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Assessment and prediction of surface water vulnerability from non-point source pollution in Midwestern watersheds

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ASSESSMENT AND PREDICTION OF SURFACE WATER VULNERABILITY FROM NON-POINT SOURCE POLLUTION IN MIDWESTERN WATERSHEDS

by

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ABSTRACT

Non-point source pollution is the leading cause of impairment in surface water in the Midwest. In this research, we seek to predict which watersheds are most vulnerable to point source pollution without field sampling using publically available GIS databases. Watersheds with higher vulnerability ratings can then be targeted for water quality monitoring, and funds used to improve watershed health can be distributed with greater efficacy. To better understand and target watershed vulnerability, we used three different approaches. In the first project, 35 sub-watersheds were sampled in the Lower Grand Watershed, which is a highly agricultural watershed in northern Missouri/southern Iowa. Statistical analyses were performed to determine which of these parameters were most correlated with water quality, and predictive relationships of water quality were developed. In the second project, a new methodology for watershed vulnerability to non-point source pollution was developed. Using the results from our first study to guide the weighting of different parameters, a weighted overlay and analytical hierarchy method was used to predict the vulnerability (poor water quality) of watersheds. This new vulnerability prediction method was tested on ten sub-watersheds within the Eagle Creek Watershed in central Indiana, which has a mixture of agricultural, forested, and urban land use. In the last project, the robustness of the new watershed vulnerability assessment method was tested using hydrological modeling. The Soil and Water Assessment Tool (SWAT) modeling program was used to model non-point source pollution in the Eagle Creek sub-watersheds. The results of these models provided a second method for verifying the robustness of the newly developed watershed vulnerability assessment method.

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1. INTRODUCTION

1.1. OVERVIEW

Water quality degradation from multiple sources of contamination has become a critical global issue. Many water bodies across the United States are classified as impaired. The United States Environmental Protection Agency (USEPA) has classified over 44% of streams and rivers and 64% of lakes and reservoirs in the United States as impaired due to agricultural activities and urbanization (USEPA 2016). In much of the Midwest of the United States, non-point source pollution from agricultural activities is the leading cause of degradation of surface waters (USEPA, 2013). The primary pollutants from agricultural activities are excessive inputs of nutrients through commercial fertilizer, pesticides, and manure, which is a primary source of nitrogen and phosphorus (Ahearn et al., 2005). Many of these pollutants reach sources of surface and underground water during the process of flow and percolation, from non-point sources of pollution.

Similarly, urbanization has become a main source of stream impairment for streams in the United States. Urbanization imposes a variety of watershed changes that immensely affect and impair aquatic systems worldwide. As a result of the human population growing and expanding, they have dramatically changed streams and other water bodies globally (Fox et al., 2012). Furthermore, it is expected that 83% of Europe and Northern Americas and 53% of the developing world will live in urban and suburban areas by 2030 (Cohen 2004). In the United States alone, urban areas currently cover 19% of the total land area and greater than 80% of Americans lived in these urbanized areas. Urbanization affects the water quality through sediment, oils, and solid wastes washed from hard surfaces, bacteria, and input of nutrients from failing septic systems and wastewater (USEPA, 2008).

Urban watersheds suffer negative effects to stream hydrology, riparian habitats, water chemistry, and biological communities (Walsh et al., 2005). Additionally, urban lands have increased the need for dealing with surface runoff and stormwater runoff, which have a higher pollutant rates than in nonurban lands because of a higher density population, and the use of chemicals such as using road salts on impervious surfaces (Kelly et al., 2012). The widespread impacts of urbanization on the physicochemical characteristics of the urban watershed which include stream systems have far-reaching implications on ecosystem function.

Understanding and evaluating the natural processes in river basins taking into account its deficiencies are still challenges for researchers and scientists. The mathematical models of basin simulation are useful tools in understanding these processes as well as to evaluate solutions and best management practices. (Borah and Bera, 2003). In recent decades, different watershed assessment methods have been developed to evaluate the cumulative impacts of human activities on watershed health and the condition of aquatic systems. These techniques are generally designated to as watershed assessments or analyses. Therefore, various methods were developed to evaluate watershed condition such as identifying the impact of land use and land cover changes (Bateni et al., 2013; Calijuri et al., 2015). Among these approaches, statistical analysis and hydrological modeling have been widely performed since they require less resources and support more flexibility. The ability of hydrological models to simulate and predict real phenomena has increased considerably in recent years. Some of the models are based on simple empirical relationships with robust algorithms, while others use equations that govern the physical base with computationally calculated numerical solutions. Simple models at some point are unable to yield results with the degree of detail, and the detailed models may be inefficient and inapplicable for large river basins, where there are difficulties in monitoring campaigns. In the current research, to better understand and target watershed vulnerability, we used three different approaches. In the first project, 34 sub-watersheds were sampled in the Lower Grand Watershed, which is a highly agricultural watershed in northern Missouri/southern Iowa. Water quality measurements from these watersheds were acquired in the fall and the following spring, and these measurements were correlated with 15 parameters that included both land use/land cover attributes and a variety of geologic/topographic variables. Statistical analyses were performed to determine which of these parameters were most correlated with water quality, and predictive relationships of water quality were developed. In the second project, a new methodology for watershed vulnerability to non-point source pollution was developed. Using the results from our first study to guide the weighting of different parameters, a weighted overlay and analytical hierarchy method was used to predict the vulnerability (poor water quality) of watersheds. This new vulnerability prediction method was tested on ten sub-watersheds within the Eagle Creek Watershed in central Indiana, which has a mixture of agricultural, forested, and urban land use. In the last project, the robustness of the new watershed vulnerability assessment method was tested using hydrological modeling. Since water quality data are limited in some sub-watersheds, the Soil Water Assessment Tool (SWAT) modeling program was used to model non-point source pollution in the Eagle Creek sub-watersheds.

2. LITERATURE REVIEW

The primary objective of this section is to review previous studies that investigated how watersheds are impacted by a multitude of variables including climate, soils, hydrology, geomorphology, and land use/land cover. Additionally, the assessment tools that have been used to evaluate the response of watersheds to different contamination impacts.

2.1. IMPACTS OF AGRICULTURAL ACTIVITIES ON WATER QUALITY

Agriculture, one of the main components of the world economy, contributes increasingly severe degradation of water quality through release of pollutants into the water. The NPS pollution can be resulting from agricultural activities such as animal feeding operations and manure, pesticides, sediments, fertilizers, overgrazing, and other sources of organic and inorganic matter. Phosphorus (P) and nitrogen (N) are environmental problemS that in excessive amounts of contamination resulting from agricultural areas. Many of these pollutants reach sources of surface and underground water during the process of flow and percolation, from non-point sources of pollution.

Numerous studies have been conducted to better understand the relationship between agricultural activities and water quality. These studies have focused to find the relationship between LULC and surface water quality to determine how changes in LULC affect the turbidity, dissolved oxygen (DO), and temperature of rivers and streams. Other studies focus on the impact of nutrient runoff into surface water (Driscoll et al., 2003). Some of the most problematic nutrients are phosphorus (P) and nitrogen (N), which are often carried into streams through overland flow during rainfall events (Mallin et al., 2008), especially before the growing season and after harvest (Zhu et al., 2012). Many studies used statistical analysis and modeling approaches to investigate the relationships between spatial and temporal watershed characteristics. For example, Wilkison and Armstrong (2015) studied the impact of commercial fertilizers, which have been widely applied in Lower Grand River watershed. The watershed has been farmed extensively for the past four decades. The average application rates of agricultural chemicals (phosphorus (P) and nitrate (N) used in this watershed for corn, soybeans and wheat crops have approximately doubled during the last four decades. In a later study, Huang et al. (2013) developed linear regression relationships between five LULC categories and five (undefined) water quality indices for one watershed in the Chaohu Lake basin in China but did not determine the significance of individual LULC categories to the relationships. The mathematical models of basin simulation are useful tools in understanding the processes that affect water quality as well as to evaluate solutions and best management practices. The ability of hydrological models to simulate and predict real phenomena has increased considerably in recent years. These models can be applied to evaluate environmental risk in order to study the impact of land use/land cover on surface water vulnerability. Water quality Risk Analysis Tool (WaterRAT) is a model recently developed for evaluating uncertainty in forecasts of surface water quality. This software was developed to support surface water quality management. This model is based on flow, water depth and temperature, in addition to nine water quality determinants (phytoplankton, measured as chlorophyll-a, slow and fast reacting organic carbon, organic nitrogen, ammonium, nitrate plus nitrite, organic phosphorus, inorganic phosphorus, and dissolved oxygen (McIntyre and Wheater, 2004).

Wang et al., 2011 used rainfall-runoff model, and water quality model for the Hanshui River to simulate transformation processes of chemical oxygen demand (COD), biochemical oxygen demand (BOD) volume, phosphorus, ammonia nitrogen, nitrate nitrogen, and dissolved oxygen (DO) within the watershed. A study conducted by Zhu and Li, 2014 used the Soil and Water Assessment Tool (SWAT) to predict the long-term influences of LULC change on streamflow and non-point source pollution for LULC record started from 1984 to 2010 in the Little River Watershed, Tennessee. This study found about 34.6% of sediment and about 10% of nutrient loads was decreased due to the decrease in agricultural land uses. Another commonly used model to predict streamflow and water quality parameters based on watershed characteristics is the BASINS tool. BASINS can compute a variety of parameters, such as surface runoff, infiltration, base flow, soil temperature, surface water temperature, dissolved oxygen, nitrogen, and phosphate, and suspended sediment using inputs that include time-series records of precipitation and potential evapotranspiration and watershed parameters, including soil texture, LULC, topographic parameters, and drainage. Also, some parameters are required to calibrate BASIN models, such as streamflow and reservoir levels (Duda et al., 2012).

2.2. IMPACTS OF URBANIZATION ON WATER QUALITY

Urbanization has negative effects on watershed health. This is mainly due to the contamination of urban water sources through the disposal of domestic and industrial effluents and storm sewers. Urbanization affects the water quality through sediment, oils, and solid wastes washed from hard surfaces, bacteria, and input of nutrients from failing septic systems and wastewater (Zhao et al., 2015; Paule-Mercado et al., 2016). Numerous studies have found that urbanization has drastic and far-reaching negative consequences on the stream quality and biodiversity (Morrissey et al., 2013; Docile et al., 2016). Geostatistical applications were used by Betts et al. (2014) to assess the vulnerability of watersheds to chloride contamination in urban streams for seven sites within four watersheds in the Greater Toronto area using the probable chloride concentration measurements and comparing the results with aquatic species that have a known range of tolerance limits.

Similarly, Rothenberger et al. (2009) developed correlations between water quality parameters and four LULC categories as well as five point-source pollution categories within the Neuse River Basin, North Carolina. They found that for portions of the study area, urban development was the most influential parameter on water quality, while industrialized animal production was the most influential parameter in the other part of the study area. Yu et al. (2015) determined that high concentrations of dissolved organic carbon and total dissolved nitrogen in forty small seasonal wetlands in South Carolina were caused by draining from pasture land and urban areas. Additionally, Xia et al. (2012) used the landscape pattern index method by applying the GIS technique, to make a comparison between the landscape patterns of the Baiyangdian Watershed in 2002 and 2007. This study found that the water quality of rivers within this watershed is highly influenced by urban and agricultural lands and there is a significant relationship between water quality and patterns of land uses.

2.3. IMPACT OF GEOLOGICAL AND HYDROLOGICAL FACTORS ON WATER QUALITY

Water quality is typically greatly affected by different types of geologic materials, such as sedimentary, igneous, metamorphic rocks, and glacial deposits. Long-term geochemical interaction (rock-water) due to different chemical processes can occur between groundwater and aquifer materials (Oelkers and Schott, 2009). When water flows through fractured rock aquifers (e.g., limestone or dolomite), the chemical properties of groundwater can be significantly changed because of the dissolution of some carbonate and evaporite minerals in the aquifer. Therefore, the quality of surface water can be affected by the exchange of water between rivers and shallow aquifers., especially in the alluvial aquifer. Water can seep from a shallow aquifer into the adjacent river and river water flows into the shallow aquifers alternately, depending on the oscillating of water table and river stage. Moreover, soil can be a source of soluble materials and suspended sediments. In general, sediment is the water pollutant which most affects surface water quality physically, chemically, and biologically. Bigger, heavier sediments like pebbles and sand settle first while smaller, lighter particles such as silt and clay may stay in suspension for long periods, contributing significantly to water turbidity. Therefore, there is a significant impact of rock and soil components on the evolution of water quality by changing the physical and chemical properties of water (Orr et al., 2016). Slopes that receive rapid precipitation play a significant role in affecting surface water quality (Chang et al., 2008; Qinqin et al., 2015). With a steep slope, this factor can increase the flow rate of a water body which can be causing soil erosion and sedimentation and carries different kinds of pollutants like nutrients, pathogens, and pesticides to nearby rivers (Aksoy and Kavvas, 2005; Bracken and Croke, 2007).

2.4. AQUATIC INSECTS (MACROINVERTEBRATES) AS INDICATOR OF WATERSHED HEALTH

Aquatic insects (macroinvertebrates) have several general characteristics which make them more useful to study and evaluate stream health (Paulsen et al., 2008). The aquatic insect diversity and sensitivity to pollution can be used as an indicator of water quality of streams and rivers. Macroinvertebrate analysis can supply information on average water quality over a more prolonged period of time without time-intensive chemical sampling (Paulsen et al., 2008). Macroinvertebrates are commonly used as indicators in assessing watershed health (Fierro et al., 2018; Jabbar and Grote 2018). The presence or absence of macroinvertebrates are used to indicate clean or contaminated water because some are more sensitive than others according to different stream conditions and levels of contamination. Since aquatic macroinvertebrates play a key role in the stream ecosystem function from impacting nutrient cycling and transporting organic material downstream, they have a particular interest when testing degraded streams. Concisely, bioassessment with benthic macroinvertebrates provides a window into a longer time frame of contamination and disturbance history in stream ecosystem, while the physical and chemical measures reflect just a snapshot in time. For instance, many aquatic macroinvertebrates species are highly sensitive to changes in water chemistry including phosphates, nitrates, pH, dissolved oxygen. The impacted water quality by pollutants and the changes in physical structure of streams can reduce abundance and diversity of aquatic macroinvertebrates (Leslie et al., 2012). The physical and chemical changes which impacting stream macroinvertebrates communities include a high suspended sediment content and chemical input into urban streams, as well as decrease in instream habitat, changes to flow patterns, and higher channelization (Schwartz and Herricks 2008).

The macroinvertebrate taxa that are more pollution sensitive, and therefore the most indicative of healthy streams, are the Ephemeroptera, Plecoptera, and Trichoptera, which are known as the EPT. A decrease in sediments grain size in streambeds has been observed in urban watersheds (Roy et al., 2003). Urban streams often have significant levels of trace metals and can contain toxic chemicals including organic compound from point sources (industrial) and nonpoint sources (residential lawns and city parks). Numerous studies have found that urbanization has drastic and far-reaching negative consequences on the stream macroinvertebrate community (Docile et al., 2016). These consequences include the reduction of high sensitivity species and dominance of the generalist species (Jones and Leather 2012) as seen in the reduction of EPT-richness, and less abundance among the most sensitive groups generally (Smith and Lamp 2008). Using stepwise regression, Potter et al. (2004) found that the topographic and LULC parameters tested explained about 50% of the variability in the macroinvertebrate index and that the proportion of forested land was the most significant variable, followed by the watershed shape. They also found that the correlations depended upon the physiographic province; in provinces where most of the land was forested, forest cover was not a significant water quality predictor.

2.5. ASSESSMENT OF WATERSHED VULNERABILITY

Quantifying the vulnerability of watersheds to NPS pollution is important for recognizing which watersheds are most at risk of impairment and determining where changes in land use/land cover (LULC) might improve water quality conditions (USEPA, 2008). Changes in land use, along with soil attributes, combined with topography, climate, hydrology, and other landscape variables are the most important factors contributing to a watershed's quality (Neupane and Kumar, 2015), so the watershed vulnerability assessment should be adaptable to potential changes. However, hydrologists and environmental scientists are becoming increasingly focused on the importance of identifying and quantifying risks to evaluate watershed health by using convenient statistical technique and risk indicators. Therefore, the use of an appropriate model for watershed assessment could be essential for evaluating continuous spatial and temporal distribution variations in watershed information. In recent decades, different watershed assessment methods have been developed to evaluate the cumulative impacts of human activities on watershed health and the condition of aquatic systems. These techniques are generally designated to as watershed assessments or analyses. Therefore, various methods were developed to evaluate watershed condition such as identifying the impact of land use and land cover changes.

Various methods, approaches, and tools have been developed by the U.S. Environmental Protection Agency (USEPA) to assess watershed susceptibility to surface water pollution, such as WRASTIC. The WRASTIC method is based on seven parameters which will affect the potential for pollution including: presence of wastewater (W), recreational activities (R), agricultural activities (A), size of the watershed (S), transportation avenues (T), industrial activities (I), and the amount of vegetative ground cover (C).This model suggested the higher WRASTIC index indicates a high vulnerability to contamination (USEPA, 2000). In the study by Eimers et al. (2000) for assessing the vulnerability of watershed to predict potential contamination that may affect the water quality in North Carolina. They used the rating of watershed characteristics depending on a combination of effective factors that contributes to the eventuality that water (with or without pollutants) reaches a surface water body by shallow subsurface flow and overland flow paths. Recently, Simha et al. (2017) applied vulnerability assessment as a quantitative technique in the island of Lesvos in Greece, where a set of 25 indicators was used to identify the influence of strategic management on the vulnerability indices. High values of vulnerability values were detected due to natural and human stresses. In this study, to better understand and target watershed vulnerability, we used three different approaches. In the first project, 34 sub-watersheds were sampled in the Lower Grand Watershed, which is a highly agricultural watershed in northern Missouri/southern Iowa. Water quality measurements from these watersheds were acquired in the fall and the following spring. Statistical analyses were performed to determine which of these parameters were most correlated with water quality, and predictive relationships of water quality were developed. In the second project, a new methodology for watershed vulnerability to non-point source pollution was developed. Using the results from our first study to guide the weighting of different parameters, a weighted overlay and analytical hierarchy method was used to predict the vulnerability of watersheds. In the last project, the robustness of the new watershed vulnerability assessment method was tested using hydrological modeling.

3. RESEARCH OBJECTIVES

The primary objective of this dissertation is to develop a new watershed vulnerability assessment approach to evaluate watershed susceptibility to pollution. The objectives of this research are divided into three main sub-objectives as following:

1. To provide relationships that can be used with readily available GIS databases and ArcGIS tools to indicate which watersheds have the combination of characteristics most likely to result in poor water quality, to assess regionally variability in water quality parameters both spatially and temporally, and to determine which water quality characteristics have the greatest impact on aquatic health. Scientists and regulators can use these results to inform sampling campaigns or to identify areas where more sophisticated modeling is appropriate.

2. Developing a new watershed susceptibility assessment method to evaluate watershed susceptibility to pollution using GIS and AHP methods and using statistical analysis and sensitivity analysis to verify the efficiency of the suggested method.

3. Using hydrological modeling (SWAT model) to emphasize the robustness of the new watershed vulnerability assessment method.

PAPER

I. STATISTICAL ASSESSMENT OF NONPOINT SOURCE POLLUTION IN AGRICULTURAL WATERSHEDS IN THE LOWER GRAND RIVER WATERSHED, MO, USA

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ABSTRACT

The water quality in many Midwestern streams and lakes is negatively impacted by agricultural activities. Although the agricultural inputs that degrade water quality are well known, the impact of these inputs varies as a function of geologic and topographic parameters. To better understand how a range of land use, geologic, and topographic factors affect water quality in Midwestern watersheds, we sampled surface water quality parameters, including nitrate, phosphate, dissolved oxygen, turbidity, bacteria, pH, specific conductance, temperature, and biotic index (BI) in 35 independent sub-watersheds within the Lower Grand River Watershed in northern Missouri. For each sub-watershed, the land use/land cover, soil texture, depth to bedrock, depth to the water table, recent precipitation area, total stream length, watershed shape/relief ratio, topographic complexity, mean elevation, and slope were determined. Water quality sampling was conducted twice: in the spring and in the late summer/early fall. A pairwise comparison of water quality parameters

acquired in the fall and spring showed that each of these factors varies considerably with season, suggesting that the timing is critical when comparing water quality indicators. Correlation analysis between water quality indicators and watershed characteristics revealed that both geologic and land use characteristics correlated significantly with water quality parameters. The water quality index had the highest correlation with the biotic index during the spring, implying that the lower water quality conditions observed in the spring might be more representative of the longer-term water quality conditions in these watersheds than the higher quality conditions observed in the fall. An assessment of macroinvertebrates indicated that the biotic index was primarily influenced by nutrient loading due to excessive amounts of phosphorus (P) and nitrogen (N) discharge from agricultural land uses. The PCA analysis found a correlation between turbidity, E. coli, and BI, suggesting that livestock grazing may adversely affect the water quality in this watershed. Moreover, this analysis found that N, P, and SC contribute greatly to the observed water quality variability. The results of this study can be used to improve decision making strategies to improve water quality for the entire river basin.

1. INTRODUCTION

Nonpoint source (NPS) pollution from agricultural activities has become the main source of contamination in surface water in the United States. In much of the U.S. Midwest, agriculture was identified as the most likely source to cause impairment in the assessed rivers and streams (USEPA 2013). The primary pollutants from agricultural activities are excessive inputs of nutrients through commercial fertilizer and manure (Ahearn et al. 2005;

Fournier et al. 2017; Chen et al. 2017; Kourgialas et al. 2017), runoff from pesticides and herbicides (Hildebrandt et al. 2008; Sangchan et al. 2013; Cruzeiro et al. 2015), and increased turbidity due to soil erosion (Zhang and Huang 2014). The most problematic nutrients are phosphorus (P) and nitrogen (N), which are often carried into streams through overland flow during rainfall events (Driscol et al. 2003; Maillard et al. 2008; Kato et al. 2009; Mouri et al. 2011; Yu et al. 2015), especially before the growing season and after harvest (Zhu et al. 2012). Excessive inputs of nutrients, such as nitrogen and phosphorus, to surface water can contribute to eutrophication, excessive algal growth, increased toxicity, and other adverse influences on fish and aquatic invertebrate communities (Xu et al. 2013; Wang and Tan 2017). Generally, all types of agricultural practices and land use, including animal feeding operations (AFOs), are treated as agricultural non-point source (NPS) pollution. NPS pollution depends on hydrological conditions and is difficult to measure or control directly. However, due to the features of NPS pollution, field measurements, and the limitations of experiments, NPS pollution management practices depend on spatial-temporal simulation modeling, a key method used to estimate NPS pollution related to spatial uncertainty (Shamshad et al. 2008; Huiliang et al. 2015).

Various approaches have been used to estimate the loads of NPS pollution, including small spatial-scale experiments and watershed-scale modeling, which accurately calculates the pollution loads of different land uses through experimental methods (Alberti et al. 2007; Pratt and Chang 2012). Thus, the methods used in field experimental methods are too time-intensive and expensive to translate into practical applications (Liang et al. 2008). Furthermore, it is difficult to extend field experimental methods to the watershed scale due to the biological and chemical reactions and the complexity of the transport mechanism in the watershed.

Some research has tried to investigate the impacts of land use and land cover on surface water quality (Haidary et al. 2013; Huang et al. 2015). The relationship between land cover and water quality has been studied to reveal the effects of the characteristics of watersheds on the dissolved oxygen (DO) turbidity and river temperature (Li et al. 2015). Other research analyzed the watershed scale in addition to using remotely sensed data and GIS as well as multivariate analysis to estimate the influence of the land cover on the nutrients, suspended sediments, and ecological integrity of rivers (Lai et al. 2011; ExnerKittridge et al. 2016). For example, when studying largely forested watersheds in North Carolina, Potter et al. (2005) applied simple regression and stepwise regression to develop relationships between eight independent variables (derived from land use/land cover (LULC) and landform characteristics) and the macroinvertebrate index. Schoonover and Lockaby (2006) and Rothenberg et al. (2009) used a similar method to develop correlations between LULC parameters (e.g., percent of impervious surface, mixed forest, evergreen forest, and pasture) and quality parameters (e.g., nutrient and bacteriological characteristics) for watersheds in the United States. Because a large number of variables are required to describe water quality and the factors that affect it, multivariate statistical analysis has become a powerful tool to investigate and interpret the results. Among the multivariate analysis approaches, principal component analysis (PCA) has been widely used to determine how different reaches of a stream contributes to the overall pollution load (Kannel et al. 2007; Bu et al. 2010; Olsen et al. 2012) or which parameters are most crucial in calculating the water quality index (WQI) (Sharma and Kansal 2011; Koçer and

Sevgili 2014; Zeinalzadeh and Rezaei 2017). Furthermore, PCA analysis can also illustrate how the variability of water quality properties changes with time (Ouyang et al. 2006; Jung et al. 2016).

Therefore, this study builds upon the results of previous research by developing correlations in a large number (35) of independent watersheds with mixed LULC (including forest, pasture, row crops, and urban areas) and investigating which combinations of LULC, geologic, and topographic properties are most predictive of both the physicochemical water quality parameters and the biotic index. The independent variables in these relationships are readily available GIS-based parameters. Although similar or more accurate results can be obtained using surface water models, such as the Soil and Water Assessment Tool or BASINS, these models require more sophisticated or temporally variable inputs than the relationships developed in this study, and thus, are much more difficult to implement. The primary objectives of this study are to provide relationships that can be used with readily available GIS databases and ArcGIS tools to indicate which watersheds have the combination of characteristics most likely to result in poor water quality, to assess regionally variability in water quality parameters both spatially and temporally, and to determine which water quality characteristics have the greatest impact on aquatic health. Scientists and regulators can use these results to inform sampling campaigns or to identify areas where more sophisticated modeling is appropriate.

2. METHODS AND MATERIALS

2.1. SITE BACKGROUND

This study was conducted in the Lower Grand River Watershed, located in north-central Missouri and south-central Iowa (Figure 1). The drainage area of the Lower Grand River Watershed is about 6,112 km2, and the Grand River drains into the Missouri River as it exits this watershed. This watershed was chosen because it is representative, in terms of land use, geomorphology, and geologic characteristics, of many watersheds in the southern parts of the U.S. Midwest. Thus, statistical correlations derived from this watershed may be applied to other regional watersheds with similar land use. The primary land use in the Lower Grand River Watershed is agricultural. About 48% of the watershed is used for pasture or hay, and 27% is used for cultivated crops, primarily corn, soybeans, and wheat. Approximately 13% percent of the land is forest, and 5% is urban. The topography of the Lower Grand River Watershed is fairly flat, with an average slope of 8°, as shown in Figure 2a.

Most of the study area is covered with Quaternary deposits of glacial drift and alluvium that are less than 30.5 m thick (Figure 2b) (Gann et al. 1973). Soils in the study area are mostly loam, with loam, clay loam, and silt loam being the most common soil textures (Figure 2c). Throughout the study area, the soils tend to be fertile and easily erodible (Detroy and Skelton 1983). The bedrock is primarily Pennsylvanian-age shale and limestone, with incised channels filled with sandstone (Vandike 1995).

According to the Midwestern Regional Climate Center (MRCC 2016), the average annual precipitation in the watershed ranges from 1,029 mm in the north to 1,054 mm in the south. The greatest volume of precipitation occurs in May and June, and stream discharge is highest during these months and lowest during the late summer and fall (USDA-SCS 1982). Since soil permeability is relatively low, most rainfall runs off into streams rather than infiltrating the groundwater, and streams typical exhibit rapid increases in discharge after precipitation, but quickly return to low flow conditions after surface runoff has stopped (MDNR 1984).

Surface water quality in the Lower Grand River Watershed is variable. According to Missouri Section 303(d), about 25% of the total length of the rivers and streams in the study area are listed as impaired (MDNR 2016). The most common types of known impairments are Escherichia coli (E. coli) contamination, high concentrations of phosphorus and nitrogen, high total suspended soils, and low DO (USEPA 2016; MDNR 2016).

These impairments seem to be primarily a result of agricultural activities, although urban activities can also contribute to surface water degradation in the few watersheds with more development. Wilkison and Armstrong (2015) studied the impact of commercial fertilizers in the Lower Grand River Watershed, finding that the average application rates of agricultural chemicals, such as phosphorus and nitrogen, in this watershed have approximately doubled during the last four decades.

2.2. DATA ACQUISITION AND PROCESSING

The Lower Grand River Watershed has been divided into 64 sub-watersheds, as defined by the United States Geological Survey (USGS) hydrologic unit code HUC12-digit watersheds.

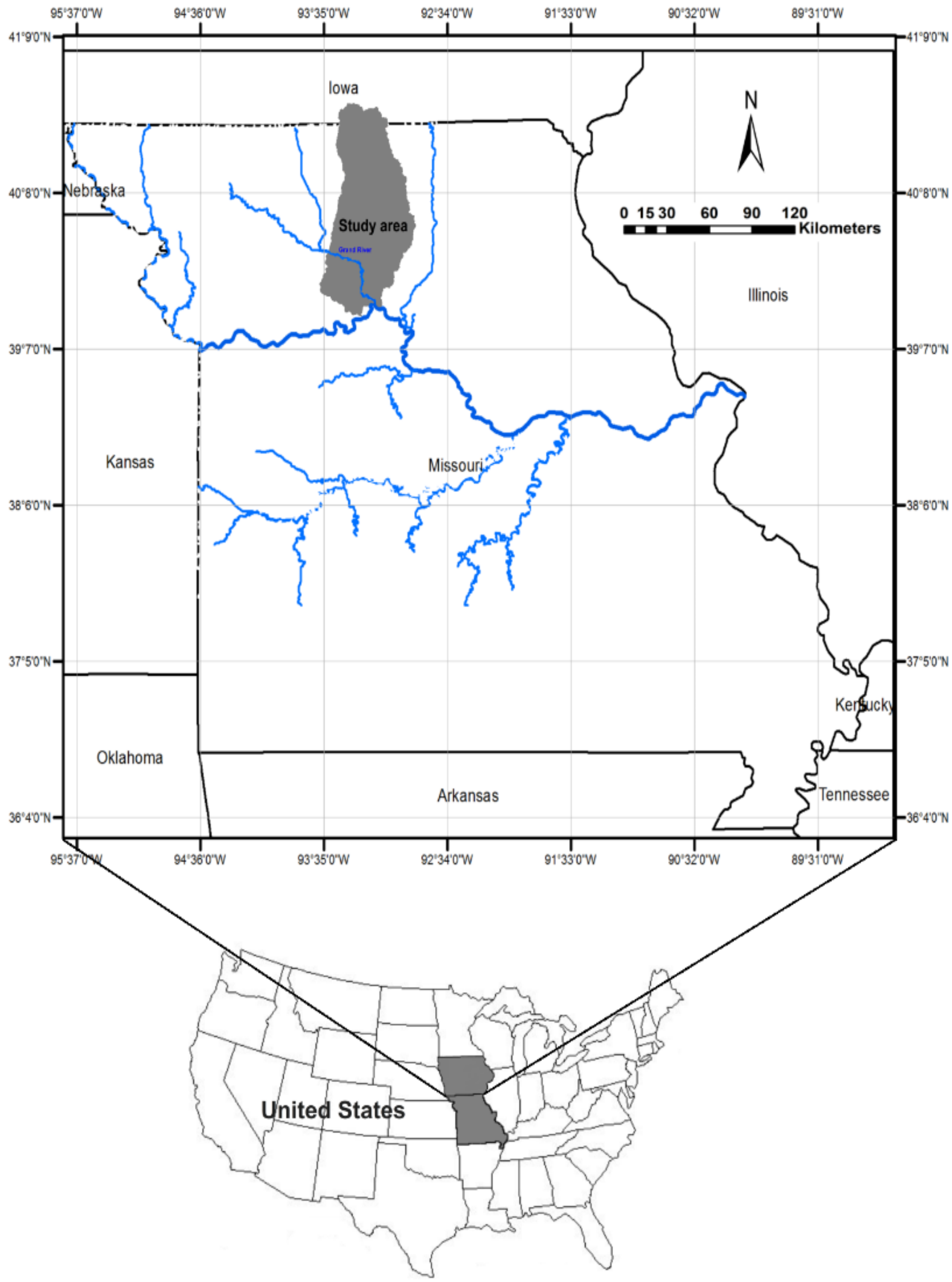


Figure 1. The location of the Lower Grand River Watershed.

Many of these sub-watersheds contain perennial streams that drain into the Grand River, although some sub-watersheds have intermittent streams (MDNR 2014). For this study, the geologic and LULC characteristics were determined for each of the 35 independent sub-watersheds in the Lower Grand basin, where an independent watershed is defined as one that receives no inflow from another watershed. Sampling was performed near the mouth of each sub-watershed (Figure 3).

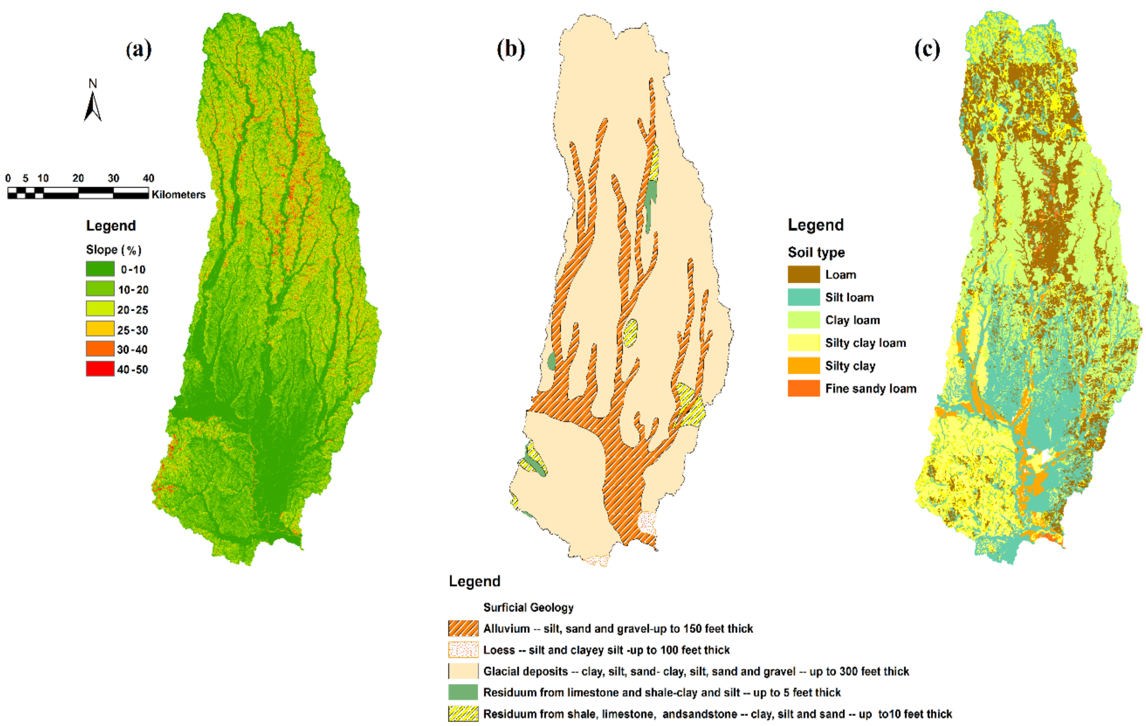


Figure 2. Characteristics of the Lower Grand River Watershed. (a) percent slope, (b) soil origin and thickness, (c) soil texture.

Surface water sampling was conducted in two major campaigns, in the late summer/fall of 2016 and spring of 2017, to monitor the streams after and before the primary growing season. For the late summer 2016 campaign, data were collected from 32 sub-watersheds over three weekends, August. 3-4, September 11-12, and September 28-29. Three additional sub-watersheds were investigated, but the streams were dry.

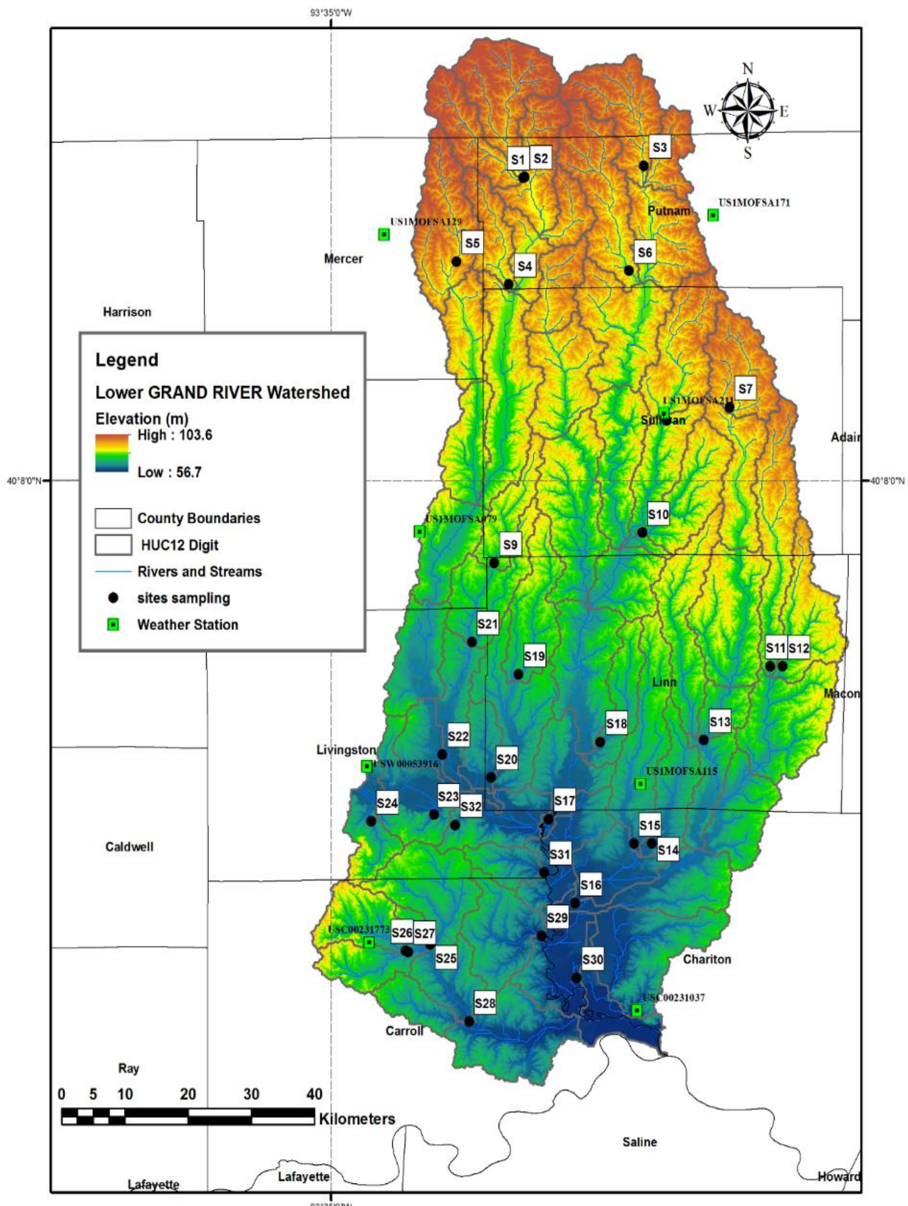


Figure 3. Map of the Lower Grand River Watershed showing HUC12-digit sub-watersheds, sampling locations, and precipitation stations.

Relatively little precipitation occurred in the two weeks preceding data acquisition in the late summer/fall; the average precipitation in the two weeks preceding these campaigns was 1.87 mm (1.37 mm, 2.48 mm, and 1.75 mm, for the first, second, and third weekends, respectively). All precipitation measurements were calculated as the arithmetic average of the precipitation measured by eight rain gauges located within or adjacent to the study area, as shown in Figure 3. Precipitation data were downloaded from the National Oceanic and Atmospheric Administration Climate Data database (NOAA 2017). In the spring 2017, data were acquired from 35 sub-watersheds on April 2-3 and April 9-10. More precipitation was received before the spring data collection; the average for the preceding two weeks before each campaign was 3.72 mm (2.74 and 4.71, for the first and second weekends, respectively). The stream discharge during each sampling campaign reflected the differences in precipitation. The average discharge of all the sampled streams during the late summer/fall was 3.6 m^3/sec, while the average discharge in the spring was 95 m^3/sec.

Although little precipitation occurred in the few weeks prior to data acquisition, the three months of 2016 preceding the late summer/fall field campaign were approximately 26% wetter than average (i.e., average precipitation from July – September in 2006 through 2017 was 317 mm, while in 2016, it was 401 mm). This above-average precipitation may influence water quality by increasing baseflow above normal levels, although the streams monitored were mostly quite small and seemed more influenced by short-term (within the past few weeks) precipitation than by longer-term precipitation, as seen in the measured discharges. During the spring campaign, precipitation was close to average; average precipitation from February – April in 2006 through 2017 was 219 mm, while in 2017, the precipitation over these three months was 223 mm.

2.3. GIS DATA PROCESSING

Data from remote sensing and field mapping techniques are available in a geographic information system (ArcGIS) database maintained by the Missouri Spatial Data Information Service (MSDIS). Figure 2 shows the slope, soil origin, and soil texture for the study area, as provided by the MSDIS. ArcGIS 10.2 was used to determine the values of the parameters for each of the 35 sub-watersheds. Some parameters, such as soil texture, LULC classification, depth to bedrock, depth to the water table, watershed area, and stream length, were obtained as shapefiles from the MSDIS. Other information, such as slope, topographic complexity, watershed shape index, watershed slope/relief ratio, and mean elevation, was derived from a 30-m resolution digital elevation model (DEM) provided by the MSDIS. ArcGIS was also used to analyze the data and to determine the average values of each parameter for each sub-watershed, as shown in Table 1.

LULC data were also analyzed using ArcGIS. The National Land Cover Database 2011 (Homer 2015) includes 15 LULC categories (Figure 4a). To reduce the number of independent variables and to create more meaningful LULC categories for this study, some of these categories were combined. All categories labeled “developed” were combined into one “urban” classification, and all categories labeled “forest” were combined into one group. Similarly, “wetland” categories were combined (Figure 4b).

2.4. PRECIPITATION

To better understand how recent precipitation affects water quality parameters, the depth of precipitation was also estimated for each sub-watershed.

Table 1. Minimum, maximum, mean, and standard deviation for independent variables.

Variable	Description	Minimum	Maximum	Mean	Std. deviation
Area (km^2)	Area of watershed	42.4	141.0	95.2	28.5
Watershed shape index	Area/square of watershed length	0.1	1.55	0.37	0.26
Average slope		1.97	7.28	4.35	1.51
Total stream length (km)	Total stream length in watershed	11.2	78.7	36.3	13.2
Topographic complexity	Standard deviation of elevation within watershed	12.90	47.7	28.9	11.2
Watershed slope/relief ratio (m/km)	Watershed elevation change/ watershed length from outlet to highest point on perimeter	2.3	7.8	4.2	1.7
Mean elevation (m)	Mean elevation of watershed	215.7	306.3	250.1	23.8
Urban (%)	Percent of watershed	2.72	10.9	4.6	1.44
Forest (%)	Percent of watershed	3.2	28.90	12.4	5.60
Pasture/hay (%)	Percent of watershed	16.3	74.24	51.2	17.71
Cultivated crops (%)	Percent of watershed	3.6	66.9	24.9	16.5
Wetland (%)	Percent of watershed	0.34	23.5	4.1	6.3
Clay + silt (%)	Percent of clay and silt content	52.8	79.05	63.7	4.8
Average depth to groundwater (m)		3.05	11.7	7.17	2.01
Average depth to bedrock (m)		8.6	56.9	35.5	12.6
Discharge (m^3/s) (measured in field) - fall		0.0085	0.95	0.16	0.22
Discharge (m^3/s) (measured in field) - spring		0.81	23.94	2.7	4.36
Precipitation (mm) fall		0.00	19.05	2.46	5.83
Precipitation (mm) spring		45.7	92.4	65.8	19.8

To obtain the most accurate precipitation information, ground-based rain gauge data were used instead of satellite data.

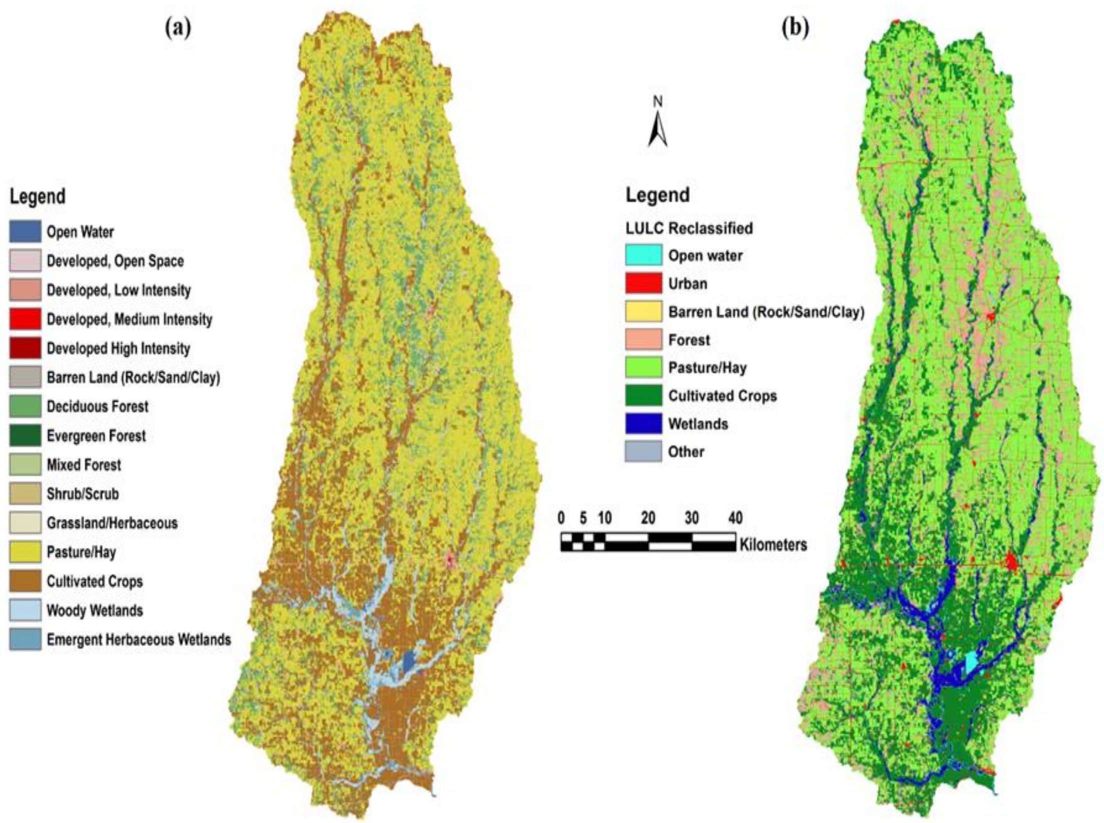


Figure 4. Land use categories (a) before reclassification, (b) after reclassification and aggregated into eight categories.

Precipitation depth was calculated as the sum of all precipitation that occurred in a two-week period prior to data acquisition at the rain gauge station closest to each drainage basin. Since rain gauge data are not available for each sub-watershed, the precipitation value is an estimate based on the closest available data.

3. WATER QUALITY PARAMETERS

3.1. DATA ACQUISITION

Surface water samples were collected from 32 sub-watersheds in August and September 2016 and from 35 sub-watersheds in April 2017. Fewer samples were collected in the fall 2016 because some streams were dry. Some water quality parameters were acquired in situ, including temperature, pH, SC, and DO, all of which were measured with a YSI ProPlus multimeter. Turbidity was also measured in the field using a Hach 2100Q portable turbidimeter. Samples were acquired in the field and tested for bacteria, phosphate (P), and nitrate (N) in the laboratory. All field measurements and samples were acquired using standard USGS procedures, including equipment calibration twice a day, cleansing of all equipment between samples, and following standard procedures to avoid contamination (USGS 2006). P and N samples were filtered on site and collected in sterilized polypropylene bottles. When needed, sulfuric acid was added to the N samples for preservation, if the samples could not be analyzed within 24 hours of collection. Sample bottles were rinsed three times with stream water from the sampling sites before the samples were collected. Bacteria samples were collected in sterilized Whirl-Pak® bags. All samples were preserved on ice during transportation and refrigerated at 4°C until they were processed. Bacteria samples were processed within 8 hours of data collection, and N and P samples were processed within 24 hours, except for a few N samples that were preserved with acid and processed within 48 hours.

Laboratory procedures were based on manufacturers' recommendations. Bacteria samples were processed using Coliscan® Easygel®, and samples were analyzed after 24 hours of incubation for E. coli concentrations. N and P (orthophosphate) were analyzed using a Hach DR 3900 spectrophotometer. N concentrations were analyzed using the chromotropic acid method (Hach Method 10020), where N reacts with chromotropic acid to change the color of the solution, with a maximum absorbance at 410 nm. Soluble reactive P concentrations were analyzed using ascorbic acid (HACH standard procedure 8048). In this process, the P in the sample reacted with ammonium molybdate to form a phospho-molybdate complex, which then reacted with the ascorbic acid reagent to change the color of the solution. For both N and P, the concentrations were determined by measuring the intensity and wavelengths of light passing through the sample after reaction with the powder-pillow reagents.

Because water quality can change quickly with time, macroinvertebrate analysis was performed to assess the average water quality over a longer time period than was used for the water chemistry measurements (Paulsen et al. 2008; Buss and Vitorino 2010; Mereta et al. 2013; López-López and Sedeño-Díaz 2014; Van Ael et al. 2015; Gezie et al. 2017). Aquatic macroinvertebrates were acquired and identified using the bioassessment protocol for Missouri (MDNR 2003). The macroinvertebrates were collected using a 1,000-micron kick net placed in the downstream section of a riffle zone. A 1-m by 1-m area immediately upstream of the net was disturbed by vigorous shuffling in the streambed. For sites that did not contain riffles, the net was placed downstream of a root mat, and the area around and underneath the root mat was disturbed. The net was then lifted, and macroinvertebrates were removed from the net, identified to the lowest taxonomic level (generally, genus), and counted. All remaining macroinvertebrates were placed into a sample jar and preserved with 80% ethyl alcohol for more rigorous identification in the laboratory. In general, macroinvertebrate collection was performed at two locations within each site. As macroinvertebrate collection at each site was very time-intensive, macroinvertebrates were acquired only during the fall 2016 and only at 16 sites.

Stream discharge was determined using standard USGS procedures. Each stream was divided into 20 evenly spaced intervals, and the water velocity and depth were measured at the center of each interval. A USGS Pygmy Meter Model 6205 was used to measure velocity. Stream discharge was calculated as the sum of the velocity, depth, and width for each interval, for all intervals of the product.

3.2. SUMMARY OF WATER QUALITY PARAMETERS

To assess stream health based on macroinvertebrate populations, the biotic index (BI) was calculated. The BI is based on the classification of macroinvertebrates depending on their tolerance of pollution and was calculated for each site using Equation (1).

$$BI = \sum_{i=1}^{s} \frac{TV_i N_i}{N_t} \tag{1}$$

where S is the number of taxa in the sample, TV_i is the pollution tolerance value of the i^{th} taxon, N_i is the density of the i^{th} species taxon as abundance (numbers per square meter), and N_t is the total number of macroinvertebrates in the sample (Lenat 1993). Tolerance values range from 0 (highly intolerant) to 10 (highly tolerant) and were chosen for each taxon using the protocol developed by Sarver (2005), which is applicable to this study area. The BI is also scored from 0 to 10 (Table 2), with 0 indicating generally excellent water quality and 10 indicating generally very poor water quality (Hilsenhoff 1988).

Stream health can also be assessed using the Water Quality Index (WQI) (Eq. 2), which was calculated using the method developed by Cude (2001).

The WQI is based on the sub-index measurements of pH, temperature, DO, biochemical oxygen demand, nitrate, total phosphorus, total dissolved solids, and fecal coliform. It provides a summary of water quality, ranging from 0 (very poor) to 100 (excellent) (Kaurish and Younos 2007; Ramos et al. 2016).

$$WQI = \sum_{i=1}^{n} SI_i W_i \qquad \textbf{(2)}$$

where *WQI* is the Water Quality Index, *SI* is sub-index *i*, and W_i is the weight given to sub-index *i*.

Table 2. Biotic Index and pollution levels.

Biotic Index	Water Quality Rating	Degree of Organic Pollution
0.00 - 3.5	Excellent	No apparent organic pollution
3.51 - 4.5	Very good	Slight organic pollution possible
4.51 - 5.5	Good	Some organic pollution probable
5.51 - 6.5	Fair	Fairly substantial pollution likely
6.51 - 7.5	Fairly poor	Substantial pollution likely
7.51 - 8.5	Poor	Very substantial pollution likely
8.51 - 10.0	Very poor	Severe organic pollution likely

3.3. STATISTICAL DATA ANALYSIS

Statistical analyses were performed using the Statistical Package for Social Sciences (SPSS) software. The water quality parameters were first analyzed using the

Cunnane probability method to determine if they were normally distributed at $\alpha = 0.01$. The critical correlation coefficients for the fall (n = 32) and spring (n = 35) data sets were 0.950 and 0.954, respectively. Some factors were normally distributed without any transformations, but others required transformation. Various transforms were tried (e.g., logarithmic, natural log, square root, and cubed root), and the transform with the highest correlation coefficient (R) (closest to the normal distribution) was applied in all further analyses. If the data were normally distributed without a transformation, no transformation was performed. All parameters were normally distributed either before or after transformation.

Six analyses were performed on the water quality data. First, the standard parametric summary statistics were calculated for each variable. Next, a pairwise comparison was performed for each water quality variable acquired in the spring and fall. The differences for each characteristic were calculated, and the Cunnane method was again employed to determine whether the differences were normally distributed. If the differences were normal, the paired-t test was employed to determine if the two data sets were statistically different. If the differences were not normal, the sign test was used. The third analysis was a simple linear regression between each independent variable (i.e., LULC, geologic, or topographic parameters) and each dependent variable (i.e., water quality parameter) to determine the strength and direction of the correlation between each pair of variables. The fourth analysis was a stepwise linear regression to determine which independent variables were most useful for predicting water quality parameters. The partial F entry test and partial F removal test had a significance level of $\alpha = 0.05$. The coefficient of multiple determination (R^2) for each regression equation indicates the proportion of the variability in the water quality parameters that can be explained by the independent variable. The fifth analysis compared the biotic index values with the WQI to determine how well the biotic index predicted the WQI. The final analysis was a principal component analysis of the physicochemical water quality variables and the BI.

4. RESULTS

4.1. SUMMARY STATISTICS OF WATER QUALITY PARAMETERS

Summary statistics for each of the water quality parameters measured in this experiment are shown in Table 3. This table shows that significant variations in water quality occurred between watersheds within each data campaign and that some parameters varied significantly between data campaigns. Temperature was much higher during the fall than during the spring, which indicates that the streams probably had a larger proportion of surface runoff compared to baseflow during the fall. Temperature was also more variable during the fall, which may be related to the generally lower discharge during this season, as smaller streams are more susceptible to changes in air temperature. Two of the least variable parameters were pH and P, with relatively little variation between watersheds or with season. SC showed significant variations between watersheds, but relatively little variation with season. DO was significantly higher during the spring, perhaps due to increased turbulence in the streams, associated with higher discharge. Turbidity, N, and E. coli counts, all of which would be expected to increase with increasing overland flow, had much higher values during the spring.

4.2. PAIRWISE COMPARISON OF FALL AND SPRING DATA

Table 4 shows the pairwise comparisons for each water quality parameter that was acquired in both the fall and spring. The fall and spring data sets were statistically different, with fairly low p-values for all water quality parameters. This suggests that temporally variable factors influencing these parameters may be more important than static factors in estimating surface water quality.

Table 3. Summary statistics of water quality parameters for two sampling campaigns.

	Fall				Spring			
Variable	Minimum	Maximum	Mean	Std. deviation	Minimum	Maximum	Mean	Std. deviation
T °C	16.10	28.60	21.55	3.62	10.10	15.40	12.3	1.53
pH	7.13	8.35	7.77	0.40	7.65	8.75	8.26	0.32
DO mg/L	0.30	9.51	3.48	2.38	4.65	11.18	9.10	1.85
SC µs/cm	205.60	605.00	307.34	99.28	150.00	461.90	271.74	78.84
Turbidity (NTU)	4.33	219.00	47.64	54.59	17.50	428.00	94.88	89.5
Phosphate mg/L	0.12	13.43	1.12	3.28	0.19	10.38	0.74	1.70
Nitrate mg/L	0.10	21.60	1.77	5.29	0.64	18.80	2.78	3.16
E. coli cfu/100ml	100.0	1350.0	509.3	347.4	0.00	4550.0	1012.8	1245.7
Biotic Index (BI)	4.0	7.42	5.35	1.02				
WQI	51.6	84.6	66.3	8.4	42.6	85.5	68.7	8.8

4.3. SIMPLE REGRESSION

Simple regression analysis was done between all water quality indicator variables and all independent variables (i.e., LULC, geologic, and topographic factors). For water quality characteristics that were not normal before transformation (i.e., turbidity, N, P, and E. coli), the transformed (square root) data were used for the correlation analysis. The correlation coefficient (Pearson's coefficient or R) and the statistical significance of each regression relationship is shown for the most significant correlations between water quality variables and the independent variables in Tables 5 and 6 for the fall and spring, respectively.

These tables illustrate that the independent variables that best correlate with water quality indicators vary with season for some water quality indicators but remain more temporally consistent with others. During the fall, the independent variable that correlated most often with water quality was the "pasture/hay" land use category; this land use was significant for N, P, E. coli, and turbidity. Since pasture includes land where livestock graze, it is probable that these water quality parameters are affected by animal waste and/or erosion created by animals near streambanks (Walters et al. 2011). The percent of urban land also correlated with multiple water quality parameters, including E. coli, P, and temperature. The Lower Grand watershed is predominantly rural, but several sub-watersheds include developed areas. Leaching from septic tanks, municipal sewage, lawn fertilizers or urban stormwater runoff may impact streams. Although the fall was relatively dry, the second most frequently observed independent variable was precipitation, which was the most significant factor related to N and SC.

Table 4. Normality test results and pairwise comparison of fall and spring data sets.

Parameter	**Fall: Normal without transform (R)**	**Fall: Best transform**	**Fall: Normal after transform (R)**	**Spring: Normal without transform (R)**	**Spring: Best transform**	**Spring: Normal after transform (R)**	**Differences between fall and spring normally distributed (R)**	**Statistical method employed**	**Statistically different in spring and fall (p-values)**
Temperature	Yes (0.991)	Square root	Yes (0.999)	Yes (0.974)	Square root	Yes (0.999)	Yes (0.986)	Paired-t test	Yes (<0.001)
pH	Yes (0.994)	Square root	Yes (0.999)	Yes (0.969)	Square root	Yes (0.999)	Yes (0.96)	Paired-t test	Yes (<0.001)
SC	Yes (0.959)	Square root	Yes (0.995)	Yes (0.982)	Square root	Yes (0.997)	Yes (0.97)	Paired-t test	Yes (0.013)
DO	Yes (0.995)	Square root	Yes (0.971)	Yes (0.994)	Square root	Yes (0.998)	Yes (0.98)	Paired-t test	Yes (<0.001)
Turbidity	No (0.667)	Square root	Yes (0.969)	No (0.827)	Square root	Yes (0.979)	No (0.89)	Sign test	Yes (0.002)
Nitrate	No (0.444)	Square root	Yes (0.962)	No (0.713)	Square root	Yes (0.968)	No (0.92)	Sign test	Yes (< 0.001)
Phosphate	No (0.516)	Square root	Yes (0.961)	No (0.512)	Square root	Yes (0.970)	No (0.68)	Sign test	Yes (0.011)
E. coli	No (0.884)	Square root	Yes (0.950)	No (0.868)	Square root	Yes (0.971)	No (0.92)	Sign test	Yes (0.016)
Biotic Index	Yes (0.973)	Square root	Yes (0.993)	NA	NA	NA	NA	NA	NA

These correlations suggest that even small amounts of precipitation can be significant for transporting nutrients and other dissolved solids to surface water

(Narasimhan et al. 2010; Jeznach et al. 2017). DO correlated best with the geologic factors of depth to bedrock and depth to groundwater, while temperature and pH had only weak or statistically insignificant correlations.

The spring data exhibited many of the same independent factors correlated to water quality parameters along with several new correlations. Unlike in the fall, cultivated crops had more effect, being significantly correlated with N, SC, and temperature. This effect might result from the timing of fertilizer application because approximately twice as much fertilizer is applied near planting time in the spring than during the fall in Missouri (Fulhage 2000; Missouri Agricultural Experiment Station 2014). The composition of the fertilizer is also significant, as approximately four times as much nitrogen is applied in the spring as in the fall, but the amount of phosphatic fertilizer is approximately equal in the spring and fall (Missouri Agricultural Experiment Station 2014). The percentage of land classified as urban was less significant during the spring, when only E. coli correlated with this parameter. An evaluation of regression coefficients indicates that only some of the factors most highly correlated with water quality indicators are seasonal. This variability is probably due to changes in the proportion of surface runoff and baseflow in streams. Geologic factors, such as depth to groundwater and slope as well as LULC factors correlated strongly with water quality indicators. This means that topographic and geologic factors cannot be neglected when determining the watersheds with the greatest risk of water quality impairment.

Table 5. Correlation coefficients between water quality indicators and watershed landscape characteristics during the fall.

Factor of correlation	R	p-value	Factor of correlation	R	p-value	Factor of correlation	R	p-value
DO			**pH**			**Temperature**		
Average depth to bedrock (m)	0.72	0.000	Discharge (m^3/s)	-0.15	0.25	Urban%	0.53	0.05
Average depth to groundwater (m)	0.52	0.006						
SC			**Escherichia coli (E. coli)**			**Turbidity**		
Precipitation (mm)	-0.47	0.012	Urban%	0.37	0.045	Clay + silt%	0.63	0.000
			Pasture/hay%	0.37	0.05	Pasture/hay%	0.58	0.005
						Average slope	0.54	0.001
Nitrate			**Phosphate**			**Biotic Index (BI)**		
Precipitation (mm)	0.6	0.013	Urban%	0.4	0.031	Turbidity (NTU)	0.58	0.008
Pasture/hay%	0.40	0.03	Pasture/hay%	0.33	0.03	Phosphate mg/L	0.47	0.031

Table 6. Correlation coefficients between water quality indicators and watershed landscape characteristics during the spring.

Factor of correlation	R	p-value	Factor of correlation	R	p-value	Factor of correlation	R	p-value
DO			**pH**			**Temperature**		
Average depth to groundwater (m)	0.55	0.000	Average depth to groundwater (m)	0.60	0.000	Pasture/hay%	0.62	0.000
Precipitation (mm)	0.30	0.040	Clay + silt%	0.47	0.02	Cultivated crops%	0.60	0.000
SC			**E. coli**			**Turbidity**		
Average slope	0.70	0.000	Urban%	0.41	0.003	Discharge (m^3/s)	0.50	0.001
Average depth to bedrock (m)	-0.55	0.000	Pasture/hay%	0.3	0.043	Average slope	0.37	0.013
Cultivated crops%	0.54	0.000						
Nitrate			**Phosphate**			**Biotic index**		
Pasture/hay%	0.40	0.012	Pasture/hay%	0.43	0.031	Nitrate mg/L	0.52	0.019
Cultivated crops%	0.30	0.020	Precipitation (mm)	0.40	0.040	Phosphate mg/L	0.45	0.040
						Turbidity (NTU)	0.30	0.012

4.4. STEPWISE MULTIPLE REGRESSION

Stepwise multiple regression was performed to determine which independent variables were most suitable for predicting water quality indicators in different seasons. Stepwise regression only employs independent variables that significantly improve the correlation after other independent variables are considered. For example, slope and topographic complexity may both correlate strongly with water quality, but these independent variables are often correlated. Therefore, it is not useful to include them both in a regression equation because it would not greatly improve the estimation of a water quality indicator. In addition, it would add unnecessary complexity to the relationship and make data acquisition more arduous. Consequently, the only parameters included in the following stepwise regression equations are those that most significantly and independently improve the correlation to water quality indicators. As with the correlation analysis, water quality parameters that were not normal before transformation were transformed prior to regression, but those that were normally distributed without a transformation were not transformed.

Table 7 displays the stepwise regression results for the fall, while Table 8 presents similar results for the spring. Table 7 shows that during the fall, a statistically significant regression equation could be generated for each of the water quality indicators, but the quality of these predictions (as shown by the R^2 value) was often low. The parameters where more than 50% of the variance could be predicted using regression relationships were temperature, DO, SC, and biotic index. In some cases, the independent variables in the regression equation were the same as those with high correlation coefficients in Table 5; however, other water quality indicators were best predicted by variables without the highest correlation. For the stepwise regression relationships with higher Pearson coefficients, geologic parameters (e.g., depth to bedrock, depth to groundwater, soil type) were often more helpful for predicting water quality indicators than were LULC characteristics. For several of the relationships with lower Pearson coefficients, precipitation was the most significant variable, suggesting that the timing of a measurement may strongly influence the result. During the spring (Table 8), the regression relationships often had lower Pearson coefficients than during the fall. Only temperature and SC had relationships where more than 50% of the variability could be explained by the correlation variables. As with the fall, geologic or topographic parameters had a greater effect than LULC variables, although urban land use was significant for E. coli and P, and pasture/hay was important for N.

A comparison of stepwise regression relationships developed using data acquired during the spring and fall show that for approximately half of the water quality parameters (e.g., temperature, E. coli, pH, DO, and turbidity), one independent variable occurs in the regression equation for both seasons. However, the relationships developed using the spring data present differing (usually additional) independent variables. The independent variable that remains significant across both seasons tends to be the most critical predictor for each water quality indicator. For some water quality indicators, such as SC, N, and P, the independent variables in the regression relationships differ completely depending on season. This suggests that the loading mechanisms for these parameters may vary significantly with season and recent land use modifications, such as fertilizer application, so different seasonal models may be required to predict water quality using simple stepwise regression relationships.

Table 7. Stepwise regression models between water quality indicators and watershed landscape characteristics during the fall.

Model for temperature	**Beta coefficients**	**R**	**R^2**	**p-value**
Average depth to bedrock	-0.07	0.84	0.70	0.000
Total stream length	0.13			
Beta coefficients (Constant) = 26.4				
Regression Equation: Temperature = 26.4 - 0.07 (Average depth to bedrock) + 0.13 (Total stream length)				
Models for *E. coli*	**Beta coefficients**	**R**	**R^2**	**p-value**
Urban	3.6	0.56	0.32	0.006
Beta coefficients (Constant) = ***-10.4***				
Regression Equation: E. coli = 3.6 (Urban) - 10.4				
Model for pH	**Beta coefficients**	**R**	**R^2**	**p-value**
Precipitation	-0.18	0.32	0.10	0.000
Beta coefficients (Constant) = 8.44				
Regression Equation: pH = 8.44 − 0.18 (Precipitation)				
Model for DO	**Beta coefficients**	**R**	**R^2**	**p-value**
Average depth to bedrock	0.04	0.72	0.52	0.007
Average depth to groundwater	0.1			
Beta coefficients (Constant) = -3.2				
Regression Equation: DO = -3.2 + 0.04 (Average depth to bedrock) + 0.1 (Average depth to groundwater)				
Model of Turbidity	**Beta coefficients**	**R**	**R^2**	**p-value**
Average slope	-0.25	0.64	0.4	0.002
Urban	-3.41			
Beta coefficients (Constant) = 119.7				
Regression Equation: Turbidity = 119.7 - 0.25 (Average slope) – 3.41 (Urban)				
Model of SC	**Beta coefficients**	**R**	**R^2**	**p-value**
Precipitation	11.06	0.83	0.70	0.002
Clay + silt	4.3			
Beta coefficients (Constant) = -309.4				
Regression Equation: SC = -341.73 + 11.06 (Precipitation) + 4.3 (Clay + silt)				
Model for Nitrate	**Beta coefficients**	**R**	**R^2**	**p-value**
Precipitation	0.46	0.53	0.28	0.001
Urban	0.37			
Beta coefficients (Constant) = -1.1				
Regression Equation: Nitrate = 0.46 (Precipitation) + 0.37 (Urban) – 1.1				
Model for Phosphate	**Beta coefficients**	**R**	**R^2**	**p-value**
Precipitation	0.07	0.57	0.32	0.02
Beta coefficients (Constant) = 0.57				
Regression Equation: Phosphate = 0.57 + 0.07 (Precipitation)				
Model for Biotic Index (BI)	**Beta coefficients**	**R**	**R^2**	**p-value**
Turbidity	0.3	0.88	0.78	0.002
Urban	-0.9			
Temperature	0.14			
Beta coefficients (Constant) = 4.25				
Regression Equation: BI = 0.3 (Turbidity) - 0.9 (Urban) + 0.14 (Temperature) + 4.25				

Table 8. The stepwise regression models between water quality indicators and watershed landscape characteristics during the spring.

Model for temperature	Beta coefficients	R	R^2	p-value
Average slope	1.2	0.78	0.61	0.000
Watershed slope/relief ratio	-0.57			
Average depth to bedrock	-0.01			
Beta coefficients (Constant) = 11.8				
Regression Equation: Temperature = 11.8 + 1.2 (Average slope) - 0.57 (Watershed slope/relief ratio) - 0.01 (Average depth to bedrock)				
Model for *E. Coli*	**Beta coefficients**	**R**	**R^2**	**p-value**
Urban	4.3	0.60	0.36	0.001
Beta coefficients (Constant) = 24.5				
Regression Equation:* E. coli *= 4.3 (Urban) + 24.5				
Model for pH	**Beta coefficients**	**R**	**R^2**	**p-value**
Average depth to groundwater	0.03	0.67	0.46	0.002
Precipitation	0.005			
Beta coefficients (Constant) = 7.03				
Regression Equation: pH = 7.03 + 0.03 (Average depth to groundwater) + 0.005 (Precipitation)				
Model for DO	**Beta coefficients**	**R**	**R^2**	**p-value**
Average depth to groundwater	0.15	0.55	0.30	0.001
Beta coefficients (Constant) = 5.42				
Regression Equation: DO = 0.15 (Average depth to groundwater) + 5.42				
Model of Turbidity	**Beta coefficients**	**R**	**R^2**	**p-value**
Discharge	0.011	0.61	0.37	0.001
Average Slope	-0.12			
Beta coefficients (Constant) = 11.35				
Regression Equation: Turbidity = 0.011 (Discharge) - 0.12(Average Slope) + 11.35				
Model of SC	**Beta coefficients**	**R**	**R^2**	**p-value**
Average slope	29.6	0.75	0.57	0.001
Average depth to bedrock	0.5			
Beta coefficients (Constant) = 82.6				
Regression Equation: SC = 29.6 (Average slope) + 0.5 (Average depth to bedrock) + 82.6				
Model for Nitrate	**Beta coefficients**	**R**	**R^2**	**p-value**
Pasture/hay	-0.02	0.43	0.18	0.053
Average slope	0.14			
Beta coefficients (Constant) = 3.03				
Regression Equation: Nitrate = 0.014 (Average slope) - 0.02 (Pasture/hay) + 3.03				
Model for Phosphate	**Beta coefficients**	**R**	**R^2**	**p-value**
Average slope	0.21	0.51	0.26	0.024
Urban	0.08			
Beta coefficients (Constant) = 3.47				
Regression Equation: Phosphate = 0.21 (Average slope) + 0.08 (Urban) + 3.47				
Model for Biotic Index	**Beta coefficients**	**R**	**R^2**	**p-value**
Nitrate	0.86	0.67	0.45	0.037
Precipitation	-0.02			
Beta coefficients (Constant) = 5.5				
Regression Equation: BI = 0.86 (Nitrate) - 0.02 (Precipitation) + 5.5				

4.5. WATER QUALITY AND BIOTIC INDEXES

The results of the Water Quality Index are shown in Figure 5. The fall WQI values ranged from 52 (very poor) to 97 (excellent), while WQI values during the spring ranged from 43 (very poor) to 86 (very good). During the spring, about 70% of the watershed sites were degraded. The lower WQI in the spring might have been caused by increased surface runoff that carried recently applied nutrients, sediment, and bacteria to the streams.

The WQI value is based on several physicochemical water quality parameters and bacterial concentration. These parameters may change with time and are difficult to measure on a continuous basis. Macroinvertebrate populations are more time-consuming to sample in the field but can provide information about average water quality over time. Figure 6a compares the WQI and biotic index for the fall data, displaying the expected trend between these variables; however, the correlation is too low to meaningfully relate these two parameters. Figure 6b presents the biotic index data acquired in the fall with the WQI calculated using water quality measurements collected in the spring. Even though these data sets were acquired at different times, there is a significantly better correlation between the WQI and the biotic index for the spring measurements than for the fall. This suggests that the water quality measurements acquired in the spring may be more indicative of the longer-term conditions for the streams in this study.

4.6. PRINCIPAL COMPONENT ANALYSIS

Three principal components were obtained with eigenvalues > 1, which accounted for 68.4% of the total variance in the data set in the fall and 69.2% in the spring. Figure 7 illustrates the first two principal components for each of these seasons, while Table 9 presents the strength of the correlation for individual parameters.

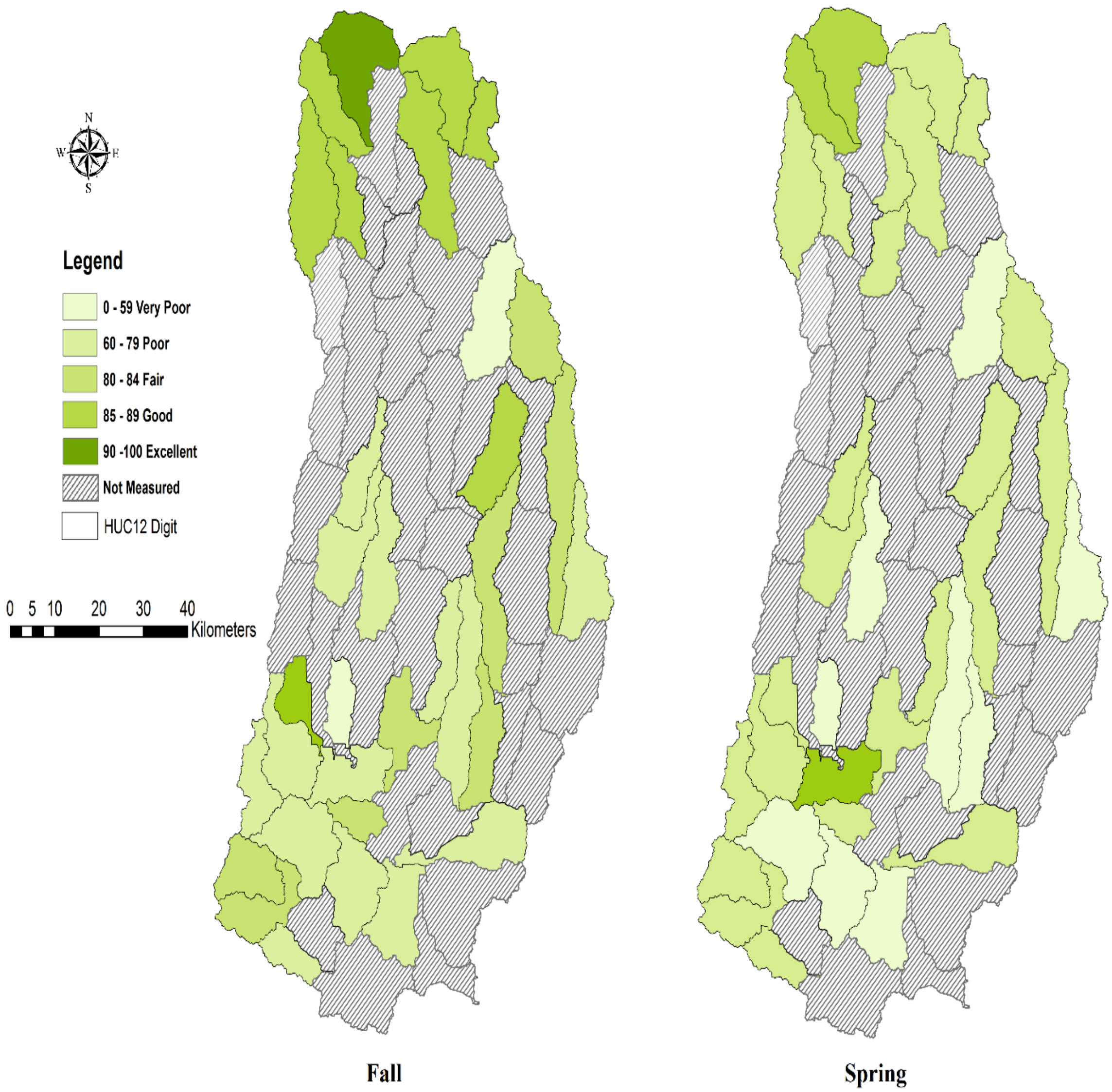


Figure 5. Spatial distribution of the WQI for the study area during the fall and spring.

In the fall, the first principal component (PC1) correlated most highly with P and N, and more weakly with SC. This component seems to be primarily associated with fertilizer runoff.

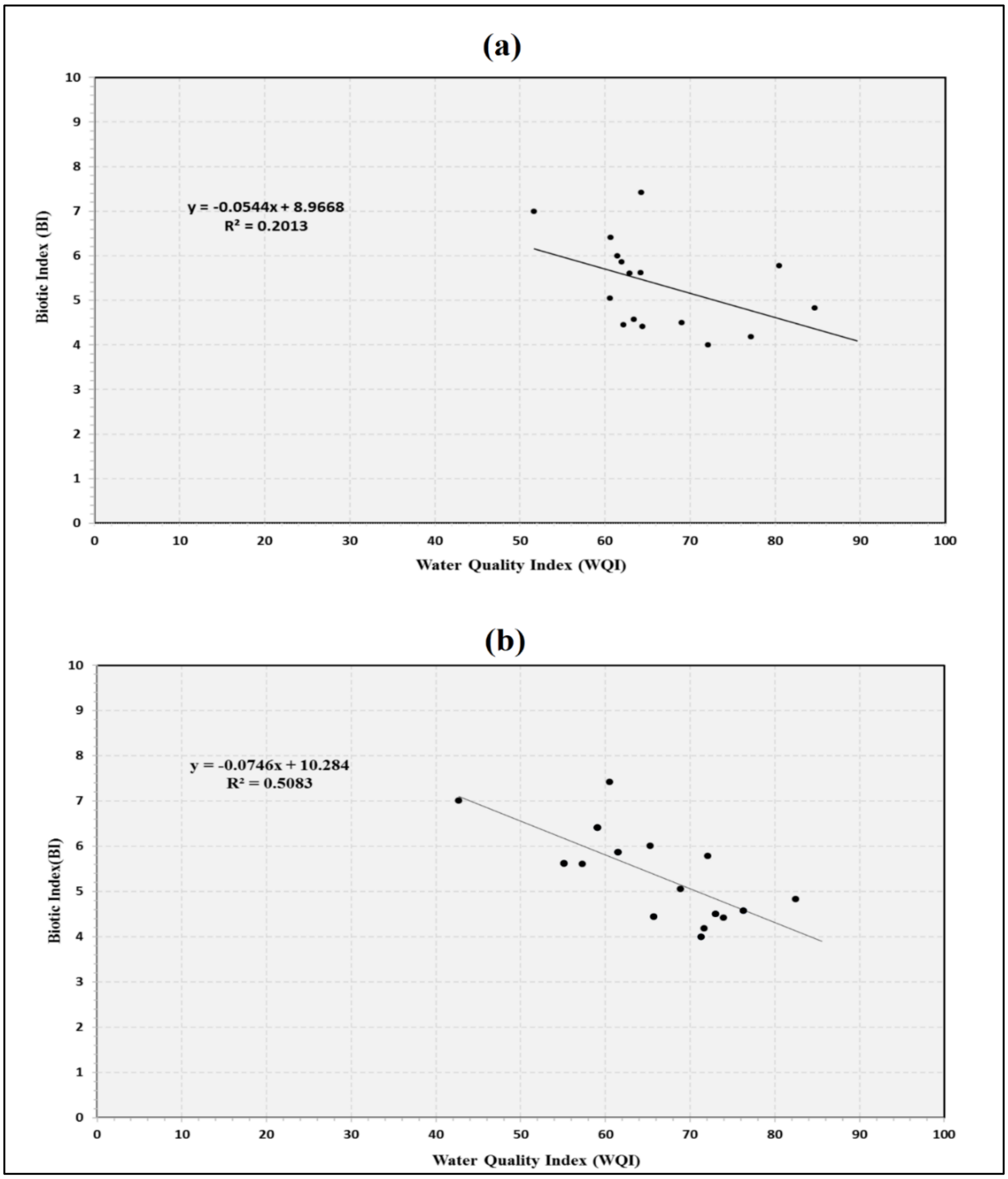


Figure 6. Comparison between the Water Quality Index (WQI) and biotic index (BI): (a) fall, (b) spring.

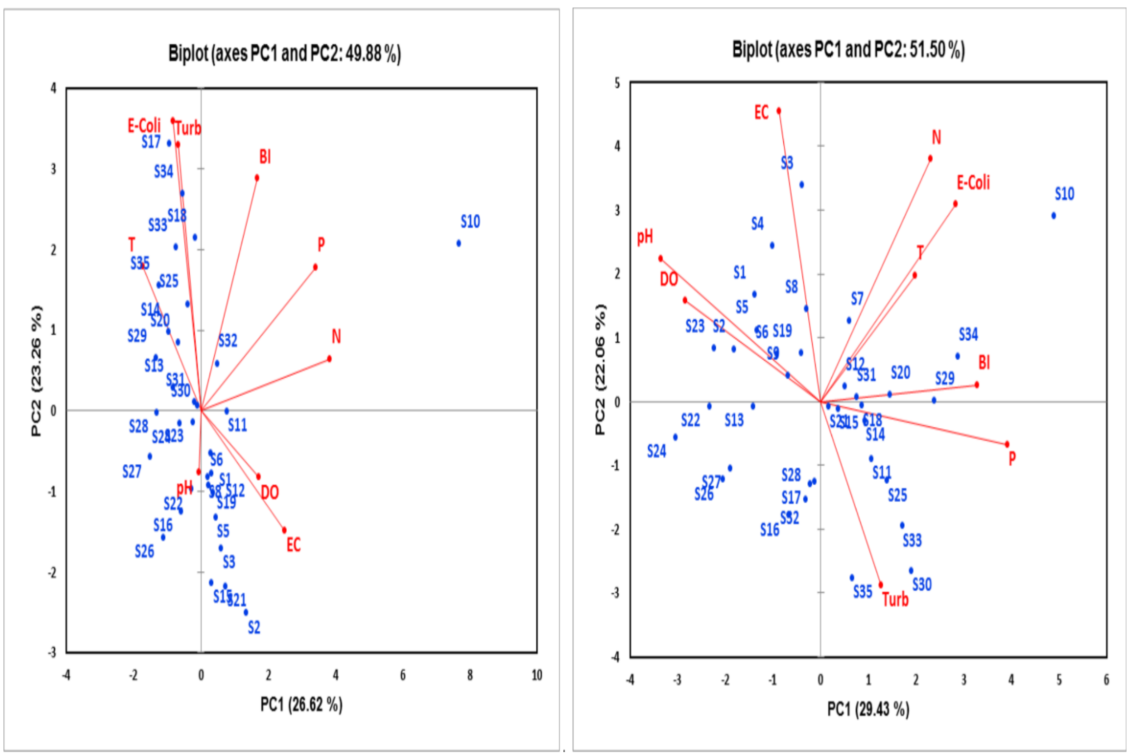
Table 9. Factor loadings values of water quality indicators for fall and spring.

	Fall			Spring		
Parameter	PC1	PC2	PC3	PC1	PC2	PC3
T	-0.411	0.397	-0.646	0.400	0.346	0.693
pH	-0.012	-0.171	0.465	-0.678	0.393	-0.313
DO	0.411	-0.185	0.727	-0.574	0.276	-0.342
EC	0.591	-0.330	-0.431	-0.176	0.796	0.507
Turbidity	-0.195	0.800	0.311	0.255	-0.503	-0.302
P	0.810	0.396	-0.201	0.790	-0.117	-0.137
N	0.912	0.142	-0.246	0.465	0.664	-0.476
E. coli	-0.159	0.732	-0.038	0.571	0.540	-0.529
BI	0.398	0.641	0.346	0.662	0.045	0.169
Eigenvalue	2.396	2.094	1.668	2.649	1.986	1.596
Total variance (%)	26.61	23.26	18.52	29.43	22.06	17.73
Cumulative variance (%)	26.61	49.88	68.41	29.43	51.49	69.23

The second principal component (PC2) correlated most highly with turbidity, E. coli, and BI. E. coli. Turbidity may be affected by manure application but may also be strongly influenced by grazing livestock and associated streambed erosion.

The correlations observed in PC2 imply that the biotic index could be more affected by livestock-related runoff (either directly from grazing livestock or from manure application to fields) than by the application of chemical fertilizers. In the spring, parameters were more similarly correlated with both PC1 and PC2, with fewer very strong correlations with either component than in the fall. PC1 was most correlated with P, pH, and BI, while PC2 was most correlated with SC and N.

Since the BI data were only acquired in the fall, the apparent correlation between BI and P in the spring (Figure 7) may not be significant. However, the correlation between N and E. coli in the spring may indicate a common livestock-based source for these factors.



Fall   Spring

Figure 7. PCA biplots of water quality indicators for fall and spring based on the first two PCs.

5. DISCUSSION

The results of this study reveal that water quality parameters can vary significantly with season and may reflect recent land use, such as fertilizer application. Many of the results followed expected patterns; DO and turbidity are both higher when discharge is larger (i.e., in the spring, in this study). SC was lower during the spring, perhaps due to dilution. P-values were higher in the fall. This can be explained by higher discharge in the spring even though fertilizers are applied in approximately equal amounts in the fall and spring. N and E. coli are significantly higher in the spring, when more nitrogen-based fertilizer is applied and when more manure may also be applied.

Compared to the literature, our study found similar results in its correlations of water quality with land use, geologic, or topographic parameters. For example, Tong and Chen (2002) studied correlations between land use and water quality parameters in watersheds in Ohio. They used data available from the United States Environmental Protection Agency (USEPA) averaged over an eight-year period and found that nitrogen, phosphorus, and fecal coliform were all positively correlated with both agricultural and urban land use. Similarly, our research found that these water quality parameters were correlated with pasture/hay land use, and E. coli and P were also correlated with the percentage of urban land. During the spring, cultivated crops were also significant for N. The correlation analysis (Spearman's rank) performed by Tong and Chen (2002) showed that the correlations between each of these water quality parameters and urban land use was greater than the correlation with agricultural land use. Even though the percent of urban land in our study was small, our results also established that the percent of urban land was significant, although not always more significant than agricultural land use. The correlation factors (i.e., Pearson's correlation coefficient) in our investigation were generally higher than those observed by Tong and Chen (2002), possibly because we collected data for a relatively short time, whereas their data over a longer time span.

Galbraith and Burns (2007) focused on the impact of land modification on water quality in non-flowing water bodies (e.g., lakes, wetlands, estuaries, etc.) in southern New Zealand. They found that the conversion of native grasslands to pasture increased nutrient concentrations and turbidity. The Lower Grand study also showed that pasture/hay land use was highly correlated to nutrient concentrations and turbidity as well as to E. coli.

The results of this study were less similar to research conducted in the eastern United States, which has a very different physiography. Potter et al. (2005) considered the impact of land use as well as of topographic and geologic factors on benthic macroinvertebrates in North Carolina, and they found that forest was the land use variable that correlated most closely with macroinvertebrate health, while watershed shape was the second most important variable. However, we found that neither of these variables showed a high correlation with macroinvertebrate health, possibly because we studied primarily agricultural watersheds, not those what were heavily forested. Also, our study correlated chemical water quality parameters with macroinvertebrate health, with nutrients and turbidity being highly correlated to the biotic index.

On the East coast, Schoonover and Lockaby (2006) studied the impact of land cover in 18 watersheds in western Georgia. The watersheds in their study were much more urbanized than the Lower Grand River watersheds, and row crops were rare. Most watersheds in their study area were dominated by a single land cover class (i.e., unmanaged forest, managed forest, pasture, developing, or urban). They found that more urbanized watersheds typically had higher nutrients and E. coli than less urbanized watersheds. In the Lower Grand watershed, the percentage of land classified as urban is small, but urban land use still occurred as a factor that correlated significantly with several water quality parameters. This suggests that runoff from developed land, septic tanks, or municipal sewage may significantly impact water quality even in areas that are predominantly rural. Schoonover and Lockaby's (2006) work also had a temporal component. They found that nutrient concentrations were higher during storm flow than during baseflow conditions. In the Lower Grand study, nutrient concentrations seemed to be more influenced by the timing of fertilizer application. As such, concentrations of N were significantly higher in the spring (when more nitrogen fertilizer is applied) than in the fall. P concentrations were higher in the fall, even though P fertilizer is applied in approximately equal amounts in the spring and fall.

PCA analysis demonstrated significant seasonal variations in PC1 and PC2 factors, as did other studies (Ouyang et al. 2006; Garizi et al. 2011). Several of the factors that influenced variability in the fall were the same as those observed by other researchers. Ouyang et al. (2006) acquired data in the fall and spring along the lower St. John's River in Florida, and they found that the most influential parameters for PC1 were N, P, and EC (related to SC) (positively correlated) and organic carbon (negatively correlated). In another study along the Nakdong River, Jung et al. (2016) discovered that PC1 was influenced by N, P, EC, organic carbon, and chemical oxygen demand. In the Lower Grand River, the fall PC1 was most influenced by N, P and SC (positively correlated). In the spring, Ouyang et al. (2006) found that PC1 was most influenced by color, organic carbon (positively correlated) as well as alkalinity and SC (negatively correlated), while our study found that SC was weakly negative correlated with PC1 but strongly and positively correlated with PC2 in the spring.

6. CONCLUSIONS

Basic water quality measurements were acquired in 35 primarily agricultural watersheds during the fall and following spring. These measurements were used to calculate the biotic index and water quality index and were correlated with a variety of geologic, topographic, and LULC parameters. Pairwise comparison of the data acquired during the fall and spring showed that all water quality parameters were statistically different data sets with $p < 0.02$ for all parameters, which suggests that the timing of water quality sampling is critical. Simple regression analysis of all variables revealed that correlations between independent variables and water quality indicators fluctuated with the season but that the “pasture/hay” LULC category (which includes livestock grazing) was statistically significant for several water quality indicators for both sampling campaigns. The percentage of land used for cultivated crops was only significant in the spring, when more fertilizer is applied. The amount of precipitation in the two weeks preceding data collection was also significant for some water quality parameters. The variation between seasons as well as the significance of precipitation to the correlations again implies that the timing of sampling campaigns may influence the correlations. Geologic parameters, such as depth to bedrock, depth to water table, slope, and soil type, were also significantly correlated to water quality parameters. Stepwise regression of independent variables and water quality indicators showed that different relationships were developed in the fall and spring. However, many of the independent variables within the stepwise regression relationships were the same for both seasons, indicating that some geologic or LULC parameters seem to consistently predict water quality. In the predictive relationships, topographic and geologic parameters occurred with the same or greater frequency as LULC parameters. Comparison of the water quality index with the biotic index demonstrated that these two indexes were best correlated during the spring, implying that the lower water quality conditions observed in the spring might be more representative of the longer-term water quality conditions in these watersheds. The correlation of turbidity, E. coli, and BI in the PCA analysis suggests that livestock grazing may adversely affect water quality in this watershed. PCA analysis also revealed that N, P, and SC contribute greatly to the observed water quality variability.

This study produced several practical implications: (1) sampling time, including both season and time since precipitation, may significantly impact correlations between water quality and LULC or geologic factors. Thus, timing should be a key aspect of the experimental design for field campaigns. (2) Both LULC and geologic/topographic variables are necessary to predict water quality indicators, so proposed best management practices to improve water quality should be undertaken with strong consideration of the geologic and topographic conditions of each site. Promoting best management practices in those watersheds that are most likely to be impaired (based upon geologic or topographic parameters) could help maximize the environmental benefit, with the least outlay of financial resources. (3) Although stepwise regression equations between water quality indicators and independent variables changed with the season, some independent variables were valuable predictors of water quality regardless of the season. This suggests that it may be possible to partially predict water quality indicators based on other factors, such as topographic, geologic, and LULC information. Predictive relationships cannot be used to provide specific values for water quality parameters but may be helpful for targeting sampling campaigns in streams most likely to experience impairment. This could create more efficient regulatory monitoring and improve resource allocation for water management. (4) The biotic index correlated most with parameters often associated with agriculture or urban runoff (i.e., N, P, turbidity), and was only weakly correlated with the WQI, calculated using Cude's (2001) generally accepted method. This implies that macroinvertebrate assessment could help to distinguish LULC inputs independently from physicochemical water parameters, and that other methods of calculating the WQI might be needed to better predict biological responses based on physicochemical properties.

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II. A NOVEL APPROACH FOR ASSESSING WATERSHED SUSCEPTIBILITY USING WEIGHTED OVERLAY AND ANALYTICAL HIERARCHY PROCESS (AHP) METHODOLOGY

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ABSTRACT

Watershed vulnerability and the characterization of potential risk are important inputs for decision support tools in assessing watershed health. Most previous studies have focused on the assessment of the environmental risk using physicochemical properties of surface water and mathematical models to predict the health of a watershed. Here, we present a new methodology for evaluating watershed vulnerability using the analytic hierarchy process (AHP) and weighted overlay analysis. The new methodology provides an inexpensive approach for assessing areas that need more investigation based on known factors such as hydrogeologic, geological and climate parameters without the need for site-specific physicochemical data. The proposed method was implemented using six main factors that influence water quality: land use, soil type, precipitation, slope, depth to groundwater, and bedrock type. Vulnerability was predicted for ten sub-watersheds within the Eagle Creek Watershed in Indiana using publically available data after input into a geographic information system. The combination of watershed susceptibility assessment and GIS spatial analysis tools were used to produce maps that show the susceptible zones within a watershed. A comparison of the resulting vulnerability estimates showed the

expected significant positive correlations with measurements of nitrate, phosphate, temperature, and electrical conductivity. Likewise, the vulnerability estimates negatively correlated with dissolved oxygen and E. coli. Furthermore, the validation of the proposed approach revealed that the areas predicted to have high vulnerability did have lower water quality indices. The results showed a high negative correlation (r^2=0.77, $p<0.05$) between water quality index (WQI) and vulnerability to pollution which strongly suggests this method can be used successfully to assess a watershed's susceptibility.

1. INTRODUCTION

Water quality degradation from multiple sources of contamination has become a critical global issue. Many water bodies across the United States are classified as impaired. Studies show that about 85% of streams and rivers and 80% of lakes and reservoirs are affected by nonpoint source (NPS) pollution (USEPA, 2016), which can be attributed to sources such as agriculture and urbanization (Huang et al., 2010; Rowny and Stewart, 2012; Liu et al., 2014). Agriculture can cause water quality degradation due to excessive inputs of nutrients through commercial fertilizer and manure (Kourgialas et al., 2017; Jabbar and Grote, 2018), runoff from pesticides and herbicides (Cruzeiro et al., 2015), and increased turbidity due to soil erosion (Zhang and Huang, 2014). Numerous studies have recorded the negative impacts of some agricultural practices on water quality (Dupas et al., 2015; Fournier et al., 2017). Likewise, urbanization affects the water quality through sediment, oils, and solid wastes washed from hard surfaces, bacteria, and input of nutrients from wastewater and failing septic systems (USEPA, 2008; Walters et al., 2011; Zhao et al., 2015; Paule-Mercado et al., 2016).

Assessment of watershed susceptibility to contamination is an important step for decision making for sustainable environmental protection. In addition to anthropogenic inputs, some features of the landscape or geologic conditions may make the watersheds more vulnerable to degradation. The vulnerability can be described as the degree to which a system or system components are presumed to be impaired due to exposure to a potential risk or stress. Quantifying the vulnerability of watersheds to NPS pollution is important for recognizing which watersheds are most at risk of impairment and determining where changes in land use/land cover (LULC) might improve water quality conditions (USEPA, 2008). Changes in land use, along with soil attributes, combined with topography, climate, hydrology, and other landscape variables, are the most important factors contributing to a watershed's quality (Bansal et al., 2014 Neupane and Kumar, 2015; Fan and Shibata, 2015; Serpa et al., 2017). However, hydrologists are becoming increasingly aware of the importance of identifying and quantifying risks to evaluate the health of watersheds by using appropriate statistical technique and risk-based indicators. Therefore, the use of a qualified model for watershed assessment could be essential for evaluating continuous temporal and spatial distribution variations in watershed information.

A number of methods have been developed to assess a watershed's susceptibility to contamination using integrated watershed models and criteria evaluation methods (Sahoo et al., 2016; Ahn and Kim, 2017; Kanakoudis et al., 2017). For example, the method for vulnerability mapping conducted by Tran et al. (2012) used the self-/peer-appraisal method and 50 variables collected by the U.S. EPA's Regional Vulnerability Program for

141 watersheds to conduct watershed-based environmental vulnerability mapping for the Mid-Atlantic region in the Northeast of the United States. In another study, geostatistical applications were used to assess the vulnerability of watersheds to chloride contamination in urban streams for seven sites in four watersheds in the Greater Toronto Area using the probable chloride concentration measurements and comparing the results with aquatic species that have a known range of tolerance limits (Betts et al., 2014). Simha et al. (2017) applied vulnerability assessment as a quantitative technique in the island of Lesvos in Greece, where a set of 25 indicators was used to identify the influence of management strategies on the vulnerability index. High values of vulnerability were detected due to natural and human stresses. Eimers et al. (2000) developed a method for assessing the vulnerability of watershed to predict potential contamination that may affect the water quality in North Carolina. They used the rating of watershed characteristics based on a combination of factors that contribute to water (with or without contaminants) reacheing a surface water body by following the path for both overland flow and/or shallow subsurface flow.

Various approaches have been developed by the U.S. Environmental Protection Agency (USEPA) to assess watershed susceptibility to surface water pollution, such as WRASTIC. The WRASTIC method is based on seven parameters that affect the potential for pollution including: presence of wastewater (W), recreational activities (R), agricultural activities (A), size of the watershed (S), transportation avenues (T), industrial activities (I), and the amount of vegetative ground cover (C). This model suggested the higher WRASTIC index indicates a high vulnerability to contamination (USEPA, 2000).

Modern geographical information system (GIS) tools are a powerful method for gathering, managing, and manipulating spatial analysis data. In addition, GIS can provide a more consistent visualization environment to display the input data and the results of the model, which is more useful in a decision-making process. The external models which linked to GIS data provide a manageable way for combining and evaluating parameters such as land use/land cover, slope, and soil types (Nigatu Wondrade et al., 2013; Yu et al., 2016).

One method of evaluating natural systems such as watersheds is to use multiple-criteria decision-making (MCDM) techniques. One of the most widely used MCDM techniques is the Analytic Hierarchy Process (AHP) (Saaty, 1980). This approach has many steps, including assigning the hierarchical structure, specifying the relative weights of the criteria and sub criteria, determining the weights of each substitute, and measuring the final score (Saaty, 2008; Moeinaddini et al., 2010). Using GIS and AHP has proven successful in analyzing natural hazards such as landslides and floods (Gamper et al., 2006; Fernández and Lutz, 2010) and environmental studies (Ying et al., 2007; Rahman et al., 2014). The GIS-based and analytic hierarchy process has been applied by Koc-San et al. (2013) to choose a suitable site for an astronomical observatory. The same technique was used in Konya, Turkey by Uyan (2013) to select the best site for solar farms. Likewise, Anane et al. (2012) applied this approach in the Nabeul-Hammamet region (Tunisia) to find suitable sites for irrigation with reclaimed water. Dong et al. (2013) used remote sensing GIS and AHP to assess a habitat suitable for water birds in the West Songnen Plain in China.

In this research, we propose a new watershed susceptibility assessment method to evaluate watershed susceptibility to pollution using GIS and AHP methods. Six main factors are suggested in this study, which include: land use/land cover, soil type, average annual precipitation, slope, depth to groundwater, and bedrock type. The general assumptions that were considered in this study of watershed vulnerability assessment are based on the response of watersheds to different contamination impacts and how the six factors work together to affect watershed health. This approach uses different databases to predict the NPS pollution in a watershed without field and lab work, which is a useful first approximation of vulnerability with minimal cost and time commitments.

2. MATERIAL AND METHODS

2.1. A CASE STUDY IN THE EAGLE CREEK WATERSHED

The Eagle Creek Watershed (ECW) is located in Central Indiana. The watershed is in the northern portion of the Upper White River Watershed that lies within the Mississippi River Basin (Figure 1). It has a drainage area of approximately 459 km^2, and there are 10 sub-watersheds within the ECW varying in size from 26.9 km^2 to 70.7 km^2 (Table 1). The ECW consists of three main branches: School branch, Fishback Creek, and Eagle Creek branch, which flow into the Eagle Creek Reservoir. The Eagle Creek Reservoir is one of the main sources of drinking water for Indianapolis. These branches are fed by eight main tributaries: Dixon Branch, Finely Creek, Kreager Ditch, Mounts Run, Jackson Run, Woodruff Branch, Little Eagle Branch, and Long Branch. The flow distributions for the three main branches are: an average flow about 2.85 m^3/s for Eagle Creek and contributing 79% of the water to the reservoir; an average flow of 1.1 m^3/s for Fishback Creek, contributing 14% of water to the reservoir; and an average flow of 0.5 m^3/s for School Branch, contributing 7% of water to the reservoir (Tedesco et al., 2005).

Table 1. Sub-watersheds and their drainage area in the Eagle Creek Watershed.

Sub watershed Name	River or Stream	Station name	Drainage Area (km^2)
Dixon Branch-Eagle Creek	Eagle Creek	Eagle Creek	42.5
Mounts Run	Mounts Run	Mounts Run	41.2
Finley Creek-Eagle Creek	Finley Creek	Finley Creek	26.9
Lion Creek-Little Eagle Branch	Little Eagle Branch	Little Eagle Branch	40.6
Jackson Run-Eagle Creek	Jackson Run		48.5
Fishback Creek	Fishback Creek	Fishback Creek	54.0
Irishman Run-Eagle Creek	Irishman Run		48.5
Eagle Creek Reservoir-Eagle Creek	School Branch	School Branch at Brownsburg	51.0
Little Eagle Creek	Little Eagle Creek	Fall Creek at 30th St.	70.7
Ristow Branch-Eagle Creek	Eagle Creek	Grande Avenue	35.1

The primary land use in the ECW is agriculture with approximately 56%, and 38% of the watersheds is covered with urban land use, mostly in the southeast part of the watershed. The substantial majority of the remaining is either forested land or grassland. Precipitation is characterized by long duration and moderate intensity storms during the cooler months, and short duration, high-intensity storms in the late spring and summer months. The average annual precipitation for the Eagle Creek Watershed is 1050 mm. The lowest rainfall occurs in February, with an average of 59.7 mm. The highest rainfall occurs in May with an average of 115.5 mm. The watershed topography is relatively flat, with slopes less than 3%, especially in the agricultural areas. Steeper slopes are found adjacent to rivers and streams. Soils in the upper portion of the watershed consist of thin loess over loamy glacial till. These soils are classified as deep and poorly drained, but in the northwest part of the watershed soils are poorly drained to well drained, while downstream areas are dominated by soils that are generally deep, well drained to slightly poorly drained, soils formed in a thin silty layer and the underlying glacial till (Hall, 1999). The bedrock units of the Eagle Creek Watershed are generally characterized by brown, fine-grained dolomite to dolomitic limestone in the far northeastern part of the watershed, and brown sandy dolomite to sandy dolomitic limestone and gray, shaley fossiliferous limestone in the southwest part. The southern part of the watershed consists of brownish-black carbon-rich shale, greenish-gray shale, and minor amounts of dolomite and dolomitic quartz sandstone (Shaver et al., 1986; Gray et al., 1987).

2.2. DATA ACQUISITION AND PROCESSING

2.2.1. GIS Data Processing. Remote sensing data were used to create thematic maps for the proposed study area (Figure 2). The general topographic surveying and mapping of the landscape features within the ECW were derived from a 30-m resolution digital elevation model (DEM) to investigate the important watershed characteristics, such as elevation variations and the slope of the land surface. The National Hydrography Dataset (NHD) and Watershed Boundary Dataset (WBD), which are managed by the USGS, were applied to calculate some watershed characteristics such as drainage networks, hydrologic units, catchment areas, and related features, including rivers and streams (USGS, 2016).

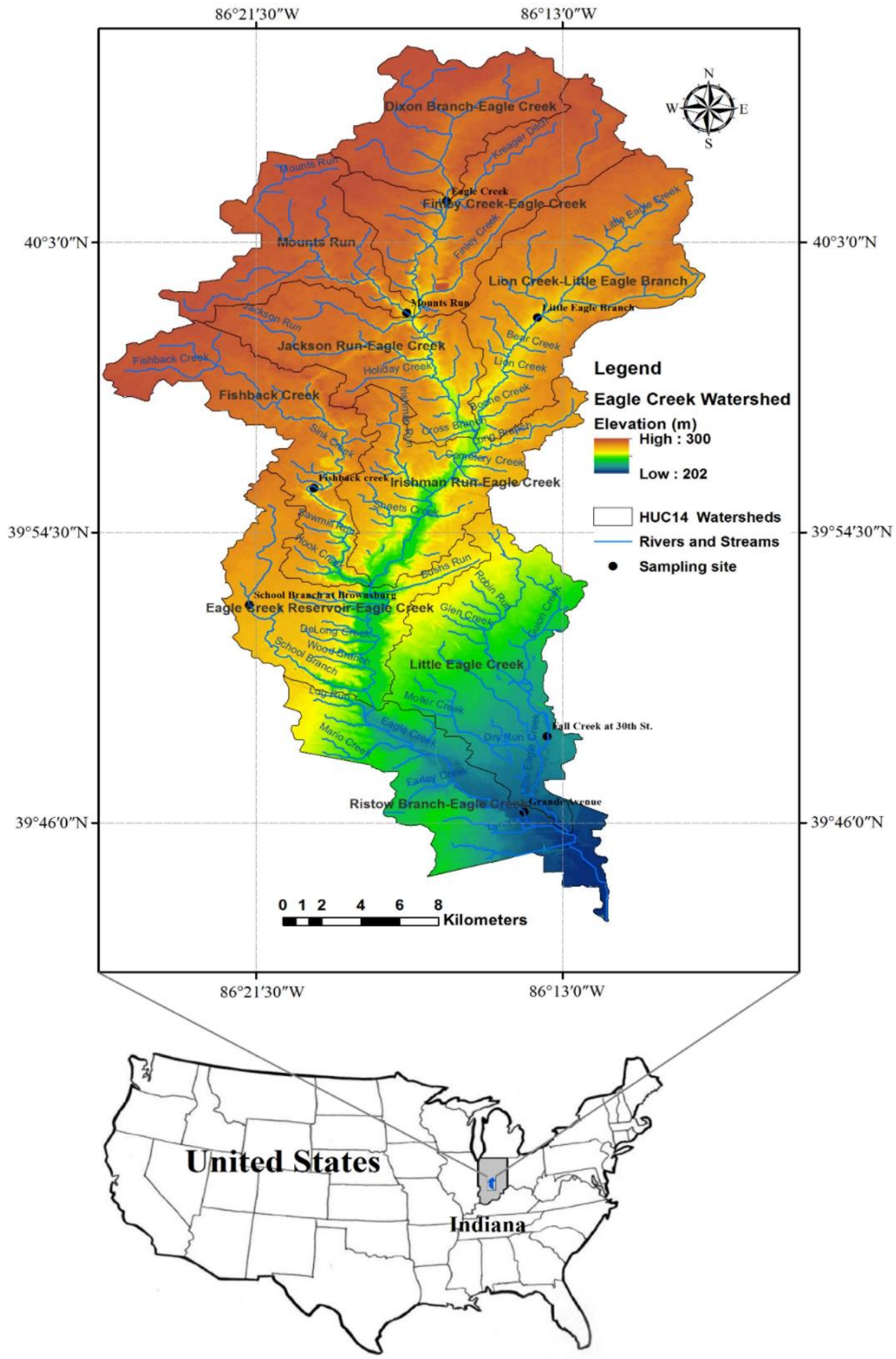

Figure 1. Location of the Eagle Creek Watershed.

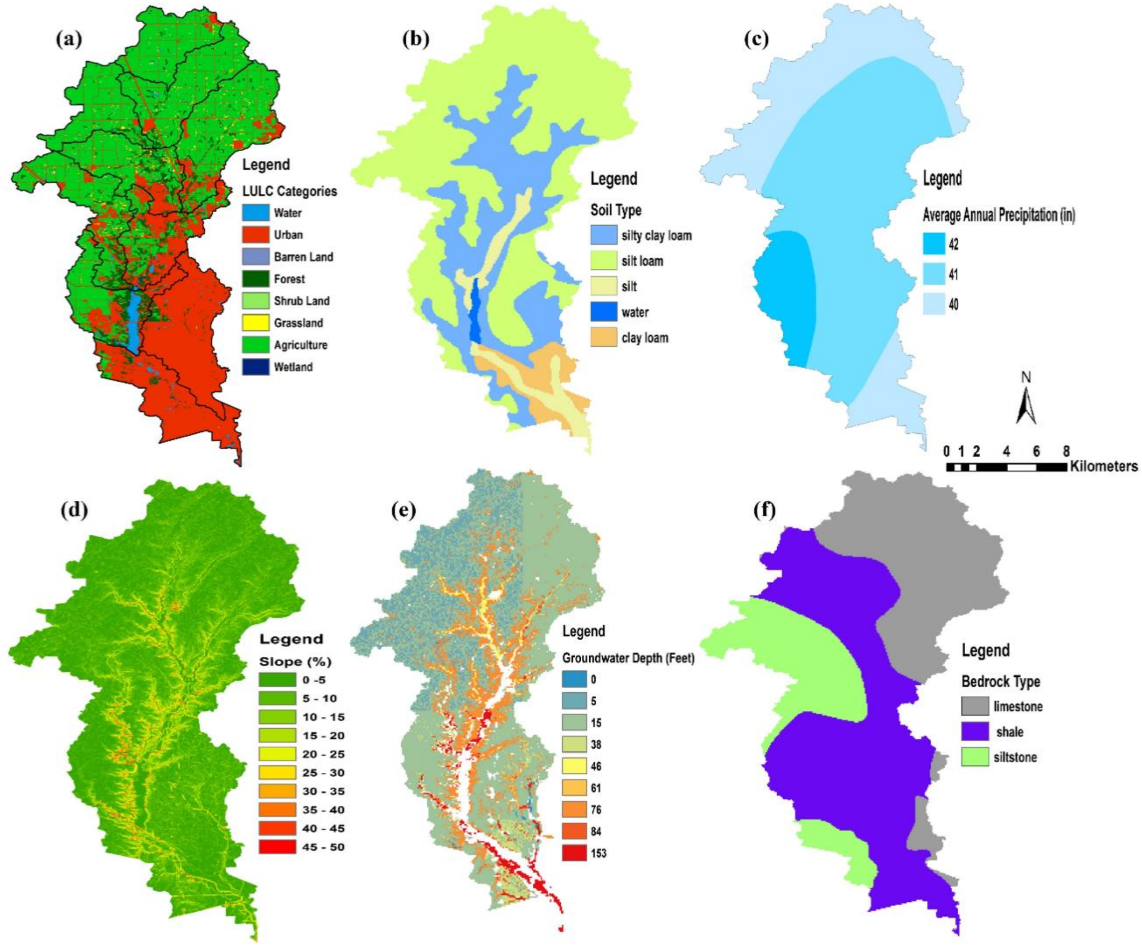

Figure 2. Thematic maps of the layers proposed for watershed susceptibility assessment method for: (a) land use/land cover, (b) soil type, (c) average annual precipitation, (d) slope%, (e) depth to groundwater, (f) bedrock type.

The National Land Cover Database 2011 (Homer, 2015), which includes 15 LULC categories, was used for this study. To reduce the number of variables and to create more meaningful LULC categories, some of these categories were combined for our analysis. All categories labeled “developed” were combined into one “urban” classification, and all categories labeled “forest” were combined into one group. Similarly, “wetland” categories were combined. ArcGIS was used to analyze the data and to determine the average values of each parameter for each sub-watershed.

The Parameter-elevation Regressions on Independent Slopes Model (PRISM) have been adopted to derive the average annual precipitation raster for the climatological data period 1961-1990 (Daly, 1996).

2.2.2. Water Quality Data. A statistical description of the water quality parameters which were measured by the Indiana Department of Environmental Management are shown in Figure 3. This figure shows that significant variations in water quality occurred between watersheds for each data collection session. Samples were collected from eight river stations which were treated as independent watersheds.

Temperature and pH showed relatively little variation and are the most constant parameters within the study area. Dissolved oxygen showed relatively slight variation for many sub-watersheds but was significantly higher in the Eagle Creek River at the Grande Ave, School Branch, and Fall Creek stations. Electrical conductivity showed more significant variation between watersheds where the minimum value was observed between (160 -640) µs/cm and the maximum value was between (523-1405) µs/cm.

Results of turbidity reveal relatively little differences between all sub-watersheds, except the highest turbidity value was observed in School Branch watershed (about 90 NTU). The measurements of *E. coli*, phosphate, and nitrate showed significant differences between sub-watersheds, where *E. coli* was somewhat higher in the southern part of the study area. Phosphate and nitrate concentrations are comparatively higher in northern sub-watersheds, where agricultural land is the most dominant land use.

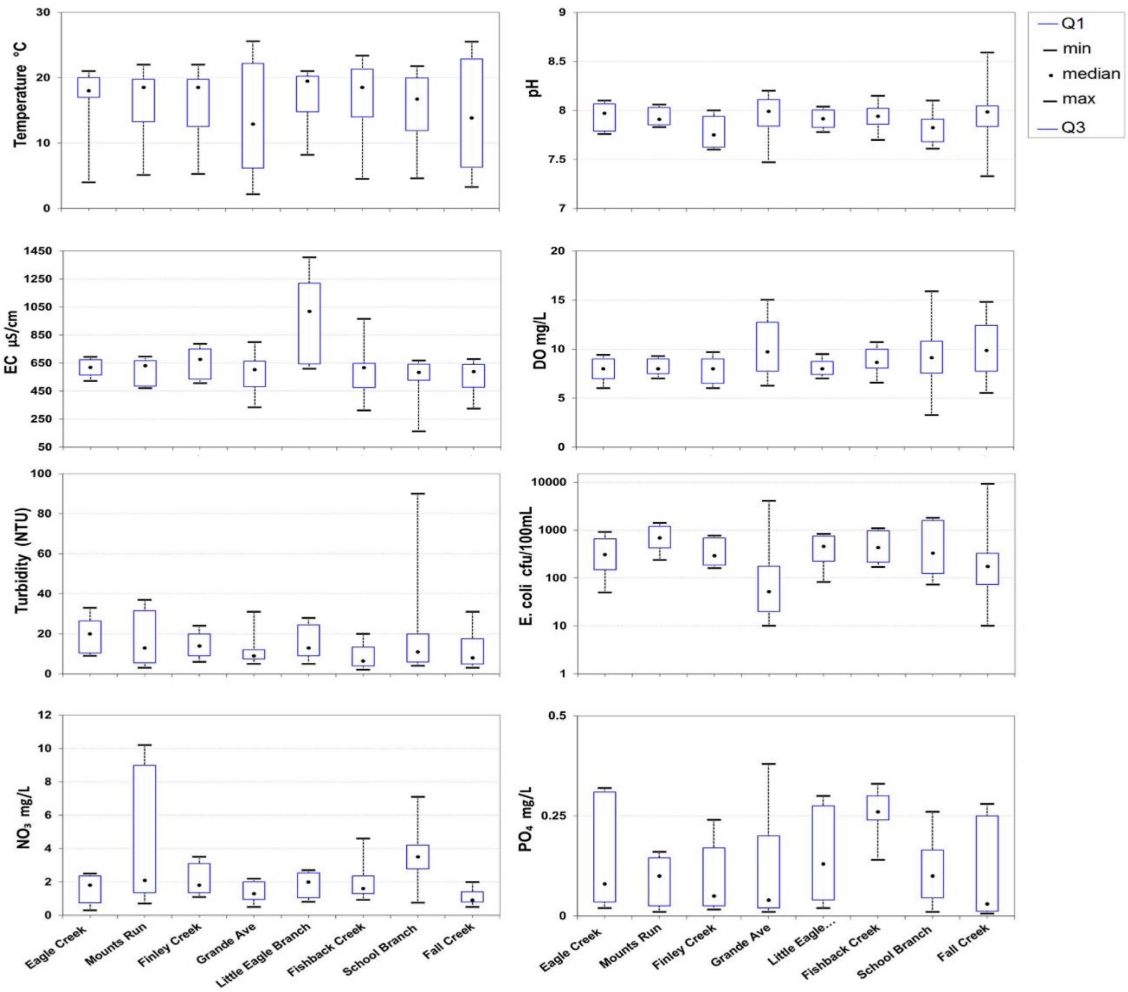

Figure 3. Boxplots showing the range of variations from minimum to maximum and the typical value (median) of water quality parameters.

3. METHODOLOGY

3.1. ANALYTICAL HIERARCHY PROCESS (AHP) EVALUATION MODEL

The AHP is an effective multicriteria decision making tool that can be used to set a systematic approach for evaluating and integrating the impacts of different factors, which include some levels of dependent or independent variables for both qualitative and quantitative information (Saaty, 1990). The AHP method can reduce problems between factors such as interrelationship and overlapping. The relative weight for each factor considered in this study was estimated using the methods of AHP and pairwise comparison matrix. The comparative scale (Saaty, 1980) is a common methodology typically performed to analyze the comparison between various factors. The relative importance between two factors is measured according to an integer numbers from 1 to 9, where 1 indicate the factors are equally important while 9 reflects that one factor is much more important than another (Table 2). The consistency ratio (*CR*) was computed to check the differences between the pairwise comparisons and the reliability of the measured weights. The consistency ratio should be <0.1 to be accepted; otherwise, it is important to check subjective judgments and recalculate the weights (Saaty and Vargas, 2001).

Table 2. Judgments scale and definitions for the pairwise comparison.

Qualitative Definition	Explanation	Intensity of Importance
Equal importance	Two activities contribute equally to the objective	1
Weak		2
Moderate importance	Experience and judgments slightly favour one activity over another	3
Moderate plus		4
Strong importance	Experience and judgment strongly favour one activity over another	5
Strong plus		6
Very strong or demonstrated importance	An activity is favored very strongly over another and dominance is demonstrated in practice	7
Very, very strong		8
Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation	9

In this study, the structure of the decision-making problem was created and consists of numbers that are represented by the symbols m and n. The values of a_{ij} ($i = 1, 2, 3\ldots, m$) and ($j = 1,2, 3..., n$) are used to indicate the performance values matrix in terms of the i^{th} and j^{th}. The upper triangular matrix was filled with the values of comparison criterion above the diagonal of the matrix, while the reciprocal values of the upper diagonal were used to complete the lower triangular of the matrix. The pairwise comparison matrix A, in which the element a_{ij} of the matrix is the relative importance of the i^{th} and j^{th} alternatives with consideration to criterion A as shown below where a_{ji} is the reciprocal values of a_{ij}.

The typical comparison matrix for any problem and the relative importance of the criterion can be shown in a decision matrix as below:

$$A = \begin{pmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & a_{23} & a_{2n} \\ \cdots & 1/a_{23} & \cdots & \cdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{pmatrix} \quad (1)$$

where, a_j; $I, j=1, 2, \ldots\ldots, n$ is the element of row i and column j of the matrix and equal to the number of alternatives.

The eigenvectors were calculated for each row using geometric principles in Equation (2):

$$Eg_i = \sqrt[n]{a_{11} \times a_{12} \times a_{13} \times \cdots \times a_{1n}} \quad (2)$$

where, Eg_i = eigenvector for the row i; n = number of elements in row i

The priority vector (Pr_i) was determined by normalizing the eigenvalues to 1 using the Equation below:

$$\mathrm{Pr}_i = Eg_i / (\sum_{k=1}^{n} Eg_k) \quad (3)$$

The lambda max (λ_{max}) was calculated from the summation of the result of multiplication between each element of the priority vector and the sum of the column of the reciprocal matrix as shown below:

$$\lambda_{\max} = \sum_{j=1}^{n} \left(W_j \times \sum_{i=1}^{m} a_{ij} \right) \tag{4}$$

where, a_{ij} = the sum of criteria in each column in the matrix; Wi = the value of weight for each criterion corresponding to the priority vector in the matrix of decision, where the values $i = 1, 2, \ldots m$, *and* $j = 1, 2, \ldots n$.

To compute the consistency ratio (CR), the following Equation was applied:

$$CR = \frac{CI}{RI} \tag{5}$$

where CI is the consistency index computed according:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{6}$$

where λ_{max} is the sum of the products between the sum of each column of the comparison matrix and the relative weights and n is the size of the matrix.

RI represents the random index that refers to the consistency of the pairwise comparison matrix which is randomly generated. It is derived as the average of the random consistency index, which was computed by Saaty (1980) using a sample of 500 matrixes randomly generated.

In the current study, weights scores for factors are obtained based on (AHP) model (Table 3). A similar approach was applied to obtain rating values for individual sub-criteria used for watershed susceptibility assessment.

To calculate the watershed susceptibility values of the study area, the weighted overlay analysis was applied based on the following equation:

$$WS = \sum_{j=1}^{n} W_j \times C_{ij} \tag{7}$$

where, *WS* is the watershed susceptibility for area *i*, W_j is the relative importance weight of criterion, C_{ij} is the grading value of area *i* under criterion *j* and n is the total number of criteria.

Table 3. A pairwise comparison matrix developed for assessing the relative importance of the criteria for watershed susceptibility assessment

Factor	**LULC**	**ST**	**BRT**	**Slope**	**AAP**	**DTG**	**Weights**
LULC	1	3	4	5	3	2	0.36
Soil type (ST)	0.33	1	5	3	2	2	0.22
Bedrock type (BRT)	0.25	0.2	1	0.33	0.33	0.5	0.05
Slope	0.2	0.33	3	1	0.33	1	0.1
Average annual precipitation (AAP)	0.33	0.5	3	3	1	3	0.18
Depth to groundwater (DTG)	0.5	0.5	2	1	0.33	1	0.09
CR Value = 0.02							

In this study, the assessment of a watershed's susceptibility was the main objective for using the decision hierarchy. The process of hierarchy structure in the decision problem involves two steps. The first step has been classified into six factors: land use, soil type, precipitation, slope, depth to groundwater, and bedrock type.

The second step includes 46 sub-categories used to evaluate the watershed's health. For this study, according to the judgment of experts and literature reviews in this field (Eimers et al., 2000; Lopez et al., 2008; Xiaodan et al., 2010; Furniss et al., 2013; USEPA, 2013; Shao et al., 2016, Siqueira et al., 2017), as well as different required and available data about the study area, each factor was classified into classes (sub-category). Then each sub-category was given a suitability rating value. After creating these factors, the maps which are required for each layer were obtained as a shapefile (vector) or raster. Shapefile maps were then converted to raster maps to be more useful in reclassifying sub-categories based on the new rating, as illustrated in (Figure 4).

To prepare each category and sub-category, a number of steps were implemented using ArcGIS 10.5 software (i.e., overlay, convert, reclassify, and raster calculator). An output watershed susceptibility map is producted by calculating weighted overlay of the land uses/land cover, soil type, average annual precipitation, slope, depth to groundwater, and bedrock type.

3.2. FACTORS USED FOR WATERSHED SUSCEPTIBILITY ASSESSMENT

To assess the watershed susceptibility to pollution, six main factors have been used in this study: land use, soil type, average annual precipitation, slope, depth to groundwater, and bedrock type. The determination of factors, the development of ratings for each, and ranking the weights were based on previous studies which were conducted to investigate potential factors and their impacts on the surface water quality.

Virtually all of these factors have been demonstrated to impact surface water quality and change essential chemical properties of the water within the watershed. The general assumptions were considered in the study of watershed vulnerability based on the response of a watershed systematically to different contamination impacts and how the six factors working together can affect the watershed’s health.

Table 4. The relative weights and rating scores of the factors and sub- criteria used for watershed susceptibility assessment.

Factor	Weighting	Sub-criteria	Rating	Normalized rating
LULC	0.36	Agriculture	10	0.33
		Urban	9	0.2
		Grassland	7	0.13
		Wetland	6	0.12
		Forest	5	0.07
		Barren land	4	0.06
		Shrubland	3	0.04
		Water	1	0.03
Soil type	0.22	Clay Loam	10	0.23
		Silty Loam	8	0.17
		Loam	7	0.15
		Clay	6	0.14
		Silt	5	0.13
		Sandy Loam	4	0.08
		Peat	3	0.07
		Sandy	2	0.04
Average annual precipitation (inch)	0.18	>75	10	0.32
		71 - 75	9	0.18
		66 - 70	8	0.12
		61 - 65	7	0.09
		56 - 60	6	0.08
		51 - 55	5	0.07
		46 - 50	4	0.05
		41 - 45	3	0.04
		35 - 40	2	0.03
		<35	1	0.02
Slope (degree)	0.10	>60	10	0.35
		31 - 60	8	0.27
		16 - 30	6	0.21
		11 - 15	4	0.07
		4 - 10	2	0.06
		<3	1	0.04
Depth to Groundwater (feet)	0.09	<5	10	0.32
		5 - 10	8	0.18
		11 - 15	6	0.15
		16 - 20	5	0.13
		21 - 25	4	0.08
		26-50	3	0.07
		51-100	2	0.05
		>100	1	0.03
Bedrock type - Depth (0 - 50 feet)	0.05	Limestone	10	0.30
		Dolomite	9	0.29
		Shale	7	0.16
		Claystone	5	0.11
		Sandstone	3	0.08
		Metamorphic/Igneous	1	0.05

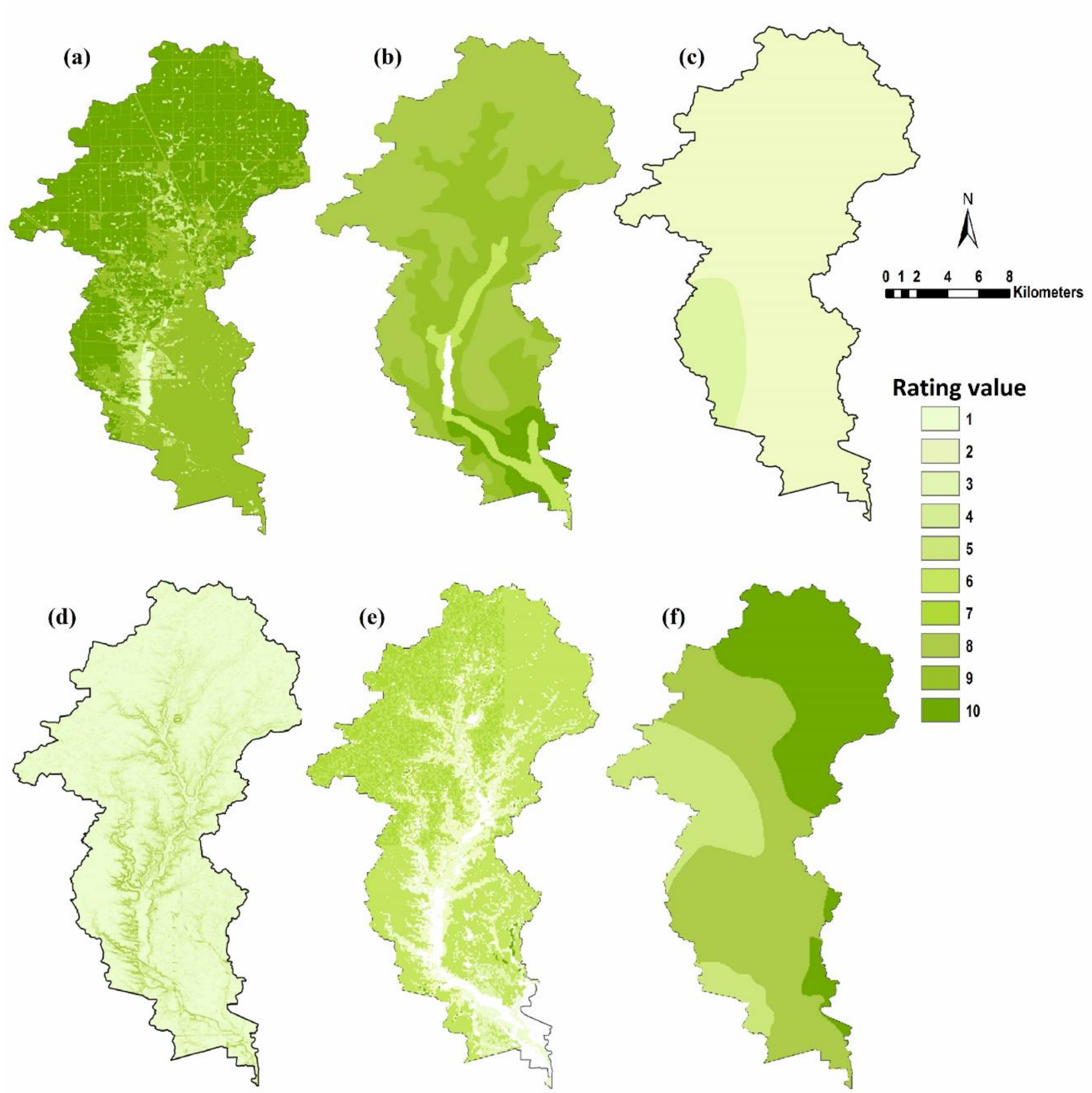

Figure 4. Thematic maps of the layers after rating for: (a) land use/land cover, (b) soil type, (c) average annual precipitation, (d) slope%, (e) depth to groundwater, (f) bedrock type.

3.2.1. Land Use/Land Cover (LULC). Watershed health is susceptible to LULC. Therefore, LULC has been regarded as one of the most important factors affecting water quality (Mouri et al., 2011; Yu et al., 2016; Ding et al., 2016). LULC can impact surface water quality as point source and nonpoint sources pollution. Generally, agricultural land use is the main provenance of NPS pollution, particularly nitrogen (N) and phosphorus (P), on surface water quality (Hoorman et al., 2008; McCarthy and Johnson, 2009). Urban lands are also reported to have considerable effects on surface water quality because of the significant load of contaminants from the point and nonpoint sources (Mallin et al., 2008). The contamination from nutrients, organic matter, and bacteria originates mainly from waste produced by municipal wastewater treatment plants and undefined anthropogenic sources (Glińska-Lewczuk et al., 2016). In this study, the LULC has been divided into eight classes based on their impact on watershed health, where the agriculture land uses that have a high impact were classified and rated by a value of (10), while "water" land use class was classified as the lowest rating (1) (Table 4).

3.2.2. Precipitation. Many studies have assumed that there is a direct relationship between precipitation and increasing pollution levels in surface water. Rapid precipitation can correspond to degradation in water quality of streams and rivers through surface runoff of pollutants (Mallin et al., 2008; Whittemore, 2012; Scott and Frost, 2017). The high rating of precipitation with watershed susceptibility is associated with rainfall magnitude and intensity due to their impact on sediment and nutrient loading. Therefore, the precipitation was divided into ten classes, where the high rating (>75 in) is represented by a value of (10), while the low precipitation had a value of (1) (Table 4).

3.2.3. Slope. Slopes that receive rapid precipitation play a significant role in affecting surface water quality (Chang et al., 2008; Qinqin et al., 2015; Meierdiercks et al., 2017). With a steep slope, this factor can increase the flow rate of a water body which can be causing soil erosion and sedimentation and carries different kinds of pollutants like nutrients, pathogens, and pesticides to nearby rivers (Aksoy and Kavvas, 2005; Bracken and Croke, 2007). The eroded soil particles can be carried to rivers, which contributes to the level of total suspended solids and a decline in the water quality. Moreover, high slopes have a significant effect on infiltration rate to groundwater, where the amount of infiltration decreases with increasing the slope (Fox et al., 1997). Therefore, this study suggested six classes of slope based on their impact on the amount of rainfall that runs off the land surface as overland flow and reaches to surface water or contributes to groundwater by infiltration. Gentle slopes are represented by a value of (1), while steep slopes are classified as a high value (10) (Table 4), because steep slopes can increase surface runoff that may cause soil erosion and carries different types of pollutants.

3.2.4. Depth to Groundwater. Surface water and groundwater are connected through a wide range of catchment processes (Dahl et al., 2007; Lehr et al., 2015). Geological factors contribute to groundwater quality, mainly through the influence of chemical processes of water-rock interaction. Therefore, there is a significant impact of rock and soil components on the evolution of water quality by changing the physical and chemical properties of water (Varanka et al., 2014; Orr et al., 2016). During rainfall periods, much of water flow into nearby rivers and streams comes from shallow pathways through macropore flow in the soil zone, when infiltration to the aquifer is a substantial quantity. The water table will rise to the surface and seep from groundwater into the river, where surface water mixes with groundwater in the hyporheic zone (Lautz and Siegel, 2006). Depth to groundwater was classified for eight classes where the shallow groundwater was classified as a high rating (10), but the deep groundwater was identified as a low rating (1) (Table 4).

3.2.5. Bedrock Type. Water quality is typically greatly affected by different types of geologic materials, such as sedimentary, igneous, metamorphic rocks, and glacial deposits. Long-term geochemical interaction (rock-water) due to different chemical processes can occur between groundwater and aquifer materials (Oelkers and Schott, 2009; Walter et al., 2017). When water flows through fractured rock aquifers (e.g., limestone or dolomite), the chemical properties of groundwater can be significantly changed because of the dissolution of some carbonate and evaporite minerals in the aquifer. Therefore, the quality of surface water can be affected by the exchange of water between rivers and shallow aquifers., especially in the alluvial aquifer. Water can seep from a shallow aquifer into the adjacent river and river water flows into the shallow aquifers alternately, depending on the oscillating of water table and river stage. In our study, rock types have been classified for six classes based on their resistance to weathering. The class of metamorphic/igneous rocks was given a low value (1), as this type of rock is normally very hard and resistant to weathering, while limestone was given a high rating (10) (Table 4).

3.2.6. Soil Type. Soil can be a source of soluble materials and suspended sediments. In general, sediment is the water pollutant that most affects surface water quality physically, chemically, and biologically. Bigger, heavier sediments like pebbles and sand settle first while smaller, lighter particles such as silt and clay may stay in suspension for long periods, contributing significantly to water turbidity. Furthermore, many types of soluble salts in the soil can affect water quality by increasing electrical conductivity (EC) (Chhabra, 1996). A high clay content will increase EC due to the high cation-exchange capacity (CEC) of clay minerals. Soil types have been classified for eight soil classes based on their impact on water quality. The sandy type of soil was given a low value (1), while clay loam was classified as given a value of (10) (Table 4), since this soil type can affect water quality by increasing turbidity and salinity.

4. RESULTS AND DISCUSSION

The watershed susceptibility assessment method uses very simple features that are weighted considering their influence in surface water pollution and calculates a single vulnerability index value for the area under consideration. The vulnerability to pollution is ranked as follows: for values of 70 -100, watershed vulnerability is very high, values of 50-70 is high vulnerability, values of 30-50 is moderate vulnerability, values of 10-30 are low vulnerability, and values of 0 – 10 are very low vulnerability to contamination. To implement the proposed method, six main factors have been identified to evaluate 10 eight sub-watersheds within the ECW. Assessment units ranked between 0 and 1 have low scores - indicating very low impact on water quality. High scores were classified as having a very high impact on water quality. Subcategories were rated between 1 to 10 where 1 refers to very low impacts on water quality while high scores generally were rated as having a very high impact. The vulnerability evaluation of each watershed was used to create maps showing relative vulnerabilities of sub-watersheds. The map of watershed susceptibility in Figure 5 shows a remarkable difference between the sub-watersheds in the vulnerability to pollution in the ECW. The upper part of the watershed, represented by Lion Creek and Finley Creek sub-watersheds, has been classified as likely to have very high vulnerability to potential contaminants. Similarly, the sub-watersheds Dixon Branch, Mounts Run, and Jackson Run are also identified as highly vulnerable to contamination based on the average value of vulnerability. Thus, around 37.6 km^2 (8%) of the total area of the ECW was classified as having a very high vulnerability to contamination, and 284.5 km^2 (57%) as a high vulnerability. The greatest area of contamination vulnerability is located in the north and middle of study area where agricultural land comprises nearly 85% of total area within the northern sub-watershed. The low and very low range of vulnerability occupies an area around 73.8 km^2 (14%) and 7.3 km^2 (1%), respectively.

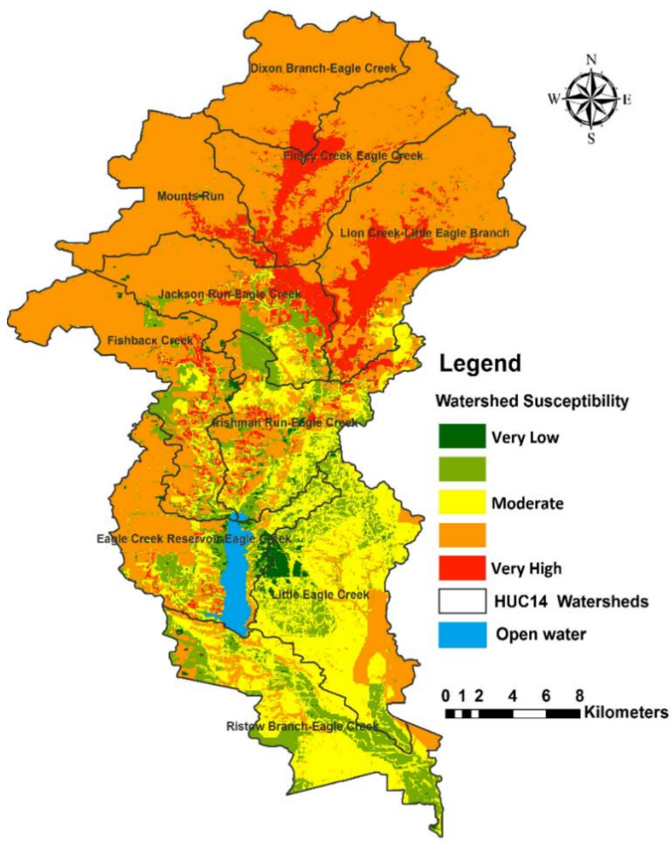

Figure 5. Watershed susceptibility distribution map of the Eagle Creek Watershed.

The results showed that very high vulnerability zones were located along the Little Eagle Creek, Finley Creek, Dixon Branch, and Mounts Run Creek. Agriculture is the main land use in this part of the study area, so the high vulnerability in this area is partially caused by agricultural runoff. In addition, the soil type could be another factor influencing water quality. Silty clay loam was the most common type of soil around the drainage channels in the northern part of the ECW. The steepest slopes in this part of the study area are also located near riverbanks. Therefore, the slope factor can increase both the surface runoff rate and soil erosion, increasing the delivery of sediments and pollutants to nearby streams (Tedesco et al., 2005). This process probably causes a deterioration of water quality by increasing electrical conductivity due to the solubility of the lime and soils that contain salts. Moreover, the type of bedrock (limestone), which is close to the surface in northern watersheds, can also lead to a declining water quality by increasing the electrical conductivity of groundwater due to the rock–water interaction in the aquifer (Walter et al., 2017). Eventually, this may later influence surface water quality through local exchange between streams and adjacent shallow aquifers (Lautz and Siegel, 2006). The electrical conductivity of groundwater ranged between (500-1000) µs/cm in many parts of the ECW. It is evident that the high values of salinity which are observed in many study area streams are likely to be a significant indication of surface water-groundwater interaction.

The vulnerability of the watersheds in the southern part of the study area was classified between medium and weak, especially in the adjacent portions of sub-watersheds along School Branch, Eagle Creek at Grande Avenue, and Little Creek at the 30th Street. Bacterial contamination (*E. coli*) is the main source of degradation in water quality in the southern part of the watershed, where the urban development is the primary land use. The urban surface runoff can carry considerable quantities of contaminants, including major nutrients and bacteria to nearby streams (Tetzlaff et al., 2010; McGrane et al., 2014). The high levels of *E. coli* that were observed in the study area may explain the negative impact of urban lands on water quality.

4.1. VALIDATION AND SENSITIVITY ANALYSIS OF A DEVELOPED METHOD

The sensitivity of the new method of calculating vulnerability was evaluated by comparing the vulnerability rating to different water quality parameters. The regression coefficients between water quality parameters and vulnerability results are shown in Figure 6. These results show that the relationship between water quality and vulnerability was a significant positive correlation with phosphates ($r^2=0.5$, $p=0.04$), nitrates ($r^2=0.4$, $p=0.03$), and electrical conductivity ($r^2=0.4$, $p=0.04$). This indicates the vulnerability would be increased with increasing concentrations of these parameters, which have been identified as the main parameters affecting water quality in the study area. The regression coefficients for dissolved oxygen ($r^2=0.54$, $p=0.036$) and E. coli ($r^2=0.6$, $p=0.02$) have shown a significant negative relationship with vulnerability. This indicates the potential for water quality degradation as a result of high concentration of bacteria and low levels of dissolved oxygen in the southern part of the study area. Generally, in most watersheds of this study area, the E. coli levels were more than the acceptable limit, but the highest level of this bacteria was observed in the southern region which was dominated by urban development. However, the negative relationship between E. coli and vulnerability reflects the impact of land uses type on water quality, where E. coli and DO seems to be highly associated with urban land use while N and P are associated with agriculture land use.

To assess the water quality of streams and rivers in Eagle Creek Watershed, the water quality index (WQI) (Equation 8), was applied based on the method developed by

Cude (2001). The WQI is according to the sub-index measurements of water quality parameters that provide a summary of water quality on a rating scale from (0) very poor – (100) excellent.

$$WQI = \sum_{i=1}^{n} SI_i W_i \tag{8}$$

where *WQI* is Water Quality Index, *SI* is sub-index *i*, and *Wi* is the weight given to sub-index *i*.

Based on the water quality index results for all eight monitoring stations, it can be concluded that the Eagle Creek Watershed ranged between poor to fair in water quality. All water quality ratings within the northern sub-watershed were poor water quality. This indicator showed fair water quality in Fall Creek and Eagle Creek at Grande Avenue, all of which are located in the southern part of the watershed. In general, E. coli, nitrate, phosphate, and electrical conductivity were the most important parameters influencing the water quality of these eight sub-watersheds. As can be seen from Figure 7, as regards the comparison between the WQI and LULC, the surface water quality in the central and northern portion of the study area is classified as poor quality probably because the vast majority of land is agriculture. Conversely, the southern part of the study area shows fair water quality, where the land uses are dominated by urban land. The results of WQI which have been described above was adopted to emphasize the efficiency of the suggested method. As illustrated in Figure 8, the regression coefficients between the WQI and watershed vulnerability showed a highly significant negative correlation ($r^2=0.77$, $p<0.05$). The results of WQI reflect the conditions of water quality in the study area which have been classified as very poor water quality (highly vulnerable to pollution) in the northern sub-watersheds, while it rated as moderate water quality (weak-moderate vulnerability) at the southern sub-watersheds. These results provide considerable evidence for adopting this method to assess a watershed's susceptibility.

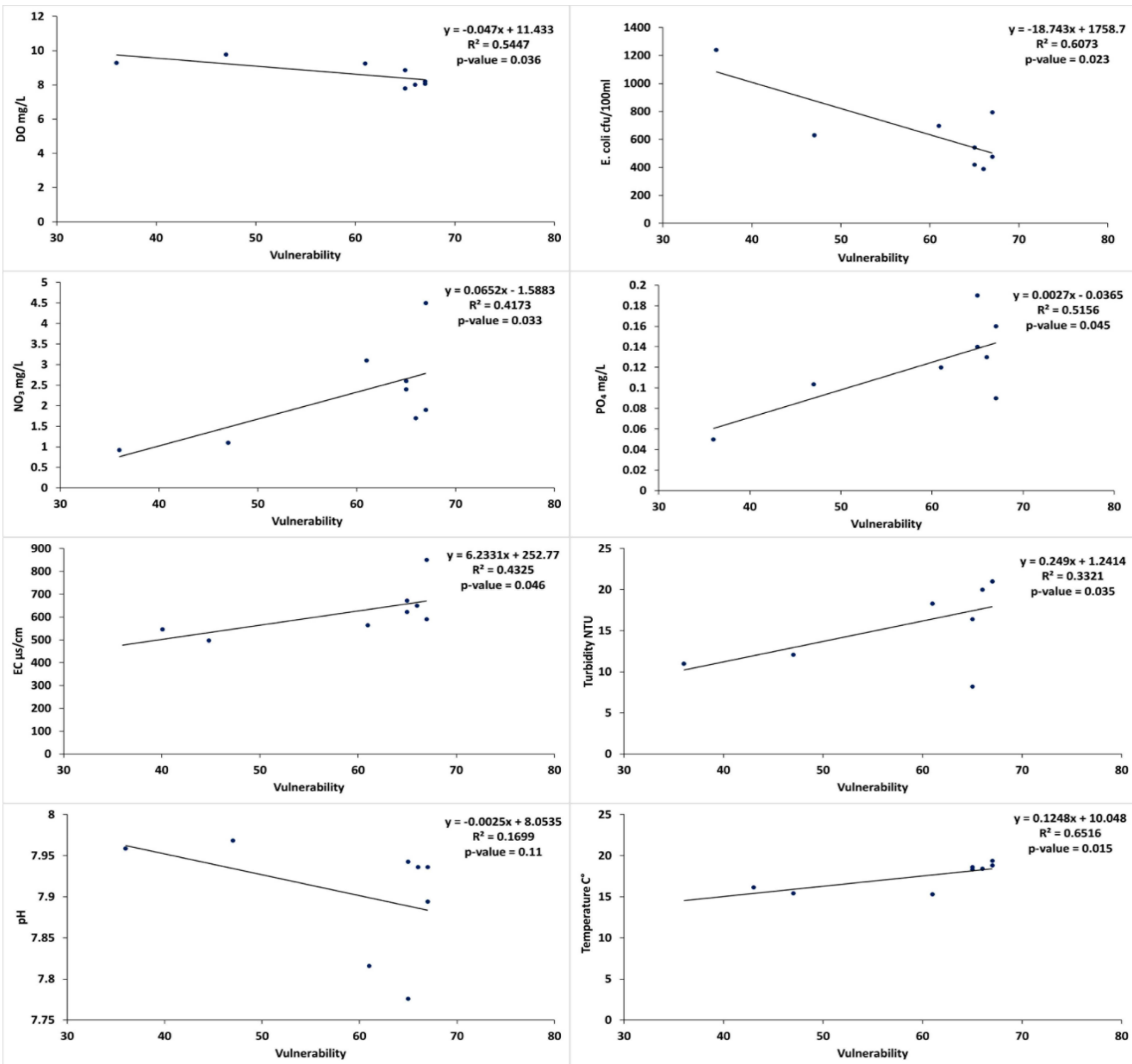

Figure 6. The relationship between watershed vulnerability and water quality parameters for ECW.

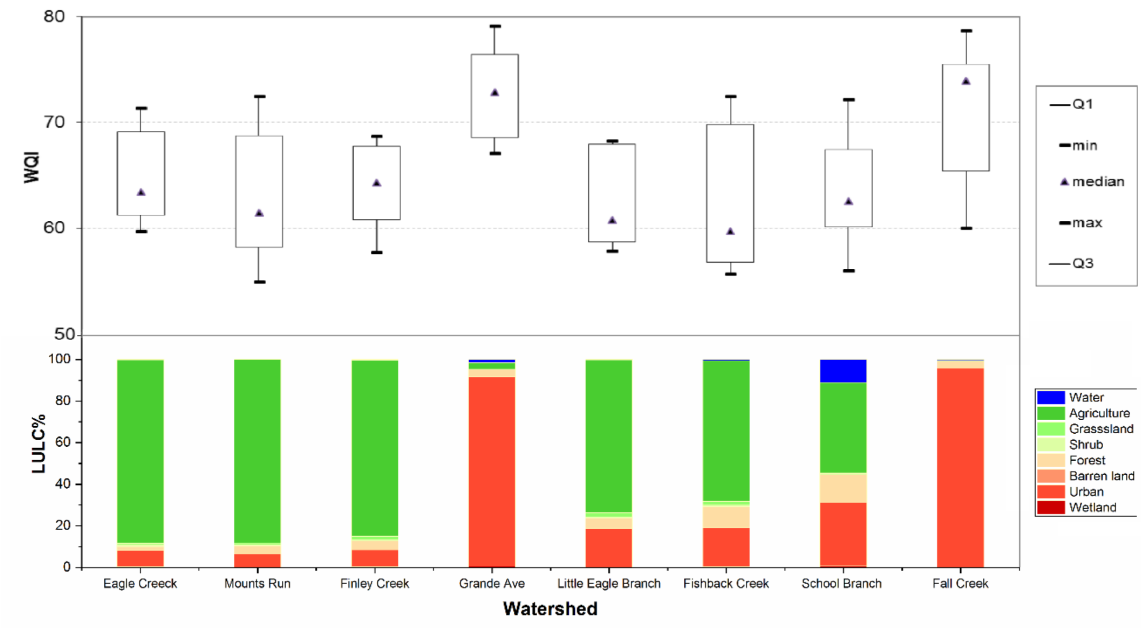

Figure 7. The relationship between land use/land cover (LULC) types and the WQI in the study area.

As a comparative study, Eimers et al. (2000) developed a method to evaluate the unsaturated zone and watershed characteristics to predict potential contamination for both public groundwater and surface water supplies. This method was applied in North Carolina for assessing more than 11,000 public groundwater supply wells and around 245 public surface water intakes. The rating of watershed characteristics was based on a combination of factors that contribute to the likelihood that water (with or without contaminants) would reach a public surface water supply intake through following overland flow or shallow subsurface flow. Factors selected for assessing the vulnerability of the unsaturated zone were vertical hydraulic conductivity, land surface slope, land cover/land use, average annual precipitation, and groundwater contribution. They suggested using statistical analysis of water quality measurements to refine and enhance factor weights and ratings. In the current study, weights and ratings scores were assigned by using the AHP model.

Additionally, statistical analysis was applied to validate the proposed method. In a recent study conducted by Arriagada et al. (2019) in the Andalién River watershed, located in mediterranean, Chile. They used a new method to evaluate watershed vulnerability index (WVI) depending on three sub-indices include anthropogenic stressors, environmental fragility, and natural disturbances. The results of WVI revealed the negative impacts of multiple stressors on watershed quality. The application of statistical analysis of water quality parameters was presented in the work of Arriagada et al. (2019) and in the current paper, the statistical analysis was applied along with WQI and the vulnerability levels to emphasize the efficiency of the suggested method.

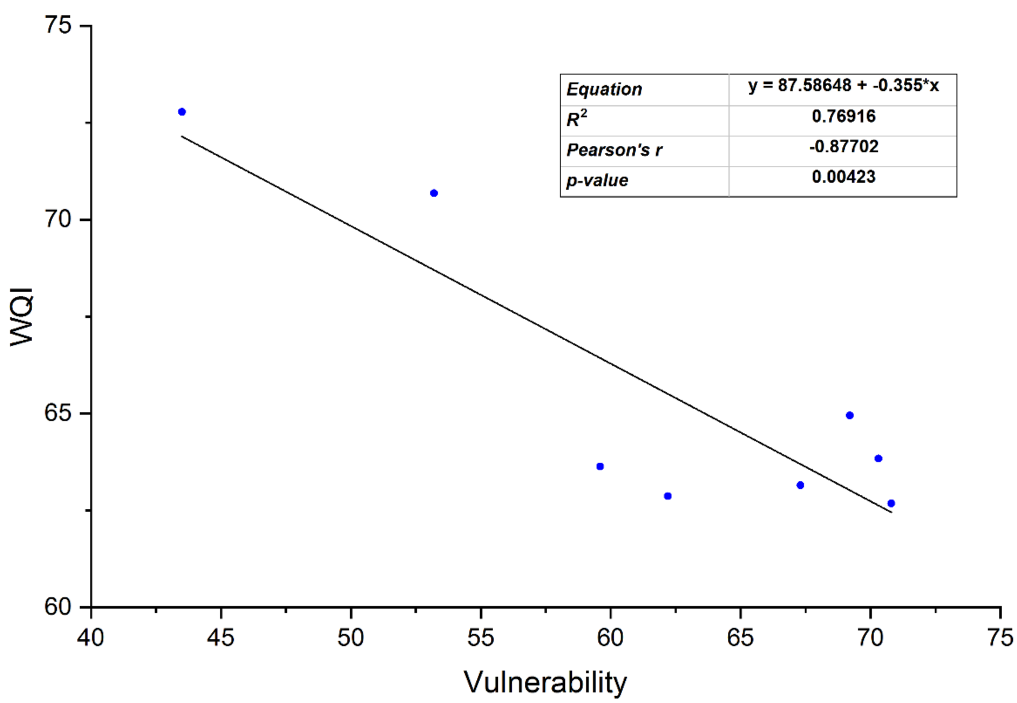

Figure 8. Comparison showing the relationship between watershed vulnerability and WQI.

5. CONCLUSIONS

In this study, we identified the primary parameters affecting watershed vulnerability and suggested new weighting factors for each parameter using AHP analysis. The proposed method was implemented using six main factors (land uses, soil type, precipitation, slope, depth to groundwater, and bedrock type) to evaluate the watershed susceptibility for 10 sub-watersheds within Eagle Creek Watershed, Indiana. A combination of watershed vulnerability assessment and GIS spatial analysis tools were used to produce the maps that show the susceptible zones for watershed. Based on the results of this method, accounting for around 37.6 km^2 (8%) of the total area of the watershed was classified as having a very high vulnerability to contamination, and 284.5 km^2 (57%) as a high vulnerability. The greatest portion of weakness is located in the middle and north of the study area where agricultural land takes up nearly 85% of the total area of northern sub-watershed, while the vulnerability for the watersheds in the southern part of the study area was classified between medium to weak. Regression relationships were used to test the effectiveness of this new method. The results demonstrated that the relationship between water quality and vulnerability was a significant positive correlation with phosphates ($r^2=0.5$), nitrates ($r^2=0.4$), and electrical conductivity ($r^2=0.43$). The values of dissolved oxygen ($r^2=0.54$) and *E. coli* ($r^2=0.6$) have shown a significant negative relationship with vulnerability. The correlation between the measured water quality index and the predicted watershed vulnerability for the method showed a high negative correlation ($r^2=0.77$) between WQI and vulnerability, indicating that the vulnerability predictions are fairly accurate. This method could be used in other watersheds to more accurately assess watershed susceptibility.

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III. EVALUATION OF THE PREDICTIVE RELIABILITY OF THE WATERSHED HEALTH ASSESSMENT METHOD USING THE SWAT MODEL

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ABSTRACT

The purpose of watershed assessments is to give baseline information about conditions of water quality, stream morphology, and biological integrity to identify the sources of stressors and their impacts. In recent decades, different watershed assessment methods have been developed to evaluate the cumulative impacts of human activities on watershed health and the condition of aquatic systems. In the current research, we proposed a new approach for assessing watershed vulnerability to contamination based on spatial analysis by using geographic information systems (GIS) and the analytic hierarchy process (AHP) technique. This new procedure, designed to identify vulnerable zones, depends on six basic factors that represent watershed characteristics. The proposed factors were land use/land cover, soil type, average annual precipitation, slope, depth to groundwater, and bedrock type. The general assumptions for assessing watershed vulnerability are based on the response of watersheds to different contamination impacts and how the six selected factors interact to affect watershed health. The vulnerability evaluation of each watershed was used to create maps showing the relative vulnerabilities of specific sub-watersheds in the Eagle Creek Watershed. The results showed a remarkable difference in watershed susceptibility between the sub-watersheds in their vulnerability to pollution. To identify

the reliability of the proposed technique, the SWAT model was applied. To simulate and predict the water quality of a watershed using the SWAT model, some parameters (e.g., total suspended solids [TSS] and nitrate) were tested based on the availability of the data needed for comparison. Both the SWAT and the newly proposed method produced good results in predicting water quality loads, which validated the proposed method. Hence, the results of the evaluation of the predictive reliability of the watershed vulnerability assessment method revealed that the proposed approach is suitable as a decision-making tool to predict watershed health.

1. INTRODUCTION

A watershed contains valuable water resources and is a dynamic part of the landscape. Therefore, understanding watersheds is essential for interpreting water quality and stream health. Watersheds are impacted by a multitude of variables, including climate, soils, hydrology, geomorphology, and land use/land cover (LULC). Watersheds are diverse, and are often evaluated by looking into river characteristics, such as sediment load (Jones et al., 2001; Mano et al., 2009; Hazbavi and Sadeghi, 2017), aquatic ecosystems (Tiner, 2004; Rodgers et al., 2012; Herman and Nejadhashemi, 2015), and water quality (Olsen et al., 2012; Luo et al., 2013; Kim and An, 2015; Jabbar and Grote, 2018).

The purpose of watershed assessment is to give baseline information about conditions of water quality, stream morphology, and biological integrity, to identify the sources of stressors and their impacts. In recent decades, different watershed assessment methods (i.e., watershed assessments or analyses) have been developed to evaluate the cumulative impacts of human activities on watershed health and the condition of aquatic systems. These methods were developed to evaluate watershed conditions, such as identifying the impact of land use and land cover changes (Bateni et al., 2013; Calijuri et al., 2015; Deshmukh and Singh, 2016; Peraza-Castro et al., 2018), climate change (Johnson et al., 2012; Fan and Shibata, 2015; Neupane and Kumar, 2015), and susceptibility to hydrologic alterations (Pyron and Neumann, 2008; Marcarelli et al., 2010). Among these approaches, statistical analysis and hydrological modeling have been widely performed because they require fewer resources and support more flexibility.

The ability of hydrological models to simulate and predict real phenomena has increased considerably in recent years. Some of the models are based on simple empirical relationships with robust algorithms, while others use equations that govern the physical base with computationally calculated numerical solutions. At some point, simple models are unable to yield results with the degree of detail needed, but detailed models may be inefficient and inapplicable to large river basins, where there are difficulties in conducting monitoring campaigns.

Simultaneously, the number of empirical parameters and physical base functions has also grown, which increases the difficulty in the process of calibration (Arnold et al., 2015). Hydrological models are simplified representations of natural systems, but the hydrological processes within the basins are more complex and variable than those represented even in the most sophisticated models (Arnold et al., 2015). Therefore, to improve the quality of the information generated by the model and to simulate scenarios of greater reliability, the calibration, validation, and uncertainty analysis steps have been studied using statistical methods and optimization algorithms.

The Soil and Water Assessment Tool (SWAT) is an effective model developed to assess hydrological processes, pollution problems, and environmental issues worldwide. It has been extensively used to investigate water quality and nonpoint source pollution problems and to predict the impact of changes in land management practices for a range of scales and global environmental conditions (Behera and Panda, 2006; Gassman et al., 2007; Zhu and Li, 2014). Additionally, this model can be applied to predict future watershed health, especially in ungauged basins. The SWAT is increasingly being applied to predict sediment yield (Xu et al., 2009; Liu et al., 2015), nutrient loadings (Hanson et al., 2017; Malagó et al., 2017), fecal coliform concentrations (Cho et al., 2012; Bai et al., 2017), and pesticide transport (Luo and Zhang, 2009; Bannwarth et al., 2014; Boithias et al., 2014). Furthermore, when comparing the SWAT model calibration with some models, the SWAT more efficiently simulates hydrological processes (e.g., Im et al. 2007; Hoang et al., 2014). For example, when Im et al. (2007) studied the Polecat Creek Watershed in Virginia, the results showed high applicability in simulating streamflow and sediment yields using the SWAT and hydrological simulation program-Fortran (HSPF) models. Similarly, Hoang et al. (2014) found that the SWAT provided highly accurate predictions for streamflow for both daily and monthly times, but that the nitrate flux simulations were highly accurate only for monthly time steps. When compared with the DAISY-MIKE SHE (DMS) model, Hoang et al. (2014) found the SWAT results for streamflow and nitrate fluxes were identical to DMS ranges during high flow times but were moderately low during low-flow times. In the current research, we proposed a new approach for assessing watershed vulnerability to contamination, this time based on spatial analysis, using the geographic information system (GIS) and analytic hierarchy process (AHP) technique. Due to its simplicity, the proposed method can easily be used to evaluate watershed vulnerability, with only a small amount of input information required and without field or lab work, which minimizes cost and time commitments. This procedure depends on six basic factors, which represent watershed characteristics, and is designed to identify vulnerable zones. The proposed factors were land use/land cover, soil type, average annual precipitation, slope, depth to groundwater, and bedrock type. Therefore, using this approach to identify the vulnerable zones within river basins can improve decision-making for professionals in the area of environmental planning and management.

2. MATERIALS AND METHODS

2.1. A CASE STUDY IN THE EAGLE CREEK WATERSHED

In Central Indiana, in the northern section of the Upper White River Watershed, located within the Mississippi River Basin, lies the Eagle Creek Watershed (ECW) (Figure 1). With a drainage area of about 459 km^2, the ECW includes 10 sub-watersheds. These range in size from 26.9 km^2 to 70.7 km^2. The ECW's three major branches (i.e., School Branch, Fishback Creek, Eagle Creek Branch) flow into the Eagle Creek Reservoir. Indianapolis depends on the Eagle Creek Reservoir as one of its primary drinking water sources. Eight major tributaries (i.e., Dixon Branch, Finely Creek, Kreager Ditch, Mounts Run, Jackson Run, Woodruff Branch, Little Eagle Branch, Long Branch) feed these branches. The three primary branches have the following flow distributions: (1) Eagle Creek–an average flow of approximately 2.85 m^3/s, which contributes 79% of the reservoir's water; (2) Fishback Creek–an average flow of 1.1 m^3/s, which contributes 14%

of the reservoir's water; and (3) School Branch—an average flow of 0.5 m^3/s, which contributes 7% of the reservoir's water (Tedesco et al., 2005).

At 56%, agriculture is the chief land use in the Eagle Creek Watershed, with urban land use at 38%, mainly in the southeastern section. Most of the remaining land is either forested or grassland. In cooler times of the year, the area receives storms of long duration and moderate intensity, but precipitation is delivered in short, high-intensity storms during late spring and summer.

The ECW receives an average annual precipitation of 1050 mm. February records the least rainfall, averaging 59.7 mm, whereas May records the most rainfall, averaging 115.5 mm. The ECW has a generally flat topography, with fewer than 3% slopes. Agricultural areas are flatter, with steeper slopes observed near streams and rivers. In the upper part of the watershed, the soil is thin loess over loamy glacial till, which is deep and poorly drained. However, in the watershed's northwest section, soils range from poorly to well drained. In addition, in the areas downstream, soils are generally deep, well drained to slightly poorly drained, and the soils create a thin, silty layer over the underlying glacial till (Hall, 1999). In the extreme northeastern section of the ECW, the bedrock is mainly brown, fine-grained dolomite to dolomitic limestone. In contrast, in the southwest section, brown sandy dolomite to sandy dolomitic limestone and gray, shaley fossiliferous limestone predominate. Brownish-black, carbon-rich shale, greenish-gray shale, and small amounts of dolomite and dolomitic quartz sandstone characterize the southern part of the ECW (Shaver et al., 1986; Gray et al., 1987).

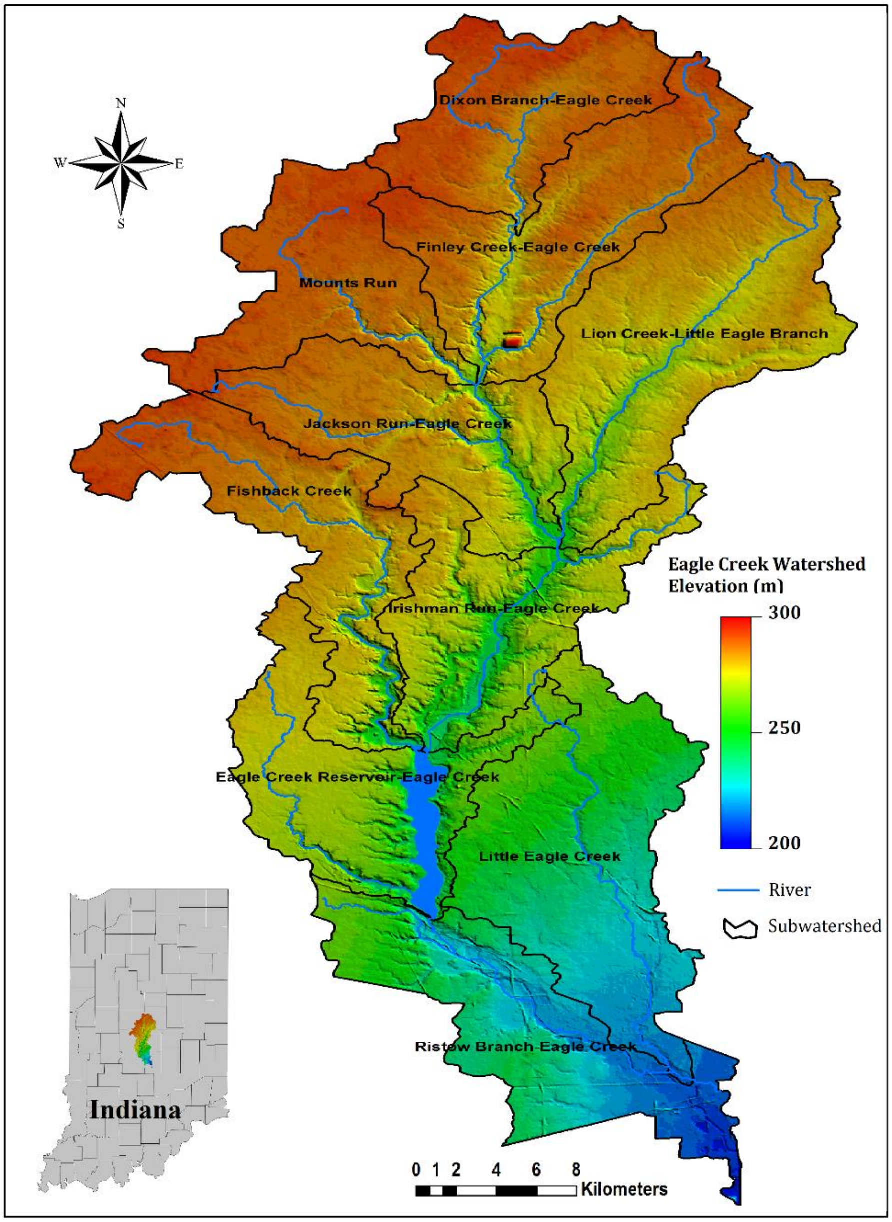

Figure 1. Location map of the study area in Indiana showing Eagle Creek Watershed.

2.2. DATA ACQUISITION AND PROCESSING

Thematic maps of the study area were generated based on remote sensing data. A 30-m resolution digital elevation model (DEM) of the topography was used to investigate key watershed characteristics, including elevation variations and slope. To calculate watershed characteristics (e.g., drainage networks, hydrologic units, catchment areas, and related features, including rivers and streams), the National Hydrography Dataset (NHD) and Watershed Boundary Dataset (WBD), both managed by the United States Geological Survey (USGS), were applied (USGS, 2016). This study relied on the National Land Cover Database 2011 (Homer, 2015), with its 15land use/land cover (LULC) classifications (Figure 2a). In our analysis, some classifications were pooled so as to reduce the number of variables and to create more meaningful LULC categories. Categories that had been termed "developed" were combined to form one "urban" category, while categories previously considered "forest" also became one group as did all "wetland" categories (Figure 2b). The data was analyzed using ArcGIS, which also provided the averages of each parameter for every sub-watershed. To obtain the average annual precipitation raster for the period 1961-1990, the Parameter-elevation Regressions on Independent Slopes Model (PRISM) was used (Daly, 1996).

3. METHODOLOGY OF WATERSHED SUSCEPTIBILITY ASSESSMENT

3.1. FACTORS USED FOR WATERSHED SUSCEPTIBILITY ASSESSMENT

To determine how susceptible the watershed was to pollution, this study looked at six major factors: (1) land use, (2) soil type, (3) average annual precipitation, (4) slope, (5) depth to groundwater, and (6) bedrock type (Figure 3).

This study relied on the literature to select factors known to influence the surface water quality, their ratings, and their ranked weights. In addition, these factors are known to change the essential chemical properties of the water within the watershed. The general assumptions considered in this study of watershed vulnerability were based on the ways in which watersheds systematically respond to various forms of contamination and also on the interaction of the six factors to impact the watershed's health. We identified six specific factors, which are used to implement this methodology.

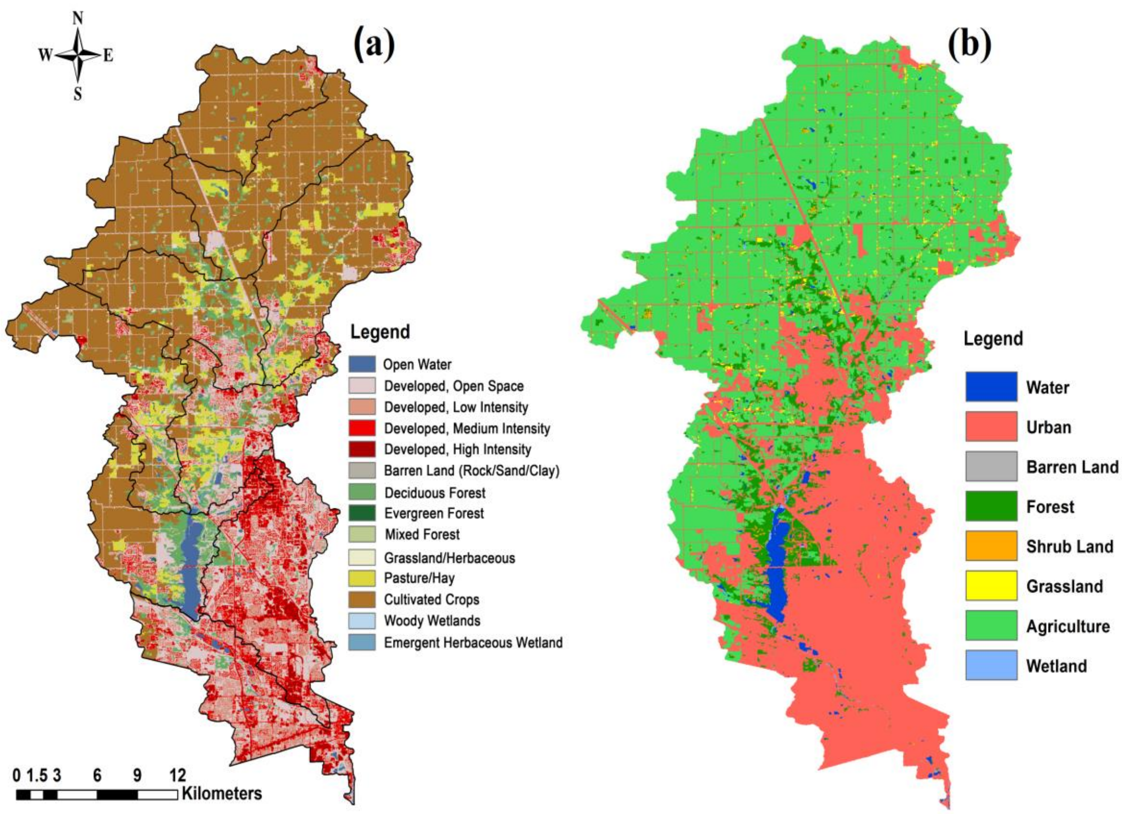

Figure 2. Land use categories (a) before reclassification and (b) after reclassification and aggregated into eight categories.

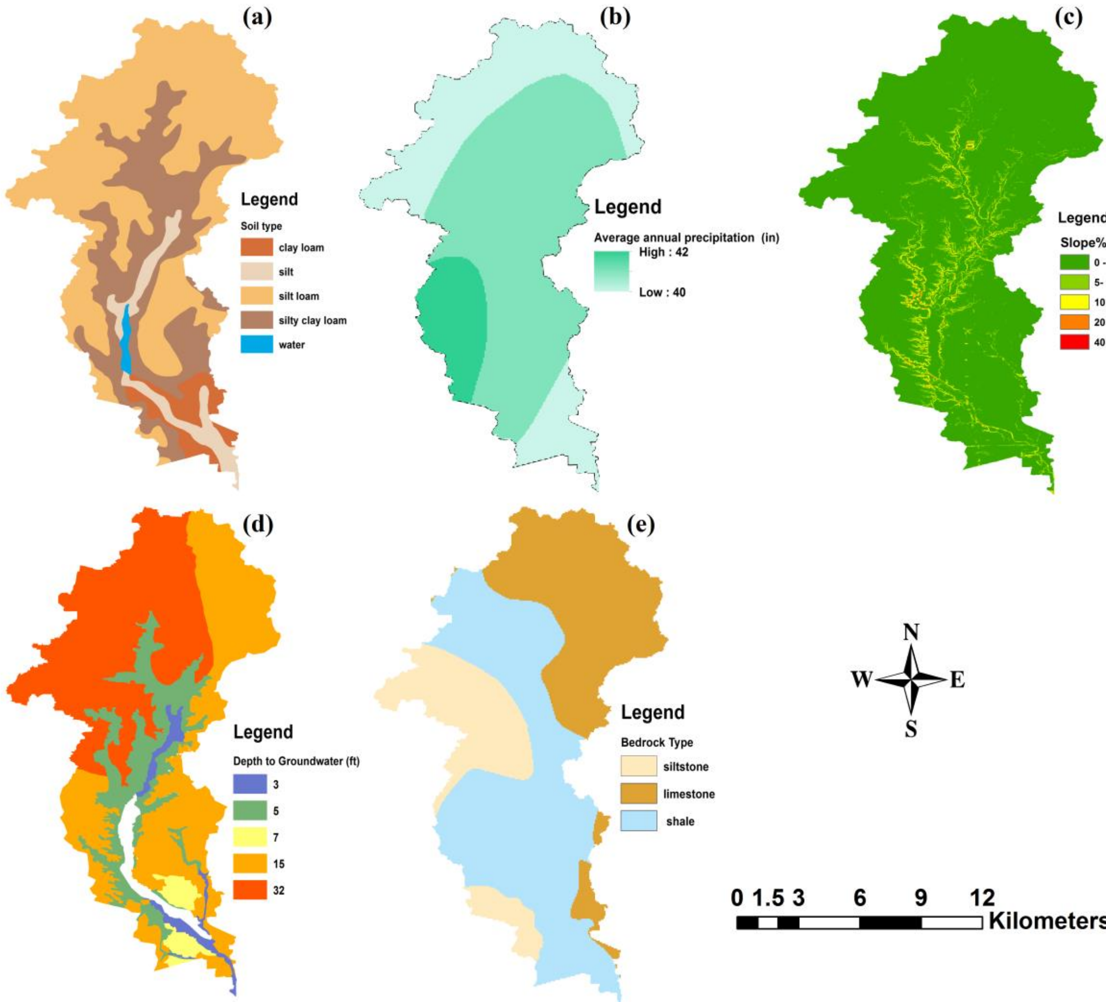

Figure 3. Thematic maps of the layers before rating for (a) soil type, (b) average annual precipitation, (c) slope%, (d) depth to groundwater, and (e) bedrock type.

3.1.1. Land Use/Land Cover. The LULC can affect surface water quality as either point or nonpoint source (NPS) pollution, making the LULC one of the primary factors affecting water quality, and therefore, watershed health (Brainwood et al., 2004; Carey et al., 2011). NPS pollution in surface water, especially increases in nitrogen (N) and phosphorus (P), is usually correlated with agricultural use (Heathwaite and Johnes, 1996;

Ma et al., 2011). Similarly, urban lands can produce great effects on surface water quality because they contain substantial amounts of point and nonpoint source contaminants (Wilson and Weng, 2010). Contamination from nutrients, organic matter, and bacteria often results from the waste generated by city wastewater treatment plants as well as from a variety of anthropogenic sources (Chang et al., 2010). Based on their impact on watershed health, for this study, the LULC was separated into eight categories. Agricultural land uses with the highest impact were rated “10,” while land use classified as “water” received the lowest rating or “1”.

3.1.2. Precipitation. Precipitation and increasing pollution levels in surface water are usually assumed to be directly related. For example, surface runoff of pollutants increases with rapid precipitation and can degrade the water quality of rivers and streams (Göbel et al., 2007; Kim et al, 2007). The high correlation of precipitation with watershed health results from the impact of rainfall magnitude and intensity on sediment and nutrient loading. Thus, in this study, precipitation was classified into 10 groups, with the highest amount of annual precipitation (> 75 in) corresponding to a value of “10,” while the lowest precipitation was given a value of “1”.

3.1.3. Slope. When rapid precipitation combines with slopes, it can greatly affect surface water quality (El Kateb et al., 2013; Meierdiercks et al., 2017). A steep slope can increase the flow rate of a water body, which causes soil erosion and sedimentation, such that many types of pollutants (e.g., nutrients, pathogens, and pesticides) can be carried to nearby rivers (Bracken and Croke, 2007). The number of total suspended solids increases as eroded soil particles are transported to rivers, negatively affecting the water quality. Additionally, it has been found that high slopes have a considerable effect on the infiltration rate to groundwater, with Fox et al. (1997) finding that the amount of infiltration decreases as the slope increases. Therefore, this study formed six categories of slope to take into account their impact on the amount of rainfall that becomes overland flow, where it eventually either connects to the surface water or adds to the amount of groundwater by infiltration. In these new categories, gentle slopes are given a value of “1,” while steep slopes were valued at “10”.

3.1.4. Depth to Groundwater. A broad range of catchment processes connects surface water to groundwater (Brunner et al., 2009; Lehr et al., 2015). In addition, geological factors play a part in groundwater quality, predominantly through the chemical processes of water-rock interactions. Therefore, rock and soil components contribute significantly to water quality because these components change the physical and chemical properties of water (Singh et al., 2005; Varanka et al., 2014). When it rains, a great deal of the water that flows into neighboring streams and rivers runs along shallow conduits through the macropore flow in the soil zone. Here, much water infiltrates into the aquifer, causing the water table to rise to the surface. Next, this groundwater seeps into the river, where surface water combine with groundwater in the hyporheic zone. Another category proposed by this study is depth to groundwater, which was classified into eight groups; shallow groundwater was given a rating of “10,” but deep groundwater was given a rating of “1”.

3.1.5. Bedrock Type. Various types of geologic materials (e.g., sedimentary, igneous, and metamorphic rocks, as well as glacial deposits) have a large effect on water quality. Due to a variety of chemical processes, long-term geochemical interactions (i.e., between rock and water) can take place between groundwater and the aquifer (Adams et al., 2001). As water runs through fractured rock aquifers, especially those made of limestone or dolomite, the groundwater's chemical properties can be considerably altered as some carbonate materials dissolve or evaporate. Thus, surface water quality can be altered when water is exchanged between rivers and shallow aquifers, particularly the alluvial aquifer. Depending on the oscillation of the water table and the river stage, water can percolate from a shallow aquifer into a nearby river, while river water can also run into shallow aquifers. This study classified rock types into six classes based on their resistance to weathering. Metamorphic and igneous rocks were given the low value "1" because these rocks are normally very hard and resist weathering, unlike limestone, which was given a high rating of "10" because it dissolves easily.

3.1.6. Soil Type. Soluble materials and suspended sediments in water can also originate from soil. Overall, sediment is the water pollutant that has the greatest affect on the quality of surface water physically, chemically, and biologically. Larger, heavier sediments (e.g., pebbles and sand) tend to settle first, with smaller, lighter particles (e.g., silt and clay) remaining in suspension for a long time, thus contributing greatly to water turbidity. In addition, a variety of soluble salts in the soil can increase the electrical conductivity (EC) of water, thereby negatively affecting its quality (Chhabra, 1996). For example, a high clay content increases the EC as a result of the high cation-exchange capacity (CEC) of clay minerals. In this study, soil types were grouped into eight soil classes relative to their impact on water quality. Sandy soil was given a low value (1), while clay loam was valued at "10" because clay loam increases turbidity and salinity.

3.2. ANALYTICAL HIERARCHY PROCESS (AHP) EVALUATION MODEL

Multiple-criteria decision analysis (MCDA) problems include criteria that vary in importance according to experts, so the process determines the weights of these criteria to indicate the relative significance of each of the chosen criteria in relation to the result. Therefore, information about the relative importance of each criteria is needed prior to assigning weights. The analytical hierarchy process (AHP) is one of the multi criteria decision-making methods created by Saaty (1980). It uses pairwise comparisons that measure all factors (criteria and sub-criteria) matched to each other. This method is founded on three major principles: (1) pairwise comparison judgments, (2) decomposition, and (3) synthesis of priorities. Saaty (1980) recommended using a scale from 1 to 9 to compare the factors, with 1 signifying that the criteria are equally important, and 9 signifying that a particular criterion is highly significant. The consistency ratio (CR) is calculated to assess the differences between the pairwise comparisons and the reliability of the measured weights. To be accepted, the *CR* should be less than 0.1. If not, subjective judgments should be rethought prior to recalculating the weights (Saaty, 2008).

The structure of the decision-making problem for this study consisted of numbers represented by the symbols m and n. The values of a_{ij} ($i = 1, 2, 3\ldots, m$) and ($j = 1,2, 3\ldots, n$) were used to represent the performance values matrix in terms of the i^{th} and j^{th} elements. The values of the comparison criterion above the diagonal of the matrix were used to fill the upper triangular matrix, and the lower triangular of the matrix used the reciprocal values of the upper diagonal. In the pairwise comparison matrix A, the matrix element a_{ij} indicates the relative importance of the i^{th} and j^{th} alternatives with respect to criterion A, where a_{ji} is the reciprocal value of a_{ij}, as shown in Equation 1.

Below is an example of a decision matrix, which combines a typical comparison matrix for any problem with the relative importance of each criterion:

$$A = \begin{pmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & a_{23} & a_{2n} \\ \cdots & 1/a_{23} & \cdots & \cdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{pmatrix} \tag{1}$$

where, a_j; *I, j = 1, 2, ……, n* is the element of row *i* and column *j* of the matrix, which is equal to the number of alternatives.

The geometric principles in Equation 2 were used to calculate the eigenvectors for each row:

$$Eg_i = \sqrt[n]{a_{11} \times a_{12} \times a_{13} \times \cdots \times a_{1n}} \tag{2}$$

where, Eg_i represents the eigenvector for the row i, and *n* represents the number of elements in row *i*. The priority vector (Pr_i) was found by normalizing the eigenvalues to 1, using Equation 3:

$$\Pr_i = Eg_i / (\sum_{k=1}^{n} Eg_k) \tag{3}$$

Lambda max (λ_{max}) was evaluated based on the summation of the result of multiplying each element in the priority vector with the sum of the column of the reciprocal matrix:

$$\lambda_{\max} = \sum_{j=1}^{n} \left(W_j \times \sum_{i=1}^{m} a_{ij} \right) \tag{4}$$

where, a_{ij} is the sum of the criteria in each column in the matrix; *Wi* is the value of the weight of each criterion corresponding to the priority vector in the matrix of decision; and where $i = 1, 2, \ldots m$, and $j = 1, 2, \ldots n$.

The consistency ratio (CR) can be found using Equation 5:

$$CR = \frac{CI}{RI} \tag{5}$$

where CI is the consistency index:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{6}$$

where λ_{max} represents the sum of the products between the sum of each column of the comparison matrix and the relative weights, while n is the size of the matrix.

RI signifies the random index, which describes the consistency of the randomly generated pairwise comparison matrix. In this study, weighted scores for each factor were obtained using the AHP model (Table 1), with a similar method employed to obtain rating values for each sub-criteria within the watershed susceptibility assessment.

Watershed susceptibility values in the study area were calculated using weighted overlay analysis:

$$WS = \sum_{j=1}^{n} W_j \times C_{ij} \tag{7}$$

where, WS represents the watershed susceptibility for area i, W_j represents the relative importance weight of criterion, C_{ij} represents the grading value of area i under criterion j, and n represents the total number of criteria.

In this study, a decision hierarchy was employed to assess the watershed's susceptibility, which involves two steps. First, categories were created, using six seemingly significant factors: land use, soil type, precipitation, slope, depth to groundwater, and bedrock type.

Table 1. A pairwise comparison matrix developed for assessing the relative importance of the criteria for watershed susceptibility assessment

Factor	LULC	ST	BRT	Slope	AAP	DTG	Weights
LULC	1	3	4	5	3	2	0.36
Soil type (ST)	0.33	1	5	3	2	2	0.22
Bedrock type (BRT)	0.25	0.2	1	0.33	0.33	0.5	0.05
Slope	0.2	0.33	3	1	0.33	1	0.1
Average annual precipitation (AAP)	0.33	0.5	3	3	1	3	0.18
Depth to groundwater (DTG)	0.5	0.5	2	1	0.33	1	0.09
CR Value = 0.02							

Second, 46 sub-categories were created in order to assess the watershed's health (Figure 4) (Table 2). This study synthesized the judgment of experts and literature reviews in this field (Blanchard and Lerch, 2000; Eimers et al., 2000; Tran et al., 2004, Lopez et al., 2008; Jun et al., 2011; Furniss et al., 2013) with other required and available data about the study area, to arrive at each factor, which was then categorized into classes or sub-categories. Next, a suitability rating value was given to each sub-category. After these factors were delineated, the maps needed for each layer were constructed as a shapefile (vector) or raster. As displayed in Figure 4, the shapefile maps were then translated to raster maps because they are more useful. Each category and sub-category went through a number of refinement steps using ArcGIS 10.5 software, such as overlay, convert, reclassify, and calculate the raster.

Table 2. The relative weights and rating scores of the factors and sub-criteria used for watershed susceptibility assessment

Factor	Weighting	Sub-criteria	Rating	Normalized rating
LULC	0.36	Agriculture	10	0.33
		Urban	9	0.2
		Grassland	7	0.13
		Wetland	6	0.12
		Forest	5	0.07
		Barren land	4	0.06
		Shrubland	3	0.04
		Water	1	0.03
Soil type	0.22	Clay Loam	10	0.23
		Silty Loam	8	0.17
		Loam	7	0.15
		Clay	6	0.14
		Silt	5	0.13
		Sandy Loam	4	0.08
		Peat	3	0.07
		Sandy	2	0.04
Average annual precipitation (inch)	0.18	>75	10	0.32
		71 - 75	9	0.18
		66 - 70	8	0.12
		61 - 65	7	0.09
		56 - 60	6	0.08
		51 - 55	5	0.07
		46 - 50	4	0.05
		41 - 45	3	0.04
		35 - 40	2	0.03
		<35	1	0.02
Slope (degree)	0.10	>60	10	0.35
		31 - 60	8	0.27
		16 - 30	6	0.21
		11 - 15	4	0.07
		4 - 10	2	0.06
		<3	1	0.04
Depth to Groundwater (feet)	0.09	<5	10	0.32
		5 - 10	8	0.18
		11 - 15	6	0.15
		16 - 20	5	0.13
		21 - 25	4	0.08
		26-50	3	0.07
		51-100	2	0.05
		>100	1	0.03
Bedrock Type - Depth (0-50 feet)	0.05	Limestone	10	0.30
		Dolomite	9	0.29
		Shale	7	0.16
		Claystone	5	0.11
		Sandstone	3	0.08
		Metamorphic/Igneous	1	0.05

The final output watershed susceptibility map was created by calculating the weighted overlay of the six classifications: land uses/land cover, soil type, average annual precipitation, slope, depth to groundwater, and bedrock type.

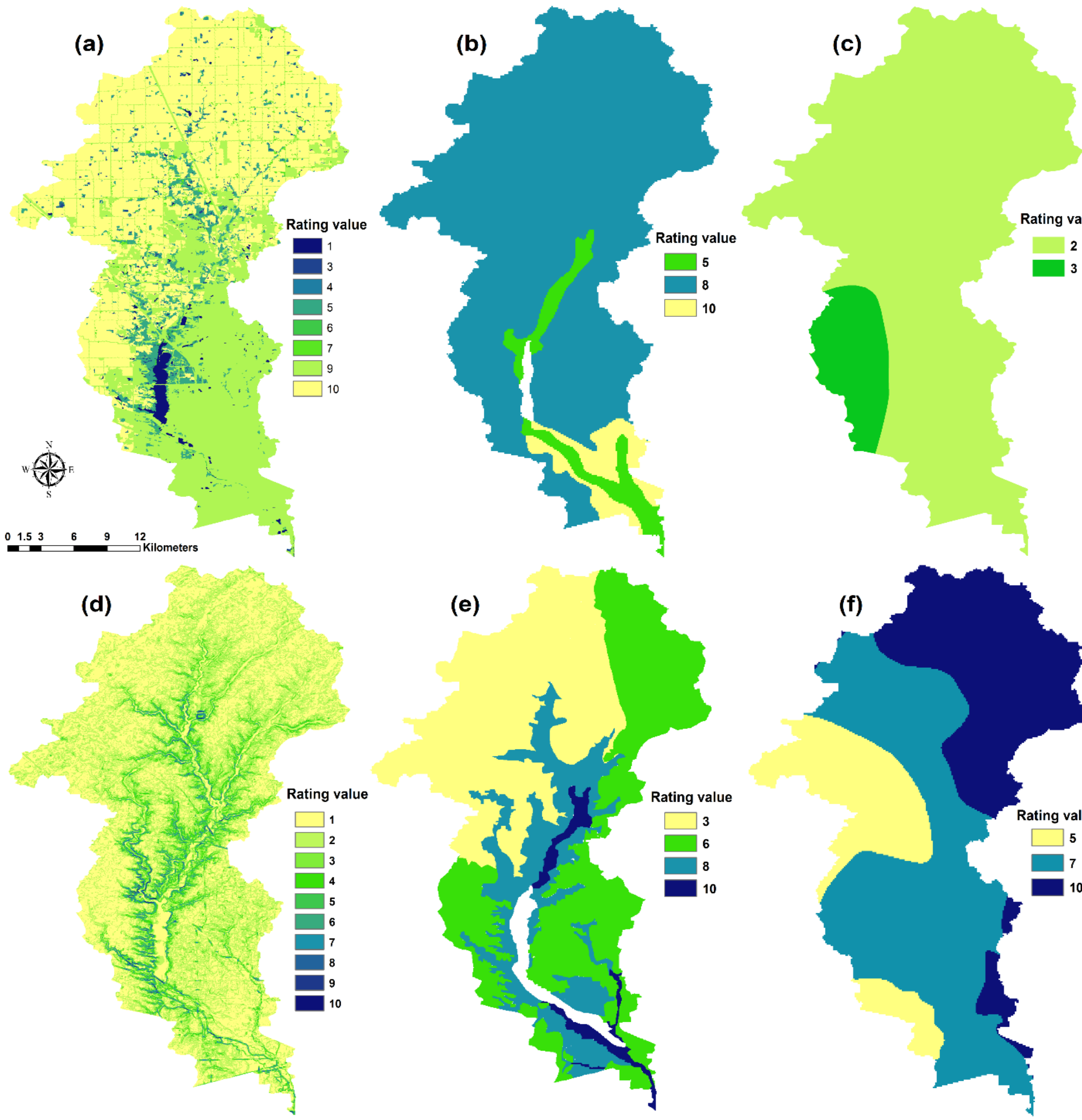

Figure 4. Thematic maps of the layers after rating for (a) land use/land cover, (b) soil type (c) average annual precipitation, (d) slope%, (e) depth to groundwater, and (f) bedrock type.

3.3. HYDROLOGIC MODELING USING SWAT

The SWAT is a hydrological model that quantifies the influence of changes in land management practices, land use and land cover changes, and climate change on water quality and hydrology for a range of scales, with a daily time step (Neitsch et al., 2011). The SWAT illustrates a variety of spatial local heterogeneity of any study area by dividing a watershed into subbasins according to topographic features. Subbasins have a special geographic position in the watershed but are spatially connected to each other. Subsequently, subbasins can be divided into small portions of the hydrologic response units (HRUs), which consist of combinations of land cover, soil, and slope. Multiple HRUs, created by dividing subbasins, can provide high accuracy and better physical descriptions. When applying the SWAT, specific data are required, such as weather, soil, land use, and topography.

The hydrological cycle can be simulated by the SWAT model using the water balance equation (Neitsch et al., 2011), as shown in Equation 8.

$$SW_t = SW_0 + \sum_{i=1}^{i=t}(P_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \tag{8}$$

where SWt and SW0 are the final and initial soil water content (mm/d), respectively; t is the time (day); Pday is the amount of precipitation (mm/d); Qsurf is the surface runoff (mm/d); Ea is the evapotranspiration (mm/d); Wseep is the percolation (mm/d); and Qgw is the amount of return flow (mm/d).

Surface runoff in the SWAT can be calculated using the Soil Conservation Service (SCS) curve number (CN) method (USDA-SCS, 1972):

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \tag{9}$$

where Qsurf and Rday are surface runoff (mm) and rainfall depth (mm) for the day, respectively; and S is the retention parameter (mm). In the current study, the SWAT model was simulated for nine years from 2010 to 2018, including a two-year warm-up period from 2010 to 2011.

3.3.1. Sensitivity Analysis. Sensitivity analysis was employed to determine if key parameters could be used to calibrate and validate the SWAT model (Zhang et al., 2009; Arnold et al., 2012). For this study, global sensitivity analysis was utilized in the SWAT-CUP 2012 version 5.1.6 (Abbaspour, 2015). To identify the significance of the sensitivity of each parameter, some indices were used, such as t-tests and p-values, where higher t-test values indicated high sensitivity, while smaller p-values indicated a more sensitive parameter (Abbaspour, 2017).

3.3.2. Calibration and Validation of the SWAT Model. Calibrating a model alters or modifies parameters based on field data to confirm the same result over time (Arnold et al., 2012). Furthermore, validation is a procedure for testing the accuracy of the identified parameters by simulating the observed data with a dataset not used in the calibration process, without modifying the model's parameters (Govender and Everson, 2005; Vilaysane et al., 2015). In the current study, the calibration was executed using five years (2012–2016) of monthly observed data for both discharge and nitrate loads, but four years (2013-2016) for sediment loads.

Calibration and validation procedures were executed in the SWAT-CUP using the sequential uncertainty fitting (SUFI-2) algorithm. The SUFI-2 is a semiautomated procedure for calibration and an uncertainty analysis algorithm (Schuol et al., 2008; Kundu et al., 2016). The SUFI-2 has been applied in many studies, such as by Setegn et al. (2008) in the Lake Tana Basin or Rai et al. (2018) in the Brahmani and Baitarani river deltas.

The parameters were modified to minimize the variation between the observed data and simulated results, using the calibration procedure. Calibration was executed for the period from 2012 to 2015, using 26 parameters (Table 3), depending on the results of the sensitivity analysis and a review of previous studies (Heathman et al., 2008; Pyron and Neumann 2008; Yen et al., 2014; Teshager et al., 2015; Jang et al., 2018). Among these, 15 parameters were considered to be more related to streamflow calibration, with six parameters associated with sediment load calibration, and five parameters more related to nitrate load calibration. The validation procedure was performed for the period from 2017 to 2018, using the parameters that had been calibrated.

To check the performance of the SWAT model, many indices can be employed. In the current research, the Nash-Sutcliffe (NS) coefficient was used for statistical evaluation. Nash-Sutcliffe efficiency (NSE) values range between $-\infty$ and 1; NSE = 1 indicates a perfect match of the simulated output data to the observed data. On the other hand, the coefficient of determination (R^2) was also employed in assessing the accuracy of the model. R^2 varies from 0 and 1, where a higher value is the optimal and perfect match between the observed and simulated data. The calculations of R^2 and NSE are computed using the Equations 10 and 11 (Moriasi et al., 2007).

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^m - Q_i^s\right)^2}{\sum_{i=1}^{n}\left(Q_i^m - Q_{mean}^m\right)^2} \tag{10}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(Q_i^m - Q_{mean}^m\right)\left(Q_i^s - Q_{mean}^s\right)\right]^2}{\sum_{i=1}^{n}\left(Q_i^m - Q_{mean}^m\right)^2 \sum_{i=1}^{n}\left(Q_i^s - Q_{mean}^s\right)^2} \qquad (11)$$

Table 3. The SWAT parameters for calibration of streamflow, sediment load, and nitrate.

Streamflow (Q)	Parameter	Description	Ranges Lower bound	Ranges Upper bound
	ALPHA_BF	Baseflow alpha factor 1/day	0.1	1
	CH_K2	Effective hydraulic conductivity (mm/hr)	5	300
	CN2	Initial SCS runoff curve number	-0.25	0.25
	ESCO	Soil evaporation compensation factor	0.01	1
	GW_DELAY	Groundwater delay time day	0.1	50
	GW_REVAP	Groundwater evaporation coefficient	0.02	0.2
	GWQMN	Depth of water for return flow (mm)	0.01	500
	OV_N	Manning’s ‘‘n’’ value for overland flow	0.01	0.6
	RCHRG_DP	Deep aquifer percolation fraction	0.01	1
	REVAPMN	Depth of water for evaporation (mm)	0.01	250
	SMFMN	Melt factor for snow on December 21 (mm/°C)	0	10
	SMFMX	Melt factor for snow on June 21 (mm/°C)	0	10
	SOL_AWC	Available water capacity of the soil layer (mm/mm)	-0.25	0.25
	SURLAG	Surface runoff lag coefficient	0.1	10
	TIMP	Snow pack temperature lag factor	0	1
Sediment (TSS)				
	CH_COV1	Channel cover factor	0	0.5
	CH_COV2	Channel erodibility factor	0	0.001
	PRF Peak	Rate adjustment factor for sediment routing in the main channel	0.5	2
	SPCON	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.0001	0.01
	SPEXP	Exponent parameter for calculating sediment reentrained in channel sediment routing	1	1.5
	USLE_P	USLE equation support practice factor	0	1
Nitrate				
	ORGN	Initial organic N in soils (kg-N ha−1)	1	10000
	ERORGN	Organic N enrichment ratio	0	5
	NPERCO	Nitrogen percolation coefficient	0	1
	SHALLST_N	Initial concentration of NO_3 in shallow aquifer (mg /l or ppm)	0	1000
	SOL_NO3	Initial NO_3 concentration in the soil layer (mg N/kg soil or ppm)	0	100

4. RESULTS AND DISCUSSION

This study uses a watershed susceptibility assessment tool that allows for the calculation of a single vulnerability index value for the watershed area being investigated, using simple features that are weighted relative to their influence on surface water pollution. Based on the index, the vulnerability to pollution can be determined: watershed vulnerability is extremely high (70-100), high (50-70), moderate (30-50), low (10-30), and very low (0-10). To use this new method, six major factors were employed to evaluate 10 sub-watersheds within the Eagle Creek Watershed. Factors ranked between 0 and 1 (i.e., low scores) have little impact on water quality, whereas factors with high scores have a large impact on water quality. Similarly, subcategories were rated from 1 to 10, with 1 meaning that there was a negligible impact on water quality, while high scores correlated with having a very high impact.

After evaluating each watershed for its vulnerability, maps were generated that displayed the relative vulnerabilities of each sub-watershed. The remarkable differences in vulnerability to pollution between the sub-watersheds in the Eagle Creek Watershed can be seen in Figure 5. It was predicted that the upper portion of the watershed (e.g., Lion Creek and Finley Creek sub-watersheds) were likely to have a very high vulnerability to potential contaminants as were Dixon Branch, Mounts Run, and Jackson Run sub-watersheds. Thus, about 37.6 km^2 (8%) of the total area of the ECW was considered to be very highly vulnerable to contamination, with 284.5 km^2 (57%) having a high vulnerability. The greatest area of vulnerability to contamination lies in the north and center of the study area, which is primarily comprised of agricultural land (85% of the total area within the northern sub-watershed). In the ECW, the area of low vulnerability is 73.8 km^2 (14%), while there is a very low vulnerability within 7.3 km^2 (1%). This study indicated that the Little Eagle Creek, Finley Creek, Dixon Branch, and Mounts Run Creek were very high vulnerability zones.

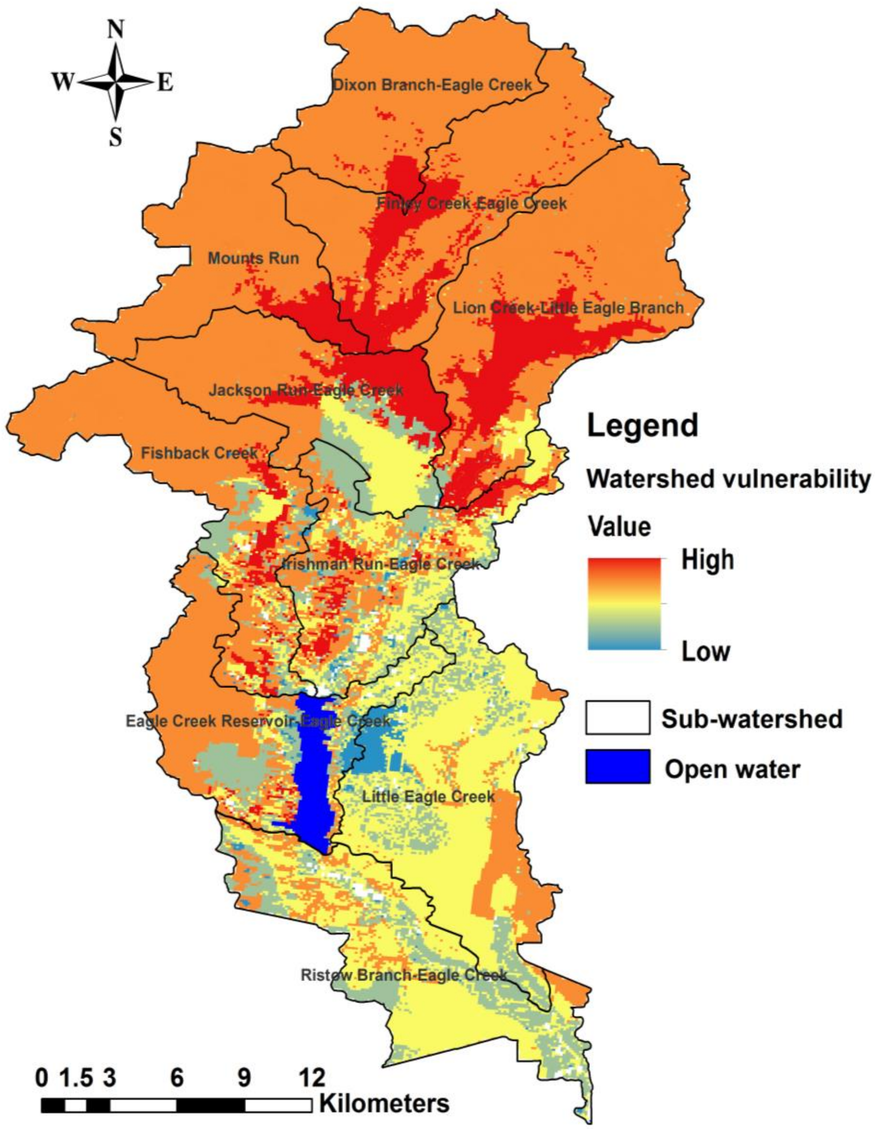

Figure 5. Watershed vulnerability distribution map of the Eagle Creek Watershed.

As agriculture is the primary land use in this portion of the study area, this high vulnerability is to some degree the result of agricultural runoff. Another relevant factor might be the soil type. The most widespread type of soil near the drainage channels in the northern portion of the Eagle Creek Watershed is silty clay loam. In this segment of the study area, the steepest slopes occur in proximity to riverbanks. Thus, the slope can raise the surface runoff rate as well as the rate of soil erosion, which increases the amount of sediments and pollutants deposited in neighboring streams (Tedesco et al., 2005). It is likely that this process degrades water quality by increasing electrical conductivity, which occurs because of the solubility of the lime and salt-containing soils. Additionally, according to Walter et al. (2017), the bedrock (in this case, limestone), which is near the surface in northern watersheds, can also contribute to declining water quality. This occurs as a result of increases in the electrical conductivity of groundwater because of the rock-water interaction in the aquifer. This might later affect the surface water quality after local exchange between streams and nearby shallow aquifers (Lautz and Siegel, 2006). In the southern part of the study area, the vulnerability of the watersheds was categorized in a range from medium and weak, especially in the nearby portions of the sub-watersheds bordering School Branch, Eagle Creek at Grande Avenue, and Little Creek at 30th Street.

The SWAT model shows the existing relationship, on a monthly basis, between the observed and simulated data. For the period from 2012 to 2016 (Figure 6a), the model has a good performance in the flow simulation, with values for the estimators of the efficiency of the model of 0.78 and 0.73, for R^2 and NSE, respectively. The slope of the regression line indicates that the model underestimated the data observed by 5%. When comparing the observed and simulated data, related to streamflow, R^2 (0.76) and NES (0.72) were slightly less than with the calibration results.

By comparing the observed and simulated flows through an analysis of linear regression, the values of R^2 and NSE (both for the calibration and validation period) exceeded 70% of the maximum possible (Figure 7a), which is statistically acceptable. However, the model continued to satisfactorily simulate the monthly average flows.

When calibrating the monthly sediment production from 2013 to 2016, the SWAT showed a slight underestimation of sediment production during the rainy season. The monthly total suspended solids (TSS) simulated by the model showed deficient values of the R^2 coefficient, with a correlation of 0.67 and an NSE of 0.64, which evinces a weak correspondence between the observed and calculated values. Figure 6b indicates that the model underestimated the materials in suspension during the rainy season in most years.

The validation procedure revealed that the coefficient of determination fell slightly to 0.65 and the NSE to 0.62 (Figure 7b), which indicates a lower predictive capacity of the SWAT model during the validation period. This lower correlation between the observed sediments and those simulated is possibly associated with changes in the vegetation cover.

As illustrated in Figure 6c, the results of the statistical analysis of the calibration of nitrate loads from 2012 to 2016 showed a good adjustment, with values of 0.74 and 0.69 for R^2 and NSE, respectively. As regards the validation results, the value of R^2 fell to 0.70 and the NSE to 0.63(Figure 7c).

To identify the reliability of the proposed technique, the SWAT model was applied.

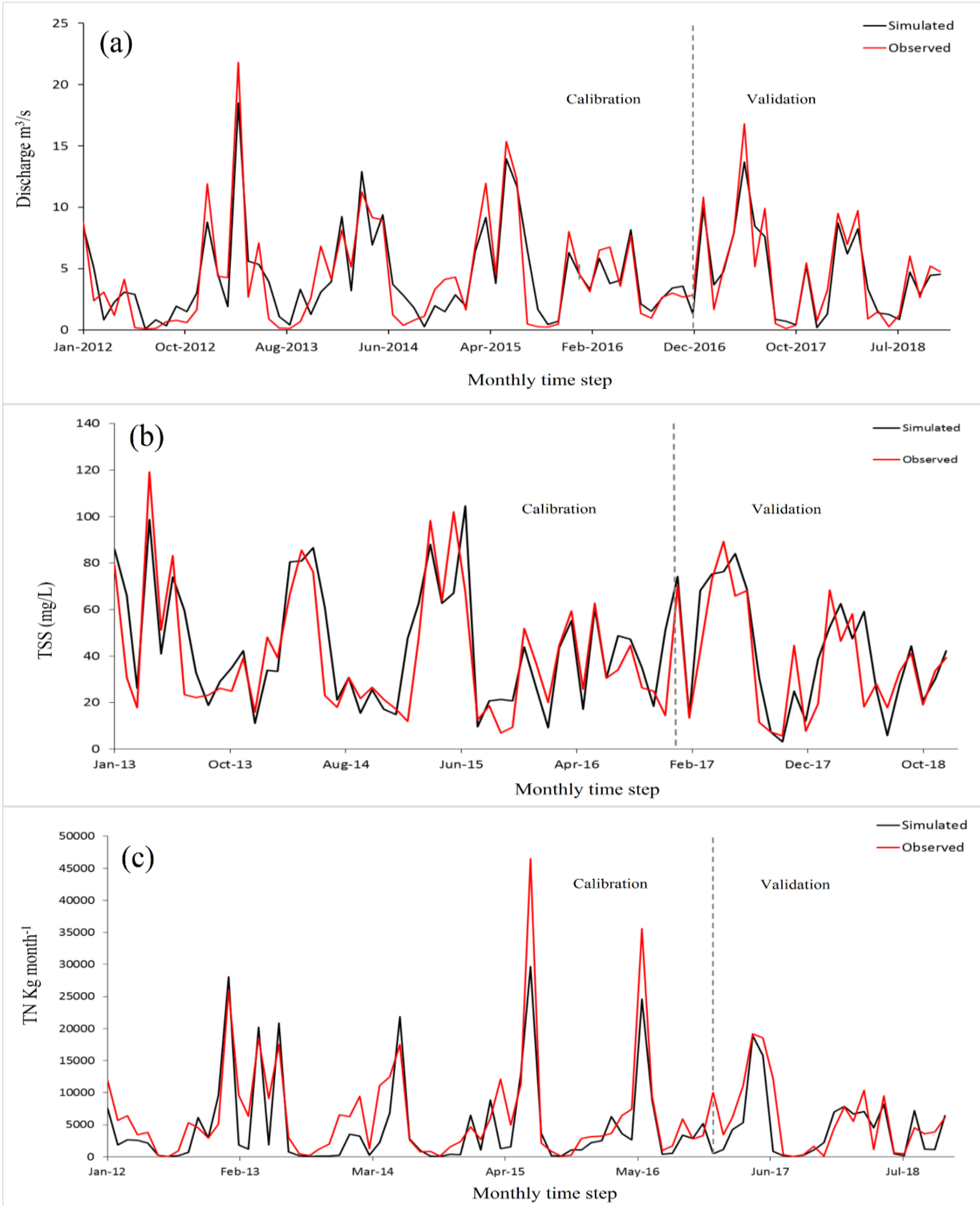

Figure 6. Comparing the results of the simulated and observed monthly data at Zionsville (USGS 03353200) for (a) discharge for the calibration period (2012-2016) and validation period (2017-2018), (b) suspended sediment for the calibration period (2013-2016) and validation period (2017-2018), and (c) nitrate load for the calibration period (2012-2016) and validation period (2017-2018).

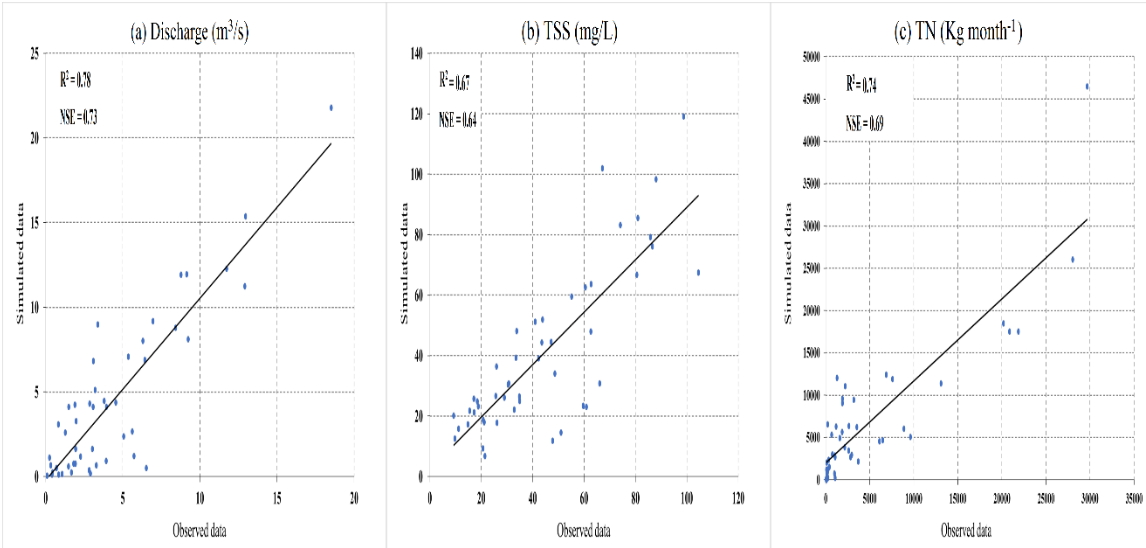

Figure 7. Regression relationship between the monthly observed and simulated data for (a) streamflow, (b) total suspended solids (TSS), and (c) nitrate loads.

For this study, with regards to simulating and predicting the water quality of watersheds using the SWAT model, some parameters (e.g., TSS and nitrate) were tested based on the availability of the data needed. Both methods produced good results for predicting that water quality loads, which are essential for validating the suggested method.

Both the TSS and nitrate load exhibited a similar trend of increasing when assessed using the SWAT model or this study's proposed method. Regarding the simulation of sediments load, the comparison of the two methods indicated a high amount of total sediment load was observed in the middle and north portion of the ECW (Figure 8). A high concentration of suspended solids in the central and upper part of the basin can be supposed to be an indicator that the highest capacity of erosion and transport occurred in these areas of the basin, where a large amount of sediment is transported by streamflow and eventually deposited before reaching the lower part of the basin.

Sediment production increased in the agricultural land due to decreases in the areas of natural forest and shrub vegetation, which also reduced the protection these provide for soil, leaving them more vulnerable to erosive processes (Bakker et al., 2008; Lenhart et al., 2011). Likewise, the difference in land use change between the upper and lower part of the ECW showed a significant effect on the simulations of the nitrate loads by the SWAT versus the proposed method.

The SWAT and the new method estimated high loads of nitrate in the central and upper part of the ECW. This occurred because agriculture is the major type of land use, representing up to 80% of the total land, which reflects the impact of agricultural activities on surface water quality (Schilling and Spooner, 2006; Laurent and Ruelland, 2011). Driscoll et al. (2003) found that rivers within watersheds in New York and New England received a significant proportion (from 6%-45%) of total nitrogen (N) from runoff from agricultural land use.

As shown in Figure 8, nitrate load in sub-watersheds ranged from 75 to nearly 30000 kg/month. The northern part of the ECW had a nitrate load greater than the sub-watershed in the southern extent of the watershed. Therefore, both types of modeling results confirmed that the high potential loads of nitrate in the ECW are primarily associated with agricultural activities, such as fertilizer input and manure application. Hence, results of the evaluation of the predictive reliability of the watershed vulnerability assessment method revealed that the proposed approach is suitable as a decision-making tool to predict watershed health.

5. CONCLUSIONS

In this research, the primary parameters affecting watershed vulnerability were identified based on the AHP technique. The vulnerability evaluation of each watershed was used to create maps showing the relative vulnerabilities of the basins. This method showed a remarkable difference between the basins in their vulnerability to pollution in the ECW. The basins in the upper portion of study area were classified as likely to have very high vulnerability to potential contaminants.

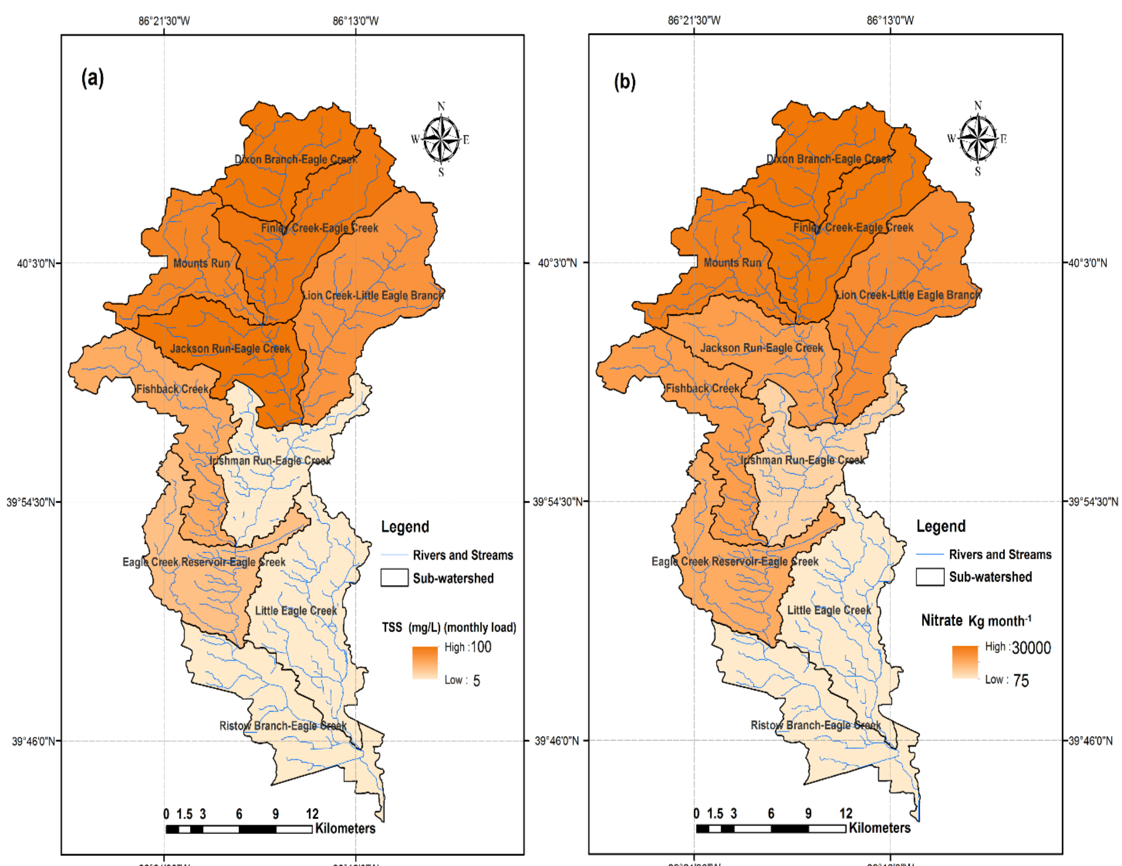

Figure 8. Spatial distribution map of the ECW showing loads of (a) TSS and (b) nitrate.

Similarly, the basins in the central part were identified as highly vulnerable to contamination based on their average value of vulnerability. The low and very low range of vulnerability was observed only in the southern portion of the ECW.

To test the reliability of the proposed approach, the SWAT model was used. In this study, some parameters, such as total suspended solids (TSS) and nitrate, were used to calibrate and validate the SWAT model.

The monthly TSS simulated by the SWAT model showed deficient values of the R^2 coefficient, reaching a correlation of 67%, with an NSE of 0.64, indicating a weak correspondence between the observed and calculated values. For the nitrate loads modeling results, statistical analysis of the calibration for the period from 2012 to 2016 showed good adjustment, with values of 0.74 and 0.69 for R^2 and NSE, respectively.

Hence, these values are statistically acceptable to predict the water quality status of the ECW. Both methods produced good results for predicting water quality loads. Hence, results of the evaluation of the predictive reliability of the watershed vulnerability assessment method revealed that the proposed approach is suitable as a decision-making tool to predict watershed health.

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SECTION

4. CONCLUSIONS AND RECOMMENDATIONS

4.1. CONCLUSIONS

This dissertation has shown through statistical analyses were performed using pairwise comparisons, stepwise multiple regression, and principal component analysis significant variations in water quality occurred between subbasins of Lower Grand River watershed within each data campaign and that some parameters varied significantly between data campaigns. The main points of the results obtained are summarized below:

1. Pairwise comparison of the data acquired during the fall and spring showed that all water quality parameters were statistically different data sets with $p < 0.02$ for all parameters, which suggests that the timing of water quality sampling is critical. Simple regression analysis of all variables revealed that correlations between independent variables and water quality indicators fluctuated with the season but that the "pasture/hay" LULC category (which includes livestock grazing) was statistically significant for several water quality indicators for both sampling campaigns. The percentage of land used for cultivated crops was only significant in the spring, when more fertilizer is applied.
2. The amount of precipitation in the two weeks preceding data collection was also significant for some water quality parameters. The variation between seasons as well as the significance of precipitation to the correlations again implies that the timing of sampling campaigns may influence the correlations.

3. Geologic parameters, such as depth to bedrock, depth to water table, slope, and soil type, were also significantly correlated to water quality parameters.
4. Comparison of the water quality index with the biotic index demonstrated that these two indexes were best correlated during the spring, implying that the lower water quality conditions observed in the spring might be more representative of the longer-term water quality conditions in these watersheds.
5. The correlation of turbidity, E. coli, and BI in the PCA analysis suggests that livestock grazing may adversely affect water quality in this watershed. PCA analysis also revealed that N, P, and SC contribute greatly to the observed water quality variability.
6. Combination of watershed vulnerability assessment and GIS spatial analysis tools were used to produce the maps that show the susceptible zones for Eagle Creek watershed. Based on the results of this method, accounting for around 37.6 km^2 (8%) of the total area of the watershed, was classified as having a very high vulnerability to contamination, and 284.5 km^2 (57%) as a high vulnerability.
7. The greatest portion of weakness is located in the middle and north of study area where agricultural land takes up nearly 85% of the total area of northern sub-watershed, while the vulnerability for the watersheds in the southern part of the study area was classified between medium to weak.
8. The correlation between the measured water quality index and the predicted watershed vulnerability for the method showed a high negative correlation

(r^2=0.77) between WQI and vulnerability, indicating that the vulnerability predictions are fairly accurate.

9. The monthly total suspended solids (TSS) simulated by SWAT model showed deficient values of the R^2 coefficient, reaching a correlation of 67%, with an efficiency NSE of 0.64 that evidences a weak correspondence between the observed and calculated values.
10. As regards the nitrate loads modeling results, statistical analysis of the calibration for the period of 2012 to 2016 showed good adjustment, with values of 0.74 and 0.69 for R^2 and NSE, respectively.
11. The results of the evaluation of the predictive reliability of the watershed vulnerability assessment method revealed that the proposed approach is suitable as a decision-making tool for prediction watershed health.

4.2. RECOMMENDATIONS

Statistical analyses were performed to determine which of watershed characteristics were most correlated with water quality parameters. Subsequently, a new methodology for assessment watershed vulnerability was developed to predict the vulnerable zones to contamination within watersheds. Based on the findings of this dissertation, the current research can be extended to include:

- Using an artificial intelligence approach to identify potential sources of water quality impacts such as nutrients loads (phosphorus and nitrogen) and E. coli concentration in a specific watershed of concern depending on wet and dry weather conditions.

- Use riparian health assessment by examining chemical, physical, and biological parameters to evaluate the condition of riparian zones. These tools will provide comprehensive information about the biodiversity along reaches of streams to identify the environmental stresses can be impacting watershed health.

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VITA

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In 2013, Fadhil was granted a scholarship from Ministry of Higher Education and Scientific Research to study PhD at Missouri University of Science and Technology. In addition, he was an active member in many professional organizations, such as Geological Society of America (GSA), the American Geophysical Union (AGU), American Institute of Professional Geologists (AIPG), American Water Resources Association (AWRA). His main research interests are hydrogeochemistry, water resources management; water quality monitoring. His work has been extended into new areas such as environmental impact assessment, watershed hydrology, ecohydrology, biodiversity monitoring. He was published a number of conference and journal papers.

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