

## J5.8

### DISTRIBUTED MODEL FLOW SENSITIVITIES TO INPUT AND PARAMETRIC UNCERTAINTY: CASE STUDIES FOR THREE WATERSHEDS IN THE CENTRAL U.S.

Theresa M. Carpenter<sup>1</sup>, Konstantine P. Georgakakos<sup>1,2</sup>, and Jason A. Sperflage<sup>1</sup>

<sup>1</sup> Hydrologic Research Center, San Diego, CA

<sup>2</sup> Scripps Institution of Oceanography, UCSD, La Jolla, CA

#### 1. INTRODUCTION

Distributed hydrologic modeling is a very active area of hydrologic research as investigators develop and enhance methods to incorporate expanding databases of spatial and temporal data. Spatially distributed precipitation estimates from weather radar is one source of information that has increased such research interest. Another is provided by various static spatial databases such as digital terrain elevation, land cover and land use, and soils databases, which serve as a basis for providing distributed model parametric information. However, significant uncertainty exists in both the values of radar rainfall estimates, and in model parameter estimates developed from existing spatial databases. This paper examines how such uncertainty can impact model simulated streamflow.

The distributed model used, HRCDHM, allows for distributed precipitation input from real-time databases of the U.S. National Weather Service WSR-88D radars, along with model parameters distributed within a given watershed based on soils information from the STATSGO database. Using data from the National Weather Service Office of Hydrology Distributed Model Intercomparison Project (DMIP), a case-study analysis was developed for the Illinois River, Blue River, and Elk River watersheds in parts of Arkansas, Oklahoma, and Missouri. The basins include NWS operational river forecast locations at: the Illinois River at Watts, OK (1644 km<sup>2</sup>); the Illinois River at Tahlequah, OK (2483 km<sup>2</sup>); the Blue River at Blue, OK (1232 km<sup>2</sup>); and the Elk River at Tiff City, MO (2258 km<sup>2</sup>). For each of these basins, a sensitivity analysis was performed to examine the impact of input and parametric uncertainty on simulated flows. A Monte Carlo simulation framework is used for the analysis. Sensitivity results are summarized in terms of

normalized measures of the range of flows computed in the Monte Carlo simulations for selected events and for various sub-catchment outlets within each watershed. The results indicate a consistent trend for scale-dependence of flow sensitivity to input uncertainty.

#### 2. MODEL OVERVIEW

HRCDHM is a catchment-based model, with model components based on operationally available databases and current operational models used by the U.S. National Weather Service (NWS). These components are applied on a sub-catchment basis within a given watershed of interest and include: (a) ingest of radar precipitation estimates from the NEXRAD radar and the computation of sub-catchment mean areal precipitation based on the gridded radar precipitation estimates; (b) soil moisture accounting and runoff generation using the Sacramento Soil Moisture Accounting model for each sub-catchment; (c) upland channel routing for streams within each sub-catchment; and (d) channel routing for the main stem rivers using kinematic routing.

A GIS is used to ingest various digital terrain and land cover databases, to delineate watershed and sub-catchment boundaries, and to compute geometric properties of the sub-catchments that are used in the hydrologic computations. Channel cross-sectional characteristics, necessary for the routing computations, are determined through regional regression relationships with the GIS-computed sub-catchment properties. Additional databases on soil characteristics and land cover can be utilized to define parameters of the hydrologic model components. For more details on model formulation, the interested reader is referred to Carpenter et al. (2001).

#### 3. CASE STUDY APPLICATION

The application basins of the Illinois, Blue and Elk Rivers fall within the umbrella of the NWS operational radar at Tulsa, OK. An archived

---

\* *Corresponding author address:* Theresa M. Carpenter, Hydrologic Research Center, 12780 High Bluff Dr, Suite 250, San Diego, CA 92130; e-mail: TCarpenter@hrc-lab.org

database of radar precipitation data (hourly resolution, Stage III product), along with hourly resolution observed streamflow records for each forecast location, was available from the DMIP website for the period 5/1993-5/1999. These records were used to develop watershed models for the four forecast locations listed in Table 1 (and in Section 1), and to calibrate the parameters of the hydrologic model components of HRCDHM. These were calibrated over the historical period with hourly resolution by assuming uniform parameters within each watershed. Once satisfied with the calibration of uniform parameters, several soil model parameters were spatially distributed within the respective watershed based on soil properties extracted from the STATSGO database (NRCS, 1994). The soil properties extracted were the available water content, permeability, and soil texture classification. Average soil properties were computed for each sub-catchment and for various depth layers consistent with the soil model. These soil properties were then related to the following model parameters: storage capacities (upper soil zone), interflow rate, and percolation parameters. The distribution of sub-catchment model parameters was based on a simple scaling of the calibrated parameter by the sub-catchment average soil property normalized by the average soil property within the watershed, and is given by:

$$PARAM_i = \frac{SOIL\_PROP_i}{\sum SOIL\_PROP_i / N} * PARAM_{cal}$$

**Table 1.** Study Watersheds and Calibration Statistics

ID #	Area*	Avg Sub. Area	TS <sup>+</sup>	CCOR	Bias
BLUO2	1232	59	49882	0.86	1.4%
TIFM7	2258	86	51372	0.82	0.7%
WTTO2	1644	84	52615	0.87	-0.4%
TALO2	2483	84	51049	0.88	1.8%

# Watershed Identifiers:

BLUO2: Blue River at Blue, OK

TIFM7: Elk River at Tiff City, MO

WTTO2: Illinois River at Watts, OK

TALO2: Illinois River at Tahlequah, OK

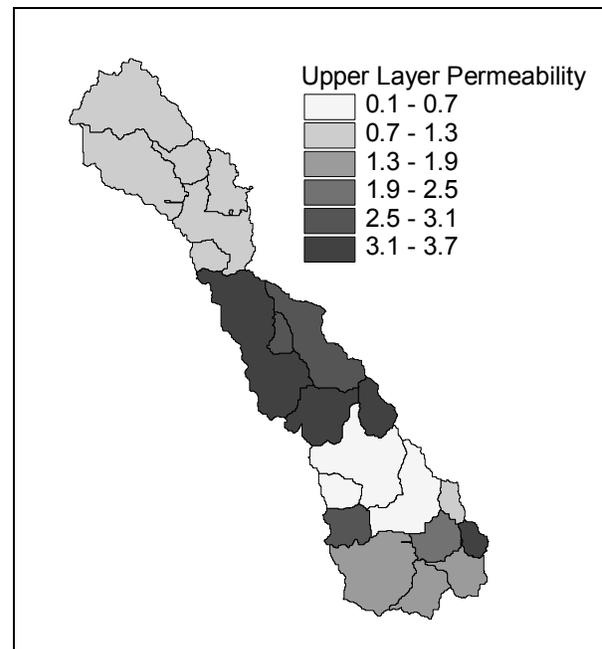
\* Drainage area at gauge location, given in [km<sup>2</sup>]

+ Number of time steps (TS) vary by location due to missing observations

where  $PARAM_i$  is the distributed parameter value for sub-catchment  $i$ ,  $PARAM_{cal}$  is the calibrated

uniform parameter value,  $SOIL\_PROP_i$  is the sub-catchment average soil property, and  $\sum SOIL\_PROP_i / N$  represents the average soil property within the watershed. This method provides a consistent and objective method for distributing model parameters based on observed soil characteristics that could be applied to any watershed within the United States. Figure 1 presents the variation of the permeability property for the Blue River watershed. For this basin, there are distinct regions, or bands, of relatively high and low values. The other study watersheds tend to be more uniform in soil distribution. Generally, the range in soil properties within the sub-catchments of a given watershed was nearly as large as the range in the average sub-catchment soil properties across the watershed. This range was used similarly in defining the parametric uncertainty.

Table 1 includes statistics between the hourly observed and simulated flows over the entire calibration period for the simulation with distributed parameters. As evident in the Table, HRCDHM was able to reproduce the observed hourly flows well for each location.



**Figure 1.** Average sub-catchment permeability in mm/hr for the Blue River, Oklahoma.

#### 4. SENSITIVITY ANALYSIS

Studied is the sensitivity of simulated flows to uncertainties in both parametric and rainfall input. The results in this section complement the results presented in Carpenter et al. (2001), which examined flow sensitivities to uncertainty in selected model parameters (applied individually) and in radar-rainfall input for a single watershed. In this section, the flow sensitivity to uncertainty in multiple model parameters (applied simultaneously) and in radar-rainfall input is examined for the four case study watersheds.

##### 4.1 Characterization of Parametric Uncertainty

The generic formulation for parametric uncertainty is given by:

$$PARAM_i^* = \mu_{pi} + \varepsilon_{pi}$$

where  $\mu_{pi}$  is the model parameter of sub-catchment  $i$ ,  $\varepsilon_{pi}$  is a uniformly distributed error in the range  $[\alpha_L, \alpha_U]$ , and  $PARAM_i^*$  is the sub-catchment model parameter with uncertainty. The methodology described to determine spatially-distributed model parameters was applied and the range in soil properties from the STATSGO database was used to determine the error bounds  $[\alpha_L, \alpha_U]$  for each sub-catchment. This parametric uncertainty was applied simultaneously to the following soil model parameters: upper soil zone capacity parameters, interflow parameters, and the percolation parameters.

##### 4.2 Characterization of Rainfall Uncertainty – Uniform case

Precipitation input given in terms of mean areal precipitation (MAP) values for each sub-catchment. Characterizing the error in radar rainfall in terms of mean areal precipitation at various scales is difficult given the lack of numerous precipitation observation stations needed to establish a “ground truth”. Therefore, uncertainty in precipitation input was defined in two ways. The first assumes no knowledge of the rainfall error structure, and the degraded sub-catchment MAP has a simple additive noise:

$$P_e = P_o * (1 + \alpha).$$

For this case,  $P_e$  is the degraded, or with uncertainty, sub-catchment MAP,  $P_o$  is the sub-catchment MAP based on observed radar

precipitation, and  $\alpha$  is random error. The value of  $\alpha$  is selected from a uniform distribution in the range  $[-0.5, +0.5]$ . Thus the sub-catchment MAP has 50% uncertainty bounds. Note that uncertainty is introduced only for non-zero MAP; therefore no precipitation error is added during dry periods.

##### 4.3 Characterization of Rainfall Uncertainty – Exponential case

The second definition of precipitation uncertainty follows the relationship introduced by Krajewski and Georgakakos (1985):

$$P_e = P_o * 10^\varepsilon$$

where, again,  $P_e$  is the degraded sub-catchment MAP, and  $P_o$  is the “observed” sub-catchment MAP. The error term,  $10^\varepsilon$ , assumes knowledge of the structure of the errors. The value of  $\varepsilon$  is selected from a uniform distribution in the range  $[-0.2, +0.2]$ , thus yielding a ratio of degraded MAP to observed MAP of 0.6 to 1.6. Again, no precipitation error is for zero-MAP values.

The uncertainty, defined through the above characterizations, was introduced in the hydrologic modeling within a Monte Carlo simulation framework. Random perturbations in the sub-catchment rainfall and/or parameters values were introduced at each sub-catchment and at each time step over selected events in the historical period. Events were selected during the historical record (5/1993-5/1999) based on the occurrence of a flow event at the basin outlet and covered a period extending approximately two days prior to the rising of the hydrograph until the basin flow condition was reached following the peak. However, uncertainty was introduced approximately two months prior to each event so that a stable initial condition in soil moisture was reached before the events. Durations of the selected event events ranged from 7 to 15 days, and in some cases, included multiple peaks. The total number of events, and uncertainty cases analyzed are given in Table 2.

#### 5. DISCUSSION OF RESULTS

For each study watershed and each event, a total of 100 Monte Carlo simulations were performed. An example of the Monte Carlo output is illustrated in Figure 2, showing 100 flow traces

**Table 2.** Number of Events Selected for Each Study Watersheds and Uncertainty Cases

	BLUO2	TIFM7	WTTO2	TAL02
# of Events	25	27	28	29

*Uncertainty Cases for all Watersheds:*

- Parametric
- Rainfall Input – Uniform Distribution
- Rainfall Input – Exponential Distribution
- Combined – Parametric & Input (Uniform)
- Combined – Parametric & Input (Exponential)

for the Illinois River at Watts, along with 2 interior watershed locations. The Figure shows the ensemble flow traces (subplot (a)), and specific cumulative flow curves (subplot (b)) for the case of combined parametric/uniform rainfall uncertainty and for the event of September 24-October 1, 1996. For the cumulative flow plot, the “nominal” case is for a model run with “nominal” distributed parameters and with no uncertainty. For each of the study watersheds, similar graphics were produced for the outlet location and for at least one other interior watershed location.

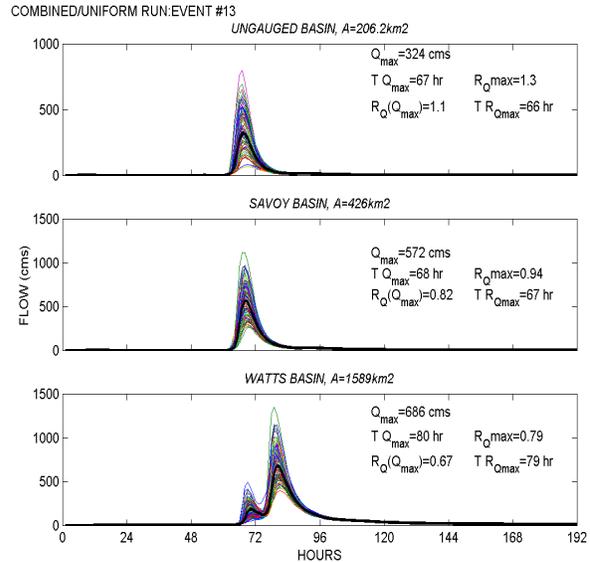
The results are summarized in terms of a measure of the variability in the ensemble of simulated flow traces. This measure, termed  $R_C$ , is defined as the difference between the 10<sup>th</sup> and 90<sup>th</sup> percentile cumulative flow, normalized by the median cumulative flow:

$$R_C = \frac{R_{C90} - R_{C10}}{R_{C50}}$$

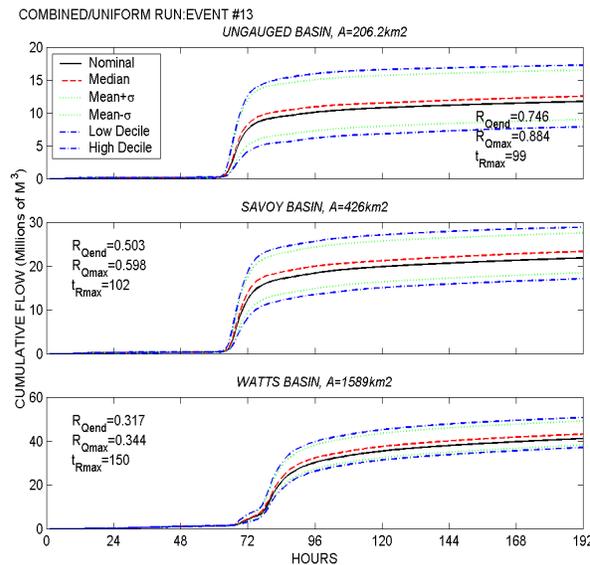
The measure was computed for each time step over the selected events, and the maximum value was reported for each event and each uncertainty case for selected locations. The values are included in subplot (b) for the example given in Figure 2. The variability in  $R_C$  values among events is substantial, ranging from nearly 0.0 to 0.8 for individual locations. However, a tendency for larger  $R_C$  values to occur for smaller drainage areas emerged. The trend was observed often, as shown in Figure 2, but not for every event or for each basin. Deviations from this trend occurred more frequently for the Blue River basin and for the cases including rainfall uncertainty.

Average values of  $R_C$  were computed over all events for each location and for each uncertainty case. In Figure 3, the average  $R_C$  values are

plotted against drainage area for three uncertainty cases: parametric, combined parametric and input with the uniform distribution for input uncertainty, and combined with the exponential distribution for input uncertainty. A line of best fit is included for each case. The trend of decreasing sensitivity with drainage area on average is clear and appears consistent over the study watersheds.

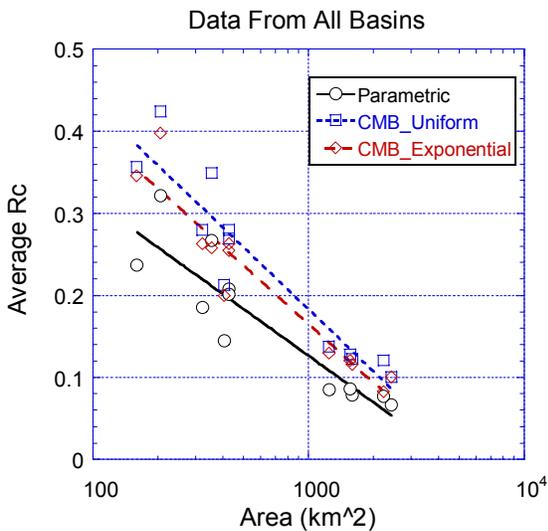


(a) Ensemble for traces



(b) Cumulative flow plots

**Figure 2.** Example sensitivity output for the Illinois River at Watts, Oklahoma watershed for combined parametric and rainfall uncertainty.



**Figure 3.** Average Sensitivity measure plotted against drainage area for all basins and for three uncertainty cases.

The difference between the parametric uncertainty case and the combined cases results from the additional uncertainty in rainfall input. The combined uncertainty increases the sensitivity of flow simulations over the case of parametric uncertainty alone. The difference in flow sensitivity between the two definitions of rainfall uncertainty is relatively small, with the uniform uncertainty case producing slightly higher sensitivity values on average. In both input uncertainty cases, the flow sensitivity is greater for the smaller sub-catchments when compared to the parametric uncertainty case, as indicated by the steeper slope of the fitted trends.

## 6. CONCLUSIONS

This paper briefly presents representative results from an extensive sensitivity analysis regarding the impact of input and parametric uncertainty on flow simulations from a distributed model. The particular distributed model is based on current operational models and databases, and allows for distributed model parameters and input forcing on a sub-catchment basis. A Monte Carlo framework is used to generate ensembles of flow simulations for given input and/or parametric uncertainty definitions for selected events and for each of the study basins. The sensitivity results are summarized in terms of the variability of the simulated flow ensembles at various locations within each watershed.

The flow sensitivity shows a consistent scale-dependent trend, with smaller basins exhibiting higher sensitivity than larger basins for a given uncertainty definition. Including uncertainty in both input and parameters increases the sensitivity over parametric or input (not shown) uncertainty alone. It also appears that the incremental sensitivity to input uncertainty, in addition to parametric uncertainty, is larger for smaller sub-catchments.

The work presented in this paper is part of ongoing research. Active extensions of this work involve: (a) the inclusion of uncertainty in channel cross-sectional characteristics; (b) development of a sub-catchment scale dependent relationship for precipitation uncertainty to represent the aggregation of radar-pixel scale uncertainty to the scale of the subbasins; and (c) an intercomparison of the sensitivity results of this distributed model with those obtained from a spatially-lumped model, based on the same hydrologic model component.

## 7. ACKNOWLEDGEMENTS

The research reported herein has been supported by an ongoing cooperative agreement between HRC and the Hydrology Laboratory (HL) of the U.S. National Weather Service. The collaboration and comments of Drs. Michael Smith, Victor Koren, and Seann Reed of HL have been invaluable throughout this research effort. The watershed locations presented in this work were selected based on HRC's participation in the HL-organized Distributed Model Intercomparison Project (DMIP).

## 8. REFERENCES

- Carpenter, T.M., Georgakakos, K.P., Sperflage, J.A., 2001, On the Parametric and NEXRAD-Radar Sensitivities of a Distributed Hydrologic Model Suitable for Operational Use. *J. Hydrology*, 254, 169-193.
- Krajewski, W.F., Georgakakos, K.P., 1985, Synthesis of Radar Rainfall Data. *Water Resources Research*, 21, 764-768.
- NRCS (Natural Resources Conservation Service), 1994, State Soil Geographic (STATSGO) Data Base: Data Use Information. *Miscellaneous Publ. 1492*, US Department of Agriculture, Fort Worth, TX.