Hydrologic Monitoring to Simulate Water Quality in Mill Creek Watershed Using Personal Computer Storm Water Management Model (PCSWMM)

by

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ABSTRACT

The Mill Creek watershed is located in the Northeast Ohio and covers an area of 78.3 square miles within the Mahoning River basin. The river has been experiencing significant water quality problems due to pollution from point and nonpoint source contributions from its tributaries. Before joining the Mahoning River, the river flows through several areas, including the City of Columbiana, Beaver Township, Boardman Township, and Youngstown. Mill Creek comprises seven major tributaries, namely Anderson Run, Cranberry Run, Indian Run, Bears Run, Ax Factory Run, Sawmill Run, and Turkey Run, all of which contribute to the degradation of the river water quality in terms of algal bloom, turbidity, and bacterial contamination. The water quality of rivers is significantly affected by several sources of contamination, such as combined sewer overflows, failing septic systems, animal waste, and runoff from agricultural and urban areas. Despite several studies conducted in the past, a hydrologic and hydraulic investigation in the context of water quality modeling has not been conducted in Mill Creek yet. To address this concern, monitoring stations were established in different locations along the river to record real-time flow depth data using HOBO loggers. In addition, sporadic water quality data from the past and the recent data collected by the Environmental Science Program at YSU have been used for water quality calibration and validation. The hydrologic and hydraulic model was developed using the Personal Computer Storm Water Management (PCSWMM) model. Data sourced from the National Oceanic and Atmospheric Administration (NOAA) of the National Climatic Data Center (NCDC), the Digital Elevation Model (DEM) from the United States Geological Survey (USGS), land cover data from the National Land Cover Datasets (NLCD), and soil data from the United States Department of Agriculture (USDA) were utilized to construct the model. The calibration and validation of the model were carried out using data from the United States Geological Survey

(USGS) gauging station, which spanned from January to June 2000. The hydraulic and hydrological components of the model were both calibrated, with the hydraulic model component of PCWMM being validated using the recorded flow depth measurements from three HOBO loggers established in the creek between May and December 2023. The model's performance was assessed through various statistical measures, including the Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R2), and Pbias, as well as through visual inspection of the time series results of the simulated versus observed data.

The NSE for hydrologic calibration statistics ranged from 0.51 to 0.53, and the coefficient of determination (R^2) ranged from 0.71 to 0.72. In order to further validate the model, recent and historical streamflow data were employed, yielding NSE values ranging from 0.43 to 0.89 and R^2 values ranging from 0.51 to 0.9. The model was also successfully calibrated and validated for water quality parameters, including dissolved oxygen (DO), five-day biochemical oxygen demand (BOD5), total suspended solids (TSS), soluble phosphorus, and nitrate, demonstrating satisfactory performance.The analysis of stream quality indicated that the upstream section of the watershed at Headwaters had elevated levels of soluble phosphorus (3474 µg/l), whereas its concentrations were significantly lower (9.44 µg/l) near the outlet of the watershed. On the contrary, the investigation revealed higher levels of TSS (150.50 mg/l) at the East Golf Hike trail monitoring station, which is located after the Indian run, and the TSS average value (12.99 mg/l) was found to be lowest at the outlet of the watershed. It was also observed that the concentration of dissolved oxygen remained consistently in a similar range (8.17mg/l to 10.41mg/l) over the entire length of the stream. As a part of the water quality investigation, the model's simulated levels of TSS, DO, BOD_5, nitrate, and soluble phosphorus were evaluated through the boxplots by comparing them to the observed values of these water quality parameters to see the overall assessment of the streams for the period of 2022 to 2023.

Mill Creek, as a recreational park with fishing and boating activities, is vulnerable to water contamination, which can have a detrimental impact on the aquatic biological life in its water bodies. To address this issue, it is crucial to monitor and model the water quality variables in the Mill Creek watershed, particularly the PCSWMM model developed in this study. By doing so, stakeholders can make well-informed decisions regarding the integration of appropriate Best Management Practices (BMPs) into the potential locations of the seven tributaries in the watershed.

Keywords: PCSWMM Model, Hydrologic and water quality calibration and Validation, Monitoring, HOBO loggers.

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BOD	Biochemical Oxygen Demand
BMP	Best Management Practices
CN	Curve Number
CSA	Critical Source Area
DEM	Digital Elevation Model
EPA	Environmental Protection Agency
EMC	Event Mean Concentration
GIS	Geographic Information System
HRU	Hydrologic Response Units
NOAA	National Oceanic and Atmospheric Administration
NCDC	National Climatic Data Center
NPS	Non-Point Source
NRCS	National Resources Conservation Services
NLCD	National Land Cover Dataset
NPDES	National Pollutant Discharge Elimination System
NSE	Nash-Sutcliffe's Efficiency
PCSWMM	Personal Commuter Storm Water Management Model
PBIAS	Percentage Bias
SMC	Source Mean Concentration
SSURGO	Soil Survey Geographic
SWAT	Soil and Water Assessment Tool
TN	Total Nitrogen

TSS	Total Suspended Solids
USACE	United States Army Corps of Engineers
USDA	United States Department of Agriculture
USGS	United States Geological Survey

USGS United States Geological Survey

Chapter 1: Introduction

Water quality problems in streams and rivers caused by an increasing amount of nitrogen, phosphorus, and sediment from both point and non-point sources (Dressel et al. 2014), has emerged as a significant concern across the world in the recent decades (Burkartaus et al. 2008; Rousseau et al. 2012). The excessive nutrient levels may lead to harmful consequences such as the development of toxic algal blooms (Glibert et al. 2017), depletion of oxygen (Breitburg et al. 2002), mortality of fish (Giardina et al. 2009), and an overall reduction in biodiversity (Niraula et al. 2013). These problems further exacerbate water quality making it unsuitable for designated uses such as drinking, industrial, agricultural, and recreational usage (Carpenter et al. 1998).

In general, the discharge of pollutants from a single identifiable source (i.e., point source) is controlled by the regulatory agencies by means of the national pollutant discharge elimination system (NPDES) (Feng et al. 2005). However, in order to comprehend the intricate mechanisms and complex processes involved in the source and transport of nonpoint sources, several watershed-scale models and tools have been developed and the best management practices (BMPs) have been implemented to control these pollutions (Geng et al. 2019; Santhi et al. 2001). These models and tools serve the purpose of comprehending non-point source (NPS) pollution and assessing water quality. The watershed models and tools have been used extensively in identifying critical source areas of pollutants (Liu et al. 2016; Niraula et al. 2013; Tuomela et al. 2019). These models also aid in the planning and execution of best management practices (BMPs) (Gitau et al. 2008; Strauch et al. 2013) and offer well-informed decision support for policymakers. Besides, watershed models are becoming indispensable instruments in the venture to mitigate the detrimental impacts of non-point source contamination (Corrales et al. 2017). However, the identification and management of nutrients and sediments from nonpoint sources bring challenges to monitor and regulate as they are generally unknown in their origination and fluctuate in space and time (Carpenter et al. 1998). The sediment and nutrient input from various locations of a watershed varies significantly. Phosphorus, a vital nutrient crucial for crop and animal production, has the potential to speed up freshwater eutrophication (Carpenter et al. 1998). Some specific and clearly defined regions contribute a significant role in the deposition of sediment, phosphorus, and nitrogen into the outflow of the watershed (Pionke et al 2000; Walter et al. 2000) contributing during very brief time periods (Dillon et al. 1997; Heathwaite et al. 2005). However, in many instances, the source areas are not clearly delineated but rather dispersed and contribute the varying rate of pollutant. For example, some particular areas characterized by distinct soil composition, land use/cover, and slope contribute higher nutrient and sediment load compared to other locations. These regions are often referred to as critical source areas (CSAs) (Niraula et al. 2013). Identifying these sources of pollutants is crucial for implementing cost-effective BMPs (Park et al. 2015). The identification of such places may be achieved by conducting water monitoring at the sub-watershed level, using simulation modeling, or employing both methods simultaneously (Sharpley et al. 2002).

The selection of an appropriate watershed model is pivotal in hydrological and hydraulic analysis (Ghonchepour et al. 2021). Previous research underscores the efficacy of specialized models, such as Personal Computer Storm Water Management Model (PCSWMM), in accurately predicting stormwater management and pollution transport within urban and mixed land use scenarios (James et al. 2012; Paule-Mercado et al. 2018; Talbot et al. 2016; Zhang et al. 2019). Therefore, the purpose of the study aims to offer a more thorough knowledge of the dynamics of mixed watersheds by using a comprehensive methodology, which strives to provide the primary hydraulic and water quality data from the field. This approach ensures high accuracy since the data were gathered through the consultation with stakeholders, which is very congruent with the complexities of actual watersheds in the real world. Therefore, the research proposes the development of the model, which strengthens the credibility and application of the PCSWMM model in the management of complex and mixed land-use watershed.

Scope and objective

1. This research study is driven by a set of carefully defined objectives focused on executing a thorough calibration and validation process for hydraulic, hydrologic, and water quality components of PCSWMM model in the Mill Creek watershed. The key objectives are outlined as below.

I. Systematic Monitoring and Data Collection

II. Deploy HOBO Loggers strategically at three distinct locations along the Mill Creek stream to acquire flow depth data.

III. Utilize water quality data for the evaluation of water quality parameters, based on the data sampled by Environmental Science Program from designated monitoring sites and subsequent analysis.

2. Model Calibration, Validation, and Water Quality Evaluation

IV. Compile relevant input data essential for the PCSWMM simulation, which includes daily climatic data (precipitation, temperature), monitored depth data, soil data, land use data, and stream flow data retrieved from the USGS gauging station.

V. Employ the compiled data to delineate the watershed within the model framework, facilitating the development of a robust PCSWMM model.

VI. Conduct a hydraulic and hydrologic model calibration and validation process to ensure accuracy and reliability of the modeling outcome.

VII. Adjust the PCSWMM model to incorporate observed water quality data as mentioned above to calibrate and validate water quality parameters effectively.

VIII. Perform a comprehensive assessment of water quality based on observed data collected from the designated monitoring stations, providing insights into the overall water quality within the Mill Creek watershed.

Thesis Structure

This thesis has been organized into three distinct sections. Chapter 1 offers an overview of the study, encompassing the context, extent, and goals of the research. Moreover, this section presents a comprehensive outline that delineates the structure of the entire thesis.

Chapter 2 is dedicated to the monitoring and collection of essential water quality and hydraulic data necessary for PCSWMM modeling. This includes a discussion on the installation of HOBO loggers and the methodology employed in surveying the sites and analyzing the water quality in the laboratory.

Chapter 3 delves into the intricacies of the comprehensive process involved in developing and refining the PCSWMM model for the Mill Creek Watershed. This chapter not only encompasses the technical aspects of model development but also includes thorough hydraulic and hydrologic calibration and validation processes. Additionally, it addresses water quality calibration and validation, providing an in-depth water quality analysis within the watershed.

Chapter 2: Monitoring Mill Creek Watershed

Study Area

The study was conducted in the Mill Creek watershed (Figure 2.1) of Mahoning River basin located in the Northeastern Ohio. The watershed, which is 78.3 square miles in size, starts just south of the city of Columbiana in the northeast part of Columbiana County and runs north through Boardman Township and Mill Creek Park before finally draining into the Mahoning River at Youngstown, Ohio. The watershed is dominated by developed (urban) land, accounting for 51.7% of the entire watershed area. Similarly, the percentage covered by waterbodies and wetlands is 5.52%, as determined by the National Land Cover Datasets (NLCD). Agricultural land use comprises 5.2% of the northern sub-watershed, 40% of the mid-western sub-watershed, and 51.9% of the southern sub-watershed (McCracken, 2007). The watershed varies the elevation range from a maximum of 1286 feet to a minimum of 826 feet. The annual precipitation in the watershed is 35.1 inches. Mill Creek is the major river in the watershed, along with seven tributaries: Bears Den run, Ax Factory run, Andersons run, Cranberry run, Indian run, Sawmill run, and Turkey run. In general, there is an order of three lakes - Newport Lake, Lake Cohasset, and Lake Glacier (ordered from upstream to downstream) - which possess significant water-holding capacities, ultimately imposing a considerable impact on the hydrology and water quality of Mill Creek. There are various potential sources of contamination in the Mill Creek watershed, such as animal waste, agricultural land, combined sewer overflows, failing septic systems, and runoff from urban areas (McCracken, 2007). These sources cause several water quality issues, including bacterial contamination, algal blooms, turbidity, and fish killing. Since Mill Creek is a recreational park with various activities including fishing and boating, water contamination can be detrimental to human health.

Hydrologic and Water Quality Monitoring

Hydraulic Monitoring

This study involves an extensive site monitoring initiative aimed at gathering essential input data for the hydraulic and hydrologic modeling component of the PCSWMM model. The study area consists of open streams, generated using the PCSWMM transects creator tool and Hydrologic Engineering Center (HEC-RAS) software utilizing 10m DEM. To instill confidence in the model, stream width and bed dimensions were meticulously measured at multiple watershed locations. These measurements are crucial for accurately representing the stream characteristics within the model. To determine stream width, a combination of total stations, GPS, and leveling instruments were employed. The measurements were obtained by carefully lowering a measuring device, such as a staff gauge or sounding rod, into the stream until it reached the riverbed. This process was repeated at various points within selected cross-sections to capture depth variability. The systematic methodology undertaken in this study aligns with best practices in scientific research and contributes to the robustness of the hydraulic and hydrologic modeling.

On the other hand, long-term and spatially distributed hydrologic data are crucial for simulation studies. Therefore, monitoring sites were established at various locations in the Mill Creek watershed, as depicted in Figures 2.2 to 2.4. HOBO loggers (Figure 2.5) were installed at these sites, spanning the entire watershed from upstream to downstream. These loggers are compact devices equipped with sensors designed to measure various environmental parameters, including water depth. They were anchored in a stable position within the water column using secure fixtures to prevent movement or displacement. HOBO loggers continuously monitor water depth over a specified period of time and record fluctuations in water levels due to natural variations in flow rates. Once the data collection period was complete, the HOBO loggers were retrieved, and the observed flow depth data was downloaded for processing in PCSWMM model. By comparing the observed depths recorded by the HOBO loggers with the simulated depths generated by the model, the model's parameters were adjusted and fine-tuned during the calibration process in PCSWMM. These measured parameters play a fundamental role in refining and validating the PCSWMM model, ensuring its reliability and applicability in representing the dynamic characteristics of the streams.

Working Principle of HOBO Loggers

The HOBO U20L water level logger (Figure 2.5) was used to monitor fluctuating water levels in various settings, such as streams, lakes, wetlands, tidal regions, and groundwater. With the help of HOBOware Pro software, we can effortlessly customize this logger to capture data on absolute pressure and temperature. To establish a connection between the HOBO water level logger and a computer, a coupler (COUPLER2-C) and either an optic base station (BASE-U-4) or a HOBO Waterproof Shuttle (Figure 2.6) are necessary. The optical interface ensures that the logger can be loaded without compromising the seals' integrity. The USB compatibility simplifies the installation process and enables rapid data transfers. This particular logger is equipped with a ceramic pressure sensor, a sturdy housing, and a protective end cap. It is designed for deployment in pre-existing wells or stilling wells. This user-friendly logger is an excellent choice for water level investigations and research as it does not require the maintenance of unwieldy vent tubes or desiccants. (ONSET User Manual 2014).

The logger measures the absolute pressure, which is then transformed into water level data using HOBOware Pro software. Within this application, the term "absolute pressure" encompasses both air pressure and the pressure exerted by a column of water. The atmospheric pressure at sea level is typically about 100 kPa (14.5 psi), however it varies depending on weather conditions and height (ONSET User Manual 2014).

Water Quality Monitoring

This study involves the monitoring and sampling of water quality in the Mill Creek watershed. Considering different land use patterns, potential sources of contamination, and natural features, eight stations were chosen after consulting with the Ohio ABC Stormwater district's stakeholders as shown in Figure 2.1. The water quality sampling and analyzing was not done by the author but by the undergraduate students from Environmental Science Program at YSU. I am writing the following discussions as I was involved in the selection of the stations and the formulation of the protocol to be adopted for water quality monitoring so that I could utilize those data for PCSWMM model.

These stations were placed carefully to cover the whole watershed. In order to ensure accuracy and consistency, certain protocols were deployed during the collection of water samples. The water samples were obtained through the grab sampling method (as illustrated in Figure 2.7) at the specified stations and subsequently transported to the laboratory for analysis of water quality. Following collection, these samples were sent to the specialized lab (Figure 2.8) for examination while adhering to strict protocols to prevent any degradation of the materials during transport. The samples were carefully examined in a laboratory setting under strict control. This analytical procedure provided priceless insights into the natural nutritional composition of the water quality, which covered a wide range of variables, from straightforward assessments of the physical properties of the water, like temperature, pH, and turbidity, for intricate analyses of its chemical makeup, such as nitrate, soluble phosphorus, dissolved oxygen, five-day biochemical oxygen demand (BOD_5) and total suspended solids. Due to the sporadic availability of water quality data between 2017 and 2018, the students from the Environmental Science Program at YSU were able to collect an average of six observations per designated monitoring station during the years 2022 to 2023. For nutrient simulation we chose manual calibration in PCSWMM using available observed nutrient data. PCSWMM is capable of simulating the delivery of pollutants through the use of buildup and wash-off equations. The parameterization of these equations for various land uses is crucial for maximizing the capabilities of the software.(Tu et al. 2018). Three separate buildup equations (exponential, power, and saturation) have been incorporated into SWMM, in addition to three wash off equations (rating curve, exponential, and event mean concentration). (Rossman, 2010). Simplified data-based model representations using Event Mean Concentration have proved efficiency in achieving reasonable calibration and validation meanwhile managing computational burden (Gaume et al. 1998; Niazi et al. 2017). So,the choice of the EMC wash-off function was made for the purpose of conducting water quality simulations.

Lab analysis

The water sampling and analysis procedure were not conducted by me but by students enrolled in the Environmental Science Program adhered to protocols to ensure accurate and reliable results. Based on my knowledge, students adopted the following section and followed the meticulous steps both during the sampling and laboratory analysis phase. I am describing the protocol followed by the students at Environmental Science Program in the following section.

Water samples were collected from streams by students wading into the water and utilizing either a long-handled dipper or a bucket. Sampling was conducted at various locations, including overpasses and bridges, to capture a representative sample of the stream's water quality.

Sample Bottle Preparation: Nalgene sample bottles underwent a thorough cleaning process prior to use to prevent any contamination. This involved multiple steps: 1) Cleaning with laboratory soap. 2) Complete rinsing to remove any residual soap. 3) Acid washing followed by rinsing with deionized water. 4) Air drying to ensure no moisture remained before utilization.

Sampling Procedure: During the sampling process, utmost care was taken to maintain the integrity of the samples. Each container used, including the dipper, bucket, and sample bottle, was meticulously cleaned three times with sample water to prevent any cross-contamination.

Sample Collection and Sealing: Water bottles were filled to their maximum capacity from each sampling location and securely sealed to prevent any alteration or contamination of the samples during transport and storage.

Sample Replication and Analysis: Each sampling location was subjected to the collection of two grab samples to ensure representativeness. Furthermore, all analyses were performed three times, with one analysis conducted for each grab sample, to validate the accuracy and consistency of the results. In case of any discrepancies observed between replicate analyses, an additional replication was conducted to corroborate the findings and ensure data reliability.

Sample Preservation: Following collection, the samples were promptly transferred to a cooler maintained at a temperature of 4°C to preserve their integrity. Subsequently, they were stored in a refrigerator until they were ready for analysis in the laboratory. This meticulous sampling and analysis protocol adhered to stringent standards to uphold the quality and reliability of the data obtained, ensuring its suitability for subsequent environmental assessments and decision-making processes.

Field Methods

Water temperature, conductivity, and pH measurements were conducted at each sampling site by students in the Environmental Science Program using a YSI Pro Plus meter. Prior to sampling, calibration procedures were implemented for each sensor using suitable standard solutions, with calibration verification performed to ensure accuracy. In the laboratory, water samples underwent comprehensive analysis to assess various parameters crucial for environmental assessment.

Biochemical Oxygen Demand

The determination of Biochemical Oxygen Demand (BOD) followed the 5-day standard test Method 5210 (Baird et al. 2017). Environmental Science Program at YSU promptly evaluated within a maximum of 24 hours after collection, with a preference for analysis completion within 6 hours post-sampling. In cases of delayed analysis, samples were stored at a controlled temperature of 4°C until examination, with meticulous documentation of any duration surpassing the 6-hour holding period. Each site sample underwent multiple dilutions, typically ranging from three to four, and was augmented with approximately three milliliters of a standard seed solution (PolySeed). Subsequently, containers were filled to their maximum capacity with dilution water comprising phosphate buffer solution, magnesium sulfate solution, calcium chloride solution, and ferric chloride solution, as stipulated in the Standard Method (Baird et al. 2017). Dissolved oxygen (DO) levels were quantified using a YSI 5100 instrument, with measures taken to prevent the presence of air bubbles by inverting the bottle post-measurement and securely stoppering it before sealing with water and capping. Incubation of all samples, including unseeded blanks, seeded blanks, and the 2% glucose-glutamic acid (GGS) standard solution, was carried out for 5 days at a controlled temperature of 20°C. Following the incubation period, samples were retrieved, and dissolved oxygen (DO) levels were reassessed. The BOD5 was subsequently determined using Equation 1.

$$BOD_5 = [(D_1-D_2) -(S_1-S_2)\ f]/\ P \quad \text{Eq.1}$$

D_1 = DO of sample immediately after preparation, mg/l

D_2 = DO of sample after 5day incubation, mg/L

S_1 = DO of seeded control immediately after preparation, mg/L

S_2 = DO of seeded control immediately after preparation, mg/L

f = fraction of seed volume in seeded test water to seeded control

P = volumetric fraction of sample used

In the experimental setting, the change in Dissolved Oxygen (DO) for the unseeded blank remains below 0.3 mg/L. Moreover, for the test environment to be considered valid and to ensure the proper functioning of the seed, the BOD of the Glucose-Glutamic Acid (GGA) solution should be within the range of 198 ± 30.5 mg/L. Adhering to these specifications is essential to maintain the integrity and accuracy of the experimental results.

Solids

Students at Environmental Science Program at YSU determined Total Solids in water, including total suspended solids and total dissolved solids in duplicate following Standard Method 2540 (Baird et al. 2017). To ensure the accuracy and precision of the methodology, standard solutions were periodically analyzed alongside samples. Samples were analyzed within 7 days. For Total Solids (TS), subsamples from each site were measured and transferred into pre-cleaned, dried, and weighed porcelain crucibles. These samples were then subjected to oven drying at 105°C, followed by cooling in a desiccator, and subsequently reweighed to determine the total solids content using equation 2. This process adhered to standardized procedures to accurately quantify the total solids content in the water samples.

$$TS = (M_2 - M_1) / V \quad \text{Eq.2}$$

M_2 = Mass of dried solids and crucible

M_1 = Mass of crucible

V = Volume of sample

Total suspended solids (TSS) were analyzed in duplicate using pre-weighted glass filter papers (Environmental Express ProWeigh). Each water sample underwent filtration based on the solids content, aiming for a dried residue ranging between 2.5 and 200 mg (typically achieved with 100-300 ml of sample). Following filtration, the filter papers were dried at 105°C until completely dry, cooled in a desiccator, and then reweighed. The determination of TSS was conducted using Equation 3.

$TSS = (M_2 - M_1)/V$ Eq.3

M_2 = Mass of filter with residue

M_1 = Mass of filter

V = Volume of sample

Total dissolved solids (TDS) can be determined by subtracting the total suspended solids from the total solids for each water sample (Eq. 4).

$TS - TSS = TDS$ Eq.4

Soluble Reactive Phosphorus

Students at Environmental Science Program at YSU quantified orthophosphate, or Soluble Reactive Phosphorus (SRP) using Standard Method 4500-P (Baird et al. 2017), commonly referred to as the Ascorbic Acid Method (4500-P E.), and consistent with EPA Method 365.2. This analytical procedure necessitated completion within 48 hours of sample collection. Prior to analysis, samples were filtered through a 0.45 µm filter to remove particulate matter. Subsequently, subsamples of each water sample were extracted in duplicate. A combined reagent, comprising 100 ml of 5N H2SO4, 10 ml of potassium antimony tartrate solution, 15 ml of ammonium molybdate solution and 60 mL of ascorbic acid (Baird et al. 2017), was freshly prepared just prior to analysis and remained effective for 4 hours. Calibration standards were meticulously prepared using stock standard solution (RICCA Chemical) to generate a calibration curve extending up to 1 mg/L PO4-P. Additionally, a spike sample was analyzed for every 20 samples to ensure method accuracy and reliability.

For analysis, all standards, spike samples, a blank, and water samples had 4 ml of combined reagent added to each 25 ml of sample. After allowing the samples to sit for 10-15 minutes to produce a blue color, absorbance was measured at 880 nm using a spectrophotometer (GENE SYS 10S VIS). The blank was utilized to zero the spectrophotometer. Absorbance readings were recorded no sooner than 10 minutes after the addition of the combined reagent but before 30 minutes. A standard curve was constructed with concentration on the x-axis and absorbance on the y-axis. The resulting regression equation derived from the standard curve was employed to determine the concentration of soluble reactive phosphorous in the samples.

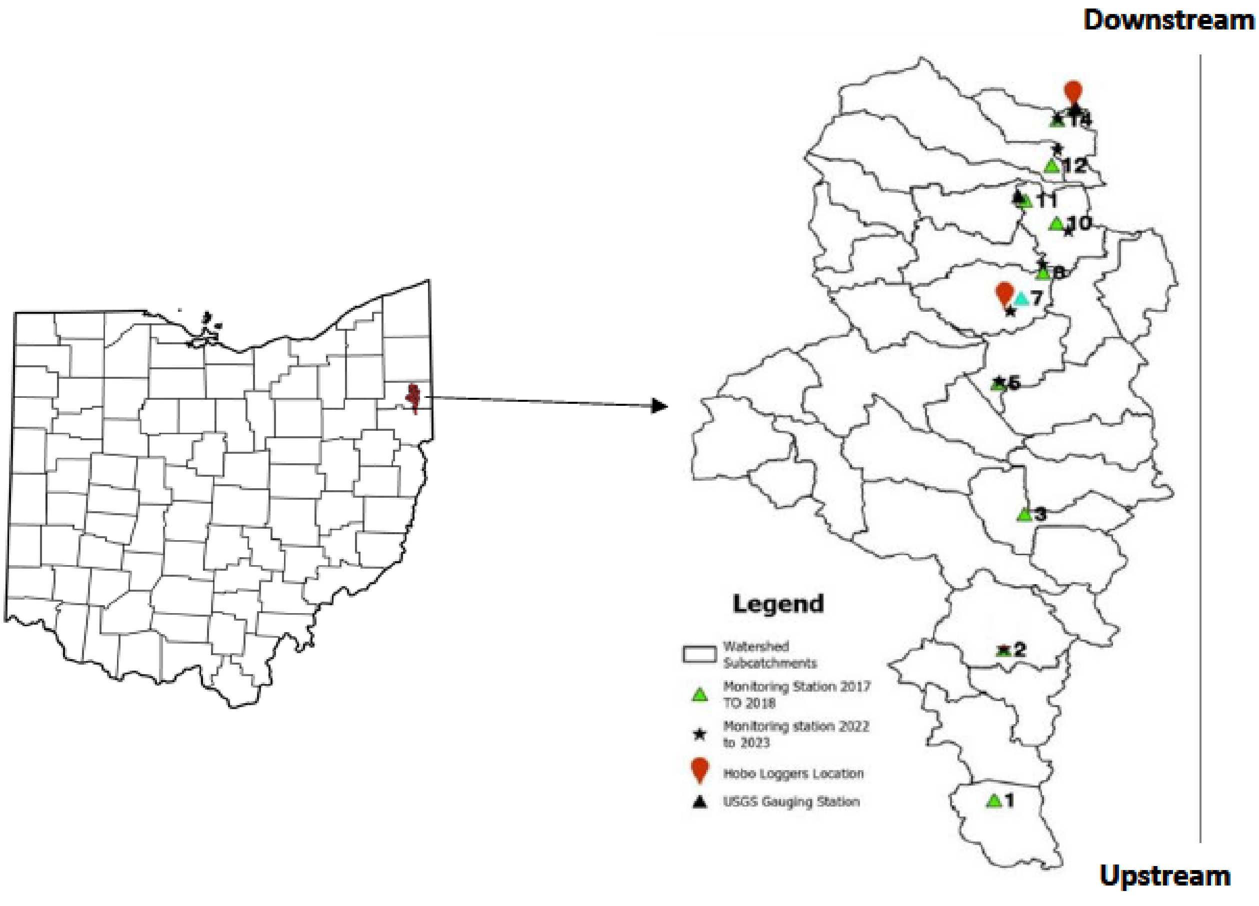
Nitrate

Students at Environmental Science Program at YSU determined Nitrate levels using the cadmium reduction method, specifically Hach method 8192, which is based on Standard Method 4500-NO3. In this method, Hach NitroVer 6 Reagent Powder (cadmium) was added to 15 mL of sample and mixed for 3 minutes, followed by an additional 2 minutes to allow for reaction without mixing. Subsequently, approximately 10 mL of the sample solution was transferred to a clean tube, leaving the cadmium behind. NitroVer 3 reagent was then added to the 10 mL sample and mixed for 30 seconds. The sample was allowed to react for 15 minutes to develop color. Calibration standards were prepared using stock standard solution from RICCA Chemical to establish a calibration curve extending up to 10 mg/L NO3-N. Additionally, a spike sample was analyzed for every 20 samples tested. Absorbance readings were measured for all samples and standards against a blank solution at 543 nm using a spectrophotometer (GENE SYS 10S VIS).

A standard curve was constructed with concentration on the x-axis and absorbance on the y-axis. The resulting regression equation derived from the standard curve was then utilized to determine the concentration of soluble reactive phosphorous in the samples.

QA/QC Protocol

The protocol followed by Environmental Science Program at YSU is briefly explained as follows. Routine evaluations of laboratory reagent blanks and other solutions were conducted as part of an ongoing commitment to quality assurance. Furthermore, matrix spike and spike duplicates (MS/MSD) analyses were performed as needed to affirm the accuracy and precision of the methodology and to monitor potential interferences within the sample matrix. The examination of laboratory blanks aimed to demonstrate the absence of contamination, while the use of laboratory duplicates served to validate results and gauge the precision inherent in the analytical procedures. These duplicates entailed two identical aliquots of the same environmental sample, subjected to identical treatment throughout the laboratory process. Quality control measures were systematically integrated into procedures to validate both the precision and accuracy of results. Such measures included the inclusion of samples with known concentrations, sourced independently from calibration standards, ensuring that the outcomes of these quality control assessments consistently met acceptable standards for precision and accuracy.



(a) (b)

Figure 2. 1 Location of study area (a) map of Ohio (b) map of Mill Creek watershed, consisting of water quality sampling stations, HOBO loggers location, and USGS gauge stations for PCSWMM model development.

Figure 2. 2 Field crew installing the 1st HOBO logger with proper guidelines at the outlet of the watershed.

Figure 2. 3 Second HOBO loggers monitoring site at East Golf Hike trail.

Figure 2. 4 Third HOBO logger monitoring site near Headwaters (Farm)

Figure 2. 5 Real time image of HOBO Logger (ONSET)

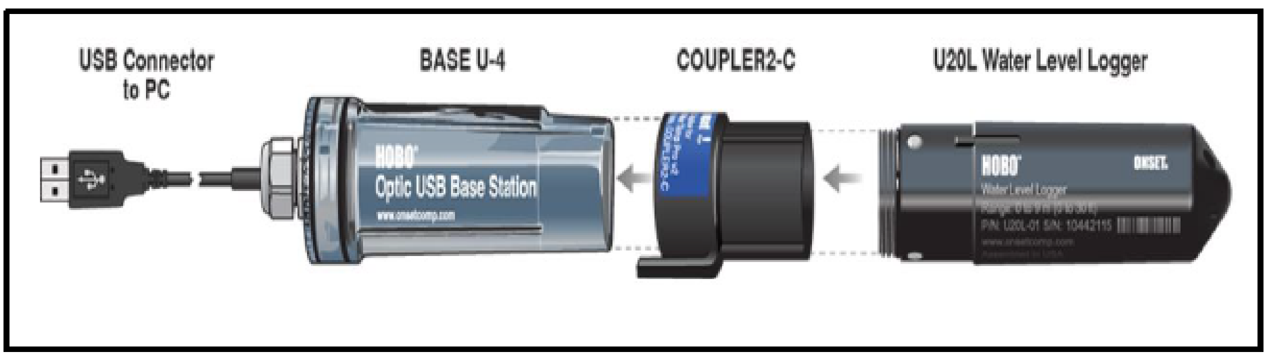


Figure 2. 6 Operational parts of a HOBO logger (source: ONSET)

Figure 2. 7 Collection of water quality samples by the students at Department of Environmental Science Graduates program

Figure 2. 8 Water quality analysis at YSU Environmental lab

Chapter 3. Evaluating the PCSWMM Model to Simulate the Flow and Nutrient in the Large Watershed Characterized with Mixed Land Use and Limited Datasets

Introduction

Water quality problems in rivers and streams have become a critical issue across the world over the past few decades due to the contamination of sediments (Dressel et al. 2014), nutrients (Burkartaus et al. 2008; Dressel, 2014; Lintern et al. 2020), and pesticides, (Carpenter et al. 1998; Dowd et al. 2008)from both point and non-point sources of pollution (Burkartaus et al. 2008; Rousseau et al. 2012). Non-point source pollution from agricultural land, industrial waste and urbanized area carries the pollutants and deposit into the rivers and streams (Ongley et al. 2010; Wu et al. 2013; Zhang et al. 2008) impacting the water quality of receiving waters and leading to adverse effects on aquatic life (Maillard et al. 2008). In addition, point sources of pollution can also significantly degrade water quality (Carey et al. 2009; Migliaccio et al. 2007; Popova et al. 2006). The stream water quality is sensitive to various anthropogenic activities (Hamid et al. 2020; Ramírez et al. 2014).and depends upon different geographical Locations (Ahearn et al. 2005; Sharma et al. 2016),. For instance, agricultural practices like livestock farming and using artificial fertilizers can lead to eutrophication in nearby water bodies (Hooda et al. 2000). While point source pollution have been extensively regulated to minimize the nutrient loadings in the streams, nonpoint source pollution has emerged as a significant and challenging contributor to waterway contamination, with agriculture notably standing out as the largest and most complex contributor (Ongley et al. 2010; Segerson et al. 1988; Shen et al. 2012). The non-point source pollution has been affected by number of factors such as physical and chemical characteristics of the watershed, amounts of pollutants, land use, soil types (Shen et al. 2013; Wu et al. 2016), basin slope (Wang et al. 2016), vegetation of the catchment (Journal et al. 1997), rainfall intensity and duration

(Egodawatta et al. 2007), and antecedent dry days (Hu and Huang, 2014). As a result, several watershed models have been used to calibrate and validate the large mixed land-use watershed, such as HEC-HMS (USACE 2024), SWAT (Srinivasan et al. 2010), LSPC (S. Sharma et al. 2015), and HSPF (Yan et al. 2014). One of the major challenges in hydrologic and water quality modeling is the lack of enough data for adequate model calibration and validation. For example, in order to develop a robust watershed model, the calibration of both hydrologic and water quality component of the model is critical which generally relies on the availability of continuous long Streamflow data. However, in many cases, hydrologists have to deal with a lack of data in modeling investigations. For example, continuous flow data especially for ungauged watersheds are not available, posing a challenge to model development and analysis (Perrin et al. 2007). Occasionally, the location of interest may include one or two gauging stations with sporadic streamflow records that can be used to calibrate model parameters. However, modelers usually have trouble with ungauged basins where streamflow measurements are not easily accessible (Sivapalan, 2003). In these circumstances, the model cannot be calibrated and is exceedingly challenging to use (Sivapalan, 2003; Sivapalan et al. 2003) for decision making. In such situations, alternative methods, such as using HOBO loggers, can be employed to gather data and bridge the data gap, enhancing the accuracy of hydrological models (Ertezaei et al. 2017). Therefore, to overcome the data scarcity, this study seeks to introduce an innovative approach to depth data collection and collects water quality samples, a methodology which is further substantiated by the calibration and validation of the model against observed data. Majority of the watershed models listed above relies on hydrologic component for model calibration and does not offer any hydraulic model calibration. On the other hand, for hydrologic calibration, the rating curve should be developed besides the continuous measurement of stage data. In order to overcome this issue, the Storm Water

Management Model (SWMM) which can utilize the flow depth data for hydraulic calibration was used in this study. Although this model has shown great efficacy in simulating urban and suburban watersheds, its efficiency in a large heterogeneous watershed has not been extensively assessed (Moynihan et al. 2014).

The main objectives of this study were to perform strategic hydrologic/hydraulic and water quality calibration, and rigorous model validation to investigate the critical source of pollutants. More importantly, vast majority of the earlier studies using the PCSWMM model have been limited to smaller catchments and mainly in urbanized watersheds. We investigated the model's performance in larger catchments where hydrologic data were unavailable with the intention of finding the critical sources of nutrients and applying BMPs in the future for pollutant reduction in the stream.

Theoretical Description

Personal Computer Storm Water Management Model (PCSWMM)

The Storm Water Management Model was developed by the United States Environmental Protection Agency (US EPA) in 1971. It functions as a rainfall-runoff model that accurately simulates the quantity and quality of runoff from both single events and continuous simulations. This model is applicable to both urban and rural environments (James et al. 2010; Talbot et al. 2016). SWMM is a decentralized discrete time simulation model which calculates updated values of its state variables throughout a series of time intervals, with each interval including a different set of external inputs as shown in Figure 3.1. As the state variables are updated, additional output variables of relevance are calculated and provided (Rossman 2010).

Despite the model's many benefits and applications, it possesses no spatial interface. In 1984, a commercially available improved version called the PCSWMM with a Geographic

Information System (GIS) interface was developed to provide a diverse range of applications. (Akhter et al. 2016). It offers a flexible and comprehensive solution for analyzing rainfall-runoff dynamics in both one-dimensional and two-dimensional scenarios (Akhter et al. 2016). PCSWMM enables the simulation of water movement through channels and overland flow (Rai et al. 2017; Talbot et al. 2016). It is reported that in addition to the urban catchments, PCSWMM is equally applicable for modeling natural watersheds (Jang et al. 2007; Rai et al. 2017) which performs comprehensive hydrological analysis on catchments (Rossman et al. 2015) by incorporating precipitation, runoff, and pollutant hydrographs, along with crucial factors like evapotranspiration, infiltration, and groundwater percolation in its calculations (Figure 3.2). SWMM utilizes many specialized objects and techniques to represent water quality. SWMM offers considerable versatility and is capable of simulating a variety of buildup and wash off processes (James et al. 2010). These processes are governed by buildup equations, which incorporate power, saturation, and exponential components, as well as wash off equations, such as event mean concentration, exponential, and rating curve equations. (Rossman 2010). These Buildup, wash off and EMC equations are illustrated by Equation 3.1, 3.2, and 3.3 respectively.

$$B = C_1(1 - e^{-C_2 t}) \tag{3.1}$$

Where C_1 = maximum buildup possible (mass per unit of area or curb length) and C_2=build up rate constant(1/days).

$$\mathrm{W} = \mathrm{C_1} * \mathrm{q}^{\mathrm{C_2}} * \mathrm{B} \tag{3.2}$$

Where W = wash off parameter, C_1 = wash off coefficient, C_2 = wash off exponent, q = runoff rate per unit area (inches/hour or mm/hour), and B = pollutant buildup in mass units.

$$\mathrm{EMC} = \frac{M}{V} \tag{3.3}$$

Where M is total mass of pollutant during the entire runoff, and V is total volume of runoff.

Materials and Methods

Study Area

The detailed study area has already been discussed in Chapter 2.

Watershed model Configuration with input data

The PCSWMM model was applied to simulate the entire hydrologic process. The modeling of stream flows requires several inputs such as land use, soil data, digital elevation model (DEM), meteorological data (as shown in Table 3.1), and site assessments for the streams cross sections, wherever required. In order to depict the geographical features of the sites with precision, we obtained high-resolution digital elevation models (DEM) with a resolution of 10 meters from the USGS National Elevation Dataset (NED). These models are in raster format and include detailed information of the topography, including slope gradient, stream networks, and slope length. The DEM datasets were employed to delineate the watershed into 36 sub-basins through the PCSWMM automated watershed delineation tool. To precisely capture the existing land use characteristics of the watershed, the study utilized data from the National Land Cover Database (NLCD) to document the current land use features of the watershed with a high degree of accuracy. In conjunction, soil plays an important role in hydrological processes. Therefore, high-resolution soil data sourced from the Soil Survey Geographic Database (SSURGO) was employed within ArcGIS Pro to compute the essential Curve Number and percentage imperviousness, which significantly impacts the determination of infiltration abstractions. The Curve Number infiltration model is widely accepted as an effective methodology for computing infiltration abstractions, with its accuracy influenced by soil properties and land use types (SCS 1964; SCS 1972)

The climate data including precipitation data was sourced from the National Oceanic and Atmospheric Administration (NOAA) for station (USW00014852), while streamflow data from two USGS gauging stations were seamlessly integrated into the model. Furthermore, deploying a strategic approach, three HOBO loggers were strategically positioned to gather daily depth data, enabling comprehensive multi-site calibration and validation of the model. Water samples were also collected from designated stations using the grab sampling method and sent to the laboratory for water quality analysis which was further used for water quality calibration and validation.

Hydraulic Model Configuration

The representation of Mill Creek and its tributaries downstream included the use of several cross sections that were determined based on the geometric characteristics of the stream network over the whole watershed. The hydraulic model comprises of a primary branch, 20.9-mile Creek, and seven tributaries, namely Bears Den Run, Ax Factory Run, Andersons Run, Cranberry Run, Indian Run, Sawmill Run, and Turkey Run. The data used to create the hydrodynamic model includes cross-sectional information for river segments at various places, as well as measured depth data and observed flows from USGS for the purpose of model calibration. The water depth of the stream was acquired by deploying HOBO loggers at three distinct locations throughout the whole watershed. Additionally, the cross-sectional data was retrieved from the 10m Digital Elevation Model (DEM) sourced from the USGS National Elevation Dataset (NED) in raster format. The river cross-section was further verified from the FEMA HEC-2 flood-forecast studies, HEC-RAS modelling, and site surveying. Channel slope was further cross validated from the watershed delineation in Arc GIS 9.2. The manning's roughness for the channel was adopted 0.03 from various research studies (Table 3.2). Meanwhile, the hydrodynamic model necessitates the specification of both the downstream initial condition and boundary condition. Due to the unavailability of observed downstream water level data, we deployed HOBO loggers to gather depth data and use it as the downstream boundary condition. Additionally, this observed depth data was used for the hydraulic calibration and validation of the model.

Model Calibration and Validation

The PCSWMM model was set up for the period of 1999 to 2000 and ran on a daily time scale after an initial 6-month warm period. Six months of daily observed flow data from 1/1/2000 to 6/10/2000 at two USGS gauging stations within the watershed were used for the model calibration. The PCSWMM sensitivity-based radio-tuned calibration (SRTC) calibration tool was used to identify the most sensitive parameters for hydrologic simulation (Talbot et al. 2016). In addition, a manual calibration was performed after the automatic calibration to precisely adjust the model parameters. (Choi et al.2002) stated that during the calibration process, the measured parameters are thought to be free from errors, but the inferred values need some adjustments. As a result, during the calibration process, inferred parameters such as depression storage, percentage of impervious infiltration parameters, channel and catchment's roughness, and pervious area, were corrected according to the data tabulated in Table 3.2.

The subsequent step involved evaluating the refined model parameters using the historical daily streamflow data spanning two decades from 1952 to 1972 at the USGS site, as documented in Table 3.6, for the purpose of validation. In addition to that, the model was also calibrated and validated by the observed hydraulic depth data ranging from May to December 2023 as shown in Figure 3.5 and Figure 3.6 respectively.

Model Evaluation Measures

The PCSWMM model's performance was determined using statistics measures including Nash - Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), Percentage Bias (PBIAS). The equations (3.4) through (3.6) mathematically express these indications.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i obs - Y_i sim)^2}{\sum_{i=1}^{n}(Y_i obs - Ymean)^2}\right] \tag{3.4}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(Y_i obs - Y_{obs}mean)(Y_i sim - Y_{sim}mean)}{\left[\sum_{i=1}^{n}(Y_i obs - Y_{obs}mean)^2 \sum_{i=1}^{n}(Y_i sim - Y_{sim}mean)^2\right]^{0.5}}\right) \tag{3.5}$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(Y_i obs - Y_i sim) \times 100}{\sum_{i=1}^{n}(Y_i obs)}\right] \tag{3.6}$$

In these equations, "n" represents the total number of observations, whereas (Y_i obs) and (Y_i sim) refer to the ith values of observed and simulated flows, respectively. (Y_{obs}) refers to the mean of observed flows, whereas (Y_{sim}) refers to the mean of simulated flows.

The model performance is tested by utilizing the NSE parameter whose value ranges from ∞ to 1. A value of 0.5 to 1 is considered good fit for the model as described by (Moriasi et al. 1983). The association between the simulated and observed data is quantified by the coefficient of determination (R^2), which ranges from 0 to 1. A number closer to 1 indicates a strong and positive relationship between the two datasets. PBIAS indicates the relative magnitude of the simulated data compared to the observed data. Simulations with a PBIAS value of 0 exhibit a perfect match with the real data, whereas those with a positive or negative value result in an underestimation or overestimation of the model.

Hydrologic and Water Quality Monitoring

Discussed in detail in chapter 2.

Water Quality Calibration

There are numerous techniques for the estimation of stormwater quality and predicting pollutant loads which employ the build-up and wash-off parameters generated by specific land use patterns (Heineman et al., 2013). The efficiency of this approach relies on the modeling objective and the data inputs available, which offer information on the accumulation of pollutants on the ground surface during dry conditions and their wash off during wet conditions (Charbeneau et al. 1998). PCSWMM simulates the buildup process using exponential functions, power functions, and saturation equations. In contrast, the wash off process is approximated using the Event Mean Concentration, exponential function, or rating curve equations (Rossman and Huber, 2016). The Buildup and wash-off equations consists of multiple parameters that are challenging to calibrate which requires different parameter values for various pollutants and study areas, which is not easily available. However, the average EMCs values for different pollutants and different land uses is easily accessible. For effective calibration and validation of the model, and for efficient modeling, simpler data-driven modeling techniques were adopted by utilizing the Event Mean Concentration (Gaume et al. 1998; Niazi et al. 2017). This method considers that the concentrations of pollutants in the runoff remain consistent throughout an event (Charbeneau et al. 1998) and eliminates the need for a buildup parameter (Rossman et al. 2016). Using the average EMC throughout the simulation of multiple events may provide similarly accurate estimates of total pollutant loads, similar to those obtained by process-based accumulation and wash-off approaches (Charbeneau et al. 1998). Therefore, in this study, instead of buildup function (Rossman et al. 2010), the EMC wash-off function was selected for water quality simulations in SWMM. Thus, the water quality simulations simply need the land cover type's unique EMC values as parameter inputs. The pollutants that were examined were total suspended solids (TSS), soluble phosphorus, nitrate, dissolved oxygen (DO), and biochemical oxygen demand (BOD_5). In the absence of local guideline values for EMC, a comprehensive assessment of relevant literature was conducted to establish potential values. The findings from such literature review are shown in Table 3.3.

Results & Discussions

Hydraulic and Hydrologic Model Calibration

The PCSWMM model demonstrated satisfactory performance in both the calibration and validation phases, which was evaluated using statistical parameters, such as NSE and R^2 as outlined in Table 3.5. Additionally, the model's performance was visually inspected by comparing the time series of simulated and observed data as illustrated in Figure 3.3. and Figure 3.4. The hydrologic calibration statistics, specifically NSE fell within the range of 0.51 to 0.53 and R^2 values fell within the range 0.71 to 0.72. Subsequent validation of the model involved historical streamflow data, yielding NSE values ranging from 0.43 to 0.89 and R^2 values spanning from 0.51 to 0.97, as tabulated in Table 3.6. On the other hand, three strategic locations were selected for the placement of HOBO loggers, tactically covering the entire watershed from upstream and, in close proximity to the outlet of the watershed at the downstream as shown in Figure 2.1. The hydraulic model calibration using the recently collected data from May to August 2023 was satisfactory at the two monitoring stations, as depicted in Figure 3.5. One of the reasons the model calibration was good in this station was because the location of the monitoring stations were relatively located in close proximity to the rain gauging Station. In contrast, the model performance in the upstream station which was relatively near the headwater stream (Figure 2.1), was not as good as other stations which is evident in the graphical representation of the simulated versus observed depth in Figure 3.5. It was not surprising as there was a rain gauge station which was located to the far downstream which was not truly representative of the actual rainfall. Subsequently, the hydraulic model validation was also conducted using recently collected data from September to December 2023, illustrated in Figure 3.6.

The comprehensive assessment of the model's performance indicated satisfactory results downstream of the watershed. However, a notable disparity was observed leading to the relatively unsatisfactory performance during hydraulic validation. As mentioned earlier, this discrepancy could be attributed to the substantial distance between the rain gauge and the upstream of the watershed which is 27 miles introducing spatial variability that adversely impacted the model's hydraulic calibration and validation. Moreover, the varying cross section of the Mill Creek stream and its tributaries posed challenges in obtaining detailed cross-sections, further complicating the calibration process. The intricacies associated with cross-sectional data significantly influenced the calibration outcomes of the model, highlighting the importance of meticulous consideration in such hydrological modeling efforts.

Water Quality Calibration

The performance of the water quality calibration and validation was assessed through the graphical representation of observed and simulated nutrient flow through visual inspection for eight different monitoring stations as shown in Figure 3.8. The collection of water quality samples was sporadic and clustered, occurring mostly during certain storm events. As a result, there was a scarcity of observed data available for the calibration procedure. During the water quality assessment of the model, a wash off parameter called event mean concentration (EMC) was selected for the whole simulation period. This parameter was chosen based on the documented value from past studies, which is listed in Table 3.3. Water quality data from the period between 2022 and 2023 was selected for calibration, while data from 2017 and 2018 were chosen for validation purposes. However, the water quality calibration of a single water quality monitoring site is presented in Figure 3.8, and the rest of the calibration results at various stations are presented in the Appendix section (Figure 4.1 to Figure 4.3).

The nutrient calibration exhibited satisfactory results at the downstream of the watershed for BOD_5, DO, TSS, Soluble phosphorus, and Nitrate (Figure 3.8). The water quality calibration assessment conducted at the start of the watershed yielded unsatisfactory outcomes, primarily attributable to the insufficient availability of sporadic nutrient data. Furthermore, a limited portion of these datasets were incorporated into the simulated datasets. The water quality calibration results were considerably affected in the upstream part of the watershed primarily because of the rain gauge being positioned outside the watershed boundary. It is noteworthy to report that water quality simulation relies on the hydrologic model performance. The hydrologic/hydraulic model performance at those particular stations was affected due to remotely located rain gauge station. The distance between the rain gauge and the farthest point in the watershed was approximately 27 miles (44,467.52m). However, it was in close proximity to the downstream part of the watershed which was 10.9 miles (17524.28m), which revealed the notably improved calibration results at the downstream of the watershed when compared with the observed upstream results.

For the simulation of pollutants, a detailed sub catchment discretization is crucial. In stormwater modeling, catchments are often categorized in accordance with land use classifications, which generally consist of residential, agricultural, commercial, industrial and forested areas. It is critical to discretize the model into very fine land use to adequately capture pollutant loading from various land use for the better model simulations. Different land use category generates different EMCs values (Butcher et al. 2003; Charbeneau et al.1998). While the use of these EMCs to model stormwater quality is a common approach, there are a lot of unknowns when modeling pollution loads with EMCs, especially when there aren't enough local data for calibration (Tuomela et al.

2019). This technique relies on concentration values found in literature and does not need substantial monitoring or parameter calibration. Since the watershed is significantly large, a comprehensive model discretization using land cover is essential to adequately divide catchment into the number of sub catchments to thoroughly represent the various land use characteristics in the model (Tuomela et al. 2019). This generally demands higher levels of effort compared to a typical and less detailed model discretization. Therefore, I discretized the study area into three land use category such as residential, agricultural, and forested, and assigned them different EMCs values from the past studies as shown in Figure 3.7. The stormwater pollutant load modeling using these literature-derived EMCs resulted in significantly fluctuating loads at some of the locations in the watershed (Figure 3.8 and Figure 3.9). The reason for this disparity is attributed due to the absence of local data for the EMCs in the source location. The simulations using alternative EMC values (Table 3.3) resulted in significant variability in the loading of soluble phosphorus at some monitoring locations (Figure 3.8). The forested area exhibited the highest concentration of TSS, resulting in the erosion and runoff of sediments due to the occurrence of heavy rainfall. During the water quality investigation, data from all the tributaries were collected and examined for parameters such as BOD5, TSS, DO, soluble phosphorus, and nitrate. The highest concentration of soluble phosphorus (3474 μg/l) was observed upstream near the first monitoring location, likely due to the presence of cattle manure or commercial fertilizer. This area is surrounded by agricultural land use. Conversely, the lowest concentration (9.44 μg/l) was found downstream near monitoring station number14. The concentration of dissolved oxygen was found to be consistent throughout all monitoring points along the stream, as shown in Figure 3.10. The Nitrate concentration was found to be elevated at just two monitoring sites in compared to the other sites, as shown in Figure 3.10.

In order to conduct comprehensive water quality analysis, we examined simulated nutrient concentrations against observed values for TSS, BOD5, DO, soluble phosphorus, and nitrate, particularly for high-intensity rainfall events (P > 0.5 inches). Overall, the model performed well in replicating mean nutrient concentrations across stations, with some discrepancies observed at a few locations. For TSS, the box plot analysis revealed that mean concentrations of simulated and observed data fell within a specific range, as depicted in Figure 3.10. Additionally, the simulated and observed DO concentrations were consistently in the similar range between 8 to 10 mg/l (Figure 3.11). Similarly, BOD simulated concentration through the model replicated the observed BOD concentration (Figure 3.12). In general, the minimum observed value was 0.44mg/l and maximum BOD were and 10.18 mg/l which is high for freshwater body.

Nitrate concentrations also demonstrated satisfactory agreement between simulated and observed values (Figure 3.13). However, soluble phosphorus concentrations exhibited poor performance at some stations (Figure 3.14) as it was crucial to calibrate the PCSWMM model for soluble phosphorus concentration. In summary, our analysis demonstrated that the model sufficiently captured mean concentration trends, as illustrated in Figures 3.10 through 3.14.

Conclusion and Recommendations

This extensive research was conducted in the Mill Creek watershed, which is a part of the larger Mahoning River Basin. The primary aim was to calibrate and validate a hydraulic and hydrological model using the PCSWMM modeling. For the calibration of the model, observed data is essential to verify against the simulated data, such as streamflow and water depth. However, due to the scarcity of hydraulic data, this study employed a new approach for the collection of primary field data, including precise water level measurements with the aid of HOBO loggers and the systematic assessment of the creek's cross-section, which was critical for fine-tuning the model's hydraulic parameters. Additionally, we relied on the invaluable streamflow data from two strategically placed USGS Gauging stations which helped us in the hydrologic calibration of the model. For further validation, the model was run for the historical events ranging from 1952 to 1972, and it was found that the model performed very well during high-volume rain events yielding good results. The model didn't perform well during periods of low rainfall events, potentially due to the rain gauge being located outside the watershed. The nearest monitoring station was located 10.9 miles (17524.28m), while the farthest monitoring station was 23.28 miles (37,469m) away from the rain gauge. The significance of accurately placing the rain gauge inside the watershed is emphasized for proper calibration of the model.

For the calibration process, PCSWMM uses a tool called SRTC. This tool helped us adjust the settings in the model to account for uncertainties in certain parameters. It does this by running the model at the high and low ends of these uncertainties. After the model simulation, the most sensitive parameter found out was the sub-catchments percentage imperviousness followed by Manning's perviousness and imperviousness. It was observed that the Manning's roughness value for open channel doesn't have a great influence on the calibration of the model. We used sliders to fine-tune the other individual parameters within the specified uncertainty range also and found out that they were insensitive for the calibration of the model.

For the water quality calibration, multiple sites within the watersheds were monitored to record a range of water quality parameters across numerous events. The site selection was based on comprehensive engagement with stakeholders to gather data and get their input on the current land use practices and agricultural trends. The water quality samples was collected, analyzed, and calibrated for TSS, BOD_5, DO, soluble phosphorus and nitrate at various monitoring locations of the watershed. In this study, the water quality calibration and validation was not as good as compared to the hydrological model calibration due to the limited datasets. The stormwater pollutant load modeling using literature-derived EMCs resulted in significantly fluctuating loads, both at the watershed level and for each land cover type. The simulated loads at times underestimated when compared to the measured values. The reason for this underestimate might be attributed to the EMC values in the literature that did not correlate with the unique regional conditions. Estimating pollutant loads using EMCs is likely to have substantial errors, particularly when there is insufficient local data available for calibration and validation of the model. However, the use of EMCs for modeling remains the prevailing method employed by experts and regarded as feasible in the absence of other data sources. Moreover, our study extended to the critical task of identifying the poor water quality sites within the watershed at various locations in the stream. The Monitoring sites were selected in such a way that they can cover the whole watershed from upstream to downstream. The assessment of stream quality revealed that the uppermost portion of the watershed experienced higher levels of soluble phosphorus, which is surrounded by the agricultural land use, whereas its concentrations were notably reduced closer to the downstream of the watershed which is mostly urbanized. In contrast, the research revealed elevated concentrations of TSS and nitrate in the immediate vicinity downstream of the watershed which is covered by the urban land use. It was noticed that the content of DO was constantly maintained within a same range across the whole length of the stream.

Despite certain uncertainties, it is essential to participate in stormwater pollution modeling and collect data on the contributions from local source areas. Further investigation is required in the future to accurately define the typical levels of pollutants in specific local weather circumstances and to get a deeper understanding of the mechanisms that influence the movement of pollutants across various interconnected land cover types. However, to enhance its calibration accuracy in such conditions, it is crucial to gather more local data that will ultimately increase our confidence in the software's ability to simulate. This developed model is anticipated to be beneficial for the stakeholders, particularly the ABC storm water district and CT consultants in the future. The model could be used to identify the critical sources of pollution and take appropriate actions by applying effective Best Management Practices in the future.

This study aimed to investigate the use of PCSWMM model in a wide mixed land use watershed, despite its previous usage being limited to urban storm water modelling. The model was able to capture the spatial and temporal variability of the stream's water quality for its most part. It was experienced that the hydraulic modeling in PCSWMM, particularly for the headwater stream, was quite challenging. The model exhibited commendable performance regarding hydrologic and water quality considerations at the upstream of the watershed. However, the discrepancy in the downstream modeling results may be attributed to the non-availability of rainfall gauging stations within the reasonable proximity. It was observed that the farthest point of watershed was approximately 24 miles from the rain gauge, causing spatial variability. Therefore, it is advisable to designate a rain gauge inside the watershed for appropriate modeling.

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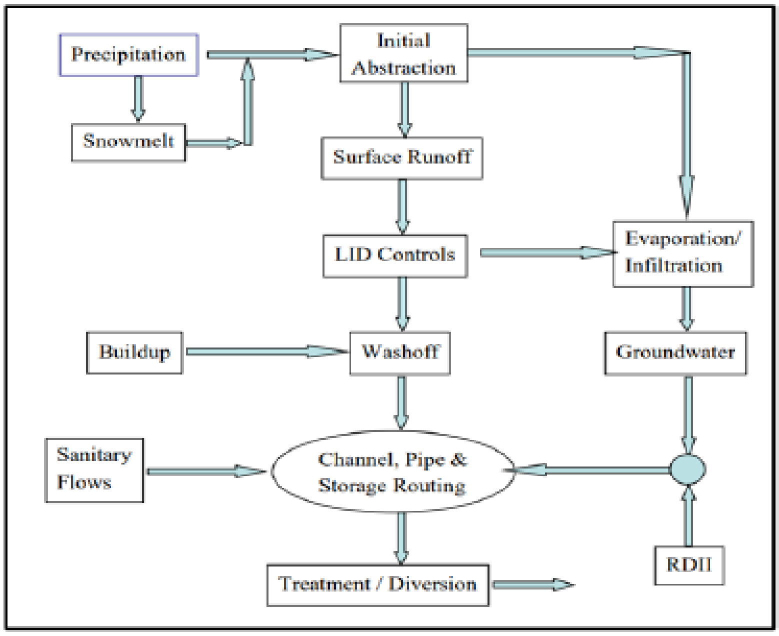


Figure 3. 1 SWMM modeling process (Source: SWMM User Manual 2016)

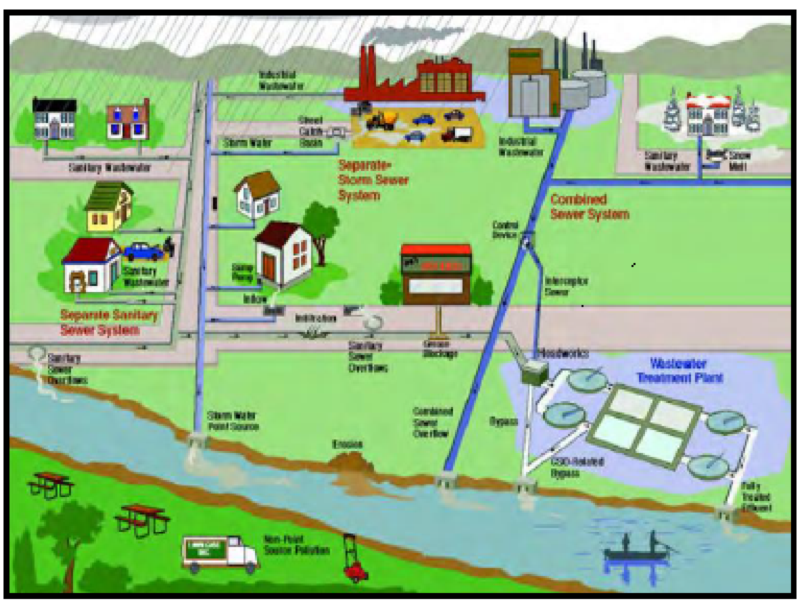
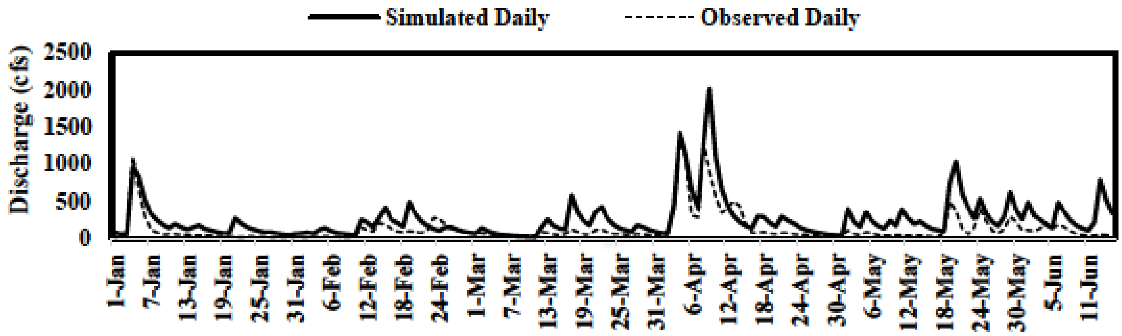
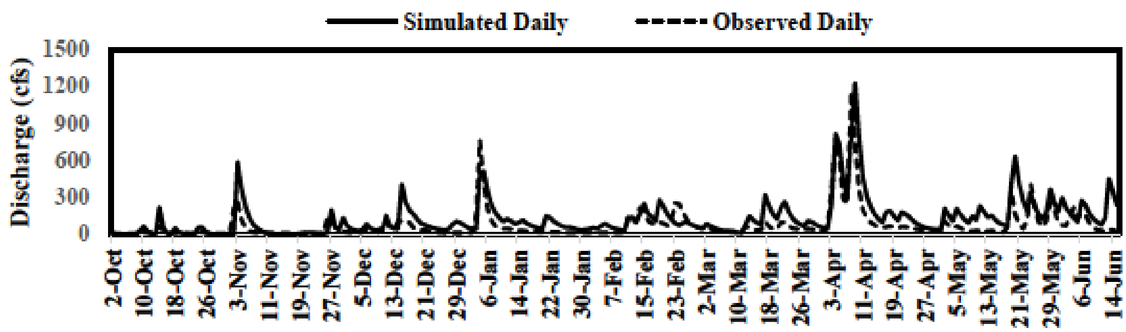


Figure 3. 2 Hydrological process in a watershed (Source: SWMM USER MANUAL)

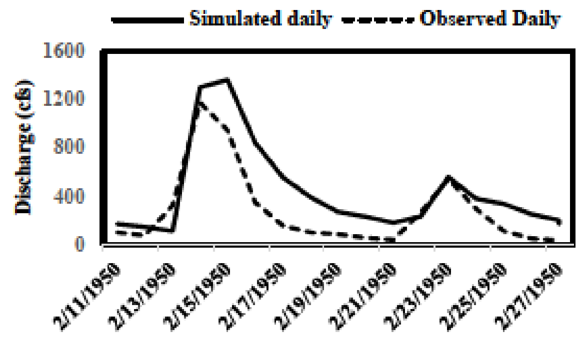


(a)

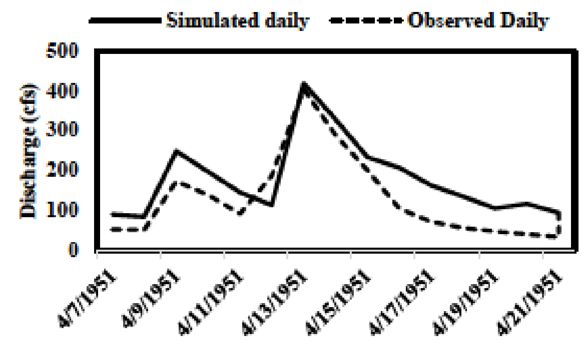


(b)

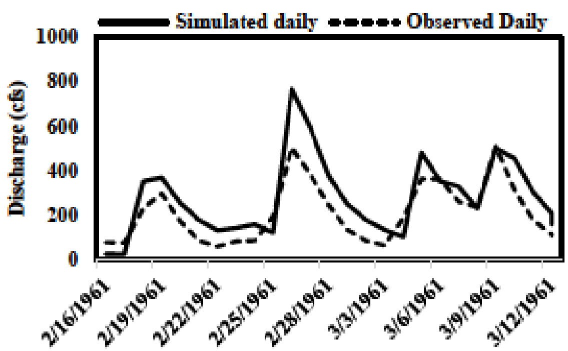
Figure 3. 3 PCSWMM model streamflow calibration (1999-2000) at 2 USGS gauge stations (a) USGS gauge 03098513 (Outlet), and (b) USGS gauge 03098500


Simulated daily
Observed Daily
Discharge (cfs)
1600
1200
800
400
0
2/11/1950
2/13/1950
2/15/1950
2/17/1950
2/19/1950
2/21/1950
2/23/1950
2/25/1950
2/27/1950

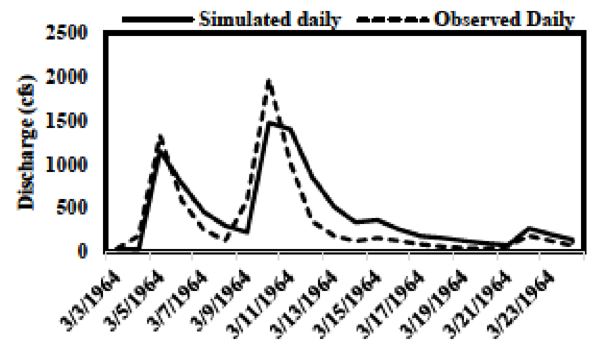
(a)


Simulated daily
Observed Daily
Discharge (cfs)
500
400
300
200
100
0
4/7/1951
4/9/1951
4/11/1951
4/13/1951
4/15/1951
4/17/1951
4/19/1951
4/21/1951

(b)


Simulated daily
Observed Daily
Discharge (cfs)
1000
800
600
400
200
0
2/16/1961
2/19/1961
2/22/1961
2/25/1961
2/28/1961
3/3/1961
3/6/1961
3/9/1961
3/12/1961

(c)


Simulated daily
Observed Daily
Discharge (cfs)
2500
2000
1500
1000
500
0
3/3/1964
3/5/1964
3/7/1964
3/9/1964
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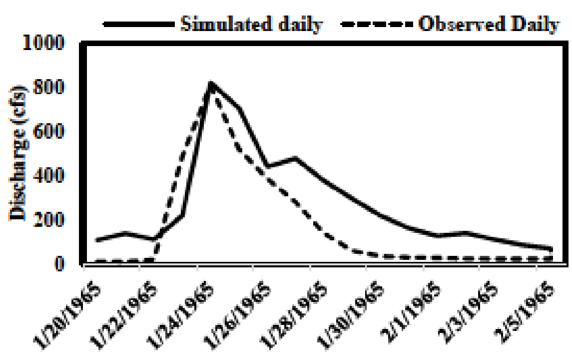
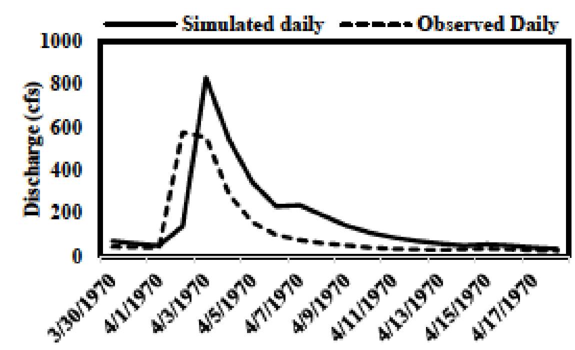
3/13/1964
3/15/1964
3/17/1964
3/19/1964
3/21/1964
3/23/1964

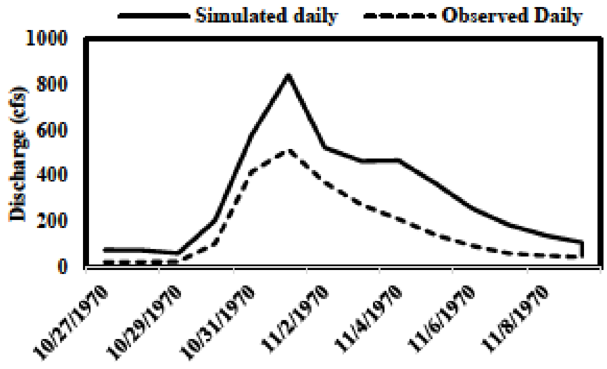
(d)


Simulated daily
Observed Daily
Discharge (cfs)
1000
800
600
400
200
0
1/20/1965
1/22/1965
1/24/1965
1/26/1965
1/28/1965
1/30/1965
2/1/1965
2/3/1965
2/5/1965

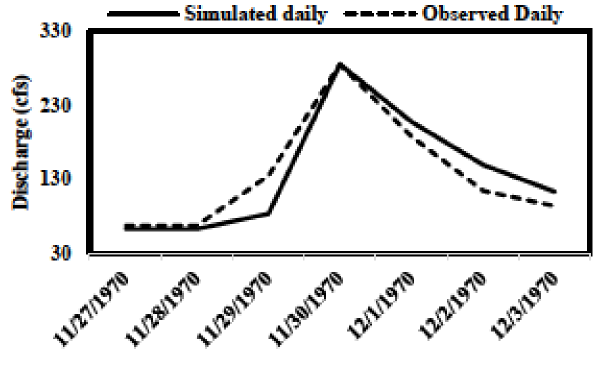
(e)


Simulated daily
Observed Daily
Discharge (cfs)
1000
800
600
400
200
0
3/30/1970
4/1/1970
4/3/1970
4/5/1970
4/7/1970
4/9/1970
4/11/1970
4/13/1970
4/15/1970
4/17/1970

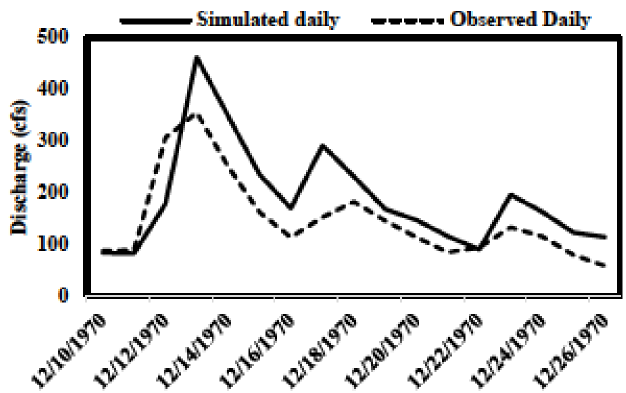
(f)



(g)

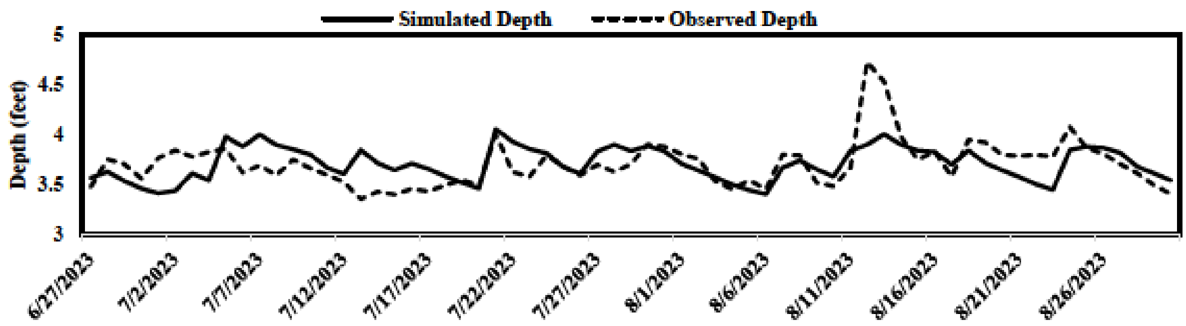


(h)

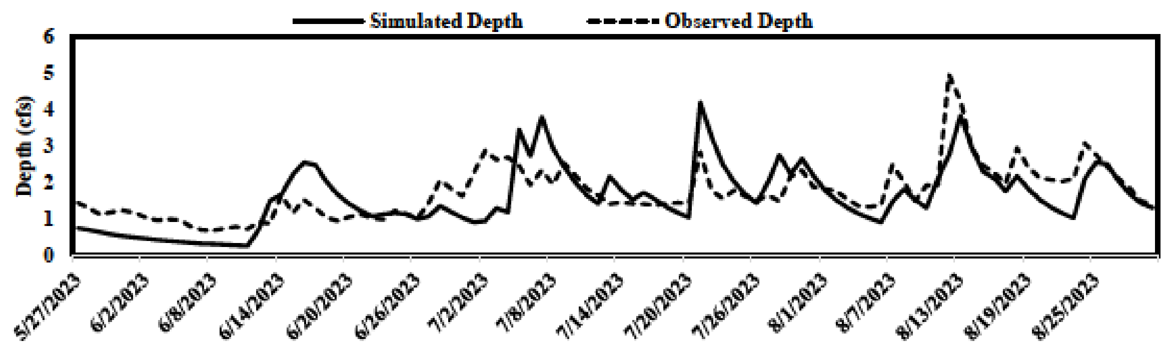


(i)

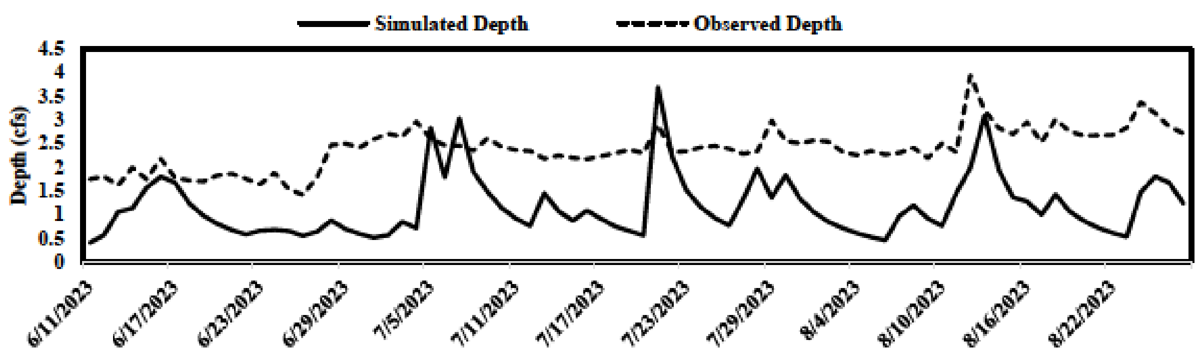
Figure 3. 4 PCSWMM model streamflow validation (1950-1970) at USGS gauge 03098500 from(a) 2/11/1950 to 2/27/1950 to (i) 12/10/1970 to 12/26/1970



(a)

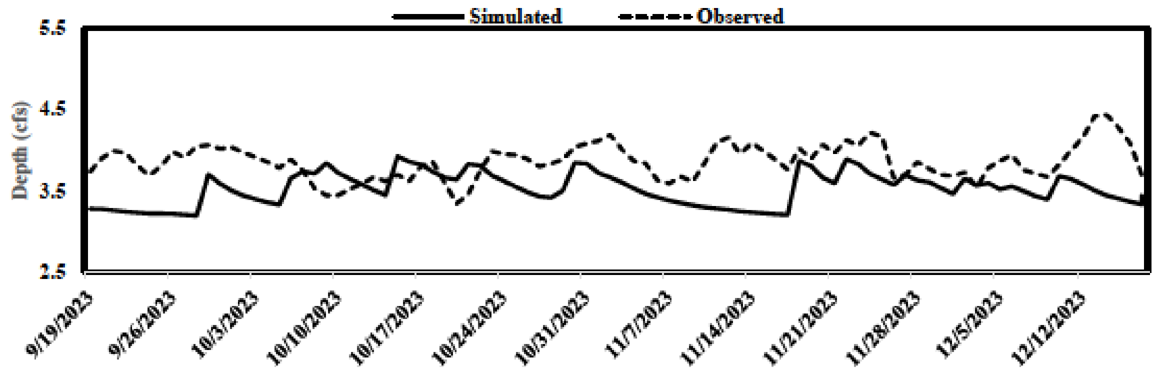


(b)

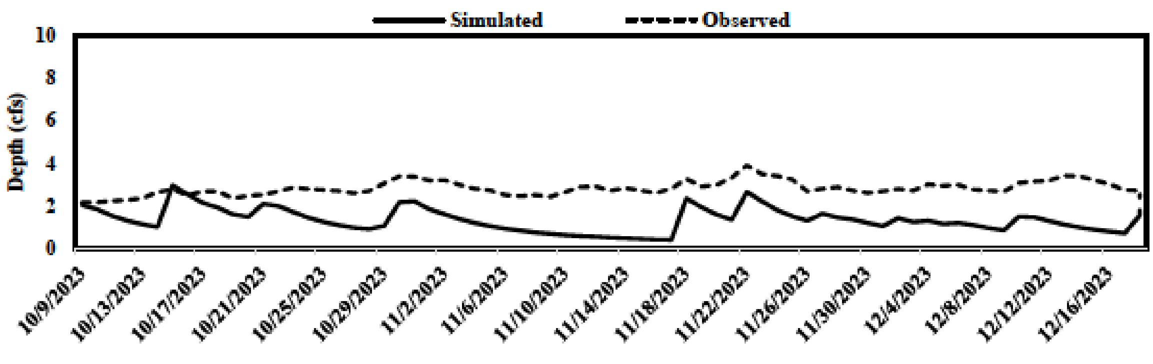


(c)

Figure 3. 5 PCSWMM model streamflow depth calibration (a) Station 1 at the outlet of the watershed (b) Station 2 located at the East Golf hike trail and (c) Station 3 located at the Renkenberger Road.



(a)



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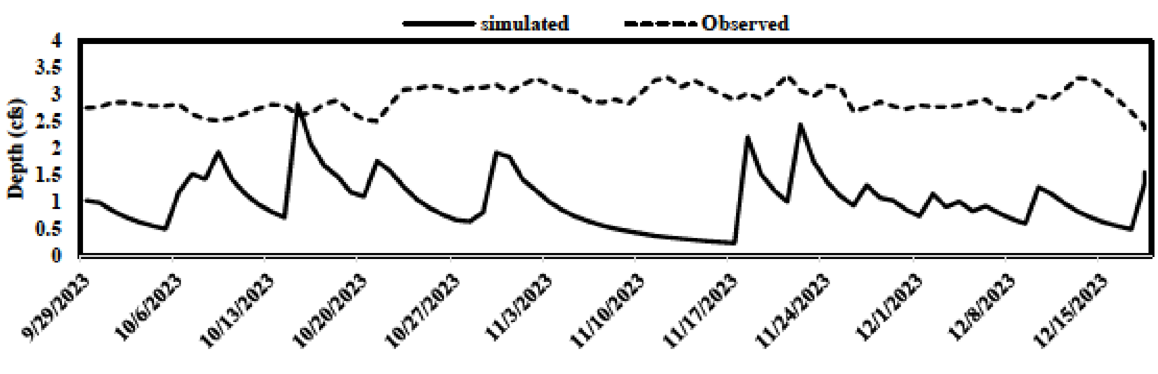


(c)

Figure 3. 6 Hydraulic validation results (a) Station 1 at the outlet of the watershed (b) Station 2 located at the East Golf Hike trail and (c) Station 3 located at the Renkenberger Road.

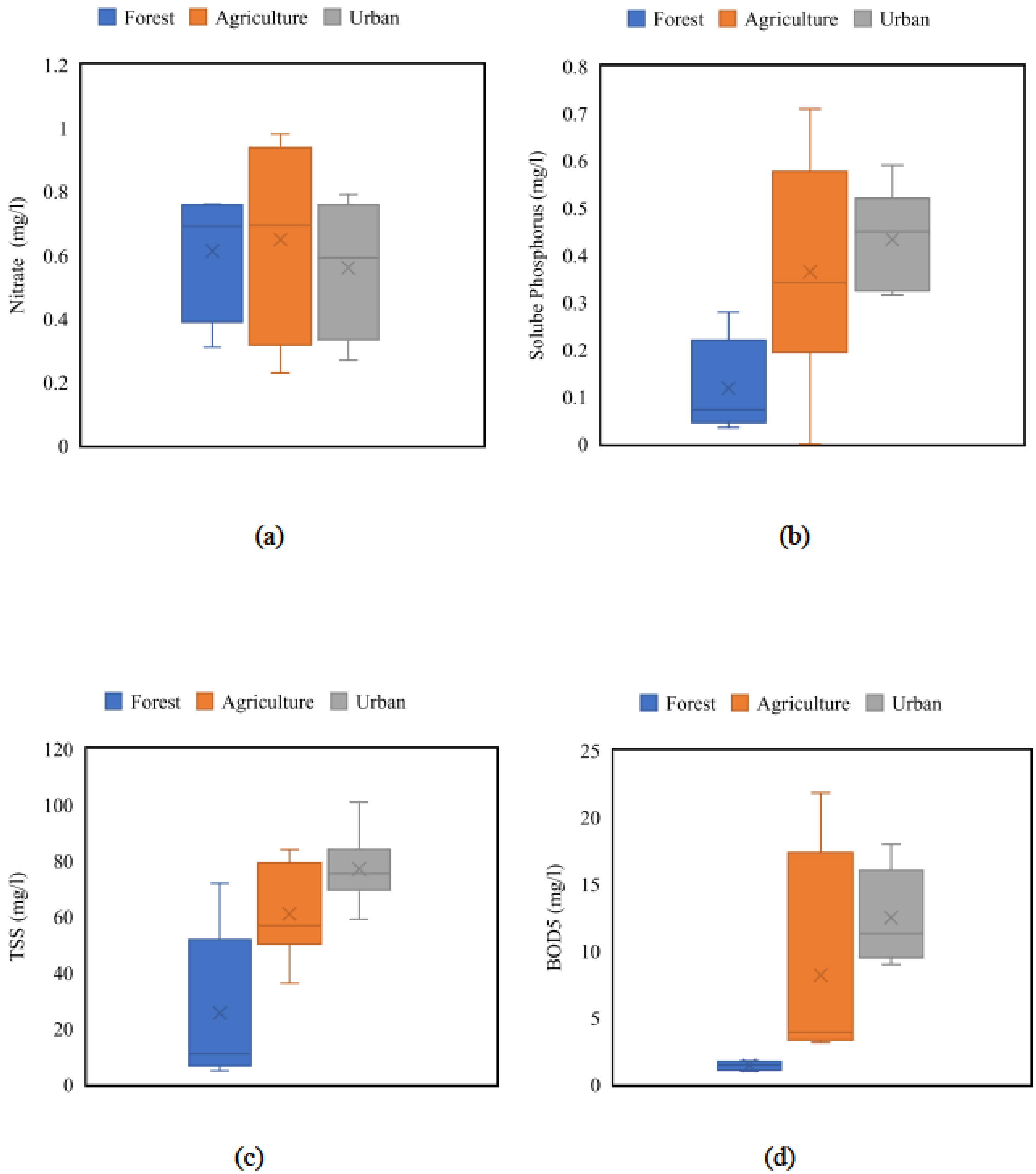


Figure 3. 7 EMC values from different literature sources (a) Nitrate (b) Soluble Phosphorus (c) TSS (d) BOD_5

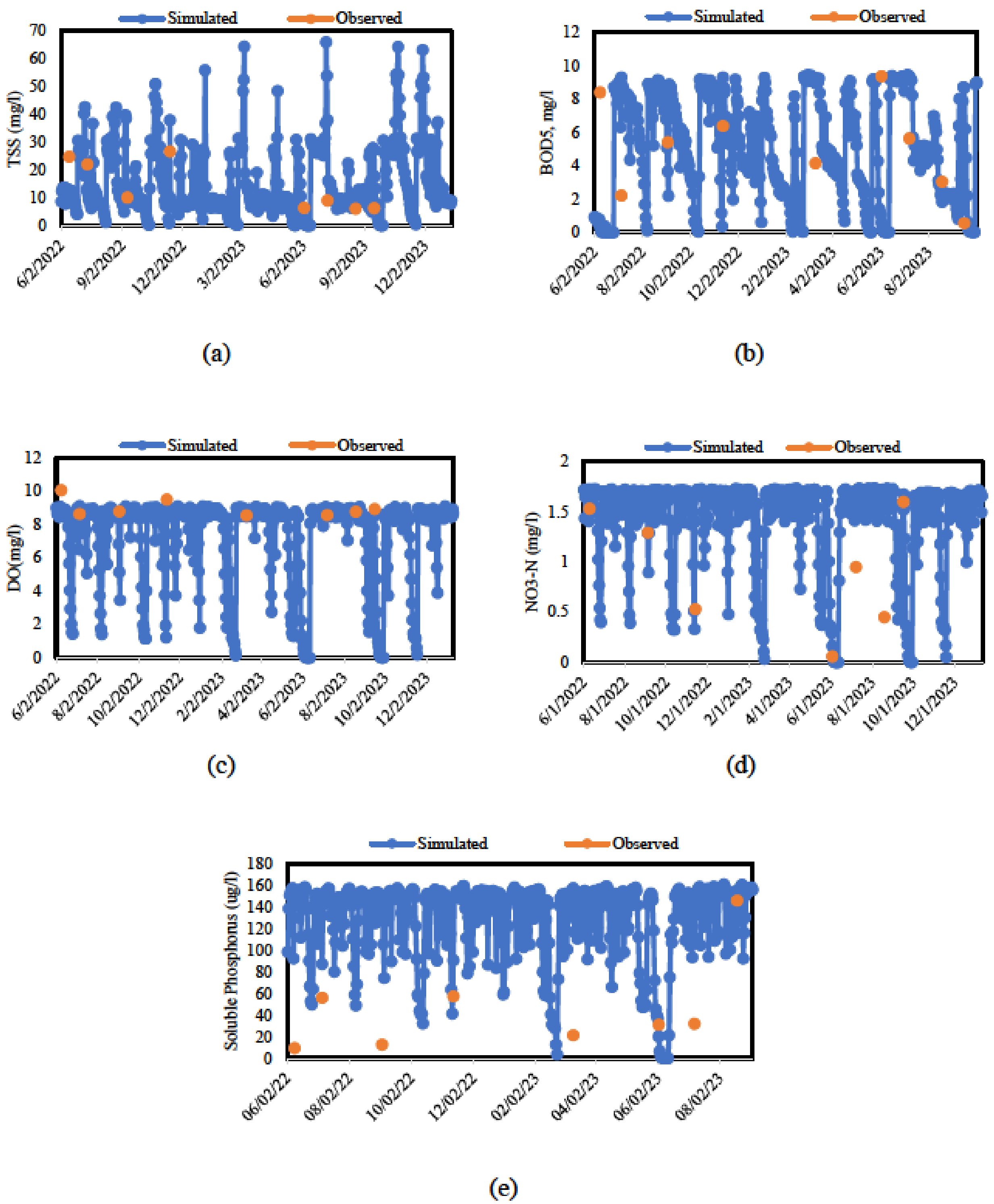


Figure 3. 8 Nutrient calibration at monitoring station 14 for the period of 2022 to 2023 (a) TSS (b) BOD_5 (c) DO (d) Nitrate (e) Soluble Phosphorus

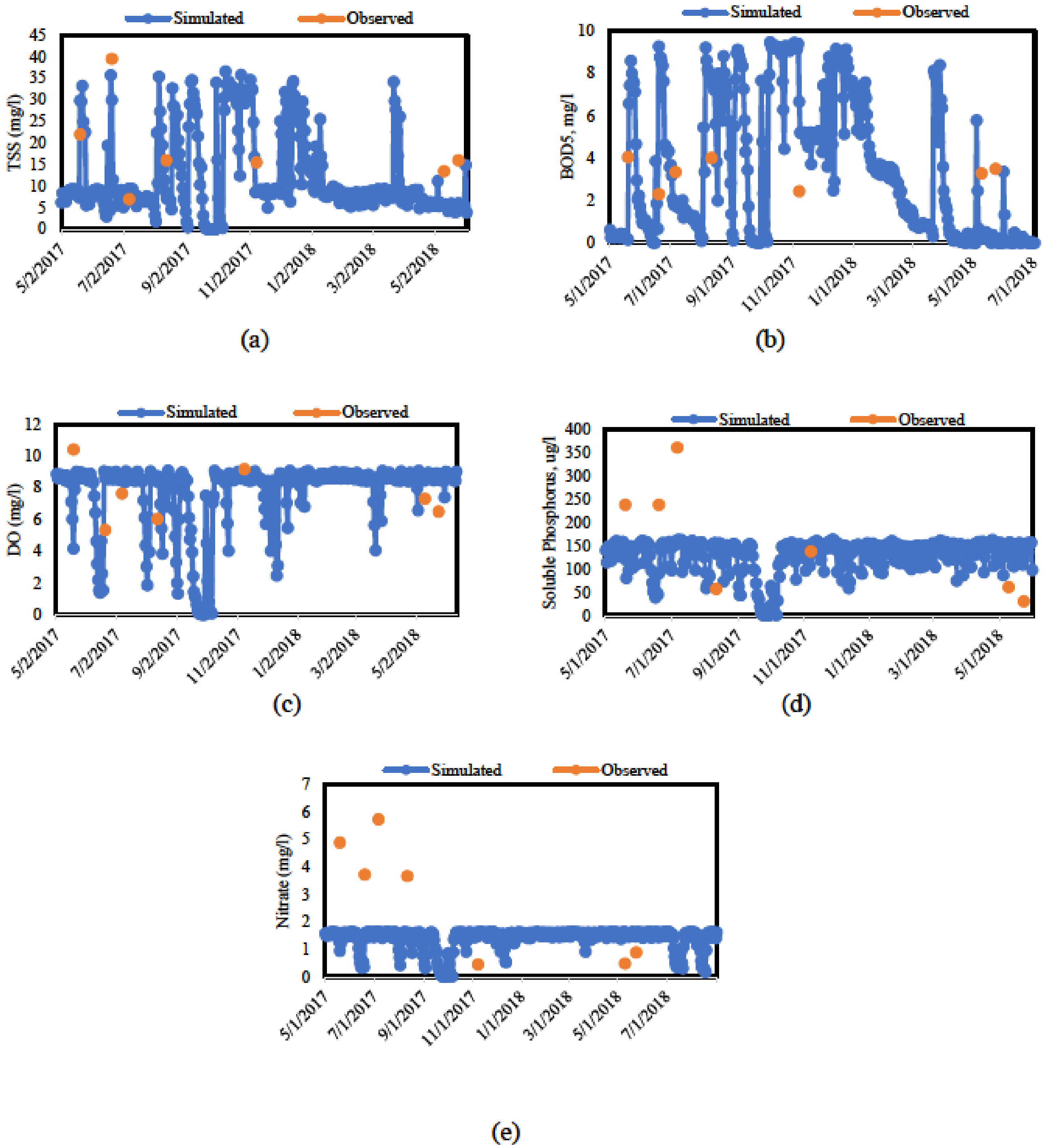
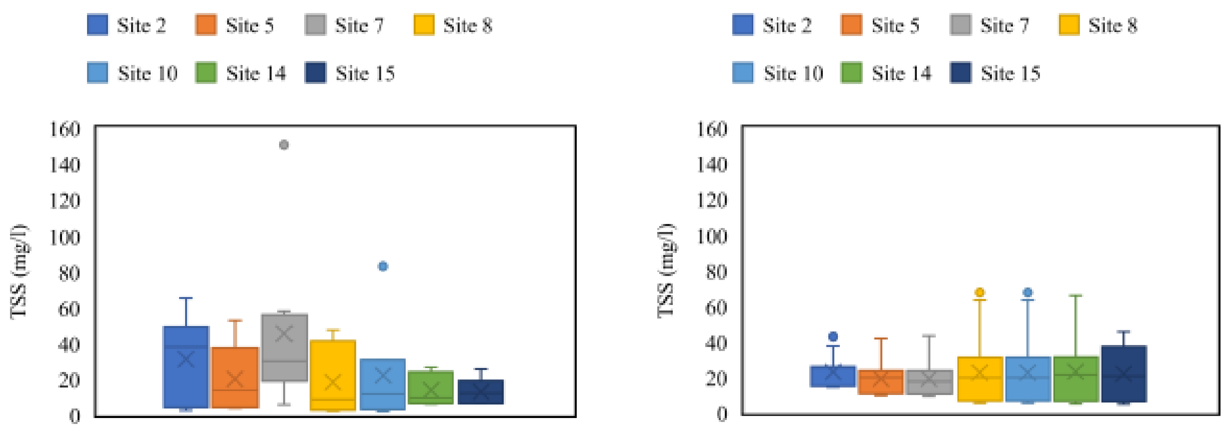
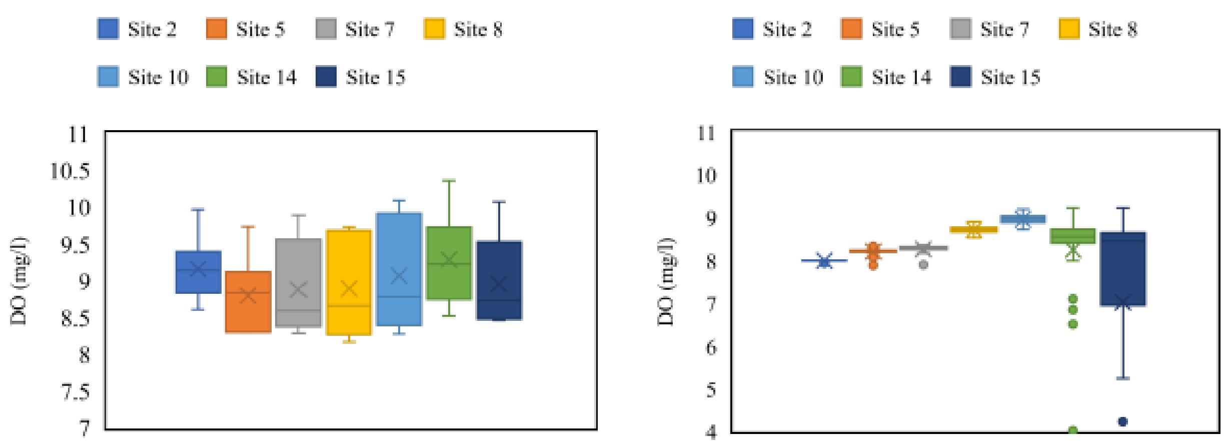


Figure 3. 9 Water quality validation at monitoring station 14 for the period of 2017 to 2018 (a) TSS (b) BOD_5 (c) DO (d) Soluble phosphorus (d) Nitrate



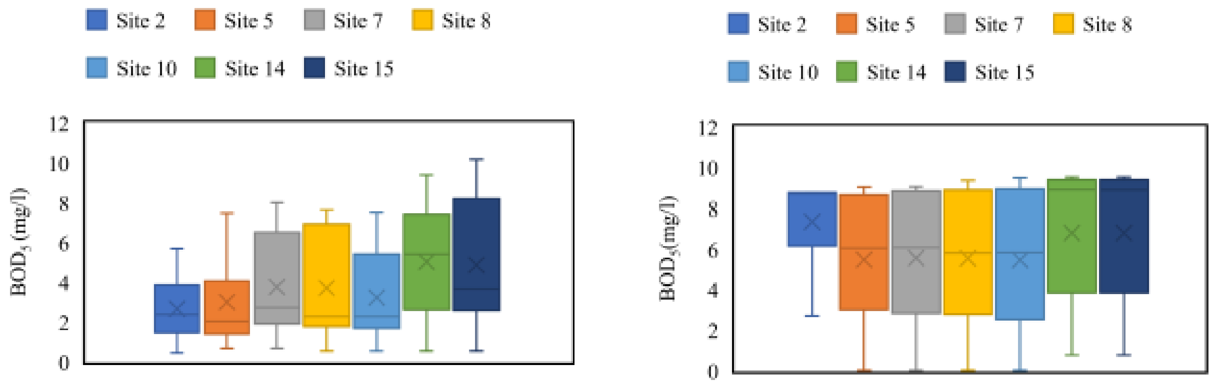
(a) (b)

Figure 3. 10 (a) Observed concentration of TSS in the stream for the period of 2022 to 2023 (b) Simulated concentration of TSS by the model for the period of 2022 to 2023 when the volume of precipitation is greater than 0.5 inches.



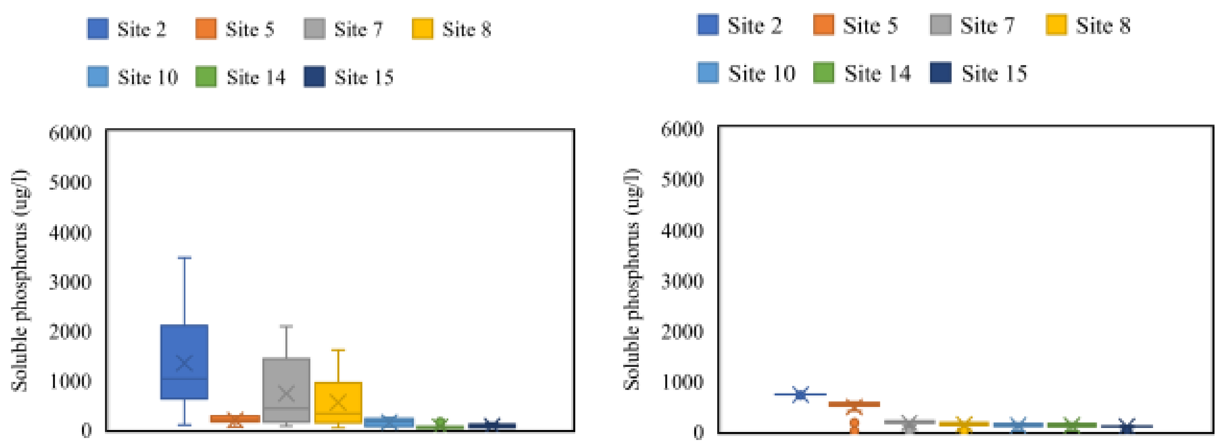
(a) (b)

Figure 3. 11 (a) Observed concentration of DO in the stream for the period of 2022 to 2023 (b) Simulated concentration of DO by the model for the period of 2022 to 2023 when the volume of precipitation is greater than 0.5 inches.



(a) (b)

Figure 3. 12 (a) Observed concentration of BOD_5 in the stream for the period of 2022 to 2023 (b) Simulated concentration of BOD_5 by the model for the period of 2022 to 2023 when the volume of precipitation is greater than 0.5 inches.



(a) (b)

Figure 3. 13 (a) Observed concentration of soluble phosphorus in the stream for the period of 2022 to 2023 (b) Simulated concentration of soluble phosphorus by the model for the period of 2022 to 2023 when the volume of precipitation is greater than 0.5 inches.

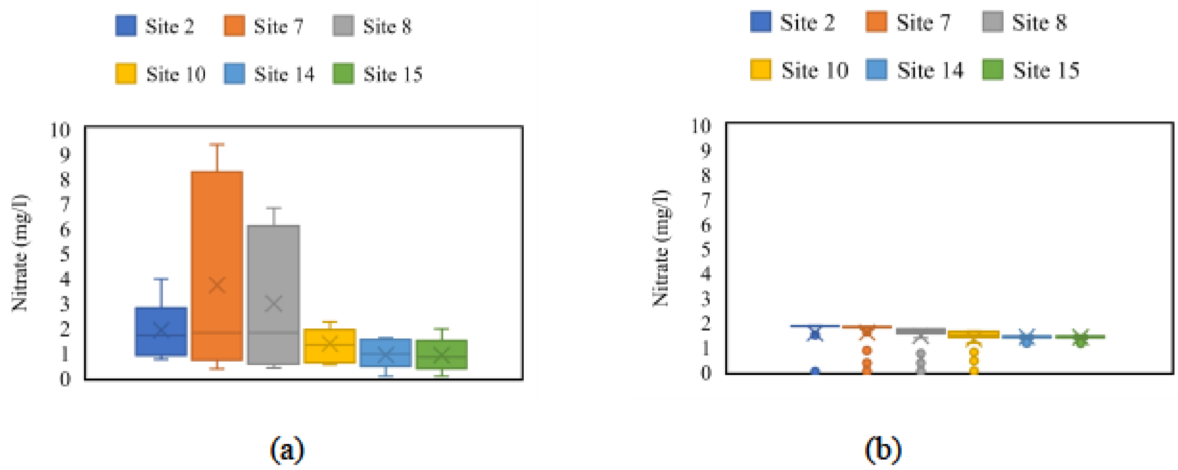


Figure 3. 14 (a) Observed concentration of nitrate in the stream for the period of 2022 to 2023 (b) Simulated concentration of nitrate by the model by the model for the period of 2022 to 2023 when the volume of precipitation is greater than 0.5 inches.

Table 3. 1 Data used for the study with their source and information.

Data	Source	Additional information
Land use, NLCD 2014	https://www.mrlc.gov/data/nlcd-2013-land-cover-conus	
Soil	websoilsurvey.nrcs.usda.gov/app/	SSURGO soil data base
DEM	https://apps.nationalmap.gov/downloader/	10-m resolution
Weather gage station	https://www.ncdc.noaa.gov/cdo-web/datasets	Station No: - USW00014852
Stream flow	https://waterdata.usgs.gov/nwis/sw	(USGS Gage 03098513&03098500)
Hydrologic (stream network) data	https://www.usgs.gov/streamstats	
Water quality data	Youngstown State University	8 stations

Table 3. 2 Model calibration parameter from different literature sources

Parameters	Initial Value	Calibrated value from Literature	Land Use	Reference
N-imperv	0.01	0.015	Mixed land use	(Rosa et al. 2015)
		0.016 (+ 23%)	Mixed land use	(Tu et al. 2018)
		0.022-0.025	mixed land-use	(James et al.,1993)
		0.02	urbanized	(Temprano et al., 2006)
		0.015	mixed land use	(Niyonkuru et al., 2018)
		0.012	urbanized	(Zakizadeh et al., 2022)
N-Perv	0.1	0.15	mixed land-use	(Rosa et al., 2015
		0.10 (-23%)	mixed land-use	(Tu et al. 2018)
		0.32-0.33	urbanized	(James et al.,1993)
		0.3	residential urban	(Temprano et al., 2006)
		0.4	urbanized	(Niyonkuru et al., 2018)
		0.131	mixed land-use	(Zakizadeh et al., 2022)
Dstore-Perv	0.05mm	5.08	mixed land-use	(Rosa et al., 2015)
		7.62 (mm) +52%	mixed land-use	(Tu et al. 2018)
		8.0-9.9	mixed land-use	(James et al.,1993)
		5.0mm	residential urban	(Temprano et al., 2006)
		6	mixed land-use	(Niyonkuru et al., 2018)
		3.8	mixed land-use	(Zakizadeh et al., 2022)
Dstore-imperv	0.05	2.54	mixed land-use	(Rosa et al., 2015)
		2.5-4.5	mixed land-use	(James et al.,1993)
		2.5mm	mixed land-use	(Temprano et al., 2006)
		3	mixed land-use	(Niyonkuru et al., 2018)
		1.35	mixed land-use	(Zakizadeh et al., 2022)
Impervious percentage	25	-10%	mixed land-use	(Tu et al. 2018)
		15.90%	residential urban	(Temprano et al., 2006)
		± 15 %	mixed land-use	(Zakizadeh et al., 2022)
Manning's n for open channels	0.01	0.031 (+3%)	mixed land-use	(Tu et al. 2018)
		0.035-0.050	76.9% Residential	(Sidek et al., 2021)
		0.05	Urban and mixed	(Xiao & Vasconcelos, 2023)

Table 3. 3 EMC values from different literature sources

Land Use Category	TSS (mg/l)	BOD (mg/l)	TP (mg/l)	NO_3–N (mg/l)	Sources
Forest	11	1	0.05	0.31	(Pitt et al., 2000)
	8.4	1.4	0.055	--	(Harper et al., 2007)
	--	1.79	0.034	0.63	(Yoon et al., 2010)
	5	--	0.28	4	(Kim et al., 2007)
	31.7	1.53	0.20	0.76	(Guk et al., 2009)
	72	--	0.09	0.75	(Minnesota Stormwater Manual., 2008)
	--	--	0.1	--	(Nazari et al., 2007)
Agriculture	55	4	0.34	0.58	(Pitt et al., 2000)
	77.60	21.82	--	0.23	(D. Sharma et al., 2012)
	55.3	3.8	0.344	--	(Harper et al., 1998)
	58.31	3.14	0.26	--	(Hu & Huang, 2014)
	--	--	0.71	0.81	(Inamdar et al., 2001)
	--	--	0.25	--	(Nazari et al., 2007)
	36.29	--	--	0.98	(Cinque & Jayasuriya, 2010)
	84	--	0.533	--	(Minnesota Stormwater Manual., 2008)
Residential	59	9	0.45	0.27	(Pitt et al., 2000)
	101	10	0.38	0.52	(NURP 1983)
	77.8	11.3	0.52	7	(Harper et al., 2007)
	73	--	0.59	--	(Line et al., 2002)
	78.4	14.1	0.315	0.79	(Smullen et al., 1999)
	73	--	0.325	0.65	(Minnesota stormwater manual.,2008)
	--	18	0.45	8	(Roger Bannerman et al., 1996)
	--	--	0.4	--	(Nazari et al., 2007)

Table 3. 4 Model event-based calibration performance on the daily streamflow data at the outlet of the watershed

			Mean Flow (cfs)	
Period	**NSE**	**R^2**	**Simulated**	**Observed**
01/02/2000 to 06/10/2000	0.53	0.73	251.9	132.6
01/02/2000 to 01/10/2000	0.761	0.905	414.5	303.5
03/31/2000 to 04/06/2000	0.911	0.948	588.4	494.5
04/06/2000 to 04/12/2000	0.293	0.601	1077	673.2

Table 3. 5 Calibration performance on the daily streamflow data at the two USGS gauging station of the watershed.

					Mean Flow (cfs)	
USGS Station	**Period**	**NSE**	**R^2**	**PBIAS**	**Simulated**	**Observed**
03098513	01/01/2000 to 06/10/2000	0.54	0.72	-130.5	250.8	132.1
03098500	01/01/2000 to 06/10/2000	0.51	0.71	-69.6	161.9	84.54

Table 3. 6 Historical validation of the daily streamflow data at the USGS gauging stations of the watershed

Events	Period	NSE	R^2	Mean Flow (cfs)	
				Simulated	Observed
1	2/12/1950 to 2/27/1950	0.458	0.804	427.6	264.4
2	01/03/1951 to 06/04/1951	0.585	0.914	335.1	233.2
3	04/07/1951 to 04/21/1951	0.626	0.846	175	128.5
4	10/14/1954 to 10/23/1954	0.584	0.867	805.7	482.3
5	02/24/1956 to 03/02/1956	0.614	0.754	343.3	253.4
6	08/04/1956 to 08/11/1956	0.46	0.732	611.2	342.9
7	04/06/1957 to 04/16/1956	0.783	0.954	362.4	279.8
8	04/24/1958 to 05/05/1958	0.792	0.965	305.4	255.6
9	12/11/1959 to 01/31/1960	0.565	0.75	180.6	130.1
10	02/16/1961 to 04/12/1961	0.633	0.808	287	213.6
11	04/15/1963 to 04/27/1963	0.492	0.952	249.5	115.6
12	03/03/1964 to 04/24/1964	0.698	0.791	407.5	323.3
13	01/20/1965 to 02/05/1965	0.548	0.773	249.2	157.7
14	04/26/1967 to 04/02/1967	0.642	0.848	220.3	154.5
15	01/26/1968 to 02/14/1968	0.546	0.968	189.1	220.5
16	12/26/1968 to 01/05/1969	0.6	0.889	328.8	187.2
17	01/26/1969 to 02/07/1969	0.747	0.926	211.5	146.5
18	03/02/1970 to 03/10/1970	0.805	0.893	165.9	183.7
19	03/30/1970 to 04/18/1970	0.425	0.514	165.5	110.6
20	10/27/1970 to 11/09/1970	0.509	0.934	305.6	169.4
21	11/27/1970 to 12/03/1970	0.89	0.891	145.1	141.4
22	12/10/1970 to 12/26/1970	0.505	0.679	198.4	154.9

APPENDICES

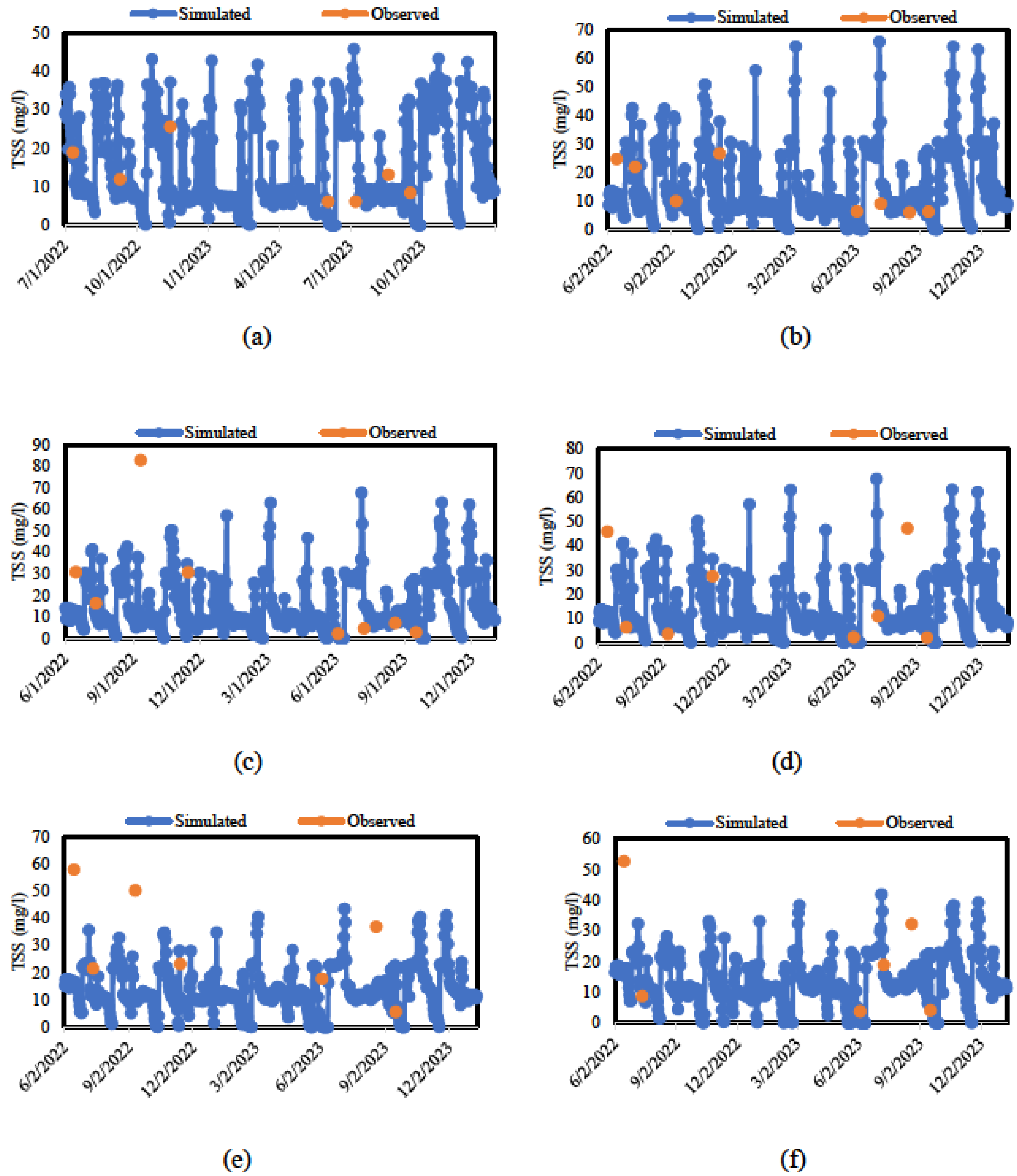


Figure 4. 1 Water quality calibration of TSS at different monitoring stations for the period of 2022 to 2023 (a) Site 15 (b) Site 14 (c) Site 10 (d) Site 8 (e) Site 7 and (f) Site 5

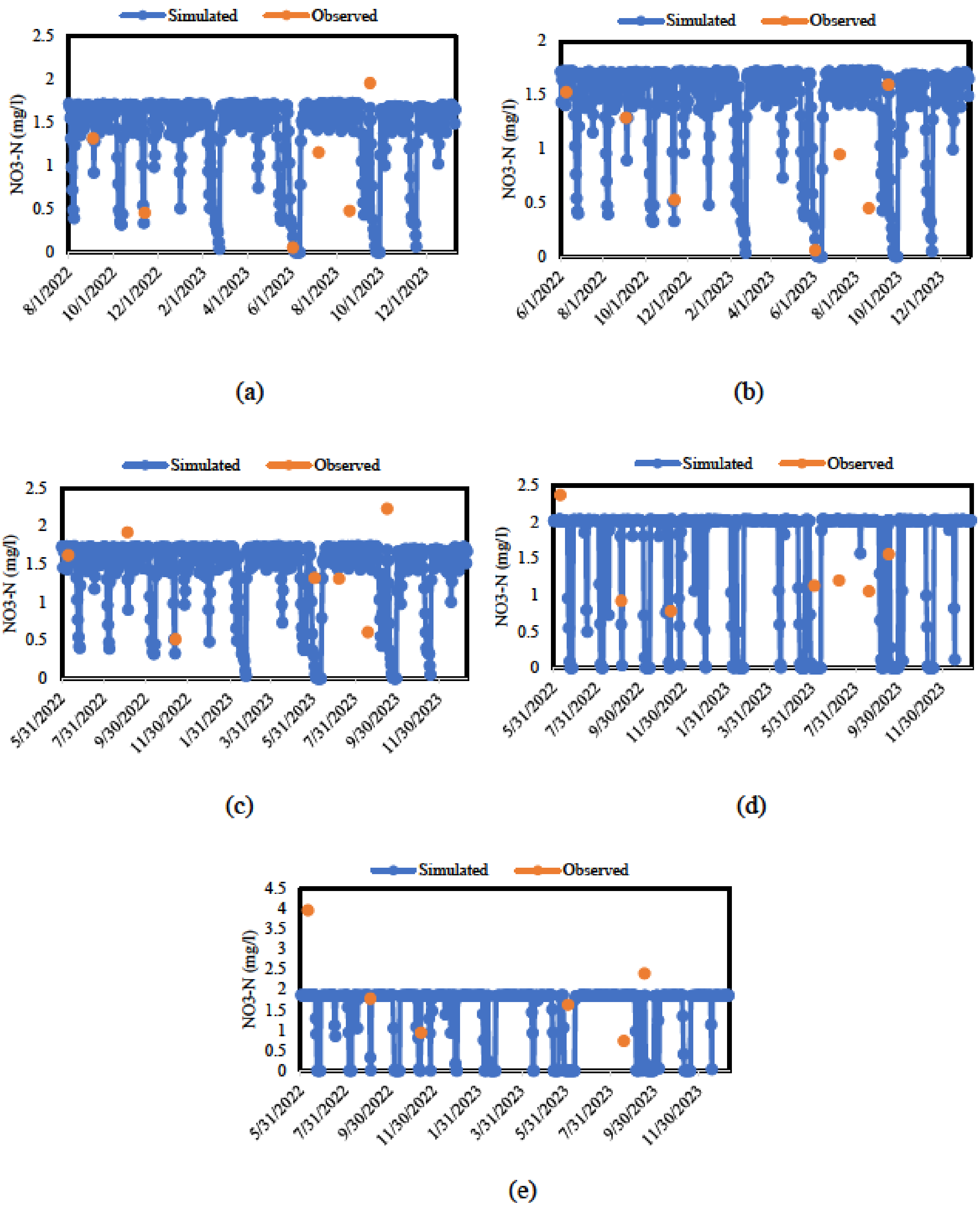


Figure 4. 2 Water quality calibration of NO_3-N at different monitoring sites for the period of 2022 to 2023 (a) Site 15 (b) Site 14 (c) Site 8 (d) Site 3 (e) Site 2

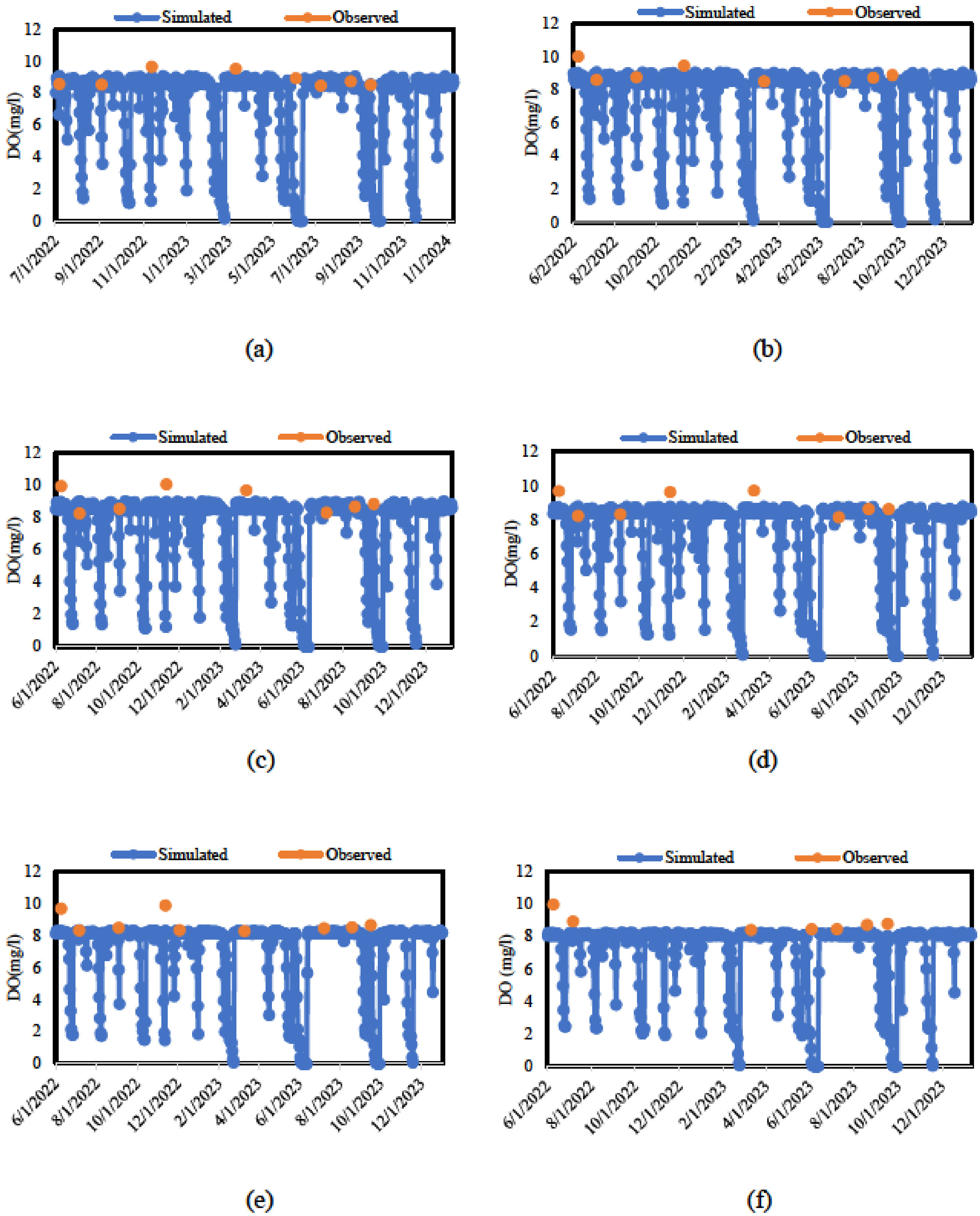


Figure 4. 3 Water quality calibration of DO at different monitoring sites for the period of 2022 to 2023 (a) Site 15 (b) Site 14 (c) Site 10 (d) Site 8 (e) Site 7 (f) Site 5

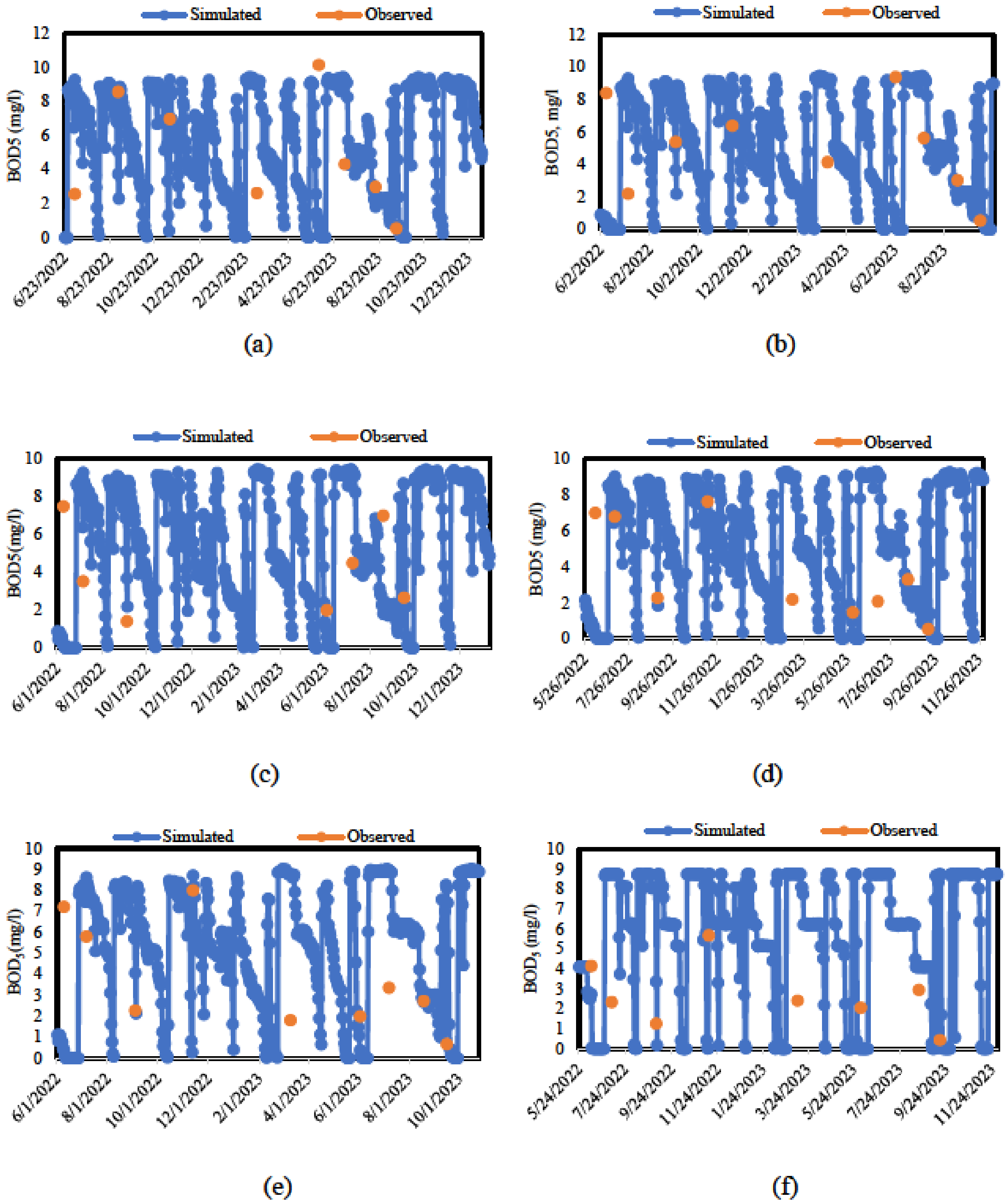


Figure 4. 4 Water quality calibration of BOD_5 at different monitoring site for the period of 2022 to 2023 (a) Site 15 (b) Site 14 (c) Site 10 (d) Site 8 (e) Site 7 (f) Site 2