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## **Fecal Bacteria Source Characterization and Sensitivity Analysis of SWAT 2005**

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**Abstract.** *The sensitivity of the Soil and Water Assessment Tool (2005) and its input parameters that impact the prediction of fecal bacteria concentrations were evaluated. The model was applied at Rock Creek watershed (77 km<sup>2</sup>), Kansas. Fecal bacteria sources were characterized to use commonly available data to describe model inputs of watershed sources of livestock, septic and wildlife loads. The flow and bacteria loads were validated reasonably for the watershed. The runoff events of the simulated period geometric mean value of the fecal coliform bacteria concentration were evaluated using a relative sensitivity index (S). The four model parameters and one input parameter were tested using Latin Hypercube Sampling (LHS) and independent parameter perturbation (IPP) methods. The model parameters showed no to very high sensitivity (S up to 8.69) and an input parameter determined no to moderate sensitivity (S up to 1.05). If the model is to be used to predict fecal coliform bacteria concentration, particular attention should be taken in characterizing sources and selection of input parameter values.*

**Keywords.** *Sensitivity analysis, fecal coliform bacteria, rainfall, runoff, SWAT, watershed.*

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## Introduction

Pathogen contamination from fecal bacteria is one of the causes of surface water-quality impairment which often results from non-point source pollution. The fecal bacteria often are present in surface water at concentrations that indicate the potential to cause severe illnesses in humans (Craun and Frost, 2002). Fecal bacteria sources include land application of manures, grazing operations, winter feeding operations, failing septic systems, and wildlife (Zeckoski et al., 2005). Surface water movement and sediment erosion increase the chance of bacteria reaching surface water systems especially during high intensity rainfall events. The current water quality assessment techniques generally include two methods (a) water quality field monitoring and (b) computer/mathematical modeling. Field monitoring method is most appropriate and reliable method to support in water quality assessment. However, it is expensive due to high costs and tremendous spatial and temporal ecosystem variability. Therefore, computer/mathematical models provide an alternative to monitoring that can save time, reduce cost, and minimize the need for testing management alternatives (Shirmohammadi et al., 2006). Models can be used to assess water quality goals on large watersheds. However, the sensitivity of mathematical model simulation results is a concern.

In recent years, the U.S. Environmental Protection Agency (EPA) has increasingly emphasized the importance of incorporating variability and uncertainty into the modeling process (US EPA, 1997). It identified probability analysis techniques like Monte Carlo analysis, as useful tools for adequately quantifying variability and uncertainty (Chang, 1999). In watershed-level assessment and management activities there are uncertainties, and the only thing we are sure of is that we are "in doubt" (Hession et al., 1996a; 1996b). There are many uncertainties inherent in watershed modeling, including monitoring/measurement error, model error, model input parameter errors, spatial variability, errors in spatial data layers within a geographic information system (GIS), the effects of aggregation of spatial data when modeling watersheds, and temporal variability. These different errors or uncertainties can be additive. Uncertainties may be classified into three categories: the inherent variability in natural processes, model uncertainty, and parameter uncertainty (Haan, 1989). The inherent variability in the natural processes is the unexplained random variability of the natural environment (Haan, 1989). This inherent variability in natural processes can be either variability in space (spatial variability) and/or variability in time (temporal variability). Spatial and temporal variability can be generally observed with environmental factors such as rainfall, temperature, and stream flow.

The model uncertainty results from faulty conceptualizations of the world (Suter et al., 1987), such as: (1) using a small number of variables to represent a large number of complex phenomena, (2) choosing incorrect functional forms for interactions among variables, and (3) setting inappropriate boundaries for components of the world to be included in the model. The parameter uncertainty is resulted when model parameters are allowed to vary around their base values independently (Tiscareno-Lopez et al., 1993, 1994) or dependently (Silberbush and Barber, 1983). The range of the perturbation may be a specific percentage (Barnes and Young, 1994) or determined from experimental measurements (Fontaine et al., 1992; Gwo et al., 1996). The most common form of sensitivity analysis is independent parameter perturbations (IPP) in which parameters are varied individually by a fixed percentage around a base value (Ferreira et al., 1995). An example of this approach is with first-order analysis (Haan and Zhang, 1996), which is most applicable to linear systems. Model output responses to parameter perturbation may be quantified by percentage change of selected output variables and relative change of output versus input (Larocque and Banton, 1994). The overall model response may be obtained by measuring the average response of selected output variables (Nearing et al., 1989). Model sensitivity can be evaluated quantitatively using either local or global analysis (Soutter and

Musky, 1999). Local techniques represent one-at-a-time parameter change from the base value, whereas global sensitivity analysis techniques include random parameters changes over their actual ranges, which generate input and output distributions that can be statistically analyzed (Soutter and Musky, 1999). Latin Hypercube Sampling-One variable At a Time (LHS) is a modified Monte Carlo simulation method that integrates local and global sensitivity of model parameters (Griensven, 2005).

Despite the benefit of evaluating an entire input-parameter space, global methods can be cumbersome and daunting when models are complex and contain numerous inputs, and extensive computational effort often is required. In these cases, single-variable analysis is often preferred (Graff et al., 2005). Independent Parameter Perturbation (IPP) from the LHS-Mean values for each model input parameter may help to compare local and global method responses. The response of the output to variations in input can be quantified using relative sensitivity for a given perturbation (Graff et al., 2005). The relative sensitivity of the model parameters may be obtained by measuring the relative response of each input vs. output variables (James and Burges, 1982; Nearing et al., 1989; White and Chaubey, 2005; Jesiek and Wolfe, 2005).

The Soil and Water Assessment Tool (SWAT) is a watershed scale process-based model developed by USDA Agricultural Research Service (ARS) (Arnold et al., 1998). The bacteria transport routines were added to the SWAT model in 2000 (Neitsch et al., 2002). The bacteria routines were improved (Sadeghi and Arnold, 2002) and the SWAT model was modified in 2005 (Neitsch et al., 2005), which allowed it to be used as a tool for addressing microbial contamination of water caused by point and non-point sources. However, sensitivity analysis of the SWAT 2005 version of the model focusing on bacteria transport part is needed to allow it to be used and parameterized appropriately. Sensitivity analysis of the microbial sub-model of SWAT (2005) has not been assessed. It is therefore important to know the influence of the model parameters and input parameter on model response. The objectives of this study were to demonstrate methods to characterize bacteria source loads and to assess the model sensitivity to model parameters, and input parameter.

## **Methods and Materials**

### ***Watershed Stream Description***

The study was done in the 77 km<sup>2</sup> Rock Creek watershed (Fig. 1), located in Douglas County, KS. The study-area land uses were primarily grassland (52%), cropland (33%), and woodland (14%) with predominately silty-clay textured soils (SSURGO: KS0457302, KS0457325, KS0458962). The pastures were native prairie, smooth brome, and tall fescue grasses. Average slope in the watershed sub-basins ranged from 3.8% to 6.3%.

Grab samples (about 250 ml) were collected from the mid point of the flowing stream at the watershed outlet. Samples were placed immediately into an ice chest and transferred to a laboratory refrigerator within two to four hours of collection. Bacteria enumeration procedures were started within 24 hours. A serial dilution method (Clesceri et al., 1998) was applied to enumerate fecal coliform bacteria colonies. Bacterial samples typically required four serial dilutions to obtain reasonable bacteria colony counts. Flow at the time of sample collection was calculated using Manning's equation, as outlined by Ward and Elliot (1995). Flow depth, cross-sectional area, and channel slope were measured, and the channel roughness factor was estimated based on channel roughness characteristics and degree of meandering (Cowan, 1956). The calculated flow was validated based on ratio of the watershed area using data from the USGS Richland gage station data (Fig. 1). The calculated flow data showed very good

correlation (>90%) with the weighted area flow data. This study used the data collected from January to December 2004.

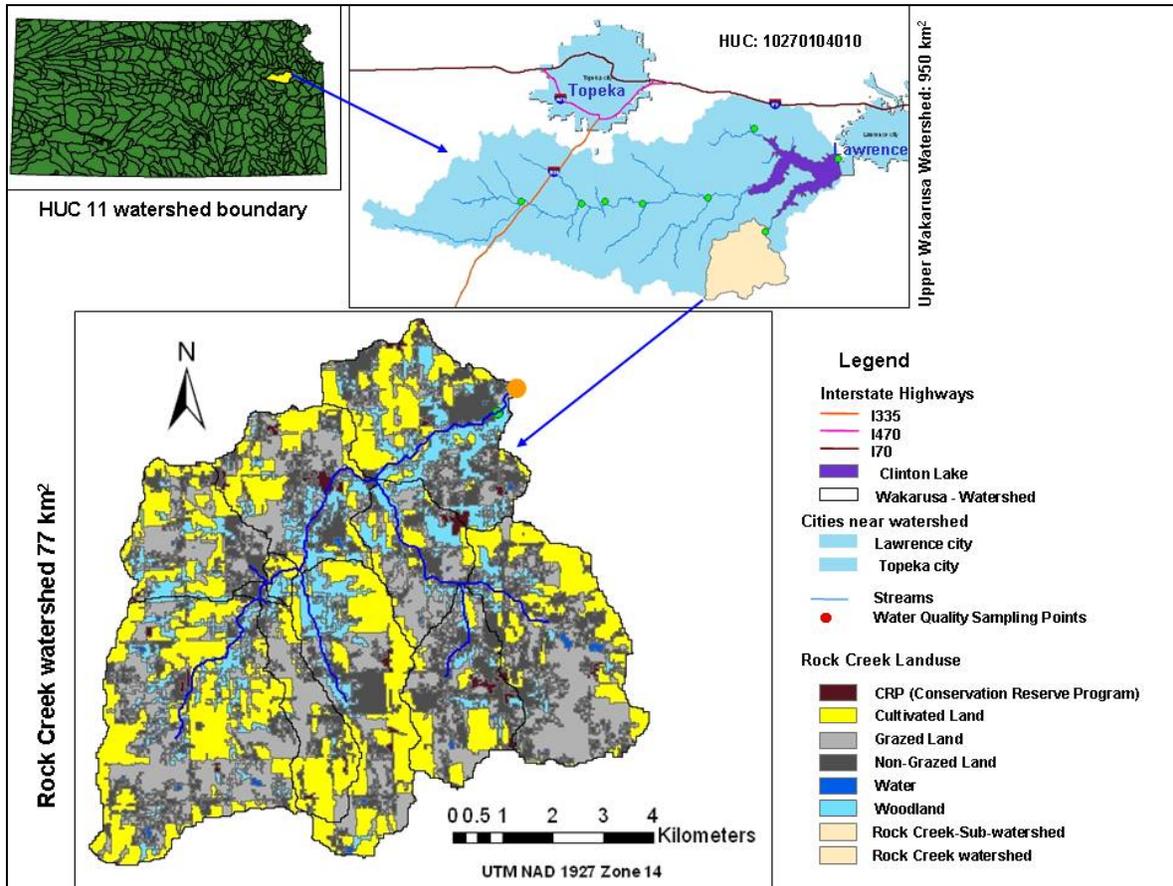


Figure 1. Location map of the Rock Creek watershed

### **SWAT model**

The SWAT watershed-scale process-based model (Arnold et al., 1998; Neitsch et al., 2002; Neitsch et al., 2005) operates on a continuous daily time step. It simulates the hydrological processes, sediment yield, nutrient loss, and pesticide losses into surface/groundwater. The microbial survival and transport sub-model, originally added in the SWAT version 2000 (Neitsch et al., 2002), was modified considerably in the 2005 version.

The SWAT model utilizes geospatially referenced data to satisfy the necessary input parameters. A United State Geological Survey (USGS, 1999) 7.5-minute digital elevation data was used to delineate the watershed boundaries and topography. Soil Survey Geographic Database (SSURGO) was utilized to create a soil database (USDA, 2005). The Gap Analysis Program (GAP) land cover data of 2001 that depicts twenty general land cover classes by Kansas Applied Remote Sensing (KARS, 2001) was used. The landuse classes were re-classified into eight classes (grazedland, non-grazedland/hay, cropland, woodland, Conservation Reserve Program, water, urban areas and quarry) based on field-verified landuse conditions (Mankin and Koelliker, 2001; Mankin et al., 2003). Parameters for each Hydrologic Response Unit (HRU) in each watershed were defined on the basis of soil, landuse, and

topographic characteristics of the watershed as described in the SWAT documentation version 2005 (Neitsch et al., 2005).

The microbial component of the SWAT simulates the fate and transport of bacterial organisms. The microbial sub-model uses the first-order decay equation as applied by Moore et al. (1989), to model fecal bacteria die-off and re-growth (Eq. 1).

$$C_t = C_o e^{-K_{20} t \theta^{(T-20)}} \quad (1)$$

where

$C_t$  = bacteria concentration at time t, count/100ml

$C_o$  = initial bacteria concentration, count/100ml

$K_{20}$  = first-order die-off rate at 20 °C, day<sup>-1</sup> (BACTKDQ in SWAT)

$t$  = exposure time, days

$\theta$  = temperature adjustment factor (TBACT in SWAT)

$T$  = temperature, °C

The less persistent fecal bacteria in manure/fertilizer were added with a different bacteria partition coefficient (0 to 1). The bacteria partition coefficient (BACTKDDB) in the fertilizer database separates bacteria concentration in sorbed and solution phases. As the bacteria partition coefficient approaches zero, bacterium is primarily sorbed to the soil particles and as it approaches to one bacterium is primarily in solution. The die-off rate of bacteria in the solution and sorbed phases impact the bacteria concentration. The BACTKDDB value used was 0.9 (Soupir et al., 2006).

The SWAT water quality model has been applied and validated for runoff, sediment yield, and nutrient losses from watersheds at different geographic locations, conditions, and management practices (Saleh et al., 1999; Spruill et al., 2000; Santhi et al., 2001; Kirsch et al., 2002; White and Chaubey, 2005). Limited research has been performed for the SWAT bacteria part of the model in predicting bacteria movement. Baffaut and Benson (2003) studied bacteria TMDLs (Total Maximum Daily Load) for the Shoal Creek watershed in southwest Missouri using the SWAT model (2000). They calibrated model using daily flow, weekly fecal coliform bacteria concentration collected from water quality grab samples, and annual hay yield reported to USDA (United States Department of Agriculture). A frequency curve analysis method was used to compare measured vs. predicted data for daily flow and fecal coliform bacteria concentration. Daily flow curve was reported reasonable except over-predictions of peak flow. The SWAT model predicted values were compared with 18 months of weekly measured fecal coliform bacteria concentration data using average plus or minus one standard deviation. The model predicted bacteria concentration validated as 70% using the frequency curve.

Several authors have previously completed sensitivity and output-uncertainty analyses for SWAT model (Lenhart et al., 2002; Eckhardt et al., 2002; Sohrabi et al., 2002; Benaman and Shoemaker, 2004; Huisman et al., 2004; Feyereisen et al., 2005) but only one (Parajuli et al., 2006) study has been done for SWAT (2000) microbial sub-model sensitivity analysis. Parajuli et al. (2006) reported low ( $S < \pm 0.50$ ) to high ( $S > \pm 1.00$ ) relative sensitivity for TBACT factor; low ( $S < \pm 0.50$ ) relative sensitivity for BACTKDQ factor; low ( $S < \pm 0.50$ ) relative sensitivity for: manure production rate, livestock stocking rate, land application method of septic effluent, moderate ( $\pm 0.50 < S > \pm 1.00$ ) to relative sensitivity for point load application method of septic

effluent; low to moderate relative sensitivity for applying wildlife bacteria source loads in the cropland, woodland, and cropland and woodland; and high ( $S > \pm 1.00$ ) relative sensitivity for bacteria concentration in livestock manure. However, sensitivity analysis of the SWAT (2005) bacteria part of the model has not been assessed.

### ***Model and Input Sensitive Parameters***

The bacteria partition coefficient in surface runoff (BACTKDQ) separate bacteria between sorbed and solution phases in surface runoff. The temperature adjustment factor (TBACT) impacts the bacteria concentration prediction by an exponential first-order-decay relationship. In order to determine sensitivity of model parameters and input parameter in the SWAT/Microbial sub-model (2005) at the watershed scale, first the SWAT/Microbial sub-model (2005) was applied to satisfy daily flow from the Rock Creek watershed. Four key model parameters were tested for sensitivity: (a) bacteria partition coefficient in surface runoff (BACTKDQ); (b) temperature adjustment factor (TBACT); (c) less persistent bacteria die-off factor in solution (WDL PQ); and (d) less persistent bacteria die-off factor in sorbed (WDLPS). Only one input parameter which is bacteria concentration in manure was tested for sensitivity. Parajuli et al. (2006) found low to moderate relative sensitivity for other input parameters such as manure production, stocking rate, land application and direct input of septic effluent, wildlife source loads applied into cropland/woodland. The lower and upper ranges of each parameter were set as: (a) BACTKDQ (0 - 500), (SWAT, 2005); (b) TBACT (0.80 - 1.20) (Moore et al., 1989; Walker et al., 1990); (c) WDL PQ (0.40 - 0.693) (McFeters and Stuart, 1972; Baffaut and Benson, 2003); (d) WDLPS (0.04 - 0.069) (Baffaut and Benson, 2003). Assuming 3 days half-life, the bacteria die-off factor of 0.40 was used for bacteria in soil solution and a factor of 0.04 was used for sorbed bacteria assuming  $1/10^{\text{th}}$  of the die-off in solution (Baffaut and Benson, 2003). Bacteria concentration in manure was used as  $1.3 \times 10^{10}$  to  $1.2 \times 10^{12}$ , based on the  $\pm 1$  standard deviation range cited for beef livestock manure (ASAE, 2000). The model predicted daily fecal bacteria concentration for 2004 were converted into geometric mean (GM) values to calculate sensitivity for the model. A geometric mean is defined as a mean of number of values (n) that is computed by taking the  $n^{\text{th}}$  root of the product of the n terms. The model predicted outputs and calculated sensitivity index values were log-transformed.

### ***Fecal Bacterial Source Characterization***

The watershed has many potential bacteria sources, the most dominant of which are categorized as livestock, failing septic tanks, and wildlife.

#### ***Livestock***

Manure applied due to grazing, feeding operations, and winter feeding areas were major bacterial sources in this study. Livestock population at the county and watershed level was estimated using agricultural census/GIS layers data (USDA, 2006). The county animal census population was equally distributed per total land-area basis to determine the fraction of total livestock in the study watershed. The USDA data were compared with Kansas Department of Agriculture farm facts data from the Kansas Department of Agriculture (KDA, 2004a). The AUs in feedlots within the watershed were estimated using active feedlot data (both federally permitted feedlots >1000 AUs and state registered feedlots > 300 AUs) from the Kansas Department of Health and Environment (KDHE) (Jepson, 2005). Permitted and registered livestock were subtracted from the total number of animals in the watershed to estimate the net grazed livestock population. Animal stocking rates in the pastureland was also validated using county-wide livestock population data (KDA, 2004b). Animals in the pasturelands could be brought from feedlots, barnyards and leasing agreements for grazing during the warm season

(generally from April to September). However, the stocking rate of the animals in the pastureland was assumed to be maintained.

The Rock Creek watershed was estimated to be populated in 1000-kg animal units of 558 beef animal units (AU) in the pastureland (based on stocking rate), 104 beef AUs in the feedlots, and 223 beef AUs in the winter feeding areas (40% of 558), which was modeled in this study to represent the current scenario of the watershed. Manure production ( $26.36 \text{ kg day}^{-1} \text{ AU}^{-1}$ ) and fecal coliform bacteria concentration ( $13 \times 10^{10} \text{ cfu day}^{-1} \text{ AU}^{-1}$ ) for each beef animal were estimated based standard production rates (ASAE, 2000). The bacteria concentration was converted into model-input units of colonies forming units (cfu) per gram of dry-weight manure using standard mean moisture content of 14% (ASAE, 2000).

### ***Failing Septic Systems***

Digital Orthophoto Quarter Quadrangles (DOQQ) (State of Kansas, 2002) of the watershed from 2002 was digitized depending on the physical context, roads, and type of houses to represent each septic system in the watershed. Each rural house was assumed to have one septic system, resulting in a total of 107 septic systems in the watershed. About 20% of the estimated septic systems (22 septic systems) were assumed failing in the watershed (KDHE, 2000). Each septic system was assumed to be used by three persons in the household that can contribute about  $0.32 \text{ m}^3$  of sewage effluent per day (US EPA, 2001). The failing septic system in the watershed was modeled using land application method. Parajuli, et al. 2006 found higher model sensitivity when applying septic effluent as direct point-load method than land application method. The fecal bacteria concentration in failing septic system was taken as  $6.3 \times 10^6$  cfu/100mL (Overcash and Davidson, 1980).

### ***Wildlife***

No comprehensive wildlife inventory was available for the Rock Creek watershed. The wildlife population density was estimated based on the information received from the Kansas Department of Wildlife and Parks (KDWP). The 2002 summer road-kill indices survey data (Peek, 2005) for Kansas were used to estimate small-mammal populations in the watershed. The information include various wild-animal species: raccoon, opossum, striped skunk, coyote, badger, bobcat, red fox, gray fox, swift fox, beaver, mink, muskrat, river otter, spotted skunk, weasel, armadillo, woodchuck and percupine. The population of raccoon, opossum, striped skunk, and coyote constituted about 81% of the total small mammals in Kansas. Population of the predominate large mammal (white-tailed deer) in the watershed was estimated based on expert opinion from the KDWP big-game coordinator (Lloyd, 2006). Similar data were collected for the predominate indigenous avian species (turkey) from the KDWP small-game coordinator (Pitman, 2006).

In order to estimate the animal units of each wildlife species in the watershed, the population data were first distributed over the potential habitat for each species. Small mammals and turkey population data were counted from a road survey. Most of the small mammals were counted dead at the road shoulder. The sight distances of 5 m for small mammals and 50 m for turkey from each side of the road were assumed, and the population density of each species was estimated as number of animal per unit area using total length of the road driven during survey. For deer, the number of deer harvested in northeastern Kansas was estimated and equally distributed in the total land area of northeastern Kansas to get the deer density. The population in 1000-kg animal units of about 60 turkeys, 24 deers, and 7 small mammals were estimated for the Rock Creek watershed to model in this study that represents the current

scenario of the watershed. Animal weights were estimated based on the information received from “mammals of Kansas” (Timm et al., 2007) and personal communication (Pitman, 2006).

## ***Management Scenarios***

### ***Pastureland***

The pastureland was simulated under two major grass-type management conditions, which represent the typical field conditions. The two major grass types in the watershed include grazed (80%, typically native prairie) and non-grazed (20%, typically smooth brome and tall fescue). The native prairie grass is typically not fertilized but tall fescue is fertilized with 70-15-0 (NPK) (Boyer, 2005). It was estimated that about  $1.81 \text{ kg ha}^{-1} \text{ day}^{-1}$  dry weight of manure is applied in the pasturelands due to grazing operation during the growing season which is one of the source of fecal bacteria simulated in this study. This estimation is based on the ASAE (2000) standards that include: (a) a AU of beef animal produces 26.36 kg of wet weight manure per day, (b) the conversion factor for wet-weight manure to dry-weight manure is 0.139, and (c) cattle are grazed for 153 days in the pastureland during April through September. It is possible that the actual animal density varies in the watershed everyday because of animal growth, and the pattern of incoming and outgoing animals. The actual manure production by each animal unit may also vary depending on dietary habit of the animal as reflected in a reported standard deviation of 17 for manure estimation (ASAE, 2000). Fecal coliform bacteria were generally estimated based on the ASAE (2000) standard, which estimated about  $13 \times 10^{10} \text{ cfu day}^{-1} \text{ AU}^{-1}$  wet weight basis bacteria concentration from the beef manure with a 12 standard deviation.

It was assumed that about 20% of the air-dry biomass is trampled every day, and about 341 kg of air-dry forage is required for an AU for 30 days (Paul and Watson, 1994). Grazing starts about a month earlier in tall fescue grasslands than in native prairie grass. All of the native prairie is grazed whereas only 80% of the tall fescue is grazed; the remaining tall fescue is un-grazed for haying and the Conservation Reserve Program (CRP). About 1.5 metric tons per acre of hay is harvested from the un-grazed area, whereas biomass is not removed from the CRP land (Boyer, 2005). Cattle density in the pastureland was estimated as 3.04 ha per pair of cow/calf based on the bluestem pasture guidelines for grazing (KDA, 2004b). Since cattle do not graze pastureland from October to March, no biomass uptake from the pastureland occurred, with no grass trampling and no manure deposition on the soil during this period.

All the source loads due to livestock in the confined animal feedlots were assumed to be applied as grazing operation in the pasturelands of the sub-watershed of the watershed where the active permitted feedlots were located. The winter feeding areas were modeled with the assumption that the estimated total numbers of AUs were confined within 40% of the grazed land of the watershed. Animals in feedlots and winter feeding areas contributed fecal bacteria for 212 days during the dormant season of the year (generally October to March). It was estimated that about  $4.52 \text{ kg ha}^{-1} \text{ day}^{-1}$  dry weight of beef manure (2.5 times greater than regular pastureland operation) was applied in the respective pasturelands of the sub-watersheds of the watersheds due to winter feeding operations, which was another source of fecal coliform bacteria simulated in this study. There is only one permitted feedlot located in the watershed at Overbrook with 288 AUs that produces about  $29.32 \text{ kg ha}^{-1}$  of solid manure to be applied in the pastureland as an additional bacterial source.

### ***Cropland and woodland***

Corn and soybeans were major warm-season crops, and winter wheat was a primary cool-season crop grown in three year's rotation in the watershed (Boyer, 2005). The warm season

crop was planted on May 1 and harvested on October 1. The cool-season crop was planted on October 20 and harvested on July 30. The crop residue is left on the cropland between the crop periods. These dates represent the typical planting and harvesting dates in the watersheds. The conservation tillage system is mostly adopted for corn-soybean-wheat in the watershed. All the wildlife generated manure was applied into the woodland to be consider as baseline.

### ***Weather and Hydrologic Data***

Daily precipitation data for the watershed were used from Overbrook weather station located about 4.8 km south of the watershed. The 2004 annual rainfall for Overbrook was about 1,126 mm (Fig. 2). Data from the Silver Lake weather station, which is located about 22.5 km south from the nearest point of the watershed, were used for the daily temperature, daily solar radiation, daily wind speed, and daily relative humidity data. The missing watershed data were adjusted using the SWAT weather generator. The SWAT model uses data from the Ottawa weather station (Franklin County), which is located about 23 km southeast from the nearest point of the Rock Creek watershed.

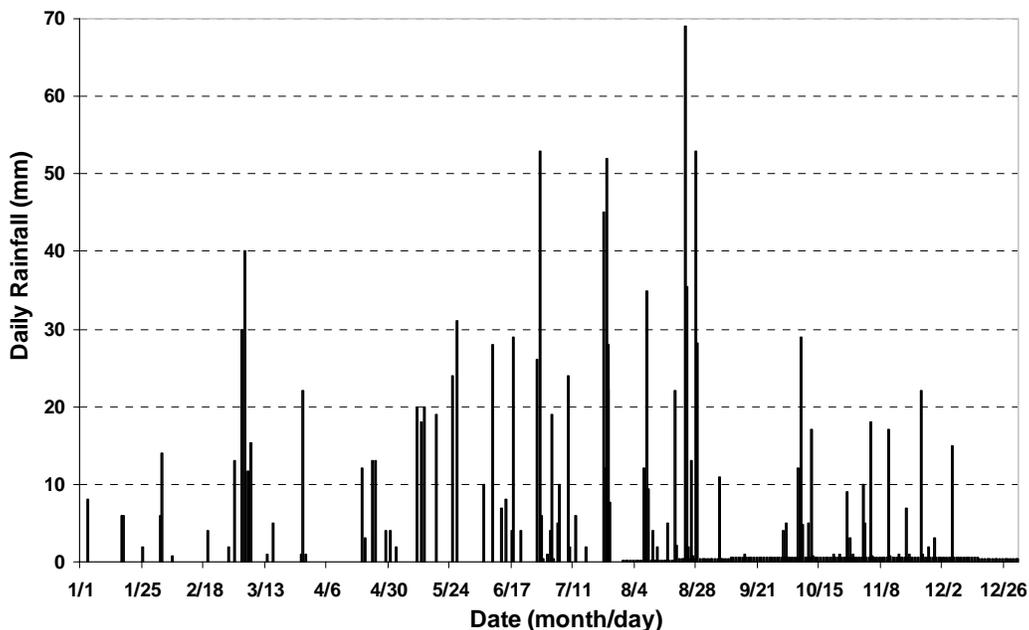


Figure 2. Distribution of daily rainfall data for Overbrook weather station, 2004

### ***Statistical Analysis Methods***

The SWAT model was validated using monitored flow and FCB concentrations from nine daily events. The statistical parameter used to evaluate measured vs predicted daily mean flow includes coefficient of determination ( $R^2$ ) and Nash-Sutcliffe Efficiency Index (E). The  $R^2$  value indicates how consistently measured vs. predicted values follow a best fit line. If the  $R^2$  value is less than or very close to zero, the model prediction is considered unacceptable or poor. If the value is 1.0, then the model prediction is perfect (Santhi et al., 2001). The E indicates how consistently measured values (range -  $\infty$  to 1.0) match predicted values (Nash and Sutcliffe, 1970).

### **LHS Sensitivity**

The LHS-OAT (One-At-a-Time) method uses a stratified sampling method, in which the range of each model input parameter is divided into  $n$  intervals of equal probability,  $1/n$ . Then, one sample is randomly generated within each interval, resulting in a total of  $n$  non-overlapping samples for each input parameter. In this study, each of the model input parameters was divided into 20 intervals of equal probability, for each of the 4 bacteria related model input parameters. In the OAT method, only one factor varies at a time while other factors are fixed. The change in model output can then be unambiguously attributed to such a change in the factor. The LHS method (Griensven, 2005) was applied to analyze sensitivity of parameter change for 100 model runs for Rock Creek watershed. A total of 103 model runs were used in the LHS analysis, including the 100 randomly generated parameter sets, two additional runs to refine model sensitivity and the baseline parameter set.

A relative sensitivity index, defined as the ratio between the relative normalized changes in output to the normalized change in related input, was calculated to facilitate a direct comparison and to avoid difficulties concerning the different orders of magnitude in input parameters (Brunner et al., 2004). The modified version of relative sensitivity ( $S$ ), equation (2) was used to consider the absolute change in model output and related input and their partial effects due to parameters change (Wang et al., 2005).

$$S = \frac{(O_2 - O_1)}{(O_2 + O_1)} * \frac{I}{\Delta I} \quad (2)$$

where

$S$  = relative sensitivity index

$O_1, O_2$  = model output values corresponding to  $I$  and  $\Delta I$  in the LHS sample

$I$  and  $\Delta I$  = base and changed input parameter in the LHS sample

Using results from 103 model runs, the relative sensitivity index as defined by equation (2) was computed for each combination of input and output for a given combination of model parameters and input parameters.

The total sensitivity for each parameter is calculated using equation 3.

$$S_{,Total} = \frac{\Sigma S}{N} \quad (3)$$

where

$S_{,Total}$  = total relative sensitivity index of the entire LHS samples parameter

$\Sigma S$  = summation of relative sensitivities of all LHS samples

$N$  = number of samples

### **IPP Sensitivity**

The most common form of sensitivity analysis is independent parameter perturbation (IPP) in which parameters is varied individually by a fixed percentage around a base value (Ferreira et al., 1995). Model output responses to parameter perturbation may be quantified by percentage change of selected output variables and relative change of output versus input (Larocque and Banton, 1994). In order to compare IPP method with LHS method, the model was run an

additional 53 times taking LHS mean value for each parameter separately and the percentage change from the LHS-Mean value (IPP) to see the model sensitivity (Table 2). For additional 53 runs samples, relative sensitivity index for each result was analyzed using equation 4 (James and Burges, 1982; Nearing et al., 1989; Kati and Chaubey, 2005; Jesiek and Wolfe, 2005):

$$S = \frac{(R - R_b)}{(P - P_b)} * \frac{P_b}{R_b} \quad (4)$$

where

S = relative sensitivity index

R = result (model output)

P = parameter (model input)

b = base scenario value

The relative sensitivity index (S) was used to test the model sensitivity for each model parameter or input parameter as described by equations 2 - 4. The relative sensitivity classes were classified based on previous references (Zerihun et al., 1996; Walker et al., 2000; Graff et al., 2005). An index of 0 indicates the output does not respond to changes in the input. An index of 1 indicates that the normalized output range is directly proportional to the normalized input range. A negative value indicates that an increase in input value caused a decrease in value. A greater absolute value of the index indicates a greater impact of an input parameter on a particular output (Walker et al., 2000). Similar to Zerihun et al. (1996), this study used five sensitivity classes:  $\pm 0 < S \leq \pm 0.10$  was no sensitivity,  $\pm 0.10 < S \leq \pm 0.50$  was low sensitivity,  $\pm 0.50 < S \leq \pm 2.00$  was moderate sensitivity,  $\pm 2.00 < S \leq \pm 5.00$  was high sensitivity and  $S > \pm 5.00$  was very high sensitivity.

## Results and Discussion

The model parameters and input parameter used in the study showed different degrees of relative sensitivity indexes (no to very high) when compared with model results using a relative sensitivity index (S). The fecal coliform bacteria concentration at the outlet of the watershed could be dependent upon several factors including the AUs in the pastureland, winter feeding areas, and confined feedlots; failing septic systems; wildlife; and daily rainfall amount that contributed to generate surface runoff. The SWAT model daily simulation covered one year period (January to December, 2004) in this study.

### **Flow Validation**

The un-calibrated SWAT model (2005), using ground-truthed land use conditions and other parameters to define current conditions, produced reasonable simulation of daily mean flow from the watershed. The SWAT model predicted the daily average flow rate of the watershed with good correlation ( $R^2=0.73$  and  $E=0.39$ ) between measured and predicted values (Fig. 3). The SWAT-model-predicted nine rainfall-runoff events were compared with the field measured data. The SWAT model under-predicted during five daily flow events due to either low rainfall events or low or no one day previous rainfall condition. The model over-predicted flow during one storm event when there was good amount of same day rainfall and one day previous rainfall. The observed reasonable correlation of un-calibrated model suggests that model input data affecting hydrologic processes were of reasonable accuracy. Baffaut and Benson, 2003 evaluated SWAT model for bacteria type of study in the Shoal Creek watershed in southwest

Missouri. The calibrated SWAT model showed  $R^2 = 0.40$  and  $E=0.21$  for daily flow whereas the model determined  $R^2=0.61$  and  $E=0.54$  during model validation in their study.

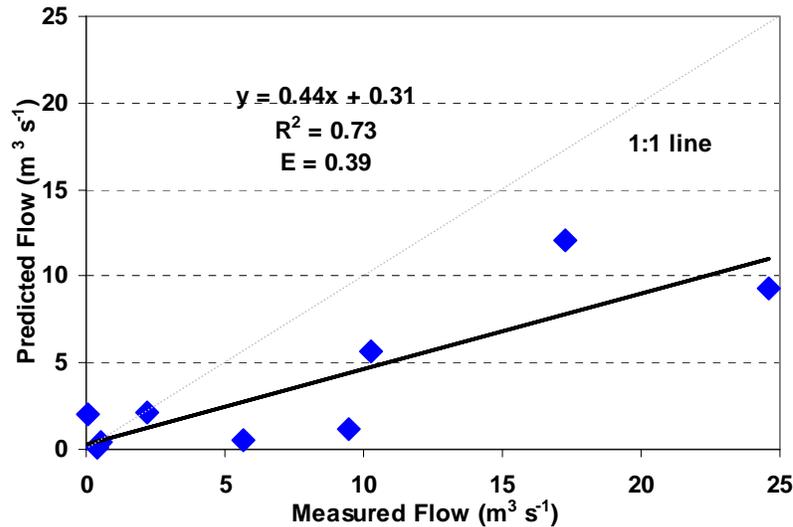


Figure 3. Model predicted daily flow showing good correlation

### ***Bacteria Load Validation***

The un-calibrated baseline SWAT (2005) model, using livestock, septic and wildlife loadings to represent current conditions under-predicted average daily fecal coliform bacteria concentration by 126% and gave a low but reasonable correlation of measured vs. predicted data with  $R^2 = 0.37$  (Fig. 4). The model under-predicted bacteria during no or low-flow event. Although the model under-predicted bacteria concentration by average of one fold of log transformation during most of the runoff events, the slope of predicted vs measured regression was 0.51, which was considered adequate to allow sensitivity analysis. Further calibration of the model was not attempted before sensitivity analysis was conducted because model still showed good relationship in regard to the source load characterization. The measured and model predicted values were varied by about a 0.8 of standard deviation. Generally, sensitive parameters identified during sensitivity analysis are used to calibrate and validate model. White and Chaubey (2005) studied sensitivity analysis of SWAT model. They identified sensitive parameters from sensitivity analysis then used those parameters for model calibration and validation for the Beaver Watershed located in northwestern Arkansas. Parameters identified by sensitivity analysis were modified during calibration.

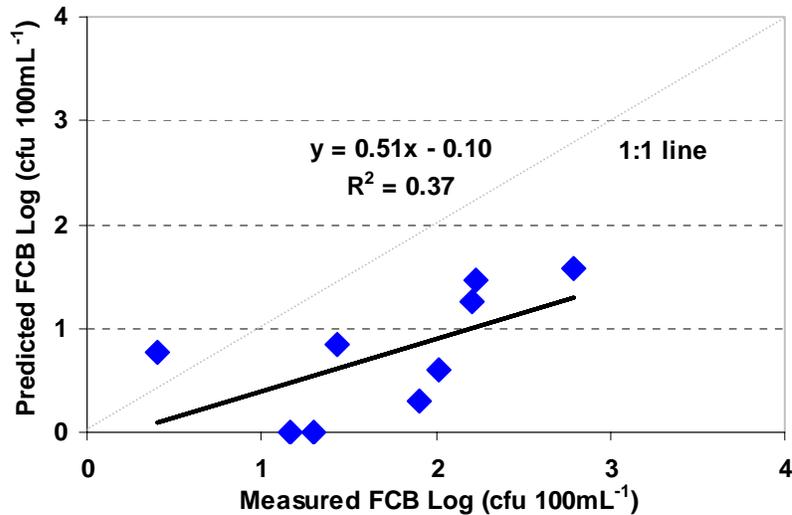


Figure 4. Measured fecal coliform bacteria (FCB) concentration model response

### Model Sensitivity

When analyzed relative sensitivity of 103 model runs, the results showed varied sensitivity of each model runs for different parameters used in this study. One thing clearly noticed that because of the interaction between parameters used some data noise can be seen while using LHS method. For example, simulation 102 predicted significantly high model outputs (Table 1) than base simulation because of the major change in BACTKDQ factor values. The impact of TBACT, WDLPQ, and WDLPS factors had very less to do with. The BACTKDQ model parameter generally showed no sensitivity with a relative sensitivity index  $< 0.10$  during LHS samples. However, the LHS samples randomly generated one hundred values only at the range from 28 to 483 for BACTKDQ parameter. When ran the model choosing lower BACTKDQ values resulted moderate to very high relative sensitivity ( $S > 5$ ). Generally, increase in the percentage input vs percentage output, increase the relative sensitivity. The LHS method of model simulations showed daunting and cumbersome performance in some areas. Although there was great increase in the percentage change in input (up to +155%), the percentage change in the output was relatively low (up to -55%). The low output was resulted due to a sudden change in the parameters in the LHS samples (Fig. 5). However, additional model runs using percentage change from the IPP method showed very good relationship between model prediction and change in the BACTKDQ factor values (Fig. 6). Actually, model showed a sensitivity of using lower values from the LHS-Mean value. The model sensitivity determined moderate to very high when used lower values of BACTKDQ.

The BACTKDQ factor is provided as an equilibrium constant in the SWAT model which shows inverse relationship between input values and model predictions. Model prediction shows power trend line relationship in the equation (Neitsch et al., 2005). But using LHS method samples model predicted data showed low power-trend line relationship ( $R^2 = 0.23$ ) which means there was no specific rate of increase in bacteria prediction with the decrease in BACTKDQ factor values. However, additional runs from the IPP samples result showed very good correlation of power-trend line relationship ( $R^2 = 0.97$ ) (Fig. 7). This result determines that local method is better than global method of sensitivity analysis. However, 103 model runs may not be enough for LHS method. More model runs such as 1000 may provide better correlation of power-trend line relationship for LHS method. The model sensitivity needs to improve especially for low BACTKDQ conditions which are less than 62. Parajuli et al. (2006) reported

that using BACTKDQ below 44 might be sensitive for SWAT 2000 version of the model. They reported BACTKDQ factor had low sensitivity because the maximum change in % output using SWAT 2000 was estimated about 51% whereas this study using SWAT 2005 determined the maximum change in % output about 359% for LHS method and about 865% for the IPP method especially only at the extreme lower values of BACTKDQ.

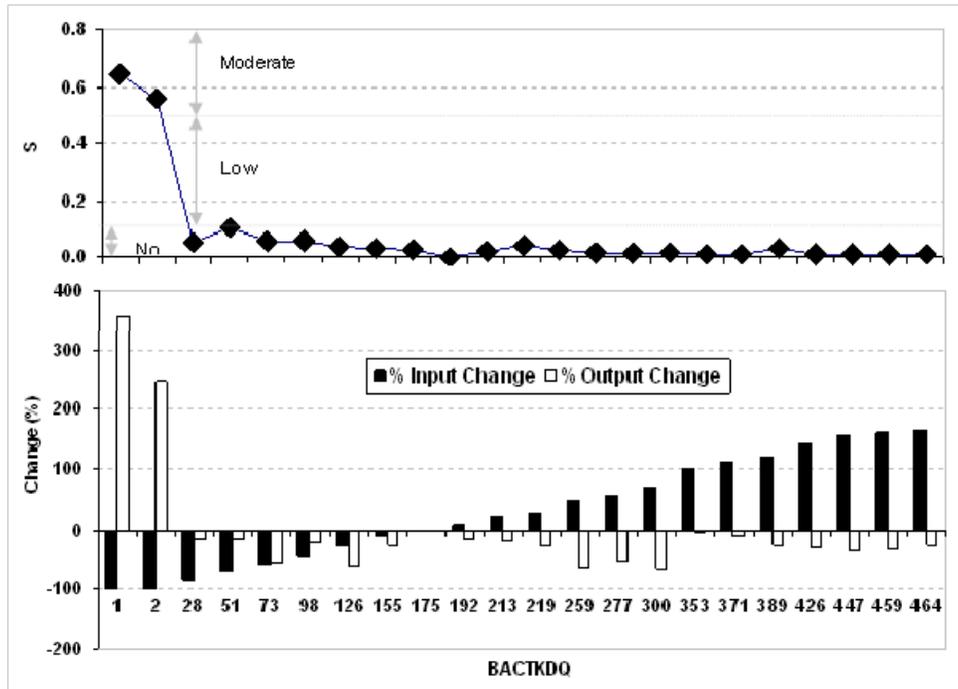


Figure 5. LHS method: bacteria partition coefficient in surface runoff (BACTKDQ) relative sensitivity index (S) response

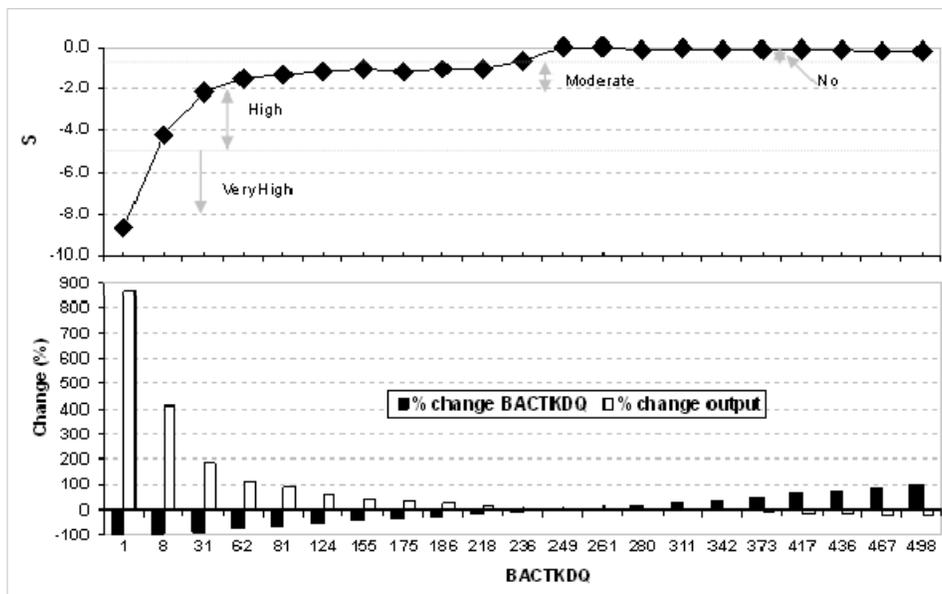


Figure 6. IPP method: bacteria partition coefficient in surface runoff (BACTKDQ) relative sensitivity index (S) response

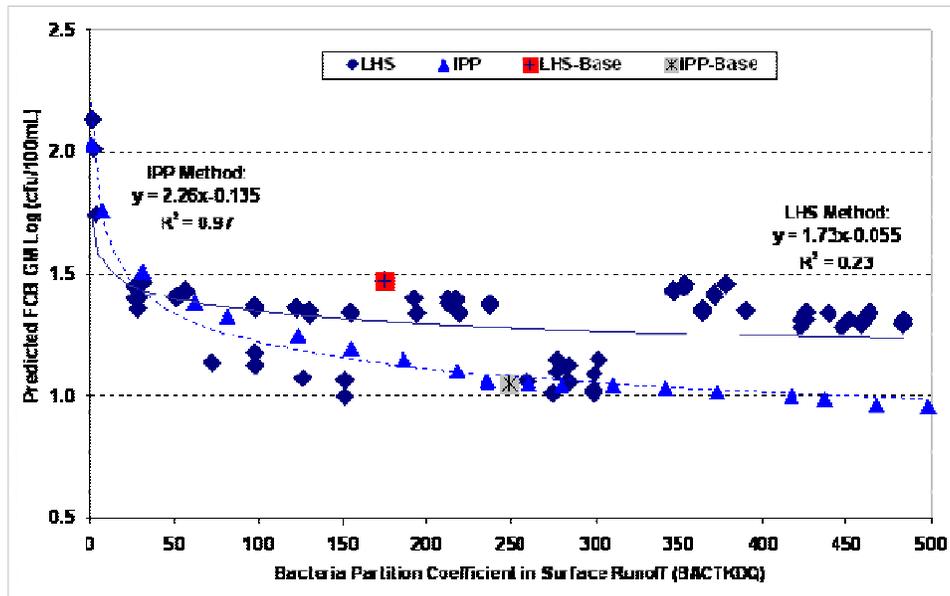


Figure 7. Power trend line showing correlation of LHS and IPP method model responses

The TBACT, model parameter showed no to high model sensitivity ( $S > 2.00$ ) and very good relationship between relative sensitivity and % input parameter and % model output change both for LHS method (Fig. 8) and IPP method (Fig. 9). The bacteria decay rate on land and in the water varies due to air or water temperatures. The TBACT may vary due to change in the daily ambient temperature. The selection of the right temperature adjustment factor is important which had low to moderate sensitivity especially either at the upper or lower range of TBACT values (example:  $>1.12$  or  $<0.86$ ). When used the TBACT factor below 0.86 in this study, model showed floating underflow error which means that model simulation exceeded range of values given in the model. The SWAT model needs to be re-compiled with larger range of values but the accuracy of the simulations was still valid (Sammons, 2007). Parajuli et al. (2006) reported that TBACT factor had low to high sensitivity using SWAT 2000 version of the model. They also reported that model sensitivity increases either at the extreme lower or upper range of TBACT values. Wang et al. (2004) calculated the TBACT factor in excreted manure as 1.026 for temperatures between 4°C and 27°C and 1.034 for temperatures between 27°C and 41°C, all within the range ( $1.07 \pm 0.05$ ). The SWAT model TBACT default value of 1.07 or  $1.07 \pm 0.05$  is reasonable to use in the model but exceeding this range could be sensitive. Although the current model of SWAT uses only one TBACT value for the entire model simulation period (365 days in this study), it is generally reasonable to represent the average condition of the watershed.

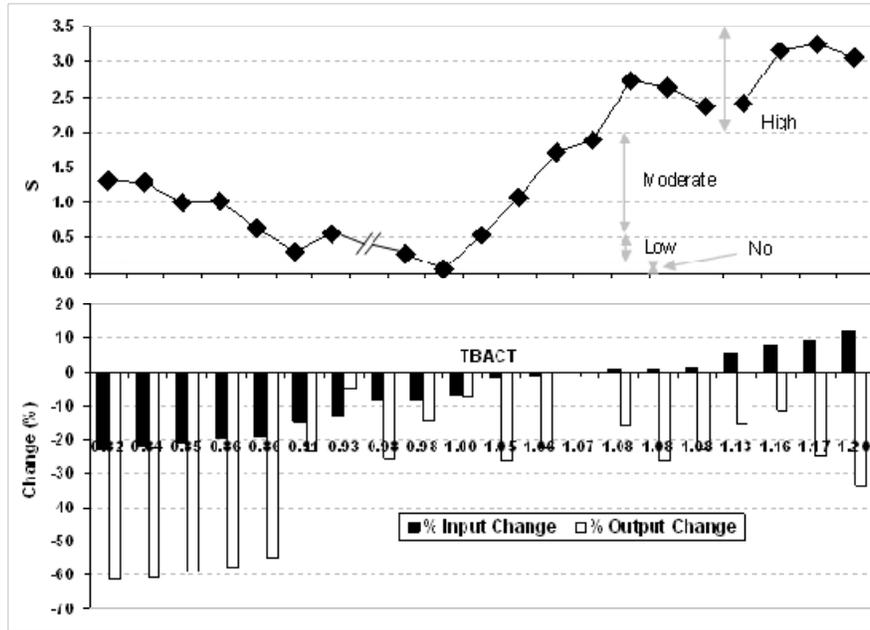


Figure 8. LHS method: temperature adjustment factor (TBACT) relative sensitivity index (S) response

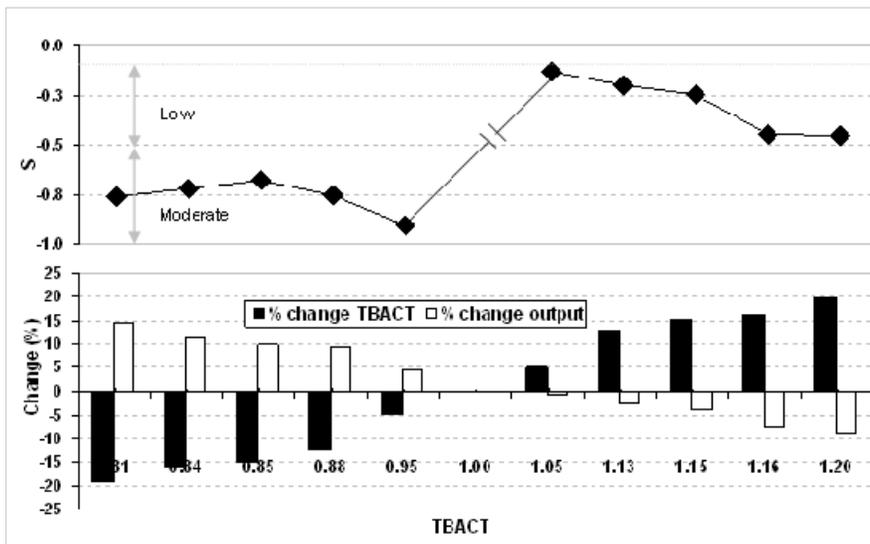


Figure 9. IPP method: temperature adjustment factor (TBACT) relative sensitivity index (S) response

Large difference between base condition model output and model predicted output due to change in input values made impact on relative sensitivity of WDLPQ and WDLPS parameters. These two parameters had low relative sensitivity in the model except for WDLPQ for IPP method model runs. The change in these two parameters had combined effect of TBACT factor and BACTKDQ. Generally, increase in the percentage input and percentage output had increased relative sensitivity. Although low sensitivity of the model simulations was determined for WDLPQ parameter (fig. 10), additional simulations (10) from the IPP method showed moderate sensitivity (S up to 0.98) with respect to percentage change in the input/output (Fig. 11). The decrease in the input values contributed to higher relative sensitivity of WDLPQ parameter.



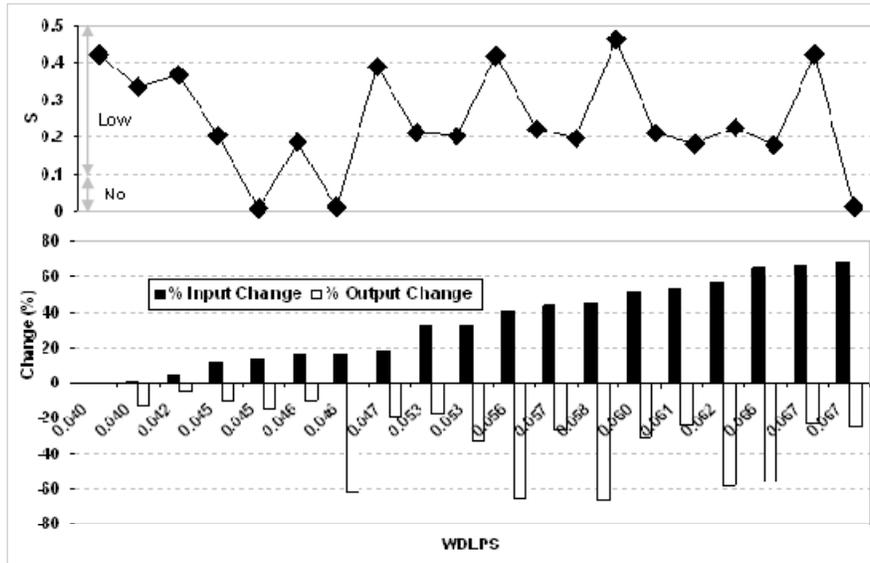


Figure 12. LHS method: less persistent bacteria die-off in sorbed (WDLPS) relative sensitivity index (S) response

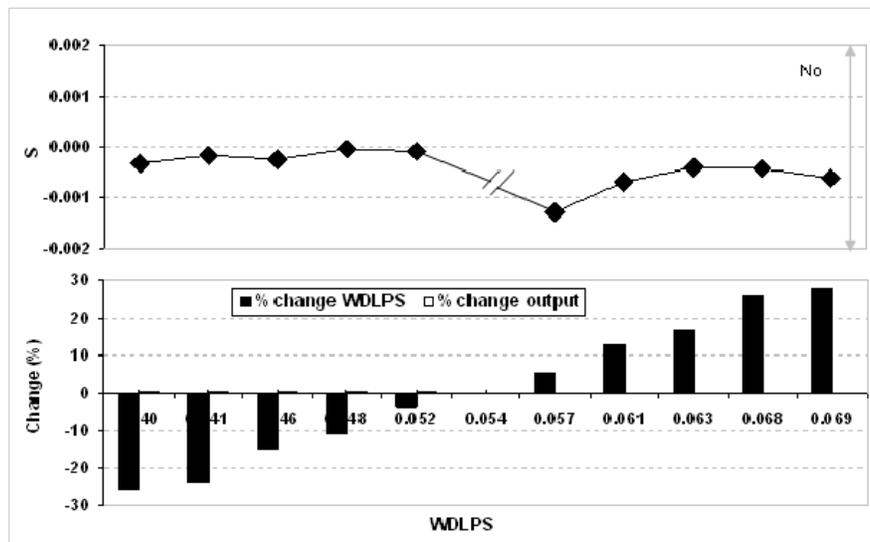


Figure 13. IPP method: less persistent bacteria die-off in sorbed (WDLPS) relative sensitivity index (S) response

Bacteria concentrations in manure showed direct relationship between bacteria concentration and bacteria prediction except at low input values. A moderate sensitivity was determined with relative sensitivity of 1.05 at -25% ( $2.6 \times 10^7$  cfu  $g^{-1}$ ) and 0.04 at +900% ( $3.5 \times 10^8$  cfu  $g^{-1}$ ) (Fig. 14). Bacteria concentration was stored in the model in floating-point 8.3 format (eight integers followed by three decimals: xxxxxxxx.xxx). When nine integer digits bacteria concentration values were input, model determined lower sensitivity predicting lower number of stream bacteria concentration than eight digit input values. If seven digit values were input, the model showed higher sensitivity ( $S = 0.99$ ) than eight digit input values ( $S = 0.84$ ). If eight digit values were input (99,999,999), the model predicted about eight times more bacteria than nine digit values input (100,000,000) with lower sensitivity (last two data points in the right, Fig 14). The SWAT model program may be recompiled to allow the model to adjust to 15.3 format

(xxxxxxxxxxx.xxx) in order to improve the current sensitivity problem due to bacteria concentration input. Parajuli et al. (2006) reported similar problems with the SWAT 2000 model.

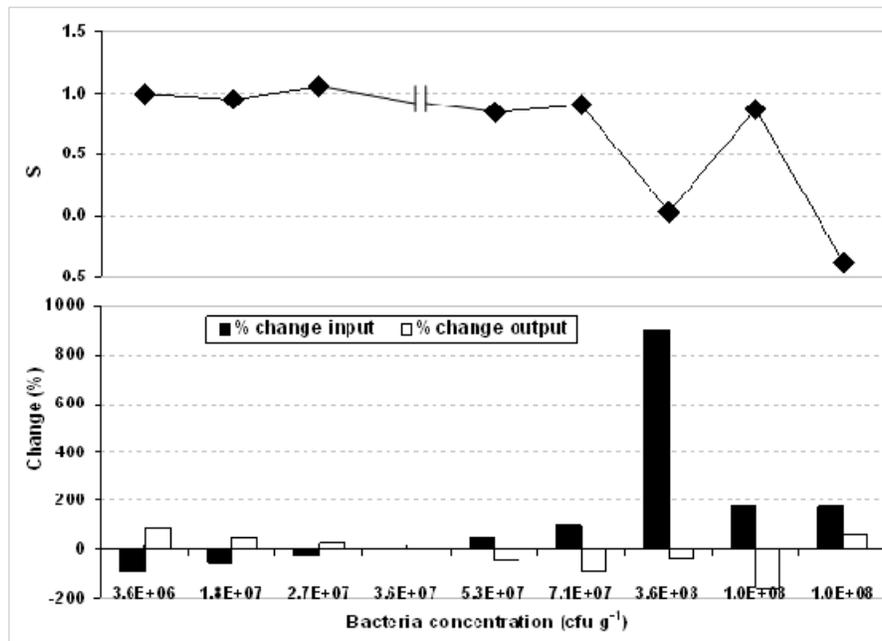


Figure 14. Bacteria concentration relative sensitivity index (S) response

The maximum relative sensitivity index absolute values for each tested parameter during LHS and IPP simulations were determined. The BACTKD and bacteria concentration parameters had high sensitivity especially when used extreme range of lower values. Otherwise, generally low sensitivity was determined. The TBACT factor generally showed moderate sensitivity especially when using either extreme low or high range of values. The WDL PQ and WDLPS factors generally showed no sensitivity except the WDL PQ showed low moderate sensitivity when using low WDL PQ values during IPP method simulations.

## Conclusions

This study demonstrated methods to characterize bacteria source loads and to assess the model sensitivity to model parameters, input parameter, and bacteria source application method. It is essential to know the influence of the model parameter and input parameters to improve model accuracy. The result of this study can help in watershed management and modeling decisions choosing more realistic model parameters to the natural life-perspectives.

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