On the ability to infer spatial catchment variability using streamflow hydrographs

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[1] Spatially distributed models can potentially provide improved hydrologic predictions because of their ability to exploit spatially distributed data while providing estimates of hydrologic variables at interior catchment locations. However, attempts to estimate spatially distributed parameter fields via model calibration have been fraught with difficulty. This paper examines the factors that can influence the ability to infer spatial properties of a distributed model when the only information available for model evaluation is catchment streamflow response. In particular, we investigate the conditions under which spatial variability in parameters and rainfall cause sufficiently strong variations in the streamflow hydrographs to justify their representation in catchment models and whether such information can be detected via commonly used model performance measures. Our results show that spatial variability in parameter and precipitation fields can, indeed, have a detectable impact on the properties of the streamflow hydrograph but that this impact can be so greatly diminished by the damping and dispersive effects of routing that it is virtually nondetectable by conventional performance measures by the time the water reaches the catchment outlet. And although measures based on information theory may be able to detect subtle variations of this kind, the information may not ultimately be useful in the face of model structure and data errors. The only reasonable way forward therefore is to explore other kinds of catchment information (including multiple interior flow gauging locations) for use in estimation of spatially distributed parameter fields.

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1. Introduction

1.1. Background

[2] Interest in the use of distributed hydrologic models for flood prediction is attributable to the availability of spatially distributed data, improvements in computation, and the need for accurate predictions of the river stage at interior locations of a catchment. In principle, a spatially discretized model should provide better predictions than its lumped counterpart because the latter does not account for spatial heterogeneities and nonlinearities that can influence the system response [*Krajewski et al.*, 1991; *Carpenter et al.*, 2001; *Smith et al.*, 2004a]. However, recent studies suggest that distributed models may not provide detectably better streamflow simulations at the catchment outlet over those achieved by lumped models [*Reed et al.*, 2004; *Smith et al.*, 2004a]. Our own previous attempts to calibrate a distributed hydrologic model to three catchments in Oklahoma [*Pokhrel et al.*, 2008; *Pokhrel and Gupta*, 2010] found that the model outlet response was not strongly sensitive to spatial variability of the parameters as indicated by the conventional mean-square error (MSE) type measures; in general the overall basin mean parameter value performed just as well. The goal of this paper is to try and understand these findings, and to investigate the factors that may influence the ability to infer spatial properties of a distributed model when only information about catchment output streamflow response is available.

1.2. Review of the Relevant Literature

1.2.1. Influence of Spatial Parameter Variability on Model Response

[3] Hydrological parameters can vary considerably in space. *Nielsen et al.* [1973], in a field measurement study of a fairly homogenous plot of land, found the variation in the soil hydraulic conductivity to be of several orders of magnitude, even in soils belonging to the same class. *Beven* [1995] pointed out that given the spatial variability of catchment characteristics, it may be impossible to specify a homogenous equivalent parameter value that correctly represents the flow characteristic of a spatially variable system.

[4] *Smith and Hebbert* [1979] provided one of the earliest demonstrations of the influence of stochastic and structured spatial variability of infiltration parameters on model response. Using a simple infiltration model consisting of *Smith and Parlange*'s [1978] equations and randomly sampled log-normally distributed hydraulic conductivity, they showed that increasing spatial variability can result in earlier occurrence of runoff. Similarly, they also demonstrated the influence of structured spatial variations in hydraulic con-

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ductivity, using a simple kinematic model. *Sivapalan and Wood* [1986] derived quasi-analytical expressions for mean infiltration rate for two cases: spatially distributed soil parameters with uniform rainfall, and distributed rainfall with uniform parameters. Using an approximate model for point rainfall infiltration, on the basis of Philip's equation [*Philip*, 1957a, 1957b, 1957c, 1957d, 1957e, 1958a, 1958b] and the time compression approximation of *Sherman* [1943] and *Reeves and Miller* [1975], they demonstrated that spatially uniform and distributed soil properties can lead to significant differences in infiltration rates. Using field measurement experiments *Seyfried and Wilcox* [1995] analyzed hydrologic responses to spatial variability over a range of scales, and reported that changes in scale or location introduced larger-scale, dominant, sources of variability that "subsumed" the smaller-scale variability. They recommend that location specific spatial characterization of larger-scale variability is required, and that smaller-scale variability can be characterized in a statistical manner. *Woolhiser and Goodrich* [1988] and *Saghafian et al.* [1995] conducted Monte Carlo studies and found significant differences in hydrographs generated using uniform and distributed hydraulic conductivity fields. They also reported that rainfall intensity affected the model sensitivity to spatial distribution. *Merz and Bárdossy* [1998] examined the influence of structured variability of infiltration parameters (created using the topographic index and soil type as external drift) on runoff response of a quasi-3-D model in southern Germany, and reported significant impacts on model response. In contrast, unstructured randomly varying parameter fields provided responses that were very similar to those from homogenous fields; overall, their findings are consistent with those of *Seyfried and Wilcox* [1995]. However, *Brath and Montanari* [2000] found the effect of spatial variability of infiltration parameters to be significant only for low-peak events in a catchment dominated by Hortonian flow processes. Similarly, *Bormann et al.* [2009, p. 191] found that neither structured nor random redistribution of the land use had any significant effect on the simulated flood response of a distributed model used for sensitivity and scenario analyses, commenting that "spatially distributed models may over-represent their advantages compared to lumped models to analyze the effects of the patterns of land use change."

1.2.2. Influence of Spatial Variability of Rainfall on Model Response

[5] It is well known that the spatial variability of a storm can potentially exert significant influence on the streamflow response of a catchment [*Wilson et al.*, 1979; *Beven and Hornberger*, 1982; *Ogden and Julien*, 1993; *Julien and Moglen*, 1990; *Krajewski et al.*, 1991; *Singh*, 1997]. Through a synthetic study, *Wilson et al.* [1979] concluded that failure to account for the spatial variability of rainfall can lead to serious errors in hydrograph simulation. *Beven and Hornberger* [1982] found the most significant influence of spatial rainfall variability to be differences in the timing of peak flows, with secondary effects on the peak magnitude; the effects on runoff volume were found to be minor. *Krajewski et al.* [1991] also found that ignoring the spatial distribution of rainfall results in severe under estimation of peak flow magnitude. *Julien and Moglen* [1990] and *Ogden and Julien* [1993] found the spatial variability of precipitation input to be significant when the storm durations are shorter than the time for kinematic equilibrium of the catchment.

[6] However, the findings seem to be different for different kinds of catchments. *Naden* [1992] found the effects of spatial rainfall variability to be negligible in the limestone- and chalk-dominated River Thames catchment; apparently storage and subsequent slow release from the hillslope effectively smoothed out the spatial effects of variation in rainfall. *Brath et al.* [2004] investigated a midsized catchment in north central Italy and reported that spatial representation of rainfall was not important to model response at the outlet. *Nicótina et al.* [2008] reported similar findings. *Obled et al.* [1994] found the outlet hydrograph peak flows to be insensitive to spatial distribution of rainfall, with the only noticeable impacts being on the secondary peaks; they speculated that the spatial variability in rainfall might not have been "sufficiently organized in time and space" to overcome the smoothing and dampening mechanism of the catchment.

[7] *Van Werkhoven et al.* [2008] conducted a global sensitivity analysis and reported that the sensitivity of parameters in a distributed model was not stationary but varied spatially in relation with the spatial distribution of rainfall. *Booij* [2002] studied the effects of coupled spatiotemporal model resolution and rainfall input resolution on the response of a large river basin in northwestern Europe and found the effects of model resolution on extreme river discharge to be more important than that of the input resolution.

[8] The Distributed Model Intercomparison Model Project Phases 1 and 2, had as its goals to encourage the development of spatially distributed catchment-scale models and to improve operational flood forecasting by the U.S. National Weather Service (NWS) [*Reed et al.*, 2004; *Smith et al.*, 2004b; http://www.nws.noaa.gov/oh/hrl/dmip/2/index.html]. The project found that, in the majority of cases (with a few noteworthy exceptions), distributed models were unable to improve upon lumped models in regard to streamflow simulations at the catchment outlet. *Smith et al.* [2004a, p. 267] therefore tried to identify under what basin and/or rainfall event configurations distributed models might perform better and examined the hypothesis that "basins characterized by (1) marked spatial variability in precipitation, and (2) less of a filtering effect of the input rainfall signal will show improved outlet simulations from distributed versus lumped models." To avoid model specific conclusions, they measured the influences of spatial rainfall variability in terms of summary indices derived from the observed rainfall and streamflow data. In a modeling exercise, applied to three basins, they found that only one basin with a substantially higher degree of spatial variability and less dampening effect (as indicated by the summary indices) demonstrated improvements resulting from distributed modeling.

1.3. Objectives, Context, and Scope of This Study

[9] There is a clear lack of consensus in the literature regarding the impacts of spatial distribution (of rainfall and parameters) on the streamflow response of a catchment. The answer to the question "Is the spatial distribution of parameters and rainfall important enough to justify their distributed representation in catchment models?" remains unclear, although it is directly relevant to the practical implementation of distributed hydrologic models. The objective of this paper is to make progress toward answering this question, which

clearly has relevance to the important issue of whether the spatial structure of parameter fields can possibly be inferred from information contained in the catchment outlet hydrograph. While this study does not provide a comprehensive investigation of the latter issue, it helps to provide some useful insights that should influence further investigations.

[10] Regarding the context and scope of this study, our interest in understanding the ability to infer the spatial distribution of parameters and rainfall arises from previous experience with spatially regularized calibration of distributed models for three DMIP2 study catchments in Oklahoma [*Pokhrel et al.*, 2008; *Pokhrel and Gupta*, 2010]. In that work, model calibrations conducted using uniform and distributed parameter fields resulted in model responses that were very similar. Further, the posterior parameter distributions obtained using different spatial regularization schemes had very similar mean values but very different variances, indicating that the model outlet responses for these basins were not strongly sensitive to spatial parameter variability. In other words, the overall basin mean parameter values performed just as well.

[11] Therefore, prior to conducting any further studies involving calibration of distributed models using outlet hydrographs (the common practice in flood forecasting applications), it is important to understand whether the variations in the model responses, caused by the inclusion of spatially distributed parameter fields, are sufficient to cause "detectable" change (as measured by some performance criteria) in the outlet hydrographs. Since this information is extracted using some kind of model performance criteria, the selection of these criteria becomes a major factor in deciding the outcome of the calibration process. A possible reason for the findings of *Pokhrel et al.* [2008] and *Pokhrel and Gupta* [2010] is that conventional measures (e.g., mean-square error of the flows or of the log-transformed flows) and/or volume bias may not be sensitive enough to detect the subtle (compared to that caused by changes in the mean of the parameter field) variations caused by the spatial variability of the parameters (or the inputs) on the outlet hydrographs. Therefore, a major issue of interest is whether some alternative criterion may be able to detect the variations, however subtle, between the modeled responses using spatially distributed and lumped representations of catchment properties and inputs. We are not aware of other studies that have addressed this issue in detail.

[12] Since our primary goal is to examine the problem of spatial parameter identifiability, we will employ a synthetic approach that allows the problems of model structural and data errors to be avoided. What remains, therefore, are the primary issues of informativeness of the data used for model identification and the method(s) used to detect that information. As in our previous studies we will use a typical distributed conceptual rainfall-runoff model structure to investigate these issues, and as such the results should prove to be generalizable to other models having similar structure. As with all synthetic studies, the results and conclusions should be interpreted and generalized with caution, and should provide useful guidance to the design of further studies using real data. The work is performed in the context of phase 2 of the Distributed Model Intercomparison Project. In section 2 we briefly discuss the data, catchment and the model used for the study; further details are given in our previous work [*Pokhrel et al.*, 2008; *Pokhrel and Gupta*, 2010] and by *Smith et al.* [2004b]. Sections 3 and 4 present the details of this study, and section 5 summarizes our findings and their implications.

2. Data, Catchment, and Model Used in This Study

2.1. Data and Catchment

[13] This study was conducted on two DMIP 2 study basins: the Illinois River basin straddling the Oklahoma-Arkansas border and the Blue River basin in southern Oklahoma (Figure 1). The Illinois has a shape that is typical and representative of catchments in the United States, while the Blue is unusual in that it is long and narrow and therefore provides an interesting case for implementation of a distributed model. The gently sloping 1645 km^2 Illinois River basin (elevation 202 to 486 m) is composed mostly of silty clay and silty clay loam. The 1233 km^2 Blue River basin (elevation 154–427 m) is a narrow, elongated river valley composed mostly of clay and loam (for details, see *Smith et al.* [2004b]). Average annual rainfall at Illinois and Blue is 1175 and 1036 mm, respectively, and average annual flow at their outlets is 302 and 176 mm, respectively, giving long-term runoff ratios of approximately 0.26 and 0.17.

[14] Spatially distributed precipitation estimates are derived from a combination of Next Generation Weather Radar (NEXRAD) and rain gage data, and quality controlled by the NWS. The distributed precipitation data are available at temporal resolution of 1 h and were aggregated to a six hourly time step (to be used in a six hourly distributed model). The data has a spatial resolution of approximately 4×4 km^2 over a rectilinear HRAP (Hydrologic Rainfall Analysis Project) grid with 100 units over the Illinois and 78 units over the Blue. Potential evaporation estimates are based on annual free water surface evaporation maps and mean monthly station data (see V. Koren et al., http://www.cbrfc.noaa.gov/present/rdhm/pet_plan_1998.pdf) available from the DMIP Web site (http://www.weather.gov/oh/hrl/dmip/2/evap.html), adjusted to account for the effects of vegetation using land cover correction factors.

2.2. Spatially Distributed Catchment Model

[15] The DHMUA model is a research version of the Hydrology Lab Distributed Hydrologic Model (HL-DHM), programmed in MATLAB™ (version 7.0.1, http://www.mathworks.com) to run at a 6-hourly time step on a personal computer. The model operates over a rectilinear HRAP grid at a spatial resolution of approximately 4×4 km^2. The water balance component consists of the Sacramento Soil Moisture Accounting Model (SACSMA) [*Burnash et al.*, 1973] having 16 parameters and 6 state variables, applied to each grid cell. The routing component has been simplified by removing within-grid hillslope routing and by using the two-parameter Muskingum approach (the parameters being spatially constant) for channel routing instead of kinematic wave; *Pokhrel* [2007] compared the streamflow response generated by DHMUA and HLDHM (both using KAP estimates) at the outlet and two interior points within the Blue River basin and found the impact of this modification to be insignificant. Simulated streamflow responses are computed at the catch-

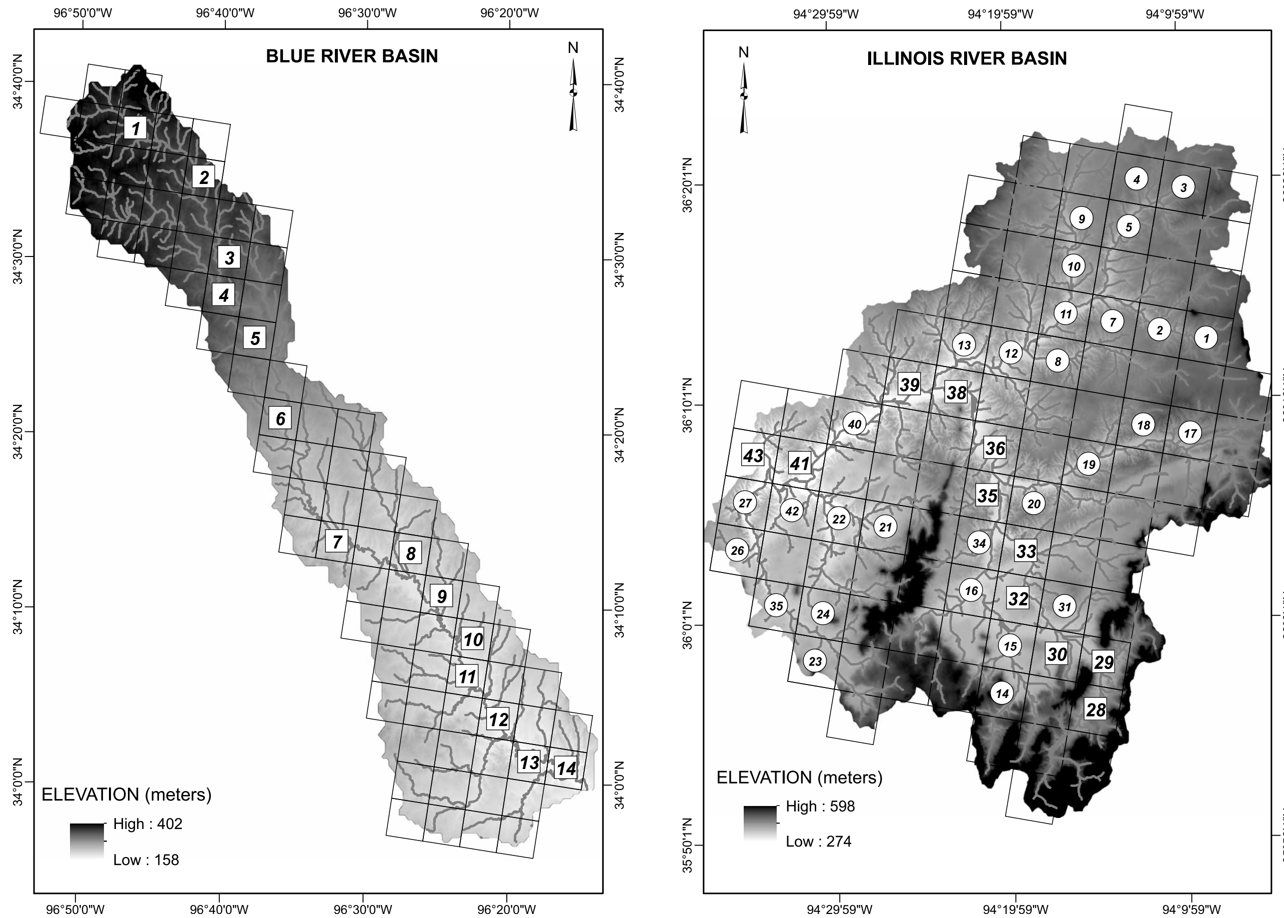

Figure 1. The study basins, showing the location of each node and the model grid overlay: (left) Blue River basin and (right) Illinois River basin. Each number (either enclosed in a circle or square box) shows the location of the node where the streamflow response was generated by the model. Although sensitivity analysis was conducted over all the nodes, this study reports results generated only at nodes that are marked by the square boxes.

ment outlet, and at several upstream locations along the river network (Figure 1).

[16] In this model, 11 of the parameters are treated as spatially distributed (Table 1), and their values were derived using the *Koren et al.* [2000] approach (hereafter called Koren a priori parameters, or KAP) described briefly below. The remaining five parameters were treated as spatially uniform; SIDE and RSERV were fixed at values specified by the NWS [*Reed et al.*, 2004], while ADIMP, PCTIM, RIVA, and the two routing parameters were adjusted to provide a close match to the observed streamflow at the outlet.

[17] The Koren methodology uses information available from soil and land cover data to derive spatially consistent parameter estimates on the basis of a series of physically based and empirical relations. The method associates the tension water capacity to "available water" and free water capacity to soil "gravitational water," which are calculated as the difference between the field capacity and wilting point and the difference between porosity and the field capacity, respectively. The values of soil porosity, field capacity and the wilting point are derived from the STATSGO soil database [*Natural Resources Conservation Service*, 1994]. The method assumes the soil column to be divided into two (upper and lower) layers. To calculate the thickness of upper soil zone it is assumed that the free water reservoir of the upper zone is empty and an initial rain abstraction (amount of water stored in the soil surface after a rainfall event prior to the start of a runoff process) satisfies the capacity of the upper soil storage under average soil moisture conditions. The initial rain abstraction is calculated using the Natural Resources Conservation Service based "curve number" methodology [*McCuen*, 1982]. The depth of the lower soil zone is taken as the difference between total soil water holding capacity (which is calculated as the sum of porosity over the entire depth) and the upper soil layer. The tension water capacity is calculated as the fraction of soil depth corresponding to the "available water." Other parameters are calculated either using physically based equations, utilizing the information available from soil hydraulic properties, or empirical relations. For additional details on the Koren approach to estimating the prior parameters of the SACSMA model, see *Koren et al.* [2000, 2003].

[18] Figure 2 shows the frequency distribution for each of the spatially distributed parameters in the two basins; in

Table 1. Sacramento Soil Moisture Accounting Model (SACSMA) Parameters, States, and Parameter Ranges Used for Calibration

Spatially Distributed SACSMA Parameters	Description	Feasible Parameter Range	
UZTWM	upper zone tension water capacity (mm)	10–300	
UZFWM	upper zone free water capacity (mm)	5–150	
UZK	interflow depletion rate from upper layer free water storage (h^{-1})	0.1–0.8	
REXP	shape parameter of the percolation curve	1–5	
LZTWM	lower zone tension water capacity (mm)	5–500	
LZFSM	lower zone supplemental free water capacity (mm)	5–400	
LZFPM	lower zone primary free water capacity (mm)	10–1000	
LZSK	depletion rate of the lower layer supplemental free water storage (h^{-1})	0.01–0.35	
LZPK	depletion rate of the lower layer primary free water storage (h^{-1})	0.001–0.05	
PFREE	percolation fraction that goes directly to the lower free water storages	0.0–0.8	
ZPERC	ratio of maximum and minimum percolation rates	5–350	
Spatially Uniform SACSMA Parameters	**Description**	**Illinois River**	**Blue River**
RSERV	fraction of lower zone free water not transferable to lower zone tension water storage	0.3	0.3
SIDE	ratio of deep percolation from lower layer free water storages	0	0
PCTIM	permanent impervious area fraction	0.005	0.005
ADIMP	maximum fraction of an additional impervious area due to saturation	0.1	0.0
RIVA	riparian vegetation area fraction	0.02	0.03
SACSMA State Variables	**Description**		
ADIMC	tension water contents of the ADIMP area (mm)		
UZTWC	upper zone tension water contents (mm)		
UZFWC	upper zone free water contents (mm)		
LZTWC	lower zone tension water contents (mm)		
LZFSC	lower zone free supplemental contents (mm)		
LZFPC	lower zone free primary contents (mm)		

each plot the dashed line indicates the "equivalent" uniformly distributed value (computed as the arithmetic average of the distributed parameter estimates), and the range of the x axis corresponds to the feasible bounds used by the NWS [*Koren et al.*, 2003] (see Table 1). The spread of values in these plots indicates the degree of spatial variability for each KAP parameter field. Note, for example, that parameter UZK in the Blue River basin is highly variable while parameter LZFSM has relatively small variability.

3. Perturbation Analysis Studies

3.1. Methodology

[19] To establish a baseline for the studies conducted here, we first ran the model with spatially distributed precipitation and parameters fields (as described in section 2.2) for eight water years (WY) 1997 to 2004; each WY runs from October 1 to September 30. One previous year (WY 1996) was used to spin-up the state variables. This provided baseline synthetic streamflow hydrographs at the catchment outlet, and at each of the upstream points along the river. In the perturbation studies that follow, we replace either the parameter or precipitation fields with spatially uniform values (equivalent to the mean of the corresponding distributed field) and examine the impacts of those actions on the streamflow hydrographs at each location. The differences between the perturbed hydrographs (the model response using the equivalent uniform field) and the baseline hydrographs were evaluated in terms of five summary statistical measures: the normalized mean-square error (NMSE), the normalized mean-square error of the log transformed flows (NMSEL), the ratios of the long-term means (α) and standard deviations (β) of the hydrographs subtracted from 1, and the entropy-based uncertainty coefficient (UC), computed as

$$\mathrm{NMSE} = \frac{\frac{1}{n}\sum_{i=1}^{n}(Q_{Bi} - Q_{Pi})^2}{\mathrm{Var}(Q_B)} \tag{1}$$

$$\mathrm{NMSEL} = \frac{\frac{1}{n}\sum_{i=1}^{n}(\log(Q_{Bi}) - \log(Q_{Pi}))^2}{\mathrm{Var}(\log(Q_B))} \tag{2}$$

$$\alpha = 1 - \frac{\mathrm{mean}(Q_P)}{\mathrm{mean}(Q_B)} \tag{3}$$

$$\beta = 1 - \frac{\text{standard deviation}(Q_P)}{\text{standard deviation}(Q_B)} \tag{4}$$

$$\mathrm{UC} = 1 - 2 \times \frac{H(Q_B) + H(Q_P) - H(Q_B, Q_P)}{H(Q_B) + H(Q_P)} \tag{5}$$

$$H(Q_B) = -\sum_k p_k \log(p_k) \tag{6}$$

$$H(Q_P) = -\sum_j p_j \log(p_j) \tag{7}$$

$$H(Q_B, Q_P) = -\sum_{k,j} p_{kj} \log(p_{kj}) \tag{8}$$

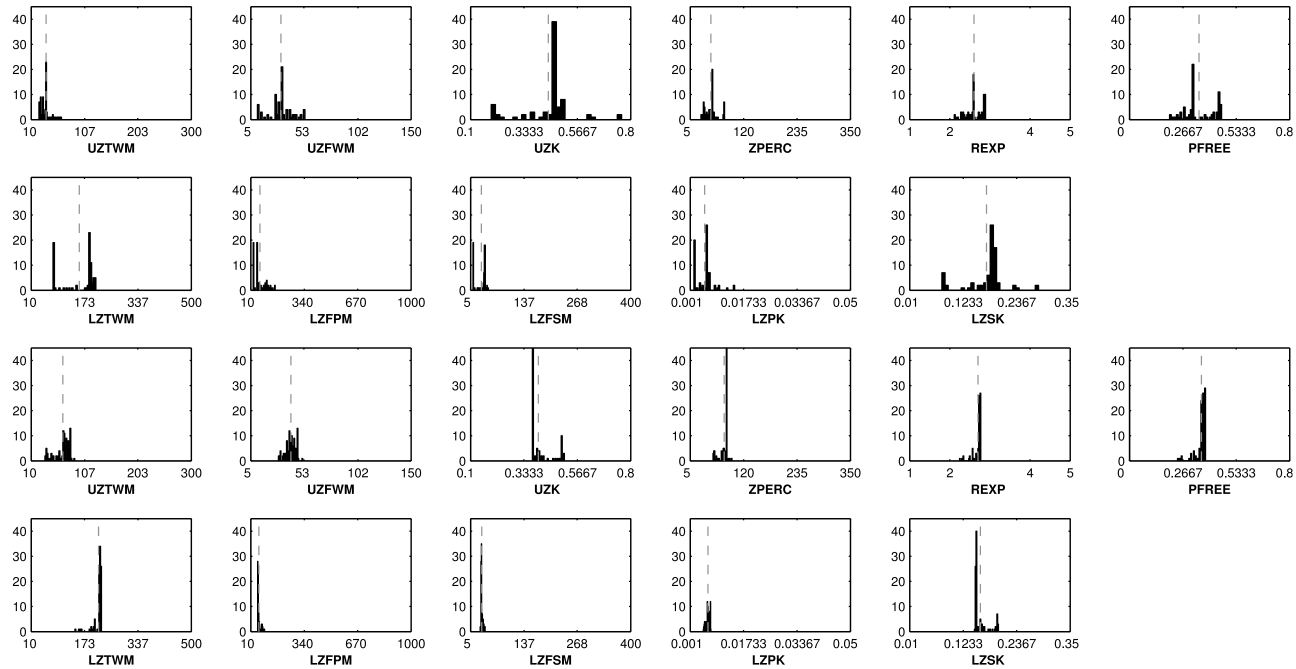

Figure 2. Parameter distributions in the Blue (first and second rows) and Illinois (third and fourth rows) river basins; the uniform parameter field is indicated by a dashed line.

where Q_B is the discharge generated using baseline conditions, Q_P is the discharge generated using a perturbation, $H(Q_B)$ is the entropy of Q_B, which represents the average information contained in observing Q_B [see *Mishra and Knowlton*, 2003], $H(Q_P)$ is the entropy of Q_P, and $i = 1$: n represents the number of time steps. To compute the entropy, we group the streamflow values into M equal mass bins so that p_k represents the probability of Q_B occurring within kth bin, p_j represents probability of Q_P occurring within jth bin, and $p_{k,j}$ represents the joint probability of Q_B occurring at kth bin and Q_P occurring at jth bin.

[20] Each measure was selected for a reason. The NMSE and NMSEL are normalized versions of statistical measures commonly used as criteria in model calibration and evaluation studies [e.g., *Pokhrel and Gupta*, 2010]. The measures have been normalized to account for differences in hydrograph variability across catchments and thereby enable better comparison of results. NMSE (or NMSEL which is equivalent to NMSE of the log transformed flow) is closely related to the well-known Nash-Sutcliff efficiency (NSE) measure (NMSE = 1 − NSE). The value of NMSE = 1 (or NSE = 0) corresponds to Q_P being a worse predictor of Q_B compared to the "no model" prediction of only using a mean (of Q_B), while NMSE = 0 would indicate a perfect match between the two. Measures α and β appear as important components in a decomposition of the *MSE* criterion [*Gupta et al.*, 2009]; they reflect signature properties of the probability distributions of the flows (commonly represented as flow duration curves, or flow exceedance probability curves) and indicate differences in water balance and hydrologic variability, respectively. In each case (α, β) a value of zero indicates no difference (in water balance, variability) between the two cases (Q_B and Q_P), while a value of ±1 indicates a 100% difference. UC measures the degree of association between two hydrographs; 1 indicates perfect association (although not necessarily equivalence) while 0 indicates no association. Unlike the linear correlation coefficient, UC measures strength of association even if nonlinear and (being based on entropy computations) is sensitive to variability at all magnitudes (while NMSE and NMSEL give differing emphases to different flow levels). We also investigated other properties of the hydrographs including rising and decaying sections [*Boyle et al.*, 2000], lag 1 autocorrelation coefficients, cross correlations [*Gupta et al.*, 2009], and properties of the model residuals, but interesting results were obtained only for the five measures presented here.

3.2. Parameter Perturbation Analysis Using A Priori Parameter Fields

[21] First we investigate the degree to which spatial variability and structure in the parameter fields has a detectable effect on the properties of the simulated streamflow hydrograph. A perturbation study was conducted in which each of the eleven spatially distributed parameter fields was replaced (one at a time) by its "equivalent" spatially uniform value, and the streamflow hydrograph for the perturbed run was compared with the baseline run.

[22] The results are shown in Figure 3; Figure 3 (top) shows the Blue, and Figure 3 (bottom) shows the Illinois. Each plot corresponds to a statistical measure with river locations (headwater to basin outlet) indicated from bottom to top and individually perturbed parameter fields indicated from left to right. An additional column (case ALLPAR) corresponds to all 11 spatially distributed parameter fields being simultaneously made uniform. The gray color scale indicates the strength of difference from the baseline hydrograph as detected by the corresponding measure; white (measure value 0.0) indicates no difference and black (measure value 1.0) indicates a significant difference. Overall, the only measure that shows significant sensitivity (greater than the 10% resolution of the plot) to spatial distribution of

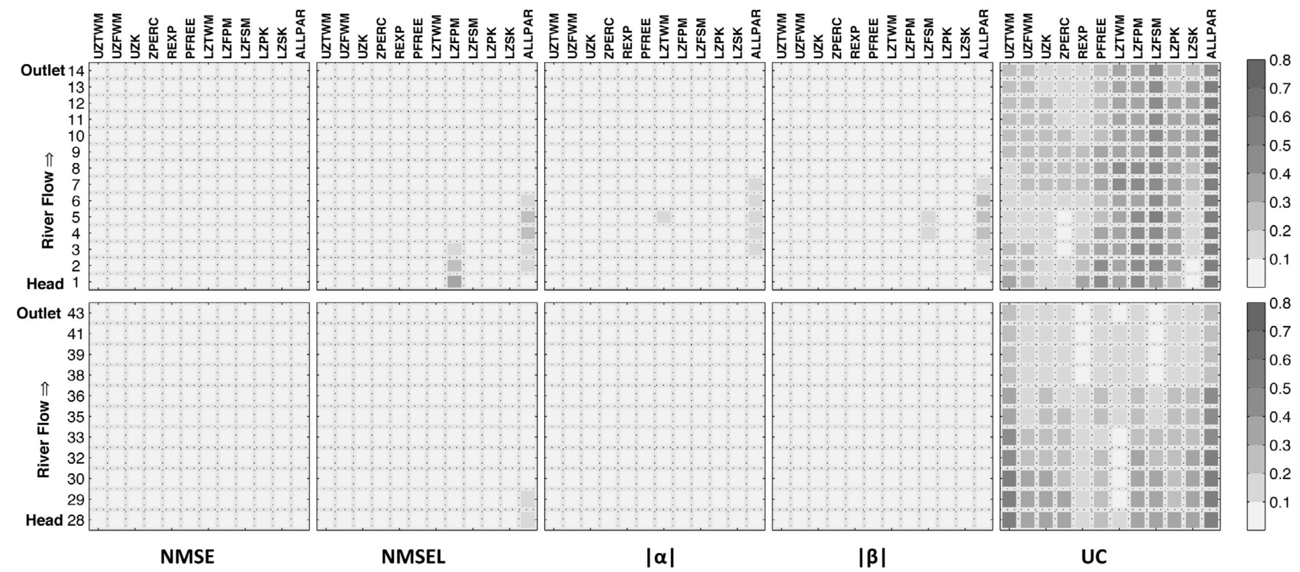

Figure 3. Parameter sensitivity analysis for (top) Blue and (bottom) Illinois river basins; case 1. For Illinois we show only results for node 43 (basin outlet) to node 28 (river head) along the main stem of the river (marked by square boxes in Figure 1).

individual parameters is UC. The other measures show some sensitivity to simultaneous perturbation of all parameters (case ALLPAR) but only at certain interior nodes and sensitivity is virtually zero at the basin outlet. Clearly, UC is the most sensitive among all the measuring criteria at all flow locations. In general, it indicates strongest sensitivity to the lower zone capacity parameters, which control the low-frequency component of catchment response.

[23] Comparing the two basins (Figures 3, top, and 3, bottom), it is clear that the Illinois is less sensitive to spatial parameter distribution (see case ALLPAR), probably because of its smaller degree of parameter variability (see Figure 2).

[24] For completeness, and to check these results, we ran three more perturbation studies, one being similar to the parameter perturbation study described above but with the precipitation fields replaced by their equivalent spatially uniform values. The other two studies were complementary to the previous cases, meaning that the baseline condition was changed to one with uniform fields and each field was then replaced (one at a time) by its spatially distributed value. The results did not add anything new and are therefore not included here.

3.3. Parameter Perturbation Analysis Using Synthetic Parameter Fields

[25] The analysis reported above indicates that basin outlet hydrographs can show relatively low sensitivity to spatial variability in the distributed parameter fields. However, the KAP parameter fields provide only a limited representation of parameter field distribution and are limited in their range of spatial variability (see Figure 2). For a more comprehensive analysis we performed a Monte Carlo study in which 2000 synthetic sets of parameter fields were randomly generated so as to preserve the spatial correlation structure (as defined by the semivariograms; see Figure 4) of the KAP parameter fields. This provided a large number of different parameter fields having realistic spatial correlation structures. By adjusting the variance and mean of each parameter field, we were able to simulate a greater degree of spatial parameter variability than with the original (KAP) fields. Note that although adjustment of the mean does not increase the variability of the parameter field directly, it does so indirectly by shifting the mean of the parameter field away from the feasible parameter bounds; e.g., if the parameter field mean is close to the bounds, the variability of the field is forced to be smaller to prevent the parameters from violating the bounds, and hence by moving the mean away from the bounds a larger parameter field variability could be achieved. In addition, varying the mean of the parameter field also better activates the "threshold" type parameters that may lack sensitivity over certain ranges of values; e.g., the upper zone surface flow parameters are activated only when upper zone tension water storage is exceeded, and hence smaller values of the upper zone tension capacity parameter result in stronger activation of the upper zone surface flow parameters.

[26] From Figure 4 we see that the KAP parameter field semivariograms for the Blue and Illinois can be modeled using either an exponential or Gaussian form, and have strong horizontal spatial structures with correlation lengths ranging from 2 to 10 grid cells (i.e., 8 to 40 km since each grid cell is approximately 4 km on a side). Using these semivariograms to generate the necessary covariance matrices (that preserve spatial correlation among the parameters), 2000 spatially correlated random parameter fields were drawn from a Normal distribution [*Rasmussen and Williams*, 2006], while varying the mean of each parameter field over 10–90% of its feasible range, and while varying the parameter coefficient of variation (CV = σ/μ) from 0.0 to 1.25. Following *Pokhrel and Gupta* [2010], a squashing function was used to prevent any of the parameters from violating the feasible parameter bounds.

[27] Figure 5 shows the results of this Monte Carlo analysis for the Blue River basin; results for the Illinois are

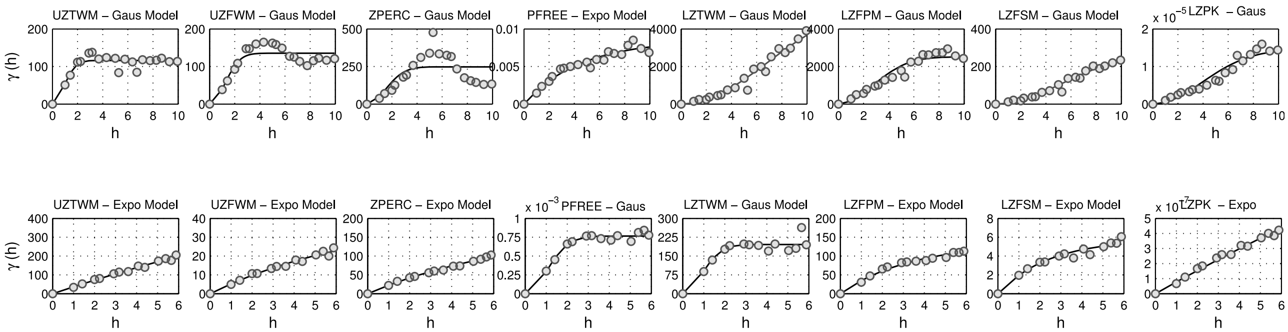

Figure 4. Variograms fitted to Koren a priori parameters in (top) the Blue River basin and (bottom) the Illinois River basin; *h* represents the horizontal lag (each unit represents a horizontal grid length of approximately 4 km), and $\gamma(h)$ is the semivariogram calculated at h.

similar (but with lower sensitivity) and are therefore omitted. Results are presented for the eight parameters (columns) showing strongest effects on the outlet hydrographs as indicated by the five measures (rows), when each parameter is perturbed (one at a time) to be spatially uniform. Each gray dot indicates one of the 2000 runs. The box plots to the right are for the case when all parameters are simultaneously perturbed to be spatially uniform (ALLPAR). We also show results for four runs generated using the actual KAP parameter fields (circles) and when increasing the variability of the KAP fields via the equation $\phi_i = \mu + (\theta_i - \mu) \times \delta$ by making δ equal to 2 (stars), 3 (diamonds), and 4 (triangles), respectively; μ is the mean of the spatial parameter field, and θ_i and ϕ_i are the KAP and correspondingly modified parameter values in the ith cell.

[28] Two things are immediately apparent. First, at the level of variability of the KAP parameter fields (CV ~ 0.25–0.5), the only measure showing significant sensitivity to spatial parameter distribution is UC (bottom row). The other measures begin to show sensitivity only when the CV exceeds 0.5, and only for some of the parameters. Second, when all parameters are simultaneously treated as spatially uniform (ALLPAR), thereby incorporating the influence of parameter interactions, the median sensitivity for measure UC is 2.5 times higher (~0.7) than for the other criteria (~0.2–0.3).

3.4. Perturbation Analysis of Both Parameter and Rainfall Fields

[29] Next, we investigate the degree to which spatial variability and structure in rainfall fields has a detectable effect on properties of the simulated streamflow hydrograph. The baseline case is the same as in section 3.2, consisting of synthetic streamflow hydrographs at the catchment outlet, and at each of the upstream points along the river, for the case of spatially distributed rainfall and parameter fields. In this study we look at two situations, one where we maintain the spatially distributed parameter fields but replace the rainfall field at each time step by its "equivalent" spatially uniform value (case PRECIP), and another where we replace both the parameter and rainfall fields by their equivalent uniform values (case BOTH). We compare these to the results of section 3.2 (case ALLPAR).

[30] Figures 6 (left) and 7 (left) show results for the Blue and Illinois, respectively. Each plot shows measure values obtained at different locations along the river from headwater to basin outlet (left to right). For the Blue it is apparent that NMSE is more sensitive to spatial variability in rainfall

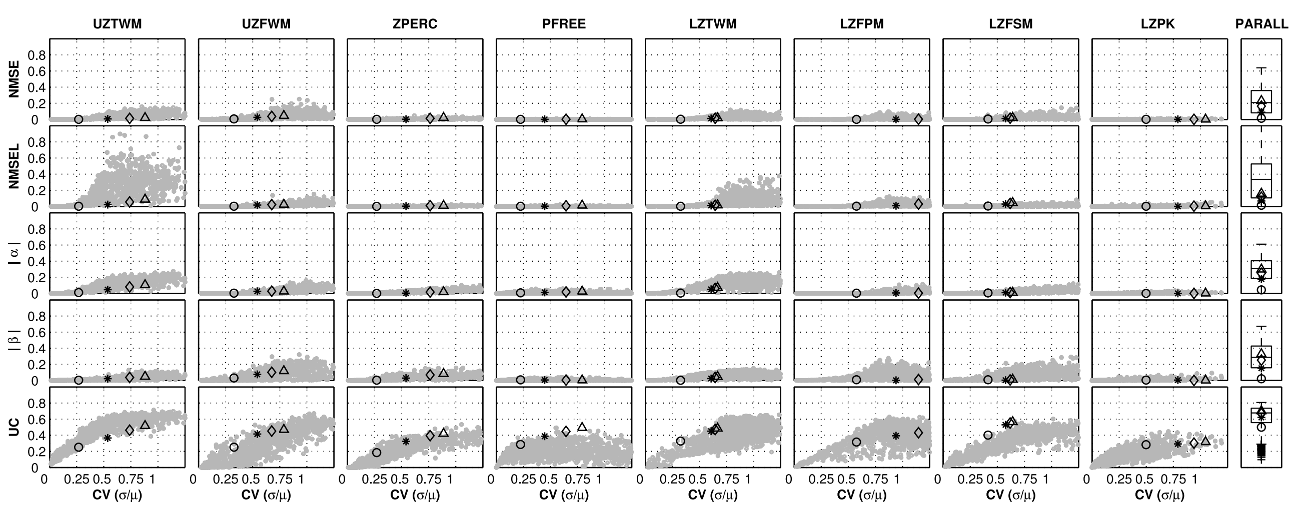

Figure 5. Results of the Monte Carlo analysis for the Blue River basin. The middle line in the box plot indicates the median, the outer lines indicate the lower and upper quartiles, the whiskers extend to 1.5 times the interquartile range, and a cross is used to denote outliers.

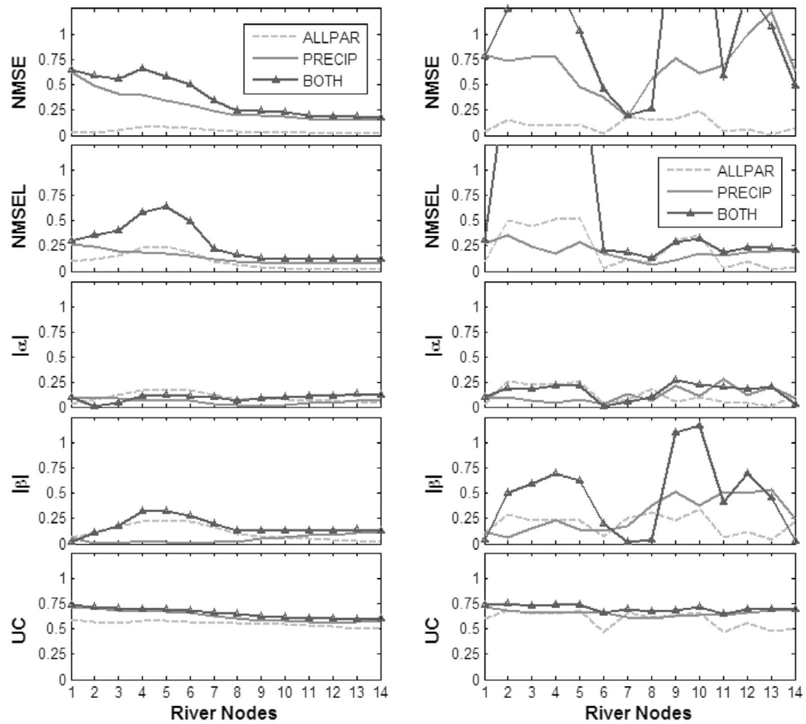

Figure 6. Sensitivity of the model to perturbation of all 11 parameters (ALLPAR), rainfall (PRECIP), and parameters and precipitation (BOTH) in the Blue River basin. (left) Results with the routing mechanism turned on and (right) results without routing.

(PRECIP) than to spatial variability in parameter fields (ALLPAR) and this sensitivity increases progressively from outlet to headwater. Interestingly, the combined effect of spatial variability in parameter and precipitation (BOTH) seems to approximately be a linear combination of the two individual effects. Note that the sensitivity remains almost

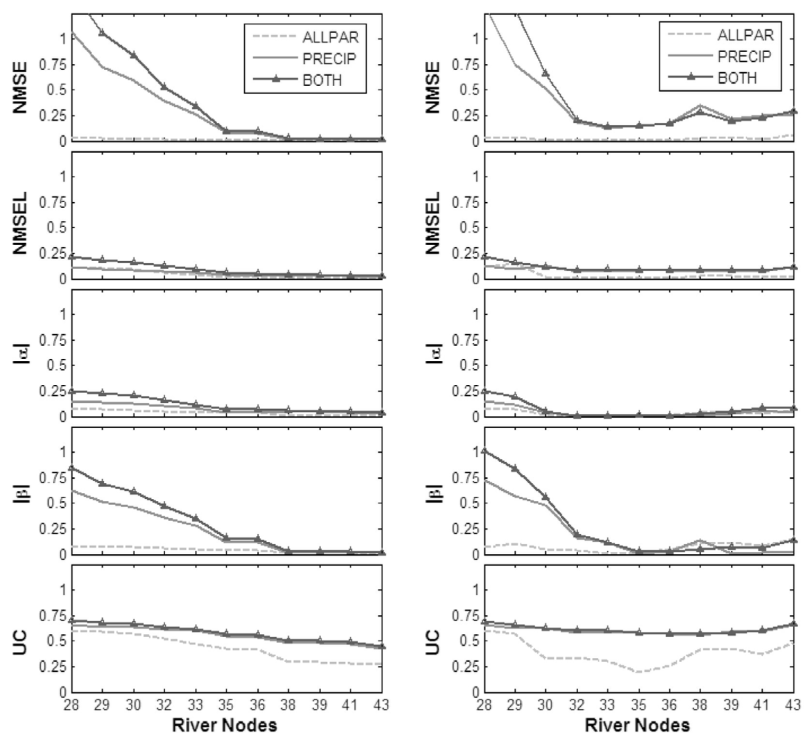

Figure 7. Sensitivity of the model to perturbation of all 11 parameters (ALLPAR), rainfall (PRECIP), and parameters and precipitation (BOTH) in the Illinois River basin. (left) Results with the routing mechanism turned on and (right) results without routing.

constant in the lower half of the basin, but increases significantly in the higher elevations. NMSEL, which is more sensitive than NMSE to changes in hydrograph recessions, shows similar sensitivity for cases PRECIP and ALLPAR. Measure α (water balance) generally shows less than 10% change, with almost no sensitivity to PRECIP close to the centroid of the basin where the rainfall events tend to be centered. Measure β (hydrograph variance) shows greater sensitivity to PRECIP than ALLPAR at the basin outlet but this sensitivity also diminishes at interior nodes. Once again, the measure showing strongest sensitivity to spatial distribution is UC, which ranges in value from 0.56 to 0.75 along the river, and the degree of sensitivity is not dramatically different among the three cases (ALLPAR, PRECIP, and BOTH). This result raises the important question as to whether the individual effects of spatial variability in parameters and precipitation can be detectable from the hydrograph.

[31] The results for the Illinois are similar (Figure 6, left), but show some additional aspects of interest. First, NMSE, NMSEL, α, and β show almost no sensitivity at the basin outlet to spatial variability in either parameters or precipitation. However, NMSE and β both show strong and increasing sensitivity to precipitation toward the upper portions of the basin. From Figure 1 we see that nodes 35 to 28 correspond to the higher and steeper elevations. There are also similar effects on NMSEL and α but these are much smaller. Clearly the structure of the catchment has a role to play here since higher intensity and more spatially variable precipitation is generally found at the higher elevations. Again UC shows strongest sensitivity, but the effects of parameter and rainfall variability do not appear to be additive in this basin.

3.5. The Information Damping Effect of River Routing

[32] The results reported in sections 3.2–3.4 indicate that conventional statistical measures such as NMSE and NMSEL, used to evaluate model performance and for calibration of parameter fields, show remarkably little sensitivity to information regarding spatial variability (in either parameters or precipitation) carried by the hydrographs. One possible reason may be that the "low-pass filter" effects of the river routing process dampen the effects of such variability en route to the basin outlet (i.e., filter out the high-frequency aspects of the signal). To investigate this, the same five statistical measures were computed at each river node with the river routing process removed. These results appear in Figures 6 (right) and 7 (right). Comparing right and left columns it is clear that the routing process plays a major role, acting to progressively reduce informativeness of the hydrograph signal from headwater to outlet, with progressively longer sections of routing having stronger damping effects. It is also clear that the nonlinear effects of combined parameter and precipitation variability are also significantly damped. In contrast, the effects of routing do not seem to strongly impact the information detection capabilities of UC, although the effects are clearly more pronounced on the Illinois than the Blue.

3.6. Summary of the Perturbation Analysis Studies

[33] The perturbation analysis results suggest several things.

[34] 1. First, spatial variability in parameters and precipitation does have a detectable impact on the properties of the streamflow hydrograph at various locations along the river, but this impact is greatly diminished by the damping and dispersive effects of routing, so much so that the effects can become quite small at the catchment outlet. When the degree of spatial variability in parameter fields is relatively small ($CV < 0.5$) the impacts are so diminished by channel routing that conventional measures such as NMSE and NMSEL are no longer able to properly detect them. In the two catchments examined, it was necessary to increase the CV of parameter variability to around 0.75 or greater before significant impacts could be detected at the catchment outlet.

[35] 2. Second, the relative impact of spatial variability in precipitation tends to be higher than that of spatial variability in the parameter fields. This is probably going to be generally true for many catchments and is likely caused by two facts, one being that the spatial CV of precipitation will typically exceed that of the parameters and the second being that the model will generally be more sensitive to percent changes in inputs (rainfall) than to percent changes in the parameters.

[36] 3. In general, the sensitivity to both parameter and precipitation variability tends to be larger in the upper portions of the catchment. This is likely caused by a combination of effects; the damping and dispersive effects are less a result of shorter channel routing lengths, and the degree of spatial variability tends to be larger in the headwater regions.

[37] 4. The uncertainty coefficient (UC), based in information theory, seems better able to detect the impacts that spatial variability can have on the streamflow hydrographs, even when these impacts are passed through the low-pass filtering effects of channel routing. As a consequence the sensitivity of this measure to spatial variability remains relatively consistent over the entire river length. One reason for this improved sensitivity is that UC measures the differences in the probability distributions of the observed and simulated hydrographs in a scale-independent manner, while conventional criteria are highly sensitive to data transformations; for catchment models MSE tends to be more sensitive to the larger errors typically associated with large flow values, whereas UC provides more even weighting to all values in the flow distribution.

4. Ability of the Measures to Distinguish Spatial Patterns in the Parameter Fields

[38] Although our results indicate that UC is more sensitive to spatial parameter variability than the other measures tested, it is still not clear whether the measure could actually be used to better inform model calibration studies. One concern is that the problem of parameter estimation is not so much one of detecting parameter variability as it is of detecting the spatial "pattern" of the variability in the parameters. To explore this issue we conducted one additional parameter perturbation experiment. As before, our baseline case consists of a model simulation using KAP spatially distributed parameter fields and spatially distributed precipitation. Next following the approach in section 3.3, we generated 1500 Monte Carlo sample parameter fields having the same mean, variance and spatial correlation structure as the KAP parameter fields. This time, in addition to mea-

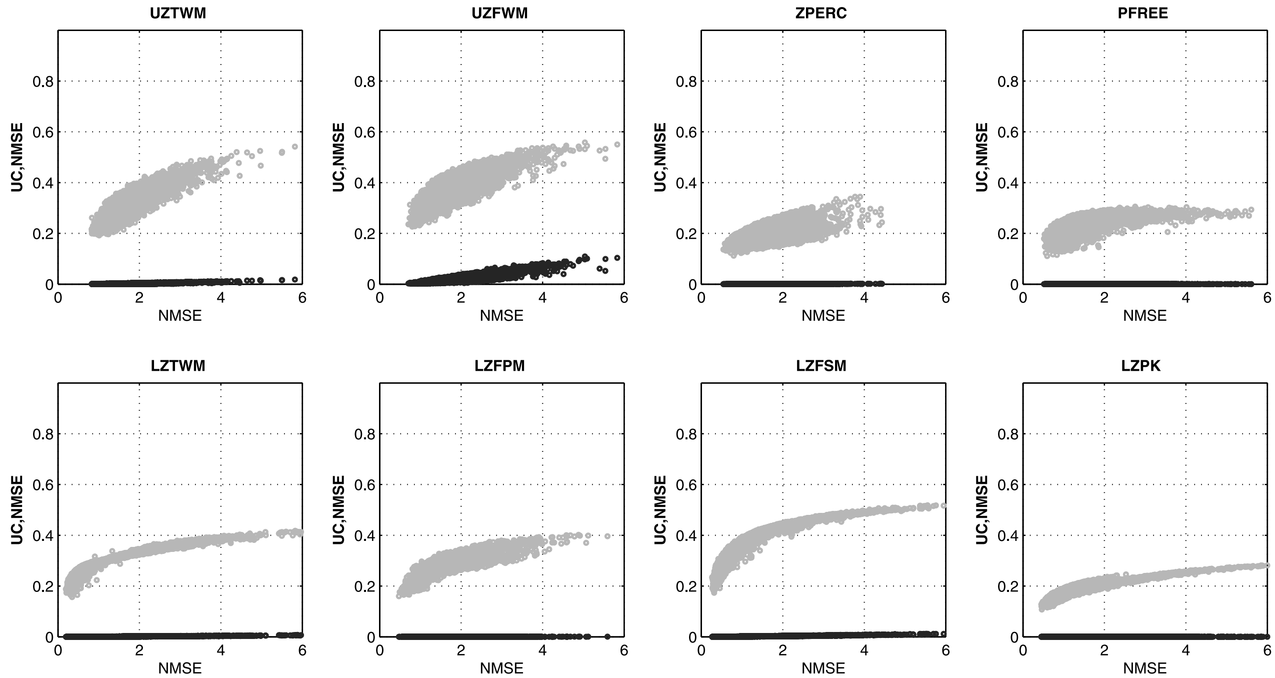

Figure 8. Sensitivity of the measures (UC and NMSE) of the difference in the spatial patterns of the parameter fields for the Blue River basin. The black dots represent the sensitivity of the model, measured by NMSE, and the gray dots represent the sensitivity measured in terms of UC. The *x* axis represents the distance of the randomly generated parameter field from KAP, measured in terms of NMSE.

suring the distance between the perturbed and baseline hydrographs (using UC), we also measure the distance between the randomly generated parameter field and the baseline (KAP) parameter fields using NMSE. In general, for UC to be potentially useful as a performance measure in calibration of spatially distributed parameter fields, we would expect its value to be low when a parameter field has a similar spatial pattern as the baseline (low NMSE) and large when the spatial pattern is dissimilar (large NMSE). Figure 8 shows the plot of model sensitivities measured by UC (gray dots) and NMSE (black dots) plotted against the differences in the spatial pattern. In general we are able to observe the expected pattern, although there is considerable scatter in the result. This result should be treated with caution because, although UC is sensitive to differences in the spatial pattern and detects small variations quite well, the degree of sensitivity decreases as the differences between parameter fields increase. This could pose an obstacle to its use for distinguishing among various spatial patterns during calibration, particularly during initial iterations when the differences in spatial patterns can be very large.

5. Conclusions and Discussion

[39] Previous attempts to calibrate distributed hydrologic models using the information in catchment outlet hydrographs, have reported that the model outlet response is not strongly sensitive to spatial variability of the parameters as indicated by conventional mean-square error (MSE) type measures, and our own studies have suggested that the overall basin mean parameter value may actually perform just as well. In this paper we have sought to understand these findings by investigating the factors that influence the sensitivity of the simulated streamflow response to spatial characteristics of the catchment (parameters and input) when only information about catchment streamflow response is available.

[40] In general, the answer to the question "Is the spatial distribution of parameters and rainfall important enough to justify their distributed representation in catchment models?" seems to be that it depends on the combined effect of two factors – the actual degree of variability of the parameter and/or rainfall field and the extent to which the hydrograph is subjected to the damping and dispersive effects of channel routing. This suggests that it might be necessary to obtain streamflow measurements at a number of gauging points along the river, spaced sufficiently close together that the dispersive effects of channel routing do not eradicate valuable information about spatial variability; that is, we cannot rely on catchment outlet hydrographs alone.

[41] Further, regarding the issue of whether some alternative measuring criterion exists that is able to detect the variations in streamflow hydrographs caused by spatial variability in the catchment properties and inputs, and consequently whether the spatial structure of parameter fields can be inferred from the information contained in the outlet hydrograph, our results appear to be mixed. The issue clearly needs more detailed investigation; while the uncertainty coefficient seems to be well suited to detecting subtle variations in a time series, in actual practice there will be many factors that give rise to such variations and it may not be possible to properly distinguish between them. In this investigation we conducted a synthetic study with no model or data error, but in practice the confounding effects of

model structure and data errors (both inputs and outputs) may act to mask our ability to detect the particular effects of spatial variability in the streamflow data. One might suspect that the answer lies, as suggested before, in the relative strengths of the different types of variability. However, as long as model structural and data errors remain larger than the hydrograph variations caused by spatial variability (then dampened by routing effects), it seems likely that attempts to calibrate spatially distributed parameter fields will be prone to failure.

[42] The only reasonable way forward therefore seems to be to insist that more and different kinds of catchment information must be exploited; examples might include spatial information about soil moisture and evapotranspiration and higher densities of streamflow gauging along the river. In the latter context, since the addition of gauging points at upstream locations can be expected to provide useful information regarding spatial processes, an important question is where such gauges should be located and how such information can best be exploited. Synthetic studies of the kind reported here can help to evaluate the potential benefits of such information for model identification. As always, we invite dialog with other investigators interested in such matters.

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References

Beven, K. (1995), Linking parameters across scales: Subgrid parameterizations and scale dependent hydrological models, *Hydrol. Processes*, *9*, 507–525, doi:10.1002/hyp.3360090504.

Beven, K. J., and G. M. Hornberger (1982), Assessing the effect of spatial pattern of precipitation in modeling streamflow hydrographs, *Water Resour. Bull.*, *18*, 823–829.

Booij, M. J. (2002), Modelling the effects of spatial and temporal resolution of rainfall and basin model on extreme river discharge, *Hydrol. Sci. J.*, *47*, 307–320, doi:10.1080/02626660209492932.

Bormann, H., L. Breuer, T. Graff, J. A. Huisman, and B. Croke (2009), Assessing the impact of land use change on hydrology by ensemble modelling (LUCHEM) IV: Model sensitivity to data aggregation and spatial (re-)distribution, *Adv. Water Resour.*, *32*(2), 171–192, doi:10.1016/j.advwatres.2008.01.002.

Boyle, D. P., H. V. Gupta, and S. Sorooshian (2000), Toward improved calibration of hydrologic models: Combining the strengths of manual and automatic methods, *Water Resour. Res.*, *36*(12), 3663–3674, doi:10.1029/2000WR900207.

Brath, A., and A. Montanari (2000), The effects of the spatial variability of soil infiltration capacity in distributed flood modeling, *Hydrol. Processes*, *14*, 2779–2794, doi:10.1002/1099-1085(20001030)14:15<2779::AID-HYP91>3.0.CO;2-X.

Brath, A., A. Montanari, and E. Toth (2004), Analysis of the effects of different scenarios of historical data availability on the calibration of a spatially distributed hydrological model, *J. Hydrol.*, *291*, 232–253, doi:10.1016/j.jhydrol.2003.12.044.

Burnash, R., R. Ferral, and R. McGuire (1973), A generalized streamflow simulation system—Conceptual modeling for digital computers, Jt. Fed. and State River Forecast Cent., Sacramento, Calif.

Carpenter, T. M., K. P. Georgakakos, and J. A. Sperfslage (2001), On the parametric and NEXRAD-radar sensitivities of a distributed hydrologic model suitable for operational use, *J. Hydrol.*, *253*, 169–193, doi:10.1016/S0022-1694(01)00476-0.

Gupta, H. V., H. Kling, K. K. Yilmaz, and G. F. Martinez-Baquero (2009), Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling, *J. Hydrol.*, *377*, 80–91, doi:10.1016/j.jhydrol.2009.08.003.

Julien, P. Y., and G. E. Moglen (1990), Similarity and length scale for spatially varied overland flow, *Water Resour. Res.*, *26*(8), 1819–1832, doi:10.1029/WR026i008p01819.

Koren, V. I., M. Smith, D. Wang, and Z. Zhang (2000), Use of soil property data in the derivation of conceptual rainfall runoff model parameters, paper presented at the 15th Conference on Hydrology, Am. Meteorol. Soc., Long Beach, Calif.

Koren, V., M. Smith, and Q. Duan (2003), Use of a priori parameter estimates in the derivation of spatially consistent parameter sets of rainfall-runoff models, in *Calibration of Watershed Models*, *Water Sci. Appl. Ser.*, vol. 6, edited by Q. Duan et al., pp. 239–254, AGU, Washington, D. C.

Krajewski, W. F., V. Lakshmi, K. P. Georgakakos, and C. J. Subashi (1991), A Monte Carlo study of rainfall sampling effect on a distributed catchment model, *Water Resour. Res.*, *27*(1), 119–128, doi:10.1029/90WR01977.

McCuen, R. (1982), *A Guide to Hydrologic Analysis Using SCS Methods*, Prentice-Hall, Englewood Cliffs, N. J.

Merz, B., and A. Bárdossy (1998), Effects of spatial variability on the rainfall runoff process in a small loess catchment, *J. Hydrol.*, *212–213*, 304–317, doi:10.1016/S0022-1694(98)00213-3.

Mishra, S., and R. G. Knowlton (2003), Testing for input-output dependence in performance assessment models, paper presented at IHLRWM 2003, Am. Nucl. Soc., Las Vegas, Nev., 30 March to 12 April.

Naden, P. S. (1992), Spatial variability in flood estimation for large catchments: The exploitation of channel network structure, *Hydrol. Sci. J.*, *37*, 53–71, doi:10.1080/02626669209492561.

Nicótina, L., E. Alessi Celegon, A. Rinaldo, and M. Marani (2008), On the impact of rainfall patterns on the hydrologic response, *Water Resour. Res.*, *44*, W12401, doi:10.1029/2007WR006654.

Nielsen, D. R., J. W. Biggar, and K. T. Ech (1973), Spatial variability of field-measured soil-water properties, *Hilgardia*, *42*(7), 215–259.

Natural Resources Conservation Service (1994), State soil geographic (STATSGO) database: Data use information, *Misc. Publ. 1492*, U.S. Dep. of Agric., Fort Worth, Tex.

Obled, C., J. Wedling, and K. Beven (1994), The sensitivity of hydrological models to spatial rainfall patterns: An evaluation using observed data, *J. Hydrol.*, *159*, 305–333, doi:10.1016/0022-1694(94)90263-1.

Ogden, F. L., and P. Y. Julien (1993), Runoff sensitivity to temporal and spatial rainfall variability at runoff plane and small basin scales, *Water Resour. Res.*, *29*(8), 2589–2597, doi:10.1029/93WR00924.

Philip, J. R. (1957a), The theory of infiltration: 1. The infiltration equation and its solution, *Soil Sci.*, *83*, 345–358, doi:10.1097/00010694-195705000-00002.

Philip, J. R. (1957b), The theory of infiltration: 2. The profile at infinity, *Soil Sci.*, *83*, 435–448, doi:10.1097/00010694-195706000-00003.

Philip, J. R. (1957c), The theory of infiltration: 3. Moisture profiles and relation to experiment, *Soil Sci.*, *84*, 163–178, doi:10.1097/00010694-195708000-00008.

Philip, J. R. (1957d), The theory of infiltration: 4. Sorptivity and algebraic infiltration equations, *Soil Sci.*, *84*, 257–264, doi:10.1097/00010694-195709000-00010.

Philip, J. R. (1957e), The theory of infiltration: 5. The influence of the initial moisture content, *Soil Sci.*, *84*, 329–340, doi:10.1097/00010694-195710000-00008.

Philip, J. R. (1958a), The theory of infiltration: 6. Effect of water depth over soil, *Soil Sci.*, *85*, 278–286, doi:10.1097/00010694-195805000-00008.

Philip, J. R. (1958b), The theory of infiltration: 7, *Soil Sci.*, *85*, 333–337, doi:10.1097/00010694-195806000-00007.

Pokhrel, P. (2007), Estimation of spatially distributed model parameters using a regularization approach, M.S. thesis, Dep. of Hydrol. and Water Resour., Univ. of Ariz., Tucson.

Pokhrel, P., and H. V. Gupta (2010), On the use of spatial regularization strategies to improve calibration of distributed watershed models, *Water Resour. Res.*, *46*, W01505, doi:10.1029/2009WR008066.

Pokhrel, P., H. V. Gupta, and T. Wagener (2008), A spatial regularization approach to parameter estimation for a distributed watershed model, *Water Resour. Res.*, *44*, W12419, doi:10.1029/2007WR006615.

Rasmussen, C. E., and C. K. I. Williams (2006), *Gaussian Processes for Machine Learning*, MIT Press, Cambridge, Mass.

Reed, S., V. Koren, M. Smith, Z. Zhang, F. Moreda, D.-J. Seo, and DMIP Participants (2004), Overall Distributed Model Intercomparison Project results, *J. Hydrol.*, *298*, 27–60, doi:10.1016/j.jhydrol.2004.03.031.

Reeves, M., and E. E. Miller (1975), Estimating infiltration for erratic rainfall, *Water Resour. Res.*, *11*(1), 102–110, doi:10.1029/WR011i001p00102.

Saghafian, B., P. Y. Julien, and F. L. Ogden (1995), Similarity in catchment response: 1. Similarity in rainstorms, *Water Resour. Res.*, *31*(6), 1533–1541, doi:10.1029/95WR00518.

Seyfried, M. S., and B. P. Wilcox (1995), Scale and the nature of spatial variability: Field examples having implications for hydrologic modeling, *Water Resour. Res.*, *31*(1), 173–184, doi:10.1029/94WR02025.

Sherman, L. K. (1943), Comparison of *F*-curves derived by the methods Sharp and Holtan and of Sherman and Mayer, *Eos Trans. AGU*, *24*, 465–467.

Singh, V. P. (1997), Effect of spatial and temporal variability in rainfall and watershed characteristics on stream flow hydrograph, *Hydrol. Processes*, *11*, 1649–1669, doi:10.1002/(SICI)1099-1085(19971015)11:12<1649::AID-HYP495>3.0.CO;2-1.

Sivapalan, M., and E. F. Wood (1986), Spatial heterogeneity and scale in the infiltration response of catchments, in *Scale Problems in Hydrology*, edited by V. K. Mupta, I. Rodriguez-Iturbe, and E. F. Wood, pp. 81–106, D. Reidel, Norwell, Mass.

Smith, M. B., V. I. Koren, Z. Zhang, S. M. Reed, J.-J. Pan, and F. Moreda (2004a), Runoff response to spatial variability in precipitation: An analysis of observed data, *J. Hydrol. Amsterdam*, *298*, 267–286, doi:10.1016/j.jhydrol.2004.03.039.

Smith, M. B., D.-J. Seo, V. I. Koren, S. Reed, Z. Zhang, Q.-Y. Duan, S. Cong, F. Moreda, and R. Anderson (2004b), The Distributed Model Intercomparison Project (DMIP): Motivation and experiment design, *J. Hydrol.*, *298*, 4–26, doi:10.1016/j.jhydrol.2004.03.040.

Smith, R. E., and R. H. B. Hebbert (1979), A Monte Carlo analysis of the hydrologic effects of spatial variability of infiltration, *Water Resour. Res.*, *15*(2), 419–429, doi:10.1029/WR015i002p00419.

Smith, R. E., and J.-Y. Parlange (1978), A parameter-efficient hydrologic infiltration model, *Water Resour. Res.*, *14*(3), 533–538, doi:10.1029/WR014i003p00533.

van Werkhoven, K., T. Wagener, P. M. Reed, and Y. Tang (2008), Rainfall characteristics define the value of streamflow observations for distributed watershed model identification, *Geophys. Res. Lett.*, *35*, L11403, doi:10.1029/2008GL034162.

Wilson, C. B., J. B. Valdes, and I. Rodriguez-Iturbe (1979), On the influence of the spatial distribution of rainfall on storm runoff, *Water Resour. Res.*, *15*(2), 321–328, doi:10.1029/WR015i002p00321.

Woolhiser, D. A., and E. C. Goodrich (1988), Effect of storm rainfall intensity patterns on surface runoff, *J. Hydrol.*, *102*, 335–354, doi:10.1016/0022-1694(88)90106-0.

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