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Use of sensitivity and uncertainty measures in distributed hydrological modeling with an application to the MIKE SHE model

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[1] A methodology to qualify and quantify uncertainty and sensitivity measures, mathematically related to a representative metamodel and correlation coefficients, using the Latin hypercube approach, is evaluated in the context of the spatially distributed hydrological model MIKE SHE. The characteristics of various outputs, such as cumulative catchment discharge, average soil water content, and groundwater elevation, are examined at different time and space scales. The soil hydraulic parameters make up the varying input. The input uncertainties and the corresponding Latin hypercube parameter perturbations are based on U.S. Department of Agriculture texture figures. Results indicate important differences between the measures, even in ranking, making combined interpretation of the measures necessary. The real-world problem of correlation among parameters adds significant complexity to the assessment of uncertainty and sensitivity and cannot be disregarded without caution. The presented methodology, though still CPU intensive, allows the hydrological modeler to cope with this complexity. *INDEX TERMS:* 1829 Hydrology: Groundwater hydrology; 1860 Hydrology: Runoff and streamflow; 1866 Hydrology: Soil moisture; 1875 Hydrology: Unsaturated zone; 3210 Mathematical Geophysics: Modeling; *KEYWORDS:* MIKE SHE, sensitivity, uncertainty, measures, hydrology, unsaturated zone

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1. Introduction

[2] Mathematical simulation models are powerful tools, presenting answers for (potential) problems. The tendency has been to use these models in a deterministic way, assuming that the input variables and parameters (together called input) represent reality in an accurate way. A calibration phase, often a time-demanding process, is a prerequisite before using complex models with many parameters. The sensitivity analysis is a phase in the modeling process that facilitates calibration in that it permits the user to focus on the - for the model-relevant or sensitive parameters. Sensitivity analysis can also contribute to the beginning phase of the modeling process, namely in the data collection: Why should people devote time and money in measuring data for which the model is insensitive?

[3] Nowadays modelers are aware of the uncertainty involved in modeling, and the necessity to quantify the model output reliability [*Beven*, 1989; *Melching*, 1995]. Models are therefore more and more applied in a stochastic sense, the so-called joint stochastic-deterministic modeling approach [*Refsgaard*, 1996]. This approach accounts for the uncertainty associated with the model input resulting in an uncertainty band around the deterministic simulations. The uncertainty in model output is function of the uncertainty related to the input (measurement errors, heterogeneity, and effective values for a grid cell), and the process description involved. Both, sensitivity (determining crucial inputs) and uncertainty (in model outputs) analyses should be part of the model evaluation, which is to be performed before or during doing model predictions.

[4] A whole variety of methods are available for sensitivity (SA) and uncertainty (UA) analyses. A short overview of different methods with their main advantages and disadvantages is given in Table 1, as well as a nonexhaustive list of example applications. For more information the reader is referred to *Iman and Helton* [1985], *Janssen et al.* [1990], *Morgan and Henrion* [1990], *Melching* [1995], and *Kleijnen* [1995]. Some of the methods have been applied in (watershed) hydrological modeling studies, but mostly to a limited extent [*Melching*, 1995]. Table 1 indicates that the Latin Hypercube based method and related techniques are the most suitable candidates for both the SA and UA [*Janssen et al.*, 1990; *Melching*, 1995]. Different measures are available to describe the sensitivity to and/or uncertainty contribution of a given input [*Iman and Helton*, 1985; *Morgan and Henrion*, 1990; *Janssen et al.*, 1992; *Melching*, 1995]. Some of the measures are based on a linear regression of the model output on the varying model input. Others find their origin in the correlation analysis. A subset of these measures is listed in Table 2, and their use is described in the following sections.

[5] In addition to the selection of the appropriate method and measure(s) for the SA and/or UA, it is important to accurately define the objectives of the analysis. If real input distributions are used in a sensitivity study, opposed to purely mathematical perturbations, the study coincides with UA. In order to assess the real output uncertainty, the key issue is to identify these correct input parameter distributions. If normality of the parameters is assumed, mean and standard deviation can quantify these distributions. It is

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Table 1. Overview of Methods Used for Sensitivity (SA) and Uncertainty (UA) Analyses

Method	SA/UA	References (Chronologically)	Advantages	Disadvantages
Individual parameter perturbation or one-dimensional SA	SA	*Janssen et al.* [1990] *Xevi et al.* [1997]	direct, simple method	fixed base point; no interactions; calculation intensive
Methods based on Taylor expansion: Differential analysis (SA) Error propagation (UA) Mean value first order second moment Advanced first order second moment Rosenblueth's point estimation method Harr's point estimation method	SA/UA	*Iman and Helton* [1985] *Rogers et al.* [1985] *Janssen et al.* [1990] *Morgan and Henrion* [1990] *Melching and Anmangandla* [1992] *Melching* [1995]	exact expression for local sensitivity a.f.o. time, follows the average a.f.o. time; large application area; certain methods allow for correlations	linear local approximation of the model; results are function of selection of base point; possible high model development, implementation and calculation costs; no interactions
Response Surface Techniques	SA/UA	*Iman and Helton* [1985] *Janssen et al.* [1990] *Morgan and Henrion* [1990] *Melching* [1995] *Kleijnen* [1995]	cost-effective; idea of global sensitivities; large application area; suitable for models with many parameters; substitution of simulation model by simple metamodel; interactions possible	selection of parameter values and metamodel can be difficult (expert knowledge); nonprobabilistic base; metamodel is an approximation; nondynamic character; limited use of rank regression and correlation techniques; indirect estimation of distributions of outputs
Monte Carlo simulation Latin hypercube sampling MCS combined with metamodel MCS as key in regional SA MCS as key-component in GLUE (generalized likelihood uncertainty estimation)	SA/UA	*Spear and Hornberger* [1980] *Iman and Helton* [1985] *Janssen et al.* [1990] *Morgan and Henrion* [1990] *Beven and Binley* [1992] *Melching and Anmangandla* [1992] *Melching* [1995] *Freer et al.* [1996] *Kleijnen* [1995]	cost-effective; local and global sensitivities; suitable for models with many parameters; large application area; representative parameter ranges can be selected; simultaneous sampling of parameters; direct estimation of distributions of outputs; direct use of rank regression and correlation; simple use and implementation	possible unwanted correlation between parameters due to sampling procedure; a priori incorporation of correlations, results are function of a priori probability density functions; meta-/regression model is an approximation[a]

[a] In case of MCS combined with metamodel.

clear that a specific variation around a specific mean will deliver results only applicable for this variation-mean value pair, given the model setup. It is also essential to specify which output variables (objective functions) are evaluated, because this will influence the results of the analysis. Furthermore, in dynamic distributed models the time and space scales must be determined: that is at which time step, aggregation of time, and location does one wish to study the selected output variables.

[6] The overall objective of this study is to evaluate a methodology that allows the quantification of the influence of variations in input variables and parameters on the model outputs in the context of distributed, hydrological catchment models. How the input distributions are established is

Table 2. Measures Describing the Sensitivity (SA) and/or Uncertainty (UA) of a Parameter[a]

Measure	Full Name (Origin)	SA/UA	Relation With Other Measures
ORC	ordinary regression coefficient	SA	
NRC	normalized regression coefficient	SA	
SRC	standardized regression coefficient	SA/UA	
PUC	partial uncertainty contribution (regression)	UA	= RTU^2; if no correlations : = SRC^2
RTU	root of uncertainty (regression)	UA	if no correlations : = SRC
LCC	linear correlation coefficient	SA/UA	if no correlations : = SRC
PCC	partial correlation coefficient	SA/UA	
SPC	semipartial correlation coefficient	SA/UA	if no correlations : = SRC

[a] After *Janssen et al.* [1992].

beyond the scope of this study. In general, two approaches are possible. The input distributions can be established a priori based on direct measurements or indirect estimations [*Parkin et al.*, 1996; *Djurhuus et al.*, 1999; *Refsgaard et al.*, 1999]. When these distributions are fed into the spatially distributed hydrological model, issues like scaling, spatial heterogeneity, measurement or estimation method error, and structural modeling error could be overlooked. As a consequence the resulting sensitivity and uncertainty are reflections of input variation that may bear little resemblance with the actual world. Others have tried to qualify the uncertainty figure respecting the output observations, addressing the risks of the a priori approach mentioned above [*Beven and Binley*, 1992; *Gupta et al.*, 1998]. These methods aim at determining both the input and output uncertainty within a single framework. Both approaches provide input distributions that can be analyzed within the presented methodology to define relative contributions to uncertainty or sensitivity. The results however, may range form a theoretical exercise to practical values depending on the soundness of the input.

[7] To illustrate the methodology, a case is presented that tackles a subset of the model input, the soil hydraulic parameters. Their input distributions are established a priori, and based on U.S. Department of Agriculture (USDA) texture figures, accounting only for soil heterogeneity in the soil hydraulic parameters. The model under study is the spatially distributed, physically based, hydrological model, MIKE SHE [*Refsgaard and Storm*, 1995]. By presenting this application, an attempt is made to demonstrate the usefulness of selected sensitivity and uncertainty measures in hydrology, not to deliver predictive uncertainty of the case study. The presented methodology is based on the Latin Hypercube technique for input-output realization, subsequently approximated by a linear metamodel. Different metamodel-related and correlation measures for input-output combinations are studied and evaluated.

2. Methodology Applied to Derive Sensitivity/ Uncertainty Measures

[8] The methodology consists of two steps. In a first step the model is executed using different sampled parameters sets in order to create model output distributions. The easiest and most efficient way to realize the input-output relations, needed to perform SA and/or UA, of models with many parameters (like most spatially distributed, physically based, hydrological catchment models), is the Latin Hypercube Technique or Simulation (LHS) [*Iman et al.*, 1980]. This technique is a stratified sampling approach (in contrast to Monte Carlo Simulation, which uses random sampling) that allows efficient estimation of the statistics of the output. The standard LHS consists of the following steps [*Janssen et al.*, 1992]:

1. Equi-probable subdivision: In LHS, the probability distribution of each basic variable (which can be input variables as well as parameters, further called for ease of use: parameters) is subdivided into S ranges or intervals each with a probability of occurrence equal to $1/S$.

2. Stratified sampling: A single value is sampled within each interval, according to the probability distribution.

3. Random pairing in the case of noncorrelated parameters, or in the case of correlation combination of the sampled values in a correlated fashion (introduction of Spearman (rank) correlations, see *Iman and Conover* [1982]): S data sets of p parameters (with p = number of parameters to be sampled) are generated.

[9] When using LHS, the parameter space is representatively sampled with only a few examples (i.e. small S). *Iman and Helton* [1985] indicate that a choice of S samples > 4/3 times p usually gives satisfactory results when performing sensitivity and uncertainty analyses of a model. But to be safe, it is better to choose S at least between 2 times p and 5 times p. The model simulation is then performed for each data set. In this regard, the approach is a marriage of probabilistic theory of random model input and deterministic theory of model simulation [*Morgan and Henrion*, 1990; *Janssen et al.*, 1992; *Melching*, 1995; *Spitz and Moreno*, 1996]. With the combination of the LHS and the model simulation, one is able to obtain probability distributions of the various model outputs.

[10] A major objective of this study is to link this total variation (given by the probability distributions of an output variable) to the uncertainty or sensitivity contribution of the different parameters. In order to be able to quantify uncertainty ranges on the model output as a function of varying model input, a regression model $\hat{y}(s)$ for the V different outputs is calculated that fits a linear combination of the varying parameters $x_i(s)$ on the model outputs $y(s)$:

$$y_v(s) = \hat{\beta}_{0,v} + \sum_{i=1}^{p} \hat{\beta}_{i,v} x_i(s) + \hat{e}_v(s) = \hat{y}_v(s) + \hat{e}_v(s) \qquad (1)$$

where

s = 1 . . . S (number of simulation runs or samples);
v = 1 . . . V (number of studied output variables);
p number of parameters;
$\hat{\beta}_{0,v}, \hat{\beta}_{i,v}$ regression coefficients; and
$\hat{e}_v(s)$ regression residual.

[11] Using this linear model (equation 1), different measures can be calculated. Next to the various regression coefficients, like for instance the standardized regression coefficient, also different correlation measures, with the linear correlation coefficient as an example, can be calculated to quantify the sensitivity or uncertainty contribution. Different measures, listed in Table 2, are discussed and examined using a case study in the subsequent sections.

[12] The whole procedure, of sampling data sets from probability distributions of parameters and calculating different measures, is programmed in the UNCSAM software package [*Janssen et al.*, 1992]. This package needs as input the probability distribution of the parameters, the rank-correlation matrix describing the correlation among the sampled parameters, and a value for S (number of samples to be taken).

3. Distributed Hydrological Model, Analyzed Input And Output

3.1. MIKE SHE Model

[13] The model used in this study is the spatially distributed, physically based, hydrological MIKE SHE model [*Refsgaard and Storm*, 1995]. The MIKE SHE model is based on the Système Hydrologique Européen (SHE)

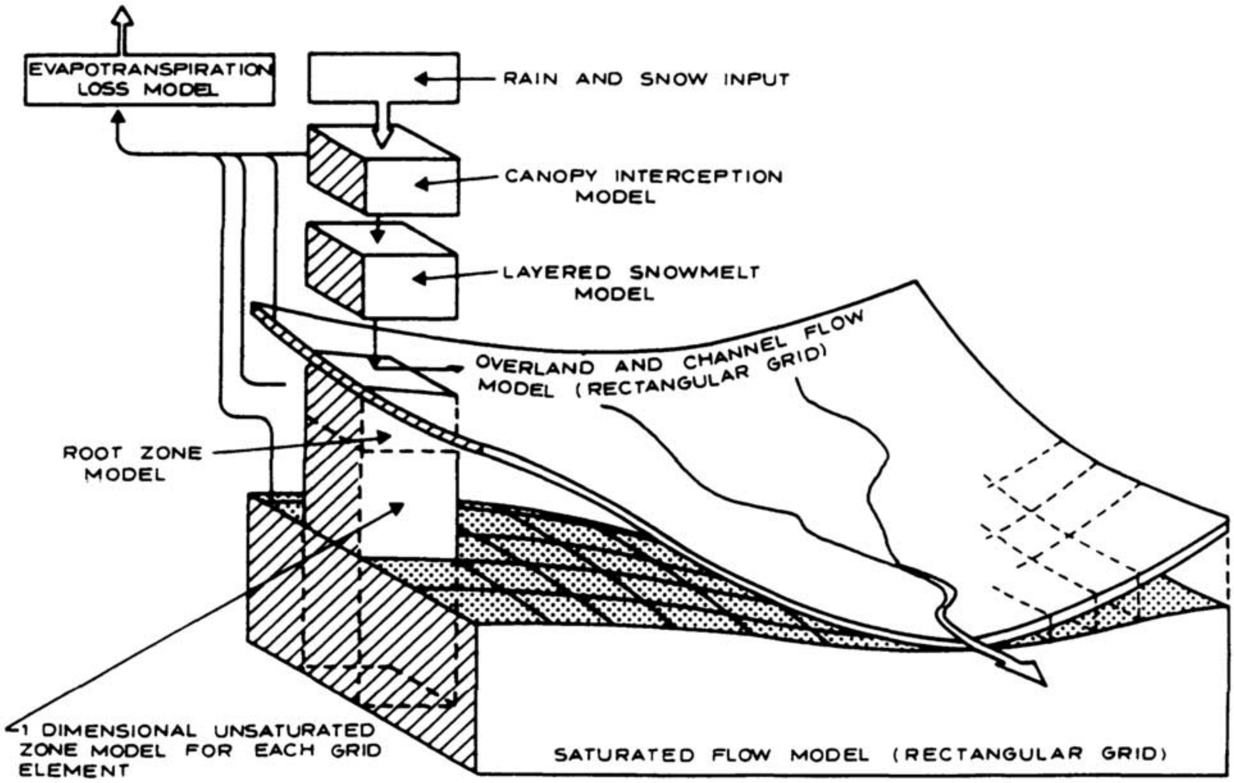

Figure 1. Schematic representation of the MIKE SHE model [after *Refsgaard and Storm*, 1995].

[*Abbott et al.*, 1986a, 1986b]. It is a complex mechanistic model, incorporating components for overland and river flow (two-dimensional and one-dimensional, Saint-Venant), transport through the soil zone (one-dimensional, Richards), and groundwater flow (three-dimensional, Boussinesq). The model covers the entire hydrological system on a catchment scale (Figure 1).

[14] By discretizing the catchment area into a large number of grid squares and layers, water flow processes can be simulated accounting for spatially variable input such as soil type (soil hydraulic parameters), field slope, land cover. The impact of grid size on simulation time is high [*Xevi et al.*, 1997]. Variability within the catchment can thus be accounted for at the cost of increased calculation time, if the available measurements have the necessary detail. The parameters of the physically based equations can in fact only be obtained through direct measurements, as long as these are compatible with the representative volumes for which the equations are derived and used at the appropriate scale in the model application [*Storm and Refsgaard*, 1996]. Interactions between grid squares occur by means of overland and groundwater flow. Water flow in the unsaturated zone is considered one-dimensional, a simplification which is built on the assumption that horizontal subsurface flow is negligible compared with vertical flow. A finite difference scheme is used to solve the numerical differential equations describing the flow processes. The MIKE SHE model is able to produce a wide variety (temporally and spatially) of outputs, such as time series of streamflow at different points on the river, two-dimensional maps of groundwater levels at arbitrary dates, among others.

3.2. Soil Hydraulic Parameters : Input To The LHS

[15] In the presented study MIKE SHE output variables are evaluated in terms of their sensitivity and uncertainty resulting from variability in soil hydraulic parameters, a subset of the parameters of the MIKE SHE model. The MIKE SHE model describes the water flow in the unsaturated zone using the one-dimensional Richards' equation. Two hydraulic functions are required as input in order to simulate water flow in the soil profile. These functions are the moisture retention characteristic (MRC) $\theta(h)$, with θ (-) the soil water content, and h (cm) the soil water pressure head; and the hydraulic conductivity curve (HCC) $K(\theta)$, with K (cm/s) the hydraulic conductivity. The parameters of the *van Genuchten* [1980] $\theta(h)$ model, given as:

$$\theta(h) = \left[(\theta_s - \theta_r)\left(\frac{1}{1+(\alpha h)^n}\right)^m\right] + \theta_r \qquad (2)$$

and the *Brooks and Corey* [1964] $K(\theta)$ model, defined by:

$$K(\theta) = K_{sat}\left(\frac{\theta - \theta_r}{\theta_s - \theta_r}\right)^N \qquad (3)$$

where

θ_s, θ_r the saturated and residual soil water content (-), respectively;

α the inverse of the air-entry value (1/cm);

n,m shape parameters (-);

K_{sat} the saturated hydraulic conductivity (cm/s); and

Table 3. Analyzed MIKE SHE Output Variables

Model component	Output	Location	Time period
River flow	cumulative discharge	outlet	entire simulation period
River flow	peak discharge	outlet	entire simulation period
River flow	average base flow	outlet	entire simulation period
River flow	cumulative discharge	outlet subcatchment	entire simulation period
River flow	cumulative discharge	outlet	every 6 months
Saturated zone	average groundwater elevation	grid cell (4, 6)	entire simulation period
Saturated zone	average groundwater elevation	grid cell (12, 13)	entire simulation period
Unsaturated zone	average soil water content	grid cell (12, 13) 25–30 cm	entire simulation period
Unsaturated zone	average soil water content	grid cell (12, 13) 55–60 cm	entire simulation period

N shape parameter (-)
are the varying inputs in this study.

3.3. Studied Output Variables

[16] The output variables, examined in this study and listed in Table 3, refer to flow processes taking place in different parts of the hydrological cycle: soil water content in the unsaturated zone, groundwater elevation in the saturated zone, and river discharge. The river discharge at the outlet is an overall output, because this value synthesizes the different flow components in the river basin. To analyze the effect of time and space scales on the sensitivity and uncertainty measures, outputs were evaluated at different time steps and at different locations. It is important to note that statistics (over a given time period) of output variables (peak, cumulative, or average value) are evaluated here. The underlying idea is to grasp as much as possible of the simulation into one output value, instead of using the dynamic output variables, like time series of groundwater elevation or discharge.

4. Experimental Field Site

4.1. Ohebach Catchment

[17] The MIKE SHE model is applied to the Ohebach catchment, which is part of the Neuenkirchen research area (south of Braunschweig, Germany). The catchment has an area of approximately 1 km^2 and is a constituent of the Krummbach catchment. It is intensively being monitored [*Bork and Rohdenburg*, 1986; *Bork et al.*, 1989]. Laboratory and field experiments, conducted by the Braunschweig Research Group, resulted in an extensive data set [*Rohdenburg et al.*, 1983, 1986]. This set includes topography, soil data, field descriptions together with crop information and farmer management practices, meteorological information, and water quantity and quality data at

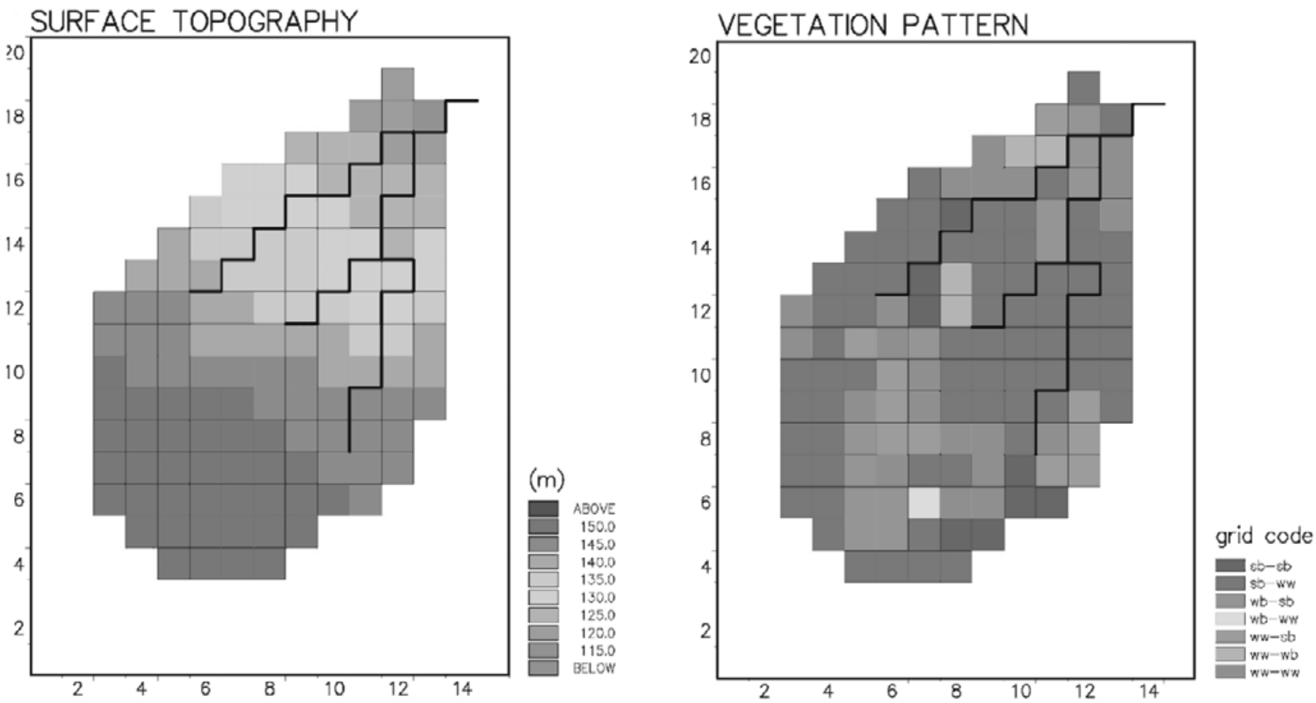

Figure 2. Topography and land use of the Ohebach catchment for 100 m by 100 m grid cells (topographical levels shown in meters above sea level, crop rotations legend: ww, winter wheat; wb, winter barley; sb, sugar beet). See color version of this figure at back of this issue.

Table 4. Probability Distributions and Their Rank Correlations of the Soil Hydraulic Parameters for the USDA Soil Texture Silt-Loam[a]

Parameter	Distribution	Average	Standard Deviation	Correlation				
				θ_s	θ_r	α, cm^{-1}	n	K_{sat}, cm s^{-1}
θ_s	normal	0.45	0.08	1	−0.01	−0.02	−0.01	−0.02
θ_r	beta	0.067	0.0142		1	−0.29	−0.59	−0.25
α	lognormal	0.0193	0.0115			1	0.74	0.8
n	lognormal	1.41	0.12				1	0.48
K_{sat}	lognormal	9.33E-05	2.24E-04					1

[a] After *Meyer et al.* [1997]. Read 9.33E-05 as 9.33×10^{-5}.

different locations in the soil, the groundwater, and the stream.

[18] The catchment topography varies between 119 and 156 m above sea level (Figure 2). One main stream, two tributaries, and a drainage system drain the catchment. The average yearly precipitation is about 580 mm/year. The major crops in the agricultural catchment are sugar beet, winter wheat, and winter barley (Figure 2). Soil textures within the catchment range from a majority of silt-loam to silty clay. The depth of the variably saturated zone varies between 0.14 and 4.74 m (the lower boundary of the aquifer is an impermeable clay-marl layer).

4.2. Model Setup

[19] The model setup was made using grid squares of 100 m $\times$ 100 m. The simulation was done for 34 months. The first 10 months were used as a warm-up period, and the following two years made up the actual simulation period (two consecutive growing seasons from 1/11 until 31/10). The model setup was visually and numerically calibrated, based on root mean square error (RMSE), using the river discharge at the outlet in the objective function. Trial and error minimization of RMSE was done by tuning (uncertain) parameters, e.g. the drain characteristics, for which little or no data were available. The calibrated model, delivering acceptable simulations, was used as the starting point for the SA and UA. Using a calibrated model also protects the LHS to a reasonable extent from numerical instabilities.

4.3. Soil Hydraulic Input: Subject to The SA/UA

[20] Parameter values for the MRC (equation (2)) and the HCC (equation (3)) were obtained from literature. The probability distributions of the soil hydraulic parameters and their correlations, proposed by *Meyer et al.* [1997], for the different USDA soil types (textures), were selected. These distributions were derived from the original distributions of *Carsel and Parrish* [1988]. The original distributions were obtained using pedo-transfer-functions from *Rawls and Brakensiek* [1985], considering more than 5000 soil samples (predictor variables were bulk density, percentage sand and clay). *Meyer et al.* [1997] resampled the distributions and derived closed-form distributions of the soil hydraulic parameters. These distributions and their correlations were used for this study. In Table 4 the values for the USDA class "Silt-Loam," the main soil type of the Ohebach catchment, are given.

[21] Note that the uncertainty incorporated by these distributions is limited to the soil heterogeneity within an USDA soil class. The significant pedo-transfer-function-regression error is neglected in this analysis, reflecting our goal to examine different measures taking into account correlations among parameters rather than an assessment of true uncertainty. Additionally, and for the same reason, pedo-transfer-function-derived soil hydraulic parameters were used as grid input, disregarding the scaling issue.

[22] The parameters, listed in Table 4, were sampled in the LHS, and provided the multivariate parameter sets needed to simulate the diverse model outputs. The soil hydraulic functions, (equations (2) and (3)), were calculated using the following relations: $m = 1 - 1/n$ in equation 2, and $N = 3 + 2/(n - 1)$ in equation 3.

5. Joint Stochastic-Deterministic Framework of the Study

[23] The LHS-model was implemented in an exhaustive way for one soil type, namely the Silt-Loam soil, the major soil type of the catchment. One combination of soil hydraulic parameters is used for all grid cells in each simulation run, disregarding spatial soil variability within the catchment. The latter enables a clear evaluation of the impact of the soil hydraulic parameter variations. The probability distributions and the correlations for the different soil hydraulic parameters for the Silt-Loam soil can be found in Table 4. In total, 25 samples (sample size equals 5 times the number of parameters) were taken from each distribution, and combined in a correlated fashion. This resulted in 25 data sets of 5 parameters, each set identifying a MRC and a HCC (Figure 3).

[24] Those different hydraulic functions were subsequently used as input for the MIKE SHE model, keeping the other parameters as calibrated. The model was run 25 times for 34 months, including a warm-up and evaluation period. Subsequently the model output time series were interpreted in statistical terms, i.e., by extracting the median and percentiles of the output distributions. This is illustrated for the simulated river discharge at the outlet of the catchment, and for the simulated groundwater level in one grid cell. Figure 4 shows next to the precipitation, the median, and the 2.5 and 97.5 percentiles of the river discharge in the catchment outlet for a 2-month summer period. The simulated median, and 2.5 and 97.5 percentiles of the groundwater depth in grid cell (4,6) for one growing season is presented in Figure 5.

[25] In addition, typical statistics of the simulated output, such as cumulative discharge, average soil water content (Table 3), were calculated. Table 5 gives a summary of the robust basic statistics of these characteristics. The median,

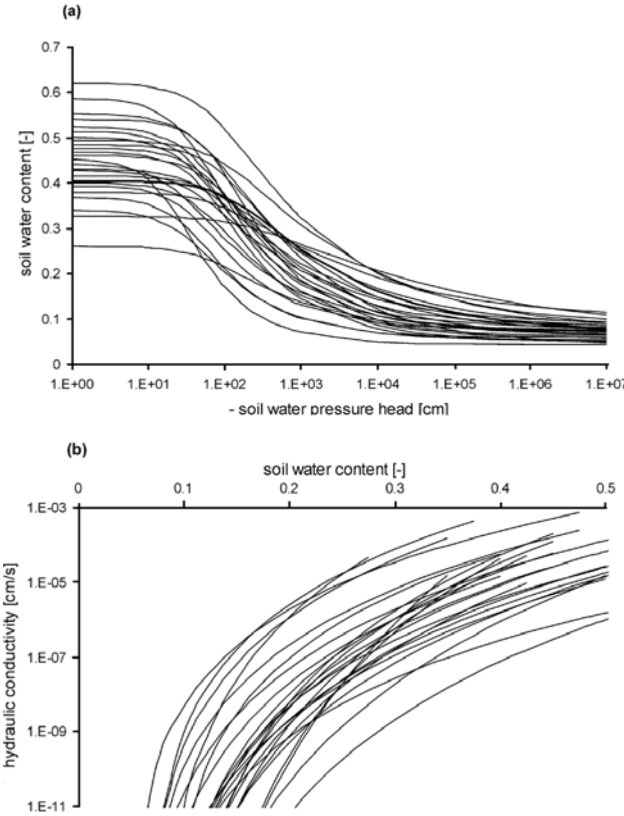

Figure 3. (a) Moisture retention curve and (b) hydraulic conductivity characteristic for the 25 sampled input data sets.

inter-quartile-range (IQR), coefficient of variation obtained using the median and IQR (CV'), and the 2.5 and 97.5 percentiles of the output variables are given. Comparison of the various discharge-related output variables indicates that peak discharge is severely influenced by variability in soil hydraulic parameters. The obtained IQR is of the same magnitude as the median value. For the groundwater elevation in the two grid cells, a similar IQR (12 cm and 23 cm) was found, resulting in a CV' of 25% and 79%, respectively, when referenced to the median (over the LHS samples) of the minimum (over time) groundwater elevation. The other output variables show a CV' between 14% and 27%.

[26] These statistics are, because real distributions, instead of mathematical parameter perturbations, were used in the LHS, a reflection of model output uncertainty resulting from uncertainty (probability distributions) in the five parameters. As stated previously, this uncertainty representation is limited to soil heterogeneity impact. At this stage one is able to quantify the output uncertainty due to the combined effect of the different uncertain parameters. The resulting distributions clearly do not exhibit symmetric uncertainty bounds.

6. Uncertainty or Sensitivity Contribution of a Specific Parameter

[27] In a second step the simulated output uncertainty is translated to the uncertainty or sensitivity contribution of a parameter. Therefore a linear metamodel was constructed (equation (1)) for every output variable (Table 3). Using this linear model, the different measures (Table 2) were calculated. Before going in detail to the measures, the relevance of the metamodel must be checked.

[28] The R^2 or coefficient of determination is a measure for the validity of the linear model to approximate the original model output. The R^2 measures the fraction of the total variance of $y(s)$ that can be explained with the (linear) regression model. A good (linear) fit gives an absolute value near 1. Table 6 shows the R^2 for different output variables. The R^2 for the average soil water content is almost 1, showing the possibility to describe the average soil water content with a linear combination of the soil hydraulic parameters. Such a high value of R^2 is not obtained for the other studied output variables (R^2 ranging from 0.57 to 0.77).

[29] In addition to the validity of the fitted linear model, the problem of multicollinearity has to be evaluated. Numerical errors due to collinearity can occur in the calculation of the different regression measures. The accuracy of the estimates of the regression coefficients will decrease with higher values for the variance inflation factor, VIF, i.e. larger variances will occur for the coefficient estimates. The VIF (with VIF_i the ith diagonal element of the inverse of the correlation matrix of the x_i) is often used as measure for multicollinearity [*Snee*, 1983]. The largest VIF must be smaller than 10 to continue with the linear regression, otherwise other regression techniques need to be selected [*Snee*, 1983; *Janssen et al.*, 1992]. The largest VIF in this study for the correlated soil hydraulic parameters is 2. When both the R^2 and VIF are acceptable, the metamodel can be used to quantify the sensitivity and uncertainty measures of model output to model input, but not for predictive purposes. It is clear that measures, similar to basic statistics, differ as a function of the selected output variable. In Table 6, output variables, reflecting the different components of the hydrological cycle, and their measures are listed. The first two columns in Table 6 list the R^2 and largest VIF.

6.1. Regression Coefficients

[30] The following columns in Table 6 show the first set of measures: ORC, NRC, and SRC. These are directly related to the linear regression model. The ordinary regres-

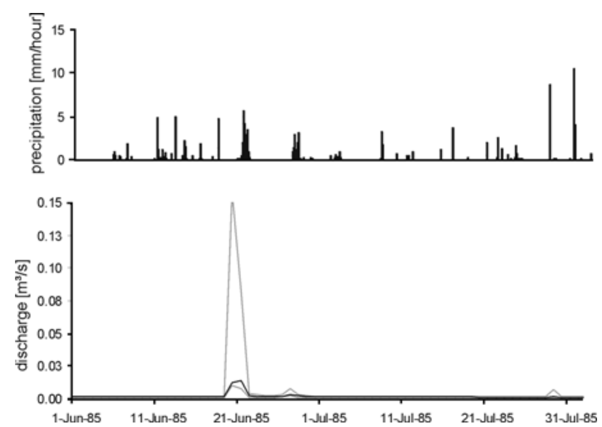

Figure 4. Precipitation and simulated median, 2.5, and 97.5 percentiles of the river discharge at the catchment outlet during one summer (1985) based on 25 runs.

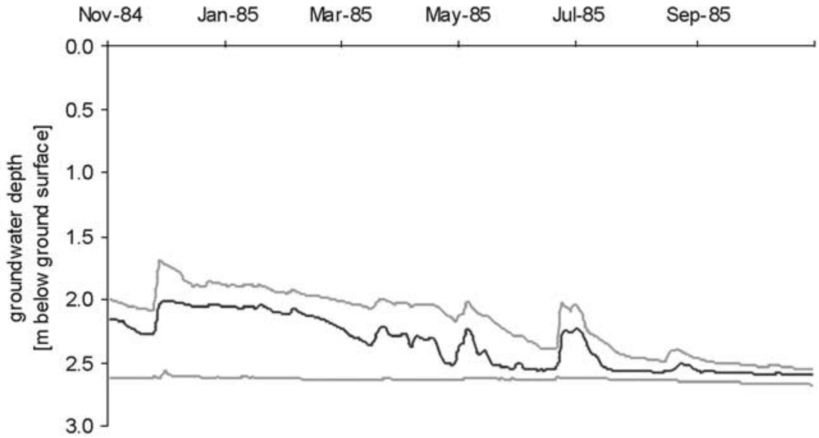

Figure 5. Simulated median, 2.5, and 97.5 percentiles of the groundwater depth in grid cell (4, 6) during one growing season (1984–1985) based on 25 runs.

sion coefficient (ORC) is $\hat{\beta}_i$ in Equation 1. It is an absolute sensitivity measure that indicates how much y will change if x_i changes in the metamodel. But it is impossible to rank the parameters on the basis of this measure because it depends on scale and dimension of the x_i. Obviously, the large ORC of K_{sat} (expressed in a small unit in Table 4) in comparison with the ORC values of the other parameters (Table 6) cannot lead to the conclusion that the model output is more sensitive to K_{sat}.

[31] There are two ways of standardizing the ORC to get rid of the scale dependency:

$$NRC = \hat{\beta}_i^{(nor)} = \hat{\beta}_i \frac{\bar{x}_i}{\bar{y}} \tag{4}$$

$$SRC = \hat{\beta}_i^{(s)} = \hat{\beta}_i \frac{s_{x_i}}{s_y} \tag{5}$$

[32] Both measures, the NRC and SRC, are relative measures. The selection between the two measures depends on how the sensitivity analysis has been performed. In this study, probability distributions were used. The only useful measure among the first three measures, for this study, is the standardized regression coefficient (SRC). The normalized regression coefficient (NRC) is interesting when, instead of real variations, fractional changes with respect to the mean are given. Since the SRC uses real variations in its calculation, it can also be an uncertainty measure. The major shortcoming of these three measures is that the correlation among the parameters is neglected in the calculation. Varying only one parameter is not realistic for highly correlated parameters. So one cannot multiply a given uncertainty of a parameter with its SRC to size the induced uncertainty on metamodel output, which can be done if the parameters are uncorrelated. In this case, due to the highly correlated soil hydraulic parameters, the SRC can only be used as representative for the sensitivity to that particular parameter. Table 6 illustrates the ranking in terms of sensitivity (SRC column) of the different output variables. The SRC is a relative sensitivity measure, and quantifies how much y of the metamodel will change relative to its standard deviation (s_y), when x_i is changing with its standard deviation (s_{xi}). This study, which evaluates only the soil hydraulic parameters, reveals that the parameter α has the highest influence on the discharge components and the average groundwater elevation in grid cell (4, 6); whereas the parameter θ_s mainly affects the soil water content (Table 6). The soil hydraulic parameter α is the inverse of the air-entry value of a soil, which describes at what soil water pressure pores start to drain, thus it is directly related to discharge. The parameter θ_s is a capacity parameter that determines the maximum storage of water in a soil, and consequently influences the soil water content.

6.2. Correlation Coefficients

[33] Other measures are proposed in literature to cope with correlations. The uncertainty in model output due to a

Table 5. Robust Descriptive Statistics of the Studied Output Variables[a]

Output	Location	Units	Median	IQR	CV', %	2.5%	97.5%
Cumulative discharge	outlet	m^3	140035	23240	17	127196	232673
Peak discharge	outlet	m^3/s	0.1181	0.1284	108	0.0274	0.2732
Average base flow	outlet	m^3/s	0.00150	0.00021	14	0.00091	0.00162
Cumulative discharge	outlet subcatchment	m^3	73921	14792	20	68003	136118
Average groundwater elevation	grid cell (4, 6)	m	151.12	0.23	0.15 (79)[b]	150.77	151.40
Average groundwater elevation	grid cell (12, 13)	m	131.25	0.12	0.09 (25)[b]	130.57	131.36
Average soil water content	grid cell (12, 13) at 25–30 cm		0.3764	0.1026	27	0.2241	0.5468
Average soil water content	grid cell (12, 13) at 55–60 cm		0.4080	0.1068	26	0.2347	0.5756

[a] All values are calculated over the entire simulation period.
[b] With reference to the median (over the LHS samples) of the minimum groundwater elevation.

Table 6. Ranking of the Sensitivity/Uncertainty Measures of the Various Output Variables[a]

Output	R^2	VIF	ORC		NRC		SRC		RTU		LCC		SPC		|LCC/SRC|		SMIR	
			Variable	Value	Variable	Value	Variable	Value	Variable	Value	Variable	Value	Variable	Value	Variable	Value	Variable	Value
Cumulative	0.57	2	K_{sat}	−8E07	θ_s	−0.22	$\boldsymbol{\alpha}$	−0.45	α	0.58	$\boldsymbol{\alpha}$	−0.64	α	−0.32	α	1.42	K_{sat}	1.00
discharge at outlet			$\boldsymbol{\alpha}$	−1E06	θ_r	−0.17	K_{sat}	−0.28	K_{sat}	0.47	n	−0.48	θ_s	−0.25	n	8	α	0.77
			θ_r	−3E05	$\boldsymbol{\alpha}$	−0.15	θ_s	−0.27	n	0.44	$\mathbf{K_{sat}}$	−0.46	K_{sat}	−0.21	K_{sat}	1.64	θ_r	0.63
			θ_s	−7E04	n	−0.14	θ_r	−0.22	θ_s	0.27	θ_s	−0.26	θ_r	−0.19	θ_s	0.96	n	0.50
			n	−1E04	K_{sat}	−0.03	n	−0.06	θ_r	0.21	θ_r	−0.16	n	−0.04	θ_r	0.72	θ_s	0.45
Peak discharge	0.77	2	$\mathbf{K_{sat}}$	−324	$\boldsymbol{\alpha}$	−0.74	$\boldsymbol{\alpha}$	−0.65	α	0.75	$\boldsymbol{\alpha}$	−0.80	α	−0.47	α	1.23	K_{sat}	1.00
			$\boldsymbol{\alpha}$	−5	$\boldsymbol{\theta_s}$	−0.70	$\mathbf{K_{sat}}$	−0.37	K_{sat}	0.59	$\mathbf{K_{sat}}$	−0.62	K_{sat}	−0.28	K_{sat}	1.67	α	0.77
			θ_r	−0.4	n	0.53	$\boldsymbol{\theta_s}$	−0.24	n	0.48	**n**	−0.55	θ_s	−0.23	n	7	θ_r	0.63
			$\boldsymbol{\theta_s}$	−0.2	θ_r	−0.21	θ_r	−0.08	θ_s	0.22	θ_s	−0.19	θ_r	−0.06	θ_s	0.79	n	0.50
			n	0.05	$\mathbf{K_{sat}}$	−0.16	n	0.07	θ_r	0.12	θ_r	−0.04	n	0.05	θ_r	0.5	θ_s	0.45
Average base flow	0.77	2	K_{sat}	0.21	n	0.45	$\boldsymbol{\alpha}$	0.51	α	0.70	$\boldsymbol{\alpha}$	0.77	α	0.36	α	1.50	α	1.00
			$\boldsymbol{\alpha}$	9.7[b]	$\boldsymbol{\theta_s}$	0.16	n	0.32	n	0.63	**n**	0.69	θ_s	0.26	n	2	K_{sat}	0.68
			θ_r	2.0[b]	$\boldsymbol{\alpha}$	0.11	$\boldsymbol{\theta_s}$	0.27	K_{sat}	0.47	$\mathbf{K_{sat}}$	0.47	n	0.21	K_{sat}	4	n	0.54
			$\boldsymbol{\theta_s}$	0.5[b]	θ_r	0.09	θ_r	0.16	θ_s	0.30	θ_s	0.31	θ_r	0.14	θ_s	1.14	θ_s	0.54
			n	0.5[b]	K_{sat}	9.5[b]	K_{sat}	0.11	θ_r	0.19	θ_r	0.08	K_{sat}	0.08	θ_r	0.5	θ_r	0.36
Average groundwater	0.75	2	$\mathbf{K_{sat}}$	576	$\boldsymbol{\alpha}$	1.3[b]	$\boldsymbol{\alpha}$	0.65	α	0.76	$\boldsymbol{\alpha}$	0.81	α	0.46	α	1.24	α	0.90
elevation in grid (4, 6)			$\boldsymbol{\alpha}$	11	θ_s	1.0[b]	$\mathbf{K_{sat}}$	0.31	K_{sat}	0.57	$\mathbf{K_{sat}}$	0.59	K_{sat}	0.24	K_{sat}	1.90	K_{sat}	0.68
			θ_r	1	θ_r	0.6[b]	θ_s	0.18	n	0.51	**n**	0.56	θ_s	0.17	n	56	θ_r	0.63
			θ_s	0.32	$\mathbf{K_{sat}}$	0.2[b]	θ_r	0.11	θ_s	0.17	θ_s	0.15	θ_r	0.10	θ_s	0.83	n	0.54
			n	−0.01	n	−0.1[b]	n	−0.01	θ_r	0.14	θ_r	0.07	n	−7.5[b]	θ_r	0.63	θ_s	0.50
Average soil water	0.99	2	K_{sat}	−8	$\boldsymbol{\theta_s}$	1.0	$\boldsymbol{\theta_s}$	0.94	θ_s	0.93	$\boldsymbol{\theta_s}$	0.92	θ_s	0.90	θ_s	0.97	θ_s	0.95
content in grid			$\boldsymbol{\alpha}$	−2	**n**	−0.37	$\boldsymbol{\alpha}$	−0.23	α	0.29	α	−0.33	α	−0.16	α	1.43	n	0.68
(12, 13) at 25–30 cm			$\boldsymbol{\theta_s}$	0.8	$\boldsymbol{\alpha}$	−0.09	**n**	−0.14	n	0.26	K_{sat}	−0.32	n	−0.09	K_{sat}	34	θ_r	0.54
			θ_r	0.1	θ_r	0.02	θ_r	0.02	K_{sat}	0.20	n	−0.18	θ_r	0.02	n	1.28	α	0.50
			n	−0.09	K_{sat}	−1.4[b]	K_{sat}	−9.3[b]	θ_r	0.11	θ_r	0.14	K_{sat}	−7.2[b]	θ_r	7	K_{sat}	0.45

[a] Bold type reflects the calculated values of ORC, NRC, SRC, and LCC that are significantly different from zero (at 95% significance level).
[b] Multiply times 10^{-3}.

specific parameter with correlation is not only function of that parameter, but the other correlated parameters also contribute. Three additional measures are shown in Table 6: the root of uncertainty (RTU), the linear correlation coefficient (LCC), and the semipartial correlation coefficient (SPC). When a given parameter does not show any correlation, the three measures will equal the SRC. The measures should be interpreted appropriately in a case involving correlation (Table 4, and note LCC/SRC in Table 6: LCC/SRC converges to 1 in the case of no significant correlation, e.g. θ_s).

[34] The LCC and the SPC are correlation coefficients that measure the linear relations between y and x_i; and y and $x_i^{adapted}$ (= x_i corrected for all correlated parameters), respectively. They are in fact both sensitivity and uncertainty measures. The PCC measure (Table 2) is not shown because it corrects both y and x_i for correlation influences. Consequently this measure cannot be compared because different $y^{adapted}$ exist for the different $x_i^{adapted}$. LCC and SPC describe the linear relation between the output variable y and one parameter x_i. If the correlation coefficient has an absolute value of 1, then a clear linear relation exists. This is illustrated with two examples. A value close to zero was obtained when the relation between residual soil water content and simulated peak discharge was analyzed (Figure 6a). A high LCC value of 0.92 was obtained for the relation between the saturated soil water content and the average simulated soil water content (Figure 6b). The LCC incorporates in its calculation the effects of other, correlated parameters. A large value of LCC implicates that this parameter is a strong source (clear (linear) relation between y and x_i) and/or strongly correlated with other parameters. SPC on the other hand corrects first the x_i for the correlated parameters, and calculates then linearity between y and $x_i^{adapted}$. A small SPC indicates a weak source and/or a strongly correlated parameter. The LCC and SPC in Table 6, describing the linear relation between average soil water content and the θ_s parameter, are 0.92 and 0.90, respectively. The combination of the two measures leads to the conclusion that the θ_s is a strong source. However, when evaluating the case of the average base flow and parameter α, the SPC (= 0.36) indicates a weak source and/or strongly correlated, and the LCC (= 0.77) implies a strong source and/or strongly correlated. Without further information it is hard to decide what kind of source α is for average base flow.

6.3. Partial Uncertainty Contribution

[35] *Janssen et al.* [1992] suggested the use of a new measure for uncertainty in case strong correlations exist: the partial uncertainty contribution (PUC). The PUC expresses the relative change in uncertainty in metamodel output y, s_y, caused by a relative change in uncertainty of the source x_i, s_{xi}. This latter change in uncertainty of the source x_i will also change the uncertainty of other sources x_j, correlated with this source. This indirect effect is accounted for in the PUC. The PUC combines in fact the SRC, the LCC, and the correlation coefficient between two parameters:

$$PUC_i = \sum_{j=1}^{p} \hat{\beta}_j^{(s)} r_{x_j y} \left(r_{x_i x_j}\right)^2 = \sum_{j=1}^{p} SRC_j LCC_j \left(r_{x_i x_j}\right)^2 \qquad (6)$$

$$RTU_i = \sqrt{|PUC_i|} \qquad (7)$$

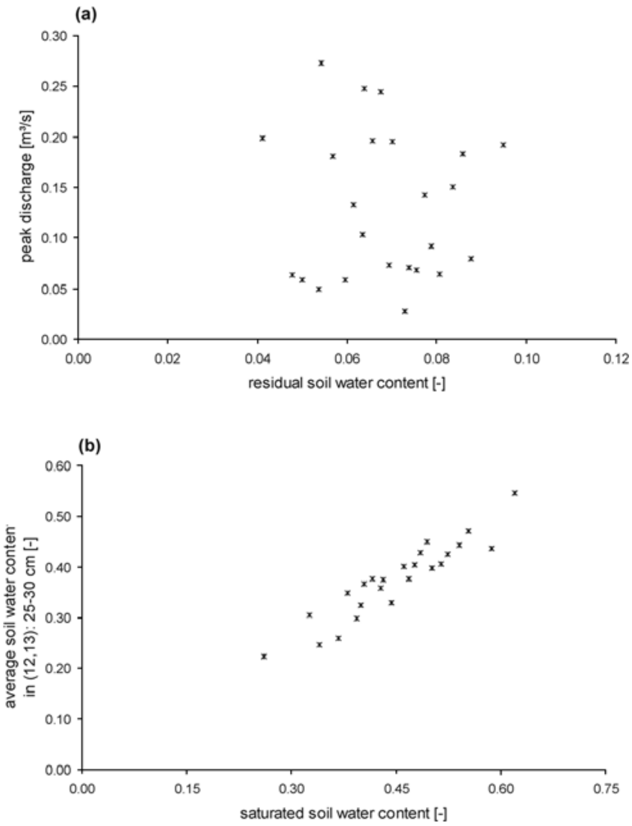

Figure 6. Scatterplots of different output variables and parameters for (a) small LCC (= −0.04) and (b) large LCC (= 0.92).

[36] However, the interpretation of this measure is also not straightforward. Two strongly correlated parameters can have an equal PUC even if $SRC_i \lll SRC_j$. To make a distinction between weak and strong parameters, a combined interpretation of the SRC and the RTU is essential. In Table 7, the contribution (SRC × LCC × 1) of a given parameter to its PUC is illustrated for the average base flow and the average soil water content. The parameter α has the largest PUC for the output "average base flow". Eighty percent of the PUC is contributed by α itself, indicating a strong source with correlations (accounting for the remaining 20 % of the PUC). This conclusion cannot be drawn from the combined LCC-SPC analysis. Table 7 illustrates that θ_s has the largest PUC for the average soil water content, whereby 99 % comes from θ_s itself. This indicates a very strong source, like previously concluded from the combined use of LCC and SPC.

6.4. A Universal Measure?

[37] The mathematical and statistical foundations of the different measures make it difficult to pinpoint one ideal measure in case correlation exists. When correlation does not exist, one can easily take any measure in the SA / UA, because SRC, RTU, LCC, and SPC will be identical. In the presence of correlation, the SRC describes the sensitivity, but the different uncertainty measures should be used in combination.

[38] One of the goals of the study was to find measures that can be used throughout different model studies. It is

Table 7. Contribution of a Parameter to Its PUC for Two Output Variables

Output	Parameter	SRC	LCC	Contribution to PUC		PUC	RTU
				Product	Percentage		
Average base flow	α	0.51	0.77	0.3927	80	0.4900	0.70
	n	0.32	0.69	0.2208	55	0.3969	0.63
	θ_s	0.27	0.31	0.0837	93	0.0900	0.30
	θ_r	0.16	0.08	0.0128	35	0.0361	0.19
	K_{sat}	0.11	0.47	0.0517	23	0.2209	0.47
Average soil water content in grid (12, 13) at 25–30 cm	θ_s	0.94	0.92	0.8648	99	0.8649	0.93
	α	−0.23	−0.33	0.0759	90	0.0841	0.29
	n	−0.14	−0.18	0.0252	37	0.0676	0.26
	θ_r	0.02	0.14	0.0028	23	0.0121	0.11
	K_{sat}	−9.3[a]	−0.32	0.0029	7	0.0400	0.20

[a]Multiply times 10^{-3}.

clear that it is not possible to transpose the uncertainty contributions to other model studies (where other parameters (not correlated with the current set) are evaluated), but for the SA it is. When multiplying the ORC with the standard deviation of the respective parameter, s_{xi}, a kind of standard measure (ORC s_{xi} = SRC s_y (see equation (5)) results for the sensitivity, which states how much y (of the metamodel) will vary, when x_i varies with its standard deviation. For example, changing K_{sat} with plus or minus one standard deviation value, will change the cumulative discharge at the catchment outlet with approximately 18,000 m^3; and the average soil water content with approximately 0.002. This measure can also be used in other model sensitivity studies of the same application area, but not for model prediction. In this way sensitivity studies can be split into different (noncorrelated) parts around the same base point in parameter space, as not to fundamentally influence the involved parameter interactions.

6.5. Location and Time Dependency

[39] It is important to note that the measures are calculated for the outputs using time statistics (average or cumulative values) at a specific location and over a certain time period. Table 8 shows the SRC, RTU, LCC, and SPC for the previously studied output variables, but now at different locations. The cumulative discharge is observed at an outlet of a subcatchment and the catchment itself. The average groundwater elevation is extracted at two different grid cells: grid cell (12,13) with a shallow, modestly fluctuating groundwater table; and grid cell (4, 6) with a slightly deeper, more dynamic groundwater table (two meters beneath the soil surface). The average soil water content is given at two depths in the same grid cell.

[40] The values and the sequence of the SRC, RTU, LCC, and SPC (Table 8) are similar for the cumulative discharge at the two locations. The same major tendencies can be found for the average soil water content. The four measures indicate clearly (value of the measures > 0.9) that θ_s is the most significant parameter for the average soil water content at the two depths. The two average groundwater elevations, however, show a different picture. The aforementioned different nature of the groundwater in the two grid cells is likely to be the reason for the different values and sequence. Table 8 demonstrates that it is important in SA and UA to specify clearly what output variable is under study.

[41] In addition to the location, the date or period of observation of a given output variable plays an important role in the calculation of the measures. Figure 7 shows the SRC (Figure 7a) and RTU (Figure 7b) for cumulative discharge at the outlet for four 6-months periods. The first 6-month period goes from 1/11/83 to 30/04/84, the second from 1/5/84 to 30/10/84, the third from 1/11/84 to 30/04/85, and the fourth from 1/5/85 to 30/10/85. A seasonal cycle in sequence of the measures can be observed, shifting from n parameter to α parameter as most significant. Including more parameters and more observation points (in time and space) should validate this.

6.6. Measures Obtained for Other Soil Types

[42] Complimentary to the Silt-Loam LHS setup, a second case was evaluated to identify the behavior of the measures for different soil types. A similar exercise was therefore performed for the twelve USDA soil types (10 parameter sets each), with emphasis on 4 "typical" soil textures: clay, silt, sand, and clay-loam (25 parameter sets each). The probability distributions and correlations, proposed by *Meyer et al.* [1997], were used. Again, the variability accounts only for soil heterogeneity. The following conclusions apply.

[43] With respect to the robust statistics often a clear difference in simulated median output and IQRs can be observed for the various studied output variables. The observed differences in simulated variations between soil types result from (i) different intrinsic model sensitivity to the different soils (resulting from base point shift in the parameter space), and (ii) different probability distributions (and variations) of the soil hydraulic parameters. When applying similar mathematical ranges for each soil type instead of those representing soil heterogeneity, the differences due to different ranges can be excluded.

[44] Concerning the measures, some tendencies can be observed. θ_s is the most important parameter for the average soil water content. Parameter α seems to be the most important parameter of the soil hydraulic parameters for the output variables related to discharge, except for the more extreme USDA texture classes, sand and clay. Important to note is that the most important parameter is determined following the current input ranges. The latter is crucial, since including other parameters in the sensitivity study or different input ranges may obviously change the "most important parameter."

Table 8. Sensitivity/Uncertainty Measures at Different Locations

Output	SRC		RTU		LCC		SPC	
	Variable	Value	Variable	Value	Variable	Value	Variable	Value
Cumulative discharge at outlet	α	−0.45	α	0.58	α	−0.64	α	−0.32
	K_{sat}	−0.28	K_{sat}	0.47	n	−0.48	θ_s	−0.25
	θ_s	−0.27	n	0.44	K_{sat}	−0.46	K_{sat}	−0.21
	θ_r	−0.22	θ_s	0.27	θ_s	−0.26	θ_r	−0.19
	n	−0.06	θ_r	0.21	θ_r	−0.16	n	−0.04
Cumulative discharge at outlet subcatchment	α	−0.42	α	0.55	α	−0.62	α	−0.30
	K_{sat}	−0.27	K_{sat}	0.45	n	−0.46	θ_s	−0.23
	θ_s	−0.25	n	0.42	K_{sat}	−0.44	K_{sat}	−0.22
	θ_r	−0.23	θ_s	0.25	θ_s	−0.24	θ_r	−0.21
	n	−0.07	θ_r	0.23	θ_r	−0.17	n	−0.04
Average groundwater elevation in grid (4,6)	α	0.65	α	0.76	α	0.81	α	0.46
	K_{sat}	0.31	K_{sat}	0.57	K_{sat}	0.59	K_{sat}	0.24
	θ_s	0.18	n	0.51	n	0.56	θ_s	0.17
	θ_r	0.11	θ_s	0.17	θ_s	0.15	θ_r	0.10
	n	−0.01	θ_r	0.14	θ_r	0.07	n	−7.5[a]
Average groundwater elevation in grid (12,13)	n	0.59	n	0.70	n	0.72	n	0.40
	θ_s	0.34	α	0.57	α	0.62	θ_s	0.32
	α	0.27	K_{sat}	0.41	θ_s	0.44	θ_r	0.20
	θ_r	0.22	θ_s	0.39	K_{sat}	0.33	α	0.19
	K_{sat}	−0.04	θ_r	0.24	θ_r	0.10	K_{sat}	−0.03
Average soil water content in grid (12, 13) at 25−30 cm	θ_s	0.94	θ_s	0.93	θ_s	0.92	θ_s	0.90
	α	−0.23	α	0.29	α	−0.33	α	−0.16
	n	−0.14	n	0.26	K_{sat}	−0.32	n	−0.09
	θ_r	0.02	K_{sat}	0.20	n	−0.18	θ_r	0.02
	K_{sat}	−9.3[a]	θ_r	0.11	θ_r	0.14	K_{sat}	−7.2[a]
Average soil water content in grid (12, 13) at 55−60 cm	θ_s	0.99	θ_s	0.99	θ_s	0.98	θ_s	0.95
	α	−0.09	n	0.14	K_{sat}	−0.20	α	−0.06
	n	−0.07	K_{sat}	0.12	α	−0.14	n	−0.05
	K_{sat}	8.7[a]	α	0.11	θ_r	0.11	θ_r	7.1[a]
	θ_r	8.0[a]	θ_r	0.09	n	−4.6[a]	K_{sat}	6.7[a]

[a] Multiply time 10^{-3}.

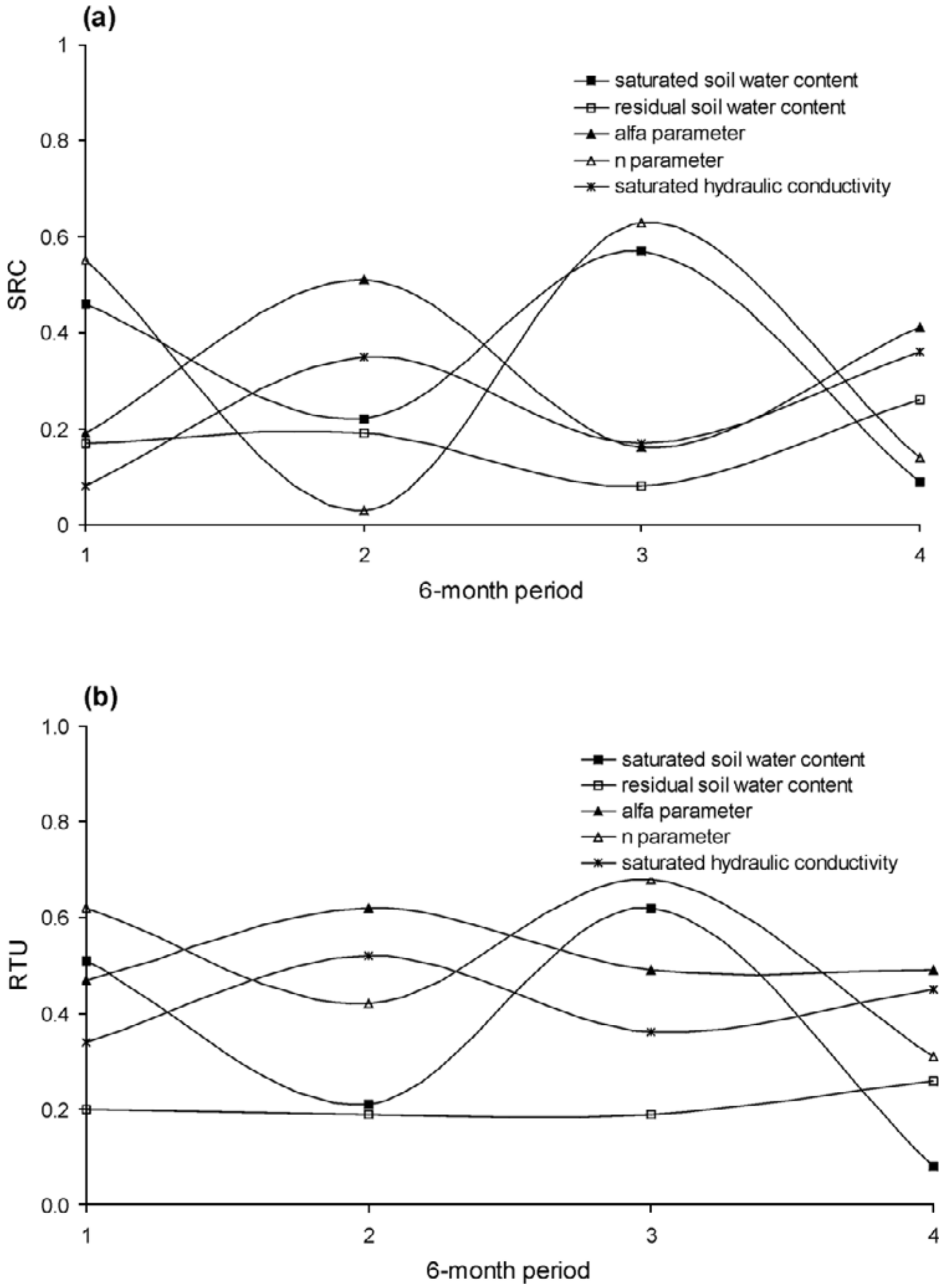

Figure 7. Seasonal dependency of (a) SRC and (b) RTU for cumulative discharge at the outlet for four 6-months periods (1: from 1/11/83 to 30/04/84; 2: from 1/5/84 to 30/10/84; 3: from 1/11/84 to 30/04/85; and 4: from 1/5/85 to 30/10/85).

6.7. Limitations of the Methodology

[45] Remark that the different (t) tests, describing whether the value calculated for a particular measure differs significantly from zero, should be checked before using the different measures in a comparison. In practice this is rarely the case for all parameters. The calculated values of ORC, NRC, SRC, and LCC that are significantly different from zero (at 95% significance level) are bold in Table 6.

[46] When the R^2 and/or the largest VIF do not meet the criteria described earlier, other techniques should be explored. One solution is to use data transformations. An example is the rank transformation. The same measures hold except that they are valid for the rank transformed data. The problem with data transformations is that the results cannot easily be recalculated to the original data. The uncertainty aspects of the original data do not have much to do with the (rank) transformed data. These rank measures can be used to distinguish between important, and less or unimportant parameters.

[47] An alternative is to use more complex, compared to linear, regression models. The difficulty here is to transfer the measures calculated for a term of the regression model back to the original parameters. The fact that the measures are established based on a (linear) metamodel, which may

not closely track the original model, is a disadvantage when trying to grasp the often high nonlinearities of hydrological behavior over a wide input range.

[48] Another option is to try to have an idea on the ranking of the parameters by using nonparametric tests [*Conover*, 1971], like the Kolmogorov-Smirnov test. In those tests, the model outputs are distributed in two parts, causing a partitioning of the parameters. The difference in these two parameter distributions describes the importance of a parameter for an output variable. Those tests do not yield a quantification of the uncertainty/sensitivity of a parameter, they only say something on the importance of a parameter. This measure shows similar trends to the others, and provides some complimentary information, though standalone interpretation is not easy (Table 6). *Spear and Hornberger* [1980] presented a nonparametric approach that partitions the parameter space based on ‘‘acceptability’’ of the model output when confronted with measurements. This tactic has evolved to regional sensitivity analysis and GLUE (Table 1).

7. Conclusions

[49] The LHS-MIKE SHE approach is adequate to assess sensitivity and uncertainty measures of different model input-output combinations. These measures allow to backtrack output uncertainty, and provide a sensitivity ranking. Attention should be given to the amount of samples taken as a function of the expected answers (probability distribution of output variables, sensitivity or uncertainty measures). It is not relevant to evaluate model sensitivity to mathematical parameter perturbations, because this does not account for the true behavior of that particular parameter. Real parameter distributions should be used to evaluate the sensitivity, making sensitivity analysis coincide with uncertainty analysis.

[50] This paper had as aim to analyze different sensitivity and uncertainty measures, available in the literature, and to determine their practical applicability in hydrology, with the MIKE SHE model and the soil hydraulic properties as an example. Two cases can be distinguished. When correlation among parameters is not substantial, SRC, as well as SPC, LCC, and RTU are suitable measures for assessing both sensitivity and uncertainty. They become the same value. When correlation exists, SRC can give a good idea of model sensitivity. In order to determine model uncertainty, however, a combined interpretation of different measures is required (SRC, LCC, and RTU). Before interpreting any measure, the CV, the R^2 of the metamodel, and the VIF should be checked.

[51] Since values of the measures cannot be transferred to other model applications, the values should be recalculated for new model applications. Nevertheless, ORC multiplied with the standard deviation of that parameter can be shared with similar model applications, whereby the sensitivity to another (independent) subset of parameters can be examined.

[52] All the measures are calculated for an output-parameter combination at/over a selected time at a specific location. The model setup is relevant as well. In this study a single soil setup was evaluated to illustrate the concepts of the measures, and to allow conclusions regarding the impact attributed to heterogeneity of one soil type. True uncertainty in model output will differ from the presented uncertainty, due to catchment soil heterogeneity as well as the inclusion of various other uncertain parameters and uncertainty sources, like model, scaling, and parameter estimation or method error influencing the input distribution.

[53] This study tackled a small subset of the input and associated uncertainties of the MIKE SHE model, and therefore a final overview of most important parameters cannot be given at this stage. For the presented case, the most important parameters among the soil hydraulic parameters for the different output variables are identified. The parameter α has the highest influence on the discharge components, whereas the parameter θ_s mainly affects the average soil water content. The soil hydraulic parameter α is the inverse of the air-entry value of a soil, which describes at what soil water pressure pores start to drain, and is directly related to discharge. The parameter θ_s is a capacity parameter that determines the maximum storage of water in a soil, and influences consequently the soil water content. No tendencies were found for the groundwater. The sensitivity of model outputs for different USDA texture types was briefly investigated with the major trends reoccurring for every soil type.

Notation

θ	soil water content (dimensionless).
h	soil water pressure head (cm).
K	hydraulic conductivity (cm/s).
θ_s	saturated soil water content (dimensionless).
θ_r	residual soil water content (dimensionless).
α	inverse of the air-entry value (1/cm).
n, m	shape parameters of the van Genuchten MRC (dimensionless).
K_{sat}	saturated hydraulic conductivity (cm/s).
N	shape parameter of the Brooks and Corey HCC (dimensionless).
S	number of samples taken in the Latin Hypercube Sampling.
s	sth sample taken.
p	number of parameters to be sampled in the Latin Hypercube Sampling.
i	ith parameter.
V	number of studied output variables within the Latin Hypercube Simulation.
v	vth studied output.
$\hat{y}_v(s)$	regression model for the sth sample and the vth output variable.
$x_i(s)$	values of the varying parameter i for the sth sample.
$y_v(s)$	model output for the sth sample and the vth output variable
$\hat{\beta}_{0,v}, \hat{\beta}_{i,v}$	regression coefficients.
$\hat{e}_v(s)$	regression residual.
$\hat{\beta}^{(nor)}$	normalized regression coefficient.
$\bar{x}_i$	mean of the varying parameter i.
$\bar{y}$	mean of the model output.
$\hat{\beta}_i^{(s)}$	standardized regression coefficient.
s_{x_i}	standard deviation of varying parameter i.
s_y	standard deviation of the model output.
$y^{adapted}$	model output corrected for correlation influences.
$x_i^{adapted}$	parameter i corrected for correlation influences.
$r_{x_j y}$	correlation among parameter i and model output.
$r_{x_j x_j}$	correlation among parameter i and parameter j.

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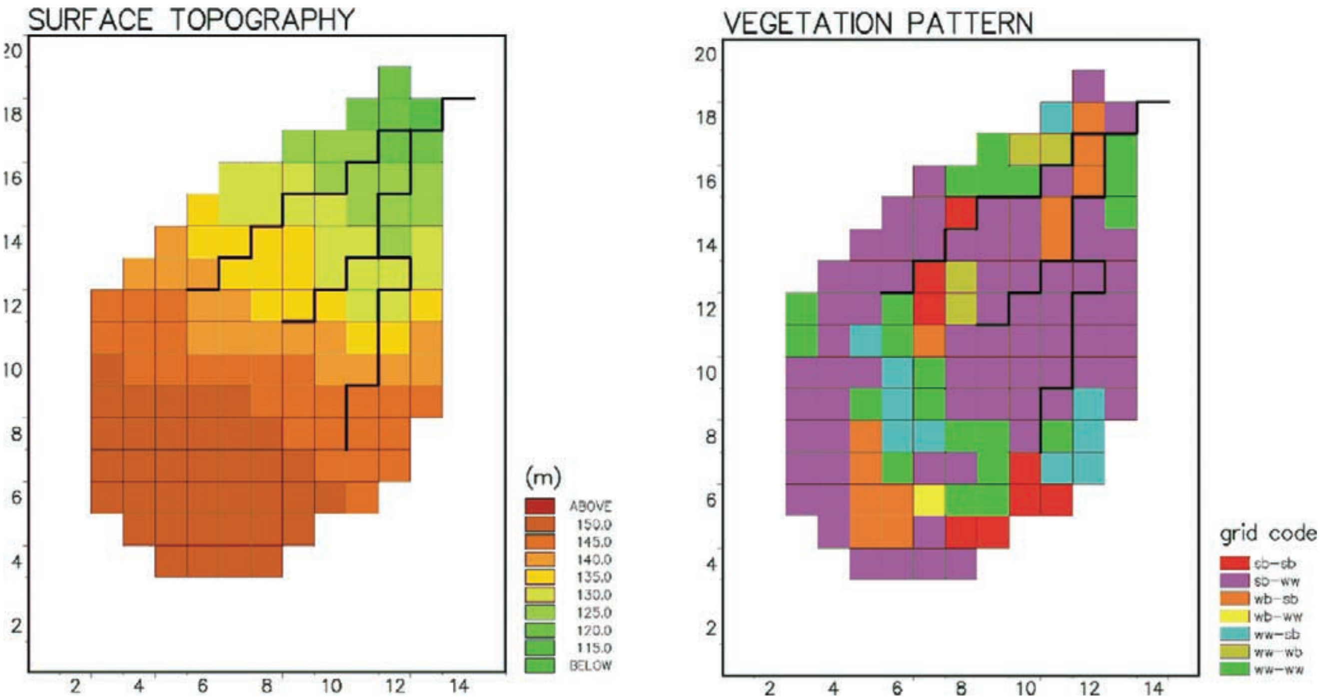

Figure 2. Topography and land use of the Ohebach catchment for 100 m by 100 m grid cells (topographical levels shown in meters above sea level, crop rotations legend: ww, winter wheat; wb, winter barley; sb, sugar beet).