JOURNAL OF
ENVIRONMENTAL HYDROLOGY

The Electronic Journal of the International Association for Environmental Hydrology
On the World Wide Web at http://www.hydroweb.com

VOLUME 19 2011

EFFECTS OF SPATIAL HETEROGENEITY ON HYDROLOGIC RESPONSES AT WATERSHED SCALE

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Spatial heterogeneity of the watershed characteristics such as soils, land use, and topography can have an important influence on the hydrologic response of large watersheds. Understanding the effects of spatial heterogeneity on hydrologic parameters is essential to develop water quality improvement programs. Hydrologic models have been used to investigate the interaction between various watershed characteristics. This study was conducted in the Upper Pearl River watershed (UPRW) in east central Mississippi to evaluate the spatial heterogeneity effect on hydrologic responses using the Soil and Water Assessment Tool (SWAT). The SWAT model was calibrated from January 1981 to December 1994 and validated from January 1995 to September 2008 using five USGS gage stations monthly measured stream flow data. The calibrated and validated SWAT model was used to evaluate spatial heterogeneity effects at the UPRW. Five sub-basins of the UPRW were selected based on their size, soils, topography, and precipitation inputs to investigate their interactions on water yield, groundwater yield, potential evapotranspiration (PET), sediment yield, and total phosphorus yield. Model results determined that the spatial heterogeneity effects were the greatest for the groundwater yield (100%) followed by sediment yield (44%), water yield (40%), total phosphorus yield (33%), and potential evapotranspiration (7%) from the selected five sub-basins. Overall, the results indicate that the UPRW hydrology is very sensitive to spatial heterogeneity of the watershed.

INTRODUCTION

Every watershed is heterogeneous in nature. Hydrologic response of the watershed is dependent on spatially variable watershed parameters such as topography, soils, landuse, and watershed management effect in the hydrologic responses of the watershed. In addition to watershed parameters, human activities also affect hydrologic processes. 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 and Koop, 2001).

Huang and Lee (2009) investigated the effects of spatially heterogeneous roughness on hydrological response systematically using a non-inertia wave model that was developed to generate hydrographs at the end of the overland plane for certain rainstorms. Spatially heterogeneous roughness had significant influence on runoff generation, which ought to be handled with care in hydrological simulations. They employed a conceptual model to represent natural watershed conditions. However land use, soil and slope characteristics of the natural watersheds may produce significantly different results.

Wang et al. (2010) examined the land use–soil interactive effects on water and sediment yields for the 1,178 km^2 drainage area within the Cowhouse Creek watershed located in north central, TX. The SWAT model was calibrated and validated using the observed daily stream flows from the USGS gage station. They found significant difference in annual water yield due to land use and soil interactions. They have compared the SWAT model results placing and removing range brush grass in different State Soil Geographic Database (STATSGO) soil polygons such as TX251 and TX609. However they did not evaluate the model results based on the size of the sub-basins or area of each soil polygons distributed in the watershed. They have 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, ND. The AnnAGNPS model outputs determined a poor correlation between observed and model predicted sediment and nutrients data. They concluded that the model's poor performance was most likely a result of the large size of the study area and the high variability in land use and management practices. Further study on interaction of land use, managements, and other factors were needed.

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 heterogeneity at 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 the top three leading pollutants in U.S. rivers and streams (USEPA, 2008). However, in Mississippi the top three causes of impairments for rivers and streams are sedimentation, biological impairments, and fecal coliform. The organic enrichment and nutrients are ranked fourth and fifth in the State of Mississippi (USEPA, 2008). The UPRW drains in to the Ross Barnett Reservoir (RBR) near Jackson, Mississippi (Figure 1). The RBR is one of the largest Mississippi's surface water reservoir used for drinking water supply. It is the main source of drinking water for about 200,000 people living in the city of Jackson and surrounding area. Accurate prediction of hydrology allows us to accurately predict loads of water quality pollutants. Despite many studies performed on the quantification of the pollutant loadings from the watershed, spatial heterogeneity 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 heterogeneity of the watershed areas help us to develop watershed management plans.

Watershed modeling tools are used to investigate hydrology and pollutant transport processes. The Soil and Water Assessment Tool (SWAT, Arnold et al., 1998) model has been extensively applied for hydrologic and pollutant transport modeling (Gosain et al., 2005; Vache et al.,2002; Varanou et al., 2002; Parajuli 2008). The SWAT water quality model has been calibrated, and validated for quantifying pollutants loads such as sediment yield, phosphorus yield from watersheds in different geographic locations, conditions, and management practices (Borah et al., 2005; Cho et al., 2009; Chu and Shirmohammadi, 2004; Qi and Grunwald, 2005; Gassman et al., 2007; Gosain et al., 2005; Parajuli et al., 2008; Parajuli et al., 2009; Vache et al.,2002; Varanou et al., 2002; Van Liew et al., 2003; White and Chaubey, 2005; Wang et al., 2006).

Studies involving the application of the SWAT model to understand the effects of spatial heterogeneity on the hydrologic response and pollutant yield from the watersheds are limited.

The objective of this research was to: (a) evaluate the spatial heterogeneity of watershed areas on hydrologic and pollutant yields within the watershed.

METHODS AND MATERIALS

Watershed

This research study was applied at UPRW, which is located in the east-central Mississippi. The UPRW is comprised of ten Counties (Choctaw, Attala, Winston, Leake, Nesobha, Kemper, Madison, Rankin, Scott and Newton), which covers area of 7,588 km^2 (Figure 1). The land use of the watershed is comprised of forest land (70%), grassland (20%), urban land (6%) and others (4%). The fine-sandy-loam and silt-loam textured soils are a major predominant soil type in this watershed.

SWAT Model

The SWAT model as described by Arnold et al. (1998) is a physically-based, watershed-scale model that operates continuously on a daily time-step. It was developed to simulate long-term runoff, sediment, nutrients, and pesticide transport from agricultural watersheds. The SWAT model uses hydrologic response units (HRUs) based on unique land use/land cover, soil, and slope. The HRUs are necessary to accurately consider possible effects of spatial and temporal variations in parameters on hydrological processes, sediment, and nutrient simulations. The hydrology component of the model calculates a soil water balance at each time step based on daily amounts of precipitation, runoff, evapotranspiration, percolation, and base flow. Simulations are performed at the HRU level and summarized in each sub-watershed. The simulated variables (water, sediment, nutrients, and other pollutants) are routed through the stream network to the watershed outlet. SWAT incorporates the effects of weather, surface runoff, evapotranspiration, crop growth, irrigation, groundwater flow, nutrient loading, pesticide loading, and water routing, as well as the long-term effects of varying agricultural management practices (Neitsch et al., 2005). In the

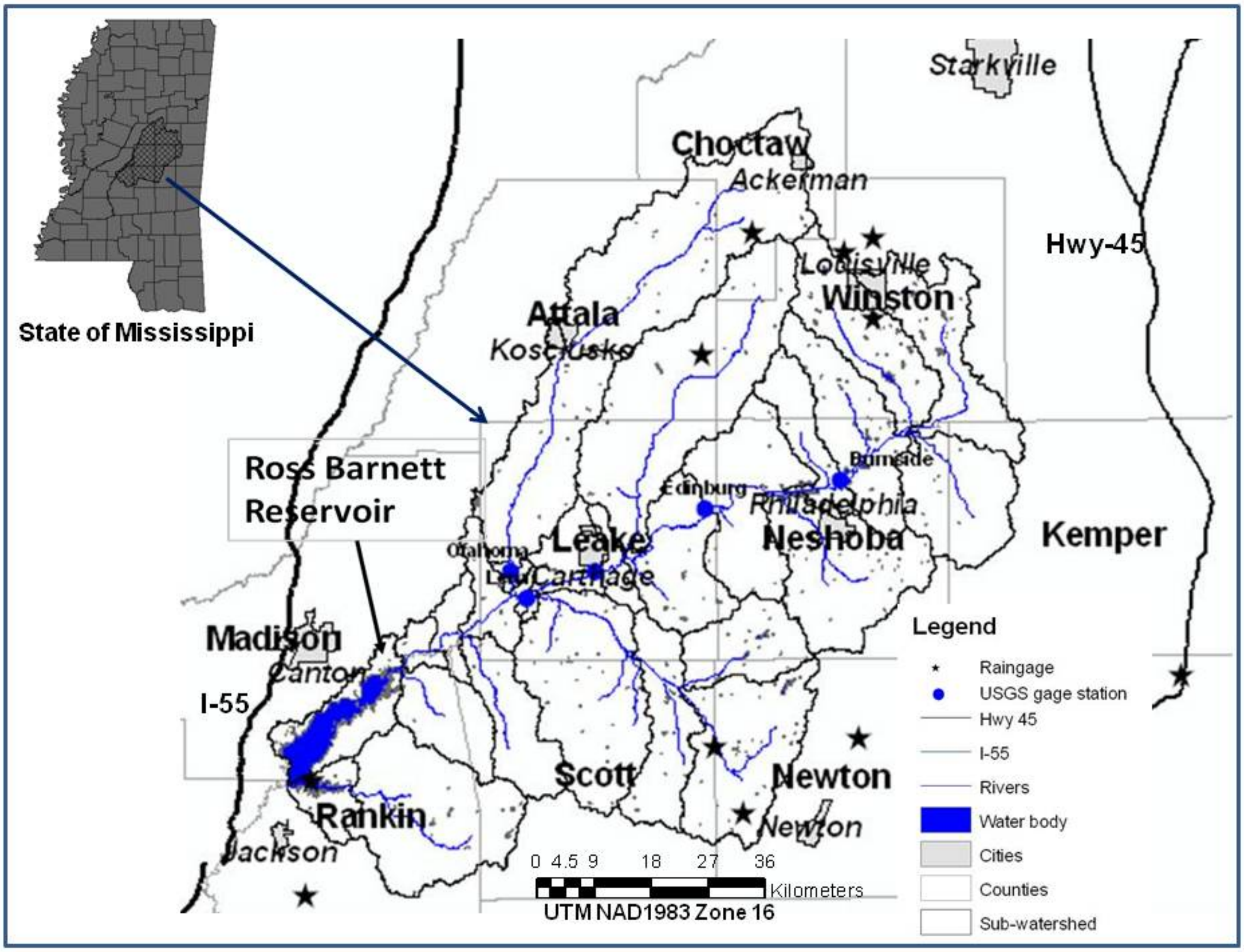

Figure 1. Location map of Upper Pearl River watershed in east-central Mississippi showing USGS streamflow gages and climate stations.

hydrologic component, runoff is estimated separately for each sub-watershed of the total watershed area and routed to obtain the total runoff for the watershed. Runoff volume is estimated from daily rainfall using modified Soil Conservation Service – Curve Number (SCS-CN) and Green-Ampt methods. Due to input data availability, the SCS-CN method (SCS, 1972) was adopted 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 and Taylor, 1972) and the Hargreaves method (Hargreaves et al., 1985). This study used Penman-Monteith method to estimate potential evapotranspiration.

SWAT Model Input

The SWAT model uses various sets of geospatially referenced data to create layers of information to satisfy the necessary input parameters. The model requires input of a Digital Elevation Model (DEM) data, land use, and soils, as well as time series of climate data such as daily precipitation, and temperature as described by Neitsch et al., (2005). United State Geological Survey (USGS, 1999) 7.5-minute (30m x 30m grid) digital elevation model (DEM) data was used to delineate watershed boundaries and topography. The STATSGO was used to create a soil database (USDA, 2005). The cropland data layer (USDA/NASS, 2008) was used to develop land use data for the watershed. The model inputs climate data from all available weather stations (NCDC, 2009) from ten Counties (Choctaw, Attala, Winston, Leake, Nesobha, Kemper, Madison, Rankin, Scott and Newton) were used.

SWAT Model Calibration and Validation

The parameters in the SWAT 2005 were manually calibrated in this study since Green and 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). The parameters were the curve number (CN), soil evaporation compensation factor (ESCO), base flow alpha factor (ALPHA_BF), surface runoff lag coefficient (SURLAG), groundwater "revap" coefficient (GW_REVAP), and threshold depth of water in the shallow aquifer (GWQMN). The six parameters calibrated in this study were selected based on previous studies (Santhi et al., 2001; Saleh and Du, 2004; White and Chaubey, 2005; Choi et al., 2005; Neitsch et al., 2005; Gassman et al., 2007; Parajuli et al., 2009).

The stream flow calibration was performed by adjusting the curve number (CN) parameters for different land uses, which include: pasture (PAST), deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), urban institutional (UINS), wetland forest (WETF), soybean (SOYB), and corn (CORN). The CN is a soil moisture balance parameter that allows the model to modify soil moisture condition of the soil to estimate surface runoff (Neitsch et al., 2005). As the value of CN is reduced, the model allows less water to runoff from the surface.

The soil evaporation compensation factor (ESCO) allows the user to modify the depth distribution used to meet the soil evaporative demand to account for the effect of capillary action, crusting and cracks. The esco must be between 0.01 and 1. As the esco value is reduced, the model is able to extract more of the evaporative demand from lower levels. The base flow alpha factor (ALPHA_BF) is a base flow recession constant, is a direct index of groundwater flow response to change in recharge. Values 0.1-0.3 are used for land with slow response to recharge and from 0.9

Table 1. Parameters range and final values used in the SWAT model calibration.

Parameter	Range	Final Values
Curve Numbers (CN)		
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)	0.01-1.0	0.4
Base flow 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

to 1.0 for land with a rapid response. The surface runoff lag coefficient (SURLAG) controls the fraction of the total available water that will be allowed to enter the reach on any one day. As surlag value decreases, more water is held in storage. The groundwater "revap" coefficient (GW_REVAP) allows the movement of water from the shallow aquifer to the overlying unsaturated zone. As the coefficient approaches 0, movement of water from the shallow aquifer to the root zone is restricted. As it approaches 1, the rate of transfer from the shallow aquifer to the root zone approaches the rate of potential evapotranspiration. Threshold depth of water in the shallow aquifer (GWQMN) is the threshold depth of water in the shallow aquifer required for return flow to occur. Groundwater flow to the reach is allowed only if the depth of water in the shallow aquifer is equal to or greater than GWQMN.

The SWAT model predicted monthly stream flow results were compared with the USGS gage stations data during the model calibration and validation process. Model predictions were statistically evaluated with the coefficient of determination (R^2), and Nash-Sutcliffe Efficiency Index (E) between measured values and model-predicted values after each model run changing parameters. Model input parameters were continuously modified during the calibration phase until simulated stream flow was within $R^2 = 0.5$ and $E = 0.5$. Stream flow calibration initially used model default parameters. The CN parameters were continuously modified within the range of values during the calibration phase to find the local maximum value that has maximum model efficiency. The CN range of 70-92 (70 for evergreen forest, 73 mixed forest, 77 deciduous forest and wetland forest, 79 for pasture, 89 for soybean and corn, and 92 for urban institutional) determined the maximum efficiency range to use in the models. Similarly, the esco factor of 0.40, base flow alpha factor of 0.9, surlag coefficient of 1, groundwater "revap" coefficient of 0.2, and threshold depth of water in the shallow aquifer of 1000 had demonstrated local maximum value of model efficiency. After model calibration, input parameters were not changed during the model validation process.

Base Flow

Separation of the base flow component from the stream flow is generally performed using base flow separation analysis. The shape of the hydrograph from the base flow separated stream flow varies depending on physical and meteorological conditions in a watershed (Bendient and Huber, 2002). Although various sections of Pearl River including its tributaries contribute low flow in various seasons, they are considered perennial streams. To accurately estimate water quality parameters using SWAT, the hydrologic component of the model is typically validated first as the hydrology is the driving force of other pollutant transport such as sediment and total phosphorus in the watershed. For validation of hydrology component of the SWAT model, direct runoff and base flow components of the stream flow hydrograph typically need to be separated because direct runoff and base flow are usually simulated separately in computer models (Srinivasan and Arnold, 1994). This study used a web-based hydrograph analysis tool for base flow separation (Kyoung et al., 2005). The recursive digital filter method (Eckhardt, 2005) was selected for base flow separation with a filter parameter of 0.98 and maximum base flow index (BFI_{max}) of 0.80. 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 UPRW. The percentage of average base flow separated from the total flow from five USGS gage stations are presented in the flow validation section of the results and discussion.

Watershed Management Conditions

The UPRW is a forest dominated watershed. Forest land consists of 22% evergreen trees, 20% mixed trees, and 30% deciduous trees. Pastureland covers about 20% of the watershed area and typically includes Bahiagrass (Curt Readus, USDA/NRCS, Pearl area office, 2009, personal communication). A minor (~2%) land use of the UPRW covers cropland. Corn, cotton, soybean, peanuts and vegetables are typically grown in the watershed. Typical planting and harvesting dates are April 15 and September 15 for warm-season crops and October 15 and June 15 for cool-season crops. Crop residue is left on the ground between the crop periods. Minimum tillage is typically applied for crop cultivation in the watershed (Curt Readus, USDA/NRCS, Pearl area office, 2009, personal communication). This study considered land application of three major nutrient pollutant sources: livestock, chicken litter, and failing septic systems in the UPRW as described by Parajuli et al., 2010.

Spatial Heterogeneity

The effects of spatial heterogeneity of this watershed was evaluated with three hundred and thirty three months (from January 1981 to September 2008) of model simulation results for monthly water yield, groundwater yield, potential evapotranspiration, sediment yield, and total

Table 2. Spatial characteristics of the selected sub-basins within the Upper Pearl River watershed.

Sub-basins	Area (km^2)	Average slope (%)	Dominant soil texture	Dominant landuse
3	1,338	3.3	Silt loam	Woodland
7	1,821	5.6	Sandy loam	Woodland
12	1,567	2.9	Silt loam	Woodland
22	1,527	3.5	Silt loam	Woodland
25	1,784	4.6	Sandy loam	Woodland

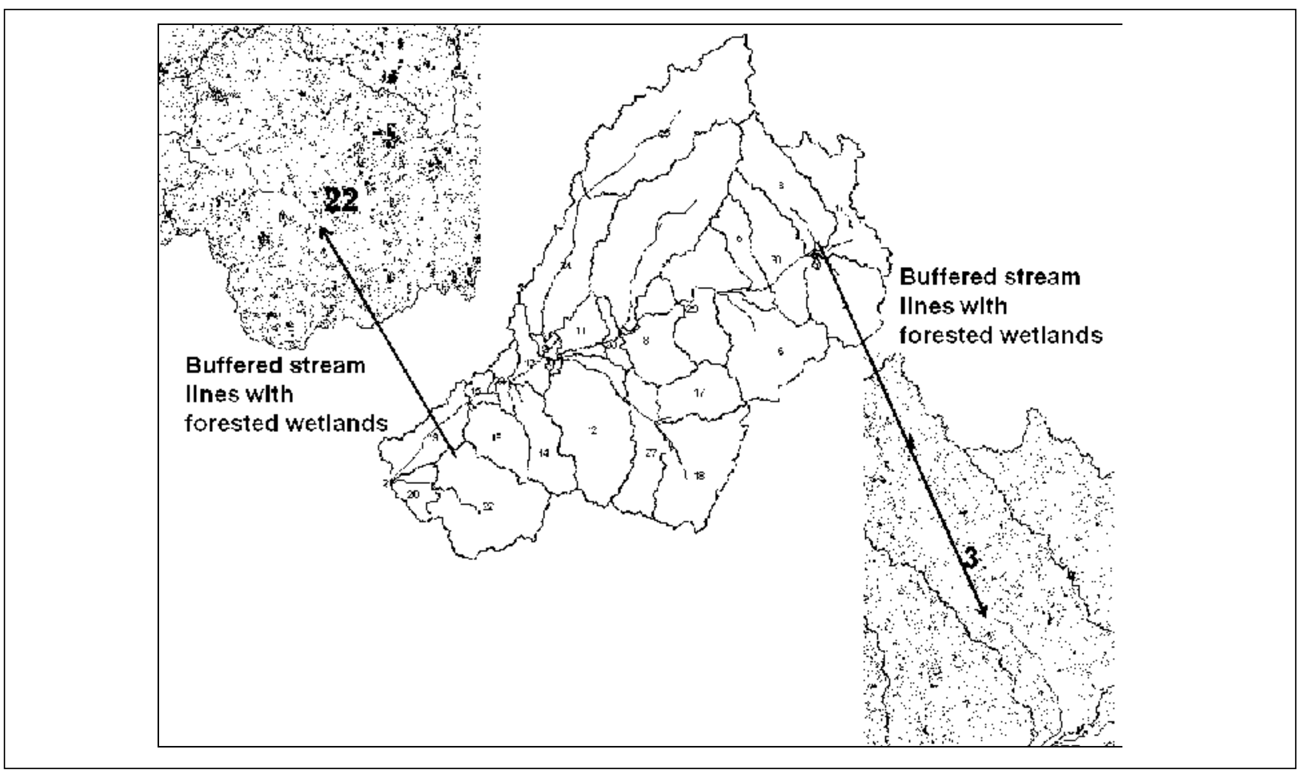

Figure 2. Five sub-basins with buffered stream lines with forested wetlands.

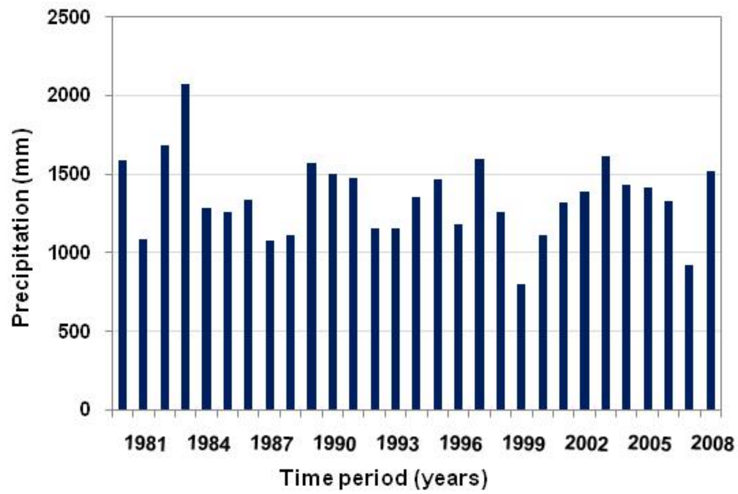

Figure 3. Long-term (1981-2008) annual average precipitation (mm) in the watershed.

phosphorus yield from the five sub-basins of the watershed (Table 2; Figure 2). Model estimated monthly precipitation values for each sub-basin were also evaluated.

Weather Data

The model inputs climatic data from eleven (Ackerman, Canton, Carthage, Forest, Gholson, Kosciusko, Louisville, Newton, Philadelphia, Ross Barnett Reservoir and Walnut) weather stations (NCDC, 2009) were used (Figure 1). Daily precipitation data for the UPRW were used from all eleven weather stations. The daily temperature data were used for six weather stations (Carthage, Forest, Kosciusko, Louisville, Newton and Philadelphia). The long-term (1981-2008) annual average daily rainfall for the entire UPRW was estimated about 1,348 mm (Figure 3). The data from six weather stations (State college, Russell, Forest post office, Meridian, Winona, and Canton) were used as input in the SWAT model. The Forest Post Office weather station is located inside the watershed whereas the other five weather stations are located between 8 to 45 kilometers from the watershed boundary.

Statistical Analysis

This study used mean monthly flow data measured by the USGS at five gage stations. Monthly measured stream flow dataset was divided into a calibration period (1981–1994) and a validation period (1995–2008). Each model performance period includes wet, dry, and normal years, providing representative years for simulating the hydrograph of the UPRW basin. In order to statistically test the accuracy of the calibrated stream flow output, this study employed two popular methods (Parajuli et al. 2008; 2009): R^2, and E. Model performances were classified as excellent for R^2 or E = 0.90, very good for R^2 or E = 0.75 to 0.89, good for R^2 or E = 0.50 to 0.74, fair for R^2 or E = 0.25 to 0.49, poor for R^2 or E = 0 to 0.24, and unsatisfactory for R^2 or E < 0 (Moriasi et al., 2007; Parajuli et al., 2008; 2009).

Coefficient of determination (R^2):

The R^2 value indicates the consistency with which measured vs. predicted values follow a best fit line (Equation 1). If the R^2 values are less than or very close to zero, the model prediction is considered unacceptable or poor. If the values are one, then the model prediction is perfect (Santhi et al., 2001). However, R^2 only describes how much of the measured dispersion is explained by the prediction, therefore R^2 is not suggested to be used alone (Maidment, 1993).

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

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 over-bar denotes the mean (measured or predicted) runoff (mm) for the entire time period of the evaluation.

Nash–Sutcliffe model efficiency index (*E*):

The E indicates the consistency with which measured values match predicted values, or the fit of the data to a linear 1:1 measured vs. predicted best-fit line (Nash and Sutcliffe, 1970). The E ranges from minus infinity (poor model) to 1.0 (perfect model). For example, if the square of the differences between the model predictions and the observations is as large as the variability in the measured data, then $E = 0.0$; if it exceeds it, then $E < 0.0$ (i.e., the measured mean is better than predictor). Thus, a value of zero for the E indicates the measured mean, O, is a predictor as good as the model while negative values indicate the measured mean is a better predictor than the model. The E has been widely used to evaluate the performance of hydrologic models (Wilcox et al., 1990). The limitation of the E is the fact that the differences between the measured and predicted values are calculated as squared values. As a result larger values in a time series are strongly overestimated whereas lower values are neglected (Legates and McCabe, 1999). The E is calculated using the following Equation (2).

$$E = 1 - \frac{\sum_{i=1}^{n} \left(O_i - P_i\right)^2}{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2} \qquad (2)$$

where, O is the measured runoff (mm), P is the predicted runoff (mm), the over-bar 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 samples measured.

RESULTS AND DISCUSSION

Table 3 summarizes the model calibration and validation efficiency values for monthly stream flows for the five USGS gage stations. Twenty eight years of monthly measured stream flow data were used to provide baseline calibration and validation for the SWAT model. Model was calibrated using five spatially distributed USGS gage stations from January 1981 to December 1994 and validated using same USGS gage stations from January 1995 to September 2008 monthly measured stream flow data within the UPRW except for the Lena USGS gage station. Lena gage station used stream flow data from October 1997 to December 2002 for model calibration and January 2003 to September 2008 for model validation.

Table 3. Model efficiency during stream flow calibration and validation period.

Station	Calibration period						Validation period				
	R^2	E	Slope				R^2	E	Slope		
Burnside	0.79	0.73	0.95				0.64	0.64	0.77		
Ofahoma	0.72	0.68	0.77				0.60	0.17	0.86		
Edinburg	0.76	0.75	0.81				0.68	0.65	0.70		
Lena	0.69	0.69	0.82				0.80	0.86	0.82		
Carthage	0.78	0.79	0.78				0.74	0.55	0.81		

Flow Validation

Average base flow separation from the total flow from five USGS gage stations showed about 29% of the base flow and 71% of the surface flow from the UPRW watershed during the study period (1981-2008), which is consistent with the 28.5% base flow and 71.5% surface flow as predicted by the SWAT model.

The SWAT model calibration results showed good to very good performance for mean monthly stream flow prediction (R^2 from 0.69 to 0.79 and E from 0.68 to 0.79; Table 3). During the model validation period SWAT model results generally demonstrated good to very good performance (R^2 from 0.60 to 0.80 and E from 0.64 to 0.86) except at Ofahoma gage station for E (Table 3).

The results of this study were also compared with calibrated result against all monthly 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 were agreed with top 40 (35%) articles reported by Gassman et.al. (2007), which had the best reported calibration and validation values. Confirmation of reasonable streamflow results provided confidence that the further application of the model to assess hydrologic responses, sediment, and phosphorus yield due to spatial heterogeneity of the watershed characteristics will have minimal bias.

Spatial Heterogeneity

The calibrated and validated SWAT model results for the five selected watershed sub-basins (Table 2) were analyzed to assess spatial heterogeneity of the watershed characteristics. These five sub-basins were selected from different part of the watershed having different size, slope, and soil textures.

Precipitation input is one of the major inputs in the SWAT model, which is a driving force for the water balance component in the model (Neitsch et al., 2005). This study used long-term precipitation data input in the model. There was up to 12% difference of average monthly precipitation input in the model for the five selected sub-basins (Figure 4). The sub-basin 12 received the lowest average monthly precipitation input (116 mm) and the sub-basin 25 received the greatest average monthly precipitation input (130 mm, Table 4).

Water yield (mm) is a total amount of water leaving the sub-basin that enters to the main channel during the model simulation period. It is the sum of surface flow, lateral flow, and groundwater flow minus transmission loss and pond abstractions (Neitsch et al., 2005). The SWAT model predicted average monthly water yield from five sub-basins showed that there was up to 40% difference between sub-basins (Table 4). The SWAT model results determined that sub-basin 3 had the lowest water yield (47 mm) and sub-basin 25 had the greatest water yield (66 mm). The average

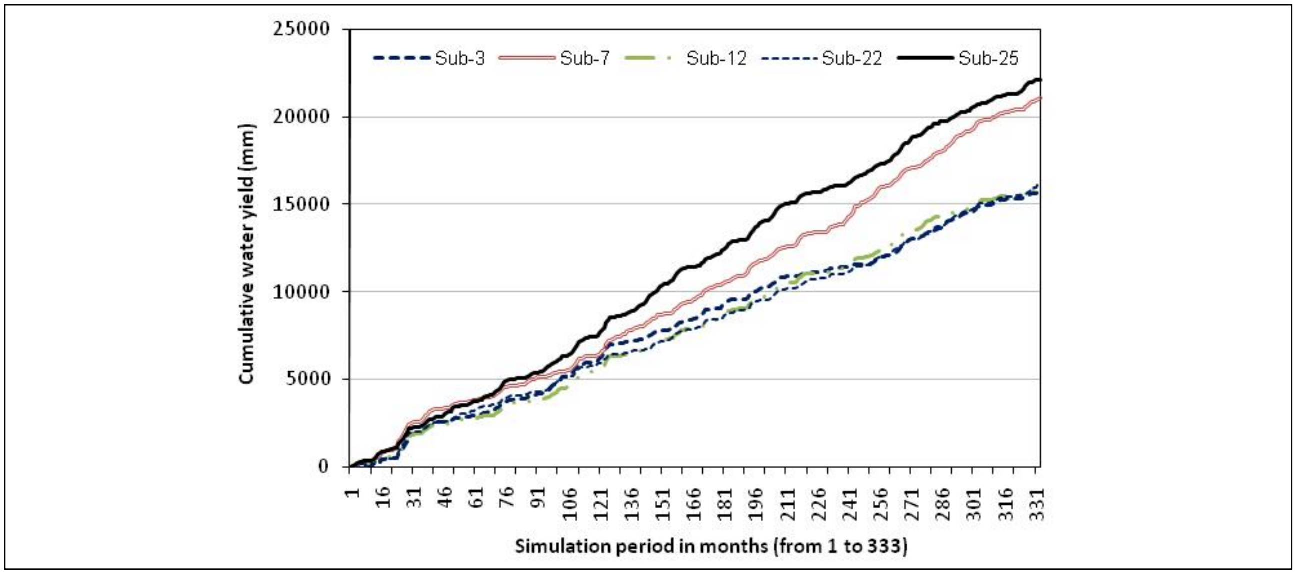

Figure 4. SWAT model cumulative precipitation data input during model simulation period.

Table 4. Monthly mean SWAT responses from five sub-basins for the five parameters.

Parameter*/Sub-basin	3	7	12	22	25
Precipitation input (mm)	120	127	116	119	130
WY (mm)	47	63	48	49	66
GWQ (mm)	16	24	16	14	28
PET (mm)	125	116	122	124	119
SYLD (metric ton/ha)	0.26	0.26	0.18	0.19	0.25
TP (kg/ha)	0.04	0.04	0.04	0.03	0.03
*WY = water yield, GWQ = ground water yield, PET = potential evapotranspiration					
SYLD = sediment yield, TP = total phosphorus yield					

monthly water yield (mm) from the sub-basins were generally correlated with the size of the sub-basins as expected (Figure 2, Figure 5, and Table 2) as the larger size of the sub-basin collects more amount of water that leaves the field. However, the water yield outputs were also influenced by the slope and precipitation input to the sub-basins as the sub-basin 25 (1,784 km^2) had the greater amount of average monthly water yield than sub-basin 7 (1,821 km^2, Table 4).

Groundwater yield (mm) is the water from the shallow aquifer that returns to the reach during the simulation period (Neitsch et al., 2005). The SWAT model predicted average monthly groundwater yields from the sub-basins were varied significantly as the such difference were found up to 100% (Table 4, Figure 6). The SWAT model results determined that sub-basin 22 had the lowest groundwater yield (14 mm) and sub-basin 25 had the greatest groundwater yield (32 mm). Although larger surface area or sub-basin size provides greater area to recharge the groundwater flow from the shallow aquifer, it is also influence by the hydraulic conductivity of the soil or aquifer. Hydraulic conductivity defined as the rate of movement of water through a porous medium such as a soil or aquifer. Hydraulic conductivity of the soil parameters can differ with several orders of magnitude each other. Hydraulic conductivity of the sandy soil can be up to 100 times higher than of silt soil (Brassington, 1988). The dominant soil textures of the three sub-basins used in this study were consists of silt loam (sub-basins 3, 12, and 22) and two sub-basins with sandy loam soils (sub-basins 7 and 25). The hydraulic conductivity of the silt-loam and sandy-loam soils in the model input were found significantly different as the hydraulic conductivity of the sandy-

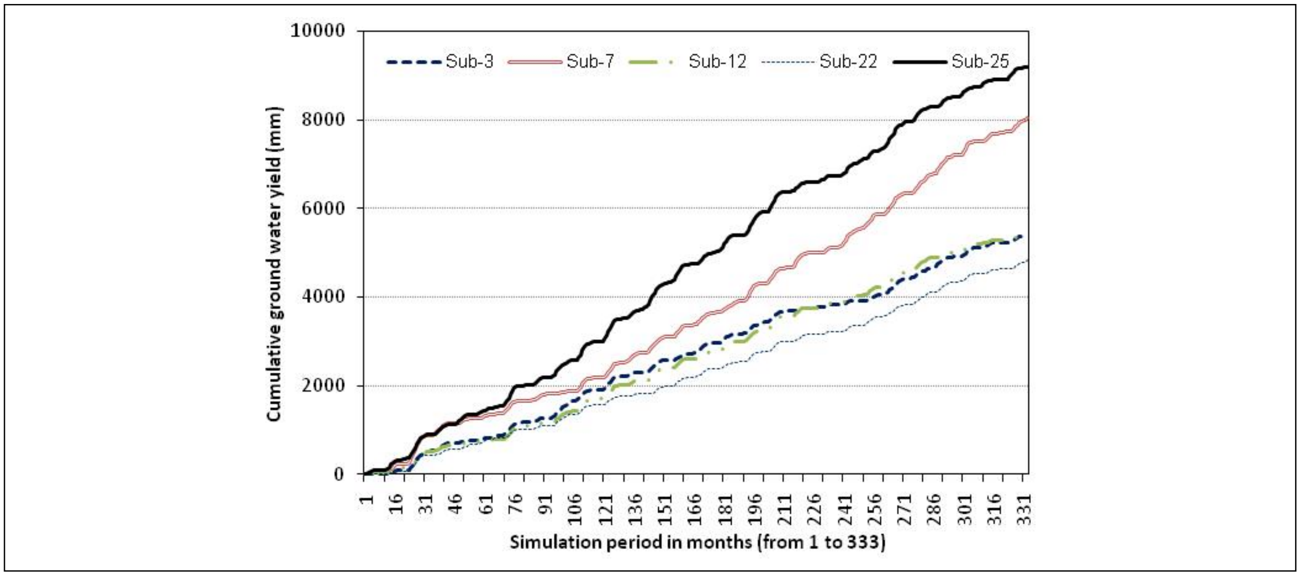

Figure 5. SWAT simulated cumulative water yield from five sub-basins in the watershed.

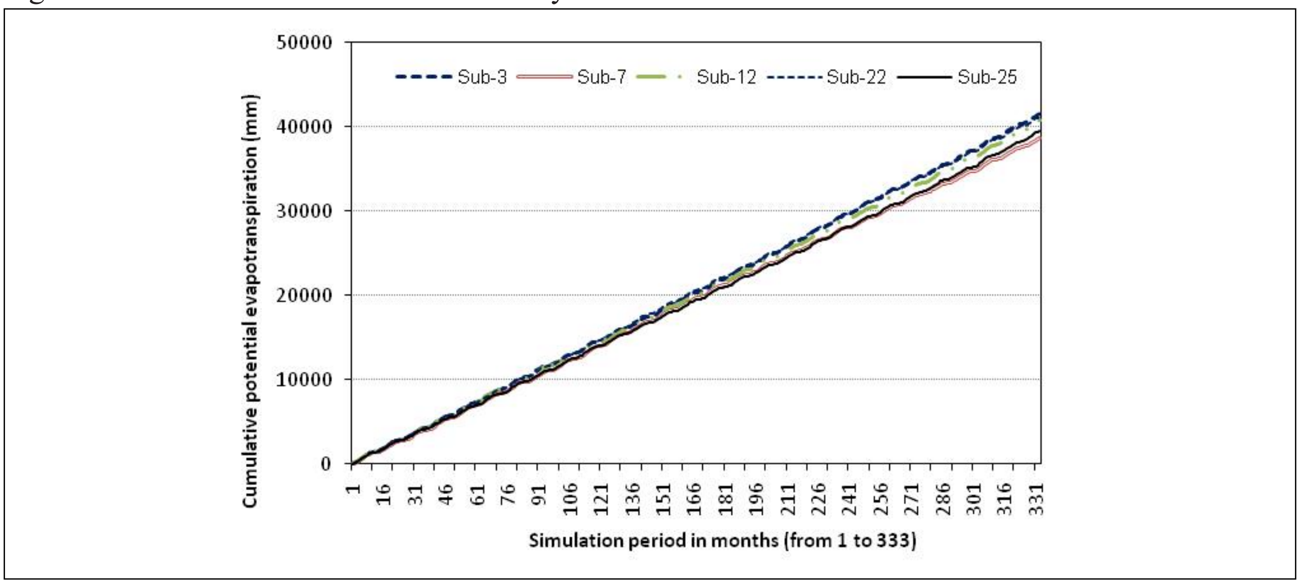

Figure 6. SWAT simulated cumulative groundwater yield from five sub-basins in the watershed.

loam soils (72 mm/hr) in the sub-basin 7 were up to 9 times higher than the silt-loam soils (8.2 mm/hr) in the sub-basin 3.

Potential evapotranspiration (mm) is the rate of evapotranspiration that would take place from a large area completely and uniformly covered with growing vegetation which has access to an limitless supply of soil water. This rate is assumed to be unaffected by microclimatic processes such as advection or heat-storage effects (Neitsch et al., 2005). The SWAT model estimates the potential evapotranspiration from the sub-basin during the simulation period. The SWAT model predicted average monthly potential evapotranspiration yields from the sub-basins were slightly varied having difference of up to 7% (Figure 7, Table 4). The SWAT model results determined that sub-basin 7 had the lowest potential evapotranspiration yield (116 mm) and sub-basin 22 had the greatest potential evapotranspiration yield (124 mm).

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 monthly sediment yield (metric ton/ha) from the sub-basins were varied having difference of up to 44%

(Figure 8). The SWAT model results determined that sub-basin 12 had the lowest sediment yield (0.18 metric ton/ha) and sub-basin 3, and 7 had the greatest sediment yield (0.26 metric ton/ha). The average monthly sediment yield (metric tons/ha) outputs from the sub-basins were correlated with the slope of the sub-basins except at sub-basin 3 (Table 2, Table 4).

Total phosphorus 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) 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 a 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 monthly total phosphorus yield (kg/ha) from the sub-basins were varied having difference of up to 33% (Table 4, Figure 9). The SWAT model results determined that sub-basin 22, and 25 had the lowest monthly total phosphorus yield (0.03 kg/ha)

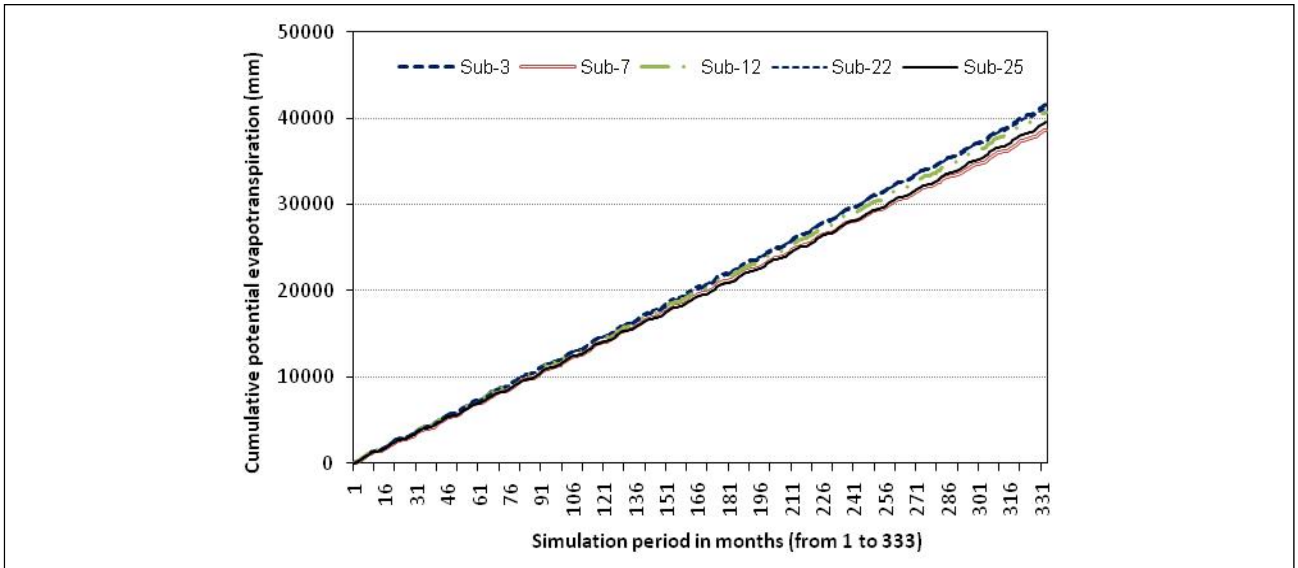

Figure 7. SWAT simulated cumulative potential evapotranspiration from five sub-basins in the watershed.

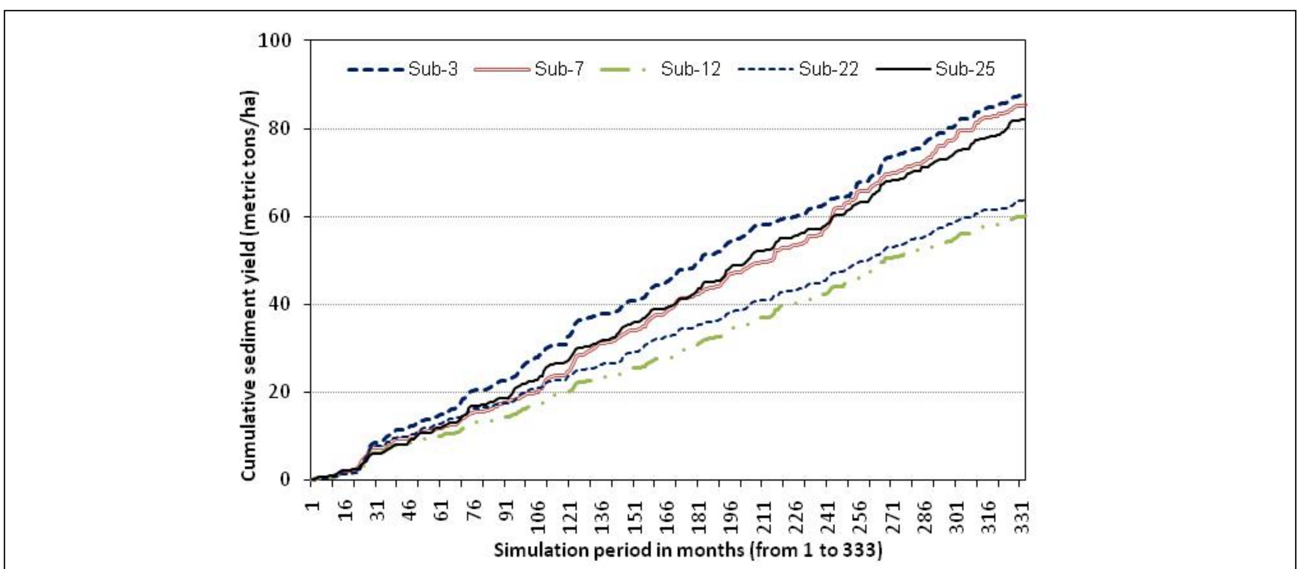

Figure 8. SWAT simulated cumulative sediment yield from five sub-basins in the watershed.

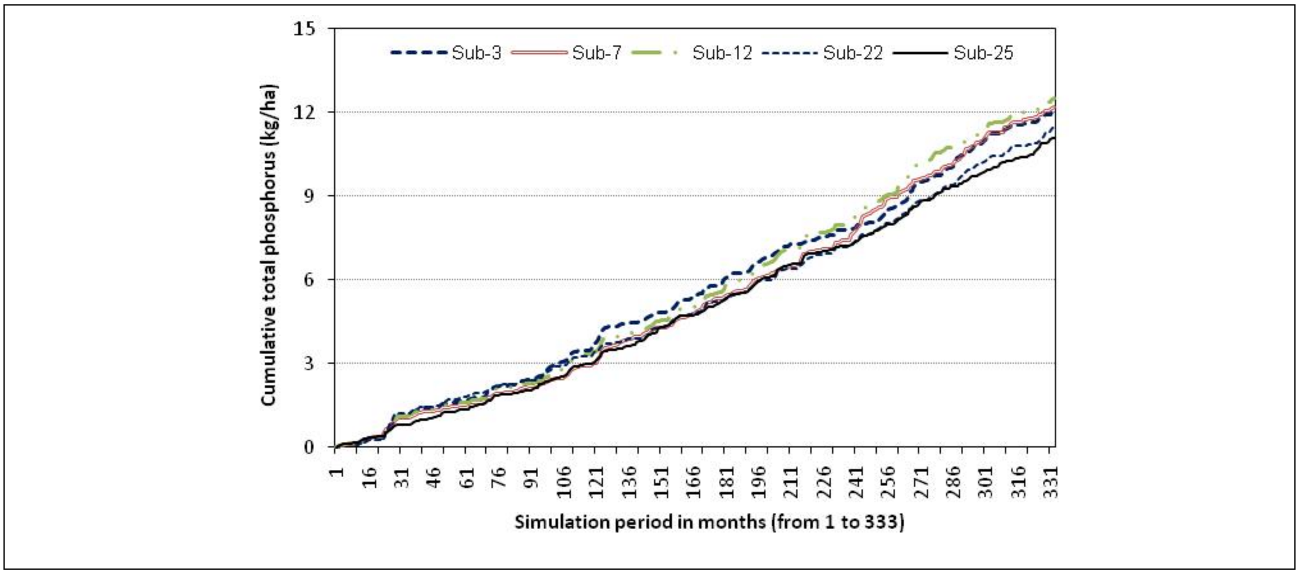

Figure 9. SWAT simulated total phosphorus yield from five sub-basins in the watershed.

and sub-basin 3, 7, and 12 had the greatest total phosphorus yield (0.04 kg/ha).

Long-term average monthly estimates of the SWAT model results especially water yield, groundwater yield, and potential evapotranspiration were interactively affected by the size of the sub-basins, slope, dominant soil texture, and hydraulic conductivity of the soil. Results of this study showed that there was no correlation of the sediment yield and total phosphorus yield from the watershed sub-basins. It is similar to other studies performed using the SWAT model (Parajuli et al., 2008; White et al., 2009). Spatial heterogeneity 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 SWAT for nutrient routing are adapted from QUAL2E (Brown and Barnwell, 1987). Table 5 below shows the total sub-basins area (km^2), area of the sub-basin receiving phosphorus inputs (km^2), stream lengths (km) and stream lengths buffered by forested wetlands (km). Non-buffered areas such as pasture land, and forested land were located adjacent to the stream. The phosphorus loading from each sub-basin were also affected by their stream lengths buffered with forested wetlands in the watershed (Table 4, Figure 2). The sub-basins 22 (80%) and 25 (69%) were the top two sub-basins that had the greatest stream lengths buffered by the forested wetlands (Table 5). The results presented here suggest that the use of more distributed approaches is important when simulations are used to identify the parameter or pollutant specific sub-basins in the watershed due to the impact of area, slope, and soil texture. Lumped models are more likely to overestimate or underestimate the stream flow and

Table 5. Area receiving phosphorus (P) input, stream lengths, and forested wetland buffered stream lengths of the sub-basins in the Upper Pearl River watershed.

Sub-basins	Area (km^2)	Area receiving P (km^2)	Stream lengths (km)	Buffered lengths (km)
3	1,338	291	16.97	8.60
7	1,821	717	48.31	26.18
12	1,567	478	25.73	4.60
22	1,527	441	19.68	15.70
25	1,784	704	34.22	23.60

pollutant loadings because they ignore the spatial effects of the watershed characteristics. The spatial location of sub-basins, and pollutant transport algorithms in the model can also affect in pollutant yield. Uncertainties in the representation of specific management actions will also vary significantly depending on the nature and location of those actions.

CONCLUSIONS

This study evaluated the performance of the SWAT hydrology component under southeastern U.S. conditions. The manual model calibration and validation process using twenty eight years of measured monthly stream flow data determined good to very good model performance during model calibration and validation (R^2 from 0.60 to 0.80 and E from 0.64 to 0.86) except at Ofahoma for E. The SWAT model over-predicted average monthly stream flow (27.05 cms vs. 19.43 cms) by 39% during model calibration and by 78% during model validation (27.64 cms vs. 15.57) at Ofahoma. The USGS measured data at Ofahoma showed 76 runoff events (> 10 cms) and the model result determined 133 runoff events (> 10 cms) during model validation. Model determined runoff events because there was consistent precipitation input in the model.

The SWAT model results were used to evaluate spatial heterogeneity effects at the UPRW. The SWAT model results demonstrated that spatial interactions between size, slope, and hydraulic conductivity of the sub-basins had great effects on various hydrologic and water quality responses from the watershed. Spatial effects of the five watershed sub-basins were investigated for their interactions on water yield, groundwater yield, potential evapotranspiration, sediment yield, and total phosphorus yield. Model results determined that the spatial heterogeneity effects were the greatest for the groundwater yield prediction (100%) followed by sediment yield (44%), water yield (40%), total phosphorus yield (33%), and potential evapotranspiration (7%) from the selected five sub-basins of the UPRW. Overall, the results indicate that the UPRW hydrology is very sensitive to spatial heterogeneity of the watershed.

ACKNOWLEDGMENTS

This material is based on work supported by the Special Research Initiatives (SRI) and the Mississippi Agricultural and Forestry Experiment Station (MAFES). I would like to acknowledge Dr. Tom Cathcart, professor and Dr. Fei Yu, assistant professor of Mississippi State University for reviewing this manuscript. I would also like to acknowledge the contributions of Mr. Kurt Readus, area conservationist, NRCS/MS; and Mr. Eugene Herring, waste water program specialist, at the Mississippi State Department of Health (MSDH).

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