

Evaluation of spatial variability on hydrology and nutrient source loads at watershed scale using a modeling approach

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ABSTRACT

Understanding the effects of spatial variability on hydrologic parameters and nutrient source load distribution is essential to develop water quality improvement programs. The objective of this research was to evaluate spatially distributed hydrologic variability, nutrient sources, and their loadings at the watershed scale using a modeling approach. The Soil and Water Assessment Tool (SWAT) was applied to assess spatial variability of annual average water, sediment, total phosphorus (TP), and total nitrogen (TN) yields from the Upper Pearl River Watershed (UPRW) in Mississippi, USA. The SWAT model was successfully calibrated, validated, and verified with good model efficiency ($R^2 = 0.70$ and $E = 0.59$) using monthly measured stream flow, daily observed flow, sediment, TP, and TN yields. The SWAT model results determined that spatial variability of annual average pollutant loads of water yield ranged from 877 to 206 mm, sediment yield ranged from 1.71 to 0.17 t ha⁻¹, TP ranged from 1.39 to 0.02 kg ha⁻¹, and TN ranged from 10.22 to 0.69 kg ha⁻¹ in the watershed sub-basins. Understanding of the spatial variability of hydrologic and nutrient source loads distribution helps watershed managers focus their management efforts to the most needy watershed sub-basins.

Key words | hydrology, nutrient, spatial variability, stream flow, SWAT, watershed

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INTRODUCTION

The responses of the watershed on hydrology and nutrient source loads are dependent on spatially variable watershed parameters such as topography, soils, land use, and watershed managements including human activities. Human activities affect in generating and carrying pollutants such as sediment, nitrogen, and phosphorus. Such diffuse pollutants can affect the quality of ground water, surface water, and the aquatic environment causing eutrophication (Davis & Koop 2001).

Water quality pollutants such as sediment and nutrients can cause environmental and economic problems if the receiving water body is polluted to the eutrophication level (Mainstone *et al.* 2000; Smith 2003). Eutrophication is typically measured as an increase in the primary production of algae, which then leads to a number of considerably undesirable changes that include a reduction in water clarity and a shift towards less diverse plant and animal communities

(Foy 2005). Changes in trophic status and nutrient supply can influence the dominance and succession of specific algal communities, some of which release toxins that threaten public and animal health (Codd *et al.* 2005). The costs of the water treatment and the potential damage to recreation, amenity and property values can be significant (Pretty *et al.* 2003; Bateman *et al.* 2006). Agricultural activities are among the major pollutant sources that deteriorate surface and ground water resources in the United States (USEPA 2001).

Spatial variations of topography, soils, land use, and agricultural management may produce significantly different results on hydrology (Huang & Lee 2009). Wang *et al.* (2010) recommended that the land use–soil interactive effects should be considered to develop the best management practices for improving watershed health and sustainability. Pease *et al.* (2010) applied Annualized Agricultural

Nonpoint Source (AnnAGNPS) model to evaluate non-point source pollution in the Pipestem Creek watershed upstream of Pingree, North Dakota. They recommended further study on interaction of land use, managements, and other factors. Nutrient export from overland flow and streams located in agriculturally dominated watersheds has been linked to large environmental pollution such as hypoxia in the Gulf of Mexico (Goolsby *et al.* 2001). However, pollutant sources in the watershed are spatially distributed. More research on spatial variability on the watershed scale would provide better understanding of the mechanisms by which pollutants are transported and potentially retained in these systems.

Pathogens, sediment, and nutrients are three main causes of the impairment in the assessed rivers and streams in the USA (USEPA 2010). However, in Mississippi the top three causes of impairments for rivers and streams are biological impairments, sedimentation, and mercury. Pathogens,

organic enrichment, pesticides, and nutrients are ranked fourth to seventh in the State of Mississippi (USEPA 2010). The Upper Pearl River Watershed (UPRW) drains into the Ross Barnett Reservoir (RBR) near Jackson, Mississippi (Figure 1). The RBR provides a source for drinking water supply to the city of Jackson and surrounding area, which has a population of approximately 200,000. Hydrologic simulation and identification of nutrient sources allows us to accurately predict pollutant loads. Despite several previous studies on the quantification of the pollutant loadings from the watershed, spatial variability of watershed characteristics (e.g. land use, soils, topography) affects the hydrologic responses and pollutant yields from the watershed is still scarce. Assessing and identifying the spatial variability of the watershed areas help us to develop watershed management plans.

Growing agricultural and non-agricultural activities in the UPRW have posed increasing threats to the water quality of the Pearl River and its tributaries including the RBR. Therefore, it

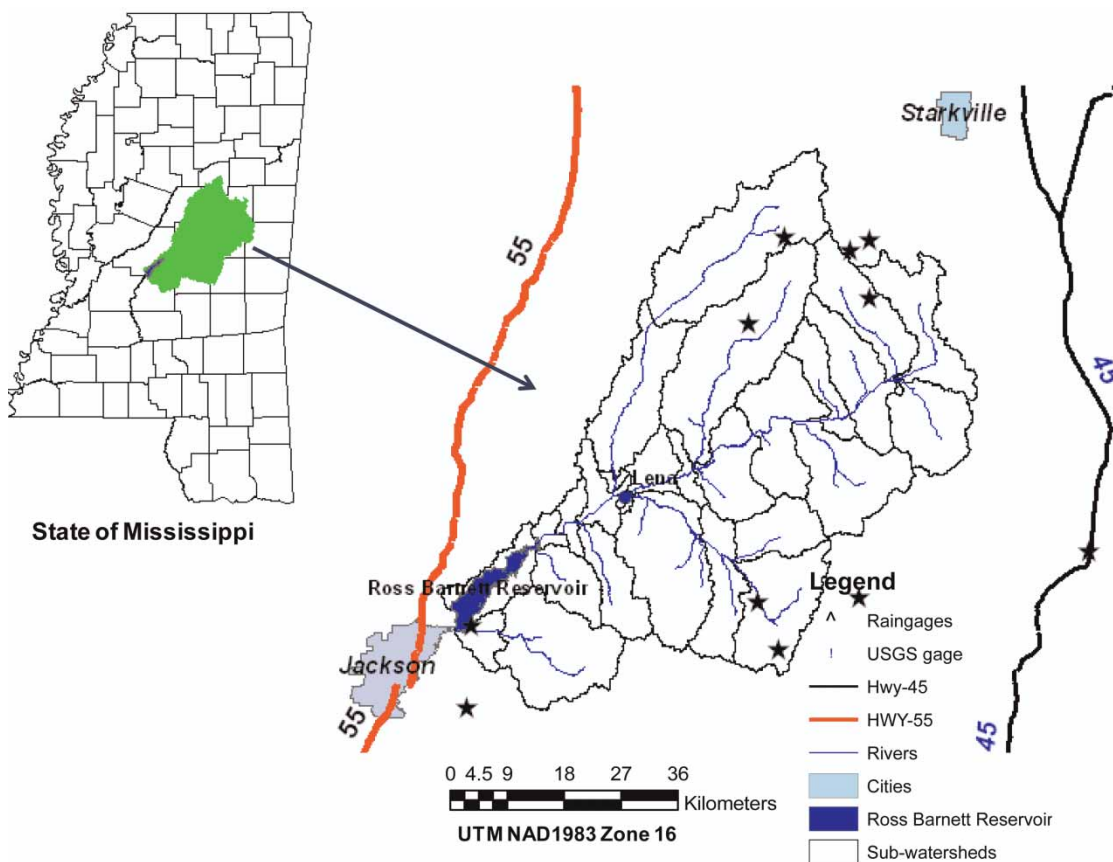


Figure 1 | Location map of the Upper Pearl River watershed in east-central Mississippi showing rainfall and USGS stream flow gauges.

is important to estimate the nutrient (N and P) loads from the UPRW and identify the nutrient sources from the watershed drainage sub-basins so that the most effective watershed management measures and nutrient control practices can be adopted in order to reduce excessive nutrient loads into the RBR. The total maximum daily loads (TMDLs) have been developed for the various tributaries of the watershed to reduce sediment and nutrient loadings to the RBR from the UPRW (MDEQ 2010). However, quantification of the effects that spatially varied nutrient sources have on water quality over time is limited. A watershed modeling approach can quantify pollutant loads, identify critical areas in the watershed, and consider spatial and temporal variations of nutrient sources and their effects on water quality across the watershed. Quantifying the water quality benefits of nutrient sources will allow policy makers and watershed program managers to evaluate the effects of current pollutant loadings and develop future programs that can more effectively and efficiently mitigate water quality pollution (Mausbach & Dedrick 2004).

The Soil and Water Assessment Tool (SWAT; Arnold *et al.* 1998) water quality model has been applied for one or more pollutant parameters such as runoff, sediment yield, and nutrient loss from watersheds at several geographic locations, under different management conditions (Chanasyk *et al.* 2003; Van Liew *et al.* 2003; Qi & Grunwald 2005; White & Chaubey 2005; Wang *et al.* 2006; Gassman *et al.* 2007; Lin *et al.* 2009; Radcliffe *et al.* 2009; Parajuli 2010a) and spatial variability of rainfall (Cho *et al.* 2009). Limited research has been performed using the SWAT 2005 model for evaluating the spatial variability of the hydrologic characteristics and nutrient sources on water quality. The overall objective of this research was to identify spatially variable hydrologic conditions and nutrient sources in the UPRW using a modeling approach.

METHODS AND MATERIALS

Watershed area and management

This research study was applied at UPRW, which is located in the east-central Mississippi. The UPRW is comprised of 10 counties (Choctaw, Attala, Winston, Leake, Neshoba, Kemper, Madison, Rankin, Scott and Newton), and covers

an area of 7,588 km² (Figure 1). The land use of the watershed is comprised of forest land (70%), pastureland (20%), urban land (6%) and others (4%). The UPRW is dominated by fine-sandy-loam and silt-loam soils. Pastureland (20%) of the watershed area typically consists of Bahiagrass (Curt Readus, USDA/NRCS, Pearl area office, 2009, personal communication). Approximately 2% land use area of the UPRW consists of cropland (e.g. corn, soybean, and hay). Typical planting date for warm-season crops (e.g. corn, soybean) was considered April 15 and harvesting date was September 15. Similarly planting and harvesting dates for the cool season crops (e.g. hay) were considered to be October 15 and June 15, respectively. Crop residues are left on-the-ground between the crop planting and harvesting periods. The reduced-tillage is typically applied in the cropland areas of the UPRW (Curt Readus, USDA/NRCS, Pearl area office, 2009, personal communication).

Stream sampling

This study utilized long-term (1997–2010) monthly flow data from the Lena USGS (US Geological Survey) gauge station (USGS 02483500) within the watershed. Daily stream grab samples were collected from the Pearl River near Lena USGS gauge stations. There were 12 storm event samples used in this study collected from February to October during 2010. Samples (about 125 mL for suspended solid; 500 mL for total nitrogen (TN) and total phosphorus (TP) combined) were collected using a 7.3 m pole swing sampler (Rickly Hydrological Company, Columbus, OH) from the mid-point of the Pearl River the Lena gauge station. About 5 mL of concentrated sulfuric acid was added to the 500 mL sample bottle collected for the TN and TP. After water quality sample collection, bottles were placed immediately into a cooler box and transferred to a laboratory refrigerator within 1–3 h at the State Chemical Laboratory at Mississippi State University. The samples were analyzed using a standard water sample analysis method such as EPA 365.3 for TP, EPA 351.2 for TN, and method EPA 160.2 for total suspended solids (APHA 1998).

Model description and input

The SWAT model is a physically based watershed-scale model with semi-distributed parameters that operates on a

continuous daily time step (Arnold *et al.* 1998). It simulates hydrological processes, sediment yield, nutrient loss, and pesticide loss into surface water, ground water and the effects of agricultural management practices on water in large, ungauged watersheds. The SWAT model considers the inputs of climate, evapotranspiration, crop growth, and management practices (Neitsch *et al.* 2005). The model uses hydrologic response units (HRUs) based on unique land use and soil types. The HRUs are essential units in order to predict the potential effects of spatial variability on hydrologic sediment and nutrient loadings.

In the hydrologic component, surface runoff is predicted from daily rainfall using modified SCS-CN and Green-Ampt methods. Due to availability of the daily input data, the SCS-CN method (SCS 1972) was used in this study. The rainfall input in the SCS-CN is a key to estimate runoff. A kinematic storage model is used to predict lateral flow in each soil layer (Sloan *et al.* 1983). The model accounts for variation in conductivity, slope and soil water content. The SWAT model uses three potential evapotranspiration methods: the Penman-Monteith method (Monteith 1965; Allen 1986; Allen *et al.* 1989), the Priestley-Taylor method (Priestley & Taylor 1972) and the Hargreaves method (Hargreaves *et al.* 1985). This study used the Penman-Monteith method to estimate potential evapotranspiration. Sediment yield is estimated using the Modified Universal Soil Loss Equation (MUSLE). The MUSLE approach of estimating sediment yield makes the sediment computation a non-linear function of the HRU area. SWAT has been applied extensively for stream flow, sediment yield, and nutrient modeling (Vache *et al.* 2002; Varanou *et al.* 2002; Gosain *et al.* 2005; Parajuli *et al.* 2008, 2009).

The SWAT model requires various sources of geospatial data to develop model input data layers. For example, Digital Elevation Data (DEM), land use, soils, and climate data (e.g. precipitation, temperature). United States Geological Survey (USGS 1999) 7.5 min DEM data were used to delineate watershed boundaries and topographic information. The State Soil Geographic Database (STATSGO) was used to develop a model input soil database (USDA 2005). The crop/landuse data layer (USDA/NASS 2009) was used to develop land use data model input for the entire watershed. The climate data inputs in the model utilizes continuous data from all available weather stations

(NCDC 2010) from 10 counties (Choctaw, Attala, Winston, Leake, Neshoba, Kemper, Madison, Rankin, Scott, and Newton).

SWAT model calibration and validation

The parameters in the SWAT 2005 were manually-calibrated in this study since Green & Griensven (2007) suggested this is the preferred method of calibrating the model. Six parameters that influence the prediction of stream flow were calibrated in this study (Table 1). These parameters were the curve number (CN), soil evaporation compensation factor (ESCO), base flow alpha factor (ALPHA_BF), surface

Table 1 | Range of calibration parameters and final values used in the model

Parameter	Range	Final values
Flow		
Landuse (Curve Numbers)		
Pasture (PAST)	74–86	79
Deciduous forest (FRSD)	70–77	77
Evergreen forest (FRSE)	70–77	70
Mixed forest (FRST)	70–77	73
Urban institutional (UINS)	77–94	92
Wetland forest (WETF)	70–77	77
Soybean (SOYB)	85–90	89
Corn (CORN)	85–90	89
Soil evaporation compensation factor (ESCO)	0–1.00	0.4
Baseflow alpha factor (Alpha_BF)	0–1.00	0.90
(Surface runoff lag coefficient (SURLAG))	1–12	1
Ground water “revap” coefficient (GW_REVAP)	0–1	0.2
Threshold depth of water in the shallow aquifer (GWQMN)	0–5000	1000
Sediment		
USLE cover and management factor (C) crop-based	0–0.50	0.2
Soybean (SOYB) and Corn (CORN)	0–0.50	0.2
Pasture (PAST)	0–0.50	0.003
Forests (FRSD, FRSE, FRST)	0–0.50	0.001
Nutrients		
Phosphorus soil partitioning coefficient	0–500	175

runoff lag coefficient (SURLAG), ground water 'revap' coefficient (GW_REVAP), and threshold depth of water in the shallow aquifer (GWQMN). The model parameters calibrated in this study were selected based on literature studies (Saleh & Du 2004; Choi *et al.* 2005; Neitsch *et al.* 2005; White & Chaubey 2005; Gassman *et al.* 2007; Parajuli *et al.* 2009; Parajuli 2010a). The stream flow, sediment, and phosphorus calibrations were executed by changing the parameters in Table 1 as described within the range in the SWAT model (Neitsch *et al.* 2005). The SWAT model predicted monthly stream flow results were compared with the Lena USGS gauge station data during the model calibration and validation process. Model simulated and measured values were statistically compared using the coefficient of determination (R^2), and Nash–Sutcliffe Efficiency Index (E) after each model run. Model input parameters were modified during the calibration process until model-predicted stream flow was within R^2 and E values exceeding or equal to 0.5. Stream flow calibration initially used model default-parameters. The final values of each calibrated parameters are mentioned in Table 1. The final values of the input parameters were not changed after the calibration process, and especially during the model validation process.

Base flow

Base flow and stream flows are generally estimated using base flow separation analysis techniques, which consider hydrograph separations from the base flow and stream flow (Bendient & Huber 2002). Although upper sections of the Pearl River and its tributaries contribute relatively low flow in various seasons, they are regarded as perennial streams. The hydrologic component of the SWAT model was validated first as it is the driving force of other pollutant transport such as sediment and nutrients in the watershed. The direct runoff and base flow components of the hydrograph are typically partitioned as they are usually simulated separately in computer models (Srinivasan & Arnold 1994). In this study a web-based hydrograph analysis tool was utilized for base flow separation (Kyoung *et al.* 2005). The recursive digital-filter-method as described by Eckhardt (2005) was used for base-flow partition. The filter parameter of 0.98 and maximum base-flow index (BFI_{max}) of 0.80 was used in the analysis tool. As described in the

web-based tool (Kyoung *et al.* 2005), the BFI_{max} indicates the ratio of base flow to the total flow. A BFI_{max} of 0.80 generally represents perennial streams with porous aquifers like the Pearl River in the watershed. The percentage of average base flow separated from the total flow from the Lena gauge station are presented in the results and discussion.

Pollutant sources

Nonpoint source pollution can originate from several sources including livestock grazing, chicken litter application, and failing septic systems. This study considered land application of three major nutrient sources: livestock, chicken litter, and failing septic systems in the UPRW. A spatially distributed county-level beef cow (beef heifers that have calved) population (USDA/NASS 2009) was analyzed for nine counties in the watershed (Choctaw, Attala, Winston, Leake, Neshoba, Madison, Scott, Newton, and Rankin). It was estimated that the temporal distribution of the average population of annual beef cows for the majority of the years during the model validation period (2003 to 2010) was not much different as compared to the spatial distribution of average annual beef cows (Parajuli 2010b). This study adopted the methods used by Parajuli (2010b) to determine the livestock, poultry, and failing septic systems input to the SWAT model.

Statistical analysis

This study used historical monthly average flow data collected by USGS from the Lena gauge station. The monthly measured stream flow data were divided into a calibration period (October 1997 to December 2002) and a validation period (January 2003 to September 2010). The SWAT model was further verified using Lena gauge station using daily observed flow data from USGS; and daily observed sediment yield, TP, and TN yield data from this study during 2010.

The SWAT model simulation period in this study covers wet, dry, and normal rainfall-runoff years, which provides years for predicting the hydrograph of the UPRW basin. For the statistical test of the model performances, this study utilized two commonly used methods (Parajuli *et al.* 2008, 2009): the coefficient of determination (R^2), and the Nash–Sutcliffe model efficiency index (E). The model performances

were categorized as excellent, very good, good, fair, poor, and unsatisfactory for R^2 or E values ≥ 0.90 , 0.75 to 0.89, 0.50 to 0.74, 0.25 to 0.49, 0 to 0.24, and < 0 , respectively (Moriassi *et al.* 2007; Parajuli *et al.* 2008, 2009; Parajuli 2010a).

Coefficient of determination (R^2)

The R^2 value measures the evenness of the measured vs. model-predicted values that corresponds to the best fit line (Equation (1)). The R^2 values close to zero are considered poor whereas the values close to one are perfect (Santhi *et al.* 2001). The R^2 only indicates how much of the measured dispersion is explained by the model prediction, therefore R^2 is not recommended to be used alone (Maidment 1993).

$$R^2 = \left(\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \right)^2 \quad (1)$$

where, O is the measured runoff (mm), P is the predicted runoff (mm), i is the time of the sample measurement, n is the total number of measurements, and the overbar denotes the mean (measured or predicted) runoff (mm) for the entire time period of the evaluation.

Nash–Sutcliffe model efficiency index (E)

The E value measures the evenness of the measured vs. model-predicted values to a linear 1:1 best-fit line (Nash & Sutcliffe 1970). The E values close to minus-infinity indicate poor model whereas close to 1.0 indicates a perfect model. The E is a commonly used parameter to assess the performance of hydrologic models (Wilcox *et al.* 1990). As the E value calculates the differences between measured vs. predicted values as squared values, the larger values are strongly overestimated whereas lower values are ignored (Legates & McCabe 1999). The E is calculated using the following equation.

$$E = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (2)$$

where, O is the measured runoff (mm), P is the predicted runoff (mm), the overbar is the mean (measured or

predicted) runoff (mm) for the entire time period of the evaluation, i is the time of the sample measurement, and n is the number of sample measured.

RESULTS AND DISCUSSION

The long-term monthly stream flow calibration and validation results at the Lena USGS gauge station, model verification of using 12 daily observed storm events, and the model-predicted spatial variability of water yield, sediment yield, TP, and TN yields from the watershed sub-basins, and the RBR inlet are presented in the following sections.

Calibration and validation

The SWAT model was calibrated (from October 1997 to December 2002) and validated (January 2003 to September 2010) using USGS monthly average measured stream flow data from the Lena USGS gauge station. Model simulated results determined good performance during calibration with R^2 and E values of 0.70 and 0.59, respectively. Model performance slightly decreased but remained close to good during the validation period with R^2 and E values of 0.64 and 0.40, respectively (Figure 2). Parajuli (2010a) calibrated and validated SWAT model for the monthly flow simulation in his previous study.

Average base flow separation from the total flow from the Lena gauge station showed about 29% of the base flow and 71% of the surface flow from the UPRW watershed during the study period (1997–2010), which is consistent with the 28.5% base flow and 71.5% surface flow as predicted by the SWAT model in the previous study (Parajuli 2010a). The SWAT model was further verified at the Lena gauge station using daily simulation (January 1 to December 31, 2010) results. The observed flow, sediment loads, TP and TN yields were estimated using USGS measured daily flow data and the field collected daily samples. The SWAT model predicted daily simulation results for the flow and water quality parameters determined slightly reduced model efficiencies as compared to monthly flow simulation. The daily model efficiency ranged from poor to very good (R^2 and E from 0.17 to 0.83, Figure 3). Some data points were

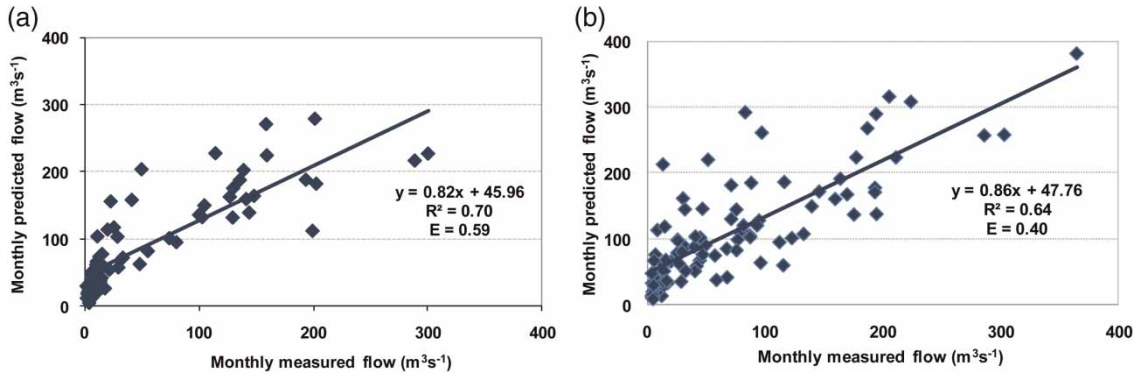


Figure 2 | Monthly measured vs model predicted flow ($\text{m}^3 \text{s}^{-1}$) during model (a) calibration and (b) validation.

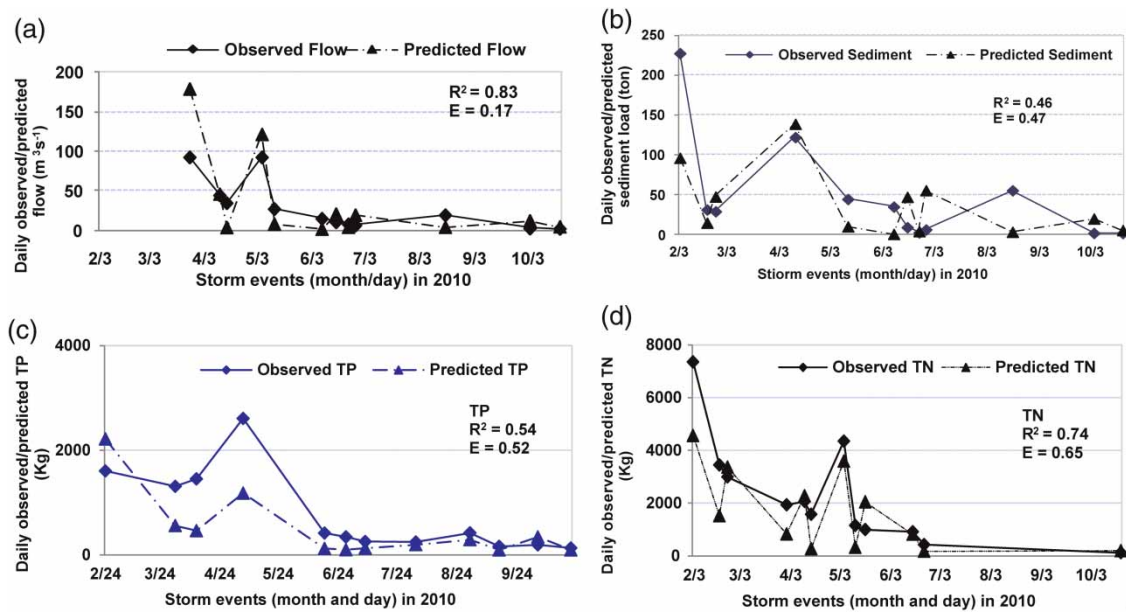


Figure 3 | Daily observed vs model predicted (a) flow ($\text{m}^3 \text{s}^{-1}$), (b) sediment load (t), (c) total phosphorus (TP, kg), and (d) total nitrogen (TN, kg) during model verification.

missing, so the statistics are based on the use of only 12 daily mean flow, sediment load, TP and TN data during 2010.

During model validation at the Lena gauge station, the daily time period model validation results at the Lena gauge station determined slightly reduced model performance but very close to good performance with R^2 , and E values ranged from 0.83 to 0.17.

When this calibrated and validated result was compared with all of the monthly and daily model statistics reported by Gassman *et al.* (2007) from an extensive literature review of 115 published SWAT hydrologic calibration and validation results for R^2 and E values, the results of this study agreed

with most of the articles which had the best reported daily calibration and validation values (Bosch *et al.* 2004; Du *et al.* 2005; Cao *et al.* 2006). All of the articles reported by Gassman *et al.* (2007) calibrated and validated only stream flow. In addition to monthly flow calibration and validation, this study demonstrated verification of the SWAT model using daily sediment and nutrients yields. The SWAT model predicted results during the model validation period (2003–2010) were analyzed to assess spatial variability of the water yield, sediment yield, TP, and TN yields from the watershed. Confirmation of reasonable streamflow, sediment and nutrient results of the model

simulation provided confidence that the further application of the model to assess hydrologic responses, sediment, and nutrient yields analysis due to spatial variability of the watershed characteristics will have minimal bias.

Spatial variability

The SWAT model-predicted average annual water yield (mm), sediment yield (t ha^{-1}), TP yield (kg ha^{-1}), and TN

yield (kg ha^{-1}) results during the model validation period (2003–2010) were analyzed (Table 2). The spatial variability of the pollutants loadings were ranked based on model predicted pollutant loads from each sub-basin.

Water yield (mm) is a total amount of water leaving the sub-basin that enters the main channel during the model simulation period. It is the sum of surface flow, lateral flow, and ground water flow minus transmission loss and pond abstractions (Neitsch *et al.* 2005). The SWAT model

Table 2 | Ranking of sub-basins based on annual (2003–2010) water yield, sediment yield, total phosphorus (TP) and total nitrogen (TN) yields with in the Upper Pearl River watershed

Rank	Sub-basin	Water yield (mm)	Sub-basin	Sediment yield (t/ha)	Sub-basin	TN (kg/ha)	Sub-basin	TP (kg/ha)
1	7	877	20	1.71	17	10.22	11	1.39
2	25	849	11	0.85	2	8.51	2	1.36
3	29	843	24	0.63	12	8.37	16	1.31
4	11	808	6	0.62	27	7.73	12	1.29
5	24	808	16	0.56	6	7.25	17	1.27
6	5	804	5	0.55	16	6.91	27	1.25
7	2	777	30	0.53	29	6.83	29	1.24
8	1	753	29	0.52	18	6.68	6	1.12
9	30	751	7	0.52	14	5.84	18	1.05
10	3	744	3	0.49	22	5.07	20	1.02
11	22	692	1	0.48	20	5.03	1	1.00
12	6	688	2	0.45	11	4.64	14	0.91
13	16	680	25	0.43	1	4.42	22	0.90
14	17	668	8	0.34	15	4.10	30	0.84
15	20	661	22	0.34	30	4.00	3	0.84
16	19	658	28	0.32	13	3.86	24	0.83
17	18	654	27	0.31	4	3.85	13	0.81
18	8	647	18	0.31	8	3.84	8	0.78
19	13	645	26	0.31	3	3.63	7	0.70
20	27	627	12	0.30	26	3.62	4	0.68
21	23	624	17	0.29	24	3.59	15	0.68
22	14	622	13	0.27	19	3.03	26	0.64
23	12	620	23	0.23	7	2.99	25	0.63
24	28	620	9	0.23	25	2.95	19	0.60
25	15	600	14	0.21	9	2.65	5	0.59
26	9	533	15	0.19	10	2.56	28	0.57
27	26	525	4	0.18	5	2.48	9	0.55
28	4	509	19	0.18	28	2.41	10	0.51
29	10	476	10	0.17	23	2.24	23	0.49
30	21	206	21	0.00	21	0.69	21	0.02

predicted average annual water yield from 30 sub-basins showed that there was up to 326% difference between sub-basins (Table 2). The average monthly water yield from the sub-basins were generally correlated with the size of the sub-basins as expected as the larger size of the sub-basin collects more water that leaves the field (Figure 1, Table 2). However, the water yield outputs could be also influenced by the slope and precipitation input to the sub-basins. Sub-basin 21 had the least amount of annual average water yield (206 mm), whereas sub-basin 7 had the greatest annual average water yield (877 mm) in this study.

Sediment yield (metric tons/ha) from the sub-basin is the quantity of sediment transported out of the reach during the simulation time step. The SWAT model predicted average annual sediment yield ($t\ ha^{-1}$) from the sub-basins would vary by up to a factor of 10 between sub-basin 20 and 10 (Table 2). The average annual sediment yield (metric tons/ha) outputs from the sub-basins were generally influenced by the slope of the sub-basins. Based on the model-predicted results, annual average sediment yield prediction was determined spatially variable from 0.00 (sub-basin 21) to $1.71\ t\ ha^{-1}$ (sub-basin 20) from the watershed. The model predicted the least water yield and sediment yield from sub-basin 21 and the greatest water yield and sediment yield from two different sub-basins, 7 and 20. It is important to note that land management practices affect the sediment yield more than the water yield in the watershed.

TP is the sum of organic phosphorus, soluble phosphorus, and sediment attached phosphorus yields estimated in this study. The organic and soluble phosphorus may be removed from the soil via mass flow of water. Organic phosphorus yield ($kg\ ha^{-1}$) is the quantity of phosphorus that is transported with sediment out of the reach during the simulation time step. Soluble phosphorus is the quantity of phosphorus that is transported by surface runoff out of the reach during the simulation time step. Mineral phosphorus is the quantity of phosphorus attached to sediment that is transported by surface runoff out of the reach during the simulation time step. The SWAT model predicted average annual TP yield ($kg\ ha^{-1}$) from the sub-basins would vary by a factor of up to 69 between sub-basin 11 and 21 (Table 2). The SWAT model results determined that sub-basin 21 had the lowest annual TP yield

($0.02\ kg\ ha^{-1}$) and sub-basin 11 had the greatest TP yield ($1.39\ kg\ ha^{-1}$). Model-predicted annual average TN yield was spatially varied from 0.69 to $10.22\ kg\ ha^{-1}$ and ranged between sub-basins 21 and 17, respectively. Although sub-basin 21 had the least amount of model-predicted TN and TP, several sub-basins in the watershed had no correlation between annual average TN and TP prediction as anticipated based on deposition of nutrient sources.

The results of this study showed that there was no correlation of the sediment yield and TP yield from the watershed sub-basins. It is similar to other studies performed using the SWAT model (Parajuli *et al.* 2008; White *et al.* 2010). Spatial variability of the soils, land use, stream processes, and governing equations used for the fate and transport of sediment and phosphorus in the model affected these results. Sediment yield prediction in the SWAT model is generally affected by factors including USLE crop management factor, USLE slope length factor, the slope of HRUs, crop practice factor for land use, tillage operations, crops residue coefficient. However, the slope of the HRUs in this study played a key role in sediment yield. Phosphorus yield is generally affected by initial concentration of the nutrient in soils, fertilizer application rates and location, initial concentration of the nutrient in soils, tillage operations, crop residue coefficient, phosphorus percolation coefficient, and phosphorus soil partitioning coefficient. In this study, beef manure, poultry litter, and nutrient source from failing septic systems were applied in the pasture and woodlands of the watershed. All of the selected sub-basins had applied fertilizers as a source of phosphorus. The in-stream water quality process in the model was active in this study. The in-stream kinetics used in the SWAT model for nutrient routing were adapted from QUAL2E (Brown & Barnwell 1987).

Based on the SWAT model-predicted values and their rankings, pollutant loadings from each sub-basin were classified in three classes. This study identified, classified, and mapped 11 watershed sub-basins with greater than 692 mm water yield; one sub-basin with greater than $0.86\ t\ ha^{-1}$ sediment yield; eight sub-basins with greater than $1.06\ kg\ ha^{-1}$ TP yield, and eight sub-basins with greater than $5.85\ kg\ ha^{-1}$ TN yield. Depending upon the pollutant of concern, these watershed sub-basins should be targeted first to implement agricultural management practices to improve water quality (Figure 4).

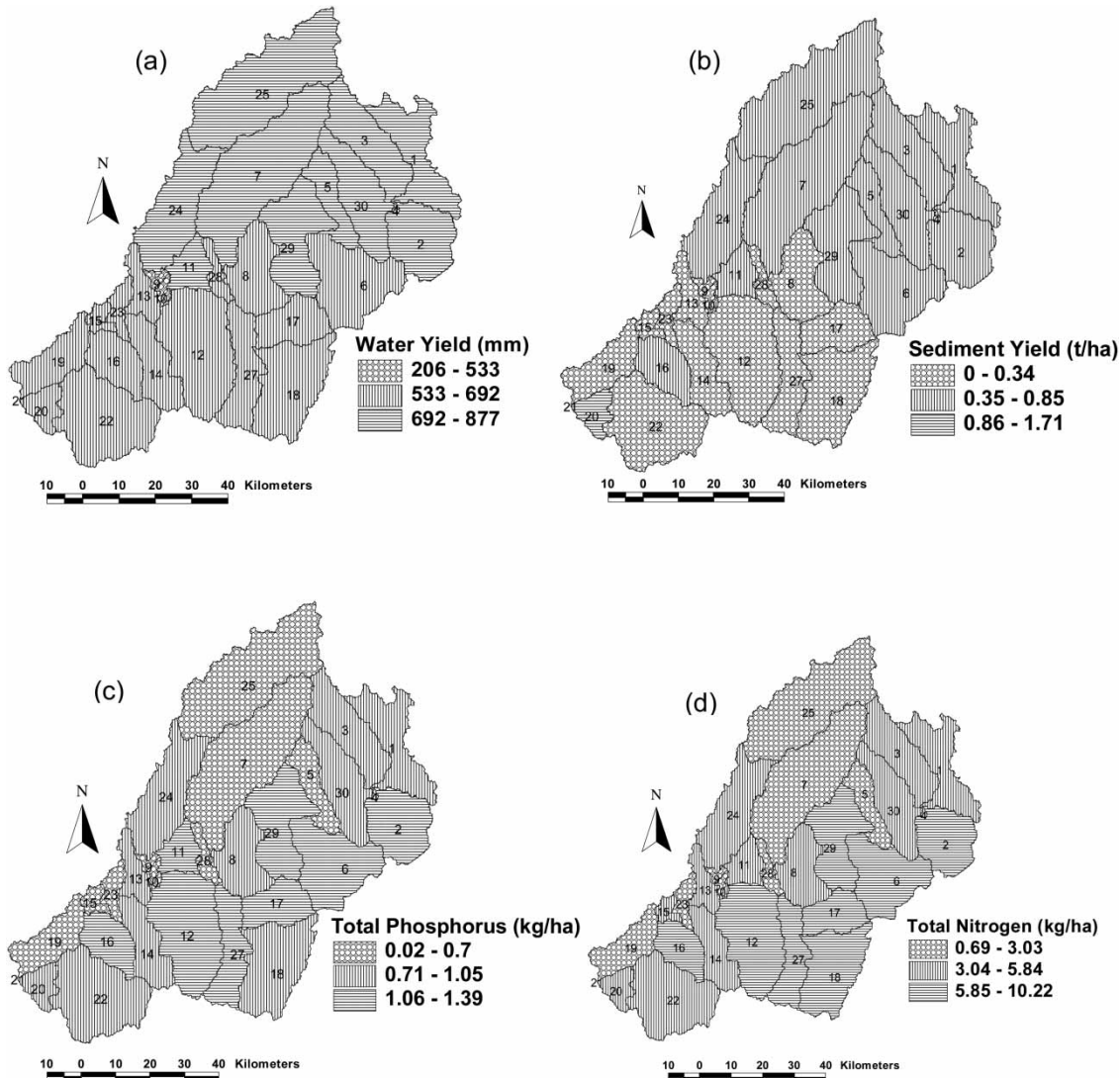


Figure 4 | Model predicted spatial variability of: (a) water yield (mm), (b) sediment yield (t ha^{-1}), (c) total phosphorus (kg ha^{-1}), and (d) total nitrogen (kg ha^{-1}) yields from the watershed sub-basins during model validation period (2003–2010).

The variability of the pollutant loads generated from the watershed to the outlet of the Lena gauge station was also analyzed (Figures 5 and 6). The SWAT model results showed that annual average sediment, TP, and TN yields from the watershed was correlated with annual average flow predicted from the watershed during the model validation period (2003–2010). The SWAT model estimated average delivery ratios (R) for the watershed sub-basins could make a difference in each pollutant transport process. The R represents the fraction of pollutants that could be transported from the selected watershed outlets

to the desired watershed outlets (Neitsch *et al.* 2005). Sediment transport determined a linear decrease in the delivery rate with increasing distance between the sub-basins and the selected watershed outlets. However, R values for water yield, TP, and TN delivery rates did not show linearity due to variability in sub-surface or lateral flow conditions.

The greatest amounts of annual average flow, sediment, and TP yields were determined during 2009 from the Lena gauge outlet of the watershed (Figures 5 and 6). However, the TN yield was the greatest during 2010, which is

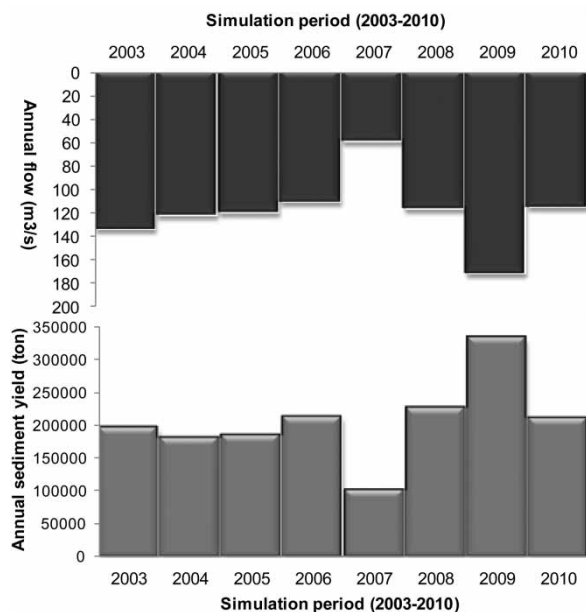


Figure 5 | Annual flow ($\text{m}^3 \text{s}^{-1}$) and sediment yield (t) during model validation period (2003–2010).

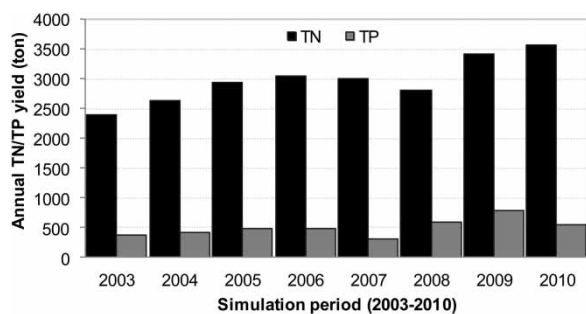


Figure 6 | Annual TN/TP yield (t ha^{-1}) during model validation period (2003–2010).

anticipated based on nutrient source input in the model. Agricultural management practices should be targeted based on the SWAT model-predicted values and their rankings.

CONCLUSIONS

The objective of this research was to identify spatially variable hydrologic conditions and nutrient sources in the UPRW using a modeling approach. The SWAT model was calibrated (1997–2002) and validated (2003–2010) using monthly measured stream flow data from the Lena USGS

gauge station. The SWAT model was further verified at Lena gauge station using daily measured flow from USGS gauge; and daily observed sediment, TP, and TN yields data from this study during 2010. The calibrated and validated model performed good with R^2 and E values (up to $R^2 = 0.83$ and $E = 0.59$). Analysis of the SWAT model results during model validation period (2003–2010) determined the spatial variability of annual pollutant loads of water yield (from 206 to 877 mm), sediment yield (from 0.17 to 1.71 t ha^{-1}), TP (from 0.02 to 1.39 kg ha^{-1}); and TN (from 0.69 to 10.22 kg ha^{-1}) in the watershed sub-basins.

The SWAT model results demonstrated that spatial interactions between size, slope, and other hydraulic characteristics of the sub-basins had great effects on various hydrologic and water quality responses from the watershed. Spatial variability effects of the watershed sub-basins were investigated for their interactions on water yield, sediment yield, TP and TN yields. Model results determined that the spatial variability effects were the greatest for the TP yield prediction (69 times) followed by TN (15 times), sediment yield (10 times compared with sub-basin 10), and water yield (four times) from the UPRW sub-basins. Although model predicted flow and pollutant loads correlated well with each other in some sub-basins, their correlations in many sub-basins were low. It is possible to have such variability due to the unique characteristics of each sub-basin and their delivery ratios used in the model. Overall, the results indicate that the UPRW hydrology is very sensitive to spatial variability of the watershed. This study helps watershed managers to focus their water quality improvement programs implementation efforts on only the most needy watershed sub-basins.

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