

The effects of radar-derived rainfall uncertainties on forecasts from a distributed hydrological model

JONATHAN J. GOURLEY & BAXTER E. VIEUX

School of Civil Engineering and Environmental Science, University of Oklahoma, Norman, Oklahoma 73019, USA

jonathan.gourley@ngsl.noaa.gov

Abstract The advent of weather radar has provided the potential to estimate rainfall accurately at high spatial and temporal resolutions. When these estimates are input to a distributed hydrological model, forecasts of streamflow may be used to anticipate, and thus mitigate, the potential hazards associated with a flash flood. In hydrological modelling, forecast uncertainty has traditionally been a function of the uncertainty in the model parameters, and in some cases the model structure. The study presented here uses the physics-based, distributed *r.water.fea* hydrological model with modifications to address the impact of uncertainties in the input rainfall estimates on streamflow predictions using an extension of the Generalized Likelihood Uncertainty Estimation methodology. The ensemble modelling approach allows us to evaluate the accuracy of different rainfall algorithms independently at the scale of an integrating watershed. The study plan and some initial results are presented.

Key words distributed hydrological model; ensemble hydrological prediction; parameter estimation; radar quantitative precipitation estimation; rainfall uncertainty

INTRODUCTION

It is well known that the accuracy of streamflow predictions from a hydrological model is heavily dependent on the accuracy of the rainfall inputs. Several efforts are underway (e.g. Gourley *et al.*, 2002) to improve quantitative precipitation estimation (QPE) by understanding the situations in which radar estimates can be erroneous and utilizing data from multiple sensors (e.g. infrared satellite, raingauges, numerical weather model output, and lightning flashes). As QPE algorithms are being formulated from emerging radar technologies such as polarization diversity, it is vital to the developers to know the error characteristics associated with the estimates. Traditionally, this has been done by comparing the remotely-sensed QPEs to raingauges at collocated grid points. In addition to the measurement errors associated with raingauges, it has been noted that the sampling sizes between a typical radar pixel and a raingauge orifice differ by about eight orders of magnitude (Droegemeier *et al.*, 2000). A methodology is proposed herein that provides the framework to evaluate potential QPE improvements at the scale of application, a watershed. In addition, the probabilistic approach enables uncertainty estimates or confidence intervals to be assigned to the predicted hydrological variables.

BACKGROUND

A model calibration methodology has been devised that is based upon the premise that multiple combinations of parameter values may yield acceptable simulations of the system, and thus the likelihood or probability of a given set of parameters producing characteristic system behaviour is desired. The generalized likelihood uncertainty estimation (GLUE) method (Beven & Binley, 1992) has been shown to provide an assessment of the uncertainty in hydrological predictions resulting from uncertainty in the model parameters. This model-ensemble approach provides the framework to reduce the number of parameter sets by rejecting those that yield behaviour that are not characteristic of the physical system. In this sense, it is used for model calibration. It is recommended in Beven & Binley (1992) and in Freer *et al.* (1996) that the different parameter sets should be allowed to interact with different model structures and different precipitation inputs. Presently, there is a lack of information regarding the error characteristics associated with radar QPEs in relation to hydrological prediction accuracy. As pointed out in Droegemeier *et al.* (2000), hydrological forecast uncertainty cannot be reasonably assessed until the uncertainty in the rainfall observations has been determined *a priori*. Entekahbi *et al.* (2002) identify the precipitation inputs as one of the major limitations to improved hydrological predictability. The study reported herein focuses on the influence of uncertainty in radar-derived QPEs on hydrological prediction accuracy of streamflow. In doing so, a methodology is devised to provide a consistent framework to compare the relative accuracy of different precipitation inputs at the scale of an integrating watershed.

DATA AND STUDY AREA

The study undertaken utilizes radar-derived precipitation estimates from a rainfall event that resulted in significant flow in the Blue River near Blue, Oklahoma, USA, beginning on 12 November 1994. Hourly rainfall estimates were obtained from the National Weather Service—Arkansas Basin River Forecast Center for a 12-day period. The rainfall estimates are derived from radar reflectivity data (using $Z = 300R^{1.4}$) and applied as a mosaic onto a 4×4 km² grid. A domain-wide mean field bias using raingauge data is applied to the estimates on an hourly basis. For the purpose of this paper, a single event is examined in order to highlight the proposed methodology of evaluating the effects of differing precipitation inputs on hydrological simulations. Future research will extend the methodology described herein to additional types of multisensor quantitative precipitation estimates, other basins, and a series of rainfall events. The goal of this is to be able to use a model of streamflow at the watershed scale to verify precipitation estimation techniques.

The hydrological simulations are performed using a modified version of the University of Oklahoma's *r.water.fea* model (Vieux & Gauer, 1994; Vieux, 2001). The model is a distributed parameter, deterministic model that formulates runoff generation and routing using conservation equations on an event basis. The parameters used in the model are distributed in space and are derived from ancillary data that are then adjusted. The Ordered Physics-based Parameter Adjustment (OPPA) calibration method described by Vieux & Moreda (2002) employs scalars to adjust parameter

maps. A majority of the ancillary data are freely available for most basins in the US in a geographical information system (GIS) format.

Observations of streamflow are needed for the evaluation component of this study. Hourly measurements of discharge at the outlet of the Blue River basin were obtained from the US Geological Survey (USGS) for the 12-day simulation period. The Blue River basin drains about 1200 km². The headwaters of the basin are about 80 km away from the nearest weather radar (KTLX located near Oklahoma City), while the basin outlet is over 200 km away.

METHODOLOGY

The ensemble methodology discussed herein inputs precipitation estimates to a distributed hydrological model to do the following:

- (a) evaluate the relative performance of different precipitation inputs based on the observed and simulated basin hydrological response and
- (b) assess the uncertainty caused by model parameterization by computing 90% simulation bounds for each input separately.

While the method is equally applicable to different sources of QPE from radar, satellite, raingauge, or combinations, the method is applied here to radar along with a scalar multiplier characteristic of a mean-field bias. The probabilistic approach yields an ensemble of results by examining the entire parameter space, thus avoiding the need to recalibrate the model for each input.

The ensemble procedure can accommodate parameters or inputs that have known ranges and/or distributions. If no information is known *a priori* about the parameter distributions, then a uniform distribution can and will be assumed. For application on the Blue River basin, parameter values for saturated hydraulic conductivity, Manning's roughness coefficient and the degree of initial soil saturation are distributed spatially. Thus, in order to allow the parameters to vary, a multiplier (the same type of scalar used in OPPA) is applied to each of the distributed parameter maps, adjusting the magnitude while preserving the spatial variation. The multipliers for saturated hydraulic conductivity and Manning's roughness coefficient vary from 50%, 75%, 100%, 133%, to 200% of their calibrated values. The initial degree of soil saturation varies from 30% (dry) to 70% (moist) in increments of 10%. The radar-derived precipitation estimates are also perturbed from 50%, 75%, 100%, 133%, to 200% of their given, deterministic values. For purposes of demonstrating the proposed evaluation methodology, the precipitation inputs are treated as if they are from different precipitation algorithms after the multipliers have been applied. Several different inputs that are truly independent could be utilized here instead of applying a bias factor to one algorithm as is done in this example. A number of hydrological simulations are then performed by uniform random sampling across the entire parameter space.

At this point, $5 \times 5 \times 5$ (= 125) hydrological simulations have been performed using all unique combinations parameter values within their specified ranges for each of the five different precipitation inputs. The next step requires the computation of observed hydrological variables. We have chosen to analyse the total volume of water discharged at the basin outlet as objective functions expressed as depth over the

watershed, the time at which the maximum discharge was realized, and the peak discharge throughout the 12-day event. The likelihood measure chosen to determine the accuracy of each simulation is the difference between the simulated and observed variables mentioned above. The errors are computed for each simulation performed and are normalized such that the sum of all errors for a given variable equals one. This normalization satisfies the conditions required for a discrete probability distribution. Histograms may now be plotted for the different precipitation inputs perturbed by a scalar multiplier. Future tests will involve precipitation inputs independently derived using various multisensor sources. For the purpose of this demonstration, the precipitation input is perturbed using scalar multipliers from 50% to 200% of the initial value. As shown in the next section, the computed error histograms reveal the impact of altering the precipitation inputs on all three objective variables. Moreover, the probability densities permit the calculation of 90% simulation bounds and thus provide a measure of uncertainty.

RESULTS

The histograms for the simulated errors in the hydrological variables for the five different precipitation inputs are shown in Figs 1–3. The observed basin-averaged flow depth throughout the event was 34.0 mm, the maximum discharge was observed to be $206.7 \text{ m}^3 \text{ s}^{-1}$, and the time of peak flow occurred at 5520 min. The histograms of the error in simulated basin-averaged flow depth and maximum discharge shown in Figs 1 and 2 indicate the expected result that increasing the magnitude of the rainfall inputs results in over-predictions of the two simulated outputs. Nonlinearity of the runoff response is evident. More importantly, the approach demonstrated is able to identify an optimal QPE calibration factor relying on streamgauge observations. The most probable rainfall multiplier that minimizes volume error is 0.75. Because the NWS has

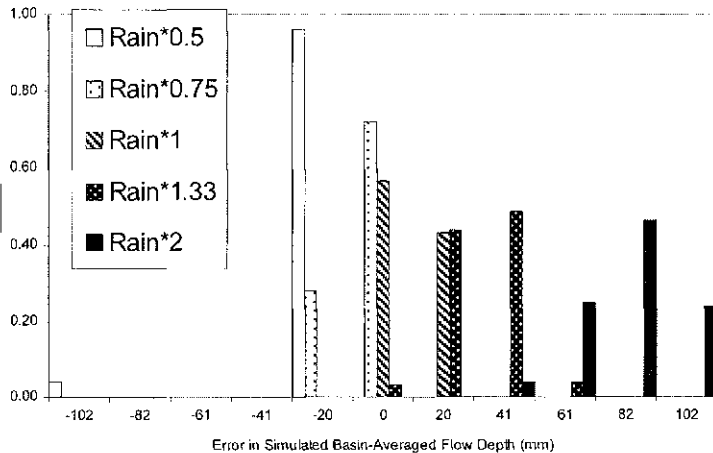


Fig. 1 Relative frequency histogram of the error between simulated minus observed basin-averaged flow depth (in mm). The patterned bars correspond to the different rainfall inputs varied from 50% (rain*0.5) to 200% (rain*2) of their default values. Observed basin-averaged flow depth was 34.0 mm.

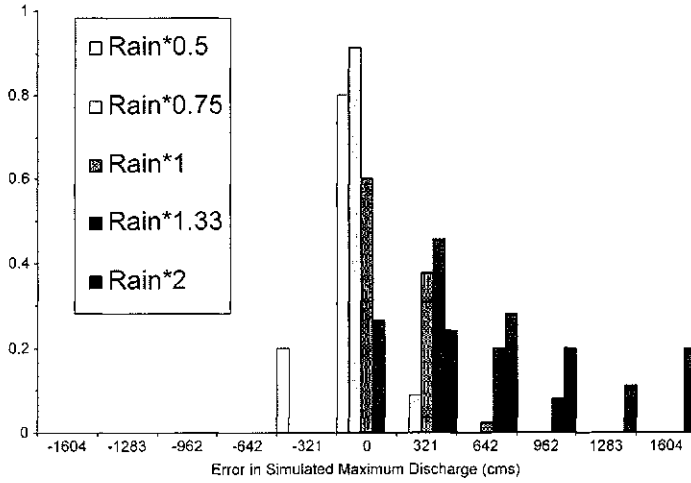


Fig. 2 Error computed as simulated minus observed maximum discharge ($m^3 s^{-1}$). Observed maximum discharge was $206.7 m^3 s^{-1}$.

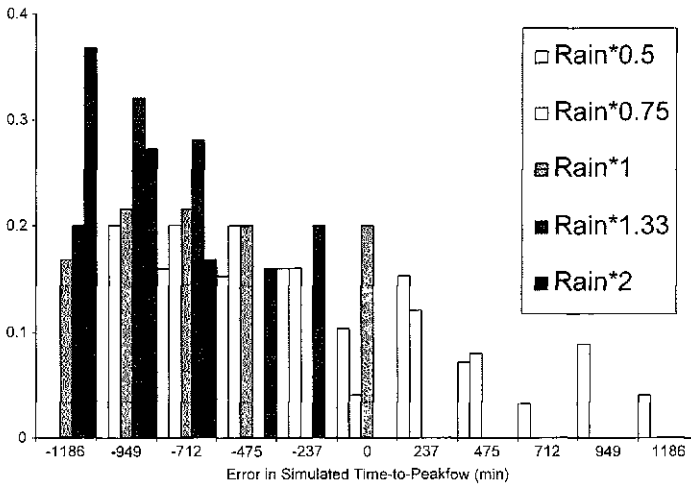


Fig. 3 Error between simulated minus observed time of maximum discharge (min). Time of maximum discharge occurred at 5520 min.

already adjusted the Stage III QPE using raingauges, the expected QPE multiplier is 1.0 rather than 0.75. One explanation is that the Stage III QPE was not tuned locally or specific to the Blue basin. Further work is needed for identification of the statistical significance of the different probability distributions, and separation of the error associated with model parameters from QPE input errors.

The error histogram for the time at which the maximum discharge was realized is shown in Fig. 3. In this case, increasing the rainfall amounts from their unperturbed values causes errors in the time-to-peak in the opposite direction relative to the total volume of flow and maximum discharge (Figs 1 and 2). Physically, soil saturation

occurs earlier in the simulation and results in runoff arriving at the basin outlet earlier than observations suggest. In this case, a majority of the simulations are shifted to the left of the bin containing zero error regardless of the scalar used to adjust the rainfall inputs. This is an informative result to the hydrological modeller because it indicates that the model has a propensity to simulate the maximum discharge earlier than the observed time-to-peak of 5520 min. The proposed methodology has thus pointed out a possible structural error in the model due to a mis-specification of the channel cross-sectional representation or hydraulics. Future studies are planned to identify and resolve the causes for this early forecast, or it will need to be considered in the ensemble in addition to the uncertainty in the initial conditions and model parameters.

Results are summarized in terms of the 90% error bounds of the three objective functions for each of the rainfall scalars as shown in Figs 4–6. The estimates of

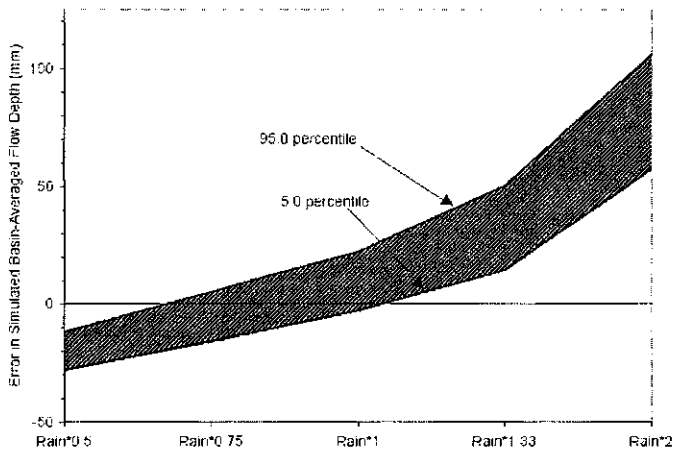


Fig. 4 Simulation bounds for the 90% error in simulated basin-averaged flow depth (mm) for the five different precipitation inputs. Hatched regions indicate simulation limits caused by uncertainty in model parameters.

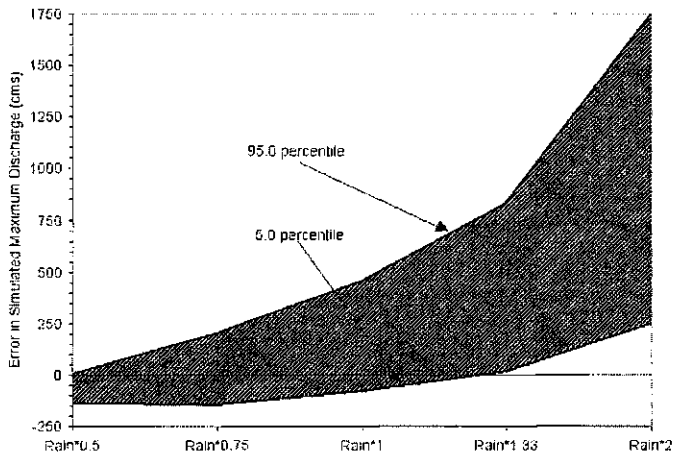


Fig. 5 Same as in Fig. 4 but for error in simulated maximum discharge ($\text{m}^3 \text{s}^{-1}$).

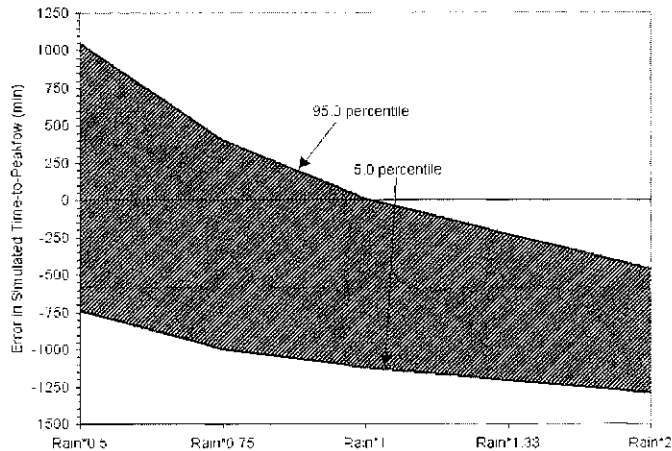


Fig. 6 Same as in Fig. 4 but for error in simulated time of maximum discharge (min).

are derived from the probability distributions shown in Figs 1–3 and should be interpreted as the 90% simulation limits caused by model parameterization alone. Volume has the narrowest range, and is relatively constant in difference between the 5- and 95-percentile indicating that scalar estimation for rainfall is best estimated using this objective function, which is consistent with expectations of a rainfall–runoff model. The imbalance in Fig. 6 between positive and negative error, with a propensity for negative (early) time-to-peak, is indicated, and is consistent with the histogram in Fig. 3. From this we can conclude that model structure or parameters representing channel hydraulics require improvement.

SUMMARY

Using streamflow and a rainfall–runoff model of a watershed, development, evaluation, and validation of new QPE algorithms can now be accomplished through comparison of simulated to observed discharge volumes. A method has been developed that can evaluate independent QPE algorithms using a hydrological model, and avoid the need to recalibrate the model to each input. The QPE validation is accomplished at the scale of a watershed that is commensurate with the goal of rainfall–runoff prediction. This method can also be used to identify the optimal bias adjustment independently from radar to gauge bias adjustment. From a statistical analysis of ensemble model simulations, sensitivity to QPE inputs and model parameters can be separated.

Acknowledgements Partial funding for this research was provided under NOAA-OU Cooperative Agreement no. NA17RJ1227. Support from the US Department of Education’s Graduate Assistantship in Areas of National Need is also gratefully acknowledged.

REFERENCES

- Beven, K. & Binley, A. (1992) The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Processes* **6**, 279–298.
- Droegemeier, K. K., Smith, J. D., Businger, S., Doswell, C., III, Doyle, J., Duffy, C., Foufoula-Georgiou, E., Graziano, T., James, L. D., Krajewski, V., LeMone, M., Lettenmaier, D., Mass, C., Pielke, R., Sr, Ray, P., Rutledge, S., Schaake, J. & Zipser, E. (2000) Hydrological aspects of weather prediction and flood warnings. Report on the ninth prospectus development team of the US Weather Research Program. *Bull. Am. Met. Soc.* **81**, 2665–2680.
- Entekahbi, D., Anderson, M. P., Avissar, R., Bales, R., Hornberger, G. M., Nuttle, W. K., Parlange, M. B., Peters-Lidard, C., Potter, K. W., Roads, J. O., Wilson, J. L. & Wood, F. F. (2002) Report of a Workshop on Predictability and Limits to prediction in Hydrological Systems. Committee on Hydrological Science, National Research Council, National Academy Press, Washington, DC.
- Freer, J., Beven, K. & Ambrose, B. (1996) Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach. *Water Resour. Res.* **32**, 2161–2173.
- Gourley, J. J., Maddox, R. A., Howard, K. W. & Burgess, D. W. (2002) An exploratory multisensor technique for quantitative estimation of stratiform rainfall. *J. Hydromet.* **3**, 166–180.
- Vieux, B. E. (2001) *Distributed Hydrological Modelling Using GIS*. Water and Science Technology Series, no. 38. Kluwer, Dordrecht, The Netherlands.
- Vieux, B. E. & Gauer, N. (1994) Finite element modelling of storm water runoff using GRASS GIS. *Microcomp. Civ. Engng* **9**, 263–270.
- Vicux, B. F. & Moreda, F. (2003) Ordered physics-based parameter adjustment of a distributed model. In: *Advances in Calibration of Watershed Models* (ed. by Q. Duan, H. V. Gupta, S. Sorooshian, A. N. Rousseau & R. Turcotte), 267–281. American Geophysical Union, Washington, DC, USA.