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Long-term flow forecasts based on climate and hydrologic modeling: Uruguay River basin

Carlos Eduardo Morelli Tucci, Robin Thomas Clarke, and Walter Collischonn
Instituto de Pesquisas Hidráulicas, Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

Pedro Leite da Silva Dias
Instituto de Astronomia, Geofísica e Ciências Atmosféricas, Universidade de São Paulo, São Paulo, Brazil

Gilvan Sampaio de Oliveira
Centro de Previsão de Tempo e Estudos Climáticos, Instituto Nacional de Pesquisas Espaciais, Cachoeira Paulista, Brazil

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[1] This paper describes a procedure for predicting seasonal flow in the Rio Uruguay drainage basin (area 75,000 km^2, lying in Brazilian territory), using sequences of future daily rainfall given by the global climate model (GCM) of the Brazilian agency for climate prediction (Centro de Previsão de Tempo e Clima, or CPTEC). Sequences of future daily rainfall given by this model were used as input to a rainfall-runoff model appropriate for large drainage basins. Forecasts of flow in the Rio Uruguay were made for the period 1995–2001 of the full record, which began in 1940. Analysis showed that GCM forecasts underestimated rainfall over almost all the basin, particularly in winter, although interannual variability in regional rainfall was reproduced relatively well. A statistical procedure was used to correct for the underestimation of rainfall. When the corrected rainfall sequences were transformed to flow by the hydrologic model, forecasts of flow in the Rio Uruguay basin were better than forecasts based on historic mean or median flows by 37% for monthly flows and by 54% for 3-monthly flows. *INDEX TERMS:* 0315 Atmospheric Composition and Structure: Biosphere/atmosphere interactions; 1833 Hydrology: Hydroclimatology; 1860 Hydrology: Runoff and streamflow; 3337 Meteorology and Atmospheric Dynamics: Numerical modeling and data assimilation; 9360 Information Related to Geographic Region: South America; *KEYWORDS:* runoff forecasting, climate modeling, hydrologic modeling, River Uruguay

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1. Introduction

[2] Theory suggests that forecasts of river flow could be obtained by using forecasts from weather- or climate-forecasting models as input to hydrologic rainfall-runoff models. In practice, however, such forecasts have rarely been used operationally because models for predicting weather and climate yield forecasts with relatively large errors, particularly for rainfall. It is expected that recent and continuing developments in forecasting, in terms of both model structure and related computational procedures, will yield quantitative estimates of rainfall of wider use in water resource planning, especially at larger scales.

[3] With some exceptions, short-term forecasts of flow in rivers over periods from a few hours to several days have commonly been made using deterministic models that described weather and hydrologic phenomena in the immediate future. Forecasts over longer periods, extending perhaps up to 6 months, have commonly used statistical procedures that relate streamflow and/or rainfall to explanatory variables such as sea surface temperatures (SST) [*Servain*, 1991; *Robertson and Mechoso*, 1998; *Diaz et al.*, 1998; *Uvo and Graham*, 1998; *Hamlet and Lettenmaier*, 1999; *Hastenrath et al.*, 1999; *Maurer*, 2002]. However, developments both in the description of physical phenomena within the climate models themselves and in computing power open up the possibility of forecasting seasonal flows from physical principles.

[4] The importance for Brazil of good estimates of future flow, with the concomitant ability to predict inflows to reservoirs, can scarcely be overestimated. The country's energy network is predominantly fed by hydropower, and good forecasts of future flow would both ensure efficient reservoir operation and give a sound basis for costing future power. In addition, prediction of water availability is important for irrigation, navigation, and consumption by the country's rapidly expanding cities.

[5] However, to extend predictions of flow beyond the period of short-term basin response requires forecasts of future rainfall. While numerical models for weather prediction give estimates of future rainfall for several hours, and climate prediction models yield rainfall sequences extending up to several months, rainfall prediction remains one of the most difficult variables to forecast in quantitative terms, although important advances in this difficult field have been reported [*Mao et al.*, 2000; *Collier and Krzysztofowicz*, 2000; *Damrath et al.*, 2000; *Golding*, 2000]. The combina-

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tion of quantitative predictions of weather and climate with hydrologic models has also been the subject of recent research [*Galvão*, 1999; *Araújo Filho and Moura*, 2000; *Hamlet and Lettenmaier*, 1999; *Ibbitt et al.*, 2000; *Kite*, 1997; *Kite and Haberlandt*, 1999; *Yates et al.*, 2000; *Yu et al.*, 1999; *Wood et al.*, 2002; *Jayawardena and Mahanama*, 2002].

[6] The benefits resulting from flow forecasts have also been widely studied. Where hydropower is generated, the benefits of prior knowledge of reservoir inflows, even when knowledge is incomplete, are that (1) spillage is minimized; (2) reservoirs can operate with greater head of water for longer periods; and (3) more energy can be generated at times when energy prices are higher [*Faber and Stedinger*, 2001; *Yeh et al.*, 1982; *Hamlet et al.*, 2002; *Maurer*, 2002]. And since, in mixed generating systems, the operational costs of hydropower production are lower than for thermoelectric and other generating systems, there is a strong economic motive for maximizing the proportion of energy generated from hydropower [*Hamlet et al.*, 2002]. One way of contributing to this maximization is to make use of hydrologic forecasts when decisions are to be made concerning power production, particularly where systems are mixed.

[7] An example is the case study of *Hamlet et al.* [2002] of the Columbia River basin on the U.S. west coast. This has installed capacity for hydropower generation of approximately 18,700 MW, and it was shown possible to increase hydropower production to a value somewhere between U.S. \$40 million and U.S. \$150 million annually by means of an empirical method of hydrologic forecasting based on predictions of SST in the Pacific Ocean and a hydrologic model of large basins [*Hamlet and Lettenmaier*, 1999].

[8] The highly nonlinear nature of meteorological processes causes uncertainty wherever hydrologic forecasts are derived from rainfall sequences derived from predictive models of weather or climate. Because of the nonlinearities, predicted rainfall sequences are strongly dependent on initial conditions [*Lorenz*, 1969]. To evaluate the uncertainty, predictions are repeated with the initial conditions slightly perturbed, resulting in an ensemble of predictions consisting of individual members [*Toth and Kalnay*, 1997]. Each member of the ensemble is used to generate a flow sequence, and variability among the set of predicted flows thus generated gives a measure of their uncertainty [*Krzysztofowicz*, 2001].

[9] Predictive models of weather and climate can operate at global or regional scales. At the global scale, the spatial resolution is of the order of 100 to 200 km, while regional-scale models have spatial resolutions from about 10 km up to 40 km over continent-sized regions. This spatial scale does not correspond to that generally used in rainfall-runoff models, where representations of hydrologic processes vary according to basin size, to the purposes for which models are applied, to the data available, and to the precision needed. Thus models that are adequate for simulating small basins are not in general appropriate for modeling large basins.

[10] Earlier work [*Collischonn and Tucci*, 2001] has described a distributed hydrologic model for use in large drainage basins, which has been used to simulate the hydrologic behavior of the Taquari Antas River in the Brazilian state of Rio Grande do Sul, and of the Taquari River, in Mato Grosso do Sul. The model was subsequently calibrated for the basin of the Rio Uruguay [*Collischonn*, 2001]. The present paper describes the use of this model for forecasting flows in the Uruguay River up to 5 months ahead, using forecasts of seasonal climate given by the global model of the Brazilian Center for Weather and Climate Forecasting (Centro de Previsão de Tempo e Clima, or CPTEC), which forms part of the Brazilian Institute for Space Research (Instituto Nacional de Pesquisas Espaciais, or INPE).

2. The Uruguay River Basin

[11] The area of the Uruguay River basin considered in this paper (Figure 1) lies within Brazilian territory extending to the frontier between Brazil and Argentina, between the latitudes 26° and 29°S. This drainage area of 75,000 km^2 has marked relief and little soil storage capacity, while aquifers linked to the drainage network exert little control over flow. The climate is characterized by cool winters, little variation in seasonal rainfall, and annual rainfall varying between 1500 and 2000 mm yr^{-1}. The original forest vegetation was extensively cleared during the twentieth century, and most of the area is now used for agriculture and cattle ranching. The most important characteristics of relevance to this paper are the absence of marked seasonality in flow, the short "memory" of the drainage basin, and the large variation in monthly flow about the historic monthly mean and median values.

[12] As a whole, the Uruguay River basin lies in the region of transition between the Brazilian southeast with dry winters and wet summers, and the region of Uruguay marked by wet winters and dry summers. There is little seasonality in basin rainfall and there is no well-defined wet or dry season.

3. Forecasting Methodology

[13] In this paper, a general circulation model (GCM) was used to obtain seasonal rainfall forecasts, and a large-basin rainfall-runoff model converted the rainfall predictions into predictions of runoff. The rainfall-runoff model described in previous papers [*Collischonn and Tucci*, 2001; *Collischonn*, 2001] used a discrete network of points derived from a grid with squares 0.1 × 0.1 degrees of latitude and longitude, corresponding to about 10 × 10 km. This grid spacing was determined by considerations of soil type and other physiographic factors. Having fitted the model using observed rainfall, it was used to accept as input the estimates of future rainfall obtained from the CPTEC climate model, so that both models were used together to give medium-term flow forecasts.

3.1. The Hydrologic Model

[14] The distributed hydrologic model for large basins [*Collischonn and Tucci*, 2001] uses information from satellite images, digital elevation models, and digitized maps of land use, vegetation cover, relief, and soils. It uses a daily time step and is similar to the LARSIM [*Bremicker*, 1998] and VIC-2L [*Wood et al.*, 1992; *Liang et al.*, 1994; *Nijssen et al.*, 1997] models. The basin area is divided into square cells, each of which is further subdivided into blocks

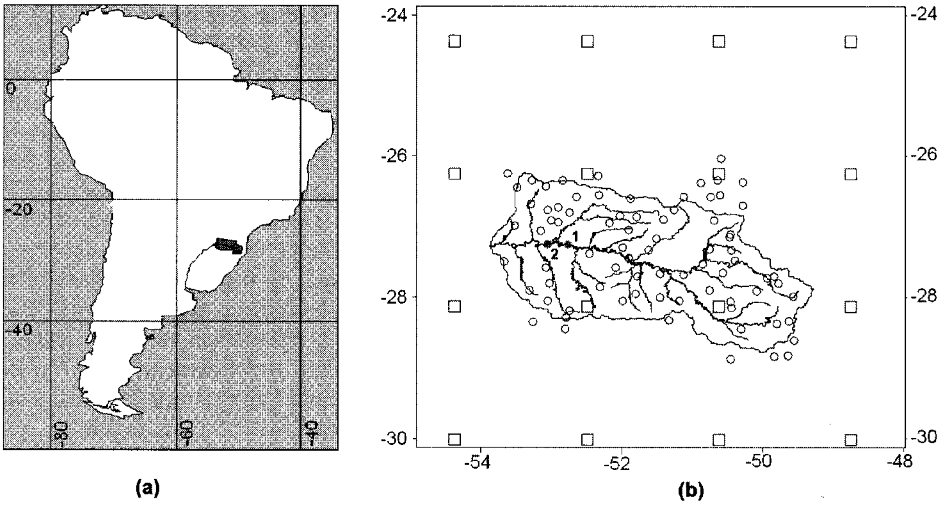

Figure 1. (a) The Uruguay River basin within Brazilian territory. (b) Cell centers for the CPTEC global climate model (squares); rain gauge sites (circles) in the Rio Uruguay basin and flow gauge locations (1, Passo Caxambu, and 2, Iraí).

representing soil type, land use, and vegetation cover. Soil water balance is computed independently for each block of each cell, considering only one soil layer. The model has components representing canopy interception, evapotranspiration, infiltration, surface runoff, subsurface flow, base flow, and soil water storage. Evapotranspiration from the soil, vegetation, and the canopy to the atmosphere is estimated from the Penman-Monteith equation [*Wigmosta et al.*, 1994]. Streamflow is propagated through the river network using the Muskingum-Cunge method with time steps of 1 day or less, depending on stream reach length and slope. Within each cell the flow is propagated using three linear reservoirs (base flow, subsurface flow, and surface flow).

[15] The model is calibrated using rainfall and meteorologic data from gauging stations within the basin. Values are interpolated spatially and at each time step to give an estimate at the center of each grid cell, using the inverse-distance-squared interpolation method. Some parameters, such as leaf area index, are not used in calibration, but are given seasonally varying values taken from the literature.

[16] The Uruguay River basin was divided into 681 cells 0.1×0.1 degrees wide, and the model was calibrated using daily streamflow and rainfall data from 1985 to 1995 and verified with data from the periods 1977–1985 and 1995–1998. A multiobjective calibration method based on a genetic algorithm [*Yapo et al.*, 1998] was used. The calibrated parameters were W, the storage capacity of the soil layer which is related to the soil and vegetation; b, a parameter defining the form of the probability distribution function of soil storage capacity; two soil drainage parameters for subsurface flow and base flow; and two parameters related to surface and subsurface flow propagation in the cells. The parameter W is the most important because it controls both the occurrence and magnitude of flow peaks, and the total volume of runoff. It has a different value for each block, and since each grid square contained up to eight blocks (combinations of soil type, land use, and vegetation cover), a total of 13 (1 + 2 + 2 + 8) parameters were calibrated. These parameters are similar to those of the LARSIM [*Bremicker*, 1998] and VIC [*Nijssen et al.*, 1997; *Liang et al.*, 1994] models.

[17] The calibration procedure required an interval to be specified for each parameter within which it was allowed to vary. Using these intervals, parameters were restricted during calibration to assume physically plausible values: For example, the soil moisture capacity in deep soils under forest was required to be greater than that of shallow soils under pasture.

[18] Flow data from five gauging stations within the basin were used jointly for model calibration. Two objective functions were used to calibrate the model parameters: namely, the Nash-Sutcliffe goodness-of-fit measure, and the absolute difference in runoff volumes. These objective functions were calculated for each of the five gauging stations, resulting in 10 (5×2) objective functions, and were combined by means of weighted averages to obtain two pooled functions, given by the following equations:

$$F1 = 1 - \sum\nolimits_{i=1}^{5} w_i NS_i \tag{1}$$

$$F2 = \sum\nolimits_{i=1}^{5} w_i |DV_i| \tag{2}$$

where i refers to the gauging station; NS_i is the Nash-Sutcliffe measure of model fit for station i; DV_i is the difference between runoff volumes; and w_i is the weighting factor for station i. The weighting factors were chosen so as to represent the importance of the gauging stations in terms of basin area and data reliability. Most weight was given to one station with a basin area of 52,671 km^2, and the remainder distributed to the other stations as shown in Table 1.

[19] Figure 2 shows observed and calculated hydrographs at the Passo Caxambu (Figure 1; area = 52,671 km^2) gauging station during 1994, where it can be seen that the floods in the Uruguay basin occur rapidly and in any season. The hydrologic model results were verified against observed data from 11 flow gauging stations of the River Uruguay with basin area larger than 5000 km^2. Despite some exceptions at

Table 1. Gauging Stations and Weighting Factors Used in the Calibration Procedure

Station	River	Code	Area, km^2	Weighting Factor
Passo Caru	Canoas	71550000	9,868	0.05
Marcelino Ramos	Uruguay	73010000	41,267	0.05
Passo Caxambu	Uruguay	73550000	52,671	0.50
Barra do Chapecó	Chapecó	73960000	8,267	0.20
Passo Rio da Várzea	Da Várzea	74270000	5,356	0.20

gauging stations with small basin area, results of the model calibration are on the whole good: Table 2 shows a summary of results during the verification period.

3.2. The CPTEC-INPE Global Circulation Model

[20] The CPTEC climate spectral model [*Marengo et al.*, 2003] is essentially a low-resolution weather prediction model with equivalent grid spacing of about 180 km with 28 levels in the vertical between the surface and the top of the model atmosphere at 1 mbar. The precipitation and its effect on the heat and moisture exchange in the atmosphere are included at two scales: (1) the grid scale, as a procedure which evaluates the degree of supersaturation at the grid point and the condensation of supersaturated vapor, eventually removed as precipitation; and (b) at the subgrid scale, in which cumulus-type clouds that build up at scales ranging from a few kilometers to a few dozen kilometers. For this second case, the CPTEC model uses the widely tested and validated Kuo parameterization [*Kuo*, 1974].

[21] Short- and long-wave radiation processes are modeled so as to describe the effects of short-wave absorption in the main bands for water vapor, ozone, and oxygen. Molecular scattering processes are included, but aerosol scattering is not, since the aerosol concentration is a variable that is neither predicted nor diagnosed. Cloudiness is represented simply but realistically, so as to allow an interaction between radiation and the convective processes as parameterized at both grid and subgrid scales. In the long-wave case, effects associated with the absorption and emission of radiative energy are modeled for the water vapor, CO_2, and O_3 bands. The presence of cloud is also considered, on the hypothesis that clouds behave as black bodies when their thickness exceeds a certain critical value.

[22] An important component of the CPTEC model is the procedure used to simulate the exchanges of heat, momentum, and water vapor from the continental surface. This component is particularly important in view of the strong control exerted by surface processes in the genesis of precipitation in tropical/subtropical regions. The CPTEC model uses the SIMPLIFIED biophere SIB2 procedure [*Sellers et al.*, 1996], modified by *da Rocha et al.* [1996] in which the role of vegetation is represented as a resistance to water vapor transport from the soil, through the root matrix, to leaf surfaces, and then from leaf surfaces to the atmosphere through the stomata. In addition, processes of radiative transfer in the vegetation canopy, interception of rainfall by the canopy, and evaporation of intercepted rainfall are also modeled realistically. The SIB2 parameters were duly calibrated using data representative of Brazilian grassland and forests [*da Rocha et al.*, 1996], so that surface processes are realistically modeled. This is an important characteristic of the CPTEC model, making it particularly relevant for studies of climate variability in South America, and for regional climate forecasting.

[23] The SST anomalies exert an important control on the precipitation in southern Brazil, primarily through the El Niño/La Niña phenomena and South Atlantic anomalies [*Grimm et al.*, 1998]. With regard to the oceans, CPTEC uses two methods for incorporating SST data into the atmospheric model during the period of integration: (1) as persistent anomalies in SST in all the oceans; and (2) as the SST predicted by the National Centers for Environmental Prediction (NCEP) in the equatorial Pacific and SST as predicted by a statistical model (SIMOC) for the tropical Atlantic [*Pezzi and Cavalcanti*, 2001]. In areas other than the Atlantic and Pacific tropical areas, and in the Indian and other oceans, the SST is given by assuming that the anomaly observed at the begining of the integration period persists throughout. The two procedures are important for testing the influence of SST anomalies which have significant impacts on climate anomalies observed in other parts of the globe.

[24] Because of the chaotic nature of the dynamics of atmospheric evolution, intrinsically associated with system nonlinearity, the CPTEC model produces ensemble forecasts [*Toth and Kalnay*, 1997]. Between 20 and 30 forecasts are calculated, every month, for the following 6 months, beginning from different initial conditions (days from $i = 1$ to $i = 20$ or 30). These can be used to estimate the degree of reliability of numerical predictions. Theoretical studies confirm that the mean of the ensemble gives better accuracy than do its individual members, and in some cases "attractors" can be observed clearly, indicating preferential climatic regimes associated with greater reliability of forecasts. In other cases, members of the ensemble diverge considerably. Experience with the CPTEC model shows that the 6-month precipitation forecasts are more reliable for some regions of Brazil, such as the south, the northern part of the Brazilian northeast, and the eastern part of Amazonia, than for others. In other regions the reliability of forecasts is low or moderate [*Marengo et al.*, 2003].

4. Results From Precipitation Forecasts

[25] The period of data extracted from files created by the CPTEC global model extended from December 1995 to February 2002. The set of seasonal forecasts reported in this

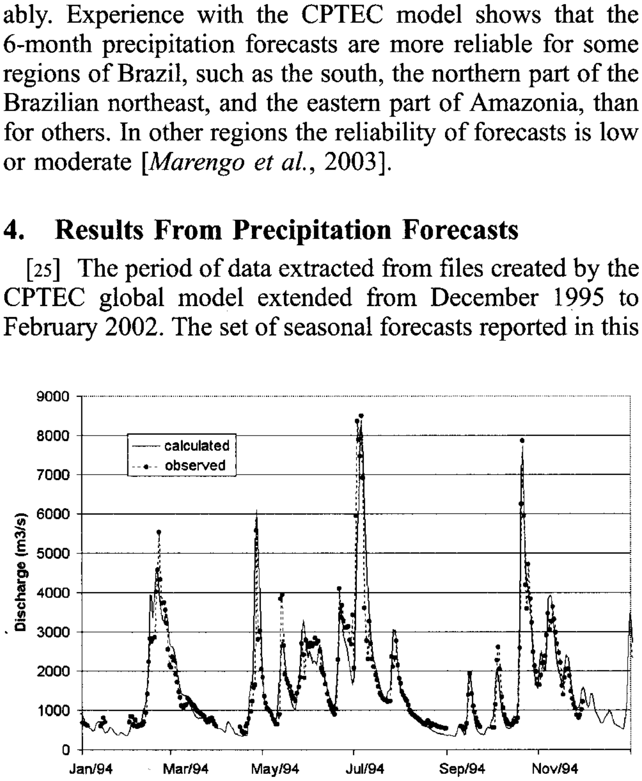

Figure 2. Observed and calculated hydrographs of River Uruguay daily discharge, at Passo Caxambu.

Table 2. Summary Results of Model Verification

Code	Area, km^2	Verification (1977–1984) NS[a]	NS_{log}[b]	DV,[c] %	Verification (1995–1998) NS	NS_{log}	DV, %
70700000	8,400	0.71	0.73	−11	0.52	0.60	−5
71550000	9,868	0.86	0.81	−12	0.83	0.85	−13
72300000	29,114	0.79	0.83	9	0.64	0.81	8
72980000	5,114	0.83	0.71	12	0.81	0.86	−3
73010000	41,267	0.89	0.85	6	0.86	0.86	4
73200000	44,350	0.91	0.82	7	0.83	0.83	−1
73550000	52,671	0.92	0.84	1	0.86	0.87	4
73770000	5,880	0.80	0.72	19	0.71	0.75	−12
73960000	8,267	0.88	0.75	21	0.78	0.83	−10
74100000	62,199	0.91	0.84	0	0.87	0.87	−9
74270000	5,356	0.72	0.75	0	0.78	0.79	−9

[a]Nash-Sutcliffe efficiency of daily discharge.
[b]Nash-Sutcliffe efficiency of logarithms of daily discharge.
[c]Difference between runoff volumes.

paper was derived using the same atmospheric model as that described by *Marengo et al.* [2003].

[26] The available forecasts were organized into 3-monthly periods, dated from at least 2 months beforehand, as shown in Table 3. Thus forecasts for the 3-month period December 1995 to February 1996 were from start dates in September 1995; those for the period March to May 1996 from start dates in December 1995; and so on. This meant that forecasts were available for nonoverlapping 3-month periods.

[27] As stated earlier, the Rio Uruguay basin exerts only a minor regulatory influence on flow, as is seen from the large hydrograph fluctuations shown in Figure 2. The greater part of rainfall is transformed to rapid runoff registered at flow-gauging stations after only 1 or 2 days. Therefore forecasts are only weakly dependent on initial conditions of soil moisture and flow in the hydrologic model, and, to simplify matters, the forecast periods were grouped in sequence without regard to initial conditions. For example, one such sequence was formed by juxtaposing the first member of the forecast for December–January–February (DJF) 1995/1996 (start date 13 September 1995) with the first member of the forecast for March–April–May (MAM) 1996 (start date 17 December 1995), and so on. Thus the initial conditions of the flow forecasts for the 3-month period September–October–November (SON) 2001, using the second ensemble member (start date 21 June 2001), were obtained directly from the simulation using the second ensemble member 2 for the period June–July–August (JJA) 2001 (start date 7 March 2001). Although it might be argued that initial conditions would be more accurately defined by considering preceding rainfall and basin wetness at the start of a forecast period, this option was discarded because of the basin's short memory. Furthermore, not all of the output from the CPTEC model needed for such calculation was available for the work reported in this paper. The CPTEC rainfall forecasts available for input to the hydrologic model were a subset of the total ensemble. Ideally, all 20–30 members of the ensemble of forecasts should be used as input to the hydrologic model, but because of time limitations, a subset of four or five ensemble members which best represented the ensemble characteristics was identified using cluster analysis.

[28] As a first step, the quality of the rainfall forecasts over the Rio Uruguay basin was analyzed by comparing annual means of forecasts and of measured rainfall for the period December 1995 to May 1999. Measured rainfall was interpolated spatially using data from rain gauge sites, and forecast rainfall was interpolated using the forecasts for each GCM cell (see Figure 1). Both interpolation procedures (for measured rainfall and for forecast rainfall) used weights equal to the inverse squares of the distances from the five nearest points (rain gauge sites, or cell centers, as appropriate). The grid spacing used for both interpolation procedures was that used by the rainfall-runoff model, 0.1×0.1 degrees.

[29] Figures 3a and 3b show the mean annual measured (Figure 3a) and predicted (Figure 3b) rainfall (the latter as the mean of interpolated values given by the four or five ensemble members used) over the Rio Uruguay basin. Comparison of the two figures shows that GCM forecasts underestimate rainfall over almost the entire area. Measured rainfall vary from 1500 mm in the east to 2600 mm in the west; forecast rainfall, however, reaches at most 1700 mm in the northeast of the basin. The difference of rainfall (forecast minus observed) is small in the eastern part of the basin, but much larger in the west.

[30] Besides the spatial distribution of error, within-year rainfall variation was also poorly reproduced in GCM forecasts. In general, winter rainfall over the basin was underestimated, with dry winters forecast similar to those of the Brazilian southeast, whereas in reality there is very little seasonal variation in rainfall with no marked wet and dry seasons. As a result, river discharge calculated by using the rainfall-runoff model to convert rainfall forecasts into runoff was particularly underestimated in July and August (Figure 4).

Table 3. Details of Periods of Forecast, Numbers of Ensemble Members Provided, and Dates When Forecasts Were Calculated Using the Global Climate Model

Period	Number of Members	Start Dates of Forecast
DJF 1995/1996	4	13, 14, 15, and 16 September 1995
MAM 1996	5	17, 19, 20, 21, and 22 December 1995
JJA 1996	5	1, 3, 4, 5, and 6 March 1996
SON 1996	5	19, 20, 21, 22, and 23 June 1996
DJF 1996/1997	4	16, 17, 18, and 19 September 1996
MAM 1997	5	24, 25, 26, 27, and 28 September 1996
JJA 1997	5	11, 13, 14, 15, and 16 March 1997
SON 1997	5	15, 16, 17, 18, and 19 June 1997
DJF 1997/1998	5	7, 8, 9, 10, and 11 September 1997
MAM 1998	5	21, 22, 23, 24, and 25 December 1997
JJA 1998	5	13, 14, 15, 16, and 17 March 1998
SON 1998	5	2, 3, 4, 5, and 6 June 1998
DJF 1998/1999	4	3, 5, 6, and 7 September 1998
MAM 1999	5	9, 10, 11, 12, and 13 December 1998
JJA 1999	4	20, 21, 22, and 23 March 1999
SON 1999	5	22, 23, 24, 25, and 26 June 1999
DJF 1999/2000	4	21, 22, 23, and 24 September 1999
MAM 2000	5	12, 13, 14, 15, and 16 December 1999
JJA 2000	4	19, 20, 21, and 22 March 2000
SON 2000	4	12, 13, 14, and 15 June 2000
DJF 2000/2001	5	18, 19, 21, 22, and 23 September 2000
MAM 2001	5	4, 5, 6, 7, and 8 December 2000
JJA 2001	4	6, 7, 9, and 10 March 2001
SON 2001	4	20, 21, 22, and 23 June 2001
DJF 2001/2002	4	24, 25, 26, and 27 September 2001

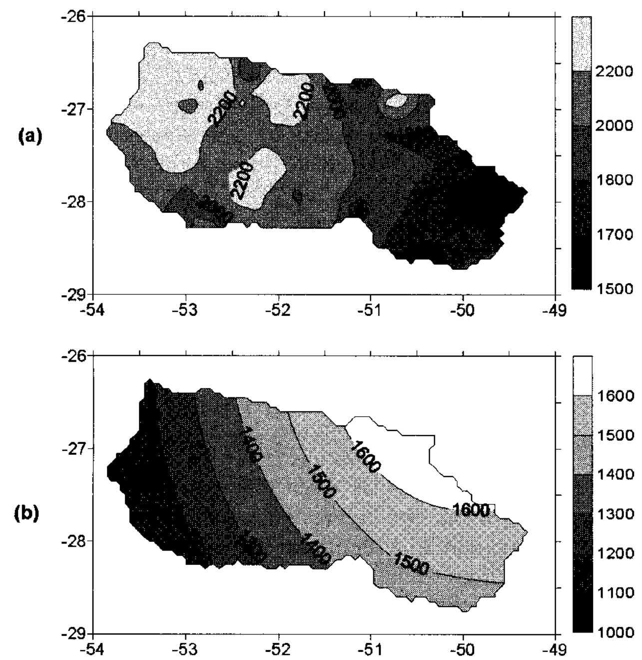

Figure 3. Mean annual (a) measured rainfall and (b) forecast rainfall in the Rio Uruguay drainage basin, for the period December 1995 to May 1999 (mm yr^{-1}).

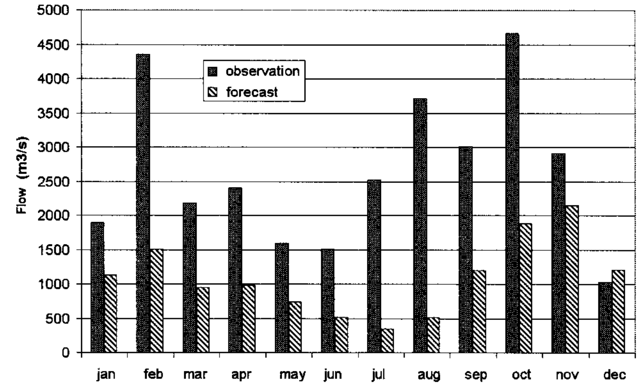

Figure 4. Observed and GCM-predicted monthly mean flows in the Uruguay River basin.

[31] The systematic errors in rainfall forecasts (underestimation in winter, and in the west of the basin) may be associated with the low spatial resolution of the model (about 200 km). Much of the rainfall in winter and transitional seasons is associated with cyclones which develop in northern Argentina, Paraguay, and Uruguay and move toward the ocean [*Gan and Rao*, 1991]. The spatial scale of these cyclones is of the order of a few hundred kilometers, and their intensity is largely dependent on the latent heat released by rain formation [*Bonatti and Rao*, 1987] so that they are not well represented at the low resolution of the climate model.

5. Method Used to Correct Rainfall Forecasts

[32] Despite the systematic difference between observed and predicted mean annual rainfall, and between observed and predicted within-year rainfall, the interannual variability was fairly well reproduced by the GCM, as discussed by *Marengo et al.* [2003]. A method was therefore used to reduce the systematic error in forecasts, while maintaining their interannual characteristics. The method adopted is similar to that of *Wood et al.* [2002], the main difference being that it is applied to daily instead of to monthly rainfall forecasts; that is, our method used the frequency distribution of predicted daily rainfall during any month, instead of the distribution of monthly totals described by *Wood et al.* [2002].

[33] The method used to correct forecasts is based on a transformation of the marginal frequency distribution of daily rainfall. Statistical theory shows that any probability density function can be transformed into any other, by first transforming it into a uniform distribution, and then using an inverse transformation from the uniform distribution to the distribution required. To use this procedure, cumulative frequency curves of observed and predicted daily rainfall were calculated for each month and for each GCM grid point. The graph in Figure 5 shows the cumulative frequency curves for the month of January, and for the cell near 54°W, 28°S (see Figure 1b).

[34] These two curves were used to correct the forecasts of daily rainfall. The probability P associated with each forecast rainfall is identified from the cumulative frequency curve for the forecast values. The corresponding corrected forecast is then obtained as that value associated with the same probability P, in the cumulative frequency curve for measured daily rainfall. Figure 5 gives an example. This procedure was used to correct each forecast value of daily rainfall, treating each month and each grid point separately: With 16 grid points and 12 months, a total of $16 \times 12 \times 2 =$ 384 cumulative frequency curves were calculated.

[35] GCMs calculate the state of the atmosphere in time steps of the order of hours, so that rainfall forecasts may be obtained in time intervals of 1 day or less. This is convenient for use with many hydrologic models, which use time

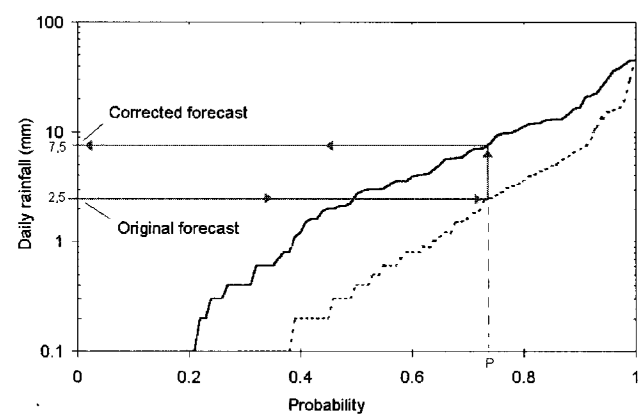

Figure 5. Cumulative frequency curves for measured and predicted rainfall at grid point near 54°W, 28°S (Figure 1b), for the month of January. Curves are calculated using measured and predicted daily rainfalls over the period December 1995 to May 1998. Solid line corresponds to measured rainfall, dashed line corresponds to GCM-forecast rainfall.

steps of this order. However, it could be argued that GCM forecasts of daily rainfall have low per-day information content and that daily forecasts should be aggregated into monthly time steps for which the information content may be higher. The disadvantage of this, however, is that the forecasts of monthly rainfall must be disaggregated again for use in a hydrologic model that uses shorter time steps. Thus *Wood et al.* [2002] used a downscaling procedure to transform monthly rainfall totals back to daily rainfall. Since the model used for the Rio Uruguay basin computed water balances at daily time steps, it was decided to work with GCM forecasts of daily rainfall and not to aggregate them into monthly totals and then disaggregate. This decision was further supported by the fact that in the eastern part of the Rio Uruguay basin, where differences between GCM forecasts and measured rainfall were smaller, the frequency distributions of both GCM forecasts and measured daily rainfall were similar. Furthermore, *Frei et al.* [2003] have reported the usefulness of GCM predictions of daily rainfall. However, the empirical correction to forecasts of daily rainfall, described above, was applied over the whole of the basin.

6. Results of Flow Forecasts

[36] The initial analysis of forecast river flows used the forecasts obtained retrospectively for the period 1995–2001. The method for correcting rainfall, described above, used the data for the period 1995–1998. Thus the rainfall forecasts for the period 1995–1998 were corrected a posteriori; that is, the correction was applied using the same data as were used to calculate the cumulative frequency curves. This procedure was used only for purposes of comparison and of course could not be used under operational conditions. So the next step was to correct the rainfall forecasts for the period 1999–2001 a priori; that is, the cumulative frequency curves used for correcting predictions of daily rainfall during this period were those that had been obtained from the data of the preceding period, i.e., 1995–1998. This method of correction could therefore be used operationally. The resulting forecasts of runoff were compared with flows recorded at the Iraí gauging station on the Rio Uruguay, where the area drained is 62,200 km^2. Figure 1b shows the position of this gauging station within the basin.

[37] Figure 6 shows flow forecasts for the period 1995–1998 using uncorrected forecasts of rainfall from the climate model. The figure shows that the forecast flow is almost always less than the observed, especially in (austral) winter months. In addition, for some months there is also great variation among flow forecasts resulting from the different GCM realizations (shaded lines).

[38] Flow forecasts for the same period, but with climate-model rainfall predictions corrected by the empirical procedure described above, are shown in Figure 7. There is great variation among the flows predicted for some months, notably February 1996 and April 1998. Figure 8 shows the mean of the monthly flow predictions given by the four or five realizations obtained from the GCM, together with monthly mean flows calculated from the historic record. This figure shows that flow predictions were better when obtained using GCM forecasts of daily rainfall; but as explained, the predicted flows in this figure were obtained

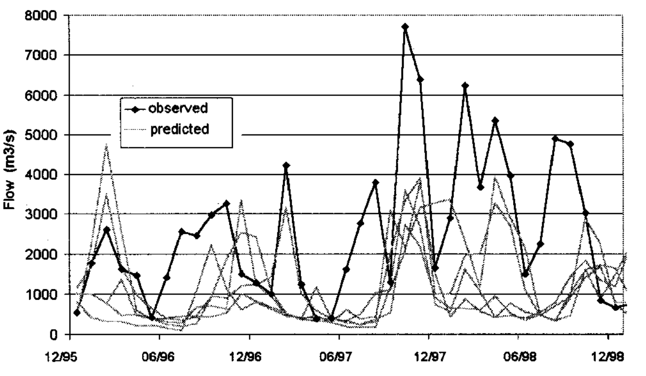

Figure 6. Forecasts of flow in the Rio Uruguay, based on uncorrected GCM forecasts of rainfall. The five shaded lines correspond to the five realizations.

by a posteriori correction of predicted rainfall. Using the fairer test of a priori correction, in which rainfall during June 1999 to October 2001 was corrected using cumulative frequency curves calculated from the earlier period 1995–1998, the flow forecasts shown in Figure 9 were obtained. Large variation among predicted monthly flows is again evident, giving an indication of the uncertainty in the forecasts.

[39] Figure 9 also shows the predicted flows from all realizations in the set in the form of a shaded band determined by the maximum and minimum predictions for each month; the fine line is the mean of the monthly predictions, and the bold line gives the observed monthly flow. The shaded band in Figure 9 is wide in most months, the difference between maximum and minimum predicted flows being as much as 5000 m^3 s^{-1} in some months, although in others it falls to about 1000 m^3 s^{-1}. In general, however, the uncertainty among the set of predicted monthly flows (as measured by the range of predicted monthly flows) is less than the the difference between the maximum and minimum monthly flows in the historic record, shown as broken lines in Figure 9. The wider limits (maximum-minimum) shown for the historical record, relative to the limits (maximum-minimum) of the predictions, are not unexpected, as they are obtained from a longer record.

[40] Nevertheless Figure 9 shows that the use of climate-model forecasts of rainfall to predict future flows can reduce their uncertainty. The mean of the set of flow forecasts generally follows the pattern of observed flows, especially in the wet period at the end of the year 2000. Moreover, in almost all months the observed flow lies within the uncertainty band defined by the range of predicted flows.

[41] A complication occurred because the period of data available for evaluating flow forecasts coincided with the completion of two dams on the Rio Uruguay. Between 1999 and 2001, two reservoirs, at Itá and Machadinho, both upstream of the river gauging station at Iraí, were completed and began to fill. Flow into the Itá reservoir began 16 December 1999, and the reservoir was full in March 2000. The Machadinho reservoir began to fill on 28 August 2001 and was full on 2 October 2001. These two periods, for which the observed flows are open to doubt, are marked in Figure 9. It can be seen that in both periods, observed flow was less than predicted flow.

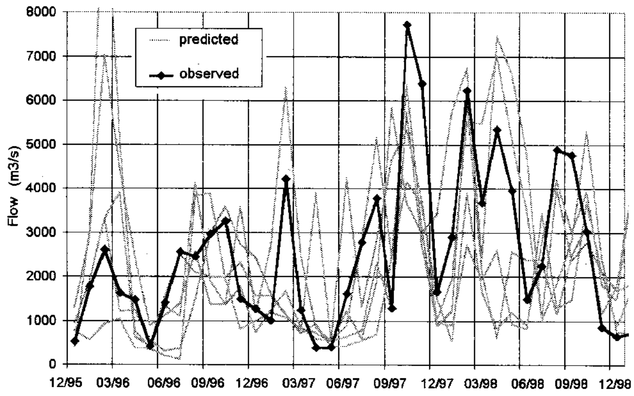

Figure 7. Predicted flows in the Rio Uruguay, after correcting for underestimation of rainfall in GCM realizations (the five shaded lines correspond to five GCM realizations).

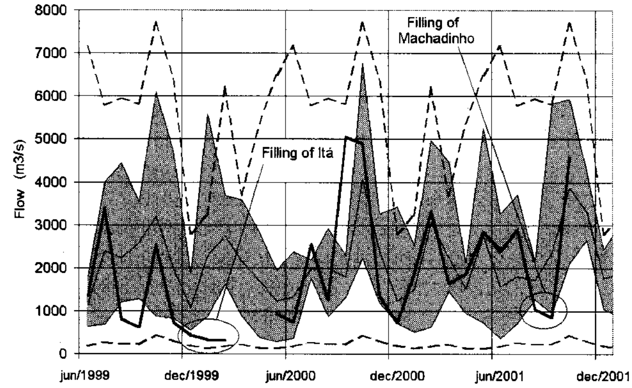

Figure 9. Range of predicted monthly flows (shaded band) compared with range of observed monthly flows in the historic record (maxima and minima shown as broken lines). The solid line shows observed flow.

[42] Figure 10 shows that the reduction in uncertainty is more evident over periods extending 3 months ahead; observed flows were then within the uncertainty band for forecasts, except when the reservoir at Itá was filling. In the Rio Uruguay basin, the uncertainty band derived from the historical record, when defined by the limits between minimum and maximum flows recorded for each month of the year, is very wide when compared to the uncertainty band of the forecasts. In part, this may be because flows were observed over a longer period (about 50 years) than the four or five members of the ensemble of forecasts. The two uncertainty bands may be better compared if they are defined as intervals of plus or minus one standard devation about the observed flows, and about the forecast flows, respectively. This is shown in Figure 11, showing that observed flows are outside the uncertainty band (historic mean ± SD) about as often as forecast flows; and in almost all months when the observed flows exceeded the upper limit of the uncertainty band, the forecast indicated correctly that greater flows could be expected.

[43] To summarize, the results presented show that the potential exists for obtaining flow forecasts for a period extending to several months ahead, by using seasonal climate forecasts given by a GCM. However, since the flow forecasts required a statistical correction to the global climate forecasts, it could be argued that the positive results obtained are simply a consequence of that correction and do not illustrate any merit in the climate forecasts themselves.

[44] To explore this possibility, an alternative analysis was undertaken which used no statistical correction, but which compared the anomalies in observed and predicted flows. The observed anomaly in a given month, for example, August 2000, is the difference between the observed mean flow for that month and the mean of the observed flows in all those Augusts for which flow was predicted by the CPTEC model, divided by the mean observed flow in all the Augusts for which predictions were available (equation (3)). Thus a month with positive (negative) anomaly has flow proportionally greater (less) than the mean observed flow, calculated over the period for which predictions were obtained from the climate model. Similarly, anomalies can be defined for the forecast series: the anomaly for August 2000 then being the difference between the predicted flow for that month, and the predicted flows available in all other Augusts for which predictions were made by the CPTEC

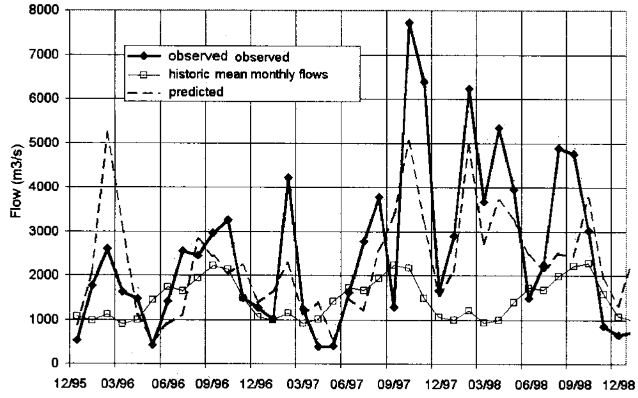

Figure 8. Predicted flows in the Rio Uruguay (the dashed line is the mean of five predictions of monthly flow from GCM realizations; the line connecting squares shows the historic mean monthly flows).

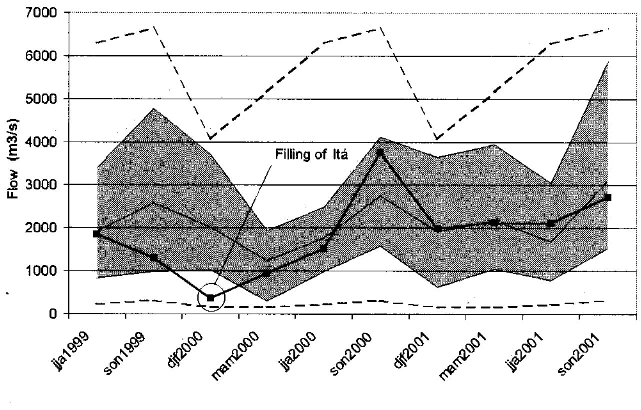

Figure 10. Range of predicted 3-monthly flows (shaded band) compared with range of observed monthly flows in the historic record (maxima and minima shown as dashed lines) and with observed flows (bold line).

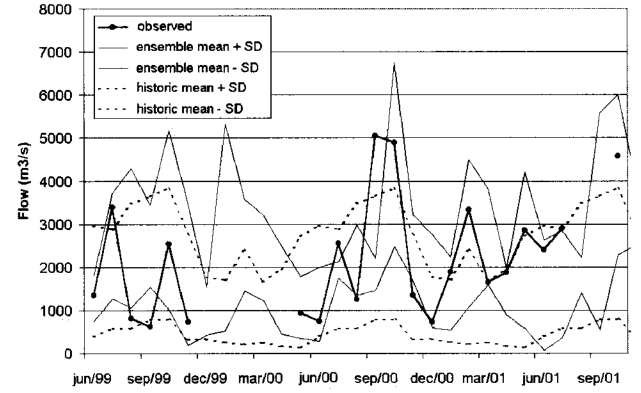

Figure 11. Intervals for predicted monthly flows (mean ± SD, shown as two solid lines) compared with intervals for observed monthly flows from the full historic record (mean ± SD, shown as two dashed lines) and with observed flows (bold line).

model, divided by the mean of all available predicted flows for that month (equation (4)).

$$AO = \frac{QO - QMO_j}{QMO_j} \tag{3}$$

$$AP = \frac{QC - QMC_j}{QMC_j} \tag{4}$$

where AO is the observed anomaly; AP is the forecast anomaly; QC is the forecast discharge; QO is the observed discharge; QMO_j is the observed mean monthly discharge for month j; and QMC_j is the forecast mean monthly discharge for month j.

[45] For example, the period for which the CPTEC global climate model gave forecasts used in this study extended from December 1995 to December 2001. Over this period, the mean value of the flows observed in the month of August was 2370 $m^3 s^{-1}$, while the mean of the flows predicted from the CPTEC model in the (six) Augusts, without any statistical correction of rainfall, was 447 $m^3 s^{-1}$. In August 2000, the observed mean flow for the month was 1247 $m^3 s^{-1}$, and the predicted mean flow, obtained using the predicted daily rainfalls without any statistical correction, was 337 $m^3 s^{-1}$. The anomaly of observed flow was therefore −0.47, obtained as (1247−2370)/2370 and the anomaly in predicted flow was −0.25, calculated as (337−447)/447. Thus the negative sign of the anomaly was adequately predicted; that is, an August drier than normal was forecast, and this is what occurred. However, the magnitude of the anomaly that really occurred was greater in absolute magnitude than the predicted anomaly.

[46] Predicted and observed anomalies were calculated for each month of the period used in the analysis (from 1995 to 2001). Figure 12 shows the results obtained for monthly flows, and Figure 13 shows the 3-month moving averages calculated from these series. In general, predicted and observed anomalies show similar behavior. The figure shows, for example, that the anomaly sign in the relatively wet period in 1997 and 1998 were positive (i.e., flow greater than "normal"), although their absolute magnitude was

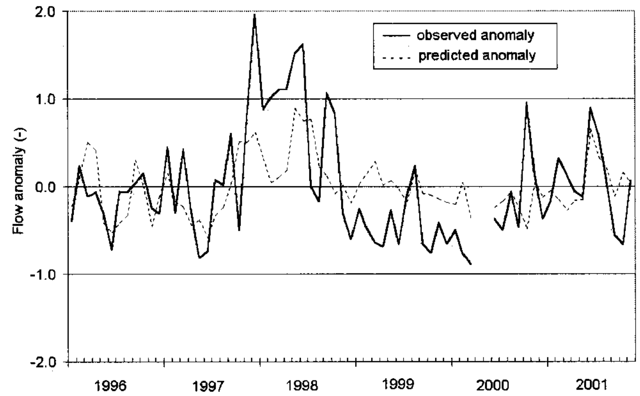

Figure 12. Anomaly in observed monthly flow (solid line) and in predicted monthly flow (dotted line), December 1995 to October 2001.

underestimated. On the other hand, the dry period 1998–1999 was forecast as a period of transition, which only came to be forecast as dry at the end of 1999.

[47] The forecasts of anomalies in flow are clearly not perfect. However, they show that at least a part of the interannual variation in flow in the Rio Uruguay can be forecast using a system that combines hydrologic simulation with seasonal climate forecasts. The analysis of anomalies also shows that the good results obtained where forecast flows were derived from statistically corrected rainfall sequences were not simply a consequence of the correction procedure.

[48] As well as qualitative and graphical analyses, results were also analyzed quantitatively in terms of comparisons between predictions derived from climate-model forecasts and predictions based on the simple use of long-term means calculated from the historic record. One measure of the value of predictions given by the climate model is the reduction in variance achieved by their use, relative to the variance obtained where forecasts of monthly flows are simply set equal to their mean values over the period of historic record. This reduction in variance can be written

$$RV = 1 - \frac{\sum_{i=1}^{n} (QC_i - QO_i)^2}{\sum_{i=1}^{n} (QM_i - QO_i)^2} \tag{5}$$

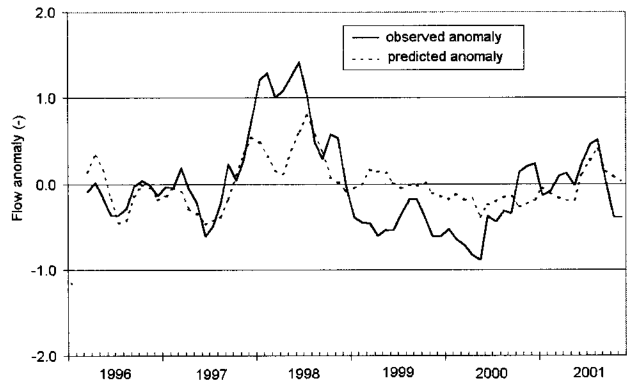

Figure 13. Three-month moving averages of observed monthly flows (solid line) and of predicted monthly flows (dotted line), December 1995 to October 2001.

where n is the number of months or 3-monthly periods, QC is the forecast of flow obtained by using the climate model, QM is the historic mean value for flow in relevant month or 3-month period, and QO is the observed flow, as before. The value of RV will be 1 (or 100%) if all the forecast flows QC are equal to observed flows, corresponding to a perfect predicition; it will have a positive value if the forecasts obtained by using the climate model are better than taking just the historic mean flows as predictions of future flow, and RV will be negative if the converse is true.

[49] For the period June 1999 to October 2001, the reduction in variance obtained by using predictions derived from the climate model, with rainfall correction, is about 0.15, a 15% reduction in variance relative to the variance where historic mean flows were taken as forecasts of future flows. If, over the same period, months are excluded for which observed flows are questionable because the reservoirs Itá and Machadinho were filling (December 1999, January and February 2000; August and September 2001), the reduction in variance rises to 37%. For this period therefore, flow forecasts obtained using rainfall forecasts given by the climate model are 37% better than simply taking historic monthly flows as forecasts of future flow.

[50] When the value of forecasts is assessed over 3-monthly instead of monthly periods, which can be regarded as more reasonable since the GCM gives forecasts for 5 months ahead and energy generation planning has a seasonal horizon, the reduction in variance rises to 54% when periods affected by the filling of the two reservoirs are omitted.

7. Conclusions

[51] The rainfall forecasts given by the CPTEC global climate model systematically underestimate rainfall in the Rio Uruguay drainage basin. This conclusion confirms the results of earlier research, that the model underestimates rainfall in the southern part of Brazil [*Marengo et al.*, 2003].

[52] The geographical distribution of rainfall predicted by the CPTEC global climate model is substantially different from the observed distribution of rainfall. While rainfall predicted by the model increases from west to east, the measured rainfall increases from east to west. In the uplands that form the extreme eastern part of the basin, the mean error in predicted rainfall is relatively small; however, in the center and western part of the basin, the accumulated error in annual total rainfall is very large, in some regions rising to more than 1000 mm yr^{-1}. Thus the model predicts too little rain in the center and west of the basin.

[53] Although the CPTEC global climate model predicts interannual variability in rainfall reasonably well, its reproduction of within-year rainfall distribution is poor. The largest errors are in (austral) winter rainfall, when model predictions systematically underestimate rainfall in the Rio Uruguay basin. Evapotranspiration is least during this period, and mean flows are consequently greater. Underestimation of rainfall in this winter period therefore has a very marked effect on flow forecasts.

[54] It was found possible to reduce the systematic errors in rainfall predicted by the CPTEC global climate model by using an empirical correction. Results obtained after this correction showed that when empirically corrected GCM daily rainfall were used as input to a large-basin model of hydrologic response, the variance of 3-month predicted flow was reduced by 54% relative to forecasts in which predictions of future flow are simply set equal to their historic mean values. When the time interval was 1 month instead of 3, the reduction in variance was 37%.

[55] Even without the statistical correction of rainfall, the anomaly in observed flow in each month (and also in each 3-month period) was predicted reasonably well when the rainfall predictions were used as input to the large-basin model of hydrologic response.

[56] The forecasts of seasonal flow that result when rainfall predicted by the global climate model is transformed into runoff by the large-basin hydrologic model appear as sets or ensembles of hydrographs. Thus the forecast of future flow is obtained together with a measure of its uncertainty. Analysis shows that the range (maximum minus minimum) of the ensemble values of flow predicted in each month gives a band of uncertainty that is narrower than the band of uncertainty given by the historic record.

[57] At the present time, decisions concerning future operations of power supply systems in Brazil are based on synthetic flow sequences generated by empirical stochastic models of ARMA type. This paper suggests that alternatives need to be explored in which GCM rainfall predictions are routed through physically based models of hydrologic response. Variability between members of the ensemble of flow sequences then gives a measure of the uncertainty in flow prediction. Furthermore, the precision of flow predictions derived from combining rainfall predictions with models of hydrologic response will increase in the future, as models of weather and climate develop still further.

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R. T. Clarke, W. Collischonn, and C. E. M. Tucci, Instituto de Pesquisas Hidráulicas, Universidade Federal do Rio Grande do Sul, Avenida Bento Gonçalves 9500, Porto Alegre CEP 915010970, RS, Brazil. (cllschnn@vortex.ufrgs.br; tucci@iph.ufrgs.br; clarke@iph.ufrgs.br)

P. L. da Silva Dias, Instituto de Astronomia, Geofísica e Ciências Atmosféricas Universidade de São Paulo, Rua do Matão 1226, 05508-900, São Paulo, SP, Brazil. (pldsdias@master.iag.usp.br)

G. S. de Oliveira, Centro de Previsão de Tempo e Estudos Climáticos, Instituto Nacional de Pesquisas Espaciais, Rodovia Presidente Dutra, Km 40, SP-RJ, 12630-000,Cachoeira Paulista, SP, Brazil. (sampaio@cptec.inpe.br)