Available online at www.sciencedirect.com
SCIENCE DIRECT®
ELSEVIER
Journal of Hydrology 324 (2006) 10–23
Journal of Hydrology
www.elsevier.com/locate/jhydrol

# A global sensitivity analysis tool for the parameters of multi-variable catchment models

A. van Griensven [a,*], T. Meixner [a], S. Grunwald [b], T. Bishop [b], M. Diluzio [c,1], R. Srinivasan [d,2]

[a] Environmental Sciences, University of California, Riverside, Riverside CA92507, USA
[b] Soil and Water Science Department, University of Florida, 2169 McCarty Hall, P.O. Box 110290, USA
[c] Environmental Blackland Research and Extension Center, Texas A&M University, 720 E. Blackland Road, Temple, TX7650, USA
[d] Spatial Sciences Laboratory, Texas A&M University, 1500 Research Parkway, Suite B223, CollegeStation,TX 77845, USA

Received 22 September 2003; revised 5 September 2005; accepted 22 September 2005

**Abstract**

Over-parameterisation is a well-known and often described problem in hydrological models, especially for distributed models. Therefore, methods to reduce the number of parameters via sensitivity analysis are important for the efficient use of these models.

This paper describes a novel sampling strategy that is a combination of latin-hypercube and one-factor-at-a-time sampling that allows a global sensitivity analysis for a long list of parameters with only a limited number of model runs. The method is illustrated with an application of the water flow and water quality parameters of the distributed water quality program SWAT, considering flow, suspended sediment, total nitrogen, total phosphorus, nitrate and ammonia outputs at several locations in the Upper North Bosque River catchment in Texas and the Sandusky River catchment in Ohio. The application indicates that the methodology works successfully. The results also show that hydrologic parameters are dominant in controlling water quality predictions. Finally, the sensitivity results are not transferable between basins and thus the analysis needs to be conducted separately for each study catchment.


*Keywords:* Model parameters; River; Sensitivity analysis; Water quality

## 1. Introduction

Over-parameterisation is a well-known and often described problem with hydrological models (Box and Jenkins, 1976), especially for distributed models (Beven, 1989). Therefore, sensitivity analysis methods that aim to reduce the number of parameters that require fitting with input–output data are common (e.g. Spear and Hornberger, 1980). These methods

* Corresponding author. Fax: +1 909 787 3993.
*E-mail addresses:* ann@biomath.ugent.be (A. van Griensven), thomas.meixner@ucr.edu (T. Meixner), sgrunwald@mail.ifas.ufl.edu (S. Grunwald), diluzio@bcr.tamus.edu (M. Diluzio), r-srinivasan@tamus.edu (R. Srinivasan).
[1] Fax: +1 264 774 6001.
[2] Fax: +1 979 682 2607.

0022-1694/$ - see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.jhydrol.2005.09.008

identify parameters that do or do not have a significant influence on model simulations of real world observations for specific catchments.

Catchment models that also aim to describe water quality variables such as sediment fluxes, nutrients and other dissolved compounds that affect stream ecology need detailed rainfall–runoff process descriptions in time and space in order to be able to mimic erosion and sedimentation processes and the aqueous residence times in the soil, groundwater reservoir or the river. Additionally, these models must account for a number of transformation processes. The increased complexity means that they have more model parameters than simpler rainfall-runoff models. The complexity also means that the models require significantly longer simulation times than equivalent rainfall runoff-models. On the other hand, there may be observations of model outputs other than water quantity that are available for model calibration and evaluation of these additional process representations. Often these additional water quality time series are of lower frequency and can have large model error residuals associated with them.

Since water quality models are over parameterized and there are multiple data sets for comparison with model predictions (e.g. flow (Q), suspended sediment, nitrogen and phosphorus), sensitivity analysis methods are needed that can accommodate a large number of parameters while considering several output variables. In this paper we develop a method based on combining existing one-factor-at-a-time methods (Morris, 1991) with latin-hypercube sampling of the parameter space (McKay, 1979). The intent is to develop a simple and effective sensitivity method that can be implemented with minimal computational cost for a river basin water quality model.

## 2. Existing methods

An important classification of the existing methods refers to the way that the parameters are treated (Saltelli et al., 2000). Local techniques concentrate on estimating the local impact of a parameter on the model output. This approach means that the analysis focuses on the impact of changes in a certain parameter value (mean, default or optimum value). Opposed to this, global techniques analyse the whole parameter space at once.

### 2.1. Local methods

A local sensitivity analysis evaluates sensitivity at one point in the parameter hyperspace. This point may be defined by default values or a crude manual model calibration. Sensitivities are usually defined by computing partial derivatives of the output functions with respect to the parameters. A sensitivity index S can be calculated for a small change of $\Delta e_i$ while the other input parameters are held constant (Melching and Yoon, 1996):

$$S = \frac{\frac{M(e_1,\ldots,e_i+\Delta e_i,\ldots,e_P)-M(e_1,\ldots,e_i,\ldots,e_P)}{M(e_1,\ldots,e_i,\ldots,e_P)}}{\frac{\Delta e_i}{e_i}} \quad (1)$$

where $M$ is the model output, $e_i$ refers to the different model parameters, and $\Delta e_i$ is the perturbation in a single model parameter. As these methods need only a few model runs, they were very popular in early studies.

### 2.2. First order second moment method

The First Order Second Moment (FOSM) method estimates the mean (first moment) and the variance (second moment) of model output through computation of the derivative of model output to model input at a single point (Yen et al., 1986). This method is initially designed for uncertainty propagation but it provides measures of sensitivity as well.

The first step in the FOSM analysis is to approximate the system output solution of interest in Taylor series form. In the simplest form, a first-order Taylor series approximation requires computing the model output at a single point and determining the derivative (i.e. change of model output due a change in model input):

$$M(e) = M(\bar{e}) + \sum_{i=1}^{p} \frac{\delta M}{\delta e_i}(e_i - \bar{e}_i) \quad (2)$$

where $e = \{e_1,\ldots,e_p\}$are the input random variables with means $\bar{e} = \{\bar{e}_1,\ldots,\bar{e}_p\}$. $\delta M/\delta e$ are derivatives evaluated at the mean values $\bar{e}$.

The mean of the output function $M$ and the standard deviation $\sigma_M$ are then calculated as:

$$\bar{M} = M(\bar{e}) \qquad \sigma_M^2 = \sum_{i=1}^{P} \left( \frac{\delta M}{\delta e_i} \sigma_{e_i} \right)^2 \tag{3}$$

with $\sigma_{ei} = \{\sigma_{e1}\ \sigma_{ep}\}$ the standard deviations for the input variables.

Special FOSM techniques, such as the Mean Value First Order Reliability Method (MFORM) and the Mean-Value Second-Order Reliability method (SORM) provide an efficient method for estimating the probability associated with engineering component failure or reliability (Saltelli et al., 2000; Yen et al., 1986). These methods seek regions of failure that are mathematically expressed as exceeding a threshold output value.

MFORM approximates the failure surface by a hyperplane and this surface is estimated from a first-order development of the model output function around a mean-value point in the parameter space. The reliability of this estimate decreases for output values far from the mean value point and is a function of the non-linear character of the model.

When the parameters are correlated, more accurate results can be obtained by SORM than by MFORM. SORM is based on the expansion up to the second order of the Taylor series for the model response function at the mean-value point in the parameter space (Saltelli et al., 2000).

$$M(e) = M(\bar{e}) + \sum_{i=1}^{p} \frac{\delta M}{\delta e_i}(e_i - \bar{e}_i) + \frac{1}{2} \times \sum_{i=1}^{p}\sum_{j=1}^{p} \frac{\delta^2 M}{\delta e_i \delta e_j}(e_i - \bar{e}_i)(e_j - \bar{e}_j) \tag{4}$$

The matrix of the second-order derivates A has the elements

$$a_{ij} = \frac{\sigma_i \sigma_j}{2} \left( \frac{\delta^2 M}{\delta e_i \delta e_j} \right) \tag{5}$$

The failure surface is then represented by a quadratic form using the eigenvalues that are obtained by diagonalisation of matrix A. While requiring more runs compared to the MFORM method, Mailhot and Villeneuve (2003) showed that the method leads to better estimates for water quality modeling applications.

### 2.3. Integration of a local method to a global method

An example of an integration of a local into a global sensitivity method is the random OAT (One-factor-At-a-Time) design proposed by Morris (1991). The method consists of repetitions of a local method whereby the derivatives are calculated for each parameter $e_i$ by adding a small change to the parameter $\Delta e_i$. The change in model outcome $M(e_1,\ldots,e_i+\Delta e_i,\ldots,e_P)$ can then be unambiguously attributed to such a modification by means of an elementary effect, $S_i$, defined by Eq. (1). $M(e_1,\ldots,e_i+\Delta e_i,\ldots,e_P)$ is usually some lumped measure like total mass export, sum of squares error between modelled and observed values or sum of absolute errors. Considering $P$ parameters (i.e. $i=1,\ldots,P$), this means that this experiment involves performing $P+1$ model runs to obtain one partial effect for each parameter according to Eq. (1). The result is quantitative, elementary and exclusive for the parameter. However, the quantitativeness of this measure of sensitivity is only relative: as the influence of $e_i$ may depend on the nominal values chosen for the remaining parameters, this result is only a sample of its sensitivity (i.e. a partial effect). Therefore, this experiment is repeated for several random sets of nominal values of the input parameters. The final effect will then be calculated as the average of a set of partial effects, and the variance of such a set will provide a measure of how uniform the effects are (i.e. the presence or absence of nonlinearities or correlation interactions with other parameters). In this way, local sensitivities get integrated to a global sensitivity measure. The elementary effects for each parameter obtained using this procedure allow the user to screen the entire set of input parameters with a low computational requirement. This approach has the advantage of not relying on predefined (tacit or explicit) assumptions of relatively few inputs having important effects, monotonicity of outputs with respect to inputs, or adequacy of low-order polynomial models as an approximation to the computational model (Morris, 1991).

The OAT approach is a very useful method for water quality models such as the Soil Water

Assessment Tool (SWAT) (Francos et al., 2001; van Griensven et al., 2002) as it is able to analyse the sensitivity of a high number of parameters with low computational cost.

### 2.4. Global sampling methods

Global sampling methods scan in a random or systematic way the entire range of possible parameter values and possible parameter sets. The sampled parameter sets can give the user a good idea of the importance of each parameter. These in turn can be used to quantify the global parameter sensitivity or the uncertainty of parameters and outputs. Essential to this method is the sampling strategy.

#### 2.4.1. Monte Carlo methods

*2.4.1.1. Monte Carlo sampling.* The Monte Carlo method provides approximate solutions to a variety of mathematical problems by performing statistical sampling experiments on a computer (Fishman, 1996). This method performs sampling from a possible range of the input parameter values followed by model evaluations for the sampled values. An essential component of every Monte Carlo experiment is the generation of random samples. These generating methods produce samples drawn from a specified distribution (typically a uniform distribution). The random numbers from this distribution are then used to transform model parameters according to some predetermined transformation equation.

*2.4.1.2. Statistical analysis.* An analysis of Monte Carlo simulations is conducted with statistical methods such as Kolmogorov–Smirnov (K-S) test (Stephens, 1970) to define whether a parameter is sensitive (Spear and Hornberger, 1980) or with the computation of regression and correlation based sensitivity measures (Saltelli et al., 1995).

A great advantage of the method is the logical combination of calibration, identifiability analysis, sensitivity and uncertainty analysis within a single modelling framework (van der Perk and Bierkens, 1997). The method can be applied to problems with absolutely no probabilistic content as well as to those with inherent probabilistic structure. It has been widely used in catchment modelling, for assessing parameter uncertainty and input uncertainty, e.g. for rainfall variability (Krajewski et al., 1991). Many examples exist that use the Monte Carlo method in combination with multi-variable water quality models, e.g. Hornberger and Spear (1980); Meixner et al. (1999).

#### 2.4.2. Latin–Hypercube (LH) simulations

*2.4.2.1. Latin Hypercube sampling.* Monte Carlo simulation and the sensitivity methods based on it are robust, but may require a large number of simulations and consequently large computational resources. The concept of the Latin-Hypercube simulation (McKay et al., 1979; Iman and Conover, 1980; McKay, 1988) is based on Monte Carlo simulation but uses a stratified sampling approach that allows efficient estimation of the output statistics. It subdivides the distribution of each parameter into $N$ strata with a probability of occurrence equal to $1/N$. For uniform distributions, the parameter range is subdivided into $N$ equal intervals. Random values of the parameters are generated such that for each of the $P$ parameters, each interval is sampled only once. This approach results in $N$ non-overlapping realisations and the model is run $N$ times.

*2.4.2.2. Statistical analysis.* The model results are typically analysed with multi-variate linear regression or correlation statistical methods (Saltelli et al., 2000). Latin–Hypercube sampling is commonly applied in water quality modelling due to its efficiency and robustness (Weijers and Vanrolleghem, 1997; Vandenberghe et al., 2001). The main drawback for statistical analysis is the assumption of linearity, i.e. that the model output is linearly related to the changes in the parameter values. If these are not fulfilled, biased results can be obtained.

#### 2.4.3. Variance-based methods

These ANOVA (ANalysis Of Variance) methods aim at a decomposition of the variance, when all inputs are varying, into partial variances.

$$V = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<m} V_{ijm} + \cdots + V_{i,j,k,\ldots P} \tag{6}$$

A partial variance $V_i$ represents the main, or first order, affect of an input i on the output that corresponds to the variance when other inputs are kept constant. Higher order effects $V_{1,2,\ldots p}$ are combined effect for 2 or more inputs. The partial effects can be calculated with special sampling schemes that are often computationally demanding (Saltelli et al., 2000).

A more efficient alternative is the Fourier amplitude sensitivity test (FAST) method (Cukier, et al., 1978; Helton, 1993; Saltelli et al., 2000). It is based on Fourier transformation of uncertain model input variables into the frequency domain, thus reducing the multi-dimensional model into a single dimensional one. FAST is a very reliable tool for analysing non-linear and non-monotonic water quality models (Melching and Yoon, 1996).

## 3. A new LH-Oat method

Previously described global sampling methods can provide interesting information on the model inputs, but the computational cost is often too high for complex water quality models. The efficient local methods on the other hand do not provide any global measure of sensitivity for the entire parameter space. Therefore, these local methods do not constitute a robust and reliable approach for distributed water quality models since output is often not linearly related to the input parameters. These models typically have a very high number of input parameters of which only a limited number are of importance for model calibration and model output for a particular basin. A method that is able to separate these important parameters from the unimportant ones would be beneficial. Therefore, such models need a global and efficient screening method. Morris OAT method can accomplish this, but random Monte Carlo sampling that underlies the OAT design needs many samples to cover the full parameter ranges, which comes at a significant computational cost. A replacement of the Monte Carlo sampling by Latin Hypercube sampling should be an improvement and should allow the user to control the total number of simulations while an optimal representation of the parameter space is established.

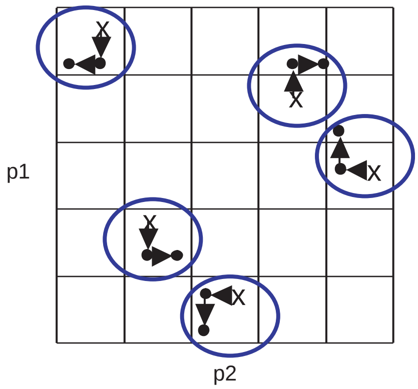


Fig. 1. Illustration of MC-OAT sampling of values for a two parameter model where X represent the Monte-Carlo points and ● the OAT points.

We therefore developed the LH-OAT method. The LH-OAT method performs LH sampling followed by OAT sampling (Fig. 1). It starts with taking $N$ Latin Hypercube sample points for $N$ intervals, and then varying each LH sample point $P$ times by changing each of the $P$ parameters one at a time, as is done in the OAT design.

The method operates by loops. Each loop starts with a Latin Hypercube point. Around each Latin Hypercube point $j$, a partial effect $S_{i,j}$ for each parameter $e_i$ is calculated as (in percentage):

$$S_{i,j} = \left| \frac{100 * \left( \frac{M(e_1,\ldots,e_i*(1+f_i),\ldots,e_P) - M(e_1,\ldots,e_i,\ldots,e_P)}{[M(e_1,\ldots,e_i*(1+f_i),\ldots,e_P) + M(e_1,\ldots,e_i,\ldots,e_P)]/2} \right)}{f_i} \right| \tag{7}$$

where $M(\cdot)$ refers to the model functions, $f_i$ is the fraction by which the parameter $e_i$ is changed (a predefined constant) and $j$ refers to a LH point. In Eq. (7), the parameter was increased with the fraction $f_i$, but it can also be decreased since the sign of the change is defined randomly. Therefore a loop requires $P+1$ runs.

A final effect is calculated by averaging these partial effects of each loop for all Latin Hypercube points (thus for $N$ loops). The method is very efficient, as the $N$ intervals (user defined) in the LH method require a total of $N*(P+1)$ runs.

The final effects can be ranked with the largest effect being given rank 1 and the smallest effect being given a rank equal to the total number of parameters analysed. Oftentimes during a sensitivity analysis for a particular dataset some parameters have no effect on model predictions or performance. In this case they are all given a rank equal to the number of parameters.

This method combines the robustness of the Latin Hypercube sampling that ensures that the full range of all parameters has been sampled with the precision of an OAT design assuring that the changes in the output in each model run can be unambiguously attributed to the parameter that was changed.

## 4. Case studies

### *4.1. The SWAT program*

The Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) is a semi-distributed, conceptual model designed to simulate water, nutrient and pesticide transport at a catchment scale on a daily time step. It represents hydrology by interception, evapotranspiration, surface runoff, soil percolation, lateral flow and groundwater flow and river routing processes. The catchment is subdivided into sub-basins, river reaches and Hydrological Response Units (HRU's). While the sub-basins can be delineated and located spatially, the further sub-divisions in HRU's is performed in a statistical way by considering a certain percentage of sub-basin area, without any specified location in the sub-basin.

### *4.2. Description of the Sandusky river catchment and SWAT model*

The Sandusky River basin, with a drainage area at Fremont of 3240 $km^2$, is located within the Lake Erie Catchment and Great Lakes basin. The Sandusky River is the second largest of the Ohio rivers draining into Lake Erie. Analysis of 1994 LANDSAT data indicated that 84% of the land is used for agriculture, 12.6% is wooded, 1.2% is urban and 1.1% is non-forested wetlands. Major crops based on county-level estimates in 1985 were corn (*Zea mays* L.) with 35.6% of cropland acreage, soybeans (*Glycine max* L.) with 44.9% and wheat (*Triticum aestivum* L.) with 19.5%. Crop production was similar in 1995 with 32.1% in corn, 49.1% in soybeans and 18.7% in wheat. Tillage practices shifted from 86% conventional management in 1985 to 50.5% in 1995, as farmers replaced conventional with conservation tillage practices. Tile drainage is used extensively throughout the catchment. Urban areas within the Sandusky river basin are Bucyrus, Fremont, Tiffin, and Upper Sandusky, and numerous smaller communities. The river and its major tributaries support important recreational uses for catchment residents. Dominant soils are Hapludalfs, Ochraqualfs, Fragiaqualfs, Medisaprists, Fluvaquents, and Argiaquolls (Natural Resources Conservation Service (NRCS) Ohio). Textures are mainly silt loam and silty clay loam.

Average annual precipitation ranges from 881 mm at Fremont to 964 mm at Bucyrus. Historic precipitation data for the catchment show highest amount for July (99 mm) and smallest for February (48 mm). Annual mean discharge for the Sandusky River catchment at Fremont is 29.1 m3 $s^{-1}$, Honey Creek at Melmore is 3.8 $m^3\ s^{-1}$, and Rock Creek at Tiffin is 0.88 $m^3\ s^{-1}$ (Sandusky River Catchment Coalition, 2000).

In this analysis, we used a DEM from the National Elevation Dataset (NED) with cell size of 30×30 m from the US Geological Survey. A digital land cover/land use map derived from Landsat ETM+ imagery [SG1](2000) was provided by the Department of Geography and Planning, University of Toledo. We used a digital soil map from the State Soil Geographic Database (STATSGO) developed by the NRCS USDA. Water quality data were collected by the Water Quality Laboratory, Heidelberg College. For more information about the water quality data refer to (Richards and Baker, 2002). The SWAT model was built using the BASINS package and the included catchment tools (Di Luzio et al., 2002) for the spatial analysis of pollution sources and water quality. The model consists of 28 sub-basins and 242 HRU's.

### *4.3. Description of the Upper North Bosque river catchment and SWAT model*

The Bosque River flows southward through Erath, Hamilton, and Bosque counties in central Texas before discharging into to Lake Waco. Our case study, the Upper North Bosque River (UNBR) catchment, covers about 932 $km^2$ in the upper portion of the North Bosque River (NBR) catchment, almost entirely within Erath county. The NBR catchment is a known problem catchment due to concentrated animal feeding operations and is of particular water quality concern since the Bosque river feeds Lake Waco which serves as a water supply reservoir for more than 200,000 people in the city of Waco and surrounding communities.

As reported by McFarland and Hauck (1999), UNBR catchment is primarily rural (more than 98%) with the primary land uses being rangeland (43%), forage fields (23%), and dairy waste application (7%). Dairy is the dominant agricultural activity. In addition, other significant agricultural practices include the production of peanut, range cattle, pecan, peaches and forage.

The catchment lies primarily in two major Land Resource Areas, known as the West Cross Timbers and the Grand Prairie. The soils in the West Cross Timbers are dominated by fine sandy loams with sandy clay subsoils, while calcareous clays and clay loams are predominant soil types in the Grand Prairie (Ward et al., 1992). The elevation in the catchment ranges from 305 to 496 m. The average annual precipitation in the area is around 750 mm and the average daily temperature ranges from 6 to 28 degrees centigrade.

Since 1991 the Texas Institute for Applied Environmental Research (TIAER) at Tarleton State University has been monitoring UNBR (McFarland and Hauck, 1999) at stormwater sites equipped with automated samplers. Those used in this study are shown in Fig. 3. Specifics of the monitoring program and loading calculations are presented in McFarland and Hauck (1995).

Topographic, landuse/cover, and soil data required by SWAT for this study were generated from the following basic GIS databases using the BASINS package and the included catchment tools (Di Luzio et al., 2002):

- Three arc-second, 1:250,000-scale, USGS DEM;
- NHD dataset for cataloging unit 12060204;
- 1: 250,000-scale, USGS Land Use and Land Cover (LULC) data;
- USDA-NRCS STATSGO soils map;
- Daily rainfall and temperatures from 14 gauges within the catchment including in part water sampling and National Weather Service stations

The catchment has been segmented into 55 sub-catchments and 172 HRUs.

### 4.4. Sensitivity criteria

This study analyses the effect of model parameters on the model output directly and on model performance, thus the errors on the output are evaluated by comparing the model output to corresponding observations.

The model performance is considered by error functions that are calculated by the sum of the squared errors for flow (Q), sediments (S), total N (N) and total P (P) for the daily observations (if available) at 5 observation sites within the basin (See Figs. 2 and 3, Tables 1 and 2). The sensitivities to the model performance give insight in parameter identifiability using the available information (what parameters can we possibly identify?). This approach is based on daily observations and model simulations for two years of simulations (1998–1999 for the Sandusky river basin and 1995–1996 for the Upper North

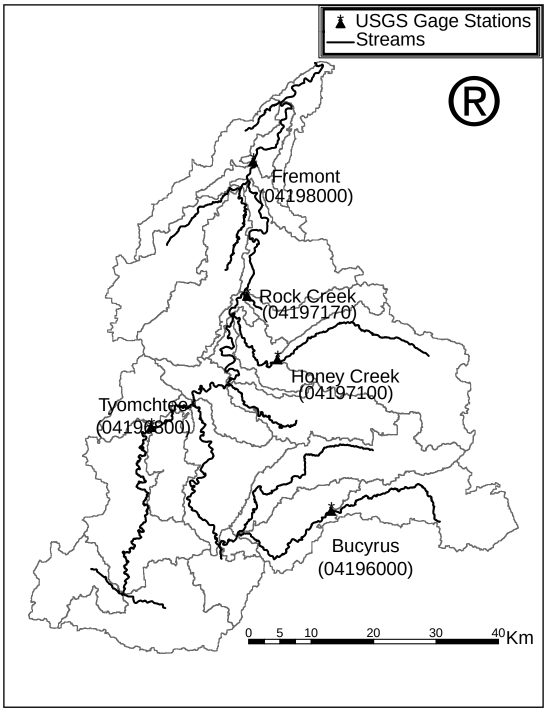


Fig. 2. Map of the Sandusky river catchment with observation sites.

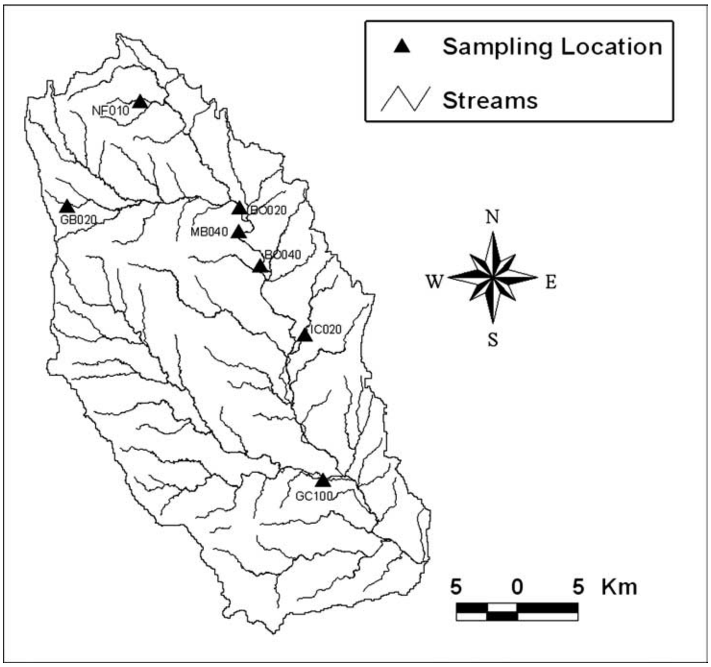


Fig. 3. Map of the Upper North Bosque river catchment with observation sites.

Bosque river basin). A half year warming up period proceeded this simulation period.

In addition, the sensitivities are also assessed for the total amount of water, sediments, nitrogen and phosphorus that leaves the catchment at the outlet over the model period. The latter is an example of model output that is typically used for basin management and indicates what parameters can influence these outputs and hence decisions based on these outputs (what parameters should we identify?).

### 4.5. Parameters

A restricted set of model parameters have been used in the sensitivity analysis in order to capture the major processes represented by SWAT (Table 3). They were selected based on the list that is used in the calibration tool of the SWAT interface (in bold in Table 3), extended by other names listed in the SWAT manual and believed to be potentially important.

Since the SWAT modelling tool was applied in a distributed way—thus with spatially varying parameter values according to soil and land use properties—this resulted in a very large number of parameters each of which has a small influence on model output. Therefore, the default values of these distributed parameters are changed in a relative way over a certain range, for instance over the range −50% and +50%. The sensitivity analysis evaluates

Table 1
Observations in the Sandusky river catchment and the number of observation for the years 1998–1999

| | Observation site | Q | S | N | P |
|---|---|---|---|---|---|
| 1 | Sand/Fremont | 689 | 723 | 318 | 716 |
| 2 | Rock Creek | 570 | 706 | 250 | 707 |
| 3 | Honey Creek | 661 | 710 | 364 | 723 |
| 4 | Tymochlee Creek | 730 | 0 | 0 | 0 |
| 5 | Sand/Bucyrus | 730 | 0 | 0 | 0 |

Table 2
Observation sites in the Upper North Bosque river catchment and the number of observations for the years 1996–1997

| | Observation site | Q | S | N | P |
|---|---|---|---|---|---|
| 1 | Mb040 | 731 | 137 | 137 | 137 |
| 2 | Bo040 | 725 | 725 | 725 | 725 |
| 3 | Ic020 | 731 | 596 | 596 | 596 |
| 4 | Gc100 | 731 | 647 | 647 | 647 |
| 5 | Gb020 | 75 | 75 | 75 | 75 |

Table 3
Parameters and parameter ranges used in sensitivity analysis (in alphabetic order)

| Name | Min | Max | Definition | Process |
|---|---|---|---|---|
| ALPHA_BF | 0 | 1 | Baseflow alpha factor (days) | Groundwater |
| BIOMIX | 0 | 1 | Biological mixing efficiency | Soil |
| BLAI[a] | 0 | 1 | Leaf area index for crop | Crop |
| CANMX | 0 | 10 | Maximum canopy index | Runoff |
| CH_Cov | −0.001 | 1 | Channel cover factor | Erosion |
| CH_EROD[a] | −0.05 | 0.6 | Channel erodibility factor | Erosion |
| CH_K2 | −0.01 | 150 | Effective hydraulic conductivity in main channel alluvium (mm/hr) | Channel |
| CH_N[a] | 0.01 | 0.5 | Manning coefficient for channel | Channel |
| CN2[a] | 35 | 98 | SCS runoff curve number for moisture condition II | Runoff |
| EPCO[a] | 0 | 1 | Plant evaporation compensation factor | Evaporation |
| ESCO | 0 | 1 | Soil evaporation compensation factor | Evaporation |
| GW_DELAY | 0 | 50 | Groundwater delay (days) | Groundwater |
| GW_REVAP | 0.02 | 0.2 | Groundwater 'revap' coefficient. | Groundwater |
| Gwno3 | 0 | 10 | Nitrate concentration in the groundwater (mg/l) | Groundwater |
| GWQMN | 0 | 5000 | Threshold depth of water in the shallow aquifer required for return flow to occur (mm) | Soil |
| NPERCO | 0 | 1 | Nitrogen percolation coefficient | Soil |
| PHOSKD | 100 | 200 | Phosphorus soil partitioning coefficient | Soil |
| PPERCO | 10 | 17.5 | Phosphorus percolation coefficient | Soil |
| RCHR_DP | 0 | 1 | Groundwater recharge to deep aquifer (fraction) | Groundwater |
| REVAPMN | 0 | 500 | Threshold depth of water in the shallow aquifer for 'revap' to occur (mm). | Groundwater |
| SFTMP | 0 | 5 | Snowfall temperature (°C) | Snow |
| SLOPE[a] | 0.0001 | 0.6 | Average slope steepness (m/m) | Geomorphology |
| SLSUBBSN[a] | 10 | 150 | Average slope length (m). | Geomorphology |
| SMFMN | 0 | 10 | Minimum melt rate for snow during the year (occurs on winter solstice) (mm/°C/day) | Snow |
| SMFMX | 0 | 10 | Maximum melt rate for snow during (mm/°C/day) | Snow |
| SMTMP | 0 | 5 | Snow melt base temperature (°C) | Snow |
| SOL_ALB[a] | 0 | 0.1 | Soil albedo | Evaporation |
| SOL_AWC[a] | 0 | 1 | Available water capacity of the soil layer (mm/mm soil) | Soil |
| SOL_K[a] | 0 | 100 | Soil conductivity (mm/h) | Soil |
| SOL_LABP | 0 | 100 | Initial labile (soluble) P concentration in surface soil layer (kg/ha) | Soil |
| SOL_NO3 | 0 | 5 | Initial NO3 concentration (mg/kg) in the soil layer | Soil |
| SOL_ORGN | 0 | 10000 | Initial organic N concentration in surface soil layer (kg/ha) | Soil |
| SOL_ORGP | 0 | 4000 | Initial organic P concentration in surface soil layer (kg/ha) | Soil |
| SOL_Z | 0 | 3000 | Soil depth | Soil |
| SPCON | 0.0001 | 0.01 | Linear parameter for calculating the channel sediment routing | Channel |
| SPEXP | 1 | 1.5 | Exponent parameter for calculating the channel sediment routing | Channel |
| SURLAG | 0 | 10 | Surface runoff lag coefficient | Runoff |
| TIMP | 0.01 | 1 | Snow pack temperature lag factor | Snow |
| TLAPS[a] | 0 | 50 | Temperature laps rate (°C/km) | Geomorphology |
| USLE_P[a] | 0.1 | 1 | USLE equation support practice (P) factor | Erosion |

[a] These distributed parameters are varied according to a relative change (± 50%) that maintains their spatial relationship.

thus the effect of such relative changes on a number of distributed parameters on the model outputs. Table 3 gives the range over which each parameter was varied (MIN and MAX value), as well as a more complete definition of the parameter. Additionally the category of the process (groundwater, soil, crop, runoff, erosion, channel, and snow) is given.

## 5. Results

Tables 4 and 5 give the sensitivity rank of all the parameters for all criteria, starting with criteria on the performance (for flow, suspended sediments, total nitrogen and total phosphorus) followed by the results for criteria on the mass balance of the model outputs.

Table 4
Sensitivity results for the SWAT parameters for stream flow (Q), sediments (S), total nitrogen (N) and total phosphorus (P) for the available observation sites in the Sandusky river catchment (parameters with no appearance of sensitivity get rank 41)

| | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 2 | 3 | 4 | 1 | 2 | 3 | OUTLET | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q | Q | Q | Q | Q | S | S | S | N | N | N | P | P | P | Q | S | N | P | G |
| **ALPHA_BF** | 8 | 18 | 8 | 5 | 8 | 1 | 3 | 1 | 1 | 15 | 2 | 2 | 9 | 2 | 5 | 2 | 2 | 1 | 1 |
| **CN2** | 1 | 2 | 3 | 1 | 1 | 2 | 1 | 2 | 5 | 8 | 9 | 4 | 1 | 3 | 1 | 1 | 3 | 3 | 1 |
| **SOL_AWC** | 12 | 5 | 10 | 8 | 10 | 15 | 4 | 3 | 3 | 1 | 3 | 10 | 4 | 5 | 6 | 12 | 6 | 13 | 1 |
| **SOL_ORGN** | 22 | 22 | 23 | 22 | 24 | 25 | 27 | 25 | 2 | 4 | 4 | 25 | 30 | 24 | 19 | 30 | 1 | 27 | 1 |
| **SOL_ORGP** | 41 | 41 | 41 | 41 | 41 | 14 | 19 | 21 | 21 | 24 | 29 | 1 | 6 | 1 | 30 | 15 | 12 | 2 | 1 |
| SOL_Z | 10 | 7 | 9 | 9 | 9 | 13 | 11 | 10 | 13 | 3 | 1 | 19 | 14 | 17 | 4 | 21 | 7 | 17 | 1 |
| SURLAG | 2 | 1 | 1 | 7 | 2 | 4 | 7 | 7 | 4 | 2 | 7 | 3 | 2 | 4 | 14 | 5 | 5 | 4 | 1 |
| **ESCO** | 11 | 9 | 12 | 11 | 11 | 17 | 2 | 8 | 19 | 11 | 6 | 18 | 8 | 15 | 8 | 16 | 13 | 12 | 2 |
| **GWQMN** | 17 | 11 | 16 | 16 | 17 | 22 | 20 | 23 | 16 | 21 | 22 | 17 | 11 | 18 | 2 | 23 | 18 | 23 | 2 |
| **SMFMX** | 3 | 4 | 2 | 2 | 3 | 21 | 16 | 17 | 12 | 10 | 12 | 12 | 19 | 11 | 3 | 7 | 9 | 6 | 2 |
| CANMX | 13 | 12 | 11 | 10 | 12 | 16 | 12 | 15 | 11 | 16 | 8 | 16 | 3 | 22 | 9 | 18 | 17 | 16 | 3 |
| **CH_K2** | 4 | 19 | 5 | 3 | 4 | 10 | 14 | 14 | 20 | 27 | 25 | 22 | 24 | 26 | 15 | 22 | 14 | 21 | 3 |
| **SFTMP** | 5 | 3 | 15 | 14 | 14 | 11 | 18 | 6 | 10 | 7 | 10 | 20 | 26 | 19 | 7 | 8 | 15 | 19 | 3 |
| **SLOPE** | 16 | 15 | 19 | 15 | 16 | 3 | 5 | 9 | 7 | 14 | 14 | 7 | 17 | 10 | 21 | 4 | 10 | 8 | 3 |
| **SOL_LABP** | 26 | 41 | 41 | 41 | 41 | 8 | 10 | 19 | 17 | 5 | 21 | 8 | 15 | 6 | 27 | 3 | 4 | 5 | 3 |
| **SMTMP** | 6 | 6 | 7 | 4 | 7 | 20 | 9 | 5 | 6 | 13 | 5 | 14 | 7 | 14 | 10 | 13 | 23 | 14 | 4 |
| **TIMP** | 7 | 8 | 4 | 6 | 5 | 9 | 15 | 11 | 9 | 9 | 18 | 9 | 16 | 12 | 11 | 9 | 16 | 9 | 4 |
| **USLE_P** | 41 | 41 | 41 | 41 | 41 | 12 | 8 | 4 | 15 | 23 | 15 | 15 | 23 | 13 | 31 | 11 | 11 | 11 | 4 |
| RCHRG_DP | 24 | 24 | 41 | 41 | 41 | 18 | 21 | 26 | 8 | 19 | 20 | 5 | 18 | 8 | 24 | 20 | 19 | 15 | 5 |
| **SMFMN** | 9 | 10 | 6 | 13 | 6 | 24 | 23 | 18 | 23 | 17 | 16 | 21 | 5 | 16 | 12 | 17 | 21 | 22 | 5 |
| **SPCON** | 41 | 41 | 41 | 41 | 41 | 5 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 19 | 41 | 41 | 5 |
| **BIOMIX** | 19 | 16 | 17 | 19 | 18 | 19 | 17 | 16 | 14 | 12 | 17 | 11 | 20 | 7 | 17 | 6 | 8 | 7 | 6 |
| **NPERCO** | 41 | 41 | 41 | 25 | 23 | 34 | 31 | 24 | 18 | 6 | 11 | 24 | 33 | 21 | 28 | 33 | 20 | 25 | 6 |
| SOL_K | 20 | 14 | 20 | 21 | 20 | 6 | 6 | 12 | 22 | 18 | 13 | 6 | 10 | 9 | 13 | 10 | 24 | 10 | 6 |
| BLAI | 41 | 41 | 41 | 41 | 41 | 7 | 13 | 20 | 30 | 29 | 31 | 13 | 12 | 20 | 40 | 14 | 26 | 18 | 7 |
| CH_N | 14 | 23 | 14 | 12 | 15 | 23 | 24 | 13 | 24 | 28 | 24 | 28 | 31 | 27 | 22 | 27 | 27 | 26 | 12 |
| **GW_DELAY** | 23 | 20 | 22 | 23 | 22 | 35 | 29 | 34 | 32 | 31 | 30 | 34 | 13 | 34 | 23 | 35 | 33 | 34 | 13 |
| **SLSUBBSN** | 15 | 13 | 13 | 18 | 13 | 29 | 25 | 29 | 28 | 22 | 27 | 27 | 21 | 28 | 20 | 26 | 30 | 32 | 13 |
| SOL_ALB | 18 | 17 | 18 | 17 | 19 | 28 | 22 | 27 | 25 | 20 | 19 | 32 | 25 | 25 | 16 | 29 | 25 | 30 | 16 |
| EPCO | 21 | 21 | 21 | 20 | 21 | 32 | 26 | 22 | 29 | 25 | 28 | 31 | 28 | 30 | 18 | 31 | 31 | 31 | 18 |
| **PPERCO** | 41 | 41 | 41 | 41 | 41 | 31 | 28 | 30 | 27 | 30 | 26 | 23 | 22 | 23 | 41 | 24 | 22 | 20 | 20 |
| **SOL_NO3** | 25 | 25 | 41 | 24 | 41 | 33 | 33 | 31 | 26 | 26 | 23 | 33 | 34 | 33 | 26 | 34 | 28 | 33 | 23 |
| **GW_REVAP** | 27 | 26 | 41 | 41 | 41 | 26 | 32 | 32 | 33 | 33 | 32 | 30 | 32 | 32 | 25 | 25 | 32 | 24 | 24 |
| GWNO3 | 41 | 41 | 41 | 41 | 41 | 30 | 30 | 28 | 31 | 32 | 33 | 26 | 29 | 29 | 41 | 28 | 29 | 29 | 26 |
| **PHOSKD** | 41 | 41 | 41 | 41 | 41 | 36 | 41 | 33 | 41 | 41 | 41 | 29 | 27 | 31 | 41 | 41 | 41 | 28 | 27 |
| **SPEXP** | 41 | 41 | 41 | 41 | 41 | 27 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 32 | 41 | 41 | 27 |
| **REVAPMN** | 28 | 41 | 41 | 41 | 41 | 37 | 41 | 41 | 41 | 41 | 41 | 35 | 35 | 41 | 29 | 36 | 34 | 35 | 28 |
| **TLAPS** | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |
| **CH_COV** | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |
| **CH_EROD** | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |

The last column in each table shows the lowest rank from all the criteria and is used to assess global parameter sensitivity for the two basins. Global ranks 1 are catetegorized as 'very important', rank 2–6 as 'important', rank 7–40 as 'slightly important' and rank 41 as 'not important'.

The results for Sandusky river basin identify 7 very important parameters (global sensitivity of 1) that cover runoff, groundwater and soil processes, and thus involve the hydrology of the system. In addition, there were 17 important parameters (global sensitivity $>1$ and less than 7) that cover all remaining processes listed in Table 3, except for crop processes. Finally, there are 13 'slightly important' parameters (global sensitivity $<28$) and 3 parameters that did not cause any change to model output at all (rank of 41).

Table 5
Sensitivity results for the SWAT parameters for streamflow (Q), sediments (S), total nitrogen (N), and total phosphorus (P) for the available observation sites for the Upper North Bosque River catchment (parameters with no appearance of sensitivity get rank 41)

| | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 | OUTLET | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q | Q | Q | Q | Q | S | S | S | S | S | N | N | N | N | N | P | P | P | P | P | Q | S | N | P | G |
| **ALPHA_BF** | 10 | 10 | 15 | 11 | 12 | 2 | 1 | 3 | 1 | 1 | 5 | 2 | 2 | 3 | 5 | 2 | 1 | 8 | 3 | 6 | 7 | 1 | 1 | 1 | 1 |
| **CN2** | 1 | 1 | 1 | 1 | 1 | 4 | 6 | 1 | 5 | 7 | 3 | 6 | 6 | 8 | 2 | 3 | 6 | 4 | 5 | 1 | 1 | 4 | 3 | 3 | 1 |
| **SMTMP** | 11 | 15 | 19 | 14 | 15 | 22 | 26 | 19 | 21 | 11 | 9 | 1 | 4 | 10 | 20 | 20 | 12 | 5 | 22 | 17 | 14 | 26 | 11 | 23 | 1 |
| **SOL_AWC** | 3 | 3 | 3 | 3 | 3 | 11 | 12 | 4 | 13 | 10 | 4 | 4 | 1 | 12 | 1 | 7 | 2 | 1 | 9 | 3 | 3 | 15 | 9 | 13 | 1 |
| **SOL_LABP** | 22 | 24 | 22 | 21 | 24 | 1 | 2 | 6 | 2 | 5 | 13 | 14 | 21 | 2 | 17 | 9 | 11 | 16 | 4 | 11 | 24 | 2 | 5 | 5 | 1 |
| **SOL_ORGN** | 14 | 11 | 9 | 10 | 10 | 20 | 15 | 16 | 24 | 21 | 1 | 5 | 11 | 7 | 7 | 18 | 21 | 25 | 24 | 14 | 10 | 12 | 2 | 20 | 1 |
| **SOL_ORGP** | 30 | 25 | 26 | 27 | 26 | 18 | 18 | 23 | 15 | 22 | 14 | 21 | 23 | 23 | 8 | 1 | 3 | 10 | 6 | 4 | 27 | 10 | 15 | 2 | 1 |
| SURLAG | 2 | 2 | 2 | 2 | 2 | 7 | 7 | 10 | 6 | 2 | 8 | 7 | 8 | 1 | 6 | 11 | 4 | 7 | 1 | 2 | 8 | 6 | 7 | 4 | 1 |
| **BIOMIX** | 16 | 18 | 12 | 16 | 16 | 6 | 4 | 12 | 4 | 6 | 10 | 13 | 13 | 4 | 12 | 6 | 8 | 12 | 2 | 10 | 13 | 7 | 13 | 9 | 2 |
| **ESCO** | 4 | 4 | 4 | 4 | 4 | 16 | 11 | 2 | 14 | 12 | 7 | 11 | 5 | 14 | 4 | 10 | 7 | 3 | 11 | 7 | 4 | 18 | 14 | 15 | 2 |
| **GWQMN** | 12 | 14 | 14 | 18 | 11 | 24 | 24 | 21 | 19 | 23 | 16 | 17 | 20 | 19 | 10 | 16 | 19 | 26 | 15 | 18 | 2 | 14 | 10 | 12 | 2 |
| SOL_Z | 7 | 7 | 6 | 8 | 6 | 10 | 10 | 5 | 17 | 18 | 2 | 12 | 3 | 11 | 3 | 4 | 9 | 2 | 7 | 5 | 6 | 19 | 4 | 10 | 2 |
| **SLOPE** | 8 | 8 | 7 | 7 | 8 | 3 | 3 | 7 | 3 | 3 | 12 | 15 | 17 | 6 | 9 | 5 | 10 | 11 | 8 | 9 | 11 | 3 | 8 | 8 | 3 |
| **SMFMX** | 19 | 17 | 18 | 17 | 17 | 23 | 23 | 26 | 25 | 14 | 15 | 3 | 14 | 26 | 23 | 24 | 24 | 15 | 26 | 21 | 19 | 28 | 16 | 25 | 3 |
| **SLSUBBSN** | 5 | 5 | 5 | 6 | 7 | 21 | 21 | 15 | 16 | 4 | 23 | 19 | 18 | 13 | 13 | 23 | 20 | 13 | 20 | 12 | 18 | 20 | 24 | 21 | 4 |
| CANMX | 6 | 6 | 8 | 5 | 5 | 19 | 14 | 9 | 12 | 9 | 6 | 8 | 10 | 5 | 11 | 12 | 5 | 9 | 10 | 13 | 5 | 23 | 17 | 14 | 5 |
| **SPCON** | 41 | 41 | 41 | 41 | 41 | 5 | 5 | 41 | 7 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 34 | 5 | 41 | 41 | 5 |
| **GW_REVAP** | 29 | 28 | 28 | 29 | 27 | 9 | 9 | 17 | 11 | 19 | 31 | 31 | 30 | 30 | 33 | 8 | 13 | 17 | 14 | 8 | 22 | 8 | 26 | 6 | 6 |
| **NPERCO** | 27 | 26 | 25 | 24 | 41 | 32 | 31 | 31 | 31 | 28 | 11 | 9 | 16 | 9 | 18 | 28 | 29 | 23 | 32 | 28 | 29 | 31 | 6 | 33 | 6 |
| SOL_K | 18 | 19 | 10 | 13 | 13 | 12 | 17 | 8 | 10 | 17 | 21 | 16 | 9 | 18 | 15 | 13 | 14 | 6 | 12 | 16 | 9 | 11 | 19 | 11 | 6 |
| **PPERCO** | 41 | 30 | 41 | 41 | 41 | 28 | 27 | 27 | 26 | 29 | 17 | 24 | 28 | 22 | 19 | 17 | 17 | 27 | 13 | 19 | 31 | 17 | 12 | 7 | 7 |
| **TIMP** | 17 | 12 | 17 | 15 | 18 | 17 | 20 | 20 | 20 | 20 | 20 | 10 | 7 | 16 | 28 | 19 | 15 | 14 | 18 | 23 | 20 | 16 | 21 | 16 | 7 |
| **USLE_P** | 25 | 41 | 41 | 30 | 41 | 8 | 8 | 14 | 8 | 8 | 19 | 25 | 24 | 25 | 21 | 21 | 16 | 24 | 19 | 22 | 32 | 9 | 20 | 17 | 8 |
| BLAI | 41 | 41 | 41 | 41 | 41 | 13 | 19 | 11 | 9 | 13 | 27 | 29 | 31 | 29 | 26 | 14 | 18 | 21 | 16 | 15 | 40 | 13 | 28 | 18 | 9 |
| **CH_K2** | 9 | 9 | 13 | 12 | 14 | 25 | 22 | 13 | 23 | 15 | 22 | 18 | 12 | 17 | 14 | 26 | 25 | 19 | 23 | 26 | 17 | 21 | 18 | 22 | 9 |
| EPCO | 13 | 13 | 11 | 9 | 9 | 27 | 28 | 22 | 29 | 27 | 25 | 20 | 19 | 21 | 16 | 27 | 27 | 22 | 21 | 24 | 12 | 30 | 29 | 29 | 9 |
| CH_N | 15 | 16 | 16 | 19 | 21 | 15 | 13 | 24 | 18 | 26 | 28 | 27 | 26 | 15 | 24 | 30 | 28 | 29 | 27 | 34 | 21 | 22 | 27 | 26 | 13 |
| **SPEXP** | 41 | 41 | 41 | 41 | 41 | 14 | 16 | 41 | 22 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 25 | 41 | 41 | 14 |
| RCHRG_DP | 26 | 29 | 41 | 25 | 41 | 30 | 32 | 18 | 28 | 33 | 24 | 26 | 25 | 27 | 32 | 15 | 22 | 18 | 17 | 33 | 15 | 24 | 22 | 19 | 15 |
| SOL_ALB | 24 | 23 | 20 | 22 | 20 | 26 | 25 | 25 | 27 | 24 | 18 | 23 | 15 | 24 | 22 | 22 | 23 | 20 | 25 | 20 | 25 | 27 | 23 | 24 | 15 |
| **GW_DELAY** | 21 | 21 | 21 | 26 | 23 | 34 | 33 | 33 | 35 | 31 | 32 | 30 | 33 | 33 | 27 | 33 | 33 | 32 | 33 | 30 | 16 | 35 | 32 | 34 | 16 |
| **SFTMP** | 28 | 27 | 27 | 31 | 25 | 29 | 29 | 28 | 34 | 16 | 30 | 32 | 27 | 32 | 29 | 25 | 26 | 28 | 29 | 25 | 26 | 32 | 33 | 28 | 16 |
| **SMFMN** | 20 | 20 | 23 | 20 | 19 | 31 | 30 | 30 | 33 | 32 | 29 | 28 | 29 | 28 | 30 | 34 | 30 | 31 | 34 | 32 | 23 | 34 | 31 | 31 | 19 |
| **SOL_NO3** | 23 | 22 | 24 | 23 | 22 | 35 | 35 | 32 | 30 | 30 | 26 | 22 | 22 | 20 | 25 | 29 | 31 | 34 | 28 | 27 | 28 | 33 | 25 | 32 | 20 |
| GWNO3 | 41 | 41 | 41 | 41 | 41 | 33 | 34 | 29 | 32 | 25 | 33 | 33 | 32 | 31 | 31 | 31 | 34 | 33 | 30 | 31 | 41 | 29 | 30 | 27 | 25 |
| **PHOSKD** | 41 | 41 | 41 | 28 | 41 | 37 | 41 | 41 | 36 | 34 | 35 | 34 | 34 | 34 | 34 | 32 | 32 | 30 | 31 | 29 | 41 | 37 | 35 | 30 | 28 |
| **REVAPMN** | 31 | 31 | 41 | 41 | 41 | 36 | 36 | 41 | 37 | 41 | 34 | 35 | 41 | 35 | 41 | 35 | 35 | 41 | 35 | 41 | 30 | 36 | 34 | 35 | 30 |
| **TLAPS** | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |
| **CH_COV** | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |
| **CH_EROD** | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |

For the Bosque Upper North Bosque river catchment, the top 7 very important parameters represented runoff, groundwater, snow and soil processes. The following 12 'important' parameters cover all other processes except for crop. There are 18 parameters that are slightly important and the same 3 parameters as in the Sandusky River catchment that have no impact at all.

## 6. Discussion

### 6.1. Criteria on model performance

The scattered appearance of the higher ranked parameters show that the ranking depends on the variable, the location and, when both tables are compared, on the case. But, some generalisations can be made such as the overall importance of curve number (CN2) and the importance of the groundwater parameter ALPHA_BF on the water quality variables. The latter is explained by the fact that water quality concentrations during low flow periods are dependent on flow estimation, as predicted concentrations can be very high when the river is simulated as drying up, which often leads to large prediction residuals. The flow calculations during these low flow periods depend on the groundwater contribution, which in turn depends strongly on the parameter 'ALPHA_BF'.

Other generally important parameters for many criteria are the soil water capacity 'SOL_AWC' and the delay on runoff 'SURLAG'. The initial soil concentrations of nitrogen and phosphorus, 'SOL_ORGN' and 'SOL_ORGP', are often important for simulating the nitrogen and phosphorus concentrations, respectively.

These results also show that the hydrologic parameters dominate the highest parameter ranks when the pollutant concentrations are considered. Some hydrologic parameters, like the already mentioned 'ALPHA_BF', appear almost only on the pollutant concentration list while being relatively unimportant for the water quantity (highest rank of 5 between both cases). This result means that water quality data are potentially capable of contributing to the identification of water quantity parameters within SWAT.

There are also clear differences between the catchments. For instance, the water flow performance in the Sandusky river depends on the snow parameters 'SMFMX', 'SFTMP', 'TIMP', 'SMFMN' and soil conductivity 'SOL_K2', while in the Upper North Bosque river basin 'ESCO', and canopy index 'CANMX' (evaporation parameters) and SLSUBBSN (a geomorphic parameter) have a high rank. The differences are obviously due to climate, given the relatively cold snowy climate of the Sandusky river basin in Ohio and the relatively high evaporation rates expected in the warm and sunny climate of the Upper North Bosque river basin in Texas. This result means that the results of sensitivity analysis on one catchment cannot directly be transferred to another one.

The results also show clear differences for the interior locations inside a basin. While the Upper North Bosque river basin does not show a high interior variability on the flows, this phenomenon is very apparent in the Sandusky basin. This result indicates that there is higher spatial variability in the processes controlling water quality within the Sandusky river basin. In both basins, the results are very scattered for the water quality variables. This result illustrates how parameter importance depends on land use, topography and soil types, meaning that a generalisation within a basin is limited.

### 6.2. Criteria on model output

Analysis of results for model output show similar results to those for model performance, but there are some differences: 'SURLAG' loses its importance, since time delay does not play an important role on the average annual output values. In return, 'GWQMN', which controls groundwater losses, has rank 2 for the averaged flow in both case studies, while not being important for the other criteria. This result suggests that their may not be enough information to identify some model parameters that control predictions of model output. And therefore some parameters may not always be identified properly, even when enough observations are provided.

### 6.3. Considerations on the simulated time period

The results of the sensitivity analysis depend on the time period of the simulations, especially for short simulation periods. Exceptional events in the data such as exceptional dry summers, heavy rains causing flooding or exceptional snow events may cause the sensitivity indexes to be biased. Especially when the dataset does not represent typical events, for instance this condition would be true if the data used for sensitivity analysis contained no snowfall while other years did have snowfall. In this case important process parameters may not be activated during the period of sensitivity study. These types of irregularities should be taken into account while interpreting the results. For the two test basins, such irregularities have not been reported. Nevertheless, it is recommended to use longer periods if possible.

## 7. Conclusion

A novel method of sensitivity was presented and applied to a multiple-variable water quality model. It provides a simple and quick way to assess parameter sensitivity across a full range of parameter values and with varying values of other parameters, thereby covering the entire feasible space. This approach results in a global sensitivity analysis that is able to detect even slight influences within a small number of iterations.

The results allow some generalisations among basins with an overall importance of curve number (CN2) and the importance of the groundwater parameter ALPHA_BF on the water quality predictions of SWAT. In general, the hydrologic parameters are dominant in controlling water quality predictions. There are also clearly different results between the catchments that are obviously due to climate, but the results also reflect differences in soil and land properties. Thus, each new basin model requires its own sensitivity analysis to select a subset of parameters to be used for model calibration or uncertainty analysis. Also interior sites show different ranks for the parameters dependent on the physical characteristics of sub-basins.

## Acknowledgements

Support for this work was provided by the National Science Foundation through a CAREER award to T. Meixner (EAR-0094312). The research on the Sandusky River catchment was supported by the Florida Agricultural Experiment Station and approved for publication as Journal Series No. R-09797. The experimental data of the Upper North Bosque River catchment were provided by the Texas Institute for Applied Environmental Research.

## References

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development. Journal of American Water Resources Association 34 (1), 73–89.

Beven, K., 1989. Changing ideas in hydrology—the case of physically-based models. Journal of hydrology 105, 157–172.

Box, G.E.P., Jenkins, G.M., 1976. Time Series Analysis: Forecasting and Control. Holden-Day, Son-Fransisco, 588 pp.

Cukier, R.I., Levine, H.V., Shuler, K.E., 1978. Nonlinear sensitivity analysis of kinetic mechanisms. International Journal of Chemical Kinetics 11, 427–444.

Di Luzio, M., Srinivasan, R., Arnold, J.G., 2002. Integration of watershed tools and SWAT model into BASINS. Journal of American Water Resource Association 4, 1127–1141.

Fishman, G.S., 1996. Monte Carlo: Concepts, Algorithms and Applications. Springer, New York, USA.

Francos, A., Elorza, F.J., Bouraoui, F., Galbiati, L., Bidoglio, G., 2001. Sensitivity analysis of hydrological models at the catchment scale: a two-step procedure. Reliability Engineering and System Safety 79 (2003), 205–218.

Helton, J.C., 1993. Uncertainty and sensitivity anlaysis techniques for use in performance assessment for radioactive waste disposal. Reliability Engineering and System Safety 42, 327–367.

Hornberger, G.M., Spear, R.C., 1980. Eutrophication in Peel Inlet, I. Problem-defining behaviour and a mathematical model for the phosphorous scenario. Water Research 14, 29–42.

Iman, R.L., Conover, W.J., 1980. Small sample sensitivity analysis techniques for computer models, with an application to risk assessment. Communications in Statistics: Theory and Methods A9 (17), 1749–1842.

Krajewski, W.F., Lakshimi, V., Georgakakos, K.P., Jain, S.J., 1991. A Monte Carlo study of rainfall sampling effect on a distributed catchment model. Water Resources Research 27 (1), 119–128.

Mailhot, A., Villeneuve, J.-P., 2003. Mean-value second-order uncertainty analysis method: application to water quality modelling. Advances in Water Resources 26, 401–499.

McFarland, A.M.S., Hauck, L.M., 1995. Livestock and the Environment: Scientific Underpinning for Policy Analysis. Texas Institute for Applied Environmental Research, Tarleton State University, Texas.

McFarland, A.M.S., Hauck, L.M., 1999. Relating agricultural land uses to in-stream stormwater quality. Journal of Environmental Quality 28, 836–844.

McKay, M.D., 1988. In: Ronen, Y. (Ed.), Sensitivity and Uncertainty Analysis Using a Statistical Sample of Input Values. CRC Press, Boca Raton, FL, pp. 145–186.

McKay, M.D., Beckman, R.J., Conover, W.J., 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21 (2), 239–245.

Meixner, T., Gupta, H.V., Bastidas, A.L., Bales, R.C., 1999. Sensitivity analysis using mass flux and concentration. Hydrological Processes 13, 2233–2244.

Melching, C.S., Yoon, C.G., 1996. Key sources of uncertainty in QUAL2E model of Passaic river. ASCE Journal of Water Resources Planning and Management 122 (2), 105–113.

Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33, nr2.

Richards, R.P., Baker, D.B., 2002. Trends in water quality in LEASEQ rivers and streams, 1975–1995. Journal of Environmental Quality 31, 90–96.

Saltelli, A., Andres, T.H., Homa, T., 1995. Sensitivity analysis of model output; performance of the iterated fractional design method. Computational Statistics and Data Analysis 20, 387–407.

Saltelli, A., Chan, K., Scott, E.M. (Eds.), 2000. Senstivity Analysis. Wiley, New York.

Sandusky River Watershed Coalition, 2000. The Sandusky River Watershed Resource Inventory. Fremont, Ohio.

Spear, R.C., Hornberger, G.M., 1980. Eutrophication in Peel Inlet, II, Identification of critical uncertainties via generalised sensitivity analysis. Water Research 14, 43–49.

Stephens, M.A., 1970. Use of the Kolmogorov Smirnov, Cramer-von Mises and related statistics without extensive tables. Journal of the Royel Statistical Society: Series B33, 115–122.

van der Perk, M., Bierkens, M.F.P., 1997. The identifiability of parameters in a water quality model of the Biebrza River, Poland. Journal of Hydrology 200, 307–322.

van Griensven, A., Francos, A., Bauwens, W., 2002. Sensitivity analysis and auto-calibration of an integral dynamic model for river water quality. Water Science and Technology 45 (5), 321–328.

Vandenberghe, V., van Griensven, A., Bauwens, W., 2001. Sensitivity analysis and calibration of the parameters of ESWAT: application to the river Dender. Water Science and Technology 43 (7), 295–301.

Ward, G., Flowers, J.D., Coan, T.L., 1992. Final Report on Environmental Water Quality Monitoring Relating to Non Point Source Pollution in the Upper North Bosque River Watershed. Texas Institute for Applied Environmental Research, Tarleton State University, Stephenville, Texas.

Weijers, S.R., Vanrolleghem, P.A., 1997. A procedure for selecting parameters in calibrating the activated sludge model no.1 with full-scale plant data. Water Science and Technology 36 (5), 69–79.

Yen, B.C., Cheng, S.-T., Melching, C.S., 1986. First order reliability analysis: stochastic and risk analysis in hydraulic engineering. In: Yen, B.C. (Ed.), Water Resources Publications, Littleton, Colorado, pp. 1–36.