4.3 Improving flood prediction using Kalman Filter, mesoscale atmospheric model forecasts and radar-based rainfall estimates

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INTRODUCTION

Amite River basin, in central and southeastern Louisiana, has exhibited a persistent flooding problem for several years, particularly in East Baton Rouge parish where about 42 per cent of the land area is within the 100-year flood plain. Recently, several severe floods occurred (1983, 1989, 1990, 1993 and 2001) resulting in cumulative damages of over several hundred millions of dollars. Improvement in the accuracy of flood forecasts could help in reducing these damages.

National Weather Service's Lower Mississippi River Forecast Center (LMRFC) has the authority to provide the public with flood forecasts as well as river stage information. In order to forecast river stages, LMRFC needs spatial precipitation estimates, as well as forecasts. The quality of flood forecasts depends on the accuracy of precipitation estimates already on the ground, and also on the quality of forecasted amounts. The LMRFC also needs reliable river gage data, updated rating curves, and properly calibrated hydrologic models. The precipitation estimates are used as input to an operational hydrologic model which forecasts future river levels and compares past forecast to observed values. LMRFC produces its own precipitation estimates (Stage III data) and relies primarily on NWS's Hydrometeorological Predication Center (HPC) for the forecast guidance. In this study, we are examining the possibility of improved precipitation forecasts using the estimated values and the forecasts.

LMRFC creates hourly Stage III precipitation product based on composite NEXRAD WSR-88D radar data, as well as hourly and daily rain gages. Hourly precipitation mosaics for the basin are generated from a 3-stage process of automatic and manual quality control in real-time at the LMRFC using hourly rainfall estimates from 25 NEXRAD WSR-88D radar sites. Data are in a binary digital (xmrg) form having a 4-km spatial resolution using a polar stereographic projection - the NWS HRAP format.

HPC QPF originates from the National Weather Service (NWS) National Centers for Environmental Prediction (NCEP) HPC. At 0000 UTC and 1200 UTC (and occasionally at 0600 and 1800 UTC) Hydrometorological Analysis and Support (HAS) personnel at the LMRFC process HPC's QPF for each six hourly time-step out to 24 hours. The forecasts are then modified, if necessary, based on the local meteorological situation. Once local modifications are complete, the forecasts are saved, then gridded (32km x 32km horizontal across the domain of the LMRFC). The gridded files are then converted to XMRG format (HRAP 4km x 4km grid) for local processing.

The LMRFC is currently running NCEP's Workstation ETA (Ws ETA), which is a version of the operational ETA model modified to run at the local office level. The Ws ETA runs twice a day at 0000 UTC and 1200 UTC, using grid dimensions 55x91x45 (20 km horizontal) across the entire LMRFC domain. The model is initialized using operational ETA output, and employs the Betts-Miller-Janjic (Betts and Miller, 1986, Janjic, 1994) convective parameterization scheme. Model output from each run is available in six-hour time-steps out to 60 hours, and includes 6-hour and 24-hour QPF amounts. Once the model finishes, the 6-hour QPF grids are saved and converted to XMRG format.

For this study, we are focusing on a large precipitation event produced by Tropical Storm Allison. In early June of 2001, Allison produced large amounts of precipitation over the Gulf coast states. Amite river basin received an average of approximately 350 mm of water over the watershed. Northern half of Amite river basin was less hit than the southern, which, at places,

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received well over 1/2 a meter over 6 days. The storm provides us with an excellent opportunity to improve the raw QPF over the Amite river basin using the spatial stage III data, with a possibility of extending the technique to a much larger spatial domain.

KALMAN FILTER

The atmospheric model QPFs contain forecasting errors. The procedure to achieve the reduction in these errors is based on Kalman filter and incorporation of remotely sensed rainfall measurements. Similar studies have been conducted over the past few years (French and Krajewski, 1994; Lee and Georgakakos, 1996). These studies have revealed that short term (1-6 hr) corrected forecasts represent improvements over raw model results over limited spatial domains. The system equation is analogous to AR(1) process, with a dynamic estimation of transition matrix of system states. Since the model QPF ($y_A(t)$) is used as the noisy estimate being corrected, the system equation is

$$y(t) = \Phi(t)\, y_A(t) + w(t) \qquad \text{……………….(1)}$$

Whereas the measurement equation becomes

$$y_R(t) = H(t)\, y(t) + v(t) \qquad \text{……………….(2)}$$

in which $y_R(t)$ is the vector of remotely sensed rainfall values, $\Phi(t)$ is the transition matrix of states in the system equation, w(t) is the system noise with 0 mean and variance Q(t), $y_A(t)$ is the vector of atmospheric model forecasts, H(t) is the measurement coefficient matrix, and v(t) is the vector of 'measurement' noise with mean 0 and variance R(t). The filter is attempting to improve QPF rainfall values, based on $\Phi(t)$, R and Q, through Kalman gain (Bergman and Delleur, 1985). The implementation of the filter involves estimation of $\Phi(t)$, which is a function of covariance structure between the filtered values and the QPFs.

An adaptive filter-parameter estimation scheme is employed (Awwad and Valdés, 1992), which alternates between the variable space filter and the parameter space filter. In contrast to the variable space filter, the parameter space filter is designed to update the $\Phi(t)$ instead of the QPF. The updated $\Phi(t)$ is then used in the variable space to continue filtering the QPF for the next time step. Thus, we have a "forecast", based on the present QPF, and known covariance structure, prior filtered QPF and past stage III data. Having forecasted the possible QPF, we introduce the observed data for the present time step to the filter, which produces the updated (or "filtered") time series. The filtered data are used in the estimation of forecast in the next time step.

PRELIMINARY RESULTS

Figure 1 shows a glimpse of the results from the filter. Inputs to the filter in this case include the most recent raw HPC QPF (referred as HPC), with stage III data. The data are the 6-hr totals from Allison, for the cell covering Baton Rouge Airport.

The filtered estimates are in close agreement with the stage III data, as expected. It can also be seen that the trends in the forecasted time series compare well with the observed data. The forecasted QPF captures the trend in the stage III fairly well, with the exception of two of the 6 large totals (10.16 cm and 6.46 cm), at which times, the raw QPF completely missed the events. However at other times, the forecasted estimates tend to bring the raw and the observed values together.

The total forecasted precipitation volume for the entire event matches closely with the stage III data. Another indicator of forecast improvements would be relative errors in the raw and the forecasted QPF. Mean absolute error as well as the root mean square error between the stage III - forecasted estimate pair is less than those between stage III - raw QPF. R^2 for the forecasted QPF is 0.4, whereas that for the raw QPF is 0.23.

A similar behavior can be seen when filtering is done using Ws-ETA QPF instead of the HPC. The Ws ETA produces somewhat lower QPF estimates than the HPC, possibly in part because at times, HPC estimates are produced more frequently (additional runs at 0600, or 1800 UTC).

Instead of the most recent QPFs, we can use an average of all the previous forecasts made for a specific time. As expected, the farther ahead in time a forecast is made, the quality of the forecast decreases, producing a more uniform QPF fields over the watershed. Therefore the improvements in the QPF using the Kalman filter are not as pronounced.

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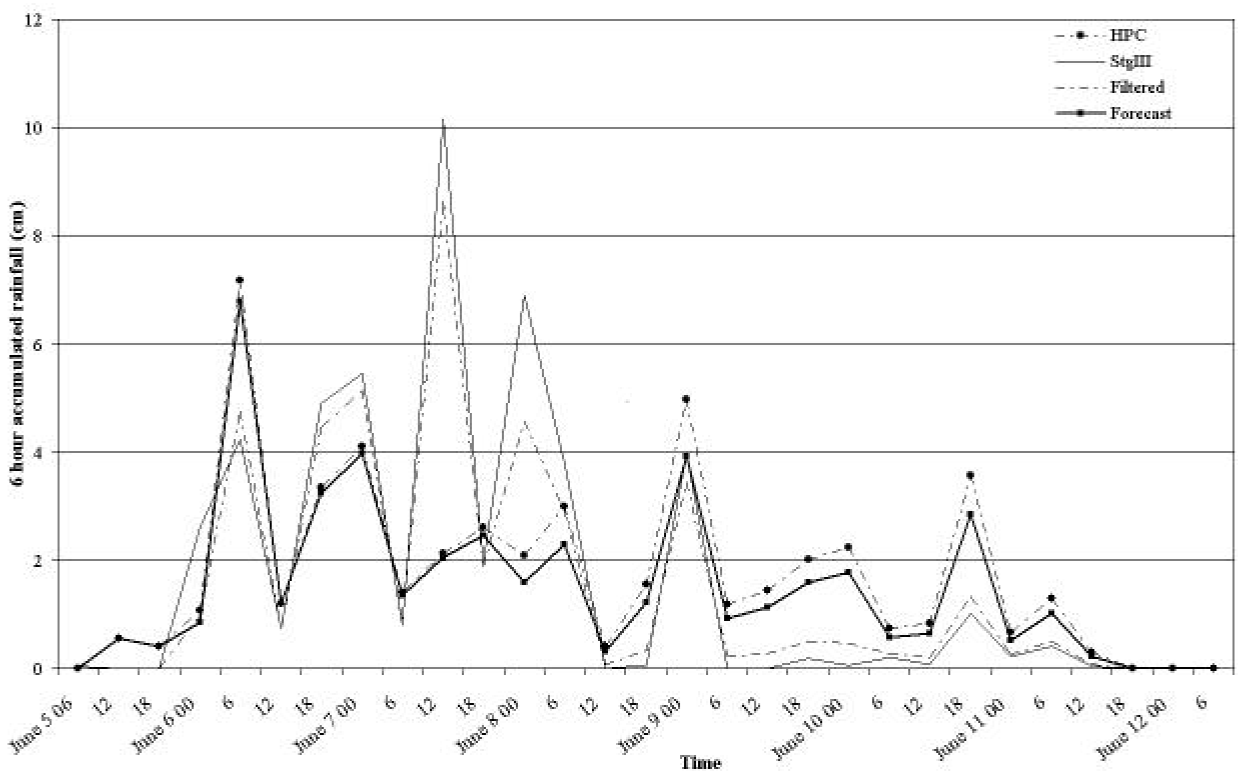

Figure 1: Filtered and forecast time series for tropical storm Allison using stage III data and HPC QPF.