J4.4 QUANTITATIVE FLOOD FORECASTS BASED ON SHORT-TERM RADAR NOWCASTING

Enrique R. Vivoni*, Matthew P. Van Horne, Valeri Y. Ivanov, Dara Entekhabi and Rafael L. Bras
Massachusetts Institute of Technology, Cambridge, MA

Christopher Grassotti and Ross N. Hoffman
Atmospheric and Environmental Research, Inc., Lexington, MA

1. INTRODUCTION

Flood forecasting can be improved through the integration of short-term radar nowcasting and distributed hydrologic modeling. For short lead times (0-3 hrs), the extrapolation of NEXRAD rainfall estimates can improve the lead time and accuracy available for issuing flood forecasts as compared to rainfall persistence or climatology. Distributed hydrologic models explicitly account for rainfall variability and provide forecasts of the lumped and distributed basin response.

In this paper, we present the use of the Growth and Decay Storm Tracker (GDST) as a quantitative precipitation forecast (QPF) input to the TIN-based Real-time Integrated Basin Simulator (tRIBS). Flood forecasts issued by the distributed model based on the extrapolation QPF are developed for two nested basins in the Illinois River for a selected squall line storm in 1998.

Quantitative Flood Forecasts (QFFs) are assessed as a function of forecast lead time and basin scale using either a single or updating forecasting mode. Comparisons to a persistence forecast illustrate the limits of predictability offered by QFFs. An analysis of the error propagation from the GDST method to the tRIBS flood forecast is also presented.

2. DISTRIBUTED FORECASTING TOOLS

2.1 Growth and Decay Storm Tracker

The Growth and Decay Storm Tracker (GDST) is a short-term radar extrapolation model originally designed for 0-1 hour radar reflectivity and gust prediction in aviation applications (Wolfson *et al.* 1999). The GDST model is distinguished by its ability to separate the storm envelope motion from embedded convective cells through the use of a scale separation filter. Recently, Van Horne *et al.* (2002) have applied and evaluated the GSDT model for 0-2 hour radar rainfall forecasting over operational watersheds in the Arkansas-Red River Basin. Results confirm that the GSDT model has skill in predicting high-resolution rainfall fields (0.25 to 1 hr, 2 to 4 km), in particular for linear, organized events driven by large-scale forcing.

2.2 TIN-based Real-time Integrated Basin Simulator (tRIBS)

The tRIBS model is a physically-based, distributed hydrologic model developed for continuous, real-time flood forecasting (Ivanov *et al.,* 2002). Modeling the coupled surface and groundwater response to rainfall is achieved by tracking infiltration moisture fronts and lateral exchanges in the vadose and saturated zones. Surface runoff is generated via four mechanisms: infiltration-excess, saturation-excess, perched subsurface stormflow and groundwater discharge. Routing of surface flow is achieved via hydrologic and hydraulic routing in overland and channel segments, respectively.

The computational structure in tRIBS is based on a triangulated irregular network (TIN) terrain model. Vivoni *et al.* (2002) demonstrated how this multiple resolution domain allows efficient modeling of mid to large-scale watersheds without the loss of topographic information. Given the advantages of TINs over grid methods, tRIBS can be applied to operational basins for real-time flood forecasting, including the prediction of spatially-distributed states and fluxes.

3. DISTRIBUTED QFF FRAMEWORK

A rainfall forecasting mode within the tRIBS model enables specifying forecast times, intervals and rainfall products. In real-time operation, a distributed QFF can be issued every time a new quantitative precipitation estimate (QPE) is available. For each QPE, a series of rainfall forecasts up to a lead time (t_L) can be issued by the GDST. Two modes of forecast operation are

* *Corresponding authors address*: Enrique R. Vivoni, 77 Mass. Ave., MIT Room 48-208, Cambridge, MA 02319; e-mail: vivoni@mit.edu

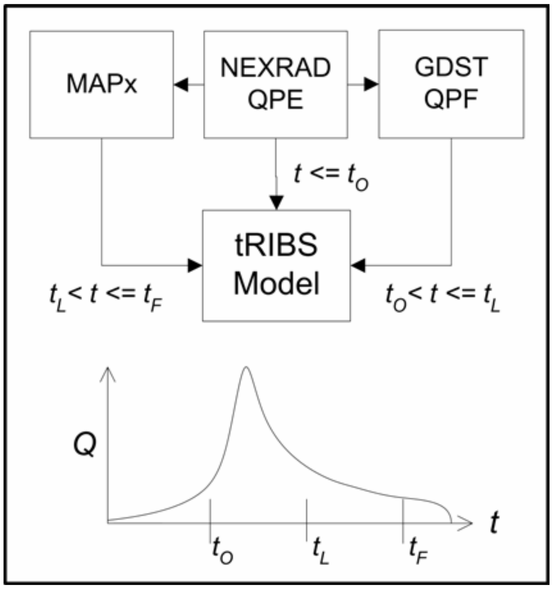

Figure 1. Single forecast QFF mode.

currently implemented: (1) single forecast issued at a specific forecast time (t_O) and (2) multiple forecasts at a specified update rate. Figure 1 illustrates the single forecast mode. The tRIBS model utilizes NEXRAD QPEs up to t_O. During the forecast interval (t_O to t_F), the model is forced with the GDST QPF up to the lead time (t_L) and then by a space/time mean rainfall (MAPx) up to the forecast interval (t_F). Both the GDST and MAPx are derived from the radar data available up to t_O. The MAPx product is computed from:

$$\overline{R} = \frac{1}{A}\int_A \left[\frac{1}{t_O}\int_{-\infty}^{t_O} R(x,y,\tau)\,d\tau \right] dA \tag{1}$$

where *R(x,y)* is the radar rainfall rate and *A* is the basin area. Determining the initial forecast time (t_O) is based on sampling the rainfall cumulative distribution at a specified percentile.

The multiple forecast mode emulates the real-time operation of a coupled forecasting system. A GDST forecast is issued for each QPE up to an update lead time t_L. The tRIBS model is forced with the forecasts up to t_L for each available rainfall data. This forecast updates the GDST model at a marching t_O with all prior QPEs. The updating mode can be applied over the entire forecast interval (t_O to t_F), eliminating the need for the MAPx product. The resulting QPF sequence consists of a temporal interpolation of available radar QPEs using the GDST model. Increasing the update lead time results in a decrease in QPF forecast skill as the extrapolation cannot properly represent storm growth and decay dynamics (Wolfson *et al*. 1999).

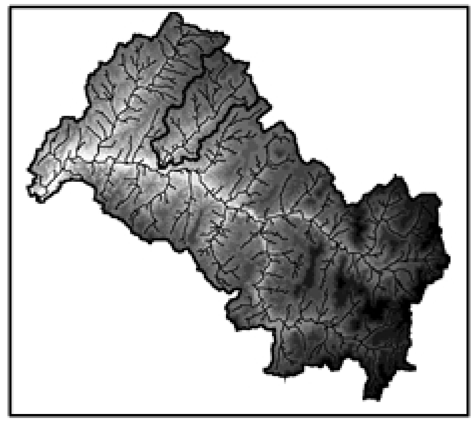

Figure 2. Baron Fork and Peacheater Creek.

4. STUDY BASINS AND DATA

Quantitative flood forecasts using the GDST and tRIBS models are developed for the Baron Fork (808 km^2) and Peacheater Creek (64 km^2) in Oklahoma. Figure 2 illustrates the topographic representation of the nested basins within the tRIBS model, including the channel network. USGS 30-m DEM data were used to develop a hydrologically-significant TIN terrain model (Vivoni *et al.*, 2002). STATSGO soil and AVHRR land cover data were used to specify model parameters prior to calibration (Ivanov *et al*., 2002).

In this study, we present the distributed QFF for one storm period in 5-6 October 1998. Rainfall forcing to the tRIBS model for each event consists of the hourly NEXRAD Stage III QPE and QPFs. Meteorological forcing used to drive the surface energy and radiation balances is obtained from gridded weather station observations. Finally, streamflow observations at the Baron Fork and Peacheater Creek USGS stations are available at hourly intervals for the storm events.

5. RESULTS

The tRIBS distributed model has been used in flood hindcasting studies in the Baron Fork basin over the 1997-2000 period using NEXRAD QPEs (Ivanov *et al*., 2002). Through these efforts, a manual calibration strategy was developed to reproduce outlet and interior flow observations. Here, we use a calibrated model run using the full radar observations (QPEs) as a benchmark for comparing flood forecasts issued in the single or updated modes. Figure 3 illustrates the calibrated model results for the 5-6 October 1998 event. Note the time to peak and recession are well reproduced while the peak discharge is slightly underestimated.

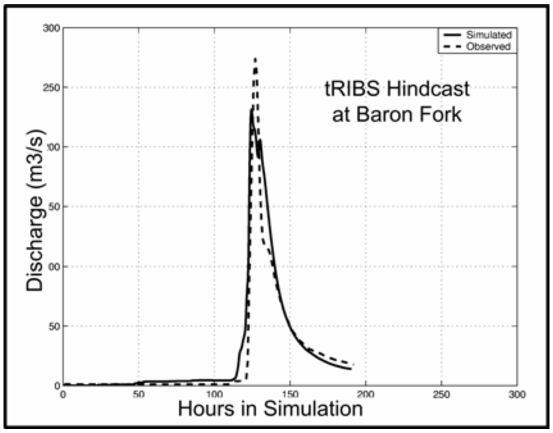

Figure 3. Observed (--) and simulated (—) flows.

5.1 Single Forecast Mode

The performance of a single GDST QPF as forcing to the tRIBS model is evaluated at various forecast times (t_O) for the storm event. Due to the hydrologic model sensitivity to rainfall, a flood forecast is a useful metric of QPF skill. Differences between QFFs and the benchmark are due to GDST errors in rainfall timing, location and intensity relative to the QPE. These errors vary along the marching forecast time.

Rainfall forecasts up to 12 hours were issued for six consecutive t_O during the rising limb of the rainfall event. The six QPF forecasts span t_O = 12 to 17 UTC on 5 October 1998. The tRIBS model is forced with the 1 to 12 hour GDST QPFs from t_O to t_L, after which the MAPx product is used. Figure 4a shows the cumulative mean areal rainfall normalized by the observed total precipitation. For small t_O, the GDST overestimates actual rainfall, while the opposite occurs as t_O increases.

tRIBS flood forecasts over a 30 hr period after t_O are shown in Figure 4b. The cumulative discharge at Baron Fork is normalized by the total runoff volume. Errors in the GDST 12-hr QPFs are amplified in the hydrologic model response. Results suggest that the model is more sensitive to rainfall overestimation. The best QFF performance is observed for t_O > 16 UTC, when more than 50% of the total rainfall has fallen.

5.2 Updating Forecast Mode

Given the limitations of the single QFFs, the rainfall-flood forecast system should utilize new rainfall estimates as these become available. In real-time operation, radar data may be updated every 6-10 minutes. For Stage III QPEs, the temporal resolution limits the update rate to hourly intervals. Improvements to the QFFs based on

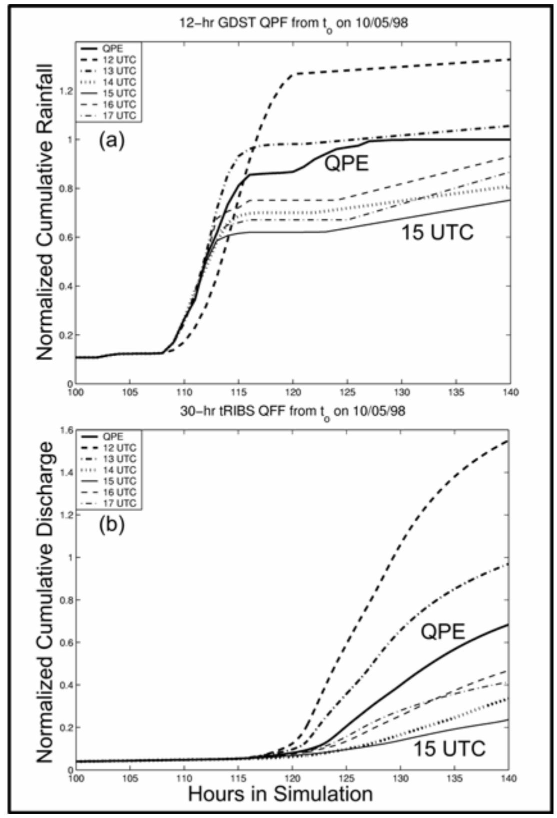

Figure 4. Single GDST QPFs and tRIBS QFFs. Normalized cumulative rain (a) and discharge (b).

updating the QPFs at different lead times (t_L) is tested for the storm event at $\boldsymbol{t_O}$ = 15 UTC on 5 October 1998. This corresponds to the 30th percentile of the cumulative rainfall. An updating forecast at $\boldsymbol{t_O}$ could have a large impact on QFF skill as compared to the single 12-hr forecast.

Figure 5a shows the normalized cumulative rainfall over the Baron Fork for the 1 to 3 hour update GDST QPFs. As anticipated, QPF performance improves with more frequent updating. These improvements translate to added QFF skill as compared to the 12-hr single QFF (Figure 5b). Additional tests for update rates t_L > 3 hrs showed a decrease in QPF and QFF skill.

5.3 QPF and QFF Skill

The performance of the distributed QPF and QFFs is quantitatively assessed for the storm event using the Nash-Sutcliffe efficiency (E) and the deviation of runoff volumes (D_v) defined as:

$$E = 1.0 - \frac{\sum_{i=1}^{N}\left(Q_{oi} - Q_{si}\right)^2}{\sum_{i=1}^{N}\left(Q_{oi} - \overline{Q}\right)^2}, \qquad (2)$$

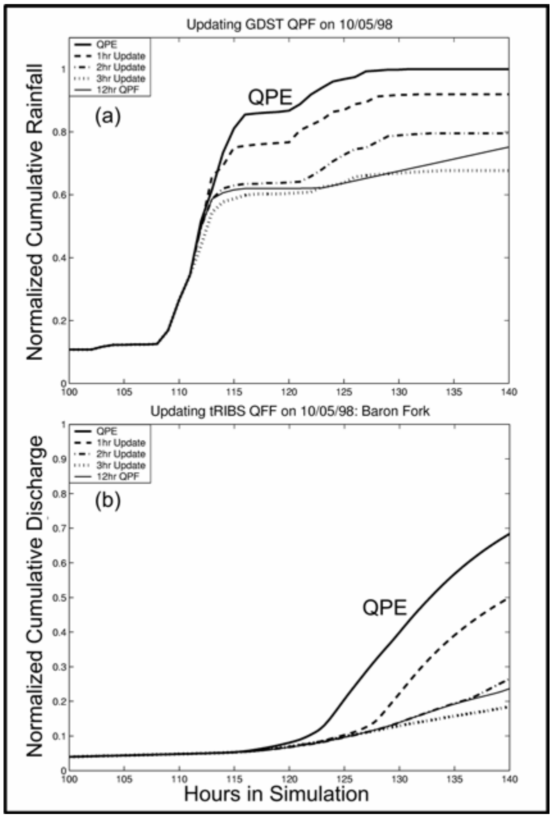

Figure 5. Updating GDST QPFs and tRIBS QFFs. Normalized cumulative rain (a) and discharge (b).

where Q_o is the observed flow, Q_s is the simulated discharge and the overbar denotes the average observed flow over the period, and

$$D_v = \frac{V_o - V_s}{V_o}, \tag{3}$$

where V_o is total observed event volume and V_s is the simulated event volume, respectively. For a perfect forecast, E = 1.0 and D_v = 0. To assess the impact of lead time and basin scale on QFFs, we use the hydrographs from the QPE-generated model run as ground-truth values in (2) and (3).

5.3.1 Lead-time dependence

The dependence of the updating forecast scheme on lead time, as measured by the metrics E and D_v, is shown in Figures 6a and b. The performance of the GDST-tRIBS forecast is gauged relative to a *Persistence Forecast* (P) issued in the updating mode. Persistence QPF is defined here as a rainfall forecast using the last available radar QPE up to the update lead time (t_L). Persistence QFF is the tRIBS model response to this persisted rainfall over the interval (t_O to t_F).

Interpretation of Figure 6 provides insight into

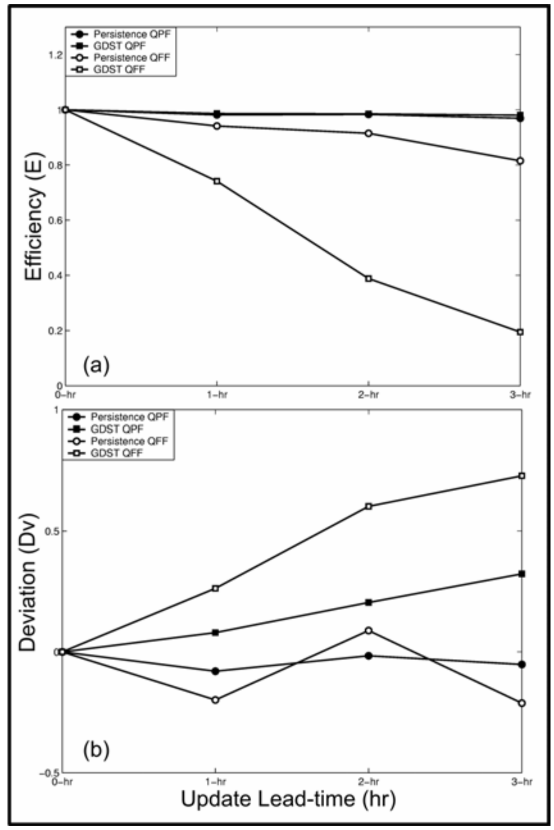

Figure 6. GDST QPF and tRIBS QFF skill as compared to Persistence for Baron Fork.

the skill of the GDST-tRIBS forecasts. The metrics are determined for both the mean areal rainfall and discharge in Baron Fork. First note from the QPFs that GDST and P have E ~ 1.0 for all lead times, suggesting the rainfall timing is similar to the QPE. Also note the QPF D_v varies with update time for the GDST but remains close to zero for P. This suggests the GDST QPF has biases in the rainfall volume relative to the QPE which increase with the update rate (32% bias at 3-hr).

The tRIBS QFFs amplify errors in rainfall volume as illustrated by D_v and E in Figure 6. A linear relation is observed between rainfall and discharge volume errors (Figure 7), suggesting an amplification factor of 2.24. These volume errors also impact the discharge E, as this is reduced by a factor 1.72 for a unit increase in rainfall D_v. Both trends suggest that GDST performance is weak in terms of predicting high rainfall intensities, as shown by Van Horne *et al.* (2002).

5.3.2 Scale dependence

The dependence of forecast skill on scale is assessed by comparing results from the pair of nested basins (Figure 1). Since tRIBS simulates

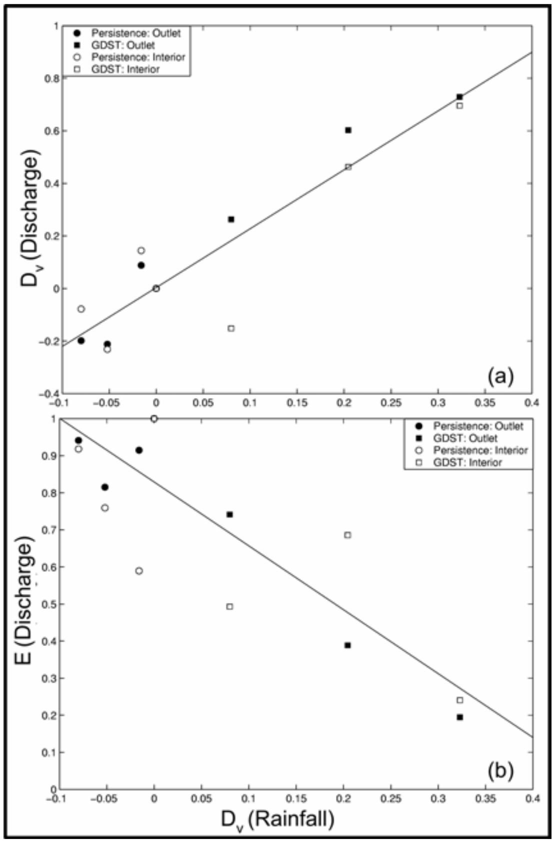

Figure 7. Propagation of volume error from QPFs to QFFs for Persistence (O) and GDST (□) over the Baron Fork and Peacheater Creek basins. (a) Discharge volume error. (b)Discharge Efficiency.

the distributed basin response, hydrographs can be produced for any interior channel node. The Peacheater Creek basin occupies nearly 8% of the Baron Fork basin, reducing the number of observed radar pixels from 50 to 4. This reduction in radar scale should affect forecast performance if the spatial variability in radar rainfall is high.

A comparison of QFFs for Baron Fork (Figure 5b) and Peacheater Creek (Figure 8) reveal notable differences. In particular, the 1-hour update QFF overestimates the QPE ground-truth at the smaller scale. This suggests that the ratio of radar to basin scales is of practical importance for distributed QFFs. Also note the 30-hr QFFs for the smaller basin includes a higher fraction of the total discharge due to the shorter basin response time.

To address issues of scale, the basin lag time (t_B) can be used to capture temporal differences among watersheds. This time scale can serve as scaling factor for QPF lead time (t_L). For equal t_L/t_B, QFF skill is expected to be similar, if t_B is an adequate scaling parameter. During this storm event, t_B = 11 and 21 hrs for the Peacheater Creek and Baron Fork, respectively. The 1-hour update

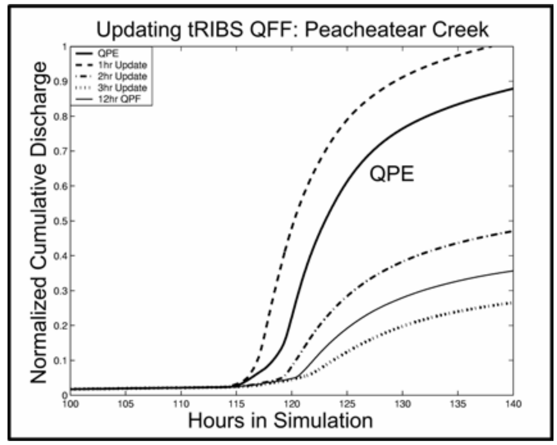

Figure 8. Updating GDST QFF for the Peacheater Creek basin.

QFF for the Peacheater Creek (*PC*) and the 2-hour update QFF for the Baron Fork (*B*F) have similar discharge efficiency (*E*) values when forced by the persistence (E_{PC} = 0.92; E_{BF} = 0.92) and GDST (E_{PC} = 0.39; E_{BF} = 0.49) rainfall forecasts. These results suggest that t_B can appropriately scale QFF skill over nested basins.

6. DISCUSSION AND CONCLUSIONS

Results from this study confirm that compared to conventional flood hindcasting, the forecasting problem is more complex. For distributed hydrologic models, this complexity is increased as the sensitivity to the intensity and spatial distribution of rainfall estimates is high. A 'perfect' flood forecast will only be achieved if the rainfall forecast can place the precise quantity of rain at the precise place and time.

In this study, we have shown how forecast errors from a short-term radar extrapolation method (GDST) and a persistence forecast (*P*) propagate and amplify in the interior and outlet flood forecasts from a distributed model. The errors in the GDST-tRIBS QFF are attributed to rainfall intensity since the model is insensitive to the rainfall spatial variability over this storm forecast interval. The low GDST accuracy for high rainfall has been credited to the lack of dynamic storm growth and decay in the extrapolation method (*e.g.*, Van Horne *et al.* 2002).

Future work with the GDST and tRIBS models will focus on the effect of storm characteristics and basin scale on QFF performance. In this study, we only illustrated results for a single storm event. GDST performance should differ for other events or sequence of events relative to the simple persistence forecast. The variation of forecast accuracy over the storm evolution also needs to be addressed. Nevertheless, we have shown with this case study how a distributed hydrologic model is a useful metric for evaluating QPF performance.

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