Application of Ensemble Kalman Filter to Gudgenby River

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Abstract The uncertainties associated with rainfall, model and discharge contribute to the uncertainty in the resulting flood forecasts. The use of Ensemble Kalman Filter (EnKF) enables all these uncertainties to be combined in a systematic way and it has been used by a number of researchers in the past(El Serafy and Mynett, 2004; Moradkhani et al, 2005; Weerts and El Serafy, 2006). In this paper, EnKF and its several variations are used with the Probability Distributed Moisture (PDM) model to forecast four flood events in Gudgenby River, Australia and quantify the uncertainty in the forecasts. The results showed that the EnKF with parameter updating performed marginally better than the other variations. However, the application of EnKF gave good results only for short lead time forecasts of up to 3 hours with the results deteriorating markedly for long lead times. The inability to give good forecasts for long lead times even with perfect knowledge of observed rainfall needs further investigation.

Ensemble Kalman Filter (EnKF)

The Ensemble Kalman filter (EnKF) is a suboptimal estimator, where the error statistics are predicted by using Monte Carlo integration methods. The starting point is choosing an ensemble of state estimates that captures the initial probability distribution of state estimates. These sample points are then propagated through the nonlinear system and the probability density function of the actual state is approximated by the ensemble of the estimates. The approximation of forecast state error covariance matrix is made by propagating the ensemble of model states using the updated state from the previous time step. It is necessary to generate the ensemble of observations at each update time by introducing noise drawn from a distribution with zero mean and covariance equal to the observational error covariance matrix; otherwise the updated ensemble will have a very low covariance. In this study, error variances of input rainfall and output discharge are specified a priori (Weerts and El Serafy, 2006; Georgakakos, 1986) and not updated. The results from the application of EnKF and its three variations with the Probability Distributed Moisture (PDM) model are described. Perfect knowledge of observed rainfall is used during the flood forecasts to eliminate the uncertainties in the forecast rainfall.

State Updating

PDM (Moore, 2007) has four stores (soil moisture, ground water and two surface runoff) and these are considered as state vectors in the application of EnKF. The root mean square error (RMSE) of 1-, 3-, 6-, 9- and 12-hour forecasts are presented in Table 1.

Table 1: RMSE for 1-, 3-, 6-, 9- and 12-hour forecasts for state updating

Event	1	3	6	9	12
1	11.04	14.36	18.85	22.40	24.95
2	14.65	17.96	21.63	24.66	27.85
3	8.52	12.01	15.81	17.73	17.83
4	10.88	12.99	16.65	18.42	18.11
Average	11.27	14.33	18.24	20.80	22.19

Parameter Updating

Of the ten PDM model parameters, three (C_{max}, b_g, and K_2) were found to be very sensitive and these four are updated. RMSE of 1-, 3-, 6-, 9- and 12-hour forecasts are presented in Table 2.

Table 2: RMSE for 1-, 3-, 6-, 9- and 12-hour forecasts for parameter updating

Event	1	3	6	9	12
1	8.07	10.09	14.16	18.02	21.19
2	9.39	14.03	17.75	21.59	25.33
3	7.77	10.23	13.16	14.45	14.55
4	9.22	10.88	13.80	15.26	15.41
Average	8.61	11.31	14.72	17.33	19.12

Dual Updating

The dual EnKF requires two separate state-space representation for the state and parameters through two parallel filters. The parameters could be updated first and then the state variables or vice versa. The two alternatives are used and the results are presented in Tables 3 and 4.

Table 3: RMSE for 1-, 3-, 6-, 9- and 12-hour forecasts for dual (parameter-state) updating

Event	1	3	6	9	12
1	13.79	17.15	21.11	24.26	26.66
2	14.34	17.91	21.72	24.33	26.65
3	9.68	12.93	16.62	18.65	19.43
4	10.83	12.81	16.20	18.36	17.93
Average	12.16	15.20	18.91	21.40	22.67

Table 4: RMSE for 1-, 3-, 6-, 9- and 12-hour forecasts for dual (state - parameter) updating

Event	1	3	6	9	12
1	9.86	13.71	18.97	23.07	25.97
2	12.82	16.62	20.78	23.93	26.92
3	6.25	9.14	12.06	13.15	12.96
4	9.96	11.57	14.61	15.98	15.89
Average	9.72	12.76	76.61	19.03	20.44

Conclusions

The ability of the EnKF with the PDM model to forecast discharge was evaluated by using four flood events in the Gudgenby River. Three variations of the EnKF, namely, the state, parameter and dual (state-parameter and parameter-state) were considered. The uncertainty in the input rainfall data and the output discharge measurements were represented by Gaussian white noise with zero mean and variance obtained from the published literature. The uncertainty in the states and the parameters was obtained by sensitivity analysis. Perfect knowledge of observed rainfall was used during the forecasts. The parameter updating performed better than the other two. However, the application of EnKF gave good results only for short lead time forecasts of up to 3 hours with the results deteriorating markedly for long lead times. The inability to give good forecasts for long lead times even with perfect knowledge of observed rainfall needs further investigation. A weakness of the EnKF approach is the need to specify a priori uncertainty in states, rainfall and discharge. This makes the elucidation of the sensitivity of the forecast errors in peak flow and timing to a priori uncertainty a pressing issue. It follows that accurate specification of those sources of uncertainty deemed as sensitive is essential. Stream gauging data can be used to quantify the errors involved in using the rating curve for obtaining the discharges from the stage measurements. Rainfall data from a dense rainfall network can give reliable estimates of the error involved in the rainfall data. Further work is in progress to quantify these sources of uncertainty

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