Ozarks Environmental and Water Resources Institute (OEWRI)
Missouri State University (MSU)

Soil and Water Assessment Tool (SWAT) simulated flow and bacteria in Little Sac Watershed: A Best Management Practice Assessment

Prepared by:
Sean J. Zeiger, Ph.D., Hydrologic Modeling Technician
Marc R. Owen, M.S., Assistant Director
Robert T. Pavlowsky, Ph.D., Director

Ozark Environmental and Water Resources Institute
Missouri State University
Temple Hall 342
901 South National Avenue
Springfield, MO 65897
Email: SeanZeiger@missouristate.edu

Completed for:
Stacey Armstrong-Smith, Projects Manager
Watershed Committee of the Ozarks
2400 East Valley Water Mill Road
Springfield, MO 65803

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Background

Watershed hydrologic models (i.e. watershed models) can be used to simulate the long-term effects of climate and land management practices on water and nonpoint source pollutant loads at large spatial scales. Such models are designed using computer programs to simulate watershed hydrologic processes using numerous physics-based equations (Borah and Bera, 2004). Watershed models are useful tools for generating science-based hydrologic information with relatively small investments of resources (i.e. raw materials, labor, time and money) in comparison to long-term direct-measurement hydrologic monitoring efforts (Borah *et al.*, 2006). While there are several watershed hydrologic models to choose from, the Soil and Water Assessment Tool (SWAT) is an internationally accepted choice for many applications such as pollutant loading estimates, receiving water quality, source load allocation determinations, and conservation practice efficacy (Borah *et al.*, 2006; Gassman *et al.*, 2007).

The soil water mass balance (Figure 1) in the SWAT model drives the loading and routing of water and pollutants across multiple hydrologic pathways (Figure 2) in the SWAT model. The model is equipped with multiple routines that can be lumped into two main phases: 1) the land phase and 2) the routing phase. During the land phase, water inputs (e.g. precipitation and irrigation) transport water and pollutant loads to receiving waters. During the routing phase, those pollutants are routed through the stream network to the watershed outlet.

The SWAT model is equipped to estimate climate and land use influences on hydrologic, sediment, chemical, and bacteria loads in ungauged watersheds with forested, agricultural, and urban land uses (Srinivasan *et al.,* 2010). However, to improve model confidence, the typical SWAT project involves model calibration and validation using observed data collected in the watershed of interest (Gassman *et al.,* 2007). Arnold *et al.,* (2012) outlined methods for calibrating the SWAT model (i.e. adjusting model parameters to improve the accuracy of modeling results).

The various strengths and weaknesses of the SWAT model have been extensively evaluated through the peer-review process [e.g. literature reviews by Borah *et al.,* (2006) and Gassman *et al.,* (2007)]. For example, the SWAT model is not as easy to use as more simplified models that rely on fewer equations to estimate water and pollutant loading (Borah *et al.,* 2006). The model is also more labor and data intensive compared to more simplified models (Borah *et al.,* 2006). The input data and work flow required in SWAT are quite extensive (Figure 3). However, SWAT is extremely robust in that hundreds of complex equations are computed in a matter of seconds accounting for differences in meteorological and hydrologic factors, physiographical watershed conditions, and human activity. Additionally, the SWAT model was designed to offer extensive analysis tools that can account for a broad array of management operations (e.g. irrigation, planting, grazing, fertilization, pesticide application, and tillage operations). For more information, a complete description of the SWAT model can be found in *Soil and Water Assessment Tool Theoretical Documentation* published by Neitsch *et al.,* (2005).

Purpose of the current work

The purpose of this modeling effort was to use SWAT to simulate long-term natural (e.g. climate) and human (e.g. land use) impacts to flow and *Escherichia coli* (*E. coli*) loading in Little Sac Watershed (LSW). Pasture (46%), forested (39%), and urban (10%) land uses dominate LSW which has a drainage area of approximately 743 km^2 and elevations that range from approximately 462 to 264 meters above mean seal level. Dominant soils in the region are characterized by an extremely gravelly reddish brown silty clay horizon from roughly 0.5 to 1.5

meters deep formed from residuum weathered from underlying cherty limestone or cherty dolomite. The watershed is karst and the recharge areas are unknown (Baffaut, 2006). The main channel, Little Sac River (approximately 66 km in length), is spring fed and much of its flow also comes from a wastewater treatment plant (design average daily flow: 2.57×10^4 m^3) (Baffaut, 2006). This modeling effort supports a broader watershed planning project being conducted by the Watershed Committee of the Ozarks (WCO), and funded by Missouri Department of Natural Resources (MDNR) in response to MDNR regulatory requirement for watershed planning to be evaluated and updated every five years in Missouri watersheds.

A TDML was completed during 2006, and a LSW management plan was completed during 2010. A 43 km segment of Little Sac River has been listed as impaired for Whole Body Contact Recreation (swimming) due to excessive fecal coliform from "point and nonpoint sources" since 2006. Currently, the WCO is leading efforts to update the watershed management plan in LSW. The management focus has shifted from fecal coliform to *E. coli* bacteria. *E. coli* are commonly measured in colony forming units in 100 ml of water (cfu 100 ml^{-1}) to estimate the number of bacteria in a water sample.

Little Sac Watershed was studied previously. Baffaut (2006) calibrated and validated a SWAT model to simulate flow and fecal coliform bacteria in LSW during 2006. Previous modeling results needed to be updated for present watershed conditions, and to evaluate Best Management Practices (BMPs) for the updated watershed management plan. The methods used by Baffaut (2006) were extensively evaluated through the peer-review process, and were therefore useful in this study. Additionally, results from Baffaut (2006) were a valuable source of baseline information in this study.

2.0 Methods

2.1 SWAT project setup

SWAT2015 Rev. 637 was chosen for the present investigation because it was the most recent version of SWAT at the time of this study. A 30 m digital elevation model was used as input data to delineate sub-basins in ArcSWAT. Sub-basins were delineated as close as possible to each HUC 12 sub-basin level. There are six HUC 12 sub-basins in LSW. Additionally, sub-basins were delineated at the end of each tributary to isolate individual reaches. A total of 24 sub-basins were delineated in this LSW model. Thus, LSW was modeled in greater detail than the HUC 12 level (Figure 4). A U.S. Geological Survey (USGS) gaging site (site #06918740) located near the outlet of LSW (i.e. outlet of sub-basin 7) (Figure 4) on Little Sac River near Morrisville, MO was selected as a sub-basin outlet for flow calibration purposes. Two reservoirs where included as inputs in the model [Fellows Lake (sub-basin 18) and McDaniel Lake (sub-basin 19)] (Figure 4).

The most recent soils and land use data were used as spatial inputs into the LSW SWAT model including the Soil Survey Geographic Database (SSURGO) and the 2011 National Land Cover Data sets (Table 1). Following Baffaut (2006), hay land use rasters were split using ArcGIS tools to create pasture, fescue, and winter pasture areas appropriate for simulating grazing rotations in LSW. A small portion of hay land cover was also split into septic fields to simulate residential rural area wastewater treatment (Baffaut, 2006). Hydrologic Response Units (HRUs) are spatially lumped areas with unique combinations of slope, soils, and land use in each sub-basin created for calculation of water and pollutant yields from lumped land areas in SWAT. Thresholds for land use, soil were set to 10, and 25%, respectively, to reduce the final number of HRUs and ultimately avoid problems with excessive computational complexity (Arnold *et al.*, 2012). Additionally, the single slope option was used to minimize the final number of HRUs. Ultimately, a grand total of 181 HRUs were used in this LSW SWAT model.

2.2 Climate input data

Climate input data of relative humidity, wind speed, and solar radiation were simulated using the SWAT model weather generator as those historical climate data were not available during the entire study period (1981 to 2015). Air temperature data were sourced from the National Climatic Data Center (https://www.ncdc.noaa.gov/data-access/land-based-station-data) sensed at the Springfield-Branson National Airport (Table 1). Climate gage density in the region was deemed insufficient for adequate representation of the spatial variability of precipitation in LSW considering there was only one monitoring location in the region (Springfield-Branson National Airport) with rainfall data during the study period (1991-2015). Mean areal precipitation data were needed to capture the spatial heterogeneity of rainfall between sub-basins in LSW. Thus, the Parameter-elevation Regression on Independent Slopes Model (PRISM) was used to capture rainfall variability between sub-basins.

The PRISM data show precipitation over an area at a 4 km spatial resolution as opposed to point gage data that represent rainfall amounts at a point location. The efficacy for using PRISM rainfall data to generate accurate SWAT model simulations of flow was validated during the study period in central Missouri where climate is similar to Little Sac Watershed (Zeiger and Hubbart, 2017). Those PRISM data were sourced from an Oregon State University website (http://www.prism.oregonstate.edu/). Thirty-five years (1981-2016) of daily precipitation data grids (4 km raster images) corresponding to the 'AN81d' data set were downloaded in bulk using 'wget' (a software tool for downloading bulk data). Models were created in ArcGIS using ‘model builder’ to extract precipitation data from each surface raster file to each sub-basin in LSW. Ultimately, each sub-basin was attributed a unique time series of daily precipitation data. Those precipitation data were input into the LSW SWAT model.

2.3 Point source inputs, springs and reservoirs

There was one relatively large wastewater treatment plant that discharged effluent into Little Sac River at the time of this study (design average daily flow: 2.57×10^4 m^3), and three smaller facilities with design average daily flows ranging from 32 to 305 m^3. Northwest Wastewater Treatment plant (NWWTP) was the only treatment plant added as a point source of *E. coli* in this LSW model. Daily flow, sediment, and nutrient loadings from the NWWTP were uploaded into the SWAT model (Table 2). Baffaut and Benson (2009) attributed 70 cfu 100 ml^{-1} of fecal coliform from the NWWTP in LSW. In the current work, fecal coliform was converted to *E. coli* using a 0.63 *E. coli* / Fecal Coliform ratio as per methods proposed by Hathaway (2014) in agreement with Environmental Protection Agency (EPA) bacteria water quality standards. The resulting *E. coli* concentration was 44.1 cfu 100 ml^{-1} in effluent from the NWWTP.

Springs were not simulated in SWAT, but were added as point sources following methods proposed by Baffaut (2006). The southern area of LSW has several springs with flow rates that range from < 0.1 to 43,215 m^3 day^{-1} (Table 3). Spring locations and flow rates were obtained from MDNR Geological Survey through Missouri Spatial Data Information Systems (MSDIS). While the relative volume of spring flow for the springs has been generally quantified over long time periods, spring flow can vary substantially at a daily time interval following large rainfall events. Capturing that daily variation in spring flow was beneficial for accurate estimates of daily average stream flow in this work. To estimate daily spring flow, base flow was separated from observed total stream flow at a USGS gage located in Morrisville toward the watershed outlet. The Boughton two-parameter algorithm for flow separation was used to separate base flow from total stream flow (Chapman, 1999):

$$Q_{base}(i) = \frac{k}{1+C} Q_{base}(i-1) + \frac{C}{1+C} Q_{total}(i) \tag{1}$$

such that

$$Q_{base}(i) \le q(i) \tag{2}$$

and

$$Q_{total} - Q_{base} = Q_{event} \tag{3}$$

where Q_{base} was base flow, i was time interval, k was a recession constant during periods of no runoff, C was a second recession coefficient, Q_{total} was total stream flow, and Q_{event} was event flow. The resulting daily timeseries baseflow was distributed among sub-basins according to the observed relative spring flow contributions in each sub-basin (Appendix A1). Water quality data [nitrogen (N), phosphorus (P), and *E. coli*] associated with each spring were derived from Adopt-A-Spring efforts in LSW. The *E. coli* values attributed to each spring in the model were the 90th percentile of *E. coli* values from the Adopt-A-Spring data set to account for sampling bias to low flows (Table 3).

Two reservoirs that were accounted for in this SWAT model application were located at Fellows Lake (sub-basin 18) and McDaniel Lake (sub-basin 19). Information was sourced from Baffaut (2006) regarding the dimensions and parameters important in defining each reservoir in LSW. Additionally, data showing recent monthly average consumptive water use (i.e. net monthly withdraws) from those reservoirs was obtained from Springfield City Utilities. Net monthly withdraws data were input in the reservoir data tab of ArcSWAT. Information regarding the monthly average consumptive water use of each reservoir is located in Table 4.

Currently, SWAT2015 simulates the effects of reservoirs on water, sediment, and nutrient yields. However, the module designed to simulate bacteria routing through reservoirs is not operational in the most current version of SWAT. As a result, initial bacteria simulations showed annual average *E. coli* export was about 600 cfu 100 ml^{-1} greater than observed data collected by Springfield City Utilities at Fellows Lake Dam during the study period. Thus, there was a need to reduce (through model calibration) simulated bacteria export from those sub-basins to better match those observed data. The following equation used in the current work to simulate reservoir trapping efficiency of bacteria in SWAT follows (Parajuli *et al.*, 2008):

$$trap_{ef,bact} = \frac{11.8+4.3*y}{100} \tag{4}$$

where $trap_{ef,bact}$ is the fraction of the bacteria loading trapped by the reservoir, and y is a calibration coefficient between 0 and 30.

2.4 Nonpoint sources

Nonpoint sources of *E. coli* (13,000 cfu 100 ml^{-1}) were added to urban storm water runoff in urban HRUs. The value of 13,000 cfu 100 ml^{-1} was derived from a U.S. Geological Survey (USGS) publication that showed *E. coli* counts in water quality samples (n = 21) collected during periods of stormflow in Springfield, MO (Richards and Johnson, 2002). Nonpoint sources of *E. coli* were also added to cattle manure (7.075 x 10^6) as per methods used by Baffaut (2006) in LSW. Additionally, *E. coli* were attributed to septage which was applied daily as a continuous fertilizer (i.e. year round) on septic HRUs in an amount that reflected the average effluent production per household as per methods used by Baffaut and Benson (2009).

2.5 Management operations

Pasture and urban management operations were sourced from Baffaut (2006). Tall fescue over-seeded with red clover was planted in hay fields and good/poor pastures. Tall fescue was planted in urban HRUs. Cattle were rotated between hay fieldsand good/poor pastures. Cattle were turned out for less time on hay fields which were reserved for seasonal hay cutting (Table 5). Cattle over-wintered in wooded winter pastures. Details regarding fertilizer schedules, hay cutting schedules, and grazing schedules in rural sub-basins were appropriate for the region (Baffaut, 2006) (Table 5). Cattle densities, manure, biomass consumed / trampled values were also appropriate for the region and sourced from Baffaut (2006). Details regarding fertilizer schedules, lawn mowing schedules, and street sweeping schedules in urban HRUs were also appropriate for the region (Baffaut, 2006) (Table 5).

2.6 SWAT model calibration and validation

The SWAT model was manually calibrated and validated to observed stream flow at a daily time step using a split-time method (Gassman *et al.,* 2007) and auto-calibration software SWAT-cup (Arnold *et al.,* 2012). Several years (1981-1991) were used to "warm-up" the model (e.g. wet up soils) as per recommendations from the literature (Arnold *et al.*, 2012). The calibration (1991-2009) and validation (2010-2015) periods included wet, average, and dry years as per recommendations from Arnold *et al.*, (2012). The SWAT model was calibrated to observed daily flow at the USGS Morrisville gage where flow has been monitored since September 1987. Calibration parameters were set to reflect physically realistic values for the watershed as per SWAT model calibration methods proposed by Arnold *et al.*, (2012).

Moriasi *et al.*, (2007) suggested the use of Nash-Sutcliffe efficiency (NSE), ratio of root mean square error to the standard deviation of observed data (RSR), and percent bias (PBIAS) to assess model performance. Model performance ratings for each of the three aforementioned model evaluation criteria at a monthly time step are provided in Table 6. Nash-Sutcliffe efficiency tests were used to quantify the variance of observed versus simulated data relative to a 1:1 best fit line; NSE values range between ∞ and one, where an NSE value of one is a perfect simulation. Any NSE value greater or equal to zero indicates that the simulated value estimated the constituent of concern better than the mean observed value. NSE values were calculated using the following equation:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{mean})^2}\right] \quad (5)$$

where Y_i^{obs} is the i^{th} observed datum for the variable being estimated. Y_i^{sim} is the i^{th} simulated datum for the variable being estimated, Y_i^{mean} is the mean of observed data for the variable being estimated, and n is the total number of observations.

Ratio of root mean square error to the standard deviation is an error index statistic. RSR values of zero equal a perfect simulation. Any RSR value less than 0.50 indicates an acceptable simulation. RSR values were calculated using the following equation:

$$RSR = \left[\frac{\sqrt{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}}{\sqrt{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{mean})^2}}\right] \quad (6)$$

Percent bias tests were used to indicate the average tendency of simulated data to be greater than or less than the observed data. Any negative PBIAS value indicated the simulated data were greater than the observed data on average. Conversely, any positive PBIAS value indicated the simulate data were less than the observed data on average. A PBIAS value of zero is a perfect simulation. PBIAS values can be calculated using the following equation:

$$PBIAS = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right) * 100}{\sum_{i=1}^{n}(Y_i^{obs})}\right] \qquad (7)$$

Once the model was deemed adequately calibrated to flow, the resulting best fit parameters were input back into SWAT. General basin parameters specific to bacteria and septic tanks were sourced from the literature (Baffuat, 2006; Baffaut and Benson, 2009). Then, SWAT was run to generate model output for assessment of sediment, nutrients, plant biomass, and bacteria against observed data collected in LSW. Minor manual calibration adjustments were made to parameters as needed until final SWAT model estimates of sediment, nutrients, bacteria, and plant biomass were deemed adequate for the region.

2.7 BMP scenario modeling

Scenario modeling efforts were completed to test the effects of selected BMPs on SWAT simulated bacteria loading (Table 7). A total of four BMP scenarios were completed including: 1) practices for conservation of soil health in pasture areas, 2) planting vegetative stream buffers in pasture areas, 3) planting vegetative stream buffers in urban areas, and 4) combination of all aforementioned BMPs. To simulate the influence of soil conservation practices on bacteria loading in pasture areas of LSW (i.e. BMP scenario #1), Soil Conservation Service Curve Numbers (SCS-CN) were reduced by a value of 3 in all hay and pasture related HRUs. Reduction of SCS-CN was performed to simulate MDNR suggested grazing management practices designed to effectively reduce runoff and soil erosion from pasture areas (https://dnr.mo.gov/env/swcp/service/grazingmanagement.htm). A SCS-CN reduction by a value of 3 was to indicate improvement of soil conditions from “fair” to “good” in pasture HRUs. To simulate the effects of vegetative buffers in pasture areas (BMP scenario #2), “vegetative filter strips" (VFS) with a width of 15 m were added to all hay and pasture related HRUs. To simulate the effects of vegetative buffers in urban areas (BMP scenario #3), VFS with a width of 10 m were added to all urban HRUs. To simulate the effects of all selected BMPs at once (BMP scenario #4), all aforementioned BMPs were included in the SWAT model. Load-weighted percent reductions of *E. coli* were quantified for each BMP separately and all BMPs. Finally, results were exported to tables and figure to provide planners with science-based information regarding the influence of BMPs on water quality in LSW.

The VFSs trap storm water runoff, sediment, and chemicals (e.g. nutrients, pesticides) making this BMP an attractive choice for reduction of excessive water and pollutant loading leading to overall water quality improvement (Parajuli *et al.*, 2008). Generally, as the width of the vegetative buffer increases, storm water runoff and pollutant load inputs to the stream decrease (Parajuli *et al.*, 2008). The equation used to estimate vegetative filter strip trapping efficiency of bacteria in SWAT follows (Parajuli *et al.*, 2008):

$$trap_{ef,bact} = \frac{11.8+4.3width_{strip}}{100} \qquad (8)$$

where $trap_{ef,bact}$ is the fraction of the bacteria loading trapped by the vegetative filter strip, and $width_{filtstrip}$ is the width of the vegetative filter strip (m). Equation 8 is quite powerful depending on buffer width. Thus, as a general rule, the buffer width considered should not exceed 75% trapping efficiency (Parajuli *et al.*, 2008).

3.0 Results and Discussion

3.1 Hydroclimate during the study

Hydroclimate during the study contained wet, average, and dry years in LSW (Table 8). A 25-year climate record showed total annual precipitation ranged from 869 to 1,620 mm with an average of 1,150 mm during the modeling period (1991-2015). Air temperature ranged from -23.3 to 42.2 °C with an average of 13.7 °C. Variability of annual precipitation translated to a variable streamflow regime in LSW. Observed streamflow ranged from 0.085 to 591 $m^3 s^{-1}$. Thus, the study period captured the variability in climate as suggested by Arnold *et al*. (2012). In fact, both calibration and validation periods contained wet, average and dry years which is beneficial for proper calibration of SWAT.

3.2 SWAT model performance and assessment

After model calibration to streamflow at the USGS Morrisville gage located in sub-basin 7 of LSW, model evaluation results showed the model was calibrated to a model performance rating of "satisfactory" for streamflow at yearly and monthly timesteps according to guidelines published by Moriasi *et al.*, (2007). Model performance was slightly less accurate during the validation period and at a daily time step which is quite common (Table 9). The 'very good' percent bias (PBIAS) values (PBAIS +/- 10 %) coupled to lower Nash-Sutcliffe efficiency (NSE), ratio of root mean square error to the standard deviation of observed data (RSR), and coefficient of determination (R^2) values were, at least in part, due to the fact that the model was calibrated to PBIAS only. The autocalibration software used in the current work (i.e. SWAT-cup) was not designed to account for multiple statistics when dialing in calibration parameters to lock on to flow targets. The PBIAS values within +/- 3 % during calibration were ideal. In fact, simulated mean streamflow (6.4 $m^3 s^{-1}$) equaled observed mean streamflow (6.4 $m^3 s^{-1}$). The other statistics where not considered during calibration, but are shown here for quality assurance. Nevertheless, model performance exceeded the threshold of 'very good' at a yearly time step for all model performance statistics assessed (i.e. PBIAS, NSE, RSR, and R^2). Thus, overall SWAT model simulated streamflow was deemed well-suited for the general purpose of the current work which was to use SWAT to simulate long-term (i.e. annual time scale) flow and bacteria loading in LSW.

There were limitations to model validation of bacteria loading in LSW including: 1) limited number of samples, 2) bacteria sampling was bias to low flows, and 3) maximum bacteria counts were unknown. While USGS collected monthly samples at Highway BB on Little Sac River at sub-basin 15, there were too few samples (n=60 monthly samples) to generate the long-term timeseries of total bacteria loading required for model calibration and validation. It has long been understood that estimates of average annual water quality loading generated from monthly samples can lead to greater than 50 % underestimations of the 'true load' when high flow events (e.g. peak flows) are not sampled (Letcher *et al*., 1999). Thus, the monthly samples that were available for assessment were bias to low flows. Additionally, observed bacteria counts greater than 8,000 cfu 100 ml^{-1} were reported as >8,000 cfu 100 ml^{-1}, and therefore, peak (i.e. maximum) bacteria loading was not observed. Ultimately, the modeled bacteria data were expected to be closer to true loading than the observed data considering 1) the model output included a completed daily timeseries (n = 9,132 days), 2) the modeled data were not bias to low flows, and 3) the modeled maximum bacteria loads were not limited by an upper threshold testing limit of 8,000 cfu 100 ml^{-1} unlike the observed data. There were other data sets showing bacteria measured in LSW (Appendix A2), but differences in sampling period, sampling regimen (daily vs. weekly or monthly), and analysis methods (cfu 100 ml^{-1} vs. MPN 100 ml^{-1}) complicated model performance assessment against those observed data as well. Nevertheless, model performance of bacteria was assessed by examining observed vs. simulated plots of water quality data and expert judgment to dial in model calibration parameters in the region (e.g. Baffuat 2006; Baffaut and Benson, 2009; Baffaut and Sadeghi, 2010).

In the current work, there was an average percent difference of 59 % between observed and simulated average annual *E. coli* counts. Results showed observed annual average *E. coli* counts ranged from 50 to 702 cfu 100 ml^{-1} with an average of 171 cfu 100 ml^{-1} at sub-basin 15, where simulated average annual *E. coli* counts ranged from 92 to 376 cfu 100 ml^{-1} with an average of 258 cfu 100 ml^{-1} (Figure 5). The trends in average annual *E. coli* counts between years were similar between observed and simulated data excepting during 2010 where a monthly sample captured bacteria during high flows that resulted in annual average bacteria load greater than 700 cfu 100 ml^{-1} (Figure 5).

While not the primary focus of the current modeling effort, it was important to assess simulations of sediment, nitrogen, and phosphorous yields to ensure model calibration parameters resulted in physically realistic water quantity and quality estimates for the study catchment especially considering *E. coli* simulations are directly dependent on water and sediment transport. Figures 7 to 9 show the spatial variability in simulated average annual sediment and nutrient yields in LSW. The module SWAT-check (an analysis tool for highlighting problems with SWAT model output), did not indicate any model problems with hydrology, sediment, or phosphorous simulations in LSW. Simulated plant biomass yields were realistic for LSW indicating proper water and nitrogen yields. Ultimately, the SWAT model performance and assessment results showed the model was well-suited for the purpose of the current modeling effort.

3.3 BMP scenario modeling

The BMP *E. coli* reductions simulated, helped to target the most appropriate BMP(s) for reducing excessive *E. coli* loading in LSW (Figures 6 to 9, Appendix A1). Average percent reductions in *E. coli* ranged from 6 % (BMP scenario #3) to 34 % (BMP scenario #4) (Table 10). These results indicated that the urban 10 m VFS (BMP scenario #3) was associated with relatively little overall reductions in *E. coli* across all sub-basins. To be clear, the percent reductions presented are not reductions at the outlet of LSW. The percent reductions were an all-sub-basin average. Thus, percent reductions of *E. coli* bacteria were at 6 % across all sub-basins, in part, due to the fact that BMP scenario #3 was only applied to urbanized sub-basins 21-24 in the southern area of LSW. While percent reductions associated with scenario #3 were 0 % for many sub-basins, percent reductions ranged from 16 to 44 % in the urbanized sub-basins 21-24 where the urban 10 m VFS were applied (please see Table A1 in appendix). Thus, the resulting all sub-basin average percent reductions of bacteria in urban areas (BMP scenario #3) were about 24 % lower compared to BMP reduction of bacteria in pasture areas (BMP scenario #2) because BMP scenario #2 was applied to all sub-basins, while BMP scenario #3 was only applied to urbanized sub-basins 21-24.

Percent reductions from BMP scenario #3 were also influenced by spring flow contributions of *E. coli* in the southern urban area of LSW. For example, percent reductions of *E. coli* were lower in sub-basin 23 where spring flow contributions of *E. coli* were estimated as 467 cfu 100 ml^{-1} compared to neighboring urbanized sub-basins 22 and 24 where spring flow contributions of *E. coli* were lesser (209 and 181 cfu 100 ml^{-1}, respectively). These results point to a need to monitor and reduce *E. coli* from major spring sources in LSW as also noted by Baffaut (2006).

When all BMPs were simulated at once (BMP scenario #4), results showed a 34 % reduction of *E. coli*. Results showed a 15 m VFS in pasture areas (BMP scenario #2) alone accounted for most of the simulated percent reductions of *E. coli*. Thus, modeling results showed BMP scenario #2 was the best choice for management efforts designed to reduce *E. coli* loading in pasture areas of LSW. That is not to say BMP scenario #2 is necessarily the best socioeconomic choice for LSW as socioeconomic analyses were beyond the scope of the current modeling effort.

In addition to *E. coli* reductions, it was important to highlight BMP reductions across multiple ecologically relevant state variables (e.g. streamflow, sediment, nutrients). Such variables have long been observed to influence *E. coli* fate and transport (Dwivedi *et al*., 2013). While BMP scenarios resulted in negligible water retention (stream flow reductions ranged from 0 to 2 %), sediment and nutrient reductions were substantial. Percent reductions ranged from 0 to 24 % (sediment), 2 to 15 % (TN), and 3 to 34 % (TP). Percent reductions associated with all BMPs (scenario #4) ranged from 15 % of TN to 34 % of TP. The simulated reduction of TN (15 %) was less than half the reductions of TP (34 %) due to the fact that the BMPs applied did not trap water soluble nitrate well, and nitrate comprised much of TN. However, all BMPs (scenario #4) caused 55 % reduction in organic N. These results highlight 1) how BMPs can reduce sediments and nutrients in addition to *E. coli*, and 2) how future management efforts focused on reducing nitrate may require a different mitigation approach.

It was important to acknowledge the estimated holistic water quality improvements associated with each BMP scenario assessed. For example, the greatest *E. coli* reductions (36.1 %) simulated were associated with a 15 m vegetative buffer in pasture areas (i.e. BMP scenario #2) (Table 10), leaving little incentive for implementing all selected BMPs (i.e. BMP scenario

#4). However, results from BMP scenario #4 indicated a nearly two-fold reduction of organic nitrogen, and a third reduction of total phosphorous loading in addition to 34 % reductions of *E. coli* highlighting the potential benefits of a multi-faceted approach to nonpoint source pollution mitigation in LSW. Additionally, while simulations showed improved soil conservation practices (BMP scenario #1) may not be the best solution to reduce *E. coli* in LSW, soil conservation efforts may reduce *E. coli* via some combination of physical, chemical, and biological processes that watershed hydrologic simulation models, like SWAT, were not designed to simulate. Ultimately, expert judgment based on observed data should continue to be considered alongside results from computer simulation modeling results.

Conclusions

The purpose of this modeling effort was to use SWAT to simulate long-term natural (e.g. climate) and human (e.g. land use) impacts to flow and *E. coli* loading in LSW to support a broader watershed planning project being conducted by the WCO. The current work updated previous modeling efforts and BMP plans were evaluated using present watershed conditions. Results provide critically needed science-based information (i.e. data) to assist management and planning efforts focused on mitigating problems associated with excessive *E. coli* presence in LSW.

Results from BMP scenario modeling evaluated percent reductions of *E. coli* from multiple BMPs including: 1) practices to improve soil health in pasture areas, 2) planting vegetative stream buffers in pasture areas, 3) planting vegetative stream buffers in urban areas, and 4) all aforementioned BMPs. While the greatest percent reductions of *E. coli* were associated with the all BMPs scenario, the greatest percent reduction of *E. coli* associated with a single BMP was BMP scenario #2 (VFS in pasture areas). Additionally, while percent reductions associated with scenario #3 (VFS in urban areas) were 0 % for many sub-basins, percent reductions ranged from 16 to 44 % in the urbanized sub-basins 21-24 where the urban 10 m VFSs were applied. Soil conservation practices in pasture areas (BMP scenario #1) resulted in less percent reduction in *E. coli* in comparison to the other BMP scenarios; however, soil conservation practices remain an attractive choice for managers who need to conserve valuable soil and water resources. Ultimately, VFSs have been shown by other published works to capture excessive agricultural and urban surface runoff thereby mitigating water quality problems associated with increased pollutant delivery to streams. Thus, results from this modeling effort in combination with previous published works show the benefits of applying VFSs in combination with soil conservation practices to reduce *E. coli* loading in LSW.

A lack of observed spring flow and bacteria data was a limitation in the current modeling effort. Future work should focus on obtaining continuous spring flow data and associated recharge areas in LSW. There is also a great need to monitor the water quality of the larger springs in the southern urbanized area of LSW. Additionally, there is need to quantify estimates of true water quality loadings (e.g. suspended sediment, nutrients, and bacteria) at the Morrisville USGS gage where flow has been continuously monitored for decades yet the true export of total pollutant loading remains unknown. Such monitoring efforts remain a rich avenue for future work with management implications for conserving water resources in LSW. Understanding source contributions (e.g. springs, point sources, nonpoint sources) of pollutants exported from the stream network of LSW is integral to securing valuable water resources in Stockton, Fellows, and McDaniel reservoirs.

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Tables

Table 1. Summary of SWAT input data and sources used in Little Sac Watershed, Missouri. Precipitation is precip. Air temp. is air temperature. Rh is relative humidity. Solar is solar radiation.

Input data	Description	Source
Topography	30 m raster	Missouri Spatial Data Information Systems (MSDIS)
Soils	30 m raster	Soil Survey Geographic Database (SSURGO)
Land use	30 m raster	2011 National Land Cover Data Set (NLCD)
Precip.	4 km raster	Parameter-elevation Regression on Independent Slopes Model (PRISM)
Air temp.	daily timeseries	National Climatic Data Center
Rh	daily timeseries	SWAT weather generator
Solar	daily timeseries	SWAT weather generator
Wind speed	daily timeseries	SWAT weather generator

Table 2. Summary of annual average effluent inputs from the Northwest Waste Water Treatment Plant to Little Sac River in Little Sac Watershed, Missouri.

Year	Flow $m^3\ day^{-1}$	TSS Mg day^{-1}	TKN kg day^{-1}	TP kg day^{-1}	NO3 kg day^{-1}	*E.coli* cfu $100ml^{-1}$
2003	14,459	0.030	---	---	---	44.1
2004	15,443	0.032	---	---	---	44.1
2005	14,383	0.026	---	---	---	44.1
2006	14,610	0.028	---	---	---	44.1
2007	15,291	0.024	35.6	59.1	154.1	44.1
2008	23,997	0.050	84.7	66.9	186.1	44.1
2009	21,196	0.051	56.1	45.3	154.6	44.1
2010	19,985	0.032	36.0	23.0	55.3	44.1
2011	18,774	0.039	42.2	16.5	46.9	44.1
2012	15,405	0.029	31.1	21.7	55.3	44.1
2013	21,234	0.049	40.5	21.9	105.1	44.1
2014	17,562	0.033	26.2	29.0	76.2	44.1
2015	22,067	0.075	41.0	10.8	72.8	44.1

Table 3. Flow rates and bacteria loadings associated with select springs in urbanized sub-basins of Little Sac Watershed, Missouri. *Escherichia coli* is *E. coli*.

Sub-basin	Spring name	Flow $ft^3\ s^{-1}$	N $mg\ l^{-1}$	P $mg\ l^{-1}$	*E. coli* $cfu\ 100ml^{-1}$
12	HEADLEE #2	0.1	1.02	0.22	209
	HEADLEE #1	0.1	---	---	---
	AUNT MAGGIE	0.05	---	---	---
15	MALENOSKY SPRING	0.1	1.02	0.22	209
	UNNAMED SPRING	0.0446	---	---	---
	UNNAMED SPRING	0.0223	---	---	---
	UNNAMED SPRING	0.0033	---	---	---
16	HAMMOND SPRING	0.2266	1.02	0.22	209
	ASHER CAVE SPRING	0.1114	---	---	---
	UNNAMED SPRING	0.0891	---	---	---
	CAVE SPRING	0.08	---	---	---
	BIRD EYE SPRING	0.0334	---	---	---
17	FLINTHILL CAVE	0.2228	1.02	0.22	209
	FLINT HILL NORTH SPR	0.2005	---	---	---
	LOWER FLINT HILL	0.0557	---	---	---
19	CRYSTAL CAVE	0.6907	1.02	0.22	209
	RHOADES SPRING	0.2228	---	---	---
	SOUTH	0.1003	---	---	---
	STAFFORD SPRING	0.0446	---	---	---
	SECTION 18 SPRING	0.0445	---	---	---
	SECTION 19 SPRING	0.0445	---	---	---
	NORTH	0.0401	---	---	---
20	WILLIAMS SPRING	1.25	1.0	1.6	114
	PARRISH SPRING	0.35	---	---	---
	WEILAND SPRING	0.05	---	---	---
	STODDARD SPRING	0.02	---	---	---
21	RITTER SPRING (EAST)	3.44	1.2	0.18	201
	RITTER SPRING (WEST)	1.324	---	---	---
	RITTER PARK SPRING	0.1	---	---	---
22	GREEN LAWN NORTH	0.156	1.1	3.7	209
	UPWELLING SPRING	0.1337	---	---	---
	GREEN LAWN SOUTH	0.0334	---	---	---
23	DICKERSON PARK	14.3	1.2	0.13	467
	FULBRIGHT SPRING	3.35	---	---	---
24	VALLEY WATER MILL	1.34	0.6	0.2	181

**E. coli* count were sourced from Adopt-A-Spring data collected in Little Sac Watershed during the study period.

Table 4. Average net monthly withdraws from Fellows Lake and McDaniel Lake located in Little Sac Watershed, Missouri.

	Net monthly withdraws (10^4 m^3 day^{-1})	
Month	Fellows Lake	McDaniel Lake
January	0.9	0.7
February	-0.6	1.8
March	1.6	1.7
April	2.4	2.4
May	1.8	3.4
June	4.2	1.9
July	5.9	3.3
August	5.6	2.1
September	2.5	-0.2
October	3.1	2.4
November	1.8	1.6
December	1.2	0.1

Table 5. Management operations in Little Sac Watershed, Missouri.

Land use	Operation	Year 1	Year 2
Pasture 1	Fertilization	55 kg $ha^{-1}$of 17-17-17 on 03/05	55 kg $ha^{-1}$of 17-17-17 on 03/12
	Grazing	Turned out 03/26 for 51 days	Turned out 05/16 for 61 days
		Turned out 07/16 for 62 days	Turned out 11/01 for 45 days
Pasture 2	Fertilization	55 kg $ha^{-1}$of 17-17-17 on 03/20	55 kg $ha^{-1}$of 17-17-17 on 03/14
	Grazing	Turned out 05/16 for 61 days	Turned out 03/26 for 51 days
		Turned out 11/01 for 45 days	Turned out 07/16 for 62 days
Hay field	Fertilization	55 kg $ha^{-1}$of 17-17-17 on 03/15	---
	Harvest	One harvest per year on 06/10	---
	Grazing	Turned out 09/16 for 46 days	---
Overwinter	Grazing	Turned out 12/16 for 100 days	---
Urban	Fertilization	12.24 kg ha^{-1} of P on 03/05 31.75 kg ha^{-1} of N on 03/05	---
	Mowing	31 harvests across the growing season each year at a 50% harvest efficiency	---
	Street sweeping	Bi-monthly	---

Table 6. Model efficiency ratings used to assess SWAT model performance of stream flow, sediment and nutrients at a monthly time step. Table recreated from Moriasi *et al*. (2007).

Rating	NSE	PBIAS%	RSR
Very good	$x \geq 0.75$	$\lvert x \rvert < 10$	$x \leq 0.50$
Good	$0.65 \leq x < 0.75$	$10 \leq \lvert x \rvert < 15$	$0.50 < x \leq 0.60$
Satisfactory	$0.50 \leq x < 0.65$	$15 \leq \lvert x \rvert < 25$	$0.60 < x \leq 0.70$
Unsatisfactory	$x < 0.50$	$\lvert x \rvert \geq 25$	$x > 0.70$

Table 7. Modeling scenarios used to test the effects of best management practices (BMPs) on SWAT simulated bacteria loading in Little Sac Watershed, Missouri.

Scenario	Brief description	Area applied
1	BMP to conserve soil health in pasture areas	Pasture
2	A 15 m vegetative buffer in pasture areas	Pasture
3	A 10 m vegetative buffer in urban areas	Urban
4	All BMPs included	Pasture and Urban

Table 8. Summary of statistics show hydroclimate during the study period (1991 to 2015) in Little Sac Watershed, Missouri. Average statistics are shown in parenthesis. Streamflow was sensed by a USGS flow monitoring gage located at sub-basin 7, near Morrisville, Missouri.

Statistic	Precipitation (mm)	Air temperature (°C)	Streamflow (m^3 s^{-1})
Minimum	869	-23.3	0.085
Median	1,130 (1,150)	13.7 (13.7)	2.10 (6.40)
Maximum	1620	42.2	592

Table 9. Model performance results for SWAT simulated streamflow in Little Sac Watershed, Missouri. Percent bias is PBIAS, Nash-Sutcliffe efficiency is NSE, ratio of root mean square error to the standard deviation of observed data is RSR, and coefficient of determination is R^2.

Timestep	Calibration (1991-2009)				Validation (2010-2015)			
	PBIAS	NSE	RSR	R^2	PBIAS	NSE	RSR	R^2
Yearly	2.7	0.89	0.34	0.93	-9.8	0.87	0.36	0.93
Monthly	2.7	0.55	0.67	0.79	-9.8	0.43	0.76	0.75
Daily	2.7	0.20	0.90	0.63	-9.8	-0.04	1.0	0.76

Table 10. Percent reductions of *Escherichia coli* (*E. coli*) from Best Management Practice (BMP) scenarios in Little Sac Watershed, Missouri.

BMP scenario	Streamflow	Sediment	Total nitrogen	Total phosphorus	*E. coli*
1	1	2	2	3	7
2	1	15	12	21	30
3	0	0	3	12	6
4	2	24	15	34	34

Figures

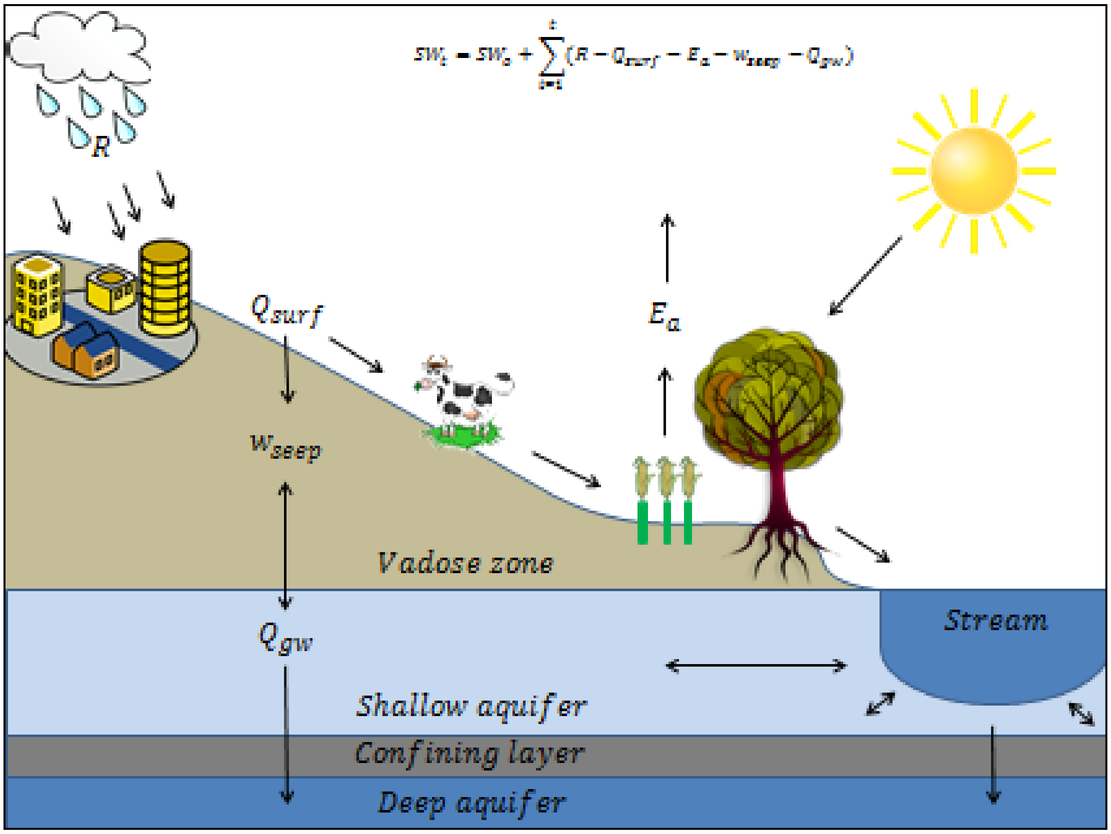

Figure 1. Schematic describing each component of the water budget for land under row crop agriculture, pasture management, forest management, and developed urban areas. SW_t is final soil water content, SW_o is the initial soil water content, R is precipitation, Q_{surf} is surface runoff, w_{seep} is water entering the vadose zone, and Q_{gw} is ground water flow. This figure was recreated from (Neitsch *et al*. 2005).

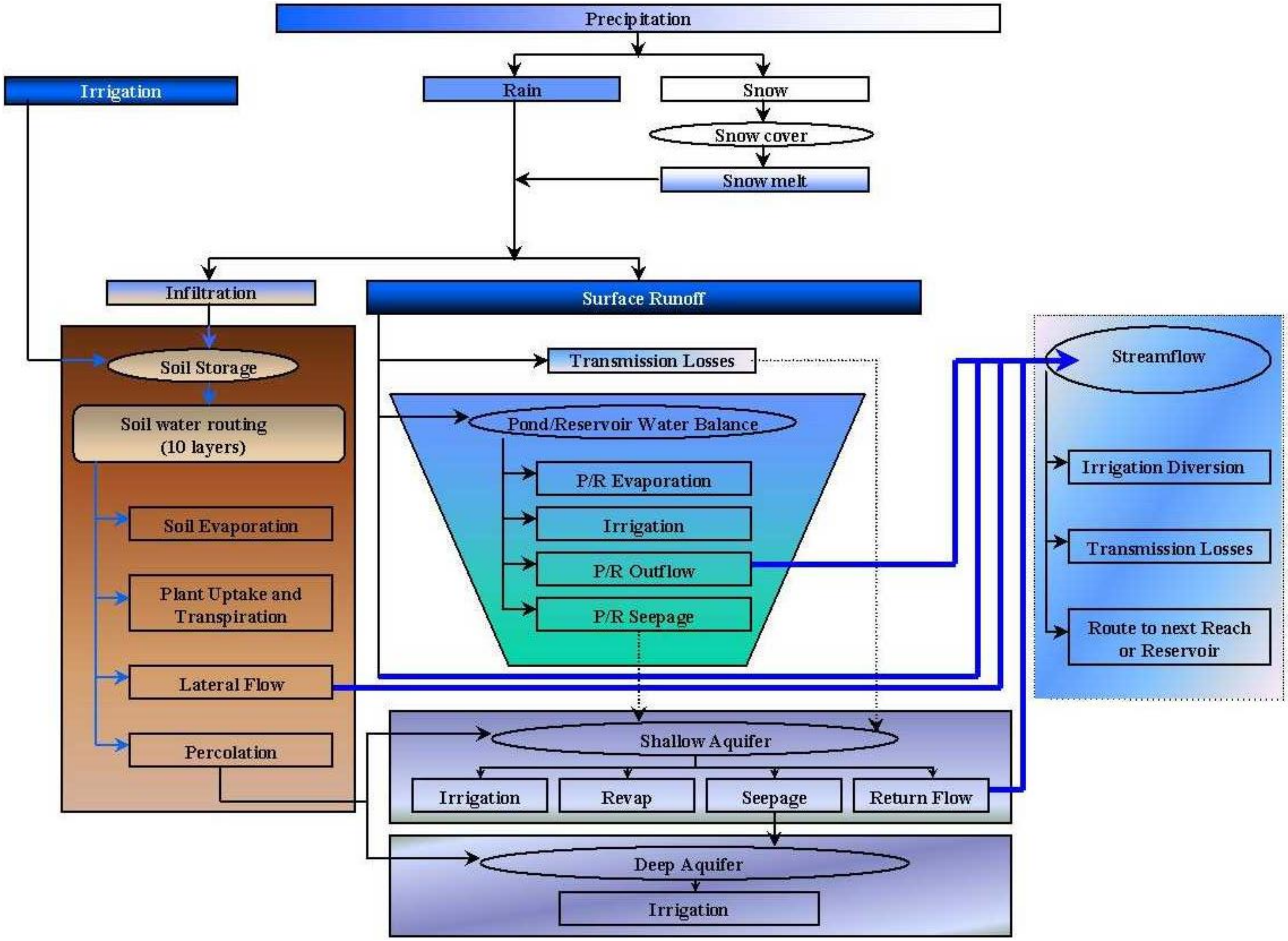

Figure 2. General pathways of water movement in SWAT (sourced from Nietch *et al*., 2005).

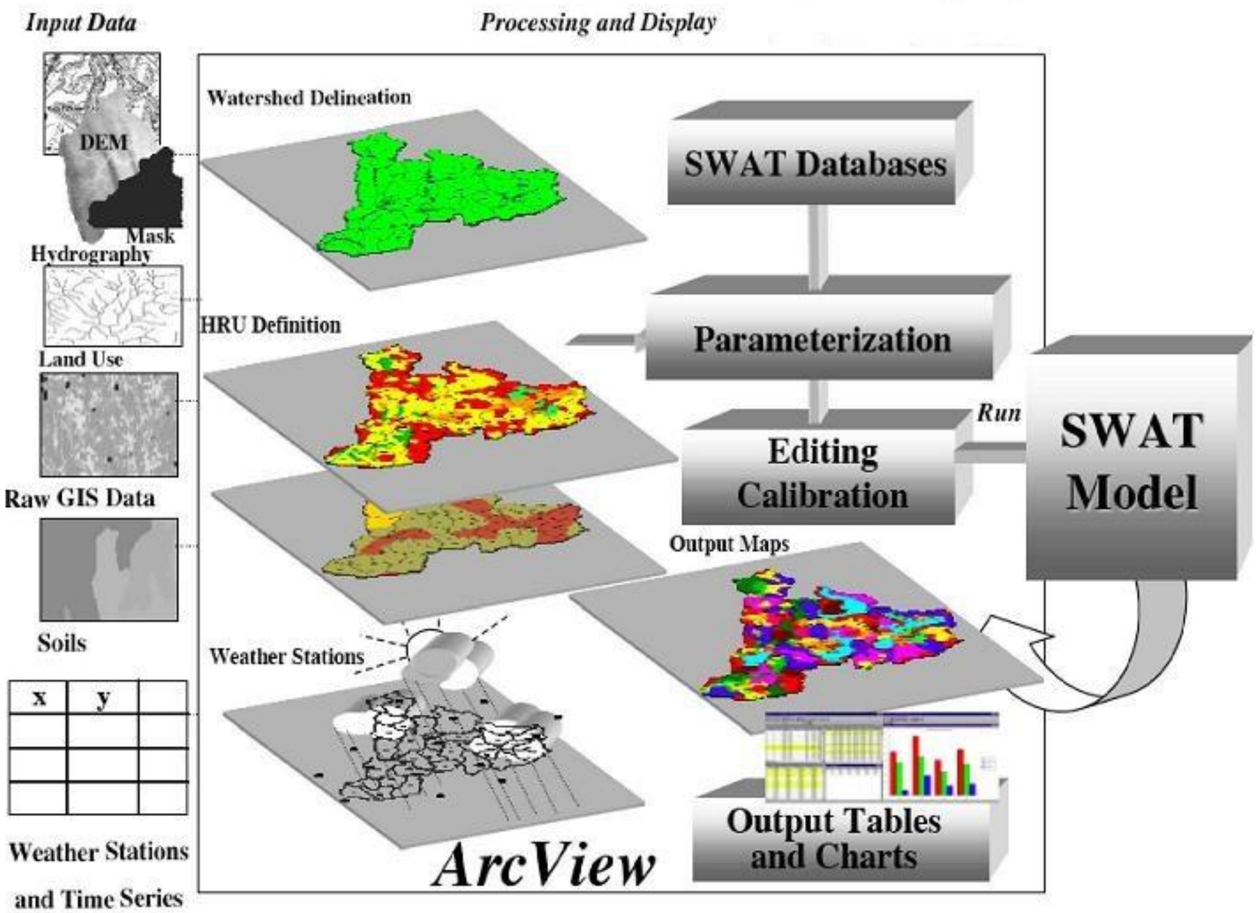

Figure 3. Schematic showing input data and general work flow of SWAT (source:geo.arc.nasa.gov).

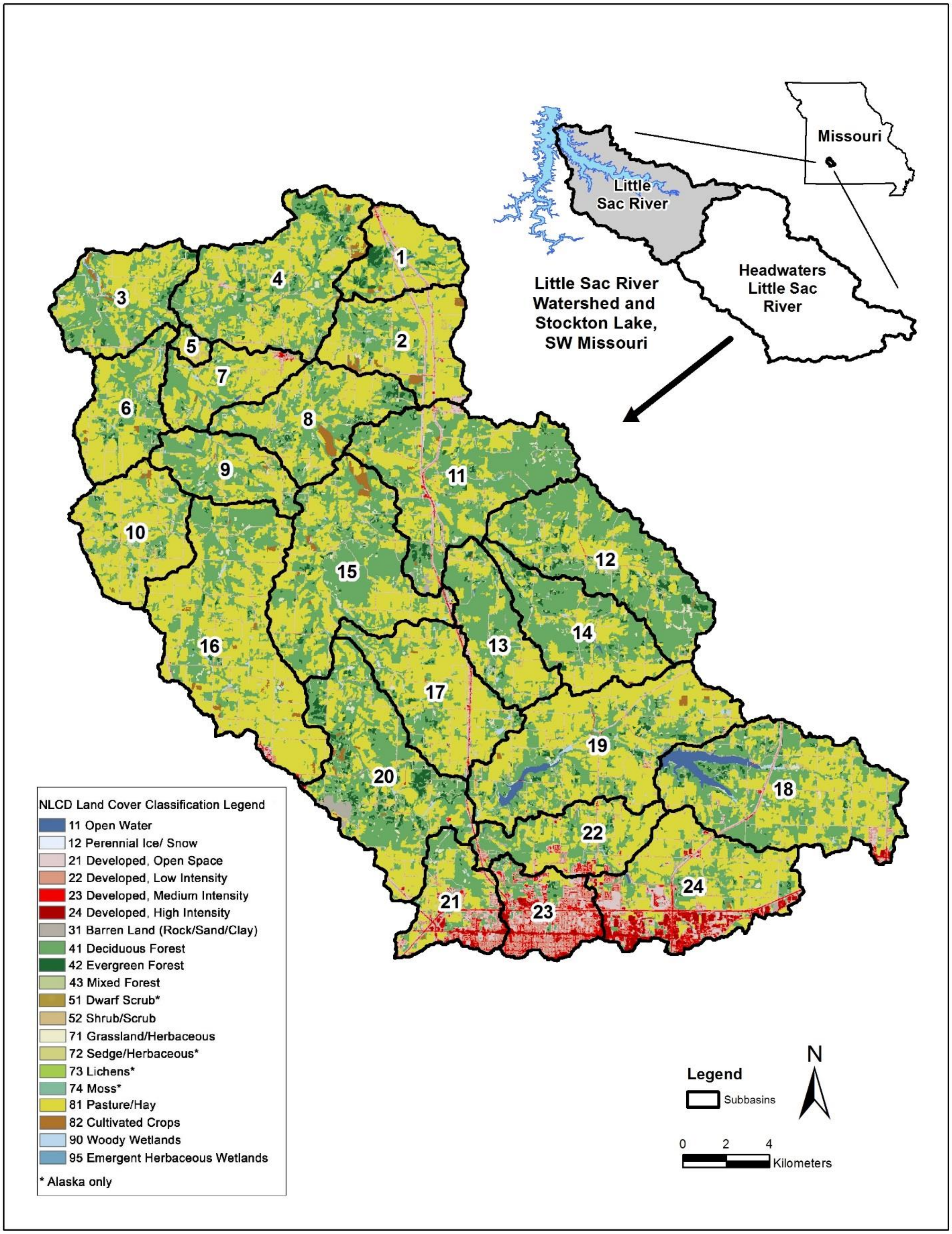

Figure 4. Watershed study design comprised of 24 sub-basins located in Little Sac watershed, Missouri, USA.

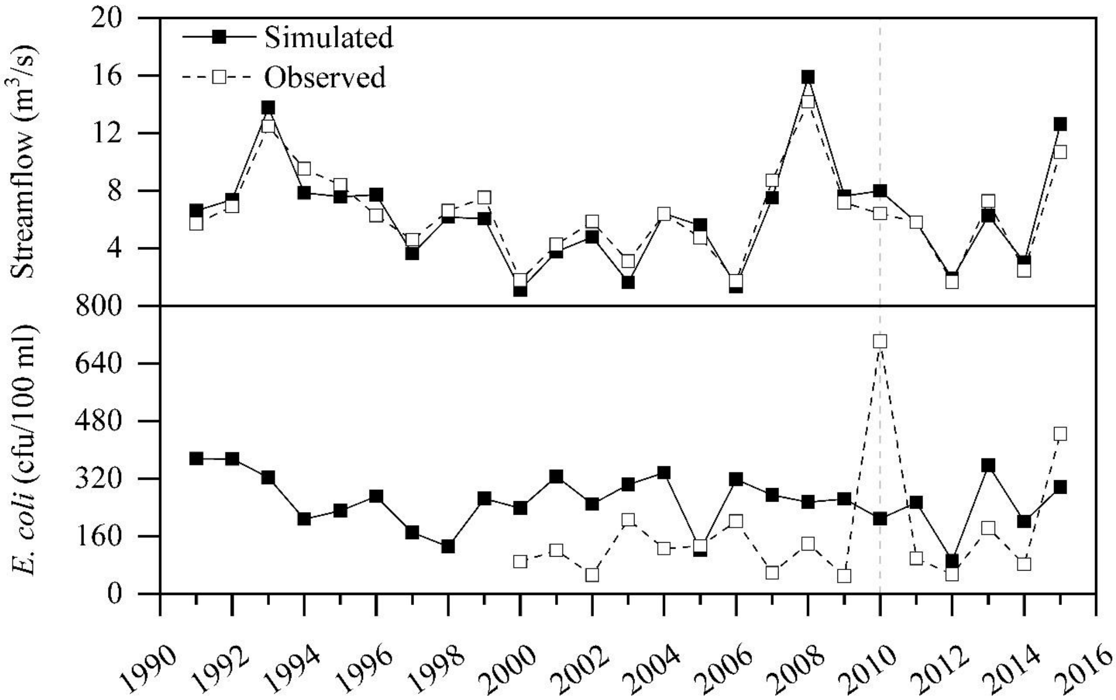

Figure 5. Simulated vs. observed annual average streamflow (top) and *E. coli* (bottom) during the study in Little Sac Watershed, Missouri. The vertical dashed line separates calibration and validation periods.

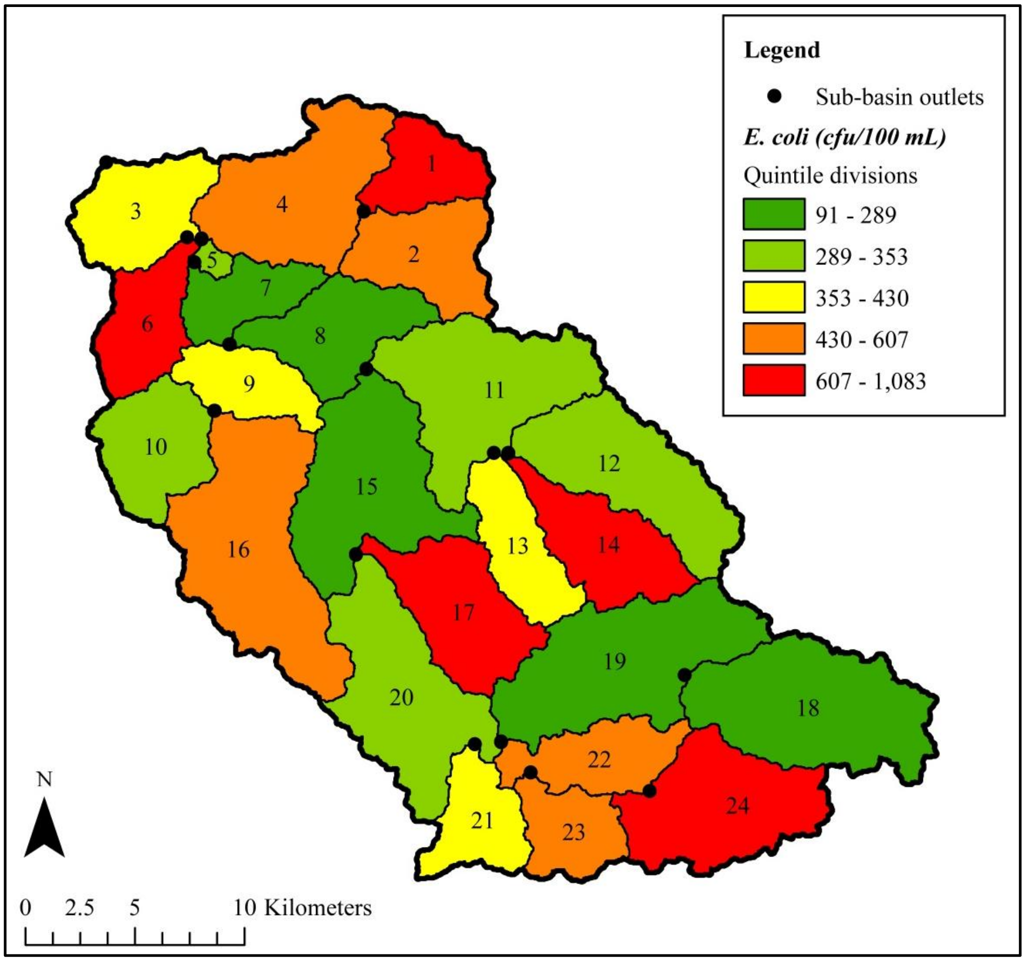

Figure 6. Simulated annual average daily *Escherichia coli (E. coli)* export during the study in Little Sac Watershed, Missouri.

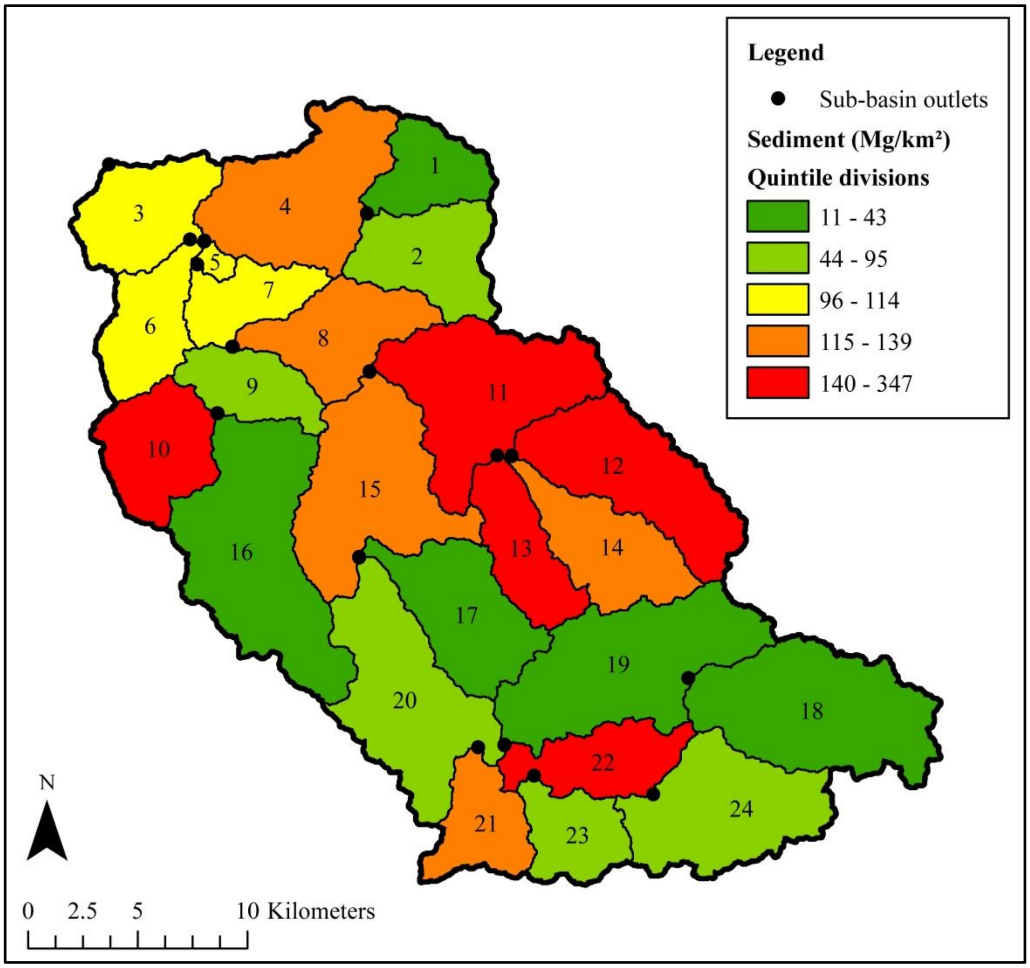

Figure 7. Simulated annual average sediment yield during the study in Little Sac Watershed, Missouri.

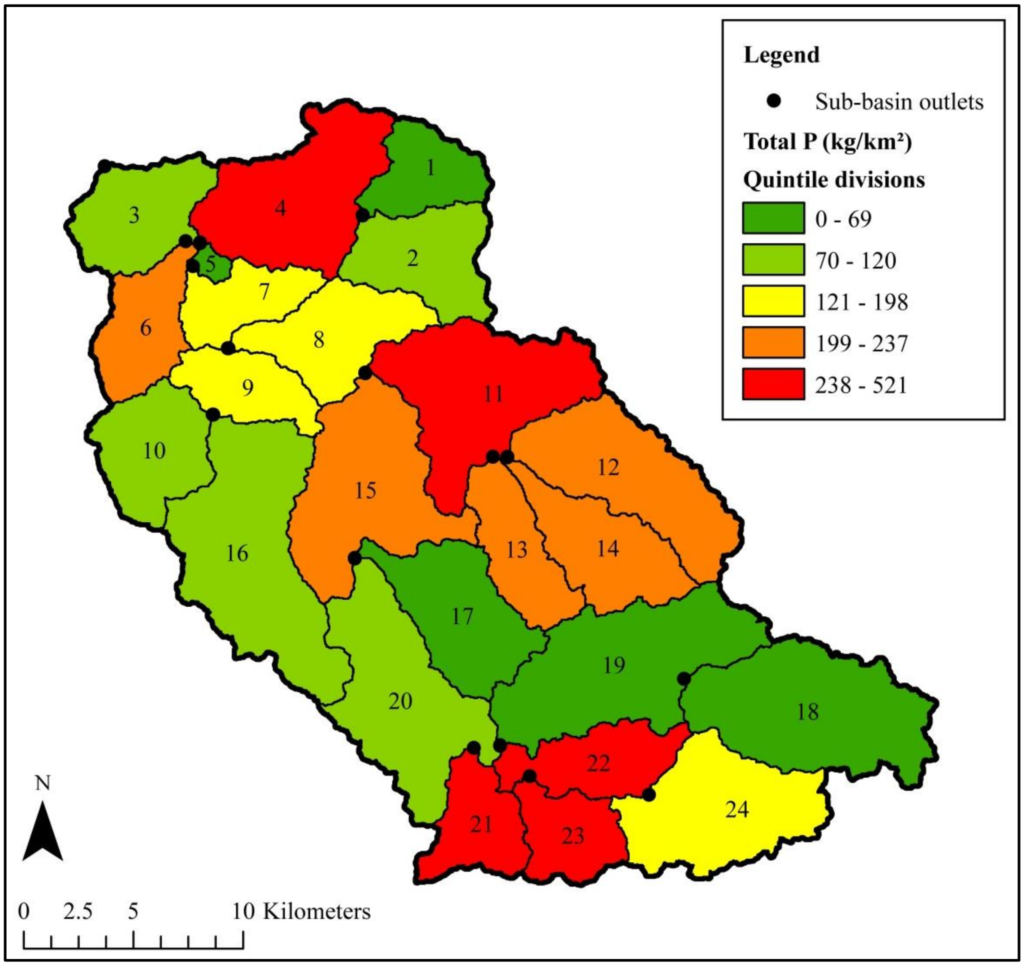

Figure 8. Simulated annual average total phosphorus (P) yield during the study in Little Sac Watershed, Missouri.

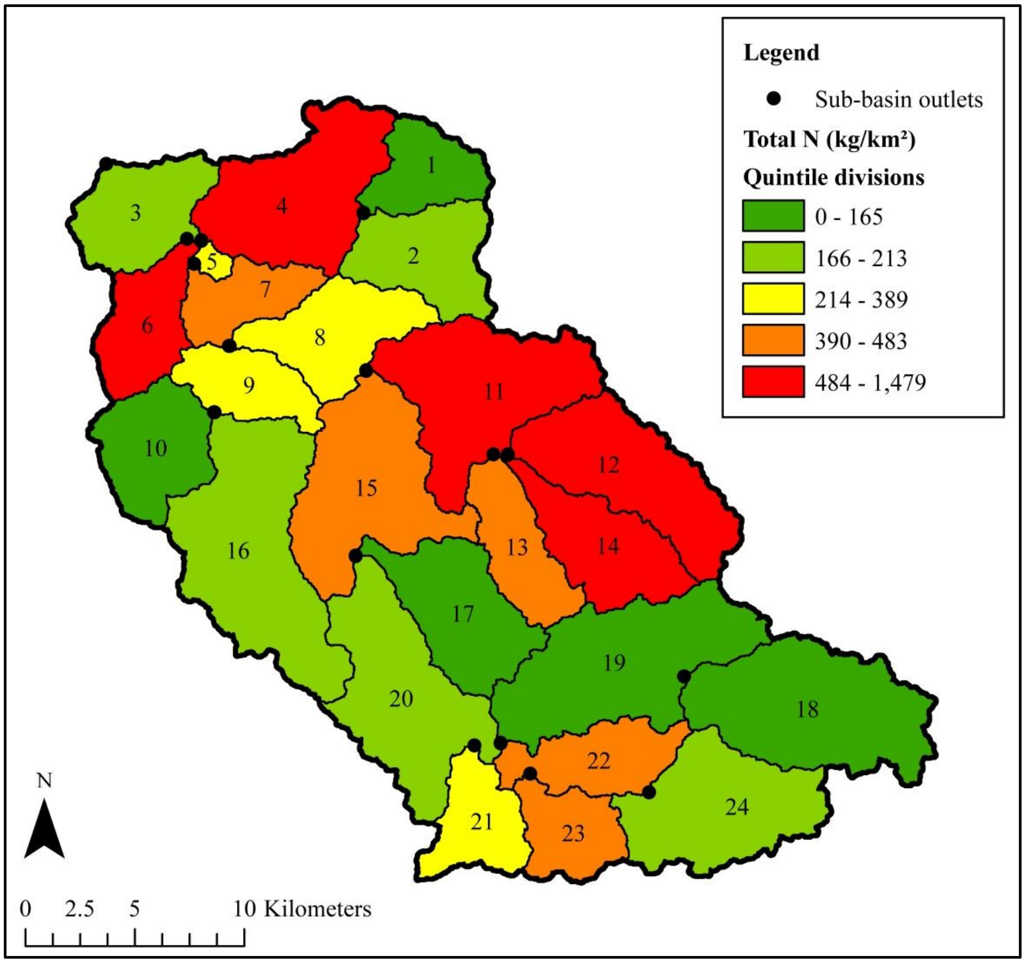

Figure 9. Simulated annual average total nitrogen (N) yield during the study in Little Sac Watershed, Missouri.

Appendix

A1. Simulated baseline annual average *Escherichia coli* (*E. coli*) export and percent reductions associated with four Best Management Practice scenarios at 24 sub-basins located in Little Sac Watershed, Missouri.

Sub-basin #	Baseline *E. coli* cfu 100 ml^{-1}	Scenario #1 % reduction	Scenario #2 % reduction	Scenario #3 % reduction	Scenario #4 % reduction
1	821	12	47	0	70
2	443	10	47	0	6
3	372	8	38	9	40
4	501	11	51	0	49
5	340	11	39	10	44
6	1,083	2	62	0	22
7	271	6	28	10	36
8	262	6	30	12	34
9	362	7	23	0	40
10	295	8	55	0	56
11	351	7	27	0	32
12	332	6	26	0	28
13	368	11	16	0	45
14	628	11	43	0	45
15	281	9	37	15	43
16	507	7	9	0	42
17	618	12	57	0	39
18	91	8	53	0	51
19	97	6	49	0	35
20	331	4	28	16	40
21	380	5	21	26	17
22	514	2	12	20	30
23	600	0	0	16	23
24	733	3	21	44	43

A2. Observed *Escherichia coli* (*E. coli*) data collected at various stream sites in Little Sac Watershed, Missouri.

SWAT ID	Site ID	Watershed	Stream	River km	Drainage Area (km2)	Location	County	Latitude	Longitude
7	M_1	Headwaters Little Sac River	Little Sac River	11.2	609.2	Little Sac River- State Hwy 215	Polk	37.48297	-93.48513
8	WCO_12	Headwaters Little Sac River	Little Sac River	21.3	485.4	Little Sac River- 111th Rd	Polk	37.44875	-93.43458
9	AC_06	Headwaters Little Sac River	Asher Creek	1.7	91.9	East 560th Street	Polk	37.43720	-93.46505
10	WG_05	Headwaters Little Sac River	Walnut Grove Tributary	0.5	25.4	Farm Road 4	Greene	37.42023	-93.47814
11	WCO_11	Headwaters Little Sac River	North Dry Sac	0.6	134.3	North Dry Sac River- 555th Rd	Polk	37.44117	-93.39087
12	WCO_7	Headwaters Little Sac River	North Dry Sac	13.6	30.6	North Dry Sac River- FR 163	Greene	37.40367	-93.29194
13	WCO_9	Headwaters Little Sac River	King Branch	1.9	18.2	King Branch-State Hwy CC	Greene	37.39499	-93.32279
14	WCO_8	Headwaters Little Sac River	Sims Branch	1.7	26.3	Sims Branch- State Hwy CC	Greene	37.39473	-93.31285
15	WCO_17	Headwaters Little Sac River	Unnamed Tributary	0.4	6.7	Tributary of Little Sac River-N FR 115	Greene	37.41744	-93.39207
16	AC_04	Headwaters Little Sac River	Asher Creek	6.6	55.7	State Hwy BB	Greene	37.40776	-93.46254
17	WCO_16	Headwaters Little Sac River	Flint Hill Branch	1.8	30.0	Flint Hill Branch- FR 117	Greene	37.3577833	-93.38025
18	LSR024	Headwaters Little Sac River	Little Sac River	76.7	18.6	Site 1B	Greene	37.31038	-93.17302
19	LSR119	Headwaters Little Sac River	Little Sac River	59.43	103.7	Site 3	Greene	37.291833	-93.323817
20	M_3	Headwaters Little Sac River	Little Sac River	43.4	241.0	Little Sac River-FR 54	Greene	37.34452	-93.39700
21	WCO_15	Headwaters Little Sac River	Spring Branch Creek	1.6	15.2	Spring Branch Creek-FR 94	Greene	37.27423	-93.33710
22	SSR120	Headwaters Little Sac River	South Dry Sac	0.2	78.8	Site 4	Greene	37.28555	-93.32457
24	WCO_0	Headwaters Little Sac River	South Dry Sac	9.7	4.6	South Dry Sac Creek-Valley Water Mill Rd	Greene	37.26602	-93.24907

SWAT ID	Site ID	Begin Date	End Date	Collecting Agency	Units	Sample Number	Arth Mean	Geo Mean	Min	25%	50%	75%	Max	Sample Frequency
7	M_1	3/23/2006	1/30/2008	WCO	MPN/100 mL	13	127	57	7.5	37	51	84	980	Weekly and Monthly, mainly in spring and summer
8	WCO_12	6/25/2003	1/30/2008	WCO	MPN/100 mL	32	134	69	6.3	39	62	141	1,046	Weekly and Monthly, mainly in spring and summer
9	AC_06	6/25/2003	10/31/2013	OEWRI/WCO	MPN/100 mL	108	400	75	0.5	17	83	291	6,867	Weekly from April-October, Monthly November-March
10	WG_05	5/3/2012	10/31/2013	OEWRI	MPN/100 mL	58	1,084	566	7.0	296	649	2,420	2,420	Weekly from April-October, Monthly November-March
11	WCO_11	6/25/2003	1/30/2008	WCO	MPN/100 mL	30	102	60	7.4	30	57	130	677	Weekly and Monthly, mainly in spring and summer
12	WCO_7	6/25/2003	9/21/2005	WCO	MPN/100 mL	20	471	139	41	68	92	193	4,611	Weekly and Monthly, mainly in spring and summer
13	WCO_9	6/25/2003	9/21/2005	WCO	MPN/100 mL	20	733	365	1.0	290	466	758	4,611	Weekly and Monthly, mainly in spring and summer
14	WCO_8	6/25/2003	9/21/2005	WCO	MPN/100 mL	19	208	62	1.0	37	74	106	2,247	Weekly and Monthly, mainly in spring and summer
15	WCO_17	6/14/2003	6/9/2005	WCO	MPN/100 mL	10	530	366	30	244	508	645	1,334	Weekly and Monthly, mainly in spring and summer
16	AC_04	2/7/2006	10/31/2013	OEWRI/WCO	MPN/100 mL	78	424	168	7.5	69	164	360	2,420	Weekly from April-October, Monthly November-March
17	WCO_16	6/25/2003	1/30/2008	WCO	MPN/100 mL	34	493	127	10	39	109	288	4,884	Weekly and Monthly, mainly in spring and summer
18	LSR024	6/3/2014	9/25/2014	CU	MPN/100 mL	10	1,268	129	17	43	86	122	10,462	Weekly May-September and Monthly October-March
19	LSR119	6/25/2003	8/24/2016	CU/WCO	MPN/100 mL	74	710	62	0.1	27	56	182	24,200	Weekly May-September and Monthly October-March
20	M_3	2/15/2006	1/30/2008	WCO	MPN/100 mL	15	81	60	15	34	65	97	291	Weekly and Monthly, mainly in spring and summer
21	WCO_15	6/25/2003	1/30/2008	WCO	MPN/100 mL	35	315	171	30	76	185	284	2,240	Weekly and Monthly, mainly in spring and summer
22	SSR120	6/25/2003	8/24/2016	CU/WCO	MPN/100 mL	100	751	148	0.5	52	112	321	15,531	Weekly May-September and Monthly October-March
24	WCO_0	6/25/2003	1/30/2008	WCO	MPN/100 mL	35	226	80	1.0	43	77	186	2,419	Weekly and Monthly, mainly in spring and summer