



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

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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.

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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

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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 Δe_i while the other input parameters are held constant (Melching and Yoon, 1996):

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

where M is the model output, e_i refers to the different model parameters, and Δe_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 $e = \{e_1, \dots, e_p\}$ are the input random variables with means $\bar{e} = \{\bar{e}_1, \dots, \bar{e}_p\}$. $\delta M / \delta e$ are derivatives evaluated at the mean values \bar{e} .

The mean of the output function M and the standard deviation σ_M are then calculated as:

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

with $\sigma_{e_i} = \{\sigma_{e_1} \sigma_{e_p}\}$ 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).

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

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

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

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 Δe_i . The change in model outcome $M(e_1, \dots, e_i + \Delta e_i, \dots, e_p)$ can then be unambiguously attributed to such a modification by means of an elementary effect, S_i , defined by Eq. (1). $M(e_1, \dots, e_i + \Delta e_i, \dots, e_p)$ 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. $i=1, \dots, P$), 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 quantitateness 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.

$$V = \sum_i V_i + \sum_{i < j} V_{ij} + \sum_{i < j < m} V_{ijm} + \dots + V_{i,j,k,\dots,P} \quad (6)$$

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 $V_{1,2,\dots,p}$ 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.

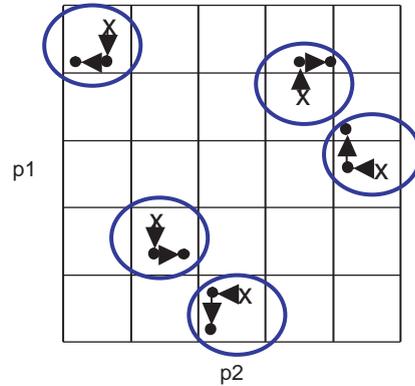


Fig. 1. Illustration of MC-OAT sampling of values for a two parameter model where X represent the Monte-Carlo points and ● the OAT points.

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):

$$S_{i,j} = \left| \frac{100 * \left(\frac{M(e_1, \dots, e_i * (1+f_i), \dots, e_p) - M(e_1, \dots, e_i, \dots, e_p)}{|M(e_1, \dots, e_i * (1+f_i), \dots, e_p) + M(e_1, \dots, e_i, \dots, e_p)|/2} \right)}{f_i} \right| \quad (7)$$

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 subdivisions 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 km², 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 m³ s⁻¹, and Rock Creek at Tiffin is 0.88 m³ 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 km² 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

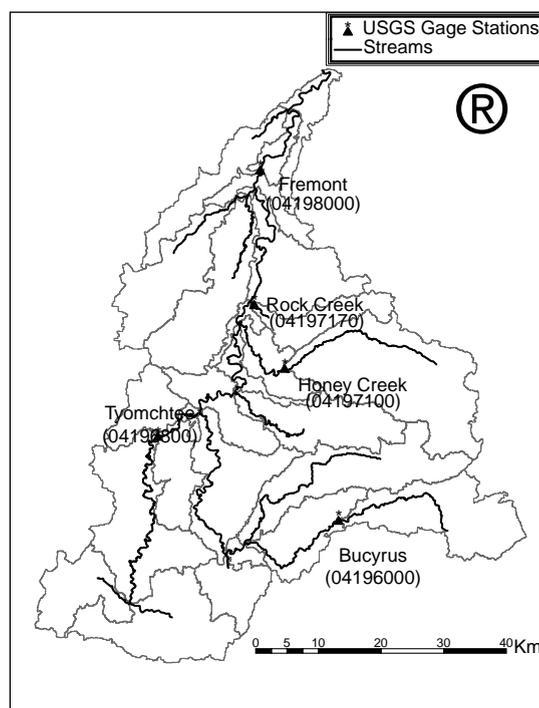


Fig. 2. Map of the Sandusky river catchment with observation sites.

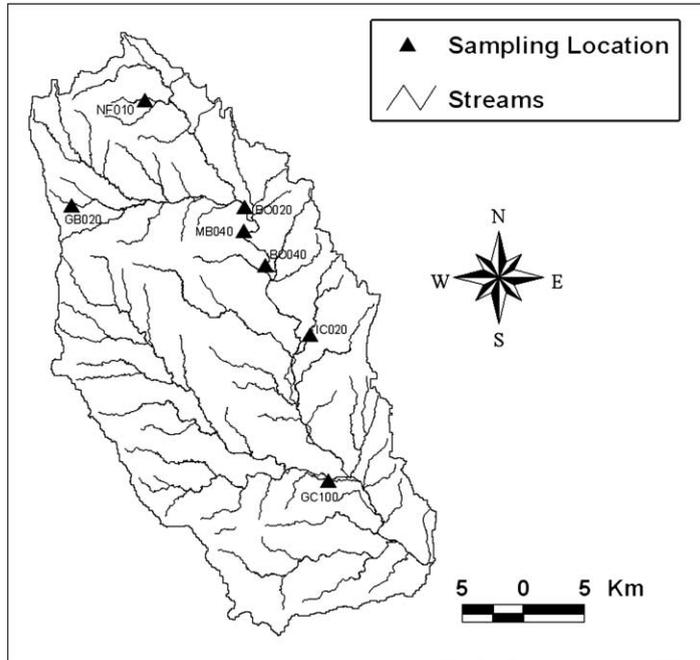


Fig. 3. Map of the Upper North Bosque river catchment with observation sites.

Bosque river basin). A half year warming up period preceded 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

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

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 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 ($\pm 50\%$) 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				OUTLET				G
	Q	Q	Q	Q	Q	S	S	S	N	N	N	N	P	P	P	P	Q	S	N	P	
ALPHA_BF	8	18	8	5	8	1	3	1	1	15	2	2	9	2	5	2	2	1	1	1	
CN2	1	2	3	1	1	2	1	2	5	8	9	4	1	3	1	1	3	3	1	1	
SOL_AWC	12	5	10	8	10	15	4	3	3	1	3	10	4	5	6	12	6	13	1	1	
SOL_ORGN	22	22	23	22	24	25	27	25	2	4	4	25	30	24	19	30	1	27	1	1	
SOL_ORGP	41	41	41	41	41	14	19	21	21	24	29	1	6	1	30	15	12	2	1	1	
SOL_Z	10	7	9	9	9	13	11	10	13	3	1	19	14	17	4	21	7	17	1	1	
SURLAG	2	1	1	7	2	4	7	7	4	2	7	3	2	4	14	5	5	4	1	1	
ESCO	11	9	12	11	11	17	2	8	19	11	6	18	8	15	8	16	13	12	2	2	
GWQMN	17	11	16	16	17	22	20	23	16	21	22	17	11	18	2	23	18	23	2	2	
SMFMX	3	4	2	2	3	21	16	17	12	10	12	12	19	11	3	7	9	6	2	2	
CANMX	13	12	11	10	12	16	12	15	11	16	8	16	3	22	9	18	17	16	3	3	
CH_K2	4	19	5	3	4	10	14	14	20	27	25	22	24	26	15	22	14	21	3	3	
SFTMP	5	3	15	14	14	11	18	6	10	7	10	20	26	19	7	8	15	19	3	3	
SLOPE	16	15	19	15	16	3	5	9	7	14	14	7	17	10	21	4	10	8	3	3	
SOL_LABP	26	41	41	41	41	8	10	19	17	5	21	8	15	6	27	3	4	5	3	3	
SMTMP	6	6	7	4	7	20	9	5	6	13	5	14	7	14	10	13	23	14	4	4	
TIMP	7	8	4	6	5	9	15	11	9	9	18	9	16	12	11	9	16	9	4	4	
USLE_P	41	41	41	41	41	12	8	4	15	23	15	15	23	13	31	11	11	11	4	4	
RCHRG_DP	24	24	41	41	41	18	21	26	8	19	20	5	18	8	24	20	19	15	5	5	
SMFMN	9	10	6	13	6	24	23	18	23	17	16	21	5	16	12	17	21	22	5	5	
SPCON	41	41	41	41	41	5	41	41	41	41	41	41	41	41	41	19	41	41	5	5	
BIOMIX	19	16	17	19	18	19	17	16	14	12	17	11	20	7	17	6	8	7	6	6	
NPERCO	41	41	41	25	23	34	31	24	18	6	11	24	33	21	28	33	20	25	6	6	
SOL_K	20	14	20	21	20	6	6	12	22	18	13	6	10	9	13	10	24	10	6	6	
BLAI	41	41	41	41	41	7	13	20	30	29	31	13	12	20	40	14	26	18	7	7	
CH_N	14	23	14	12	15	23	24	13	24	28	24	28	31	27	22	27	27	26	12	12	
GW_DELAY	23	20	22	23	22	35	29	34	32	31	30	34	13	34	23	35	33	34	13	13	
SLSUBBSN	15	13	13	18	13	29	25	29	28	22	27	27	21	28	20	26	30	32	13	13	
SOL_ALB	18	17	18	17	19	28	22	27	25	20	19	32	25	25	16	29	25	30	16	16	
EPCO	21	21	21	20	21	32	26	22	29	25	28	31	28	30	18	31	31	31	18	18	
PPERCO	41	41	41	41	41	31	28	30	27	30	26	23	22	23	41	24	22	20	20	20	
SOL_NO3	25	25	41	24	41	33	33	31	26	26	23	33	34	33	26	34	28	33	23	23	
GW_REVAP	27	26	41	41	41	26	32	32	33	33	32	30	32	32	25	25	32	24	24	24	
GWNO3	41	41	41	41	41	30	30	28	31	32	33	26	29	29	41	28	29	29	26	26	
PHOSKD	41	41	41	41	41	36	41	33	41	41	41	29	27	31	41	41	41	28	27	27	
SPEXP	41	41	41	41	41	27	41	41	41	41	41	41	41	41	41	32	41	41	27	27	
REVAPMN	28	41	41	41	41	37	41	41	41	41	41	35	35	41	29	36	34	35	28	28	
TLAPS	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	
CH_EROD	41	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 categorized 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					OUTLET								
	Q	Q	Q	Q	Q	S	S	S	S	S	N	N	N	N	N	N	N	N	N	N	P	P	P	P	P	P	P	P	P	P	Q	S	N	P
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	1	1	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	1	1	1	1	1	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	1	1	1	1	1	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	1	1	1	1	1	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	1	1	1	1	1	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	1	1	1	1	1	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	1	1	1	1	1	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	1	1	1	1	1	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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
SLSUBSN	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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
SPCON	41	41	41	41	41	5	5	41	7	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	5	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
BLAI	41	41	41	41	41	13	19	11	9	13	27	31	29	26	14	18	21	16	15	40	13	28	18	9	1	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
SPEXP	41	41	41	41	41	14	16	41	22	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	25	41	41	41	41	41	41			
RCHRGP_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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			
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	1	1	1	1	1	1			

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.

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