

RESEARCH ARTICLE

Addressing data challenges in riverine nutrient load modeling of an intensively managed agro-industrial watershed

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Funding information

United States National Science Foundation (INFEWS/T1), Grant/Award Number: 1739788

Abstract

Data limitations often challenge the reliability of water quality models, especially in intensively managed watersheds. While numerous studies report successful hydrological model setup and calibration, few have addressed in detail the data challenges for multisite and multivariable model calibration to an intensively managed watershed. In this study, we address some of these challenges based on our reflective experience calibrating the Soil and Water Assessment Tool (SWAT) to the Upper Sangamon River Watershed in central Illinois based on daily flow, annual crop yield, and monthly sediment, nitrate, and total phosphorus loads. We highlight some challenges in SWAT calibration processes due to data errors and inconsistencies, and insufficient precipitation and water quality observations. Following, we demonstrate the merits of additional weather and water quality observations that could help reduce input uncertainties, and we provide suggestions for selecting appropriate observations for the model calibration. After dealing with the data issues, we show that the SWAT model could be calibrated with acceptable results for the case study watershed.

KEYWORDS

data challenges, water quality, SWAT, multisite and multivariable calibration, Corn Belt watersheds

1 | INTRODUCTION

Physically distributed hydrological models are increasingly popular in seeking effective solutions to ameliorate regional water quality issues, for example, eutrophication in the Great Lakes (Gildow et al., 2016; Merriman et al., 2019) and hypoxia in the Gulf of Mexico (Santhi et al., 2014; Yuan et al., 2018). These models are often coupled with environmental and economic models (Housh et al., 2015; Li, Cai, et al., 2021) to assist in developing pragmatic water management and ecosystem policies (Van Delden et al., 2011). Model reliability is important in both understanding historical (Kim et al., 2008; Zhang et al., 2016) and predicting future (Bucak et al., 2017; Verma et al., 2015) water quantity/quality status. However, creating a reliable model for an intensively managed watershed is challenging (Molina-Navarro et al., 2017) given their extensive input data requirements, as well as structural deficiency in representing the complex catchment processes.

The availability and quality of data contributes to the reliability of a water quality model, especially for an agro-industrial watershed which requires large sets of meteorological, water constituent, and watershed management data. Although water quality modeling may benefit from high frequency sample observations, data collection methods are not designed to satisfy such modeling requirements (Fu et al., 2020). Instead, water quality constituent loadings are still largely determined with discrete samples collected weekly to quarterly to assess whether

Research Impact Statement

Addressing data challenges to simulate nutrient loads in an intensively managed watershed based on authors' reflective experiences of conducting multisite and multivariable model calibration.

designated water quality standards have been met. However, the low-frequency discrete samples do not adequately capture the temporal dynamics of the constituent (Jones et al., 2012), especially, since a few peak flow events can contribute to a significant portion of annual nutrients and sediments loads (Hirsch, 2012; Royer et al., 2006). If the sampling process misses such peak events, uncertainties in load estimation will increase and may lead to biased results. In addition to the lack of data, there are data quality issues as observations often consist of sampling and measurement errors. Uncertainty in measured water quality data can occur from multiple sources: streamflow measurement, sample collection, sample preservation/storage, and laboratory analysis (Harmel et al., 2006). Such uncertainties in the measured data may result in uncertain model outcomes leading to an unsatisfactory model performance (Renard et al., 2010). One possible solution to address data availability and data quality issues is to enrich the primary database by combining water quality observations measured by multiple monitoring agencies. However, this approach may require more caution because of the inconsistent metadata practices adopted by monitoring agencies. For example, reporting observations with incomplete or missing filtration status, logging data with improper or missing units and using different nomenclatures/terminologies for a constituent across monitoring agencies (Sprague et al., 2017) all may limit data harmonization across agencies and pose challenges on the utility potential of the observations.

Data issues reviewed above challenge model reliability, especially when model results are intended for a holistic water quality assessment, which often involves multiple components such as flow, sediments, nutrients, and crop yield. Some guidelines in the literature have been provided for better model setup, which in part consider these challenges. For instance, Engel et al. (2007) recommended following a standard modeling protocol during hydrological and water quality modeling for a reliable model setup and highlighted 11 major issues to be considered in the protocol. Baffaut et al. (2015) provided guidelines in selecting appropriate spatiotemporal scales of model processes for model calibration and recommended considering the extent and resolution of data availability and the scale of intended modeling objectives. Likewise, Arnold et al. (2015) recommended using both hard and soft data for effective model calibration. Similarly, Daggupati et al. (2015) recommended a generalized structure to assist modelers in developing a calibration and validation strategy considering the modeling goals, data availability, and their limitations. Given the general recommendations provided in these studies, detailed discussion on specific data issues may be helpful for modelers to apply a watershed model to a complex watershed with multiple outstanding ecosystem conservation issues including crop production, industrial and domestic water supply, wastewater discharges, and water quality protection.

Both data limitation and model structure deficits affect model reliability, and in this paper, we focus on the data limitation issues. Soil and Water Assessment Tool (SWAT; Arnold et al., 1998)—a widely used model to simulate hydrology and water quality responding to land and water use activities—is chosen as the watershed model for its proven usefulness. The model is applied to the Upper Sangamon River Watershed (USRW) (Figure 1), a typical agro-industrial watershed providing multiple ecosystem services but threatened by outstanding water quality problems. After identifying and resolving data errors, and inconsistencies, SWAT is calibrated to the observations of flow, sediments, nitrate (NO_3), total phosphorus (TP), and crop yield at multiple sites in the USRW. The overall purpose of this paper is to highlight the data limitations in water quality modeling and provide potential approaches to deal with such limitations, based on our reflective experience in calibrating SWAT to an agro-industrial watershed.

2 | CASE STUDY WATERSHED: THE USRW

The watershed has a humid continental climate with a mean annual temperature of 11°C and mean annual precipitation (2000–2018) of 1006 mm. USRW is an intensively managed watershed and has complex food–energy–water (FEW) systems issues (Li, Cai, et al., 2021). Agriculture dominates the land use in USRW, where 80% of the total area has row cropping with a corn–soy rotation (Li, Wallington, et al., 2021). Flat topography and subsurface (tile) drainage are common. A dam constructed in 1922 formed Lake Decatur (Fitzpatrick et al., 1987), which supplies water to the City of Decatur and nearby grain processing industry. The dam causing sediment deposition, requires frequent dredging to maintain active lake storage. Downstream of the lake, there is a wastewater treatment plant operated by the Sanitary District of Decatur (SDD) which discharges phosphorus (P) and nitrate (NO_3) into Sangamon River at varying concentrations ($6\text{--}10\text{ mg NO}_3\text{-N/L}$ and $5\text{--}30\text{ mg P/L}$) (Li, Cai, et al., 2021). In addition, the watershed has three corn grain processing facilities and a dairy feedlot producing about $9.4 \times 10^6\text{ kg}$ of manure annually (Li, Cai, et al., 2021). Hence, both agricultural runoff and wastewater sources impact the water quality in the USRW. To evaluate the impact on water quality from these multiple sources and understand their role in nutrient recycling for enhancing FEW resilience of an agro-industrial watershed, we choose SWAT (SWAT2012) as a tool to simulate the processes of water and nutrient flows in both landscapes and streams.

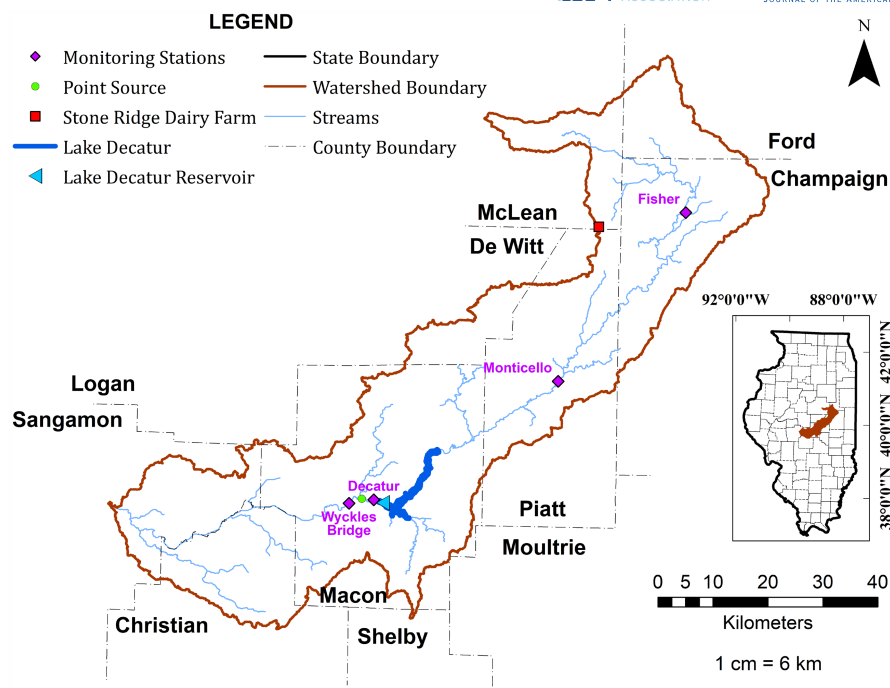


FIGURE 1 Case study watershed: the Upper Sangamon River Watershed (USRW) in Central Illinois. The bold black text nearby county boundary shows the county name.

SWAT is a semi-distributed hydrological model that discretizes the watershed in user-defined hydrologic response units (HRU) based on land use, soil type, and slope. For each HRU, the model simulates water balance, sediments, nutrients, and crop yield as a response to weather forcing, catchment properties, and management decisions. The model also simulates the transport of flow and pollutants along stream channels and provides an aggregated watershed response. Our effort in modeling the water quality of the USRW uses substantial observation data on weather, discharge, sediments, nutrients, crop yields, and agricultural management practices. These inputs including the management operations and schedules are provided in the Supporting Information (see [Tables S1](#) and [S2](#)).

3 | DATA ISSUES AND DISCUSSIONS

In this section, we discuss some data issues and their impacts on model calibration and validation, with a focus on the observation issues with precipitation, phosphorus, and fertilizer application. In addition, we discuss our approach in modeling manure and biosolids application in SWAT given limited data.

3.1 | Precipitation observation errors

Despite quality control, weather datasets collected over a wide range of networks could still possess some errors. For instance, Chen et al. (2020) assessed anomalies in the National Climatic Data Center (NCDC; NCEI, 2021) weather data at some stations in northern regions of the Upper Mississippi River Basin, which is inconsistent with what is found in the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al., 2008) and Livneh et al. (2013) weather datasets. Our preliminary input data assessment revealed a similar unexplained precipitation observation at one of the rain gauges stations in the USRW. [Figure 2](#) shows the cumulative daily precipitation from December 2015 to February 2016 at three sites in the USRW upstream. For a few days in January, Fisher has an exceptionally high precipitation record compared to the nearby sites, Rantoul and Mahomet. Fisher, on 11th and 20th January 2016, reports 50.8 and 88.9 mm of rainfall, respectively, while Rantoul and Mahomet report no rainfall on 11th January and both stations report less than 6 mm rainfall on 20th January ([Figure 2](#)). Ideally, these three sites should have similar precipitation given their geographical locations ([Figure 3](#)) and similar weather conditions (temperature and snowfall depth). Such observation errors in winter could result from erroneously reporting snow depth as liquid water during the data collection.

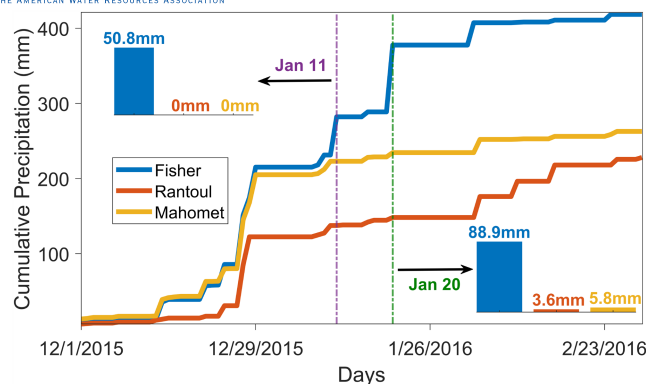


FIGURE 2 Cumulative daily precipitation at Fisher, Monticello, and Mahomet stations from December 2015 to February 2016. The two vertical dotted lines indicate January 11, 2016 and January 20, 2016, and bar plot indicates station-wise rainfall on these two dates.

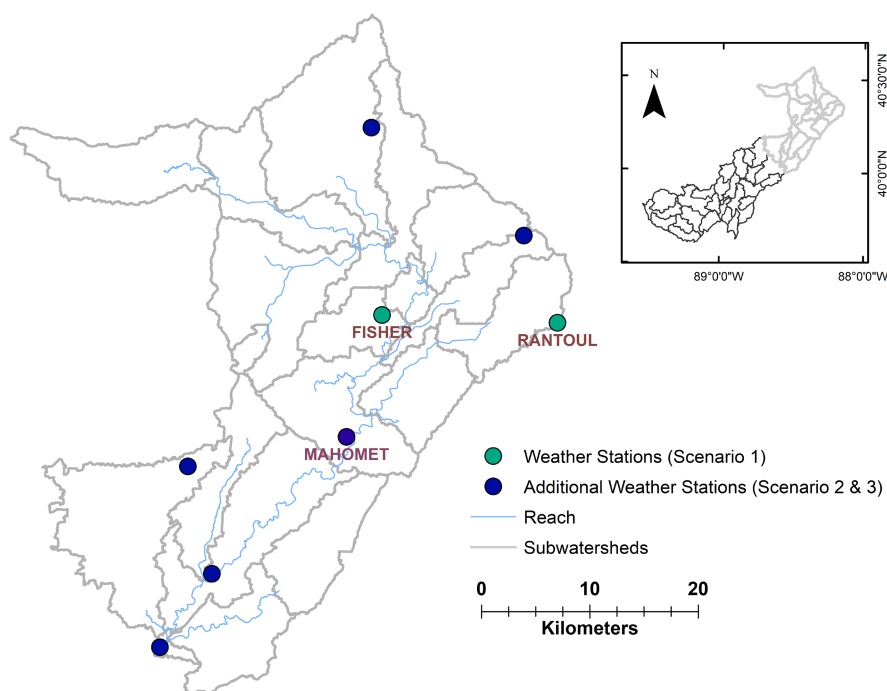


FIGURE 3 Location of weather stations in the USRW upstream.

A user might fail to notice some erroneous data in simulating a large watershed often involving many weather stations. Moreover, inaccurate data are difficult to distinguish, as precipitation can vary significantly over time and space. Erroneous data in model inputs have the potential to mislead model parameters, especially during flow calibration. The implication of erroneous data in model performance is demonstrated in the following section (Scenario 4). Thus, it is advisable to conduct quality control to such observation inaccuracy at the watershed scale before feeding them as model inputs. One viable approach is to compare the data obtained from additional sources, if available (McIsaac et al., 2004; Robinson, 1990), or compare it with nearby existing station data, as shown in Figure 2. This approach could help reduce model uncertainties and also allows to explore the sources of errors in observations.

3.2 | Role of spatially and temporally varying precipitation

Missing rainfall observations in the weather stations are common and the gauge stations in the USRW were no exception. As missing precipitation data in considerable length (months to annual) could impact hydrological and water quality simulation results (Chen et al., 2018; Tan & Yang, 2020), we initially selected weather stations which had more than 95% of daily precipitation available in the modeling period (2000–2018). The effectiveness of this selection and a few others (discussed below) were tested by setting multiple modeling scenarios. For each

scenario, the simulated flow under default model parameters (before calibration) was compared with the observed flow at a sample upstream site in Monticello. The Nash–Sutcliffe efficiency (NSE; Nash & Sutcliffe, 1970) was used to compare model performance in each scenario.

Scenario 1, as shown in Figure 4a, compares observed flow with flow modeled under two NCDC rain gauge stations (Figure 3) which had on average 98% of daily precipitation available from 2000 to 2018. For each subwatershed, SWAT assigns rainfall using the observation from the weather station that has the nearest distance to the centroid of the subwatershed (Cho et al., 2009; Galván et al., 2014). Therefore, rainfall in a subwatershed (Figure 3) under Scenario 1 was assigned from either of the two weather stations. However, simulated flow under Scenario 1 shows poor performance which was unlikely to be fixed by parameter calibration. This unsatisfactory model performance was possibly due to inadequate representation of the spatial variability in precipitation caused by an insufficient number of weather stations in the model. Thus, under Scenario 2, six rain gauge stations were added, as shown in Figure 3, and the flow was re-simulated. Although the added stations on average had only 35% of precipitation observations available in the modeling period, the simulated flow in Scenario 2 shows some improvement in model performance compared to Scenario 1, as shown in Figure 4b. This improvement in hydrological simulation due to increased weather stations (Tan & Yang, 2020; Xue et al., 2019) highlights the significance and necessity of including spatially varying precipitation, especially in modeling a large watershed.

Despite some improvements, the model could not adequately simulate the flow seasonality when tested with Markham's seasonality measure (Markham, 1970)—an angular measure that treats mean monthly flow as a vector quantity where the resultant of such 12 monthly vectors represents the degree of flow seasonality (magnitude) and period of seasonal concentration (direction). More details on the estimation of Markham's seasonality are shown in Supporting Information.

Scenario 2 shows a relatively poor degree of flow seasonality and period of seasonal concentration compared to the estimates obtained from observed flow, as shown in Figure S1. This inadequate simulation of flow seasonality was likely due to poor representation of temporal variability in precipitation caused by sporadically missing observations in the precipitation time series. As SWAT uses stochastic weather generators (Schuel & Abbaspour, 2007) to fill in the missing precipitation, the outputs from these generators are often skewed toward their historical inputs and do not accurately estimate wet or dry spells (Sitterson et al., 2017). Thus, instead of relying on stochastic estimates, a secondary dataset like PRISM (Daly et al., 2008) was preferred to fill the missing NCDC precipitation observations. The use of secondary observations and their implications on monthly simulated flow is demonstrated in Scenario 3. This scenario had an equal number of gage stations similar to Scenario 2, but the PRISM data were plugged in days of missing NCDC observations. For each NCDC gage site, the approximate PRISM grid was selected, and the reliability of PRISM precipitation data was tested (by comparing it with the available daily NCDC data) before filling the missing data. Scenario 3 shows improved model performance with better flow seasonality than Scenario 2, highlighting the importance of

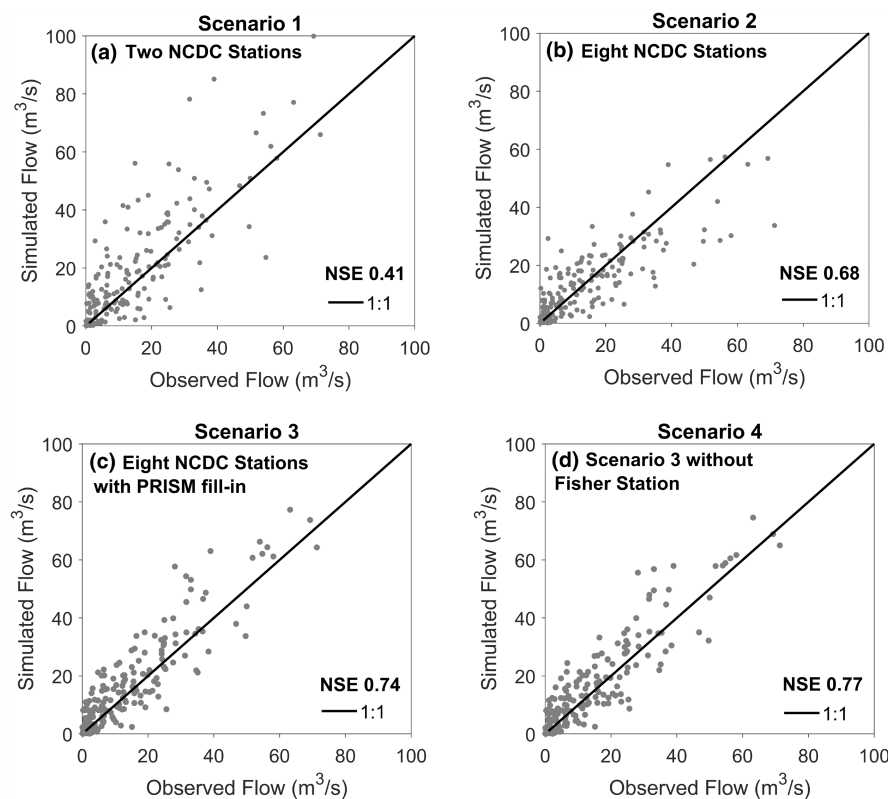


FIGURE 4 Simulated and observed monthly streamflow at Monticello under (a) Scenario 1 (b) Scenario 2 (c) Scenario 3 and (d) Scenario 4.

better representation of temporal variability in precipitation in model inputs. In addition, the improved model performance shows the merits of using secondary observations in watershed modeling and also suggests PRISM as a better input choice over the stochastic weather generator in the USRW.

Moreover, erroneous data, as in Figure 2, could be removed from the analysis to improve the model performance. Scenario 4 excludes the Fisher gauge station, and modeled flow shows a slightly improved performance, as shown in Figure 4d. Thus, in the model setup for the entire watershed (Figure 1), we selected 15 NCDC gauge stations (excluding Fisher), filled in the PRISM data wherever required, and checked for any observation errors. However, the spatial coverage of the NCDC gauge stations is unevenly distributed across the watershed, especially downstream of Monticello (Figure S2). Thus, to improve the spatial coverage, we added precipitation from the PRISM grids (i.e., which were treated as weather stations) at four selected locations. All weather stations (19) used in this study are shown in Figure S2.

3.3 | Inconsistent nutrient concentration records

While multiple data sources for the same water constituent can explain a catchment better, it also allows for independent verification of these data sources. If data from multiple sources for the same site differ significantly, it is essential to find the most accurate dataset or determine the cause of such difference. In our study, a preliminary data screening revealed some differences in TP concentrations obtained from two different sources downstream of Lake Decatur. Independently measured TP by SDD (SDD-TP) at its upstream location was set to evaluate the SWAT simulated phosphorus loads at Decatur because of its larger sample observations measured at higher frequency in the modeling period. Illinois Environmental Protection Agency (IEPA) measured TP (IEPA-TP) in the same site served as secondary data to SDD-TP. These datasets are plotted together with daily discharge in Figure 5a. As shown, IEPA-TP has fewer observations due to lower sampling frequency and the observations are consistently lower than SDD-TP prior to February 2012. In addition to some very high SDD-TP concentrations between 2000 and 2012, there is a sudden 10-fold increase in TP concentration (indicated by orange ellipse in Figure 5a), reported by SDD from August 25, 2011 to February 23, 2012, unexplained by flow or the metadata. This increase is likely an analytical or documenting error (Sprague

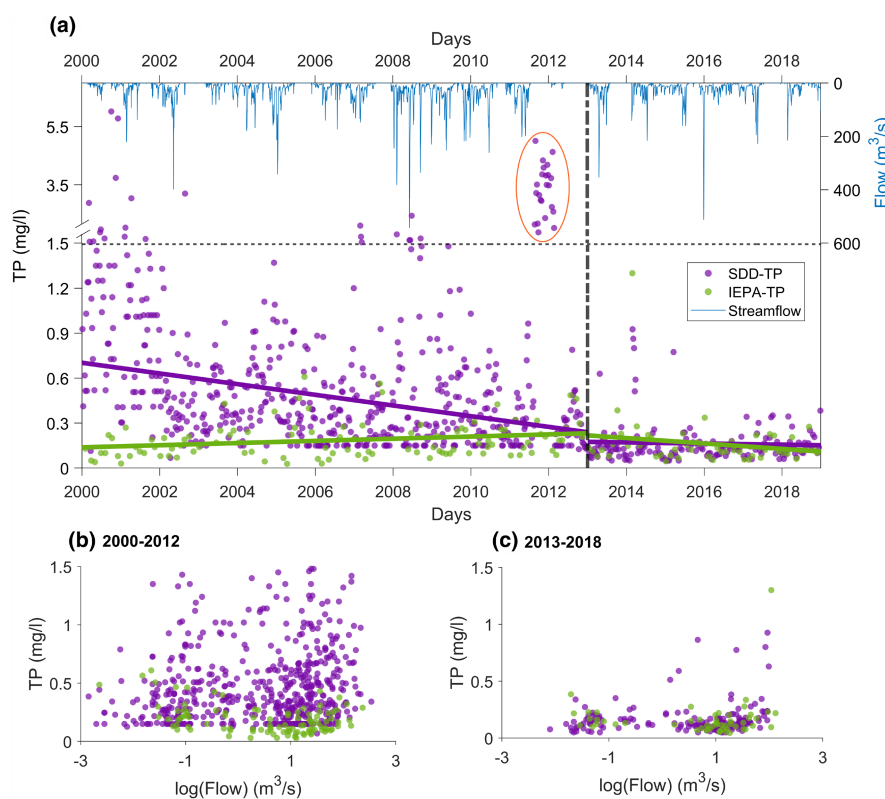


FIGURE 5 (a) Total phosphorus and discharge (2000–2018) downstream of Lake Decatur obtained from IEPA and Sanitary District of Decatur sources. Note the change of scale in the left vertical axis at 1.5 mgP/L. The dark vertical dotted line in 01/01/2013 separates two time periods: 2000–2012 and 2013–2018. The solid-colored lines (purple and green) represent the trend shown by two different total phosphorus (TP) concentration data in two different periods. The right vertical axis refers to daily streamflow (blue) at Decatur in 2000–2018. (b) TP concentration versus discharge (log) from two data sources for 2000–2012. (c) TP concentration versus discharge (log) from two data sources for 2013–2018.

et al., 2017) in the SDD-TP data and thus were excluded from the analysis as it lacked appropriate explanation. On the other hand, IEPA-TP records are more consistent over the years with no sharp fluctuations in their sample observations.

Despite a few discrepancies, SDD-TP was expected to be useful when combined with the IEPA-TP records. However, it was first necessary to ensure its reliability, which was tested with a concentration–time regression model built for two different periods: 2000–2012 and 2013–2018. The two periods were selected to best represent the calibration (2003–2012) and validation period (2013–2018) of this study. To reduce the influence of very high SDD-TP concentrations (outliers) noted above, concentrations greater than 1.5 mg/L were excluded from analysis. The best fit lines for both data sources in the given periods are shown by solid lines in Figure 5a. The concentration–time regression model reveals contrasting temporal trends between SDD-TP and IEPA-TP records in the calibration period. As depicted in Figure 5a, the SDD-TP line shows decreasing temporal trend while IEPA-TP shows a mild increase in TP concentration from 2000 to 2012. Although trends in TP obtained from multiple agencies could differ due to their differences in measurement techniques, sampling frequency, and time of measurement, it is interesting to observe a similar temporal trend between these two data sources after 2012.

In addition, the relationship of concentration with flow was also examined with TP datasets described above. The concentration–discharge (C–Q) plots for the two time periods are shown in Figure 5b,c. While most of high SDD-TP concentrations are associated with high flow events, there are numerous higher concentrations associated with the low discharge. The C–Q relationship of SDD-TP also shows a contrast to the C–Q relationship produced by the IEPA-TP data during 2000–2012. Interestingly, the SDD-TP has limited instances of higher TP concentrations under low flow events after 2012 and the C–Q relationship looks similar to that of IEPA-TP.

The differences in temporal trend and C–Q relationship between the SDD-TP and IEPA-TP records could lead to an ambiguous understanding of TP loads in the watershed. It could also impact the model calibration process, as parameters are dependent on TP observation loads and affect the reliability of simulated loads. Making an appropriate input choice for model calibration under these conditions would be challenging without understanding the cause of such differences. Thus, we communicated this issue with SDD, and it was found that in 2012, there was a method change from manual to automated analyzer to measure TP at SDD (personal communication from Keith Richards, SDD laboratory chemist) and the manual measurements before 2012 had data quality issues. Due to this difference within the SDD-TP data, SDD-TP observations only after 2012 were combined with IEPA-TP data for model evaluation.

3.4 | Inconsistent fertilizer application records

There are many inventories of fertilizer database available based on survey (USDA-ERS, 2021; USDA-NASS, 2020), sales (AAPFCO, 2021; Gronberg & Spahr, 2012), and data fusion methods (Cao et al., 2018; IPNI, 2011; Xia et al., 2021). However, there is no thorough documentation on the amount of fertilizers applied at the watershed scale. Instead, most modeling studies rely on two primary fertilizer datasets in the United States (U.S.): U.S. Geological Survey (USGS) county-level nitrogen (N) and phosphorus (P) fertilizer sales data (Gronberg & Spahr, 2012) and U.S. Department of Agriculture (USDA) state-level surveys of nitrogen and phosphate (P_2O_5) fertilizer application rate (USDA-NASS, 2020). For a reliable model input formation, it is worth checking whether these two datasets result in a consistent nutrient application rate at the scale of interest. In the section below, we compare the two-fertilizer database to select one for SWAT model setup in the USRW.

The USGS provides N and P fertilizer sales data at the county level during 1987–2012 while the USDA provides crop-specific N and P_2O_5 fertilizer application rates at the state level along with the percentage of crop area receiving N and P_2O_5 fertilizer. The USDA dataset is available from 1964 to 2018 (most recent) but has several missing values after 2000 in Illinois. For a consistent comparison between two data sources, (1) necessary adjustment was made to convert P_2O_5 to P in the USDA data and (2) the USDA state-level application rate was converted to the county level using the following equation.

$$FR_j^c = \frac{\sum_i F_i^j R_i^j A_i^c}{\sum_i A_i^c}, \quad (1)$$

where i is the cultivated crops (corn, soy, and wheat), j is the type of fertilizer applied (N and P), and c is the county of interest. FR_j^c (kg/ha) is the application rate of fertilizer j in county c , while F_i^j (kg/ha) is the USDA state-level application rate of fertilizer j for crop i , R_i^j is the area fraction of cultivated crop i receiving fertilizer j , and A_i^c (ha) is the cultivated area of crop i in county c .

Equation (1) assumes that the state-level N and P fertilizer application applies to the county scale. F and R in the equation were obtained from the USDA, while A_i^c was obtained from the Cropland Database Layer (CDL; Boryan et al., 2011). CDL provides the land area covered by different crops across the U.S. since 2008; Illinois is one of the few states with publicly available cropland database since 1999. Following, the ratio of USGS county-level fertilizer sales data to the total cropland area (obtained from CDL) yielded the corresponding USGS county-level N and P fertilizer application rate. For the following comparison, we chose several years from early 2000s based on the availability of USGS and USDA fertilizer data for Illinois within our modeling period.

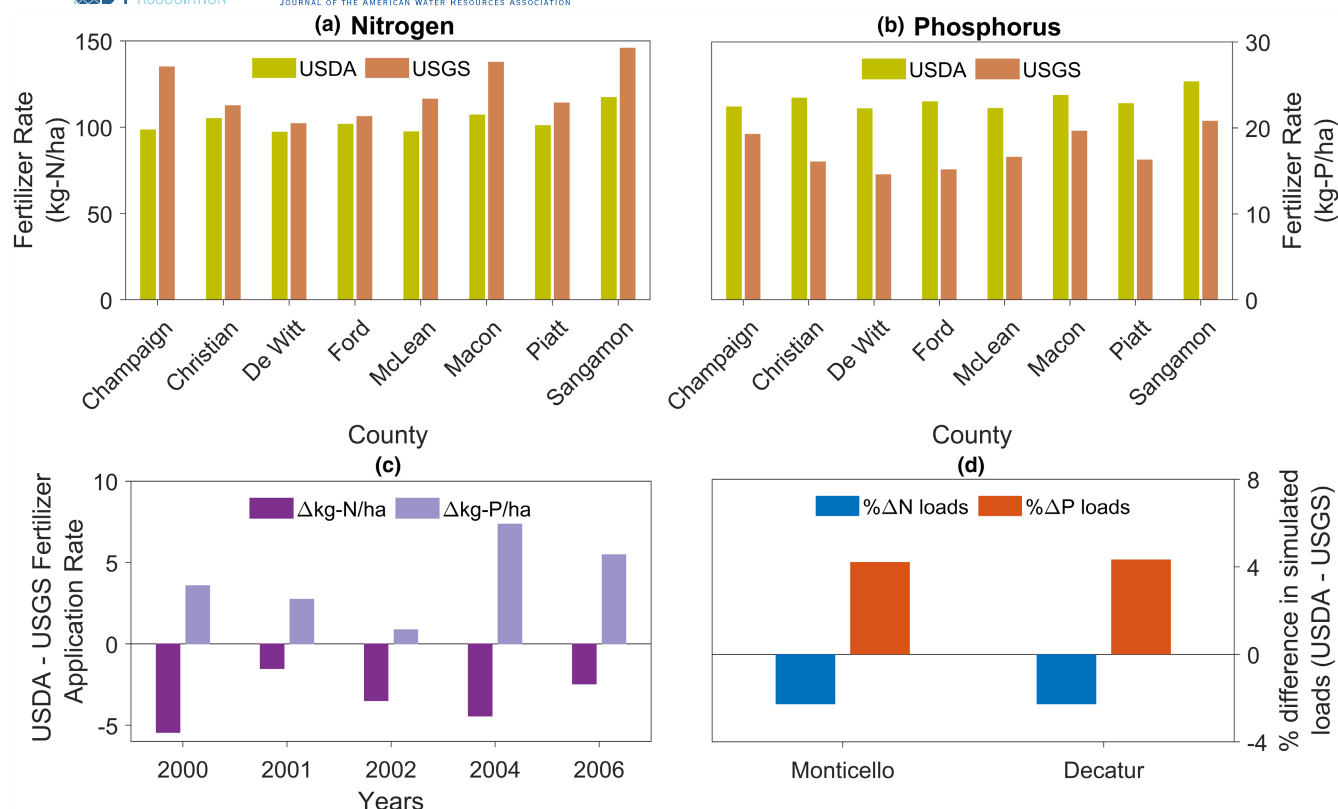


FIGURE 6 U.S. Geological Survey (USGS) and U.S. Department of Agriculture (USDA): (a) nitrogen and (b) phosphorus fertilizer application rate in eight IL counties in 2004. (c) Eight counties average differences in USDA and USGS fertilizer application rate (N and P respectively). (d) Difference between USDA and USGS fertilizer inputs driven simulated annual average (2003–2018) nitrate and phosphorus loads at Monticello and Decatur.

Figure 6a,b compares the N and P fertilizer application rate obtained from the USDA and USGS for a sample year, 2004, for eight counties that fall within the USRW boundary. The difference between USDA-N and USGS-N fertilizer application rates is minimal in most counties and on average USDA-N rates are only 3% less than the USGS-N estimates. On the other hand, the USDA-P application rates are consistently greater than the USGS-P application rates in all the counties. The USDA-P rates are, on average, 53% greater than the USGS-P estimates.

Further comparison of fertilizer rates in different years (2000, 2001, 2002, and 2006) reveals a similar difference between USDA and USGS estimates across the watershed. Figure 6c shows the difference between USDA and USGS application rate (average of eight counties) for the corresponding nutrients in different years, where USDA-N are lower, and USDA-P are higher than the USGS estimates. Such inconsistency in fertilizer datasets can affect simulated nutrient loads and alter the understanding of nutrient dynamics in the watershed. Figure 6d shows the implication of inconsistent fertilizer inputs on simulated nitrate and phosphorus loads under two SWAT scenarios (before calibration), driven by USDA and USGS fertilizer inputs, respectively, with other management practices (Table S2) remaining unchanged. The difference between the annual average nutrient loads (2003–2018) at two sites, Monticello and Decatur, reveals the difference in fertilizer inputs shown in Figure 6c. The simulated nitrate loads under USDA fertilizer inputs are 2% lesser than the nitrate loads estimated by the USGS inputs; with a relatively high P application rate with the USDA inputs, the simulated phosphorus loads are about 4% higher than that of the USGS fertilizer inputs. In our model setup, we chose the annual average USDA state-level corn P fertilizer rate (95 kg P_2O_5 /ha), as it approximately matches the recommended fertilizer application provided in Illinois Agronomy Handbook (Fernández & Hoef, 2009). The crop P requirement (100%) and N requirement (18%) was met by the application of diammonium phosphate (DAP), while the rest of N requirement (for a total of ~224 kg N/ha; Farmdocdaily, 2019; Merriman et al., 2018) was met by anhydrous ammonia and urea (Table S2).

3.5 | Modeling additional nutrient sources: Dairy feedlot and biosolids

In addition to fertilizer applications and point sources, animal farms and concentrated animal feeding operations (CAFOs) can leach nutrients in a watershed (Brown et al., 2020; Burkholder et al., 2007). Due to the lack of a consistent national inventory on the number, size, and location of CAFOs (Handan-Nader & Ho, 2019), these farms are usually difficult to identify and locate in watersheds, and thus are more likely to be

missed in the watershed model configuration. As these farms have a potential to elevate riverine nutrients, it is essential to consider them in modeling analysis. However, the data on nutrient balance of these farms might not be available and expert knowledge is generally essential to estimate the model inputs to yield better model results. We encountered a dairy feedlot operated by the Stone Ridge Dairy Farm in the USRW upstream (see [Figure 1](#)) with limited information on their nutrient contribution to the watershed. To include the farm in the model, we used the available information with a few necessary assumptions. The dairy feedlot in SWAT was modeled in the following steps. (1) Given 3100 lactating cows in the Stone Ridge Dairy farm, dry manure produced from the farm was estimated to be 9.4×10^6 kg per year (ASAE, 2000). (2) Assuming 4.5 g/kg of P in the animal feed with 10% Corn Gluten Feed (12 mg P/g) (Juneja et al., 2019), the phosphorus content in manure was estimated to be around 9 g P/kg (Powell et al., 2002). (3) Considering N:P ratio of 3:1, the N content in manure was estimated to be 27 gN/kg and to meet the agronomic nitrogen requirements (~ 224 kg N/ha), dry manure application rate was estimated to be 8300 kg/ha. (4) These estimates provided a tentative manure application area of 1000 ha. (5) Assuming the manure from the dairy was applied in the farm vicinity, a dedicated subbasin was manually delineated in SWAT with an area of similar size (980 ha) surrounding the dairy farm to simulate nutrient contribution due to manure. This specific subbasin was set to simulate corn silage in SWAT to support animal feed on the farm. (6) The nutrient content of the manure was added as a new fertilizer in SWAT and the management files were updated accordingly.

Similarly, biosolids could be an additional source of nutrients in a watershed to supplement or replace commercial fertilizers in promoting crop yield (Cogger et al., 2006). Biosolids contain more than 50% of N in the organic form (Lu et al., 2012; Sommers, 1977) and they slowly release nitrate in soils. With slow nutrient release, biosolids can nourish plants over a longer time and they are less likely to pollute groundwater and streams than the application of commercial fertilizers, which are usually water soluble and can easily cause nutrient loss through groundwater leaching (Lu et al., 2012; USEPA, 2000). Biosolids also differ from commercial fertilizers in terms of application sites and frequency. As biosolids can impact watershed nutrient dynamics, any biosolids application sites should be included in the model, if possible. In our model setup, we simulated biosolids in SWAT downstream of the SDD where biosolids have been applied over several decades. SDD provided the dry sludge application rate of 5.87×10^6 kg with 5.4% of total nitrogen for the year 2019 and also provided the application sites which had an area of 647.5 ha in 2017. Although information on biosolids application rate and sites was limited to a single year, the following steps were taken to model biosolids in SWAT with few assumptions. (1) Assuming a similar dry sludge application rate as of 2019 in the simulation period (2003–2018), the annual dry biosolids application rate was estimated to be 8220 kg/ha. (2) Five relevant SWAT HRUs were selected based on similar soil types and land slopes that best matched the 2017 biosolids application sites. (3) These HRUs with a total area of 647.5 ha were set to grow corn and soy under 2 years of crop rotation where biosolids were applied for corn grown years only. (4) The biosolids were added to SWAT fertilizer database and the management files for the selected HRUs were modified.

Although a limited dataset was available for the manure and biosolids application, these processes were included in SWAT with reasonable inputs generated from the steps described above. These two interventions in the USRW were extended over a small area and representing them in the model facilitated a more realistic model simulation.

4 | CALIBRATION

By addressing various data issues described above, we calibrated and validated SWAT to the observations of USRW with reasonable results. The model was calibrated from 2003 to 2012 and validated from 2013 to 2018, with the first 3 years (2000–2002) subjected to model spin-up. The model performance was tested with correlation coefficient squared (R^2), NSE, and percent bias following the guidelines discussed in Moriasi et al. (2007). The sediments and nutrient observation time series were generated from available discrete sample observations ([Table S1](#)), using the Weighted Regression on Time, Discharge and Seasons (WRTDS) algorithm (Hirsch et al., 2010). WRTDS estimates daily concentration using time, discharge, and season as explanatory variables, and accounts for the temporally varying seasonal- and discharge-related patterns of a water quality constituent (Hirsch et al., 2010, 2015). We used SWAT-CUP sufi-2 algorithm (Abbaspour et al., 2018) with parallel processing as a model calibration tool. The calibration approach started with the selection of sensitive parameters, followed the calibration of (1) daily flow, (2) annual crop yield, and monthly (3) nitrate loads, (4) sediment loads, and (5) TP loads. The discussion on each of these calibration stages together with calibrated parameters and their ranges are provided in the [Supporting Information](#). Our approach was similar to a four-stage calibration process proposed by Nair et al. (2011) but included two additional variables (sediment and TP loads). The calibrated model adequately simulates daily flow, monthly nitrate, sediment, and TP loads at multiple sites within USRW during the calibration and validation period ([Table S4](#)). The simulation results, in general, are in good agreement with the observations with slightly better performance during the calibration period.

It should be noted that although the work around with calibration can fix some modeling issues to a certain degree, it is not a panacea to deal with insufficient observations. For instance, high-resolution field-scale soil parameters are usually limited in a study region, especially in large watersheds. Under many cases, coarse resolution STATSGO or SSURGO soil data are usually the choice as model inputs, despite that each input can generate dissimilar simulation results (Geza & McCray, 2008; Kumar & Merwade, 2009; Wang & Melesse, 2006), due to their

differences in the HRU discretization. One possible approach to obtain high-resolution soil parameters across a watershed is to utilize DEM-derived hydrologic parameters and/or use machine learning tools like artificial neural networks, as described in Zhao et al. (2009).

Similarly, calibration process cannot negate the effects of a deficient model structure. The deficit in model structure, that is, the inadequate representation of catchment process or oversimplification of natural systems (Giudice et al., 2015), also affects model reliability. The current suite of popular water quality models lacks important natural processes that affect sediment and nutrient dynamics. For instance, phosphorus legacy in the watershed with long term application of fertilizers (Jarvie et al., 2012; Sharpley et al., 2013) plays a crucial role in driving nutrient variability, but is poorly simulated in the current version of SWAT. Similarly, role of soil microbes, impact of flow turbulence, and in-stream processes such as advection, dispersion, and biochemical degradation are poorly represented in the model (Fu et al., 2020). In addition, the missing sediment-dissolved phosphorus relationship in streams and the lack of P leaching through soils and tile drains in SWAT add more uncertainty to simulate in-stream P loads. Such deficiencies in model structure could benefit from more rigorous soil and in-stream nutrient modules rather than adjusting parameters for a realistic riverine load assessment.

5 | CONCLUSION

In this study, we present our reflective experiences in calibrating the SWAT model with respect to multiple variables including flow, sediments, nitrate, TP, and crop yield at multiple sites of a heavily managed agro-industrial watershed impacted by point and non-point nitrate and TP sources. This study focuses on the identification and treatment of inconsistent data from multiple sources that affect model calibration and model reliability. In particular, under data limitations with SWAT, we discuss the errors in precipitation observations, showing the importance of spatiotemporal variability of precipitation affected by missing observations; we discuss the effects of inconsistent nutrient observations and illustrate the effects of varying fertilizer observations on the simulated nutrient loads; we also demonstrate steps to simulate watershed interventions such as manure and biosolids applications under limited data. We deal with these issues by following these measures: (1) conducting data quality assessment (e.g., by comparing one data source with other available sources or with nearby gage stations) to avoid the propagation of any input errors to the model outcomes; (2) using data from additional sources to handle missing precipitation observations (e.g., PRISM) and the spatiotemporal variability of precipitation; (3) identifying the causes of any discrepancies between observations reported by multiple agencies (e.g., by communicating with data providers) to ensure their usability (especially in the evaluation of sediments and nutrient loads); and (4) creating model inputs for significant interventions such as dairy feedlots and biosolids with certain assumptions based on existing literature. Resolving these data issues results in a satisfactory multivariable and multisite model applied to an intensively managed agro-industrial watershed, of which the simulated variables are reasonably in agreement with the observations.

Through this study, we hope to inform modelers about some common but often not sufficiently addressed issues in data processing when calibrating a complex watershed hydrological model like SWAT. However, we do not address all data challenges as our experiences are specific to one case study watershed. Nevertheless, we believe highlighting the challenges and suggestions may benefit other modelers, especially those using SWAT.

AUTHOR CONTRIBUTIONS

Sundar Niroula: Conceptualization; data curation; formal analysis; methodology; validation; visualization; writing – original draft; writing – review and editing. **Kevin Wallington:** Conceptualization; data curation; validation; writing – review and editing. **Ximing Cai:** Conceptualization; data curation; writing – review and editing.

ACKNOWLEDGMENTS

This work was funded by the U.S. National Science Foundation (INFEWS/T1 award number 1739788). The authors would like to thank Gregory McIsaac, Haw Yen, Linda Sims, Shaobin Li, and Benjamin Gramig for providing helpful suggestions to improve the quality of the manuscript.

CONFLICT OF INTEREST

All authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

All the source of the dataset used in this study can be found in the Supporting Information (Table S1).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Niroula, Sundar, Kevin Wallington and Ximing Cai. 2023. "Addressing data challenges in riverine nutrient load modeling of an intensively managed agro-industrial watershed." *Journal of the American Water Resources Association* 59(2): 213–225. <https://doi.org/10.1111/1752-1688.13097>.