Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences Discussions
Open Access

SWAT Modeling of Water Quantity and Quality in the Tennessee River Basin: Spatiotemporal Calibration and Validation

Gangsheng Wang[1,2,*], Henriette I. Jager[1,2], Latha M. Baskaran[1], Tyler F. Baker[3], Craig C. Brandt[4]

[1]Environmental Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831 USA

[2]Climate Change Science Institute, Oak Ridge National Laboratory, Oak Ridge, TN 37831 USA

[3]Tennessee Valley Authority, Knoxville, TN 37902 USA

[4]Biosciences Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831 USA

*Corresponding Author: **Gangsheng Wang**
Bldg 4500N, Room F129S, MS-6301
Oak Ridge National Laboratory
Oak Ridge, TN 37831-6301
wangg@ornl.gov

Notice: This manuscript has been authored by UT-Battelle, LLC under Contract No. DE-AC05-00OR22725 with the US Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Abstract

Model-data comparisons are always challenging, especially when working at a large spatial scale and evaluating multiple response variables. We implemented the Soil and Water Assessment Tool (SWAT) to simulate water quantity and quality for the Tennessee River Basin. We developed three innovations to overcome hurdles associated with limited data for model evaluation: 1) we implemented an auto-calibration approach to allow simultaneous calibration against multiple responses, including intermediate response variables, 2) we identified empirical spatiotemporal datasets to use in our comparison, and 3) we compared functional patterns in landuse-nutrient relationships between SWAT and empirical data. Comparing monthly SWAT-simulated runoff against USGS data produced satisfactory median Nash-Sutcliffe Efficiencies of 0.83 and 0.72 for calibration and validation periods, respectively. SWAT-simulated water quality responses (sediment, TP, TN, and inorganic N) reproduced the seasonal patterns found in LOADEST data. SWAT-simulated spatial TN loadings were significantly correlated with empirical SPARROW estimates. The spatial correlation analyses indicated that SWAT-modeled runoff was primarily controlled by precipitation; sedimentation was controlled by topography; and NO_3 and soluble P were highly influenced by land management, particularly the proportion of agricultural lands in a subbasin.

Keywords: model calibration, validation, reservoir, runoff, SWAT, Tennessee River, water quality

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences Discussions
Open Access

1 Introduction

The Energy Independence and Security Act (EISA) of 2007 set a target for US production of over 36 billion gallons of renewable fuels annually by 2022 (EISA, 2007). Because agricultural development has historically been associated with impacts on water quality (Dodds and Oakes, 2008), converting the lands needed to meet EISA targets heightened concerns for the nation's rivers and lakes, as well as for downstream estuaries. The health of waters in the Tennessee River Basin (TRB) is of particular interest because this region supports one of the most biologically diverse river fauna in North America (Haag and Williams, 2014; Keck et al., 2014). Previous studies have shown higher nutrient and sediment loadings in non-forested, human influenced watersheds in the TRB (Scott et al., 2002). Evaluating changes in water quality associated with large-scale regional shifts in land-use and management requires process-based modeling of hydrology and nutrient dynamics (Wellen et al., 2015). Process-based models are favored whenever projections beyond historical conditions are needed because these models incorporate the processes leading to change and do not require extrapolation of statistical relationships beyond the range represented in the data.

Process-oriented models like the Soil & Water Assessment Tool (SWAT) (Arnold and Fohrer, 2005; Srinivasan et al., 1998) incorporate current understanding of linkages between watershed properties and water quality responses, but they are also difficult to calibrate (Wang and Chen, 2012). Although evaluation of multiple responses simulated by spatially-distributed process-based models over time and space is strongly encouraged (Cao et al., 2006; Wellen et al., 2015), such comprehensive evaluations are limited by the availability of spatial and long-term temporal data. This challenge is compounded for models applied at a regional scale because monitoring efforts tend to be local in scale and of short duration, especially for water quality (Hoos and

McMahon, 2009). As such, we see a role for empirical models in the calibration and validation of regional-scale models.

Empirical models have previously been fitted to spatial and temporal nutrient loads in the US (Saad et al., 2011). The monthly instream nutrient fluxes were estimated using LOADEST (LOAD ESTimator) developed by the United States Geological Survey (USGS) (Runkel et al., 2004; USGS, 2015). LOADEST assists in developing regression models for estimating nutrient loads or fluxes over a user-defined time interval based on functions of streamflow, time, and additional user-specified variables (Runkel et al., 2004). The SPARROW (SPAtially Reference Regressions On Watershed attributes) is also a model developed by USGS that relates water quality measurements to characteristics of watersheds (Hoos and McMahon, 2009; Saad et al., 2011) to estimate nutrient loads/fluxes. Both models represent empirical relationships most important during the historical period and smooth out the noise inherent in fine-resolution temporal water-quality measurements.

When seeking regional surveys suitable for calibration, data may not be available for exactly the outputs produced by the model. However, flexibility in assimilating data can be achieved by comparing against intermediate or synthetic response variables. Several SWAT calibration tools are available, e.g., SWAT-CUP 2012 (Abbaspour, 2014), the Auto-Calibration tool (Van Griensven, 2005), and the R-SWAT-FME framework (Wu and Liu, 2014); however, these tools do not include intermediate or synthetic response variables to compare against. This limitation prevented us from calibrating SWAT using the final water quantity and quality responses if the corresponding observations (or datasets) were not available.

This paper presents solutions to the aforementioned challenges, including fitting regional-scale SWAT model when there is limited spatial and long-term water quality data available and

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Discussions

representation of reservoirs in a highly regulated watershed. We describe efforts to implement SWAT modeling of water quantity and quality for the TRB including the configuration of 22 reservoirs. We incorporate the Shuffled Complex Evolution algorithm (Duan et al., 1992) into SWAT2012 to enable auto-calibration of the model against multiple hydrologic (i.e., water quantity) and water quality response variables (including intermediate and synthetic response variables) at multiple sites. We calibrate and validate SWAT water quantity and quality against empirically modeled datasets available from the USGS throughout the conterminous US. We also used functional validation to compare primary drivers controlling runoff and water quality in the process-based SWAT model and the empirical models. Functional validation goes beyond adding a stamp of approval (i.e., validation), instead comparing relationships to understand differences and guide future modeling or data collection efforts. The approach described here can be applied in other regions of the US where the required empirical models have been developed.

2 Materials and Methods

2.1 Study Area

The Tennessee River Basin (TRB), a tributary basin of the Mississippi River Basin, is located in the southeastern part of the United States (USGS, 2014b) (Fig. 1). There are significant physiographic differences in the eastern and western portions of the basin (Price and Leigh, 2006). Forest cover is the dominant natural vegetation in the basin. In the western portion, alluvial plains produced rich soils. The middle of the basin, which was historically covered by bottomland forest and prairie, now supports high percentages of pasture and cropland. Eastward, the geology becomes more mountainous and dominated by limestone with sandstone ridges. The easternmost portion of the basin lies in the rugged Blue Ridge and Southern Appalachian provinces with relatively poor soils (Price and Leigh, 2006). The TRB area has a subtropical climate (warm, humid summers, mild winters) (Sagona, 2003). December through early May is the major flood season (TVA, 2014). Since the 1930's, the TRB has been impounded by a series of dams (reservoirs), most of which are managed by the Tennessee Valley Authority (TVA). Main-stem Tennessee River dams are operated in "run-of-river" mode to support river navigation and generate hydroelectric power. Dams on the tributaries function as storage impoundments and are used primarily for flood control (TVA, 2014). Kentucky Dam is 35 km (22 mi) upstream from Paducah, Kentucky, where the Tennessee River flows northwest into the Ohio River (Fig. 1).

2.2 Watershed Delineation and Definition of SWAT Hydrologic Response Units

SWAT (Version 2012/Revision 627) was used to model water quantity and water quality (Arnold et al., 2012). The Digital Elevation Model (DEM) data (1-arc-second, c.a. 30 m) for TRB was downloaded from the National Elevation Dataset (http://nationalmap.gov/elevation.html). We conducted watershed delineation in ArcSWAT (Winchell et al., 2013) based on (i) USGS-defined 8-digit Hydrologic Unit Codes (Jager et al., 2015) (HUC8, Fig. 1), and (ii) major stream gages and reservoirs (Fig. 1). Watershed delineation of the TRB using the DEM resulted in a drainage area of 106,124 km^2. Twenty-two (22) reservoirs were included in the SWAT setup (Fig. 1). SWAT includes a reservoir module that can represent these waterbodies in the watershed (Chen et al., 2015; Wang and Xia, 2010). The reservoir outflow may be calculated by one of the four methods provided by SWAT (Arnold et al., 2012): (i) average annual release rate for uncontrolled reservoir; (ii) measured monthly outflow; (iii) simulated controlled outflow with target release; and (iv) measured daily outflow.

The last method (i.e., IRESCO = 3, measured daily outflow) was adopted in this study and TVA provided daily reservoir outflow rates from 1985 to 2013.

Hydrological Response Units (HRUs) represent unique combinations of soil type, slope, and land use or land cover. STATSGO soil map units (Soil Survey Staff, 1994) that comprised more than 10% of a subbasin were retained. We discretized slope into four categories: <1%, 1–2%, 2–5%, and >5%. We used the 2009 Cropland Data Layer (CDL-2009) (USDA-NASS, 2014) to represent land use/land cover (Jager et al., 2015). Natural vegetation in TRB is dominated by forest (59.4%) and grassland (11.7%). The major crops in TRB are hay (non-Alfalfa, 9.7%), soybeans (1.7%), and corn (1.5%). We retained land-use classes that comprised more than 2% area of a subbasin. This protocol created a total of 4,026 distinct HRUs in 55 subbasins.

2.3 Meteorological Forcings

We downloaded historical meteorological observation from DAYMET (Thornton et al., 1997) estimated for the center of each HUC8 (Fig. 1) over the period 1980–2014 (35 years). Daily meteorological variables include total precipitation (mm), maximum and minimum temperatures (^oC), and solar radiation (MJ m^{-2} d^{-1}). Two additional variables (wind speed and relative humidity) were estimated by the SWAT model's climate generator (Gassman et al., 2007). The mean annual precipitation (MAP) on HUC8 units ranged from 1129 to 1715 mm with an average of 1433 mm during 1980-2014.

2.4 Model Calibration

Existing auto-calibration routines in the SWAT model are not designed to calibrate against intermediate response variables (e.g., HUC8 runoff and NO_3+NO_2). For this effort, we incorporated the Shuffled Complex Evolution (SCE) algorithm (Duan et al., 1992) into the source code of SWAT2012 model to implement auto-calibration (Fig. 2). SCE is a stochastic

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

optimization algorithm that has been widely used in calibration of hydrological models including SWAT (Wang and Xia, 2010; Zhang et al., 2009). We calibrated 39 parameters (Table 1) governing the hydrologic (i.e., water quantity) and water quality processes in SWAT. The 39 parameters were selected based on the sensitivity analyses in previous studies (Abbaspour et al., 2007; Baskaran et al., 2010; Bekele and Nicklow, 2007; Santhi et al., 2001; Wang et al., 2014; Wu and Liu, 2012). Generally, these parameters were calibrated step by step. The hydrologic parameters (No. 1–14) were first calibrated against hydrologic response variables (i.e., water quantity variables, e.g., streamflow or runoff). The second step was to calibrate the water quality parameters (No. 15–39) using water quality measurements (e.g., sediment, nitrogen, and/or phosphorus), where a subset of the parameters might be calibrated depending on the response variables as described below.

Fifteen types of calibrations with regard to various response variables (See Supplement Table S1) were defined in our current auto-calibration tool. The first five types correspond to five hydrologic response variables: daily streamflow, monthly streamflow, daily reservoir storage, daily soil water content, and monthly runoff on subbasin or HUC8; the next five types include monthly nutrient (sediment, nitrogen, phosphorus) fluxes (metric tons per month); and the last five types refer to instream monthly nutrient concentration (mg/L). Other response variables could also be defined and added to this calibration framework.

Criteria used to assess model performance include:

(1) Nash-Sutcliffe Efficiency (NSE, Eq. 1):

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left[Y_{sim}(i) - Y_{obs}(i)\right]^2}{\sum_{i=1}^{n}\left[Y_{obs}(i) - \overline{Y}_{obs}\right]^2} \qquad (1)$$

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

where Y_{obs} and Y_{sim} are the observed and simulated data, respectively; $\overline{Y}_{obs}$ is the mean value of observations; and n and i denote the number of data points and the ith data, respectively. NSE is less than or equal to 1 and may be negative (Moriasi et al., 2007).

(2) Percent Bias (PBIAS, Eq. 2):

$$PBIAS = \frac{\overline{Y}_{obs} - \overline{Y}_{sim}}{\overline{Y}_{obs}} \times 100\% \qquad (2)$$

where PBIAS (Moriasi et al., 2007) denotes the deviation of predicted mean value ($\overline{Y}_{sim}$) from observed mean value ($\overline{Y}_{obs}$) as a percentage of $\overline{Y}_{obs}$.

According to Moriasi et al. (2007), model simulation is satisfactory if $NSE > 0.5$ and if $|PBIAS| \leq 25\%$ for streamflow (runoff), $|PBIAS| \leq 55\%$ for sediment, and $|PBIAS| \leq 70\%$ for nitrogen (N) and phosphorus (P).

The overall objective function is the weighted average of individual objective functions:

$$F = \sum_{j=1}^{k} \left(w_j \cdot f_j \right) \qquad (3)$$

where F denotes the overall objective function of k individual objective functions; f_j is the jth objective function that could be calculated as NSE or $|PBIAS|$ of interested response variable; and w_j is the weighting factor for each f_j.

2.5 Calibration and Validation of Runoff

Because streamflow (discharge) at a station within the TRB is largely a measure of the outflow from the upstream reservoir(s) and because observed reservoir outflow was used in this study, we calibrated hydrologic parameters based on runoff (i.e., total water yield) instead of streamflow. We used the USGS computed monthly runoff (1985–1995) in HUC8(USGS, 2014a)

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences Discussions

as reference for SWAT calibration, with one year (1985) for model spin-up and 10 years (1986–1995) for model calibration. Another 18 years (1996–2013) of data were used for model validation. The USGS HUC8 runoff estimates were generated by combining historical flow data at USGS stream gages and the corresponding drainage basin boundaries and hydrologic units boundaries.(USGS, 2014a) In a previous study, this dataset was used to calibrate the Variable Infiltration Capacity (VIC) model for the conterminous US (Oubeidillah et al., 2014). The objective of our multi-site calibration of runoff was to calibrate hydrologic parameters (No. 1–14) of the subbasins within each HUC8. For example, when we implemented calibration in terms of the HUC8-06010102, the parameters in four subbasins (1, 4, 5 and 6) in this HUC8 were calibrated. We calculated simulated HUC8 runoff as the area-weighted-average of runoff from subbasins within each HUC8:

$$R_{HUC8} = \sum_{j=1}^{m} \left[R_{sub}(j) \times Area_{sub}(j) / Area_{HUC8} \right] \qquad (4)$$

$$Area_{HUC8} = \sum_{j=1}^{m} \left[Area_{sub}(j) \right] \qquad (5)$$

where R_{HUC8} is the runoff in a HUC8; $R_{sub}(j)$ and $Area_{sub}(j)$ are the simulated runoff (mm) and the area (km^2) in the jth subbasin; and $Area_{HUC8}$ is the total area of the HUC8 that includes m subbasins. The *NSE* of monthly HUC8 runoff was defined as the objective function in hydrologic calibration.

2.6 Calibration and Validation of Monthly Nutrient Fluxes

Nutrient measurements are sparse in rivers of the TRB. We have attempted to collect in-situ water quality monitoring data from over 6,000 USGS and EPA (Environmental Protection Agency) stations within the TRB through the National Water Quality Monitoring Council

(NWQMC)'s online Water Quality Portal (WQP) (NWQMC, 2015). However, we did not find long-term water quality data that coincided with our model simulation period (i.e., after 1980's). Therefore, we used the LOADEST (LOAD ESTimator) dataset (Runkel et al., 2004) as reference to calibrate water quality parameters. The LOADEST dataset provided estimates of monthly nutrient fluxes (1996–2006) at the Tennessee River near Paducah, KY (i.e., the outlet of TRB) (USGS, 2015). We used three-year (1994–1996) of data for model spin-up and 10 years (1997–2006) for model calibration. Another seven years (2007–2013) of data were used for model validation. Four water quality variables were available from the LOADEST dataset: sediment, total phosphorus (TP), total nitrogen (TN), and NO_3+NO_2. The hydrologic parameters (No. 1–14) calibrated against runoff were fixed during the calibration of water quality parameters (No. 15–39). The *NSE* of monthly water quality was defined as the objective function during SWAT calibration. When multiple response variables (e.g., Sediment, TP, TN, NO_3+NO_2) were considered in model calibration, we used Eq. (4) to calculate the overall objective function. In addition, the spatial distribution of mean annual nutrient loadings estimated by the SPARROW model (Hoos and McMahon, 2009) was employed as another dataset for model validation at the HUC8 level. The mean annual loads (MAL) of nutrients at the HUC8 level were calculated as the area-weighted average of the MALs at all subbasins within the HUC8.

2.7 Spatial Correlation Analyses

Understanding how water yield and nutrient loadings vary with watershed characteristics is important for quantifying primary drivers controlling water quantity and quality and for developing nutrient management policies (Hoos and McMahon, 2009). To this end, we implemented spatial correlation analyses between response variables and watershed attributes. For this study, two variables were considered highly correlated if the absolute value of

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Discussions
Open Access

correlation coefficient (|*r*|) was greater than 0.6 and the correlation was significant (p-value < 0.05), and moderately correlated if |*r*| was between 0.2 and 0.6 and the correlation was significant.

Based on the 29-year (1985–2013) simulation results from the calibrated SWAT model, we calculated the mean annual values of response variables including Runoff, RC (Runoff Coefficient, i.e., the ratio of runoff to precipitation), Sediment, OrgP (organic phosphorus), SolP (soluble P), MinP (mineral P attached to sediment), TP, TN, OrgN (organic N), and NO_3. We first conducted spatial correlation analysis between these response variables at the subbasin level. We implemented spatial correlation analysis between the response variables and the subbasin attributes (explanatory variables): Precipitation (mm), Subbasin_Slope (subbasin slope, %), Elevation_Drop (difference between highest and lowest elevations, m), and fractions of major land-use types (Forest_Fraction, Grassland_Fraction, Hay_Fraction, Crop_Fraction, Shrubland_Fraction, Wetlands_Fraction, Water_Fraction, Developed_Fraction, see Supplement Fig. S1).

3 Results and Discussion

In the sections below, we describe calibration and validation of different SWAT model responses including runoff and water quality metrics.

3.1 Runoff

SWAT simulations of TRB runoff were implemented with regard to the period from 1985 to 2013. We divided the 29-year runoff dataset into three sub-datasets: (i) a 1-year spin-up period (1985), (ii) a 10-year calibration period (1986–1995), and (iii) an 18-year validation period (1996–2013). The spatial resolution was the 8-digit hydrologic units (HUC8s) throughout the TRB.

Hydrologic parameters (No. 1–14 in Table 1) were calibrated by comparing simulated monthly HUC8 runoff with the USGS dataset. As an example, Fig. S2 shows the comparison between the SWAT-simulated monthly runoff (i.e., water yield, denoted by 'Sim') and USGS runoff (denoted by 'Obs') in HUC8-06040006, which is the outlet HUC8 of TRB. The *NSE* values for this HUC8 were 0.90 and 0.70 for model calibration and validation, respectively.

Values of *NSE* across the 32 HUC8s (Fig. 3a) ranged from 0.56 to 0.93 with 50% confidence interval (CI) of 0.74–0.88 (median 0.83); the *PBIAS* values (Fig. 3b) were within a narrow range (−7%–13%). The model also performed well over the validation period, although *NSE* was lower than that during the calibration period, as one would expect. The median *NSE* was 0.72 with 50% CI of 0.57–0.77; and the *PBIAS* values were within the satisfactory range, i.e., ±25%,(Moriasi et al., 2007) except for two HUC8s (06010108 and 06010204). Regarding the whole dataset for the combined calibration and validation periods (1986–2013), the median *NSE* was 0.79 (50% CI: 0.69–0.84) and all of the *PBIAS* values were within ±25% except for one HUC8 with a marginally satisfactory *PBIAS* (−26%).

The SWAT-simulated mean annual runoff (MAR) in the two aforementioned HUC8s (06010108 and 06010204) might be more reasonable than the USGS-estimated MAR. We analyzed the mean annual precipitation (MAP) and MAR data from 1986–2013 and found that the runoff in these two HUC8s might be underestimated in the USGS dataset to some degree (See Fig. S3).

3.2 Water Quality

The SWAT simulation of water quality began with the year 1996 owing to data availability. The 20-year (1994–2013) water quality dataset was also divided into three sub-datasets: (i) a 3-year spin-up period (1994–1996), (ii) a 10-year calibration period (1997–2006), and (iii) a 7-year validation period (2007–2013).

The water quality parameters (No. 15–39 in Table 1) were calibrated against the LOADEST dataset by taking into account multiple objectives, i.e., four response variables, including sediment, TP, TN, and NO_3+NO_2. Calibration greatly improved the performance of the model, particularly for sediment (*NSE* = −100 and 0.06 for pre- and post-calibration, respectively), TP (*NSE* = −2.5 and 0.44 for pre- and post-calibration, respectively), and TN (*NSE* = 0.02 and 0.38 for pre- and post-calibration, respectively) (See Supplement Table S2). The *NSE* values for model validation were not as good as the *NSE* for calibration, but the *PBIAS* values (Table S2) were satisfactory except for NO_3+NO_2 (−157%). The squared correlation coefficients (r^2) for TN and TP during both calibration and validation periods equaled or exceeded 0.4 whereas the r^2 values for sediment and inorganic N were less than 0.4 (Table S2). SWAT-simulated water quality responses reproduced the seasonal patterns found in LOADEST data during both calibration and validation periods (See Fig. S4).

We further conducted the water quality simulation for a longer period of time (1985–2013) than the period for model calibration and calibration (1997–2013). The spatial distributions of SWAT-simulated MALs (1986–2013) of TN and TP were comparable to the SPARROW estimates. The spatial patterns of SWAT-simulated TN and TP at the subbasin level are shown in Fig. 4 and other variables (runoff, RC, sediment, and NO_3) are shown in Fig. S5. The spatial MALs of TN and TP from SWAT were compared with the SPARROW dataset (MALs from 1975–2004) at the HUC8 level (Fig. 5). The *PBIAS* values (between SWAT and SPARROW) for TN (Fig. 5a) at 26 out of 32 HUC8 units were within the range of ±70%, and the *PBIAS* values at three HUC8 were higher than 80%. The 50% CIs of MAL of TN were 2.5–6.7 kg N/ha and 4.7–

7.4 kg N/ha by SWAT and SPARROW, respectively. The SWAT-simulated MAL of TN across the 32 HUC8 units was 5.5 kg N/ha, which was 12% lower than the TN loading (6.2 kg N/ha) estimated by SPARROW.

As for phosphorus (Fig. 5b), the SWAT-simulated MAL of OrgP+SolP (organic P + soluble P) was 48% lower than the SPARROW-modeled TP, while the SWAT-simulated MAL of TP (organic P + soluble P + mineral P) was 50% higher than the SPARROW-modeled TP. This was because mineral P contributed most (75.2%) to the TP yield and organic P contributed least (8.5%) to TP. The SWAT-simulated MAL of OrgP+MinP (organic P + mineral P, 0.93 kg P/ha) was comparable to the SPARROW-estimated TP (0.88 kg P/ha).

The spatial patterns of TN from the two models (SWAT and SPARROW) were significantly correlated with each other ($r = 0.54$, p-value < 0.001). The spatial pattern of SPARROW-estimated TP was not significantly correlated with SWAT-simulated TP, but moderately correlated with SWAT-simulated OrgP+SolP ($r = 0.38$, p-value $= 0.03$) and highly correlated with SWAT-simulated TN ($r = 0.84$, p-value < 0.001).

Different from the multi-site hydrologic calibration for each HUC8, water quality was calibrated against data from one site owing to data availability. Notice that this site (Paducah, KY) is located at the outlet of TRB. In addition, 10 out of 25 water quality parameters are basin-wide parameters (Table 1, denoted by 'basins.bsn') that are spatially identical in SWAT. Therefore, current water quality calibration could represent the overall water quality regime in the watershed. In summary, the temporal comparison of water quality simulations between SWAT and LOADEST and the spatial comparison between SWAT and SPARROW showed a correspondence between process-based SWAT modeling results and those from empirically modeled data in the TRB.

3.3 Spatial Correlation between Response Variables

Functional validation seeks to compare key functional relationships found in process-based models with those in data. This approach goes beyond simple 'validation' or casting a stamp of approval on a model to understand the reasons for any remaining differences. We found that SWAT-simulated MALs of MinP (mineral P attached to sediment) and TP were highly correlated with sediment, which confirms that sediment plays an important role in watershed phosphorus dynamics (Fig 6a). The TN yield was highly correlated with NO_3. TN loadings were dominated by NO_3, i.e., the fraction of TN that was NO_3 ranged from 37% to 99% with an average of 80%. TP was not correlated with TN, but OrgP (organic P) was moderately correlated with OrgN (organic N) and SolP (soluble P) was moderately correlated with NO_3, which implies similarity between SolP and NO_3 dynamics and similarity between OrgP and OrgN dynamics in SWAT (Neitsch et al., 2011). The SPARROW-estimated spatial patterns of TN and TP were correlated with each other; however, the SWAT-simulated spatial distributions of TN and TP were decoupled because the MinP component (attached to sediment) in SWAT and TN was dominated by inorganic nitrogen. Nutrient (Sediment, P and N) loadings were not significantly correlated with runoff (Fig. 6a), suggesting that nutrient point-source and non-point sources and other physical landscape variables (Hoos and McMahon, 2009) control variation in nutrient loadings simulated by SWAT.

3.4 Correlation between SWAT Response Variables and Subbasin Attributes

The spatial correlation analyses showed that the response variables differed in their controlling factors. Runoff was highly correlated with precipitation (r = 0.68) and moderately and positively related to Forest_Fraction (r = 0.36). The runoff coefficient (RC) was moderately and positively correlated with Elevation_Drop (r = 0.32) and Subbasin_Slope (r = 0.31) (Fig. 6b).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Sediment loadings were moderately and positively correlated with Elevation_Drop (r = 0.47), which verifies that the representation of topography and topology in this mountainous region drives sediment dynamics (Wellen et al., 2015). We did not find any significant correlation between TP and the aforementioned subbasin attributes. However, OrgP (organic P) was highly associated with Developed_Fraction (r = 0.64) that represented human activities in urban area (Hoos and McMahon, 2009); SolP (soluble P) was moderately correlated with Hay_Fraction (r = 0.43) indicating the influence of agricultural fertilization; and MinP (mineral P) was moderately correlated with Elevation_Drop (r = 0.37) that was the primary driver for sediment generation.

Organic N (OrgN) was moderately correlated with Wetlands_Fraction (r = 0.27) and Shrubland_Fraction (r = −0.30). NO_3 was highly correlated with Hay_Fraction (r = 0.63) and moderately correlated with Crop_Fraction (r = 0.48), mostly owing to the response of NO_3 yield to agricultural fertilization. In addition, NO_3 showed a moderate negative correlation with Forest_Fraction (r = −0.54), Subbasin_Slope (r = −0.44), and Elevation_Drop (r = −0.34). Note that TRB subbasins with steeper slopes generally had more forest and less cropland. The primary drivers controlling TN were the same as those for NO_3 as TN was dominated by NO_3.

4 Summary

Model-data comparisons are always challenging, especially when working at a large spatial scale and evaluating multiple response variables. We developed three innovations to overcome hurdles associated with limited data for model testing: 1) we implemented an auto-calibration approach to allow simultaneous calibration against multiple responses, including intermediate response variables, 2) we identified empirical modeled datasets interpolated in space and time to use in our comparison, and 3) we compared functional patterns in landuse-nutrient relationships between SWAT and empirical data. Using these innovations, we were able to successfully implement a calibrated model for the river basin and to evaluate performance. The SWAT calibration tool developed in this study can be accessed upon request via GitHub (https://github.com/wanggangsheng/SWATopt.git).

In addition to quantitative performance evaluation, we also discerned what the most important influences on SWAT responses were. Runoff was mainly controlled by precipitation; runoff coefficient and sedimentation were controlled by topographic attributes; whereas NO_3 and soluble P were highly influenced by land use types, particularly the croplands (hay and other crops). This is likely because our management of these croplands included applying fertilizers containing N and P. Patterns in phosphorus dynamics differed more between the empirical and process-based model than patterns in nitrogen dynamics, suggesting an area for future exploration.

AUTHOR INFORMATION

Corresponding Author

*Tel: +1 (865)576-6685. E-mail: wangg@ornl.gov.

Notes

The authors declare no competing financial interest.

Acknowledgements

This material is based upon work supported by the U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy's Bioenergy Technology Program. Oak Ridge National Laboratory is managed by UT-Battelle, LLC for the U.S. Department of Energy under Contract No. DE-AC05-00OR22725. We thank Michelle Thornton for providing DAYMET data and

David Gorelick and Jasmine Kreig for discussion on this study. In addition, we appreciate the insightful reviews of Drs. Shih-Chieh Kao and Sujithkumar Surendran Nair.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

References

Abbaspour, K. C.: SWAT-CUP 2012: SWAT Calibration and Uncertainty Programs - A User Manual, Swiss Federal Institute of Aquatic Science and Technology (Eawag) Duebendorf, Switzerland, 2014.

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., and Srinivasan, R.: Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT, Journal of Hydrology, 333, 413-430, 2007.

Arnold, J. G. and Fohrer, N.: SWAT2000: current capabilities and research opportunities in applied watershed modelling, Hydrological Processes, 19, 563-572, 2005.

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., and Neitsch, S. L.: Soil and Water Assessment Tool Input/Output Documentation Version 2012, Texas Water Resources Institute, College Station, TXTR-439, 650 pp., 2012.

Baskaran, L., Jager, H., Schweizer, P. E., Srinivasan, R., Douglas-Mankin, K., and Arnold, J.: Progress toward evaluating the sustainability of switchgrass as a bioenergy crop using the SWAT model, Transactions of the Asabe, 53, 1547-1556, 2010.

Bekele, E. G. and Nicklow, J. W.: Multi-objective automatic calibration of SWAT using NSGA-II, Journal of Hydrology, 341, 165-176, 2007.

Cao, W. Z., Bowden, W. B., Davie, T., and Fenemor, A.: Multi-variable and multi-site calibration and validation of SWAT in a large mountainous catchment with high spatial variability, Hydrological Processes, 20, 1057-1073, 2006.

Chen, Y., Ale, S., Rajan, N., Morgan, C. L. S., and Park, J.: Hydrological responses of land use change from cotton (Gossypium hirsutum L.) to cellulosic bioenergy crops in the

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Southern High Plains of Texas, USA, GCB Bioenergy, doi: 10.1111/gcbb.12304, 2015. n/a-n/a, 2015.

Dodds, W. K. and Oakes, R. M.: Headwater influences on downstream water quality, Environmental Management, 41, 367-377, 2008.

Duan, Q. Y., Sorooshian, S., and Gupta, V.: Effective and efficient global optimization for conceptual rainfall-runoff models, Water Resources Research, 28, 1015-1031, 1992.

EISA: Energy Independence and Security Act of 2007. 110-140, 2007.

Gassman, P. W., Reyes, M. R., Green, C. H., and Arnold, J. G.: The soil and water assessment tool: Historical development, applications, and future research directions, Transactions of the ASABE, 50, 1211-1250, 2007.

Haag, W. R. and Williams, J. D.: Biodiversity on the brink: an assessment of conservation strategies for North American freshwater mussels, Hydrobiologia, 735, 45-60, 2014.

Hoos, A. B. and McMahon, G.: Spatial analysis of instream nitrogen loads and factors controlling nitrogen delivery to streams in the southeastern United States using spatially referenced regression on watershed attributes (SPARROW) and regional classification frameworks, Hydrological Processes, 23, 2275-2294, 2009.

Jager, H. I., Baskaran, L. M., Schweizer, P. E., Turhollow, A. F., Brandt, C. C., and Srinivasan, R.: Forecasting changes in water quality in rivers associated with growing biofuels in the Arkansas-White-Red river drainage, USA, Global Change Biology: Bioenergy, 7, 774-784, 2015.

Keck, B. P., Marion, Z. H., Martin, D. J., Kaufman, J. C., Harden, C. P., Schwartz, J. S., and Strange, R. J.: Fish functioanl traits correlated with environmental variables in a temperate biodiversity hotspot, PLOS ONE, 9, e93237, 2014.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R., and Veith, T.: Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, Transactions of the Asabe, 50, 885-900, 2007.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., and Williams, J. R.: Soil and Water Assessment Tool Theoretical Documentation. Version 2009, Texas Water Resources Institute, Texas A&M University System, College Station, TX, 647 pp., 2011.

NWQMC: Water Quality Portal. National Water Quality Monitoring Council, 2015.

Oubeidillah, A. A., Kao, S. C., Ashfaq, M., Naz, B. S., and Tootle, G.: A large-scale, high-resolution hydrological model parameter data set for climate change impact assessment for the conterminous US, Hydrol. Earth Syst. Sci., 18, 67-84, 2014.

Price, K. and Leigh, D. S.: Morphological and sedimentological responses of streams to human impact in the southern Blue Ridge Mountains, USA, Geomorphology, 78, 142-160, 2006.

Runkel, R. L., Crawford, C. G., and Cohn, T. A.: Load Estimator (LOADEST): A FORTRAN program for estimating constituent loads in streams and rivers, U.S. Geological Survey, Reston, Virginia2328-7055, 2004.

Saad, D. A., Schwarz, G. E., Robertson, D. M., and Booth, N. L.: A Multi-Agency Nutrient Dataset Used to Estimate Loads, Improve Monitoring Design, and Calibrate Regional Nutrient SPARROW Models, Journal of the American Water Resources Association, 47, 933-949, 2011.

Sagona, F. J.: Tennessee River Basin Watershed Management Plan, Tennessee River Clean Water Partnership, Rainsville, AL, 148 pp., 2003.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
EGU
Discussions

Santhi, C., Arnold, J. G., Williams, J. R., Dugas, W. A., Srinivasan, R., and Hauck, L. M.: Validation of the SWAT model on a large river basin with point and nonpoint sources, Journal of the American Water Resources Association, 37, 1169-1188, 2001.

Scott, M. C., Helfman, G. S., McTammany, M. E., Benfield, E. F., and Bolstad, P. V.: Multiscale influences on physical and chemical stream conditions across Blue Ridge landscapes, Journal of the American Water Resources Association, 38, 1379-1392, 2002.

Soil Survey Staff: U.S. General Soil Map (STATSGO), Natural Resources Conservation Service, U.S. Department of Agriculture, Washington, D.C. , 1994.

Srinivasan, R., Arnold, J., and Jones, C.: Hydrologic modelling of the United States with the soil and water assessment tool, International Journal of Water Resources Development, 14, 315-325, 1998.

Thornton, P. E., Running, S. W., and White, M. A.: Generating surfaces of daily meteorological variables over large regions of complex terrain, Journal of Hydrology, 190, 214-251, 1997.

TVA: http://www.tva.gov, last access: 8/8/2014 2014.

USDA-NASS: http://www.nass.usda.gov/research/Cropland/SARS1a.htm, last access: 3/16/2014, 2014.

USGS: http://waterwatch.usgs.gov/index.php?id=romap3, last access: 10/1/2014 2014.

USGS: http://tn.water.usgs.gov/lten/tenn.html, last access: 4/8/2014 2014.

USGS: Streamflow and Nutrient Flux at Tennessee River at Highway 60 near Paducah, Kentucky. U. S. Geological Survey, 2015.

Van Griensven, A.: Sensitivity, auto-calibration, uncertainty and model evaluation in SWAT2005, UNESCO-IHE, Delft, Ntherlands, 2005.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences Discussions
Open Access

Wang, G., Barber, M. E., Chen, S., and Wu, J. Q.: SWAT modeling with uncertainty and cluster analyses of tillage impacts on hydrological processes, Stochastic Environmental Research and Risk Assessment, 28, 225-238, 2014.

Wang, G. and Chen, S.: A review on parameterization and uncertainty in modeling greenhouse gas emissions from soil, Geoderma, 170, 206-216, 2012.

Wang, G. and Xia, J.: Improvement of SWAT2000 modelling to assess the impact of dams and sluices on streamflow in the Huai River basin of China, Hydrological Processes, 24, 1455-1471, 2010.

Wellen, C., Kamran-Disfani, A.-R., and Arhonditsis, G. B.: Evaluation of the Current State of Distributed Watershed Nutrient Water Quality Modeling, Environmental science & technology, 49, 3278-3290, 2015.

Winchell, M., Srinivasan, R., Di Luzio, M., and Arnold, J. G.: ArcSWAT Interface for SWAT2012 User's Guide, Blackland Research and Extension Center, Temple, TXTR-439, 464 pp., 2013.

Wu, Y. and Liu, S.: Improvement of the R-SWAT-FME framework to support multiple variables and multi-objective functions, Science of the Total Environment, 466, 455-466, 2014.

Wu, Y. and Liu, S.: Modeling of land use and reservoir effects on nonpoint source pollution in a highly agricultural basin, Journal of Environmental Monitoring, 14, 2350-2361, 2012.

Zhang, X., Srinivasan, R., Zhao, K., and Liew, M. V.: Evaluation of global optimization algorithms for parameter calibration of a computationally intensive hydrologic model, Hydrological Processes, 23, 430-441, 2009.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences Discussions

Tables

Table 1. Selected SWAT parameters for model calibration

No	Parameter[a]	Description	Default	Min	Max	Input file	Fortran code
1	CN2	Initial SCS curve number II	85	35	98	*.mgt	Readmgt.f
2	ESCO	Soil evaporation compensation factor	0.95	0.01	1	*.hru	Readhru.f
3	EPCO	Plant uptake compensation factor	1	0.01	1	*.hru	Readhru.f
4	OV_N	Manning's n value for overland flow	0.1	0.01	0.6	*.hru	Readhru.f
5	CH_N2	Manning's n value for main channel	0.014	0.01	0.5	*.rte	Readrte.f
6	CH_K2	Channel effective hydraulic conductivity (mm/hr)	0.001	0.001	150	*.rte	Readrte.f
7	ALPHA_BF	Baseflow alpha factor (days)	0.048	0.001	1	*.gw	Readgw.f
8	GW_DELAY	Ground water delay (days)	31	0.0001	500	*.gw	Readgw.f
9	RCHRG_DP	Deep aquifer percolation fraction	0.05	0.0001	1	*.gw	Readgw.f
10	GW_REVAP	Groundwater revap coefficient	0.02	0.02	0.2	*.gw	Readgw.f
11	GW_SPYLD	Specific yield for shallow aquifer (m^3/m^3)	0.003	0.0001	0.4	*.gw	Readgw.f
12	SOL_AWC	Available water capacity (mm H_2O/mm soil)	0.2	0.01	0.4	*.sol	Readsol.f
13	SOL_K	Saturated hydraulic conductivity (mm/h)	10	0.01	100	*.sol	Readsol.f
14	SURLAG	Suface runoff lag coefficient (days)	4	0.5	12	sub.lag	Readhru.f
15	SPCON	Linear re-entrainment parameter	0.0001	0.0001	0.01	basins.bsn	Readbsn.f
16	SPEXP	Exponent re-entrainment parameter	1	1	2	basins.bsn	Readbsn.f
17	PRF	Adjustment factor for sediment routing in the main channel	1	0.001	2	basins.bsn	Readbsn.f
18	ADJ_PKR	Adjustment factor for sediment routing in tributary channels	1	0.5	2	basins.bsn	Readbsn.f
19	CH_COV	Channel cover factor	0.001	0.001	1	*.rte	Readrte.f
20	CH_EROD	Channel erodibility factor	0.001	0.001	1	*.rte	Readrte.f
21	USLE_K	Soil erodability factor	0.28	0.01	0.65	*.sol	readsol.f
22	BIOMIX	Biological mixing coefficiency	0.2	0.01	1	*.mgt	Readmgt.f
23	RSDCO	Residue decomposition factor	0.05	0.02	0.1	basins.bsn	Readbsn.f
24	NPERCO	Nitrogen percolation factor	0.2	0.001	1	basins.bsn	Readbsn.f
25	N_UPDIS	N uptake distribution parameter	20	0.001	100	basins.bsn	Readbsn.f
26	NSETLR	N settling rate in reservoir (m/yr), Line 7 & 8	5.5	1	15	*.lwq	Readlwq.f
27	SHALLST_N	Concentration of NO_3 in groundwater (mg N/L)	0.0001	0.0001	1000	*.gw	Readgw.f
28	ERORGN	Organic N enrichment for sediment	0.001	0.001	5	*.hru	Readhru.f
29	SOL_ORGN	Initial organic N concentration (mg N kg^{-1} soil)	0.01	0.01	50	*.chm	Readchm.f
30	SOL_NO3	Initial NO_3 concentration in the soil layer (mg N kg^{-1} soil)	0.01	0.01	50	*.chm	Readchm.f
31	PPERCO	Phosphorus percolation factor (10 m^3 Mg^{-1})	10	10	17.5	basins.bsn	Readbsn.f
32	PHOSKD	Phosphorus soil partitioning coefficient (m^3 Mg^{-1})	175	100	200	basins.bsn	Readbsn.f
33	PSP	P sorption coefficient	0.4	0.01	0.7	basins.bsn	Readbsn.f
34	PSETLR	P settling rate in reservoir (m/yr), Line 5 & 6	10	2	20	*.lwq	Readlwq.f
35	BC4	Rate const for mineralization of organic P to dissolved P (1/d)	0.35	0.01	0.7	*.swq	Readswq.f
36	RS5	Organic P settling rate (1/d)	0.05	0.001	0.1	*.swq	Readswq.f
37	ERORGP	Organic P enrichment ratio with sediment loading	0.001	0.001	5	*.hru	readhru.f
38	SOL_ORGP	Initial organic P (mg P kg^{-1} soil)	0.01	0.01	50	*.chm	Readchm.f
39	SOL_SOLP	Initial soluble P concentration in the soil layer (mg P kg^{-1} soil)	5	0.01	50	*.chm	Readchm.f

[a]Four groups of parameters: No. 1–14: Water quantity; No. 15–21: Sediment; No. 22–30: Nitrogen; No. 31–39: Phosphorus.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Figure Captions

Figure 1. Fifty-five subbasins and 22 reservoirs of the Tennessee River Basin (TRB) in the Soil and Water Assessment Tool (SWAT). The mainstem Tennessee River runs from east to west, exiting the basin below Kentucky Dam.

Figure 2. Integrating the Shuffled Complex Evolution (SCE) algorithm into the Soil and Water Assessment Tool (SWAT) permitted calibration against intermediate response variables.

Figure 3. Model calibration of SWAT-modeled runoff by optimizing hydrologic parameters and validation. The distribution shows values for 32 HUC8 units (8-digit Hydrologic Unit Codes). Measures of model performance are (a) Nash-Sutcliffe Efficiency (NSE), (b) Percent Bias (PBIAS).

Figure 4. Spatial distribution of SWAT-simulated mean annual values at 55 subbasins: (a) TN yield (kg N/ha), (b) TP yield (kg P/ha).

Figure 5. Comparison of spatial distribution of TN and TP yield between SWAT simulation and SPARROW dataset at 32 HUC8 units. SWAT metrics: OrgP_SolP = OrgP (organic P) + SolP (soluble P); OrgP_MinP = OrgP + MinP (mineral P attached to sediment); SolP_MinP = SolP + MinP; and TP = OrgP + SolP + MinP.

Figure 6. Spatial correlation analysis (a) between response variables (mean values from 1996 to 2013), (b) between response variables and subbasin attributes. Larger circle denotes higher

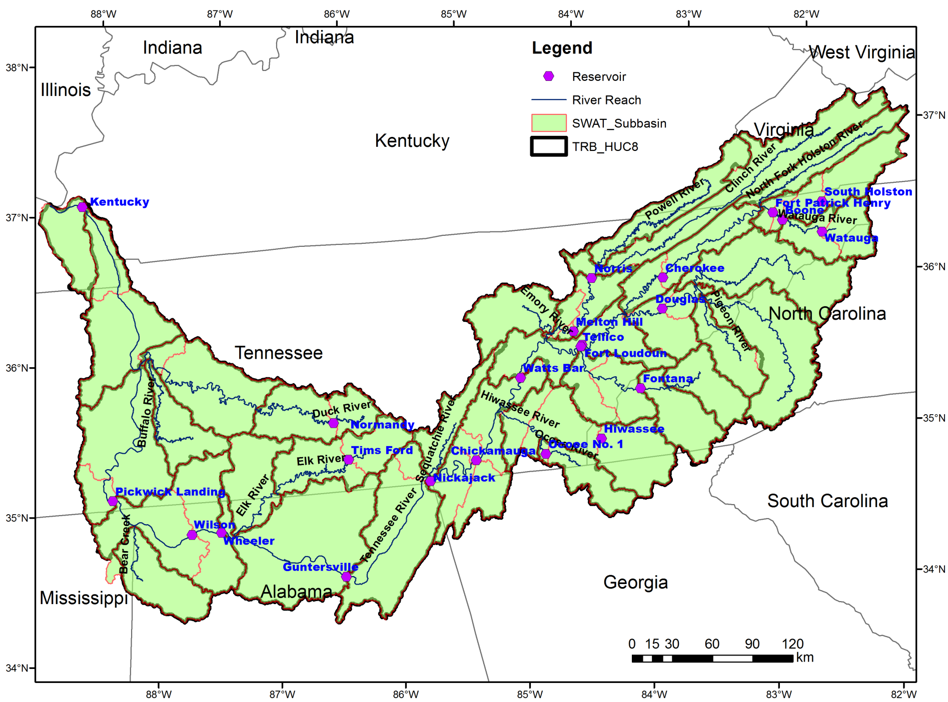
Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
Discussions

correlation coefficient and only significant correlations (p-value < 0.05) are shown. Numbers in (a) denote correlation coefficients. Response variables are: sediment yield (kg TSS/ha), organic phosphorus yield (OrgP, kg P/ha), soluble P yield (SolP, kg P/ha), mineral P yield attached to sediment (MinP, kg P/ha), total P yield (TP = OrgP + SolP + MinP, kg P/ha), total nitrogen yield (TN, kg N/ha), organic N yield (OrgN, kg N/ha), nitrate yield (NO3, kg N/ha), runoff depth (mm), and runoff coefficient (RC, ratio of runoff to precipitation).

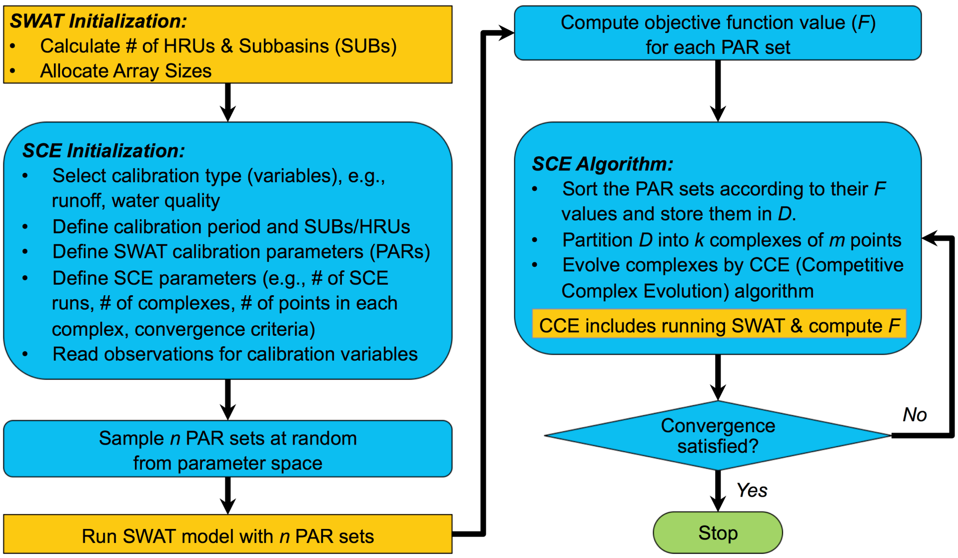
Figures

Figure 1



Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

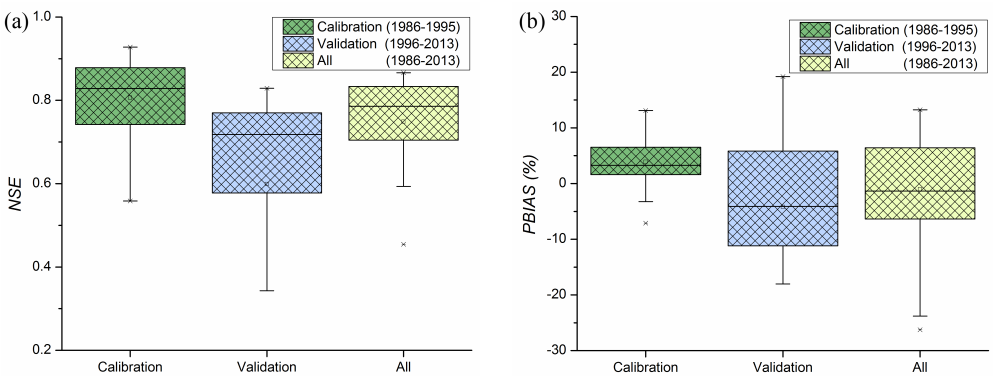
Figure 2



Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
Discussions

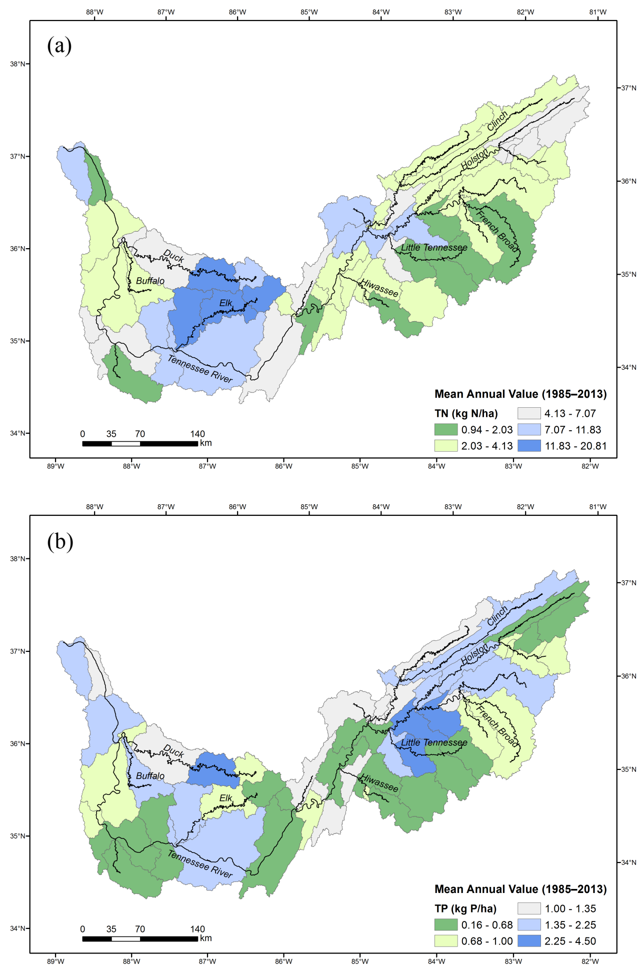
Figure 3



Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
Discussions

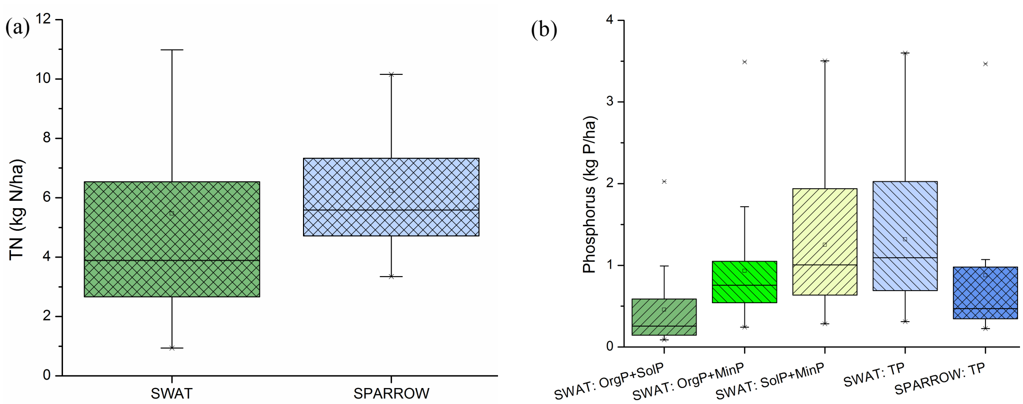
Figure 4



Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Figure 5



Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-34, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 25 January 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Figure 6