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Medium-range reservoir inflow predictions based on quantitative precipitation forecasts

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Summary Forecasts of inflow into major reservoirs of the Brazilian hydroelectric power system are needed for the operational planning over periods ranging from a few hours to several months ahead. Medium-range forecasts of the order of a few days to two weeks have usually been obtained by simple ARMA-type models, which do not utilize information on observed or forecast precipitation, nor streamflow observations from upstream gauging stations. Recently, several different hydrological models have been tested to assess the potential improvements in forecasts that could be obtained by using observed and forecast precipitation as additional inputs. We present results from the use of a large-scale hydrological model applied to part of the Paranaíba river basin between Itumbiara and São Simão power plants (75,000 km^2) using precipitation forecasts from the regional Eta model run by the Brazilian Center for Weather Prediction (CPTEC). Results were compared with those from the currently-used ARMA model and it is shown that forecast errors can be reduced considerably, during both wet and dry seasons. Further reductions in prediction errors may be anticipated from improved rainfall forecasts and of data quality used by the hydrological model.

Introduction

The Brazilian power distribution system is largely based on hydropower production and is interconnected over most of

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the country, which is very extensive. Energy demands not met by hydropower are met by thermoelectric plants, but at higher costs. Operation of the whole system of 103 major hydropower plants and 37 thermal plants is planned to minimize the use of thermal plants. The whole system is optimized by a chain of models: one for long-range operational planning (5 years), another for seasonal operational planning (12 months), another for monthly operational planning, and finally a model for making operational decisions in the coming week. Forecasts of inflows to all reservoirs are used with all planning horizons, and forecast errors influence decision making, leading to sub-optimal operation when water is released unnecessarily from reservoirs, or when thermal power plants are activated needlessly. Currently-used forecasting models do not include any information on weather or climate forecasts, but are based on Periodic Auto-Regressive (PAR), or Auto-Regressive Moving Average (ARMA) models (Maceira and Damázio, 2005).

Planning and optimization of the country's power system is made by the Operador Nacional do Sistema Elétrico (ONS – National Electric System Operator), which recently initiated efforts to improve inflow forecasts by testing and comparing several streamflow-forecasting models which make use of observed and predicted precipitation as input variables. As a first step, medium-range forecasts over coming 10-day periods were addressed.

Quantitative Precipitation Forecasts (QPFs) are highly uncertain and are still not widely used as input to operational flood-forecasting or streamflow-forecasting models for large catchments. However, an increasing number of results suggest that progress is being achieved towards bringing QPFs to the stage of operational usefulness for hydrological applications (Hollingsworth, 2003; Collier and Krzysztofowicz, 2000; Damrath et al., 2000; Golding, 2000; Mao et al., 2000; McBride and Ebert, 2000; Mullen and Buizza, 2001), while other authors highlight the limitations of these forecasts in the case of extreme events (Meneguzzo et al., 2004; Bartholmes and Todini, 2005).

The use of QPFs obtained by numerical weather prediction models (NWPs) as input data to run hydrological rainfall–runoff models, thereby obtaining extended streamflow forecasts, has been explored by several authors (Yu et al., 1999; Ibbitt et al., 2000; Anderson et al., 2002; Jasper et al., 2002; Koussis et al., 2003; Habets et al., 2004; Collischonn et al., 2005) who in general concluded that QPFs were useful, although their usefulness was limited by their great uncertainty. There have been recent attempts to consider the uncertainty in forecasts, using ensemble rainfall forecasts (Bartholmes and Todini, 2005; Goweleeuw et al., 2005) and to combine the inherent uncertainty of hydrological models with ensemble forecasts (Pappenberger et al., 2005). Most of these results are from work that is still at the research stage, since operational-forecasting systems still rely more on radar estimates and telemetry of measured rainfall or short-range nowcasting (Moore et al., 2005). Nevertheless, QPFs are gradually being introduced in operational streamflow-forecasting systems in an attempt to extend the range of forecasts, but the extended streamflow forecasts that are obtained serve basically as early warning indicators, because of high uncertainty of QPFs (Bremicker et al., 2006; Moore et al., 2005).

In some cases it is not necessary to have very precise forecasts, since relatively rough estimates can improve the operation of hydraulic structures, or can yield estimates of the risk that rivers will exceed specified discharge thresholds (Rabuffetti and Barbero, 2005). This is the case for forecasts of inflows to reservoirs in the medium range, where it is important to know water volumes in advance, while errors in flow peak magnitude and timing are less important than for flood forecasting. The present work describes the use of QPFs as input to a large-scale hydrological model for streamflow forecasts in a sub-basin of the Paranaíba river in Brazil. Streamflow forecasts were obtained for ranges of 1–10 days in daily time-steps and results were compared with forecasts obtained by the auto-regressive models at present used by ONS to manage all 103 reservoirs in the system when making decisions concerning power generation.

The MGB-IPH hydrological model

Many hydrological models can be used to make streamflow forecasts based on predicted rainfall, and the comparative study developed in Brazil by ONS also included lumped rainfall–runoff models, more complex distributed hydrological models, and black-box models based on neural networks.

The question whether a distributed rainfall–runoff model performs better than simpler models has been posed repeatedly in the past. It has been argued that distributed models would perform better where distributed input data were available, such as rainfall estimated by radar. But a recent study – the Distributed Model Intercomparison Project – showed that lumped models performed comparatively well even using radar rainfall data, although in one basin with elongated shape (Blue River), distributed models outperformed lumped models (Reed et al., 2004). Distributed models also appear to perform better when uncertainties in input data and parameter values are considered (Carpenter and Georgakakos, 2006). It can also be argued that distributed or semi-distributed models should be used in large basins where spatial variability in rainfall and runoff generation processes may play a larger role, and the results presented in this paper were all obtained using the distributed large-scale hydrological model MGH-IPH (Collischonn et al., 2007; Collischonn and Tucci, 2001).

This is a large-scale distributed hydrological model developed for use in large South American basins, where densities of hydrological instrument networks are relatively low and records are commonly short. Using the classification proposed by Beven (2001), the model can be classified as a *hydrological response unit* model. It uses input data derived from Geographical Information Systems giving information on basin characteristics such as land use, topography, vegetation cover and soil types, which guide the calibration of parameter values. The MGB-IPH model was developed from the LARSIM (Bremicker, 1998) and VIC (Liang et al., 1994; Nijssem et al., 1997) models, with some changes in the evapotranspiration, percolation and streamflow propagation modules. It has modules for calculating the soil water budget; evapotranspiration; flow propagation within a cell, and flow routing through the drainage network. The drainage basin is divided into elements of area – normally on a square grid of 10×10 km — connected by channels, with vegetation and land use within each element categorized into one or more classes, the number of vegetation and land-use types being at the choice of the user. The Grouped Response Unit (GRU) (Kouwen et al., 1993) approach is used for hydrological classification of all areas with a similar combination of soil and land cover without consideration of their exact locality within the grid (or cell). A cell contains a limited number of distinct GRUs. Soil water budget is computed for each GRU, and runoff generated from the different GRUs in the cell is then summed and routed through the river network. This approach has been used in other large-scale hydrological models, such as VIC (Wood et al., 1992; Liang et al., 1994; Nijssem et al., 1997) and WATFLOOD (Kouwen and Mousavi, 2002; Soulis et al., 2004).

The soil water balance is computed independently for each GRU of each cell, using components describing canopy interception, evapotranspiration, infiltration, surface runoff, sub-surface flow, baseflow and soil water storage. Rainfall values are interpolated spatially and at each time step to give an estimate at the center of each grid cell using inverse-distance-squared interpolation. Flow generated within each cell is routed to the stream network using three linear reservoirs (baseflow, sub-surface flow and surface flow). Streamflow is propagated through the river network using the Muskingum—Cunge method. A more comprehensive description of the model, including results from a proxy-basin test, is given by Collischonn et al. (2007) and further applications are presented by Allasia et al. (2006), Collischonn et al. (2005) and Tucci et al. (2003).

Hydrological model updating

Hydrological models can be operated in simulation mode and in adaptive mode. In simulation mode the model output is calculated from previous model inputs, in particular rainfall. In adaptive mode, model output is calculated not only from previous model inputs but also from observations of basin streamflow which are used to update the model before each new forecast is issued. Real-time forecasting requires a model operating in adaptive mode (Moore et al., 2005). This is because there are inadequacies of model structure and uncertainties in parameter values and initial conditions (Wagener et al., 2004). Where no updating procedure is applied relatively large errors occur, even for forecasts with very short lead-times.

Model updating through assimilation of new data can be classified according to the variables that are modified: whether input variables, model states, model parameters or output variables (WMO, 1992; Madsen and Skotner, 2005). The most widely-used updating procedures update the state variables or the output variables. A very common approach to model updating focuses on the prediction of future model errors, based on past model errors. Toth et al. (1999), for instance, used ARMA models to predict forecasting errors of a deterministic rainfall—runoff model, and Goswani et al. (2005) assessed the performance of eight real-time updating procedures, based mostly on error prediction. The advantage of this approach is that it can be easily applied to complex models such as full hydrodynamic flood propagation models (Madsen and Skotner, 2005).

Updating of state variables can be based on observed errors in river flow or stage, and can use empirical methods or more formal Kalman filtering (Moore et al., 2005; Romanowicz et al., 2006). For more complex distributed and non-linear models, Kalman filtering may lead to highly complex computations while results are not necessarily better that those obtained by simpler empirical schemes (Moore et al., 2005; O'Connell and Clarke, 1981). The empirical updating procedure used in the present work was designed to make use of data from several stream gauging points distributed throughout the river basin, both on the main channel and on its tributaries, and which could be integrated into the structure of the MGB-IPH model. The first version of this updating procedure was described in Collischonn et al. (2005), for a smaller basin with only two gauging sites. The updating method used in the present work was based on continuous comparison between observed and calculated flows during a warming up or filtering period of 6—18 months, prior to the time of forecast initiation. It can use information from several gauging points along the basin and acts on two state variables: river flow and groundwater flow (or slow response reservoir storage).

For each gauging station p where observed streamflow is available, an updating correction factor (FCA) is calculated according to Eq. (1):

$$\mathrm{FCA}_p = \frac{\sum_{t=t_0-t_a}^{t_0} Q_{\mathrm{obs}}^t}{\sum_{t=t_0-t_a}^{t_0} Q_{\mathrm{calc}}^t} \tag{1}$$

where Q_{obs} and Q_{calc} are observed and calculated streamflow; t is the time step; t_0 is the time at which forecasts are issued, and t_a defines a period over which averages are calculated. The value of $t_0 - t_a$ may be one day, but since observed streamflow measurements have noise, obtaining the correction factor FCA using just one day of observations can give rise to fluctuations and instability in the updating process. The value of t_a should therefore be set to two or more days when streamflow measurements are noisy, as in the case of daily observations in rivers subject to reservoir regulation. After the FCA value for gauge p is calculated, discharge from each cell upstream of the gauge is updated according to Eq. (2):

$$Q_{\mathrm{up}_{i,k}} = \mathrm{FCA}_k \cdot Q_{\mathrm{calc}_i} \cdot \left(\frac{A_i}{A_k}\right) + Q_{\mathrm{calc}_i} \cdot \left(1 - \frac{A_i}{A_k}\right) \tag{2}$$

where k is the gauge considered; $Q_{\mathrm{up}_{i,k}}$ is the updated value of discharge at cell i, located upstream of gauge k; A_i is the drainage area upstream of the ith cell and A_k is the drainage area upstream of gauge k.

Eq. (2) shows that corrections to calculated discharge are weighted according to the reliability of the information at the streamgauge. At the cell where the streamgauge is located, observed flows are used in place of calculated ones, and for cells close to it, the scheme assumes that flow recorded at the streamgauge is virtually correct. For cells far upstream of the gauge, however, calculated flows are assumed to be more reliable, and corrections are damped out by use of the equation.

The updating procedure described above refers to discharge, and a similar procedure is adopted to correct volumes in groundwater storage. Each cell of the model has three linear reservoirs representing the retention and delay of water subsequently released as surface, sub-surface and groundwater flow. Outflow from these reservoirs in each cell becomes inflow to the river network and is routed using the Muskingun–Cunge method (Collischonn et al., 2007). During long dry periods, the greater part of flow comes from groundwater storage. The model maintains a continuous record of the fraction of flow in the drainage network that comes from surface, sub-surface and groundwater. Groundwater storage in each cell upstream of streamgauge k is updated using the same correction factor (FCA) used for river flow, but unlike discharge, groundwater storage updating is not weighted by drainage area relations between cell and gauging point, but by the fraction of river flow that is of groundwater origin (PB_i), according to (3)

$$\mathrm{VB}_{\mathrm{up}_i} = (\mathrm{FCA}_k)^{bx} \cdot \mathrm{VB}_i \cdot (\mathrm{PB}_i) + \mathrm{VB}_i \cdot (1 - \mathrm{PB}_i) \quad (3)$$

where $\mathrm{VB}_{\mathrm{up}_i}$ is the updated storage in the groundwater reservoir of cell i; VB_i is the calculated storage at cell i; PB_i is the fraction of river flow at cell i that originated from groundwater, and bx is an updating parameter with values between 0 and 1. When bx is close to 1, groundwater updating is relatively rapid; when bx is close to 0, the correction is somewhat smoothed, therefore taking longer to make the necessary corrections. On the other hand, smaller values of this parameter lead to more stable results, since real-time observed streamflow values may have random errors that would, otherwise, result in overcorrection. The influence of this parameter was briefly tested and bx was set to 0.2 (Paz et al., 2007).

The updating technique described here is empirical and is under continual development for further applications. In some respects, the proposed dependence of correction weighting with drainage area is similar to the pre-defined gain functions used by Madsen and Skotner (2005).

Precipitation forecasts

The QPF forecasts were provided by the Eta Model described by Mesinger et al. (1988) andBlack (1994). This is a grid-point model and was configured to run over a domain that covers most of South America and parts of adjacent oceans (Chou, 1996). The model has been used for short-range weather forecasts by CPTEC on an operational basis since 1996. One of the major features of the model is the vertical η coordinate defined by Mesinger (1984). Near mountainous regions, this coordinate stays approximately horizontal, which reduces errors from calculations of horizontal derivatives in those regions. The model variables are distributed on the Eta-grid. The time scheme uses forward–backward scheme for the adjustment terms, and first-forward-then-centered for the advection terms.

The model was configured with horizontal resolution of 40 km and 38 vertical layers. Highest vertical resolution is near the surface, where the first model layer thickness is 20 m. Resolution decreases with height, except near the tropopause where a secondary maximum of vertical resolution occurs. The model has about 13 levels within the convective layer. The top of the model is at 25 h Pa. In the vertical, the variables are distributed in a Lorenz type of grid (Chou, 1996).

The model's estimate of total precipitation is the sum of convective and stratiform precipitation; the former is given by the Betts–Miller scheme (Betts and Miller, 1986) and the latter uses the Zhao cloud scheme (Zhao and Carr, 1997). Atmospheric turbulence is modeled by the Mellor–Yamada 2.5 scheme (Mellor and Yamada, 1982) with forecasts of turbulent kinetic energy. Exchanges between vegetation, soil and atmosphere are modeled using the scheme proposed by Chen et al. (1997) with two soil layers, 12 vegetation cover types and nine soil types. Model shortwave radiation is treated by the Lacis and Hansen (1974) scheme, and for longwave radiation the procedure proposed by Fels and Schwarzkopf (1975) is used. Longwave and shortwave fluxes are calculated every model hour. The initial conditions were taken from NCEP daily global analyses with a resolution of about 100 km and 28 vertical layers. The lateral boundary conditions were taken from the CPTEC global model (Bonatti, 1996) forecasts at a horizontal resolution of approximately 100 km. These boundaries were updated every 6 h.

Ten-day Eta forecasts were produced for the period from 1996 to 2003. The runs started at 1200 UTC every Wednesday, to fit the ONS weekly operational procedures. Variables forecast by the Eta model, such as precipitation, were output every 6 h on 0.4×0.4 latitude–longitude grid.

Precipitation forecasts given by the Eta model over South America have been shown to be useful for short-period weather forecasts (Chou and Justi da Silva, 1999; Bustamante et al., 1999), extended forecasts (Chou et al., 2000; Chou et al., 2002) and seasonal forecasts (Chou et al., 2005). The precipitation forecasts tend to overestimate at lower rates and to underestimate at heavier rates. In the central part of the continent, a small underestimate is generally found (Chou and Justi da Silva, 1999). In the evaluation performed by Bustamante et al. (1999) precipitation forecasts tended to show larger bias at the initial forecast hours; however, at about 36 h and 48 h, precipitation forecasts tended to reduce the initial bias. In a comparison study carried out by Gonçalves et al. (2006), in general, the Eta model precipitation forecasts outperformed the remotely sensed precipitation products in South America. In extended- and seasonal-range forecasts, the model exhibits clear positive systematic bias along the northeastern coast of Brazil and southern part of Chile (Chou et al., 2000; Chou et al., 2002; Chou et al., 2005).

Description of the study basin and data

The Paranaiba River is one of the main rivers of the Parana river basin, which contains 60% of the Brazilian hydropower production capacity. The Paranaiba drains the central region of Brazil where altitude is between 1200 and 400 m. The study reported in this paper concentrated on the sub-basin of the Paranaíba between the two major hydropower plants Itumbiara and São Simão. The incremental drainage area between the two dams is 76,746 km^2 with five major tributaries: Prata and Tijuco from the left bank and Meia-Ponte, Bois and Preto from the right. Time of concentration for the incremental basin is between 1 and 2 days.

Annual rainfall is close to 1500 mm and is concentrated in summer from November to March. Soils are relatively deep and the natural vegetation of forests and *cerrado* (Eiten, 1972), a savanna-like vegetation, has been almost completely replaced by agriculture and pasture (Fig. 1).

The model MGB-IPH was applied with the basin divided into cells of 6×6 min of latitude and longitude, and considering six different GRUs, according to Table 1. Soils where classified as deep or shallow and were combined with vegetation or land-use characteristics to define the GRUs. The most important GRU in the basin is *Agriculture over deep soils*, which covers almost 60% of the basin.

Hydrological records provided by ONS consisted of data from 26 daily raingauges and 10 daily streamgauges. Two time series of inflow to the Sao Simão reservoir were provided: one representing overall inflow to the reservoir and the other representing just the fraction generated in the incremental basin, defined as the area between São Simão and Itumbiara upstream. The objective was to obtain forecasts of inflow contribution from the incremental basin, termed incremental inflow. Incremental inflow is not actually observed, but is calculated from water budgets of the downstream reservoir minus water releases from the upstream reservoir in monthly time-steps. Daily incremental inflow values are then obtained by distributing the monthly volume according to the shape of the daily hydrograph of the most important tributary. Consequently, the observed incremental inflow is actually a result of a series of transformations of data from reservoir water budgets and observed discharges at stream gauges, all of them subject to error. The reason for focussing on incremental inflows is that the operation of the whole system of reservoirs is operationally managed based on optimization methods that use forecasts of incremental inflows.

Table 1 Grouped response units considered in the hydrologic discretization of the basin

GRU	Fraction of the basin (%)
Cerrado SS	5.7
Cerrado DS	9.2
Agriculture DS	59.3
Agriculture MS	20.1
Agriculture SS	4.4
Water	1.3

SS: shallow soils; DS: deep soils; MS: medium deep soils.

Average incremental inflow is 960 $m^3 s^{-1}$ which is nearly 40% of the total inflow to the downstream reservoir São

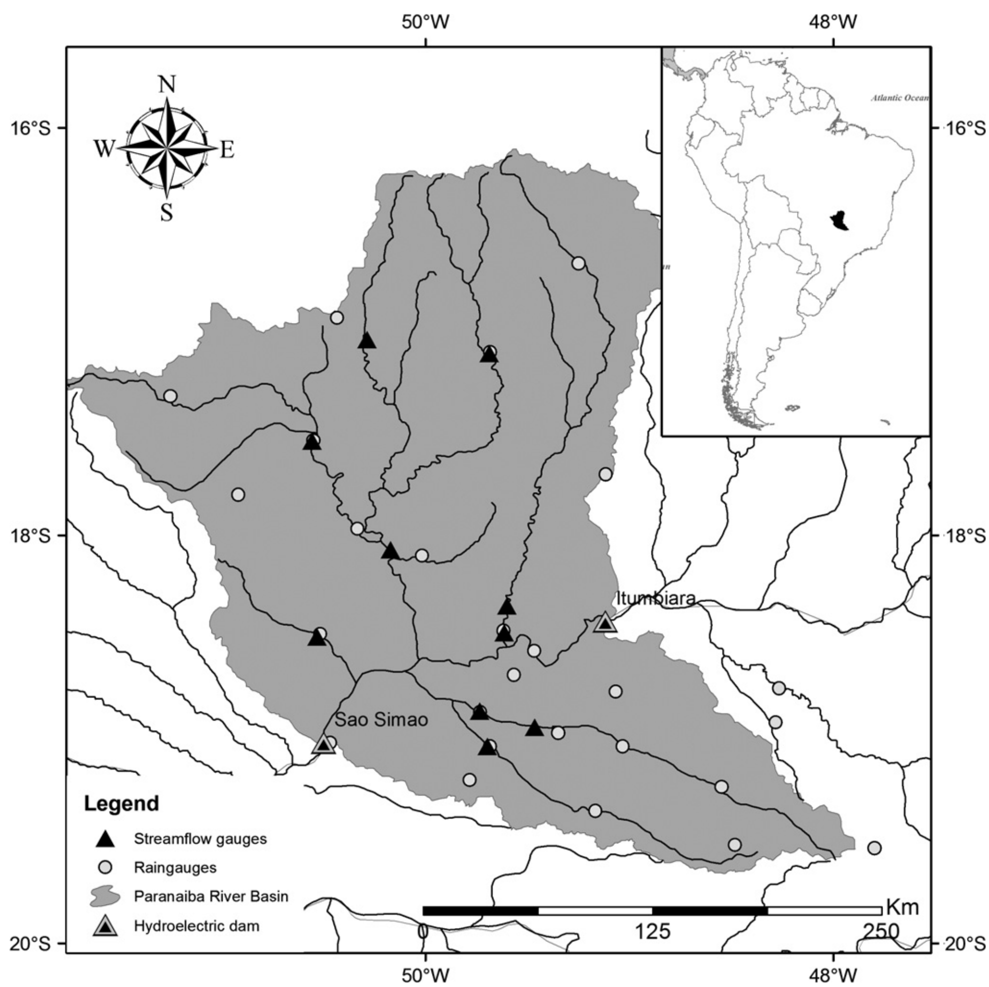

Figure 1 The Paranaiba basin showing the location of raingauges, stream gauges and the Itumbiara and São Simão dams.

Simão. Maximum incremental inflow occurred in 1982 with 6200 $m^3 s^{-1}$, and values close to the minimum occur every year in August or September, with values commonly in the range 300–400 $m^3 s^{-1}$.

Data on surface temperature, wind velocity, air moisture, hours of sunshine, and atmospheric pressure were obtained from seven meteorological stations operated by INMET (National Institute of Meteorology). QPFs were obtained from the Eta CPTEC model as explained above, with a spatial resolution of $0.4 \times 0.4°$. Precipitation forecasts were interpolated to the 6×6 min resolution of the hydrological model, using inverse-distance-squared weighting. Observed and forecast precipitations were available for daily time-steps while other meteorological data were available only as mean monthly values. Precipitation and meteorological data were interpolated to the MGB-IPH model grid using inverse-distance-squared weighting.

Model calibration

Calibration of the model is in three stages: first guesses, manual fitting, and automatic multi-objective calibration. First estimates of parameter values come from physical considerations and prior applications in similar basins or basins nearby. The second step is to improve model results by manual calibration of the parameters. This normally consists of a trial-and-error procedure, using visual comparison of observed and calculated hydrographs of single rainfall–runoff events and of the whole annual hydrograph. If the overall volume of runoff obtained from calculated and observed hydrographs is in reasonable agreement, and if calculated streamflow during peaks and recessions is of the same order of magnitude as that observed, the manual calibration phase is complete. This phase is based on visual comparison and statistics and objective functions are not evaluated. During the third and final phase, the MOCOM-UA (Yapo et al., 1998) algorithm is used to obtain the final calibration, based on *a priori* defined ranges of parameter values, and considering three objective functions: the Nash–Sutcliffe coefficient of efficiency (NS); the Nash–Sutcliffe coefficient of efficiency of logarithms of streamflow (NS log); and relative volume errors (ΔV). The MOCOM-UA algorithm was applied using a population of 100 parameter sets and the final solution was chosen arbitrarily between the three with best NS coefficients.

Parameters are related to GRUs and in usual applications of the model the same parameter values are adopted for each GRU, regardless of where it lies within the basin (Collischonn et al., 2007). However for forecasting applications the calibration is repeated for each sub-basin, so that different parameter values for the same GRU may be found for different sub-basins. This means that physical meaning of the relation between land-use and soil classes and model parameters is somewhat sacrificed in order to get better results at the sub-basin outfall.

The model was calibrated using data from 1991 to 2001 and verified using data from 1981 to 1990. Table 2 shows the results at each gauging station and for the estimated incremental inflow to the São Simão dam (last line in Table 2). Larger basins give better results, and Nash–Sutcliffe coefficients are very similar for calibration and verification periods.

Configuration of forecasting tests and method used to evaluate model efficiency

Successive forecasts were made every week, starting on Wednesday, and extending for 10 days up to Friday of the week following. For each forecast the hydrological model was run with observed rainfall data during a warm-up period that lasted a few months, extending from the middle of the dry season (July) of the preceding year up to the Tuesday preceding the forecast period. Calculated and observed discharge values were compared at several sites, and the updating procedure was applied each day during this warming up period. Forecasts were compared with observed incremental inflows and with forecasts obtained from the model in current operational use, known as PREVIVAZ (CEPEL, 2004; Maceira et al., 1997).

PREVIVAZ is a program that uses several different configurations of ARMA(p, q) and Periodic ARMA models, with values for p in the range 1 to 4 and q not larger than 1, possibly

Table 2 Model results during calibration and verification

River	Gauging station	Area (km^2)	Calibr. (1991–2001)			Verific. (1981–1990)		
			NS	NS log	ΔV	NS	NS log	ΔV
Meia Ponte	Ponte Meia Ponte	11483	0.80	0.84	4.8	0.83	0.88	−10.7
Meia Ponte	Ponte Go-206	12256	0.79	0.84	−1.5	NA	NA	NA
Dos Bois	Fazenda Boa Vista	4569	0.62	0.69	13.8	0.68	0.82	0.0
Turvo	Faz. Nova do Turvo	2436	0.63	0.74	8.1	0.68	0.78	−16.4
Verde	Ponte Rio Verdão	8651	0.80	0.85	6.2	0.80	0.81	−6.7
Dos Bois	Abaixo B. R. Verde	30491	0.87	0.90	1.8	0.91	0.94	−6.3
Preto	Quirinópolis	1657	0.58	0.53	−5.7	0.44	0.45	10.6
Prata	Ponte do Prata	5266	0.72	0.84	1.3	0.76	0.82	0.3
Tijuco	Ituiutaba	6383	0.74	0.78	−10.0	0.78	0.79	7.1
Tijuco	Cach. do Gambá	6998	0.64	0.68	−9.0	0.80	0.84	1.0
Paranaíba	São Simão (increm.)	76746	0.90	0.89	0.6	0.92	0.90	−1.9

The Nash–Sutcliffe coefficient of efficiency (NS); the Nash–Sutcliffe coefficient of efficiency of logarithms of streamflow (NS log); and relative volume errors (ΔV) expressed in percentage terms.

with Box—Cox transformation of streamflow values (CEPEL, 2004). Different configurations of the model are tested every week before the forecast is issued, so as to identify the best amongst all the possible model configurations. The historical record is therefore divided into two halves, and for each week, the parameters of every model in the set are estimated using data from the first half, after which Root-Mean-Square Errors (RMSEs) are calculated using the second half of the record. The procedure is then reversed: PREVIVAZ estimates the parameters for every model for each week of the second half of the record, with RMSEs calculated using data from the first half. The average of the two RMSEs, from the two halves of the record, is then calculated for each possible model and that model is selected for which this average is smallest. After this selection procedure, PREVIVAZ once again estimates the parameters, this time using the full record, and the whole procedure is repeated each week; rainfall, whether observed or forecast, is not used.

Results

Results are presented in both fixed-origin and fixed lead-time form (Bell and Moore, 1998). Fixed-origin presentation shows forecasts issued in one day, with lead-times from one to 10 days, extending up to the forecasting horizon; forecasts are therefore compared that were issued on different days, but with the same lead-time. Fixed-origin forecasts are presented as hydrographs of daily streamflows which partly overlap because (in the work reported here) they are issued each Wednesday, and are extend to 12 days, i.e., two days beyond the range of rainfall forecasts.

Fig. 2a shows successive forecasts issued every Wednesday during the 2002 summer (wet season) compared with the observed hydrograph. To analyze whether the errors arise from incorrect rainfall forecasts or from other sources, Fig. 2b shows forecasts for the same periods that were obtained using observed rainfall. It can be seen that some of the errors are clearly related to poor rainfall forecasts; surprisingly, however, the flow peak of late February is more seriously overestimated when observed rainfall was used. This may be related to the density of the rain gauge network used to estimate observed rainfall, which is much lower than gauge densities recommended by WMO (1994).

The analysis for the summer of 2002 shown in Fig. 2 was repeated for every week from January 2002 to December 2003 (103 weeks in all). To assess the decline in forecasts quality with increasing leading time, the NS coefficient of efficiency was calculated for both flow forecasts based on QPFs and for forecasts based on observed rainfall, for lead-times from 1 to 12 days. Results are shown in Table 3.

It can be seen that performance of forecasts decreases in both cases, and that the decline is greater where forecasts are calculated from QPFs. From days 7 to 12, the NS efficiencies remain relatively stable around 0.92 to 0.94 in the case of observed rainfall, and about 0.83 in the case of forecast rainfall. High values of the coefficient for short leading times are due to the updating procedure used by the model.

The positive effect of model updating on the results can be evaluated by comparing model efficiencies for short lead-times (Table 3) with model efficiencies during calibration and verification of the hydrological model (Table 2). During calibration and verification, the calculated NS efficiency was close to 0.90, while during the forecasting tests its value was as high as 0.98, on the first day of forecast, when observed rainfall was used as input.

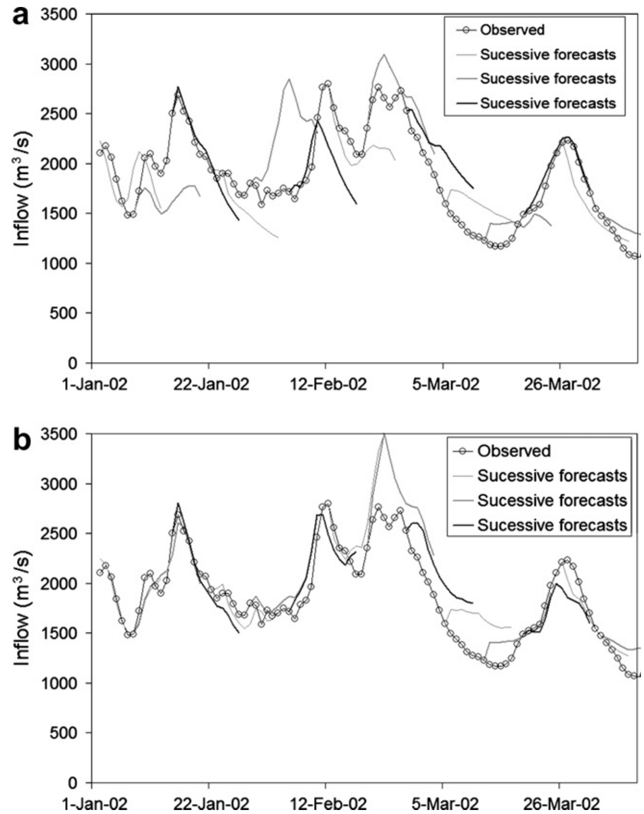

Figure 2 Successive forecasts issued every Wednesday during the summer of 2002: (a) forecast rainfall; (b) observed rainfall.

Table 3 Nash—Sutcliffe (NS) efficiency coefficients for incremental inflow forecasts at São Simão based on forecast and observed rainfall, for lead-times extending to 12 days

Lead-time (days)	NS obs	NS prev
1	0.98	0.97
2	0.97	0.96
3	0.94	0.94
4	0.94	0.91
5	0.95	0.89
6	0.95	0.86
7	0.94	0.82
8	0.95	0.83
9	0.94	0.86
10	0.92	0.84
11	0.92	0.83
12	0.94	0.83

'NS obs' shows the NS efficiency when observed rainfall is used; 'NS prev' gives the NS efficiency using rainfall forecasts from the Eta model.

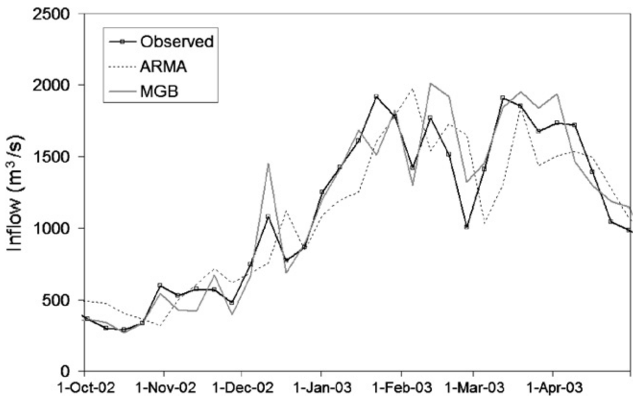

Figure 3 Hydrographs of observed and predicted weekly averages of inflow from October 2002 to April 2003.

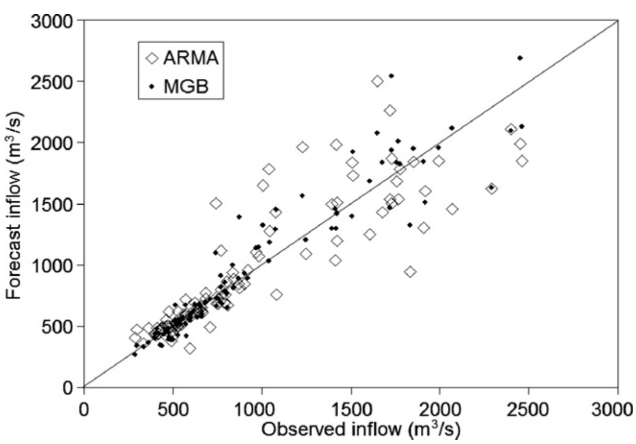

Figure 4 Scatterplot of observed versus predicted inflows using the MGB-IPH model with rainfall forecasts and the ARMA model.

A particularly important analysis is that of weekly average flows. Seven-day averages of incremental inflow, obtained from the MGB-IPH model using input from QPFs, were compared with forecasts obtained by the PREVIVAZ ARMA-type model currently in use. Fig. 3 presents hydrographs of observed and predicted weekly average flows from the end of the dry season of 2002 to the end of the wet season (April) of 2003. Fig. 3 shows a graph of fixed lead-time, since the points in the hydrograph correspond to streamflow forecasts issued with lead-time of one week.

It can be seen that forecasts obtained by the MGB-IPH model are closer to observed streamflow in most cases, especially for the three first weeks of the period, which correspond to the end of the recession of the dry season, and for the rising parts of the hydrograph. The ARMA forecasts show a clear pattern of a one week delay with maximum and minimum values postponed by one week, which is a consequence of the model structure. The value of including new information given by rainfall forecasts can be seen during periods when the hydrograph is rising and during sharp changes in inflow when the hydrograph may increase or decrease.

Fig. 4 compares observed and forecast inflows considering both the MGB-IPH hydrological model with input from QPFs and the currently used PREVIVAZ ARMA-type model during two years (2002 and 2003). It can be seen that for low flows both forecasting models perform relatively well, with points representing the MGB-IPH forecasts rather closer to the line of perfect forecasts. For flows larger than 800 $m^3\,s^{-1}$ points are considerably more dispersed with a clear pattern of larger dispersion for the ARMA model.

Several error analyses compared forecasts obtained with the MGB-IPH model with QPF inputs with forecasts obtained from the ARMA model. The results are given in Table 4, showing that the MGB model performed better in all cases. The reduction of average absolute errors (ABE) is of the order of 34% and the improvement in other statistics is similar. It is not possible to say at present whether this improvement results in better decisions in reservoir opera-

Table 4 Error statistics for seven-day average incremental inflow forecasts obtained with the MGB large-scale distributed model using rainfall forecasts and forecasts obtained by the ARMA model for years 2002 and 2003

Statistic	Statistic measure	ARMA	MGB + QPF
Average absolute error ABE	$\frac{1}{N}\sum um_{i=1}^{N}\lvert P_i - O_i\rvert$	170	113
Average relative error ARE	$\frac{1}{N}\sum_{i=1}^{N}100\cdot\frac{\lvert P_i - O_i\rvert}{O_i}$	16.1	10.8
Root mean square error RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}$	274	186
Nash—Sutcliffe efficiency NS	$1-\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O})^2}$	0.76	0.89

tion, however we expect that better forecasts will probably lead to better decisions.

Conclusions

A methodology for forecasting streamflow based on both observed rainfall and quantitative precipitation forecasts (QPFs) obtained from numerical weather prediction models has been presented, and tested, using a large-scale hydrological model to estimate streamflow from rainfall. An updating method used with the hydrological model, based on observed streamflow at several stream gauges, has also been presented.

The forecasts were tested over a two-year period on a weekly basis, according to current operational practice, for a segment of a river basin lying between two reservoirs that form an important part of the Brazilian hydropower generating system. Daily streamflow forecasts were issued on Wednesday of each week and extended up on Sunday of the week following, giving a 12-day lead-time; the forecasts of streamflow used rainfall forecasts for the first 10 days and assumed that no rain falls during the last two days up to the 12-day forecasting horizon.

The quality of forecasts was first assessed by comparing them with observed streamflow on a daily basis. For the first four days the performance of forecasts was very good, with Nash—Sutcliffe efficiencies remaining above 0.90. For days 6—12, this coefficient was stable around 0.83.

It has also been clearly shown that model updating has a positive effect on forecast performance by raising the Nash—Sutcliffe efficiency from 0.90 during model calibration to 0.98 during the forecast period, for one-day-ahead forecasts using observed rainfall.

As expected, forecasts obtained using observed rainfall are clearly better than forecasts obtained using QPFs. Although QPFs are improving with time, they are still a long way from being better than observations, even with the low density raingauge network in the basin used for the study. However, despite its better quality, observed rainfall cannot be used to forecast streamflow operationally in the medium-range period of several days, because the rain that generates flow during the forecast horizon falls during the period after streamflow forecasts are issued. QPFs must therefore be used for operational forecasting, because they are available at the time they are needed. Streamflow forecasts derived from observed rainfall were reported here only for comparative purposes.

The most important result reported in this paper was given by comparing forecasts of seven-day average discharge with observed streamflow and with results from the ARMA-forecasting model in current use, and which makes no use of rainfall, whether observed or forecast. This comparison shows clearly that the MGB-IPH model performed better than the ARMA model, both in terms of error statistics and of visual inspection of hydrographs and scatter plots.

It seems likely that for Brazilian conditions, streamflow forecasts given by the MGB-IPH model when using rainfall forecasts from the Eta Model run by CPTEC, can be further improved by modifying the convective precipitation scheme of the Eta model, and by improving the updating procedures in the MGB-IPH. Better results would probably also follow from denser instrument networks.

The use of ensembles of QPFs may also lead to improvements in streamflow forecasts. Ensembles were not used in the work reported here because they were not available; at present, the optimization procedures routinely used by ONS for reservoir operation assume the existence of a single forecast trace extending to the forecast horizon. Whilst it is possible that in the future ensembles of streamflow forecasts could be obtained by using ensembles of QPFs as input data to the hydrological model, this would mean that either (i) members of the ensemble of streamflow forecasts would need to be averaged to give a single forecast trace, or (ii) that the optimization procedure currently in use would need to be adapted to use multiple traces.

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