Incorporating Forecasts of Rainfall in Two Hydrologic Models Used for Medium-Range Streamflow Forecasting

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Abstract: This study reports on the performance of two medium-range streamflow forecast models: (1) a multilayer feed-forward artificial neural network; and (2) a distributed hydrologic model. Quantitative precipitation forecasts were used as input to both models. The Furnas Reservoir on the Rio Grande River was selected as a case study, primarily because of the availability of quantitative precipitation forecasts from the Brazilian Center for Weather Prediction and Climate Studies and due to its importance in the Brazilian hydropower generating system. Streamflow forecasts were calculated for a drainage area of about 51,900 km^2, with lead times up to 12 days, at daily intervals. The Nash–Sutcliffe efficiency index, the root-mean-square error, the mean absolute error, and the mean relative error were used to assess the relative performance of the models. Results showed that the performance of streamflow forecasts was strongly dependent on the quality of quantitative precipitation forecasts used. The artificial neural network (ANN) method seemed to be less sensitive to precipitation forecast error relative to the distributed hydrological model. Hence, the latter presented a better skill in flow forecasting when using the more accurate perfect precipitation forecast. The conceptual hydrological model also demonstrates better forecast skill than ANN models for longer lead times, when the representation of the rainfall-runoff process and of the water storage in the watershed becomes more important than the flow routing along the drainage network. In addition, results obtained by incorporating a quantitative precipitation forecast in both models performed better than the current streamflow obtained by the Brazilian national electric system operator using statistical models which do not utilize information on precipitation, whether observed or forecast.

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Introduction

Reservoirs are used worldwide for many purposes including flood control, hydropower generation, irrigation, water supply, and navigation (Guo et al. 2004; Wurbs 1996). To fulfill these purposes, good reservoir management is essential, requiring knowledge of future water inflows and demand. Forecasts of atmospheric and hydrologic conditions at different time and space scales may be useful for forecasting reservoir inflows, leading to benefits in terms of flood damage reduction, increased dam security, and improvement of power generation efficiency (Hamlet et al. 2002; Maurer and Lettenmaier 2004; Bravo 2006). If knowledge of future atmospheric behavior could be shown to improve the accuracy of hydrologic forecasts this would, for example, add to the usefulness of flood warning systems by giving a longer lead time during which action to mitigate impacts of extreme events could be planned and executed.

Streamflow forecasting is one of the techniques used to allow for climate impacts to be considered on water resources management (Tucci and Collischonn 2003). Real-time streamflow forecasting in reservoir operation aims to maximize benefits related to specific water uses (e.g., hydropower generation, navigation, irrigation, water supply) and/or to minimize conflicts among the multiple reservoir water uses (Yeh et al. 1982; Mishalani and Palmer 1988; Maurer and Lettenmaier 2004; Bravo 2006).

Rainfall-runoff models based on the mathematical representation of watershed processes have long been applied to streamflow forecasting (Lettenmaier and Wood 1993; Bell and Moore 1998; Anderson et al. 2002; Jasper et al. 2002; Collischonn et al. 2007a). However the more complex distributed rainfall-runoff models developed in recent years typically require more extensive data and considerably more effort is needed to estimate model parameters for purposes of model calibration and verification (Wu et al. 2005). Empirical models based on the principle of artificial neural networks (ANNs) have therefore been considered as an alternative to physically based distributed models, due to their simplicity and because they are less demanding in terms of de-

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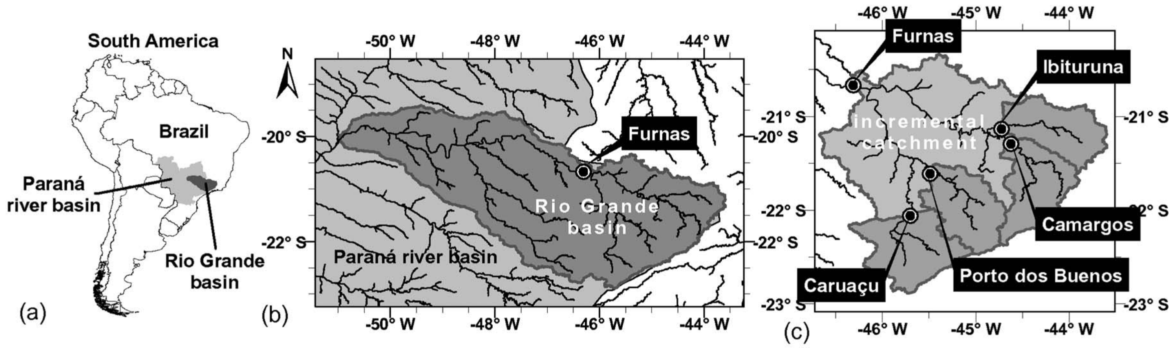

Fig. 1. Location of Furnas Reservoir in Brazil and in Rio Grande Watershed

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tailed watershed data (Dawson and Wilby 2001). ANNs have become an attractive empirical technique for approaching many hydrologic and water resources problems. Multilayer feedforward artificial neural networks (MFANNs) are the most common type of ANN, and have been widely used for streamflow forecasting (Dawson and Wilby 2001; Maier and Dandy 2000).

Hydropower generation is the principal purpose of major water reservoirs in Brazil, where total installed capacity accounts for about 76% of the national total electricity production (ANEEL 2005). Currently, real-time operation of these reservoirs is based on medium-range streamflow forecasts produced by statistical models, such as periodic autoregressive (PAR), or autoregressive moving average (ARMA) models (Maceira and Damazio 2005; Guilhon 2002) which do not utilize information on precipitation, whether observed or forecast. It is possible that quantitative precipitation forecasts (QPFs) could be used to extend the streamflow forecast horizon, and therefore improve Brazilian real-time reservoir operation, as pointed out by previous studies (Collischonn et al. 2007a, 2005).

In this study, two different techniques—a multilayer feedforward neural network and a distributed hydrological model—were used to give daily forecasts of inflows into the Furnas Reservoir sited in the Rio Grande Watershed, Brazil, whose drainage area is about 51,900 km^2. Both methods used available QPFs as input. The performance of both models was assessed by calculating several error statistics and by comparing their forecasts with those given by the procedure currently used by the Brazilian national electric system operator (ONS).

Study Region and Data Sets

The Furnas Reservoir was selected for study because QPFs were available in the upstream watershed and because of its importance to the Brazilian hydropower generating system. Fig. 1 shows its location. The Rio Grande is the main tributary of the upper Rio Paraná, and is used extensively for hydropower generation; it has a total installed capacity of about 7,722 MW, about 11.7% of the Brazilian total (ANEEL 2005).

The mean annual rainfall over the basin is approximately 1,400 mm and is highly concentrated during the austral summer. The inflows to Furnas are therefore strongly seasonal, varying from 350 m^3/s during low flows to more than 2,000 m^3/s in the summer, with flood peaks typically reaching 4,000 m^3/s.

The Rio Grande drainage area upstream of Furnas Reservoir may be divided in five subcatchments according to data availability [Fig. 1(c)]: Ibituruna (6,054 km^2), Camargos (6,322 km^2), Porto dos Buenos (6,331 km^2), Caruaçu (7,376 km^2), and the incremental catchment (25,819 km^2), totaling 51,902 km^2 for the whole watershed. Daily streamflow data at the Porto dos Buenos and Caruaçu gauging stations were available from 1950 to 2003 (ANA 2005) and from 1931 to 2001 at the outfalls of the Ibituruna and Camargos catchments, and at the outfall of the Furnas watershed (data provided by ONS). Daily precipitation data are available for nearly 130 rainfall gauges over the period 1950–2003 (ANA 2005).

For the forecasting test described here, QPFs were provided by the ETA regional model (Mesinger et al. 1988; Black 1994), run at the Brazilian Center for Weather Prediction and Climate Studies (CPTEC). The ETA model is 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 forecasting in Brazil on an operational basis since 1996. Precipitation forecasts given by the ETA regional model over South America have 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 ETA QPFs were provided by CPTEC with a time horizon of 10 days at daily intervals and a horizontal resolution of about 40 km. Precipitation forecasts are produced on a weekly basis and issued every Wednesday. The period for which QPFs were available extended from January 1996 to December 2000, a total of 260 weeks.

Methodology

As previously stated, the two models used were a multilayer feedforward artificial neural network and a distributed hydrological model. Both models use a combination of observed and forecast precipitation data. Daily streamflow forecasts were obtained up to a time horizon of 12 days; in this paper, t represents the day in which the forecast is made, $t+1$ is the day after, and $t+12$ is the forecast horizon. The description of both models and the specific methodologies adopted within each one is set out in the following sections.

Observed daily precipitation data at 130 gauging stations were used up to the forecasting starting day, while QPF data were used for the next 10 days. Both observed and forecast precipitation data were first interpolated to the 0.1° resolution grid of the large-scale distributed hydrological model using the inverse distance squared method. This gridded precipitation data were used directly by the distributed hydrological model, while areal average

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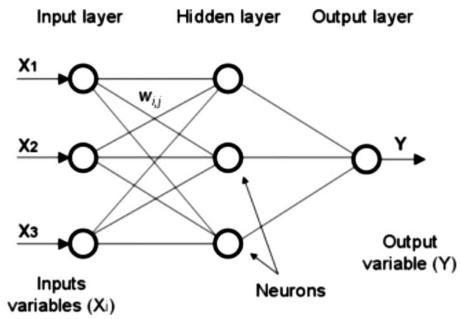

Fig. 2. Multilayer feed-forward neural network architecture

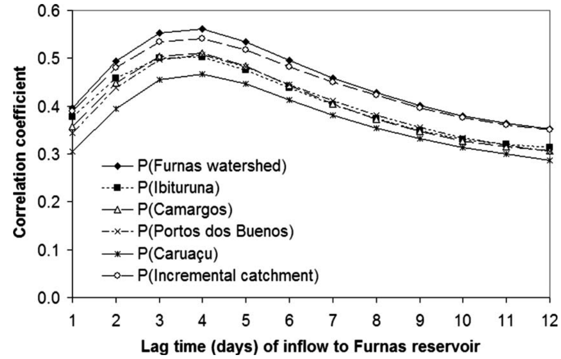

Fig. 3. Correlation coefficient between potential input variables (daily precipitation in watershed and catchments) and inflow to Furnas Reservoir considering lags of 1–12 days

values over each sub-basin were calculated from the gridded data to be used by the ANN models.

No bias correction for the QPF was performed for this study. We assumed that QPFs are free from systematic errors. This assumption was done because this study is a first approach to the problem, and there are no conclusive studies on the regional model forecast bias in this region.

Artificial Neural Networks

Artificial neural networks have shown a good performance for the modeling and forecasting of water resources variables (Maier and Dandy 2000; Dawson and Wilby 2001). The ANN architecture is defined by an arrangement of processing units, called artificial neurons, in processing layers. Each single artificial neuron has one or more inputs but usually only one output, the value of which is computed from the weighted sum of all its inputs applied to an activation function (Dawson and Wilby 2001).

Among different existing ANN architectures, the MFANN is currently the most widely used (Birikundavyi et al. 2002; Dawson et al. 2002; Stokelj et al. 2002; Dawson and Wilby 2001). The MFANN (Fig. 2) has an input layer, one or more hidden layers, and an output layer. In an MFANN, each single artificial neuron may receive input values from external inputs or from neurons in the layer preceding it. Input values are processed through an activation function and the resulting values are passed to the neurons in the next layer. The strength of the connection between each two linked neurons is measured by a weight, and the weights of all connections constitute the MFANN parameters to be defined through an optimization process termed ANN training. In this process, weight values are determined by minimizing the difference between the observed and calculated outputs. The agreement between them may be described in terms of different performance measures, with the mean square error the most commonly used (Maier and Dandy 2000; Dawson and Wilby 2001).

Three-layer MFANN models were used in this study (i.e., with just one hidden layer) to calculate a forecast of inflow to the Furnas Reservoir for each day up to the forecast horizon of 12 days. Thus, the output layer of the ANN model contains only one neuron. Once the ANN output variable is defined, the subsequent steps for developing the ANN models are summarized by Dawson and Wilby (2001) as follows: (1) selection of the input variables; (2) selection of ANN type; (3) data selection and preprocessing; (4) ANN training; and (5) ANN performance assessment. These steps are described in the following sections.

Input Variables

Maier and Dandy (1997) showed that the selection of input variables based on statistical analyses (cross-correlation) might improve ANN performance in some cases. Bowden et al. (2005) suggest a combination of partial mutual information and self-organizing map techniques, allowing the detection of nonlinear dependence between variables. Other techniques used for the selection of ANN input variables include principal component analysis and singular spectrum analysis (Stokelj et al. 2002). It is important to know the watershed characteristics and the hydrological processes governing its behavior before applying neural networks to the available data (Dawson et al. 2002). For this study, the relevant physical processes and available data suggest three kinds of input data as variable predictors for the ANN models: namely, precipitation within the drainage area, streamflow at the outfall of each watershed, and streamflow at the forecast site. The selection of input variables was therefore based on cross-correlation analysis between the available data sequences and the inflow to the Furnas Reservoir (the ANN output variable) during the period from January 12, 1970 to December 31, 1980, at daily time steps.

Correlation coefficients between observed areal average rainfall and inflow to the Furnas Reservoir were calculated separately for each watershed (Ibituruna, Porto dos Buenos, Camargos, Caruaçu, and Furnas incremental catchment) and for the whole Furnas drainage basin considering lags from 1 to 12 days (Fig. 3). Daily precipitation on the Furnas incremental watershed had the highest correlation with Furnas inflows, albeit modest (correlation coefficient approaching 0.6 for 4 days lag).

In an attempt to find variables based on precipitation data having higher correlation with inflow to Furnas, watershed daily precipitation data were accumulated through different time ranges (2, 3, . . . up to 13 days). These time series of accumulated precipitation were correlated with the inflow to Furnas at time $t+1$. As shown in Fig. 4, correlation between accumulated daily precipitation and inflow to Furnas Reservoir in $t+1$ increases at longer accumulation periods. This trend persists up to a 12-day accumulation period, when it reaches the maximum value of 0.82. Thus, the precipitation accumulated over 12 days (PCA12) was adopted as an ANN input variable. However, when used as a predictor, the variable PCA12 must be calculated from both observed and forecast precipitation data, according to the time horizon. For example, for lead time of 1 day ($t+1$), PCA12 is obtained solely from observed precipitation accumulated over time steps $t-11$ to t (Fig. 5). For lead time of 2 days ($t+2$), PCA12 is a sum of the observed precipitation accumulated over time steps $t-10$ to t and precipitation forecast for $t+1$. This procedure of combining observed and forecast precipitation contin-

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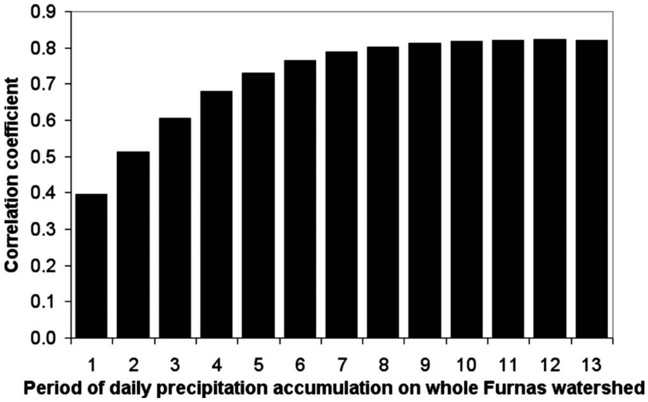

Fig. 4. Correlation coefficient between potential input variables (daily precipitation at Furnas outlet watershed accumulated through different time periods) and inflow to Furnas Reservoir with 1-day lag

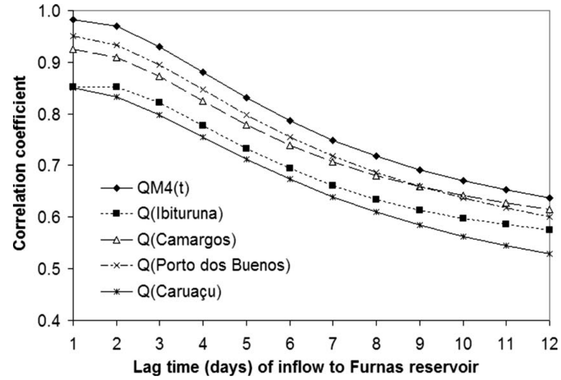

Fig. 6. Correlation coefficient between potential input variables [daily outlet streamflow of each catchment and average value of them, QM4(t)] and inflow to Furnas Reservoir considering lags of 1–12 days

ues up to the last lead time ($t+12$), when PCA12 is obtained from the forecast precipitation accumulated over time steps t to $t+10$. For this case, streamflow forecast at $t+12$ is produced assuming that there is no precipitation on day $t+11$, since ETA precipitation forecasts extend only up to 10 days (up to $t+10$).

Streamflow records from each of the four watersheds (Ibituruna, Porto dos Buenos, Camargos, and Caruaçu) and the average value of these four variables were correlated with the inflow to Furnas for lags of 1–12 days. The best correlation was obtained for the daily average value (QM4(t)), as shown in Fig. 6. This variable and its incremental value [ΔQM4(t)=QM4(t) $-$QM4($t-1$)] were selected as ANN input variables representing the upstream streamflow information. The use of ΔQM4(t) as an input variable enabled the ANN to distinguish between hydrograph rising limbs and periods of recession.

Finally, regarding streamflow information at the forecast site (Furnas), two input variables were used: the inflow to Furnas at time step t (QF(t)) and its incremental value (ΔQF(t)=QF(t) $-$QF($t-1$)). The ΔQF(t) input variable was also selected to facilitate the distinction between hydrograph rising limbs and recessions.

Following this analysis, the ANN gave forecasts of inflow to Furnas using five input variables, as shown in Fig. 7. Four of these variables were derived from streamflow data: the average value of daily streamflow at the outfall of the four watersheds (QM4(t)) and its incremental value between days $t-1$ and t (ΔQM4(t)); inflow to Furnas at time step t (QF(t)) and its incremental value between days $t-1$ and t (ΔQF(t)). The values of these four input variables were the same for a forecast initiated on day t, independent of lead time ($t+i$). The fifth input variable was defined by watershed 12-day accumulated precipitation (PCA12($t+i-1$)), combining observed and forecast precipitation data. This input varied for each lead time.

ANN Type Selection

Twelve three-layer MFANNs were designed and trained. Each ANN estimated the inflow forecast to Furnas for each day up to the forecast horizon (recalling that the output layer had only one neuron) based on five input variables (input layer with five neurons). The number of neurons in the hidden layer was determined independently for each ANN configuration by a trial-and-error pruning process (see, for example, Birikundavyi et al. 2002). This pruning process starts considering a large number of neurons in the hidden layer (ten neurons, in this study), and removing, successively, one neuron at each training and performance assessment. This procedure continues until a configuration with satisfactory performance is achieved with the smallest number of neurons in the hidden layer.

As a result, MFANNs for streamflow forecasts with lead times of 1–7 days were designed with two hidden-layer neurons (denoted by MFANN(5-2-1), see Fig. 7), while MFANNs for streamflow forecasting with lead times of 8–12 days used three neurons in the hidden layer (MFANN(5-3-1)). For all designed MFANNs, the hidden layer consists of neurons with logistic sigmoid activation function [Eq. (1)], while the linear activation function [Eq. (2)] was used in the output layer

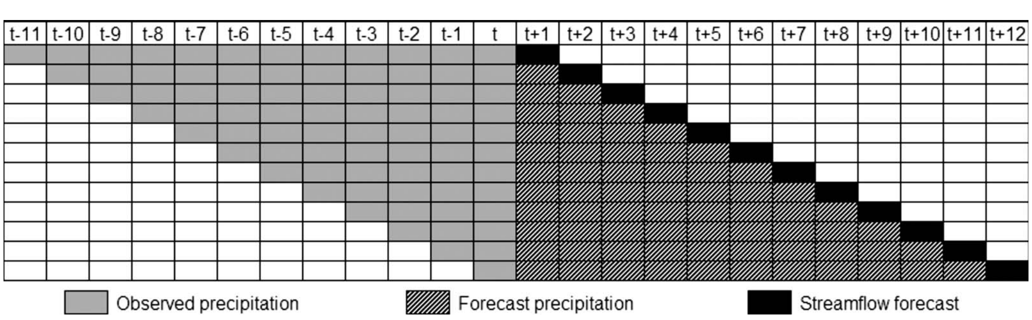

Fig. 5. Definition of input variable PCA12(t)—daily accumulated precipitation over 12 days at Furnas watershed—as function of streamflow forecast lead-time day (lead-time one is equal to $t+1$)

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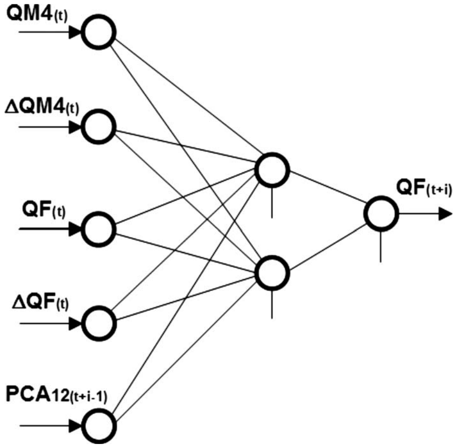

Fig. 7. MFANN(5-2-1) architecture for streamflow forecasting

$$\log \text{sig}(n) = \frac{1}{1+e^{-n}} \tag{1}$$

$$\text{linear}(n) = n \tag{2}$$

Data Division and Preprocessing

The available records were split into three periods for training, testing, and validation. This division was made in order to use cross-validation or early stopping, a common and practical method to determine the moment for stopping the training process to avoid overfitting, so that a proper generalization is ensured (Bishop 1995). Overfitting occurs when ANN models reproduce existing noises in the training set, losing its ability to generalize when other data sets are used. Prevention of overfitting can be achieved using a testing set for the assessment of the performance of the training process (Tchaban et al. 1998; Maier and Dandy 2000). For cross-validation, weight values were adjusted based on training set error, and the ANN training process was stopped when the error in the testing set reached a minimum value. Thus, the validation set was not used in the ANN training process, although it is very important for evaluating the extent to which the ANN model can be generalized.

As stated earlier, the ETA forecasts were issued every Wednesday over a period extending from January 1996 to December 2000 (260 weeks). This is a relatively short period of data to be used for the ANN training, and specific methods to deal with limited data sets should be employed, such as those reviewed by Maier and Dandy (2000). The method used in this study, however, consisted of taking the precipitation that was recorded over the forecasting period as a perfect precipitation forecast for the ANN training. Thus, the observed precipitation was used as a forecast of precipitation during ANN training and testing, while ETA model precipitation forecasts were used only during validation. With this approach, training and testing data sets are larger, since observed data were plentiful and could be used as a 12-day forecast issued on a daily basis, instead of the weekly basis of ETA forecasts. Moreover, using this method, different versions and modifications of the regional ETA model throughout time will not affect the quality of ANN training. This is a very frequent problem in training or calibration of hydrological models using results from meteorological models (J. F. Jónsdóttir and C. B. Uvo personal communication 2007).

Table 1. Input Variables Average (μ) and Standard Deviation (σ) Values in Training and Testing Sets

	Training set		Testing set	
Inputs	μ	σ	μ	σ
PCA12(t)	47.93	42.52	43.73	42.35
QF(t)	886.53	595.29	859.46	546.87
ΔQF(t)	0.42	98.98	−0.129	90.74
QM4(t)	127.63	80.00	123.76	71.24
ΔQM4(t)	0.079	17.10	−0.007	14.68

The division of ANN input data into training and testing periods aimed at obtaining sets with similar mean (μ) and standard deviation (σ). Data from January 12, 1970–December 31, 1980 were split into two sets (Table 1):

1. Training data set: observed daily data from January 12, 1970 to July 17, 1974 and from October 13, 1978 to December 31, 1980, a total of 2,461 samples; and
2. Testing data set: observed daily data from July 18, 1974 to October 12, 1978, a total of 1,548 samples.

Two validation sets were used to assess ANN performance, both for the period of January 12, 1996–December 31, 2000, a total of 260 samples (each forecast issued at weekly intervals). In both validation sets, the streamflow-based input variables are the same. However, the variable representing accumulated precipitation (PCA12(t)) differed between the two sets: the first set used a combination of observed precipitation and ETA precipitation forecasts while the second used a combination of observed precipitation and a perfect precipitation forecast in which future precipitation at each rain gauge was assumed known. All the ANN input and output data were standardized using the following equation:

$$x_{\text{new}} = 0.1 + \left(\frac{x_{\text{orig}} - x_{\min}}{x_{\max} - x_{\min}}\right) \times 0.8 \tag{3}$$

where x_{new}=standardized value of the variable x in the range [0.10, 0.90]; x_{orig}=original value of x in its appropriate unit; and $x_{\min}$ and $x_{\max}$=respectively, minimum and maximum original values of x (considering training and testing sets) in the appropriate units.

ANN Training

The MFANN models were trained using a supervised training procedure known as the scaled conjugate gradient method (SCGM) (Moller 1993). This is an iterative second-order local search method that considers second-order derivatives of the activation functions during ANN training (Moller 1993; Maier and Dandy 2000). The search direction in the process of optimizing weight values of MFANN models is defined based on the values of these derivatives. Performance of the MFANN models during training was assessed in terms of the root-mean-square error (RMSE).

Distributed Rainfall-Runoff Model

The second model used in this study was the distributed large-scale hydrological model MGB-IPH (Collischonn et al. 2007a,b; Collischonn and Tucci 2001). This model was developed for use in large South American basins, based on LARSIM (Ludwig and Bremicker 2006) and VIC (Liang et al. 1994; Nijssem et al. 1997) models, with some changes in the evapotranspiration, percolation,

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and streamflow propagation modules. It consists of modules for calculating soil water budget, evapotranspiration, flow propagation inside a cell, and flow routing through the drainage network. The drainage basin is represented by square-grid cells connected by channels, each one of the cells containning a limited number of distinct grouped response units (GRUs), i.e., grouped areas with a similar combination of soil and land cover (Kouwen et al. 1993). Soil water budget is calculated for each GRU, and runoff generated from the different GRUs in the cell is then summed and propagated to the stream network using three linear reservoirs (base flow, subsurface flow, and surface flow). Streamflow is routed through the river network using the Muskingum–Cunge method. Applications of the MGB-IPH model for streamflow forecasting in large basins have been reported by Collischonn et al. (2007a), Allasia et al. (2006), Collischonn et al. (2005), and Tucci et al. (2003).

Spatial Discretization and Input Datasets

The MGB-IPH model was applied to the Rio Grande Watershed with a spatial discretization of square-grid cells of $0.1 \times 0.1°$. The 90 m SRTM digital elevation model was used to determine the river drainage network used in the hydrological model, giving flow direction and cumulated drainage area of each cell, as well as length and slope of river reaches for flow routing, following procedures described in Paz et al. (2006) and Paz and Collischonn (2007). Soils were characterized using data available from a 1:1.000.000 RADAMBrasil survey (Projeto RADAMBRASIL 1982) and from the soil map published by FAO (1974, 1988). Several Landsat7 ETM+ images were analyzed to obtain land-use classification. Combining soil type and land use, six GRUs were defined, aiming essentially to distinguish among shallow, intermediate, or deep soils, and agriculture, forest, or water.

Hydrological records of the Furnas watershed were provided by ONS and ANA, the Brazilian Water Agency, and consisted of rainfall data from 130 stations and flow time series at the outfalls of the Furnas watershed and at each one of the four sub-basins. Data on surface temperature, wind velocity, air moisture, solar radiation, and atmospheric pressure were obtained from seven meteorological stations provided by CPTEC. Observed precipitation was available for daily time steps while the other meteorological data were given as mean monthly values. Precipitation and meteorological data were interpolated to the center of each grid cell of the hydrological model at each time step, using the inverse-distance-squared method.

Model Calibration and Validation

The calibration of the MGB-IPH model is achieved by changing values of parameters while maintaining relations between land use and parameter values (Collischonn et al. 2007b). The multiobjective MOCOM-UA optimization algorithm (Yapo et al. 1998) is used with three objective functions: volume bias (ΔV); Nash–Sutcliffe efficiency index for streamflow (NSS); and Nash–Sutcliffe efficiency index for the logarithms of streamflow ($\mathrm{NSS}_{\log}$)

$$\Delta V = \frac{\Sigma Q_{\mathrm{calc}}(t) - \Sigma Q_{\mathrm{obs}}(t)}{\Sigma Q_{\mathrm{obs}}(t)} \tag{4}$$

$$\mathrm{NSS} = 1 - \frac{\Sigma[Q_{\mathrm{obs}}(t) - Q_{\mathrm{calc}}(t)]^2}{\Sigma[Q_{\mathrm{obs}}(t) - \overline{Q_{\mathrm{obs}}}]^2} \tag{5}$$

$$\mathrm{NSS}_{\log} = 1 - \frac{\Sigma[\log Q_{\mathrm{obs}}(t) - \log Q_{\mathrm{calc}}(t)]^2}{\Sigma[\log Q_{\mathrm{obs}}(t) - \overline{\log Q_{\mathrm{obs}}}]^2} \tag{6}$$

where $Q_{\mathrm{obs}}(t)$, $Q_{\mathrm{calc}}(t)$=observed and calculated discharges, respectively, at time step t, and $\overline{Q_{\mathrm{obs}}}$=average observed discharge.

The MGB-IPH model was calibrated by fitting model parameter values to each watershed, using values from the appropriate outfall cell to compare observed and calculated daily streamflow through the three objective functions. The period 1970–1980 was used for model calibration, and the period 1981–2001 for model validation. As a result of the multiobjective optimization, several Pareto optimal solutions were found, and a single solution was chosen among them, aiming to provide an acceptable tradeoff in fitting the different parts of the hydrograph, as suggested by Bastidas et al. (2002). The model was found to fit well, as the NSS and $\mathrm{NSS}_{\log}$ index values ranged from 0.82 to 0.93 in all the catchments in both calibration and validation. The errors in volume between observed and fitted hydrographs were also acceptable, with values less than 0.05% during calibration and less than 6% at validation.

Forecast Procedure

When the MGB-IPH model is used for streamflow forecasting, variables are updated using streamflow data observed at certain strategic gauging stations, for which correction factors are determined based on differences between observed and calculated values. These correction factors are applied to the streamflow along the entire drainage network upstream from the gauging station. However, the area drained by each cell is used as a weighting for damping out the correction upstream of the gauge. It ensures that the correction is complete in the cell in which the gauging station lies, and is least in the cells farthest upstream (Paz et al. 2007; Collischonn et al. 2005). Several configurations of the empirical updating procedure were tested for flow forecasting with the MGB-IPH model, varying the values of its parameters, as presented in Paz et al. (2007). For this study, the configuration with the best results in terms of NSS, $\mathrm{NSS}_{\log}$, and ΔV coefficients values was selected.

Since the precipitation forecasts given by the ETA model are issued weekly, daily streamflow forecasts were also calculated on a weekly basis, starting on Wednesday. QPFs from the ETA model were interpolated to the grid points of the hydrologic model using the inverse-distance-squared method. Streamflow forecasts were calculated with lead times up to 12 days, according to the following procedure:

1. The hydrologic model is initialized in simulation mode using observed precipitation up to the instant at which precipitation forecasts are issued;
2. Forecasts of streamflow are calculated for the next 10 days, using the precipitation forecast from the ETA model; and
3. Streamflow forecasts for the last 2 days are calculated, assuming that there is no further precipitation (since ETA precipitation forecasts are available for only 10 days ahead).

Model Skill Assessment

The performance of both ANN and MGB-IPH models was assessed over the period 12 Jan 1996 to 31 Dec 2000 using forecasts calculated at weekly intervals. This period was reserved for model validation and was not used during the ANN training and the MGB-IPH calibration.

The Nash–Sutcliffe efficiency index (NS), the RMSE, the

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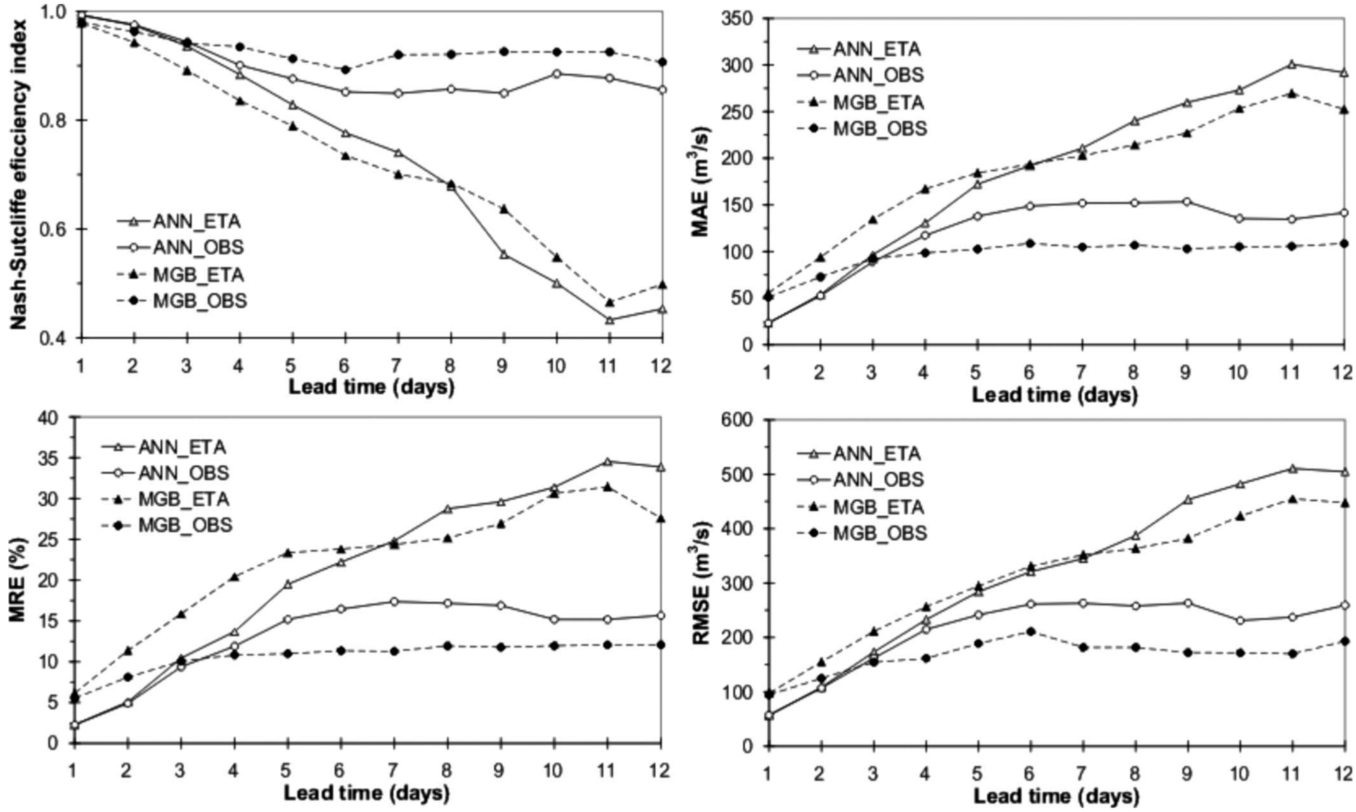

Fig. 8. Forecast performance measures as function of lead time: (a) Nash–Sutcliffe efficiency index; (b) mean-absolute error (MAE); (c) mean-relative error (MRE); and (d) root-mean-square error (RMSE)

mean-absolute error (MAE), and the mean-relative error (MRE) were used to assess model performance, defined as follows:

$$\mathrm{RMSE}_j = \left[\frac{1}{N}\sum_{i=1}^{N}(Q_{\mathrm{for}_{i,j}} - Q_{\mathrm{obs}_{i,j}})^2\right]^{1/2} \tag{7}$$

$$\mathrm{MAE}_j = \frac{1}{N}\sum_{i=1}^{N}|Q_{\mathrm{for}_{i,j}} - Q_{\mathrm{obs}_{i,j}}| \tag{8}$$

$$\mathrm{MRE}_j = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Q_{\mathrm{for}_{i,j}} - Q_{\mathrm{obs}_{i,j}}}{Q_{\mathrm{obs}_{i,j}}}\right| \tag{9}$$

$$\mathrm{NS}_j = 1 - \frac{\sum_{i=1}^{N}(Q_{\mathrm{obs}_{i,j}} - Q_{\mathrm{for}_{i,j}})^2}{\sum_{i=1}^{N}(Q_{\mathrm{obs}_{i,j}} - \overline{Q_{\mathrm{obs}}})^2} \tag{10}$$

where $Q_{\mathrm{for}_{i,j}}$ and $Q_{\mathrm{obs}_{i,j}}$=streamflow forecast and observed values at lead time j on sample i, respectively; $\overline{Q_{\mathrm{obs}}}$=average observed streamflow value in the validation set; N=total number of samples in the validation set; and the lead time j varies from 1 to 12 days.

The performance of both models was also compared with that of the procedure currently adopted by the ONS. Typically, ONS uses two performance measures: the MRE for the fourth day lead time (MRE_j, for $j=4$), namely MRE4, and the MRE considering the average of forecast values issued for lead times fourth to tenth, namely MRE4-10.

Operational Streamflow Forecasts Currently Produced

The present methodology used by ONS to forecast flow uses different configurations of ARMA(p,q) and periodic ARMA models, with values for p in the range 1–4 and q not larger than 1, possibly with Box–Cox transformation of streamflow values (CEPEL 2004; Maceira et al. 1997). This method uses only streamflow information, and neither observed precipitation nor QPFs are used.

Results and Discussion

Fig. 8 shows performance measures of inflow forecasts to the Furnas Reservoir, relative to the validation period. Results of both models are summarized using ETA forecasts and perfect precipitation forecasts (i.e., using the precipitation observed subsequently as if it were a forecast). Errors in inflows tend to increase as the lead time increases, and when ETA precipitation forecasts are used, the increase in forecast error is larger than where observed future precipitation is used as a forecast (perfect forecast). This shows that forecast inflows could be improved by better precipitation forecasts.

Where the perfect precipitation forecast is used, the results show that ANN performs better than the MGB-IPH model in forecasting daily inflows for lead times up to 3 days ahead, but for subsequent time horizons the hydrologic model performs better. Due to the lag between precipitation and streamflow, the streamflow forecast for the first three lead times is strongly dependent on the amount of water that is already in the river drainage network, i.e., the current flow. In this situation, ANN models

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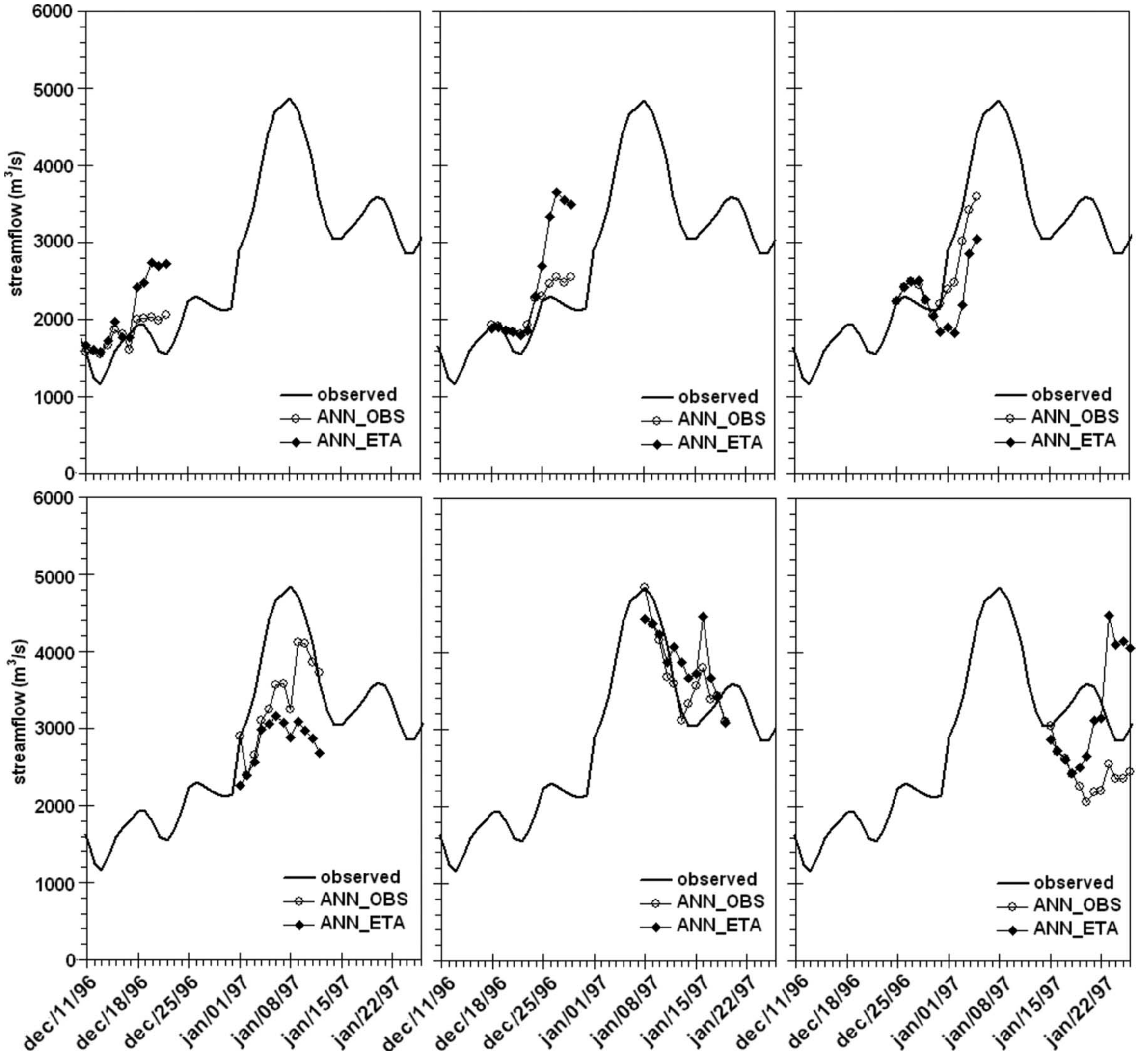

Fig. 9. Inflow forecasts to Furnas Reservoir using ANN for the period of December 11, 1996–January 26, 1997

have remarkable performance in streamflow forecasting, as outlined by several previous studies. However, when the forecast horizon increases, the processes related to the rainfall-runoff transformation and the water storage and delay in the watershed become more important. In this case, the conceptual distributed hydrological model tends to outperform ANN models.

The difference in the performances between MGB-IPH and ANN models changed with the use of QPF from the ETA model. Better forecast skill was obtained with ANN models for up to 7 days ahead, while the MGB-IPH model achieved better results for the last 5 days of the forecast period. This result indicates that ANN seems to be less sensitive to the error in precipitation forecasts than the hydrological model.

Figs. 9 and 10 present an example of successive inflow forecasts to the Furnas Reservoir using ANN and MGB-IPH models, respectively, for the period December 11, 1996 to January 26, 1997. In both figures, there are six graphs showing the forecast issued in successive weeks. The traces on each graph refer to the two different precipitation forecasts used for streamflow forecasting.

In general, both forecasting methods perform well in the period shown in Figs. 9 and 10. Clearly, these figures illustrate how the quality of streamflow forecast is dependent on the QPFs used. For example, the streamflow forecast issued on December 18, 1996 (see the central upper graph of each figure) has anticipated and overestimated the peak flow when using ETA precipitation forecast, while the use of the perfect precipitation forecast led to streamflow forecasts that agree better with observed values.

Performance of the methodology currently used by ONS for medium-range inflow forecast to several Brazilian reservoirs is available in terms of MRE4 and MRE4-10 indexes (Guilhon 2007). Comparison between these values and that obtained with the methodologies presented in this paper are summarized in Table 2. The MRE4 and MRE4-10 values relative to ONS methodology represent typical values obtained in the study area, while the values of such indexes relative to ANN and MGB-IPH applications correspond to the validation period. It can be seen that both methods used in this study perform better, in all cases, than the current ONS forecasting procedures. For example, regarding the use of the ETA precipitation forecast, the MRE4 decreases from 22% (ONS method) to 13.7% (QPF of ETA model+ANN model) and to 20.4% (QPF of ETA model+MGB-IPH model). Still better results are achieved using the perfect precipitation forecast. Reductions in error performance reach 50% in all cases. In terms of the MRE4 index, the value of 22% obtained by ONS methodology decreases to 11.9 and 10.8% when using ANN and

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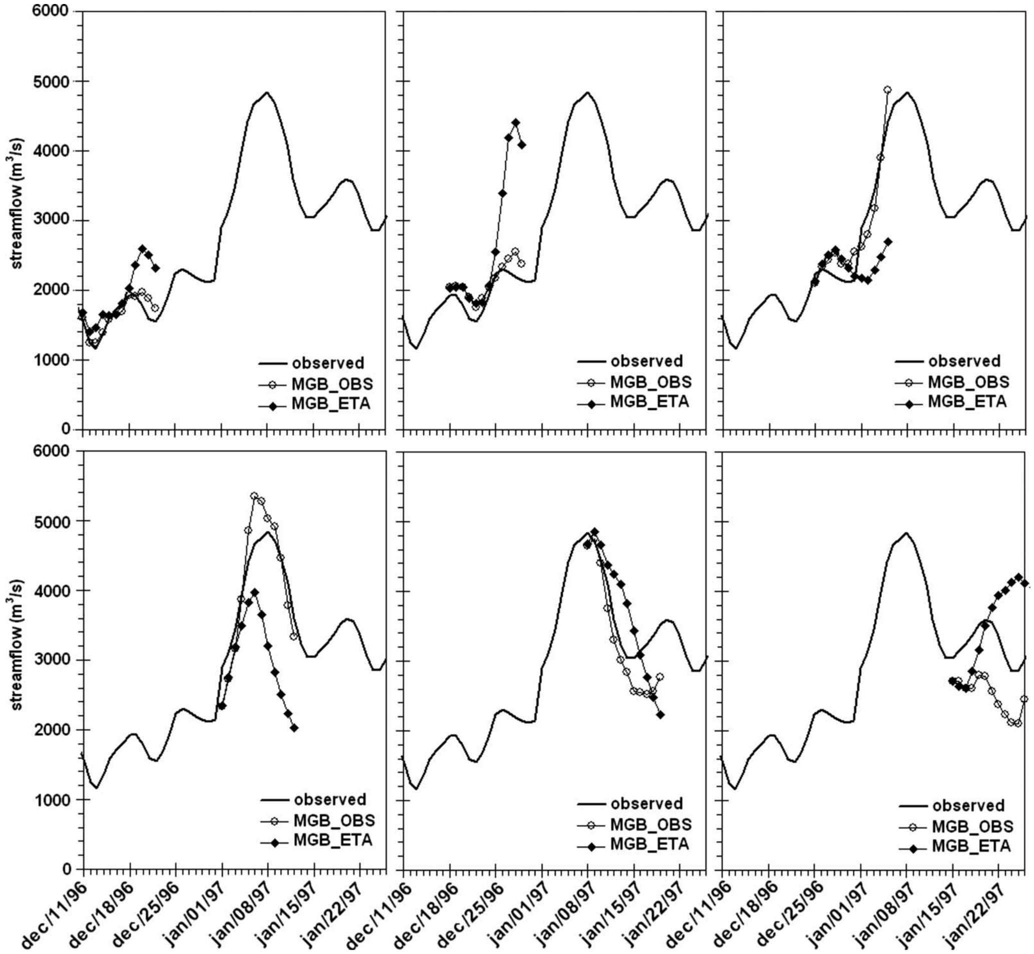

Fig. 10. Inflow forecasts to Furnas Reservoir using MGB-IPH model for the period of December 11, 1996–January 26, 1997

MGB-IPH, respectively. Obviously, the perfect precipitation forecast can never be achieved in practice, but it provides a measure of forecast performance unaffected by errors or uncertainties in precipitation forecasts.

Summary and Conclusions

The work reported here used two different techniques—a MFANN and the distributed hydrological model MGB-IPH—to give forecasts of daily inflows to the Furnas Reservoir in the Rio Grande Watershed, Brazil, for lead times up to 12 days ahead. Both models used QPFs from the ETA regional model. The scenario of perfect precipitation forecast, i.e., using the precipitation observed subsequently as if it were a forecast, was also considered.

Table 2. Performance Measures of Currently and Developed Models in Forecasting Daily Inflow to Furnas Reservoir

Forcast model	MRE4 (%)	MRE4-10 (%)
Current ONS model	22.0	27.9
ANN_ETA	13.7	22.0
MGB_ETA	20.4	22.7
ANN_OBS	11.9	13.8
MGB_OBS	10.8	9.8

Results showed that the performance of streamflow forecasts was strongly dependent on the quality of QPFs used. The simplest models, like the ANN method, seem to be less sensitive to precipitation forecast error relative to a distributed hydrological model. Hence, the latter presented a better skill in flow forecasting when using the more accurate perfect precipitation forecast. The conceptual hydrological model also demonstrates better forecast skill than ANN models for longer lead times, when the representation of the rainfall-runoff process and of the water storage in the watershed become more important than the flow routing along the drainage network.

Currently, the Brazilian national electric system operator (ONS) uses forecasts of daily inflows to major Brazilian reservoirs without the use of precipitation data or precipitation forecasts. The results given in this paper, although limited to one reservoir, show that streamflow forecasting using ANN and MGB-IPH models and incorporating QPFs perform better than the methodology currently used by ONS. Reduction in the forecast errors relative to the ONS method was about 20% when using QPF provided by the ETA model, and up to 50% using the perfect precipitation forecast. Although the latter can never be achieved in practice, these results suggest that improving QPFs would lead to better forecasts of reservoir inflows.

Future development of this work will include the assessment

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of the impact of the data assimilation method used in the distributed hydrological model and the possible bias correction of the rainfall forecasts.

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Notation

The following symbols are used in this paper:

MAE_j = mean absolute error at lead time j;
MRE_j = mean relative error at lead time j;
NS_j = Nash–Sutcliffe efficiency index at lead time j;
NSS = Nash–Sutcliffe efficiency index for streamflow;
$\mathrm{NSS}_{\log}$ = Nash–Sutcliffe efficiency index for logarithms of streamflow;
$\mathrm{PCA12}(t)$ = precipitation accumulated over 12 days;
$Q_{\mathrm{calc}}(t)$ = calculated discharge at time step t;
$\mathrm{QF}(t)$ = inflow to Furnas Reservoir at time step t;
$Q\mathrm{for}_{i,j}$ = streamflow forecast at lead time j on sample i;
$\mathrm{QM4}(t)$ = average of outfall streamflows from four watersheds (Ibituruna, Porto dos Buenos, Camargos, and Caruaçu) at time step t;
$Q_{\mathrm{obs}_{i,j}}$ = observed streamflow at lead time j on sample i;
$Q_{\mathrm{obs}}(t)$ = observed discharge at time step t;
$\overline{Q_{\mathrm{obs}}}$ = average observed discharge;
RMSE_j = root-mean-square error at lead time j;
$x_{\max}$ = maximum original variable value in appropriate units;
$x_{\min}$ = minimum original variable value in appropriate units;
x_{new} = standardized variable value;
x_{orig} = original variable value in appropriate units;
$\Delta\mathrm{QF}(t)$ = incremental value of inflow to Furnas Reservoir between times step t and $t-1$;
$\Delta\mathrm{QM4}(t)$ = incremental value of average outfall streamflow from four watersheds between time steps t and $t-1$;
ΔV = volume bias;
μ = average value; and
σ = standard deviation.

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