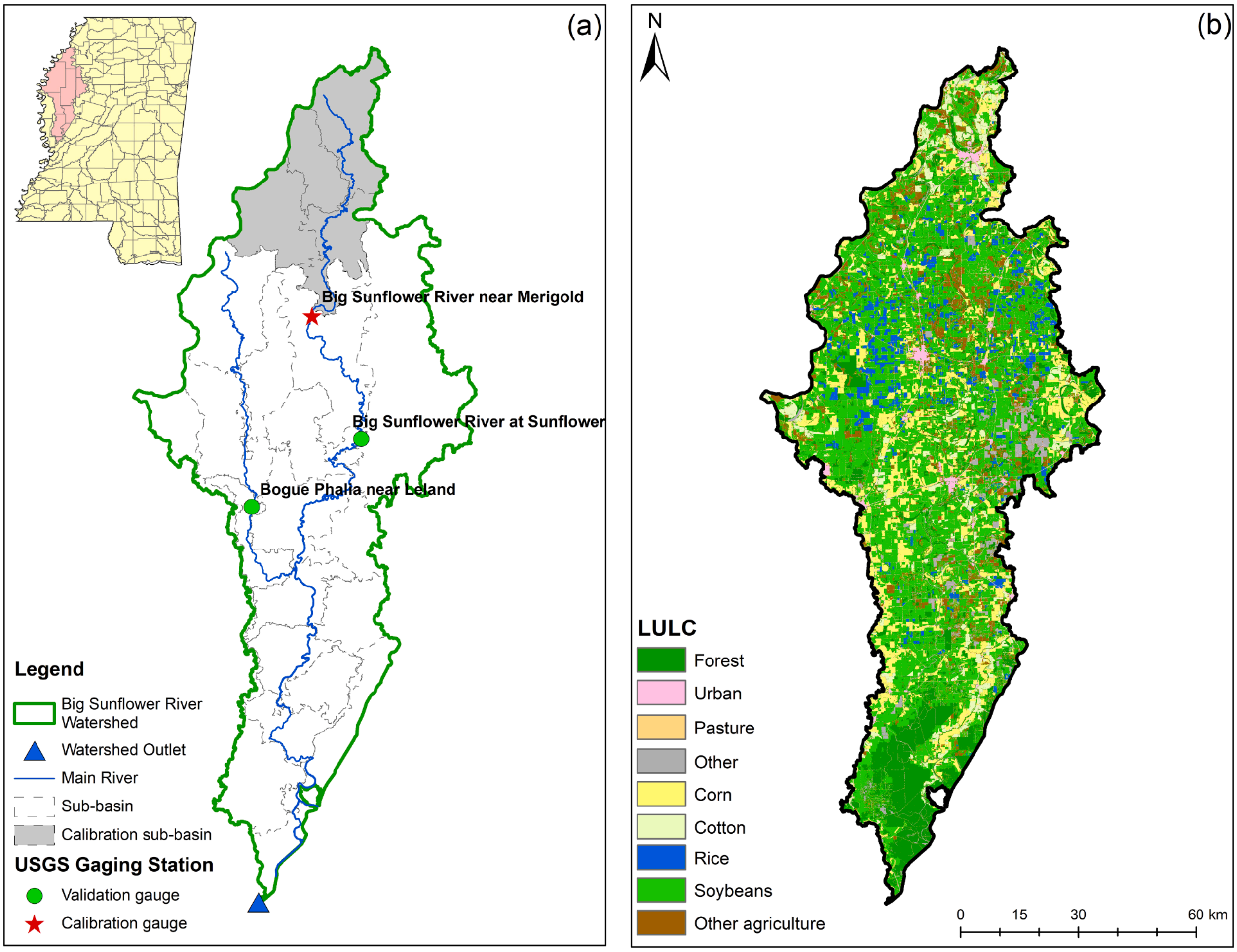

Fig. 1. Big Sunflower River Watershed spatial information, (a) study area and USGS gaging stations; (b) 2016 LULC (USDA/NASS, 2016).

soybean total yield is smaller and there has less residue to remain *in situ* following harvest (Kaspar et al., 2001; Laflen and Moldenhauer, 1979). Moreover, corn cultivation lead to lower nitrate loads, while soybean cultivation results in elevated nitrate loads due to the joint effect of faster decomposition of soybean residues and lower N utilization efficiency of soybean compared to corn (Piske and Peterson 2020). Thus, finer details of crop conversion within a singular LULC like agriculture lands need to be considered when investigating LULC change impacts on hydrology and surface water quality.

Recent development in spatial data including the crop data layer (CDL) from the United States Department of Agriculture (USDA), have been widely used for modeling LULC in agricultural watersheds (Giri et al., 2012; Srinivasan et al., 2010). Integration of existing modeling frameworks for LULC change with annual spatial data such as CDL may provide this information. There, in this study we combined LULC change analysis to simulate the impacts on hydrology and surface water quality in a large agricultural watershed in the Lower Mississippi Alluvial Valley. The specific objectives of this study were to: (i) investigate LULC change trends in a large agricultural watershed, and (ii) demonstrate LULC change impacts on hydrology and stream water quality (total suspended sediment (TSS), total nitrogen (TN), and total phosphorus (TP)) by taking into account annual seasonal crop rotations that are frequent and widespread across the agricultural landscape of the region.

2. Method

2.1. Study area

The Mississippi Big Sunflower River Watershed (BSRW) was selected for this study (Fig. 1). The BSRW is the major sub-watershed of the Mississippi Delta region within the Lower Mississippi Alluvial Valley, which is known for heavy crop production. More than 80% of the area is covered by agricultural crops, including corn, soybean, cotton, and rice (USDA/NASS, 2016) and the remaining 20% includes pasture, urban and wetland forest (Fig. 1).

2.2. SWAT model

The Soil and Water Assessment Tool (SWAT; (Arnold et al., 1998; Neitsch et al., 2011) with comprehensive crop management operation simulation module was selected to conduct hydrologic and water quality assessment within the BSRW. The BSRW was divided into 22 sub-basins (Fig. 1a). The sub-basins were further divided into hydrologic response units (HRUs) based on soil type, land use type, and slope length. Soil types with areas greater than 5% of overall sub-basin area were considered for simulation. Similarly land use and slope length thresholds were 1%, and 5% respectively.

2.2.1. Model input data

Model inputs include Digital Elevation Model (DEM) (USGS, 1999), soil type from SSURGO database (USDA, 2005), land use and cover data from CDL (USDA/NASS, 2016), and weather data from the Climate

Table 1
Hydrological parameters acronyms, description, and fitted values used in model calibration.

	Parameter Name	Description	Fitted Value
1	ESCO	Soil evaporation compensation coefficient	0.537
2	ALPHA_BF	Base flow recession constant	0.675
3	GW_DELAY	Delay of time for aquifer recharge	93.278
4	CH_N2	Manning’s coefficient for the main channel	0.014
5	RCHRG_DP	Aquifer percolation coefficient	0.468
6	GW_REVAP	Groundwater revap coefficient	0.170
7	GWQMN	Threshold water level in shallow aquifer for base flow	884.565
8	EPCO	Plant uptake compensation factor	0.896
9	SURLAG	Surface runoff lag coefficient	9.362
10	REVAPMN	Threshold water level in shallow aquifer for revap	261.813
11	CN2	SCS curve number	68–93

Table 2
Parameter acronyms, description, and fitted values used in model calibration of total suspended sediment (TSS), total nitrogen (TN), and total phosphorus (TP).

	Parameters	Description	Fitted value
TSS	CH_COV1.rte	Channel erodibility factor	0.192
	CH_COV2.rte	Channel cover factor	0.208
	USLE_K.sol	USLE equation soil erodibility (K) factor	0.040–0.390
	SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing	0.004
	CHERODMO.rte	Channel erodibility factor	0.600
TN	ERORGN.hru	Organic N enrichment ratio	0.318
	CH_ONCO.rte	Organic nitrogen concentration in the channel (ppm)	14.700
	RS4.swq	Rate coefficient for organic N settling in the reach	0.090
	BC1.swq	Rate constant for biological oxidation of NH4 to NO2 in the reach	0.177
	BC2.swq	Rate constant for biological oxidation of NO2 to NO3 in the reach	1.817
	BC3.swq	Rate constant for hydrolysis of organic N to NH4 in the reach	0.314
	RCN.bsn	Concentration of nitrogen in rainfall	1.775
	N_UPDIS.bsn	Nitrogen uptake distribution parameter	98.567
	NPERCO.bsn	Nitrogen percolation coefficient	0.739
TP	PSP.bsn	Phosphorus sorption coefficient	0.436
	ERORGP.hru	Organic P enrichment ratio	4.878
	BC4.swq	Rate constant for mineralization of organic P to dissolved P in the reach	0.068
	RS5.swq	Organic phosphorus settling rate in the reach	0.009
	P_UPDIS.bsn	Phosphorus uptake distribution parameter	1.567
	PPERCO.bsn	Phosphorus percolation coefficient	16.428
	CH_OPCO.rte	Organic phosphorus concentration in the channel (ppm)	17.900
	PPERCO_SUB.chm	Phosphorus percolation coefficient	16.543

Forecast System Reanalysis (CFSR) database (NCDC, 2016) and the Global Historical Climatology Network (GHCN)–Daily database (NOAA, 2016). The crop management practices implemented in the model simulations are shown in Table A1 summarized from Parajuli et al. (2013) and Mississippi State Agricultural and Forest Experiment Station (MAFES) annual report (MAFES, 2002-2014).

To estimate LULC change trend, the CDL from 2011 to 2016 was applied. The crop type information contained in the CDL dataset have an accuracy of 90% (USDA/NASS, 2006–2016), while other datasets have land use accuracies ranging from 28% to 76% (Homer et al., 2007; Homer et al., 2015; Wickham et al., 2010; Wickham et al., 2017).

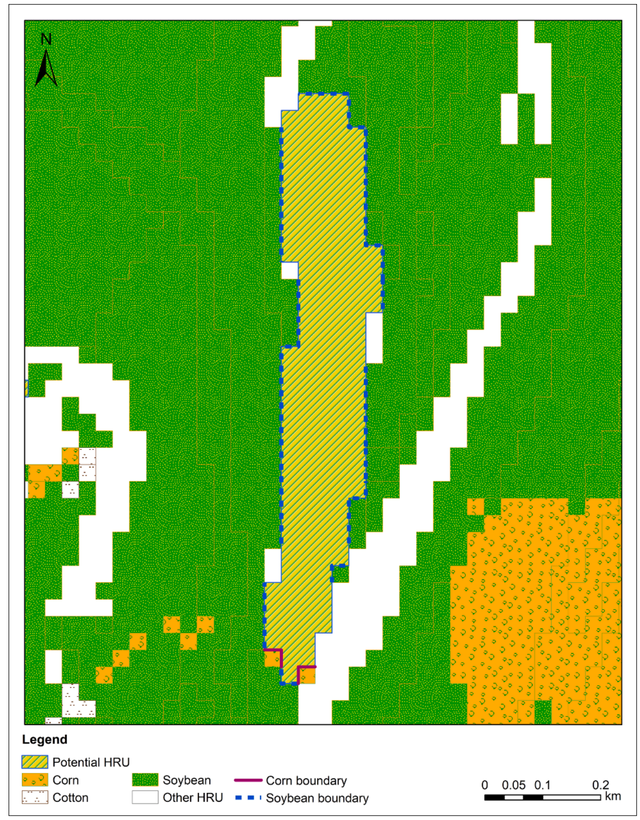

Fig. 2. Example of the longest adjacent boundary method.

2.2.2. Model calibration and validation

The SWAT model was calibrated by both automatic and manual methods and evaluated by two statistical parameters: the coefficient of determination (R^2) and the Nash–Sutcliffe model efficiency index (NSE). For auto-calibration, the auto-calibration algorithm, SWAT-CUP sequential uncertainty fitting procedure (SUFI2), was applied to obtain optimized parameter values. SUFI2 applies a global search procedure on simulations with various sets of parameter values to obtain a set of parameter values resulting in a best objective function (Abbaspour et al., 2004). The auto-calibration was run for 1500 plus 1500 simulations with different parameter values based on the recommendation from SWAT-CUP (Abbaspour, 2013). A set of fitted values of hydrological parameters with the best NSE scores were obtained from 3000 total simulations, with the exception of the Soil Conservation Service (SCS) curve number (Table 1). Manual calibration of the SCS curve number was performed with a range of −30% to 30% of defaulted values according to Cronshey (1986).

For stream discharge calibration and validation, monthly stream discharge from the Big Sunflower River near Merigold, MS USGS gaging station (07288280) was used to calibrate hydrological parameters of BSRW from 2007 to 2016, while monthly stream discharge from two other gaging stations (Big Sunflower River at Sunflower, MS: 07288500; Bogue Phalia near Leland, MS: 07288650) were used for model validation for the same time period used for calibration (Fig. 1).

Water quality parameters were auto-calibrated (Table 2). Daily water quality indicators including TSS concentrations, TN, and TP yields from 2013 to 2015, were auto-calibrated similarly to stream discharge calibration. To avoid interactions among water quality parameters that have been noted in previous studies, TSS was calibrated first and then, TN and TP were calibrated simultaneously (Santhi et al., 2001; Shen et al., 2008; White and Chaubey, 2005).

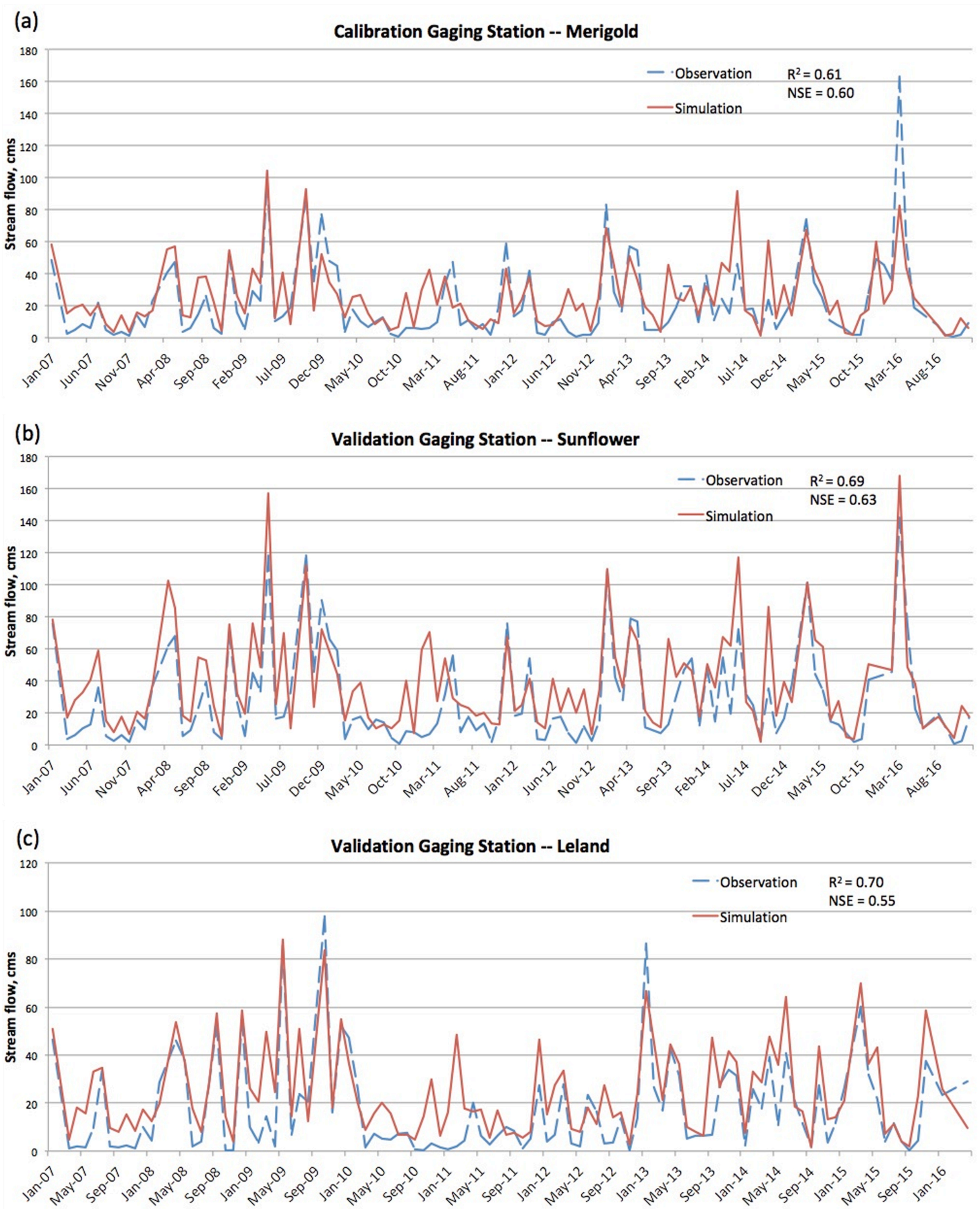

Fig. 3. Stream discharge observations versus simulations: during model calibration (a) Merigold, and validation (b) Sunflower, and (c) Leland.

2.3. LULC model scenarios

Two scenarios were considered in this study over a five year period (2017–2022). The first scenario was the baseline scenario in which LULC was obtained from the CDL dataset for the period of 2011 to 2016. This is referred to as the “base” scenario. This scenario simulates the recent historical trends in LULC for the region. The second scenario uses a projection of what LULC may be in the near future. This scenario is referred to as the “land use change” scenario. To establish the LULC projection for this scenario, a LULC change trend was determined by analyzing the land area changed in each land use category in the study area. Then the spatial change was simulated by calculating the longest adjacent boundary. Lastly, different management schedule combinations were applied to represent LULC change in the SWAT model (Table A1). Both scenarios used climate data from 2011 to 2016.

2.3.1. LULC change trend

The first step was to determine the local LULC change trend. In the

Table 3
Model performance for water quality parameters for the period between 2013 and 2015. Performance ratings from monthly time scales from Moriasi et al., 2015 were used when daily time scales were not available.

	Location	R^2	Performance Rating	NSE	Performance Rating
TSS	Calibration–Merigold	0.49	Satisfactory	0.47	Satisfactory
	Validation–Sunflower	0.57	Satisfactory	0.44	Not Satisfactory
	Validation–Leland	0.56	Satisfactory	0.52	Satisfactory
TN	Calibration–Merigold	0.46	Satisfactory	0.56	Very Good
	Validation–Sunflower	0.65	Good	0.34	Satisfactory
	Validation–Leland	0.75	Very Good	0.50	Good
TP	Calibration–Merigold	0.83	Very Good	0.45	Satisfactory
	Validation–Sunflower	0.88	Very Good	0.64	Good
	Validation–Leland	0.82	Very Good	0.38	Not Satisfactory

study area, cropland is the dominant land cover and occupies approximately 80% of the BSRW watershed (USDA/NASS, 2016). Since the approach used for obtaining CDL data has been relatively consistent since 2011, the period of 2011 to 2016 was selected for this study. A single linear regression was used to determine the change in cropland from 2011 to 2016. The annual cropland area increased by 68 km^2 per year within BSRW over this time period, representing 0.8% of the entire BSRW. The cropland area was divided into four crop species: soybean (62.6%), corn (27.4%), cotton (4.7%), and rice (5.3%). The annual change in cropland was then weighted based on these ratios to determine annual area increase of each crop species. Afterward, this trend was applied to predict annual LULC change from 2017 to 2022.

2.3.2. Simulation of LULC changes

After obtaining the annual increase in the area of cropland, the next goal was to estimate LULC spatial change. For each HRU, it was determined whether the HRU would be changed to cropland and, if so, what type of crop it would change to. The processes involved randomly selecting HRUs with potential to be converted into cropland each year, and then determining the crop species planted on that HRU by analyzing its adjacent LULC. Due to lack of LULC change probability data, it was assumed that each HRU had same probability to change to cropland. According to CDL data approximately 15% of the BSRW area was wetland forest, and 4% was urban (USDA/NASS, 2016). Compared to urban land use, forest cover was more likely to be converted to cropland (Etter et al., 2006; Lambin and Meyfroidt, 2011). Thus, HRUs with existing LULC of wetland forest were used in the random selection pool of HRUs to be convert to cropland in this analysis.

Fig. 4. Monthly stream discharge at the watershed outlet in the baseline scenario and land use land cover (LULC) change scenario, from 2017 to 2022.

Fig. 5. Monthly total suspended sediment (TSS) concentrations at the watershed outlet in baseline scenario and the land use land cover (LULC) change scenario, from 2017 to 2022.

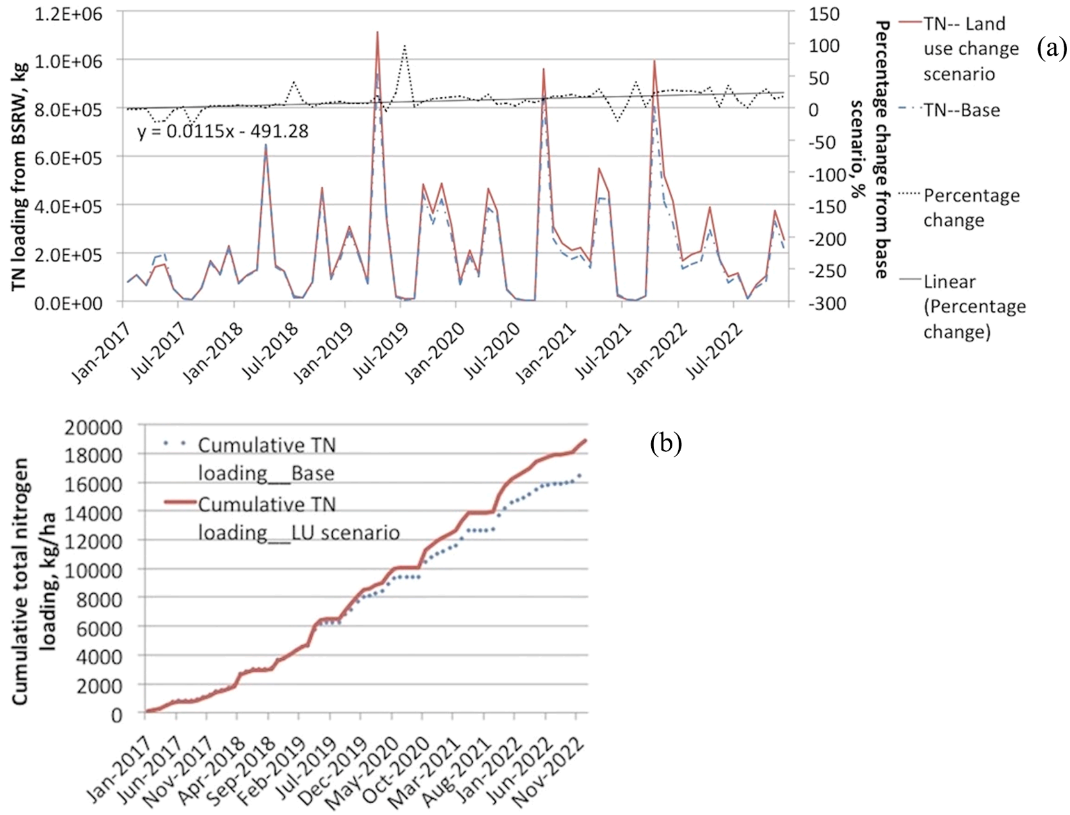

Fig. 6. (a) Monthly and (b) cumulative total nitrogen (TN) loads at the watershed outlet in the baseline scenario and the land use land cover (LULC) change scenario, from 2017 to 2022.

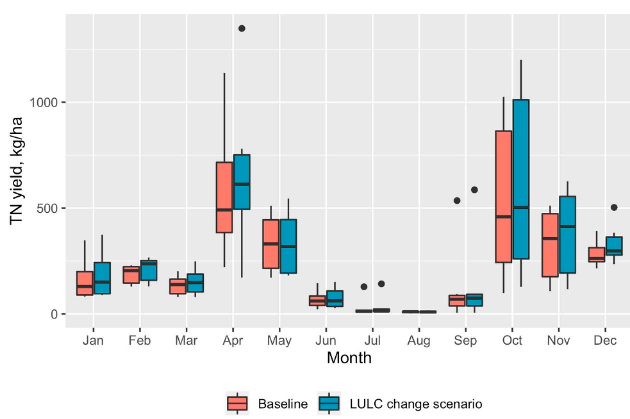

Fig. 7. Monthly total nitrogen (TN) yield from BSRW in the baseline scenario and the land use land cover (LULC) change scenario, from 2017 to 2022.

For the HRUs that were converted to cropland, the crop species planted was determined by the longest adjacent boundary method (Fig. 2). In Fig. 2, the potential HRU was surrounded by soybean fields, corn fields, and other HRUs. The crop species planted on the potential HRU was defined as the one sharing longest adjacent boundary with the potential HRU. Thus, the HRU shown in Fig. 2 would be converted to soybean. If the potential HRU were not adjacent to existing cropland, the HRU would not be selected change to cropland in the future. In order to develop land use change scenarios, a 5.4% increase in cropland area by HRUs within the BSRW was defined, with the change gradually occurring over 6 years (2017–2022).

3. Results and discussion

3.1. Model calibration and validation

Fig. 3 shows model calibration and validation results for monthly stream discharge from the three USGS gaging stations within BSRW. The model performance using USGS gage station data of Merigold during calibration ($R^2 = 0.61$, NSE = 0.60) was considered as “Satisfactory” according to criteria established by Moriasi et al. (2015) (Fig. 3a). The values of R^2 during model validation period were 0.69 (Good) and 0.70 (Good), respectively, for the USGS gages at Sunflower and Leland, which indicated slightly better model performance than in model calibration (Fig. 3). NSE values were in agreement and both Satisfactory. The discrepancy between model calibration and validation could be attributed to the large peak flows at Merigold in March 2016 which was not well-modeled during the calibration phase. However, both calibration and validation results indicate that the model has the ability to represent the study area.

Model calibration of water quality parameters, including TSS, TN, and TP, achieved R^2 and NSE values considered Satisfactory to Very Good according to Moriasi et al. (2015) (Table 3).

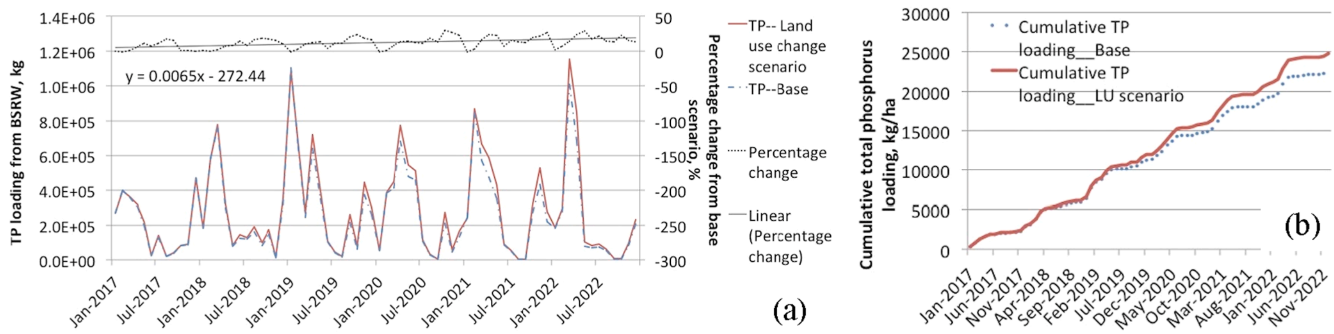

Fig. 8. (a) Monthly and (b) cumulative total phosphorus (TP) loads at the watershed outlet in the baseline scenario and the land use land cover (LULC) change scenario, from 2017 to 2022.

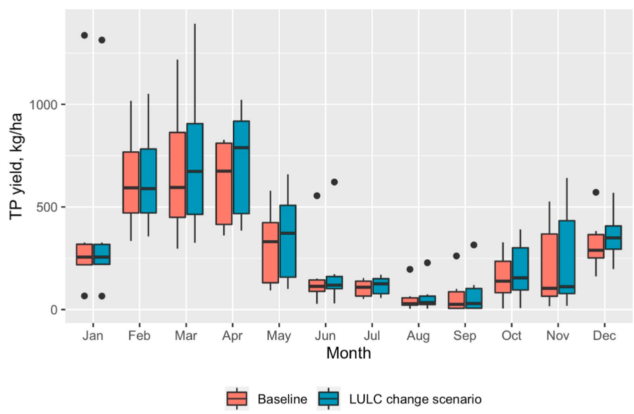

Fig. 9. Monthly total phosphorus (TP) yield from BSRW in the baseline scenario and the land use land cover (LULC) change scenario, from 2017 to 2022.

3.2. Impacts of LULC on stream discharge and water quality

To evaluate the impacts of LULC change on the BSRW watershed, model simulated stream discharge, TSS concentrations, TN, and TP yields from the LULC change scenario were compared with the baseline scenario from 2017 to 2022.

3.2.1. Stream discharge

Fig. 4 shows monthly stream discharge between the LULC change scenario and the baseline scenario, at the watershed outlet, from 2017 to 2022. Monthly discharge ranged from −10% to 10% of the baseline condition over the 6 year simulation, with most time steps having a lower monthly discharge in the LULC change scenario compared to baseline discharge (Fig. 4). The overall average monthly discharge in the LULC change scenario (162 m^3/s) was similar to the baseline scenario (161 m^3/s). However, there was a general trend of increasing discharge as the simulation progressed. Long-term studies have indicated that increasing cropland could result in more stream discharge (Yan et al., 2013; Zhang and Schilling, 2006). In this study, the change was not as evident, possibly due to the relative short time period and small LULC change area of this study. For example, the duration of the Yan et al. (2013) study was 20 years and cropland changed from −80% to 30% of the study area. By contrast, in this study, the study time period was 6 years and only 0.8% of the watershed was converted to cropland annually, because most of the land area in the study watershed was already occupied by agriculture.

3.2.2. Sediment

Fig. 5 shows the comparison of TSS concentrations in stream water between the LULC change scenario and the baseline scenario, at the watershed outlet, from 2017 to 2022. TSS changed from −3% to 25% in the LULC scenario compared to the baseline scenario. Overall, there was a 1.9% increase in average TSS concentrations in the LULC change scenario compared to the baseline scenario. Previous studies have indicated that decreasing forest cover and increasing cropland area resulted in greater sediment yield (Sharma et al., 2011; Yan et al., 2013), which is consistent with result of this study. Compared to forests, cultivated lands involve more frequent vegetation removal and exposure of bare mineral soil, increasing the likelihood of erosion.

3.2.3. Total nitrogen

Fig. 6 shows the comparison of TN yield from the entire BSRW between the LULC change scenario and the baseline scenario, from 2017 to 2022. Monthly TN yield differences between the two scenarios ranged from −0.05 kg/ha to 0.22 kg/ha, which represents a variation of −26% to 96% of the TN yield compared to the baseline scenario (Fig. 6a). Cumulative TN yield from the entire watershed in the LULC change scenario was 12.7% higher than in the baseline scenario (Fig. 6b). There was a slightly increasing trend in TN yield with cropland expansion, which is consistent with previous studies and can be attributed to fertilizer applications (Piske and Peterson, 2020; Schilling and Spooner, 2006).

On average, the largest TN load difference between the two scenarios occurred in the month of April with a total overall increase of 122 kg/ha in that month alone (Fig. 7). This likely coincided with application of fertilizers at the onset of the growing season in croplands planted with corn (Table A1), since conversion to corn represented 27.4% in the LULC change scenario. Other studies have indicated that cornfields were the main source of nitrogen export due to their high yields and large fertilizer usage (Hendricks et al., 2014; Jayasundara et al., 2007). On the contrary, Piske and Peterson (2020) detected a decrease on nitrate export with increasing corn cultivation compared to soybean, which cannot be investigated in this study as single crop species impact was not separately analyzed due to data unavailability.

3.2.4. Total phosphorus

TP yield in the LULC change scenario changed from −1.7% to 30.2% compared to the baseline scenario (Fig. 8a). There was a 10.2% increase in cumulative TP load in the LULC change scenario compared to the baseline scenario (Fig. 8b). Udawatta et al. (2011) demonstrated that croplands generally had more phosphorus export than forest and pasture due to the fertilization of croplands. Thus, in this study, croplands that replaced forests resulted in higher TP yield due to fertilization and increased erosion. However, unlike for TN corn, soybean was the main source of TP. Soybean, as the dominant crop in BSRW, was fertilized with 12-22-22 fertilizer (Table A1) that contains 9.6% mineral phosphorus. Thus, the large area occupied by soybean production in conjunction with higher quantities of P fertilization led to soybean fields contributing more to TP yield compared to other crops.

Monthly TP loads for stream water closely followed tillage activities, with peaks occurring during bed preparation prior to planting in the spring and during harvesting activities in the autumn (Fig. 9). The Mississippi Delta agricultural region does not rely on tile drainage like other large agricultural regions in the Midwestern US, which are installed to reduce soil erosion. As a result, more soil erosion occurs in the Mississippi Delta (Lindstrom et al., 1992; Takken et al., 2001), leading to phosphorus-bound sediments serving as the primary source of TP (Fig. A1). Thus, it is reasonable that monthly TP yields followed tillage patterns. In addition to tillage, soybean fields are more prone to erosion compared to cornfields due to less crop residue in soybean fields (Kaspar et al., 2001; Laflen and Moldenhauer, 1979). Thus, TP yield changed more in March and April when soybean tillage occurred compared to corn tillage.

4. Conclusion

In this study, we analyzed changes in land use and land cover taking into account past trends and spatial availability of land use data. We applied LULC changes in a watershed model to evaluate the impacts on stream discharge, sediment concentrations, TN yield, and TP yield. The model performance regarding stream discharge and water quality was considered as acceptable for LULC impacts evaluation.

In the LULC change scenarios, small remaining forested area were converted to cropland. In these scenarios, annual sediment concentrations increased by a modest 1.9% while TN and TP yields increased by 12.7%, and 10.2%, respectively over a 6 years simulation period. However, no changes were observed in stream discharge, suggesting that changes in flow were not the cause of changes in sediment and nutrient concentrations. Instead, crop management practices were likely the cause of the observed changes. Expansion of corn was more closely related to the increased in TN yield, while expansion of soybean was more closely related to the increase in TP yield. This study demonstrates how GIS-based watershed models can be used to assess LULC change in agricultural-dominated watersheds being easily applied in similar landscapes around the world. Moreover, the results of this study could help agricultural and environmental managers defining sustainable agricultural LULC changes for the future.

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

(see Fig. A1 and Table A1)

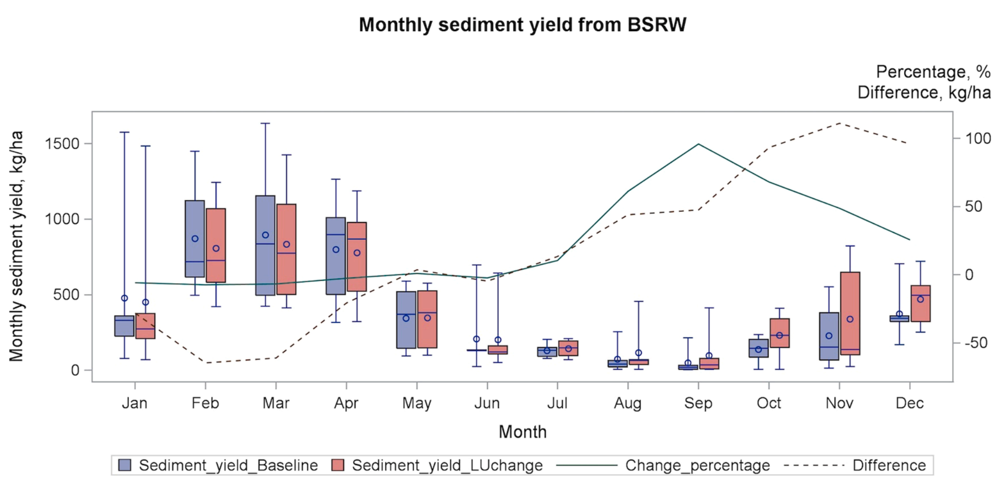

Fig. A1. Monthly TSS yield from BSRW comparison between the LULC change scenario and the baseline scenario.

Table A1
Crop management practices simulated in the SWAT model.

Field	February	March	April	May	June	July	August	September	October
Soybean		Tillage	Tillage Planting	Fertilization (12–22-22)	Irrigation	Irrigation	Irrigation	Irrigation	Harvesting
Corn	Tillage	Tillage Planting	Fertilization (Element N)	Fertilization Irrigation	Irrigation	Irrigation	Irrigation	Harvesting	
Cotton			Tillage	Tillage Planting	Fertilization (03–27-06) Irrigation	Irrigation	Irrigation		Harvesting
Rice	Tillage	Tillage	Planting	Fertilization (Urea) Irrigation	Irrigation	Irrigation	Irrigation		Harvesting

Note: 12–22-22, Element N, 03–27-06 and Urea were set according to Arnold et al. (2013).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2020.105055.

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