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Evaluation of landscape and instream modeling to predict watershed nutrient yields

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Abstract

The project goal was to loosely couple the SWAT model and the QUAL2E model and compare their combined ability to predict total phosphorus (TP) and NO_3-N plus NO_2-N yields to the ability of the SWAT model with its completely coupled water quality components to predict TP and NO_3-N plus NO_2-N yields from War Eagle Creek watershed in Northwest Arkansas. Model predictions were compared using a statistical approach to identify significant differences between the two modeling methods. Results from two variations of the Pearson product-moment correlation ($p < 0.05$) indicated that correlation coefficients and regression slopes for the two data sets were not significantly different. This implies that neither modeling method was significantly better in predicting monthly TP and NO_3-N plus NO_2-N yields from the watershed. Additionally, no significant differences were present between predicted outputs of the SWAT model with instream components active compared with when instream components were inactive, indicating a need for further testing and refinement of the SWAT algorithms simulating instream processes. We can further infer that the instream processes available in SWAT may not be enhancing its predictive abilities as far as simulating instream components.

Keywords: QUAL2E; SWAT; Nutrients; Model coupling; Watershed; Stream

1. Introduction

Excessive nutrient loads from upstream watershed activities such as agriculture, hydrological modifications, and urban runoff, have been identified as the leading cause of impairment in assessed lakes and reservoirs (USEPA, 2000). Excessive nutrients' loads into lakes and reservoirs are a concern because of the potential to accelerate eutrophication rates, resulting in aesthetic and water quality problems. As reservoirs become eutrophic, they are often characterized by hypolimnetic dissolved oxygen depletion, increases in suspended solids, progression from a diatom population to a blue-green or green algae population, changes in food web structure and fish species composition, and decreasing light penetration (OECD, 1982; Henderson-Sellers and Markland, 1987).

Management of nutrient loads into reservoirs requires knowledge of nutrient transport and delivery from the watershed−stream system. Nutrients are generally transported from the landscape into streams during runoff events; however, they may also enter stream flow from other sources such as groundwater recharge and point source effluent discharges. As water transports nutrients downstream, they cycle through the stream ecosystem in biotic and abiotic forms. These nutrients are eventually delivered to downstream water bodies such as lakes and reservoirs.

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The mechanisms that govern nutrient sources, transport, and delivery from watersheds to lakes and reservoirs are most efficiently evaluated using computer models. Computer models are available that simulate nutrient transport from a watershed to a stream, such as Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) and Agricultural Nonpoint Source Pollution (AGNPS) (Bingner et al., 2001). Landscape or watershed models generally predict flow volume, nutrient yields, and sediment yield leaving the landscape from a specified boundary to a designated outlet point while not considering instream biotic and abiotic processes.

One approach to overcome these limitations is to incorporate instream processes from a stream water quality model into a watershed model. However, outputs from a watershed model with incorporated stream water quality model algorithms may not be the same as outputs generated from the stand alone stream water quality model. This phenomenon occurs because of nonlinearities within the system being modeled and differences in parameters affecting model outputs; similar problems have occurred when incorporating other models. For example, the integration of the USLE model into different field-scale and watershed models (CREAMS, SWRRB, EPIC, and AGNPS) was shown by Binger et al. (1992) to result in different sediment yield predictions for each model. While it is common to completely couple components, such as USLE into a more comprehensive model; a loose coupling of different modeling components may also be selected to combine modeling tools.

The loosely linked approach of integrating instream processes to a watershed model might include established stream water quality models such as QUAL2E (Brown and Barnwell, 1987) and CE-QUAL-RIV1 (USACE, 1995). One limitation in loosely linking watershed and instream models is that many instream water quality models do not possess spatial distinctions such as stream reaches and tributaries and are classified as point models (e.g., AQUATOX model, Park and Clough, 2004). Stream water quality models also are often steady state and provide little to no dynamic simulation abilities (e.g., QUAL2E). Hence, loose linkage can become challenging because of inherent differences in how two models characterize information spatially and temporally.

A landscape model with broad application in model coupling is SWAT, which has been coupled to an array of models to extend its applications including the Regional Climate Model (Stone et al., 2001), an economic model and various habitat models (Frede et al., 2002), and the Agriculture Policy eXtender model (Gassman et al., 2002). The SWAT model has been widely used (see White and Chaubey, 2005); recent applications include assessments of water quality management plans (Bärlund et al., 2007; Santhi et al., 2006) and uncertainty and integrated modeling (Krysanova et al., 2007). The SWAT model has been implemented globally and is often incorporated into spatially characterized tools that group multiple models for watershed level analysis (Miller et al., 2007).

An instream water quality model that is often linked to other models is QUAL2E, which has been generally coupled to models that do not provide adequate surface water routing and/or adequate surface water quality components (Wagner et al., 1996; Dia and Labadie, 2001). The QUAL2E model has been linked with estuary models (Ribeiro and Araújo, 2002) and river basin network flow models in conjunction with a model for estimating quality of irrigation return flows (Dia and Labadie, 2001).

The recognition of the strengths and limitations of SWAT and QUAL2E has led to the integration of QUAL2E into SWAT by model developers. Basically, SWAT developers modified a portion of the equations from the QUAL2E model and provided options within the SWAT model to include or exclude these calculations in watershed model simulations (Neitsch et al., 2001). However, very little published information currently exists comparing the ability of the SWAT model to simulate water quality processes and corresponding outputs to stand alone instream water quality model outputs (Houser and Hauck, 2002).

The goal of this project was to loosely couple these two models and compare the combined ability to predict total phosphorus (TP) and NO_3-N plus NO_2-N (hereafter, NO_3-N) yields from a watershed to model output predicted using SWAT with its completely coupled stream water quality components. We define loose model coupling as a process in which output from one model (i.e., SWAT) is used as an input to another model (i.e., QUAL2E) by interchange of data file either in ASCII format or using GIS. Complete model coupling can be defined as coding equations of one model completely within the framework of another model. Our objectives were to: (1) predict monthly TP and NO_3-N watershed yields using SWAT with the completely coupled instream components (method 1); (2) predict monthly watershed TP and NO_3-N yields using SWAT with a loosely coupled QUAL2E model (method 2); and (3) determine if significant differences exist between the relationship of measured yields and predicted yields from the two modeling methods.

2. Study site

The study site was War Eagle Creek watershed in Northwest Arkansas, USA. War Eagle Creek is one of the main tributaries to Beaver Reservoir, which is the primary drinking water supply for Northwest Arkansas. War Eagle Creek watershed encompasses approximately 68,100 ha with land use distributions of 63.7% forest, 35.6% pasture, 0.5% urban, and 0.2% water (CAST, 2002). The watershed was delineated into 13 subbasins using the GIS tool provided with the SWAT model (Fig. 1). The most downstream subbasin and the location of the watershed outlet are in subbasin 13.

Nutrient nonpoint sources in the watershed include land application of animal manure and agricultural production facilities for chickens, turkeys, swine, and cattle; other nonpoint sources would include natural background nutrient loading and that from the small urban area within the catchment. The dominant point source in the watershed is the Waste Water Treatment Plant (WWTP) effluent discharge from the city of Huntsville, Arkansas. Nutrients from nonpoint and point

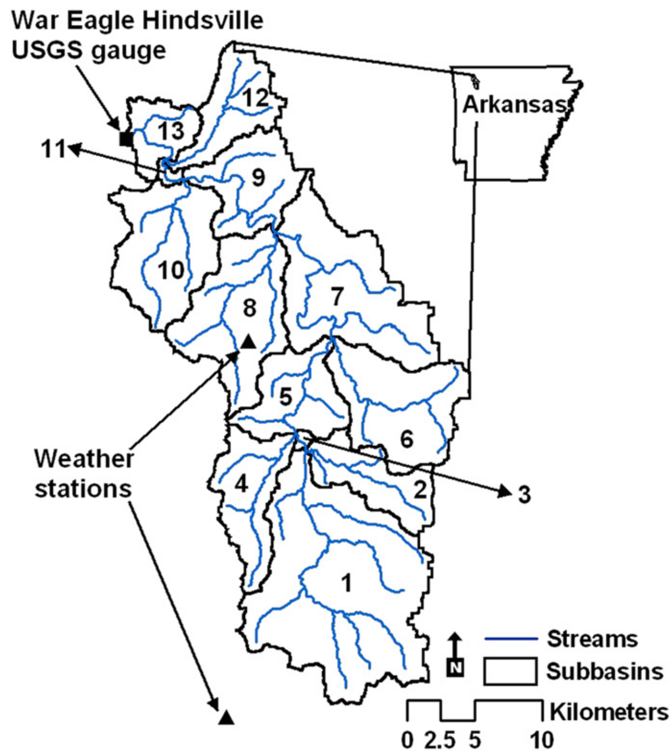

Fig. 1. Location of War Eagle Creek Watershed with subbasins and streams.

sources are a concern in War Eagle Creek watershed because of the potential influence on eutrophication rates in the downstream Beaver Reservoir.

3. Methods

3.1. SWAT model with completely coupled instream components

The SWAT model is a widely used, physically based, watershed model developed by US Department of Agriculture-Agricultural Research Service (USDA-ARS) (Arnold et al., 1998; Srinivasan et al., 1998). It functions on a continuous time step with input options for hydrology, nutrients, erosion, land management, main channel processes, water bodies, and climate data. The SWAT model predicts the influence of land management practices on constituent yields from a watershed and includes agricultural components such as fertilizer, crops, tillage options, and grazing; SWAT can also include point source discharges (Neitsch et al., 2001). Arnold and Fohrer (2005), Jayakrishnan et al. (2005), and White and Chaubey (2005) have provided summary of model applications in making watershed response predictions under various land use, soil, and climate conditions.

We used AvSWAT2000 in this application, which was the current version of the model at the beginning of the project (USDA-ARS, 2004). The following GIS data were used to develop the War Eagle Creek watershed model to simulate watershed response from 1999 to 2002: 30-m DEM (US Geological Survey), 28.5-m 1999 land use and land cover image file (CAST, 2002), and STATSGO soils shape file (USEPA, 2004). Based on threshold specifications and the DEM, the delineation tool in the ArcView interface was used to divide the watershed into 13 subbasins (Fig. 1). Point and nonpoint sources were included in the model such as WWTP effluent discharges, animal manure and litter applications, and commercial fertilizer usage. Weather data from the stations within the region were incorporated to provide the most representative precipitation and temperature data available.

SWAT model users have an option to include or exclude instream processes in SWAT simulations. When the instream component is included, the model routes the state variables through additional algorithms that have been completely coupled from QUAL2E. These QUAL2E additional algorithms are included to simulate instream processes that are otherwise not considered by SWAT.

The differences between the algorithms used in SWAT and QUAL2E are predominantly related to model characteristics of being a dynamic (SWAT) or steady-state model (QUAL2E). The steady-state constituent concentrations are calculated in the QUAL2E model using a mass transport equation that includes advection, dispersion, dilution, constituent reactions and interactions, and sources and sinks components (Brown and Barnwell, 1987):

$$\frac{\partial C}{\partial t}=\frac{\partial\left(A_x D_{\mathrm{L}}\frac{\partial C}{\partial x}\right)}{A_x\partial x}-\frac{\partial(A_x\overline{u}C)}{A_x\partial x}\frac{\mathrm{d}C}{\mathrm{d}t}+\frac{s}{v} \tag{1}$$

where C is concentration, A_x is cross-sectional area, D_{L} is dispersion coefficient, $\overline{u}$ is mean velocity, s is external sources or sinks, and v is incremental volume. Each QUAL2E constituent concentration is solved using Eq. (1) with constituent respective parameters. For example, in QUAL2E organic phosphorus (P) is calculated as:

$$\frac{\mathrm{d}P_1}{\mathrm{d}t}=\alpha_2\rho A-\beta_4 P_1-\sigma_5 P_1 \tag{2}$$

where P_1 is the concentration of organic P in the water, α_2 is the P content of algae, ρ is algal respiration rate, A is algal biomass concentration, β_4 is the organic P decay rate, and σ_5 is the organic P settling rate. The QUAL2E organic P differential equation and other QUAL2E differential equations are solved using the classical implicit backward difference method (Brown and Barnwell, 1987).

A comparison between QUAL2E and SWAT model constituent concentration equations indicated minimal differences between the two. This can be illustrated by comparing the QUAL2E model organic P equation (Eq. (2)) with the SWAT model organic P equation (Eq. (3)). Organic P in SWAT was calculated as:

$$\Delta\mathrm{orgP_{str}}=\left(\alpha_2\rho_{\mathrm{a}}\,\mathrm{algae}-\beta_{\mathrm{P},4}\mathrm{orgP_{str}}-\sigma_5\mathrm{orgP_{str}}\right)\mathrm{TT} \tag{3}$$

where $\Delta\mathrm{orgP_{str}}$ was the change in organic P concentration, α_2 was the fraction of algal biomass that is P, ρ_{a} was the local respiration or death rate of algae, algae was the algal biomass concentration at the beginning of the day, $\beta_{\mathrm{P},4}$ was the rate constant for mineralization of organic P, $\mathrm{orgP_{str}}$ was the organic P concentration at the beginning of the day, σ_5 was the rate coefficient for organic P settling, and TT was the flow travel time in the reach segment for that day (Neitsch et al., 2001). Hence, the dominant difference between the two is that the SWAT equation includes a dynamic variable 'TT' for variable rates of flow travel time. The SWAT model also allows the user to adjust organic P inputs on a daily basis, which is not available in QUAL2E. This results in the $\mathrm{orgP_{str}}$ variable being dynamic in the SWAT model instead of a steady-state constraint as in QUAL2E. Similar comparisons can be made for other nutrients simulated by the two models (organic nitrogen (N), ammonium, nitrite, nitrate, and dissolved inorganic P), but are not detailed in this manuscript for brevity.

In calibrating the SWAT model for War Eagle Creek watershed, we activated the instream processes by manually selecting them 'on' within the model; this was done through the ArcView interface on the simulation window screen. Sensitivity analysis, calibration, and validation of the SWAT model were completed with instream components turned 'on'. Sensitivity analysis was conducted to determine the influence a set of parameters had on predicting total flow, sediment, TP, and NO_3-N. Sensitivity was approximated using relative sensitivity (S_{r}) defined as:

$$S_{\mathrm{r}}=\frac{x}{y}\frac{y_2-y_1}{x_2-x_1} \tag{4}$$

where x is the parameter and y is the predicted output. x_1, x_2 and y_1, y_2 correspond to $\pm10\%$ of the initial parameter and output values, respectively (James and Burges, 1982). The greater the S_{r} the more sensitive a model output variable was to that particular parameter. Parameters were selected for sensitivity analysis by reviewing previously used calibration parameters and by reviewing documentation from the SWAT manuals. Parameters that were found to influence output variables of interest (i.e., those having greater S_r values) were modified during the model calibration.

The War Eagle Creek SWAT model was calibrated using data collected at the US Geological Survey (USGS) gauging station: War Eagle Creek near Hindsville (USGS 07049000) (Fig. 1). About twice-a-month water quality sampling occurred at this USGS gauge, therefore daily measured constituent concentrations were not available. Daily concentrations were estimated from collected samples using the LOADEST2 software (Crawford, 1991, 1996). Measured flow data were available from 1999 to 2002 at the War Eagle Creek gauge. Therefore, 1999 and 2000 flow data were used for model calibration and 2001 and 2002 flow data were used for model validation. For this time period (1999–2002), water quality data were only available for 2001 and 2002. Water quality variables included in calibration were sediment, TP, and NO_3-N. Water quality data for 2001 and 2002 were used for constituent calibration and validation, respectively.

For calibration, monthly and annual time steps were used in optimizing the objective function as defined by the following three statistics for flow, sediment, TP, and NO_3-N. SWAT model annual calibration was performed by minimizing the % relative error (RE) at the gauge location:

$$\mathrm{RE}(\%) = \left|\frac{(O-P)}{O}\right|100 \tag{5}$$

where O was the measured value and P was the predicted output. The SWAT model was further calibrated monthly using the R^2_{NS}, which is defined as:

$$R^2_{\mathrm{NS}} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_{\mathrm{avg}})^2} \tag{6}$$

where O is measured values, P is predicted outputs and i = number of values (Nash and Sutcliffee, 1970). Monthly coefficient of determination (R^2) was also calculated since R^2_{NS} is sensitive to outliers (Kirsch et al., 2002). The R^2 statistic was calculated as:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - O_{\mathrm{avg}})(P_i - P_{\mathrm{avg}})}{\left[\sum_{i=1}^{n}(O_i - O_{\mathrm{avg}})^2 \sum_{i=1}^{n}(P_i - P_{\mathrm{avg}})^2\right]^{0.5}}\right)^2 \tag{7}$$

Combining the three test statistics, output variables of interest, and temporal components, the multi-objective function (F) was described by:

$$F(O,P) = \left\{\begin{array}{l} \text{minimize} \sum_{i=1}^{y}\left(\sum_{k=1}^{v}\mathrm{RE}(O,P)\right) \\ \text{optimize} \sum_{l=1}^{m}\left(\sum_{n=1}^{w}R^2_{\mathrm{NS}}(O,P), R^2(O,P)\right) \end{array}\right\} \tag{8}$$

where y was the number of years, v was the number of variables evaluated annually, m was the number of months, w was the number of variables evaluated monthly. For our evaluation y was 4, v was 6, m was 48, and w was 4. Calibration was considered successful if the optimization of Eq. (8) resulted in statistical parameters' values that were better than or the-same-as previously published values for comparable applications.

SWAT model validation required calculation of Eqs. (5), (6), and (7), similar to calibration. However, validation was evaluated using a different data set and without modifying model parameters. Validation was considered successful if results for Eqs. (5), (6), and (7), were similar to those determined during calibration.

3.2. SWAT model loosely coupled to a QUAL2E model

The SWAT parameter set identified for the calibrated SWAT model with instream components active was used for the loosely coupled modeling method. By using the calibrated parameter set, we were able to provide the best estimated values for input into the stream at each reach. However, when linking the SWAT model to the QUAL2E model, instream components in the SWAT model were turned 'off'. Turning 'off' the SWAT instream components provided us with a model that simulated constituent loads and flow entering each reach with no accountability for instream processes. Therefore, the SWAT model was used to predict flows and constituent yields leaving the watershed while the separate QUAL2E model was used to simulate all instream processes.

The QUAL2E model is a one-dimensional instream water quality model that includes dissolved oxygen (DO), biological oxygen demand, temperature, algae as chlorophyll-a, N, P, coliforms, arbitrary nonconservative constituent, and three conservative constituents. The model simulates interactions between constituents such as nutrient cycles, algae production, benthic oxygen demand, carbonaceous oxygen uptake, and atmospheric aeration (Brown and Barnwell, 1987). The QUAL2E model was chosen as the instream water quality model because of its ability to simulate a stream system comprised tributaries and headwater reaches. This model has been widely implemented since its completion in 1985 to simulate water quality response to changes in constituent loads (e.g., Thakar and Rogers, 1994; Ning et al., 2001; Ribeiro and Araújo, 2002). In addition, the QUAL2E model was an ideal choice since the algorithms within QUAL2E were used to develop the instream components available in SWAT.

However, QUAL2E model users are subject to a substantial constraint, and this constraint is its steady-state characteristic which hinders its appropriateness to predict constituent concentrations in a dynamic system (Zhang et al., 1996). This is concern, particularly, when using QUAL2E to predict variables that are influenced by dynamic processes, such as nonpoint source pollution and hydrologic events. To accommodate for this limitation, three QUAL2E models were parameterized for War Eagle Creek to represent seasonal differences: winter–spring (high flow), summer (low flow), and fall (low flow after leaf abscission). Winter–spring, summer, and fall were considered by months as January through June, July through September, and October through December (Table 1). These seasons were chosen to account for differences in stream flow and nutrient dynamics that occur throughout the year (Haggard et al., 2003). Estimation of monthly constituent yields using three seasonal QUAL2E models reduced the error introduced by using a steady-state model to simulate dynamic processes.

Inputs for QUAL2E that describe the stream's physical characteristics (length, slope, network) did not change between the three seasonal QUAL2E models (Fig. 2). The War Eagle Creek watershed was divided into 13 reaches in the QUAL2E model, as defined by the SWAT delineation. Each subbasin (as defined in Fig. 1) was identified as a separate reach. Reach hydraulic characteristics, such as slope and cross-section features were measured in the field using GPS surveying equipment. For areas with a dense riparian zone that prevented GPS surveying, GIS data and ESRI software were employed to acquire stream slopes.

Initial conditions for chlorophyll-a, organic N, NH_3-N, NO_2-N, NO_3-N, organic P, and dissolved P were estimated for each QUAL2E model reach by season using SWAT model monthly predicted outputs for 2001 and 2002. The QUAL2E input constituent concentrations were calculated by dividing SWAT predicted constituent yields by respective SWAT predicted flow volumes to obtain a flow-weighted concentration for each reach-season combination. These concentrations became the values for QUAL2E model initial conditions.

Table 1
Average seasonal values for measured data at War Eagle Creek near Hindsville (USGS 07049000)

	Average flow rate (m^3/s)	Average TP yield (kg/day)	Average NO_3-N plus NO_2-N yield (kg/day)
High flow	13.7	53	1717
Low flow	1.5	5	152
Low flow with leaf litter	5.6	30	883

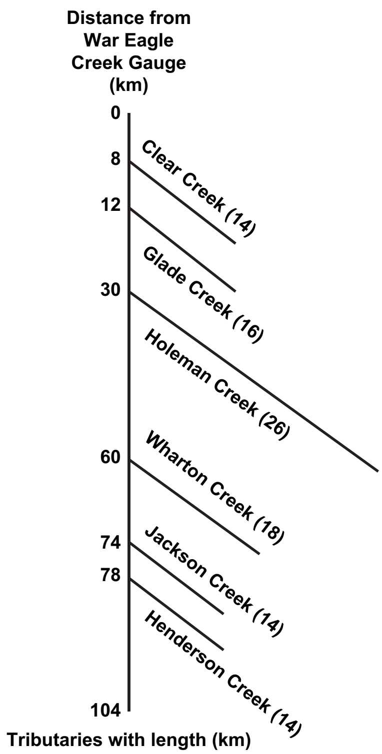

Fig. 2. Schematic of QUAL2E model tributaries and main head waters reaches.

Similar to initial condition inputs, QUAL2E model headwater source inputs were derived by season and reach from SWAT predicted values. Headwater source inputs refer to flow and constituent concentrations that enter the stream network as a tributary or headwater reach. Initial conditions and headwater stream values for temperature and DO were estimated using field data collected for each reach during each season. These parameters were collected during the summer and fall of 2003 and winter–spring of 2004. Field measured values were used instead of SWAT predictions for stream temperature and DO because of SWAT process deficiencies for simulating DO, lacking calibration data for stream temperature and DO, and temperature not being a readily available SWAT output.

Three water samples were also collected at each site for each season. TP was analyzed using the automated ascorbic acid reduction method on an unfiltered water sample that was digested with persulfate in an autoclave. NO_3-N was determined using cadmium–copper reduction and colorimetric analysis. Also, it is important to note that water samples were collected during baseflow conditions when instream processes have greater influence on nutrient dynamics.

To simulate groundwater, transmission losses, and evaporation occurring in the main reach; QUAL2E model incremental flows were defined. SWAT model output for groundwater, transmission losses, and evaporation was aggregated into one flow and was input into the QUAL2E model as incremental flows. Climatology is represented in the QUAL2E model by air temperature, dew point temperature, wind direction, wind speed, and cloudiness. These values were estimated by season using data from the Huntsville weather station (Fig. 1).

Sensitivity analysis was performed as described by Eq. (4). Sensitivity analysis included parameters that influenced QUAL2E model TP and NO_3-N predicted yields. Flow was not considered in QUAL2E parameter sensitivity analysis because all flow parameters were from SWAT model predictions and considered known inputs. Hence, parameters considered in sensitivity analysis were temperature correction factors; SOD/DO reaction rates; N, P, and algae coefficients; and global kinetic coefficients.

The three seasonal QUAL2E models were calibrated for the years 2001–2002 optimizing the statistic in Eq. (5) for each season. QUAL2E model calibration using Eq. (5) was performed as follows:

(1) Measured data from the USGS gauge for each season were evaluated to determine a measured seasonal yield (M_{SY}) for TP and NO_3-N:

$$M_{SY} = \frac{\sum_{i=1}^{n} M_{MY_i}}{Y} \tag{9}$$

where M_{MY} was the measured monthly yield for the respective constituent, Y was the number of years of data, and n was the number of months of data for the respective season.

(2) QUAL2E model predicted yields for each season were estimated from QUAL2E model outputs of flow [$m^3\,s^{-1}$] and constituent concentrations [$mg\,L^{-1}$]. For each season a yield was determined based on the respective annual time (3-months for summer season and fall season and 6-months for winter–spring season) and model flow and constituent concentration outputs.

(3) Results from steps 1 and 2 become O and P, respectively, in Eq. (5).

Using this approach, QUAL2E was calibrated to estimate seasonal TP and NO_3-N yields leaving War Eagle Creek watershed.

No measured data for each reach were available to quantitatively calibrate or validate the QUAL2E model. We performed a qualitative validation of QUAL2E using measured data from 2003 and 2004. The validation was considered successful if general trends in model predicted TP and NO_3-N between seasons and reaches were similar considering model predicted values and 2003–2004 measured values. To verify the approach of using this qualitative validation, SWAT model predictions with instream components active for each reach were compared. This comparison was done on a seasonal basis for 1999 and 2000 to determine if a general trend in measured and predicted TP and NO_3-N concentrations was present across subbasins. Although there were some variations between years, similarities in measured and predicted TP and NO_3-N plus NO_2-N concentrations were dominant, indicating that the relative rankings of the measured and predicted water quality outputs could be compared to qualitatively validate the model. The winter/spring season results are presented in Table 2.

Qualitative validation using general trends was evaluated for the loosely coupled models as follows: (1) order each data set from the smallest to the greatest concentration, (2) rank each concentration based on its order position, and (3) compare the rankings of measured and predicted concentrations. There were six measured and six predicted data sets: winter–spring TP, summer TP, fall TP, winter–spring NO_3-N, summer NO_3-N, and fall NO_3-N.

Table 2
Ranking by reach of TP and NO_3-N plus NO_2-N concentrations predicted by the SWAT model

Reach	Winter/spring season ranking[a]			
	TP		NO_3-N plus NO_2-N	
	1999	2000	1999	2000
1	1	1	1	1
2	5	5	8	10
3	4	2.5	2	2
4	2.5	4	5	8
5	6	5	6	5
6	2.5	2.5	3	6
7	7	7	7	7
8	13	13	13	13
9	10	9	12.5	12.5
10	9	11	9	4
11	8	8	12.5	12.5
12	11	10	4	3
13	12	12	10	9

[a] A ranking of 1 indicates the lowest concentration and a ranking of 13 indicates the highest concentration.

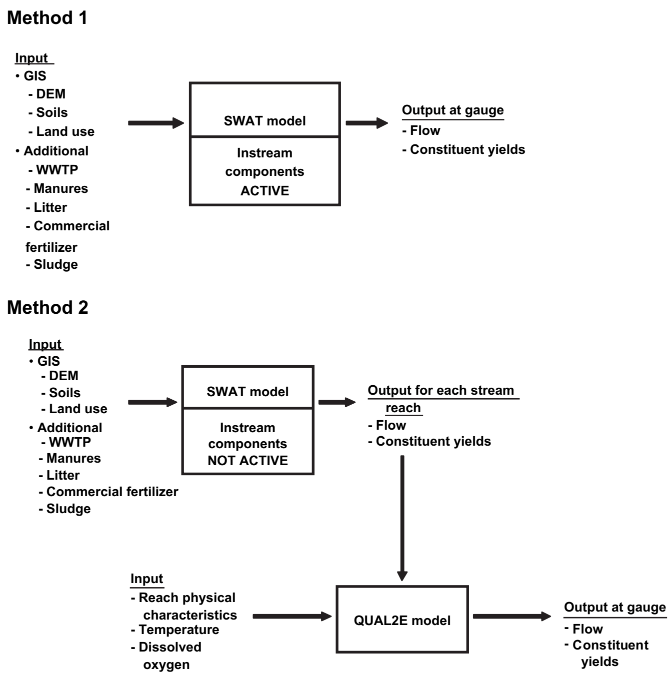

Fig. 3. Flowcharts for each modeling method.

In interpreting validation results, the coefficient of variability (CV) was also used where:

$$\mathrm{CV} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}}{O_{\mathrm{avg}}} \tag{10}$$

3.3. Comparing two modeling methods

Monthly TP and NO_3-N yields were compared using SWAT with completely coupled instream components (method 1 in Fig. 3) and using SWAT loosely coupled to QUAL2E (method 2 in Fig. 3). Results were compared to determine if the relationship between predicted and measured monthly TP and NO_3-N yields were significantly different between the two modeling methods. The statistical tests used to evaluate this were two variations of the Pearson product-moment correlation coefficient ($p < 0.05$). The first Pearson product-moment correlation was evaluated such that:

$$\begin{aligned} &\mathrm{H_o}: \rho_1 = \rho_2 \\ &\mathrm{H_a}: \rho_1 \neq \rho_2 \end{aligned} \tag{11}$$

where ρ = the population correlation, '1' subscript refers method 1 and '2' subscript refers to method 2. The second test evaluated the following hypotheses:

$$\begin{aligned} &\mathrm{H_o}: \beta_1 = \beta_2 \\ &\mathrm{H_a}: \beta_1 \neq \beta_2 \end{aligned} \tag{12}$$

where β = slope of a regression line (Sheskin, 2000).

4. Results and discussion

4.1. Method 1 — SWAT model with completely coupled instream components

Parameters identified in the SWAT model sensitivity analysis as having the greatest influence on flow, sediment, and nutrients outputs are listed in Table 3. Several parameters, such as the curve number (CN2) and USLE parameters were found to influence more than one output variable. This indicates the dependency of multiple output variables of interest on a similar set of parameters.

The multi-objection function for SWAT model calibration was achieved by modifying the parameters listed in Table 4 for their respective variables. Statistical values from the War Eagle Creek SWAT model calibration and validation are provided in Tables 5 and 6. Annual and monthly calibration statistics as described by the multi-objective function were closer to optimization or the-same-as those reported in published literature (White and Chaubey, 2005). Hence, the SWAT model of the War Eagle Creek watershed model was considered to reasonably predict representative flow volumes, sediment yields, TP yields, and NO_3-N yields leaving the War Eagle Creek watershed.

4.2. Method 2 — the SWAT model loosely coupled to the QUAL2E model

Sensitivity analysis was completed for the QUAL2E model with parameters that most influenced TP and NO_3-N output identified in Table 7. The results of the QUAL2E sensitivity analysis suggested that relatively fewer parameters influenced predicted TP or NO_3-N yields. However, generally the same parameters influenced both predicted TP and NO_3-N yields.

Seasonal calibration of SWAT loosely coupled to QUAL2E resulted in different values for some of the QUAL2E parameters amongst the seasons (Table 8). This variation in parameter values by season suggests that temporal distinction for the identified parameters may be important in modeling the

Table 3
List of parameters and their ranking that produced the five highest relative sensitivity for each SWAT model output

Variables	Ranking[a]				
	1	2	3	4	5
Surface runoff	CN2.mgt	ESCO.hru	CNOP.mgt	SOL_AWC1.sol	SLSUBBSN.hru
Total flow	ESCO.hru	CN2.mgt	SOL_AWC1.sol	SOL_BD1.sol	CNOP.mgt
Sediment	CNOP.mgt	SLOPE.hru	ESCO.hru	EPCO.hru	USLE_P.mgt
Organic N	USLE_P.mgt	SLOPE.hru	CNOP.mgt	USLE_K.sol	SOL_BD1.sol
NO_3-N	CNOP.mgt	CN2.mgt	ESCO.hru	USLE_P.mgt	EPCO.hru
Organic P	SPEXP.bsn	EVRCH.bsn	EPCO.hru	USLE_P.mgt	FERT_LY1.mgt
Soluble P	USLE_P.mgt	CNOP.mgt	EPCO.hru	SPEXP.bsn	EVRCH.bsn

[a] Ranking of 1 is equal to the highest calculated S_r.

Table 4
List of calibration parameters with input file extension for each output of interest for the War Eagle Watershed SWAT model

Flow	Sediment	TP	NO_3-N plus NO_2-N
ALPHA BF.gw	AMP.bsn	AI2.wwq	NPERCO.bsn
CN2.mgt	CH_N1.sub	BC4.swq	RS4.swq
ESCO.hru	OVN.hru	CMN.bsn	
SURLAG.bsn	PRF.bsn	ERORGP.hru	
	ROCK.sol	FRT_LY1.mgt	
	SLOPE.hru	PHOSKD.bsn	
	SLSUBBSN.hru	PPERCO.bsn	
	SPCON.bsn	RS5.swq	
	USLE_K.sol	UBP.bsn	
	USLE_P.mgt		

transport of TP and NO_3-N through streams when considering instream processes. Interestingly, many of these parameters are also included in the instream components completely coupled into SWAT. However, no temporal capabilities are currently present in the SWAT model to account for seasonal differences in their values, even though instream nutrient processes have been shown to exhibit seasonal difference due to changes in light, nutrient supply, flow sources, and temperature (Rosemond et al., 2000). It is important to note that the seasonal differences in parameterization would not be accounted for in QUAL2E if only one model was used to represent the entire simulation period instead of the three seasonal models.

Percent RE values from the calibrated models using modeling method 2 are presented by season for TP and NO_3-N in Table 9. Percent RE values from SWAT loosely coupled to QUAL2E (method 2) for TP and NO_3-N were greater than those determined using SWAT with completely coupled QUAL2E components (method 1) output for winter–spring and fall. The differences observed in %RE for these seasons were likely a result of the steady-state limitations imposed by QUAL2E which prevents temporal changes in flow and constituent yields that are needed to represent hydrologic processes in the watershed. Alternatively, the SWAT loosely coupled to QUAL2E (method 2) predicted monthly TP and NO_3-N yields more closely to measured values than the SWAT model with completely coupled instream components (method 2) for the summer season. This could be the result of the inability to change some of the parameters temporally

Table 5
War Eagle Creek SWAT model calibration and validation results for annual RE (%) by constituent

Year	Total flow	Baseflow	Runoff flow	Sediment	TP	NO_3-N plus NO_2-N
Calibration						
1999	17.0	−8.2	33.4			
2000	−6.3	−26.1	1.1			
Validation						
2001	−8.5	−10.0	−7.9	14.4	−2.1	28.2
2002	−5.6	−11.2	−0.9	12.4	10.6	−6.5

Table 6
War Eagle Creek SWAT model calibration and validation results for monthly R^2_{NS} (R^2)

Year	Total flow	Sediment	TP	NO_3-N plus NO_2-N
Calibration				
1999	0.81 (0.65)			
2000	0.89 (0.91)			
Validation				
2001	0.72 (0.77)	0.43 (0.45)	0.51 (0.58)	0.29 (0.47)
2002	0.73 (0.81)	0.32 (0.77)	0.67 (0.76)	0.49 (0.71)

in the SWAT model that influence TP and NO_3-N transport through stream channels.

TP and NO_3-N concentrations measured during 2003–2004 field work and the respective model predicted concentrations are compared by reach in Figs. 4 and 5. The results suggested that predicted TP and NO_3-N plus NO_2-N concentrations across the defined stream reaches least closely followed measured concentrations during the summer season. A likely factor contributing to the differences observed in the summer season is that many of the headwater reaches are intermittent and contain water only in pools during the summer that are hydrologically connected via subsurface flow through the hyporheic zone. Reaches where water samples came from sampling pools that were not hydrologically connected by surface water flow included reaches 1, 2, 3, 4, and 6.

Reach 8 was generally higher in TP and NO_3-N concentration than other reaches during all seasons. This was most likely from the impact of the WWTP effluent discharge in that subbasin. Effluent from WWTPs has been identified as a substantial source of nutrient in this ecoregion due to poultry processing plants and minimal effluent permit restrictions for nutrients, particularly TP (Haggard et al., 2001, 2004). Similarly, nutrient concentrations also appear to be generally greater further downstream from reach 8 at War Eagle Creek during all seasons.

Greater disparity was present in the qualitative comparison between measured and predicted NO_3-N concentrations than

Table 7
List of parameters and their ranking that produced the five highest relative sensitivity for each QUAL2E model output

Ranking[a]	Variables	
	TP	NO_3-N plus NO_2-N
1	Temperature coefficient for algal growth	Algal P half saturation coefficient
2	Temperature coefficient for algal settling[b]	Temperature coefficient for algal growth
3	Chlorophyll-*a* algal concentration[b]	Temperature coefficient for algal settling
4	Algal P content[b]	Algal N content
5	Algal maximum specific growth rate[b]	Algal maximum specific growth rate

[a] Ranking of 1 is equal to the highest calculated S_r.
[b] All parameters had the same S_r.

Table 8
QUAL2E model calibration parameters for each season

Parameter	Winter–spring (January–June)	Summer (July–September)	Fall (October–December)
Algal maximum specific growth rate	2.8	2.8	2.4
Algal N content	0.09	0.09	0.08
Algal P half saturation coefficient	0.01	0.06	0.03
Algal settling rate	0.3048	0.3048	0.5
Chlorophyll-*a* to algae ratio	75	10	60
Manning's *n*	0.035	0.035	0.035
Non-algal light extinction coefficient	0.03	0.03	0.03
Rate coefficient for organic P settling	0.1	0.1	0.01
Temperature coefficient for algal growth	1.1	1.1	1.1
Temperature coefficient for algal settling	1.1	1.024	1.1

that found with comparisons of TP concentrations. These results were similar to those results reported by Ramanarayanan et al. (1996). This coincided with SWAT model calibration statistics from method 1 and SWAT loosely coupled to QUAL2E calibration statistics from method 2 which indicated that TP predicted outputs are more closely matched measured values than did NO_3-N predicted outputs. The poor predictability of NO_3-N concentrations in our evaluations and in past literature model applications indicated a limitation in using these models to predict NO_3-N concentrations accurately. This implied that further investigation and development of these processes are needed if the models are to be used in a quantitative application of NO_3-N predictions.

Seasonal model validation of these methods suggested that summer model calibrations were the most uncertain. Predictive limitations were indicated by method 1 TP results where CV values were 0.49, 4.47, and 0.79 for winter–spring, summer, and fall seasons, respectively. Hence, the summer season was characterized by the greatest variability between predicted and measured values for both modeling methods. This observation is not surprising given that instream processes would likely be most important during summer and that many of the smaller reaches were intermittent and not connected hydrologically by surface discharge.

4.3. Comparison of the two modeling methods

Average monthly predicted TP yields from the two modeling methods and USGS measured data are presented in Table 10. In addition, SWAT predicted TP yields with instream components inactive are provided. In comparison, differences between monthly TP yields from SWAT with instream components active and inactive were between 4 and 254 kg P, while annual TP yield was different by only 14 kg P. The differences between TP yields from SWAT with active or inactive instream components were not consistent across the annual timeframe and did not suggest any seasonal influence.

Monthly NO_3-N predicted and measured yields are presented in Table 11. Similar to TP, minimal differences were present between NO_3-N predicted yields from SWAT with instream components active and inactive. Differences between monthly NO_3-N yields varied between 11 and 199 kg N with an annual average difference of 839 kg N. In contrast to TP, predicted NO_3-N yields were always less when SWAT instream component was inactive.

The data presented in Tables 10 and 11 suggested that SWAT monthly predictions of TP and NO_3-N yields were not substantially influenced by whether or not instream processes are included in the model simulations. In addition, annual yields do not seem to differ substantially between results with and without SWAT instream components. This implies that the instream components available in SWAT have minimal influence on TP and NO_3-N transport from War Eagle Creek watershed. Hence, we can further infer that the instream processes available in SWAT may not be enhancing its predictive abilities as far as simulating instream processes.

Coefficients and correlations are presented in Table 12 from regression of monthly TP predictions with measured values. The first Pearson product-moment correlation for monthly TP from the two modeling methods resulted in a z (Fisher's z) value of 0.70, which was less than $z_{0.05}$ (1.96). Therefore, we failed to reject the null hypothesis (Eq. (11)) and the populations represented by the two samples had correlation values that were not significantly different. The second Pearson product-moment correlation evaluated for monthly TP from the two modeling methods resulted in a test statistic of t (Student's t distribution) =1.51. Since $t_{0.05}$ is 2.09, we failed to reject the null hypothesis (Eq. (12)). Hence, the slopes of the regression lines of the two data sets were not significantly different.

NO_3-N plus NO_2-N monthly predicted and measured yields (Table 11) were also evaluated using the two previously described Pearson product-moment correlation

Table 9
Percent RE for TP and NO_3-N plus NO_2-N for the three seasonal SWAT loosely coupled with QUAL2E model

Variable	Winter–spring (January–June) (%)	Summer (July–September) (%)	Fall (October–December) (%)
TP	44.5 (1.7)[a]	−80.0 (−617)	18.8 (−17.1)
NO_3-N plus NO_2-N	58.6 (13.2)	4.0 (−190)	47.8 (30.0)

[a] Values in parentheses are from the SWAT model with completed coupled instream components.

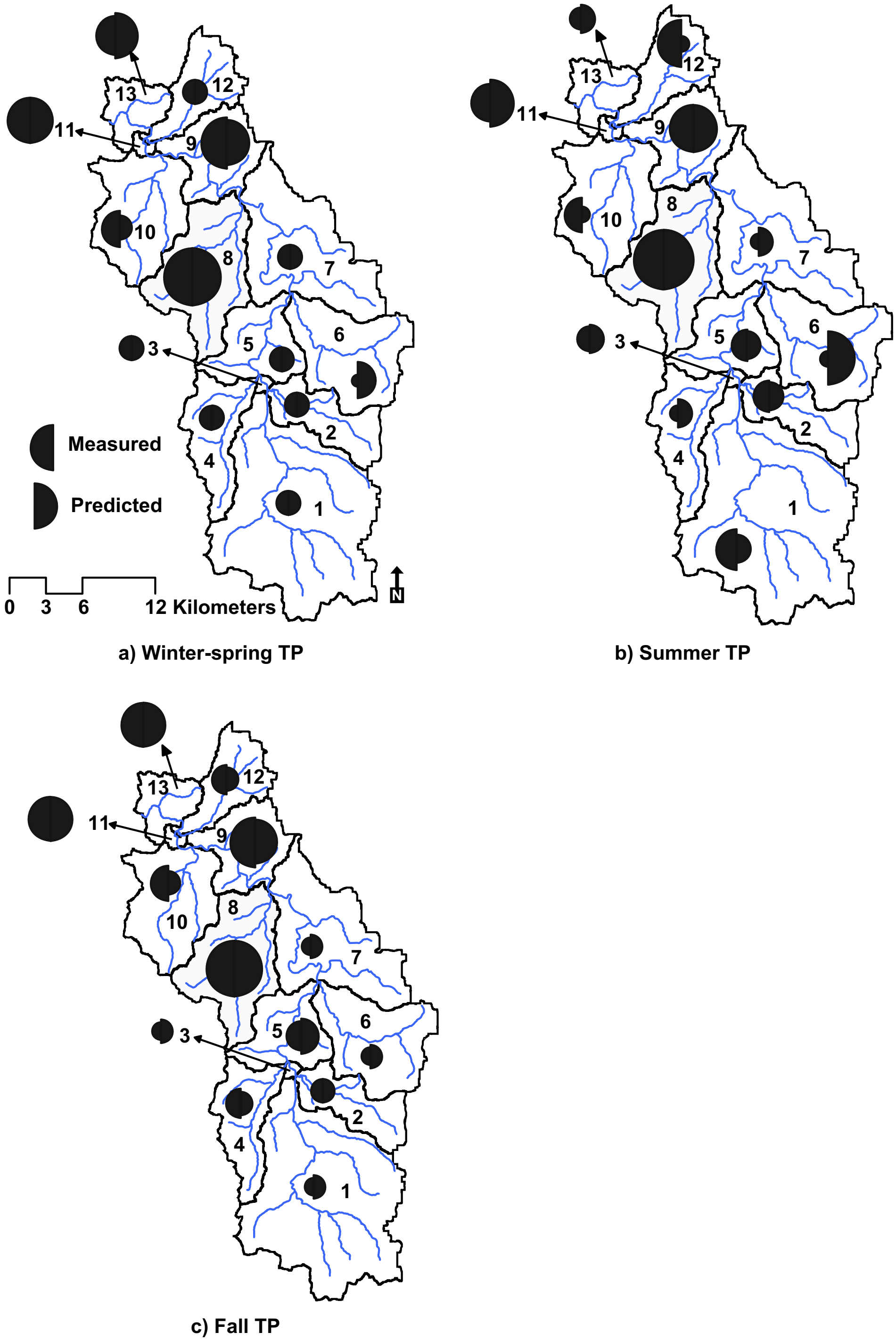

Fig. 4. Qualitative comparison of measured and QUAL2E predicted TP concentrations by reach for each season with concentrations ranked within each data set and represented with increasing symbol size corresponding to increasing concentration.

coefficients and regression analyses (Table 13). For the null hypothesis presented in Eq. (11), the resulting z value was 0.0 comparing the two modeling methods, which is less than $z_{0.05}$ (1.96), hence we failed to reject the null hypothesis. In addition, the NO_3-N plus NO_2-N monthly data set was evaluated for the hypotheses presented in Eq. (12). The test statistic for this hypothesis was $t = 0.26$. Thus, t is less than 2.09, so we failed to reject the null hypothesis. Therefore, the slopes of the regression lines of the two NO_3-N plus NO_2-N modeling method data sets were not significantly different.

The correlation coefficients and slopes of the regression lines relating monthly predicted and measured TP and NO_3-N yields were not significantly different between the two modeling methods. Thus, simulating monthly TP and NO_3-N yields using SWAT with instream components active

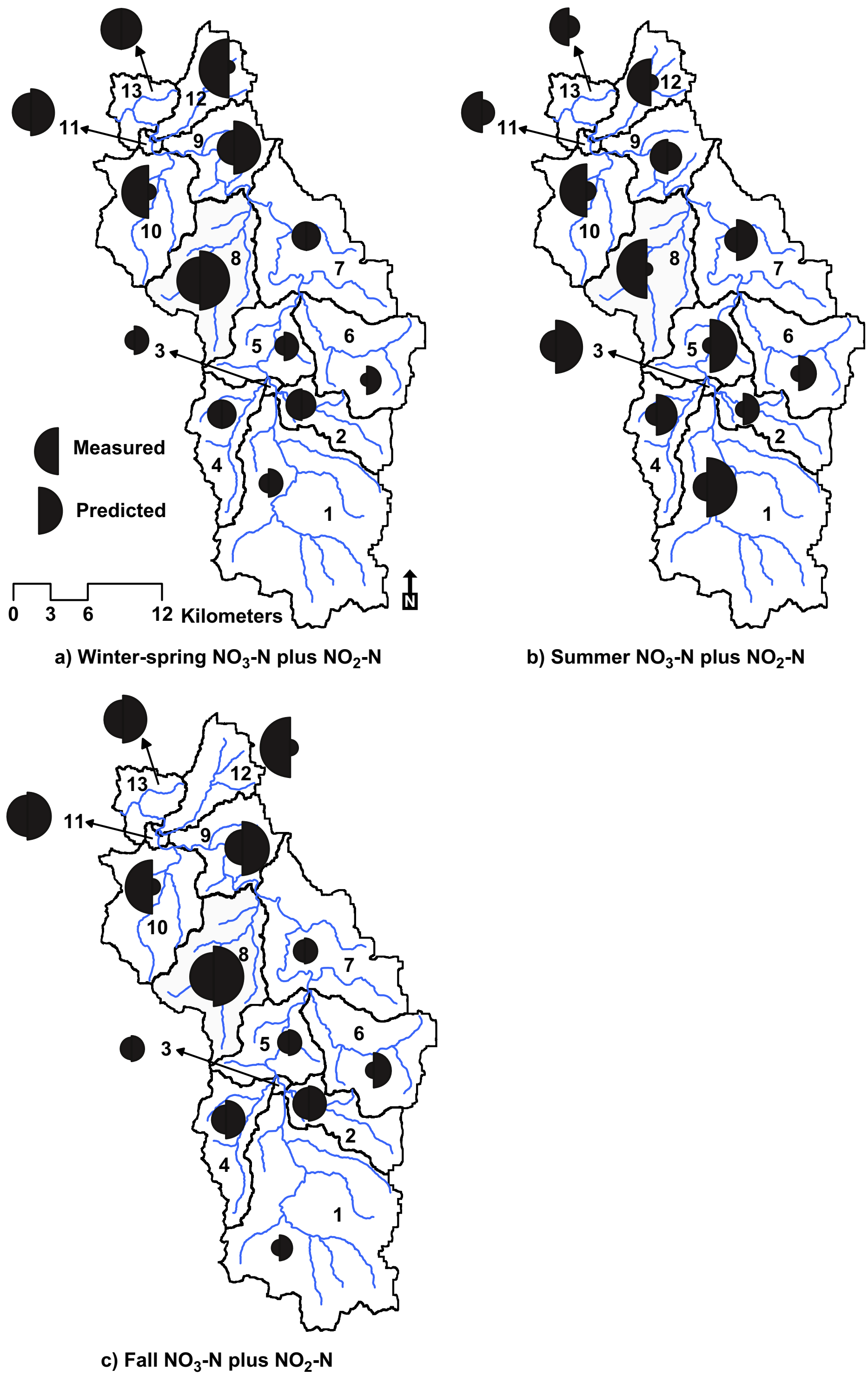

Fig. 5. Qualitative comparison of measured and QUAL2E predicted NO_3-N plus NO_2-N concentrations by reach for each season with concentrations ranked within each data set and represented with increasing symbol size corresponding to increasing concentration.

and using SWAT loosely coupled QUAL2E model were not significantly different from each other, as indicated by their correlation statistics and the regression slopes. This implies that no additional predictive ability was gained concerning monthly TP or NO_3-N yields from the War Eagle Creek watershed by loosely coupling the detailed QUAL2E model to the SWAT model with instream components inactive.

Furthermore, the lack of significant differences between predicted outputs of SWAT with instream components active and inactive indicates a need for further testing and refinement of the algorithms simulating instream processes within SWAT.

Table 10
Measured TP yield (USGS gauge) and model predicted TP yields

Month	USGS gauge (kg P)	SWAT with instream components active[a] (kg P)	SWAT − QUAL2E[b] (kg P)	SWAT with instream components inactive (kg P)
January	959	1712	988	1458
February	2622	1295	988	1203
March	2143	1241	988	1337
April	2591	1916	988	2077
May	629	599	988	527
June	635	855	988	804
July	195	735	281	731
August	157	865	281	993
September	85	779	281	805
October	193	584	719	665
November	110	322	719	343
December	2488	1298	719	1244
Total	12,807	12,201	8928	12,187

[a] Modeling method 1.
[b] Modeling method 2.

Currently, many of the parameters affecting the fate and transport of these constituents are held constant as a function of time in the SWAT model, which limits the ability of SWAT to simulate temporal changes that occur with many instream processes. There is a need to assess improvement in the model performance when these parameters are made dynamic to accurately reflect seasonal variations. The SWAT model developers have also indicated that all aspects of stream routing need further testing and refinement (Arnold and Fohrer, 2005).

5. Conclusions

Objective 1: The SWAT model with completely coupled instream components was successfully calibrated and validated for War Eagle Creek watershed to estimate predicted monthly TP and NO_3-N yields during 2001 and 2002.

Objective 2: The SWAT model with inactive instream components was loosely coupled to an independent QUAL2E model to determine their combined estimation of predicted monthly TP and NO_3-N yields during 2001 and 2002; the linked models were successfully calibrated and validated.

Objective 3: No statistically significant differences were determined between the two modeling approaches when evaluated with two variations of the Pearson product-moment correlation coefficient that tested differences in regression correlation coefficients and slopes.

The results of this research indicated that there were no added benefit to loosely coupling an instream model (QUAL2E) to SWAT compared to using the SWAT model with active instream components to predict monthly TP and NO_3-N transport from War Eagle Creek watershed. In addition, minimal differences were found in TP and NO_3-N yields between the SWAT model with instream components active and inactive. Because many of the SWAT model parameters affecting instream transport of these constituents are considered static over time, the model should be refined to enable a user to make these parameters dynamic to accurately reflect seasonal variability.

Table 11
Measured NO_3-N plus NO_2-N yield (USGS gauge) and model predicted NO_3-N plus NO_2-N yields

Month	USGS gauge (kg N)	SWAT with instream components active (kg N)[a]	SWAT plus QUAL2E (kg N)[b]	SWAT with instream components inactive (kg N)
January	30,040	38,958	21,491	38,910
February	83,027	26,552	21,491	26,505
March	70,167	23,747	21,491	23,672
April	84,879	129,131	21,491	128,932
May	21,474	29,801	21,491	29,790
June	21,170	25,152	21,491	25,111
July	6448	16,273	4503	16,197
August	4935	13,362	4503	13,263
September	2645	12,198	4503	12,103
October	5722	10,778	14,098	10,721
November	3393	14,353	14,098	14,333
December	72,088	32,517	14,098	32,446
Total	405,988	372,822	184,749	371,983

[a] Modeling method 1.
[b] Modeling method 2.

Table 12
Regression statistics from comparing measured and predicted TP monthly values using both modeling methods

Modeling method	Regression statistics		
	R^2	β_1[a]	β_0[b]
SWAT model with instream components active	0.578	0.342	652
SWAT model linked to QUAL2E model	0.339	0.165	568
SWAT model with instream components inactive	0.580	0.340	653

[a] Slope of the regression line.
[b] *Y*-intercept of the regression line.

Table 13
Regression statistics from comparing measured and predicted NO_3-N plus NO_2-N monthly values using both modeling methods

Modeling method	Regression statistics		
	R^2	β_1[a]	β_0[b]
SWAT model with instream components active	0.369	0.582	11,392
SWAT model linked to QUAL2E model	0.369	0.132	10,936
SWAT with instream components inactive	0.369	0.582	11,341

[a] Slope of the regression line.
[b] *Y*-intercept of the regression line.

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Appendix. SWAT parameters referred to in this paper

Parameter abbreviation	Input file	Description
AI2	.wwq	Fraction of algal biomass that is N
ALPHA_BF	.gw	Baseflow alpha factor
APM	.bsn	Peak rate adjustment factor for sediment routing in the subbasin
BC4	.swq	Rate constant for mineralization of organic P
CH_N(1)	.sub	Manning's *n* value for the tributaries
CMN	.bsn	Rate factor for humus mineralization of active organic nutrients (N and P)
CN2	.mgt	Initial SCS runoff curve number for moisture condition II
CNOP	.mgt	SCS runoff curve number for moisture condition II
EPCO	.hru	Plant uptake compensation factor
ERORGP	.hru	Phosphorus enrichment ratio for loading with sediment
ESCO	.hru	Soil evaporation compensation factor
EVRCH	.bsn	Reach evaporation adjustment factor
FRT_LY1	.mgt	Fraction of fertilizer applied to top 10 mm of soil
NPERCO	.bsn	Nitrate percolation coefficient
OVN	.hru	Manning's *n* value for overland flow
PHOSKD	.bsn	Phosphorus soil partitioning coefficient
PPERCO	.bsn	Phosphorus percolation coefficient
PRF	.bsn	Peak rate adjustment factor for sediment routing in the main channel
ROCK	.sol	Rock fragment content
RS4	.swq	Organic N settling rate coefficient
RS5	.swq	Organic P settling rate coefficient
SLOPE	.hru	Average slope steepness
SLSUBBSN	.hru	Average slope length
SOL_AWC	.sol	Available water capacity of the soil layer
SOL_BD	.sol	Moist bulk density
SPCON	.bsn	Linear parameter for calculating the maximum amount of sediment that can be re-entrained during channel sediment routing
SPEXP	.bsn	Exponent parameter for calculating sediment re-entrained in channel sediment routing
SURLAG	.bsn	Surface runoff lag coefficient
UBP	.bsn	Phosphorus uptake distribution parameter
USLE_K	.sol	USLE equation soil erodibility K factor
USLE_P	.mgt	USLE support practice factor

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