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Modelling Microbial Pollution in the Lake Clair Watershed within Essex County Using SWAT

By

Israt Jahan

A Thesis
Submitted to the Faculty of Graduate Studies
through the Department of Civil and Environmental Engineering
in Partial Fulfillment of the Requirements for
the Degree of Master of Applied Science
at the University of Windsor

Windsor, Ontario, Canada

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Declaration of Originality

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Abstract

A record number of beach closures and warnings during the summer season have drawn region-wide attention because of the importance of beach water quality to the public. Identification and quantification of the pollutant loadings from the local subwatersheds is imperative to improve beach water quality. To understand the contribution of local subwatersheds into the south shore region of Lake St. Clair, a semi-distributed watershed simulation model, the Soil and Water Assessment Tool (SWAT), was employed. The overall goal was to identify impaired subwatersheds for pathogens by determining the major water budget components of subwatersheds, and the model parameters that control the fate and transport of *Escherichia coli (E. coli)*. Agricultural management, crop rotation, and tile drainage parameters were incorporated to obtain accurate water balance. Sensitivity analysis was performed for both flow and *E. coli*. This research was the first attempt to perform a water budget analysis and to simulate *E. coli* with SWAT for the Lake St. Clair watershed located within the Essex region. For the daily hydrologic calibration process, the model performance provided a "good" prediction of watershed (Nash-Sutcliffe Efficiency [E]>0.6). Monthly calibration and validation of the pathogen fate and transport model was conducted for *E. coli* at five sampling locations, and the calibration results indicate a "good" prediction for *E. coli* (E = 0.74) while at the downstream calibration locations the results compared well with many similar *E. coli* modelling studies (0.13 < E < 0.46). The livestock manure from feedlots was identified as the major non-point source pollutant to local subwatersheds of the Lake St. Clair region, contributing the most (>55%) to the total *E. coli* concentrations. This research has mapped critical source areas from a microbial loading point of view where best management practices can be implemented.

Dedication

To my Parents and my beloved children,

Iffat and Iraj

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At first, I would like to thank the almighty for giving me the courage, patience, and blessings to successfully accomplish this effort. This journey would not have been possible without the emotional and spiritual support of my father who is no longer alive. The caring and support that I always receive from my mother is immeasurable. I thank my daughter, son, brother, and sister for their endless support.

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List of Abbreviations

AQ	Aquifer
C	Celsius
CanSIS	Canadian Soil Information System
Cap	Capita
CBC	Canadian Broadcasting Corporation
cfu	colony-forming unit
Conc.	Concentration
CUP	Calibration and Uncertainty Procedure
DEM	Digital Elevation Model
E	Nash-Sutcliffe Efficiency Coefficient
E. coli	Escherichia c*oli*
ERCA	Essex Region Conservation Authority
ESRI	Environmental Systems Research Institute
FM	Fecally-derived Microorganism
GIS	Geographic Information System
GLUE	Generalized Likelihood Uncertainty Estimation
gm	Gram
Ha	Hectare
HRU	Hydrologic Response Units
HSPF	Hydrological Simulation Program—FORTRAN
Kg	Kilogram
KGE	Kling and Gupta Efficiency
l	Litre
LSCCWCC	Lake St. Clair Canadian Watershed Coordination Council
LSPC	Loading Simulation Program in C++
MCMC	Markov chain Monte Carlo
MOECC	Ministry of the Environment and Climate Change
MOHLTC	Ontario Ministry of Health and Long- Term Care
msl	Mean sea level
MUSLE	Modified Universal Soil Loss Equation
MWASTE	Event Based Compartmental Model
N	North
N	Nitrogen
NAD	North American Datum
NSDB	National Soil Database
NSE	Nash-Sutcliffe Efficiency
OMAFRA	Ontario Ministry of Agriculture, Food and Rural affair
P	Phosphorus
Parasol	Parameter Solution

PBIAS	Percent BIAS
PET	Potential Evapotranspiration
PWQMN	Provincial Water Quality Monitoring Network
PWQO	Provincial Water Quality Objectives
R^2	Coefficient of Determination
RSR	Ratio of the Root Mean Square Error to the Standard Deviation of Measured Data
SBR	Sequential Batch Reactor
SLC	Soil Landscapes of Canada
SOLRIS	Southern Ontario Land Resource Information System
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWMM	Storm Water Management Model
US EPA	United States Environmental Protection Agency
UTM	Universal Transverse Mercator
UV	Ultraviolet
W	West
WAMView	Watershed Assessment Model View
WARMS	Water Resources Management System
WECHU	Health Unit of Windsor Essex County
WGEN	Weather Generator
WHO	World Health Organization
Windsor A	Windsor Airport
WMS	Watershed Modelling System
WPCP	Water Pollution Control Plant

Chapter 1:

Introduction

Background of the Study

The surface water quality of local streams has experienced mostly poor to very poor grades (Essex Region Conservation Authority [ERCA], 2018); these degrading watershed conditions are distressing. Furthermore, during the summer seasons, a bacteria pollution spike leads to a number of beaches being shut down in the Essex region due to increased *Escherichia coli* (*E. coli* bacteria) levels in local streams. This degradation has exerted a pervasive and profound influence on watershed health management.

Non-point source pollution is the key issue of the Essex region's watershed which comes from many sources and occurs when rainfall and snowmelt runs off from fields, streets, parking lots etc., carrying soil particles and pollutants into the waterbodies. One of the major contributors of the environmental degradation within rural watershed is the runoff from agronomic activities that utilize animal manure contaminated with pathogenic or parasitic organisms to watershed or basin contaminations (Sadeghi & Arnold, 2013; Dorner et al., 2006). In Southwestern Ontario, Canada, subsurface tile drainage which is installed to remove excess water quickly from the agricultural field also enhances non-point source agricultural pollution by increasing the translocation of sediments, nutrients, and pesticides from fields to streams and lakes, especially during the non-growing season and after heavy summer rains (Liu et al., 2011). A major portion of the Essex region watershed drains to Lake St. Clair. The land drained by local tributaries into Lake St. Clair is characterized as one of the most productive agricultural areas in Canada.

Land use is considered as the single largest stressor in the Lake St. Clair watershed. Inappropriate management of this watershed stressor results in the degradation of the water quality of Lake St. Clair (Lake St. Clair Canadian Watershed Coordination Council [LSCCWCC], 2008). Additionally, Lake St. Clair receives treated wastewater (with fine screening, grit removal, four sequential batch reactors (SBRs), and UV disinfection, an average daily sewage flow of 13,640 m^3/d) from the Denis St. Pierre water pollution control plant (WPCP) located in the Town of Lakeshore (Stantec, 2018). There are three recreational beaches located on the Canadian side of Lake St. Clair, which are Sandpoint beach, Belle River beach, and Michelle beach. Sandpoint beach and Belle River beaches are located within the Essex region and are identified by Health Canada for significant levels of microbial pollution, the principal health risk with exposure to recreational water quality hazards (Health Canada, 2012).

Need for Beach Water Quality Control for Lake St. Clair

In 2010, over 73 million tourists visited in the Great Lakes Region with estimated spending of $12.3 billion in consumable goods and equipment. Great Lakes recreational anglers support more than $600 million to Ontario's economy. One of the challenges for the Great Lakes today is excessive bacteria levels in beaches, meaning that swimming is not safe (Ontario Ministry of the Environment and Climate Change [MOECC], 2019). Numerous closures of beaches and recreation areas due to health concerns cause loss of revenue/ tourism (Lehouillier, 2015). Though significant success was achieved in restoring and protecting Lake St. Clair, bacterial pollution is overwhelming old solutions. Lake St. Clair, located in the central region of the North American Great Lakes basin between Lakes Huron and Erie, serves as an international shipping channel and provides source of drinking water for over 750,000 people (Gewurtz et al., 2007). Preserving Lake St. Clair beach water quality, which depends greatly on the water quality in the larger system of lakes, is vital to protecting public health and is an important economic consideration as well. Since swimmable, drinkable, and fishable lakes all contribute to a high quality of life, the beach water quality control is essential to the Lake St. Clair watershed.

Current Beach Water Quality and Monitoring

Beach closures and warnings against swimming in local waterways have been numerous in summer. Bacteria of fecal origin are the primary causes of surface water contamination. *E. coli* is fecal coliform bacteria found in large intestine of warm blooded animals. *E. coli* is used as an indicator of fecal contamination, and the detection of *E. coli* in a water body above regulatory standards poses a potential health hazard (Gregory, 2008)**.** The existence of *E. coli* bacteria is a strong indicator that there may be other disease-causing organisms in the watercourse. In Ontario, the provincial recreational water quality guideline for *E. coli* is 100 cfu/100 ml (Hayman, 2009) whereas the Canadian recreational water quality guideline is 200 cfu/100 ml (Health Canada, 2012). The Health Unit of Windsor Essex County (WECHU) monitors water quality of nine public beaches on a weekly basis throughout the summer to ensure public health protection. A warning sign is posted if the *E. coli* levels exceed 200 cfu/100 ml of water, which means swimming is not recommended. If the *E. coli* counts are 1000 cfu/100 ml of water or higher, the beach will be closed because swimming is not safe. The nine locations of the beaches monitored results for more recent year of 2018 within the Essex region watershed are shown in Table 1.

Table 1: *WECHU 2018 Beach Sampling Results*

Name of Beach	# of Times Beach Closed	# of Times Beach Under Warning	# of Times Sampling Done	% of Closure	% of Warning
Sandpoint Beach	4	1	17	23.53	5.88
West Belle River Beach	1	6	15	6.67	40.00
Point Pelee North West Beach	0	3	14	0.00	21.43
Seacliff	0	3	14	0.00	21.43
Mettawas Beach	0	6	14	0.00	42.86
Cedar Beach	0	1	14	0.00	7.14
Holiday Beach	0	2	14	0.00	14.29
Colchester Beach	1	3	15	6.67	20.00
Cedar Island Beach	0	2	14	0.00	14.29

(*Source*: M. Bamotra, Personal Communication, April 5, 2019)

Table 1 shows the percentage of weekly samples exceeded the recreational water quality guideline of *E. coli* in several Beaches. Along the Lake St. Clair shoreline within the Essex region, the West Belle River and Sandpoint beaches are sampled. Both of these beaches have incidents of involving high bacterial counts.

Bacterial monitoring for the public beaches during summer seasons by WECHU was started in 2010. WECHU currently samples for *E. coli* to take decision for the recreational activities. Therefore, bacterial contamination as measured by the presence of *E. coli* is employed as the determinant of pollution levels.

Non-point Source Microbial Pollution

Agricultural non-point source pollution is the significant source of water quality problem for any region (Green et al., 2007). The most common non-point source pollutants in agricultural watersheds are sediment and nutrients. Microbial pollution at the nearshore beaches of the Essex region persists for over a decade. Non-point source is more complex to identify and control than the point source pollution because of various potential sources causing bacterial pollution in stream are normally quite difficult to identify. It can potentially originate from various sources i.e., the defecation of animals in streams, manure storage facilities, land application of manure, grazed pastures, and faulty septic systems (Niazi et al., 2015; Fall, 2011)**.** Since the primary source of bacteriological inputs to the environment is represented by non-point sources, more attention has been given to non-point source pollutants.

Surface Water Quality Modelling

Non-point source pollution modelling was started since 1970s (Oudin et al., 2008). *E. Coil* can be analyzed through various models. However, it has to be site specific. It is vital to identify critical source areas for the bacterial loadings and to apply best management practices as soon as possible. Because of the costing and time associated with the monitoring of bacteria in each local stream, water resources managers were looking for spatial and temporally distributed computer modelling techniques to predict the levels of microbial pollution in rural watersheds. Since the predicted numbers of *E. coli* were observed to be clearly linked to hydrologic processes (Dorner et al., 2006), water budget analysis needs to be performed prior to surface water quality modelling. For the Essex region, the conceptual water budget report (ERCA, 2008) and the Tier 1 water budget report were based on only the subwatersheds having gauge station (ERCA, 2015). To identify the critical source areas of the Lake St. Clair region watershed with respect to bacterial risk, water budget analysis needs to be done at the local subwatersheds.

The Soil and Water Assessment Tool (SWAT) has been used to predict different components of water budget and the *E. coli* concentrations at watershed scale in several studies both nationally and internationally. This study will perform the water quantity and quality analysis using the SWAT model following parameter regionalization approach at local subwatersheds in the Lake St. Clair region watershed.

Purpose of the Study

Watershed modelling can be used to predict *E. coli* levels in recreational water. With sufficient data and observations, watershed modelling may allow public health inspectors to assess conditions of recreational water at public beaches in real time (Ontario Ministry of Health and Long- Term Care [MOHLTC], 2018). Watershed level hydrologic budget analysis using the SWAT model determines the surface and groundwater flow conditions; and quantifies the amount of runoff, recharge, and evapotranspiration within a watershed in seasonal, monthly, and yearly basis. In fact, the longer-term seasonal conditions for flow make the calibration of pathogen model more reliable (Niazi et al., 2015). Therefore, it is essential to conduct water budget analysis at spatial and temporal scales for water quality management.

This research proposes the application of the SWAT watershed model in the Lake St. Clair region watershed in order to identify critical source areas in a microbial point of view following the water budget analysis. The SWAT-CUP (calibration and uncertainty procedures), developed for calibration, would be used following manual calibration to calibrate the SWAT model for years 2003-2010 to fit with the observed hydrographs. The SWAT pathogen model will be calibrated for *E. coli* following the calibration of the hydrologic model.

Thesis Objectives

The objectives of this study are to:

1. Develop the SWAT model and quantify water budget components at spatial and temporal scales in the tile drained agricultural Lake St. Clair watershed within the Essex region
2. Model the microbial loadings in the Essex region's Lake St. Clair watershed and delineate the critical source areas

To facilitate the microbial analysis with the SWAT model, the study is divided into four chapters. The first chapter presents the introduction of the study. The 2nd chapter deliberates the water budget analysis for local subwatersheds in the Essex region's Lake St. Clair watershed following the calibration and validation of the SWAT model. The 3rd chapter discusses the quantification of *E. coli* concentrations from local subwatersheds following the SWAT pathogen and fate model calibration and validation. Finally, the conclusions and recommendations are described in Chapter 4.

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Chapter 2:

Develop the SWAT Model and Quantify Water Budget Components at Spatial and Temporal Scales in the Tile Drained Agricultural Lake St. Clair Watershed within the Essex Region

Introduction

Water budget analysis is the first step for source water protection through the identification of water sources, assessment of contamination, and elimination of the contamination (Ontario Ministry of the Environment and Climate Change [MOECC], 2006). Water budget analysis enables us to quantify the water resources of the hydrological cycle within various reservoirs including precipitation, runoff, evapotranspiration, and recharge, and to understand the water movement within the watersheds (Essex Region Conservation Authority [ERCA], 2008). Since watersheds located upstream of receiving waterbodies seem to be affecting the quality of those waterbodies, the impact of the hydrological processes on the transport of non-point source pollutants is substantial (Parajuli & Ouyang, 2013). For example, the presence of fecal molecules in an aquatic environment indicates the fate and transport of bacteria from the watershed. In the process, water quality management follows the estimation of pollutant loads; both follow the water budget process (ERCA, 2008). Additionally, water budget analysis can quantify the water resources spatially and temporally which helps in understanding non-point source pollutant loadings at spatial and temporal scales in a watershed (Ayivi & Jha, 2018).

Measurement of every data in the hydrological process is impractical due to watershed heterogeneity and the limitation of data measurement in cost and time (Teshager et al., 2016; Mengistu & Woyessa, 2019). Hydrological models represent the natural systems physically by acting as a mediator between mathematical theory and the real world. Prior to estimating the pollutant loads, the hydrologic model should be developed for the watershed (United States Environmental Protection Agency, 2015). Hydrological models can simulate the hydrologic processes and be used as a tool for linking pollutants to the receiving streams following quick and cost-effective assessment of water quality conditions. Hydrological models can take account of watershed heterogeneity and can extrapolate information spatially and temporally to the watershed scale (Beven, 1991).

Currently, the Soil and Water Assessment Tool (SWAT), which acts as a watershed scale model, is widely used as a physically based semi-distributed hydrologic model worldwide. SWAT was first designed to simulate management impacts on water and sediment movement in ungauged rural basins across United States (Gassman et al., 2007). Later, SWAT was applied widely for data-scarce catchment by transferring calibrated parameters identified through the regionalization approach to the ungauged catchment. The regionalization approach means the parameters obtained through the calibration for a "gauged" catchment will be extended to ungauged watershed. This method has been widely used in the prediction of hydrologic variables in ungauged watersheds (Oudin et al., 2008; Mengistu et al., 2019; Gitau & Chaubey, 2010; Emam et al., 2017). Generally, there are three methods to undertake the regionalization approach: spatial proximity, regression method, and physical similarity. The spatial proximity approach is assumed for neighboring catchments, which have similar hydrological responses with homogeneous physical and climate conditions. Hence, calibrated parameters could be transferred from gauged to ungauged neighboring catchments. For the calibration with regression methods, some empirical relationships are established between catchment descriptors and model parameter values. The regionalization with physical similarity depends on the similarity between an ungauged catchment and gauged donor catchment. According to Mengistu et al. (2019), there will be higher uncertainty of model output if the calibration and validation is conducted outside the target catchment. Therefore, the focus will be given on the parameter regionalization approach with spatial proximity. Both Oudin et al. (2008), and Gitau and Chaubey (2010) followed the basics of spatial proximity approach by computing the mean of the parameters from gauged watersheds and using the mean value of each parameter to the ungauged watersheds. Oudin et al. (2008) expressed that parameter averaging using more than five catchments decreases the model efficiency. In this present study, the basics of the spatial proximity approach will be followed. Since, only one flow gauging station is available in the Lake St. Clair region watershed, the model will be calibrated for that subwatershed, and the calibrated parameters will be transferred to the other ungauged subwatersheds to perform water budget analysis.

In most cases, the first step to develop the hydrologic model is to calibrate the model against the streamflow since the availability of flow data is abundant and any type of loads will follow the streamflow. Water budget analysis is always the next step once the hydrologic calibration is done (Tyagi & Rao, n.d.; Ayivi & Jha, 2018; Dhami et al., 2018). Researchers found that the performance of SWAT in a rural agricultural watershed works quite well for the hydrologic simulation on the basis of sensitivity analysis and most commonly used statistical measures, such as the Coefficient of Determination (R^2) and the Nash-Sutcliffe Efficiency (NSE) (Mocan, 2006; Parajuli, 2007; Fall, 2011; Teshager et al., 2016). For modelling a tile drained agricultural watershed using SWAT, researchers found that the incorporation of the tile drainage parameter helps in obtaining realistic water balance for the watershed (Green et al., 2006).

Tyagi & Rao (n.d.) suggests the SWAT model as a promising tool for water balance analysis for sustainable water management. Dhami et al. (2018) tested the SWAT model for the hydrologic calibration in the Karnali River basin, Nepal, and used SWAT-CUP (calibration and uncertainty procedures) for the sensitivity analysis in order to perform water balance analysis. The study recommended the SWAT model performance was satisfactory for water budget analysis. There is a wide application of SWAT-CUP that is applied in a number of hydrologic analysis studies to use the SWAT model to perform sensitivity analysis (Tang & Xu, 2012). SWAT-CUP links other uncertainty analysis techniques, i.e., Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (Parasol), Sequential Uncertainty Fitting (SUFI-2), and Markov chain Monte Carlo (MCMC) procedures, to SWAT whereas SUFI-2 is the more frequently used calibration and sensitivity analysis method.

In 2007, the major components of water budget were estimated for the Lake St. Clair drainage area by reviewing the data for drainage, landuse, soil, geology, hydrogeology, climate, and streamflow (ERCA, 2008), and no modelling approach was followed. The major water budget components were computed using the gauge stations' data and were assumed as a regional estimate for the Lake St. Clair drainage area. Additionally, the tile drainage component was considered as a data gap and was recommended to be incorporated for future water budget analysis. A similar approach was followed in the TIER 1 water budget analysis where water budget analysis using the gauge station data was assumed to be representative for the ungauged station (ERCA, 2015).

The Ruscom River Watershed had previously been calibrated using the SWAT model on a monthly basis for the period of 1990 to 1994 (Rahman et al., 2010), and the neighbouring subwatersheds were not incorporated in the SWAT model. Due to the unavailability of the old model, changes in the land management practices, and the necessity of doing sensitivity analysis, a revised calibration for the Ruscom River watershed is necessary to perform the water budget analysis for the local subwatersheds. In fact, the impact of land management practices has significant influence on runoff and sediment characteristics of any catchment (Arnold et al., 2012; Abbaspour et al., 2015; Worku et al., 2017). Considering the background of the study, a revised water budget analysis is necessary for local subwatersheds of the Lake St. Clair region watershed by incorporating tile drainage parameters and performing sensitivity analysis of the SWAT model.

Objectives of the Study

The main goal of this study is to analyse different components of water budget throughout the local subwatersheds of the Lake St. Clair region watershed using the SWAT hydrologic model. The key objectives of this study are:

1. To incorporate tile drainage parameters, agricultural management, and crop rotation to obtain more accurate water balance
2. To perform sensitivity analysis of the hydrologic model through the process of calibration and validation at daily time step to identify the highly sensitive parameters
3. Transfer calibrated parameters to the ungauged watersheds as a method of parameter regionalisation to understand the water budget at spatial scale

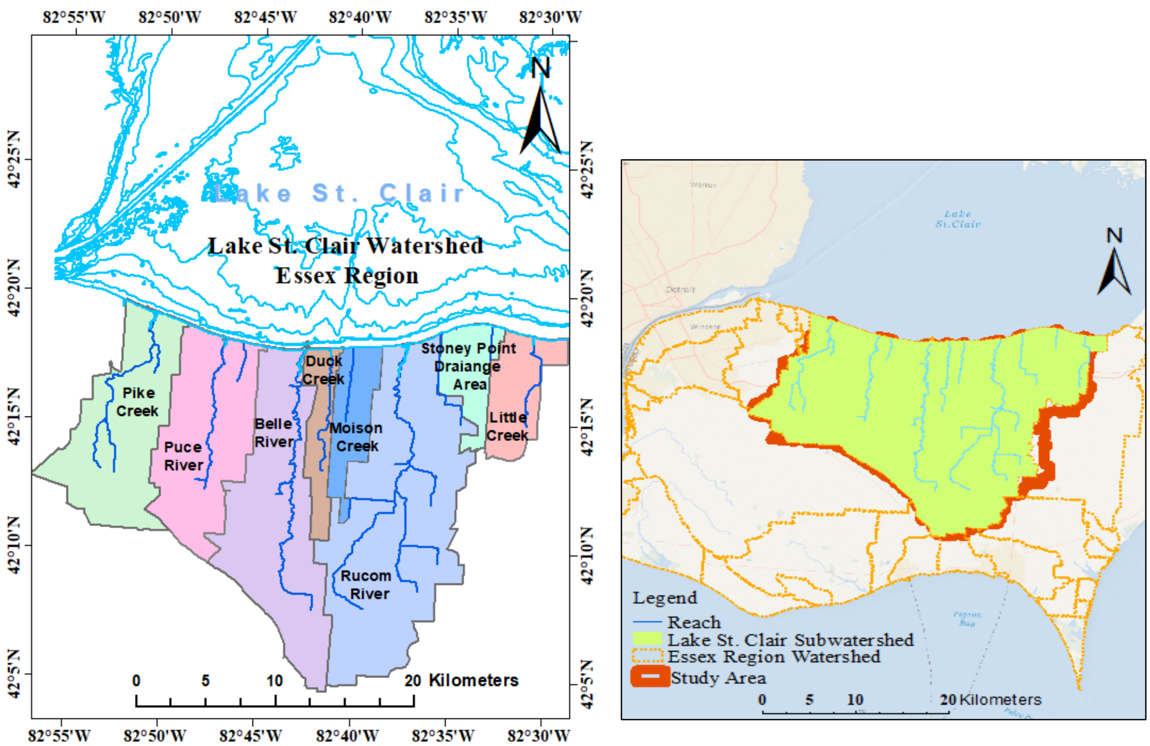
4. To quantify water budget components including evapotranspiration, surface runoff, tile drainage flow, groundwater flow, and water yield at both spatial and temporal scales

Description of the Study Area

Study Area Boundary

Based on the data availability and problem identification, the Canadian side of the Lake St. Clair watershed located the Essex region was selected as a study area. This study area is one of the major subwatersheds in the mainland of the Essex region that drains into Lake St. Clair and consists of eight individual subwatersheds including Pike Creek, Puce River, Belle River, Duck Creek, Moison Creek, Ruscom River, Stoney Point Drainage, and Little Creek, respectively. The total area of this watershed is 577 km^2 (Figure 2- 1).

Figure 2- 1: *Study Area Boundary at the Lake St. Clair Watershed, Essex County*



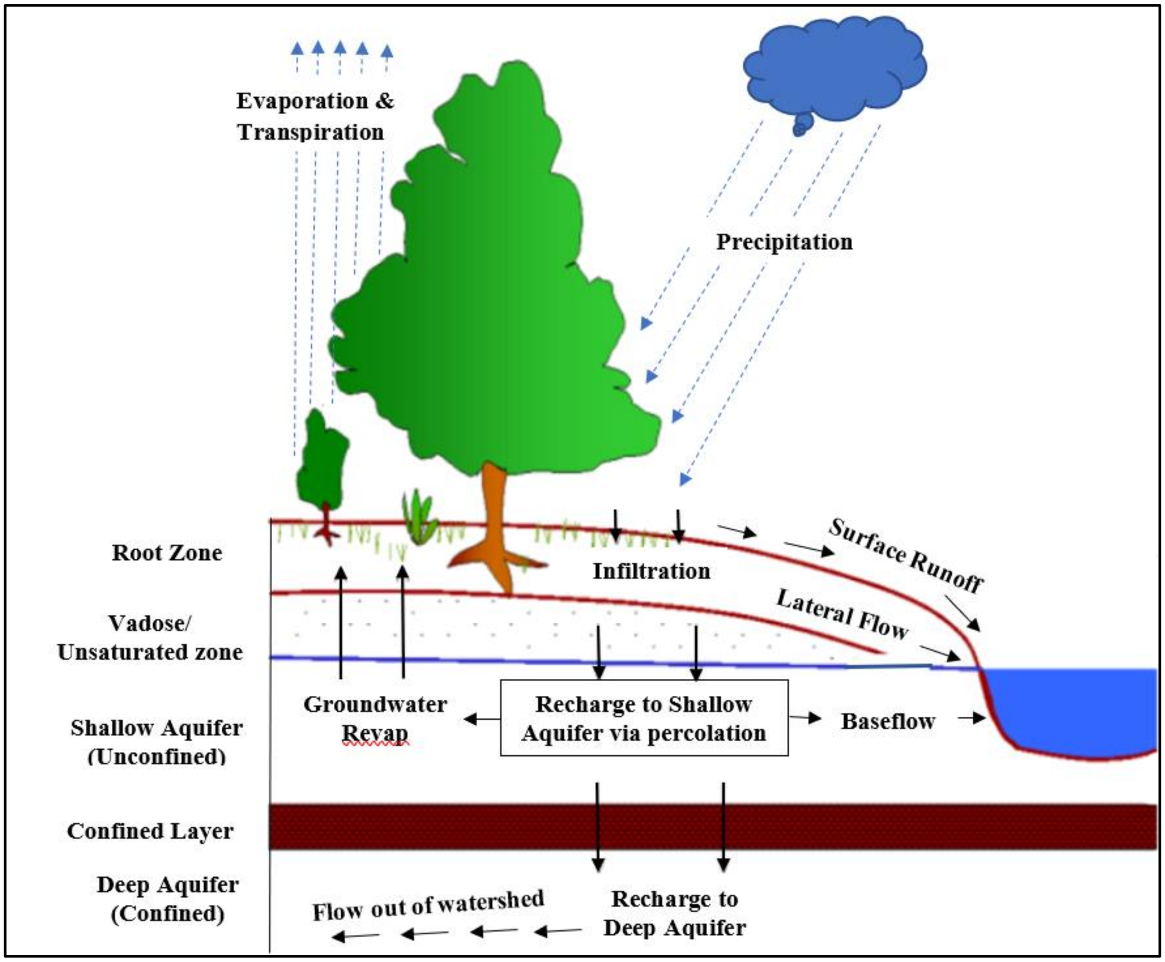
Hydrology, Geology, and Hydrogeology

The Essex region watershed is predominantly made up of flat land, and the predominant land use of this watershed is agricultural which is more than two thirds of the area of the watershed. The reminder of the watershed is urban land use and natural heritage. The agricultural fields in the watershed region are extensively drained by tile drains and man-made drains. According to the Conceptual Water Budget Report (ERCA, 2008), the annual mean temperature lies above 9°C. The annual means of daily maximum temperature and minimum temperature range between 13.0°C - 14.7°C and 1.7°C - 6.7°C, respectively. The mean annual rainfall range between 686 mm and 849 mm in the mainland of the Essex region based on the climate data period of 1950 to 2005. The highest recorded annual rainfall was 1152 mm in 1983, and the lowest recorded rainfall was 569 mm in 1988. The actual evapotranspiration rates ranged from 545 to 590 mm which was equivalent to 65 - 85% of precipitation. The Essex region has lower baseflow rate and the percentage of baseflow range is 6 - 16% of precipitation. The geology and hydrogeology of the Essex region/Chatham-Kent region was evaluated by Dillon (2004). The Region's surficial geology is dominated by glacial tills and lacustrine clays, that both have very low permeability (Dillon, 2004), The near-surface tills and clays are the primary controlling factor for maintaining shallow groundwater environment. The study indicates that the glacial sediments in the northern portion of the section are dominated by clay soil with only a minor presence of contact aquifer. In the southern portion, a very thick sand and gravel deposit represents the Leamington-Harrow Aquifer at the base of glacial material. Dillon (2004) did not quantify the tile drainage impacts and had expressed that a portion of shallow groundwater diverted by tiling would either evaporate or move laterally into the surface water regime of its own accord.

Overview of the Soil and Water Assessment Tool

Understanding of the methods for model development is very important because the methodology used for modelling can significantly influence the model output results (Parajuli & Ouyang, 2013). The SWAT simulation of the hydrology is separated into two divisions, which are land phase and routing phase, respectively. Land Phase controls the movement of water and pollutants from each subbasin to the main channel. Routing phase controls the movement of water and pollutants from the channel network of the watershed to the outlet. Figure 2- 2 represents the schematic representation of the hydrologic cycle.

Figure 2- 2: *Schematic Representation of the Hydrologic Cycle (Adapted from Neitsch, 2009)*

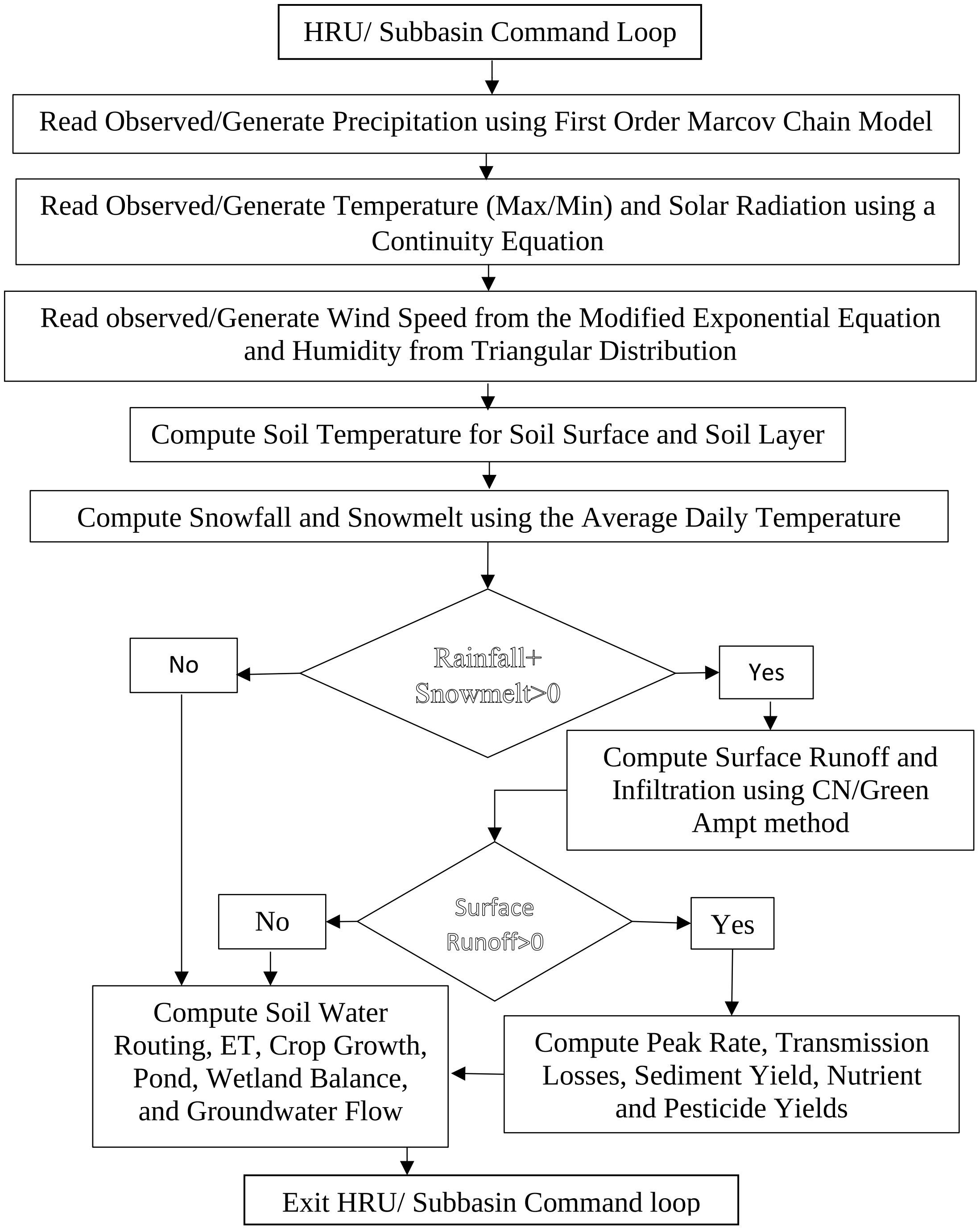


The land phase of the SWAT hydrologic cycle is based on the following water balance equation:

$$SW_d = SW_o + \sum_{n=1}^{d}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \qquad (2.1)$$

where SW_d is the final soil water content (mm H_2O), SW_o is the initial soil water content on day n (mm H_2O), d is the time (days), R_{day} is the amount of precipitation on day n (mm H_2O), Q_{surf} is the amount of surface runoff on day n (mm H_2O), E_a is the amount of evapotranspiration on day n (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day n (mm H_2O), and Q_{gw} is the amount of return flow in day n (mm H_2O). The flow chart as shown in Figure 2- 3 explains the land phase of the hydrologic cycle of the watershed:

Figure 2- 3: *Processes in the Land Phase of Hydrologic Cycle in SWAT*

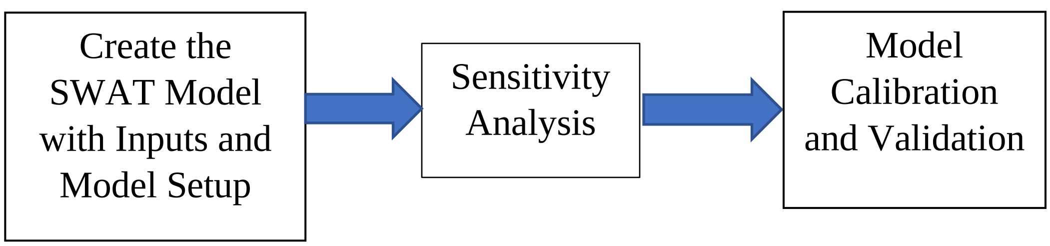


SWAT has three methods to incorporate potential evapotranspiration (PET): the Hargreaves method (Hargreaves et al., 1985), the Priestley-Taylor method (Priestley & Taylor, 1972), and the Penman-Monteith method (Monteith, 1981). SWAT computes surface runoff using either from the Curve number method which operates in a daily time step or the Green & Ampt method which requires subdaily precipitation. Peak runoff predictions are made with a modification of the rational methods. The details of this model can be found in the theoretical document for SWAT (Neitsch et al., 2011).

Methodology

There are three preliminary Steps (Figure 2- 4) for building the SWAT hydrological model, which are described in the following subsections.

Figure 2- 4: *Components of Building SWAT Model*



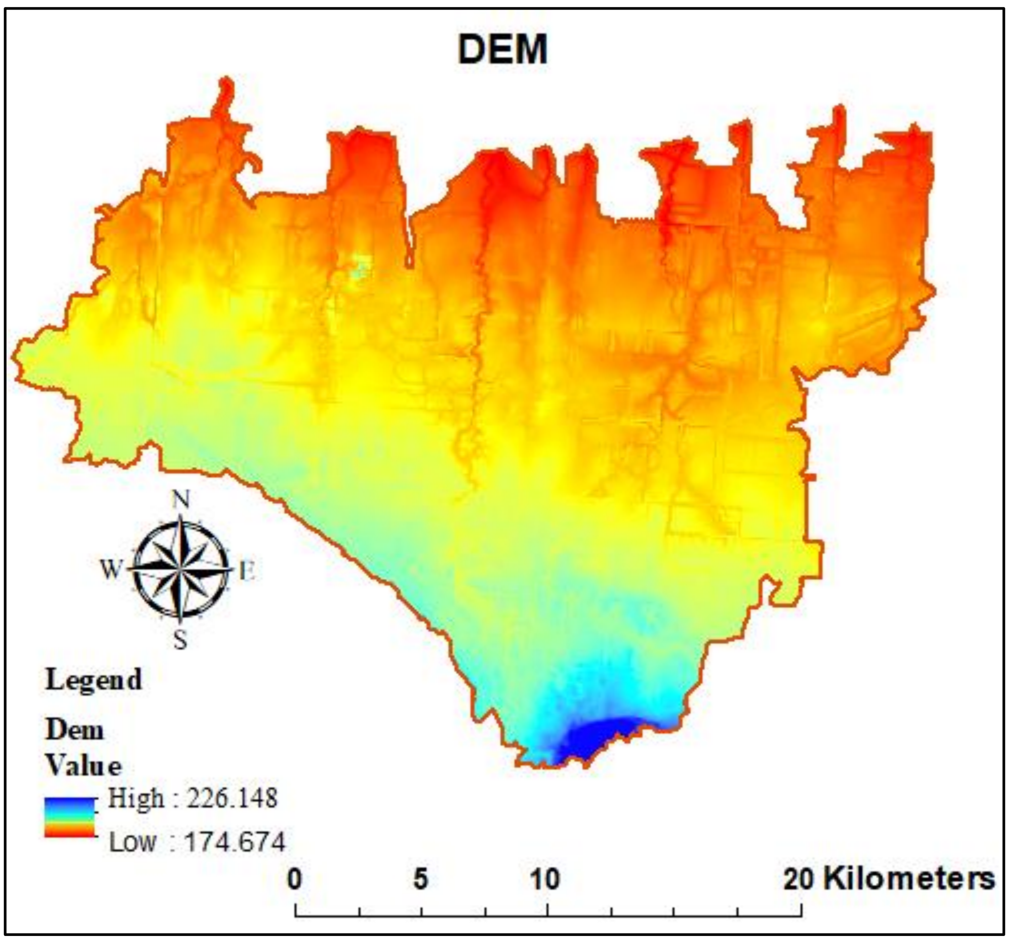
Create the SWAT Model with Inputs

Since SWAT is a physically based model, it requires specific information about topography, soil properties, climate, and land management practices occurring in the watershed to model the physical processes i.e., hydrology, sediment movement, bacterial transport.

Digital Elevation Model (DEM). A digital elevation model (DEM) represents the topography of the watershed and is the foundation for GIS interfaced hydrologic modeling.

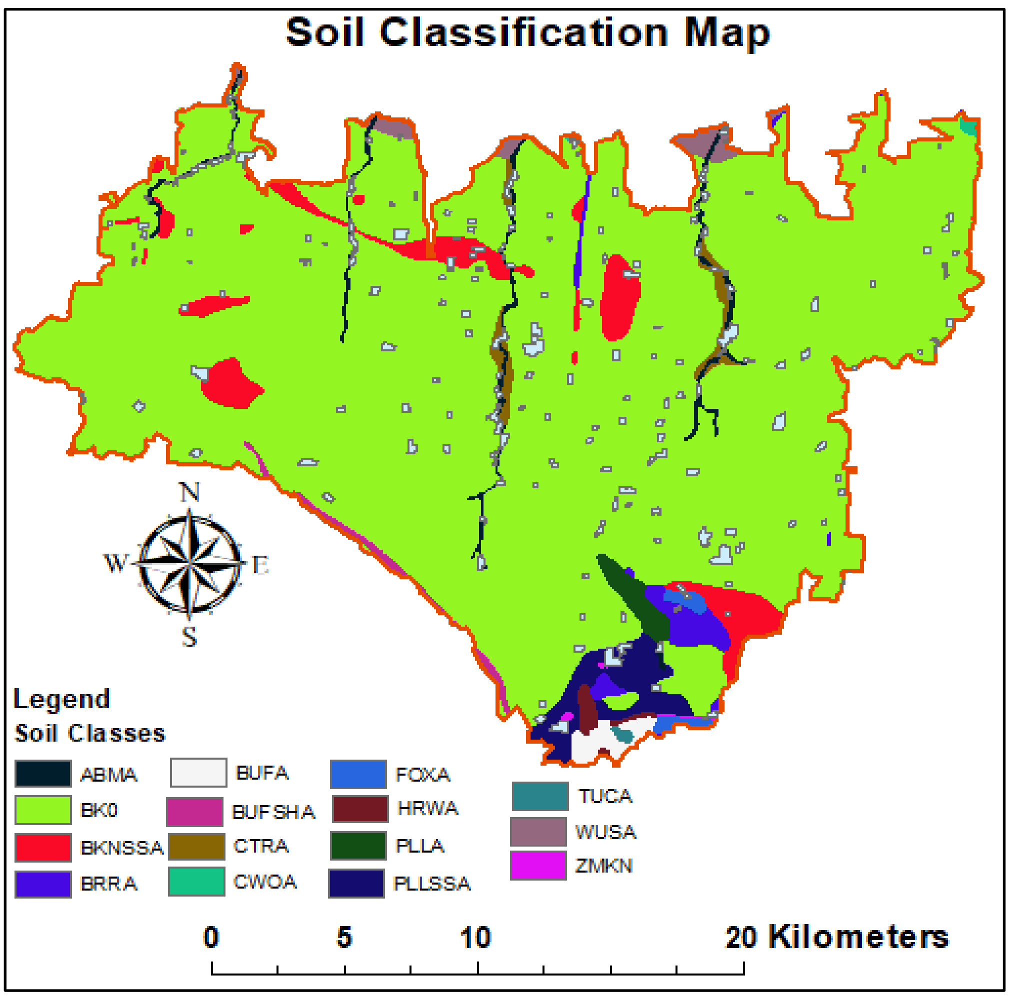
DEM data is presented in raster format, where each map cell represents the elevation of any point in a given area. The 10 m x 10 m resolution DEM data for the Lake St. Clair watershed was downloaded from Natural Resources Canada under the license agreement that limits use to educational purposes (http://ftp.geogratis.gc.ca/pub/nrcan_rncan/vector/index/html/geospatial_product_index_en.html#link). In this study area, the elevation varies from a minimum 175 above mean sea level (msl) to a maximum 226 msl. Figure 2- 5 depicts the image of the DEM for the study area watershed.

Figure 2- 5: *Digital Elevation Model Map of the Lake St. Clair Watershed, Essex County*



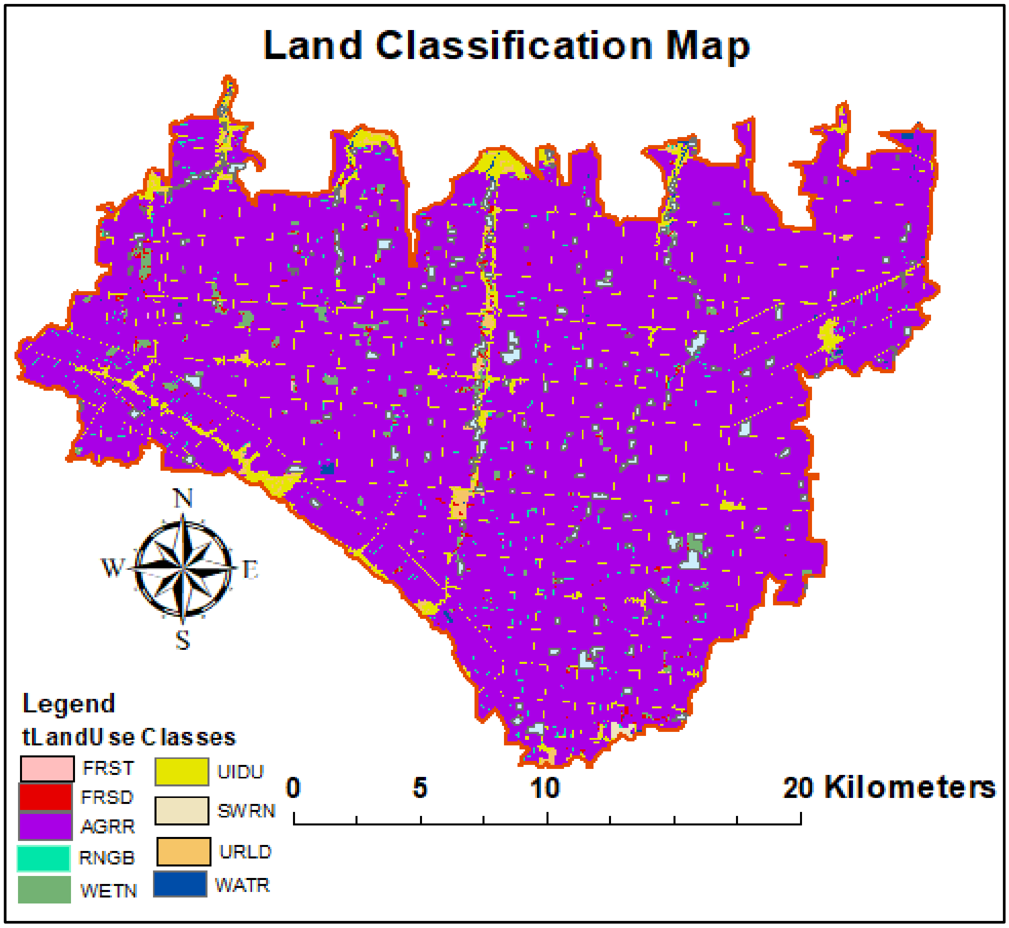
Soil Data. The version 3.2 of soil dataset was obtained utilizing the available dataset (Soil Landscapes of Canada [SLC] Working Group, 2010) at a scale of 1 in 1 million which contains detailed information about the agricultural soils of Canada (http://sis.agr.gc.ca/cansis/nsdb/slc/index.html). SLC Working Group (2010) is part of National Soil Database (NSDB) of Canadian Soil Information System (CanSIS). In total, 15 different soil types were identified and Brookston Clay (BK0) was the major soil found in the catchment area covering approximately 87%. The soil contained clay 47%, silt 37%, sand 1%, and organic C 2%. Figure 2- 6 explains the soil classification map.

Figure 2- 6: *Soil Map of the Lake St. Clair Watershed, Essex County*



Landuse Data. Version 2.0 of the landuse dataset for the current study was downloaded from Southern Ontario Land Resource Information System (SOLRIS) which is a landscape-level inventory of natural, rural and urban areas for southern Ontario (https://geohub.lio.gov.on.ca/datasets/0279f65b82314121b5b5ec93d76bc6ba). The primary landuse is agriculture, which constitutes 90% of the total catchment area. Figure 2- 7 represents the landuse classification map.

Figure 2- 7: *Landuse Map of the Lake St. Clair Watershed, Essex County*



Climate data. For climate, SWAT requires daily data for precipitation, minimum and maximum temperature, wind speed, relative humidity, and solar radiation along with the geographic location of weather stations for simulating climate distribution within the watershed. SWAT requires long term climate data to study long term impacts of gradual build up pollutants. The precipitation, maximum and minimum temperature data were retrieved from Environment Canada's website (https://climate.weather.gc.ca/historical_data/search_historic_data_e.html) and missing data was filled up from nearby climate station. The data as wind speed, relative humidity, and solar radiation are usually simulated by the SWAT model using the WGEN weather generator (Green et al., 2006; Paul et al., 2017; Mengistu et al., 2019). The detail information of the location of climate station is given in the Table 2- 1.

Table 2- 1: *Climate Station Location*

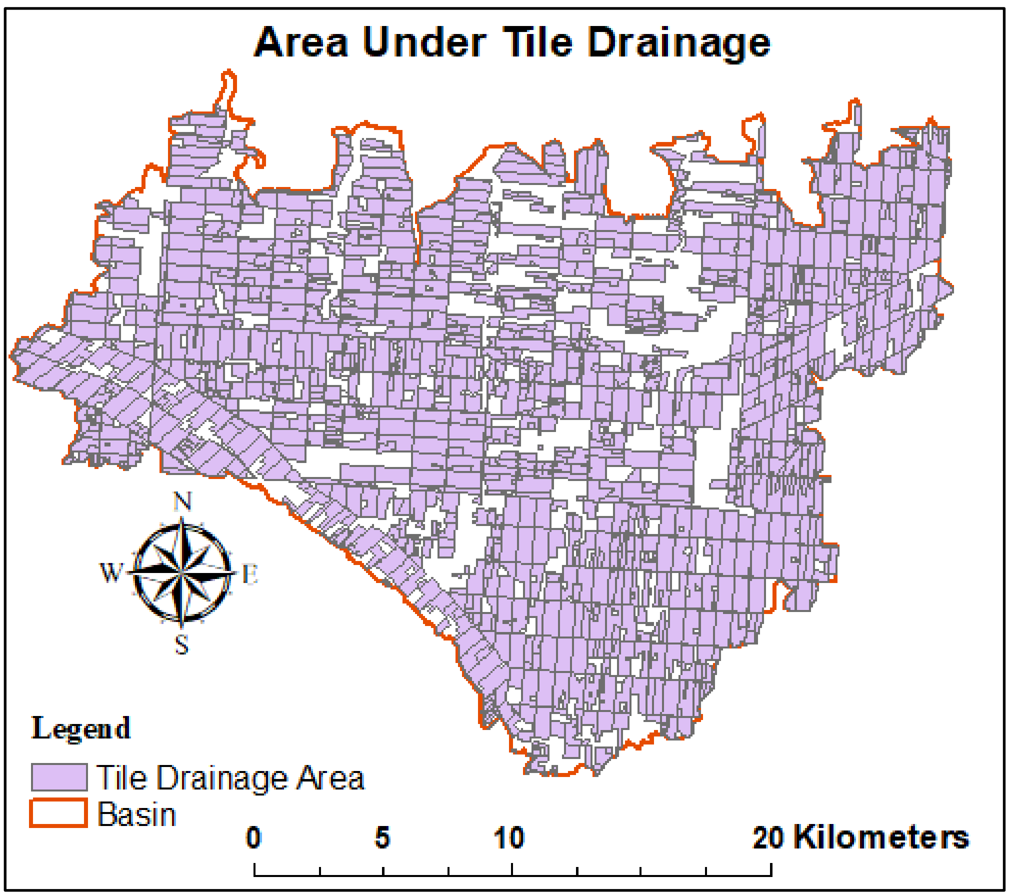
Station No.	Climate Station Name	Latitude	Longitude	Elevation	Data Period
6139525	WINDSOR A	42.275556	-82.955556	189.6	1998-2014
6139527	WINDSOR A	42.275556	-82.955556	189.6	2014-2018

Flow Data. Often, the first step in developing a hydrologic program for a watershed is calibrating the model for streamflow, and the data from stream gauge provide much needed information for model calibration (Schilling & Wolter, 2008). A gauge station named Ruscom River Station is located at Ruscom River and the daily flow data was retrieved from the Environment Canada's website for the period of 1998 to 2018.

Tile Drain. The GIS shape file for tile drainage was extracted from Landuse Information Ontario (LIO). The area under tile drainage has been clipped for Lake St. Clair Watershed. It was found that approximately 51 km^2 out of 577 km^2 is tile drained (Figure 2- 8). To simulate tile drainage in an HRU, the SWAT needs input for the soil surface depth to the drains (DDRAIN), the amount of time required to drain the soil to field capacity

(TDRAIN), and the amount of lag between the time water enters the tile until it exits the tile and enters the main channel (TDRAIN) (Neitsch et al., 2011). Researchers found that lagging the tile flow affects the timing and thus the daily peaks but not the total tile flow volume (Khalil et al., 2013). Tile drainage occurs when the soil water content exceeds field capacity in the soil layer where the tile drains are installed (Arnold et al., 1993). In this study, the input values for DDRAIN, TDRAIN, and GDRAIN were given 700 mm, 24 h, and 20 h, respectively, based on the previous study in southern Ontario conducted by Liu et al. (2011), and Tan and Zhang (2016).

Figure 2- 8: *Tile Drainage Area Map of the Lake St. Clair Watershed, Essex County*



Crop Management Data. According to the information from Ontario Ministry of Agriculture, Food, and Rural Affair (OMAFRA) on agricultural profile of Essex County, there are wide variety of crops that Essex County Produces include field crops, fruit crops, and vegetable crops whereas field crops covers almost 94% of agricultural land (Statistics Canada, 2017). Essex County produces nine different field crops include winter wheat, oats for grain, barlie for grain, mixed grains, corn for grain, corn for silage, hay, soybeans, and potatoes. Among these nine different field crops, ninety seven percent (97%) of area are covered by winter wheat, soybeans and grain (Statistics Canada, 2017). Generally, heavy clay soil areas are suitable for these crops. The Essex region's conceptual water budget report divides the region for growing crops in the ratio of 64:21:15 for soybean, corn and winter wheat, respectively. The general common rotation practice is corn or wheat followed by soybeans or corn followed by wheat (Rahman, 2007). In Ontario, winter wheat often follows soybean harvest date. Soybeans and corn are planted during mid-May to early-June, and the crops are harvested in October-November. To avoid delay for wheat planting, early soybean planting is preferable (OMAFRA, 2017). Table 2- 2 discusses the schedule for soybean, corn, and winter wheat chosen for this study as part of agricultural land management input in SWAT.

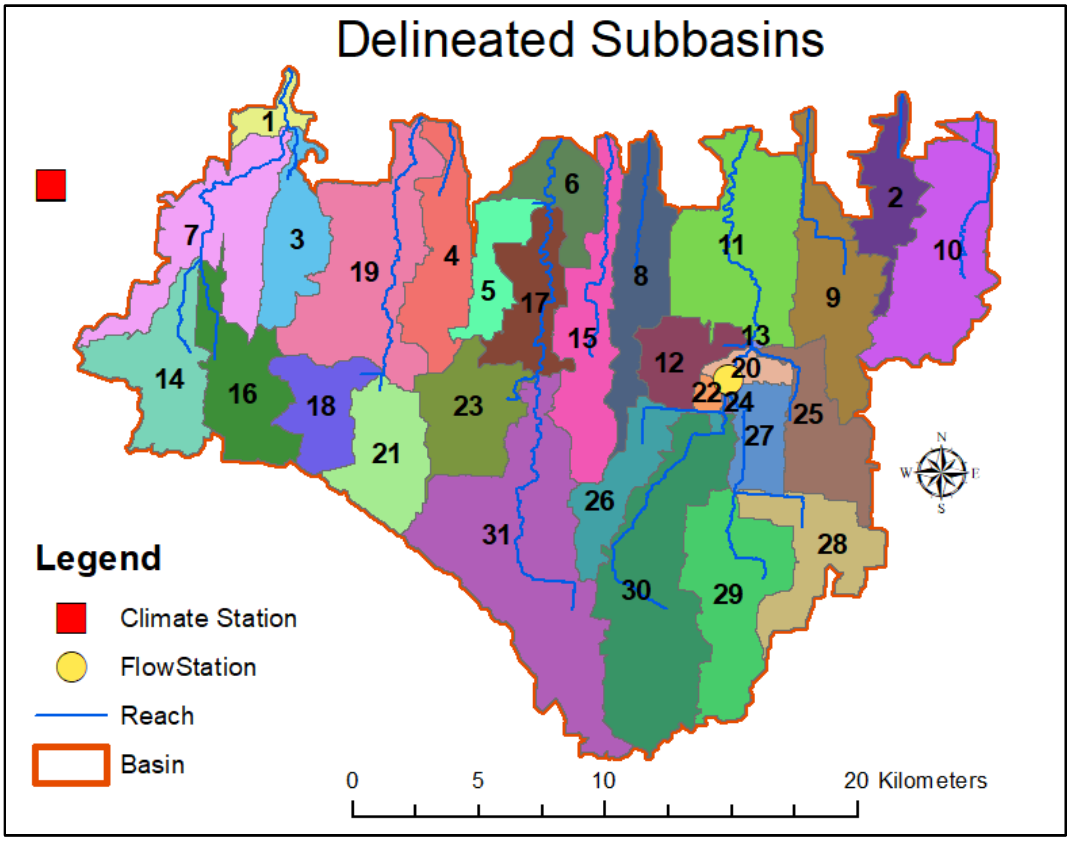
Table 2- 2: *Crop Schedule*

Crop Name	Date of Planting	Date of Harvest and Kill
Soybean	June 1	30 October
Corn	June 1	30 November
Winter wheat	November 10	30 July

Model Setup

Watershed delineation is the first step of the SWAT simulation process. During the delineation of the watershed, the Digital Elevation Model (DEM) data was used for the delineation of a stream network using GIS interface of the Soil and Water Assessment Tool (SWAT 2012) to define watershed boundary and computation of surface slope. The input of user defined threshold drainage area was given to define the size of the subbasins. Stream network is required to route flows and contaminants through subbasins, and the surface slope data is required to determine runoff (Neitsch et al., 2011). An outlet was added at the location of Ruscom river gauge station to compare the simulated flow with the observed flow. The next step is Hydrologic Response Units (HRUs) definition, which was also done in the SWAT2012 interface. HRUs are lumped land areas within the subbasin, which are consisting with unique land cover, soil, and management combinations. The Landuse, soil, and slope data were given as an input for definition of HRU using a 5% threshold for landuse and 20% for soil and slope to reduce the HRU number for avoiding excessive computational demand. The SWAT model requires the same projection of these spatial datasets, which is NAD_1983_UTM_Zone_17N for the study area. SWAT partitions the watershed into number of subbasins based on the user-defined threshold area and this partition is beneficial because the user can reference different areas of the watershed to one another spatially based on the landuse or soil dissimilar enough in properties to impact the hydrology. The SWAT model predicts runoff for each HRU and routed to obtain the total runoff of the watershed. This way SWAT gives much better physical description of the water balance and increases the accuracy. Each subbasin is grouped into the following categories: climate, HRUs, ponds, groundwater, and the reach draining the subbsain. The details of these processes can be found in the SWAT theoretical document (Neitsch, 2009; Winchell et al., 2013). In this study, the Essex region Lake St. Clair watershed was divided into 31 subwatersheds which is depicted is Figure 2- 9.

Figure 2- 9: *Delineated Subbasins at the Lake St. Clair Watershed, Essex County*



The third step is to provide the weather data, which are rainfall, maximum and minimum temperature, relative humidity, wind speed, and solar radiation. Daily measured data of rainfall and minimum and maximum temperature were entered. The weather generator tool was used to generate relative humidity, solar energy, and wind speed. The Curve number method was set for the computation of surface runoff. Potential evapotranspiration was estimated by Penman-Monteith equation, and the variable storage coefficient method was chosen for flow routing. A four-year crop rotation was provided.

The final stage is model simulation once all the processes described above are completed. During the simulated process, five years of warm-up period was selected based on the observation of achieving relatively stable outflow since warm-up can define more real initial soil moisture if the SWAT model is warmed-up (Tang et al., 2012; Dhami et al., 2018).

Model Calibration, Validation, and Sensitivity Analysis

One flow gauging station located on Ruscom River was used for model calibration and transferring the calibrated parameters as a regionalization approach using the SWAT autocalibration tool to the other ungauged catchments located within the study area. The flow data was downloaded for the period of 1998 to 2018 on daily basis which includes 2003 to 2010 as calibration period and the validation period from 2011 to 2018. Approximately 20% of the watershed drains through this gauge station. The regionalization approach of the SWAT model calibration was followed by available literature on the SWAT calibration techniques (https://swat.tamu.edu/publications/calibrationvalidation-publications/). To alleviate the high baseflow condition, significance groundwater parameters including the threshold groundwater depth for return flow (GWQMN), groundwater "revap" coefficient (GW_Revap), deep aquifer percolation fraction (RCHRG_DP), reevaporation threshold (REVAPMN), groundwater delay time (GW_Delay), and baseflow alpha factor-baseflow recession constant (ALPHA_BF) were chosen based on the past SWAT expression with modified studies (Ahl et al., 2008; Gitau & Chaubey, 2010; Cho et al., 2012; Niraula et al., 2013; da Silva et al., 2015; Paul et al., 2017; Dhami et al., 2018; Mengistu et al., 2019). To improve the lag between simulated and observed flow, snowfall temperature (SFTMP), snow melt base temperature

(SMTMP), melt factor for snow on June 21 (SMFMX), melt factor for snow on December 21 (SMFMN), minimum snow water content that corresponds to 100% snow cover (SNOCOVMX), fraction of SNOCONMX that provides 50% cover (SNO50COV), snow pact temperature lag factor (TIMP), average slope length (SLSUBBSN), and the average slope steepness (HRU_SLP) were chosen based on the values accustomed by Ahl et al. (2008), Gitau and Chaubey (2010), Cho et al. (2012), Asadzadeh et al. (2015), Silva et al. (2015); Teshager et al. (2016), Begou et al. (2016), Khalid et al. (2016), and Mengistu et al. (2019). Furthermore, to lessen the low surface flow and high baseflow conditions, other significant parameters including initial SCS runoff curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), plant uptake compensation factor (EPCO), depth to impervious layer in soil profile (DEP_IMP), depth from soil surface to bottom of layer (SOL_Z), soil saturated hydraulic conductivity (SOL_K), available soil water capacity (SOL_AWC), and main channel hydraulic conductivity (CH_K2) were chosen to iterate between surface flow and baseflow until the model's flows fall within the acceptable ranges following past studies (Begou et al., 2016; Khalid et al., 2016; Guo et al., 2018; Mengistu et al., 2019; Ahl et al., 2008; Cho et al., 2012; Green et al., 2007; Koch et al., 2013).

The effectiveness of a hydrologic model after simulation depends on how well the model is calibrated (Gupta, 1999). Sensitivity analysis eliminates the parameters, which are not sensitive, that helps to reduce the number of parameters during calibration. Calibration is performed by changing the most sensitive parameter estimated from sensitivity analysis, which refers to the identification of the most important parameter that influences the model output (Abbaspour et al., 2017). It can be done either manually

(Brouziyne et al., 2017) or by using auto-calibration tools (Tang et al., 2012; Yang et al., 2009; Paul et al., 2017; Parajuli et al., 2009; Fall, 2011; Coffey et al., 2010) by changing one parameter at a time or multiple variables at same time. The auto-calibration tool is supportive to achieve more accurate model simulation (Abbaspour et al., 2015).

In this study, the calibration process was completed by varying the calibration parameters value within their acceptable range following the trial and error manner as depicted in Table 2- 3. The SWAT manual calibration tool was used to obtain a reasonable level of simulation. The SWAT-CUP was subsequently applied for achieving more accurate model simulation. Table 2- 4 describes the details of SWAT default values, initial values followed by manual calibration, and the SWAT-CUP calibrated parameters. The calibrated parameters identified during the regionalization approach of calibration was tested for validation period of 2011 to 2018.

The Sufi-2 Model. In SUFI-2, P-factor of 1.0 and R-factor of 0.0 means that the predicted results corresponds to measured data (Tang et al., 2012; Khalid et al., 2016). The degree to which P-factor and R-factor are away from these values can be used to judge the strength of calibration. The P-factor>0.5 and R-factor <1 was considered good model performance (Tang et al., 2012 ; Khalid et al., 2016; Hallouz et al., 2018). In the present study, the focus was given to the global sensitivity analysis because it produces results that are more reliable. For global sensitivity analysis, 500 -1000 or more number of simulations are required because all parameters are changing to identify their effect on model output or objective function. In addition, parameter sensitivities are determined by calculating the multiple regression systems (t-stat and p-value), which regresses the latin hypercube generated parameters against the objective function values. If the absolute t-stat values are larger and P-values close to zero, the parameter sensitivity becomes significance. In this study, the objective function of sensitivity analysis was set as NSE 0.5. Parameters identified by their ranking through sensitivity analysis were used to calibrate the hydrologic model of SWAT using measured flow. The equations for computing the P-factor and R-factor can be expressed as follows:

$$\text{P-factor} = \frac{\sum_{n=1}^{d} I[Y_n]}{n} \tag{2.2}$$

With $I[Y_n] = \begin{cases} 1, & if\ Y_{n,2.5\%} < Y_n < Y_{n,97.5\%} \\ 0, & else \end{cases}$

$$\text{R-factor} = \frac{\sum_{n=1}^{d} \left(Y_{n,97.5\%} - Y_{n,2.5\%}\right)}{dS} \tag{2.3}$$

where $Y_{n,2.5\%}$ and $Y_{n,97.5\%}$ are the lower and upper limit of 95 PPU, respectively, and S is the standard deviation of observed flow.

Statistical Measures

When values of P-factor and R-factor are accepted, further goodness of fit can be quantified by co-efficient of determination (R^2), Nash-Sutcliffe efficiency (NSE) index, percent bias PBIAS, ratio of the root mean square error to the standard deviation of measured data (RSR), and Kling and Gupta Efficiency (KGE). The NSE and R^2 are widely used and potentially reliable statistics for assessing the goodness of fit of hydrologic models (McCuen, 2006; Green et al., 2007). The R^2 value can range from zero to one where zero means no correlation and one means perfect correlation. The R^2 value shows how the observed versus predicted values tract a best-fit line. The NSE value can range from negative infinity to one where negative infinity means poor performance and one means perfect. Moriasi et al. (2007) recommended if NSE > 0.50 and RSR < 0.70, and if PBIAS ± 25% for streamflow, then the model simulation can be judged as satisfactory. PBIAS value negative means model overestimates the flow and PBIAS value positive means model underestimates the flow. Another measures, KGE is used to understand the model efficiency which measures the Euclidian distance of three components include correlation, bias, and variability from the ideal point; and the values of KGE ranges from –∞ to 1, where 1 means the perfect match (Gupta et al., 2009).

Equation for NSE:

$$\text{Nash Sutcliffe Efficiency} = 1 - \frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o})^2} \tag{2.4}$$

Equation for PBIAS:

$$\text{PBIAS} = \frac{\sum_{i=1}^{n}(o_i - p_i) * (100)}{\sum_{i=1}^{n}(o_i)} \tag{2.5}$$

Equation for RSR:

$$\text{RSR} = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}(o_i - p_i)^2}}{\sqrt{\sum_{i=1}^{n}(o_i - \bar{o})^2}} \tag{2.6}$$

Where,

o_i= Observed value

p_i= Predicted value

$\bar{o}$= Average observed value

n= number of sample size

The equation for KGE:

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (2.7)$$

Where, r is the linear regression coefficient between observed and simulated data

$\alpha = \frac{Coefficient\ of\ variation\ of\ simulated\ data}{Coefficient\ of\ variation\ of\ observed\ data}$, and $\beta = \frac{Mean\ of\ simulated\ data}{Mean\ of\ observed\ data}$

Table 2- 3: *List of Parameters for Model Calibration for the Study Watershed*

Parameter	Min	Max	Scale of Input	Adjustment	Reference
r__CN2.mgt	-0.06	0.06	HRU	Relative	Begou et al. (2016)
v__ALPHA_BF.gw	0.5	0.999	Watershed	Replace	da Silva et al. (2015)
v__GW_DELAY.gw	100	400	Watershed	Replace	Mengistu et al. (2019)
v__GWQMN.gw	2	1020	Watershed	Replace	Niraula et al. (2013)
v__SFTMP.bsn	-1.5	1.1	Watershed	Replace	Teshager et al. (2016)
v__SMTMP.bsn	0.1	0.4	Watershed	Replace	Cho et al. (2012)
v__SMFMN.bsn	1.09	1.2	Watershed	Replace	Cho et al. (2012)
v__SMFMX.bsn	3.1	3.5	Watershed	Replace	Neitsch et al. (2011)
v__TIMP.bsn	0.5	0.9	Watershed	Replace	Cho et al. (2012)
v__SNOCOVMX.bsn	10	20	Watershed	Replace	Ahl et al. (2008)
v__SNO50COV.bsn	0.5	0.501	Watershed	Replace	Ahl et al. (2008)
r__SLSUBBSN.hru	-0.8	0.8	HRU	Relative	Khalid et al. (2016)
r__HRU_SLP.hru	-0.001	0.001	HRU	Relative	da Silva et al. (2015)
v__ESCO.hru	0.7	0.9	HRU	Replace	Mengistu et al. (2019)
v__EPCO.hru	0.001	0.05	HRU	Replace	Khalid et al. (2016)
r__SOL_Z().sol	-0.15	-0.02	HRU	Relative	Khalid et al. (2016)
r__SOL_AWC().sol	-0.02	1.4	HRU	Relative	Khalid et al. (2016)

Parameter	Min	Max	Scale of Input	Adjustment	Reference
r__SOL_K().sol	-0.89	-0.5	HRU	Relative	Khalid et al. (2016)
r__GW_REVAP.gw	-0.051	-0.048	Watershed	Relative	Dhami et al. (2018)
v__REVAPMN.gw	450	550	Watershed	Replace	Cho et al. (2012)
r__RCHRG_DP.gw	-9.1	-8.9	Watershed	Relative	Mengistu et al. (2019)
v__CH_K2.rte	150	160	Reach	Replace	Mengistu et al. (2019)
v__DEP_IMP.hru	3400	3600	HRU	Replace	Guo et al. (2018)

Results and Discussions

Sensitivity Analysis

Sensitivity analysis was performed to find the parameters to which the watershed is sensitive. To perform sensitivity analysis, 23 parameters were selected initially. Eight parameters were found to be more sensitive, which are Alpha_bf, SFTMP, SLSUBBSN, CN2, TIMP, SOL_Z, ESCO, and GWQMN (P-value = 0.0000) to affect the SWAT watershed hydrologic simulation. A snow parameter was identified as highly sensitive, which is SFTMP (snowfall temperature), and also a set of parameters were identified as sensitive parameters as compared to the previous studies in the Essex region (Rahman, 2007). Additionally, if the climate station was close to the flow station, a larger P-factor and smaller R-factor could be achieved. Table 2- 4 shows that 23 hydrologic parameters were identified with their fitted value for the sensitivity analysis and calibration.

Table 2- 4: *SWAT-CUP Sensitivity Analysis*

Parameter	t-Stat	p-value	Rank	Default Value	Initial Value	Fitted Value	Reference
ALPHA_BF	72.7215	0.0000	1	0.048	0.998	0.54	Paul et al. (2017)
SFTMP	-38.465	0.0000	2	1	-1.26	-0.146	Cho et al. (2012)
SLSUBBSN	-19.745	0.0000	3	121.95	46.6	52	Gitau and Chaubey (2010)
CN2	-16.082	0.0000	4	78	82.05	77.89	Green et al. (2007)
TIMP	14.2932	0.0000	5	1	0.81	0.69	Cho et al. (2012)
SOL_Z	-9.3172	0.0000	6	Layer 1: 250 mm Layer 2: 650 mm Layer 3: 1000 mm	Layer 1: 210.5 Layer 2: 547.3 Layer 3: 842	Layer 1: 206 mm Layer 2: 535 mm Layer 3: 824 mm	Koch et al. (2013)
ESCO	-8.3184	0.0000	7	0.95	0.81	0.76	Cho et al. (2012)
GWQMN	4.4169	0.0000	8	1000	1100	690	Cho et al. (2012)
SMFMN	3.8905	0.0001	9	4.5	1.1	1.11	Begou et al. (2016)
SMTMP	-3.2808	0.0011	10	0.5	0.367	0.222	Cho et al. (2012)
SOL_AWC	-2.4494	0.0144	11	Layer 1: 0.2 Layer 2: 0.05 Layer 3: 0.2	Layer 1: 0.36 Layer 2: 0.22 Layer 3: 0.15	Layer 1: 0.14 Layer 2: 0.09 Layer 3: 0.06	Koch et al. (2013)
CH_K2	-2.1413	0.0324	12	0	160	156	Koch et al. (2013)

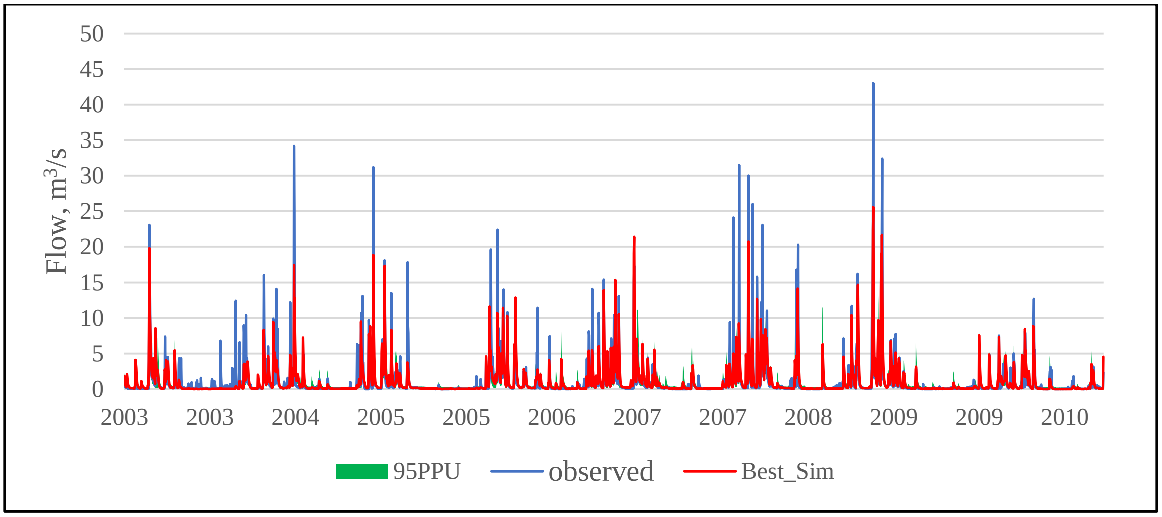
Parameter	t-Stat	p-value	Rank	Default Value	Initial Value	Fitted Value	Reference
DEP_IMP	1.9123	0.056	13	6000	3600	3444	Cho et al. (2012)
SOL_K	-1.8135	0.0699	14	Layer 1: 3.36 Layer 2: 2.05 Layer 3: 1.44	Layer 1: 0.46 Layer 2: 0.11 Layer 3: 0.05	Layer 1: 0.63 Layer 2: 0.15 Layer 3: 0.07	Ahl et al. (2008)
SMFMX	1.7371	0.0825	15	4.5	3.4	3.3	Mengistu et al. (2019)
SNO50COV	1.6694	0.0952	16	0.5	0.501	0.5	Asadzadeh et al. (2015)
GW_DELAY	1.5704	0.1165	17	31	370	219	Gitau and Chaubey (2010)
EPCO	-1.5344	0.1251	18	1	0.01	0.04	Mengistu et al. (2019)
HRU_SLP	0.9547	0.3399	19	0.016	0.005	0.0051	da Silva et al. (2015)
RCHRG_DP	-0.747	0.4552	20	0.05	0.1	0.5	Mengistu et al. (2019)
GW_REVAP	-0.5986	0.5495	21	0.02	0.021	0.02	Ahl et al. (2008)
REVAPMN	-0.3783	0.7053	22	750	750	500	Cho et al. (2012)
SNOCOVMX	-0.0723	0.9423	23	1	12.83	15	Gitau and Chaubey (2010)

Uncertainty Analysis

The P-factor of 0.65 and an R-factor of 0.23 were found in the calibration period using the SWAT-CUP uncertainty analysis on daily time step. The percentage of data being bracketed by 95 PPU (P-factor) was 65% in the calibration period from 2003 to 2010

(Figure 2- 10). Some observed data were not bracketed by the prediction band and occurred during peak flow periods of calibration. The possible reasons could be that the SWAT model was run on a daily basis and peak flow occurred on an hourly basis, and also the climate station is located outside of the study area.

Figure 2- 10: *95PPU Plot Between Observed and Simulated Flow*



Daily Flow Calibration and Validation

The model was calibrated for the period of 2003 to 2010 using the parameter values identified during the sensitivity analysis for the daily flow simulation at the Ruscom River station. Using the same parameter values, the model was simulated for the periods of 2011 to 2018 to validate the model. Figures 2- 11 and 2- 12 show graphical representations of the comparison between simulated flow and observed flow with corresponding precipitation on daily conditions. The results indicate that the SWAT prediction was accurate for daily flow except some random occurrences of underprediction of peaks. The possible reason could be that the peak occurs within certain hours and the SWAT model simulates the peak during daily time step. In addition, the spatial variation of precipitation is absent because the climate station is located outside the watershed. In fact, the scatter plots of observed versus simulated flow (Figure 2- 13) show stronger correlation between observed and simulated flow during the calibration period as compared to the validation period, indicating better performance during calibration periods for streamflow of this watershed. The model predicted flow closely matched with observed flow measured at the Ruscom River station. This accuracy was further confirmed by the statistical revelations of NSE, R^2, PBIAS, RSR, and KGE whereas NSE, R^2, and KGE range from 0.56 to 0.7 (>0.55), RSR range from 0.60 to 0.65 (<0.7), and PBIAS range within ± 25% as shown in Table 2- 5.

Figure 2- 11: *Daily Flow Calibration from 2003 to 2010*

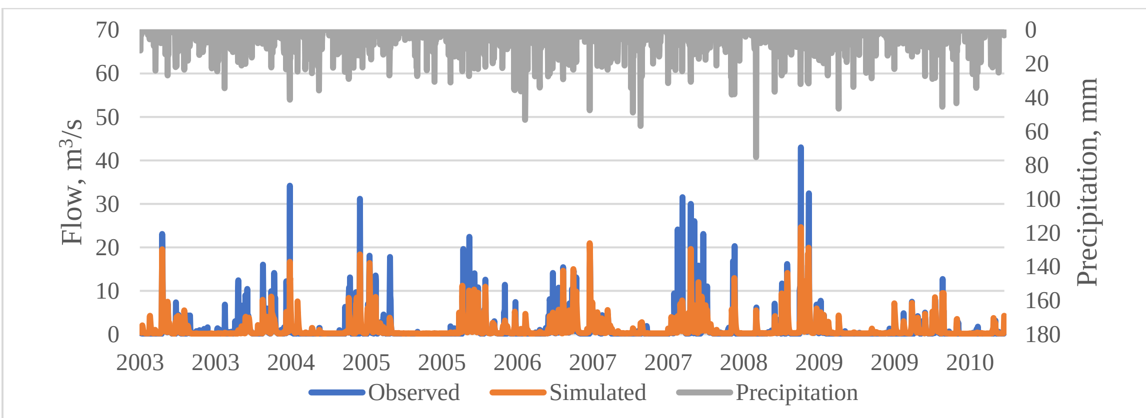


Figure 2- 12: *Daily Flow Validation from 2011 to 2018*

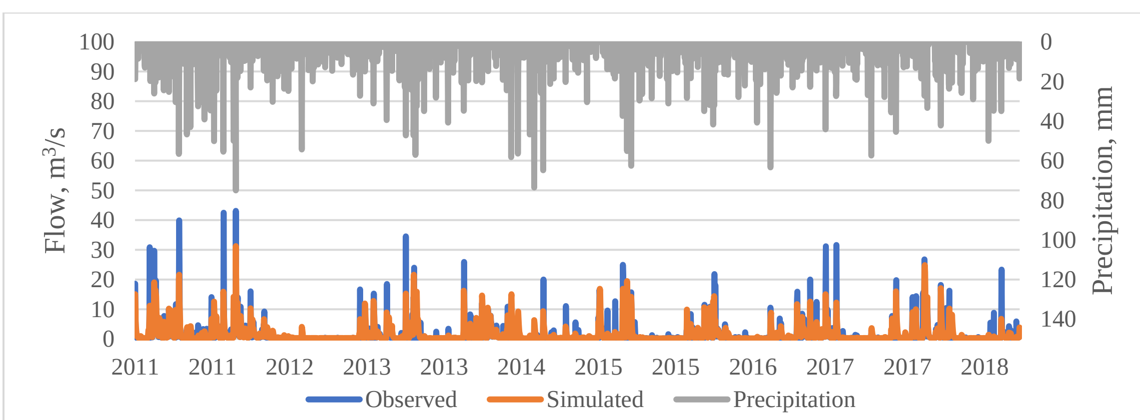
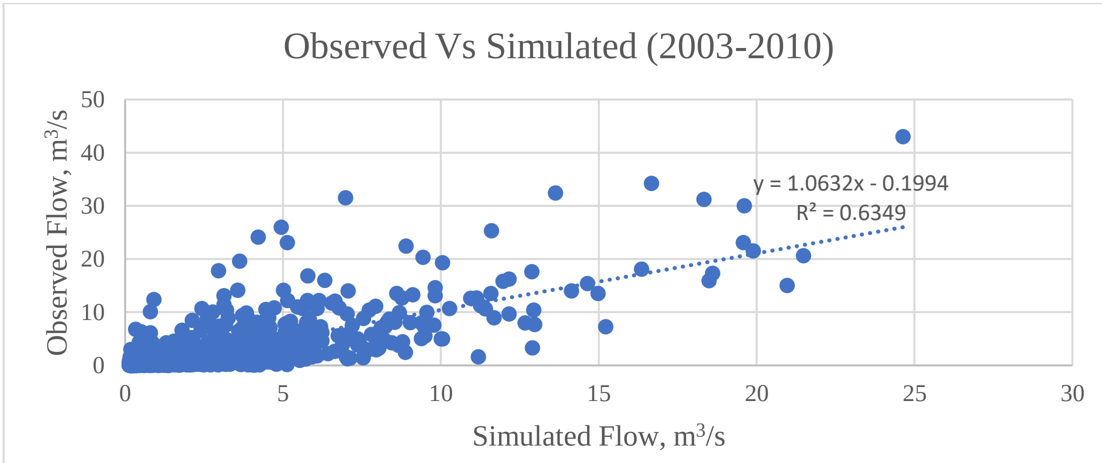


Figure 2- 13: *Scattered Plot of Observed Vs Simulated Flow for Calibrtion and Validation periods*



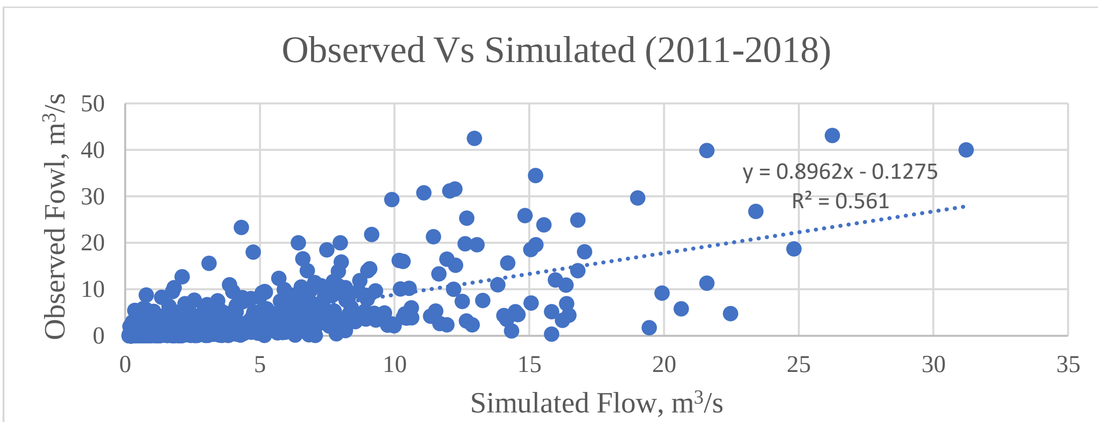


Table 2- 5: *Statistical Measures of SWAT Predicted Flow Vs Observed Flow*

Calibration Period (2003 to 2010)					
	NSE	**R^2**	**PBIAS**	**RSR**	**KGE**
Daily Conditions	0.64	0.64	-4.5	0.6	0.7
Validation Period (2011 to 2018)					
Daily Conditions	0.57	0.58	-22.02	0.65	0.58

Annual, Seasonal, and Monthly Water Budget Analysis

Annual Water Budget Analysis. The SWAT model was re-run for the period of 1998 to 2018 using calibrated parameters, which were identified during the sensitivity analysis. The average annual values of different water balance components are presented in Table 2- 6 based on the SWAT generated average annual watershed values output Table. The result shows that the annual precipitation of the basin was 1,017 mm out of which the snowfall was 9% (94 mm). According to Dhami et al. (2018), if snowfall is more than snowmelt+ sublimation (converted directly from solid form to vapor form), then this snow may get compacted and form ice/glaciers over the years. In this present study, the summation of sublimation and snowmelt was 93 mm, which is less than the snowfall depth. Hence, there is no possibility of ice/glaciers occurring over the years. The annual evapotranspiration (ET) from the watershed was about 59% of the annual precipitation (602 mm out of 1,017 mm). Total water yield is computed from surface runoff, lateral flow, and baseflow or return flow, and it represents the streamflow available at the basin outlet. The annual water yield at the basin outlet was 395 mm out of which surface runoff contributed 284 mm; lateral subsurface flow or tile drainage flow, which originates below the surface but above the saturated zone, contributed 37 mm (approximately 9% of total water yield), and left over flow was the contribution of base flow originated from groundwater (shallow aquifer). In fact, about 9% of annual precipitation was retained as shallow and deep aquifer. Water entering in deep aquifer is assumed to contribute somewhere outside of the watershed and considered to be lost from the system. As a result, deep aquifer is not considered in future water budget calculations. The amount of water moved from the shallow aquifer into the overlying unsaturated zone during dry periods is referred to as Revap.

Table 2- 6: *Average Annual Basin Values for Lake St. Clair Region Watershed*

Water Balance Components	Volume (mm)
Precipitation	1,017
Snow fall	94
Snow melt	86
Sublimation	7
Total Water Yield	395
Actual Evapotranspiration	602
Potential Evapotranspiration	885
Surface Runoff, Surf Q	284
Lateral Soil, Lat Q	0.1
Tile Drainage, Tile Q	37
Ground Water (Shallow AQ)	27
Revap (Shal AQ=> Soil/ Plants)	19
Deep AQ recharge	46
Total AQ recharge	92
Percolation Out of Soil	94

The annual water budget for the selected years during calibration and validation periods is presented in Figure 2- 14. In Figure 2- 14, the annual water budget for the evapotranspiration, total water yields, surface runoff, ground water, and tile drainage is shown in terms of percentage of annual precipitation, which varied from 42%-69%, 28% to 53%, 19% to 42%, 2%-3%, and 3%-6%, respectively. According to the conceptual water budget report, the percentage of actual evapotranspiration and baseflow ranges from 65-85% and 6-16% of the precipitation (ERCA, 2008), and SWAT simulated evapotranspiration and base flow were within this range. As a result, these annual water budget analyses represent that SWAT can predict water budget components accurately.

Figure 2- 14: *Annual Water Budget for the Years of 2003, 2004, 2010, 2011, 2016 & 2017*

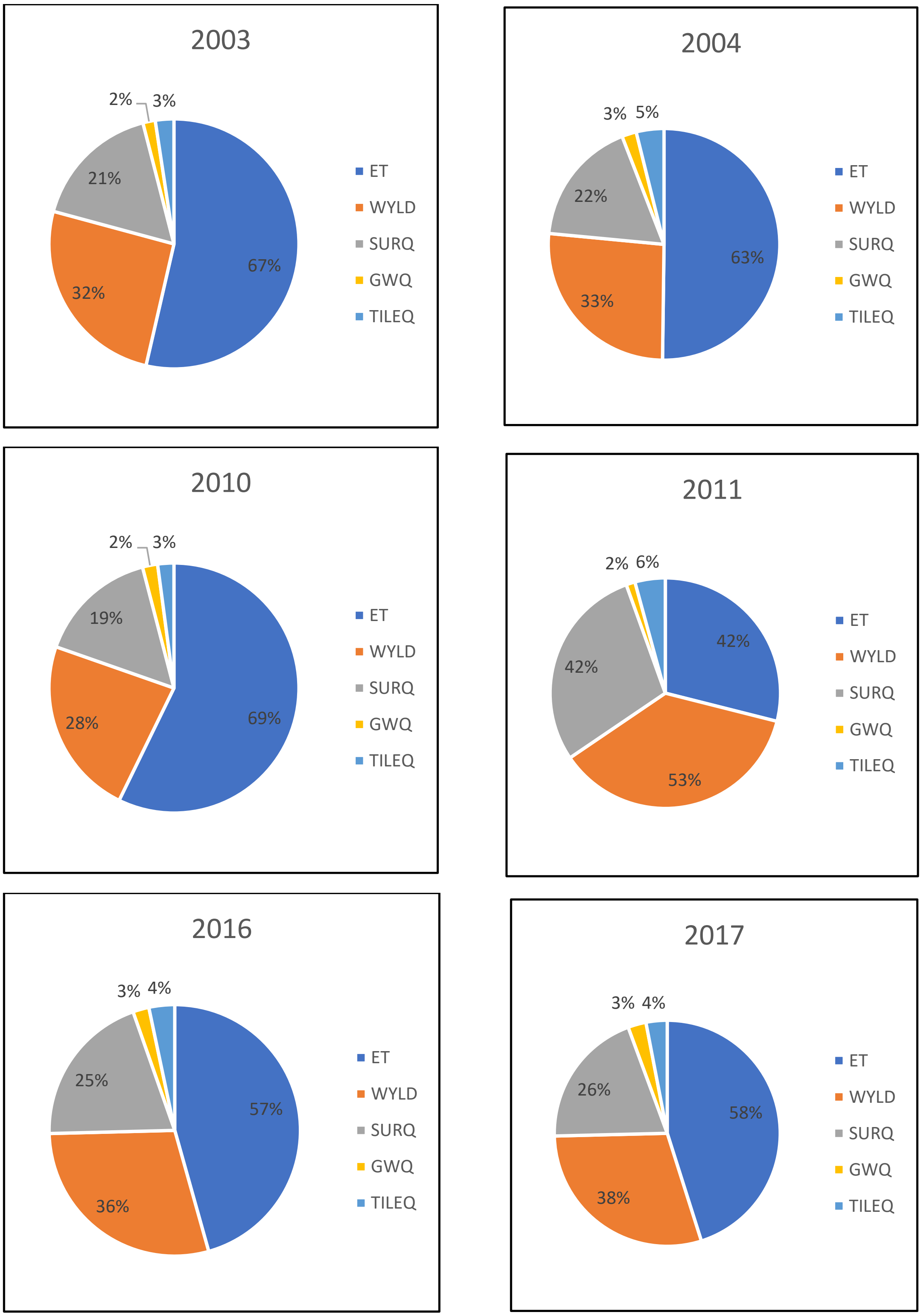


Figure 2- 15 and Table 2- 7 represent the annaul water budget from 2003 to 2018. According to Table 2- 7, the average annual precipitation varied from 782 mm to 1,568 mm. The number of annual water budget components varies with the variations of precipitations. In 2011, the amount of rainfall was the highest as compared to other years. The amount of water yield, tile drainage, and surface runoff were highest for 2011 as compared to other years. Overall, surface runoff contributes highest in the water yield (71%) as compared to tile drainge (9%) and baseflow (18%). The clay soil and low permeability could be the reason for high surface flow and low subsurface and ground flow.

Figure 2- 15: *Annual Water Budget Analysis from 2003 to 2018*

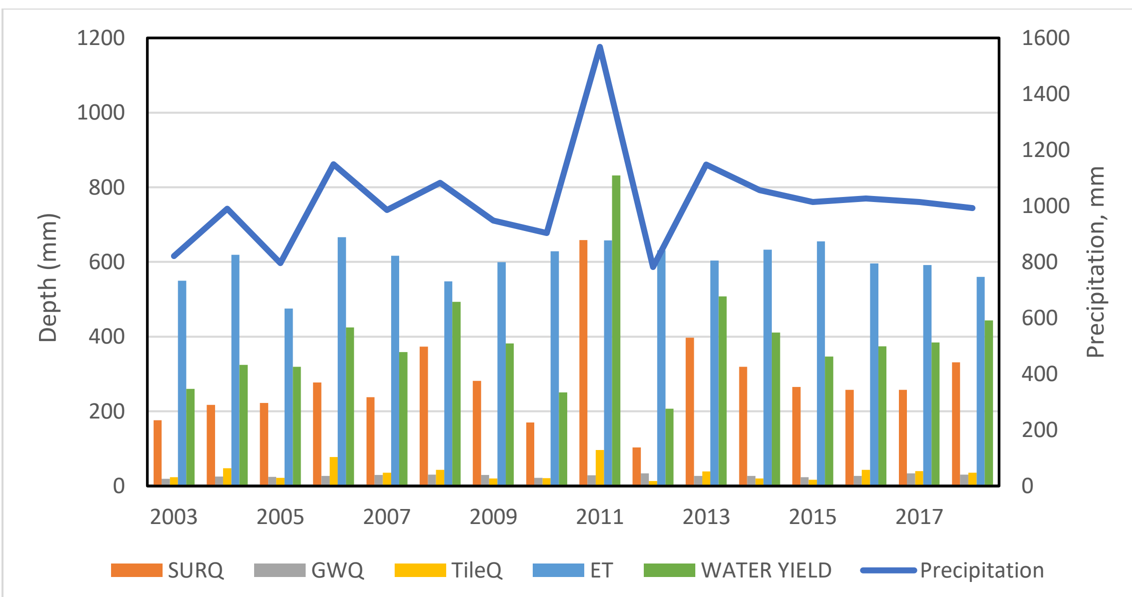


Table 2- 7: *Annual Water Budget Components from 2003 to 2018*

Year	Precipitation, P [mm]	Evapotranspiration [mm (% P)]	Water Yield, Q [mm (% P)]	Water Yield Components		
				Surface Runoff, mm (% Q)	Tile Drainage Flow, mm (% Q)	Base flow, mm (% Q)
2003	821	549 (66)	259 (31)	176 (67)	23 (9)	60 (23)
2004	990	619 (62)	324 (32)	217 (66)	47 (14)	59 (18)
2005	796	475 (59)	319 (40)	222 (69)	22 (6)	74 (23)
2006	1,149	666 (57)	424 (36)	277 (65)	77 (18)	69 (16)
2007	986	616 (62)	358 (36)	238 (66)	35 (9)	85 (23)
2008	1083	548 (50)	493 (45)	373 (75)	42 (8)	77 (15)
2009	948	599 (63)	382 (40)	281 (73)	19 (5)	80 (21)
2010	904	628 (69)	250 (27)	170 (67)	20 (8)	59 (23)
2011	1,568	657 (41)	831 (53)	658 (79)	96 (11)	76 (9)
2012	782	631 (80)	207 (26)	102 (49)	13 (6)	90 (43)
2013	1,148	604 (52)	508 (44)	397 (78)	39 (7)	71 (14)
2014	1,057	632 (59)	410 (38)	319 (77)	19 (4)	71 (17)
2015	1,015	655 (64)	346 (34)	265 (76)	17 (4)	64 (18)
2016	1,026	595 (58)	373 (36)	257 (68)	43 (11)	72 (19)
2017	1,014	591 (58)	384 (37)	257 (67)	39 (10)	87 (22)
2018	992	559 (56)	443 (44)	331 (74)	35 (8)	76 (17)
Average	**1,017**	**602 (59)**	**394 (38)**	**284 (71)**	**37 (9)**	**73 (18)**

Seasonal Water Budget Analysis. Seasonal water budget analysis was performed based on four seasons: winter (December, January, February, and March), spring (April and May), summer (June, July, August, and September), and fall (October and November). Table 2- 8 represents water budget components for the selected years and shows both winter and fall seasons' evapotranspiration was about 10% of annual ET, which is the lowest compared to other seasons. Summer season's ET was observed highest, which was around 54% to 61% whereas spring season's evapotranspiration was about 20%. The low temperature in winter and high temperature in summer influence the amount of evapotranspiration.

Table 2- 9 represents average values of seasonal water budget for the period of 2003 to 2018. The seasonal water budget analysis for each year is provided in Appendix A. Surface runoff, tile drainage, and base flow contribution were observed highest during winter season, and the possible reason could be the snow melting period and low evapotranspiration. During summer, the tile drainage was very low due to high evapotranspiration, and baseflow was comparatively higher than spring and fall seasons due to high precipitation. During summer, only 20% of the precipitation was contributed to the water yield.

Figure 2- 16 shows the annual average of the seasonal water budget components for the period of 2003 to 2018. This figure shows that summer has the highest precipitation and evapotranspiration, and the water yield was lower. Fall season has the lowest precipitation and water yield. Winter season’s water yield was observed highest as well. Spring season’s surface runoff was higher than that of summer and fall seasons.

Table 2- 8: *Seasonal Water Budget Components (2003 to 2018)*

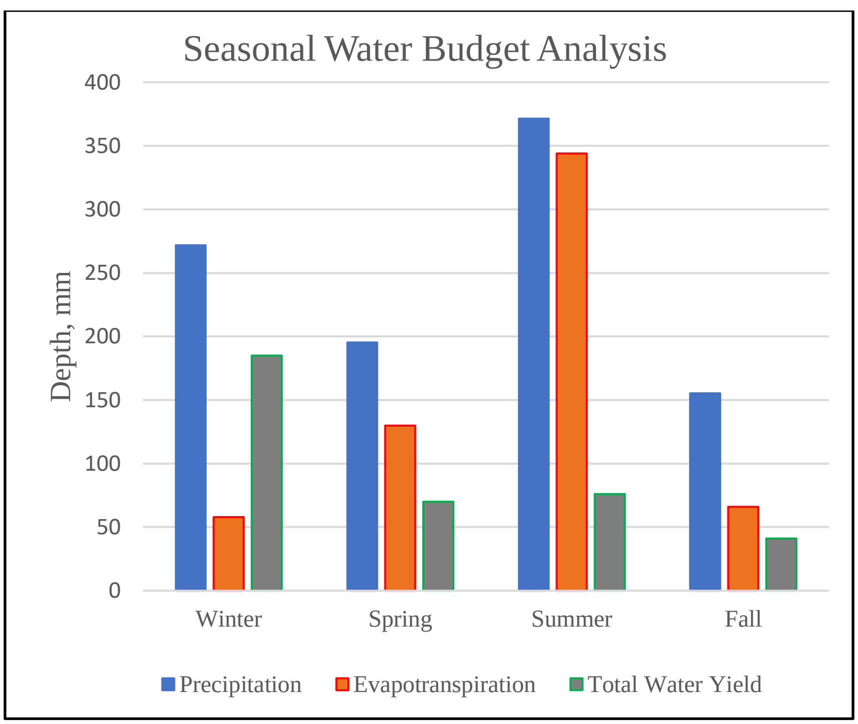
Year	Season	Precipitation [mm (%)]	Evapotranspiration [mm (%)]	Water Yield [mm (%)]
2003	Winter	220 (26)	54 (9)	145 (55)
	Spring	209 (25)	122 (22)	64 (24)
	Summer	247 (30)	299 (54)	30 (11)
	Fall	143 (17)	72 (13)	19 (7)
	Annual	**820**	**549**	**259**
2004	Winter	282 (31)	57 (11)	165 (55)
	Spring	214 (23)	119 (23)	87 (29)
	Summer	244 (27)	266 (53)	24 (8)
	Fall	156 (17)	58 (11)	17 (5)

Year	Season	Precipitation [mm (%)]	Evapotranspiration [mm (%)]	Water Yield [mm (%)]
	Annual	**898**	**502**	**295**
2010	Winter	164 (18)	70 (11)	88 (35)
	Spring	218 (24)	146 (23)	74 (29)
	Summer	369 (40)	341 (54)	58 (23)
	Fall	150 (16)	69 (11)	29 (11)
	Annual	**903**	**628**	**250**
2011	Winter	364 (23)	51 (7)	332 (40)
	Spring	334 (21)	127 (19)	174 (21)
	Summer	575 (36)	401 (61)	154 (18)
	Fall	293 (18)	77 (11)	169 (20)
	Annual	**1568**	**657**	**831**
2016	Winter	348 (33)	68 (11)	216 (57)
	Spring	132 (12)	123 (20)	51 (13)
	Summer	403 (39)	326 (54)	46 (12)
	Fall	141 (13)	76 (12)	59 (15)
	Annual	**1026**	**595**	**373**
2017	Winter	294 (29)	57 (9)	172 (44)
	Spring	193 (19)	145 (24)	83 (21)
	Summer	298 (29)	327 (55)	44 (11)
	Fall	227 (22)	60 (10)	84 (21)
	Annual	**1013**	**591**	**384**

Table 2- 9: *Annual Average of Seasonal Water Budget Major Components (2003 to 2018)*

Season ---------	**Precipitation [mm]**	**Evapotranspiration [mm (%P)]**	**Total Water Yield, mm (%P)**	**Water Yield Component**		
				Surface Runoff, mm (%Q)	**Tile Drainage Flow, mm (%Q)**	**Baseflow, mm (%Q)**
Winter						
Average	272	58 (21)	185 (68)	139 (74)	19 (10)	26 (14)
Spring						
Average	195	130 (66)	70 (36)	49 (69)	9 (12)	12 (17)
Summer						
Average	371	344 (92)	76 (20)	51 (66)	2 (3)	22 (29)
Fall						
Average	155	66 (42)	41 (26)	27 (64)	3 (8)	11 (26)

Figure 2- 16: *Seasonal Water Budget*



Monthly Water Budget Analysis. Table 2- 10 represents the monthly average water budget components for the period of 2003 to 2018. The highest precipitation was observed in the month of May and lowest in January. Evapotranspiration was higher in the months of July and August. The lowest surface runoff was observed in the month of August due to the dry season. The months of February and March are considered as snow melting period, and the water yield was higher for these months. The tile drainage flow was observed highest in the month of March and lowest in the month of August. This monthly water budget analysis also asserts that the model prediction was reasonable.

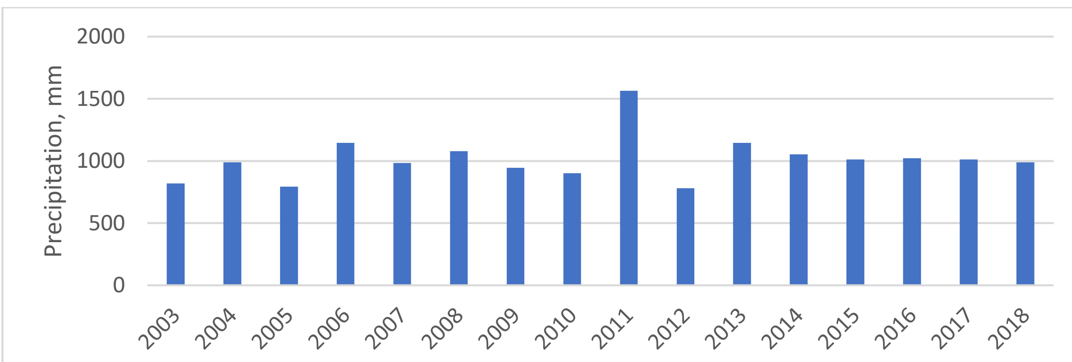
Table 2- 10: *Monthly Water Budget Major Components (2003 to 2018)*

Month	Precipitation (mm)	Potential Evapo-transpiration (mm)	Evapotranspiration (mm)	Percolation (mm)	Surface Runoff (mm)	Tile Drainage Flow (mm)	Groundwater Flow (mm)	Total Water Yield (mm)
Jan	68	11	6	12	29	6	3	44
Feb	69	13	8	9	46	2	3	53
Mar	79	46	35	16	53	8	3	68
Apr	83	73	56	13	19	5	2	31
May	112	96	75	11	30	4	2	39
Jun	91	128	86	7	17	1	2	25
Jul	107	150	107	4	16	1	1	23
Aug	81	140	88	1	7	0	1	12
Sep	92	103	63	2	11	1	2	17
Oct	75	67	42	3	8	1	2	15
Nov	80	39	25	6	19	3	3	26
Dec	80	17	12	10	30	5	3	42
Annual	**85**	**74**	**50**	**8**	**24**	**3**	**2**	**33**

Subwatershed Based Water Budget Analysis

In the watershed area, each subwatershed's contribution to the precipitation, evapotranspiration, groundwater, surface runoff, and total water yield during the simulation period were examined using the calibrated model. No considerable variation of precipitation distribution was observed spatially; one reason could be that only the one climate station located outside the study area was considered. The precipitation range varies from 780 mm to 1,564 mm from 2003 to 2018 for every 31 subwatersheds as presented in Figure 2- 17. The highest rainfall of 1,564 mm was recorded in the year of 2011.

Figure 2- 17: *Annual Precipitation from 2003 to 2018*



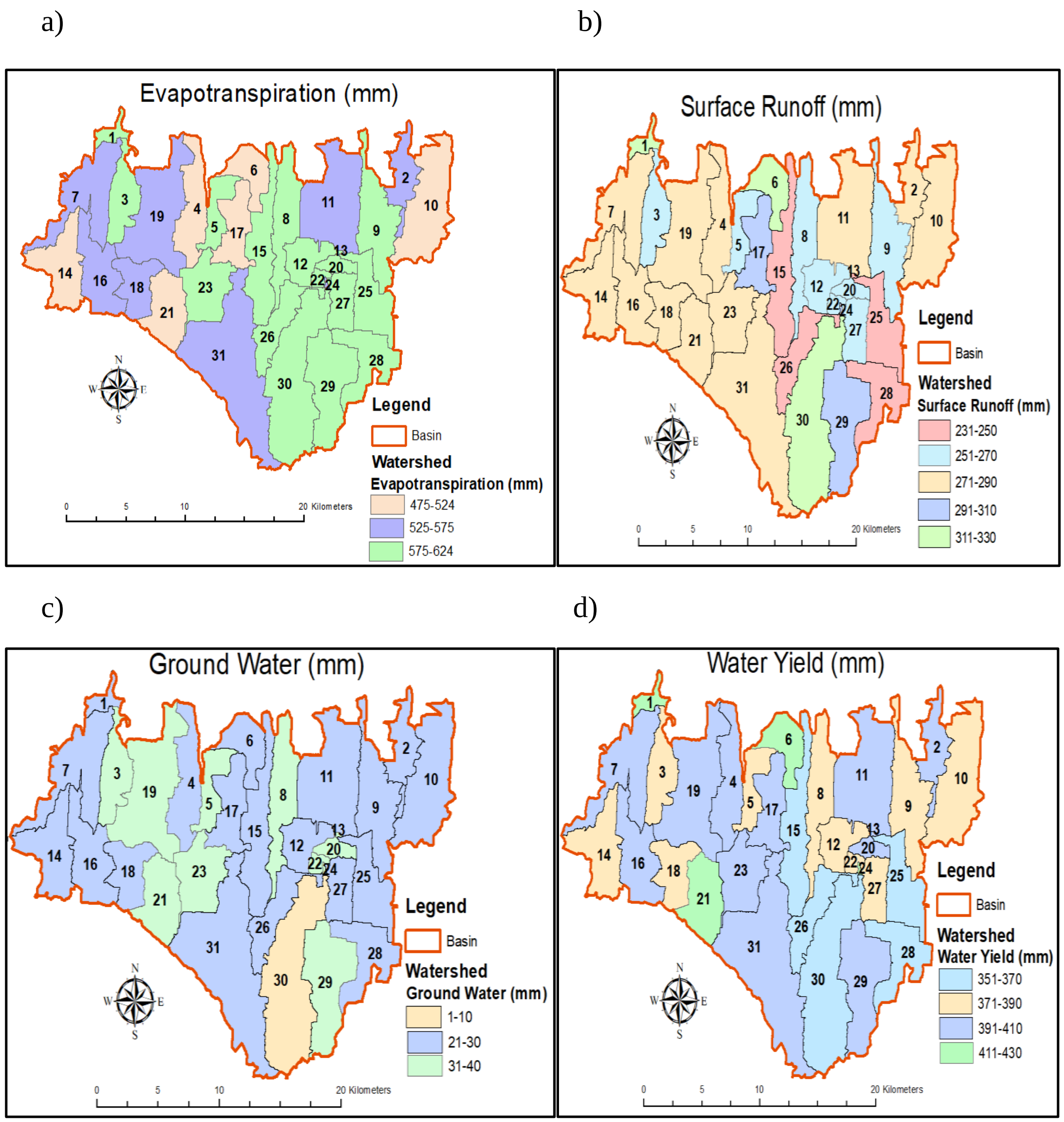
Evapotranspiration. The evapotranspiration (ET) distribution in different subbasins of Lake St. Clair subwatershed is shown in Figure 2- 18a. About 45% of the area of the watershed (subbasins 1, 3, 5, 8, 9, 12, 15, 20, 22, 23, 24, 25, 26, 27, 28, 29, and 30) experiences a large amount of water loss in the range of 575 to 624 mm (56 to 61% of precipitation), and is located in the downstream of Pike Creek, a small portion of Belle River, Moison Creek, Duck Creek, and in the major portion of the Ruscom River watersheds. Approximately 20% of the area (subbasins 4, 6, 10, 14, 17, and 21) loses water through the ET process in the range of 475 to 524 mm (47 to 51% of precipitation) and is located in the upstream of Pike Creek and Puce River, downstream of Belle River, and Little Creek watersheds. The 35% remaining watersheds' (subbasins 2, 7, 11, 13, 16, 18, 19, and 31) water loss through the ET process ranged from 525 to 575 mm (52-56% of precipitation). Vegetation diversity and associated high temperature could be the reason of high volume of water loss from these areas.

Surface Runoff. Figure 2- 18b represents that 10% of the area of the watershed (subbasins 1, 6, and 30) located in the downstream of Pike Creek, Belle River, and some upstream portion of Ruscom River contribute high surface runoff, which is about 28% to 32% of precipitation. Only 12% of the area of the watershed (subbasins 15, 25, 26, and 28) located within the upstream of Ruscom River, and Duck Creek watersheds contributes low surface runoff, which is about 22-24% of precipitation. The remaining area of the watershed adds surface runoff about 25-27% of precipitation. Since the precipitation distribution was similar for the subbasins, the topography, land use and soil type play a significant role in the surface runoff distribution within the watershed.

Ground Water. The highest ground water contribution was observed in subbasin 29, (10% area of the watershed) located in the upstream of Ruscom River where the sandy soil is present. About 25% of the area of the watershed contributes ground water in the range of 31-40 mm, which contributes about 4% of the precipitation. The remaining 68% of the area of the watershed contributes groundwater in the range of 21-30 mm (Figure 2-18c). Since this watershed is predominantly clay soil and extensively tile drained except the southern portion of the watershed, it is apparent that low soil permeability causes low groundwater contribution.

Water Yield. The water yield distribution is presented in Figure 2- 18d, which varied from 364 mm to 426 mm. It can be seen that the western portion of the watershed has higher yield than the eastern part of the watershed. Maximum water yield occurred at the outlet of Pike Creek, Belle River, and upstream of Puce River (subbasins 1, 6, and 21), which is about 40- 42% of precipitation. About 7% of the watershed area located in the Duck Creek watershed and a major portion of Ruscom River watershed have the lowest water yield (subbasin 15, 25, 26, 28 and 30), which contributes 35-36% of precipitation.

Figure 2- 18: *Annual Water Budget Components Distribution (mm) in the Lake St. Clair Subwatershed, (a) Evapotranspiration, (b) Surface Runoff, (c) Ground Water, (d) Water Yield*



Changes from Previous Study

The Tier 1 water budget report was prepared based on the climate data period from 1950 to 2005 (ERCA, 2015), and the water budget components identified for the gauged stations watersheds were representative of the ungauged four local subwatersheds including Pike Creek, Puce River, Belle River, and Little Creek. The present simulation period was based on more recent climate data period from 1998 to 2018. As compared to the Tier 1 water budget report, the present study identified increments of water budget components for the local subwatersheds of Pike Creek, Puce River, Belle River, Ruscom River, and Little Creek.

Table 2- 11 shows that the present modelling work identified an increment of water budget components for these subwatersheds, which vary from 5% to 14% for annual average ET, and 16% to 33% for annual average surface runoff as described in Table 2-11. In addition, the annual average evapotranspiration and surface runoff over the period of 2003 to 2018 increased to 11% and 23%, respectively as depicted in Table 2- 11. The possible reasons could be the increased amount of average annual precipitation (1,017 mm) for the present study as compared to the previous study (887 mm), and no modelling work being performed for these local subwatersheds in the Tier 1 Water Budget Report except the Ruscom River subwatershed.

Table 2- 11: *Comparison with Previous Water Budget Report*

SubWatershed	ET			Surface Runoff		
	Tier 1 Report	Present Study	%Change	Tier 1 Report	Present Study	%Change
Pike Creek	547	573	+5	243	331	+36
Puce River	547	589	+8	243	284	+16
Belle River	531	566	+7	253	323	+28
Duck Creek	--	628	--	--	256	--
Moison Creek	--	611	--	--	260	--
Ruscom River	531	605	+14	213	263	+23
Stoney Point	--	591	--	--	283	
Little Creek	531	601	+14	213	284	+33
Average	**537**	**596**	**+11**	**233**	**286**	**+23**

Conclusions

This study focuses on the prediction of water budget analysis in the Essex region's Lake St. Clair watershed using the SWAT model interfaced with ArcGIS software. The SWAT simulated model outputs were compared with the measured data at the Ruscom River gauge station for both calibration (2003-2010) and validation (2011-2018) periods. The statistical measures of NSE, R^2, KGE (0.57 to 0.70), RSR (<0.7), and PBIAS value (within ±25%) for daily time step indicate that the model accurately simulated daily streamflow. The calibrated parameters were transferred to neighbouring catchments to study water budget for each individual subwatershed. The subwatershed based water budget analysis results show that the percentage of evapotranspiration and surface runoff increased by 11% and 23%, respectively in comparison with the previous water budget analysis study within the Essex region. Overall, modelling results indicate that a major portion of the watersheds of Pike Creek, Puce River and Belle River, located on the western portion of the watershed, had relatively lower evapotranspiration and higher water yield as compared to the eastern portion of the watersheds of Duck Creek, Moison Creek, Ruscom River, and Stoney Point drainage area. The ground water contribution is low for the watershed, which ranges from 6 mm to 40 mm, and the probable reason could be that the watershed has predominantly clay soil. The upstream of the Ruscom River watershed had the highest groundwater flow (32% of precipitation) where the sandy soil is present compared to the other watersheds. A major portion of the watershed had surface runoff of about 28% of precipitation. The results from the water budget analysis indicate that the SWAT model is an effective tool to support water resource managers in the Essex region’s sustainable development. Future studies should incorporate more climate stations to capture localized rainfall, gauge stations at local streams, and updated land management information for improved prediction results.

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Chapter 3:

Model the Microbial Loadings in the Essex Region's Lake St. Clair Watershed and Delineate the Critical Source Areas

Introduction

Fecal pathogen contamination of surface waters is considered as one of the major water-quality impairments which can result in illness and death (Parajuli, 2007). In the summer of 2016, there were many doctor visits because of gastroenteritis, ear, eye, nose and throat infections, as well as skin infections due to high fecal content after swimming at the Cap Brûlé Beach (Fahmy, 2017). Also, the outbreak in Walkerton, 2002 caused gastroenteritis infection of 2,300 people and several deaths, and another outbreak in Milwaukee, 1993 caused similar illness of 400,000 people due to the fecal contamination in drinking water (Dorner et al., 2006; Fall, 2011). Researchers found mechanistic linkage between watershed hydrology and waterborne diseases. The presence of fecally-derived microorganisms (FMs), including both pathogens (bacteria, fungi, viruses, protozoa, and helminths) and microbes, in an aquatic environment indicates the fate and transport of bacteria from the watershed (Dorner et al., 2006). Fecal coliform bacteria that are not pathogenic e.g., *Escherichia coli (E. coli)* and enterococci often are used as indicators of the potential presence of fecal pathogens due to the well correlation that exists between the presence of pathogens and the presence of fecal contamination (Cho et al., 2016; Tallon et al., 2005).

In 1978, the Environmental Health Directorate, Canada-Health Branch agreed that *E. coli* is the most suitable indicator. One of the key factors that led to use *E. coli* as a preferred indicator for the fecal contamination detection was the development of improved testing methods for *E. coli* (Tallon et al., 2005). Windsor-Essex County Health Unit (WECHU) currently sample *E. coli* test results to make decisions for recreational activities. Hence, bacterial contamination as measured by the presence of *E. coli* is employed as the determinant of pollution levels.

People will not be infected in the bacterial polluted water unless the bacterial concentration exceeds the water quality criteria. The provincial water quality objective (PWQO) for *E. coli* in Ontario is 100 cfu/100 ml (Hayman, 2009) and the Canadian recreational water quality guideline is 200 cfu/100 ml. The United States Environmental Protection Agency (US EPA) believes that the recreation water quality guidelines are protective of public health, regardless of the source of fecal contamination (United States Environmental Protection Agency [US EPA], 2012). Two Canadian public beaches located along the Lake St. Clair shoreline within the Essex region, Sandpoint Beach and West Belle River Beach, often exceeded the recreational water quality guideline during the summer season.

Figure 3- 1: *WECHU Beach Sampling Results 2018 (Source: M. Bamotra, Personal Communication, April 5, 2019)*

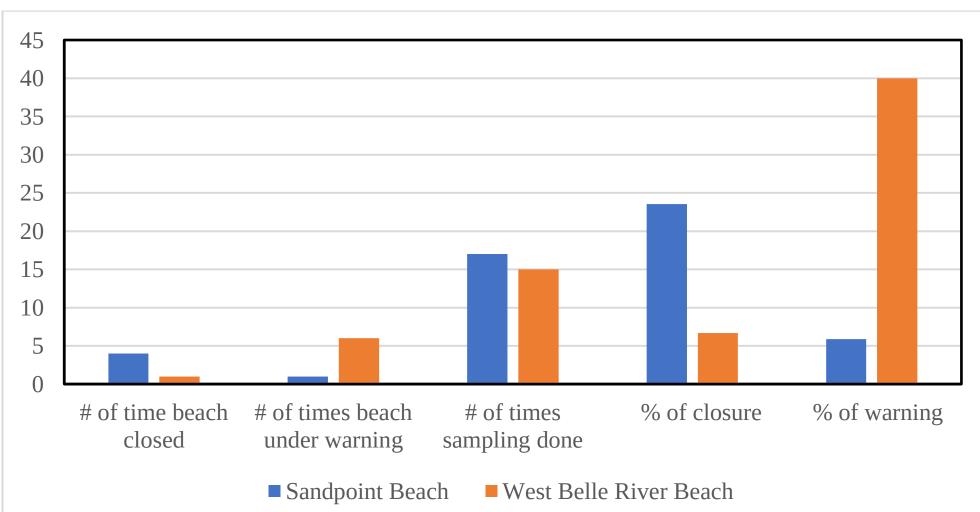


Figure 3- 1 shows that in 2018, over the number of times sampling was done, the percentage of warning signs for West Belle River Beach and Sandpoint Beach were 40% and 6%, respectively, and the percentage of closures were 7% and 24%, respectively. This graph represents high bacterial counts during the summer season. According to the Lake St. Clair Canadian watershed report (Lake St. Clair Canadian Watershed Coordination Council [LSCCWCC], 2008), both the West Belle River and Sandpoint beaches have had incidents involving high bacterial counts due to non-point source pollution and urban development resulting in beach postings and beach closings (Essex Region Conservation Authority [ERCA], 2015a). In addition to this, both of these beaches had occasion of exceedance of *E. coli* counts of over 1000 per 100 ml during non-storm events, and over 5000 per 100 ml in the tributaries discharging into Lake St. Clair. These levels of *E. coli* counts are likely to have contributed to the postings of these beaches (LSCCWCC, 2008). In fact, failing septic systems, which are considered as rural non-point sources, are considered as key contributors of bacteria to the tributaries. The Essex Region Conservation Authority has surface water quality monitoring sites along some tributaries discharging into Lake St. Clair including Pike Creek, Puce River, Belle River, Duck Creek, and Little Creek to support rural non-point source program, and the *E. coli* levels routinely exceeded the PWQO at all sites over the period of 2000 to 2007. However, no previous study demonstrated the quantification of *E. coli* at spatial and temporal scale in the Lake St. Clair region watershed.

Surface water quality is one of the criteria to define the health of the watershed (Tallon et al., 2005; ERCA, 2015a) which can be degraded by both point and non-point source pollution. Identifying the non-point source pollution is more complex compared to the point source pollution because of the difficulty of identification of various sources and management control (Green et al., 2007). Since the primary source of bacteriological inputs to the environment is represented by non-point sources, more attention has been given to non-point source pollutants. The impact of individual subwatersheds on the nearshore beaches becomes complex due to the other factors include lake dynamics, wind and wave action, large monitoring data. The identification and quantification of different sources as well as the mechanism of transport of *E. coli* from the individual subwatersheds is required to eliminate bacterial contamination in nearshore beaches ensuring public health. It is important to identify the sources of pollutants to implement best management practices (Tallon et al., 2005), and it is already proved that controlling the pollution loads can improve the health of the watersheds (Kim et al., 2012).

Background of the Study

The background of the study was conducted by assembling information on bacteria survival, transport mechanism, and modelling approach from the established literature following the different sources of microbial pollution.

Sources of Microbial Pollution

The degradation of surface water quality triggered by microbial pollution, especially point and non-point source pollution indicates the health of the Essex Region's watershed is degraded (ERCA, 2015b). Point source discharges are distinct and identifiable. Combined sewers and sanitary wastewaters, as well as stormwater are identified as point sources. Discharges from these sources are typically treated before being released to a watercourse through a sewer for sanitary sewage or ditch for stormwater. Non-point source microbial pollutants include the defecation of animals in streams, manure storage facilities, land application of manure, and grazed pastures (Mocan, 2006; Cho et al., 2016; Dorner et al., 2006). Runoff due to increased agricultural activities and urbanization have impaired the quality of the basin, which leads to recreational activities and swimming being banned a number of times each year. In fact, the current technologies for large scale treatment processes of animal manures before the application to agricultural lands are not adequate (Sadeghi & Arnold, 2013). The major non-point sources of microbial pollution in the Lake St. Clair watershed include faulty septic systems, runoff from agricultural activities; and direct fecal deposit by livestock and wildlife into streams (Bradshaw et al., 2016). Furthermore, livestock manure has great influence in the transport of pathogen organisms and *E. coli* in the runoff (Sadeghi, 2002; Sadeghi & Arnold, 2013; Green et al., 2007). Miller and Beasley (2008) applied livestock manures in clay soil to analyze *E. coli* concentrations, and the values were particularly higher for beef, chicken and hog manures. Nevers et al. (2018) applied human, gull, and canine fecal sources with gulls being the dominant source. Englande et al. (2002) applied the sources of microbial contamination including septic tanks, dairy and cattle farms and wildlife, and found direct bacteria inputs into streams appeared to have a major impact on the model results. With respect to livestock grazing, both Fall (2011) and Mocan (2006) considered typical value of one cattle per hectare as the grazing density. Mocan (2006) specified cattle grazing period in the absence of snow starting from April 15 for a period of 210 days whereas Fall (2011) specified that the cattle grazing its about 150 days in Eastern Ontario starting from the end of May to the end of October. The same is nearly applicable to the present subwatersheds.

According to the Town of Lakeshore Water and Wastewater Master Plan 2018, malfunctioning septic systems were a source of pollution in local watercourses throughout Lighthouse Cove, Rochester Place, Belle River Road Corridor, and Essex Fringe which were serviced through septic systems. Additionally, approximately 100 homes have operational overflow pipe which are no longer acceptable, and 50 percent of the lot area designed for septic tanks were considered undersized as compared to the modern standards (Stantec, 2018). *E. coli* concentration varies in the animal manures depending on age group, diet, animal species, the method of storage, and storage period. As an example, *E. coli* concentration in different sources are presented in Table 3- 1.

Table 3- 1: *E. coli Concentration in Different Non-Point Sources*

Variables	***E. coli* Concentration**	**Unit**	**References**
Beef Manure	4.0×10^{3} - 1.3×10^{7}	cfu/g (dry weight)	Rhoades et al. (2009) Kessel et al. (2007)
Cattle	3.35×0^{2} - 1.74×10^{7}	cfu/g (dry weight)	Padia et al. (2012) Sanderson et al. (2005)
	1×10^{5} - 1.9×10^{5}	cfu/ml (wet weight)	Blaustein (2014)
Geese	1×10^{2} - 1.8×10^{8}	cfu/g (dry weight)	Meerburg et al. (2011), Alderisio and Deluca (1999)
Septic	3.6×10^{3} - 1.2×10^{6}	cfu/l00 ml (wet weight)	Pang et al. (2003), Ferguson et al. (2009)

Fate and Transport of Bacteria in Different Media

There are various studies on bacterial transport through sediment, soil solution, and runoff. In all cases, the bacteria die-off is assumed to follow first-order kinetics. The fate and transport of *E. coli* depends on various environmental factors i.e., available nutrients, soil moisture content, soil type, temperature, UV-moisture content, rainfall, and resuspension of *E. coli* in stream. Elevated *E. coli* concentrations are primarily associated with the surface water runoff periods following rainfall events, and low flow rate will decrease the density of pathogenic microorganisms (Schilling, 2008**;** Skraber et al., 2002). Cho et al. (2012) studied fecal coliform in the stream and demonstrates that solar radiation is one of the most significant fate factors of fecal coliform. Karthikeyan (2012) used fecal samples from cattle and raccoon to observe the survival of *E. coli* at different temperature and moisture conditions. The study found maximum *E. coli* survival and growth was at 20°C water temperature and no growth at 50°C. In addition, 25% moisture content was found suitable conditions for survival and growth of *E. coli*, and greater rate of decay for *E. coli* in soil was observed at 4% moisture content. Wang et al. (2004) suggested that if manure can be detained at higher temperatures (e.g., 41°C) as part of agricultural management practices, the *E. coli* and fecal coliform populations will be decreased whereas Miller and Beasley (2008) found stored manure at 4°C can minimize the *E. coli* concentration. Depending on the different media (soil solution, adsorbed to soil particles, and stream), the die-off rates for *E. coli* can be ranged from 0.01 to 1.5 per day (Mocan, 2006). Another study by Kessel et al. (2007) concluded that die-off rates for *E. coli* are found to be different in fields and laboratory conditions for similar temperatures.

Watershed Modelling

Several watershed scale fate and transport of bacterial models i.e., HSPF, LSPC, SWMM, WAMView, WMS, WARMS, MWASTE, and Coli, are used to model the water quality analysis without subsurface tile drainage (Fall, 2011). Dorner et al. (2006) applied WATFLOOD fate and transport model in the tile drained Canagagigue Creek watershed located in Southwestern Ontario where tile drainage systems were considered as the interflow component of the water balance without specifying tile trained parameters. The Soil and Water Assessment Tool (SWAT) model was developed for agricultural watershed, and has proven to be a robust tool for assessing water resource and nonpoint-source pollution problems both locally and internationally.

In the SWAT2000 version, bacteria routine was added (Sadeghi, 2002) and it was improved in SWAT2009. Several water quality assessment studies were published using the SWAT model, and it was able to yield results with an acceptable performance of *E. coli* simulation based on the limited monitoring data (Coffey et al., 2010). Cho et al. (2012) applied the SWAT model for predicting fecal coliforms assuming the grazing and livestock manure were evenly distributed in all land area in the watershed, and found that SWAT reasonably simulated the range and frequencies of bacteria concentrations. Fall (2011) applied the SWAT model to simulate *E. coli* and fecal coliform densities for the agricultural dominated Payne River watershed located in Ontario. This study concluded that model prediction was well for periods of lower *E. coli* and fecal coliform loadings instead of higher microbial loads.

SWAT was first designed to simulate management impacts on water and sediment movement for ungauged rural basins across the U.S (Gassman et al., 2007). Later, for data-scarce catchment, SWAT was applied to transfer calibration parameters from gauged catchment to the ungauged catchment using the regionalization approach (Oudin et al., 2008; Mengistu et al., 2019; Emam et al., 2017). The present study will be focused on transferring calibrated parameters from gauged to ungauged neighbouring catchments assuming the parameter regionalization approach with spatial proximity. Spatial proximity means having similar hydrological response with homogeneous physical and climatic conditions within the neighbouring catchment.

The Soil and Water Assessment Tool

Prior to water quality modelling, SWAT simulates the hydrologic cycle based on the following water balance equation:

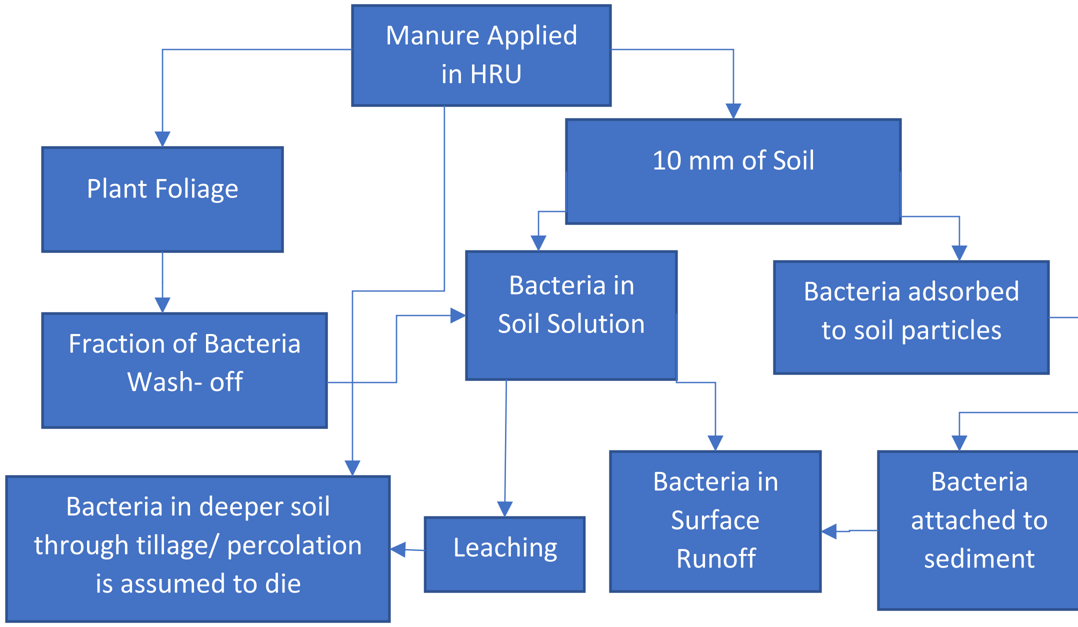
$$SW_d = SW_o + \sum_{n=1}^{d}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \tag{3.1}$$

where SW_d is the final soil water content (mm H_2O), SW_o is the initial soil water content on day n (mm H_2O), d is the time (days), R_{day} is the amount of precipitation on day n (mm H_2O), Q_{surf} is the amount of surface runoff on day n (mm H_2O), E_a is the amount of evapotranspiration on day n (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day n (mm H_2O), and Q_{gw} is the amount of return flow in day n (mm H_2O).

SWAT can compute potential evapotranspiration (PET) using three different methods: the Hargreaves, the Priestley-Taylor, and the Penman-Monteith method. For surface runoff, SWAT has two different methods: The Curve number and the Green & Ampt method. SWAT estimates sediment yield using the modified universal soil loss equation (MUSLE). The details can be found in the SWAT theoretical document (Neitsch et al., 2011).

SWAT Bacterial Sub Model. When bacteria in manure is applied to each HRU, some fraction intercept by plant foliage and the remainder reach to the soil. SWAT monitors the two bacteria populations in plant foliage and in the top of 10 mm of soil that interacts with surface runoff. The portion of bacteria that is washed off from the foliage is assumed to be in solution in the soil surface layer. Depending on the precipitation, SWAT calculates the amount of bacteria as washed off from the plant/ foliage. Bacteria incorporated in deep soil through tillage or transport via percolation are assumed to die. Bacteria leaching from the soil solution are also assumed to die in the deeper soil layer. Bacteria adsorbed to the soil particles can be transported by surface runoff to the main channel. In this study, due to the unavailability of the measured fecal coliform concentration, the focus will be given on *E. coli* which is considered as persistent bacteria in the SWAT model. The flow chart of transport of bacteria in surface runoff due to manure application is depicted in Figure 3- 2.

Figure 3- 2: *Bacteria Transport in Surface Runoff due to Manure Application*



SWAT uses Chick's Law first order decay equation (Equation 3.2) to determine the quantity of removed daily bacteria level through-die-off in different pools (foliage, soil solution, and sorbed to the soil).

$$E_i = E_{i-1}.e^{(-\mu)} - E_{min} \tag{3.2}$$

The first order decay equation (equation 3.3) is used to calculate changes in bacteria concentrations for bacteria routing in the stream:

$$E_i = E_{i-1}.e^{(-\mu)} \tag{3.3}$$

where E_i is the amount of *E. coli* in different pools (#cfu/m^2) and on stream (#cfu/100 ml) on day i, E_{i-1} are the amount of *E. coli* in different pools (#cfu/m^2) and on stream (#cfu/100 ml) on day i-1, μ is the overall rate constant for die-off of *E. coli* in different media (foliage, soil solution, adsorbed to soil solution, and stream) (1/day), and E_{min} is the minimum daily loss of *E. coli*.

The die-off rate constants are adjusted for temperatures using equation 3.4:

$$\mu = \mu_{20}.\theta^{(T-20)} \tag{3.4}$$

where μ is the die-off rate constants in different media (1/day), μ_{20} is the die-off rate constant of *E. coli* in different media at 20ºC (1/day), ϴ is the Temperature adjustment factor for *E. coli* die-off, and T is the temperature (ºC).

SWAT considers direct input of bacteria from the watershed system as point source on a daily, monthly, yearly or average annual basis along the stream. Point source can be manually added or one point source per subbasin can be assigned by default, and it follows the first order decay equation (equation 3.3).

Bacteria in surface runoff only partially interacts with the bacteria present in the soil solution. SWAT uses the bacteria soil partitioning coefficient which is the ratio of the bacteria concentration in the surface 10 mm of soil solution to the concentration of bacteria in surface runoff. The equation 3.5 describes the amount of *E. coli* transported in surface runoff:

$$E_{surf} = \frac{E_{sol} \cdot Q_{surf}}{\rho_b . depth_{surf} . k_{E,surf}} \tag{3.5}$$

where E_{surf} is the amount of *E. coli* lost in surface runoff (#cfu/m^2), E_{sol} is the amount of *E. coli* present in soil solution (#cfu/m^2), Q_{surf} is the amount of surface runoff on a given day (mmH_2O), ρ_b is the bulk density of the top 10 mm (Mg/m^3), $depth_{surf}$ is the depth of the “surface layer” (10 mm), and $k_{E,surf}$ is the *E. coli* soil partitioning coefficient (m^3/ Mg).

In the SWAT model, the decay rates at 20ºC for different media are specified separately: WDPQ is the die-off factor for persistent bacteria in soil solution, WDPS is the die-off factor for persistent bacteria adsorbed to soil particles, WDPF is the die-off factor for persistent bacteria on foliage, WDPRCH is the die-off factors for persistent bacteria in streams (moving water), WDPRES is the die-off factors for persistent bacteria in streams (still water). The temperature adjustment factor, minimum daily loss of *E. coli*, and the *E. coli* soil partitioning coefficient are defined as THBACT, BACTMINP, and BACTKDQ, respectively. The details on computing the transport and routing of bacteria in surface runoff, and amount of bacteria attached to sediments can be found in the SWAT Theoretical document (Neitsch et al., 2011).

Study Objectives

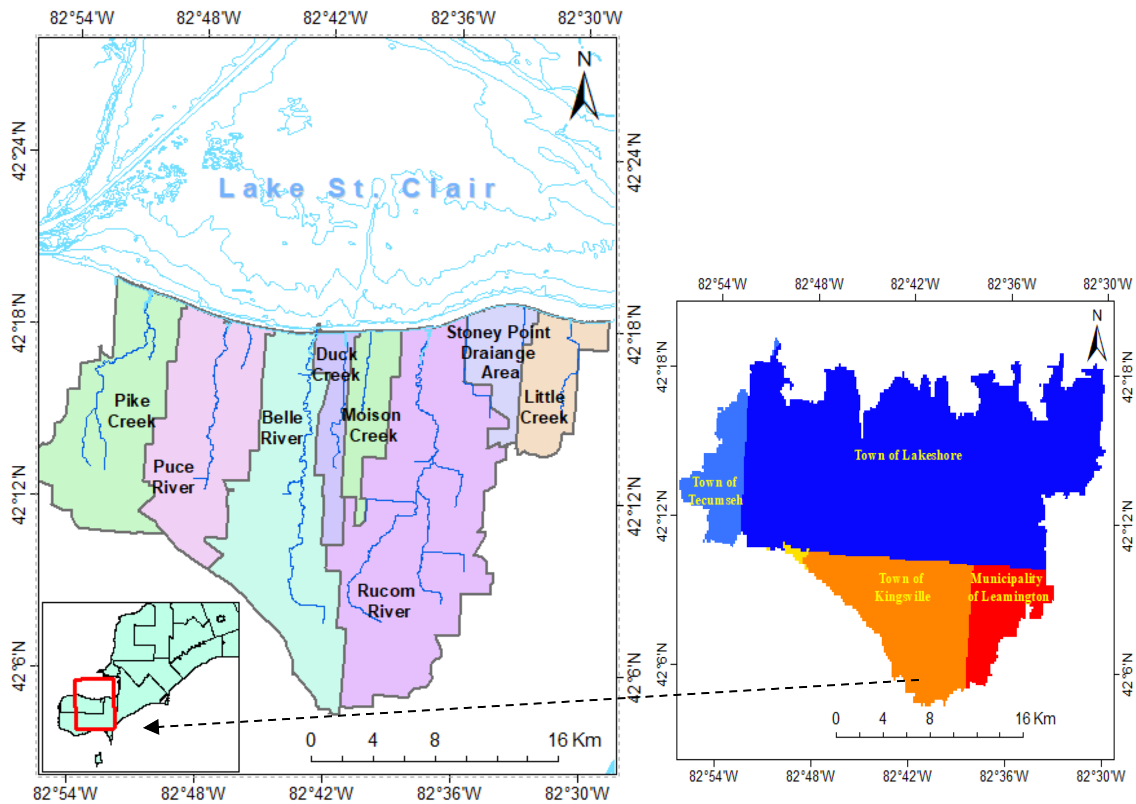
Based on the problem identified as described above, the main goal of this study is to identify and quantify *E. coli* concentrations spatially resulting from various sources in the local watersheds using the SWAT model. The key objectives of this study are:

1. To perform sensitivity analysis of *E. coli* model through the process of calibration and validation to identify the sensitive parameters
2. To quantify relative contribution of different sources for *E. coli* concentration and map the critical source areas of microbial loadings

Study Area

The Lake St. Clair subwatershed drains 577 km^2 in eight northward subwatersheds including Pike Creek, Puce River, Belle River, Duck Creek, Moison Creek, Ruscom River, Stoney Point Drainage, and Little Creek and discharges directly to Lake St. Clair. It is located approximately between 82°54′W to 82°30′W, and between 42°18′N to 42°6′N, respectively. The western side of the study area bounded by the subwatersheds discharge directly to the Detroit River. The eastern boundary of the study area is shared with the Lower Thames Valley Conservation Authority. Subwatersheds located on the southern side of the study area discharge directly to Lake Erie. Figure 3- 3 presents the study area map of the Lake St. Clair Essex region's watershed.

Figure 3- 3: *Location of Each Subwatershed in the Essex Region's Lake St. Clair Watershed*



Methodology

DEM, Soil, Landuse, and Weather Data

It is essential to perform water budget analysis prior to the water quality modelling since the predicted numbers of *E. coli* are clearly linked to the hydrologic processes. (Dorner et al., 2006). In order to identify the critical source areas with respect to microbial loadings, water budget analysis needs to be done at the local subwatersheds. The SWAT 2012 hydrologic model was calibrated and validated, and all the major components of the water balance were estimated using SWAT 2012 as discussed in Chapter 2. For the SWAT simulation, a digital elevation model (DEM) was obtained from Natural Resources Canada for the watershed delineation process (http://ftp.geogratis.gc.ca/pub/nrcan_rncan/vector/index/html/geospatial_product_index_en.html#link). For the HRU analysis, the soil dataset (Version 3.2) was obtained from the National Soil Database of Canadian soil information system (http://sis.agr.gc.ca/cansis/nsdb/slc/index.html), and landuse dataset (version 2.0) was downloaded from the Southern Ontario Land Resource Information System (SOLRIS) (https://geohub.lio.gov.on.ca/datasets/0279f65b82314121b5b5ec93d76bc6ba). Jeswiet et al. (2015) mentioned that the Canadian agricultural landscape comprises six different categories which include cropland, summer fallow, tame or seeded pasture, natural land for pasture, woodlands and wetlands. The shape file for tile drainage areas was downloaded from the Scholars geoportal website to determine the percentage of tile drainage agricultural land. To simulate tile drainage, SWAT needs input for the soil surface depth to the drains (DDRAIN), the amount of time required to drain the soil to field capacity (TDRAIN), and the amount of lag between the time water enters the tile until it exits the tile and enters the main channel (TDRAIN) (Neitsch et al., 2011). In this study, the values for DDRIAN, TDRAIN, and GDRAIN were selected as 700 mm, 20h, and 24h, respectively. The daily maximum and minimum temperature data and precipitation data was downloaded for the period of 1998 to 2018 from Windsor Airport Station. WGEN weather generator data was used for wind speed, relative humidity, and solar radiation data.

The Curve number was set for the Rainfall-Runoff method. The potential evapotranspiration was estimated using the Penman-Monteith equation, and the Variable Storage Routing was used for the channel water routing. Once these processes were completed, the warmup period was selected from 1998 to 2002 (5 years) for the SWAT simulation. The simulation period was set to run from 1998 to 2018 including the warm-up period.

Landuse and Soil Classifications. Table 3- 2 describes that the land use classification contained five land classes: forest, agricultural, wetland, urban, and water. The agricultural land use combined with pasture grazed areas incorporates almost 90 percent of this watershed. So, agricultural management practice for manure use and grazed pasture has great influence on the generation of microbial pollution of this watershed. Table 3- 3 describes the major soil (Brookston Clay) properties occupied in this watershed, which has higher clay percentage. ERCA (1988) found clay soil causes higher sediment and phosphorus yield. Also, higher clay content in the soil increases the retention of pathogens and indicator microorganisms (Reddy et al., 1981). In addition, high clay content results in high sediment bacteria concentration and comparatively low decay rate of bacteria (Cho et al., 2012).

Table 3- 2: *Landuse Classification of the Lake St. Clair Watershed, Essex County*

Land use Classes	**Watershed Area (km^2)**	**% of Watershed Area**
Agricultural Land-low crops (AGRR)	476.32	88.6
Pasture Grazed Areas	6.65	1.2
Forest-Mixed (FRST)	0.51	0.1
Forest-Deciduous (FRSD)	4.34	0.8
Range-Bush (RNGB)	4.1	0.8
Industrial (UIDU)	29.01	5.4
Southwestern US (Arid) Range (SWRN)	0.41	0.1
Residential-Low Density (URLD)	5.1	0.9
Wetlands-Non-Forested (WETN)	9.94	1.8
Water (WATR)	1.7	0.3

Table 3- 3: *Soil Properties for Brookston Clay Soil (BK0)*

Soil Properties	**Value**	**Unit**
Percentage of Area Covered	87.34	%
Moist Bulk density	1.27	g/cm^3
Available water capacity	0.46	mm/mm
Clay	47	%
Silt	37	%
Sand	16	%

Sampling Data: E. coli

The Provincial Water Quality Monitoring Network (PWQMN) surface water quality monitoring site is located at Ruscom River and the monthly *E. coli* data is available for the period of 2014 to 2018. ERCA has surface water quality monitoring sites at Pike

Creek, Puce River, Belle River, Duck Creek, and Little Creek, and monthly *E. coli* data was available from 2011 to 2018 except for Little Creek. Only a few *E. coli* data were available for Little Creek in the year of 2018. A single grab sample was collected on a monthly basis at these sampling locations, and the samples were taking to Caduceon labs where they were analyzed for a number of things including *E. coli* (Source: K. Stammler, Personal Communication, February 6, 2020).

Agricultural Land Management Practices

The SWAT model requires the detailed agricultural land management information including crop planting and harvest dates, tillage, and manure application.

Crop Management with No-Till. No-till option is to minimize disturbance of the soil and seedbed. There are several studies in relation to tillage incorporation. Tan and Zhang (2011) used no-tillage option for corn-soybean rotation. Sharpley and Smith (1994) considered both the impact of conventional-till and no-till for wheat, and found that no till reduced sediment, P and N losses, and considered best management practices to reduce soil erosion. Jeswiet et al. (2015) indicates that no-till increases soil organic matter and help for retaining soil moisture. In addition, manure application with no till system helps to improve soil health by providing organic matter contributions as well as to feed crops and soil microorganisms. The negative affect of no-till seeding would be more dependence on pesticides to control weeds and insects. To consider manure with no-till system, the Ontario Ministry of Agriculture, Food and Rural affair (OMAFRA) recommended to consider crop rotations and in-crop applications of manure (The Ontario Ministry of Agriculture, food and Rural affair [OMAFRA], 2017). In this study, no tillage was chosen for four years soybean-corn-winter wheat rotation.

Crop Rotation. According to the information from OMAFRA's Agricultural profile, Essex County produces nine different field crops; of which winter wheat, soybeans, and corn covers over 90% of agricultural land (OMAFRA, 2017). In this study, a ratio of 64:21:15 was chosen for model input for soybean, corn, and winter wheat, respectively (ERCA, 2008). A private communication was made to ascertain more detailed information in the scheduling of plating, grazing, and manure application with the Ministry of the Agriculture at 1-877-424-1300 on 18 November, 2019. However, since the agricultural practice depends on weather, so no approximate date and time for these applications were provided. In Ontario, the general common rotation practice is corn or wheat following soybeans or corn following wheat (Rahman, 2007). According to OMAFRA (2017), the best option for the timing of manure application is as soon as possible after wheat harvest before regrowth. For the corn, the manure should be applied on dry soil to avoid compaction. If manure is incorporated in the spring, at least two weeks waiting period is recommended before planting. Significant residual nitrogen will be available for a crop when solid manure is applied regularly to the same field. The management operation schedule for crop rotation and manure application for the Lake St. Clair region watershed are provided in Table 3- 4.

Table 3- 4: *Operations for Crop Management in Four Years Rotation*

Year of Rotation	Crop Name	Date for Planting	Date for Harvest and Kill	Date for Manure Application
Year 1	Corn	01-Jun	30-Nov	1 April (Spring) 1 June (Summer)
Year 2	Soybean	01-Jun	30-Oct	1 April to 2 May (Spring)
	Winter Wheat	10-Nov	-	-

Year of Rotation	Crop Name	Date for Planting	Date for Harvest and Kill	Date for Manure Application
Year 3	Winter wheat		30-Jul	1 June to 30 July (Summer)
Year 4	Corn	01-Jun	30-Nov	1 April (Spring) 1 June (Summer)

Pathogen Source Characterization for the SWAT Model

Three sources, including feedlot livestocks, livestock grazing, and wildlife grazing, were identified as indirect non-point source pollutants; and two sources, including effluent from faulty septic tanks and direct deposit of cattle standing on stream, were considered as direct non-point source pollutants.

Feedlot Livestock Numbers and Manure Production. Livestock manure contains various types of bacteria, potassium, phosphorus, and nitrogen, which can provide adequate nutrients for crop production without the addition of commercial fertilizers. Application of manure to the soil can also reduce the risk of soil erosion and enhance the water retention capacity of the soil. It has environmental benefits but in certain conditions, livestock manure can have a negative impact on the environment if not managed properly. Manure can be a risk of pathogenic organisms, including Cryptosporidium, Salmonella, and Escherichia coli 0157:H7 (Sadeghi & Arnold, 2013). In addition, manure produced in one part of a basin can affect other areas of the same basin, whether that area is agricultural, urban or has another use.

Livestock manure coefficient (kg/year) for difference kinds of animal is described in the report of “Geographical Profile of Manure Production in Canada, 2001” (Hofmann & Beaulieu, 2001). Table 3- 5 indicates the manure co-efficient for different species and age groups of livestock cows. For agricultural management practices, either soil manure can be incorporated or liquid manure can be injected into the soil. In 2016, in the Town of Lakeshore, 39 farms out of 41 reported solid manure application whereas only two farms reported on liquid manure injection. Therefore, the application of manure was considered to be solid manure for this present study. The livestock head numbers data are collected for the Towns of Lakeshore, Tecumseh, Kingsville, and Municipality of Leamington from Statistics Canada (Statistics Canada, 2017). Since percentage of area covered by the Towns of Lakeshore, Kingsville, Tecumseh, and Municipality of Leamington in the study area are 75%, 35%, 21%, and 35%, respectively, the livestock head numbers were counted accordingly ("Town of Leamington," n.d.**;** "Municipality of Leamington," n.d.**; ;** "Town of Kingsville," n.d.**;** "Town of Lakeshore, Ontario," n.d.)**.** Table 3- 6 describes the compilation of livestock head numbers (cows) and computation of total dry manure for each of these towns located within the Essex region's Lake St. Clair watershed. In this study, livestock manure was assumed to be distributed uniformly in the agricultural area. The details of the livestock manure application rate in the agricultural land are provided in Table 3- 7.

Table 3- 5: *Livestock Manure Coefficients*

Variable	**Average animal Weight (kg)**	**Manure (Kg/ Year)**
Beef cows	635	13,444
Bulls	726	15,364
Calves	204	4,321
Heifers	421	8,904

Variable	Average animal Weight (kg)	Manure (Kg/ Year)
Dairy cows	612	22,706
Steers	454	9,603

Table 3- 6: *Compilation of Livestock Heads and Manure Production in the Study area*

Variable	Town of Lakeshore	Town of Kingsville	Municipality of Leamington	Town of Tecumseh
Beef cows	878	757	878	469
Bulls	30	30	30	17
Calves	1,087	1,924	560	1,185
Heifers	331	426	118	429
Dairy cows	73	575	73	210
Steers	251	98	91	60
Total Head	2,650	3,810	1,750	2,370
% of Total Heads	1,987 (75%)	1,333 (35%)	613 (35%)	498 (21%)
Total Dry Manure (kg/year)	17,982,596	12,859,623	6,393,308	4,378,724

Table 3- 7: *Livestock Manure Application Rate in Each of the Subbasins*

Town Name	Subbasin no.	Agricultural Area, ha	90% Area	Effluent, kg/year	Manure Application Rate, kg/ha
Town of Lakeshore	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27	38,129	34,316	17,982,596	524
Town of Kingsville	30, 31	9,536	8,582	12,859,623	1,498

Town Name	Subbasin no.	Agricultural Area, ha	90% Area	Effluent, kg/year	Manure Application Rate, kg/ha
Municipality of Leamington	29, 28	4,210	3,789	63,933,08	1,687
Town of Tecumseh	14	1,913	1,722	4,378,724	2,542

Livestock Grazing. Cattle grazing was considered as livestock grazing and the head numbers were estimated based on the Essex region's agricultural census over time (Statistics Canada, 2017). The Essex region's agricultural census estimates pasture areas in terms of seeded pasture and natural land pasture alongwith the number of farms for both winter grazing and rotational grazing. For this study, a typical value of one cow per hectare was applied for the grazing density. To get the location of pasture areas, a shape file of the pasture area map was downloaded from the Scholar's Geoportal website as depicted in Figure 3- 4. Table 3- 8 represents the estimation of livestock grazing cattle in this watershed. The livestock manure coefficient for cattle from Table 3- 5 was applied to estimate the total dry manure for grazing cattle. The manure from livestock grazing cattle was assumed to be uniformly distributed in the agricultural pasture land. The details of grazing manure application rate for each of the towns are provided in Table 3- 9.

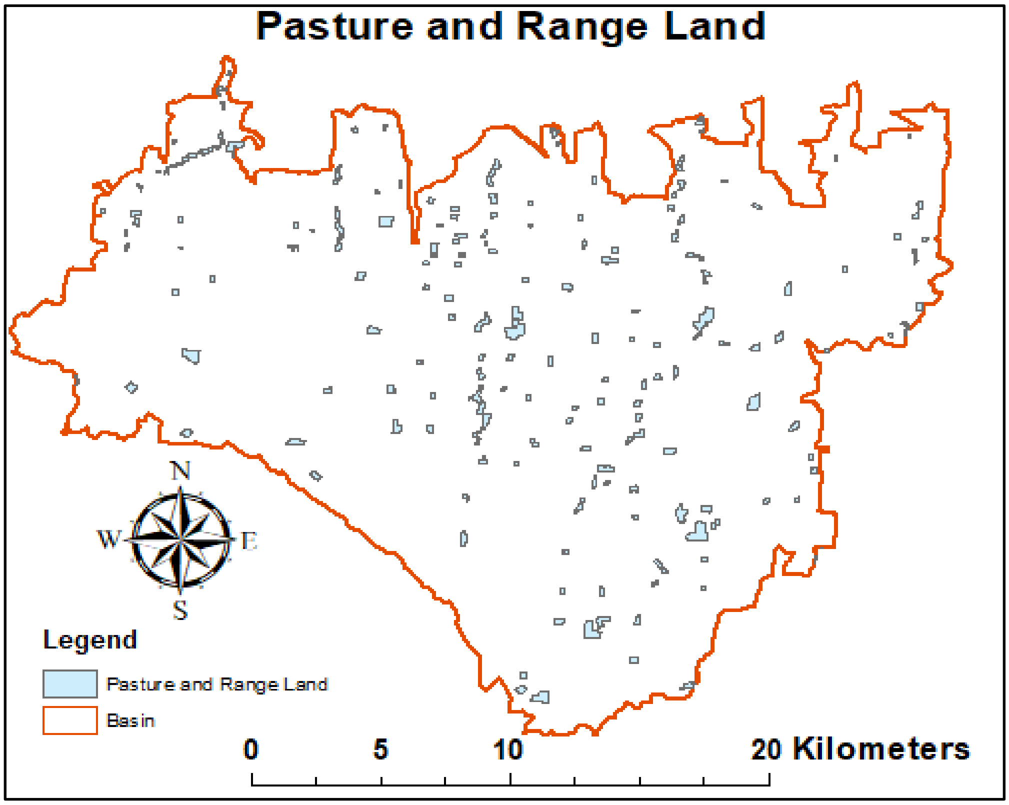
Table 3- 8: *Compilation of Livestock Grazing Cattle and Manure Production*

Area	**Pasture Area** ha	**Grazing Cattle** Total heads	**Total Dry Manure** Kg/150 Days
Town of Lakeshore	707	707	1,255,458
75% of area and heads	**530.25**	**530**	**941,593**
Town of Kingsville	231	231	410,199
35% of area and heads	**80.85**	**81**	**143,570**
Town of Tecumseh	32	32	56,824
35% of area and heads	**6.72**	7	**11,933**
Municipality of Leamington	135	135	239727
21% of area and heads	**47.25**	**47**	**83,904**

Table 3- 9: *Livestock Grazing Manure Application Rate and Date of Application*

Area	**Pasture Area, ha**	**Head no.**	**Total Manure Kg/150 days**	**Density (Head/ha)**	**Application Rate kg/ha/day**	**Date of Application For 150 days**
Town of Lakeshore	530	530	9,41,593	1	12	25 May
Town of Kingsville	81	81	1,43,570	1	12	25 May
Town of Tecumseh	7	7	11,933	1	11	25 May
Municipality of Leamington	47	47	83,904	1	12	25 May

Figure 3- 4: *Pasture Land in the Lake St. Clair Watershed*



Wildlife Grazing. Only Canada geese were assumed as wildlife grazing for this study since the estimates of other wildlife data are unavailable for this watershed. Both tame or seeded pasture and natural land for pasture are used for wildlife including many birds benefiting from livestock grazing. Canada geese breed in temperate regions, such as southern Ontario. According to the Canadian wildlife service estimation, there are more than 400,000 temperate-breeding Canada geese in Ontario (Environment Canada, 2006). Breeding-nesting starts during mid-March to late March. Depending on weather and food availability, sub-arctic breeding geese migrates during fall. The peak number of the Canada geese occurs during mid-March to late October. Kear (1962) estimated that the production of dry manure per English Canada goose was 175 gm per day. Fall (2011) assumed 50-500 geese were present per km^2 during the nesting period. However, during the peak period in fall season, the assumption was made of 50-250 geese per km^2. In this research, 50-500 geese per km^2 was assumed from mid-March to late October and the manure from Canada geese was assumed to be uniformly distributed in the agricultural land. Table 3- 10 shows the geese number and the details of application rate.

Table 3- 10: *Compilation of Geese Number and Manure Application Rate*

Agricultural Area, ha	**Density Head/ha**	**Total Geese no.**	**Manure per geese gm/day**	**Total Manure kg/225 days**	**Application Rate kg/ha/d**	**Date of Application for 225 days**
48300	0.5-5	24,150-241,500	175	950,906-9,509,062	0.1-1	15 Mar

Effluent from Faulty Septic Tanks. The minimum input data to model the bacterial transport using the SWAT model are available from government agencies. A GIS layer associated with rural houses was obtained from (Environmental Systems Research Institute [ESRI], 2017) and used to estimate houses located in proximity of 30 m of stream. According to ESRI (2017), 89 septic tanks are located in proximity of 30 m from the streams throughout the watershed. In this study, 20% of the dwellings with septic systems located within 30 m proximity to stream were assumed to have failing systems. Similar assumption was made in the study by Fall (2011). An average population number of 2.7 people per dwelling and an average residential water use of 160 l/cap/day were assumed for estimating effluent from faulty septic systems. The details of the effluent discharge from faulty septic systems for 31 subbasins are provided in Appendix B. The effluent from faulty septic tanks was considered as a direct non-point source pollutant on a monthly basis by selecting point sources for relevant subbasins. The monthly average *E. coli* concentration was assumed as $1.6x10^4$/100 ml as calibration input for all the subbasins.

Direct Deposition from Cattle. Due to the unavailability of wildlife population information from the available literature, cattle standing on the stream was considered as another source of direct non-point source. For modeling input, 7%, 7%, 7%, 7%, and 4% of the total grazing manure were assumed to be directly deposited in the stream for the month of June, July, August, September, and October, respectively. Similar assumption was made in the study of Baffaut et al. (2003). Figure 3- 4 identifies the location of grazing areas onto the streams and considered as direct non-point sources for cattle direct deposition. Table 3- 11 describes the estimates of monthly distribution of manure deposition due to cattle standing in the stream. The model assumption for average monthly concentration of *E. coli* as wet weight were considered as calibration input and provided in Table 3- 12.

Table 3- 11: *Quantification of Manure Deposited from June to October*

	Manure Deposited (%)	**Town of Lakeshore**		**Town of Kingsville**		**Town of Tecumseh**		**Municipality of Leamington**	
		Manure Deposited in-Stream	**No. of Cattle in stream.**	**Manure Deposited in-Stream**	**No. of Cattle in stream**	**Manure Deposited in-Stream**	**No. of Cattle in stream**	**Manure Deposited in-Stream**	**No. of Cattle in stream**
June	7	439	37	67	6	6	0	39	3
July	7	439	37	67	6	6	0	39	3
Aug	7	439	37	67	6	6	0	39	3
Sep	7	439	37	67	6	6	0	39	3
Oct	4	251	21	38	3	3	0	22	2
	Total	**2,008**	**170**	**306**	**26**	**26**	**0**	**178**	**16**

Table 3- 12: *Average E. coli Conc. from Cattle Direct Deposit*

Month	cfu/100 ml
June	$2.9x10^5$
July	$2.9x10^5$
August	$2.9x10^5$
September	$2.9x10^5$
October	$2.12x10^5$

Bacteria Input Data and Parameters

The SWAT requires input of bacterial concentration and partitioning co-efficient for manure applied in the model. The *E. coli* concentration range in the manure of beef, cattle, and septic systems identified in some available literature are described in Table 3-1. The model assumption for bacterial concentration is presented in Table 3- 13. Bacteria are partitioned into soluble and sorbed phases during their initial release from manure, overland and subsurface transport, and streambed transport. Coffey et al. (2010) and Coffey et al. (2013) found high attachment rates of bacteria to the soil particles and selected bacteria partitioning coefficient 0.9. In this study, the bacteria partitioning coefficient was identified as calibration input and was set to 0.9. In SWAT, the bacteria concentration and partitioning co-efficient for each kind of manure is defined as BACTPDB and BACTKDDB.

The magnitude of parameter "Die-off factor" varies depending of physical, chemical and biological factors. To simulate microbial loadings, the die-off rates were selected based on the sensitivity analysis through the combination of model fitting during sensitivity analysis which was based on observed data and previously reported inactivation/ die-off rates. During sensitivity analysis, the observed *E. coli* concentrations measured in the Ruscom River PWQMN station was used for the calibration of SWAT bacterial parameters. The calibrated parameters were transferred to the subwatersheds of Pike Creek, Puce River, Belle River, Duck Creek, Moison Creek, Stoney point drainage, and Little Creek. ERCA has monitoring stations for *E. coli* at outlets of Pike Creek, Puce River, Belle River, and Duck Creek. The model simulated *E. coli* concentrations at these outlets were compared with the measured data.

Table 3- 13: *Model Assumption for E. coli Concentration*

Source	***E. coli* Concentration**
Livestock	$9.5x10^5$ (#cfu/g) (dry weight)
Cattle	$2.1x10^4$ (#cfu/g) (dry weight) 2.9 $x10^5$ (#cfu/100 ml) (June -September) 2.1 $x10^5$ (#cfu/100 ml) (wet weight) (October)
Geese	$1.53x10^4$(#cfu/g) (dry weight)
Septic System	1.6 $x10^4$(#cfu/100 ml) (wet weight)

Statistical Measures

The performance of pathogen model was evaluated using statistical analysis. For the goodness-of-fit measures, the Nash-Sutcliffe efficiency index (NSE) and co-efficient of determination (R^2) are widely used and potentially reliable statistics for assessing the hydrologic models (McCuen, 2006; Moriasi et al., 2007).The model performance ratings can be judged as satisfactory if the NSE and R^2 >0.5 (Moriasi et al., 2007; Green et al., 2006). The equation for NSE is given below:

Equation for NSE:

$$\text{Nash Sutcliffe Efficiency} = 1 - \frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o})^2} \quad (3.6)$$

Where,

o_i= Observed value

p_i= Predicted value

$\bar{o}$= Average observed value

n= number of sample size

Results and Discussions

Sensitivity Analysis

In the SWAT model, there are 16 parameters for the *E. coli*, which are used for the fate and transport equations. Out of these 16 parameters, three parameters are related to bacteria regrowth, and no sensitivity was performed for these parameters since little quantifiable data on the natural environment is available (Fall, 2011). To evaluate the model parameters' influences on predicted output, each of the parameters were changed by ±20% of the initial value while keeping the rest of the parameters' values constant. The results of the sensitivity analysis of seven sensitive pathogen parameters are illustrated in Figure 3- 5. It is apparent that four parameters, which are concentration of persistent bacteria in manure (BACTPDB), bacteria partitioned co-efficient (BACTKDDB), die-off factor for persistent bacteria in soil solution at 20°C (WDPQ), and die-off factors for persistent bacteria in streams (moving water) at 20°C (WDPRCH), had significant effects on model predictions and were identified as the most sensitive model inputs. Altering BACTPDB by ±20% made ±12% variation in *E. coli* output. When BACTKDDB was increased by 20%, the resulting *E. coli* output increased by 4%. Therefore, the higher the *E. coli* concentration in manure, the more bacteria will be transported in surface runoff. Furthermore, uncontrolled agronomic activities will increase the *E. coli* concentration in the stream.

A 20% increase in WDPQ decreased the model output by approximately 3%. For ±20% change in WDPRCH, ±2% change was observed in model output. The clay soil plays a significant role in model outputs for changing these parameters.

Three parameters including minimum bacteria daily loss (BACTMINLP), die-off factor for persistent bacteria adsorbed to soil particles at 20°C (WDPS) and die-off factor for persistent bacteria in water bodies (still water) at 20°C (WDPRES) were identified as the least sensitive parameters since the ±20% change did not have any significant impact on the model output. As described in Chapter 2, the model encountered less percolated water for this watershed. High attachment rates of bacteria in clay soils made these parameters non-sensitive to the watershed.

Figure 3- 5: *Sensitivity Analysis for Bacteria*

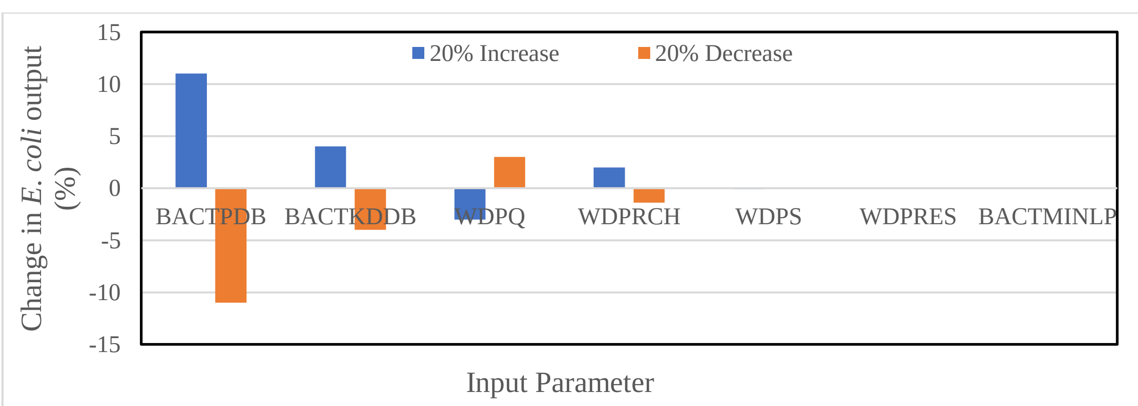


Table 3- 14: *List of SWAT E. coli Model Calibrated Parameters*

Parameter	Definition	Default Value	Manual Calibration	Reference
BACTPDB	Concentration of persistent bacteria in manure (#cfu/g manure)	0	various	-
BACTKDDB.fert.dat	Bacteria Partitioned co-efficient	0	0.5	(Niazi et al., 2015), (Parajuli, 2007)
WDPQ.bsn	Die-off factor for persistent bacteria in soil solution at 20°C (1/day)	0	0.3	(Niazi et al., 2015), (Mocan, 2006)
WDPRCH.bsn	Die-off factors for persistent bacteria in streams (moving water) at 20°C (1/day)	0	0.5	(Fall, 2011)
WDPRES.bsn	Die-off factor for persistent bacteria in water bodies (still water) at 20°C (1/day)	0	0.1	(Fall, 2011)
WDPS.bsn	Die-off factor for persistent bacteria adsorbed to soil particles at 20°C (1/day)	0	0.03	(Mocan, 2006), (Parajuli, 2007)
BACTMINLP.bsn	Minimum bacteria daily loss (#cfu/m^2)	0	0.1	-

Bacteria Calibration and Validation

The model parameters identified during sensitivity analysis for calibration are provided in Table 3- 14 along with the default and calibrated values. The SWAT model was manually calibrated and validated for *E. coli* at five sampling locations on a monthly basis. At the Ruscom River PQWMN station, the SWAT model was calibrated for the period of April 2014 to November 2015 and validated from April 2015 to September 2018, and the model provides a “good” prediction of *E. coli* (E = 0.74). For the other four sampling stations including Pike Creek, Puce River, Belle River, and Duck Creek, the SWAT model was calibrated from 2011 to 2015 (0.13 < E < 0.46) and validated from 2016 to 2018 (0.15 < E < 0.41). The model efficiency compared favourably with many other similar pathogen modelling studies (Niazi et al., 2015; Coffey et al., 2010). The average of measured values for each month was compared to the monthly simulated values for *E. coli* at these five sampling stations (Figures 3- 6, 3- 7, 3- 8, 3- 9, 3- 10, 3- 11, 3- 12, 3- 13, 3- 14, 3- 15, and 3- 16). The *E. coli* calibration and validation results for each of these five sampling stations are described in the following sections.

Bacteria Calibration and Validation at the Ruscom River PWQMN Station. The model performance was found to be “very good” during the calibration period (NSE:0.74, and R^2: 0.75) at the Ruscom River station. Using the same parameter values, the SWAT model was validated for the period of 2016 to 2018, and the model performance was satisfactory (NSE:0.42 and R^2: 0.43). Most of the reported studies calibrated the SWAT model for bacteria using one year of monthly observations, and model efficiency was found to be satisfactory (Niazi et al., 2015; Coffey et al., 2010). The present study used two years of monthly observations for calibration and three years for validation at the Ruscom River PWQMN station. Figures 3- 6 and 3- 7 are a stark illustration that the SWAT model was able to accurately predict the trend of *E. coli* for seasonal variations except for some months in which the model underpredicted and over predicted. Furthermore, a “very good” correlation was observed between observed and simulated *E. coli* concentrations in the calibration period as depicted in Figure 3-8. Since the monthly *E. coli* simulation does not allow for evaluation of the peaks in detail (Iqbal et al., 2019), the focus was given to long-term trends.

Figures 3- 6 and 3- 7 show that the monthly mean observed *E. coli* concentrations in Ruscom River routinely exceeded the provincial water quality standard (100 cfu/100 ml) from 2014 to 2018. The *E. coli* concentration peaks in the range of 400 to 1,600 cfu/100 ml were observed for several months: two months (May and June) in 2014, three months (April, June, and July) in 2016; and September 2018. The SWAT model was able to predict the trends accurately but had underpredictions as illustrated in Figure 3- 6, having the concentrations range from 350 to 750 cfu/100 ml. Conversely, the SWAT model had overpredictions for peaks in the range of 229 to 500 cfu/100 ml for several months: two months (September and October) in 2015, three months (May, August, and October) both in 2016 and 2017; and two months (June and August) in 2018. These variations indicate that a number of factors contribute to the uncertainty with the SWAT watershed input. These factors include the seasonal variation in farm practices, animal grazing, and faulty septic systems. Moreover, no wildlife data was available for this region, and the wildlife contribution was not considered during *E. coli* simulation.

In the SWAT model simulation period from 1998 to 2018, assumptions for the application period for non-point source loading include the following: livestock manure from April to May for this subwatershed, cattle direct deposit from June to October, grazing geese manure from mid-March for 225 days, cattle graze manure from May 26 for 150 days, and faulty septic effluent from January to December. In addition, the model assumption for the *E. coli* concentration and loading amount are provided in Tables 3- 5, 3- 7, 3- 9, 3-10 and 3- 13. The possible reason for the model underprediction could be that the number of loadings for non-point sources in the real field was higher for these months as compared to Tables 3- 7, 3- 9, 3- 10, and 3- 13. Another reason would be the time period of manure application and livestock grazing in the real field, which depends on the weather. Similar reasons would be applied for model overpredictions as compared to observed *E. coli*.

Therefore, more accurate data for seasonal effects of wildlife, grazing animals, farm practices for agronomic activities, and effluents from faulty septic systems is required in order to accurately simulate *E. coli* concentrations in local streams.

Figure 3- 6: *E. coli Calibration at the Ruscom River PWQMN Station*

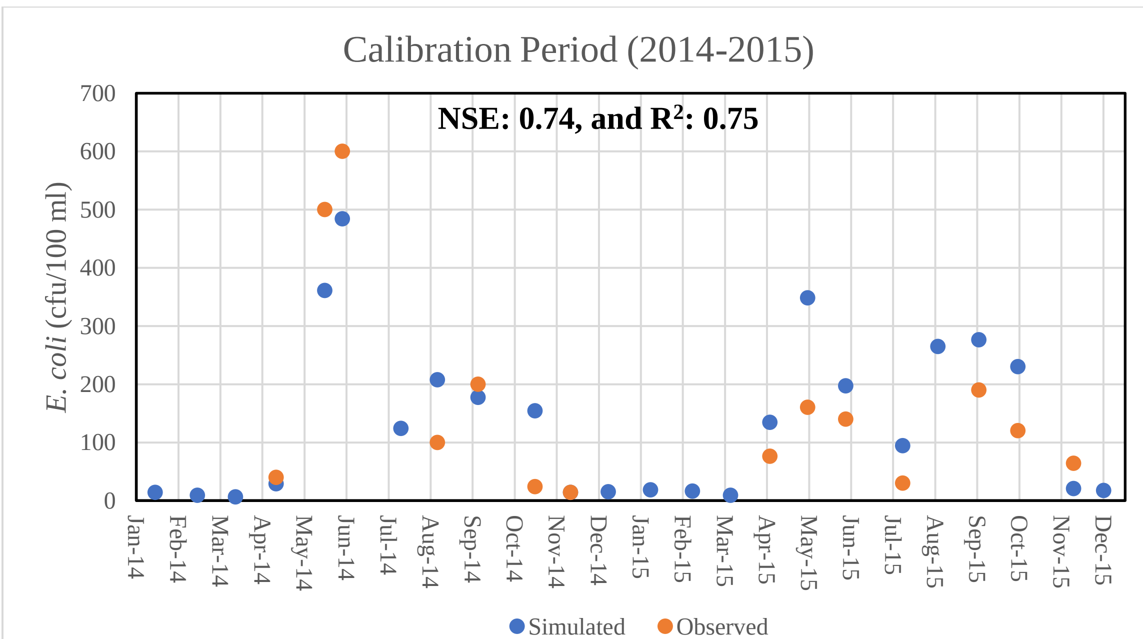


Figure 3- 7: *E. coli validation at the Ruscom River PWQMN Station*

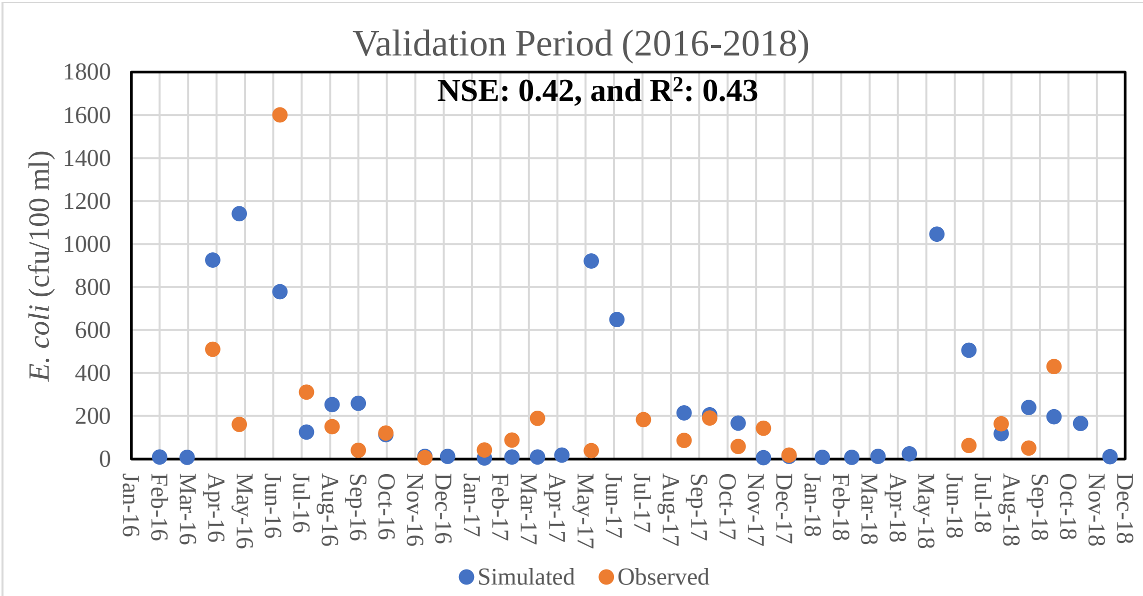
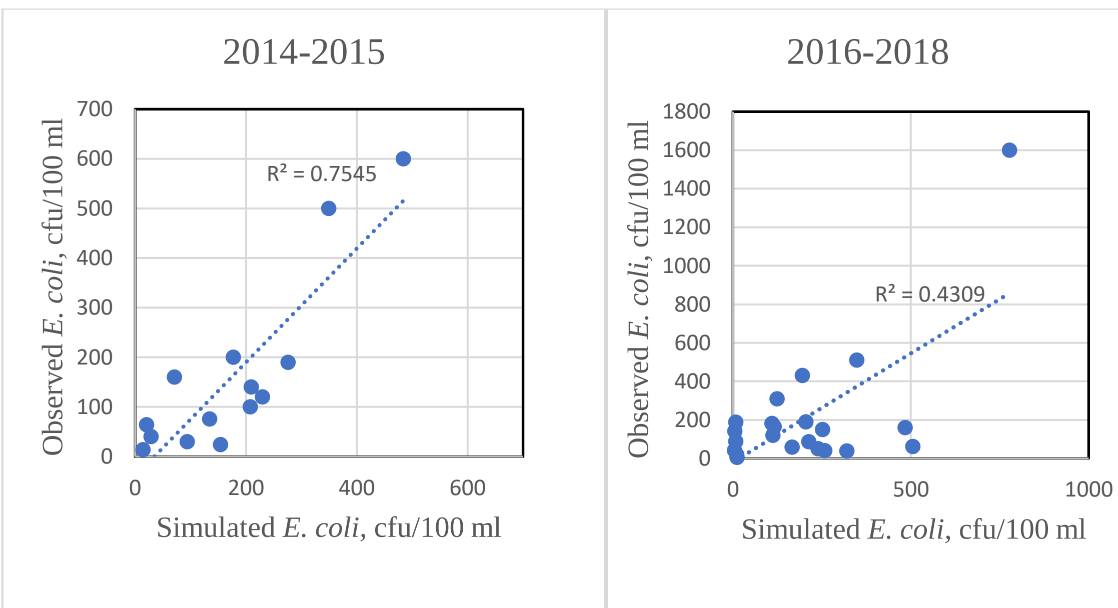


Figure 3- 8: *Scattered plot of E. coli calibration and validation*



Bacteria Calibration and Validation at the Pike Creek Sampling Station. The SWAT model was calibrated from 2011 to 2015 and validated from 2016 to 2018 at the Pike Creek sampling station (0.21< NSE <0.46, 0.28< R^2 <0.48) as depicted in Figures 3- 9 and 3- 10. The observed and predicted *E. coli* concentrations were relatively higher (>

200 cfu/100ml) during summer than spring, fall and winter. *E. coli* concentration above 200 cfu/100 ml was found in fall 2011 and 2012, spring 2018, and winter 2014 (Figures 3- 9 and 3- 10). The model was able to predict the seasonal variations accurately except some underpredictions and overpredictions, and the possible reasons could be the unaccounted factors as discussed above.

Figure 3- 9: *E. coli Calibration at the Pike Creek Sampling Station*

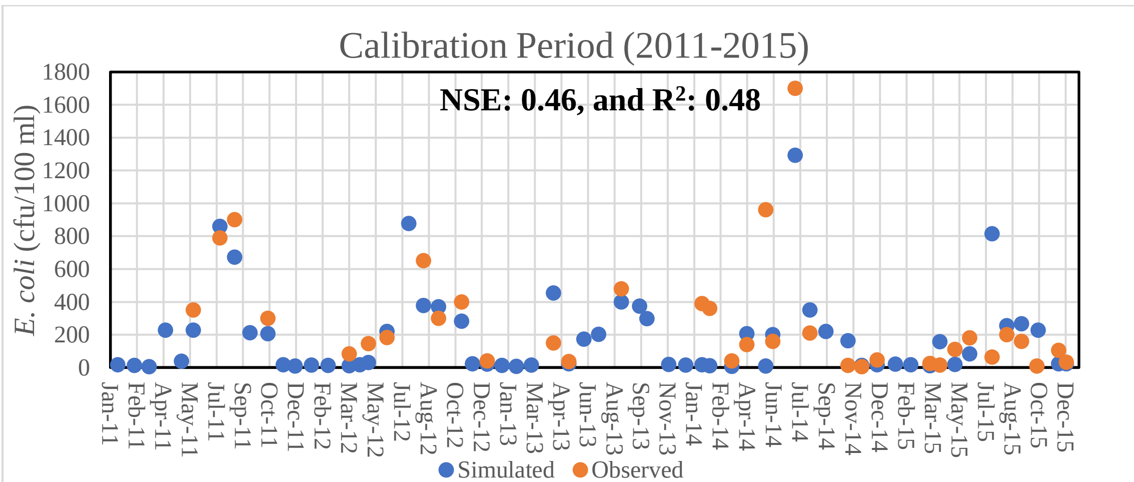
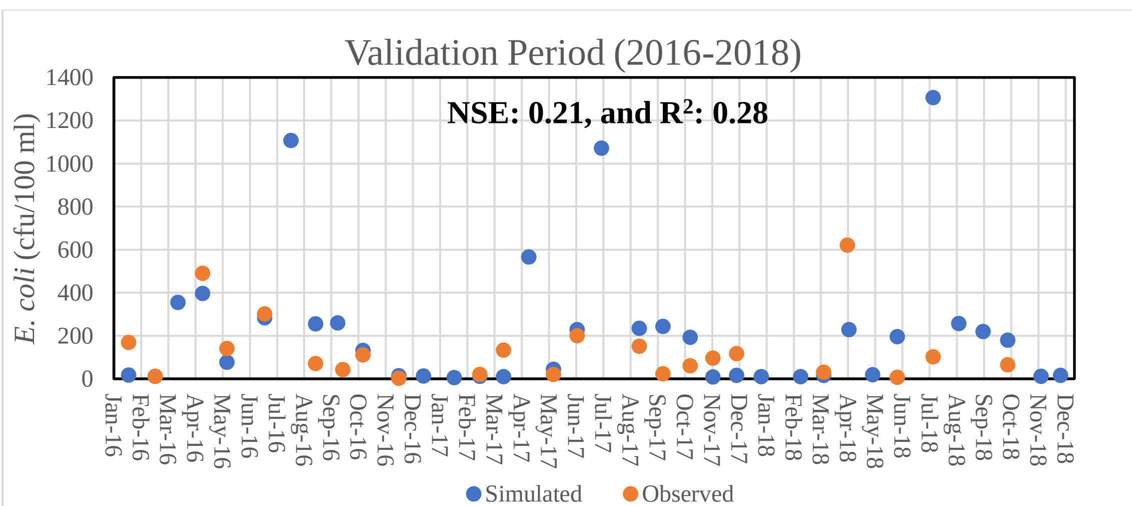


Figure 3- 10: *E. coli Validation at the Pike Creek Sampling Station*



Bacteria Calibration and Validation at the Puce River Sampling Station. Figure 3- 11 shows the calibration results from 2011 to 2015, and Figure 3- 12 shows the validation results from 2016 to 2018 at the Puce River sampling station (0.13< NSE <0.18, 0.16< R^2 <0.28). Puce River's seasonal variation for *E. coli* concentration was similar to that of Pike Creek. Summer season's *E. coli* concentration was observed higher (>200 cfu/100 ml) as compared to the other seasons except for in the year of 2018. The observed *E. coli* concentrations were low in summer 2018, and the model shows limitations to predict low concentration in summer 2018. High *E. coli* concentration was observed in 2012, 2014, and 2016 during summer season, and the model shows limitations to capture these peaks. *E. coli* concentrations above 200 cfu/100 ml were observed to be higher in fall 2012, 2013 and 2018; spring 2014, 2016 and 2018; and winter 2014, and 2015. The model was able to predict the seasonal variation of observed *E. coli* accurately for these years except some under predictions and over predictions for the unaccounted factors as described above.

Figure 3- 11: *E. coli Calibration at the Puce River Sampling Station*

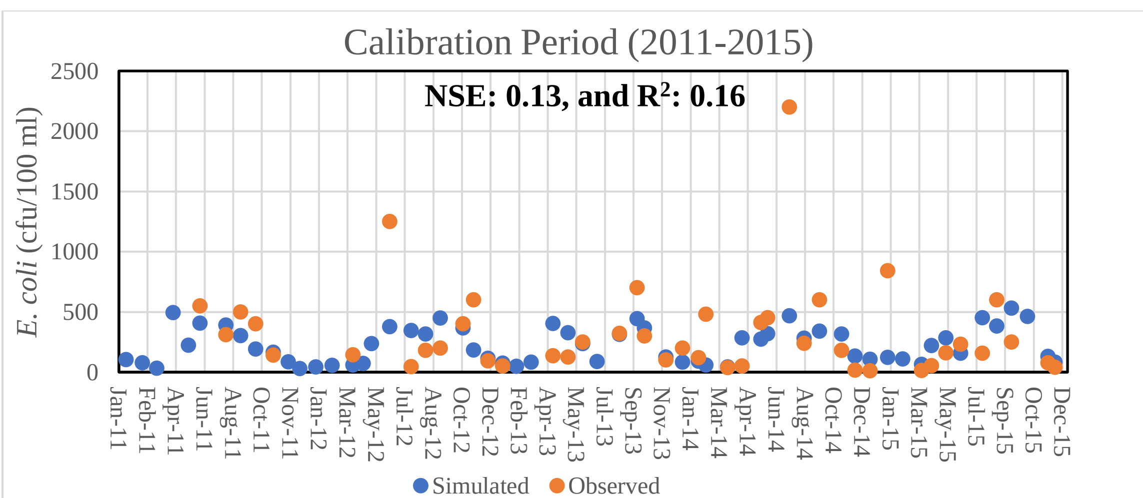
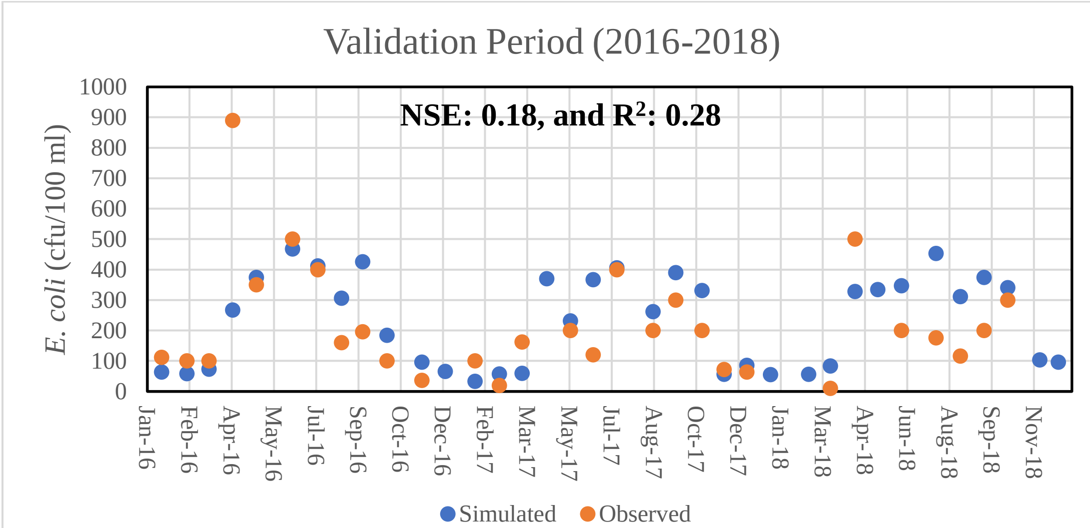


Figure 3- 12: *E. coli Validation at the Puce River Sampling Station*



Bacteria Calibration and Validation at the Belle River Sampling Station. Figures 3- 13 and 3- 14 show the calibration and validation results at the Belle River sampling station. The SWAT model was calibrated from 2011 to 2015 and validated from 2016 to 2018 (0.15< NSE <0.17, 0.18< R^2 <0.35). Unlike Pike Creek and Puce River, the Belle River watershed's observed *E. coli* concentration was higher during spring, fall and winter seasons as compared to summer season except for the years of 2011, 2014 and 2017 in which summer *E. coli* concentration was observed to be higher (Figures 3- 13 and 3- 14). There could be agricultural practice during winter and fall seasons that may influence these concentrations. The SWAT model's prediction of *E. coli* was relatively higher during summer and fall in the Belle River watershed. The possible reasons could be the application of loadings as discussed above.

Figure 3- 13: *E. coli Calibration at the Belle River Sampling Station*

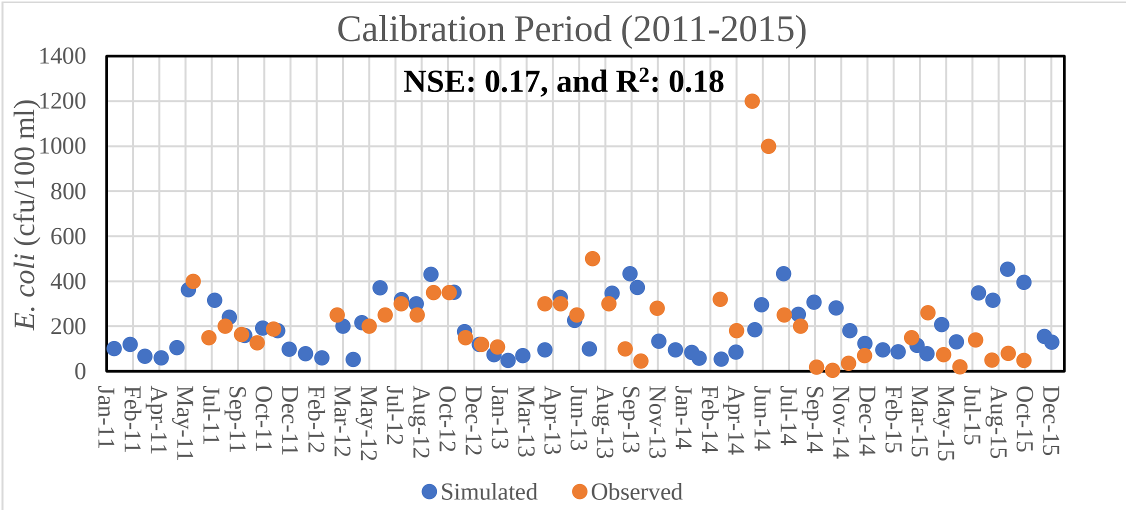
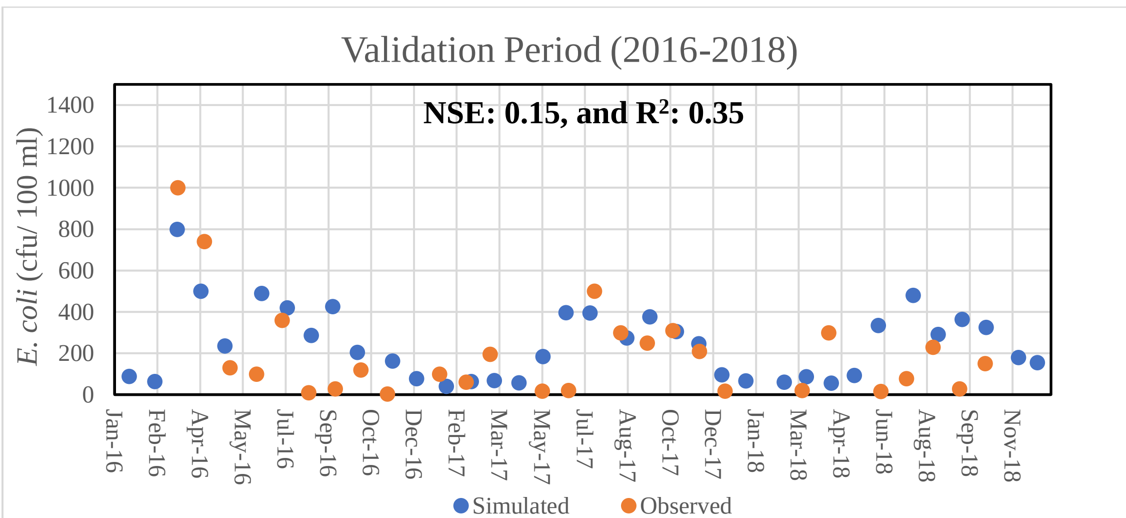


Figure 3- 14: *E. coli Validation at the Belle River Sampling Station*



Bacteria Calibration and Validation at the Duck Creek Sampling Station. The SWAT model was calibrated from 2011 to 2015 and validated from 2016 to 2018 at the Duck Creek sampling station (0.27 < NSE <0.41, 0.31< R^2 <0.42) as shown in Figures 3- 15 and 3- 16. For the Duck Creek watershed, summer season's *E. coli* concentration was found to be higher in 2011, 2012, 2013, 2014, and 2016 as compared to other seasons. For some months in 2011, 2013 and 2016, fall season's *E. coli* concentration was greater than

200 cfu/100 ml. Spring season's *E. coli* concentrations were observed to be higher than 200 cfu/ 100 ml in some months of 2014 and 2016. Winter season's *E. coli* concentration was found to be low from 2011 to 2018. The SWAT model was able to predict the seasonal variations except for some months that had higher predictions and others with low predictions due to some unaccountable factors as discussed above.

Figure 3- 15: *E. coli Calibration at the Duck Creek Sampling Station*

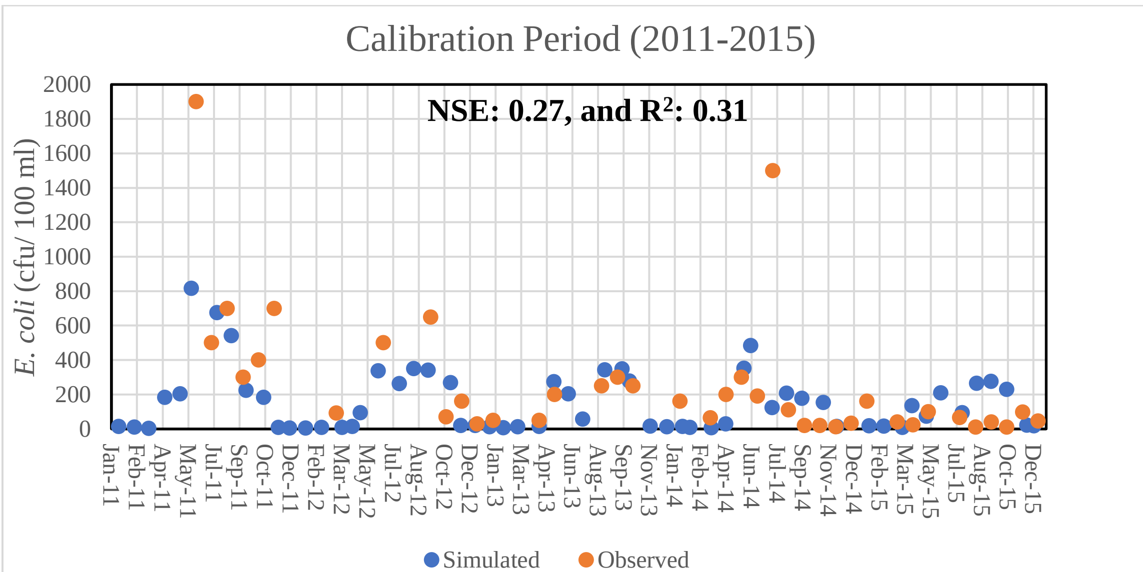
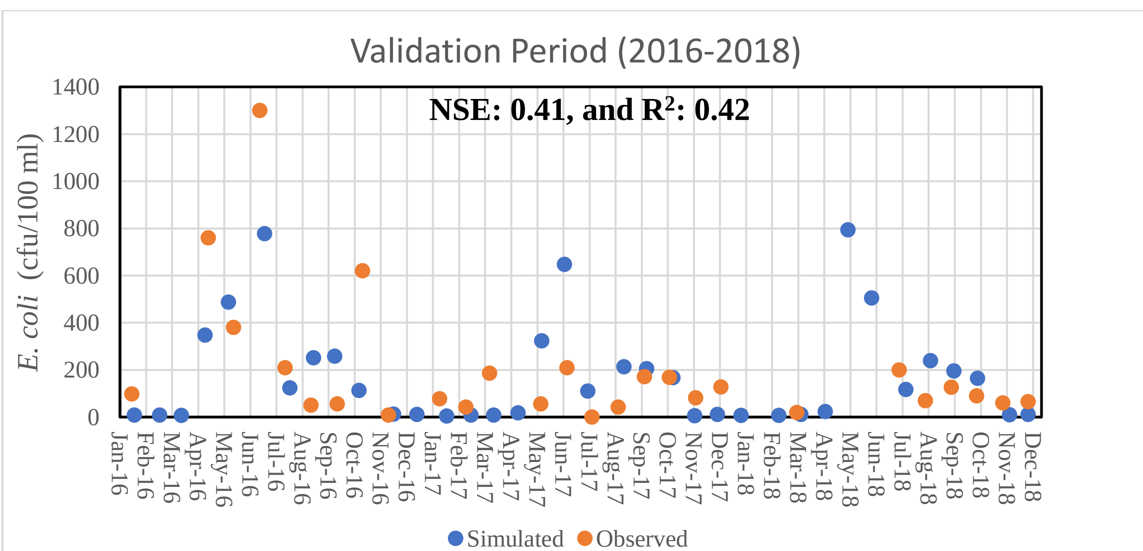


Figure 3- 16: *E. coli Validation at the Duck Creek Sampling Station*



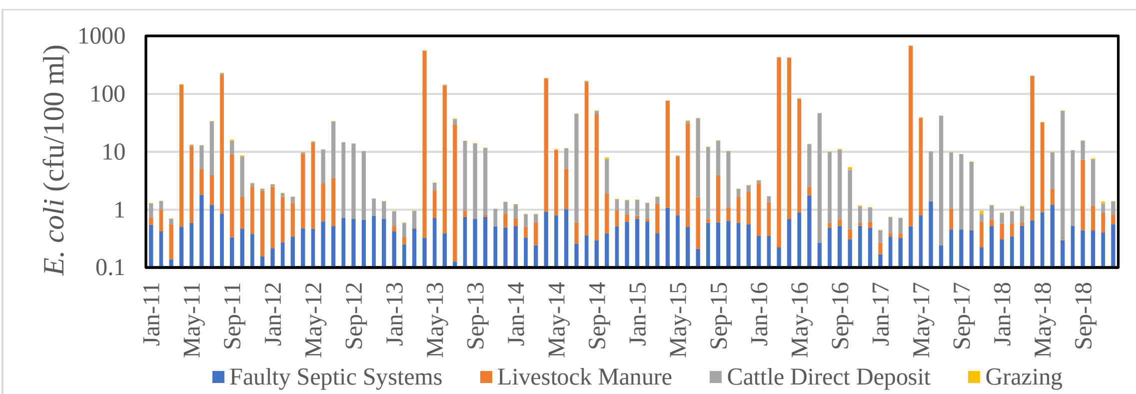
Contribution of the Contaminated Sources

In order to understand each of the non-point sources' contributions to the total *E. coli* concentrations in local subwatersheds, the SWAT model was simulated separately for each of the sources, and their share in the total concentration was calculated for the simulation period of January 2011 to December 2018 for the four major subwatersheds, including Pike Creek, Puce River, Belle River, and Ruscom River as depicted in Figures 3- 17 and 3- 18. The details of calculating each source's contribution for each of these local subwatersheds are provided in Appendix B. For the small subwatersheds including Duck Creek, Moison Creek, Stoney Point Drainage, and Little Creek, both the faulty septic systems in 30 m proximity of streams and direct cattle deposit were absent, and livestock manure was the contributing non-point source pollutant for these subwatersheds.

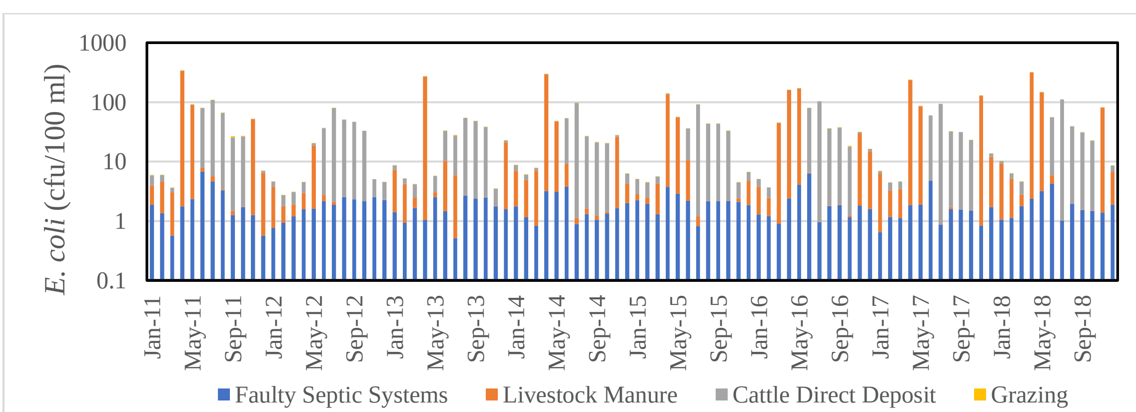
The monthly average *E. coli* concentration from livestock manure was the highest as compared to the other non-point sources. The maximum monthly average *E. coli* concentrations in Pike, Creek, Puck River, Belle River and Ruscom River were found to be 670, 336, 714, and 815 cfu/100 ml, respectively as depicted in Figure 3- 17. The contribution of livestock manure to the total *E. coli* concentrations for Pike Creek, Puce River, Belle River and Ruscom River were found to be 85%, 57%, 65%, and 59% as depicted in Figure 3- 18. The *E. coli* concentration was usually higher in the spring and summer seasons staring from April to June when the manure was applied. Both the cattle grazing and geese grazing had the lowest contribution to the simulated *E. coli* concentrations, and the maximum monthly average *E. coli* concentration was observed to be 3 cfu/100 ml in the Ruscom River subwatershed. The probable reason would be the application of a low number of loadings. The contribution from direct deposit of grazing cattle standing in the stream from June to October was found to be higher, and the maximum monthly average concentrations were found in the range of 50 to 203 cfu/100 ml in local subwatersheds. The contribution of cattle direct deposit to the total *E. coli* concentrations for the Pike Creek, Puce River, Belle River, and Ruscom River were found to be 14%, 39%, 32%, and 37%, respectively as depicted in Figure 3- 18. There were no *E. coli* loadings due to cattle direct deposit from January-May and November-December. The maximum monthly average *E. coli* concentration from faulty septic systems could range from 1.8 to 11 cfu/100 ml in local subwatersheds. Overall, the livestock manure was found to be the major non-point source pollutant for the Lake St. Clair region watershed.

Figure 3- 17: *Simulated E. coli Concentration from Each Non-Point Source Pollutant, a) Pike Creek, b) Puce River, c) Belle River, d) Ruscom River*

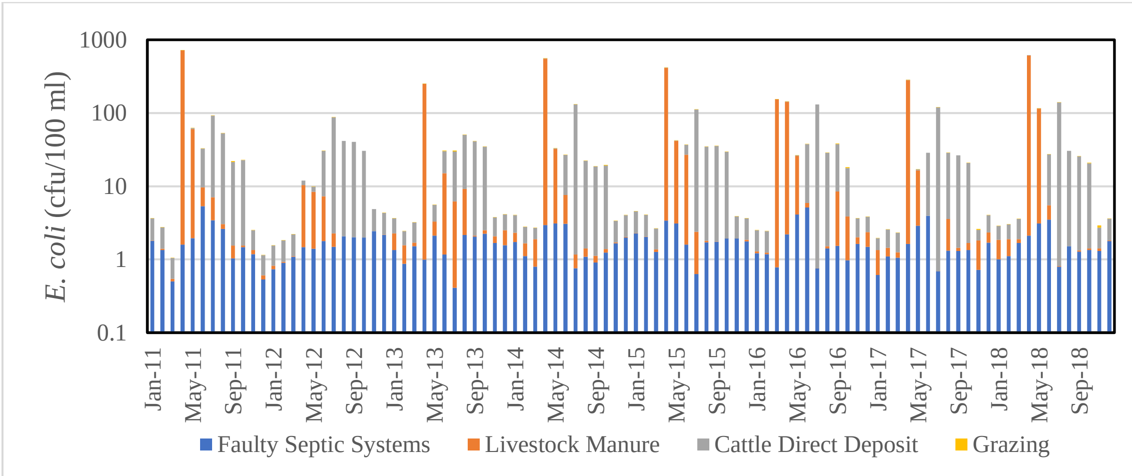
a)



b)



c)



d)

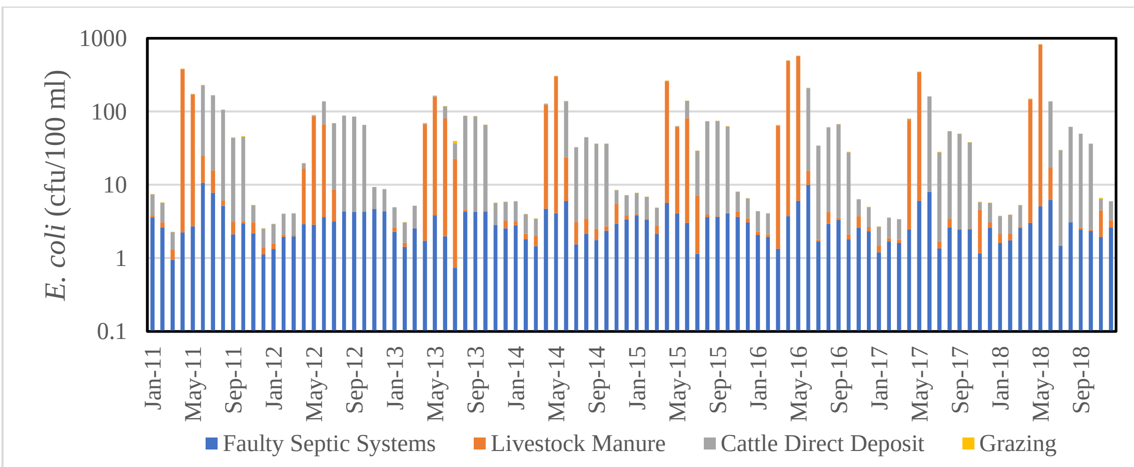
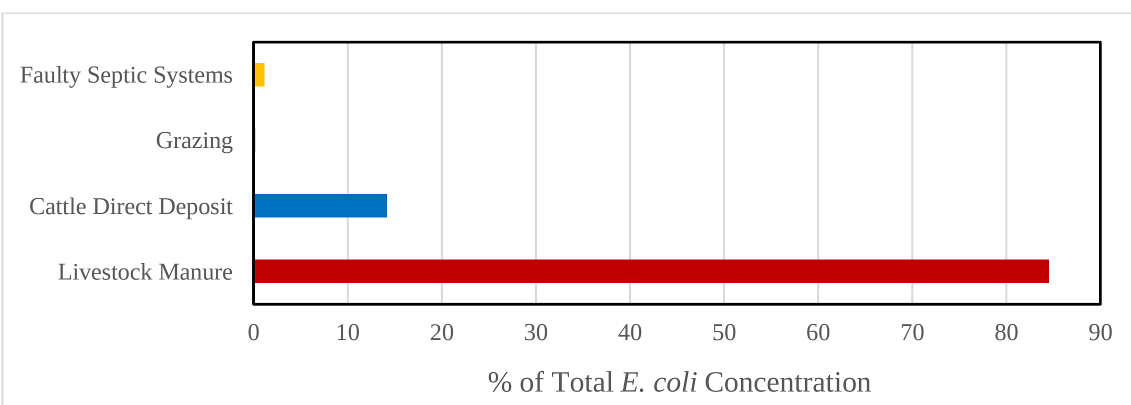
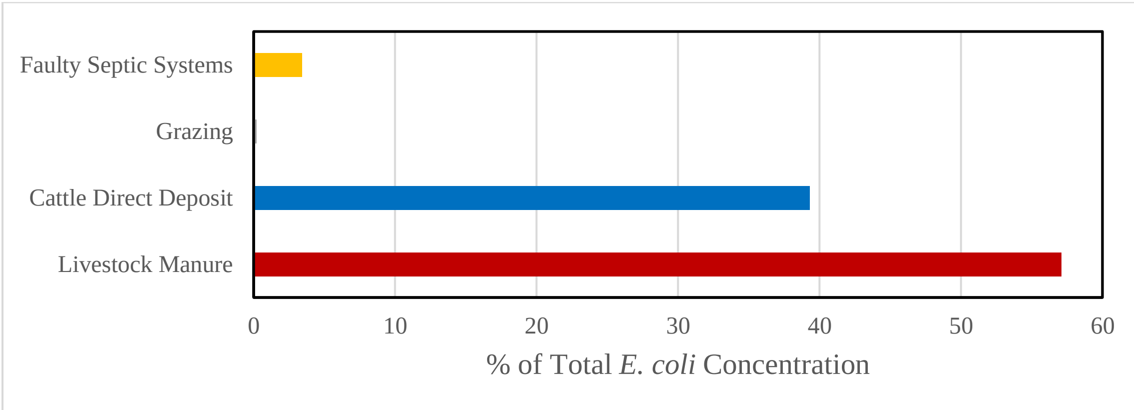


Figure 3- 18: *Contribution of Different Non-Point Source Pollutants to the Total E. coli Concentration, a) Pike Creek, b) Puce River, c) Belle River, d) Ruscom River*

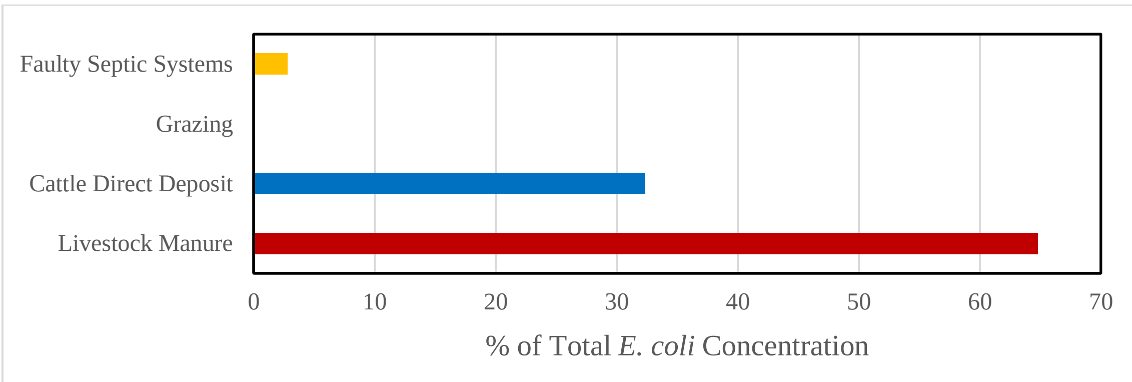
a)



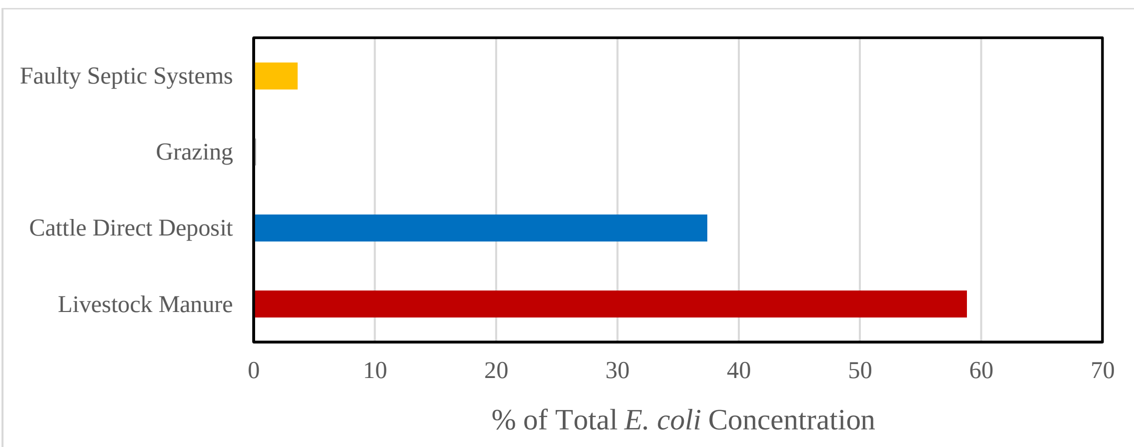
b)



c)



d)



Identification of Critical Source Areas

Figure 3- 19 shows the results of the SWAT model predicting seasonal *E. coli* concentration at the outlet of each subbasin in the Lake St. Clair region watershed. The

predicted monthly average *E. coli* concentration for the subbasins was low during winter, varying from 0-200 cfu/100 ml. Based on the simulation results, the higher *E. coli* concentration occurred where the surface runoff is higher as well as in areas where agricultural activities are higher and in the areas that are vulnerable due to the direct animal deposition. The *E. coli* concentration was found to be the highest in the Belle River watershed in all the seasons. In addition, the simulation results found that the predictions of the monthly average *E. coli* concentration routinely exceeded the recreational water quality guideline (200 cfu/100 ml) in the local streams including Pike Creek, Puce River, Belle River, and Ruscom River as depicted in Figure 3- 20.

Pike Creek. High spatial variability in seasonal *E. coli* concentration was observed in the Pike Creek subwatershed as depicted in Figure 3- 19. The concentration was lower than 50 cfu/100 ml during winter and in the range of 150-200 cfu/100 ml during fall. In spring, the predicted concentration was observed to be more than 200 cfu/100 ml in the upstream subbasins of this subwatershed. In summer, the concentration can vary from 400 to 1,200 cfu/100 ml in the subbasins located downstream of this subwatershed. Overall, the monthly average concentration in the downstream subbasin was predicted in the range of 400 to 500 cfu/ 100 ml and identified as critical as compared to the upstream subbasins as depicted in Figure 3- 20.

Puce River. As per the spatial distribution of *E. coli* concentration on a seasonal basis (Figure 3- 19), winter's *E. coli* concentration was lower than the other seasons. In the upstream subbasins, the concentration varied from 300-600 cfu/100 ml during spring and fall seasons, and 600 to 1,000 cfu/100 ml during summer (Figure 3- 19). The major portion of the watershed was identified to be impaired since the monthly average *E. coli* concentration was higher than the recreational water quality guideline (200 cfu/100 ml) as depicted in Figure 3- 20.

Belle River. In the Belle River subwatersehd, higher spatial variability was observed on a seasonal basis as compared to the other subwatersheds. The downstream subbasins were observed to be more impaired than upstream subbasins in all four seasons. The winter concentration was observed to be low, and the summer season's *E. coli* could be as high as 1,200 cfu/100 ml. The fall and summer seasons' *E. coli* concentrations were observed from 200 to 700 cfu/100 ml. The monthly *E. coli* concentration (Figure 3- 20) shows that all the subbasins of the Belle River subwatershed were found to be impaired since the spatial variations of the monthly average *E. coli* concentration were exceeded both the recreational water quality guide and PWQO (100 cfu/100 ml).

Ruscom River. Unlike Pike Creek, Puce River, and Belle River subwatersheds, the seasonal *E. coli* concentration for the major part of Ruscom River watershed was comparatively lower as depicted in Figure 3- 19. The winter *E. coli* concentration was lower than 50 cfu/100 ml in all the subbasins. The spring *E. coli* concentration was predicted to be in the range of 200-800 cfu/100 ml in the middle and upstream subbasins. During fall, *E. coli* concentration varied from 0-400 cfu/100 ml. A major part of the watershed's *E. coli* concentration ranged from 0-200 during fall and 200-400 during summer. A small portion of the watershed located in the middle of the subwatershed had *E. coli* concentration in the range of 200 to 400 cfu/100 ml in spring and 600 to 1,200 cfu/ 100 ml in summer. The monthly average *E. coli* concentration was lower than 200 cfu/100 ml for a major portion of the subwatershed as shown in Figure 3- 20. Only a small portion of the watershed had monthly average *E. coli* concentration that varied from 300 to 600 cfu/100 ml.

Duck Creek, Moison Creek, Stoney Point Drainage and Little Creek. According to Figure 3- 19, the winter and fall seasons' *E. coli* concentration for Duck, Moison and Little Creeks, and Stoney Point Drainage area was lower than 100 cfu/100 ml. In spring, the *E. coli* concentration was found to be lower than 100 cfu/ 100 ml for Duck Creek and Stoney Point drainage, in the range of 101 to 200 cfu/100 ml for Little Creek, and 201 to 300 cfu/100 ml in Moison Creek. In summer, the *E. coli* concentration was lower than 200 cfu/100 ml for these subwatersheds. The monthly average *E. coli* concentration was lower than 100 cfu/100 ml as shown in Figure 3- 20. The possible reasons would be lower agricultural activities, the absence of direct animal deposit, and faulty septic systems in 30 m proximity of local streams.

Figure 3- 19: *Seasonal Spatial Distribution of the E. coli Concentrations at Each of the Subbasins, a) Spring, b) Summer, c) Fall, d) Winter*

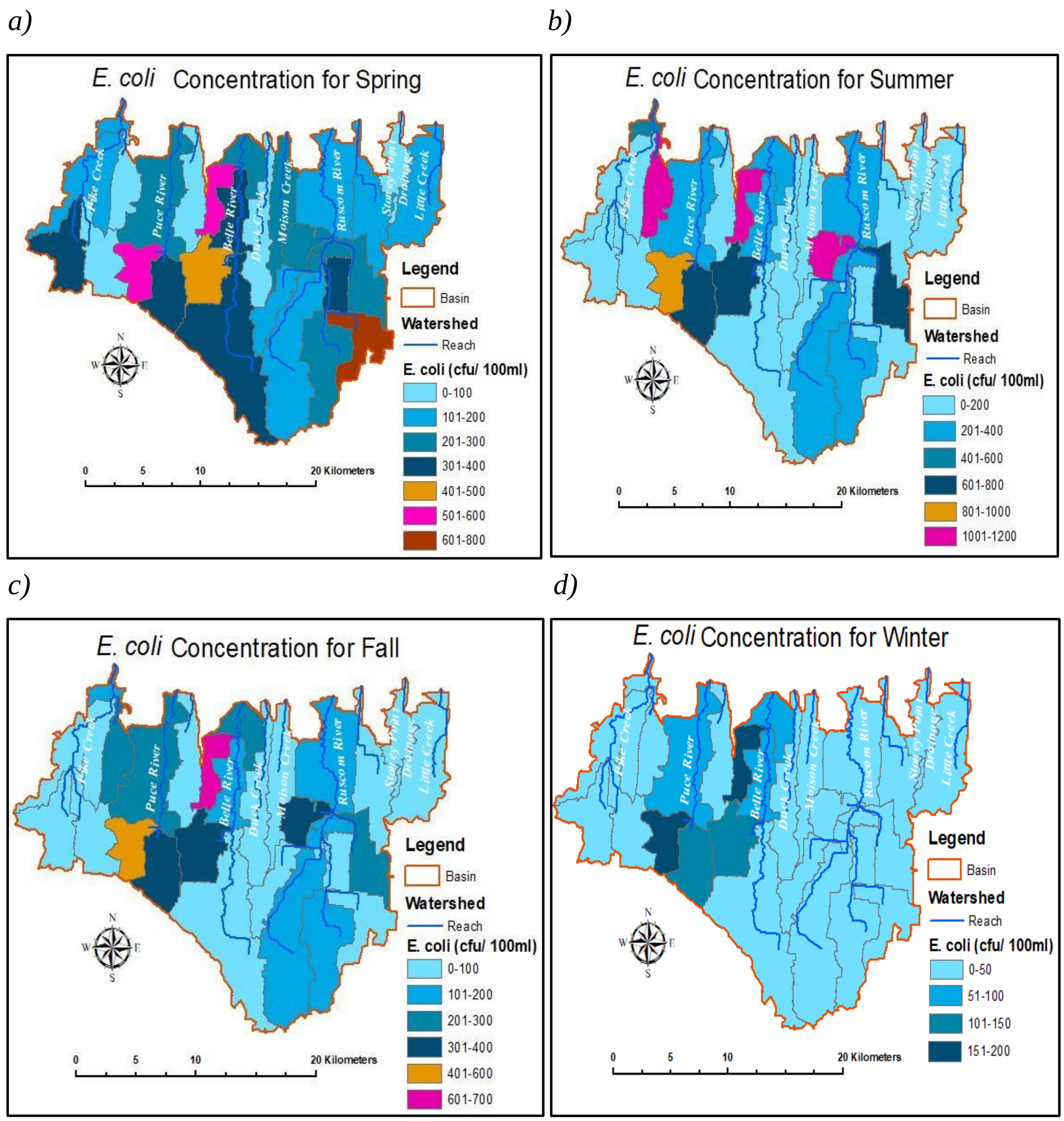
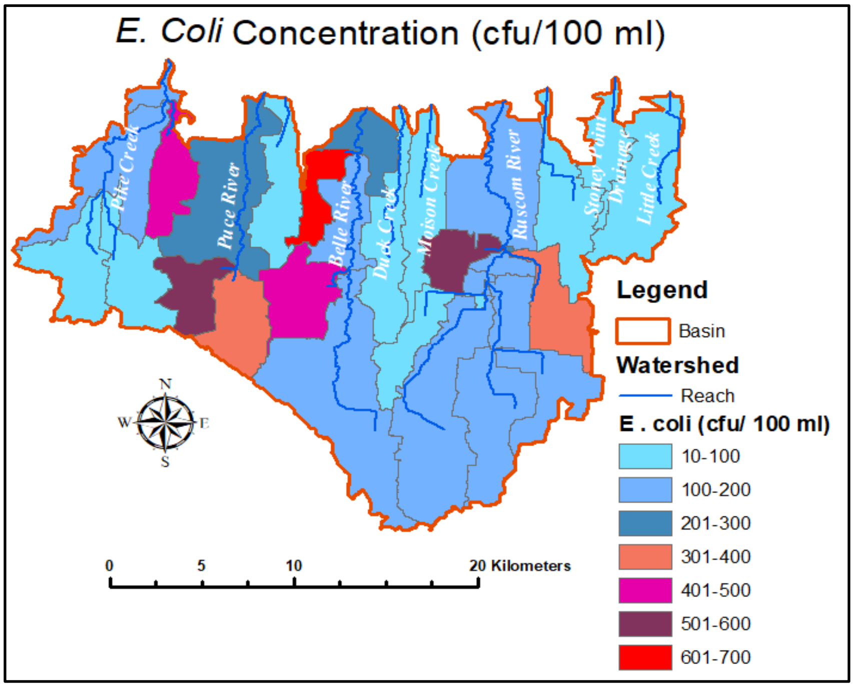


Figure 3- 20: *Spatial Distribution of the Monthly Average E. coli Concentrations at Each of the Subbasins*



Conclusions

The application of the SWAT model to the Essex region's Lake St. Clair watershed represents perhaps the first qualitative modelling approach to identify bacterial risk spatially for this watershed. Monthly mean *E. coli* data was used to calibrate and validate the model on a monthly basis at five sampling locations including the Ruscom River PWQMN station, and Pike Creek, Puce River, Belle River and Duck Creek sampling stations. At the Ruscom River PQWMN station, the model provides a "good" prediction of *E. coli* (E = 0.74) for the calibration period of April 2014 to November 2015. For the other four sampling stations, the model efficiency (0.13 < E < 0.46) compared favourably with many other similar pathogen modelling studies for the calibration period of 2011 to 2015. The model was able to simulate the seasonal variation of *E. coli* concentration accurately at these sampling stations except some incidents of under prediction and over prediction. In addition, each of the non-point sources' contribution to the total *E. coli* concentration was evaluated in the Pike Creek, Puce River, Belle River, and Ruscom River subwatersheds, and the contribution from livestock manure was found to be the highest (>55%) compared with other non-point source pollutants including cattle direct deposit, faulty septic systems, and animal grazing. For the Duck Creek, Moison Creek, Stoney Point Drainage, and Little Creek subwatersheds, livestock manure was the major non-point source pollutant due to the absence of faulty septic systems and cattle direct deposit.

The spatial distribution of seasonal *E. coli* concentration results show that summer season's *E. coli* concentration was observed to be the highest, and the monthly *E. coli* concentration range was 1,001-1,200 cfu/100 ml at the downstream of Pike Creek, Belle River, and in a small portion of the watershed located at the middle of the Ruscom River subwatershed. In spring, downstream of Belle River had the highest *E. coli* concentration in the range of 601 to 700 cfu/100 ml, and the concentration was 601 to 800 cfu/100 ml in fall. In winter, the monthly average *E. coli* concentration was lower than 200 cfu/100 ml in all the subbasins.

The Belle River subwatershed was identified as the most impaired watershed compared to other local subwatersheds where the monthly average *E. coli* concentration varied from 201 to 601 cfu/100 ml. Furthermore, higher monthly average *E. coli* concentrations were observed in the subbasins located downstream of Pike Creek and upstream of Puce River. For the subwatersheds of Duck Creek, Moison Creek, Stoney Point area, and Little Creek, monthly average *E. coli* concentrations were found to be lower than the PQWO (100 cfu/100 ml). The possible reasons would be fewer agricultural activities and the absence of discharge from cattle's direct deposit and faulty septic systems in 30 m proximity. For the Ruscom River subwatershed, a major portion of the subwatershed's monthly average *E. coli* concentration was lower than the recreational water quality guideline (200 cfu/100 ml) but higher than the PWQO (100 cfu/100 ml).

The monthly average *E. coli* concentration ranges from 10-700 cfu/100 ml at various points located at the near shore regions discharging to Lake St. Clair. Additionally, more reliable watershed input for non-point source pollutants with respect to manure application, animal grazing, faulty septic systems, and direct animal deposition could improve the model prediction. The simulation results reveal that the subwatersheds located on the western side of the Lake St. Clair region watershed have comparatively higher *E. coli* concentrations than the subwatersheds located on the eastern side of the watershed. The outputs of the model should be used to drive best management practices.

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Chapter 4:

Conclusions and Recommendations

Conclusions

The application of the SWAT model to the Essex region's Lake St. Clair watershed represents the quantitative and qualitative identification that explains the water budget analysis and bacterial risk spatially. In Chapter 2, the SWAT hydrologic model was calibrated and validated on a daily time step using the Ruscom River gauge station. For the calibration period from 2003 to 2010, the NSE, R^2, RSR, and KGE were observed to be 0.6 to 0.70 and PBIAS -4.5. For the validation period from 2011 to 2018, the NSE, R^2, RSR, and KGE were observed to be 0.57 to 0.65, and PBIAS -24.61. The predicted streamflow highly corresponded with the monitored data on a daily basis. The calibrated parameters were transferred to the neighbouring ungauged watersheds using the parameter regionalization approach to analyze the major components of water budget for each individual subbasin. The average annual evapotranspiration is 59% of precipitation and the surface runoff contributes 71% of the total water yield as compared to tile drainge (9%) and baseflow (18%) for the Lake St. Clair region watershed. The water budget analysis results are in line with the previous water budget analysis report in the Essex region and are considered reasonable at this time. The local subwatershed based water budget analysis for Pike Creek, Puce River, Belle River, Ruscom River and Little Creek identified increments in the water budget components as compared to previous water budget studies. The annual average increments of 11% and 23% were observed for evapotranspiration and surface runoff, respectively.

This annual water budget helps in understanding the water movement spatially for each of the subbasins which satisfies the main objective of Chapter 2. The water budget analysis results indicated that the subbasins located in the eastern portion of the watershed have relatively low evapotranspiration and high water yield compared to the watersheds located on the western side of the study area.

In Chapter 3, the fate and transport model was calibrated at five sampling locations on monthly basis including the Ruscom River PWQMN station, and Pike Creek, Puce River, Belle River, and Duck Creek sampling stations. The model provides a “good” prediction of *E. coli* (E = 0.74) at the Ruscom River PQWMN station during the calibration process. For the other four sampling stations, the model efficiency ($0.13 < E < 0.46$) compared favourably with many other similar pathogen modelling studies. The summer season’s *E. coli* concentration was observed highest and the monthly average *E. coli* concentration range was 1,001-1,200 cfu/100 ml at the downstream of Pike Creek and Belle River, and a small portion of the watershed located in the middle of the Ruscom River subwatershed. In spring and fall, downstream of Belle River’s *E. coli* concentration was highest (601 to 800 cfu/100 ml) as compared to other subwatersheds. Winter season’s monthly average *E. coli* concentration was lower than 200 cfu/100 ml for this Lake St. Clair subwatershed. Four different non-point source pollutants were considered to simulate the *E. coli* concentrations, including faulty septic systems, cattle direct deposit, livestock manure, and animal grazing, of which the livestock manure was found to be the highest (>55%) contributor to the simulated *E. coli* concentration for the local subwatersheds of the Lake St. Clair region. The predicted monthly average *E. coli* concentrations in the local streams range from 10 to 700 cfu/100 in the upstream of local streams, and 10-500 cfu/100 ml at various outlets. The outlets of Pike Creek, Puce River, and Belle River have higher *E. coli* concentrations (>200 cfu/100 ml) than other watershed outlets. The Belle River subwatershed was found to be the most impaired watershed when compared to the other local subwatersheds. In addition, the subwatersheds located in the western portion of the watershed (Pike Creek, Puck River, and Belle River) are more impaired due to the non-point source pollutant as compared to the subwatersheds located in the eastern portion of the watershed (Duck Creek, Moison Creek, Ruscom River, Stoney Point drainage, and Little Creek). A small portion of the Ruscom River subwatershed (Subbasins 12 and 25) encountered higher *E. coli* concentration (400-600 cfu/100 ml) as compared to the upstream and downstream subbasins. These higher concentrations of *E. coli* would incorporate higher level of *E. coli* at the near shore beaches. The SWAT hydrologic and pathogen transport model's results are considered reasonable and useful at this time.

Overall, one of the greatest benefits from this research is identifying the critical subwatersheds for bacterial risk which can be used for future research for the best management practices.

Recommendations for Future Work

This study was performed with one climate station, located outside the study area boundary. Improvements can be made by the establishment of more climate stations within the Lake St. Clair subwatersheds to capture localized precipitation variations, which will improve the model prediction. Additionally, installation of gauge stations at the local streams will reduce uncertainties. In this study, the Ruscom River flow station was used to calibrate the model and the calibrated parameters were transferred to the other ungauged subwatersheds as a parameter regionalization approach. Installation of gauge stations to the other subwatersheds would help to calibrate those subwatersheds.

The calibrated parameters can be used for future climate and land use change impact and assessment of various water quality parameters (i.e., sediment, nutrient, and phosphorus). The identification of critical subwatersheds is essential to control the microbial pollution by providing best management practices. This calibrated model can be used for the future research on best management practices.

To improve the simulation results for the pathogen model, reliable input data with respect to the land management practices spatially (crop rotation, time and rates for manure applications, and animal grazing), direct deposition from wildlife and livestock, and accurate information for the effluent from failing septic systems are required. In addition, long-term continuous water quality monitoring data at the outlet of local streams will help the calibration process.

Appendix

Appendix A: Supplementary Information for Chapter 2

Table A1: *Seasonal Water Budget Major Components (2003 to 2018)*

Season --------- Year	Precipitation [mm]	Evapotranspiration [mm (%P)]	Total Water Yield [mm (%P)]	Water Yield Component Surface Runoff [mm (%Q)]	Tile Drainage Flow [mm (%Q)]	Baseflow [mm (%Q)]
Winter						
2003	221	54 (24)	145 (65)	106 (73)	14 (10)	23 (16)
2004	282	57 (20)	165 (58)	115 (69)	33 (20)	16 (9)
2005	324	44 (13)	250 (77)	198 (79)	20 (8)	31 (12)
2006	341	71 (21)	240 (70)	153 (63)	58 (24)	28 (11)
2007	332	62 (18)	232 (70)	165 (71)	32 (13)	34 (15)
2008	56	4 (7)	10 (18)	0 (0)	0 (0)	10 (99)
2009	332	63 (19)	251 (75)	208 (82)	12 (5)	30 (12)
2010	165	70 (42)	88 (53)	54 (62)	11 (12)	21 (24)
2011	364	51 (14)	332 (91)	241 (72)	40 (12)	51 (15)
2012	277	99 (35)	126 (45)	78 (62)	13 (10)	33 (26)
2013	276	53 (19)	193 (70)	157 (81)	11 (5)	25 (13)
2014	226	44 (19)	177 (78)	148 (83)	2 (1)	26 (14)
2015	226	61 (27)	139 (61)	107 (77)	7 (5)	23 (17)
2016	349	68 (19)	216 (62)	170 (78)	23 (10)	22 (10)
2017	294	57 (19)	172 (58)	129 (74)	19 (11)	23 (13)
2018	283	67 (23)	232 (82)	190 (82)	15 (6)	25 (10)
Average	**272**	**58 (21)**	**185 (68)**	**139 (74)**	**19 (10)**	**26 (14)**
Spring						
2003	209	122 (58)	64 (30)	51 (79)	7 (11)	5 (8)
2004	215	119 (55)	87 (40)	64 (73)	11 (13)	11 (13)
2005	118	115 (98)	28 (24)	14 (49)	1 (5)	12 (44)
2006	182	134 (74)	43 (23)	23 (54)	7 (17)	12 (28)
2007	155	136 (87)	46 (30)	30 (65)	1 (2)	14 (31)
2008	109	129 (118)	33 (30)	8 (25)	7 (22)	17 (52)
2009	207	144 (69)	70 (34)	49 (70)	6 (9)	13 (19)
2010	218	146 (67)	74 (34)	57 (77)	6 (8)	10 (14)

Season --------- Year	Precipitation [mm]	Evapotranspiration [mm (%P)]	Total Water Yield [mm (%P)]	Water Yield Component		
				Surface Runoff [mm (%Q)]	Tile Drainage Flow [mm (%Q)]	Baseflow [mm (%Q)]
2011	335	127 (38)	174 (52)	138 (79)	26 (15)	9 (5)
2012	135	138 (103)	24 (18)	6 (27)	0 (0)	17 (72)
2013	206	114 (55)	74 (36)	48 (65)	14 (19)	11 (15)
2014	227	131 (58)	90 (39)	69 (76)	12 (13)	8 (9)
2015	222	134 (60)	53 (23)	56 (106)	1 (2)	0 (0)
2016	133	123 (93)	51 (38)	22 (43)	11 (22)	17 (34)
2017	194	145 (75)	83 (42)	49 (59)	10 (12)	23 (28)
2018	262	127 (48)	131 (50)	100 (76)	16 (12)	14 (10)
Average	**195**	**130 (66)**	**70 (36)**	**49 (69)**	**9 (12)**	**12 (17)**
Summer						
2003	247	299 (121)	30 (12)	8 (27)	0 (0)	22 (72)
2004	336	383 (113)	53 (15)	31 (57)	1 (2)	21 (39)
2005	245	266 (108)	24 (10)	5 (20)	0 (0)	19 (79)
2006	415	387 (93)	65 (15)	44 (67)	0 (0)	21 (32)
2007	370	357 (96)	57 (15)	33 (57)	1 (1)	23 (40)
2008	402	314 (78)	102 (25)	71 (70)	6 (6)	23 (23)
2009	291	323 (111)	42 (14)	18 (43)	0 (0)	23 (56)
2010	370	341 (92)	58 (15)	38 (65)	1 (2)	18 (31)
2011	576	401 (69)	154 (26)	123 (79)	11 (7)	20 (13)
2012	286	337 (118)	41 (14)	16 (38)	0 (0)	25 (61)
2013	535	366 (68)	219 (41)	184 (83)	13 (5)	22 (10)
2014	465	381 (82)	109 (23)	82 (75)	3 (2)	23 (21)
2015	431	393 (91)	137 (31)	94 (69)	7 (5)	35 (25)
2016	403	326 (81)	46 (11)	33 (72)	0 (0)	12 (26)
2017	298	327 (109)	44 (14)	19 (43)	0 (0)	25 (56)
2018	274	299 (109)	35 (12)	11 (32)	0 (0)	23 (67)
Average	**371**	**344 (92)**	**76 (20)**	**51 (66)**	**2 (3)**	**22 (29)**
Fall						
2003	144	72 (50)	19 (13)	9 (49)	0 (4)	8 (45)
2004	157	58 (37)	17 (11)	6 (34)	0 (3)	10 (62)
2005	110	49 (45)	14 (13)	3 (25)	0 (0)	10 (74)
2006	212	72 (34)	75 (35)	56 (74)	11 (15)	7 (10)
2007	129	60 (47)	21 (16)	7 (37)	0 (3)	12 (58)

Season --------- Year	Precipitation [mm]	Evapotranspiration [mm (%P)]	Total Water Yield [mm (%P)]	Water Yield Component		
				Surface Runoff [mm (%Q)]	Tile Drainage Flow [mm (%Q)]	Baseflow [mm (%Q)]
2008	138	60 (43)	29 (21)	17 (58)	1 (4)	11 (37)
2009	118	68 (57)	18 (15)	5 (28)	0 (0)	12 (70)
2010	151	69 (46)	29 (19)	19 (65)	2 (6)	8 (27)
2011	293	77 (26)	169 (57)	155 (91)	18 (10)	0 (0)
2012	84	55 (65)	14 (17)	1 (7)	0 (0)	13 (92)
2013	131	69 (53)	20 (15)	6 (33)	0 (2)	13 (63)
2014	140	74 (53)	34 (24)	19 (56)	2 (6)	12 (37)
2015	135	65 (48)	16 (12)	5 (33)	0 (2)	10 (64)
2016	142	76 (54)	59 (42)	30 (51)	8 (14)	20 (34)
2017	227	60 (26)	84 (37)	60 (71)	9 (11)	14 (16)
2018	173	65 (37)	44 (25)	28 (63)	2 (6)	13 (30)
Average	**155**	**66 (42)**	**41 (26)**	**2764)**	**3 (8)**	**11 (26)**

Appendix B: Supplementary Information for Chapter 3

Table B1: *Estimation of Effluent from Faulty Septic systems from Each of the Subbasins*

Subbasin ID	Septic tank within 30m distance of stream	Average Number of Inhabitants per dwelling	Total number of Inhabitants contributing to septic system	Average Residential Water use l/cap/day	Effluent Discharge m^3/day	Failing Septic System, 20%
1	0	0.0	0.0	0.0	0.0	0.0
2	0	0.0	0.0	0.0	0.0	0.0
3	5	2.7	13.5	160	2.2	1.1
4	3	2.7	8.1	160	1.3	0.6
5	2	2.7	5.4	160	0.9	0.4
6	4	2.7	10.8	160	1.7	0.9
7	25	2.7	67.5	160	10.8	5.4
8	0	0.0	0.0	0.0	0.0	0.0
9	0	0.0	0.0	0.0	0.0	0.0
10	0	0.0	0.0	160	0.0	0.0
11	5	2.7	13.5	160	2.2	1.1
12	2	2.7	5.4	160	0.9	0.4
13	2	2.7	5.4	160	0.9	0.4
14	0	0.0	0.0	0.0	0.0	0.0
15	0	0.0	0.0	0.0	0.0	0.0
16	0	0.0	0.0	0.0	0.0	0.0
17	6	2.7	16.2	160	2.6	1.3
18	2	2.7	5.4	160	0.9	0.4
19	2	2.7	5.4	160	0.9	0.4
20	1	2.7	2.7	160	0.4	0.2
21	1	2.7	2.7	160	0.4	0.2
22	0	2.7	0	160	0.0	0.0
23	2	2.7	5.4	160	0.9	0.4
24	0	0.0	0	0.0	0.0	0.0
25	4	2.7	10.8	160	1.7	0.9
26	0	0.0	0	0.0	0.0	0.0
27	0	0.0	0.0	0.0	0.0	0.0
28	0	0.0	0.0	0.0	0.0	0.0
29	1	2.7	2.7	160	0.4	0.2
30	6	2.7	16.2	160	2.6	1.3
31	16	2.7	43.2	160	6.9	3.5

Table B2: *Percentage of each Non-Point Source's Contribution to the Total Concentrations in the Pike Creek Subwatershed*

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Jan-11	0.55	0.19	0.55	0.00	1.28
Feb-11	0.42	0.57	0.42	0.00	1.42
Mar-11	0.14	0.42	0.14	0.01	0.71
Apr-11	0.51	143.27	0.51	0.03	144.31
May-11	0.59	11.92	0.62	0.02	13.15
Jun-11	1.81	3.21	7.75	0.15	12.91
Jul-11	1.20	2.69	29.46	0.28	33.63
Aug-11	0.85	211.47	16.28	0.01	228.61
Sep-11	0.33	8.71	6.40	0.64	16.07
Oct-11	0.47	1.20	6.70	0.32	8.70
Nov-11	0.38	2.09	0.38	0.03	2.87
Dec-11	0.16	1.96	0.16	0.00	2.28
Jan-12	0.22	2.27	0.22	0.00	2.71
Feb-12	0.27	1.38	0.27	0.00	1.93
Mar-12	0.34	0.97	0.34	0.00	1.65
Apr-12	0.47	8.75	0.47	0.00	9.70
May-12	0.46	14.02	0.49	0.00	14.98
Jun-12	0.63	2.21	8.05	0.02	10.91
Jul-12	0.52	2.98	30.00	0.13	33.64
Aug-12	0.73	0.00	13.89	0.00	14.62
Sep-12	0.69	0.00	13.11	0.00	13.80
Oct-12	0.67	0.00	9.52	0.00	10.19
Nov-12	0.78	0.00	0.78	0.00	1.55
Dec-12	0.69	0.00	0.69	0.00	1.38
Jan-13	0.42	0.10	0.42	0.01	0.94
Feb-13	0.25	0.08	0.25	0.00	0.59
Mar-13	0.47	0.01	0.47	0.00	0.95
Apr-13	0.32	557.70	0.32	0.00	558.35
May-13	0.71	1.41	0.76	0.00	2.89
Jun-13	0.39	136.19	5.02	0.74	142.35
Jul-13	0.13	29.23	7.26	0.78	37.41
Aug-13	0.75	0.21	14.32	0.00	15.29
Sep-13	0.69	0.00	13.16	0.00	13.86
Oct-13	0.75	0.06	10.73	0.05	11.59
Nov-13	0.51	0.00	0.51	0.00	1.03
Dec-13	0.49	0.36	0.49	0.01	1.35
Jan-14	0.52	0.19	0.52	0.00	1.23
Feb-14	0.33	0.18	0.33	0.00	0.84
Mar-14	0.24	0.35	0.24	0.01	0.84

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Apr-14	0.92	183.42	0.92	0.00	185.26
May-14	0.80	9.80	0.13	0.40	11.13
Jun-14	1.02	4.02	6.37	0.16	11.57
Jul-14	0.26	0.35	44.38	0.01	44.99
Aug-14	0.36	159.21	6.85	0.01	166.42
Sep-14	0.29	44.59	5.57	0.07	50.52
Oct-14	0.39	1.50	5.54	0.49	7.93
Nov-14	0.51	0.47	0.51	0.03	1.53
Dec-14	0.61	0.22	0.61	0.00	1.45
Jan-15	0.70	0.08	0.70	0.00	1.48
Feb-15	0.62	0.07	0.62	0.00	1.31
Mar-15	0.39	0.88	0.39	0.01	1.67
Apr-15	1.08	74.40	1.08	0.01	76.57
May-15	0.80	7.55	0.17	0.01	8.54
Jun-15	0.50	30.39	3.11	0.60	34.59
Jul-15	0.21	1.43	36.35	0.38	38.36
Aug-15	0.59	0.11	11.30	0.02	12.01
Sep-15	0.61	3.27	11.58	0.00	15.46
Oct-15	0.64	0.47	9.07	0.01	10.19
Nov-15	0.59	1.07	0.59	0.00	2.26
Dec-15	0.55	1.52	0.55	0.00	2.63
Jan-16	0.35	2.50	0.35	0.00	3.21
Feb-16	0.35	0.99	0.35	0.00	1.69
Mar-16	0.22	422.56	0.22	0.00	423.00
Apr-16	0.69	418.06	0.69	0.00	419.44
May-16	0.90	81.66	0.18	0.00	82.74
Jun-16	1.77	0.73	11.04	0.04	13.58
Jul-16	0.27	0.00	46.25	0.00	46.52
Aug-16	0.49	0.10	9.32	0.00	9.92
Sep-16	0.53	0.14	10.12	0.31	11.10
Oct-16	0.31	0.15	4.41	0.52	5.39
Nov-16	0.53	0.07	0.53	0.06	1.18
Dec-16	0.48	0.13	0.48	0.01	1.10
Jan-17	0.17	0.10	0.17	0.01	0.44
Feb-17	0.34	0.05	0.34	0.00	0.74
Mar-17	0.32	0.07	0.32	0.00	0.72
Apr-17	0.52	670.74	0.52	0.00	671.78
May-17	0.80	37.71	0.14	0.00	38.65
Jun-17	1.39	0.00	8.63	0.00	10.02
Jul-17	0.24	0.00	41.75	0.00	41.99
Aug-17	0.45	0.58	8.67	0.02	9.72
Sep-17	0.45	0.00	8.60	0.00	9.05
Oct-17	0.44	0.01	6.27	0.02	6.74

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Nov-17	0.22	0.40	0.22	0.12	0.96
Dec-17	0.52	0.15	0.52	0.00	1.20
Jan-18	0.30	0.26	0.30	0.01	0.88
Feb-18	0.35	0.24	0.35	0.00	0.94
Mar-18	0.53	0.07	0.53	0.00	1.13
Apr-18	0.65	202.01	0.65	0.00	203.31
May-18	0.90	31.13	0.08	0.56	32.67
Jun-18	1.20	1.07	7.48	0.03	9.77
Jul-18	0.29	0.01	50.67	0.00	50.97
Aug-18	0.53	0.00	10.05	0.00	10.58
Sep-18	0.44	6.76	8.40	0.14	15.74
Oct-18	0.44	0.72	6.21	0.26	7.63
Nov-18	0.40	0.47	0.40	0.11	1.39
Dec-18	0.56	0.26	0.56	0.01	1.40
Average	**0.55**	**36.99**	**6.19**	**0.08**	**43.81**
% Contribution	**1.25**	**84.44**	**14.13**	**0.18**	

Table B3: *Percentage of each Non-Point Source's Contribution to the Total Concentrations in the Puce River Subwatershed*

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Jan-11	1.87	2.09	1.87	0.00	5.84
Feb-11	1.36	3.25	1.36	0.01	5.97
Mar-11	0.57	2.49	0.57	0.01	3.63
Apr-11	1.77	335.95	1.77	0.00	339.50
May-11	2.34	86.12	2.49	0.48	91.44
Jun-11	6.83	1.10	71.70	0.13	79.76
Jul-11	4.59	1.07	102.32	0.11	108.08
Aug-11	3.28	0.13	62.73	0.01	66.16
Sep-11	1.25	0.21	23.96	1.30	26.73
Oct-11	1.72	0.03	24.46	0.67	26.88
Nov-11	1.26	49.97	1.26	0.05	52.55
Dec-11	0.57	5.84	0.57	0.01	6.99
Jan-12	0.77	3.04	0.77	0.01	4.58
Feb-12	0.93	0.84	0.93	0.00	2.71
Mar-12	1.19	0.70	1.19	0.00	3.09
Apr-12	1.57	1.39	1.57	0.00	4.53
May-12	1.62	17.01	1.72	0.10	20.44
Jun-12	2.17	0.58	33.66	0.05	36.46

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Jul-12	1.88	0.21	77.57	0.06	79.72
Aug-12	2.53	0.00	48.45	0.00	50.98
Sep-12	2.30	0.00	44.08	0.00	46.38
Oct-12	2.16	0.00	30.71	0.00	32.86
Nov-12	2.52	0.00	2.52	0.00	5.04
Dec-12	2.25	0.05	2.25	0.00	4.55
Jan-13	1.40	5.86	1.40	0.01	8.67
Feb-13	0.94	3.28	0.94	0.00	5.17
Mar-13	1.66	0.81	1.66	0.00	4.13
Apr-13	1.05	267.42	1.05	0.00	269.52
May-13	2.52	0.51	2.67	0.01	5.71
Jun-13	1.45	8.82	22.52	0.75	33.54
Jul-13	0.51	5.33	21.50	0.68	28.02
Aug-13	2.70	0.03	51.58	0.00	54.31
Sep-13	2.38	0.00	45.45	0.00	47.82
Oct-13	2.50	0.01	35.61	0.06	38.18
Nov-13	1.75	0.00	1.75	0.02	3.52
Dec-13	1.58	19.60	1.58	0.01	22.77
Jan-14	1.76	5.25	1.76	0.01	8.79
Feb-14	1.16	3.74	1.16	0.00	6.06
Mar-14	0.83	6.14	0.83	0.01	7.81
Apr-14	3.21	289.96	3.21	0.00	296.38
May-14	3.10	44.28	0.50	0.57	48.44
Jun-14	3.80	5.37	44.08	0.35	53.59
Jul-14	0.89	0.24	95.72	0.01	96.86
Aug-14	1.31	0.30	25.08	0.01	26.70
Sep-14	1.04	0.20	19.94	0.14	21.33
Oct-14	1.32	0.08	18.79	0.42	20.62
Nov-14	1.66	24.40	1.66	0.03	27.76
Dec-14	2.00	2.25	2.00	0.00	6.26
Jan-15	2.22	0.62	2.22	0.00	5.05
Feb-15	1.98	0.51	1.98	0.00	4.47
Mar-15	1.32	2.94	1.32	0.01	5.57
Apr-15	3.77	132.18	3.77	0.00	139.72
May-15	2.90	52.76	0.65	0.41	56.71
Jun-15	2.20	8.27	25.34	0.71	36.52
Jul-15	0.83	0.37	89.63	0.11	90.94
Aug-15	2.15	0.01	41.17	0.00	43.34
Sep-15	2.15	0.00	41.13	0.00	43.28
Oct-15	2.17	0.00	30.98	0.02	33.18
Nov-15	2.11	0.27	2.11	0.01	4.49
Dec-15	1.85	2.92	1.85	0.00	6.62

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Jan-16	1.29	2.47	1.29	0.00	5.05
Feb-16	1.22	1.23	1.22	0.00	3.67
Mar-16	0.90	43.36	0.90	0.00	45.15
Apr-16	2.41	156.62	2.41	0.00	161.45
May-16	4.10	165.86	0.65	0.22	170.82
Jun-16	6.26	0.12	73.06	0.02	79.45
Jul-16	0.96	0.00	102.81	0.00	103.77
Aug-16	1.79	0.04	34.25	0.00	36.08
Sep-16	1.85	0.04	35.29	0.38	37.56
Oct-16	1.16	0.07	16.52	0.68	18.43
Nov-16	1.81	27.58	1.81	0.07	31.26
Dec-16	1.60	13.05	1.60	0.01	16.26
Jan-17	0.65	5.61	0.65	0.01	6.92
Feb-17	1.17	2.10	1.17	0.00	4.44
Mar-17	1.13	2.31	1.13	0.00	4.58
Apr-17	1.85	233.67	1.85	0.00	237.36
May-17	1.90	83.18	0.49	0.11	85.68
Jun-17	4.75	0.00	55.42	0.00	60.17
Jul-17	0.87	0.00	93.02	0.00	93.88
Aug-17	1.59	0.14	30.32	0.02	32.06
Sep-17	1.56	0.00	29.90	0.00	31.46
Oct-17	1.51	0.00	21.46	0.02	22.99
Nov-17	0.84	126.91	0.84	0.16	128.74
Dec-17	1.71	10.24	1.71	0.01	13.68
Jan-18	1.06	8.07	1.06	0.01	10.20
Feb-18	1.12	4.09	1.12	0.01	6.34
Mar-18	1.78	1.02	1.78	0.00	4.57
Apr-18	2.37	311.25	2.37	0.00	316.00
May-18	3.20	142.71	0.30	0.82	147.03
Jun-18	4.26	1.61	49.65	0.09	55.60
Jul-18	1.02	0.00	109.98	0.00	111.01
Aug-18	1.95	0.00	37.30	0.00	39.25
Sep-18	1.54	0.03	29.45	0.11	31.12
Oct-18	1.48	0.02	21.06	0.23	22.79
Nov-18	1.40	78.77	1.40	0.19	81.75
Dec-18	1.88	4.82	1.88	0.01	8.59
Average	**1.93**	**29.52**	**20.33**	**0.11**	**51.89**
% Contribution	**3.72**	**56.88**	**39.18**	**0.21**	

Table B4: *Percentage of each Non-Point Source's Contribution to the Total Concentrations in the Belle River Subwatershed*

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Jan-11	1.80	0.02	1.80	0.00	3.63
Feb-11	1.34	0.05	1.34	0.01	2.74
Mar-11	0.50	0.04	0.50	0.01	1.05
Apr-11	1.59	714.30	1.59	0.00	717.49
May-11	1.95	58.11	2.07	0.00	62.13
Jun-11	5.33	4.36	22.89	0.14	32.72
Jul-11	3.44	3.67	84.52	0.14	91.76
Aug-11	2.61	0.43	49.95	0.01	53.00
Sep-11	1.04	0.51	19.88	0.53	21.95
Oct-11	1.48	0.07	21.07	0.35	22.97
Nov-11	1.18	0.16	1.18	0.03	2.55
Dec-11	0.53	0.08	0.53	0.01	1.15
Jan-12	0.73	0.08	0.73	0.00	1.56
Feb-12	0.90	0.03	0.90	0.00	1.83
Mar-12	1.09	0.03	1.09	0.00	2.20
Apr-12	1.48	8.93	1.48	0.00	11.89
May-12	1.41	6.95	1.49	0.01	9.86
Jun-12	1.79	5.52	23.01	0.03	30.35
Jul-12	1.49	0.78	85.44	0.14	87.84
Aug-12	2.07	0.00	39.67	0.00	41.74
Sep-12	2.01	0.00	38.43	0.00	40.44
Oct-12	2.00	0.00	28.43	0.00	30.43
Nov-12	2.43	0.00	2.43	0.00	4.86
Dec-12	2.17	0.00	2.17	0.00	4.34
Jan-13	1.35	0.93	1.35	0.00	3.63
Feb-13	0.87	0.69	0.87	0.00	2.43
Mar-13	1.52	0.17	1.52	0.00	3.21
Apr-13	1.00	247.31	1.00	0.03	249.34
May-13	2.11	1.17	2.25	0.00	5.53
Jun-13	1.17	13.81	15.02	0.77	30.76
Jul-13	0.41	5.78	23.57	1.00	30.77
Aug-13	2.17	6.99	41.42	0.01	50.58
Sep-13	2.05	0.07	39.22	0.00	41.35
Oct-13	2.25	0.26	32.12	0.03	34.67
Nov-13	1.68	0.40	1.68	0.00	3.77
Dec-13	1.57	0.95	1.57	0.01	4.10
Jan-14	1.73	0.59	1.73	0.00	4.05
Feb-14	1.11	0.56	1.11	0.00	2.77

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Mar-14	0.80	1.10	0.80	0.00	2.70
Apr-14	2.94	550.59	2.94	0.00	556.48
May-14	3.10	29.38	0.42	0.32	33.22
Jun-14	3.06	4.52	19.07	0.35	27.01
Jul-14	0.75	0.41	129.80	0.02	130.99
Aug-14	1.09	0.32	20.80	0.02	22.23
Sep-14	0.91	0.21	17.38	0.08	18.58
Oct-14	1.24	0.14	17.71	0.44	19.53
Nov-14	1.65	0.05	1.65	0.03	3.39
Dec-14	1.99	0.04	1.99	0.00	4.03
Jan-15	2.27	0.01	2.27	0.00	4.56
Feb-15	2.03	0.02	2.03	0.00	4.07
Mar-15	1.26	0.11	1.26	0.00	2.64
Apr-15	3.41	407.96	3.41	0.00	414.78
May-15	3.10	38.53	0.53	0.00	42.17
Jun-15	1.59	25.35	9.91	0.56	37.40
Jul-15	0.63	1.74	109.06	0.17	111.61
Aug-15	1.72	0.08	32.83	0.00	34.63
Sep-15	1.75	0.01	33.52	0.00	35.29
Oct-15	1.93	0.01	27.49	0.01	29.44
Nov-15	1.93	0.00	1.93	0.00	3.87
Dec-15	1.77	0.09	1.77	0.00	3.64
Jan-16	1.21	0.08	1.21	0.00	2.51
Feb-16	1.18	0.06	1.18	0.00	2.43
Mar-16	0.78	152.98	0.78	0.00	154.55
Apr-16	2.19	139.20	2.19	0.00	143.58
May-16	4.10	21.91	0.54	0.03	26.58
Jun-16	5.11	0.78	31.85	0.06	37.81
Jul-16	0.76	0.00	130.40	0.00	131.16
Aug-16	1.42	0.10	27.11	0.01	28.63
Sep-16	1.53	6.94	29.29	0.43	38.18
Oct-16	0.97	2.89	13.86	0.51	18.24
Nov-16	1.63	0.38	1.63	0.05	3.69
Dec-16	1.48	0.88	1.48	0.01	3.85
Jan-17	0.61	0.72	0.61	0.00	1.96
Feb-17	1.10	0.35	1.10	0.00	2.55
Mar-17	1.06	0.19	1.06	0.02	2.33
Apr-17	1.63	279.40	1.63	0.02	282.67
May-17	2.90	13.64	0.42	0.02	16.98
Jun-17	3.95	0.00	24.63	0.00	28.59
Jul-17	0.69	0.00	119.50	0.04	120.24
Aug-17	1.32	2.24	25.22	0.02	28.79

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Sep-17	1.31	0.14	25.08	0.00	26.53
Oct-17	1.34	0.33	19.14	0.02	20.83
Nov-17	0.72	1.10	0.72	0.06	2.61
Dec-17	1.69	0.65	1.69	0.00	4.03
Jan-18	1.01	0.85	1.01	0.00	2.86
Feb-18	1.11	0.79	1.11	0.00	3.01
Mar-18	1.68	0.20	1.68	0.00	3.57
Apr-18	2.12	610.82	2.12	0.00	615.06
May-18	3.10	111.63	0.24	0.43	115.40
Jun-18	3.49	1.99	21.76	0.13	27.37
Jul-18	0.80	0.01	137.74	0.00	138.55
Aug-18	1.52	0.00	29.04	0.00	30.56
Sep-18	1.27	0.06	24.37	0.17	25.87
Oct-18	1.35	0.06	19.18	0.29	20.88
Nov-18	1.31	0.10	1.31	0.19	2.90
Dec-18	1.79	0.03	1.79	0.01	3.62
Average	**1.72**	**36.42**	**18.12**	**0.08**	**56.34**
% Contribution	**3.06**	**64.64**	**32.16**	**0.14**	

Table B5: *Percentage of each Non-Point Source's Contribution to the Total Concentrations in the Ruscom River Subwatershed*

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Jan-11	3.61	0.22	3.61	0.00	7.44
Feb-11	2.64	0.45	2.64	0.01	5.73
Mar-11	0.95	0.37	0.95	0.01	2.27
Apr-11	2.24	376.97	2.24	0.01	381.46
May-11	2.71	167.66	2.88	0.01	173.27
Jun-11	10.62	14.23	203.20	0.29	228.35
Jul-11	7.84	7.90	149.88	0.25	165.87
Aug-11	5.19	0.93	99.18	0.02	105.31
Sep-11	2.11	1.04	40.44	1.00	44.60
Oct-11	2.97	0.20	42.33	0.64	46.14
Nov-11	2.18	0.91	2.18	0.05	5.32
Dec-11	1.12	0.29	1.12	0.01	2.53
Jan-12	1.34	0.26	1.34	0.01	2.94
Feb-12	1.96	0.13	1.96	0.00	4.05
Mar-12	1.98	0.10	1.98	0.00	4.06
Apr-12	2.93	13.91	2.93	0.00	19.76

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
May-12	2.85	83.20	3.03	0.00	89.08
Jun-12	3.63	63.50	69.47	0.04	136.64
Jul-12	3.17	5.52	60.57	0.19	69.45
Aug-12	4.36	0.00	83.45	0.00	87.82
Sep-12	4.27	0.00	81.58	0.00	85.84
Oct-12	4.32	0.00	61.59	0.00	65.91
Nov-12	4.70	0.00	4.70	0.00	9.40
Dec-12	4.38	0.01	4.38	0.00	8.77
Jan-13	2.28	0.35	2.28	0.01	4.92
Feb-13	1.42	0.21	1.42	0.00	3.06
Mar-13	2.55	0.07	2.55	0.01	5.18
Apr-13	1.73	65.70	1.73	0.02	69.17
May-13	3.88	155.71	4.12	0.01	163.71
Jun-13	1.99	78.15	38.15	1.22	119.52
Jul-13	0.74	21.84	14.18	3.04	39.80
Aug-13	4.30	0.29	82.21	0.02	86.81
Sep-13	4.28	0.01	81.88	0.01	86.17
Oct-13	4.33	0.07	61.73	0.09	66.21
Nov-13	2.82	0.01	2.82	0.01	5.66
Dec-13	2.55	0.72	2.55	0.01	5.83
Jan-14	2.81	0.35	2.81	0.00	5.97
Feb-14	1.83	0.33	1.83	0.00	3.98
Mar-14	1.45	0.55	1.45	0.01	3.46
Apr-14	4.73	118.69	4.73	0.00	128.14
May-14	4.10	299.40	0.70	0.16	304.36
Jun-14	6.01	17.81	114.93	0.36	139.12
Jul-14	1.55	1.57	29.58	0.04	32.73
Aug-14	2.15	1.31	41.03	0.02	44.51
Sep-14	1.77	0.75	33.80	0.09	36.41
Oct-14	2.37	0.35	33.72	0.40	36.85
Nov-14	2.95	2.55	2.95	0.03	8.48
Dec-14	3.40	0.43	3.40	0.00	7.23
Jan-15	3.82	0.11	3.82	0.00	7.75
Feb-15	3.36	0.11	3.36	0.00	6.82
Mar-15	2.14	0.60	2.14	0.00	4.89
Apr-15	5.64	252.67	5.64	0.00	263.94
May-15	4.10	58.18	0.97	0.01	63.26
Jun-15	3.02	78.44	57.80	0.89	140.15
Jul-15	1.14	6.05	21.88	0.41	29.49
Aug-15	3.64	0.33	69.54	0.01	73.51
Sep-15	3.67	0.06	70.23	0.00	73.96
Oct-15	4.12	0.03	58.70	0.04	62.88

Year	Faulty Septic Systems	Livestock Manure	Cattle Direct Deposit	Grazing	Total Conc.
Nov-15	3.67	0.67	3.67	0.00	8.01
Dec-15	3.07	0.41	3.07	0.00	6.55
Jan-16	2.08	0.22	2.08	0.00	4.38
Feb-16	1.95	0.17	1.95	0.00	4.07
Mar-16	1.35	62.47	1.35	0.00	65.17
Apr-16	3.76	486.81	3.76	0.00	494.33
May-16	6.10	565.30	0.96	0.00	572.36
Jun-16	10.08	5.49	192.74	0.10	208.40
Jul-16	1.70	0.09	32.55	0.00	34.34
Aug-16	2.96	1.32	56.58	0.01	60.87
Sep-16	3.32	0.26	63.45	0.46	67.49
Oct-16	1.79	0.32	25.57	0.57	28.25
Nov-16	2.61	1.13	2.61	0.06	6.41
Dec-16	2.33	0.33	2.33	0.01	4.99
Jan-17	1.20	0.28	1.20	0.01	2.69
Feb-17	1.69	0.17	1.69	0.00	3.56
Mar-17	1.61	0.18	1.61	0.02	3.41
Apr-17	2.48	74.35	2.48	0.02	79.33
May-17	6.10	338.37	0.73	0.04	345.25
Jun-17	8.03	0.00	153.51	0.00	161.53
Jul-17	1.36	0.32	26.08	0.52	28.30
Aug-17	2.64	0.82	50.49	0.02	53.98
Sep-17	2.46	0.02	47.10	0.00	49.58
Oct-17	2.48	0.05	35.40	0.05	37.98
Nov-17	1.17	3.43	1.17	0.14	5.90
Dec-17	2.60	0.47	2.60	0.00	5.68
Jan-18	1.61	0.53	1.61	0.01	3.75
Feb-18	1.75	0.42	1.75	0.00	3.93
Mar-18	2.58	0.13	2.58	0.00	5.29
Apr-18	3.05	142.18	3.05	0.00	148.28
May-18	5.10	814.06	0.38	0.27	819.80
Jun-18	6.26	11.06	119.78	0.24	137.34
Jul-18	1.47	0.05	28.15	0.00	29.67
Aug-18	3.08	0.00	58.97	0.00	62.06
Sep-18	2.46	0.14	47.12	0.17	49.90
Oct-18	2.37	0.12	33.81	0.31	36.60
Nov-18	1.95	2.53	1.95	0.20	6.63
Dec-18	2.64	0.66	2.64	0.01	5.95
Average	**3.14**	**46.01**	**29.24**	**0.13**	**78.52**
% Contribution	**4.00**	**58.60**	**37.23**	**0.17**	

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