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Distributed model flow sensitivity to uncertainty in radar-rainfall input

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Abstract The aim of the current research is to assess the sensitivity of the range of flow simulations produced by a distributed hydrological model, suitable for use in an operational environment, under various definitions of uncertainty in the radar rainfall estimates. Monte Carlo sensitivity analysis is used, sampling from various assumed distributions of mean areal precipitation error, and the variation in resulting ensembles of flow simulations is measured using a normalized range of 10% high minus 10% low flows. The results show that the average flow ensemble range over all events in a given sub-catchment possesses significant spatial-scale dependence for all assumed radar rainfall uncertainty characterizations.

Key words distributed hydrological model; ensemble flow forecasts; radar rainfall data

INTRODUCTION

The widespread implementation of weather radar has been accompanied by increased interest and research into the development and application of hydrological models that can use to advantage the high spatial and temporal resolution of the precipitation estimates from the radars. Such distributed hydrological models, several of which are summarized in Ogden *et al.* (2001), allow for spatially-distributed precipitation input and to varying degrees, spatially distributed parametric input. Often, digital databases of terrain elevation, soils, and land use characteristics are used in defining the spatial distribution of parametric input. Although more complex than traditional spatially-lumped hydrological models, distributed models have the potential to provide additional insight on hydrological conditions, such as soil moisture and streamflow, at locations without existing flow observations. However, significant uncertainty exists both in radar rainfall estimates obtained from radar reflectivity, and in hydrological parameters derived from available spatial databases, which exhibit great spatial heterogeneity. How do these uncertainties affect the output of distributed models? Does such an effect vary for different locations within a given watershed?

This paper examines the influence of uncertainty in radar rainfall estimates on distributed hydrological model simulations under operational environment data conditions. The model HRCDHM (Hydrologic Research Center Distributed Hydrologic Model) was applied to four rivers in the central United States. The study watersheds ranged in area from approximately 1000 km^2 to 2500 km^2. For distributed modelling, sub-catchments were defined within each study watershed of area in the range 45–85 km^2. HRCDHM was developed as a transitional step between existing operational hydrological models, which are spatially-lumped in precipitation and parametric input, and future distributed hydrological models. It is built upon model components that are adaptations of existing operational models, and features a GIS link to allow for ease of data ingest. The model is shown to reproduce observed flows well for all the case study watersheds under the assumption of no uncertainty in the input radar rainfall.

This paper presents a brief description of the model and study watersheds, followed by a discussion of the sensitivity analysis framework with explicit uncertainty characterization. The sensitivity analysis output is summarized in terms of flow variability for several locations within each study watershed. Conclusions and potential future studies are discussed in the final section of the paper.

MODEL OVERVIEW

HRCDHM is a catchment-based model. The hydrological model components are applied on a sub-catchment basis within a given watershed of interest. These components include: (a) ingest of radar precipitation estimates from the US NWS operational weather radar (WSR-88D, also called NEXRAD) and 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 based on geomorphic consideration; and (d) channel routing for the main stem rivers using kinematic routing.

HRCDHM is linked with a GIS to ingest digital terrain databases, to delineate watershed and sub-catchments boundaries, and to compute geometric properties of the sub-catchments that are used in the hydrological computations, e.g. sub-catchment drainage area, length, and slope. Channel cross-sectional characteristics, which are necessary for the routing computations, are determined through regional regression relationships with the GIS-computed sub-catchment properties. Additional databases of soil characteristics and land cover are utilized to define parameters of the hydrological model components. The use of a specific soils database in estimating the distribution of model parameters for the study watersheds will be described in the following section. For more details on model formulation the interested reader is referred to Carpenter *et al.* (2001).

CASE STUDY BASINS

This study focused on several watersheds within the south-central US, which fall under the umbrella of coverage of the NEXRAD radar at Tulsa, Oklahoma. The river basins include: the Blue River in south-central Oklahoma; the Illinois River in eastern Oklahoma and western Arkansas; the Baron Fork in Oklahoma; and the Elk River in Missouri. The Elk River watershed lies northeast of the Illinois River basin, which falls directly north of the Baron Fork. The Blue River lies to the south and away from the other basins and differs from the others in its fairly narrow, elongated shape. The land surface of all of the watersheds is a mixture of agricultural/pasture lands and forest, with small variations of soil properties across each watershed. Generally, the

Table 1 Study watersheds and calibration statistics.

Basin	Area (km^2)*	Avg sub. area (km^2)	of TS+	CCOR	Bias
Blue R, Blue OK	1232	59	49882	0.86	1.4%
Baron Fork, Eldon OK	795	45	52530	0.87	3.2%
Elk R, Tiff City MO	2258	86	51372	0.82	0.7%
Illinois R, Watts OK	1644	84	52615	0.87	–0.4%
Illinois R, Tahlequah OK	2483	84	51049	0.88	1.8%

*Drainage area at gauge location.

+Number of time steps varies by location due to missing observations.

terrain is mildly sloping, with silty-loam soils. The drainage area ranges from 1000 to 2500 km^2. The catchment delineation yielded sub-catchments with average sizes of the order of 45–85 km^2.

For the application of HRCDHM, outlet locations with existing flow observations were selected for each river basin. Using the GIS, the watershed boundaries for these locations, along with a sub-catchment delineation level, were determined. The locations and drainage areas are summarized in Table 1. An archive of the operational precipitation estimates from the Tulsa radar, along with historical observed flow records with hourly resolution, were available for the period May 1993–May 1999. Using these records, the parameters of the hydrological soil-channel model component of HRCDHM were calibrated over the historical period with hourly resolution for each of the five watersheds. The model parameters were calibrated assuming uniform parameters within each watershed. Once satisfied with the calibration, several soil model parameters were spatially distributed within the watershed based on properties of the soils from available databases.

Specific soil properties were extracted from the STATSGO database (NRCS, 1994) and related to parameters of the Sacramento model. The soil properties 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 Sacramento model definition of an upper and lower soil zone. 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 ($PARAM_i$) was based on a simple scaling of the calibrated parameter (based on uniform parameters, $PARAM_{cal}$), by the sub-catchment average soil property ($SOIL\_PROP_i$) normalized by the average soil property within the watershed ($\Sigma SOIL\_PROP_i/N$):

$$PARAM_i = \frac{SOIL\_PROP_i}{\sum SOIL\_PROP_i / N} * PARAM_{cal} \tag{1}$$

This provides a consistent and objective method for distributing model parameters based on observed soil characteristics. As the STATSGO database has national coverage, this method could be applied to any watershed within the United States.

Table 1 includes statistics between the hourly observed and simulated flows over the entire calibration period for the simulation with distributed parameters. Due to fairly homogeneous soil properties, the statistics for the uniform parameter case were similar to those presented in Table 1. As evident in the statistics, HRCDHM was able to reproduce the observed hourly flows well for each location.

SENSITIVITY ANALYSES

Precipitation input in the model is 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:

$$P_e = P_o \times (1 + \alpha) \tag{2}$$

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 α is random error. The value of α is selected from a uniform distribution in the range [–0.5, +0.5]. Thus the sub-catchment MAP has 50% uncertainty bounds. This uncertainty definition is termed "uniform" in the following discussion.

The second definition of precipitation uncertainty follows an exponential relationship (Krajewski & Georgakakos, 1985):

$$P_e = P_o \times 10^{\varepsilon} \tag{3}$$

where, again, P_e is the degraded sub-catchment MAP, and P_o is the "observed" sub-catchment MAP. The error term, 10^{ε}, assumes knowledge of the structure of the errors. The value of ε is selected from a uniform distribution in the range [–0.2, +0.2], thus yielding a ratio of degraded MAP to observed MAP of 0.6–1.6. This uncertainty definition is term "exponential" in the following discussion.

To assess the impact of such precipitation uncertainty on flow simulations, a Monte Carlo simulation framework was employed. Random perturbations in the sub-catchment precipitation values were introduced given the uncertainty definitions above. These perturbations were applied at each sub-catchment and at each time step over selected events in the historical period. Uncertainty was introduced only for non-zero precipitation, and therefore, no precipitation error is added during dry periods. Event dates were selected within the May 1993–May 1999 time period based on the occurrence of a flow event at the basin outlet. Using the simulated flows at the basin outlet, events were selected, starting approximately two days prior to the rising of the hydrograph, and extend until the basin flow condition was reached following the peak. Thus, events ranges from seven to 15 days in length, and in some cases, included multiple peaks. Given the proximity of the basins and types of storms common in the region, there was a significant overlap of events in the basins, with a total of 25–30 events selected for each watershed. In the sensitivity runs, uncertainty in precipitation input was introduced approximately two months prior to the start of each event to allow adjustment of initial conditions for the model soil water, and continued through each event.

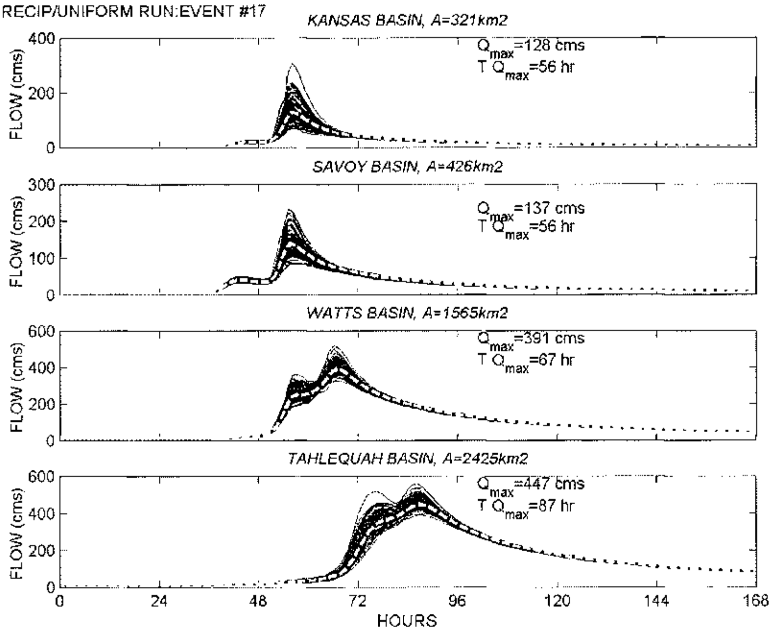

Fig. 1 Ensemble flow traces (100) generated by the Monte Carlo simulation methodology for each of four locations within the Illinois River watershed with outlet at Tahlequah and for the event of 19–25 February 1997. This is for uniform radar rainfall uncertainty. The nominal simulation is shown with the dashed white lines. $Q_{\max}$ and $T_{Q\max}$ denote the peak flow magnitude and timing for the nominal simulations.

For each watershed and each event, a total of 100 Monte Carlo simulations were performed. An example of the Monte Carlo output is illustrated in Fig. 1, showing 100 flow traces for the Illinois River at Tahlequah location, along with three interior watershed locations. For each of the five study watersheds listed in Table 1, similar graphics were produced for the outlet location and at least one other interior watershed location. The results were then 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 90th and 10th percentile cumulative flow, normalized by the median cumulative flow:

$$R_C = \frac{R_{C90} - R_{C10}}{R_{C50}} \tag{4}$$

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 variability in R_C values among events is substantial, ranging from nearly 0.0 to 0.6 for individual locations. However, a tendency for larger R_C values to occur for smaller drainage areas emerged. The trend was observed often, but not for every event or for each basin. Deviations from this trend occurred more frequently for the Blue River basin.

An average value of R_C was computed over all events for each location. These average R_C values are plotted against drainage area for each uncertainty case (uniform

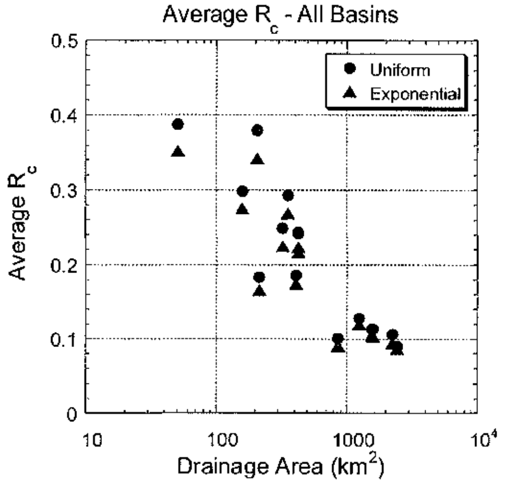

Fig. 2 Average flow ensemble range, R_C, as a function of drainage area for all watershed locations. ●: uniform mean areal rainfall uncertainty, ▲: exponential mean areal rainfall uncertainty.

and exponential) in Fig. 2. The plot shows that this trend of decreasing sensitivity with drainage area holds on average over all events and over all study watersheds. The plot also indicates that on average, the uniform uncertainty case produces higher sensitivity in ensemble range than the exponential uncertainty case.

CONCLUSIONS AND FUTURE WORK

This paper presents results of a sensitivity analysis of a catchment-based distributed hydrological model to uncertainty in rainfall input. The hydrological model allows for both distributed precipitation input and distributed hydrological model parameters, and for this work, the model is applied to five watersheds in the central United States. With calibration, and assuming no uncertainty in the input, the model is able to reproduce the historical observed flows quite well.

The sensitivity analysis was performed in a Monte Carlo framework, for selected events in each watershed. Two definitions of the rainfall uncertainty were used: one assuming no knowledge on the structure of precipitation errors, and the second, assuming the error structure has an exponential form. For each study watershed and each event, a total of 100 Monte Carlo simulations were performed for each uncertainty distribution. The sensitivity results were summarized in terms of an average measure of the flow ensemble range for several watershed locations. These average measures reveal a decreasing trend in normalized flow ensemble range as drainage area increases. This new finding is indicative of the ability of larger watersheds to act as low pass filters to precipitation input uncertainty, and it complements the already well known finding that large watersheds act as low pass filters on high-frequency temporal rainfall variability. This finding is consistent with that of earlier work by the authors (Carpenter *et al.*, 2001), which examined fewer locations and events.

An on-going research effort refines the uncertainty models by introducing rainfall uncertainty at the radar-pixel scale, as opposed to at the sub-basin MAP scale as presented in this work. Effort has begun to examine the relationship of rainfall uncertainty introduced at each radar pixel and the resulting MAP uncertainty for varying sized sub-basins and for various spatio-temporal dependence assumptions of the pixel-scale radar rainfall error for these case study watersheds. Application of the methodology presented in this work to other geographic locations and possibly other distributed hydrological model structures is warranted and should be attempted.

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