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ADAPTIVE FLOOD FORECASTING: AN APPLICATION TO THE WAIMAKARIRI RIVER

V.J. Bidwell[1], G.A. Griffiths[2]

[1]*Agricultural Engineering Institute, Lincoln University, Canterbury, New Zealand.*

[2]*Canterbury Regional Council, P.O. Box 345, Christchurch, New Zealand.*

ABSTRACT

A general method for flood forecasting, suited to telemetered rainfall and river stage data, was developed using data from eight major floods on the Waimakariri River. Rainfall-stage and upstream stage-downstream stage relationships were identified as autoregressive moving-average (ARMA) models with time-varying parameters. Parameter values were estimated in adaptive real-time mode by incorporating the ARMA models into the Kalman filter algorithm. The method is an acceptable alternative to the RORB model with lower data and operational resource requirements. Implementation requires only commercial PC-based software.

INTRODUCTION

Mathematical models for forecasting floods are either hydrologic, involving prediction of river stage (or outflow) from measured storm rainfalls, or hydraulic, involving prediction of downstream stage (or outflow) from upstream stage (or inflow). Some include both features. Some models are physically based, such as the non-linear network hydrologic model RORB (Laurenson and Mein, 1985; Auckland Regional Water Board, 1989; Griffiths et al., 1989; Pearson, 1990) or HYCEMOS (National Water and Soil Conservation Authority, 1988; Ibbit et al, 1990) and various hydraulic models founded on the unsteady flow equations for open channels (Goring, 1988, 1992). Others are empirical, predicting flood stage (or outflow) from storm rainfall or stage (or inflow) series (Goring, 1984; O'Donnell et al., 1988).

This paper reports an empirical approach to forecasting using an autoregressive moving-average (ARMA) model with time-varying parameters. Using data from floods of the Waimakariri River, the model is used to forecast river stage from telemetered storm rainfall data, and forecast downstream stage from stage data telemetered from an upstream recording station. These forecasts are compared with those provided by the RORB model (Griffiths et al., 1989) to evaluate the potential of the ARMA model in operational flood forecasting.

The aim is to provide flood forecasts for basins with highly non-linear runoff response to rainfall, using a model which requires little input data and few resources to install and operate.

ADAPTIVE FORECASTING

Forecasting the future behaviour of any system involves both prior knowledge of the system characteristics, and observation of its current behaviour. The characteristics of a system may be expressed in terms of a mathematical model, with parameter values estimated from measurements of concurrent input and output. In adaptive forecasting the parameters of the prior model are continually adjusted in response to current measurements of output, in order to obtain the best forecast.

THE PRIOR MODEL

This study uses the linear transfer function or autoregressive moving-average (ARMA) model. The general form of this model is:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_r y_{t-r}$$
$$+ b_1 x_{t-d} + b_2 x_{t-d-1} + \ldots + b_s x_{t-ds+1} + n_t \qquad (1)$$

where y_t is the output at time t, x_t is the input at time t,n_t is an error term, and d is the delay time before the input influences the output. This delay time is not the same as the lag time between rainfall peak and flood peak, for example.

A wide range of physical phenomena, e.g., surface runoff (Spolia and Chander, 1974), dispersion of pollutants in rivers (Beer and Young, 1983), and sediment transport (Lemke, 1991), can be approximated using ARMA models, especially if the parameters a_i, b_i are allowed to vary with time. Computer software is available for selecting the ARMA model with the least number of parameters using objective statistical criteria. The mathematical procedure for adjusting parameter values in response to observations of current system behaviour is more reliable and stable when used in conjunction with a linear model.

The general model described by equation (1) can be referred to as a (r,s,d) model, where the number of autoregressive terms r, moving-average terms s, and time delay d are to be determined by a statistical fitting procedure. This study uses the Recursive Instrumental-Variable algorithm (Young, 1984) in the commercial software MICROCAPTAIN (Young and Benner, 1991). The algorithm incorporates a fitting criterion, called YIC, which trades off explained output variance R^2 against parameter variance to obtain an adequately explanatory model with a minimum number of parameters. MICROCAPTAIN supports recursive estimation algorithms for both ordinary least squares (LS) and instrumental variable (IV) methods. Consistent parameter estimates can be obtained from the latter even when some of the underlying assumptions of least squares are violated. Simple linear models can be used for forecasting the behaviour of a complex non-linear river catchment because the continual parameter adjustment allows satisfactory short-term prediction. Wood and Szollosi-Nagy (1978) used an ARMA model (r=2, s=3) to forecast river flow from real-time rainfall and river flow data. In this study this concept is extended to forecasts of flood level based on rainfall and river level.

REAL-TIME ESTIMATION

The Kalman filter is the mathematical procedure used to adjust the model parameters in response to new observations of the input and output data. It was developed by Kalman (1960) in the context of engineering systems control but has widespread applications in a number of disciplines. Harvey (1984) describes the central role of the Kalman filter in statistical forecasting, and its application in hydrological forecasting is reviewed by O'Connell and Clarke (1981), and Wood and O'Connell (1985).

The form of the Kalman filter used in this study is the Dynamic Linear Model (Harrison and Stevens, 1976) in which a linear equation, such as equation (1), constitutes a measurement of the parameters at time t, expressed as y_t. The parameters themselves evolve in time according to a known model.

Consider the ARMA (1,1,d) model:

$$y_t=a_t y_{t-1}+b_t x_{t-d}+n_t \tag{2}$$

where the error n_t has zero mean, known variance R.

The parameters a_t,b_t vary in time as a "random walk" process:

$$a_t=a_{t-1}+u_t \qquad b_t=b_{t-1}+v_t \tag{3}$$

The random components u_t and v_t are independent, zero mean, with known variances U and V respectively. The parameters a_t, b_t have variances (Paa_t, Pbb_t) and covariances (Pab_t, Pba_t) which are estimated as part of the algorithm.

At time t-1 an estimate of the future, but unknown, value of y_t (called $y_{t/t-1}$) can be obtained from equation (2):

$$y_{t/t-1}=a_{t/t-1}y_{t-1}+b_{t/t-1}x_{t-d} \tag{4}$$

where, for the random walk process, $a_{t/t-1}=a_{t-1}$ and $b_{t/t-1}=b_{t-1}$.The associated parameter variances and covariances are:

$$\begin{aligned} Paa_{t/t-1}&=Paa_{t-1}+U \qquad & Pab_{t/t-1}&=Pab_{t-1} \\ Pba_{t/t-1}&=Pba_{t-1} \qquad & Pbb_{t/t-1}&=Pbb_{t-1}+V \end{aligned} \tag{5}$$

When the measurement y_t becomes available the forecast error e_t can be calculated:

$$e_t=y_t-y_{t/t-1} \tag{6}$$

and the parameters corrected to their new values:

$$a_t=a_{t-1}+Ka_t e_t \qquad b_t=b_{t-1}+Kb_t e_t \tag{7}$$

The correction factors Ka_t and Kb_t (called the Kalman gain) are derived from the Kalman filter algorithm to give:

$$Ka_t = \frac{(Paa_{t/t-1} y_{t-1} + Pab_{t/t-1} x_{t-d})}{KR_t}$$

$$Kb_t = \frac{(Pba_{t/t-1} y_{t-1} + Pbb_{t/t-1} x_{t-d})}{KR_t} \qquad (8)$$

$$KR_t = R + Paa_{t/t-1} y^2_{t-1} + (Pab_{t/t-1} + Pba_{t/t-1}) y_{t-1} x_{t-d} + Pbb_{t/t-1} x^2_{t-d}$$

Therefore, the correction applied to a parameter is:

(a) proportional to the magnitude of the error;

(b) proportional to the sum of the magnitudes of the causative factors multiplied by the associated parameter variance/covariance;

(c) inversely proportional to the variance of the estimation process, indicated by KR_t.

The final part of the iterative process for time t is to update the parameter variances and covariances:

$$Paa_t = Paa_{t/t-1}(1 - Ka_t y_{t-1}) - Pba_{t/t-1} Ka_t x_{t-d}$$
$$Pab_t = Pab_{t/t-1}(1 - Ka_t y_{t-1}) - Pbb_{t/t-1} Ka_t x_{t-d}$$
$$Pbb_t = Pbb_{t/t-1}(1 - Kb_t x_{t-d}) - Pab_{t/t-1} Kb_t y_{t-d}$$
$$Pba_t = Pba_{t/t-1}(1 - Kb_t x_{t-d}) - Paa_{t/t-1} Kb_t y_{t-d} \qquad (9)$$

The algorithm has optimal statistical estimation properties provided that the system and its inputs are known exactly; if not, the optimality, stability, and convergence of the algorithm are not guaranteed. The art of applying the Kalman filter lies in identifying a system model which is described only by those parameters which can be adequately estimated from the data, and in sensible use of other elements of prior knowledge. These issues, in a hydrological context, are disscussed by Wood and O'Connell (1985), and Bras and Rodriguez-Iturbe (1985).

In their report on New Zealand flood forecasting procedures Pearson and Jordan (1991) stated:

"....a reliable forecast is one that is available for dissemination at least three hours before the actual peak occurs, and which estimates peak flow to within + or -20% of the eventual measured value...",

and referred to the difference between forecast and actual as the peak magnitude error. For stage forecasts, the low flow datum and non-linearity of the stage-discharge rating were used to estimate error tolerance. The authors doubled the stage errors for comparison with flow forecasts.

Duckstein et al. (1985) report two objective measures of forecast reliability which relate the forecast error variance to the total variance of the time series (correlation index) or to the variance of the inertial forecast (coefficient of efficiency). The inertial forecast is that the variable being predicted will continue to have its present value. The coefficient of efficiency is a good measure of overall forecast reliability but is not sensitive to the flood peak forecast which is better assessed by the peak magnitude error.

Four-hour forecasts were evaluated because they provide adequate warning and make best use of telemetered data within the flood-wave travel times typical of the catchment. Forecast performance was measured by:

(a) the timing error between the actual flood peak and the peak forecast value,
(b) the difference between the actual peak and the peak forecast value of stage or flow, and
(c) the forecasted stage or flow error at the time of the actual peak.

The errors are expressed as positive time in hours for early arrival of the forecast, percent of actual peak flow, and percent of actual peak stage above the base stage just prior to the flood.

The Kalman filter for the present study was applied using QUATTRO PRO 3.0 spreadsheet software on a 386SX PC with maths coprocessor. The algorithm for the simple two-parameter model with one output utilizes spreadsheet cell formulas.

TABLE 1—Major Floods of the Waimakariri River (1957-1988)

Flood	Data	Gorge stage (mm)		OHB stage (mm)		OHB flow (m^3/s)	
event	use	Init.	Peak	Init.	Peak	Init.	Peak
27/12/57	Test	1899	4915	2700	5510	464	3990
11/03/67	Anal.	1850	4129	946	3657	78	2052
31/08/70	Test	1385	4209	930	4069	51	2487
02/04/75	Anal.	2054	4525	1310	3480	155	1772
03/12/79	Test	1721	4650	1420	4757	137	2843
24/11/84	Anal.	1649	4497	1307	4700	90	2825
20/05/88	Test	2043	4105	1410	4061	137	1972
13/09/88	Anal.	1809	4374	1217	4422	153	2291

Note:
(1) Initial stage (at Gorge and OHB) and flow (at OHB) are the values at the start of the flood wave. OHB is the Old Highway Bridge.
(2) Catchment area is 2460km^2 at the Gorge and 3210km^2 at OHB .

DATA

Test data for the model were from eight major floods of the Waimakariri River between 1957 and 1988. These events have also been the subject of a comprehensive flood modelling study by Griffiths et al. (1989). A summary of the stage and discharge data for the flood events is given in Table 1. Although there are several telemetric raingauges in the catchment, only the Arthurs Pass rainfall data were used: this minimises the number of input parameters in the system model. The Arthurs Pass station recorded the highest rainfall in each event and is a good estimator of rainfall regime in the catchment headwaters. The effect of non-uniform rainfall distribution is expected to be accounted for to some extent by the time-varying model parameters.

The water-level gauge at the Waimakariri Gorge is not rated for discharge because the river bed is unstable. However, the Gorge station is an important part of the flood warning network, and the time-varying properties of the model were expected to be effective in extracting information. Goring (1988) has described Gorge flood data in more detail.

The water-level gauge at the Old Highway Bridge (OHB) is rated for discharge, but only stage data were used in the study. Although the model would be equally applicable to discharge, the use of stage data allows for floods in which river banks are broken or overtopped or the bed level changes. Forecasted stage was converted to flow for comparison with RORB where a rating was available.

The rainfall data are hourly totals in mm, and the stage data are instantaneous values at the end of each hour, in mm above the gauge datum.

Data from four of the eight floods were used to obtain prior knowledge about the model structure, and the adaptive forecasting algorithm was applied to the other four events. The floods selected for analysis were those used by Griffiths et al. (1989) so that results for the four test floods could be compared with the RORB model. In chronological order, the even numbered events were used for analysis and the odd numbered for testing.

TABLE 2—Arthurs Pass - Gorge, Model Identification Parameters

Flood event	AR coeff. a	MA coeff. b	Time delay (hours)	R^2	Error variance
11/03/67	0.90+0.03	17.2+4.1	6	0.93	21687
02/02/75	0.87+0.04	24.5+5.7	6	0.85	53761
24/11/84	0.93+0.02	13.1+3.1	4	0.88	64742
13/09/88	0.91+0.03	16.9+5.5	7	0.90	45164
Mean	0.90	17.9	5.75		46338
Variance	0.0005	17.0			

RESULTS

Model Identification

For each flood, MICROCAPTAIN was used to identify the particular structure (r,s,d) of equation (1) which best accounted for the relationship between hourly rainfall at Arthurs Pass and hourly instantaneous stage at the Gorge. The

(1,1,d) structure was determined as the best for all events, using the YIC fitting criterion, with d varying between events (Table 2). Rainfall data were not modified (this assumes no losses) but the stage data were transformed by using the initial stage for each event (Table 1) as the base datum, to increase the sensitivity of the estimation procedure.

The model parameter values obtained by the instrumental variable method did not differ signifcantly from those for ordinary least squares. This has implications for the consistency of parameter estimation when using the Kalman filter, an issue discussed by Young (1984). For this reason the least-squares results were used (Table 2). The means and variances of the results in Table 2 form part of the prior knowledge to be incorporated into the Kalman filter.

The relationship between hourly instantaneous stage at the Gorge and the Old Highway Bridge (OHB) for each flood was identified, and the least-squares results (Table 3) were used for the prior knowledge base.

Adaptive Forecasting

On the basis of the results (Table 2), the measurement equation for the Arthurs Pass-Gorge system was:

$$GS_t = a_t GS_{t-1} + b_t AP_{t-5} + n_t \tag{10}$$

where GS_t is the Gorge stage, AP_t is Arthurs Pass rainfall, and n_t is model error.

The error variance R_t of this measurement was set to an arbitrary large number (10^7) until the Gorge stage began to rise, and was then set to 50000 (mean error variance in Table 2 is 46338). The reason for this rule is that the time delay in the measurement equation was fixed at 5 hours (mean=5.75) for all floods whereas the actual value varies. This approximation is adequate because successive values of hourly rainfall or stage are quite highly correlated. However, on the steep rising front of some floods the approximation is poor and the high initial value of R_t reflects the prior uncertainty until the system activates.

The parameter transition equations were:

$$a_t = a_{t-1} + u_t \qquad\qquad b_t = b_{t-1} + v_t \tag{11}$$

The initial values were: a_0=0.95; b_0=18; Paa_0=0.0005; Pbb_0=17. The covariances Pab_0, Pba_0 were set to zero to allow some independence between the parameters during the initial adaptation to each event. Subsequently, the algorithm develops the full covariance structure as the data is processed.

The variances U and V (of u_t and v_t) were not determined from Table 2, but by subjective judgement about the rate (standard deviation per time increment) at which the parameters should be able to change in the time-varying system model. Initially, a rather arbitrary rate of one significant digit per hour was assumed. This gives U=0.0001, V=1. After reviewing plots of parameter variation with time, U was reduced to 0.00001 to smooth fluctuations to more acceptable levels.

TABLE 3—Gorge - Old Highway Bridge, Model Identification Parameters

Flood event	AR coeff. a	MA coeff. b	Time delay (hr.)	R^2	Error variance
11/03/67	0.87±0.03	0.22±0.05	4	0.95	21989
02/04/75	0.71±0.05	0.35±0.06	6	0.89	37896
24/11/84	0.90±0.03	0.17±0.04	4	0.93	60703
13/09/88	0.95±0.03	0.10±0.04	1	0.91	74777
Mean	0.85	0.21	3.75		48841
Variance	0.008	0.008			

The model identification results (Table 2) were obtained with stage measured from the initial value for the event as datum. The Kalman filter also worked quite successfully with raw stage data. This change to the datum is the reason for setting a_0=0.95 rather than 0.90 (Table 2). All the forecasting results were obtained with raw stage data.

The Kalman filter incorporating the above measurement equation, parameter transition equations, and prior parameter data was used on the four test floods. Forecasts of stage at lead times of 1, 2, 3, and 4 hours were calculated by successively applying the equation:

$$GS_{t+n/t}=a_t GS_{t+n-1/t}+b_t AP_{t+n-5/t} \qquad \text{for } n=1,2,3,4. \tag{12}$$

For the assumed parameter transition model, a_t and b_t are the best estimates of future values of these parameters. This may not be true for more general transition models. The 4-hour forecasting results are shown in Table 4. The lack of a flow rating at the unstable Gorge site precludes the use of the RORB flow-based model for comparison.

From the results in Table 3 the measurement equation for the Gorge-OHB system is:

$$OS_t=a_t OS_{t-1}+b_t GS_{t-4}+n_t \tag{13}$$

where OS_t is the stage at Old Highway Bridge, GS_t is the stage at the Gorge, and n_t is model error. The model structure is the same as that for the Arthurs Pass-Gorge system except for the 4-hour time delay. The measurement error variance R_t was set to 10^7 until the OHB stage begins to rise, and then R_t was reduced to 50000.

The parameter transition model is also the same, with initial values (from Table 3): a_0=0.85; b_0=0.21; Paa_0=0.008; Pbb_0=0.008.

The parameter transition variances were set on the same basis as the Arthurs Pass-Gorge model at: U=0.00001 and V=0.0001.

After estimating a_t and b_t with the Kalman filter, the forecast equation:

$$OS_{t+n/t}=a_t OS_{t+n-1/t}+b_t GS_{t+n-4} \qquad \text{for n=1,2,3,4} \qquad (14)$$

provided the 1-, 2-, 3-, and 4-hour forecasts. The 4-hourforecast performance is shown in Table 5 for stage and, where a rating was available, the equivalent flow for the forecasted stage. For comparison, Table 5 also includes the 4-hour flow forecast performance of the RORB model. Forecasting performance and associated variations in model parameters are illustrated for two of the test events, each with different characteristics: a two peak flood on 31 August 1970 (Fig. 1) with a moderate rate of change of stage; and a rapidly rising single-peak flood on 20 May 1988 (Fig. 2).

TABLE 4—Performance of ARMA 4-hour Flood Forecasts at Waimakariri Gorge

Flood event	Peak time error (hr)	Peak stage error (%)	Stage error at peak time (%)
21/12/57	-4	+25	-6
31/08/70	-1	+4.6	-5
03/12/79	-1	+43	+7
20/05/88	-2	+41	-20

Note:
(1) Stage errors are percent of (peak stage-initial stage); refer to Table 1.
(2) Positive peak error implies over-estimation.
(3) Positive time error implies early arrival of forecast peak.

DISCUSSION

The results in Table 2 and Table 3 demonstrate that a simple linear model can provide a reasonable dynamic relationship between flood-producing rainfall and river stage, as well as between upstream and downstream river stage. For each event a model with one autoregressive, one moving-average, and a time-delay parameter was the best linear fit to the data according to predetermined statistical fitting criteria. The model parameters have different values for each event, but the inference is that the same model structure, with time-varying parameters, could fit all events and even improve the fit for each event given an objective parameter modification procedure.

The Kalman filter algorithm provides the objective, statistically optimal method for combining this knowledge of the model structure, obtained from prior analysis, with real-time data obtained through the telemetric network. The Kalman filter requires a linear or linearised prior model, and the ARMA model is easily incorporated if a fixed time delay is adopted. The results in Tables 2 and 3 provided all the necessary prior knowledge except for rates of parameter variation, for which reasonable assumptions were made.

The prior knowledge derived from four floods was incorporated into the adaptive forecasting algorithm used to forecast the remaining four floods. The four-hour forecasts for the ARMA model at Old Highway Bridge (Table 5) show that the stage and flow forecast errors for each event are of similar percent magnitude, because of the choice of base stage level. The + or -20% peak error criterion (Pearson and Jordan, 1991) is thus suitable for both flow and stage.

The results in Tables 4 and 5 show that the ARMA model forecasts stages at the time of the actual peak which meet the criterion in three of the four events (different events for Gorge and OHB). Peaks, however, were forecast for up to four hours later than actual peak time and were over-estimated by more than 20% at the Gorge site for three of the events. The RORB model forecasts peaks up to two hours early, and the peak magnitude errors for the set of four events are no better or worse than the ARMA model. The consistent early peak times forecast by the RORB model made it unnecessary to calculate the magnitude errors at the actual peak times as was required for assessing the flood warning capabilities of the ARMA model.

The performance of the ARMA model in stage-input to stage-output mode is comparable, for the test events, to the rainfall-input to flow-output RORB model. However, the large forecast peak errors at the Gorge for the ARMA model in rainfall-input to stage-output mode suggest that, although the model provides adequate flood warning, its magnitude forecasts are overestimates. The consistently late forecast peak is due to the inability of the Kalman filter estimation to track rapid changes in parameter values near the peak (Fig. 2), given the assumed random walk parameter model. Improvements to the ARMA model are most likely to lie in development of the parameter variation model beyond the simple random walk structure.

TABLE 5—Comparison of RORB and autoregressive moving average (ARMA) 4-hour Flood Forecasts at Old Highway Bridge

RORB			ARMA				
Flood event	Peak time error (hr)	Peak flow error (%)	Peak time error (hr)	Peak stage error (%)	Peak flow error (%)	Stage error at peak time (%)	Flow error at peak
21/12/57	+2	-3	-1	+7	+8	-3	-4
31/08/70	0	-16	-4	-4	-5	-5	-6
03/12/79	+1	+20	-4	+2	+2	-21	-24
20/05/88	+2	-5	-2	+19	**	+9	**

** Flow rating not available for stages greater than flood flow at this unstable site.

Note:

(1) Stage errors are percent of (peak stage-initial stage); refer to Table 1.

(2) Flow errors are percent of peak flow.

(3) Positive peak error implies over-estimation.

(4) Positive time error implies early arrival of forecast peak.

The main advantages of the ARMA model are:

(a) The model can be applied to basins with only one telemetered raingauge, provided it is sufficiently diagnostic for basin rainfall-runoff response (this applies to the Waimakariri, Rakaia and Ashley basins of Canterbury for example), or used to relate upstream and downstream flood stage.

(b) Stage-discharge rating of hydrological recording sites is not necessary —"stage only" sites can be used for forecasting.

(c) The model is relatively easy to calibrate, software is inexpensive and it can be run on a PC.

(d) Little training of staff is required to run the model and forecasts can be updated in a matter of minutes.

Disadvantages include:

(a) The model is a "black box" which does not transparently simulate the physics of the rainfall-runoff process.

(b) Hydrologists may have less confidence than they would with RORB, for example, in applying the model to storm conditions different from those used in calibration.

(c) The ARMA model is probably less accurate than a process-based hydrologic model with appropriate data support.

We recommend use of the ARMA model as a primary forecasting system in basins where potential flood damage costs are comparatively low (e.g. Rakaia, Waiau and perhaps Ashburton basins of Canterbury), and as a secondary or back-up system where costs are high (e.g. Waimakariri and Ashley basins in Canterbury).

CONCLUSIONS

A simple linear ARMA model incorporated into the Kalman filter adaptive algorithm is a method of flood forecasting which could improve forecasting where subjective methods are used with minimal data. The adaptive estimation of model parameters can accommodate changes in model error due partly to unmeasured changes in catchment conditions, which vary slowly relative to the flood wave dynamics. The continual adjustment to current observed conditions allows for stage data from rivers with unrated or unstable sites, unmeasured tributary inflow, and for overtopping of river banks. PC-based commercial software (statistical regression and spreadsheet) can be used for both off-line analysis and on-line forecasting. Further development is needed to improve performance where parameters change rapidly during floods. Where an adequate data base exists, the more complex physically-based hydrological models may be superior.

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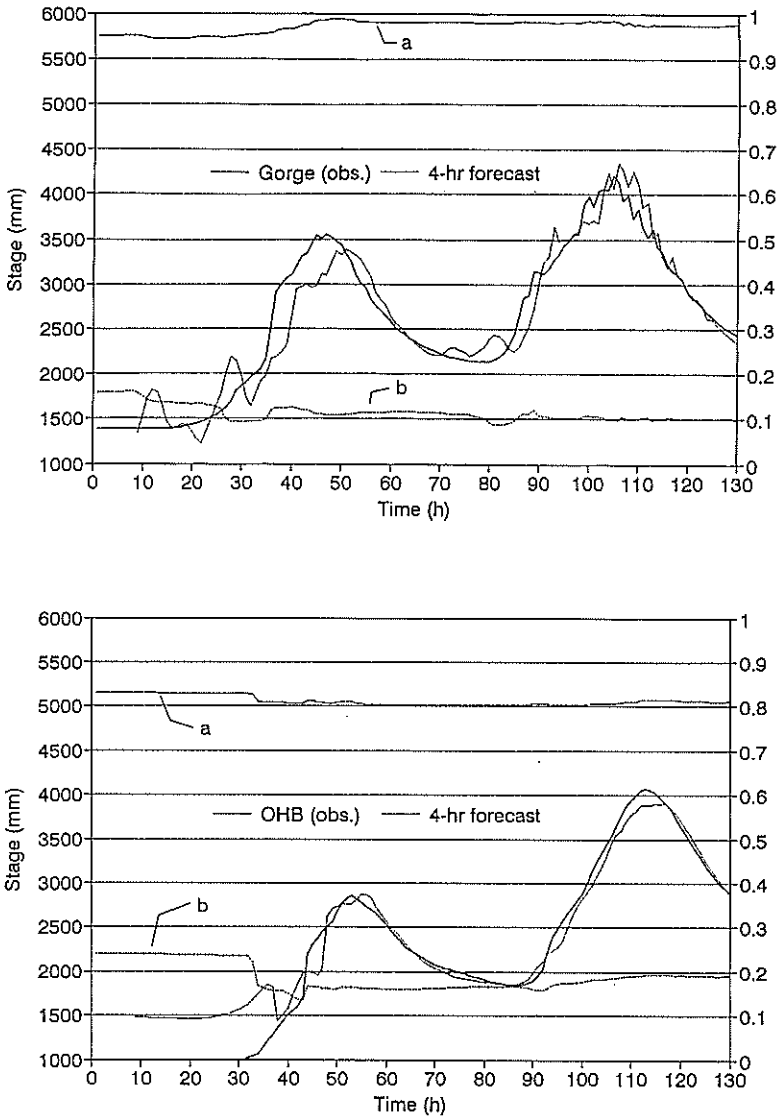

FIG. 1—Comparison of 4-hour forecast and observed stage, and time variation of model parameters, at Waimakariri Gorge and Old Highway Bridge, for a flood on 31 August 1970.

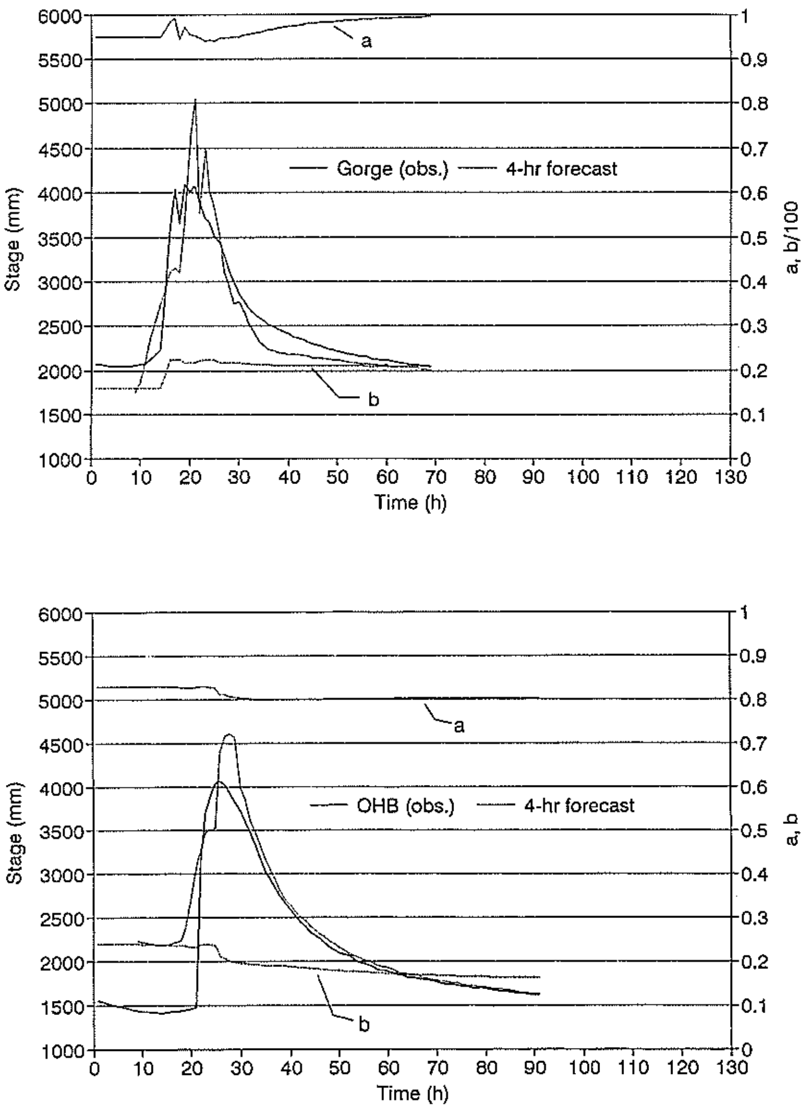

FIG. 2—Comparison of 4-hour forecast and observed stage, and time variation of model parameters, at Waimakariri Gorge and Old Highway Bridge, for a flood on 20 May 1988.

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