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Multi-site watershed model calibration for evaluating best management practice effectiveness in reducing fecal pollution

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ABSTRACT

In this study, the Soil and Water Assessment Tool (SWAT) is coupled with the Bacteria Source Load Calculator (BSLC) to develop alternative scenarios of agricultural best management practice (BMP) implementation and septic system repair to achieve total maximum daily load (TMDL) targets for *Escherichia coli* (*E. coli*) in a small agricultural watershed located in Michigan, USA. Due to the uncertainty involved in bacterial source estimation from wildlife and failing septic systems in agricultural watersheds, we propose a method for estimating their respective bacteria loading during SWAT calibration, which was performed at eight sampling locations and validated at a ninth. BMP implementation scenarios were prioritized based on their ability to meet TMDL targets at the lowest cost using a spatially targeted subwatershed ranking identifying the greatest *E. coli* source contribution. BMP effectiveness is driven by *E. coli* source locations defined in the BSLC-SWAT linkage. The framework developed here, from linking BSLC to SWAT to ranking subwatersheds, was effective in meeting the TMDL targets and is readily transferable to other watersheds. Agricultural BMPs were unsuccessful in meeting TMDL targets, but the target can be met by repairing about 60 of 110 estimated failing septic tanks.

Abbreviations: ALPHA_BF: baseflow alpha factor; ARS: agricultural Research Service; BACT_SWF: fraction of manure applied to land areas that has active colony forming units; BACTKDQ: bacteria partition coefficient in surface runoff; BACTMINP: minimum daily bacteria loss; BACTMIX: bacteria percolation coefficient; BMP: best management practice; BSLC: bacteria source load calculator; CDL: cropland data layer; CH_K2: effective hydraulic conductivity in main channel alluvium; CH_N2: manning's "*n*" value for the main channel; CN2: initial runoff curve number for moisture condition II; DEM: digital elevation model; DO: dissolved oxygen; *E. coli*: *Escherichia coli*; EBC1: *E. coli* monitoring station 1; EBC2: *E. coli* monitoring station 2; EBC3: *E. coli* monitoring station 3; EBC4: *E. coli* monitoring station 4; EBC5: *E. coli* monitoring station 5; EBC6: *E. coli* monitoring station 6; EBC7: *E. coli* monitoring station 7; EBC8: *E. coli* monitoring station 8; EBC9: *E. coli* monitoring station 9; EBCC: East Branch Coon Creek; EPA: environmental protection agency; EPCO: plant uptake compensation

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/10807039.2019.1680526 factor; ESCO: soil evaporation compensation factor; FIO: fecal indicator organism; GW_DELAY: groundwater delay time; GW_REVAP: groundwater "revap" coefficient; GWQMN: threshold depth of water in the shallow aquifer required for return flow to occur; HRU: hydrologic response unit; HSPF: hydrological Simulation Program – Fortran; HUC: hydrologic unit code; MDEQ: Michigan Department of Environmental Quality; MDNR: Michigan Department of Natural Resources; MST: microbial source tracking; NASS: National Agricultural Statistics Service; NED: National Elevation Dataset; NRCS: Natural Resources Conservation Service; NSE: Nash-Sutcliffe efficiency; OV_N: Manning's "*n*" value for overland flow; PBIAS: percent bias; RCHRG_DP: deep aquifer percolation fraction; REVAPMN: threshold depth of water in the shallow aquifer for "revap" or percolation to the deep aquifer to occur; RSR: root mean square error-observations standard deviation ratio; SOL_AWC: available water capacity of the soil layer; STEPL: spreadsheet tool for estimating pollutant load; SURLAG: surface runoff lag coefficient; SWAT: soil and water assessment tool; THBACT: temperature adjustment factor for bacteria die-off/growth; TMDL: total maximum daily load; TN: total nitrogen; TP: total phosphorus; USDA: United States Department of Agriculture; USGS: United States Geological Survey; WDPF: die-off rate for bacteria in foliage; WDPQ: die-off rate for bacteria in soil solution; WDPRCH: die-off rate for bacteria in streams (moving water); WDPS: die-off rate for bacteria adsorbed to soil particles; WGPF: growth rate for bacteria in on foliage; WGPQ: growth rate for bacteria in soil solution; WGPS: growth rate for bacteria adsorbed to soil particles; WOF_P: wash-off fraction for bacteria on foliage; WWTP: wastewater treatment plant;

1. Introduction

Fecal pollution in surface waters originates from point and nonpoint sources, which increases human exposure to waterborne pathogens, resulting in illnesses and death worldwide (Pandey et al. 2014). Pathogens are the leading cause of river and stream impairment in the United States, with more than 300,000 km impaired (USEPA 2017). This has significant economic impacts, as the presence of waterborne pathogens disrupts activities related to recreation, irrigation, and aquaculture. For instance, estimated annual healthcare costs of recreational waterborne illnesses in the U.S. is ~\$2.9 billion (DeFlorio-Barker et al. 2018). The impacts of pathogens are also felt regionally: Song et al. (2010) estimated a seasonal economic loss ranging from \$360,000 to \$24 million for closing an individual Great Lakes beach.

Microbiological water quality status is usually monitored through the detection of fecal indicator organisms (FIOs) such as *Escherichia coli* (*E. coli*) and intestinal enterococci. *E. coli* is considered a pathogen indicator as defined by the U.S. Clean Water Act and the USEPA (2012) recommends its use as an indicator of fecal contamination in recreational waters. Although the existence of FIOs does not necessarily confirm the presence of pathogenic organisms, higher concentrations are indicative of higher risks to human health (Cho et al. 2016b). FIOs have a ubiquitous nature and their detection in water or sediment samples is not enough to identify the sources of fecal pollution. Therefore, additional efforts in determining fecal pollution loading and identifying fecal pollution sources are needed.

Approaches for identifying FIOs sources include field surveys (e.g. inspection of agricultural facilities, identification of failing on-site sewage/septic systems), microbial source tracking (MST), and modeling tools (Devane et al. 2018; Oliver et al. 2016; PSC 2018). Field inventories are spatially explicit, but the surveying process is time consuming and its scope is limited at large scales. MST techniques have been successful in discriminating targeted pollution sources (e.g. human, bovine, porcine, avian wildlife) and can provide watershed-level summaries of relative contributions from different sources (Bradshaw et al. 2016; Santo Domingo et al. 2007). These techniques do not provide specific locations of major pollution sources, are expensive, and require skilled personnel (Wu 2019). Modeling tools are faster and less expensive alternatives for understanding fecal pollution fate and transport in large watersheds. They can predict the impacts of different natural and human-induced activities on water quality and are commonly supplemented with remote sensing products to support the identification and quantification of major sources of fecal pollution (de Brauwere et al. 2014; Reder et al. 2015). Although there are advantages to modeling, its success is limited and uncertainty in model predictions is usually high due to factors such as complex microorganism life cycles, lack of long-term data availability for calibration/validation purposes, limited spatial and temporal bacterial loading characterization, and limited representation of fate and transport processes (de Brauwere et al. 2014; Frey et al. 2013). Despite these concerns, models are useful tools for evaluating different bacterial loading scenarios, determining the relative importance of specific management practices to improve water quality, and assisting policy-makers in the implementation of risk management strategies (Coffey et al. 2013; Parajuli et al. 2008). When available, integrating MST data with statistical and modeling tools may improve source identification and model performance (Hyer and Moyer 2004; Jeong et al. 2019; Oliver et al. 2016; Wu 2019).

The most widely used process-based hydrological models in FIOs fate and transport studies are the Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998) and the Hydrological Simulation Program – Fortran (HSPF) (Bicknell et al. 1996). SWAT has advantages over other modeling approaches because it simultaneously simulates processes in manure, animal waste, and soil (i.e. survival, sorption, and transport in saturated and unsaturated zones); processes of release from different materials; overland transport; and in-stream fate and transport (Cho et al. 2016b). SWAT can simulate two forms of bacteria, which include persistent bacteria, such as *E. coli* and *Cryptosporidium*, and less persistent bacteria, such as fecal coliforms (Sadeghi and Arnold 2002). Adjustments to SWAT source code also improve the representation of in-stream processes such as sediment interactions (i.e. release, deposition, fate) (Kim et al. 2010; Pandey et al. 2016), and seasonal variability (Cho et al. 2016a). Recent SWAT applications in FIOs fate and transport studies can be found in Iqbal and Hofstra (2019), Jeong et al. (2019), and Kim et al. (2018). Cho et al. (2016b) gives a comprehensive review of different watershed models for simulating fate and transport of FIOs and Borah et al. (2019) provides a thorough review of the most widely used watershed models in total maximum daily load (TMDL) development and implementation. Similar process-based models such as the Integrated Catchment Model have been extended to simulate FIOs fate and transport in watersheds at similar levels of complexity as SWAT (Whitehead et al. 2016). In agricultural contexts, SWAT is preferred because it comprehensively represents the impacts of agricultural operations and conservation practices on water quality.

Although SWAT simulates major FIO watershed processes, source load characterization is a necessary model input (Cho et al. 2016; Jeong et al. 2019; Niazi et al. 2015). Multiple software tools have been developed for quantifying the FIO source loadings in a watershed (Whelan et al. 2018), including the Spatially Explicit Load Enrichment Calculation Tool (Borel et al. 2017; Teague et al. 2009), the Bacterial Indicator Tool (USEPA 2000), and the Bacterial Source Load Calculator (BSLC) (Zeckoski et al. 2005). These tools calculate fecal landscape-level pollutant loadings by considering land use and sources such as wastewater treatment plants (WWTP), livestock (manure land application, grazing), septic systems, pets, and wildlife.

A benefit of implementing agricultural best management practices (BMPs) is the removal of contamination and improvement of water quality conditions in the downstream areas. Identifying the best location for implementing BMPs to have the highest impacts on water resources can be challenging (Abouali et al. 2018). Coupled with often limited companion water quality data when sampling for FIOs, models' uncertainty can be high. However, when analyzing different BMP scenarios, process-based models can be used as a first approximation in providing relative comparisons of BMP performance.

Despite the vast literature in FIOs modeling using SWAT and other process-based watershed models, there are few peer-reviewed studies evaluating the effects of different implementation scenarios in reducing fecal pollution by using these models. Naramngam and Tong (2013) used SWAT to simulate the impacts of different tillage, cropping, and fertilization practices in reducing nutrient loads and fecal coliform concentrations, including the economic returns associated with those practices. Mishra et al. (2018, 2019) developed and implemented various probabilistic frameworks to evaluate the reliability of different load reduction scenarios using HSPF. These loading scenarios considered unlawful sewer connections removal and different reduction levels in cropland loading and cattle and wildlife direct deposit. Other modeling studies have evaluated specific practices such as the application of infiltration basins (Fonseca et al. 2018), vegetative filter strips (Bai et al. 2016; Parajuli et al. 2008), and changes in land use (Fonseca et al. 2018).

In this study, we propose a systematic approach for evaluating BMPs implementation scenarios in reducing fecal pollution. This approach seizes the availability of FIOs data at multiple sampling locations under conditions of scarce water quality and sediments data. In the process, we developed spatially-explicit load reduction scenarios based on several pollution loadings from individual subwatersheds, developed a load reduction scenario based on uncertainty in loads from septic systems and wildlife, and ranked the implementation scenarios at the watershed-scale considering environmental benefits and economic costs. This workflow was implemented in the East Branch Coon Creek (EBCC), a small agricultural watershed in Michigan, United States. The specific objectives of this study were to: (1) calibrate and validate a SWAT model for *E. coli* concentrations using multiple sampling locations; (2) simulate the effect of different BMPs implementation scenarios on improving water quality within the study area under scarce data conditions; and (3) identify the optimal implementation scenario based on cost to attain the *E. coli* TMDL goal.

2. Materials and methods

2.1. Study area

The EBCC watershed is located within the Macomb and St. Clair counties of Michigan and is part of the Clinton River watershed (Figure 1). The study area contains two 12-digit Hydrologic Unit Code (HUC) watersheds: East Branch Coon Creek (040900030303) and Highbank Creek (040900030302). Due to water quality degradation caused by sediment, heavy metals, polychlorinated biphenyls (PCBs) and oil and grease, along with high concentrations of fecal coliform bacteria and nutrients, the Clinton River watershed was designated as a Great Lakes Area of Concern by the USEPA in 1987 under the Great Lakes Water Quality Agreement (USEPA 2018).

The EBCC watershed is 188 km^2 and its elevation ranges from 252 meters above sea level in the northwest to 184 m above sea level at the watershed outlet (Figure 1). Land use is predominantly agricultural, with row crops (primarily corn and soybeans) and pasture making up 44.7% and 19.8% of the watershed, respectively (U.S. Department of Agriculture-National Agricultural Statistics Service (USDA-NASS 2012)). Other portions of the watershed are forest (18%) and woody wetlands (4.5%), while 6.6% is developed.

The EBCC watershed is impaired by *E. coli* and low dissolved oxygen (DO). *E. coli* impairment for recreation is present from McPhall Road downstream to the confluence of the EBCC with Highbank Creek (Figure 1). Exceedances of the water quality standard for *E. coli* at all sampling locations during the total body contact recreational season of May one through October 31 have been documented from monitoring data collected by the Michigan Department of Environmental Quality (MDEQ) (Cooper and

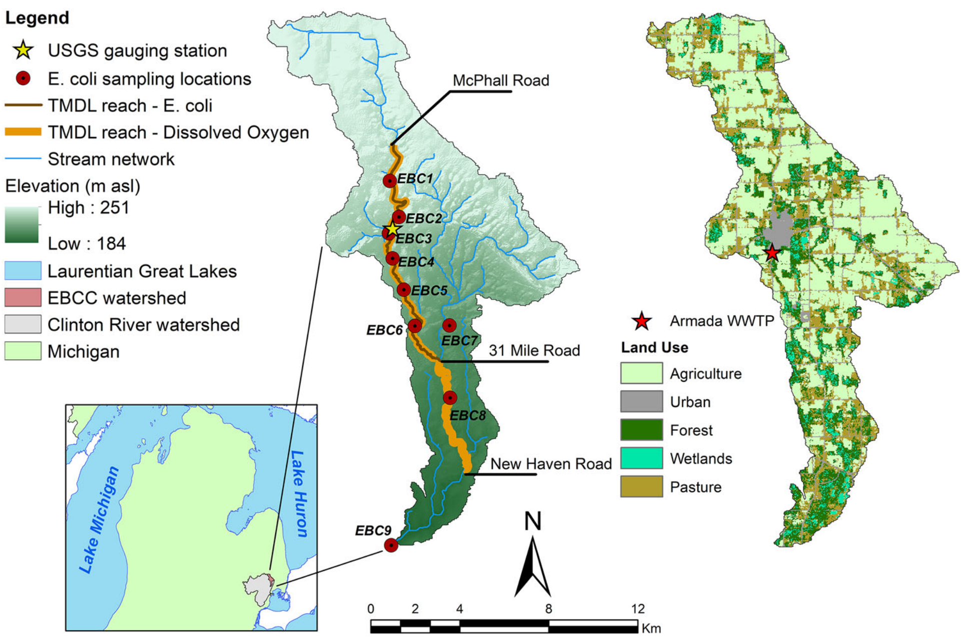

Figure 1. Location of the East Branch Coon Creek watershed and sampling locations. Note: EBCC, East Branch Coon Creek; TMDL, total maximum daily load; USGS, U.S. Geological Survey; and WWTP, wastewater treatment plant.

Alexander, 2006). The DO impairment extends from McPhall Road downstream to New Haven Road (Figure 1).

2.2. Data collection

Land use data for the EBCC watershed was obtained from the USDA-NASS (2012) Cropland Data Layer (CDL) (USDA-NASS 2012). The digital elevation model (DEM) for the EBCC watershed was obtained from the United States Geological Survey (USGS) 10 m resolution National Elevation Dataset (NED) (USGS 2018a). Soil data maps were obtained from the Natural Resources Conservation Service (NRCS) Soil Survey Geographic Database (SSURGO 2018) for Macomb and St. Clair counties. Daily climate data from five National Climatic Data Center weather stations located near the EBCC watershed (NOAA 2018) were used, each having varying amounts of available precipitation and temperature data for the study time period (2001–2011). One streamflow monitoring station (i.e. USGS gauging station 04164300, East Branch Coon Creek at Armada) is located within the EBCC watershed, with records spanning from 10/1/1958 to present (USGS 2018b).

Nine *E. coli* sampling locations were located within the study area (Figure 1). The MDEQ measured *E. coli* at eight locations (EBC1 to EBC8) in 2004 (Cooper and Alexander 2006). Three samples were taken weekly at each location from 5/12/2004 to 9/30/2004. Additional weekly sampling was performed by the MDEQ from 6/5/2008 to 10/1/2008 at EBC9 (MDEQ 2011).

2.2.1. Sources of bacteria pollution

Information for livestock, wildlife, septic systems, and pets to quantify the bacterial loading from non-point sources were obtained from national and local sources. Livestock locations were obtained from aerial maps and watershed surveys, while population estimates were obtained from the USEPA Spreadsheet Tool for Estimating Pollutant Load (STEPL 2006). This consisted of one beef operation, one dairy operation, and two horse farms, all confirmed by stakeholders. Deer density in Macomb County, obtained from the Michigan Department of Natural Resources (MDNR), is 16–19 deer per square mile in the Northern portion of the county and 8–12 deer per square mile overall (Kafcas and Payne 2005). Data for other wildlife populations were unavailable. Estimates for bacteria from pets were based on information from the American Veterinary Medical Association (AVMA), estimating 0.632 dogs per household in the United States (AVMA 2007).

The number of houses with septic systems and sewered houses in the watershed were determined using aerial maps. The EBCC watershed has one WWTP within its boundaries, located in Armada, Michigan. The discharge from this WWTP was considered as a point source in SWAT. Sewered homes were assumed to be located within the village of Armada boundary and served by the Armada WWTP, while unsewered homes were assumed to be located outside of the Armada boundary. From aerial maps, we identified 1,371 households with septic systems, while there are 530 households served by the Armada WWTP. The number of persons per sewered/unsewered houses was determined from 2000 census data block groups from the United States Census Bureau TIGER products, which gives an average occupancy of 3.14 persons per household and the population of 4,345 people in the study area. According to the National Small Flows Clearinghouse (1992–1998) (NESC 2018), the septic system failure rate in the watershed is 1.14%, which was confirmed by the Macomb County Health Department. However, based on the revised *E. coli* TMDL (MDEQ 2011), septic system failures occur at varying degrees and can be defined as any time that sewage enters surface water (such as situations with poor soils, old septic systems, septic systems too close to a water body, equipment failure, etc.). Using this definition, the overall septic system failure rate based on the revised TMDL was defined as 12% for Macomb County (MDEQ 2011).

2.3. Bacteria fate and transport modeling

The overall modeling process (Figure 2) consisted of three major steps. In the first step, the EBCC watershed was delineated into 78 subwatersheds, which were further divided into 2591 HRUs using land use, soil, and slope thresholds of 5%, 20%, and 20%, respectively. In the second step, the BSLC tool was used with various spatial data (i.e. land use, livestock and wildlife inventories, septic systems, and population) to estimate the bacterial loading in each subwatershed. In the third and final step, BSLC loadings were input into the SWAT model, which was developed using topographic, land use, soil, and climate data. This model was then employed to simulate the bacteria transport overland and through the stream network of the EBCC watershed.

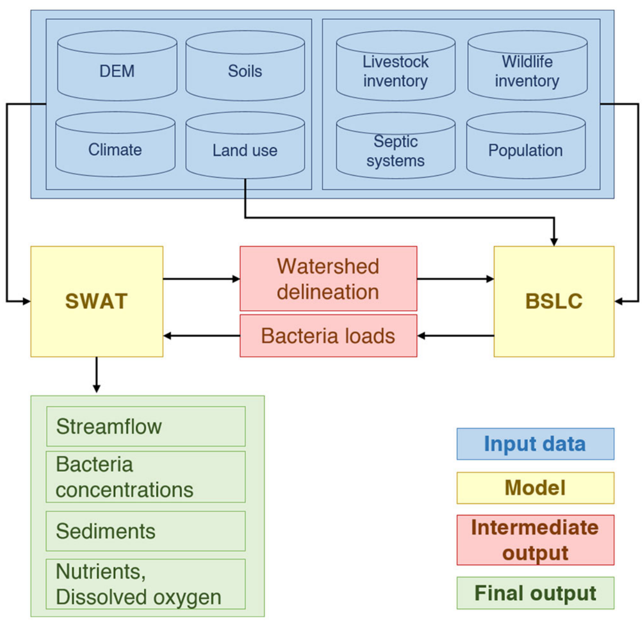

Figure 2. Modeling framework. Note: BSLC, bacteria source load calculator; DEM, digital elevation model; and SWAT, Soil and Water Assessment Tool.

2.3.1. Watershed model

The SWAT version 2012 is a semi-distributed, physically based watershed model developed by the USDA – Agricultural Research Service (Gassman et al. 2014). SWAT uses spatial data for topography, land use, soils, weather, and land management to predict land-based water, sediment, nutrient, pesticide, and bacteria yields, which are routed through the watershed river network. The watershed delineation tool within SWAT divides a watershed into multiple subwatersheds based on a DEM and stream network. The subwatersheds are further divided into hydrologic response units (HRUs), which are characterized by homogeneous land use, soil, and slope within a subwatershed. SWAT models runoff, soil erosion, soil water, evapotranspiration, soil nutrient cycling, crop growth, bacteria growth and die-off, and pesticide transport over long simulation periods (Gassman et al. 2014). Channel simulation components include flow routing, sediment deposition and entrainment, and nutrient, pesticide, and bacteria transport. The model operates on a daily time-step and results can be aggregated on a monthly or annual basis.

2.3.2. Bacteria growth and die-off simulation in the watershed model

Up to two different forms of bacteria (persistent and less-persistent) can be modeled in SWAT. For each form, SWAT simulates deposition of manure from a land application and livestock grazing, adsorption to soil, decay, infiltration, tillage incorporation, overland flow, and in-stream processes (Baffaut and Sadeghi 2010). The 10-mm topsoil layer and streams are the two subsystems where bacteria processes are simulated by solving mass balance equations. In the topsoil layer, the surface loading is linearly partitioned into bacteria in soil solution and bacteria adsorbed to soil particles, where each partition has its own decay/re-growth rate. The surface loading from manure is calculated as a function of the total bacteria content in the manure and the fraction of active colony forming units (BACT_SWF). The latter fraction typically ranges from 0 to 0.5 (Baffaut and Sadeghi 2010). In SWAT, when bacteria in manure are applied, some fraction is intercepted by plant foliage and the remainder reaches the soil. A portion of bacteria on plant foliage can be washed-off during precipitation events, which is controlled by the wash-off fraction for bacteria (WOF_P). Bacteria in the soil layer can be redistributed to lower soil layers or removed by runoff, infiltration, and erosion. The number of bacteria transported by surface runoff is controlled by the bacteria partition coefficient in surface runoff (BACTKDQ) with optimal values around 175 (Parajuli et al. 2009). Infiltration is controlled by the bacteria percolation coefficient (BACTMIX), which typically ranges from 7.0 to 20.0 (Coffey et al. 2010). Redistributed and percolated bacteria are assumed to die. Thus, transport via groundwater is not considered in SWAT (Cho et al. 2016b), which is a limitation compared to other models such as HSPF. Transport by sediments is not user-specified and it is determined by the sediment yield, the enrichment ratio for bacteria, and the concentration of bacteria attached to sediments in the soil (Baffaut and Sadeghi 2010).

In streams, bacteria concentrations depend on the contributions from runoff and sediment transport; direct inputs such as WWTP, wildlife, and other discharges; and in-stream bacteria decay/re-growth (Baffaut and Sadeghi 2010). A first-order decay equation (Chick's law) is used in SWAT to model bacteria removal from a system through die-off and added to the system by re-growth. This equation was further modified for foliage, soil solution, and soil particles to include a user-defined minimum daily loss (BACTMINP). Different decay/re-growth rates at 20 °C are used in the model such as the die-off/re-growth rate for bacteria in foliage (WDPF/WGPF), die-off/re-growth rate for bacteria in soil solution (WDPQ/WGPQ), die-off/re-growth rate for bacteria absorbed to soil particles (WDPS/WGPS), and die-off rate for bacteria in streams (WDPRCH). These decay/re-growth rates are affected by a temperature adjustment factor (THBACT) with a typical value of 1.07 following the Arrhenius equation.

2.3.3. BSLC-SWAT integration

The BSLC version 3.0, developed by the Center for TMDL and Watershed Studies at Virginia Tech University, was used in this study for estimating the bacteria loading. The goal of the BSLC is to organize and process inputs necessary for developing a TMDL to address fecal pollution impairments (Zeckoski et al. 2005). Inventory of bacteria sources (e.g. septic systems, wildlife, and livestock) and land use distribution are used to calculate bacteria loading to subwatersheds within a watershed. Land use in the BSLC is defined by four categories: agriculture, pasture, forest, and residential. The land use types of the CDL layer and subsequent SWAT subwatershed land use data were classified based on these four categories. The watershed inventory is completed externally and input into the BSLC, where monthly land surface loadings and direct stream discharges are generated. Livestock census data were allocated to the subwatershed in which they were located. This information was only available for cattle and horses (locations and number of swine, sheep, chickens, turkeys, and ducks were unknown), and therefore, only cattle and horses were used in the BSLC. Manure produced by the livestock was applied to the cropland in these subwatersheds. Cattle stream access was included in the BSLC when visually confirmed using aerial maps and watershed surveys. A deer population of 19 per square mile was used based on MDNR deer population estimates (Kafcas and Payne 2005), where deer density was multiplied by subwatershed area. Subwatersheds completely within the village of Armada boundary were assumed to have zero deer (these subwatersheds contain only urban land use). Deer populations of subwatersheds intersecting with the Armada boundary were calculated by excluding urban land use area from the calculation and multiplying the deer density by the new area. The number of pets per household was assumed to be uniform across the EBCC watershed (i.e. 0.632 pets per household) (AVMA 2007), which was applied to all households in the watershed, estimated from aerial maps.

BSLC outputs were integrated into the SWAT model using the monthly bacteria (colony-forming units CFU/month) land-based and stream load output. These values were converted into CFU/day for each month. A new manure type was created in the SWAT manure database with only the BACTPDB (concentration of bacteria in manure – CFU/g manure) defined with a value of 110,000 CFU/g manure (the maximum value possible in the SWAT model). Using the CFU/day from BSLC and the BACTPDB (CFU/g manure), a load application in kg/day was calculated. The load application was implemented in the SWAT management files using the continuous fertilizer command to represent bacteria load. The fertilizer frequency (IFRT_FREQ) was set to 1, indicating an application once per day. The load application (CFRT_KG) was obtained in the previous step using BACTPDB and BSLC results. The number of days for continuous application (FERT_DAYS) was set to equal the number of days for each month. Using this process, the monthly bacteria loads obtained from BSLC were applied in the SWAT model through evenly distributed daily loads.

2.3.4. Sensitivity analysis and model calibration and validation

Streamflow sensitivity analysis was performed at the USGS gauging station and the bacterial sensitivity analysis was performed at each *E. coli* sampling location (EBC1 through EBC9). The results of the sensitivity analysis were used to calibrate SWAT for streamflow and bacteria. Streamflow- and bacteria-relevant variables were varied 50 times each within the range recommended by the SWAT model manual while all other model parameters remained constant in a one-at-a-time sensitivity analysis (Arnold et al. 2012; Luo and Zhang 2009). The relative sensitivity index was calculated for each parameter using the following equation (Luo and Zhang, 2009).

$$S = (y_i - y_0) \times x_0/(x_i - x_0) \times y_0 \tag{1}$$

where, S is the relative sensitivity index, x_i is the ith parameter value, x_0 is the initial parameter value, y_i is the model prediction of a specific output variable at x_i, and y_i is the initial model prediction at x_0. A greater magnitude of S indicates a higher sensitivity. A positive S indicates that increasing the parameter value results in an increase in the value of model output variable, while a negative S indicates an inverse relationship between the parameter and the model output variable (e.g. decreasing the parameter value increases the value of the model output variable).

Calibration is an iterative process of model parameter adjustment that compares simulated and observed data of interest (e.g. streamflow, *E. coli*). Validation examining model performance for a different time assures the model reliability (Zeckoski et al. 2014). The SWAT model was calibrated for streamflow and *E. coli*. SWAT could not be calibrated for sediment, nutrient, and DO because either no monitoring data exist (i.e. sediment and nutrients) or the number of observations were not sufficient (i.e. for DO, no site within the watershed has more than six observations points in five years (2004–2008)). Since we are using a process-based model, sediment, nutrients and DO predictions are used as a first approximation in evaluating relative changes over time and space.

Three statistical measures were used to evaluate model performance for both streamflow and *E. coli*: Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and root mean square error-observations standard deviation ratio (RSR). For *E. coli*, the percent difference in the average, geometric mean, and median values were also considered. Moriasi et al. (2007, 2015) and Ahmadisharaf et al. (2019) determined guidelines for model performance statistics on a monthly basis for streamflow, whereas Kim et al. (2007) determined performance criteria for average, geometric mean, and median percent differences for bacteria. A model simulation for monthly streamflow can be considered satisfactory if NSE $\geq$ 0.5, RSR $\leq$ 0.7, and the absolute value of PBIAS $\leq$ 15%, whereas bacteria simulation is satisfactory when the absolute percent differences between modeled and observed values is below 100%.

The NSE ranges from $-\infty$ to 1, where one indicates a perfect fit. NSE is calculated using Eq. (2) (Nash and Sutcliffe 1970).

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

where, Y_i^{obs} is the ith observation (streamflow or *E. coli*), Y_i^{sim} is the ith simulated value, Y^{mean} is the mean of the observed data, and n is the number of observations.

Percent bias measures the tendency of the model to over- or under-predict the observed data. Low magnitude PBIAS values indicate good model simulation, where the optimal PBIAS value is 0%. Positive values indicate the model generally under-predicts, while negative values indicate the model generally over-predicts. PBIAS is calculated using Eq. (3) (Moriasi et al. 2015).

$$\mathrm{PBIAS} = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - Y_i^{\mathrm{sim}}\right) * 100}{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}}\right)}\right] \tag{3}$$

Root mean square error-observations standard deviation ratio standardizes the root mean square error using the standard deviation of the observations. RSR varies from 0 (optimal) to large positive values, where smaller values indicate better model performance. RSR is calculated using Eq. (4) (Moriasi et al. 2015).

$$\mathrm{RSR} = \frac{\sqrt{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - Y_i^{\mathrm{sim}}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - Y^{\mathrm{mean}}\right)^2}} \tag{4}$$

Regarding percent differences between averages, geometric means, and medians of modeled and observed bacteria concentrations, negative values indicate the model under-predicts, while positive values indicate the model over-predicts. Since 30-day geometric mean *E. coli* concentrations were evaluated, other performance metrics such as percent differences in violation rates or percent of observed values within 5-day minimum-maximum simulated range are not applicable and were not considered in this study.

The SWAT model was calibrated for monthly discharge from 2003 to 2005 and validated from 2006 to 2008 at USGS gauging station 04164300. *E. coli* was calibrated and validated in the SWAT model using the observed 30-day geometric mean data. Locations EBC1 through EBC8 were calibrated for 2004, while location EBC9 was used for validation in 2008. Calibration was performed by manually adjusting SWAT model parameters, starting with the most upstream sampling location and systematically moving downstream and only including those subbasins immediately draining to the sampling location of interest without influencing another upstream sampling location. Additional *E. coli* loads were also required to calibrate bacteria in the SWAT. These additional loads were attributed to input data uncertainty regarding various wildlife populations and locations of failing septic systems. The loads were approximated as direct discharges in the SWAT model.

2.4. Load reduction scenarios

E. coli and DO TMDLs for the EBCC were completed by the MDEQ and approved by the USEPA. The TMDL sets a 50% reduction target for total suspended solid loads (point and non-point sources) to achieve a DO standard of 5 mg/l as a daily minimum. The targeted reduction of the 30-day geometric mean for *E. coli* was 130 CFU/100 ml and the daily geometric mean of 300 CFU/100 ml from May one to October 31.

Load reduction scenarios were developed to determine the high priority locations for BMP implementation. Three land-based load reduction scenarios were used for addressing land-based *E. coli* and DO impairment sources: based on *E. coli* loads (*E. coli* targeting), based on the combination of sediment, total nitrogen (TN), and total phosphorus (TP) loads (DO targeting), and based on the combination of the first two (*E. coli* and DO targeting). An additional load reduction scenario was used to account for *E. coli* loads related to input data uncertainty regarding unknown wildlife populations and failing septic system locations. Although the DO TMDL targets sediment reduction for achieving the DO standard, it acknowledges N and P contributions to DO standard non-attainment, warranting inclusion of TN and TP in the load reduction scenarios.

The land-based load reduction was in accordance with annual average *E. coli* yield (CFU/ha), sediment yield (kg/ha), TN (kg/ha), and TP (kg/ha) at the subwatershed level. The *E. coli* targeting priority was based on the greatest yield (highest priority) to the lowest yield (lowest priority). The DO targeting priority was based on the sum of sediment, TN, and TP priority. That is, each subwatershed was ranked from 1 (lowest priority) to 78 (highest priority) for each pollutant individually and the sum of the ranks for each subwatershed determined the ultimate ranking order. The *E. coli* and DO targeting was a 50/50 weight between *E. coli* and DO (i.e. sediment, TN, and TP). Priority was determined using the sum of the *E. coli* rank and the average of the sediment, TN, and TP ranks. Ties in priority were broken by the higher rank sum of sediment, TN, and TP. By using sediment, TN, and TP to break ties, we expected that the targeting would capture the co-benefits of addressing soil erosion and *E. coli* adsorbed to eroded soil. The additional load reduction scenario based on *E. coli* loads to the stream due to input data uncertainty was based on BSLC estimates and the calibrated *E. coli* loads (i.e. direct discharges in the SWAT model). The average annual load was used to establish targeting priority.

2.4.1. BMP implementation

Multiple BMPs as defined by stakeholders, were implemented in SWAT (Supporting Information (SI) Section A1 and Tables A1 through A10 in the Appendices): conservation-till farming, no-till farming, rye cover crop, red clover cover crop, edge-of-field filter strips (10 m and 30 m width), nutrient management (20% and 50% reduction of fertilizer application), and reduction of *E. coli* load from failing septic systems/wildlife (20% reduction, 40% reduction, 60% reduction, 80% reduction, and 100% reduction).

All BMPs (except septic systems/wildlife) were implemented on agricultural HRUs in priority order based on the three land-based load reduction scenarios. The failing septic systems/wildlife *E. coli* reduction BMP was only implemented under the load reduction scenario addressing input data uncertainty regarding the *E. coli* sources. Two livestock operations were identified in the EBCC watershed. One site was not located near a stream, while livestock at the second site previously had access to the stream, but fencing was constructed to limit access following the development of the original *E. coli* TMDL in 2006. Therefore, no additional BMP to address livestock access was modeled.

BMP implementation was systematically assessed by analyzing the resulting instream bacteria and water quality concentrations starting with the most upstream sampling location and moving downstream. We only included those subwatersheds draining to the nine monitoring locations and considered the targeting priority within this set of subwatersheds for BMP placement. For each monitoring station, the procedure for implementing the BMPs within SWAT was to place each BMP at the highest priority subwatershed, then the second highest, and so forth until all subwatersheds contain a BMP. This approach not only covers the entire study area but also examines how incremental implementation can impact meeting the water quality requirement for the TMDL plan at the lowest cost. Therefore, for each BMP and priority combination there are 78 SWAT model runs to determine the impact of the BMP on *E. coli* and DO.

There were eight agricultural BMPs and three land-based load reduction scenarios for a total of 24 BMP-targeting scenario combinations. Additionally, there were five *E. coli* load reduction scenarios (20%, 40%, 60%, 80%, and 100% reduction). This resulted in 29 scenarios, in which the SWAT model was run 78 times (once for each subwatershed), for a total of 2,262 simulations. The methods for implementing the agricultural BMPs in the SWAT model in addition to conventional-till farming, which represents the base scenario, are presented in SI Section S1. Crop rotations were obtained from local NRCS offices.

Septic system repair was modeled by reducing the number of *E. coli* directly applied to the stream by various percentages (20%, 40%, 60%, 80%, 100%). These numbers were used with the estimated number of septic systems in each subwatershed (Section 2.3.1) to determine how many septic systems should be repaired. Three scenarios were developed based on the input data uncertainty regarding the *E. coli* source: 100% human (septic systems), 50% human and 50% wildlife, and 100% wildlife. Using the 12% septic system failure rate, a 100% human contribution to the stream keeps the failure rate at 12%, a 50% human/50% wildlife contribution to the stream brings the failure rate to 6% (12% × 50%), and the 100% wildlife contribution brings the failure rate to 0%. It is important to note that pollutant allocation scenarios with wildlife load reduction are not favored due to technical infeasibility and high probability of harming wildlife habitat.

2.4.2. Cost of BMP scenarios

BMP costs were obtained from the 2010 Michigan Statewide Conservation Practice Typical Installation Cost guide (NRCS 2010). Costs for each agricultural BMP are presented in the SI Appendices (Table A11). For all land-based BMPs, excluding filter strips, the total cost was calculated by multiplying the implementation area (area of the agricultural HRU—corn, soybean, or wheat) by the cost per unit area. Filter strips were implemented using a defined width along the edge of a field and an assumed square-shaped implementation area for each agricultural HRU. To find the length of the edge-of-field filter strip, the square root of the area was used. Implementation area was found by multiplying the edge-of-field length (square root of HRU area) by the filter strip width (10 m or 30 m). The filter strip implementation area was multiplied by the cost per unit area to calculate implementation cost.

To determine the septic system cost, the subwatersheds and the number of septic systems they contain in each load reduction scenario (25%, 50%, 75%, and 100%) were identified. Septic system repair cost was estimated to be $10,000 per system by the Macomb County Health Department (L. Pobanz, personal communication, 2013). The failing septic system value was multiplied by the percent human contribution. Finally, the percent reduction (20%, 40%, 60%, 80%, and 100%) was multiplied by the number of failing septic systems to determine the number of septic systems repaired in each scenario. The number of septic systems was multiplied by the cost to determine the cost to achieve TMDL targets for each location (EBC1 through EBC9). We did not consider a cost associated with the possibility of requiring wildlife management in relation to the stream load.

3. Results and discussion

3.1. Sensitivity analysis and model calibration and validation

Parameters that were adjusted and their final values are presented in SI Table A14. Calibration results for the model evaluation criteria are presented in Table 1. The plot of observed and simulated streamflow is presented in Figure 3. The results confirmed that the overall model performance is satisfactory according to the acceptability criteria, although monthly streamflow is underpredicted for the validation period according to the PBIAS statistic (Ahmadisharaf et al. 2019; Moriasi et al. 2007, 2015).

Parameters adjusted for bacteria calibration are presented in SI Table A15. Bacteria calibration and validation results are presented in Table 2. Time-series figures of observed vs simulated 30-day geometric mean of *E. coli* concentrations are presented in Figure 4 for EBC1 through EBC9. The results of the bacteria calibration and validation were satisfactory for all monitoring stations, except for site EBC7, where the absolute percent difference in observed and simulated medians exceeded 100%. In this site, SWAT over-predicted *E. coli* concentrations during August and September 2004, indicating either an over-estimation of bacteria loading at the subwatersheds draining to the monitoring station, or an under-estimation of the stream's bacteria assimilative capacity. EBC7 site is the only monitoring station located in a tributary to the EBCC main stem, hence less information was available for model calibration due to policies that limit data

Table 1. Streamflow calibration and validation results (USGS gauge 04164300).

Statistical measures*	Calibration (2003–2005)	Validation (2006–2008)	Overall (2003–2008)
NSE	0.79	0.66	0.72
PBIAS	−0.91%	21.42%	12.21%
RSR	0.21	0.34	0.28

*NSE: Nash-Sutcliffe efficiency; PBIAS: percent bias; RSR: root mean square error-observations standard deviation ratio.

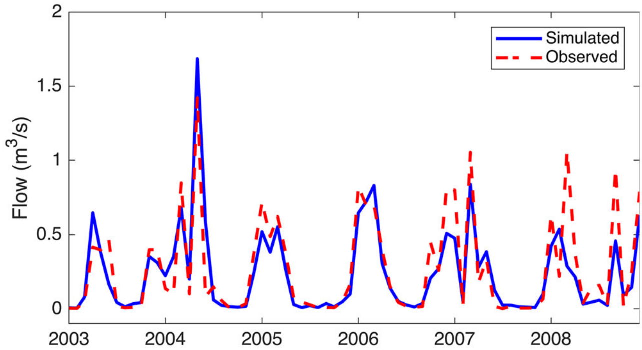

Figure 3. Streamflow calibration and validation results (USGS Gauge 04164300).

Table 2. Bacteria calibration and validation results.

Performance metrics*	*E. coli* monitoring stations								
	EBC1	EBC2	EBC3	EBC4	EBC5	EBC6	EBC7	EBC8	EBC9
NSE[a]	0.77	0.52	0.59	0.55	0.61	0.43	−2.01	−0.83	0.56
PBIAS[a]	−7%	23%	22%	−18%	11%	18%	−51%	16%	−3%
RSR[a]	0.48	0.70	0.64	0.67	0.63	0.76	1.73	1.35	0.67
Average[b]	−18%	−41%	−72%	−41%	−45%	−44%	23%	−13%	−3%
Geometric mean[b]	−6%	−11%	−12%	−8%	−9%	−23%	64%	−19%	−25%
Median[b]	11%	53%	66%	34%	−20%	−19%	119%	−11%	−45%

*NSE: Nash-Sutcliffe efficiency; PBIAS: percent bias; and RSR: root mean square error-observations standard deviation ratio.
[a]Based on 30-day geometric mean values.
[b]Based on the percent difference between simulated (mean) and observed (geometric mean) daily values.

sharing in agricultural sectors (Abouali et al. 2018). The sole dairy operation in EBCC drains to EBC7; it was assumed that all the produced manure from livestock was uniformly land-applied within the corresponding subwatershed where the operation unit was located. At the remaining sites, 30-day geometric mean *E. coli* concentrations were generally under-predicted according to the percent differences in observed and simulated averages and geometric means reported in Table 2. The order of magnitude and seasonality of concentrations at all monitoring sites are captured by the model, including the validation site (EBC9) located at the watershed outlet. Order of magnitude has been used as a calibration criterion in previous studies (Jeong et al. 2019; Pandey et al. 2016). While results of calibration and validation were acceptable, global sensitivity analysis has the potential to further improve the calibration results through capturing interactions between parameters.

3.2. Load reduction scenarios

Load reduction scenarios were developed based on land-based *E. coli* yield, DO (sediment, TN, and TP) yield, *E. coli* and DO combined, and *E. coli* loads from unknown wildlife populations and failing septic system locations. Table 3 summarizes the estimated relative contribution from different land-based fecal pollution sources considered in the BSLC (along with the Armada WWTP). The highest fecal pollution contribution came from the dairy operation unit located within the area draining into the EBC7

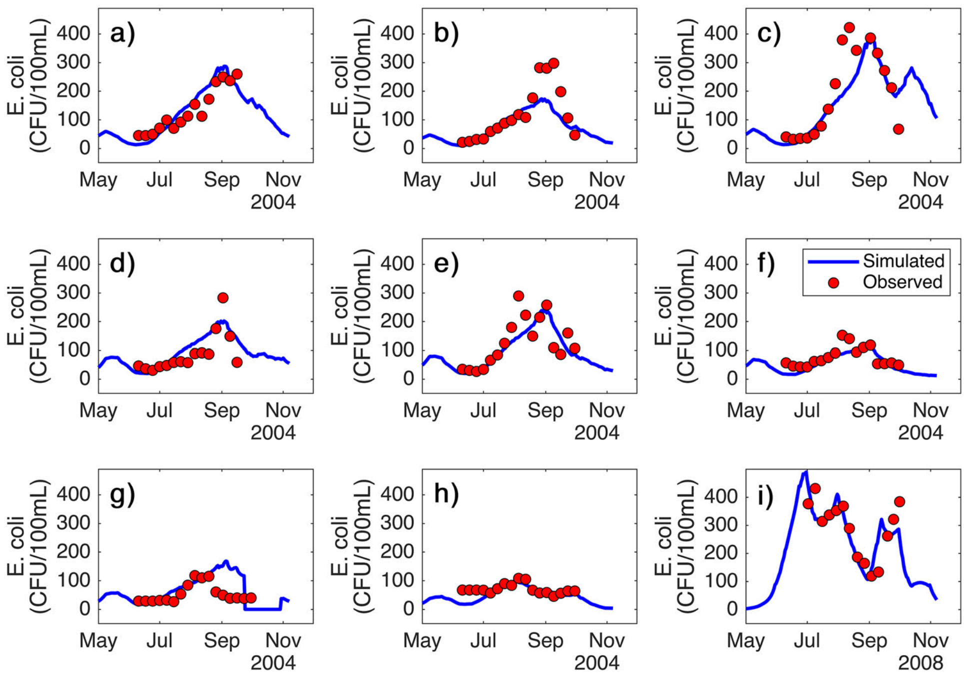

Figure 4. *E. coli* calibration and validation results at: (a) EBC1, (b) EBC2, (c) EBC3, (d) EBC4, (e) EBC5, (f) EBC6, (g) EBC7, (h) EBC8 and (i) EBC9 stations. Both simulated and observed values correspond to 30-day geometric mean values.

Table 3. Estimated relative contribution of fecal pollution sources using BSLC and Armada WWTP data for the study area.

Source		Percentage contribution
Livestock	Dairy cattle	41.8%
	Beef cattle	23.6%
	Horses	1.7%
Wildlife	Deer	10.5%
Residential	Septic tanks	1.9%
	Pets	20.5%
	WWTP*	0.01%

*WWTP, wastewater treatment plant.

monitoring station, followed by the beef operation unit located within the area draining into the EBC1 monitoring station. The highest residential fecal pollution source was pets, which also ranked as the third highest contribution source among all the sources considered. Wildlife, represented by deer, was the fourth highest fecal pollution source, whereas horses and the Armada WWTP were the lowest *E. coli* contributors. Bacteria load contribution from different land uses was as follows: pasture (64%), residential (25%), cropland (7%), forest (3%), and streams (i.e. direct deposit, 1%). The high pasture contribution is primarily due to the dairy, beef, and horse operations. Most wildlife was not considered in BSLC due to lack of data, including avian (geese, ducks, and turkeys) and non-avian (rodents and coyotes) sources, making this estimate low. Septic system failures from homes located in and near riparian areas is also a concern not captured by the BSLC.

To develop the load reduction scenarios for BMP implementation, subwatersheds were ranked from one (least priority) to 78 (highest priority). The *E. coli* targeting map is presented in Figure 5a. Sediment, TN, and TP individual targeting maps are presented in SI Figures A1, A2, and A3, respectively. The combination of these maps (DO targeting) is presented in Figure 5b, the combination of *E. coli* and DO targeting is presented in Figure 5c, and the targeting map related to possible failing septic systems/ wildlife *E. coli* loads is presented in Figure 5d. Detailed targeting order of subwatersheds for each load reduction scenario is presented in SI Table A16.

The final rankings for the different load reduction scenarios are consistent with the land use distribution within the EBCC watershed. High rankings for *E. coli* yield correspond to developed areas and pasturelands. Developed areas' loading was primarily from pets, whereas pasturelands are closely related to the four dairy, beef and horse operation units. These are the main fecal pollution sources reported in Table 3. High rankings in the DO targeting scenario are concentrated in agricultural areas that are sources of non-point source pollution. In general, increases in cropland areas are related to loss of

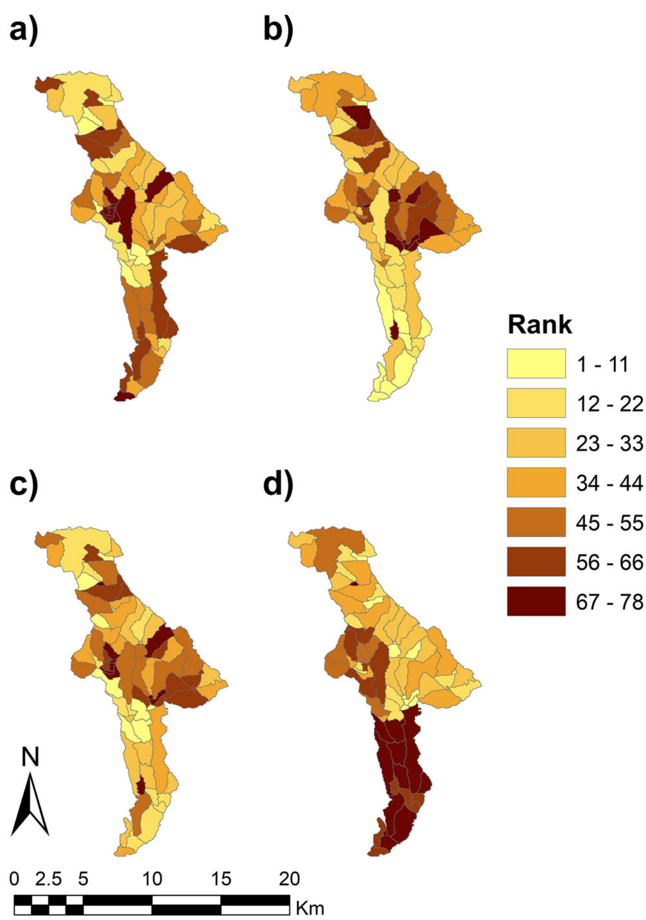

Figure 5. Targeting results (rank one has the lowest priority and rank 78 has the highest priority) for (a) *E. coli*, (b) DO, (c) *E. coli* + DO and (d) *E. coli* (failing septic systems/wildlife).

forestlands, increasing TN, sediments and runoff volumes (Lacher et al. 2019). These increases likely result in eutrophication and reflect low DO concentrations in streams.

The priority areas are similar for DO and *E. coli* + DO load reduction scenarios (Figure 5b,c), indicating a balance in considering fecal pollution, nutrients, and sediment yields. Previous studies have found that increases in pasturelands and low developed urban areas can result in higher TP loadings (Lacher et al. 2019; Walters et al. 2018). Along with higher TN and sediment loadings from agricultural areas, these increases ultimately affect DO concentrations. Since cropland, pastureland, and low-density residential areas are closely related to increases in bacteria loading from pets, livestock and failing septic tanks (Nshimyimana et al. 2018; Verhougstraete et al. 2015), the similarity between DO and *E. coli* + DO load reduction scenarios is expected. Finally, higher rankings in the *E. coli* (failing septic systems/wildlife) targeting scenario (Figure 5d) are concentrated in the Southern streams of the EBCC, which is mostly covered by pastures, wetlands, and forests. These land use categories are expected to have higher wildlife-related fecal pollution. The uncertainty in determining bacteria loading from wildlife populations is spatially consistent with land use distribution and observed *E. coli* concentrations. It is worth noting that observed data for *E. coli* at the EBC7 monitoring site indicated a possible over-estimation in fecal loading from agricultural areas during the calibration process. Since this over-estimation may be related to inflated septic tanks failure rates, multi-site calibration data provided a spatial constraint and allowed for higher uncertainty in fecal pollution loadings from wildlife in the Southern reaches of the EBCC, which is consistent to the corresponding land uses found there.

3.2.1. BMP implementation

Each BMP scenario was implemented for 2004, which was the year with *E. coli* monitoring data. BMP implementation results for conservation-till, clover cover crop, rye cover crop, filter strips (10 m and 30 m), no-till, and nutrient management (20% and 50% nutrient application reduction) are presented in SI Tables A17–A88 for each targeting method at the nine *E. coli* sampling locations (EBC1 through EBC9). Scenarios meeting the TMDL requirements (50% reduction in sediment for DO) are highlighted in each table. The 10 m and 30 m filter strips were the only BMPs able to meet the sediment reduction requirements for DO, with no-till providing the third-most sediment reduction.

Agricultural BMPs were unable to meet the *E. coli* TMDL requirements (zero days with daily average *E. coli* concentration <300 CFU/100 ml; zero days with 30-day geometric mean *E. coli* concentration <130 CFU/100 ml) (MDEQ 2011). Their inability to mitigate *E. coli* concentrations is due to the sources identified within the watershed. There are relatively few livestock, they lack stream access, and synthetic fertilizer usage on cropland is typically preferred over manure. Inability to achieve water quality standards in Texas using conservation practices was found by Jeong et al. (2019), but *E. coli* concentrations were still reduced, and probability of exceedance declined. In contrast, Parajuli et al. (2008) found targeted implementation of filter strips was effective in reducing fecal contamination in a Kansas watershed, although manure from livestock grazing and feeding operations was identified as a major bacterial source. If manure application on cropland or livestock grazing were widespread in the EBCC, we expect that agricultural BMPs would be effective in reducing in-stream *E. coli* concentrations. Although agricultural BMPs were unsuccessful in meeting the TMDL goals, they are broadly effective in reducing *E. coli* (Jeong et al. 2019; Parajuli et al. 2008) and must be tailored to the major sources of fecal contamination. BMP implementation must consider co-benefits in addressing a wide array of nonpoint source pollution; agricultural BMPs reduced sediment and nutrient loads to the stream network to meet the DO TMDL goal, with the added benefit of addressing some agricultural *E. coli* sources.

Reduction scenarios (20%, 40%, 60%, 80%, and 100%) of *E. coli* load (from input data uncertainty regarding septic systems/wildlife) are presented for different implementation area milestones (25%, 50%, 75%, and 100%) in SI Tables A89–A124 for EBC1 through EBC9. Scenarios meeting the TMDL requirements for *E. coli* are highlighted in each table. *E. coli* load reduction scenarios that meet the TMDL requirements vary for each sampling site, balancing the proportion of upstream area in which septic systems were repaired and the total number of septic systems repaired within that area. For each sampling location, implementation was required in at least 25% and sometimes 50% of the watershed area, with load reduction (repair) rates as low as 20% (EBC8) and up to 80% (EBC2 and EBC3) required. If we assume bacteria loads in-stream completely attributable to septic systems (ignoring wildlife), 58 septic systems would require repair. Ignoring wildlife is unrealistic, and other studies have found that non-avian wildlife can be significant contributors to *E. coli* contamination, even in watersheds with considerable livestock populations (Jeong et al. 2019). Nevertheless, this estimate gives the upper-bound on septic system repair requirements in the EBCC.

3.2.2. Cost of BMP implementation scenarios

3.2.2.1. Agricultural BMPs. Filter strips (10 m and 30 m) are the only land based BMPs that meet the DO TMDL targets. BMPs that meet DO TMDL criteria for all load reduction scenarios at the lowest cost are presented in Table 4 for each sampling location. The lowest cost BMP implementation scenario to meet the DO TMDL requirement of 50% sediment reduction is the 10 m filter strip targeting DO. There was one exception at location EBC7, in which the lowest cost was based on *E. coli* targeting (slightly less expensive than DO targeting of $24,615 not shown in Table 5). For all implementation

Table 4. Land-based BMPs and targeting scenarios that meet DO TMDL criteria.

Monitoring station	BMP	Targeting*	Area	Sediment Reduction (ton)	Cost	$/ton Reduction
EBC1	Filter strip (10 m)	DO	100%	2276.9	$20,731	$9.1
EBC2	Filter strip (10 m)	DO	75%	2143.1	$18,502	$8.6
EBC3	Filter strip (10 m)	DO	75%	2349.8	$21,344	$9.1
EBC4	Filter strip (10 m)	DO	75%	2707.6	$25,908	$9.6
EBC5	Filter strip (10 m)	DO	75%	2708.8	$25,908	$9.6
EBC6	Filter strip (10 m)	DO	75%	2718.8	$26,551	$9.8
EBC7	Filter strip (10 m)	*E. coli*	75%	2952.4	$24,197	$8.2
EBC8	Filter strip (10 m)	DO	75%	5571.3	$51,166	$9.2
EBC9	Filter strip (10 m)	DO	100%	7181.1	$72,119	$10.0

*DO: dissolved oxygen.

Table 5. Least expensive scenarios meeting *E. coli* TMDL targets.

Monitoring station	Area (%)	Reduction (%)	Total septic systems	Septic fail/repair (100% human: 0% wildlife)	Cost (100% human: 0% wildlife)
EBC1	50	60	103	12.4/7.4	\$74,160
EBC2	25	80	4	0.5/0.4	\$3,840
EBC3	50	80	177	21.2/17.0	\$169,920
EBC4	50	40	235	28.2/11.3	\$112,800
EBC5	50	60	249	29.9/17.9	\$179,280
EBC7	50	40	34	4.1/1.6	\$16,320
EBC8	25	20	111	13.3/2.7	\$26,640

strategies to meet the TMDL target, greater than 75% of agricultural land should install filter strips. This is challenging because the recommended implementation plan is unenforceable, although there are many voluntary incentive programs available to farmers (Sowa et al. 2016).

BMPs were considered one-at-a-time with sequential implementation starting in the highest priority critical source areas (subwatersheds for implementation are presented in SI Figure A4–A12). There is certainly potential that implementing multiple concurrent BMPs (e.g. implementing filter strips and no-till in the same subwatershed) would further improve reduction efficiency when coupled with spatial multi-objective algorithms for optimization of cost and pollution reduction (Liu et al. 2019a; Pyo et al., 2017). However, Liu et al. (2019b) found that BMPs implemented in-series were not as cost effective as individual BMP implementation even though they reduced more pollution. This is perhaps a tradeoff, with the potential of in-series BMPs to limit the required area for implementation to only those most critical sources but at greater localized cost. Paired with voluntary incentive programs referenced by Sowa et al. (2016), this may be more feasible than implementing filter strips on 75% of the agricultural land in the EBCC.

3.2.2.2. Septic system repair. The cost of implementation to meet the *E. coli* TMDL varies largely based on the source of pollution. If all implementation dollars go to fixing septic tanks, the cost varies from less than \$4,000 (EBC2) to around \$180,000 (EBC 5) and is a function of the number of septic systems in the subwatersheds draining to each sampling location. The most cost-effective scenarios (percent implementation area and percent reduction) that meet the *E. coli* TMDL targets are presented in Table 5 for each sampling location. Locations EBC6 and EBC9 already met the targets prior to implementation and excluded from Table 5. The subwatersheds upstream of each location in which addressing the *E. coli* load is required to meet the reduction target are presented in SI Figures A13–A19. It is unsurprising that the greatest cost is in subwatersheds that have the most septic systems and drain into the monitoring locations that experience the highest *E. coli* concentrations.

There is some uncertainty in estimating septic system repair cost and load reduction, both spatially and in terms of condition. Failure rates of 12% were estimated in the TMDL, but other studies have put rates as varying between 1% and 35% (Frey et al. 2013; Jeong et al. 2019; Petersen et al. 2009). It is impossible to know the exact locations of failures, their degree of failure, and potential cost to repair without comprehensive sampling, source tracking, and surveying. However, by identifying individual housing units outside of the public sewer service area and the locally estimated failure rate, we mitigated model error and uncertainty in human-derived *E. coli* sources.

Wildlife management was not considered as a cost here, but population control is essential when wandering animals are potential vectors for the spread of pathogens (USDA-NRCS 2007). By lumping septic system failure and wildlife contributions to *E. coli* loads, we acknowledge their presence and uncertainty in estimating both sources without MST. Other *E. coli* modeling studies have found that wildlife can be the primary cause of fecal contamination as identified by MST, although simple representation of that contribution in SWAT can result in model error (Jeong et al. 2019). Future studies should examine systematic integration of MST data sources with SWAT and potential scenarios of wildlife population management and land use planning to determine if they would be cost effective compared to the implementation options considered here.

3.3. Sources of uncertainty in the modeling process

Since the uncertainty quantification of the outcomes from the modeling process presented herein is beyond the scope of this study, only the main sources of uncertainty and their expected effects on *E. coli* simulation are acknowledged. Following Ahmadisharaf et al. (2019), the epistemic uncertainty is considered as the most relevant uncertainty source because it can be reduced by systematically improving the conceptual and mathematical representation of physical, chemical and biological processes, numerical methods, measuring techniques, data collection, and modeling practices. Epistemic uncertainty relies on the model structure and parameters (including the model code), initial conditions, and input data. The SWAT version used in this study has a limited representation of in-stream bacteria processes, such as fate in sediments and sediment-water column exchanges along with the lack of bacteria transport via groundwater (Cho et al. 2016b). As a result, die-off rates are not accurately determined in the calibration process (i.e. parameter uncertainty), and bacteria transformation processes in the soil have limited connection to receiving waters, resulting in a lack of sensitivity in model parameters related to fate and transport in soils. Moreover, seasonal variability representation can be limited because bacteria contributions from intermediate and slow inflows are not considered. Since daily simulations were performed, peaks in bacteria concentrations driven by subdaily rainfall events are missed. However, daily simulations are considered sufficient for this study because the main interest was the simulation of 30-day geometric mean *E. coli* concentrations rather than daily or instantaneous values. The lack of water quality and sediment data in EBCC for model calibration does not justify the use of a more complex version of SWAT including detailed sediment transport and interactions.

In this study, the most important sources of uncertainty are limited information for agricultural operations involving manure land application, livestock and wildlife populations, and locations and rates of failing septic systems. Also, there is a lack of accurate temporal information on bacteria loads from the various sources. Input data uncertainty has a direct effect on model parameter estimation and reduces overall model predictive capability (Ahmadisharaf et al. 2019). Additional limitations related to parameter uncertainty include the limitation of SWAT in assigning spatially variable bacteria die-off rates and other model parameters, spatial discretization, and limited representation of extreme streamflow events. In future research we recommend using recent approaches for uncertainty quantification developed for water quality modeling and TMDL studies (e.g. Camacho et al. 2018; Chaudhary and Hantush 2017; Hantush and Chaudhary 2014; Jia and Culver 2008; Mishra et al. 2018, 2019).

4. Conclusions

Meeting both the *E. coli* and DO TMDL targets throughout the EBCC was a function of type of BMP and location implemented. There was no single implementation strategy that concurrently achieved both TMDL targets; the locations where BMPs were effective in achieving the *E. coli* reduction target were pasture and developed areas, while meeting the DO target was achieved by targeting implementation in subwatersheds dominated by cultivated cropland. The most effective BMPs also differed between TMDL targets. Septic system repair met the *E. coli* TMDL target and vegetated filter strips on cropland achieved the best load per cost reduction of sediment as required to meet the DO target. Location and BMP effectiveness is ultimately driven by *E. coli* sources defined in the BSLC-SWAT linkage. The framework developed here, from linking BSLC to SWAT to using the subwatershed ranking method to determine BMP implementation location, was effective in meeting the TMDL targets and is readily transferable to other watersheds. Our method of ranking subwatersheds for BMP implementation is advantageous due to its ease of interpretation, although spatial optimization algorithms may achieve an optimal reduction at lowest cost while considering multiple locations and BMPs concurrently.

The systematic modeling framework developed here that incorporated data on septic system locations and failure rates, livestock populations, and uncertainty in wildlife populations was successful in identifying potential sources of contamination. However, integrating MST into BSLC and SWAT would provide more nuances to spatial targeting and BMP selection. Load estimators driven with information on livestock and human populations, manure application, and other fecal sources are useful when coupled with SWAT, but can be highly uncertain with respect to the spatial scale of input data, number of unknowns (e.g. wildlife populations) and widely varying estimates of input parameters (e.g. septic system failure rates). Using MST to quantify the varying contributions of FIO sources in monitoring data is more comprehensive and would likely reduce model uncertainty. As organizations tasked with monitoring FIOs in recreational waterbodies transition to MST, uncertainty in the *E. coli* TMDL implementation process will decline, both in model development and design of BMP implementation plans to meet TMDL goals.

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Conflict of interest

No financial interest or benefit was arisen from the direct applications of this research.

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