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Autocalibration in hydrologic modeling: Using SWAT2005 in small-scale watersheds

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Abstract

SWAT is a physically based model that can simulate water quality and quantity at the watershed scale. Due to many of the processes involved in the manual- or autocalibration of model parameters and the knowledge of realistic input values, calibration can become difficult. An autocalibration-sensitivity analysis procedure was embedded in SWAT version 2005 (SWAT2005) to optimize parameter processing. This embedded procedure is applied to six small-scale watersheds (subwatersheds) in the central Texas Blackland Prairie. The objective of this study is to evaluate the effectiveness of the autocalibration-sensitivity analysis procedures at small-scale watersheds (4.0–8.4 ha). Model simulations are completed using two data scenarios: (1) 1 year used for parameter calibration; (2) 5 years used for parameter calibration. The impact of manual parameter calibration versus autocalibration with manual adjustment on model simulation results is tested. The combination of autocalibration tool parameter values and manually adjusted parameters for the 2000–2004 simulation period resulted in the highest E_{NS} and R^2 values for discharge; however, the same 5-year period yielded better overall E_{NS}, R^2 and P-values for the simulation values that were manually adjusted. The disparity is most likely due to the limited number of parameters that are included in this version of the autocalibration tool (i.e. Nperco, Pperco, and nitrate). Overall, SWAT2005 simulated the hydrology and the water quality constituents at the subwatershed-scale more adequately when all of the available observed data were used for model simulation as evidenced by statistical measure when both the autocalibration and manually adjusted parameters were used in the simulation.
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Keywords: SWAT; Hydrologic modeling; Autocalibration; Watershed; Nutrients; Sediment

1. Introduction

Public concern regarding the degradation of water quality due to nonpoint sources and point sources has driven policy regulators to scrutinize land management practices and examine how water quality conditions can be improved. Agricultural practices are commonly regarded as being sources of water and soil contamination (Sharpley, 1995; Abbozzo et al., 1996; Burkholder et al., 1997). Land application of manure provides nutrients and organic matter that enhance crop growth and can improve soil physical properties; however, when applied in excess, runoff from manured lands can result in the impairment of nearby water resources. Phosphorus (P) is a recognized contaminant that can cause adverse conditions in surface waters (Sharpley et al., 1994; Grobbelaar and House, 1995; Sims et al., 1998; Daniel et al., 1998).

Environmental regulation has expedited the necessity of agricultural producers to design and implement more environmentally suitable practices. There is a need to identify critical nutrient and their loss/transport potentials. Computer models can simulate multiple watershed management scenarios that can help environmental policy managers make decisions that could ultimately reduce P and N loss from agricultural lands. Models are inexpensive tools that can identify optimum watershed management practice scenarios for pollutant transport reduction.

Limited monitoring data exist at the watershed-scale for poultry litter application sites due to naturally inherent

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Notations

c threshold for a "good" parameter
θ^* parameter set
p free parameters

complexities such as rainfall variation, the requirement for a large amount of land, and the equipment and personnel required for data collection (Harmel et al., 2003a,b; Gilley and Risse, 2000). Long-term watershed monitoring data are rare due to the expense involved (Santhi et al., 2006); however, long-term simulations are needed to account for the inherent environmental variability (Rao et al., 2007). The ability of water quality models to accurately estimate environmental impacts from manure application needs to be determined.

Grayson et al. (1992) provided guidelines for analyzing any model which included testing measured data against simulated data and for a model's hydrologic processes to be tested over a wide range of watersheds and conditions, with both positive and negative results reported (Arnold et al., 1999; Chu and Shirmohammadi, 2004; and Rosenthal et al., 1995). Small-scale watershed studies have been conducted by Fohrer et al. (2001) and Srinivasan et al. (2005) at 26 and 39.5 ha, respectively. Fohrer et al. (2001) successfully analyzed the SWAT model (Arnold et al., 1998; Arnold and Fohrer, 2005) model for sensitivity to crop parameters and land use change. These studies are considered "small-scale" due to the relative size of watersheds that have been simulated with SWAT.

Barlund et al. (2007) used the SWAT model in a Finnish catchment to assess its usefulness to evaluate management impacts, such as nutrient load reductions. While the model proved its worthiness, it also demonstrated the necessity to adequately parameterize, calibrate and validate the model. These authors identify the need to include a parameter sensitivity analysis to concentrate on the more influential parameters that impact calibration. Krysanova et al. (2007) and Rao et al. (2007) agree with the previous authors that there is a demonstrated need for powerful calibration and validation techniques for hydrological models. In addition, there is a need to identify the criteria to achieve an adequate validation, which is based on sensitivity and uncertainty analyses to determine the most influential parameters and evaluate the model's uncertainty in relation to input data. Miller et al. (2007) emphasize the importance of the process used for parameter estimation; the higher the degree of spatial variability, the greater the complexity of correctly estimating parameter values.

This study evaluates the SWAT model's autocalibration-sensitivity analysis embedded procedures to simulate the stream discharge, sediment, organic nitrogen (N) and P, soluble P, and nitrate-N (NO_3-N) loss after poultry litter application to small-scale agricultural land at a research site in central Texas. The periods of calibration and validation are also tested to emphasize the impact that the calibration time period has on model autocalibration results. The purpose of applying the SWAT model to these subwatersheds is to test if the autocalibration-sensitivity procedures embedded in SWAT2005 can be applied to small-scale watersheds (4.0–8.4 ha) resulting in realistic output.

2. SWAT model background

The SWAT model is a continuation of modeling efforts by the U.S. Department of Agriculture Agricultural Research Service (USDA ARS; Arnold et al., 1998; Arnold and Fohrer, 2005) and has become an effective means for evaluating nonpoint source water resource issues (flow, sediment, and nutrients) for a large variety of national and international water quality applications. The model is part of the U.S. Environmental Protection Agency (USEPA) Better Assessment Science Integrating Point & Nonpoint Sources (BASINS) software package (Di Luzio et al., 2002) and is being used by many U.S. federal and state agencies. For example, SWAT has been used to validate flow, sediment and nutrients in the Bosque River Watershed in Texas for Total Maximum Daily Load (TMDL) analyses (Srinivasan et al., 1998; Santhi et al., 2001a). The SWAT model is one of the models selected by the U.S. Department of Agriculture Conservation Effects Assessment Project (CEAP) established in 2003 by the Agricultural Research Service and the Natural Resources Conservation Service to measure environmental impacts of conservation efforts at the national and benchmark watershed scale (Mausbach and Dedrick, 2004).

SWAT is a continuous time watershed-scale model that operates on a daily time step. The model is physically based, uses readily available inputs, is computationally efficient for use in large watersheds, and is capable of simulating long-term yields for determining the impact of land management practices (Arnold and Allen, 1996). Components of SWAT include: hydrology, weather, sedimentation/erosion, soil temperature, plant growth, nutrients, pesticides, and agricultural management. SWAT simulates the organic and mineral N and P fractions by separating each nutrient into component pools, which can increase or decrease depending on the transformation and/or the additions/losses occurring within each pool. A mass balance is calculated on a daily time scale to capture the series of changes addressed through the respective processes' equations. Neitsch et al. (2002a,b) describe the details of the nutrient process equations.

SWAT contains several hydrologic components (surface runoff, ET, recharge, and stream flow) that have been developed and validated at smaller scales within the EPIC, GLEAMS and SWRRB models. Interactions between surface flow and subsurface flow in SWAT are based on a linked surface–subsurface flow model developed by Arnold et al. (1993). Characteristics of this flow model include nonempirical recharge estimates, accounting of percolation, and applicability to basin-wide management assessments with a multi-component basin water budget. Surface runoff volume and infiltration are computed with the curve number equations or Green and Ampt. The peak rate component uses Manning's formula to determine the watershed time of concentration and considers both overland and channel flow. Lateral subsurface flow can occur in the soil profile from 0–2 m, and groundwater flow contribution to total streamflow is generated by simulating shallow aquifer storage (Arnold et al., 1993). Flow from the aquifer to the stream is lagged via a recession constant derived from daily streamflow records (Arnold and Allen, 1996).

The previous SWAT model flow versions have been validated in many river basins throughout the U.S. Current SWAT reach and reservoir routing schemes are based on the ROTO (a continuous water and sediment routing model) approach (Arnold et al., 1995), which was developed to estimate flow and sediment yields in large basins using subarea inputs from SWRRB. Configuration of routing schemes in SWAT is based on the approach given by Arnold et al. (1994). Water can be transferred from any reach to another reach within the basin. The model simulates a basin by dividing into subwatersheds that account for differences in soils and land use. The subbasins are further divided into hydrologic response units (HRUs). These HRUs are the product of overlaying soils and land use.

3. Autocalibration and sensitivity analysis in SWAT2005

SWAT is a complex model with many parameters that can complicate manual model calibration. A parameter sensitivity analysis tool is embedded in SWAT to determine the relative ranking of which parameters most affect the output variance due to input variability (van Griensven et al., 2002). The SWAT model, version 2005 (SWAT2005) has an embedded autocalibration procedure that is used to obtain an optimal fit of process parameters. This procedure is based on a multi-objective calibration and incorporates the Shuffled Complex Evolution Method algorithms. The optimization uses a global optimization criterion through which multiple output parameters can be simultaneously evaluated (van Griensven et al., 2002). This method allows for the aggregation of objective functions for individual variables, therefore eliminating the weighting problem. A statistical method uses the fit of the observed series to its related simulated series and translates the normalized values of the objective functions (van Griensven and Bauwens, 2003) per variable. These objective functions are then aggregated to a single global criterion determined by optimal fit (maximum E_{NS} value, Nash and Sutcliffe, 1970), which considers all of the participating variables rather than by means of a weighted sum. van Griensven and Bauwens (2003) describe the details of the optimal fit and the weighting dilemma for global optimization measures.

3.1. One-factor-at-a-time method

A sensitivity analysis is performed to limit the number of optimized parameters to obtain a good fit between the simulated and measured data. The optimization of parameters allows for models to better match realistic conditions. This approach is based on the One-At-a-Time (OAT; Morris, 1991) design, which is a method of incorporating local to global parameter sensitivity. In local methods, each run has only one parameter changed per simulation which aides in the clarity of a change in outputs related directly to the change in the parameter altered. This approach disregards the relative importance of particular variables and their effects in computational modeling (Morris, 1991). The change in model outcome is usually a lumped measure such as the sum of squares. Altering one parameter at a time can be monotonous and time consuming. Quantitative results for the measure of sensitivity for the parameters are relative and rely on the boundaries imposed. Therefore, the experiment is repeated several times (i.e. 20000 iterations) in which the variance of the parameters included will provide a measure of how uniform the effects are (i.e. the presence or absence of nonlinearities or mixed effects with other parameters). van Griensven et al. (2002) and Francos et al. (2003) state that the OAT design for SWAT is useful since it is able to analyze parameter sensitivity for a large number of variables.

3.2. Optimization method: the shuffled complex evolution algorithm

van Griensven and Bauwens (2001) describe the method in which the objective function (OF) is defined for each output variable for which observations are available. This OF is an indicator of the differences between the observations and the simulations. To identify the solution from different objectives, a single global optimization criterion (GOC) must be defined. The minimization of the GOC leads to the optimal parameter set which includes all errors (model errors and errors in the input and output variables).

The Shuffled Complex Evolution Algorithm is a global search algorithm for the minimization of a single function up to 16 parameters (Duan et al., 1992). It combines the direct search method of the simplex procedure with the concept of a controlled random search of Nelder and Mead (1965), a systematic evolution of points in the direction of global improvement, competitive evolution (Holland, 1975) and the concept of complex shuffling. In the first step (zero-loop), the shuffled complex evolution-uncertainty analysis (SCE-UA) procedure selects an initial "population" by random sampling throughout the feasible parameters space for p parameters to be optimized (delineated by given parameter ranges). The population is portioned into several "complexes" that consist of $2p+1$ points. Each complex evolves independently using the simplex algorithm. The complexes are periodically shuffled to form new complexes in order to share the gained information. This methodology is based on a normalization of the individual OFs to the range of 0−1. An initial random sampling within the parameter space is used to define the distribution function, the mean and the variance of a OF via random sampling. The following optimization stage uses the cumulative probability of the OF values (F(OF)) instead of the actual OF values. It searches over the whole parameter space and finds the global optimum with a success rate of 100% (Sorooshian et al., 1993).

In order to calculate the global optimization criterion (GOC), the values of the cumulative probabilities for the different objective functions are summed (within the range of 0−1):

$$\mathrm{GOC} = \sum_{J-i,k} F(\mathrm{OF}) \tag{1}$$

SCE-UA has been widely used in watershed model calibration and other areas of hydrology such as soil erosion, subsurface hydrology, remote sensing and land surface modeling

(Duan, 2003). It was generally found to be robust, effective and efficient (Duan, 2003). The SCE-UA has also been applied with success on the SWAT model version 2000, for the hydrologic parameters (Eckhardt and Arnold, 2001) and hydrologic and water quality parameters (van Griensven et al., 2002).

3.3. The uncertainty analysis method

The uncertainty analysis divides the simulations that have been performed by the SCE-UA optimization into 'good' simulations and 'not good' simulations. The simulations gathered by SCE-UA are very valuable as the algorithm samples over the entire parameter space with a focus of solutions near the optimum/optima.

There are two separation techniques; both are based on a threshold value for the objective function (or global optimization criterion) to select the 'good' simulations by considering all the simulations that give an objective function below this threshold. In this study the threshold value is defined by χ^2-statistics where the selected simulations correspond to the confidence region (CR).

3.4. χ^2-method

For a single objective calibration for the sum of squares (SSQ; Eq. (2)), which aims at matching a simulated series to a measured time series, the SCE-UA will find a parameter set (θ*) consisting of the "p" free parameters (θ_1*, θ_2*, ... θ_p*) that corresponds to the minimum of the sum the square SSQ.

$$\mathrm{SSQ} = \sum_{i=1,n} \left[x_{i,\mathrm{measured}} - x_{i,\mathrm{simulated}}\right]^2 \quad (2)$$

where n is the number of pairs of measured (x_{measured}) and simulated ($x_{\mathrm{simulated}}$) variables.

According to χ^2 statistics, we can define a threshold "c" for "good" parameter set using the following equation:

$$c = \mathrm{OF}(\theta^*)\left(1 + \frac{\chi^2_{p,0.95}}{n-p}\right) \quad (3)$$

whereby the $\chi_{p,\,0.95}^2$ is assigned a higher value for more free parameters p.

For multi-objective calibration, the selections are made using the GOC of Eq. (1) that normalizes the sum of the squares for n, equal to the sum of n number of observations 1 (nobs1) and n number of observations 2 (nobs2). A threshold for the GOC is then calculated by:

$$c = \mathrm{GOC}(\theta^*)\left(1 + \frac{\chi^2_{p,0.95}}{\mathrm{nobs1} + \mathrm{nobs2} - p}\right) \quad (4)$$

3.5. Parameter sensitivity analysis

A parameter sensitivity analysis allows the model to focus on the parameters that contribute the most to the output variance due to input variability (Holvoet et al., 2005). Whether the calibration is manual or automated, a complex hydrologic model contains several parameters of which, depending on the study, can have only a few or several sensitive parameters. The performance of the calibration is evaluated by the E_{NS}. The autocalibration-parameter sensitivity analysis procedure embedded in SWAT is used to obtain an optimal parameter fit, based on E_{NS} values, for the following parameters: the SCS runoff curve number for moisture condition II (CN2), the soil evaporation compensation factor (ESCO), surface runoff lag time (SURLAG), and initial soil water content expressed as a fraction of field capacity (FFCB).

4. The Riesel research site as a case study

Data used in this study were obtained from an experimental research site located at the USDA ARS Grassland, Soil, and Water Research Laboratory near Riesel, Texas (31.1°N, 97.32°W) (Harmel et al., 2004; Wang et al., 2006). The simulated areas at Riesel are designated as "subwatersheds" due to their small size. The numerical distinction between labeling an area as a subwatershed versus a watershed in the literature is unclear. However, since the Riesel areas being simulated are some of the smallest SWAT has simulated thus far it is justifiable to denote them as "subwatersheds." The subwatersheds are denoted as Y6, Y8, Y10, Y13, W12, and W13 (Fig. 1). Each subwatershed was simulated as one subbasin and one HRU because of the homogeneous land use and dominant soil combination. These subwatersheds are terraced, corn and wheat rotations are planted on the contour, and each has an established grassed waterway. The areas and upland slopes range from 4.0 to 8.4 ha and from 1.1 to 3.2%, respectively (Table 1). Houston Black is the dominant soils series (fine, smectitic, and thermic Udic Haplusterts); its physical and chemical properties are listed in Table 2. The soil layer properties include depth, bulk density, texture fractionation, soil pH, and percent organic C, saturated conductivity, and

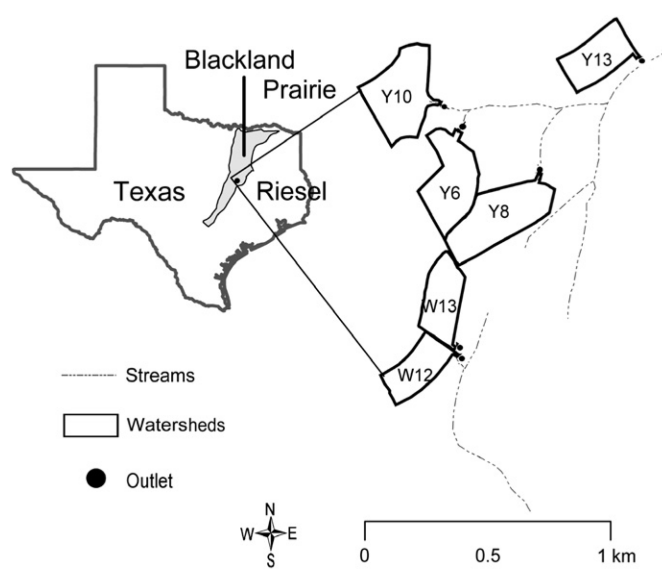

Fig. 1. Locations of the six cultivated subwatersheds near Riesel, Texas.

Table 1
Site features of the six subwatersheds near Riesel, Texas

Feature	Y6	Y8	Y10	Y13	W12	W13
Upland slope (%)	3.2	2.2	1.9	2.3	2.0	1.1
Area (ha)	6.6	8.4	7.5	4.6	4.0	4.6
Channel slope (%)	2.1	2.2	1.4	1.5	1.3	0.8
Channel length (km)	0.44	0.46	0.52	0.35	0.32	0.4

available water capacity; these data were obtained from the Natural Resource Conservation Service's (NRCS) Soil Survey Geographic Database (SSURGO). The clays/silty-clays present in the Houston Black soil have a shrink–swell potential of 1.3–10.2 cm and cracks can occur to a depth of 30.5 cm or more (http://soils.usda.gov/technical/classification/osd/index.html). These cracks exist throughout each of the six subwatersheds. Further details of the subwatersheds are available in Harmel et al. (2004).

4.1. Precipitation, flow and temperature data

Daily precipitation totals were obtained from onsite gauges for the 5-year (2000–2004) simulation period. The mean and standard deviation for the annual precipitation from 2000 to 2004 ranged from 1055 to 1062 mm and from 226 to 260 mm, respectively. These ranges reflect the variability inherent in the rainfall that occurs at this site where there is only a 2-km distance among the subwatersheds. Average rainfall for this area is about 890 mm per year (Harmel et al., 2003a,b). The Hargreaves potential evapotranspiration method (Hargreaves and Samani, 1985) was used for all model simulations due to its robustness and lack of requiring data for relative humidity, wind speed and solar radiation. Each of the six subwatersheds contained a flow control structure through which flow rate was recorded in 10-min intervals and water quality samples were obtained (Fig. 1).

4.2. Fertilizer applications

The year 2000 is considered the control year in which initial conditions were established; fertilizer was not applied during this year. The initial soil N and P levels ranged from 0.11% to 0.13% and from 0.05% to 0.07%, respectively (Table 2). The range of poultry litter application rates were selected in anticipation of those used by agricultural producers. The application rates were determined a priori and were randomly assigned to the subwatersheds (Harmel et al., 2004). Table 2 includes the poultry litter and additional N and P commercial fertilizer inputs.

The control subwatershed, Y6, did not have poultry litter applied and is compared to five treated subwatersheds that received varied rates of poultry litter. A target N rate of 170 kg ha^{-1} is common for this Blackland Prairie region and follows corn production recommendations (Gass, 1987). This N rate was accomplished via the addition of supplemental N in the form of urea and ammonium nitrate (1:1 liquid urea: ammonium nitrate). Additional N was applied in February 2002 and January 2003. The Y6 subwatershed also received supplemental P (36 kg ha^{-1}) in January 2003. For the wheat crop, the Y6 control subwatershed had additional inputs of 67 and 34 kg P ha^{-1} in October 2003. Commercial fertilizer additions followed crop production recommendations for the Blackland Prairie in central Texas.

From 2002 through 2004, management for each of the six subwatersheds included: tillage, planting, harvesting, and nutrient supplementation from poultry litter and/or inorganic N and P inputs (Harmel et al., 2004); 2001 was a fallow year. The tillage system included one or two field cultivation operations for seedbed preparation; fertilizer was incorporated using a disc and sweep chisel. Corn was planted in March and harvested in August for the 2002 and 2003 field years. Wheat was planted in October, 2003 and harvested in May/June, 2004. The potential heat unit (PHU) (growing degree days in °C from planting to maturity) was set to an average of 1800 for corn and wheat. The W13 subwatershed had the highest yields of all the subwatersheds (Table 3), received the second highest fertilizer inputs (Table 2) and has the lowest slope (Table 1).

Table 2
Average poultry litter and inorganic commercial fertilizer rates applied to the six cultivated subwatersheds near Riesel, Texas from 2001–2004

	Y6	Y8	Y10	Y13	W12	W13
Litter rate (Mg ha^{-1} yr^{-1})	0.0	13.4	6.7	4.5	9.0	11.2
Mean N rate[a] (kg ha^{-1} yr^{-1})	168	370	278	237	296	328
Mean P rate[b] (kg ha^{-1} yr^{-1})	19	358	196	122	229	286

[a] Mean N rate is the mean of N inputs, including poultry litter and inorganic commercial fertilizer, for the 2001–2004 crop years.

[b] Mean P rate is the mean of P inputs, including poultry litter and inorganic commercial fertilizer, for the 2001–2004 crop years.

5. Model evaluation methods

The performance of SWAT was evaluated using statistical analyses to determine the quality and reliability of the predictions when compared to observed values. Summary statistics included the mean and standard deviation (SD), which were used to assess SWAT's ability to reproduce the distribution of the observed data and to assess the variability between the observed and simulated data. The goodness-of-fit measures used were the coefficient of determination (R^2; Eq. (5)) and the Nash–Sutcliffe efficiency (E_{NS}) value (Eq. (6)) (Nash and Sutcliffe, 1970). Percent error (PE; Eq. (7)) was used to assess the

Table 3
Crop type and yield for 2002–2004 for the six subwatersheds near Riesel, Texas

Year (crop type)	Crop yield (kg ha^{-1})					
	Y6	Y8	Y10	Y13	W12	W13
2002 (corn)	6600	7100	7900	8250	7000	8050
2003 (corn)	5400	6700	6100	5100	7050	6450
2004 (wheat)	1650	2400	2700	2650	2500	2300
Total yield	13,650	16,200	16,700	16,000	16,550	16,800

systematic over- or under-prediction and when the absolute value is applied it shows the magnitude of error. The R^2, E_{NS}, and PE values are explained in Eqs. (5), (6), and (7), respectively,

$$R^2 = \frac{\left(\sum_{i=1}^{n}(O_i - \overline{O})(P_i - \overline{P})\right)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2 \sum_{i=1}^{n}(P_i - \overline{P})^2} \tag{5}$$

$$E_{NS} = \frac{\sum_{i=1}^{n}(O_i - \overline{O})^2 - \sum_{i=1}^{n}(P_i - O_i)^2}{\sum(O_i - \overline{O})^2} \tag{6}$$

$$\mathrm{PE} = \frac{P_i - O_i}{O_i}100 \tag{7}$$

where n is the number of observations during the simulated period, O_i and P_i are the observed and predicted values at each comparison point i, and $\overline{O}$ and $\overline{P}$ are the arithmetic means of the observed and predicted values. The E_{NS} value was used to compare predicted values to the mean of the average monthly observed values for the subwatershed where a value of 1 indicates a perfect fit. The E_{NS} describes the explained variance for the observed values over time that is accounted for by the SWAT model. The R^2 was used to evaluate how accurately the model tracks the variation of the observed values. The difference between the E_{NS} and the R^2 is that the E_{NS} can interpret model performance in replicating individually observed values while the R^2 does not. For this study, the criteria of $E_{NS} > 0.4$ and $R^2 > 0.5$ were chosen to assess how well the model performed (Green et al., 2006) with results greater than 0.4 and 0.5 for E_{NS} and R^2, respectively, meaning that the model performed satisfactorily and results below those numbers intending that the model did not perform well. Santhi et al. (2001a,b) and Ramanarayanan et al. (1997) used criteria of $R^2 > 0.6$ and $E_{NS} > 0.5$ to determine how well the model performed. Chung et al. (1999, 2002) used standards of $E_{NS} > 0.3$ and $R^2 > 0.5$ with EPIC simulations to determine if the model results were satisfactory.

6. Model simulation approach

The initial N and P values were extrapolated from the percent organic carbon values and model defaults were utilized for the nutrient pools. The model defaults were used when initial values were not obtainable. The parameter values were allowed to vary within reasonable uncertainty ranges (Table 4) to calibrate for monthly and daily discharge, and monthly sediment and nutrient loss values.

Two data scenarios were used to demonstrate the impact of using all of the data available. Santhi et al. (2006) state that a minimum of a few years of data are essential for effectively simulating watershed conditions. Having a sufficient amount of measured data can also help reduce uncertainty. The first model simulation uses all of the subwatershed data (2000–2004) while the second scenario uses only the data from 2002. While typically data sets are separated into calibration and validation periods, the carryover effect of the fertilizer inputs need to be accounted for and the model needs time to initialize parameter values. The year 2002 was selected since it is the first year that both the fertilizer and tillage operations occurred. Since the ultimate goal of model simulation is the prediction of hydrology and water contaminants, it appears that model simulation efforts need to be adjusted to focus on this goal when less data are available.

Table 4
Autocalibrated parameters selected for discharge, sediment and nutrient simulation of the SWAT2005 model for the six subwatersheds near Riesel, Texas

Parameter	Description	Range
ESCO	Soil evaporation compensation factor	0.01–1.0
FFCB	Initial soil water storage expressed as a fraction of field capacity water content	0–1.0
SURLAG	Surface runoff lag coefficient (days)	0–4
Nperco	Nitrogen percolation coefficient ($10\ m^3\ Mg^{-1}$)	0–1
Pperco	Phosphorus percolation coefficient ($10\ m^3\ Mg^{-1}$)	10–17.5
ErorgN	Nitrogen enrichment ratio for sediment loading	0.5–3.0
ErorgP	Phosphorus enrichment ratio for sediment loading	0.5–5.0
CN2	Initial SCS runoff curve number to moisture condition II	30–100
Phoskd	Phosphorus soil partitioning coefficient ($m^3\ Mg^{-1}$)	100–175

Calibration parameters that impact runoff, and, therefore water quality values, include the SCS runoff curve number for moisture condition II (CN2), the soil evaporation compensation factor (ESCO), the surface runoff lag time (SURLAG), and initial soil water content expressed as a fraction of field capacity (FFCB). The CN2 parameter was originally set a value of 81 as recommended by the USDA-SCS National Engineering Handbook (USDA-SCS, 1972) for these hydrologic groups. The other parameters (SURLAG, ESCO, and FFCB) used SWAT's default values (4 days, 0.95, and 0, respectively).

6.1. Autocalibration-sensitivity analysis tool

Using only manually calibrated parameter values in the autocalibration process is as follows. First the parameters are manually calibrated for the time period of choice until the model simulation results are acceptable as per the E_{NS} values and difference of means. Next, the final parameter values that were manually calibrated are used as the initial values for the autocalibration procedure. Maximum and minimum parameter value limits are used to keep the output values within a reasonable value range. Finally, the autocalibration tool is run with the optimal fit values to provide the best fit between the measured and simulated data as determined by the E_{NS} values and how reasonable the values are. The autocalibrated determined parameter values can then be adjusted to ensure that they are reasonable. The user has a large role in determining if the values are realistic for their application and can override the output manually.

Table 5
Autocalibration tool simulation values per subwatershed near Riesel, Texas for the two time periods, 2000–2004 and 2002

Parameter	Subwatershed					
	Y6	Y8	Y10	Y13	W12	W13
CN2	78	74	78	78	76	77
ESCO	0.002	0.23	1.0	0.27	0.002	0.001
FFCB	0.26	0.37	0.65	0.76	0.27	0.64
SURLAG (days)	0.80	0.81	0.72	1.22	0.16	1.47

Table 6
Final simulation values as a function of autocalibrated tool inputs and manually adjusted parameter values per subwatershed near Riesel, Texas for the two time periods, 2000–2004 and 2002

Parameter	Subwatershed					
	Y6	Y8	Y10	Y13	W12	W13
CN2	78	74	78	78	76	77
ESCO	0.80	0.80	0.80	0.80	0.80	0.80
FFCB	0.26	0.32	0.35	0.26	0.27	0.24
SURLAG (days)	0.80	0.81	0.72	0.94	0.91	1.13

Each subwatershed's optimum parameter's value for a maximum E_{NS} value was determined using SWAT's embedded autocalibration tool for two time periods (2000–2004 and 2002) run on a monthly time step. The maximum number of trials allowed was 20,000 before optimization was terminated with the complex shuffling set at 97.5% probability. The ranges for these parameters were set as follows: CN2 $\pm$ 6; ESCO range from 0.001 to 1.0; SURLAG range from 0.5 to 10.0; and FFCB range from 0.0 to 1.0. The resulting parameter ranges adjusted via autocalibration were: FFCB, 0.24–0.35; SURLAG, 0.72–1.13; CN2, 74–78; and ESCO, 0.42–0.52. While the autocalibration tool was used to identify optimum parameter values, model user knowledge must be used to evaluate the resulting values and how reasonable the values are. For example, the autocalibration routine elicited ESCO values ranging from 0.001 to 1.0 for the six subwatersheds (Table 5). The low values obtained through using the autocalibration tool are unrealistic as these soils have more evaporative demand from the upper levels and a value closer to SWAT's default value of 0.95 should have been concluded. A value of 0.80 was selected to represent a high evaporative soil demand.

Finally, all of the SURLAG parameter values for each subwatershed should have values close to 0.80 since the subwatershed area is small and has a time of concentration less than one day so that most of the surface runoff should reach the main channel on the day it is generated. Since the SURLAG values were close to one day, considering error uncertainty, the values were not changed. The values discerned by the autocalibration tool are listed in Table 5 while the final simulation parameter values, as a combination of autocalibration values and manually adjusted values, per subwatershed are listed in Table 6. The disparities in the ESCO, FFCB and SURLAG parameter values may reflect model and/or experimental error.

7. Results and discussion

7.1. Sensitivity analysis

Using SWAT's parameter sensitivity analysis procedure resulted in a slight variability amongst the six subwatersheds with CN2 and ESCO alternating as the most responsive parameter. The CN2 and ESCO parameters were found to be more sensitive to input variability than the SURLAG and FFCB parameters. The autocalibration tool embedded in SWAT allows the option of including sediment, organic N and P, and soluble P; however, the nitrate parameter is not yet included in the tool's options. As the autocalibration tool develops additional parameters will be added.

7.2. Hydrologic and water quality results

The results from manually adjusted data without using the autocalibration tool are presented in Tables 7 (2000–2004) and 8 (2002). The results from using the autocalibration tool with the manually adjusted values indicated that using the 5 years of data (2000–2004) (Table 9), rather than only the autocalibrated with manual parameter adjusted simulation year 2002 (Table 10) improved model runoff, sediment and nutrient results as evaluated using the E_{NS}, PE, R^2, and P-values. The average values for Tables 7–10 were achieved by totaling the observed or simulated data and dividing by the number of days or months accordingly. Average monthly PE decreased from 10.9% for the 2002 autocalibrated simulation (Table 10) to 9.9% for the 5-year autocalibrated simulation (Table 9). The monthly and daily E_{NS}/R^2 values for 2000–2004 (Table 9) and 2002 (Table 10) were at least 0.82/0.86 and 0.80/0.81 and 0.84/0.88 and 0.71/0.75, respectively. Comparing the

Table 7
SWAT2005 monthly and daily observed and manually adjusted parameter simulation runoff summary statistics for the six subwatersheds near Riesel, Texas for 2000–2004

Subwatershed	Observed (mm month^{-1}/mm day^{-1})		Simulated (mm month^{-1}/mm day^{-1})		E_{NS} (month/day)	R^2 (month/day)	PE (%) (month/day)
	Mean	SD	Mean	SD			
Y6	20.6/0.68	40.4/4.6	21.7/063	34.9/3.9	0.95/0.81	0.96/0.82	5.3/−7.4
Y8	17.9/0.59	33.3/3.6	17.3/0.51	29.0/3.3	0.92/0.85	0.93/0.85	−3.4/−13.6
Y10	24.6/0.81	43.2/4.6	21.6/0.75	32.2/4.1	0.83/0.84	0.87/0.84	−12.2/−7.4
Y13	23.9/0.78	43.2/4.9	20.0/0.63	29.3/3.9	0.80/0.81	0.88/0.83	−16.3/−19.2
W12	18.9/0.62	33.1/4.7	18.6/0.55	29.5/3.8	0.85/0.80	0.85/0.81	−1.6/−11.3
W13	19.4/0.64	36.0/4.5	18.5/0.57	29.2/3.9	0.81/0.86	0.82/0.86	−4.6/−10.9

Table 8
SWAT2005 monthly and daily observed and manually adjusted parameter simulation runoff summary statistics for the six subwatersheds near Riesel, Texas for 2002

Subwatershed	Observed (mm month^{-1}/mm day^{-1})		Simulated (mm month^{-1}/mm day^{-1})		E_{NS} (month/day)	R^2 (month/day)	PE (%) (month/day)
	Mean	SD	Mean	SD			
Y6	17.2/0.56	30.0/3.31	19.3/0.64	28.7/2.9	0.91/0.69	0.92/0.70	12.2/14.3
Y8	15.0/0.50	24.6/2.7	14.4/0.50	22.7/2.5	0.92/0.68	0.92/0.69	−4.0/0.0
Y10	24.7/0.81	40.9/4.5	17.5/0.56	23.5/2.9	0.72/0.63	0.88/0.66	−29.2/−30.9
Y13	19.1/0.63	31.5/3.6	16.8/0.53	23.2/3.1	0.88/0.74	0.93/0.74	−12.0/−15.9
W12	13.5/0.45	22.1/2.9	14.3/0.49	21.7/2.7	0.76/0.61	0.77/0.63	5.9/8.9
W13	16.2/0.53	30.2/3.7	14.2/0.49	21.5/2.7	0.59/0.53	0.60/0.53	−12.4/−7.6

manually adjusted parameter values to that combined with the autocalibration tool improved the monthly E_{NS} average from 0.86 to 0.87 (Tables 7 and 9) and the daily E_{NS} average from 0.65 to 0.76 (Tables 8 and 10). Overall, the best runoff simulation, as indicated by the statistics, is the combination of autocalibrated and manually adjusted parameter input values for 2000–2004 (Table 9). The same period for the manual parameter adjustment remains to have the best statistics for nutrients and sediment as indicated by higher P-values, E_{NS} and R^2 values; therefore, it will be the simulation presented (Table 11) unless stated otherwise.

Although SWAT's monthly manual adjusted parameter simulation of NO_3-N only yielded one subwatershed P-value indicating a significant difference in means ($\alpha = 0.5$, Table 11), the E_{NS} and R^2 values are lower than 0.5 indicating that SWAT did not adequately match the measured data. Two E_{NS} values for the W13 and Y8 subwatersheds are slightly above 0.4, and all of the R^2 values are below 0.5, which according to the criteria established for this study means that the model did not perform acceptably. Corn was planted in March and wheat was planted in October for these subwatersheds yet the fertilizer was applied while the plants were not growing (July 2001; February and September 2002; January and September 2003; and August 2004) leaving the nutrients exposed to movement with sediment (P) or by water (nitrate). The subwatershed with the highest total crop yield was W13 (Table 3), which received the second highest total N inputs (Y8 had the highest fertilizer/poultry litter inputs). The subwatersheds that received the highest total N rates (Y8 > W13 > W12 > Y10 > Y13 > Y6; 2000–2004) were not the ones with the most NO_3-N measured (Tables 11 and 12). The three subwatersheds with the lowest amount of N or poultry litter applied (Y6, Y10, and Y13) had the highest NO_3-N concentrations measured in runoff (Y10 > Y13 > Y6 > W13 > Y8 > W12) due to the higher amount of inorganic N present. Also, Y10, Y13 and Y6 had the highest runoff amounts (Tables 7 and 8), which may have attributed to the increased amounts of NO_3-N available for transport especially due to application near a large rain event. The disparity between the measured and simulated values may be attributable to the proximity of large rain events that occurred soon after poultry litter had been applied (Table 2). Rain events that resulted in greater than 50 mm runoff followed fertilizer/poultry litter applications in August 2001; October 2002; February 2003; and September/October 2003. Percent error measurements showed that the SWAT model tends to overestimate runoff during the dry periods and underestimate during the wet periods.

Sediment loss is most likely due to land management practices rather than slope since the control watershed (Y6, Table 2) has the steepest gradient and four of the subwatersheds had higher monthly sediment loss means (Tables 11 and 13). The E_{NS} and R^2 sediment values are affected by SWAT's overestimation of sediment in 2000 and 2001. None of the sediment-related P-values were significant (Table 11). The N and P simulated organic loads were not significantly ($\alpha = 0.05$) different from the measured loads. Organic N and organic P followed the trend of sediment loss (Y13 > W12 > W13 > Y8 > Y6 > Y10) in both the measured and simulated data (Table 11). The subwatersheds with the highest soluble P applied via poultry litter and commercial fertilizer also had the highest soluble P measured in runoff (W13 and Y8, respectively). The control watershed had the lowest soluble P runoff concentration. The model was able to track measured soluble

Table 9
SWAT2005 monthly and daily observed and autocalibration tool and manual parameter adjustment discharge simulation statistics for the six subwatersheds near Riesel, Texas for 2000–2004

Subwatershed	Observed (mm month^{-1}/mm day^{-1})		Simulated (mm month^{-1}/mm day^{-1})		E_{NS} (month/day)	R^2 (month/day)	PE (%) (month/day)
	Mean	SD	Mean	SD			
Y6	21/0.68	40/4.56	20/0.63	34/3.86	0.94/0.81	0.96/0.82	−4.76/−7.35
Y8	18/0.59	33/3.63	16/0.51	27/3.28	0.90/0.85	0.93/0.85	−11.11/−13.55
Y10	25/0.81	43/4.59	21/0.75	33/4.07	0.89/0.84	0.94/0.84	−16.0/−7.4
Y13	24/0.78	43/4.94	21/0.63	31/3.91	0.82/0.81	0.86/0.83	−12.5/−19.2
W12	20/0.62	36/4.75	17/0.56	27/3.85	0.82/0.80	0.86/0.81	−15.0/−9.68
W13	20/0.64	36/4.52	20/0.57	31/3.86	0.86/0.86	0.87/0.86	0.0/−10.93

Table 10
SWAT2005 model monthly and daily observed and autocalibration tool and manual parameter adjustment discharge simulation statistics for the six subwatersheds near Riesel, Texas for 2002

Subwatershed	Observed (mm $month^{-1}$/mm day^{-1})		Simulated (mm $month^{-1}$/mm day^{-1})		E_{NS} (month/day)	R^2 (month/day)	PE (%) (month/day)
	Mean	SD	Mean	SD			
Y6	17.2/0.56	30.0/3.3	19.3/0.64	28.6/2.9	0.92/0.79	0.92/0.79	12.2/12.8
Y8	15.0/0.49	24.6/2.7	15.4/0.52	25.1/2.8	0.87/0.73	0.88/0.75	2.7/6.1
Y10	24.7/0.81	40.9/4.5	20.1/0.77	29.1/3.4	0.84/0.76	0.91/0.77	−18.6/−4.9
Y13	19.1/0.63	31.5/3.6	19.6/0.67	28.6/3.4	0.89/0.76	0.89/0.77	−2.1/6.4
W12	13.5/0.45	22.1/2.9	16.2/0.56	24.8/3.2	0.89/0.71	0.93/0.76	20.0/24.4
W13	16.2/0.54	30.2/3.7	17.7/0.58	27.0/3.2	0.95/0.80	0.95/0.80	9.8/9.4

P concentrations due to its predominant transport in surface runoff rather than leaching.

Comparing the simulated data for the control subwatershed, Y6, with the five treated subwatersheds resulted in a significant difference ($\alpha = 0.05$) in the average water quality parameters (organic N, organic P, soluble NO_3-N, soluble P, and sediment; Table 11). Almost all of the subwatersheds that had poultry litter applied resulted in higher sediment, organic N, organic P, and soluble P losses than the control subwatershed.

Table 11
Monthly measured and validation simulation from manually adjusted parameters of water quality constituent summary statistics per subwatershed in Riesel, Texas for the years 2000–2004

Water quality constituent	Statistical measure		Subwatershed					
			Y6	Y8	Y10	Y13	W12	W13
Sediment	Measured (Mg ha^{-1})	Mean	0.14	0.16	0.11	0.29	0.26	0.22
		SD	0.34	0.59	0.25	0.92	0.82	0.72
	Simulated (Mg ha^{-1})	Mean	0.13	0.15	0.25	0.15	0.17	0.16
		SD	0.30	0.39	0.60	0.35	0.33	0.35
	E_{NS}		0.50	0.60	−2.92	0.48	0.46	0.60
	R^2		0.53	0.61	0.44	0.72	0.62	0.74
	P-value*		0.97	0.73	0.94	0.11	0.41	0.23
Organic N loss	Measured (kg ha^{-1})	Mean	0.28	0.33	0.24	0.55	0.39	0.34
		SD	0.63	0.98	0.50	1.51	1.05	0.83
	Simulated (kg ha^{-1})	Mean	0.26	0.34	0.25	0.55	0.40	0.36
		SD	0.56	0.88	0.57	1.25	0.78	0.82
	E_{NS}		0.57	0.66	0.28	0.80	0.67	0.78
	R^2		0.58	0.67	0.48	0.80	0.67	0.79
	P-value*		0.66	0.52	0.93	0.39	0.28	0.90
NO_3-N loss	Measured (kg ha^{-1})	Mean	1.2	0.94	1.8	1.26	0.67	0.91
		SD	4.3	2.1	4.96	3.29	1.8	2.4
	Simulated (kg ha^{-1})	Mean	1.1	0.94	1.7	1.30	0.70	0.93
		SD	1.3	1.7	2.52	2.29	1.2	1.7
	E_{NS}		0.22	0.46	0.069	−0.62	0.13	0.42
	R^2		0.26	0.46	0.10	0.092	0.19	0.42
	P-value*		0.39	0.30	0.047[a]	0.17	0.18	0.26
Organic P loss	Measured (kg ha^{-1})	Mean	0.09	0.12	0.066	0.21	0.16	0.13
		SD	0.21	0.42	0.14	0.66	0.46	0.34
	Simulated (kg ha^{-1})	Mean	0.09	0.12	0.064	0.21	0.16	0.12
		SD	0.20	0.34	0.15	0.56	0.35	0.32
	E_{NS}		0.59	0.65	0.47	0.82	0.61	0.89
	R^2		0.61	0.65	0.56	0.83	0.61	0.89
	P-value*		0.81	0.50	0.77	0.34	0.39	0.91
Soluble P loss	Measured (kg ha^{-1})	Mean	0.023	0.12	0.11	0.081	0.07	0.13
		SD	0.049	0.31	0.23	0.17	0.16	0.33
	Simulated (kg ha^{-1})	Mean	0.024	0.12	0.10	0.073	0.07	0.13
		SD	0.054	0.25	0.20	0.16	0.15	0.27
	E_{NS}		0.29	0.80	0.81	0.87	0.80	0.90
	R^2		0.47	0.80	0.81	0.87	0.80	0.92
	P-value*		0.75	0.23	0.67	0.98	0.88	0.98

*Ho: the mean of the measured monthly values is not significantly different from the mean of the simulated values; Ho is not accepted if the *P*-value is less than the level of significance ($\alpha = 0.05$).

[a] The only value that is failed to be accepted ($\alpha = 0.05$).

Table 12
Monthly measured and manually adjusted parameters simulation water quality constituent summary statistics per subwatershed in Riesel, Texas for the year 2002

Water quality constituent	Statistical measure		Subwatershed					
			Y6	Y8	Y10	Y13	W12	W13
Sediment	Measured (Mg ha^{-1})	Mean	0.13	0.12	0.11	0.16	0.15	0.13
		SD	0.24	0.21	0.17	0.30	0.31	0.22
	Simulated (Mg ha^{-1})	Mean	0.16	0.21	0.17	0.29	0.24	0.12
		SD	0.14	0.27	0.24	0.39	0.33	0.16
	E_{NS}		0.60	0.28	−0.38	0.45	0.58	0.58
	R^2		0.67	0.69	0.40	0.80	0.72	0.59
	P-value*		0.82	0.40	0.48	0.36	0.51	0.81
Organic N loss	Measured (kg ha^{-1})	Mean	0.40	0.39	0.34	0.51	0.38	0.36
		SD	0.76	0.61	0.52	0.98	0.82	0.63
	Simulated (kg ha^{-1})	Mean	0.48	0.74	0.70	1.09	0.97	0.55
		SD	0.59	1.0	0.90	1.3	1.3	0.75
	E_{NS}		0.68	−0.82	−0.82	0.16	−0.75	0.017
	R^2		0.70	0.51	0.62	0.78	0.54	0.42
	P-value*		0.77	0.32	0.25	0.24	0.20	0.50
NO_3-N loss	Measured (kg ha^{-1})	Mean	1.0	1.5	2.3	1.3	1.1	1.2
		SD	2.5	2.4	3.5	2.4	2.4	2.8
	Simulated (kg ha^{-1})	Mean	1.02	0.11	0.14	0.11	0.10	0.12
		SD	0.16	0.23	0.24	0.19	0.18	0.22
	E_{NS}		−0.14	−0.22	−0.38	−0.24	−0.13	−0.013
	R^2		0.016	0.66	0.10	0.033	0.15	0.80
	P-value*		0.21	0.060	0.21	0.11	0.17	0.22
Organic P loss	Measured (kg ha^{-1})	Mean	0.13	0.15	0.091	0.19	0.17	0.14
		SD	0.24	0.26	0.14	0.35	0.40	0.25
	Simulated (kg ha^{-1})	Mean	0.038	0.074	0.043	0.13	0.14	0.040
		SD	0.044	0.12	0.053	0.16	0.19	0.058
	E_{NS}		0.12	0.15	0.38	0.50	0.29	0.062
	R^2		0.72	0.23	0.72	0.65	0.30	0.41
	P-value*		0.20	0.39	0.27	0.62	0.80	0.18
Soluble P loss	Measured (kg ha^{-1})	Mean	0.021	0.11	0.15	0.068	0.05	0.14
		SD	0.044	0.22	0.28	0.13	0.11	0.32
	Simulated (kg ha^{-1})	Mean	0.058	0.06	0.039	0.023	0.04	0.048
		SD	0.01	0.12	0.068	0.042	0.08	0.094
	E_{NS}		0.25	0.66	0.23	0.41	0.78	0.30
	R^2		0.91	0.87	0.97	0.98	0.82	0.66
	P-value*		0.26	0.49	0.17	0.26	0.73	0.34

*Ho: the mean of the measured monthly values is not significantly different from the mean of the simulated values; Ho is not accepted if the *P*-value is less than the level of significance ($\alpha = 0.05$).

The comparison of the manual parameter simulation for 2000–2004 of sediments and nutrients (Tables 11 and 12) to the statistics of the combination of autocalibrated and manually adjusted parameters (Tables 13 and 14) demonstrates the difference in results that can be obtained depending on the input parameter values. The first simulation has less significant *P*-values (soluble P and organic N) and higher E_{NS} and R^2 values for the majority of the water quality constituents. The difference in the statistics is most likely due to the limited amount of parameters that can be adjusted in the autocalibration tool (i.e. Nperco, Pperco, and nitrate). Due to the carryover effect of the fertilizer, separating the data into calibration and validation periods is inappropriate. In order to predict runoff, sediment, and nutrient concentrations as best as possible, it is valid in this study to use the all of the data available to achieve this task. Utilizing all of the data rather than only the year 2002 (Tables 11–14) provides better statistics, and therefore, can more adequately predict hydrologic and water quality constituents in both the autocalibration and manual simulations.

8. Conclusions

The ability of the SWAT model, version 2005, to simulate runoff, sediment, and nutrient loss data from small-scale subwatersheds in Texas was assessed in this study. Six subwatersheds were evaluated for sediment and nutrient water quality effects from poultry litter randomly applied in rates of 0–13.4 Mg ha^{-1} using both manual and autocalibrated adjusted parameters. Two data scenarios were employed, 2000–2004 and 2002. The first used data from 2000 to 2004 to demonstrate the carryover effect of fertilizer, and the second scenario used only the year 2002 to emphasize the impact that time period for model parameter initialization and the

Table 13
Monthly measured and autocalibration tool and manually adjusted parameter simulation of water quality constituent summary statistics per subwatershed in Riesel, Texas for the years 2000–2004

Water quality constituent	Statistical measure		Subwatershed					
			Y6	Y8	Y10	Y13	W12	W13
Sediment	Measured ($Mg\,ha^{-1}$)	Mean	0.14	0.16	0.11	0.29	0.26	0.22
		SD	0.34	0.59	0.25	0.92	0.82	0.72
	Simulated ($Mg\,ha^{-1}$)	Mean	0.14	0.16	0.26	0.42	0.18	0.17
		SD	0.32	0.41	0.62	0.83	0.35	0.36
	E_{NS}		0.48	0.58	−3.2	0.59	0.48	0.61
	R^2		0.53	0.58	0.43	0.63	0.62	0.73
	P-value*		1.0	0.97	0.082	0.44	0.47	0.63
Organic N loss	Measured ($kg\,ha^{-1}$)	Mean	0.28	0.33	0.24	0.55	0.39	0.34
		SD	0.64	0.98	0.50	1.51	1.05	0.83
	Simulated ($kg\,ha^{-1}$)	Mean	0.62	0.70	1.13	1.67	0.86	0.82
		SD	1.3	1.81	2.54	3.17	1.64	1.84
	E_{NS}		−1.52	−0.36	−22.4	−1.61	−0.12	−1.37
	R^2		0.60	0.74	0.48	0.63	0.65	0.77
	P-value*		0.071	0.099	0.009[a]	0.016[a]	0.063	0.07
Organic P loss	Measured ($kg\,ha^{-1}$)	Mean	0.090	0.12	0.066	0.21	0.16	0.13
		SD	0.21	0.42	0.14	0.66	0.46	0.34
	Simulated ($kg\,ha^{-1}$)	Mean	0.044	0.059	0.059	0.18	0.10	0.053
		SD	0.098	0.18	0.14	0.39	0.22	0.14
	E_{NS}		0.47	0.56	0.41	0.69	0.46	0.56
	R^2		0.63	0.79	0.49	0.77	0.53	0.86
	P-value*		0.13	0.27	0.80	0.70	0.40	0.13
Soluble P loss	Measured ($kg\,ha^{-1}$)	Mean	0.023	0.12	0.11	0.081	0.072	0.13
		SD	0.049	0.31	0.23	0.17	0.16	0.33
	Simulated ($kg\,ha^{-1}$)	Mean	0.034	0.052	0.038	0.024	0.037	0.052
		SD	0.073	0.12	0.080	0.053	0.083	0.12
	E_{NS}		−0.11	0.43	0.36	0.34	0.56	0.46
	R^2		0.54	0.64	0.70	0.78	0.73	0.84
	P-value*		0.36	0.12	0.027[a]	0.016[a]	0.14	0.080

*Ho: the mean of the measured monthly values is not significantly different from the mean of the simulated values; Ho is not accepted if the P-value is less than the level of significance ($\alpha = 0.05$).
[a] The only value that is failed to be accepted ($\alpha = 0.05$).

amount of data available for simulation have on model simulation and prediction. Both manually adjusted parameters and a combination of autocalibration tool parameters values with manual adjustment were used to evaluate SWAT's ability to simulate the subwatershed processes and to evaluate the adequacy of the autocalibration tool. The goodness-of-fit measures demonstrated that SWAT simulations (manually and combination of autocalibration and manual adjusted parameter values) explained the monthly and daily runoff variations in the measured data well ($E_{NS} > 0.4$ and $R^2 > 0.5$). The combination of autocalibration tool parameter values and manually adjusted parameters for the 2000–2004 simulation period resulted in the highest E_{NS} and R^2 values for discharge; however, the same 5-year period yielded better overall E_{NS}, R^2 and P-values for the simulation values that were manually adjusted. The disparity is most likely due to the limited number of parameters that are included in this version of the autocalibration tool (i.e. Nperco, Pperco, and nitrate).

The control watershed's water quality results were significantly different ($\alpha = 0.05$) from the treated watersheds. Almost all of the subwatersheds that had poultry litter applied resulted in higher sediment, organic N, organic P, and soluble P losses than the control subwatershed upon averaging the monthly validation values. The monthly manually adjusted parameter simulation of sediment and nutrient (organic N and P, NO_3-N, and soluble P) E_{NS} and R^2 values were generally above 0.4 and 0.5, respectively. Monthly sediment and nutrient losses showed that their respective simulated means were not significantly different from the measured values ($\alpha = 0.05$), except for NO_3-N losses for the Y10 subwatershed as evidenced by paired t-tests. Organic N and P followed the sediment transport trend in both the measured and simulated values. The subwatersheds that had less amounts of commercial fertilizer and/or poultry litter lost more sediment than the subwatersheds that received the higher litter treatments possibly due to less crop growth resulting in reduced nutrient uptake and exposure to sediment erosion. The observed trends included SWAT's overestimation of runoff in the dry periods and underestimation in the wet periods.

The autocalibration-parameter sensitivity analysis procedure embedded in SWAT was used to obtain an optimal parameter fit, based on the E_{NS} values, to determine the relative ranking of the most sensitive parameter to input variability. The analysis resulted in a slight variability among the six subwatersheds with CN2 and ESCO alternating as the most

Table 14
Monthly measured and autocalibration tool and manually adjusted parameter simulation of water quality constituent summary statistics per subwatershed in Riesel, Texas for the year 2002

Water quality constituent	Statistical measure		Subwatershed					
			Y6	Y8	Y10	Y13	W12	W13
Sediment	Measured (Mg ha^{-1})	Mean	0.13	0.12	0.11	0.16	0.15	0.13
		SD	0.24	0.21	0.17	0.30	0.31	0.22
	Simulated (Mg ha^{-1})	Mean	0.14	0.14	0.13	0.33	0.14	0.12
		SD	0.19	0.19	0.15	0.43	0.21	0.17
	E_{NS}		0.63	0.32	0.63	−0.44	0.25	0.78
	R^2		0.63	0.40	0.65	0.46	0.28	0.80
	P-value*		0.93	0.82	0.75	0.28	0.97	0.92
Organic N loss	Measured (kg ha^{-1})	Mean	0.40	0.39	0.34	0.51	0.38	0.36
		SD	0.76	0.61	0.52	0.98	0.82	0.63
	Simulated (kg ha^{-1})	Mean	0.64	0.58	0.62	1.47	0.75	0.67
		SD	0.88	0.86	0.71	2.11	1.18	0.97
	E_{NS}		0.22	−0.36	0.30	−3.38	−0.94	0.12
	R^2		0.52	0.39	0.82	0.28	0.21	0.80
	P-value*		0.48	0.049[a]	0.29	0.17	0.38	0.36
Organic P loss	Measured (kg ha^{-1})	Mean	0.13	0.15	0.09	0.19	0.17	0.14
		SD	0.24	0.26	0.13	0.35	0.40	0.25
	Simulated (kg ha^{-1})	Mean	0.044	0.053	0.037	0.17	0.10	0.05
		SD	0.062	0.09	0.049	0.25	0.18	0.081
	E_{NS}		0.18	−0.009	0.29	0.084	−0.012	0.21
	R^2		0.56	0.13	0.69	0.18	0.062	0.51
	P-value*		0.24	0.25	0.21	0.87	0.60	0.24
Soluble P loss	Measured (kg ha^{-1})	Mean	0.021	0.11	0.15	0.068	0.054	0.14
		SD	0.044	0.22	0.28	0.13	0.11	0.32
	Simulated (kg ha^{-1})	Mean	0.011	0.065	0.047	0.033	0.051	0.062
		SD	0.017	0.13	0.090	0.062	0.099	0.12
	E_{NS}		0.46	0.75	0.33	0.59	0.93	0.55
	R^2		0.75	0.93	0.87	0.87	0.93	0.98
	P-value*		0.46	0.54	0.21	0.41	0.94	0.43

*Ho: the mean of the measured monthly values is not significantly different from the mean of the simulated values; Ho is not accepted if the *P*-value is less than the level of significance ($\alpha = 0.05$).
[a] The only value that is failed to be accepted ($\alpha = 0.05$).

responsive parameter and with the SURLAG and FFCB parameters being less sensitive. The autocalibration tool results indicate that additional work must be completed to improve its optimal parameter fit process.

With E_{NS} values above 0.8 for the monthly and daily runoff and values generally above 0.4 for sediment and nutrients, this study has shown that SWAT's runoff and water quality processes and output are reasonable and can be used at the subwatershed level. A more realistic fit is achieved when the autocalibration tool is used in conjunction with knowledgeable manual calibration. Having a longer period of discharge and nutrient and sediment data records may improve the simulation results in that anomalies in the data may not be abnormal in the long-term. Overall, SWAT2005 simulated the hydrology and the water quality constituents at the subwatershed-scale more adequately when all of the data were used with a combination of manual and autocalibration methods as evidenced by statistical measures.

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