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Monte Carlo sensitivity analysis of land surface parameters using the Variable Infiltration Capacity model

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[1] Current land surface models use increasingly complex descriptions of the processes that they represent. Increase in complexity is accompanied by an increase in the number of model parameters, many of which cannot be measured directly at large spatial scales. A Monte Carlo framework was used to evaluate the sensitivity and identifiability of ten parameters controlling surface and subsurface runoff generation in the Variable Infiltration Capacity model (VIC). Using the Monte Carlo Analysis Toolbox (MCAT), parameter sensitivities were studied for four U.S. watersheds along a hydroclimatic gradient, based on a 20-year data set developed for the Model Parameter Estimation Experiment (MOPEX). Results showed that simulated streamflows are sensitive to three parameters when evaluated with different objective functions. Sensitivity of the infiltration parameter (b) and the drainage parameter (exp) were strongly related to the hydroclimatic gradient. The placement of vegetation roots played an important role in the sensitivity of model simulations to the thickness of the second soil layer ($thick_2$). Overparameterization was found in the base flow formulation indicating that a simplified version could be implemented. Parameter sensitivity was more strongly dictated by climatic gradients than by changes in soil properties. Results showed how a complex model can be reduced to a more parsimonious form, leading to a more identifiable model with an increased chance of successful regionalization to ungauged basins. Although parameter sensitivities are strictly valid for VIC, this model is representative of a wider class of macroscale hydrological models. Consequently, the results and methodology will have applicability to other hydrological models.

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1. Introduction

[2] Better process understanding, more complete data sets and increased computing power have led to the development of increasingly complex land surface models (LSMs) [e.g., *Nijssen and Bastidas*, 2005; *Pitman*, 2003]. This increase in model complexity has been accompanied by a large increase in the number of model parameters. As a result, equally good model simulations can result from different subsets of parameters, leading to poor identifiability of model parameters or equifinality [*Freer et al.*, 1996]. Some model parameters can be estimated at the scale of application on the basis of field or remote sensing measurements, for example vegetation type, leaf area index, and albedo [e.g., *Cohen et al.*, 2003]. Other parameters, for example those describing subsurface processes, are mostly determined through small-scale, in situ or laboratory measurements. For many of them, such as saturated hydraulic conductivity, measurement and estimation methods have shown poor consistency even at small spatial scales. For example, *Walker et al.* [2004] reports large discrepancies between several methods to estimate the vertical distribution of hydraulic conductivity in unconsolidated formations. Consequently, when applied over large areas, these parameters lose most of their physical meaning and often become little more than calibration parameters.

[3] In hydrology, there is a long tradition and a large body of work of research and applications in model calibration, parameter estimation, and parameter sensitivity methods, both in surface and subsurface hydrology [e.g., *Hogue et al.*, 2006; *Wagener et al.*, 2003; *Gupta et al.*, 2003; *Chen and Chen*, 2003; *Madsen et al.*, 2002; *Thiemann et al.*, 2001; *Van Geer and Van Der Kloet*, 1985; *Smith and Piper*, 1978]. Despite some notable exceptions [*Hogue et al.*, 2005; *Sieber and Uhlenbrook*, 2005; *Liu et al.*, 2004; *Gupta et al.*, 1999; *Bastidas et al.*, 1999; *Gao et al.*, 1996], relatively little of this work has been applied to parameter estimation and sensitivity of LSMs. We see two reasons for this. One is that researchers in the LSM community hail from a variety of backgrounds, such as meteorology, biology, and earth system science, in which calibration or parameter estimation techni-

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ques have been less commonly used than in hydrology. The other, and perhaps more important reason, is that LSMs typically have a large number of parameters, while most techniques for parameter sensitivity analysis in hydrology are developed and applied to models with relatively few parameters. As a result, it is not always clear how these techniques can be employed to provide insight into the performance of LSMs.

[4] The purpose of this paper is twofold. The main aim is to investigate the sensitivity of simulated runoff to the parameters that control its generation in the Variable Infiltration Capacity (VIC) model [*Liang et al.*, 1994, 1996; *Liang and Guo*, 2003; *Wood et al.*, 1992]. Of particular interest is how the sensitivity of these parameters changes with changes in soil, vegetation and climate conditions. LSMs are typically calibrated for specific climatic environments, if at all. However, because of the scale of application, the models are applied over domains in which soil, vegetation and climate conditions vary considerably. Hence it becomes essential to understand how the sensitivity of the model parameters changes with changes in the physical environment. Four climatic regions with different levels of moisture availability were tested to estimate the impact of different hydroclimatic environments on the sensitivity of the model parameters. A secondary objective is to further demonstrate the use of tools for evaluating parameter sensitivity outside of the traditional application area of parameter-sparse rainfall-runoff models.

[5] The paper is organized as follows: Section 2 presents a brief review of sensitivity analysis techniques commonly implemented in hydrology. The methodological approach is introduced in section 3. Results of baseline experiments and case studies are outlined in section 4 and 5 respectively. Finally, main conclusions of the study are presented in section 6.

2. Background

[6] Sensitivity analysis techniques have the objective of identifying whether a perturbation of parameters has a significant impact on the response of the model, that is, on the variable of interest. If the impact is small, the model can be simplified either by replacing the relevant parameters by constants or by eliminating them altogether [*Wagener et al.*, 2001]. This is not only of interest for model construction, but also for model calibration or parameter estimation. *Bastidas et al.* [1999], using the BATS (Biosphere-Atmosphere Transfer Scheme) LSM in two different climatic regions of the United States, showed that a sensitivity analysis performed before the calibration process reduced the number of parameters prompted for calibration. Their findings suggested that a formal sensitivity analysis significantly reduced the computational time needed for calibration (a factor of five in their study).

[7] Several methods have been presented in the literature to evaluate the sensitivity of LSM output to its parameters. In the "one-at-a-time" method each parameter value is changed independently and its impact on model performance is analyzed. This method has been widely used for sensitivity studies because of its simplicity [*Pitman*, 1994]. The method has the disadvantage of not being efficient in detecting parameter interactions. The Factorial Design technique is also simple to implement, but can deal with interactions between parameters. In a factorial experiment, all parameters are perturbed simultaneously to different high/low values called levels. Each combination of high/low values constitutes an experimental run. However, the method cannot deal with model nonlinearity and is not flexible enough to evaluate multiple system responses [*Liang and Guo*, 2003; *Henderson-Sellers*, 1993]. The Fourier amplitude sensitivity test (FAST) is based on determining fractional contributions of individual factors to the variance of the output [*Saltelli*, 1999; *Collins and Avissar*, 1994]. The main drawback of FAST is its deficiency in detecting interactions between model parameters.

[8] The Regional Sensitivity Analysis method (RSA) is based on a Monte Carlo sampling of the parameter space [*Hornberger and Spear*, 1981; *Freer et al.*, 1996]. RSA is a nonparametric method that evaluates sets of parameter values in terms of model performance without making assumptions about their statistical distributions. It has been widely used in the chemical and biochemical sciences to assess parameter sensitivities [*McIntyre et al.*, 2004; *Meixner et al.*, 2002; *Osidele and Beck*, 2001; *Hornberger et al.*, 1985; *Hornberger and Spear*, 1981; *Spear and Hornberger*, 1978]. A multicriteria method based on RSA was presented by *Bastidas et al.* [1999]. This method introduced the concept of a Pareto set to select between behavioral and nonbehavioral model parameters (that is, "good" or "bad" model performances with respect to certain performance criteria). The Pareto set represents the group of solutions that minimize the multicriteria space. The main drawback of this method is the selection of a threshold to split behavioral from nonbehavioral parameters. Except for a few studies such as *Hogue et al.* [2006] and *Bastidas et al.* [1999], RSA application to hydrological models has largely been limited to simple rainfall-runoff models with few parameters or to more complex models without consideration of the impact of different climatic regions on model parameters [*Sieber and Uhlenbrook*, 2005; *Wagener et al.*, 2001, 2003].

[9] The RSA method is implemented within the Monte Carlo Analysis Toolbox (MCAT [*Wagener et al.*, 2001]). MCAT is a combination of analysis tools taken from the Generalized Likelihood Uncertainty Estimation technique [*Beven*, 2001], multiobjective approaches [*Gupta et al.*, 1999], and newly developed methods [*Wagener and Kollat*, 2007]. MCAT implements a modification to the RSA introduced by *Freer et al.* [1996], which unlike the original algorithm does not rely on the selection of a performance or behavior threshold to split a population between behavioral and nonbehavioral parameters. The new method ranks the parameter population with respect to different objective functions and divides it into ten groups of equal size. The marginal cumulative distribution of the parameters in each group is plotted with respect to the model performance to evaluate the sensitivity of each individual parameter.

3. Methodology

3.1. Approach

[10] Four river basins located in dissimilar hydroclimatic environments were chosen to evaluate the impact of ten specific model parameters on the overall performance of the model. The basins were selected to represent various soil,

vegetation and climate conditions. Daily streamflow values were used to measure the performance of model simulations. Streamflows act as a spatial and temporal filter of high-frequency variabilities present in the different components of the hydrological cycle. It is also an important output variable of hydrological models and is the best documented component of the hydrological cycle in the four basins.

[11] VIC is a land surface model that simulates the partitioning of incoming energy and moisture at the land surface into the separate components of the energy and water balance (see section 3.2 for a more complete description of the model). VIC uses ten vegetation parameters to simulate evapotranspiration from the canopy and bare soil. Some parameters, such as the Leaf Area Index, need to be specified at a monthly basis. There are twenty-one soil related parameters, eleven of which need to be specified for each of the three soil layers. From the pool of soil parameters, we selected ten parameters controlling the generation of surface and subsurface flow to be included in the sensitivity analysis. Each parameter was considered independent and uniformly distributed within its feasible range. Simulated streamflow series were evaluated with MCAT. A set of baseline experiments was performed to assess the overall sensitivity of parameters of interest in the different hydroclimatic environments. These were followed by a series of case studies that further explored the influence of porosity and plant available water on parameter sensitivity, and the identifiability of base flow related parameters during the occurrence of high-flow events.

3.2. Variable Infiltration Capacity (VIC) Model

[12] The VIC model is a macroscale hydrological model that represents surface and subsurface hydrologic processes on spatially distributed grid cells. Distinguishing characteristics of the model include the representation of subgrid-scale variability in vegetation coverage, topography, precipitation, and soil moisture storage capacity [*Liang et al.*, 1994, 1996]. The model has been used for a large number of hydrological studies in different climatic environments [*Maoyi and Liang*, 2006; *Liang and Guo*, 2003; *Maurer et al.*, 2002; *Nijssen et al.*, 2001; *Liang et al.*, 1994, 1996; *Wood et al.*, 1992].

[13] For details of the mathematical formulation, readers are referred to *Liang et al.* [1994, 1996]. Here we limit ourselves to a description of the representation of subsurface processes, because these are the processes for which the parameter sensitivity is investigated. In our implementation, the subsurface is represented by three soil layers. Evapotranspiration can occur from soil moisture stored in the three layers, while slow response runoff or base flow is only generated from the third layer. Following *Nijssen et al.* [2001], base flow (Q_b) is modeled as

$$Q_b = \begin{cases} d_1 W_3 & 0 \le W_3 \le d_3 \\ d_1 W_3 + d_2 (W_3 - d_3)^{d_4} & d_3 \le W_3 \le W_3^{\max} \end{cases} \quad (1)$$

where W_3 is the soil moisture content of the third layer, $W_3^{\max}$ is the maximum moisture content of this layer, d_1 is a linear reservoir coefficient, d_2 is a nonlinear reservoir coefficient, d_3 is a soil moisture threshold above which the base flow response becomes nonlinear, and d_4 is the exponent of the nonlinear part of the curve. This is functionally similar to the Arno base flow formulation proposed by *Todini* [1996].

[14] The relationship between the unsaturated hydraulic conductivity and the soil moisture content is modeled using a power law following *Brooks and Corey* [1964], while drainage between the three layers is represented as a gravity-driven process [*Liang et al.*, 1994].

$$Q_{i,i+1} = k_{s,i} \left(\frac{W_i - \theta_{r,i}}{W_i^{\max} - \theta_{r,i}} \right)^{\exp_i} \quad (2)$$

where $Q_{i,i+1}$ is the vertical drainage between layers i and i + 1 (i = 1, 2), W_i is the soil moisture content of layer i, $W_i^{\max}$ is the maximum soil moisture content of layer i, $\exp_i$ is a function of the pore size distribution, $k_{s,i}$ is the saturated hydraulic conductivity for layer i and, $\theta_{r,i}$ is the residual moisture content of layer i. The maximum soil moisture content of each layer is described by the following equation:

$$W_i^{\max} = thick_i * \phi_i \quad (3)$$

where $thick_i$ is the thickness of layer i and ϕ_i is the porosity of each layer, which is considered to be the same for the three layers.

[15] To represent the subgrid spatial variability in soil moisture storage, the model assumes that the infiltration capacity is a nonlinear function of the soil moisture storage within the grid cell [*Liang et al.*, 1994; *Zhao and Liu*, 1995]. This is represented as:

$$i = i_m \left[1 - (1 - A)^{1/b} \right] \quad (4)$$

where i and i_m are the infiltration capacity and maximum infiltration capacity respectively, A is the fraction of area for which the infiltration capacity is less than *i* and b is the infiltration shape parameter. An increase in b results in a decrease in the infiltration capacity, and thus a decrease in the amount of moisture entering the subsurface. Note that this formulation implies that all fast response runoff is generated through a saturation excess rather than an infiltration excess or Hortonian mechanism.

[16] The VIC model can operate both in an energy balance and a water balance mode. In the latter mode not all surface energy fluxes are calculated, which results in fewer iterations and faster execution speed. Because our interest focused on subsurface streamflow generation mechanisms, and to allow multiple model simulations, the model was used in water balance mode at a daily time step (VIC Version 4.0.4). VIC was implemented as a lumped model for each basin and no separate routing model was used. Figure 1 shows a description of the fluxes simulated by VIC, E represents evaporation from bare soil, E_t represents evapotranspiration, E_c represents evaporation from water intercepted by the canopy, S is the sensible heat flux, L is the latent heat flux, R_L is longwave radiation, R_s is shortwave radiation, tG is the ground heat flux, I represents infiltration, Q represents percolation, Q_d represents surface runoff, Q_b represents base flow, and W_n represents soil moisture content in the deepest soil layer.

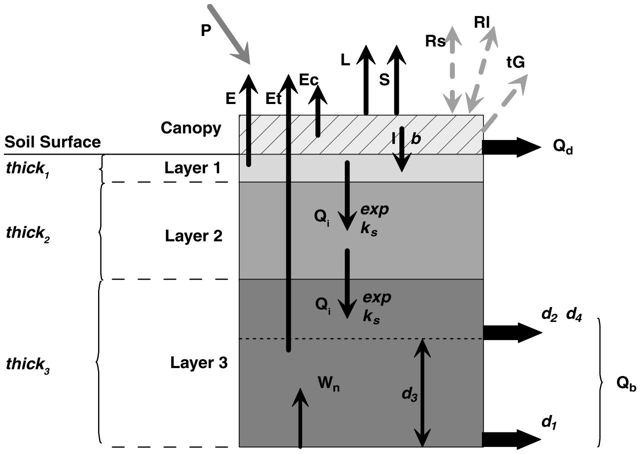


Figure 1. Schematic representation of the three-layer structure of VIC. Black arrows correspond to fluxes calculated in water balance mode; gray arrows represent additional fluxes explicitly accounted for in energy balance mode. d_1, d_2, d_3 and d_4 are base flow related parameters; b is the infiltration shape parameter and exp and k_s are the exponent of the drainage equation and the saturated hydraulic conductivity, respectively. For full description of fluxes, see section 3.2.

3.3. Data Sources

[17] Model simulations were performed using daily meteorological data from the Model Parameter Estimation Experiment (MOPEX) archives, including daily minimum and maximum temperature, precipitation and wind speed. MOPEX was carried out to develop and evaluate techniques to estimate model parameters used in land surface parameterization schemes [*Duan et al.*, 2006].

[18] On the basis of the Dryness Index (DI) and the Runoff Efficiency coefficient (RE) (Table 1), four basins located in the United States were chosen to represent different hydroclimatic environments (Figure 2). We deliberately excluded basins in regions where snow is a predominant mechanism to avoid hydrological memory due to snow and frozen ground. The hydroclimatic characterization based on DI and RE is a relative wetness classification used to differentiate the amount of water stress experienced by each of the four basins. The study basins are referred to hereinafter as "driest," "dry," "wet" and "wettest" (see Table 1 for details of each basin).

[19] The Guadalupe River Basin in Texas was chosen as the driest environment and the French Broad River Basin in North Carolina was selected as representative of the wettest environment. The other two basins were located in climatic regimens situated between these two extremes: the Spring River Basin in Missouri and the Amite River Basin in Louisiana. Figure 3 shows the hydroclimatic gradient of monthly precipitation and streamflows for the selected basins during the analysis period.

[20] Soil and vegetation characteristics for each basin were obtained from gridded data sets developed for the Land Data Assimilation System (LDAS) [*Mitchell et al.*, 1999]. LDAS vegetation data represent twelve vegetation coverages. Vegetation types existent in each basin were weighted on the basis of their coverage percentages for each grid cell and subsequently averaged to obtain a mean value for each basin. Leaf Area Index (LAI) and other vegetation related parameter did not change from year to year in this study.

3.4. Model Parameters

[21] The sensitivity of streamflow simulations to ten model parameters related to the generation of direct and base flow was investigated. These parameters were selected because their values are typically subject to calibration rather than direct measurement. The parameters include the base flow parameters d_1, d_2, d_3 and d_4 (equation (1)), the thickness of the three soil layers $thick_1$, $thick_2$, and $thick_3$ (equation (3)), the saturated hydraulic conductivities of the top two layers $k_{s,1}$ and $k_{s,2}$ (equation (2)), the exponents of the Brooks-Corey relationship, exp_1 and exp_2 (equation (2)), and the infiltration shape parameter b (equation (4)). Since the saturated hydraulic conductivity ($k_{s,i}$) and the exponent (exp_i) were assumed to be the same for each layer, this effectively resulted in ten individual parameters. Figure 1 presents a schematic representation of a single column showing the model parameters controlling surface and subsurface runoff generation that were included in the sensitivity analysis.

[22] Feasible ranges for each parameter were based on the minimum and the maximum parameter values in the LDAS

Table 1. Characteristics of the MOPEX Basins Selected in the Study for the Period 1960–1999

	Guadalupe (Driest)	Spring River (Dry)	Amite River (Wet)	French Broad (Wettest)
Latitude/longitude	−98.38/29.86	−94.56/37.24	−90.99/30.46	−82.57/35.60
Area, km^2	3405	3014	3315	2447
Elevation,[a] m	289	254	0	594
Mean temperature, °C	11.0	7.4	12.43	5.27
Mean precipitation (P), mm/yr	765	1076	1564	1383
Mean streamflow (Q), mm/yr	116	299	610	800
Mean potential evaporation (Ep),[b] mm/yr	1529	1095	1073	819
Mean daily flow, mm	0.31	0.81	1.67	2.19
Q/P = runoff efficiency (RE)	0.15	0.27	0.38	0.57
Ep/P = dryness index (DI)	2.0	1.0	0.68	0.59
Dominant vegetation type,[c] %	wooded grassland (78)	cropland (76)	evergreen needleleaf forest (32)	deciduous broadleaf forest (52)

[a]Gauge station datum.
[b]*Farnsworth et al.* [1982].
[c]*Hansen and Reed* [2000].

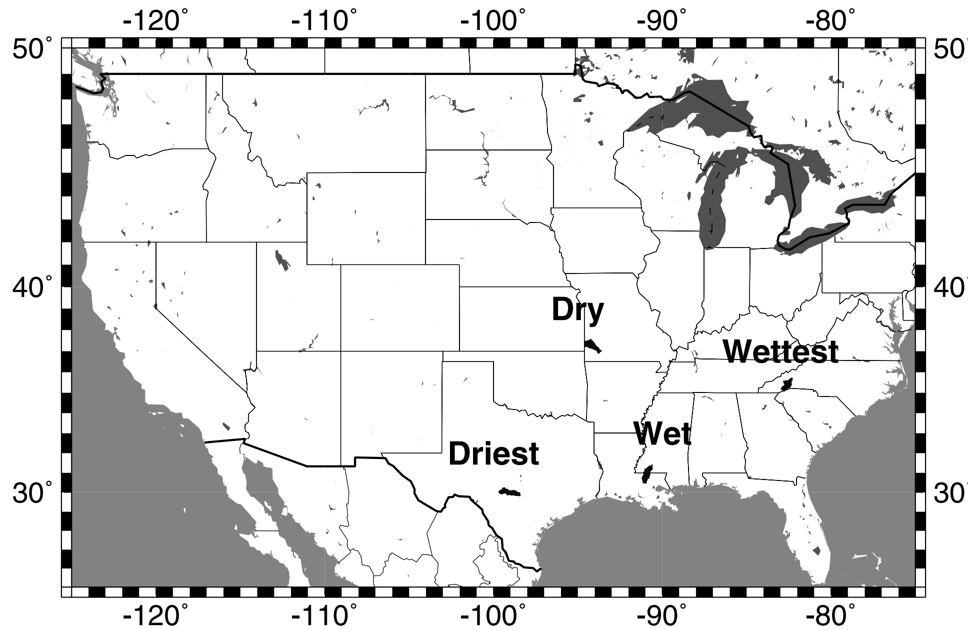


Figure 2. Geographic location of the MOPEX basins.

data set for the entire contiguous United States. Table 2 shows the range, a description of each parameter analyzed and its impact on the model response. Each feasible range was divided into three bins and each parameter was randomly sampled within each bin using a stratified sampling algorithm. This method assured that a sample was taken from each bin increasing the coverage of individual parameters. Model parameters were assumed uniformly distributed within each bin, ensuring a unique parameter combination for each model simulation and a fairly evenly distributed selection of values from the feasible parameter range [*Beven and Binley*, 1992]. This Monte Carlo procedure generated 59,049 ($\sim 3^{10}$) unique parameter sets. To reduce the dimensionality of the parameter space, those parameters of the model not included in the sensitivity study were kept at the default values.

3.5. Objective Functions and the Monte Carlo Analysis Toolbox (MCAT)

[23] Three independent objective functions were selected to analyze the goodness of the fit between observations and simulations (Table 3): root-mean-squared error (RMSE), which evaluates the ability of the model to simulate peaks in streamflows; Absolute value of the relative bias (Absrbias), which is a global measure of the conservation of mass in the model; and root-mean-squared error of the Box-Cox transformed streamflows ($\mathrm{RMSE}_{\text{box-cox}}$) which emphasizes the performance of the base flow component of the hydrograph. A Box-Cox parameter λ equal to 0.3 was used on the basis of recommendations by *Misirli et al.* [2002].

[24] MCAT was used to analyze the results from the model simulations. MCAT was designed to investigate the structure, sensitivity, parameter uncertainty and output uncertainty of mathematical models, with the aim of helping the modeling community in the identification of model parameters. It includes a modification of the Regional Sensitivity Analysis (RSA) introduced by *Freer et al.* [1996]. This method allows the user to visually inspect the sensitivity of different parameters with respect to the performance of the model and to identify insensitive parameters that can be fixed or eliminated from the representation of the system. In this approach, appropriate lower and upper boundaries for each parameter are established (feasible parameter range) and the parameter population is split into ten sets of equal size based on model performance. These sets are ranked and their marginal cumulative distributions

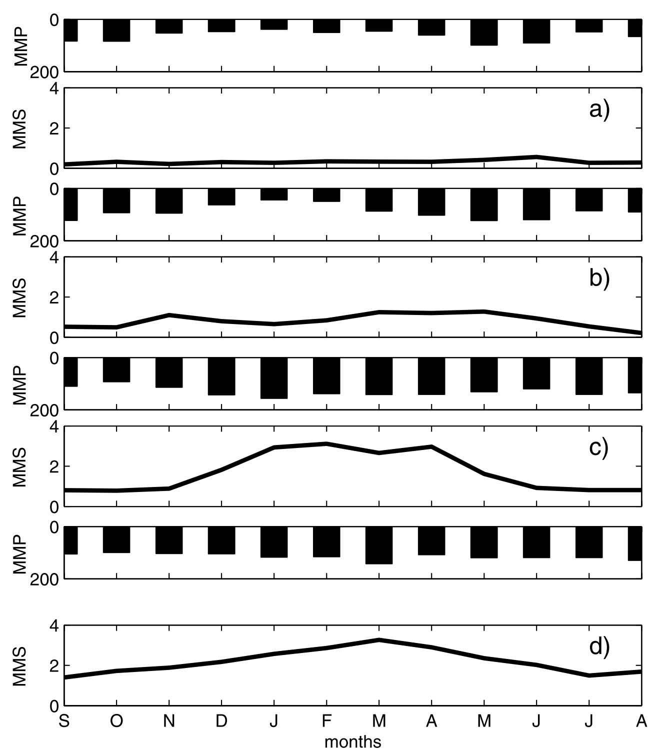


Figure 3. Mean monthly precipitation in mm (MMP) and mean monthly streamflows in mm (MMS) at the four sites: (a) driest, (b) dry, (c) wet and (d) wettest.

Table 2. List of Names, Feasible Ranges, Description, and Model Response of Parameters for Monte Carlo Simulations

Parameter	Range	Units	Description	Model Response
d_1	0–1	1/day	linear reservoir coefficient base flow equation	base flow
d_2	0–1	1/day	nonlinear reservoir coefficient base flow equation	base flow
d_3	0–(W_3 × porosity)[a]	mm	soil moisture threshold between linear and nonlinear	base flow
d_4	1–4	N/A	exponent nonlinear part base flow equation	base flow
b	0.001–0.8	N/A	infiltration shape controlling surface runoff	direct flow
k_s	1–10,000	mm/day	saturated hydraulic conductivity	drainage
exp	8–30	N/A	exponent of the Brooks-Corey drainage equation	drainage
$thick_1$	0.01–0.5	m	thickness of soil layer 1 (uppermost)	drainage
$thick_2$	0.1–2	m	thickness of soil layer 2	drainage
$thick_3$	0.1–2	m	thickness of soil layer 3 (lowermost)	base flow

[a]Upper limits for d_3 are 933 mm (driest), 944 mm (dry), 938 mm (wet) and 811 mm (wettest).

are plotted. A straight line represents insensitivity of the parameters whereas a group of lines with different shapes and separated from each other indicates sensitivity. Identifiability of parameters is evaluated through scatterplots (also called dotty plots) which are a projection of the parameters and of their goodness of fit in a surface response diagram [*Beven*, 2001]. These representations are a powerful tool to detect identifiable parameters from the parameter space, that is, regions of the parameter space where there is an optimum. Parameters that are clearly identifiable present a well-defined minimum, whereas those that are unidentifiable present a flat or unstructured surface across the whole feasible space.

4. Baseline Experiments

4.1. Experiments

[25] In the baseline experiments the ten subsurface parameters were varied as discussed in section 3.4, resulting in 59,049 Monte Carlo simulations for each of the four sites. Model simulations for the period January 1961 to December 1979 were evaluated at a daily time step using the three objective functions described in Table 2. The year 1960 was used for model spin-up and was excluded from the analysis. The ability of the model to simulate streamflow at the four sites was assessed and parameter sensitivity was evaluated with the help of MCAT. On the basis of the results from this baseline experiment additional case studies were performed as described in section 5.

4.2. Results

4.2.1. Model Performance

[26] Figure 4 demonstrates the ability of the model to simulate the hydrological cycle in the different hydroclimatic environments. Although no formal calibration was done to determine the optimal parameter sets, Figure 4 shows the best model runs from the pool of simulations selected following the procedure described below. To ensure a correct simulation of the volume of runoff generated by the model, the fifty best model performances with respect to Absrbias were first selected. From these, the twenty best performing simulations with respect to RMSE were selected to ensure that the peaks were matched. Finally, to match the base flow recessions, the five best performing simulations were selected with respect to $RMSE_{box\text{-}cox}$. This procedure guarantees the selected model run simulates the correct runoff volume and makes a skillful representation of peak and recession flows. The best overall run for each basin is shown in Figure 4. Model performance is worst in the driest basin. *Wooldridge et al.* [2003], *Abdulla and Lettenmaier* [1997], and *Nijssen et al.* [1997] have all discussed weaknesses of the VIC model when simulating the hydrological cycle in dry climates. VIC limitations to adequately represent streamflows in water-limited environ-

Table 3. Objective Functions Used for the Regional Sensitivity Analysis

Name	Description	Equation
RMSE[a,b]	root-mean-squared error	$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(O_t - Y_t)^2}$
Absrbias	absolute relative bias	$Absrbias = Abs\left(\frac{\sum_{t=1}^{n} Y_t}{\sum_{t=1}^{n} O_t} - 1\right)$
$RMSE_{box\_cox}$	root-mean-square error of Box Cox Transformation	$RMSEbox\_cox = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(O_t^* - Y_t^*\right)^2}$ $Y_t^* = Y_t^\lambda/\lambda, \quad O_t^* = O_t^\lambda/\lambda$
Abias[c,d]	absolute bias	$Abias = \frac{abs(Q_{bas}) - abs(Q_{non-lin})}{n}$
R	correlation coefficient	$r = \frac{\sum\left((Q_{bas}-\overline{Q_{bas}})(Q_{non\_lin}-\overline{Q_{non-lin}})\right)}{\sqrt{\sum\left((Q_{bas}-\overline{Q_{bas}})^2\sum(Q_{non\_lin}-\overline{Q_{non-lin}})^2\right)}}$

[a]O_t = observed streamflows (mm/day).
[b]Y_t = simulated streamflows (mm/day).
[c]Q_{bas} = simulated base flow runoff using original model formulation (mm/day).
[d]$Q_{non\text{-}lin}$ = simulated base flow runoff using nonlinear model formulation (mm/day).

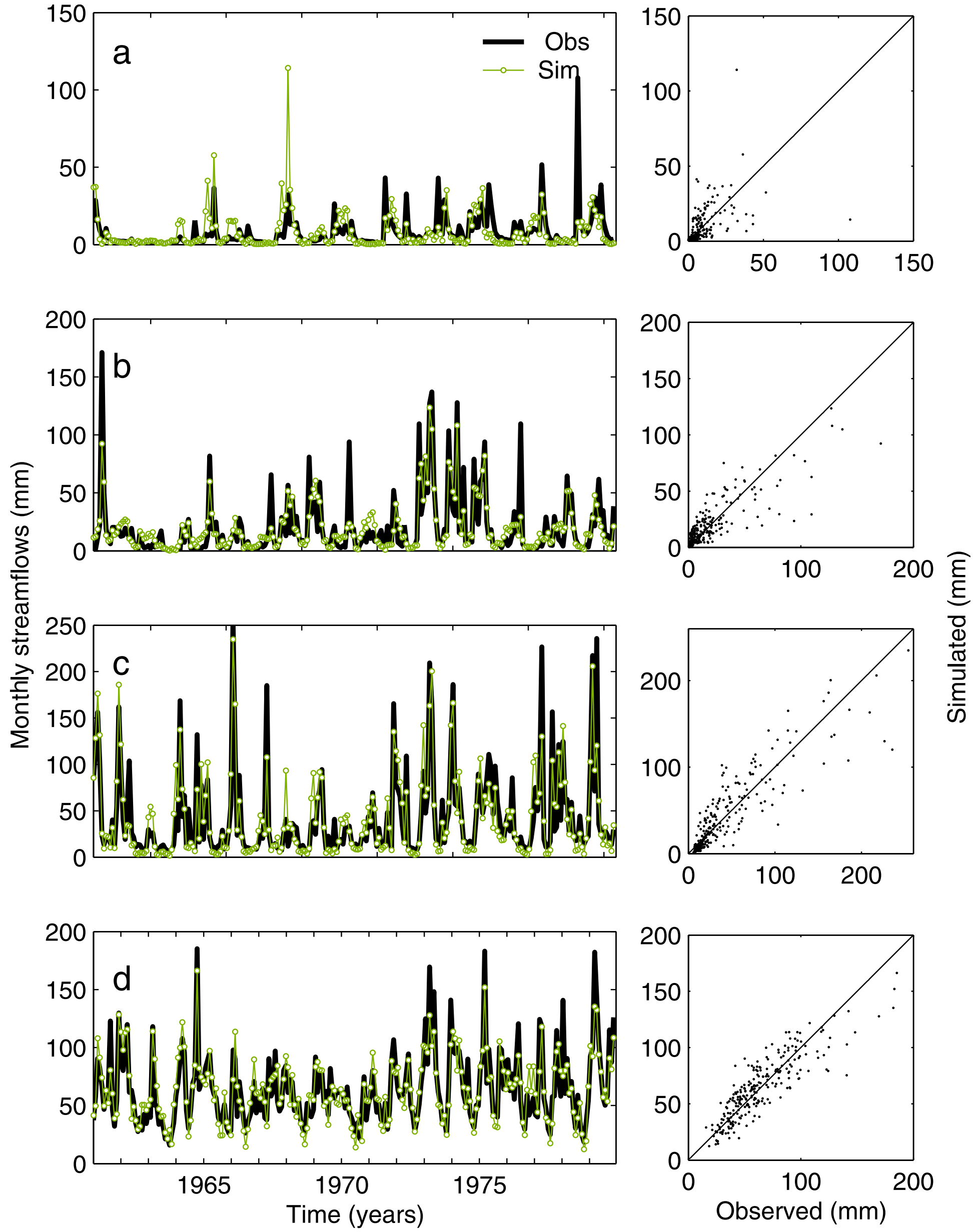


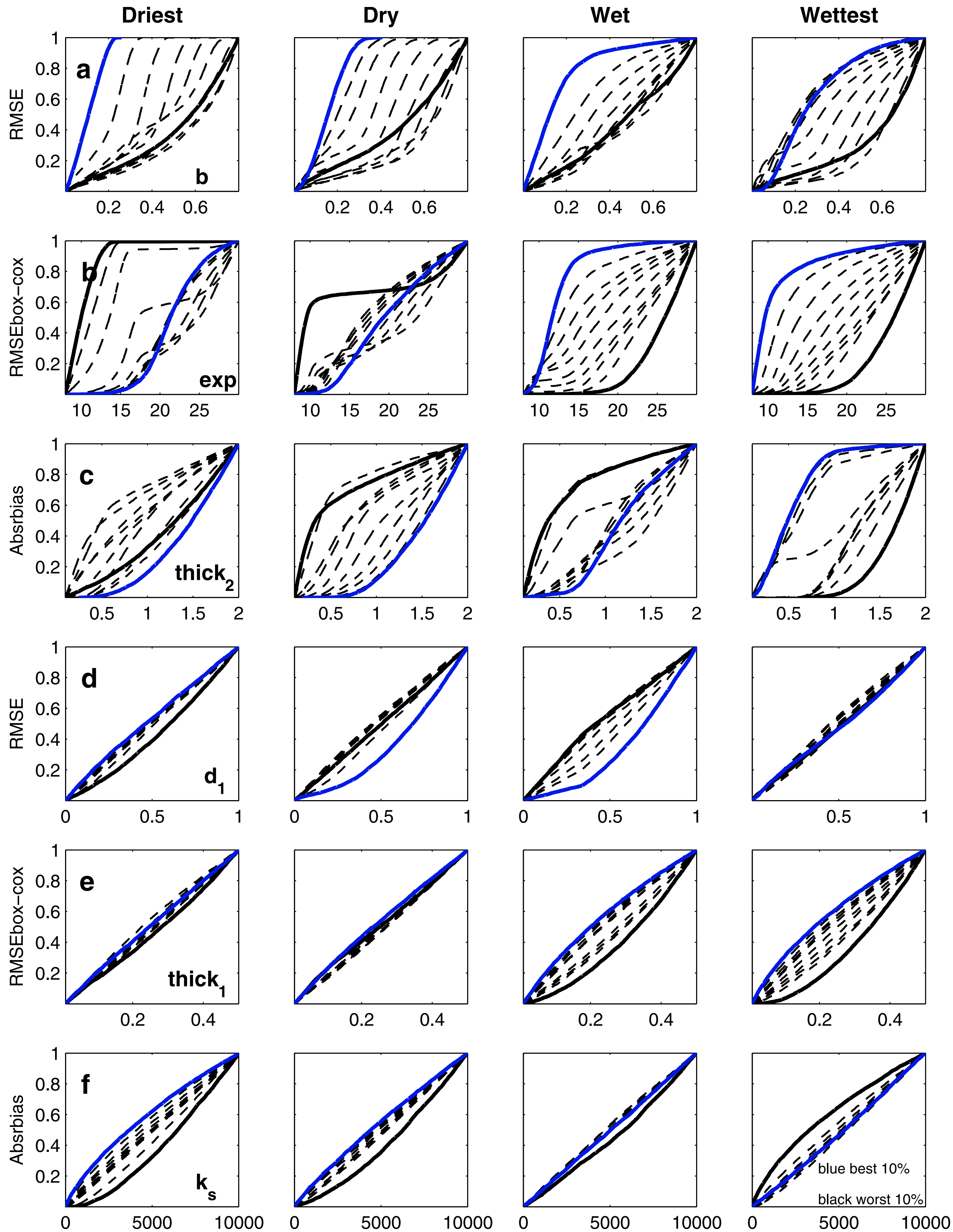
Figure 4. Model performance for basins: (a) driest, (b) dry, (c) wet and (d) wettest. Plots on the left show monthly simulated streamflows (green line with circles) and monthly observed streamflows (black line) for the period 1961–1979. Plots on the right show monthly observed (*x* axis) versus monthly simulated streamflows (*y* axis) in mm for the same time frame.

ments may be linked to the lack of an infiltration excess runoff formulation (Hortonian runoff), although it is unclear how important such a formulation is for model calculations at a daily time step. Other limitations in representing hydrological processes in ephemeral catchments are the lack of a representation of surface-groundwater interactions and transmission losses, which are of fundamental importance in desert environments.

4.2.2. Sensitivity and Identifiability Analysis

[27] Figure 5 shows the RSA results for selected parameters and objective functions. To produce the individual panels, the following procedure was applied. First, for each site and each parameter, the Monte Carlo simulations were ranked and equally divided into ten bins based on the value of the objective function. Thus the first bin contained the best 10% of the simulations, the second bin the next best

Figure 5. Results of regional sensitivity analysis (RSA) for those parameters that are proved sensitive. Cumulative distribution of the best 10% performing parameters (blue line) and cumulative distribution of the worst 10% performing parameters (black line). Dashed lines represent cumulative curves for the rest of the bins. (a) Parameter b, (b) parameter exp, (c) parameter $thick_2$ (m), (d) parameter d_1 (1/day), (e) parameter $thick_1$ (m), and (f) parameter k_s (mm/day).



Driest
Dry
Wet
Wettest
a
b
c
d
e
f
RMSE
RMSEbox-cox
Absrbias
b
exp
thick2
d1
thick1
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blue best 10%
black worst 10%

Figure 5

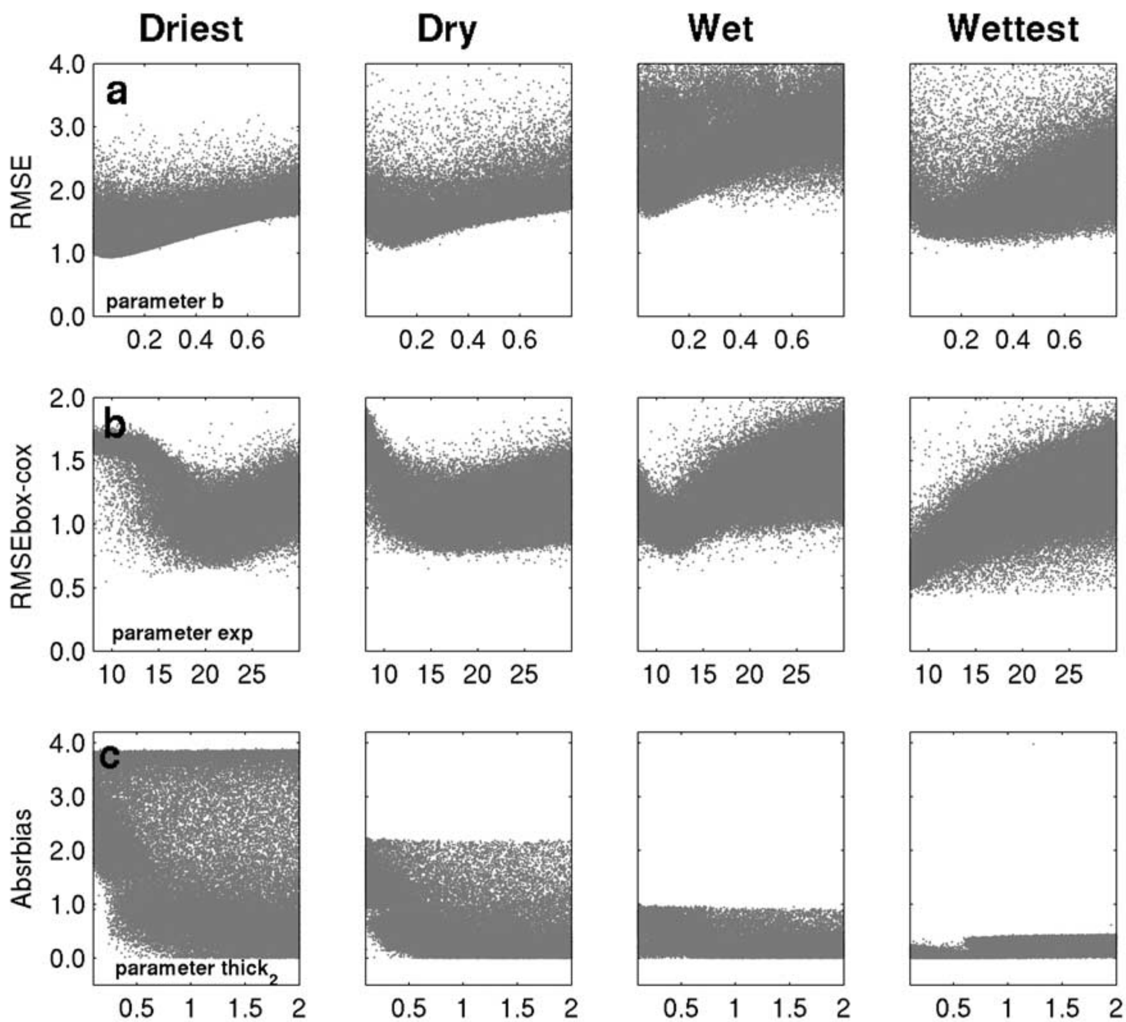

Figure 6. Scatterplots between the three most sensitive model parameters and three different objective functions. (a) Parameter b, (b) parameter exp and (c) parameter $thick_2$ (m).

10%, and so forth. Next, the values of the objective function in each bin were normalized so they ranged from 0 to 1. Finally, these normalized objective function values were plotted as a cumulative distribution function of the parameter value. Thus, for each panel in Figure 5, there are ten curves, each corresponding to a single bin. In general, an insensitive parameter will produce a straight one-to-one line whereas a sensitive model parameter will show differences in separation and form between the cumulative frequency distribution curves.

[28] Objective function values were highly sensitive to three model parameters (b, exp and $thick_2$) and only slightly sensitive to three other parameters (d_1, $thick_1$ and k_s). Figure 5 only shows the RSA curves for the objective functions that were most sensitive to changes in parameter values. Base flow parameters, d_2, d_3 and, d_4 presented a straight line for all three objective functions during the sensitivity analysis, indicating that the response of the system is insensitive to their values (not shown). A similar response was found for parameter $thick_3$, the depth of the third soil layer.

[29] Parameters are characterized as identifiable, if there is a distinct minimum in the scatterplots showing the objective function value as a function of the parameter value (Figure 6). Lack of a distinct minimum indicates the difficulty to find a single optimal value that provides good model performances, hence the parameter is termed poorly identifiable. Figure 6 shows scatterplots of model simulations for the three model parameters shown to be most sensitive in the RSA. The same objective functions are shown as in Figure 5, that is, the objective functions that provide the most information regarding the model's response for each particular parameter. The b parameter controls the shape of the variable infiltration curve in VIC, and effectively dictates the partitioning of rainfall into infiltration and surface runoff. Small values of this parameter increase the model infiltration and diminish the generation of direct runoff. Parameter b (Figure 6a) is best defined for the driest basin, with a marked minimum located near the lower limit of the feasible range. On the other hand, the same parameter is poorly identifiable in a wettest environment. The transition in the identifiability of parameter b with the hydroclimatic gradient indicates that this parameter is playing a key role in the generation of direct runoff in water stressed environment, whereas a correct system representation in a wet environment is less depen-

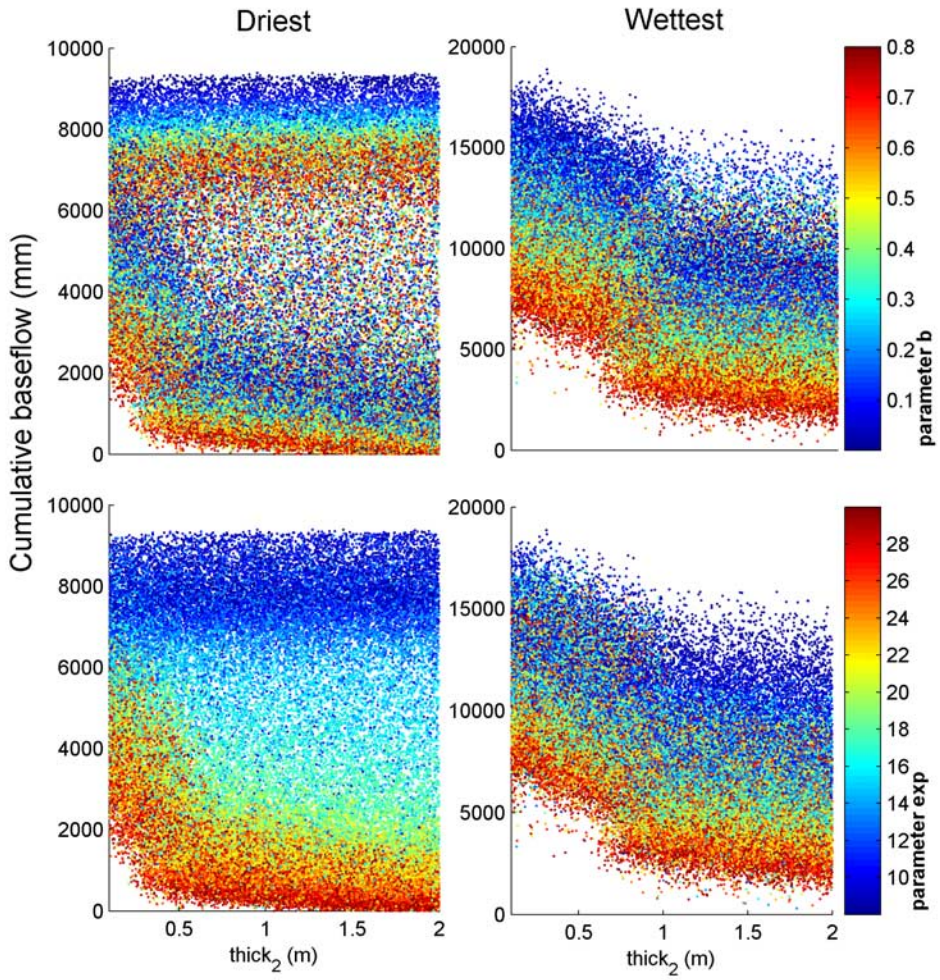

Figure 7. Scatterplots between cumulative base flow (mm) and parameter thick$_2$. (top) Parameter b in the vertical bar. (bottom) Information for parameter exp.

dent on an accurate specification of this parameter. Note that the RMSE objective function is most sensitive to the value of the b parameter, indicating that this parameter strongly influences both the magnitude and timing of the simulated peak flows. *Atkinson et al.* [2002] arrived at a similar conclusion in a study evaluating the model complexity needed to represent hydrologic processes in different climates and at different spatial and temporal scales. Their findings showed that the dominant parameter controlling streamflow variability was a field capacity related parameter. Streamflow prediction was found to be more sensitive to this parameter in dry catchments than in wet catchments, therefore more accurate predictions can be made using more simple models in a wet basin.

[30] In contrast, the exp parameter, which controls the vertical drainage between layers, is best identified using the $RMSE_{box\text{-}cox}$ objective function, which focuses on base flow recessions and low flows. This parameter shows a well-defined minimum located at the center of the parameter space for the driest basin while this minimum moves toward the lower boundary in the wettest basin (Figure 6b). A small value for the exp parameter increases the drainage between layers for the same soil moisture content and hence increases base flow generation. In our implementation, soil moisture in the subsurface is no longer available for evaporation once it reaches the third soil layer and thus contributes to an increase of the total runoff by augmenting base flow. In dry environments, most of the soil moisture eventually evaporates and little contributes to slow response runoff. In the model, this is expressed by the minimum in the $RMSE_{box\text{-}cox}$ objective function located at relatively high parameter values, resulting in little to no drainage. In wetter climates, where more of the rainfall contributes to slow response runoff, there is a shift toward lower values for the exp parameter.

[31] Simulated streamflows show large sensitivity to parameter thick$_2$ when model performance is measured with the three selected objective functions. We selected the Absrbias to present the results of the RSA. In Figure 6c, the model systematically overpredicts the total runoff volume in the driest basin for almost the entire feasible range of parameter values. The spread in Absrbias decreases as water availability increases in the environment indicating that VIC better captures the mass balance in wetter environments. There is a slight tendency for better model simulations for thick$_2$ values larger than 0.7 m for the driest and dry sites. However, the flat response surface in the four basins indicates redundancy with respect to predicting streamflows and no optimum parameter value is found for this parameter.

[32] Figure 7 shows scatterplots between total cumulative base flow and parameter thick$_2$ for the basins located at the

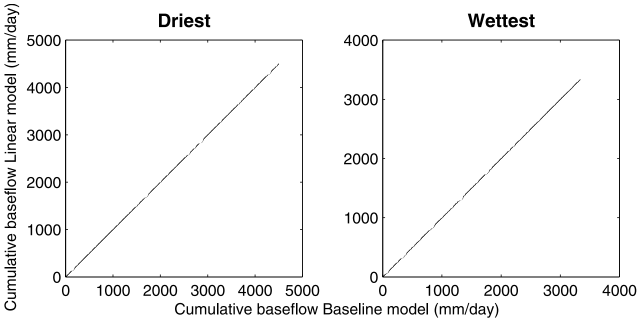

Figure 8. Scatterplots between daily cumulative base flow calculated with the original (baseline) base flow parameterization and with the linear parameterization. Period January 1961 to December 1979. Results (left) in the driest basin and (right) in the wettest site.

extremes of the hydroclimatic gradient. The color bar located at the right hand side shows the variation in a second parameter: parameter b for the top row and parameter exp for the bottom row. The plots show that large base flows occur when parameters b and exp are located at the lower end of the feasible range. This parameter configuration maximizes base flow generation in the model, since infiltration and vertical drainage are large. In this scenario, soil moisture is not retained in the upper two soil layers, evapotranspiration is at a minimum, and VIC systematically overpredicts base flow runoff. This behavior becomes more significant in the driest basin where plant available water (difference between soil moisture content at field capacity and at wilting point) is extremely low. Base flow is relatively large, because the amount of soil moisture that can be used effectively by the vegetation for evapotranspiration is small. In addition, evaporation from bare soil is diminished when soil moisture is vertically drained because of the combination of b and exp. Contrarily, at the wettest site, a larger amount of soil moisture, that is, large plant water availability, is available for evapotranspiration; and thus not contributing to base flow runoff. When the soil layer is thin, insufficient moisture is stored in the soil to satisfy atmospheric and vegetation requirements and streamflows tend to be overpredicted by the model. When $thick_2$ is large, especially combined with large values of $thick_1$ and exp (small vertical drainage), streamflows are underpredicted, because most of the soil moisture is stored in the top two soil layers, resulting in excess of evapotranspiration in the model simulations. The relationship between soil characteristics and climate is further discussed in section 5.3.

5. Case Studies

[33] On the basis of the outcomes of the baseline experiments, a set of follow-up experiments was conducted to further investigate the sensitivity of model simulations to parameters of interest. In particular, model experiments were designed to address the following questions: (1) Under what conditions are the parameters, which control the nonlinear part of the base flow equation, sensitive and identifiable? (2) What is the role of vegetation in the sensitivity of the model to the thickness of the second soil layer? (3) Are differences between sites climate or soil-driven?

5.1. Sensitivity and Identifiability of Parameters Controlling Nonlinear Base Flow Response

[34] One of the outcomes of the baseline experiments was that none of the three objective functions demonstrated sensitivity to changes in the parameters controlling the nonlinear part of the base flow generation function (equation (1)). Following equation (1), the nonlinear part of the base flow generation function only activates when the moisture storage in the third layer is above a threshold (d_3). In that case, for the same soil moisture, the nonlinear formulation produces more base flow than the linear formulation (assuming d_4 greater than 1), resulting in rapid drainage from the bottom soil layer. Because the base flow parameters controlling the nonlinear part are activated during wet conditions, we recalculated the performance of the model with the three objective functions for the observed flows that are only exceeded 2% of the time. The expected outcome was an increase in the sensitivity of those parameters involved in the nonlinear component of equation (1). However, no improvements in the sensitivity of parameters d_2, d_3 and d_4 occurred in the RSA for any of the basins or objective functions. Plots similar to those in Figure 5 showed no difference in parameter sensitivity whether all flows (baseline experiment) or only the high flows were considered (not shown).

[35] To evaluate the impact of removing the nonlinear base flow component on the sensitivity of the other parameters, a new RSA was performed in which seven parameters (that is, excluding d_2, d_3, and d_4) were again randomly sampled. The nonlinear part of the base flow generation equation was inactivated by setting d_2 equal to zero. Results of the new RSA did not show any changes in the sensitivity of the objective functions to the parameters compared to the baseline experiments (not shown). Cumulative base flow simulations with and without the nonlinear base flow generation component are shown in Figure 8 for the period January 1961 to December 1979 for those basins located at the extremes of the hydroclimatic gradient. In these two simulations, parameter d_3 was expressly chosen small for the baseline experiments, to ensure that the soil moisture in the third layer exceeded this threshold and the nonlinear part of the equation was activated. For small d_3 values exclusively, simulations with the baseline model formulation showed a slight increase in base flow. This increase can be seen in Figure 8 as little waves. The total number of days showing larger base flows in the baseline experiment represented approximately 1% of the cases. Correlation coefficients (r) between base flow simulations with and without the nonlinear component were found to be 0.84 and 0.83 for the driest and wettest basin respectively. Absolute bias (Absbias) between both model simulations was equal to 0.0048 mm for the driest basin and 0.025 mm for the wettest basin. Relatively high correlation coefficient values along with small Absbias between the data sets indicate that the nonlinear model offers little improvement compared to a simple linear model for base flow generation at a daily time step. Note that the r-values were calculated for the worst case scenario in which d_3 is close to zero and where the nonlinear component is often activated. For larger values of

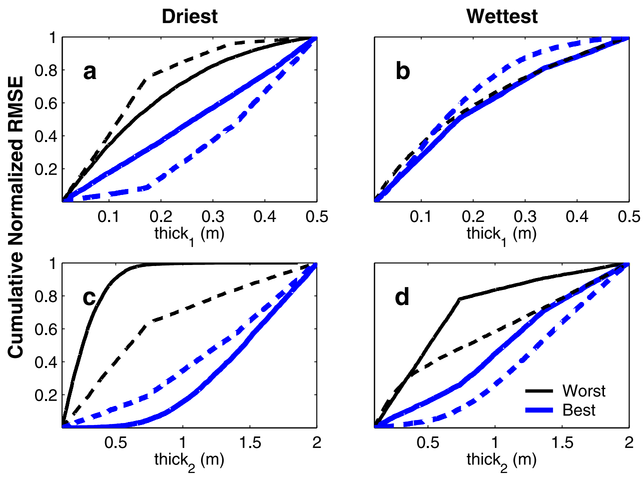

Figure 9. Impact of vegetation on sensitivity of the model layer thickness ($thick_1$ and $thick_2$). The black line represents the worst performing parameters (10%), and the blue line represents the best performing parameters (10%). Solid lines correspond to baseline simulations, and dashed lines correspond to runs where the vegetation was only located in the upper model layer.(a and b) Sensitivity of the upper model layer (parameter $thick_1$) and (c and d) sensitivity for the second model layer (parameter $thick_2$).

d_3 the correlation coefficient is equal to 1 and the Absbias equal to 0, indicating that the base flow generation was not affected by the presence or absence of the nonlinear component. High correlation between simulations with and without the nonlinear component indicates the existence of overparameterization in the base flow model formulation.

[36] The existence of interactions between base flow parameters was assessed with a nonparametric test introduced by *Spearman* [1904]. Spearman rank correlation coefficients were computed for pairs of d_1, d_2, d_3 and d_4 parameters. Correlation coefficients showed that the relationship between pairs was not statistically significant at a 95% confidence level indicating that the insensitivity of base flow parameters was not the result of interactions between them (not shown).

[37] These findings indicate that the parameters controlling the nonlinear base flow generation function are poorly identifiable. In other words, their values are difficult to determine using manual or automated calibration procedures based on streamflow alone. Because this part of the model formulation is purely conceptual and the values of the parameters cannot be determined by direct measurement, we suggest that the nonlinear part of the base flow formulation can be left out for VIC model simulations in water balance mode at the daily timescale. These results agree with those from *Huang and Liang* [2006] who showed that a one-parameter subsurface parameterization could successfully capture the base flow component of hourly streamflow simulations.

5.2. Role of Vegetation in the Sensitivity of the Thickness of the Second Soil Layer

[38] The thickness of the second soil layer ($thick_2$) was found to be one of the most sensitive parameters in the baseline experiments. In our model setup, vegetation roots penetrated all three layers of the soil profile and most of them were located in the second layer. In this section we examine whether the high sensitivity of parameter $thick_2$ (Figure 6c) is a result of the presence of most of the vegetation roots in this layer.

[39] Vegetation parameters were not included in the sensitivity analysis; furthermore, root allocation in the subsurface, as well as vegetation coverage, were adopted from the LDAS data set. In the driest basin, 65–70% of the roots, depending on the vegetation type, were allocated to the second soil layer. In the wettest basin, this distribution varied from 45% to 65%. The impact of the root distribution on the sensitivity of the second layer was evaluated by restricting all the roots to the uppermost soil layer. New model simulations were obtained with the same 59,049 parameter set. Changes in the root allocation resulted in a decrease in evapotranspiration, which was now restricted by the amount of soil moisture in the uppermost layer. Soil moisture that was not consumed by evapotranspiration percolated to deeper layers resulting in an increase of simulated base flow.

[40] Figure 9 shows the sensitivity of the RMSE objective function to the thickness of the upper two soil layers ($thick_1$ and $thick_2$, respectively), for baseline experiments (solid line) and for the new experiments (dashed line). For the driest basin, there is a marked increase in the sensitivity of parameter $thick_1$ when roots are mobilized to the uppermost layer. The change in sensitivity is evident in a larger separation between best and worst 10% performing $thick_1$ parameters in Figure 9a. The sensitivity of parameter $thick_2$ diminishes when vegetation roots are moved indicated by a smaller separation between lines (Figure 9c). This pattern is less marked in the wettest basin where no significant changes in sensitivity are found for parameter $thick_1$ (Figure 9b). In the case of parameter $thick_2$, there is a small shift in the position of the curves linked to changes in root allocation but not a significant increase in the sensitivity (Figure 9d). This can be directly linked to the fraction of roots that was originally allocated to the second soil layer. In the baseline runs, a smaller percentage of roots was allocated to the second layer of the model in the wettest basin than in the driest basin therefore the impact of root distribution was less marked. A similar pattern in the sensitivity of these parameters was also found for Absrbias and $RMSE_{box\text{-}cox}$ objective functions (not shown).

5.3. Are Differences Between Sites Climate- or Soil-Driven?

[41] The same methodology was used to assess whether the sensitivity of streamflows to the selected VIC parameters was solely due to hydroclimatic conditions rather than to the soil characteristics of each basin. To estimate whether the sensitivity of parameters b, $thick_2$ and exp (section 4.2.2) was influenced by soil properties (that is, soil porosity, plant available water, bulk density and particle density), we transferred the soil properties of the driest basin to the wettest site. That is, VIC was driven using the atmospheric forcings from the wettest basin and the transferred soil parameters from the driest basin. Changes in soil porosity and plant available water introduced significant changes in the performance of the model. Soil porosity increased from a value of 0.406 (wettest site) to 0.473 (driest site) and plant

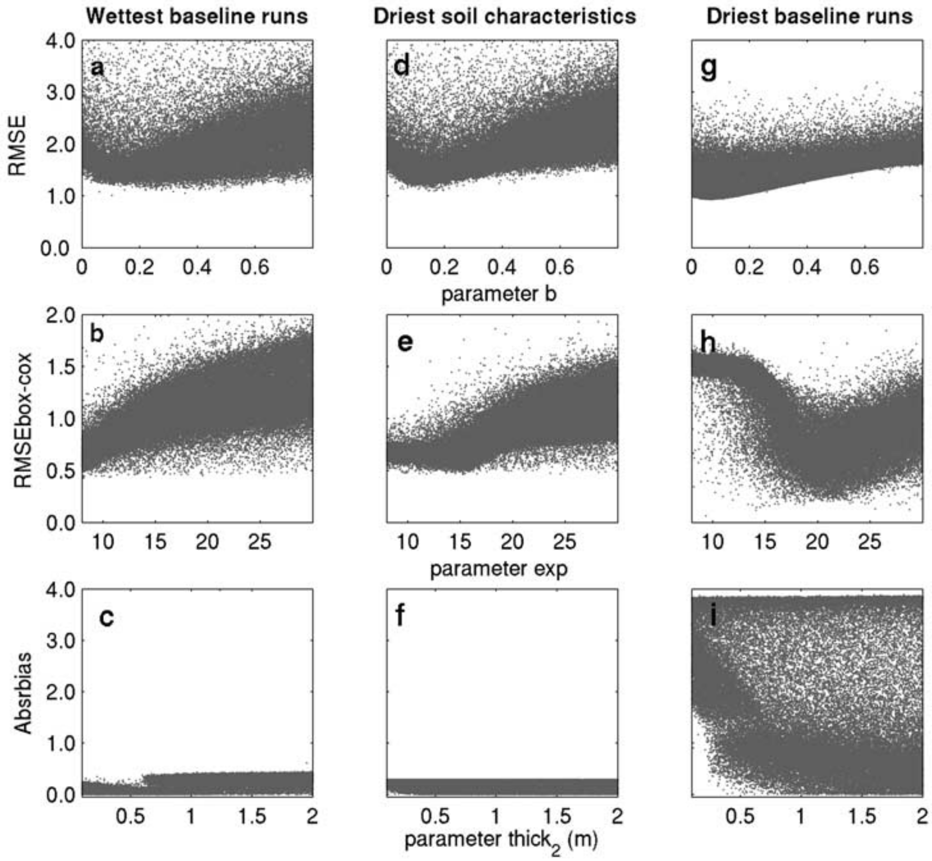

Figure 10. Scatterplots between the three most sensitive parameters and three different objective functions. (a–c) Baseline simulations for the wettest basin. (d–f) Model simulations using the meteorological forcings of the wettest basin and soil characteristics of the driest basin. (g–i) Baseline simulations for the driest basin.

available water (difference between soil moisture content at field capacity and at wilting point) decreased from 0.162 to 0.02 respectively. We generated a new set of 59,049 streamflow simulations and evaluated model performance with the objective functions presented in Table 3.

[42] Figure 10 shows scatterplots between the three selected objective functions and three different model setups: the left column represents baseline runs for the wettest basin, the center column shows simulation with the soil parameters of the driest basin and the atmospheric forcings of the wettest basin, and the right column shows baseline simulations for the driest basin. No significant changes in the shape of the scatterplot between RMSE and parameter b (Figures 10a, 10d and 10g) were found when soil parameters were transferred from the driest to the wettest basin. This indicates that the sensitivity of parameter b is not affected by the transferred parameters and climatic conditions are solely responsible for it. The shape of the new scatterplot (Figure 10d) remains almost identical to the shape found for the baseline runs in the wettest basin (Figure 10a) rather than being similar to the shape found for the driest basin (Figure 10g).

[43] For parameter exp, the shape of the scatterplot changes slightly (Figure 10e) compared to the baseline simulations. There is a tendency for better performing parameters toward the lower end of the chosen parameter range in concordance with values found for the wettest basin (Figure 10b). Baseline runs for the driest basin presented optimum values for parameter exp located in the middle of the feasible range (Figure 10h). The new model simulations show equally good performing parameters located at the lower end of the feasible range.

[44] The scatterplot between parameter $thick_2$ and Absrbias does not indicate an improvement of the overall model performance when soil characteristics are transferred to the wettest basin. The main change in the shape of Figure 10f compared to Figure 10c is a flat horizontal upper limit located at high Absrbias values. This limit is the result of a decrease in plant water availability, which produces a decrease in evaporation rates. Since atmospheric forcings remain the same in Figures 10c and 10f, soil moisture that was not utilized by the vegetation contributes to excess base flow. The combination of small values for parameter b and large values for parameter exp increases base flow generation, resulting in an overprediction of base flow runoff as explained in section 4.2.2.

6. Conclusions

[45] The results presented in this paper demonstrate that the identifiability of LSM parameters can be troublesome and that the sensitivity of model parameters is closely

connected to the hydroclimatic characteristics of the basin. Four climatic regions, ranging from driest to wettest, were selected to assess the impact of hydroclimatic conditions on parameter sensitivity. Ten VIC parameters involved in direct and base flow generation were targeted for the study. The sensitivity of these parameters was studied in a Monte Carlo framework.

[46] Results indicated that three of the parameters evaluated in this study dominated the VIC model streamflow simulations. The infiltration shape parameter, parameter b, was found to be crucial for the correct representation of the system in a dry environment, whereas its impact on model performance was not significant in wet sites. This behavior emphasized the key role that parameter b plays in partitioning rainfall into soil moisture and surface runoff in dry environments. A similar climate driven pattern was found for parameter exp which presented an optimum centered in the middle of the feasible range for a dry environment. This optimum moved toward smaller values for wetter climates. This displacement in the parameter optimum allowed the model to adjust the amount of soil moisture allocated to satisfy evapotranspiration demands. Greater sensitivity to soil model parameters in dry sites compared to wet environments was also found by *Liang and Guo* [2003] and *Atkinson et al.* [2002].

[47] In VIC, base flow generation is represented by a combination of a linear and a nonlinear formulation. The latter accounts for rapid base flow generation during extremely wet conditions when the amount of moisture in the lowermost model layer is large. Parameters of the base flow formulation are purely empirical and are obtained through calibration. RSA revealed that this base flow formulation is overparameterized for water balance simulation at a daily time step. Analysis of model simulations with and without the nonlinear component indicated that the nonlinear component of the base flow equation was unnecessary for the correct representation of the system. A simple linear reservoir could efficiently represent the base flow generation in the model reducing the number of base flow parameters that required calibration from four to one. These results are strictly valid only for VIC model simulations using water balance mode at a daily time step. The nonlinear base flow formulation may prove important at shorter time steps.

[48] Results revealed that the distribution of vegetation roots had a large impact on the sensitivity of the model simulations to changes in the thickness of the second soil layer ($thick_2$). Experiments restricting roots to the top layer of the model showed that the sensitivity of parameter $thick_2$ was linked to the percentage of roots allocated to that layer. Therefore parameter $thick_2$ cannot be determined independently of vegetation parameters. Sensitivity was larger in the driest site than in the wettest because of the root distribution in the baseline model formulation.

[49] A detailed analysis of the impact of changing soil properties at the wettest site showed no influence in the sensitivity of parameter b. Slight changes in the shape of scatterplots between parameter exp and $RMSE_{box\text{-}cox}$, and parameter $thick_2$ and Absrbias were related to changes in plant water availability. However, no improvements in model performance were evident for both parameters indicating the soil properties were not playing a dominant role in their sensitivity.

[50] This study demonstrated that care has to be taken when formulating the sensitivity analysis to ensure that the impact of parameters is appropriately captured. Equally accurate, but more identifiable models can be obtained using this approach, eventually leading to a more parsimonious model with a higher chance of successful regionalization to ungauged locations.

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