

**LONG TERM FLOW FORECAST BASED ON CLIMATE AND HYDROLOGICAL
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, RS, Brazil

Pedro Leite da Silva Dias

Instituto de Astronomia, Geofísica e Ciências Atmosféricas – Universidade de São Paulo

São Paulo, SP, Brazil

Terms from AGU Index Set: 0315 : Biosphere/atmosphere interactions

1833 : Hydroclimatology

1860 : Runoff and streamflow

3337 : Numerical modeling and data assimilation

9360 : South America

August 2002

e-mail contact: clarke@iph.ufrgs.br

ABSTRACT

This paper describes a procedure for predicting seasonal flow in the Rio Uruguay drainage basin (area 75000 km² lying in Brazilian territory), using sequences of future daily rainfall given by the global climate model of the Brazilian agency for climate prediction CPTEC-INPE. Sequences of future daily rainfall given by this model were used as input to a rainfall-runoff model appropriate for large drainage basins. Retrospective forecasts of flow in the R. Uruguay were made for the period 1995-2001 and were compared both with observed flows and with simplistic forecasts using monthly mean or median flows obtained from the historic record. Analysis showed that the global climate model underestimated rainfall over almost all the basin, particularly in winter, although it reproduced inter-annual variability in regional rainfall 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 R. Uruguay basin were better than forecasts based on historic mean or median flows by 37% for monthly flows, and by 54% for three-monthly flows.

INTRODUCTION

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, both in terms of model structure and related computational procedures, will yield quantitative estimates of rainfall of wider use in water resource planning, especially at larger scales.

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 six 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]. However developments in both 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.

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.

However, to extend predictions of flow beyond the period of short-term basin response requires forecasts of future rainfall. Whilst 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 combination 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].

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]. And since, in mixed generating systems, the operational costs of hydropower production are lower than for thermo-electric 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.

As one example, Hamlet et al. [2002] took as a case study the Columbia River basin on the US west coast, with installed capacity for hydropower generation of approximately 18.700 MW, and demonstrated that it was possible to increase hydropower production to a value somewhere between 40 and 150 million dollars 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].

The highly non-linear 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 non-linearities, 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 amongst the set of predicted flows thus generated gives a measure of their uncertainty [Krzysztofowicz, 2001].

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, whilst regional-scale models have spatial resolutions of several dozen km (from less than 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 with basin size, and according 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.

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 Uruguay River [Collischonn and Tucci, 2002]. The present paper describes the use of this model for forecasting flows in the Uruguay River from 3 to 5 months ahead, using forecasts of seasonal climate given by the global model of the Brazilian Center for Weather and Climate Forecasting (CPTEC: Centro de Previsão de Tempo e Clima), which forms part of the Brazilian Institute for Space Research (INPE: Instituto Nacional de Pesquisas Espaciais).

THE URUGUAY RIVER BASIN.

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 km² has marked relief and little soil storage capacity, whilst aquifers linked to the drainage network exert little control over flow. The climate is characterized by cool winters, little variation in seasonal rainfall, and with 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 small variation in flow of different seasons, the short “memory” of the drainage basin, and the large variation in monthly flow about the historic monthly mean and median values.

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

FORECASTING METHODOLOGY

In this paper, a global circulation model 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 and Tucci, 2002*], used a discrete network of points derived from a grid with squares 0.1 x 0.1 degrees of latitude and longitude, corresponding to about 10 x 10 km. This grid spacing was determined by considerations of soil type and other

physiographic factors. The model was calibrated using recorded rainfall as described earlier [Collischonn and Tucci, 2002].

Having fitted the model using observed rainfall, it was then adapted to receive rainfall sequences derived from the model giving estimates of future seasonal rainfall, so that both models were used together to give medium-term flow forecasts.

THE HIDROLOGIC MODEL

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

Soil water balance is computed independently for each block of each cell, considering only one soil layer. Processes of flow routing and storage that are included in the model are canopy interception, evapotranspiration, infiltration, surface runoff, subsurface flow, baseflow and soil water storage.

Evapotranspiration from the soil, vegetation and the canopy to the atmosphere is estimated through the Penman – Monteith equation as described by Wigmosta *et al.* [1994]. Streamflow is propagated through the river network using the Muskingum – Cunge method with time steps less than one day, according to the stream reach length and slope. Within each cell the flow is propagated using three linear reservoirs (baseflow, sub-surface flow and surface flow).

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 the Leaf Area Index, are not used in calibration, but are given fixed values determined from the literature; seasonal variation may be included.

The Uruguay River basin was discretized into 681 cells 0.1 x 0.1 degrees wide, and the model was calibrated using streamflow and rainfall data from 1985 to 1995 and verified with data from 1977 to 1985. A multi-objective calibration method based on a genetic algorithm [Yapo *et al.*, 1998] was used to calibrate the model parameters in each block defined by soil type, land use and vegetation cover. Data from five gauging stations within the basin were used simultaneously for model calibration.

Results of the model calibration in the Uruguay River basin were very good, with Nash-Sutcliffe efficiency criterion of 0.91 at the Iraí gauging station (area = 62200 km²) during the verification period. Figure 2 shows the observed and calculated hydrographs at the Passo Caxambu (area = 52671 km²) 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 on 20 flow gauging stations of the River Uruguay and for the larger tributaries the goodness of fit was only slightly worse during the verification period than during the calibration period.

THE CPTEC-INPE GLOBAL CIRCULATION MODEL

The CPTEC climate spectral model is essentially a low-resolution weather prediction model with equivalent grid spacing of about 180 km with 28 vertical levels between the surface and the top of the model atmosphere at 1 mb. The model is based on

the FORTRAN code used by the Center for Ocean and Land Studies (COLA) which is described in Marengo et al. [2002]. It predicts five variables: zonal and meridional windspeed, virtual temperature (i. e., allowing for water vapor effects on air density), specific humidity and surface pressure. Vertical motion is obtained from the the continuity equation and knowledge of wind divergence. Derivatives in the horizontal are calculated using the spectral method which represents each variable as a sum of spherical harmonics. A run simulating one month takes about 35 minutes on a parallel-processing (NEC-SX4) computer.

The model includes the following diabatic effects: water vapor condensation, short- and long-wave radiation processes, turbulent exchange of heat, momentum and water vapor between the surface and atmosphere, and turbulent transport of heat, momentum and water vapor within the atmosphere.

The effects of heat exchange in evaporation-condensation processes are included at two scales: (a) at 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 sub-grid scale, in which cumulus-type clouds that build up at scales ranging from a few kilometers to a few dozen km. For this second case, the CPTEC model uses the widely-tested and validated Kuo parameterization [*Kuo, 1974*], which takes the quantity of rainfall to be proportional to the moisture convergence at the cloud base, as determined by local thermodynamic criteria. The vertical heat profile associated with the phase change from water vapor to precipitation is determined by the temperature difference between a volume of air which rises without mixing with the air surrounding it.

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 resulting from solar radiation are included, but aerosol scattering is not, since the aerosol concentration is a variable that is neither predicted nor diagnosed. Cloudiness is represented simplistically but realistically, so as to allow an interaction between radiation and the convective processes as parameterized at both grid- and sub-grid scales. In the long-wave case, effects associated with the absorption and emission of radiative energy are modeled for the water vapor, CO₂ and O₃ 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.

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. The CPTEC model uses the SIMplified Biophere SIB2 procedure [*Sellers et al.*, 1996], modified by 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, and interception of rainfall by the canopy (from which it later evaporates) are also modeled realistically. The SIB2 parameters were duly calibrated using data representative of Brazilian grassland and forests [*Rocha et al.*, 1996], so that surface processes are realistically modeled. This is an important characteristic of the CPTEC model which makes it particularly relevant for studies of climate variability in South America, and for regional climate forecasting.

In the oceans, exchanges of heat, momentum and water vapor depend on sea surface temperature (SST). CPTEC uses two methods for incorporating SST data into the

atmospheric model during the period of integration: (a) as persistent anomalies in SST in all the oceans; and (b) 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 *et al.*, 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 beginning of the integration period persists throughout. The two procedures are necessary because the CPTEC model is not coupled to a model of oceanic behavior. They are also important for testing the influence of SST anomalies which have significant impacts on climate anomalies observed in other parts of the globe. In particular, SST anomalies in the Equatorial Pacific exert important controls on climate in southern Brazil, by means of the el Niño/la Niña phenomena [Grimm *et al.*, 1998].

Because of the chaotic nature of the dynamics of atmospheric evolution, intrinsically associated with system non-linearity, the CPTEC model produces ensemble forecasts [Toth and Kalnay, 1997]. Between 20 and 30 forecasts are calculated, every month, for the following six months, beginning from different initial conditions (days from $i=1$ to $i=20$ or 30). These can be used to estimate the degree of predictability (i.e., 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 significantly, indicating little reliability of forecasts. Experience with the CPTEC model shows that the six-month forecasts are more reliable for some regions of Brazil (the south, the northern part of the Brazilian North-East, and the eastern part of Amazonia) than for

others. In other regions the reliability of forecasts is low or moderate. [Marengo *et al.* 2002].

The forecasts produced by CPTEC as ensembles were available as computer files showing the daily evolution of temperature, geopotential height of standard pressure levels, specific humidity, pressure reduced to sea-level, wind (zonal and meridional components), and total daily rainfall.

RESULTS FROM PRECIPITATION FORECASTS.

The period of data extracted from files created by the CPTEC global model extended from December 1995 to February 2002. Data from this period were put into a form appropriate for input and interpolation by the rainfall-runoff model.

The extracted rainfall data correspond to an *ensemble* of 4 or 5 runs by the climate model, each with a three-month duration. Each run corresponds to a forecast with given boundary and initial conditions. A set of runs is needed because of uncertainties in the initial conditions, to which climate models are particularly sensitive. The uncertainties arise because the relevant meteorological variables and sea-surface temperatures are determined by a sampling procedure, so that knowledge about them is incomplete. In consequence, forecasts obtained with initial conditions determined from measurements made on any one given day will in general be different from forecasts initiated from measurements taken the day after.

The forecasts of rainfall available for study were the sets of forecasts each extending over a three-month period, beginning on 1 December 1995 up to 28 February 2002. Each set consisted of 4 or 5 realizations selected by cluster analysis from the 24 original realizations given by the climate model, which best represented the variability in the

original set. The realizations were obtained using the meteorological conditions on successive days to determine the initial conditions for each model run.

As a first step, the quality of the rainfall forecasts over the R. Uruguay basin was analysed 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 cell given by the climate model. (Figure 3). The forecast rainfall corresponded to the mean of the 4 or 5 realizations available for the period. 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 x 0.1 degrees.

Figure 3 and 4 show the mean annual measured and predicted rainfall respectively (the latter as the mean of the 4 or 5 realizations used) over the R. Uruguay basin. Comparison of the two figures shows that climate-model forecasts underestimate rainfall over almost the entire basin. Measured rainfall varies from 1500 mm in the east to 2600 mm in the west; forecast rainfall, however, reaches at most 1700 mm in the north-east of the basin. Figure 6, giving the rainfall errors (forecast minus observed), shows that this difference is small in the eastern part of the basin, but much larger in the west.

Besides the spatial distribution of error, variability in rainfall throughout the year was also poorly represented by the forecasting model. In general, winter rainfall over the basin was underestimated, with dry winters forecast similar to those of the Brazilian south-east, 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 6).

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 towards 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 e Rao, 1987] so that they are not well represented at the low resolution of the climate model.

METHOD USED TO CORRECT RAINFALL FORECASTS

Despite the systematic difference between observed and predicted mean annual rainfall, and between observed and predicted seasonal rainfall within the year, the inter-annual variability was fairly well reproduced by the climate model. A method was therefore used to reduce the systematic error in forecasts, whilst maintaining the inter-annual structure of rainfall forecasts.

The method used to correct forecasts is based on a transformation of the marginal probability 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 model grid-point. The

graph in Figure 8 shows the cumulative frequency curves for the month of January, and for the cell at point 9 (see Figure 9).

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 7 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.

RESULTS OF FLOW FORECASTS.

The initial analysis of forecast river flows used the forecasts obtained retrospectively for the period 1995 to 2001. The method for correcting rainfall, described above, used the data for the period 1995 to 1998. Thus the forecasts for 1995 to 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 could not be used under operational conditions. Next, the rainfall forecasts were corrected *a priori* for the period 1999 to 2001: that is, the cumulative frequency curves used for correcting predictions of daily rainfall had been obtained using data from the preceding period, (1995 to 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 R. Uruguay, where the area drained is 62.200 km². Figure 10 shows the position of this gauging station within the basin.

Figure 11 shows flow forecasts for the period 1995-8 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 amongst flow forecasts resulting from the different climate-model realizations (grey lines).

Flow forecasts for the same period, but with climate-model rainfall predictions corrected by the procedure described above, are shown in Figure 12. There is great variation amongst the flows predicted for some months, notably February 1996 and April 1998. Figure 13 shows the mean of the monthly flow predictions given by the 4 or 5 realizations obtained from the climate model, together with monthly mean flows calculated from the historic record.

Figure 13 clearly shows that there is a gain when flows are predicted using rainfall predicted by the climate model. However, the predicted flows in this figure were obtained by *a posteriori* correction of predicted rainfall: that is, after the rainfall actually observed in the period was known. The benefit resulting from the use of climate-model forecasts of rainfall is therefore overestimated.

A fairer test was obtained using the period June 1999 to October 2001, using the same procedure for correcting the predicted rainfall, but with the cumulative frequency curves calculated from the earlier period of record, 1995-8. Figure 14 shows the predicted flows thus derived, using all available climate-model realizations. Large variation amongst

predicted monthly flows is again evident, giving no indication of the uncertainty in the forecasts.

Figure 15 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 thick line gives the observed monthly flow. The shaded band in Fig. 13 is wide in most months, the difference between maximum and minimum predicted flows being as much as $5000 \text{ m}^3 \cdot \text{s}^{-1}$ in some cases, although in some months this difference falls to about $1000 \text{ m}^3 \cdot \text{s}^{-1}$. In general, however, the uncertainty amongst the set of predicted monthly flows (as measured by the range of predicted monthly flows) is less than the difference between the maximum and minimum monthly flows in the historic record, shown as broken lines in Fig. 13.

Figure 15 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.

A complication occurred because the period of data available for evaluating flow forecasts coincided with the completion of two hydraulic works on the R. 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 reached spill-way level by March 2000. The Machadinho reservoir began to fill on 28 August 2001 and was completed on 2 October 2001. These two periods, for which the observed flows are open to doubt, are marked in Figure 15. It is important to note that in both periods, observed flow was less than predicted flow.

Figure 15 shows that the reduction in uncertainty is more evident over periods extending three months ahead; observed flows were then within the uncertainty band for forecasts, except when the reservoir at Itá was filling.

In the Uruguay river 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 4 or 5 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 deviation about the observed flows, and about the forecast flows, respectively. This result is shown in Figure 17, in which the reduction in uncertainty becomes less clear; the observed flows are outside of the uncertainty band as often for observed flows as for forecast flows. However, for almost all of the months when the observed flows were beyond the upper limit of its uncertainty band, the forecast indicated correctly that greater flows could be expected.

To summarise, 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 global climate model. 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.

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 1). 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 model, divided by the mean of all available predicted flows for that month (equation 2).

$$AO = \frac{QO - QMO_j}{QMO_j} \quad (1)$$

$$AP = \frac{QC - QMC_j}{QMC_j} \quad (2)$$

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.

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 m³ s⁻¹, whilst the mean of the flows predicted from the CPTEC model in the (six) Augusts, without any statistical correction of rainfall, was 447 m³ s⁻¹. In August 2000, the observed mean flow for the

month was $1247 \text{ m}^3 \text{ s}^{-1}$, and the predicted mean flow, obtained using the predicted daily rainfalls without any statistical correction, was $337 \text{ m}^3 \text{ s}^{-1}$. 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.

Predicted and observed anomalies were calculated for each month of the period used in the analysis (from 1995 to 2001). Figure 18 shows the results obtained for monthly flows, and Figure 19 shows the three-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 under-estimated. On the other hand the dry period 1998-99 was forecast as a period of transition, which only came to be forecast as dry at the end of 1999.

The forecasts of anomalies in flow are clearly not perfect. However they show that at least a part of the inter-annual variation in flow in the R. 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.

As well as qualitative and graphical analyses, results were also analysed 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

$$RV = 1 - \frac{\sum_{i=1}^n (QC_i - QO_i)^2}{\sum_{i=1}^n (QM_i - QO_i)^2} \quad (3)$$

where n is the number of months or three-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 three-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 prediction; 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.

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.

When the value of forecasts is assessed over three-monthly instead of monthly periods, which can be regarded as more reasonable since the climate model gives forecasts for three 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.

CONCLUSIONS

The *rainfall forecasts* given by the CPTEC global climate model systematically under-estimate rainfall in the R. Uruguay drainage basin. This conclusion confirms the results of earlier research, that the model under-estimates rainfall in the southern part of Brazil [*Nobre et al., personal communication*].

The geographical distribution of rainfall predicted by the CPTEC global climate model is substantially different from the observed distribution of rainfall. Whilst 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. In summary, the model predicts too little rain in the center and west of the basin.

Although the CPTEC global climate model predicts inter-annual variability in rainfall reasonably well, its prediction of seasonal rainfall within years is poor. The largest

errors are in (austral) winter rainfall, when model predictions systematically under-estimate rainfall in the R. Uruguay basin. Evapotranspiration is least during this period, and mean flows are consequently greater. Under-estimation of rainfall in this winter period therefore has a profound effect on the results of hydrologic forecasts.

It was possible to reduce the systematic errors in rainfall predicted by the CPTEC global climate model by using an empirical correction. The results obtained using this correction show that the combination of corrected rainfalls obtained from the global climate model, with a large-basin model of hydrologic response, reduced the variance of three-month predicted flow 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 one month instead of three, the reduction in variance was 37%.

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

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 give a band of uncertainty that is narrower than the band of uncertainty given by the historic record.

At the present time, decisions concerning future operations of power supply systems are frequently based on synthetic flow sequences generated by empirical stochastic models of autoregressive, moving-average type; this is certainly true of Brazil which depends heavily on hydropower generation. This paper suggests that alternatives need to be

explored in which rainfall predictions given by models of global climate are routed through physically-based models of hydrologic response; variability between members of the *ensemble* of flow sequences 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.

Acknowledgements

The authors acknowledge with gratitude the support of the Brazilian national electricity agency ANEEL.

REFERENCES.

- Araújo Filho, P. F.; Moura, G. B. A. 2000 Use of the ETA model to provide information on the flood control system of the river Capibaribe (in Portuguese). *Anais V Simpósio de Recursos hídricos do Nordeste*. ABRH. Natal RN, pp. 338-349, June 2000.
- Bonatti, J. P. and V. B. Rao, 1987: Moist Baroclinic Instability in the Developmet of North Pacific and South American Intermediate-Scale Disturbances. *J. Atmos.Sci.*, 44, 2657-2667.
- Bremicker, M. 1998 *Aufbau eines Wasserhaushaltsmodells für das Weser und das Ostsee Einzugsgebiet als Baustein eines Atmosphären-Hydrologie-Modells*. Dissertation Doktorgrad, Geowissenschaftlicher Fakultät der Albert-Ludwigs-Universität. Freiburg. Juli.
- Collier, C. G.; Krzysztofowicz, R. 2000 Quantitative precipitation forecasting. *Journal of Hydrology* Vol. 239 pp. 1-2.

- Collischonn, W. 2001 *Hydrologic simulation of large basins* (in Portuguese). PhD Thesis IPH UFRGS, Brazil.
- Collischonn, W.; Tucci, C. E. M. 2001 Hydrologic simulation of large basins (in Portuguese) *Revista Brasileira de Recursos Hídricos*. Vol. 6 No. 1.
- Collischonn, W.; Tucci, C. E. M. 2002 Seasonal prediction of flow in the Rio Uruguay basin 1: Calibration of a distributed hydrologic model (in Portuguese). Submitted for publication in *Revista Brasileira de Recursos Hídricos*.
- Damrath, U.; Doms, G.; Frühwald, D.; Heise, E.; Richter, B.; Steppeler, J. 2000 Operational quantitative precipitation forecasting at the German Weather Service. *Journal of Hydrology* Vol. 239 pp. 260-285.
- Diaz, A. F.; Studzinski, C. D.; Mechoso, C. R. 1998 Relationships between precipitation anomalies in Uruguay and Southern Brazil and sea surface temperature in the Pacific and Atlantic Oceans. *Journal of Climate*, Vol. 11 No. 2 pp. 251-271.
- Faber, B. A.; Stedinger, J. R. 2001 Reservoir optimization using sampling SDP with ensemble streamflow prediction (ESP) forecasts. *Journal of Hydrology* Vol. 249 pp. 113-133.
- Galvão, C. O. 1999 *Water resource applications of long-term rainfall forecasting in the Brazilian north-east* (in Portuguese) PhD Thesis, Instituto de Pesquisas Hidráulicas. UFRGS. Porto Alegre. Brazil, 151 p.
- Gan, M. A.; Rao, V. B. 1991 Surface cyclogenesis over South America. *Monthly Weather Review*, Vol. 19 pp. 1293-1302.
- Golding, B. W. 2000 Quantitative precipitation forecasting in the UK *Journal of Hydrology* Vol. 239 pp. 286-305.

- Grimm, A. M., S. E. T. Ferraz e J. Gomes, 1998: Precipitation anomalies in Southern Brazil associated with El Niño and La Niña events. *J. Climate*, 11, 2863-2880.
- Hamlet, A. F.; Lettenmaier, D. P. 1999 Columbia river streamflow forecasting based on ENSO and PDO climate signals. *ASCE Journal of Water Resources Planning and Management*, Vol. 125 No. 6 pp. 333-341.
- Hamlet, A. F.; Huppert, D.; Lettenmaier, D. P. 2002 Economic value of long-lead streamflow forecasts for Columbia river hydropower. *ASCE Journal of Water Resources Planning and Management*, Vol. 128 No. 2 pp. 91-101.
- Hastenrath, S.; Greischar, L.; Colon, E.; Gil, A. 1999 Forecasting the anomalous discharge of the Caroni River, Venezuela. *Journal of Climate*, Vol. 12 No. 8 pp. 2673-2678.
- Ibbitt, R. P.; Henderson, R. D.; Copeland, J.; Wratt, D. S. 2000 Simulating mountain runoff with meso-scale weather model rainfall estimates: a New Zealand experience *Journal of Hydrology* Vol. 239 pp. 19-32.
- Khan, V.; Zavialov, P. 1998 Interannual to interdecadal variability of precipitation in southern Brazil. *X Congresso brasileiro de meteorologia*. Brasília. Outubro.
- Kite, G. W. 1997 Simulating Columbia river flows with data from regional-scale climate models. *Water Resources Research* Vol. 33 No. 6. pp. 1275-1285, June.
- Kite, G. W.; Haberlandt, U. 1999 Atmospheric model data for macroscale hydrology. *Journal of Hydrology*, Vol. 217 pp. 303-313.
- Kuo, H. L., 1974 Further Studies of the Parametrization of the Influence of Cumulus Convection on Large Scale Flow. *J. Atmos. Sci.*, 31, 1232-1240.
- Krzysztofowicz, R. 2001 The case for probabilistic forecasting in hydrology *Journal of Hydrology* Vol. 249 pp. 2-9.

- Liang, X.; Lettenmaier, D. P.; Wood, E. F.; Burges, S. J. 1994 A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*, Vol. 99, No. D7, pp. 14415-14428.
- Lorenz, E. N. 1969 The predictability of a flow which possesses many scales of motion. *Tellus* 21, 289-307.
- Mao, Q.; Mueller, S. F.; Juang, H-M H. 2000 Quantitative precipitation forecasting for the Tennessee and Cumberland river watersheds using NCEP Regional Spectral Model. *Weather and Forecasting* Vol. 15 pp. 29-45.
- Marengo, J.; Cavalcanti, I.; Satyamurty, P.; Trosnikov, I.; Nobre, C.; Bonatti, J.; Camargo, H.; Sampaio, G.; Sanches, M.; Manzi, A.; Castro, C. A. C.; D'Almeida, C. 2002 Ensemble simulation of regional rainfall features in the CPTEC-COLA atmospheric GCM. Skill and predictability assessments and applications to seasonal climate prediction. Accepted for publication in *Climate Dynamics*.
- Nijssen, B; Lettenmaier, D. P.; Liang, X.; Wetzel, S. W.; Wood, E. F. 1997 Streamflow simulation for continental-scale river basins. *Water Resources Research*, Vol. 33 No. 4 pp. 711-724, April.
- Pezzi, L. P. and Cavalcanti I. F. A.; 2001: The relative importance of ENSO and tropical Atlantic sea surface temperature anomalies for seasonal precipitation over South America: a numerical study. *Climate Dynamics*, Vol. 17: (2-3) 205-212.
- Robertson, A. W.; Mechoso, C. R. 1998 Interannual and decadal cycles in river flows of Southeastern South America. *Journal of Climate*, Vol. 11 No. 10, pp. 2570-2581.
- Rocha, H.R. da; C.A. Nobre; J.P. Bonatti; I. R. Wright; P. J.Sellers 1996 A vegetation-atmosphere interaction study for Amazonia deforestation using field data and a "single column" model. *Quart. J. Roy. Meteor. Soc.*, 122, 567-594.

- Sellers. P. J., Randall, D., Collatz, G., Berry, J., Field, C., Dazlich, D. A., Zhang, C., Collelo, G., Bounoua, L., 1996: A revised land-surface parameterization (Sib2) for atmospheric GCMs. Part I. Model formulation. *J. of Climate*, Vol. 9, pp. 676-705.
- Servain, J. 1991 Simple climatic indices for the tropical Atlantic Ocean and some applications. *Journal of Geophysical Research* Vol. 96 (C8), No. 15 pp. 137-146.
- Toth, Z. e E. Kalnay, 1997: Ensemble forecasting at NCEP and the breeding method. *Mon.Wea.Rev.*, Vol. 125, pp. 3297-3319.
- Uvo, C. B. and Graham, N. E. 1999 Seasonal runoff forecast for northern South America: A statistical model. *Water Resources Research*, Vol. 34, No. 12 pp. 3515-3524.
- Wigmosta, M. S.; Vail, L. W.; Lettenmaier, D. P. 1994 A distributed hydrology-vegetation model for complex terrain. *Water Resources Research* Vol 30 No. 6 pp. 1665-1679.
- Wood, A.W., Maurer, E.P., Kumar, A. and D.P. Lettenmaier, 2002 *Journal of Geophysical Research* (in press). Long Range Experimental Hydrologic Forecasting for the Eastern U.S. .
- Wood, E. F.; Lettenmaier, D. P.; Zartarian, V. G. 1992 A land surface hydrology parameterization with subgrid variability for general circulation models. *Journal of Geophysical Research*, Vol. 97, No. D3, pp. 2717-2728.
- Yapo, P. O.; Gupta, H. V.; Sorooshian, S. 1998 Multi-objective global optimization for hydrologic models. *Journal of Hydrology*, Vol. 204 pp. 83-97.
- Yates, D. N.; Warner, T.T.; Leavesley, G. H. 2000 Prediction of a flash flood in complex terrain. Part II: A comparison of flood discharge simulations using rainfall input from radar, a dynamic model, and an automated algorithmic system. *Journal of Applied Meteorology* Vol. 39 No. 6 pp. 815-825.

Yeh, W. W-G.; Becker, L.; Zettlemaoyer, R. 1982 Worth of inflow forecast for reservoir operation. *Journal of Water Resources Planning and Management*. Vol. 108 No. WR3, pp. 257-269.

Yu, Z.; Lakhtakia, M. N.; Yarnal, B.; White, R. A.; Miller, D. A.; Frakes, B.; Barron, E. J.; Duffy, C.; Schwartz, F. W. 1999 Simulating the river basin response to atmospheric forcing by linking a mesoscale meteorological model and hydrological model system. *Journal of Hydrology*, Vol. 218 pp. 72-91.



Figure 1: The Uruguay river basin within Brazilian territory.

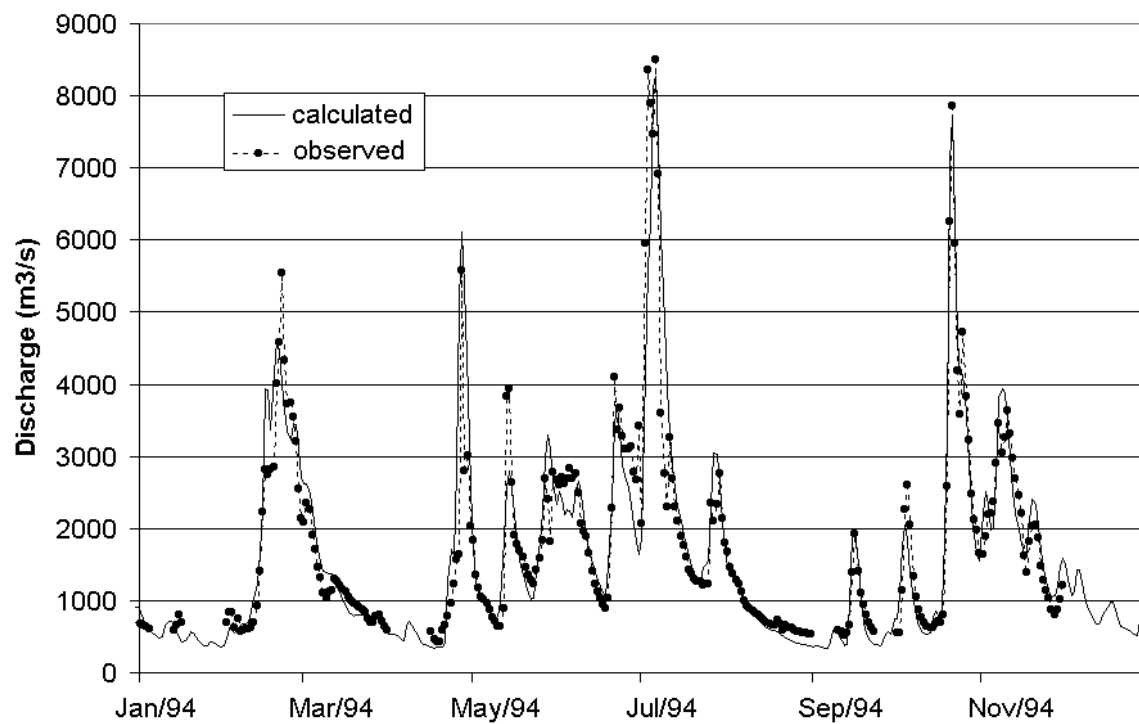


Figure 2: Observed and calculated hydrographs in the rio Uruguay, at Passo Caxambu.

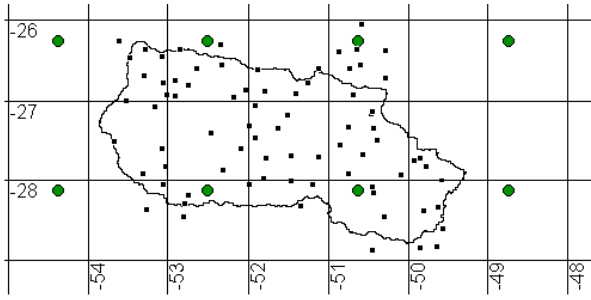


Figure 3: Cell centers for the CPTEC global climate model (large points) and rain-gauge sites (small points) in the R. Uruguay Basin.

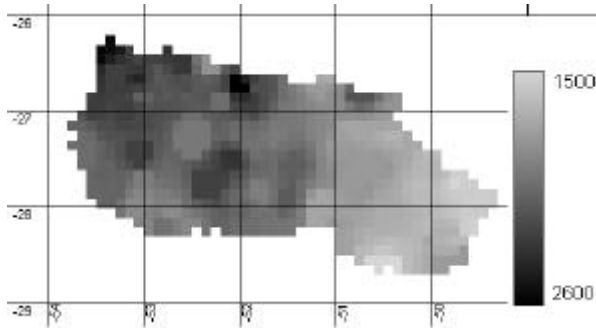


Figure 4: Mean annual measured rainfall in the R. Uruguay drainage basin, for period December 1995-May 1999.

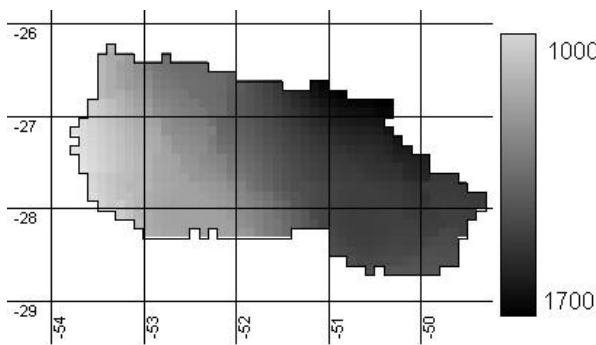


Figure 5: Mean annual forecast rainfall in the R. Uruguay drainage basin, for period December 1995- May 1999.

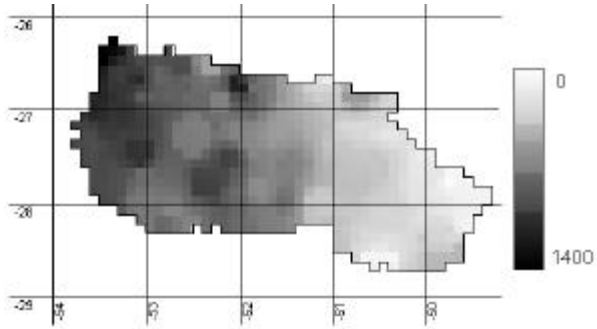


Figure 6: Error in mean annual rainfall calculated from global climate model: means for period December 1995 to May 1999, 4 or 5 realizations.

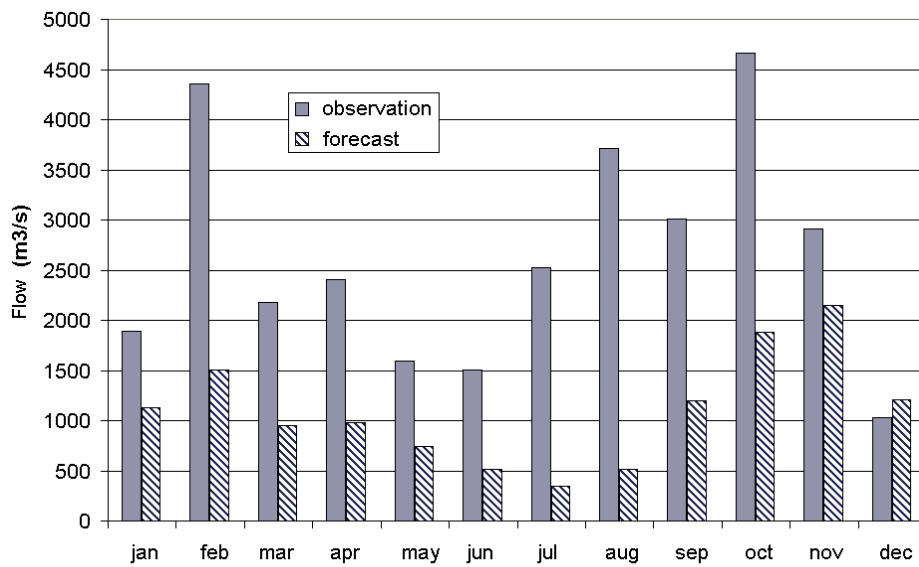


Figure 7: Observed and predicted monthly mean flows in the Uruguay River basin.

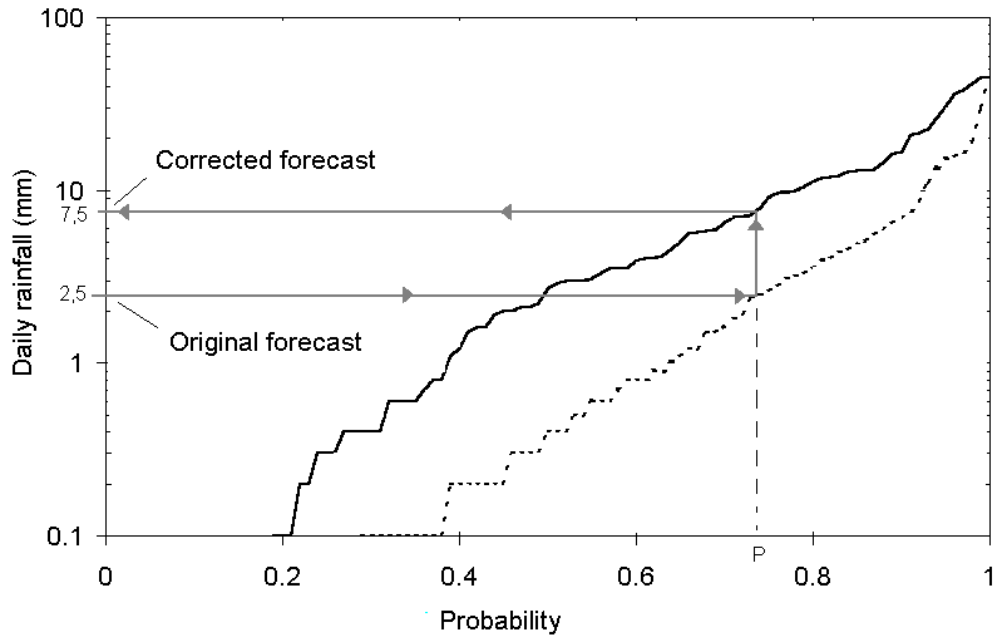


Figure 8: Cumulative frequency curves for measured and predicted rainfall at point 9, for the month of January: curves calculated using measured and predicted daily rainfalls over the period December 1995-May 1998. Continuous line corresponds to measured rainfall, broken line to forecast rainfall.

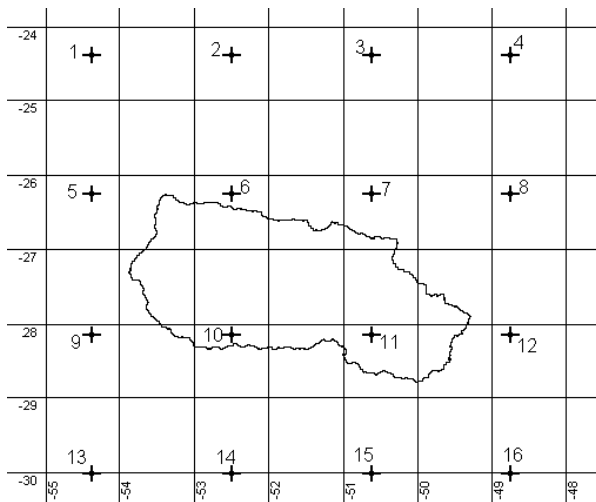


Figure 9: Points in and around the R. Uruguay basin for which the CPTEC model of global climate gave rainfall forecasts (points shown are the cell midpoints of the model).

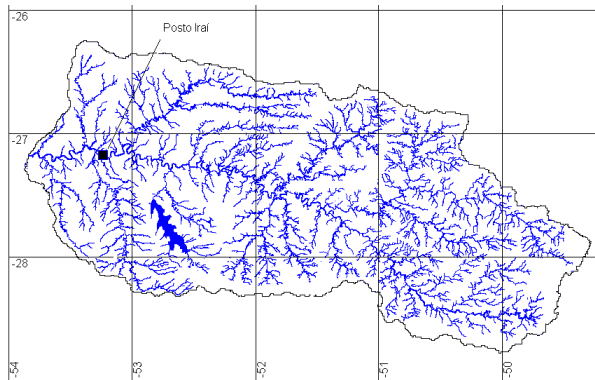


Figure 10: Site of river gauging station Iraí, on the R. Uruguay.

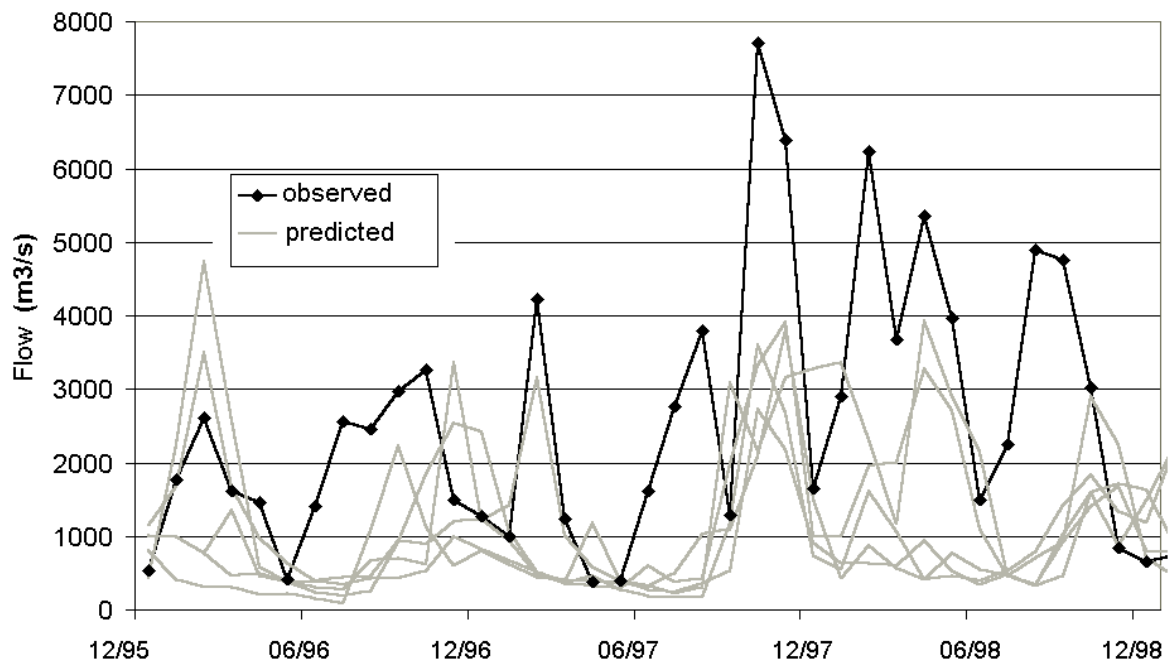


Figure 11: Forecasts of flow in the R. Uruguay, based on uncorrected forecasts of rainfall from the climate model (The 5 grey lines correspond to the 5 realizations).

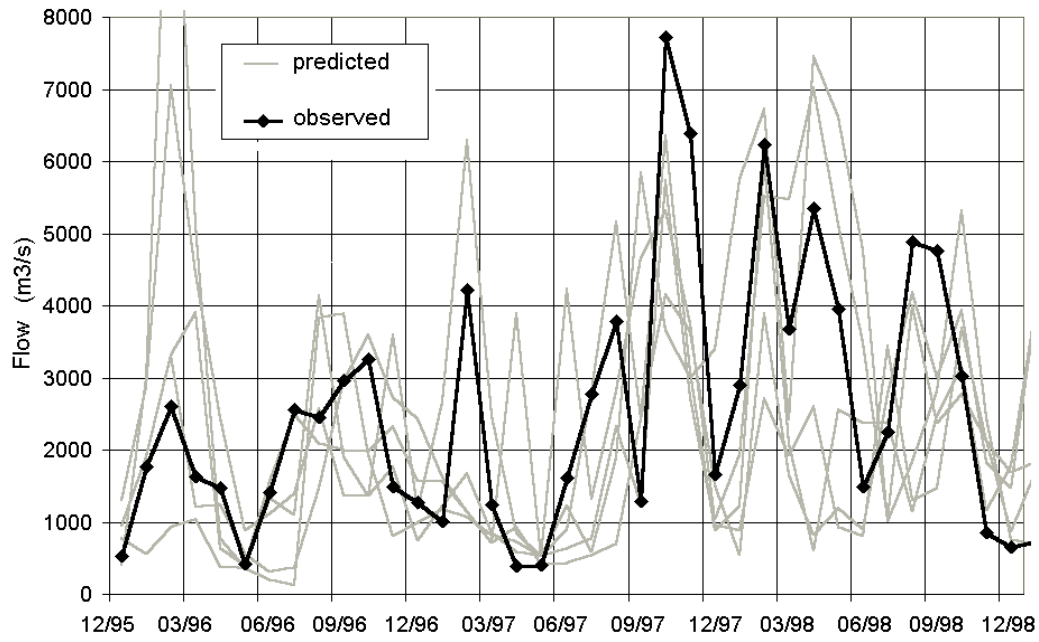


Figure 12: Predicted flows in the R. Uruguay, after correcting for under-estimation of rainfall in climate-model realizations. (the 5 grey lines correspond to 5 realizations given by the climate model).

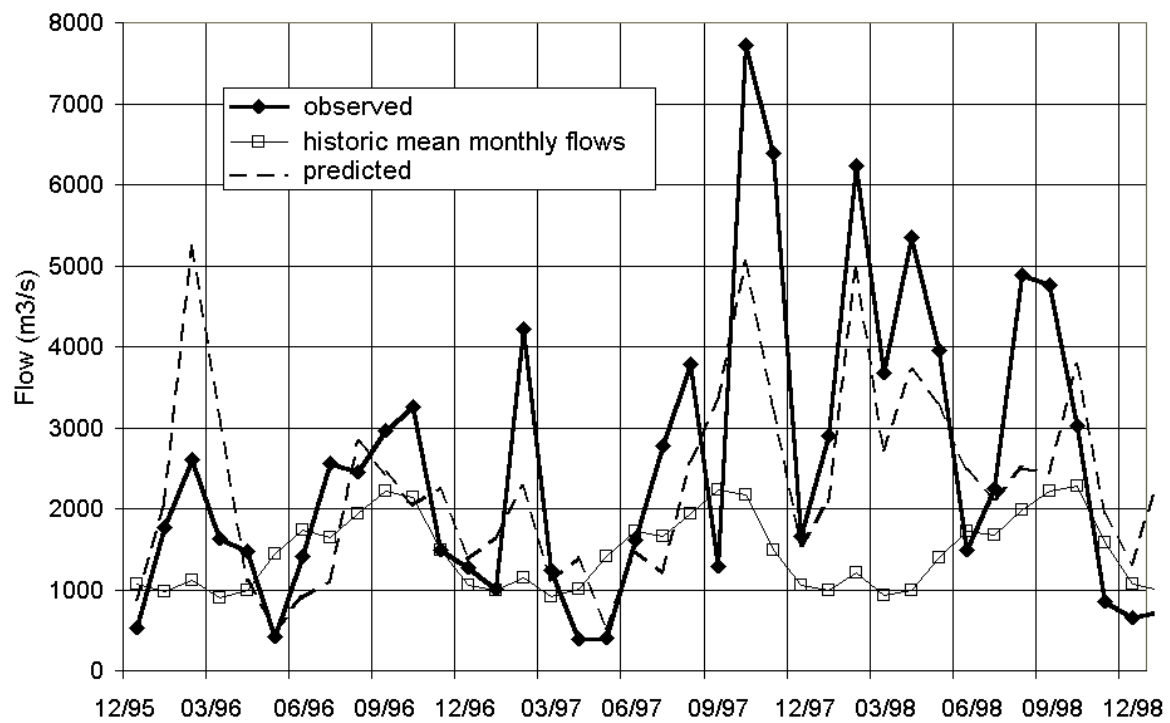


Figure 13: Predicted flows in the R. Uruguay (the broken line is the mean of 5 predictions of monthly flow from climate-model realizations; the line connecting squares shows the historic mean monthly flows).

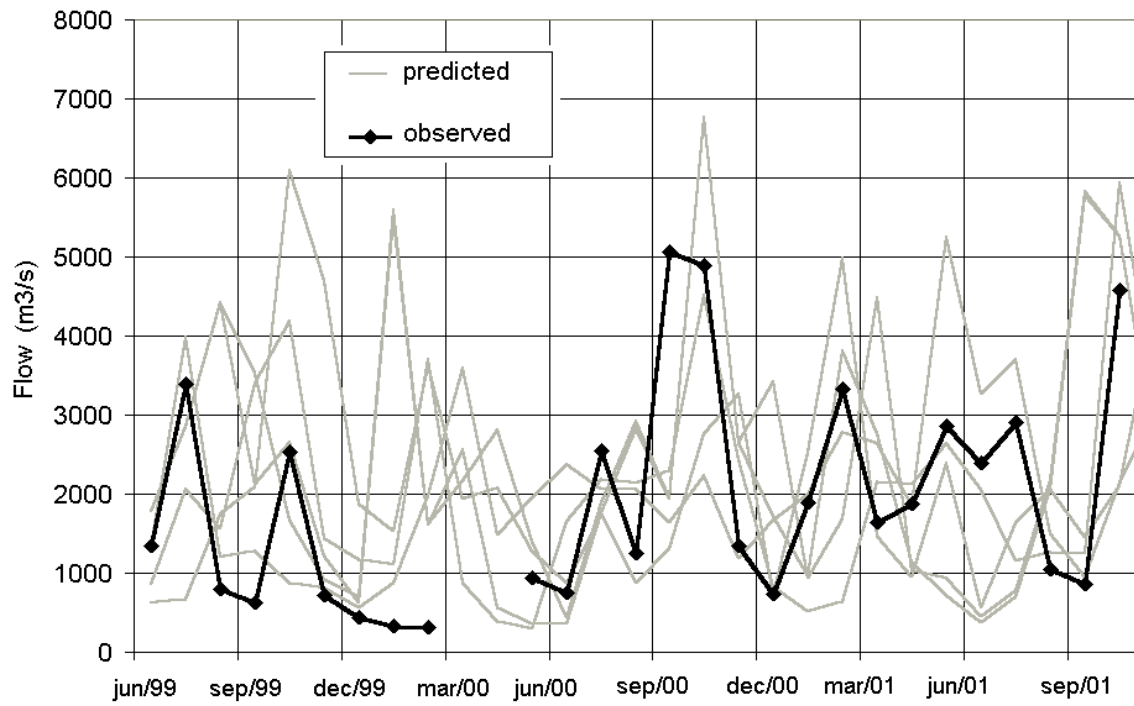


Figure 14: Predicted flows in the R. Uruguay, based on *a priori* correction of rainfall predicted by the climate model (the 5 grey lines correspond to 5 climate-model realizations).

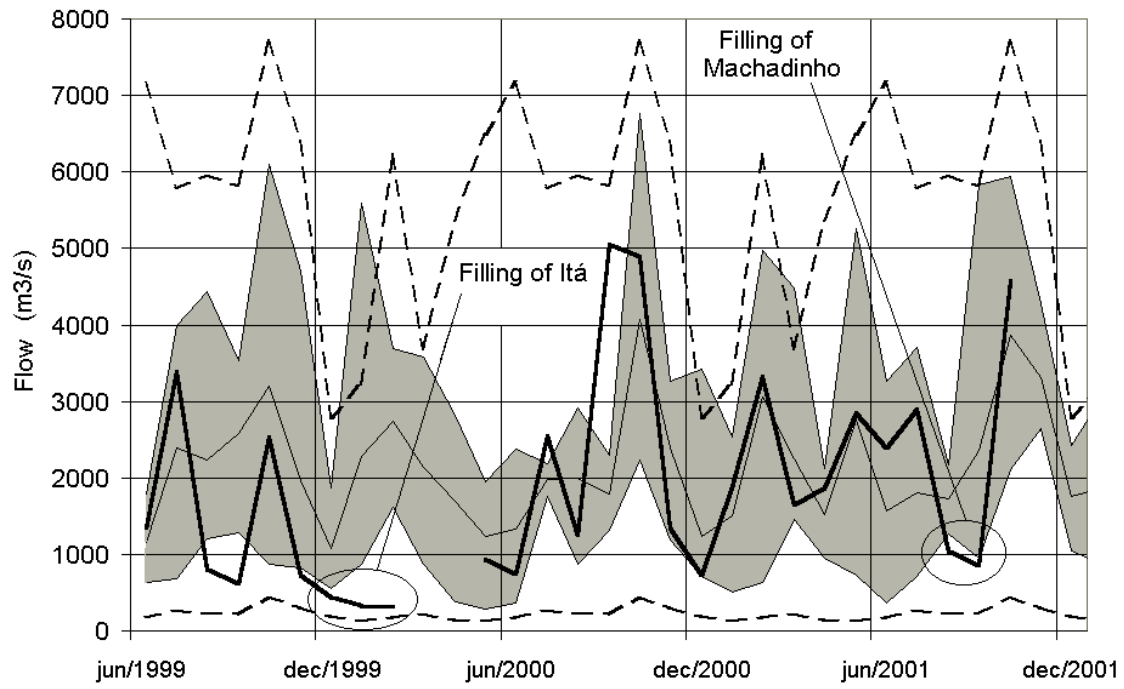


Figure 15: Range of predicted monthly flows (shaded band) compared with range of observed monthly flows in the historic record (maxima and minima shown as broken lines). The heavy black line shows observed flow.

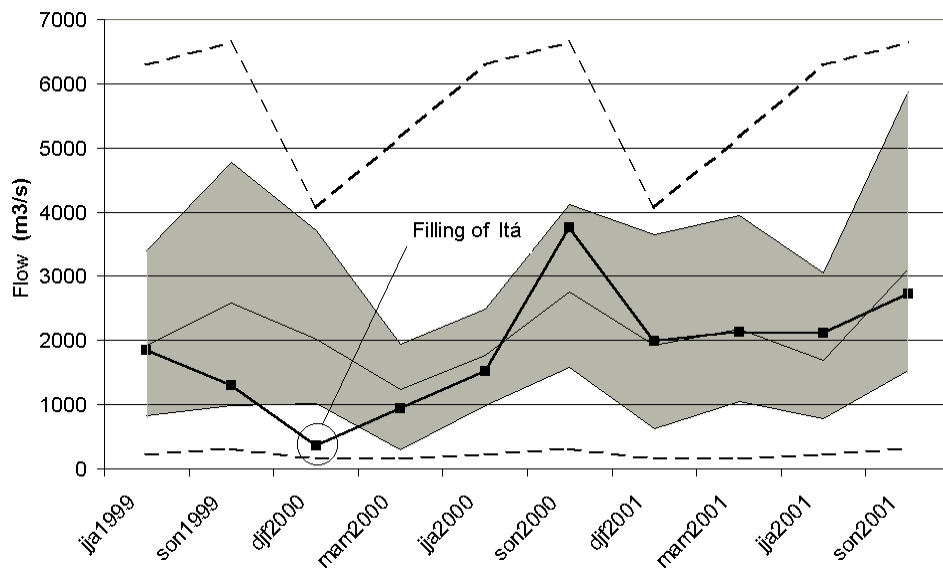


Figure 16: Range of predicted three-monthly flows (shaded band) compared with range of observed monthly flows in the historic record (maxima and minima shown as broken lines) and with observed flows (dark line).

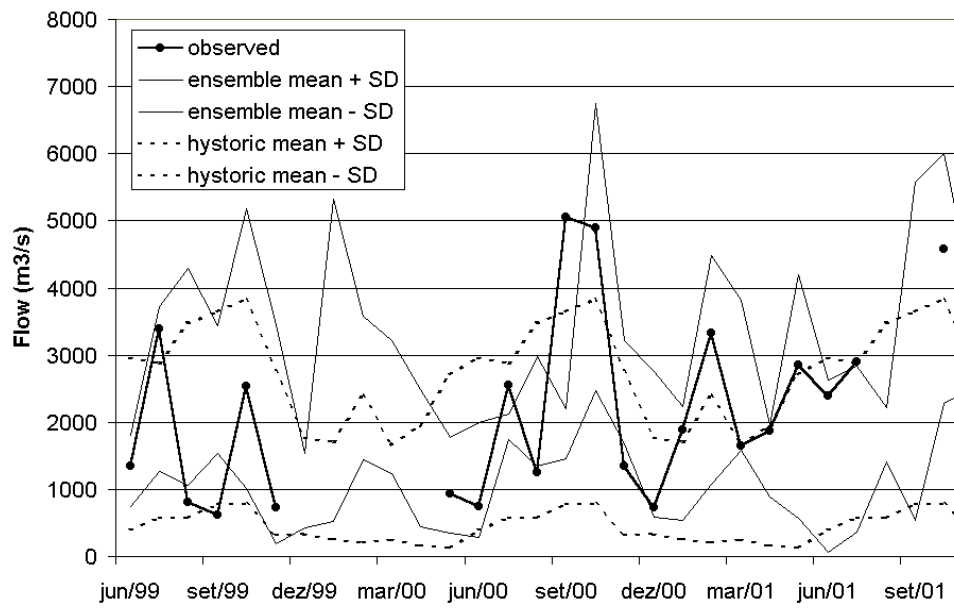


Figure 17: Range of predicted monthly flows (mean + standard deviation and mean – standard deviation shown as continuous lines) compared with range of observed monthly flows in the historic record (monthly mean + standard deviation and mean – standard deviation shown as broken lines) and with observed flows (dark line).

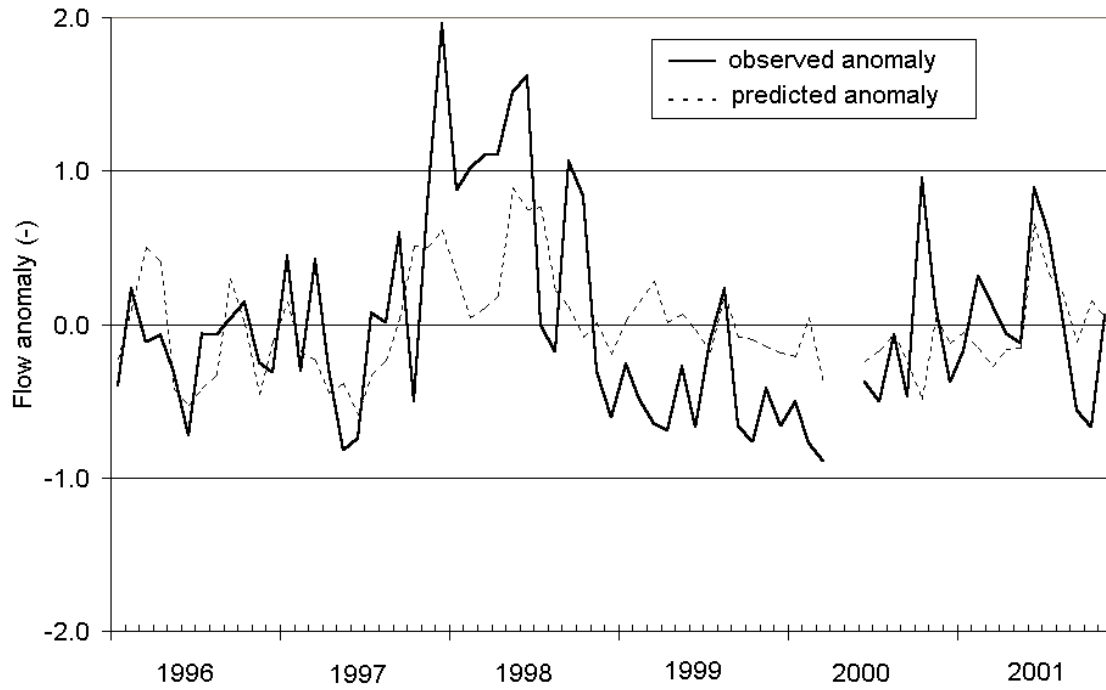


Figure 18: Anomaly in observed monthly flow (continuous line) and in predicted monthly flow (dotted line) : December 1995 to October 2001.

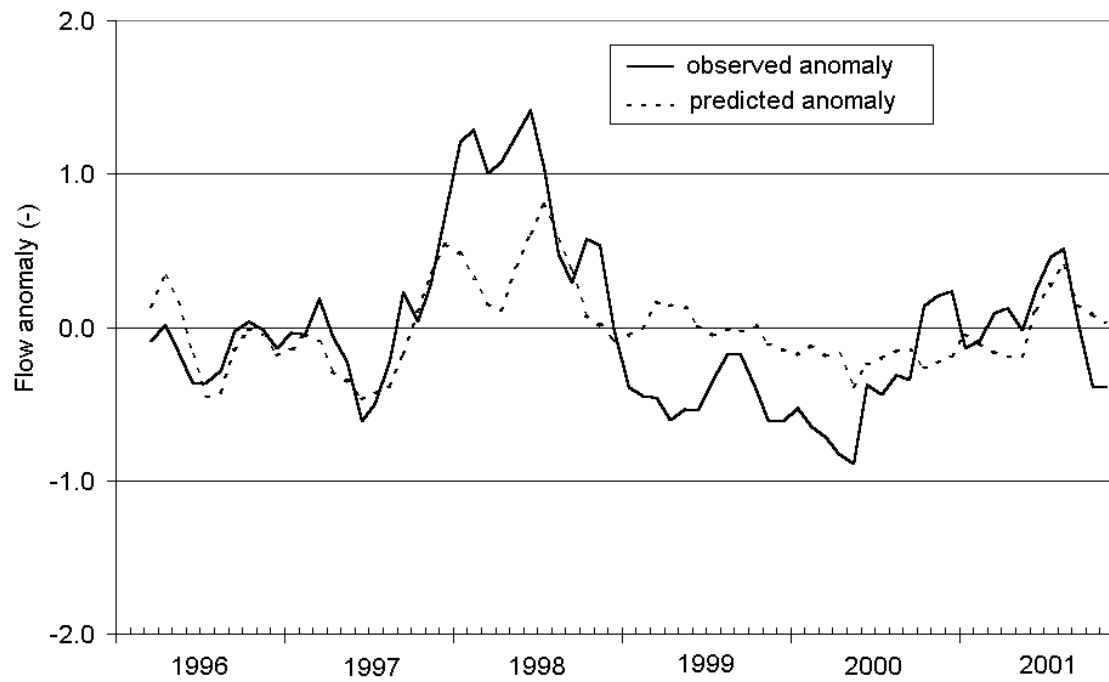


Figure 19: Three-month moving averages of observed monthly flows (continuous line) and of predicted monthly flows (dotted line): December 1995 to October 2001.