# A Bayesian approach for multi-model downscaling: Seasonal forecasting of regional rainfall and river flows in South America

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*This study addresses three issues: spatial downscaling, calibration, and combination of seasonal predictions produced by different coupled ocean-atmosphere climate models. It examines the feasibility of using a Bayesian procedure for producing combined, well-calibrated downscaled seasonal rainfall forecasts for two regions in South America and river flow forecasts for the Paraná river in the south of Brazil and the Tocantins river in the north of Brazil. These forecasts are important for national electricity generation management and planning. A Bayesian procedure, referred to here as forecast assimilation, is used to combine and calibrate the rainfall predictions produced by three climate models. Forecast assimilation is able to improve the skill of 3-month lead November-December-January multi-model rainfall predictions over the two South American regions. Improvements are noted in forecast seasonal mean values and uncertainty estimates. River flow forecasts are less skilful than rainfall forecasts. This is partially because natural river flow is a derived quantity that is sensitive to hydrological as well as meteorological processes, and to human intervention in the form of reservoir management.*

## 1. Introduction

Physically-derived seasonal climate predictions are currently produced by either atmospheric or coupled ocean-atmosphere climate models. These models are used to produce ensemble predictions (i.e. a group of forecasts produced with slightly different initial conditions) at coarse spatial resolutions of the order of a couple of degrees of latitude and longitude. Coupled model prediction data are often not adapted to the spatial horizontal resolution required by end-users' application models. End-users need forecast information at specific regions and locations in order to drive impact models such as crop yield and tropical disease models (e.g. Cantelaube & Terres 2005; Challinor et al. 2005; Marletto et al. 2005; Morse et al. 2005). There is therefore a need for downscaling predictions from coarse resolutions to specific regions and locations.

In addition to the problem of poor spatial resolution, climate models can also drift substantially away from the observed climate, and therefore calibration of forecasts against observation is required (Stockdale 1997). Furthermore, seasonal climate predictions are now being produced by several different climate models (i.e. the multi-model ensemble approach) to address the problem of structural model errors. A procedure is required for combining predictions to produce a single combined and well-calibrated forecast that gathers all available information dealing at the same time with the need of higher spatial resolution.

This study aims to address the spatial downscaling, calibration, and combination issues. It explores the feasibility of using a Bayesian forecast assimilation procedure (Coelho 2005; Stephenson et al. 2005) for producing combined and well-calibrated downscaled

seasonal rainfall forecasts for two regions in South America and river flow forecasts for the Paraná river at Itaipu (25.43°S, 54.60°W) in the south of Brazil, and for the Tocantins river at Tucuruí (3.75°S; 49.68°W) in the north of Brazil. Itaipu is the largest and Tucuruí the second largest hydropower station in Brazil, capable of producing peak power of 12600 MW and 4240 MW, respectively. Brazil produces more than 90% of its electricity from hydropower stations (http://www.ons.org.br). Itaipu and Tucuruí together produce around 30% of the electricity consumed in Brazil. Itaipu still produces more than 90% of the electricity consumed in Paraguay. These figures emphasise the need for good quality seasonal rainfall and river flow forecasts for use in the hydroelectricity sector (Zubair 2004; McEnery et al. 2005). The provision of well-calibrated rainfall and river flow seasonal forecasts – for example, one season in advance – would allow the hydropower sector to have improved reservoir management capability for electricity production. South America is a particularly interesting continent to study because it has regions where the seasonal climate is predictable (Ward & Folland 1991; Graham 1994; Folland et al. 2001; Cavalcanti et al. 2002; Marengo et al. 2003; Moura & Hastenrath 2004). Skilful and useful seasonal forecasts are possible for some of these regions (Coelho et al. 2005b).

Statistical modelling methods have been developed previously for the calibration of deterministic predictions produced by individual physically-derived dynamical models. The calibration of deterministic predictions of individual models against past observations is known as model output statistics (Glahn & Lowry 1972). Model output statistics downscaling methods (see Wilby et al. 1998 and references therein for a comprehensive review on statistical downscaling methods) have been applied for single model seasonal rainfall and temperature ensemble predictions by Feddersen et al. (1999) and Feddersen (2003). These studies have found that a model output statistics method based on the maximum covariance analysis (MCA) of the cross-covariance matrix between model outputs and observations was able to skilfully downscale seasonal rainfall and temperature for a number of locations in Europe and the USA. This paper proposes instead the use of Bayesian forecast assimilation for simultaneously downscaling, combining and calibrating multi-model ensemble predictions produced by three coupled models as part of the Development of a European Multimodel Ensemble system for seasonal to inTERannual prediction (DEMETER) project (Palmer et al. 2004). The three DEMETER models are the European Centre for Medium-range Weather Forecasts (ECMWF) model, the United Kingdom Met Office (UKMO) model and the Météo-France model. These three models form the basis of the real-time European Seasonal to Inter-annual Prediction (EURO-SIP) multi-model system. Forecast assimilation is a unified framework that generalises model output statistics for the use with multi-model

ensemble predictions (Coelho 2005; Stephenson et al. 2005).

A simple Bayesian method has been used to combine single model ensemble predictions with historical empirical data to produce calibrated probabilistic interval forecasts of a single variable (Niño-3.4 index) (Coelho et al. 2004). The method was also used by Coelho et al. (2003) to assess the skill of various seasonal forecasts of the Niño-3.4 index produced by different versions of the ECMWF seasonal forecasting system. Stephenson et al. (2005) generalised the approach to many variables and to deal with more than one model and named it *forecast assimilation*. Forecast assimilation can therefore produce calibrated probabilistic forecasts from multi-model predictions of spatially gridded fields. Coelho et al. (2005a, 2005b) used forecast assimilation to combine and calibrate multi-model predictions for producing a single probabilistic rainfall seasonal forecast for each grid point over South America. Here we use Bayesian forecast assimilation for combining, calibrating and downscaling multi-model seasonal rainfall forecasts for two regions and river flow forecasts for two locations in South America. The Bayesian approach has also been used in climate studies by Epstein (1985), Berliner et al. (2000a, 2000b), Rajagopalan et al. (2002) and Robertson et al. (2004).

The next section briefly describes the observational datasets used in this study. Section 3 provides a summary of the Bayesian forecast assimilation procedure. Section 4 shows two examples of application of forecast assimilation for regional downscaling of seasonal rainfall anomalies in South America. Section 5 presents two examples of the use of forecast assimilation for local downscaling of river flow anomalies for the Paraná and Tocantins rivers. Finally, section 6 concludes the article with a summary of findings, some suggestions for future applications of the Bayesian forecast assimilation procedure and also some comments about the need of future work for the improvement of downscaled seasonal rainfall and river flow forecasts.

## 2. Observational datasets

The observed rainfall used in this study was obtained from the 50-year 1950–2001 global monthly 2.5° latitude/longitude gridded analysis of precipitation reconstructed over land (PREC/L) (Chen et al. 2002), which is based on gauge observations. Historical monthly mean natural river flow data for the Paraná and Tocantins rivers were obtained from the national operator of the Brazilian electric system (ONS 2001). The monthly natural river flow is produced using a reconstruction method where, in additional to hydrological observations, some elements of the hydrological balance (e.g. evaporation) and reservoir management activities (e.g. use of reservoir water for agriculture) are also taken into account for the estimation of the flow. These datasets have been used because they are among the

most complete with the longest records available for climate and water resources research in Brazil and South America.

## 3. Bayesian forecast assimilation

The Bayesian method (Bayes 1763) is a procedure for updating prior information when new information becomes available. Prior information about a particular variable of forecast interest *y* (e.g. a regional rainfall index or river flow at a particular location) can be represented mathematically by the probability density function *p(y)*. If one has some initial knowledge of *p(y)*, and additional (new) forecast information, *x* becomes available (e.g. an ensemble of rainfall predictions), then it is possible to update *p(y)* to obtain the posterior conditional probability density function *p(y | x)* by making use of Bayes's theorem

$$p(y \mid x) = \frac{p(y)p(x \mid y)}{p(x)}.$$

The likelihood *p(x | y)* is an essential ingredient in the Bayesian procedure. It can be estimated by regression of past (hindcast) ensemble climate model predictions *x* (e.g. gridded rainfall predictions of different coupled climate models) on past observations *y* (e.g. a regional rainfall index or river flow at a particular location).

Model predictions are best considered as proxy information that can be used to infer the probability of future observables (Wilks 2000; Glahn 2004; Stephenson et al. 2005). Because of uncertainties in model formulation and in initial conditions, climate predictions of *x* drift away from the observed values *y*. Unrealistic predictions can also be caused by errors in the methods used to generate ensembles (Atger 2003; Vialard et al. 2005). Hence, calibration by inflation of the ensemble spread is sometimes performed in order to improve *forecast reliability* (e.g. Hamill & Colucci 1998; von Storch 1999). Reliability refers to the correspondence between the forecast probability of an event and the relative conditional frequency of the event, stratified upon the forecast probability (Jolliffe & Stephenson 2003 and references therein). Just as data assimilation is needed to map observations into climate model state (i.e. into gridded model space), a procedure is required to map the model-predicted state back into observation space (Stephenson et al. 2005). Because of this analogy with data assimilation, the Bayesian procedure used here is referred to as forecast assimilation.

The likelihood *p(x | y)* is essential for the combination and the calibration of different climate model predictions. Note here that by including in *x* all the predictions of all climate models on a common 2.5° latitude/longitude grid the calibration and combination of predictions is performed in a single step. Note also that if *y* contains observations representative of a region (e.g. a regional index) or a particular location (e.g. station
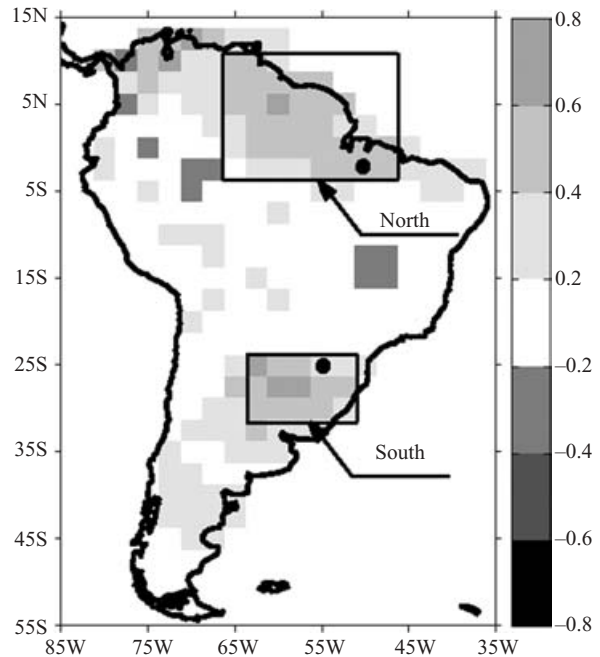


**Figure 1.** *Correlation map of 3-month lead November-December-January 1959–2001 multi-model rainfall anomaly predictions. The multi-model is composed by three DEMETER coupled models (ECMWF, UKMO and Météo-France). Multi-model predictions are obtained by computing the mean of the 27 member ensemble (9 members of each coupled model). The map shows correlations between observed and predicted anomaly time series at each grid point. The 'north' and 'south' boxes are regions where regional downscaling of rainfall is performed. The dot inside the 'north box' shows the location of Tucuruí hydropower station (3.75°S, 49.68°W). The dot inside the 'south box' shows the location of Itaipu hydropower station (25.43°S, 54.60°W).*

data), then forecast assimilation provides regional or local downscaling of model predictions *x* at the region or location where y is observed. In other words, forecast assimilation simultaneously performs calibration, combination and downscaling. For the examples presented in Section 4 below, the observations *y* were composed by rainfall indices produced by averaging the gridded observations inside the 'south' and 'north' boxes in Figure 1. For the examples presented in Section 5 the observations *y* were composed by the observed station river flow data at Itaipu and Tucuruí.

However, because of the large dimensionality of gridded data sets compared to the number of independent forecasts and the dependency between values at neighbouring grid points, dimensional reduction is first required prior to performing the calibration and combination through the regression of past predictions on past observations (Stephenson et al. 2005). For the examples presented in the following section, the three coupled models each provided a total of 630 grid points over the South American land and ocean region displayed in Figure 1 to compose *y* in the forecast assimilation procedure, and dimensional reduction is clearly needed. The reduction is achieved by performing the maximum

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covariance analysis on the cross-covariance matrix between the observations, *y*, and climate model predictions, *x*. The first three leading maximum covariance modes between the observations and coupled model predictions of South American rainfall were used in the forecast assimilation procedure. Forecast assimilation was tested with up to eight retained modes. It was found that forecast assimilation with three modes gave the best cross-validated forecast results, which are shown in the next section.

As described in Coelho et al. (2003, 2004), the Bayesian updating procedure has three main steps: (a) choice of the prior distribution $p(y)$; (b) modelling of the likelihood function $p(x|y)$; and (c) determination of the posterior distribution $p(y|x)$. The prior distribution was estimated using rainfall and river flow observations over the calibration period 1959–2001, when both rainfall hindcasts and past rainfall and river flow observations were simultaneously available. For simplicity, it has been assumed that both prior and likelihood distributions are normal (Gaussian), leading to a normal posterior distribution that is specified by two parameters: the posterior mean and the posterior variance. Estimates of these two parameters are then used to construct interval forecasts. Analysis of a moment measure of skewness (shown in Coelho et al. 2005b, Fig. 3) reveals that the normality assumption is reasonable for seasonal rainfall anomalies over the South American regions here investigated (Figure 1). However, the normality assumption is less acceptable for seasonal river flow anomalies, which are positively skewed. The normality assumption is also less well justified for predictions over shorter time scales (e.g. monthly means). The full set of forecast assimilation equations are given in Coelho (2005) and Stephenson et al. (2005). As for any calibration approach, the major drawback of forecast assimilation is the need to re-estimate the calibration parameters every time the forecasting system changes. To avoid artificial skill, all results presented here were obtained with the cross-validation 'leave one out' method (Wilks 1995, section 6.3.6).

## 4. Regional downscaling examples: rainfall forecasts

This section shows two examples of regional downscaling using 3-month lead November-December-January seasonal mean rainfall anomaly predictions (i.e. started with initial conditions of the first day of August) for the period 1959–2001 produced by the three DEMETER coupled models here investigated. The examples presented here are for the two regions illustrated by the boxes in Figure 1 in the north (4°S–11°N; 66°W–46°W) and south (33°S–24°S; 64°W–51°W) of South America. These boxes were chosen because rainfall predictions for these two regions produced by the three DEMETER coupled models have larger

predictive skill than for most other South American regions. This is illustrated in Figure 1 by the larger correlation between observed and predicted anomalies over these regions when compared to most other South American regions. Furthermore, the boxes in Figure 1 are located in regions of important power production in South America. The two largest hydropower stations in Brazil (Itaipu and Tucuruí) are located inside these two boxes.

The observed November-December-January rainfall of all grid points inside each box of Figure 1 was averaged to produce an index. The ultimate aim of this study is to produce skilful forecasts of these indices (i.e. skilful regional downscaled rainfall forecasts for each box). The production of regional downscaled forecasts makes this study distinct from Coelho et al. (2005a, 2005b), which aimed to produce rainfall forecasts for each grid point over South America. The indices were computed for all the years in the period 1959–2001 in order to produce a 43-year-long time series. These indices were used to compose the vector of observations *y* used in the forecast assimilation procedure.

Figure 2 shows multi-model ensemble and forecast assimilation rainfall anomaly forecasts for the 'south' box of Figure 1. The multi-model ensemble mean prediction is produced by averaging the 27-member ensemble of the three DEMETER coupled models (i.e. nine members of each coupled model) at all 15 land grid points inside the 'south' box. In other words, a total of 405 (i.e. 15 x 27) values are averaged to produce the multi-model ensemble mean prediction for each year. The multi-model ensemble prediction uncertainty estimate for each year is obtained by computing the standard deviation of the 27-member averages over this region. Predictions in Figure 2 are given by the predicted mean anomaly value (solid line) and the 95% prediction interval (grey shading). The 95% prediction interval is defined by the predicted mean anomaly value plus or minus 1.96 times the prediction standard deviation (i.e. the prediction uncertainty estimate). A good (reliable) forecasting system should have no more than 5% of observations falling outside the 95% prediction interval. The multi-model predictions are not in good agreement with the observations (Figure 2a) whereas the forecast assimilation (Figure 2b) is in much better agreement with the observations. Table 1 shows that forecast assimilation forecasts have a smaller mean squared error and a higher correlation with the observations than multi-model predictions. Forecasts obtained with forecast assimilation are also more reliable than multi-model predictions in that they have fewer observations outside the 95% prediction interval. The better reliability of forecast assimilation forecasts is because forecast assimilation provides larger and better estimates of forecast uncertainty than do the simple multi-model predictions (Table 1). Such an improvement in forecast uncertainty estimation is also noted in the Brier score (Brier 1950) calculated for the event
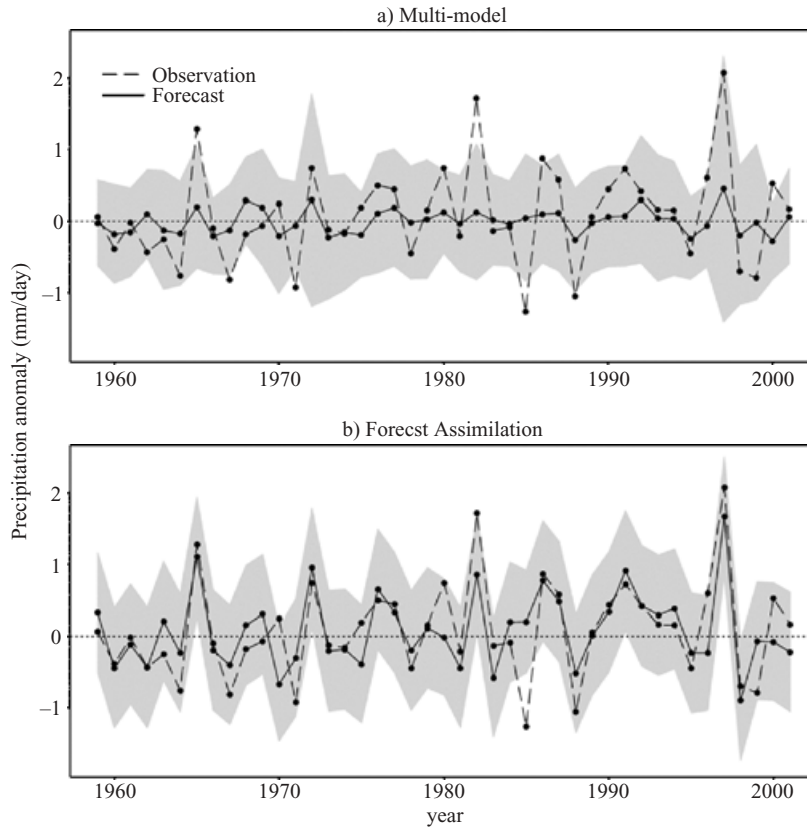
**Figure 2.** *(a) Multi-model (i.e. raw, uncalibrated predictions) and (b) forecast assimilation 3-month lead November-December-January 1959–2001 cross-validated seasonal mean rainfall anomaly forecasts (in mm/day) for the 'south box' in Figure 1. Mean predicted anomaly (solid line), observed anomaly (dashed line) and the 95% prediction interval (grey shading).*

Table 1. *Skill and uncertainty measures of 3-month lead November-December-January 1959–2001 rainfall anomaly predictions for the two regions defined in Figure 1. Mean squared error (MSE) in mm², correlation, mean predicted uncertainty in mm, Brier score for the event 'rainfall anomaly less than or equal to zero'.*

| Forecast | MSE (mm$^2$) | Correlation | Uncertainty (mm) | Brier Score |
|---|---|---|---|---|
| *South:* Multi-model | 0.37 | 0.57 | 0.39 | 0.22 |
| Forecast Assimilation | 0.21 | 0.74 | 0.42 | 0.17 |
| *North:* Multi-model | 0.43 | 0.62 | 0.49 | 0.21 |
| Forecast Assimilation | 0.39 | 0.63 | 0.55 | 0.18 |

'anomaly less than or equal to zero' (Table 1). The Brier score is a negatively oriented measure of probabilistic skill, meaning that smaller values indicate more skilful predictions. Forecasts with Brier score less than 0.25 are more skilful than the climatological forecast of the event.

Figure 3 shows rainfall anomaly predictions for the 'north' box in Figure 1. Both multi-model predictions (Figure 3a) and forecast assimilation forecasts (Figure 3b) reproduce the observed anomalies remarkably well. Note, however, that forecast assimilation provides some improvements. A close comparison of Figures 3a and 3b reveals that forecasts obtained with forecast assimilation are in better agreement

with observation than multi-model predictions. The better agreement of forecast assimilation forecasts with the observations is also reflected in the smaller mean squared error and the slightly larger correlation of forecast assimilation compared to multi-model predictions (Table 1). Forecast assimilation forecasts have larger forecast uncertainty estimates and a smaller Brier score than multi-model predictions, indicating that downscaled combined forecasts obtained with forecast assimilation are better calibrated than are multi-model predictions. The larger effect of forecast assimilation in the 'south' box rather than in the 'north' box is related to the fact that the three coupled models are not able to reproduce extratropical anomalies as appropriately as they are able to reproduce tropical anomalies. The three coupled models have systematic errors in the location and strength of extratropical El Niño-Southern Oscillation teleconnections that form the basis for the skill of the forecasts.

## 5. Local downscaling examples: river flow forecasts

This section provides two examples of the application of the use of forecast assimilation for producing 3-month lead November-December-January seasonal mean flow forecasts for the Paraná river at Itaipú (25.43°S, 54.60°W) and Tocantins river at Tucuruí
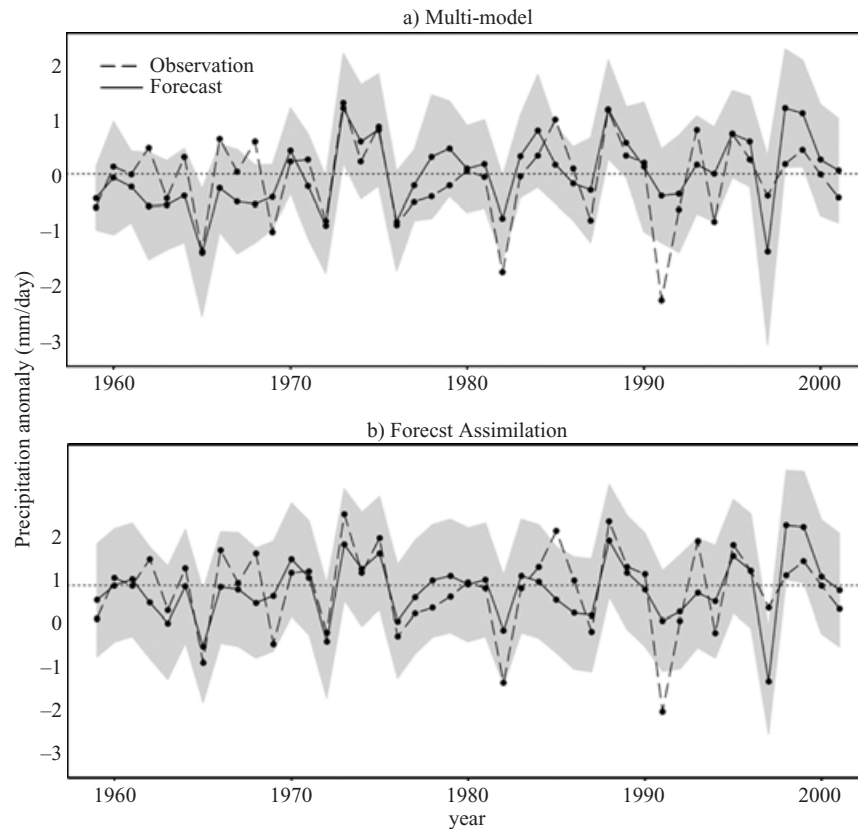
**Figure 3.** *(a) Multi-model (i.e. raw, uncalibrated predictions) and b) forecast assimilation 3-month lead November-December-January 1959–2001 cross-validated seasonal mean rainfall anomaly forecasts (in mm/day) for the 'north box' in Figure 1. Mean predicted anomaly (solid line), observed anomaly (dashed line) and the 95% prediction interval (grey shading).*
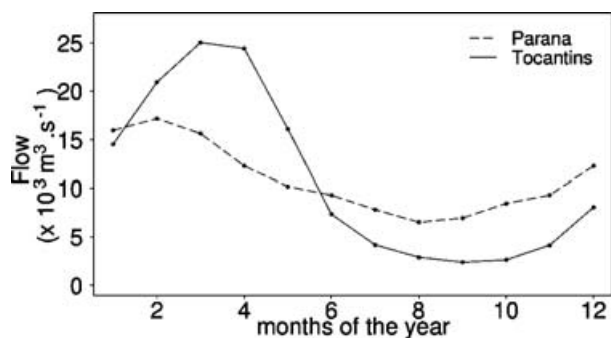


**Figure 4.** *Flow rate mean annual cycle (in m³/s) for the Paraná river at Itaipu (dashed line) and the Tocantins river at Tucuruí (solid line). Months of the year from January to December are numbered from 1 to 12 on the horizontal axis.*

(3.75°S, 49.68°W). The location of these two rivers is marked with a dot inside the 'south' and the 'north' boxes in Figure 1, respectively. November-December-January seasonal mean forecasts are important because this is the period when the flow of the two rivers begins to increase due to the start of the austral summer rainy season over South America (Figure 4). The ability to forecast mean seasonal flow three months in advance is very desirable and valuable, in particular for the hydropower production sector.

South American river flow forecasts on seasonal to interannual time scales have primarily been produced

using empirical approaches based on lagged regression models that use as predictors Pacific and Atlantic sea surface temperatures of the previous season (Uvo & Graham 1998; Uvo et al. 2000; Robertson & Mechoso 2001; Souza Filho & Lall 2003). Another approach for long-term flow forecasting has been to use bias-corrected daily rainfall forecasts produced by an atmospheric global general circulation climate model to initialise a hydrologic model (Tucci et al. 2003). However, to our knowledge no study has attempted to downscale coupled multi-model seasonal rainfall predictions to produce river flow forecasts for South America. This study therefore provides the first step towards the use of coupled multi-model seasonal forecasts for local river flow forecasting. Forecast assimilation, as described in Section 3, is the methodology used for this downscaling.

Forecast assimilation has been performed using the observed 1959–2001 November-December-January mean Paraná and Tocantins river flow time series. These flow time series formed the vector $y$ used in the forecast assimilation procedure. The predictions that were used to compose $x$ consisted of 3-month lead 1959–2001 November-December-January mean rainfall predictions produced by the three DEMETER coupled models investigated here. Only predictions of the grid points over land inside the 'south' and 'north' boxes in Figure 1 have been used in the forecast assimilation
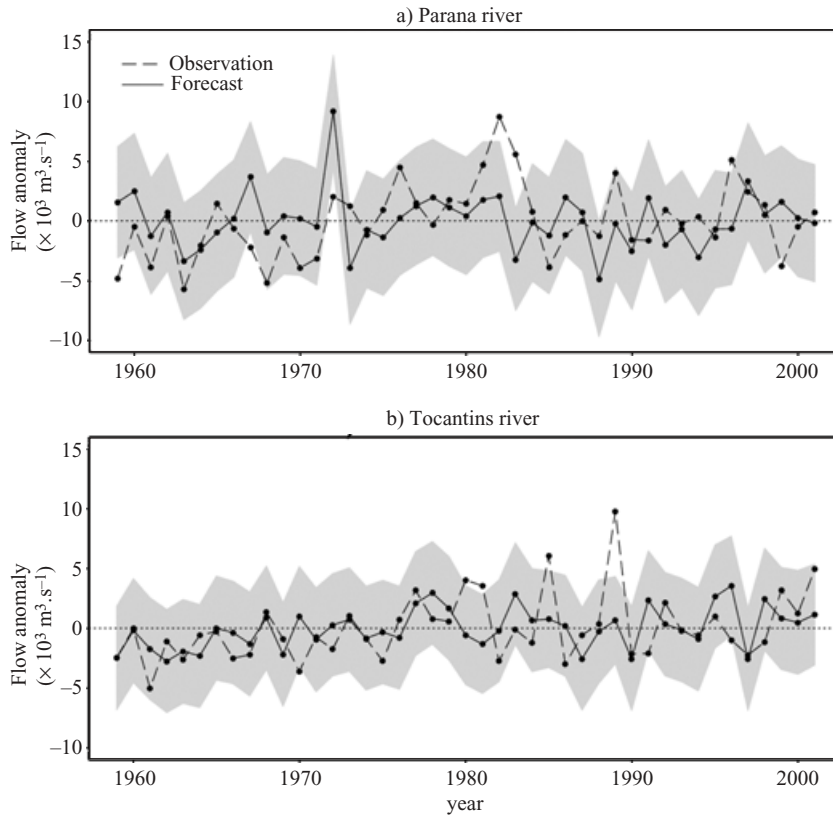
**Figure 5.** *(a) Paraná river at Itaipu (25.43°S, 54.60°W) and (b) Tocantins river at Tucuruí (3.75°S, 49.68°W) 3-month lead November-December-January 1959–2001 cross-validated seasonal mean flow anomaly forecasts (in m³/s) obtained with forecast assimilation (solid line). Observed anomalies are represented by the dashed line. The 95% prediction interval is represented by the grey shading.*

Table 2. *Skill and uncertainty measures of 3-month lead November-December-January 1959–2001 flow anomaly forecasts for the Paraná and the Tocantins rivers. Mean squared error (MSE) in (m³/s)², correlation, mean predicted uncertainty in m³/s, and Brier score for the event 'rainfall anomaly less than or equal to zero'.*

| Forecast | MSE ($\times 10^6$) (m³/s)² | Correlation | Uncertainty (m³/s) | Brier Score |
|---|---|---|---|---|
| Paraná river | 12.5 | 0.16 | 2300 | 0.25 |
| Tocantins river | 7.8 | 0.29 | 2200 | 0.22 |

procedure for the Paraná and Tocantins river flow downscaling forecasts, respectively.

Figure 5 shows November-December-January mean river flow forecasts for the Paraná river (panel a) and the Tocantins river (panel b) obtained with forecast assimilation (solid lines). The observed river flow is shown with dashed lines. The Tocantins river forecasts are more skilful than the Paraná river forecasts. The former have smaller mean squared error, larger correlation with the observations and smaller Brier score than the latter (Table 2). Both river forecasts have similar mean uncertainty estimates (2300 and 2200 m³/s). The Tocantins river forecasts have more observations within the 95% prediction interval (grey shading) than the Paraná river forecasts, indicating that the Tocantins river

forecasts are more reliable than the Paraná river flow forecasts. Note, however, that the river flow forecasts of Figure 5 are less skilful than the regional rainfall forecasts of Figures 2 and 3. Even so these forecasts still provide useful probabilistic information for water resources management and electricity production since the observed flow generally falls inside the 95% prediction interval. The downscaling of natural river flow is a particularly difficult task because, unlike rainfall, the natural river flow is not directly measured. Natural river flow is a derived quantity that also takes into account human interventions in reservoir management, and therefore is exposed to large uncertainties in its estimates. This is a possible reason why downscaled river flow forecasts had poorer skill than downscaled regional rainfall forecasts. In addition, forecast assimilation assumes that the river flow is a normally distributed variable, and as previously mentioned in section 3, river flow is a positively skewed variable. A close inspection of the observed Paraná and Tocantins river flows (Figure 5) reveals slightly increasing time trends, indicating non-stationarity on the time series. All these factors may have contributed to the deterioration of forecast skill. Finally, there may exist a lag of a month or two between observed rainfall and river flow. In such a situation it would be more relevant in the forecast assimilation procedure to use the coupled model rainfall predictions for the one or two months that precede the target season.

## 6. Conclusions

This paper has tested the use of Bayesian forecast assimilation for regional downscaling of multi-model ensemble rainfall seasonal predictions. Forecast assimilation has been used successfully to combine and calibrate multi-model rainfall climate predictions. It has improved the skill of 3-month lead November-December-January multi-model rainfall predictions of two South American regions. Forecast assimilation has improved both predicted seasonal mean values and prediction uncertainty estimates. Larger improvements have been found for the 'south' region of South America than the 'north' region (see Figure 1). Raw (i.e. before calibration) multi-model predictions for the 'north' region of South America already have good skill. This region is located in the tropics where seasonal forecast skill is generally higher than in other parts of the world (Goddard et al. 2001). Coupled models are better able to reproduce teleconnections inside tropical regions than outside the tropics. This is possibly the reason for the smaller improvement provided by forecast assimilation for the 'north' region compared with the 'south'.

Forecast assimilation has also been shown to be a useful tool for downscaling 3-month lead November-December-January South American multi-model seasonal rainfall predictions for the production of river flow forecasts for the Paraná river at Itaipu and the Tocantins river at Tucuruí. River flow forecasts obtained with forecast assimilation provided reliable interval forecasts. These are encouraging results but further work is still needed to improve the quality of downscaled river flow forecasts, which are inferior to the quality of downscaled regional rainfall forecasts. River flow forecasts are important for electricity generation management and planning, and forecast assimilation is able to provide useful probabilistic forecast information for these purposes. For instance, the hydroelectricity sector in Brazil could use river flow forecasts obtained with forecast assimilation as an additional source of information for decision-making.

Although the two rainfall examples focused on regional downscaling, the method can also be used for local (single-site) downscaling. For this purpose, instead of using an observed index constructed by averaging the observed rainfall over a region, the observed time series of a particular meteorological station can be used in the forecast assimilation procedure. The Bayesian method also allows the combination of empirical and coupled-model predictions (Coelho et al. 2004). One can, for example, use an empirical forecast model to estimate the prior distribution. Given the availability of both empirical and coupled multi-model predictions, the proposed method can be used to produce a single well-calibrated combined forecast that gathers all available forecast information at the time the forecast is issued. Future studies using Bayesian forecast assimilation could be performed for regions where empirical approaches have demonstrated some good predictive skill. For instance, combined (i.e. empirical plus coupled-model) forecasts of the Niño-3.4 index in the equatorial Pacific are more skilful than either approach alone (Coelho et al. 2004). Such a combination could potentially improve the skill of seasonal rainfall and river flow forecasts in some regions of South America.

It is worth noting that forecast assimilation is based on several assumptions that deserve further attention (e.g. normal assumption for both prior and likelihood distributions; likelihood modelling is performed via linear regression of forecasts on observation; assumption of stationarity of climate while performing forecast calibration). More flexible forecast assimilation procedures need to be developed so that, in the future, studies other than the normal distribution can be used for the prior and the likelihood distributions, non-linear models can be used to calibrate forecasts, and non-stationarity of climate can be taken into account. This will hopefully help to improve the quality of rainfall and river flow downscaled forecasts.

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