Ensemble long-term soil moisture forecast using hydrological modeling

Previsão por conjuntos de umidade do solo para longo prazo usando simulação hidrológica

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ABSTRACT

Long-term soil moisture forecasting allows for better planning in sectors as agriculture. However, there are still few studies dedicated to estimate soil moisture for long lead times, which reflects the difficulties associated with this topic. An approach that could help improving these forecasts performance is to use ensemble predictions. In this study, a soil moisture forecast for lead times of one, three and six months in the Ijuí River Basin (Brazil) was developed using ensemble precipitation forecasts and hydrologic simulation. All ensemble members from three climatologic models were used to run the MGB hydrological model, generating 207 soil moisture forecasts, organized in groups: (A) for each model, the most frequent soil moisture interval predicted among the forecasts made with each ensemble member, (B) using each model's mean precipitation, (C) considering a super-ensemble, and (D) the mean soil moisture interval predicted among group B forecasts. The results show that long-term soil moisture based on precipitation forecasts can be useful for identifying periods drier or wetter than the average for the studied region. Nevertheless, estimation of exact soil moisture values remains limited. Forecasts groups B and D performed similarly to groups A and C, and require less data management and computing time.

Keywords: Soil moisture; Ensemble forecast; Hydrological modeling.

RESUMO

A previsão a longo prazo da umidade do solo permite melhor planejamento em áreas como a agricultura. No entanto, há ainda poucos estudos dedicados à especificamente estimar umidade do solo para longos horizontes de tempo, o que reflete as dificuldades associadas a este tipo de previsão. Uma abordagem que pode ajudar a melhorar a performance destas previsões é a utilização de previsões por conjuntos (*ensemble*). Neste estudo, uma previsão de umidade do solo para horizontes de tempo de um, três e seis meses foi desenvolvida na bacia do rio Ijuí (Brasil) usando uma combinação de previsões por conjuntos de precipitação e simulação hidrológica. Todos os membros dos conjuntos de três diferentes modelos climatológicos foram utilizados para rodar o modelo hidrológico MGB, gerando 207 previsões de umidade do solo, organizadas em quatro grupos: (A) para cada modelo, o intervalo de umidade mais frequentemente previsto entre as previsões feitas com cada membro do *ensemble*, (B) usando a precipitação média de cada modelo, (C) considerando um superensemble, e (D) o intervalo de umidade do solo médio previsto entre as previsões do grupo B. Os resultados mostram que a umidade do solo a longo prazo estimada com base em previsões de precipitação pode ser útil para identificar períodos mais secos ou mais úmidos do que as condições médias para a região estudada. Contudo, a estimativa dos valores exatos de umidade do solo ainda é bastante limitada. Previsões realizadas com os grupos B e D tiveram performance similar as dos grupos A e C, e requerem menor análise e processamento de dados e esforço computacional.

Palavras-chave: Umidade do solo; Previsão por conjuntos; Modelagem hidrológica.

INTRODUCTION

Long-term forecasting of soil moisture allows for better agricultural management (Saldanha et al., 2012). Soil moisture can be obtained by hydrological simulations in the absence of observed data. It can be estimated using a combination of precipitation forecasting by general circulation models (GCM) with a soil water content estimation from a hydrological rainfall-runoff model.

Forecasting hydrological variables, such as precipitation, is the prediction of future states of hydrological phenomena. This forecast is affected by model uncertainties of parametrization, physical process simplifications, and data input quality. The need to assess and quantify uncertainties has increased the use of ensemble forecasts in the past several years (Demargne et al., 2014).

An ensemble is formed using different members of a model, where each member represents a different trajectory of the atmospheric conditions during the forecast lead time. Members can be generated by small differences in initial conditions. In this case, the scattering among the members allows quantifying the relative uncertainty related to the initial conditions. A multi-model approach allows quantifying uncertainties due to model formulation (Kirtman & Pirani, 2009).

Saldanha (2009) and Saldanha et al. (2012) developed a long-term soil moisture forecast using a rainfall forecast from a global model climate forecast system and soil moisture forecasts from the MGB (Modelo de Grandes Bacias – Large Basins Model) hydrologic model (Collischonn, 2001). The average of 14 members of the ensemble of the precipitation forecasts were used as input data to the hydrological model, which was fit with observed discharge. The simulation results were compared to the soil moisture calculated using observed rainfall to forecast soil moisture with reasonable accuracy for up to three months of lead time.

The uncertainties in the forecasting are in the initial conditions (members of a model) and model structure. Yao & Yuan (2018) used a set of soil moisture hindcasts directly from multiple GCMs to investigate soil moisture predictability and forecast ability in China. The soil moisture from six models of the North American Multi-Model Ensemble (NMME) (Kirtman et al., 2014) were verified against ERA Interim reanalysis (Dee et al., 2011). A multi-model super-ensemble approach was used – when all ensemble members from different models are used together. The results showed that the simple mean of the models provided better soil moisture forecasts than any individual model. Also, an optimized super-ensemble mean (with different weights for different models) led to even better results.

Spennemann et al. (2017) assessed the performance of seasonal soil moisture forecasts in southern South America, for lead times up to nine months. The results showed that the forecast skill decreased as the lead time increased. There was almost no improvement over using climatology data for lead times longer than three months.

Currently, there is an operational soil moisture forecasting system for the continental United States, the Surface Water Monitor (SWM). The forecast is performed using the VIC model (Gao et al., 2009) and a multi-model (outputs from different models used together) approach with lead times up to three months. The predictions use historical meteorological data from the same period of the year of interest, and the hydrological model is initialized with current state information regarding, mainly, soil moisture and snow water equivalent. More information about the Surface Water Monitor, a project conducted by the University of Washington, can be found in Wood (2008).

Some previous studies have worked with long term soil moisture prediction. However, there are still few applications specifically dedicated to estimate soil moisture with long term lead times. It reflects the difficulties and limitations associated with this kind of forecast, when compared, for example, with short term flow forecasting. Considering the studies conducted so far, it is possible that using different approaches of ensemble precipitation and hydrological modelling could lead to better performance of long-term soil moisture forecast.

The objective of the study here conducted was to evaluate the ability of using hydrological simulation and forecasted precipitation to estimate soil moisture for long term lead times. This research aimed to evaluate different approaches of employing the information from a set of members of ensemble forecasts, in order to analyze if it would lead to improved forecast results.

METHODOLOGY

This study uses three GCM model ensembles precipitation forecasts with bias correction in a hydrologic model fitted to flow for estimating soil moisture. Monthly soil moisture forecasts were compared with the soil moisture estimated by the hydrologic model with the observed precipitation, called the pseudo-observed soil moisture.

All ensemble members of each climatic model were used to perform soil moisture forecasts. Also, a multi-model approach was assessed, which allowed the uncertainties associated to the models to be considered.

Framework

The steps of this methodology are as follows (see Figure 1):

- *Hydrologic model parameters calibration*: the MGB hydrological model (Collischonn et al., 2007) was fit using rainfall and runoff observed in the basin;

- *Pseudo-observed soil moisture estimation*: using observed precipitation, the soil moisture was estimated by the hydrological model for the same period used for forecasting (January 1st, 2005 to December 31, 2013);

- *Precipitation forecast*: the forecasted rainfall was obtained from the IRI (International Research Institute for Climate and Society, Columbia University, USA) (International Research Institute for Climate and Society, 2013). Three databases of three models were selected: CCM3v6, ECPC, and GFDL;

- *Forecasted precipitation bias correction*: comparing the precipitation data from previous periods identified a bias in the precipitation forecast. This was statistically corrected before used in the hydrological model for soil moisture estimation;

- *Temporal disaggregation of the precipitation*: the outputs from the GCMs were at monthly intervals and the hydrologic

model used daily precipitation. An empirical procedure was developed to distribute the monthly precipitation in daily values;

• *Soil moisture forecast*: soil moisture was estimated using the forecasted precipitation in the hydrological model. Daily values were transformed to monthly values. Pseudo-observed and forecasted soil moisture values were compared to assess the forecast performance, since no in situ soil moisture data was available.

The simulations were developed for three lead times: 1, 3, and 6 months. The forecasted soil moisture was classified as humid (above the mean soil moisture for that month), normal (mean), or dry (below the mean), when compared to the pseudo-observed soil moisture.
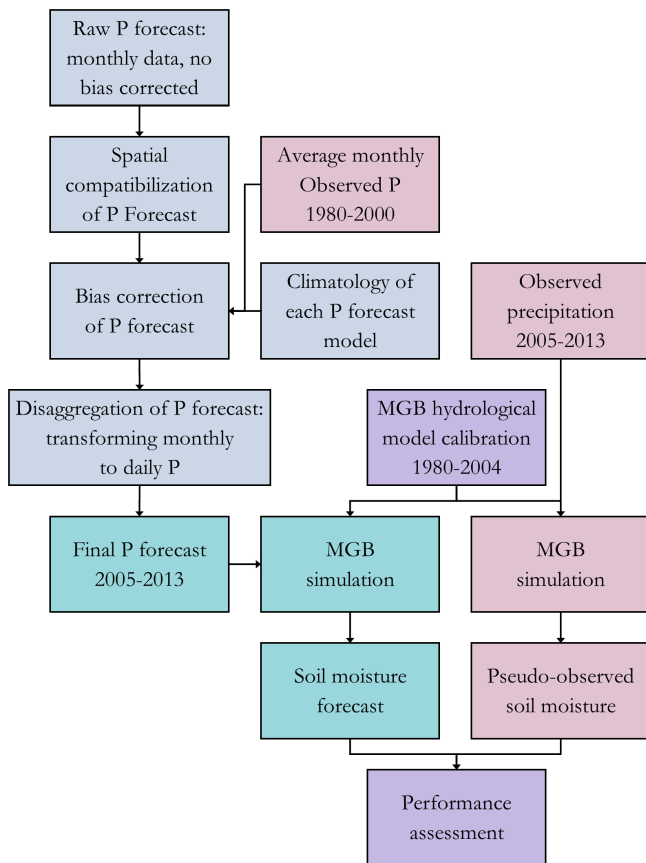

Figure 1. Main framework.

Hydrologic model

Soil moisture was estimated through the water balance module of the MGB hydrological model (Collischonn et al., 2007). Despite being conceived as a rainfall-runoff model, MGB properly represents other elements of the hydrological cycle. Paz et al. (2014) analyzed the effects of representing vertical hydrological processes in simulations of Pantanal floods, and Ruhoff et al. (2013) compared the evapotranspiration estimated using Moderate Resolution Imaging Spectroradiometer (MODIS) and the one simulated using MGB. Colossi et al. (2017) compared MGB simulated soil

saturation degree with a SMOS-based (Soil Moisture and Ocean Salinity mission) soil water index and observed that the MGB estimate of the soil moisture was a satisfactory representation of the water conditions on a weekly/monthly timescale.

MGB is a rainfall-runoff semi-distributed model. The basin is discretized in unit-catchments, each containing one stream segment. Areas with similar hydrological behaviors, classified according to soil type and land use, are combined into Hydrological Response Units (HRU). The soil water balance, evapotranspiration, interception, surface runoff, sub-surface flow, and groundwater flow are simulated using a daily or smaller time step. Vertical processes (interception, evapotranspiration, surface, sub-surface flow generation, and percolation to the aquifer) are simulated for each HRU in each unit-catchment. Volumes generated at each HRU are summed for each unit-catchment and routed using linear reservoirs. At this application, surface runoff is propagated through the stream network using the Muskingum-Cunge method (Collischonn, 2001). Other versions of MGB model are available at Paiva et al. (2013) (using full Saint-Venant equations) and at Pontes et al. (2017) (inertial formulation). Evapotranspiration is calculated by Penman-Monteith method, as shown in Shuttleworth (1993). The soil water balance follows a Dunnian process and uses an approach like the Arno model (Todini, 1996). Equation 1 and Figure 2 show the water balance calculation. All variables are in units of mm:

$$W_{i,j}^t = W_{i,j}^{t-1} + \left(P_{i,j} - ET_{i,j} - Dsup_{i,j} - Dint_{i,j} - Dbas_{i,j} + Dcap_{i,j} \right) \qquad (1)$$

where $W_{i,j}^t$ is the water stored in the soil layer at the end of the time period at unit-catchment i and in HRU j, $W_{i,j}^{t-1}$ is the water in the soil layer at the beginning of the time period, $P_{i,j}$ is the precipitation that reaches the soil, $ET_{i,j}$ is the evapotranspiration, $Dsup_{i,j}$ is the surface runoff, $Dint_{i,j}$ is the subsurface flow, $Dbas_{i,j}$,
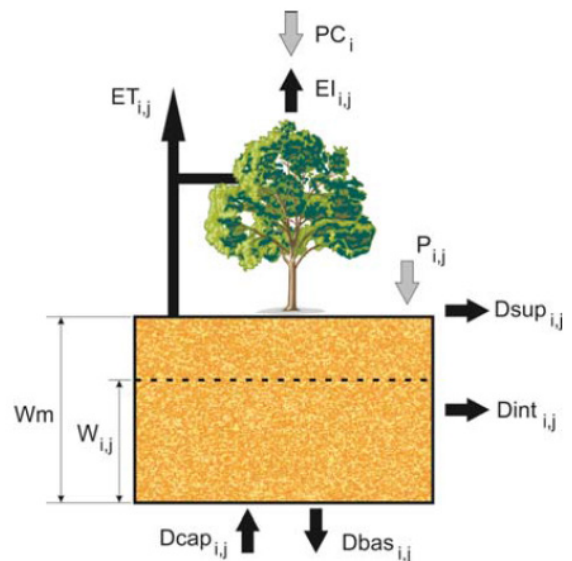

Figure 2. MGB-IPH water balance. PC [mm] is the precipitation over the canopy. EI [mm] is the evaporation from the intercepted water layer. Wm [mm] is the maximum storage capacity for the soil layer. All other variables have the same meaning as in Equation 1.

is the flow to the aquifer, and $Dcap_{i,j}$ is the flow from the aquifer to the soil layer.

Soil moisture is represented by the soil saturation degree, calculated as the fraction of the maximum water storage Wm that the current water depth W represents. Values are calculated as:

$$S_i^t = \frac{W_i^t}{Wm_i} = \frac{\sum_{j=1}^{j\,max}\left(W_{i,j}^t \cdot \frac{A_{i,j}}{A_i}\right)}{\sum_{j=1}^{j\,max}\left(Wm_{i,j} \cdot \frac{A_{i,j}}{A_i}\right)} \qquad (2)$$

where S is the current saturation degree at unit-catchment i, Wm_i is the maximum water depth at unit-catchment i, j is the HRU, $A_{i,j}$ is the area of the unit-catchment i in HRU j, and A_i is the total area of the unit-catchment i.

The model discretization uses a Digital Elevation Model (DEM) to extract the physical characteristics of the basin. The MGB model plugin, code, and other information are available at https://www.ufrgs.br/lsh.

The calibration period was from 01/01/1980 to 12/31/2004, and the forecast period was from 06/01/2005 to 12/31/2013. The period of verification of calibration is the same of forecast. The MGB hydrological model was calibrated with discharge data only. A similar procedure was used by Sípek & Tesar (2013). It is assumed that the calibrated hydrological model properly represents the basins water cycle, which includes the soil moisture. Thus, uncertainties related to the hydrological modeling and parametrization were not analyzed. Only those related to the precipitation forecast were assessed.

Precipitation forecast

Ensemble forecasted precipitation was obtained from IRI. Based on the data series coverage and forecast horizon, three databases of three models were selected: CCM3v6, ECPC, and GFDL (see Table 1). More details about the model selection can be seen at Colossi (2015).

Rainfall bias correction

General Circulation Models may exhibit a bias when applied on a regional scale. This bias, if not corrected, can cause significant errors (Ahmed et al., 2013).

The procedure used to bias correction was based on the systematic error found between the statistical distribution of the monthly observed precipitation and of the forecasting model climatology. These distributions were developed for each month (Jan-Dec) and each model ensemble mean precipitation. Correction was applied to each ensemble member.

Rainfall disaggregation

The forecasted precipitation was in a monthly interval, and the hydrologic model simulates the soil humidity on a daily basis. To transform the forecasted monthly precipitation in daily precipitation, the distribution of the total monthly precipitation was transferred from one of the observed precipitation series, in a procedure similar to the fragments method proposed by Svanidze (1980, apud Farias, 2003). The following procedure was used to transform monthly precipitation into daily values:

- Observed precipitation series from 1980 to 2004 from gauges were selected. This data was also used for model calibration;

- For each series of predicted precipitation (each member of each model) and each month of the simulation period (2005-2013), the employed rainfall distribution over the month was the one from a month in the observed series which total monthly precipitation was closer to the total forecasted (bias corrected). For example, if the forecasted precipitation for Jan/2010 for member 3 of the model XX is 50 mm, in the historical observed precipitation series (1980-2004) the January whose total precipitation was closer to 50 mm (January of YYYY) was identified. Then, the daily distribution of rainfall of Jan/YYYY was applied for Jan/2010 for member 3 of model XX. This introduces uncertainty at the daily prediction level, but the comparison of the results of the soil moisture is performed at the monthly level.

Table 1. Information regarding selected databases.

Model	Description	Spatial resolution	Members
CCM3v6-SSST	CCM3.6 is a version of NCAR'S Community Climate Model. See Hack et al. (1998), Hurrell et al. (1998), and Kiehl et al. (1998).	2.8125° × 2.789327° (T42)	24 members
ECPC-SSST	This is the model of the Experimental Climate Prediction Center, developed and run at the Scripps Institution of Oceanography, University of California, USA (International Research Institute for Climate and Society, 2014).	1.875° × 1.904128°	12 members
GFDL-SSST	Forecasts from the AM2 model of the Geophysical Fluid Dynamics Laboratory from Princeton University were employed. See Delworth et al. (2006) and GFDL Global Atmospheric Model Development Team (2004).	2.5° × 2.0°	30 members

STUDY AREA

The Ijuí River basin is in the Rio Grande do Sul state, Brazil. The basin has an area of about 10800 km², centered at 54.076°W / 28.387°S. The Ijuí River is a tributary of the Uruguay River, a major component of La Plata Basin (Figure 3). This region has a humid subtropical climate (Cfa) under the Köppen classification. The average total annual precipitation ranges from 1790 to 1950 mm, without strong seasonality over the year.

About 40% of the Ijuí River basin area is used for agricultural activities (Brasil, 2006). Almost all Uruguay River basin has an important agricultural role (see Figure 4); however, only 7% of the cultivated area is irrigated (Agência Nacional de Águas, 2013).

SRTM Digital Elevation Model 90 m resolution (as processed by Weber et al., 2004) was used to extract topological information of the basin. HRUs were defined using land use information with a 300 m spatial resolution (European Space Agency, 2010) and soil type data in a 1:5000000 scale (Embrapa, 1981 apud Brasil [20--]). The Ijuí River basin is extensively used for agricultural purposes, primarily crops, and pasture areas, with fragments of forest spread across the basin (see Figure 4).

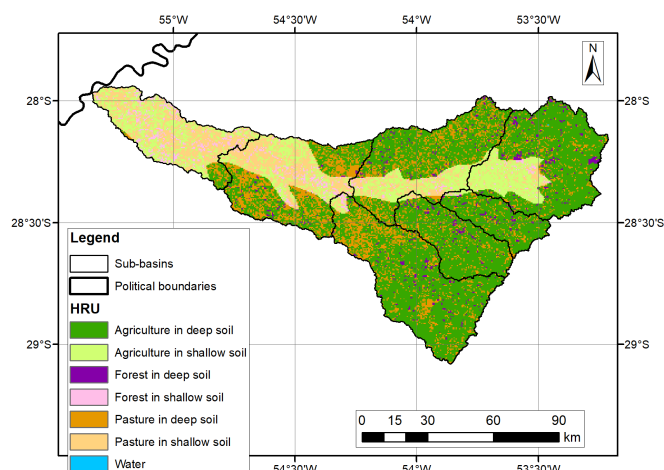**Figure 3.** Ijuí River basin location.

Figure 4. Ijuí River basin hydrological response units (HRUs).

Precipitation gauges are shown in Figure 5. Data from 26 stations was used for model calibration and bias correction, and data from 35 gauges was used to estimate the pseudo-observed soil moisture.
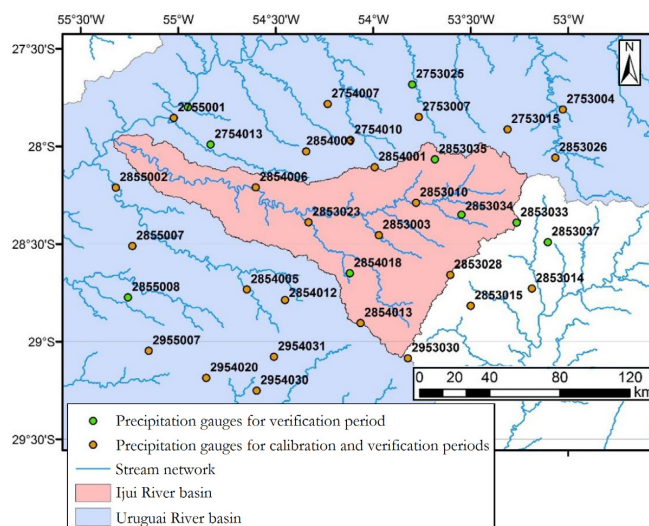

Figure 5. Precipitation gauges.

Hydrologic model calibration and verification

The MGB model was calibrated using discharge data only, available at seven fluviometric gauges (Figure 6). The calibration period was from 01/01/1980 to 12/31/2004, and the forecast/verification period was from 06/01/2005 to 12/31/2013.

Calibration led to Nash-Sutcliffe efficiency coefficient (NS) higher than 0.7, and discharge logarithm Nash-Sutcliffe efficiency coefficient (NSlog) higher than 0.8 in all gauges, which shows that there was good agreement between observed and simulated discharges. Volume error was smaller than │3%│ for all gauges, which indicates good performance for the water balance.

For the verification period, NS was higher than 0.6 for all gauges, and NSlog, higher than 0.8. Volume error was smaller than │15%│, also for all analyzed points. Flow duration curves from simulated discharges were still very similar to observed ones. Therefore, the hydrological model is considered able to well represent hydrologic process in the basin for the interest period (2005-2013). Colossi (2015) presents the model parametrization and efficiency scores for calibration and verification of all gauges.

Precipitation forecast

Figure 7 shows the grid for the precipitation forecast model near the application basin. For each member of each model, the nine (3×3) nearest forecast points were selected, so the basin and its surroundings were covered.
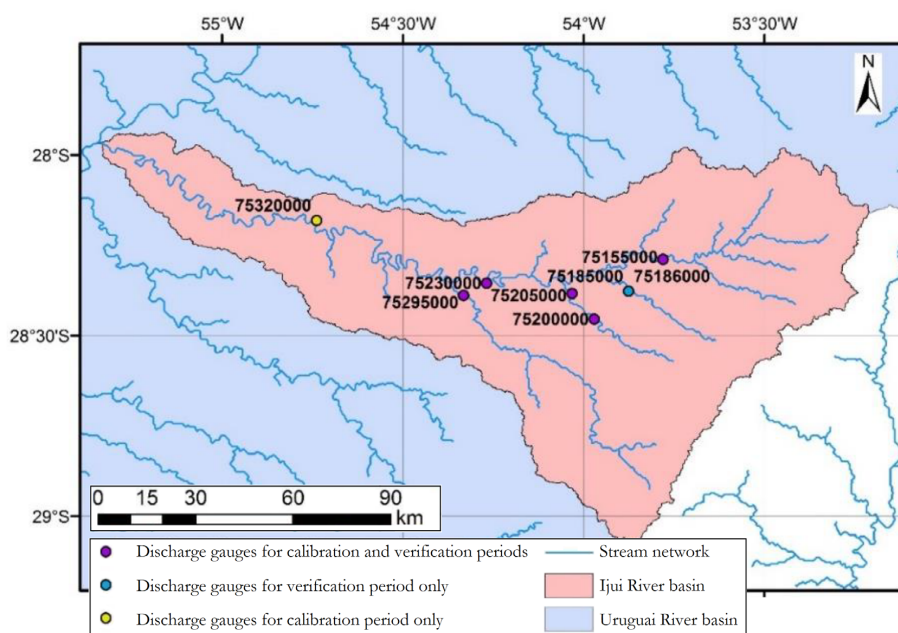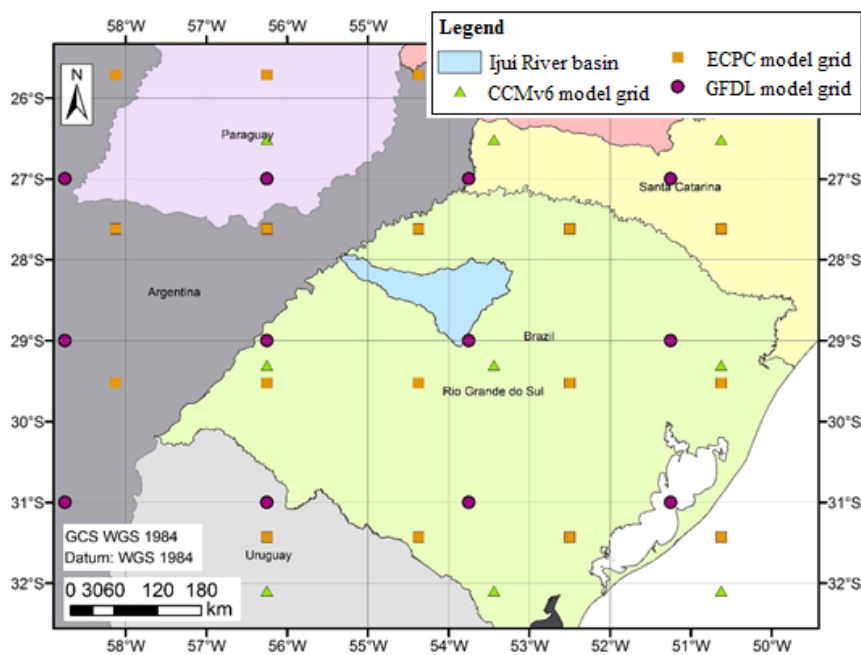
Figure 6. Fluviometric gauges.

Figure 7. Precipitation forecast grid points.

Forecasted precipitation bias correction

Figure 8 shows an example output of the bias correction improvement for the forecasted precipitations. The original forecasted precipitation strongly underestimated the observed precipitation. After the bias correction, the predictions showed better agreement with the observed values and exhibited a variation range closer to that of the basin.

Table 2 shows the mean error of the monthly precipitation for the forecast period (June/2005-Dec/2013). The error is defined as the difference between basin average monthly precipitation forecasted by the model and the observed precipitation.

$$Mean\ absolute\ error = \frac{\Sigma\left(Py - Pobs\right)}{n} \tag{2}$$

where Py [mm] is the monthly precipitation to be analyzed, with or without the bias correction, $Pobs$ [mm] is the observed precipitation
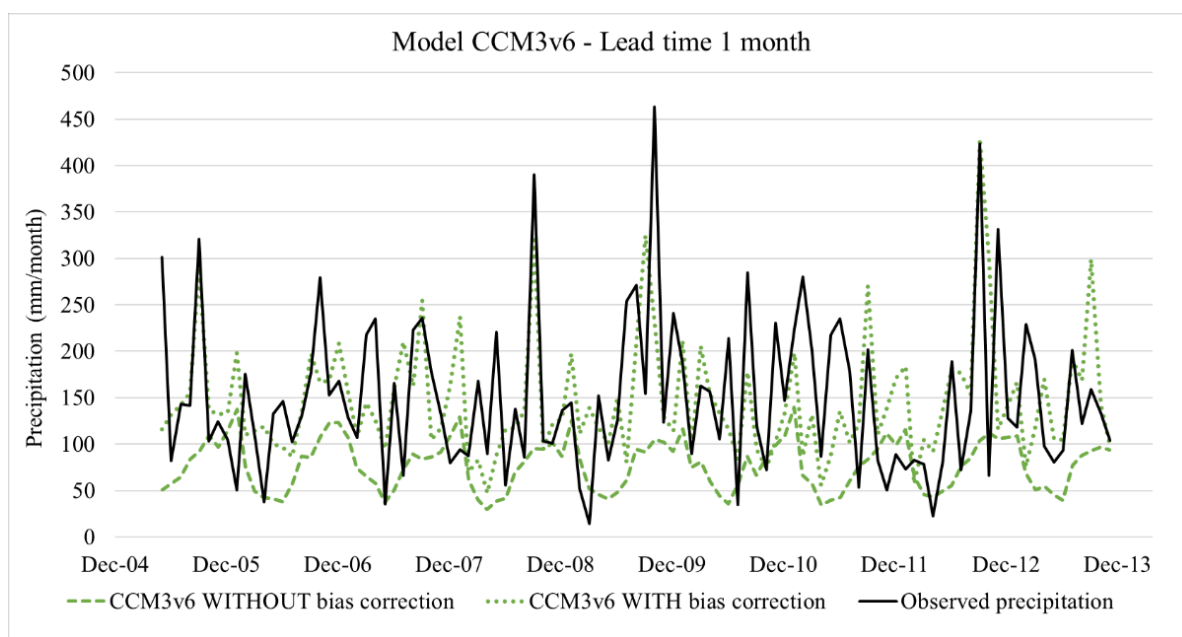
Figure 8. Example of rainfall bias correction effect. Ijuí River basin average precipitation, ensemble mean.

Table 2. Mean absolute error of monthly forecasted precipitation comparing to observed precipitation.

Model	Lead time (months)	Mean error without bias correction (mm)	Mean error with bias correction (mm)	Error reduction
CCM3v6	1	-72.6	-3.2	-96%
	3	-71.0	1.0	-99%
	6	-69.8	6.7	-90%
ECPC	1	-27.1	13.8	-49%
	3	-21.5	16.6	-23%
	6	-19.1	18.0	-6%
GFDL	1	-85.4	-16.6	-81%
	3	-82.3	-6.4	-92%
	6	-82.4	-12.7	-85%

for the month, and n is the number of months between June/2005 and Dec/2013.

The absolute mean error dropped up to 99% after applying the bias correction. The best performance was observed for model CCM3v6. Similar results were found for model GFDL. However, the GFDL model still tended to underestimate the basin's precipitation, although less than when no bias correction was introduced. Model ECPC, which had a negative bias before the bias correction procedure (forecasted precipitation < observed precipitation), exhibited a positive bias after the correction but with a smaller magnitude than prior correction. For the model ECPC, forecasts with a 1 month lead time were slightly better than those for 3 and 6 months of lead time. However, for the CCM3v6 and GFDL models,

the smallest mean error values were found for 3 months of lead time.

SOIL MOISTURE FORECAST

Soil moisture forecasts were generated from running MGB hydrological model with forecasted precipitations. These precipitations are ensemble members from the models presented at Table 1, or the mean of the members of each model.

MGB model was run 207 times (see Table 3 and Figure 9 at "Simulations" section, next), generating 207 monthly soil moisture series. Each soil moisture result was classified as humid, normal or dry, when compared with the mean historic soil moisture for the basin (see Table 4 and Figure 10 at "Pseudo-observed soil moisture" section). Next sections show how these results were grouped and evaluated.

Simulations

Precipitation forecasts from three models were used in this study. Each model has a set of members: 24 for model CCM3v6, 12 for ECPC, and 30 to GFDL. The ensemble average precipitation for each model was estimated. The MGB hydrological model was used to simulate soil moisture for each precipitation forecast (each member of each model: 66 soil moisture series; each model ensemble average: 3 forecasts), which resulted in 207 soil moisture series (three lead times × 69 forecasts). These soil moisture forecasts are organized in four groups:

- Group A - considering the ensemble of members of each model: with each ensemble member, MGB model was run and soil moisture was predicted and classified as humid, normal or dry. The most frequent (the mode) soil moisture class predicted among the members of a model was considered the forecast of that model's ensemble. That means, from the 24 members of CCM3v6, one soil moisture forecast is considered. From the 12 members of ECPC, another. And from the 30 members of GFDL, a third forecast;

- Group B - considering the ensemble mean precipitation of each model: the ensemble mean precipitation was estimated. With this precipitation, MGB was run, generating one soil moisture forecast for each model. This way, the soil moisture prediction is the one from the model's ensemble mean precipitation;

- Group C - for the super-ensemble: all members, of all three model, were used to individually run MGB. The resulting forecast is one value, the most frequent soil moisture class predicted among all members of all three models. It is the mode of soil moisture class predicted for all members of all models;

- Group D - for the model ensemble (multi-model approach): result is the average of the three soil moisture forecasts from Group B. The mean soil moisture class predicted among the three forecasts with the mean precipitation.

Considering the three climatic models and the four criteria groups, for each lead time, there were eight soil moisture forecasts, identified by a 'forecast id', as shown in Table 3 and Figure 9. Forecasts 1, 2, and 3, according to its forecast id, are the Group A forecasts, for models CCM3v6, ECPC, and GFDL, respectively. Forecasts 4, 5, and 6 are those from Group B, for models CCM3v6, ECPC, and GFDL, respectively. Forecast 7 is the super-ensemble, the Group C forecast, and forecast 8 is the Group D forecast.

In Table 3, the column 'precipitation forecasts' indicates how many precipitation forecasts were employed to produce the soil moisture forecast. The column 'soil moisture simulations' refers to how many times the MGB hydrological model was run to generate the soil moisture series. Finally, the 'characteristic of the soil moisture forecast' informs how the soil moisture simulations or the precipitation forecasts were analyzed to became one soil moisture forecast.

Pseudo-observed soil moisture

The forecasted saturation degree for each month was compared to the pseudo-observed soil moisture. The results were compared not as exact values, but as a class of soil moisture. The soil moisture for each month of the forecast period was classified according to its deviation from the historical mean as humid (code +1), normal (0), or dry (-1) (see Table 4).

Table 3. Soil moisture forecasts for each lead time.

Forecast id	Climatic model	Forecast criteria group	Precipitation forecasts	Soil moisture simulations	Characteristic of the soil moisture forecast
1	CCMv6	A	24, from the 24 members of the model	24	Mode of 24 members
2	ECPC	A	12, from the 12 members of the model	12	Mode of 12 members
3	GFDL	A	30, from the 30 members of the model	30	Mode of 30 members
4	CCMv6	B	1, the mean precipitation from the 24 ensemble members of CCM3v6	1, ran with the ensemble mean precipitation	Mean of 24 members
5	ECPC	B	1, the mean precipitation from the 12 ensemble members of ECPC	1, ran with the ensemble mean precipitation	Mean of 12 members
6	GFDL	B	1, the mean precipitation from the 30 ensemble members of GFDL	1, ran with the ensemble mean precipitation	Mean of 30 members
7	All three models	C	66, all members of the three models (24 from CCM3v6, 12 from ECPC, and 30 from GFDL)	66. Each ensemble member of each model ran the hydrological model	Mode of 66 members
8	All three models	D	3, the ensemble mean precipitation of each model	3, ran with the ensemble mean precipitation of each model	Mean of the mean of three models

Table 4. Soil moisture classes. Sm is the monthly mean observed soil moisture.

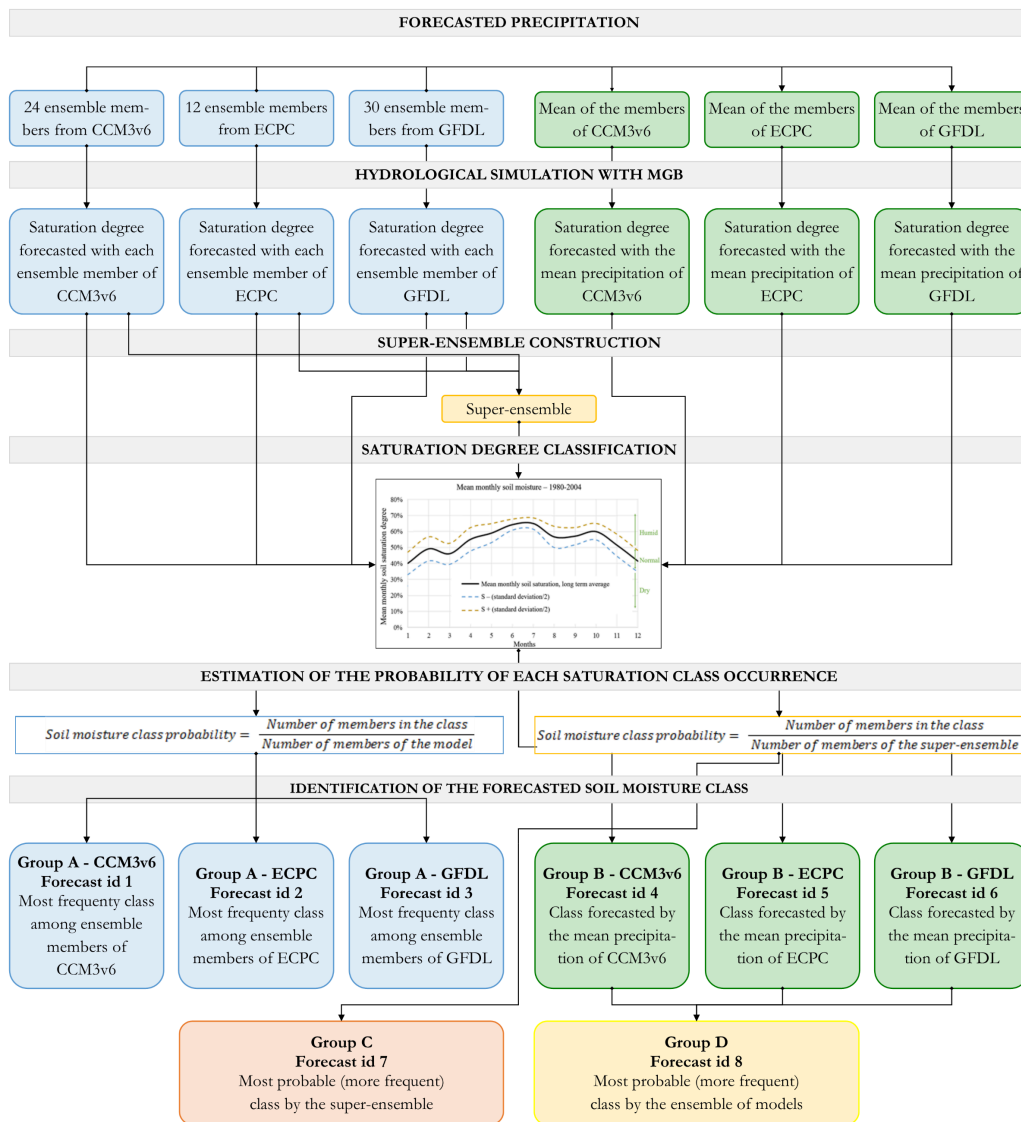| Soil moisture class	Soil moisture class code	Lower limit	Upper limit
Humid	+1	Sm + (standard deviation /2)	
Normal	0	Sm - (standard deviation /2)	Sm + (standard deviation /2)
Dry	-1		Sm - (standard deviation /2)

Figure 9. Flowchart representing the soil moisture forecast and results classification.
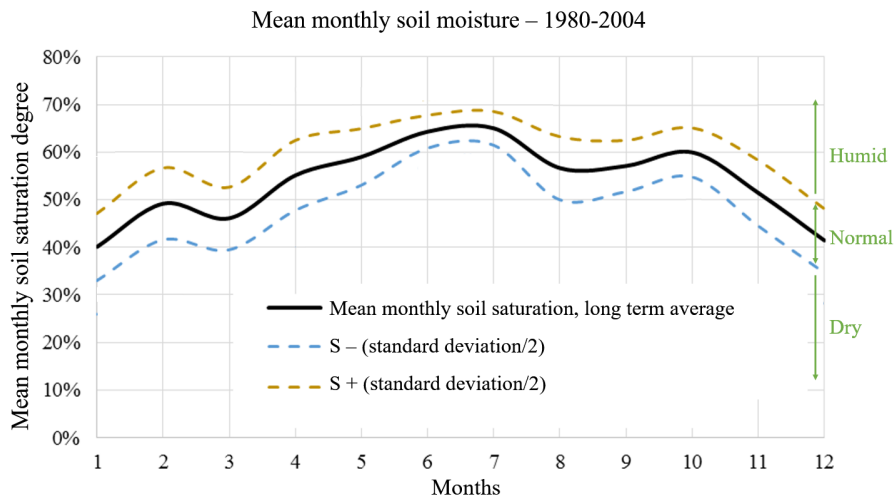

Figure 10. Ijuí River basin average soil moisture for the period between 1980 and 2004, its standard deviation, and the classification of the saturation degree.

The soil moisture historical mean in the basin was estimated through hydrological simulation using the observed rainfall for the period of 1980-2004. Figure 10 shows the monthly mean pseudo-observed soil moisture in the basin, classified as dry, normal, or humid, according to Table 4.

Performance evaluation of soil moisture forecasts

The soil moisture forecast performance was evaluated by a comparison with the pseudo-observed soil moisture classes. The results were analyzed for the mean soil saturation degree of the Ijuí River basin (no spatial variability was analyzed) and for the mean monthly values in the forecast period.

Success and error indicator

For each month of the forecast period, the error of the soil moisture class estimate was calculated as:

$$Error = (Forecasted\ soil\ saturation\ class) - (Pseudo\text{-}observed\ soil\ saturation\ class) \quad (3)$$

where the soil saturation classes are estimated as Table 4 and Figure 10 in +1 (humid), 0 (normal) or -1 (dry).

According to Equation 3, a positive error indicates that the forecasted soil saturation class was more humid (or higher, according to the second column of Table 4) than the observed soil saturation. A negative error indicates that forecast underestimated observed soil moisture. For example, error -2 happens when forecasted soil saturation class was dry (code -1 according to Table 4) and observed soil saturation class was humid.

The success index of the forecast is:

$$Success = \frac{Number\ of\ months\ where\ the\ forecast\ error\ is\ zero}{n} \quad (4)$$

The forecast errors can vary from -2 to +2, and are assessed by:

$$(Rate\ of\ Error = +2) = \frac{Number\ of\ months\ where\ the\ forecast\ error\ is\ +2}{n} \quad (5)$$

$$(Rate\ of\ Error = +1) = \frac{Number\ of\ months\ where\ the\ forecast\ error\ is\ +1}{n} \quad (6)$$

$$(Rate\ of\ Error = -1) = \frac{Number\ of\ months\ where\ the\ forecast\ error\ is\ -1}{n} \quad (7)$$

$$(Rate\ of\ Error = -2) = \frac{Number\ of\ months\ where\ the\ forecast\ error\ is\ -2}{n} \quad (8)$$

Where n is the number of months in the forecast period.

Contingency table

A 2 × 2 contingency table can be established by splitting the simulated soil moisture series into three groups comparing with the pseudo-observed soil moisture: dry, normal, and humid

classes. The contingency table, shown in Figure 11, contains four types of values:

a: successes, events correctly forecasted;

b: false alarms, events predicted but not observed;

c: observed events that were not forecasted;

d: correct rejection, events not observed and not predicted.

Figure 11. Contingency table for binary events. Source: Wilks (2006).

Based on the contingency table for each series (dry, normal, and humid), the results were analyzed for the Probability of Detection (POD), Probability of False Detection (POFD), False Alarm Ratio (FAR), and Bias. These measures are (Wilks, 2006):

$$POD = \frac{a}{a+c} \quad (9)$$

$$POFD = \frac{b}{b+d} \quad (10)$$

$$FAR = \frac{b}{a+b} \quad (11)$$

$$BIAS = \frac{a+b}{a+c} \quad (12)$$

POD quantifies the number of events correctly predicted compared to the observed total. It varies from 0 to 1, and values closer to 1 correspond to better results. POFD evaluates the proportion of events not observed but forecasted, and FAR is the ratio of events predicted but not observed over the total of forecasted events. Both measures vary from 0 to 1, where 0 is the ideal result. Finally, the Bias indicates the relation between the total number of predicted events and observed ones. Bias values greater than 1 indicate that the forecast predicted a greater number of events than actually occurred. Results lower than 1 indicate that the forecast underestimated them.

RESULTS

Soil moisture forecasts group A — Ensembles of the GCM models (ids 1, 2, and 3)

Soil moisture forecasts, compatibilization for a monthly time scale, and classification according to Figure 10 were carried for each member of each model. For each month of the simulation period and each model, the forecasted soil moisture class was the most common among those predicted by the members of a model. This way to present and analyze the results was chosen because it simplifies the user's understanding and decision making. This type of presentation is easier for the user to analyze than a fully probabilistic forecast, but still has advantages over a completely deterministic forecast (World Meteorological Organization, 2012).

Figures 12, 13, and 14 show examples of group A forecast results for different lead times. The results show that forecasts from group A tend to underestimate soil moisture. This trend is quite prominent for the GDFL model for lead times of 1 and 3 months. Furthermore, there were only a few occurrences during the simulation period where the exact pseudo-observed saturation class was identified by the forecast. However, in several cases the forecasted soil moisture class was one class immediately higher or lower than the observed class. This indicates that, despite not being able to identify the exact saturation class at most times, the forecast exhibited better performance for recognizing the soil moisture overall behavior.

Soil moisture forecasts group B — Mean of the ensemble members (ids 4, 5, and 6)

Figures 15, 16, and 17 show examples of the soil moisture forecast results from the ensemble mean precipitation forecast of each model. The results show that the performance of the group B forecast was better than that of group A for identifying the exact soil moisture class pseudo-observed. The ECPC model (forecast id 5), for a lead time of 1 month, tended to overestimate the soil moisture class. This trend was intensified for lead times of 3 and 6 months. The GFDL model (id 6) tended to overestimate the moisture class for a lead time of 3 months. This tendency was even greater for a 6 months lead time. Finally, model CCM3v6 (forecast id 4) was the one

who better identified the soil saturation class. This result is coherent with the comparison of forecasted and observed precipitations.

Soil moisture forecasts group C — Super-ensemble (id 7)

The super-ensemble systematically tended to underestimate the soil saturation, as shown in Figure 18. This can be mainly attributed to the members distribution and bias correction. The precipitation bias correction was applied to every member but was determined with the members mean. However, members spreading was not homogeneous (several members with low precipitation and a few with very high precipitation). When using every member to perform an individual soil moisture prediction, many members generate a low soil moisture class as a result. When counting the number of members in each soil moisture class, estimating the probability of each saturation degree, the dryer classes tended to have higher probability, leading to an overall underestimate of the predicted soil moisture. This effect was already apparent from the predictions using all ensemble members considering each model individually (forecasts group A). With the super-ensemble, the effect is intensified, and the resulting forecast is affected.

Soil moisture forecasts group D — Models ensemble (id 8)

Figure 19 and Figure 20 show, for lead times of one and six months, the soil moisture predicted using the mean class of the classes forecasted by the ensemble mean of each model. In other words, forecast group D is a rounded average of forecasts group B.

Despite exhibiting better agreement with the pseudo-observed soil moisture than forecasts group C, forecasts group D hardly can correctly predict the soil moisture class. Furthermore, group D tended to overestimate the soil moisture, especially for lead times of 3 and 6 months.

ANALYSIS AND DISCUSSIONS

Tables 5, 6, and 7 show the performance of the forecasts. The error is defined as the predicted soil moisture class minus the pseudo-observed class, as presented in the "Performance
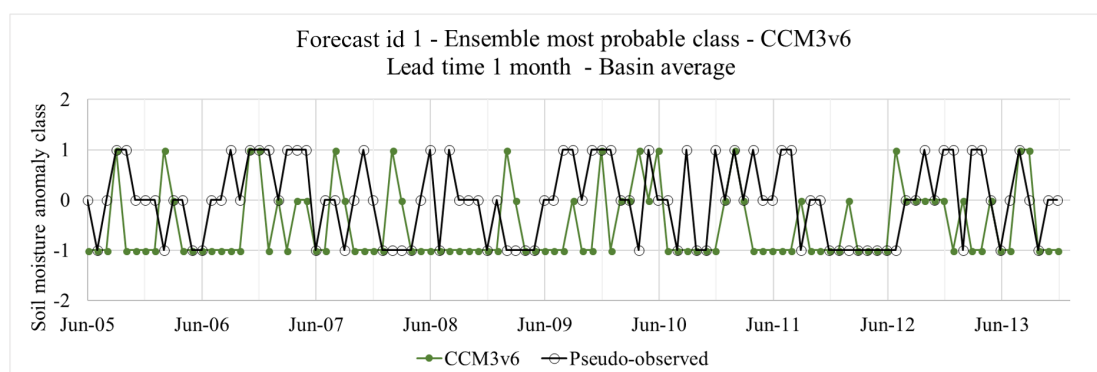

Figure 12. Soil moisture pseudo-observed class and forecast id 1 for a lead time of 1 month. Anomaly class -1 indicates a month dryer than the historical mean, 0 indicates normal soil moisture, and +1 indicates a more humid period.
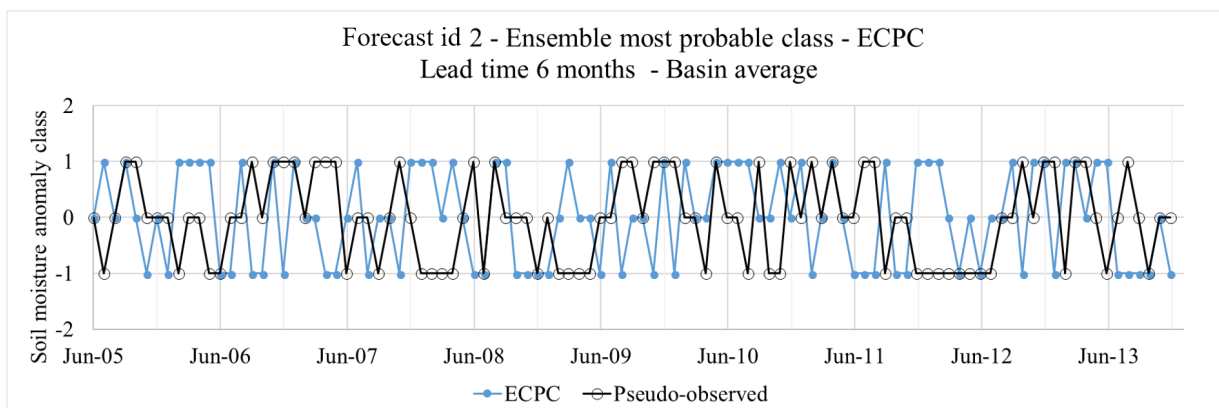
Figure 13. Soil moisture pseudo-observed class and forecast id 2 for a lead time of 6 months.
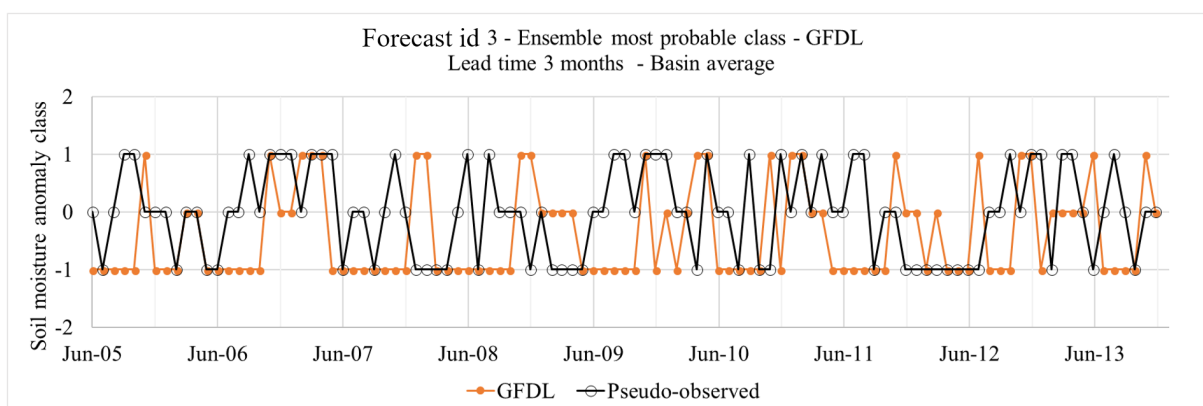

Figure 14. Soil moisture pseudo-observed class and forecast id 3 for a lead time of 3 months.
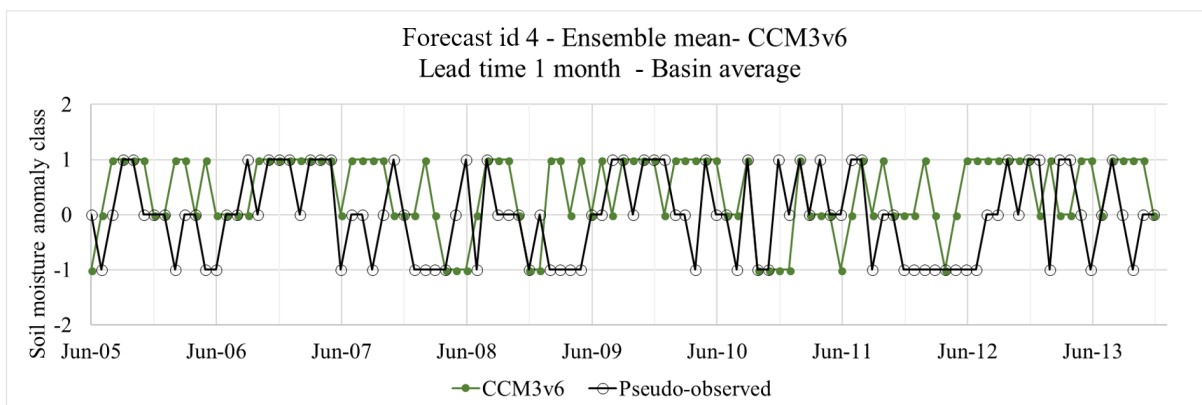

Figure 15. Soil moisture pseudo-observed class and forecast id 4 for a lead time of 1 month.

Figure 16. Soil moisture pseudo-observed class and forecast id 5 for a lead time of 3 months.

Figure 17. Soil moisture pseudo-observed class and forecast id 6 for a lead time of 6 months.

Figure 18. Soil moisture pseudo-observed class and forecast id 7 for a lead time of 3 months.

Figure 19. Soil moisture pseudo-observed class and forecast id 8 for a lead time of 1 month.
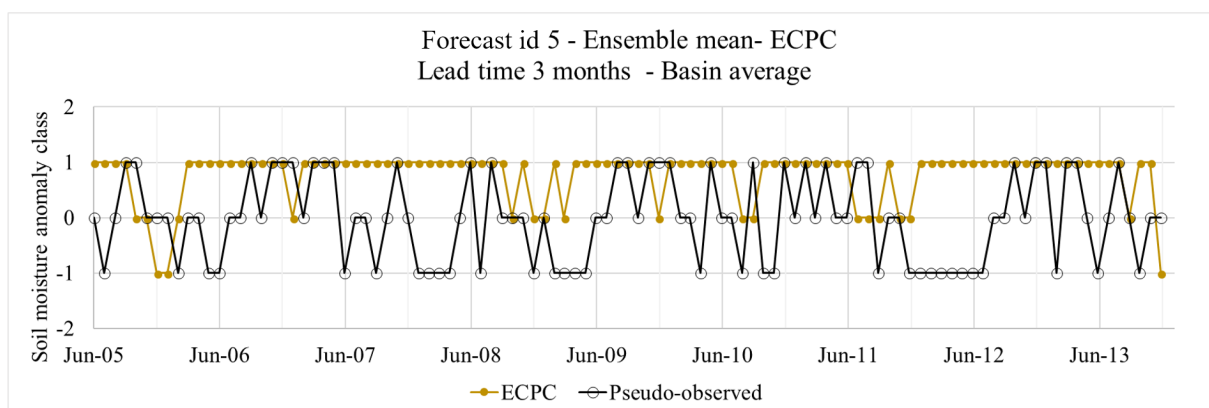

Figure 20. Soil moisture pseudo-observed class and forecast id 8 for a lead time of 6 months.
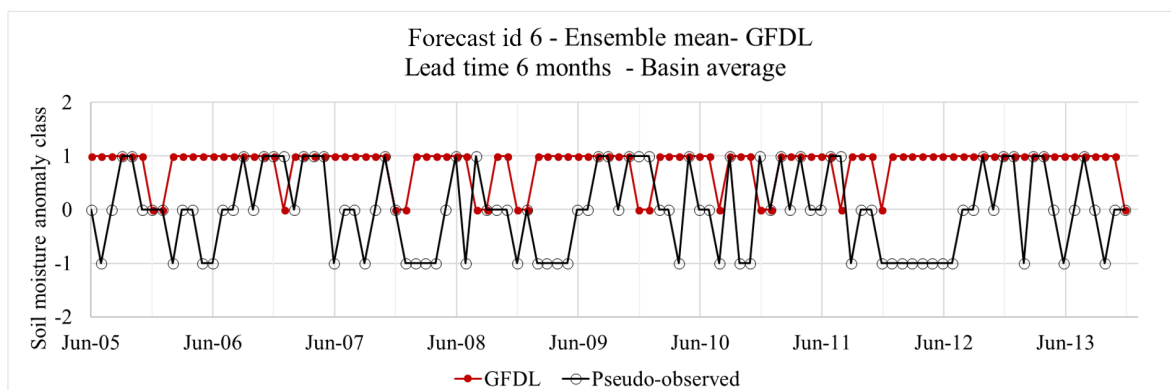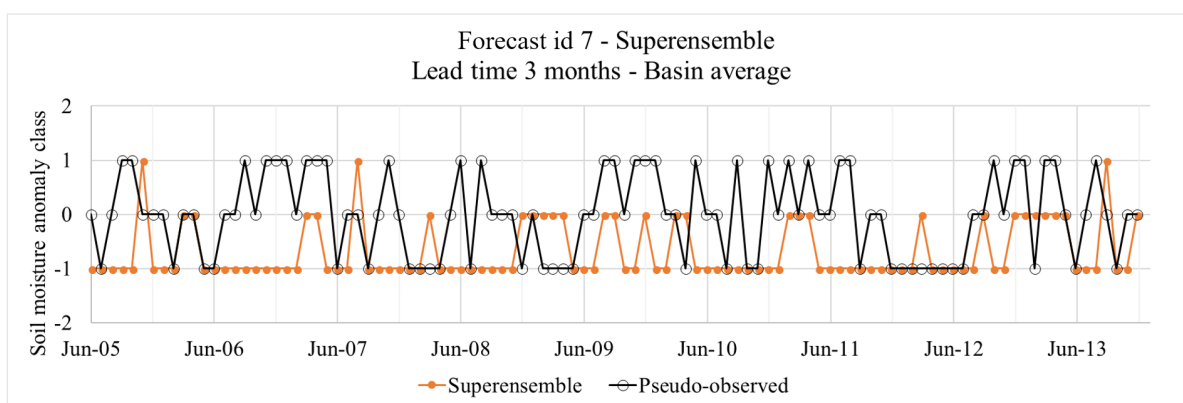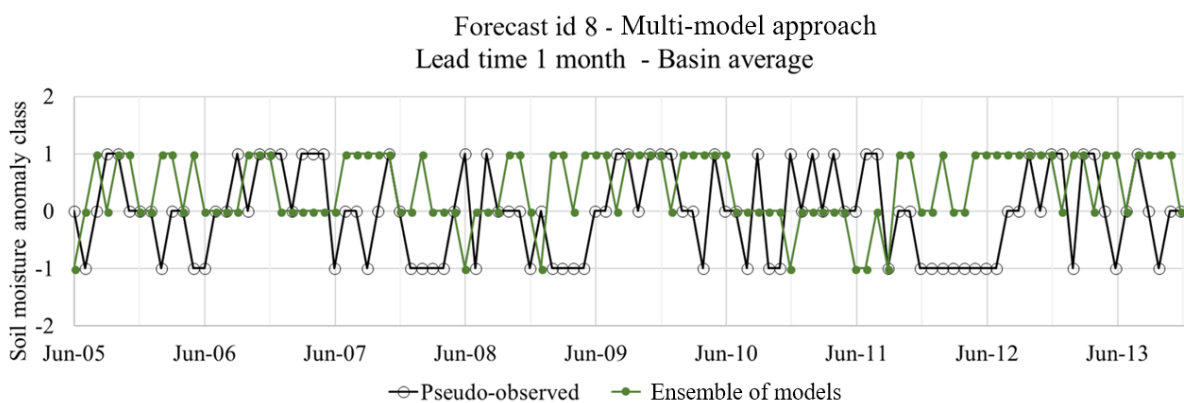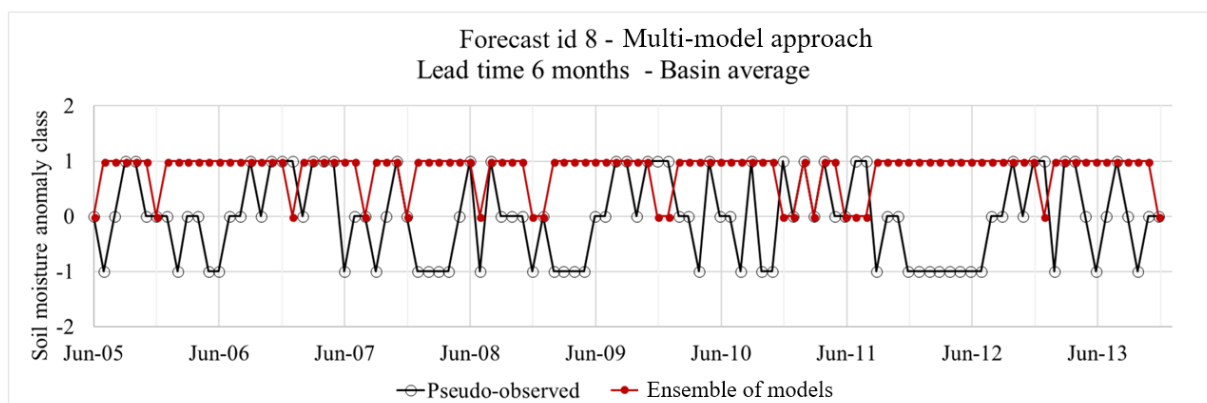
evaluation of soil moisture forecasts" section. Thus, error=0 corresponds to a successful forecast. Positive errors indicate an overestimation of the forecast, while negative errors show underestimation.

The results show that the success rate, error=0, was less than 37% for all eight forecasts. However, an important amount of errors is ±1, which indicates that most of the time, the soil moisture forecast misses between dry and normal or normal and humid classes. The percentage of errors=±2 was at maximum of 30%. That means, forecasts of dry conditions when the soil was actually humid, or vice versa, happened for 30% of the simulation period at maximum.

Establishing a 2 × 2 contingency table for each saturation class (dry, normal, and humid), the results were analyzed for the probability of detection (POD), probability of false detection (POFD), false alarm ratio (FAR), and Bias. Figures 21, 22, and 23 show these results.

The ideal result would be POD=1 and POFD=0. However, the predictions were far from the ideal case. For the three models, all eight forecasts tended to have PODs similar to their POFDs, and non-zero values.

Analyzing the FAR and BIAS, the performance tended to be better for the normal class, which demonstrates the difficulty of detecting the occurrence of extreme events.

For all models and lead times, the forecasts for the dry class with the ensemble (group A) and the super-ensemble (group C) tended to have higher values of POD and POFD than the predictions using the average precipitation of each model (group B) and with the ensemble of the models (group D). This is related to the members dispersion and the bias correction results. The prediction with all members of a model (ids 1, 2, and 3) tended to underestimate the predicted class, and this effect was intensified when the forecast was made with the super-ensemble. This caused a greater number of predicted dry events, but not all actually occurred. This increased the POD and POFD. This effect can also be found in the Bias, which was greater than 1.0 in almost all the predictions of dry class made with the ensemble of members (group A) or with the super-ensemble (group C).

For the wet class, the prediction with the ensemble mean (ids 4, 5, and 6) and with the multi-model approach (id 8, group D) had POD and POFD values higher than those from the forecasts performed with the ensemble (ids 1, 2 and 3) and the super-ensemble (id 7, group C). The Bias in these cases was almost always higher

than 1.0, which indicates that there were more wet events predicted than occurred. This may be related to the predominance of La Niña events over the simulated time interval. In the southern region of Brazil, the occurrence of the La Niña phenomenon is associated with intense droughts, while El Niño is linked to abundant rainfall. The precipitation forecasting models possibly did not captured the dry tendency resulting of the La Niña events that happened during the study period.

For the BIAS, with 1 and 3 months lead times, the performance of the multi-model approach (id 8) for the normal class was better than any other prediction and near the ideal value (1.0), indicating that there was no tendency to underestimate or overestimate the number of forecasted months in the normal soil moisture class. Analyzing the three classes, the group D prediction tended to overestimate the number of wet events and underestimate the number of dry events. This may be related to the characteristic of the occurrence of the El Nino Southern Oscillation (ENSO) phenomenon over the simulated period, as discussed previously.

For the forecast with a 6 months lead time in the dry category, the false alarm ratio, probability of false detection, and BIAS were zero for group D forecasts (id 8), because there were no dry months predicted for this lead time.

The super-ensemble (forecast id 7) for lead times of 1 and 3 months for dry conditions has a POD higher than those of the other predictions, except for one (the average precipitation of the ECPC model for wet conditions with a 3 months lead time). However, it also has the highest value of POFD. This occurred because, as already discussed, the super-ensemble has a strong tendency to underestimate the monthly saturation class. This trend can also be confirmed through the BIAS, which had a value greater than 1.5 for the dry class for the three lead times, and a value of 2.5 for 1 month lead time. The FAR was always around 0.9, indicating that approximately 90% of the predicted events (months of soil moisture below normal) were not observed.

For the humid class, for all lead times, the forecast of the super-ensemble had POD and POFD close to zero due to the low incidence of months predicted in the humid class. The BIAS in these cases was always below 0.16, indicating a strong underestimation of the number of events observed. The FAR, also for all lead times, was equal to 1.0, which shows that, in addition to underestimating the number of wet events (months where

Table 5. Successes and errors of forecasts for 1 month lead time.

Forecast id	1	2	3	7	4	5	6	8
Error type	Ensemble			Super-ensemble	Mean			Multi-model
	CCM3v6	ECPC	GFDL		CCM3v6	ECPC	GFDL	
Error= 0	36%	27%	25%	28%	37%	21%	37%	27%
+1	9%	19%	13%	9%	34%	38%	22%	38%
-1	33%	33%	38%	40%	14%	14%	17%	19%
+2	5%	8%	6%	1%	14%	22%	17%	15%
-2	17%	13%	18%	22%	2%	5%	8%	1%
Successes: Error= 0	36%	27%	25%	28%	37%	21%	37%	27%
Positive errors	14%	27%	18%	10%	48%	60%	39%	52%
Negative errors	50%	46%	56%	62%	16%	18%	24%	20%

soil saturation was considered above normal for the month), the super-ensemble never correctly predicted a month with wet class.

For normal class predictions (soil moisture within the expected class for the month), the performance of the super-ensemble was better than for the dry or wet classes in terms of

FAR and BIAS. There was still a tendency to underestimate the number of months in the normal class, in addition to having a high incidence of false alarms. For all lead times, the POFD was larger than the POD.

Table 6. Successes and errors of forecasts for 3 months lead time.

Forecast id	1	2	3	7	4	5	6	8
Error type	Ensemble			Super-ensemble	Mean			Multi-model
	CCM3v6	ECPC	GFDL		CCM3v6	ECPC	GFDL	
Error= 0	31%	31%	31%	31%	32%	28%	35%	33%
+1	16%	23%	14%	11%	36%	38%	29%	38%
-1	32%	23%	32%	40%	16%	9%	16%	12%
+2	7%	12%	7%	0%	16%	25%	15%	17%
-2	15%	11%	17%	18%	1%	0%	6%	0%
Successes: Error= 0	31%	31%	31%	31%	32%	28%	35%	33%
Positive errors	22%	35%	20%	11%	51%	63%	44%	55%
Negative errors	47%	34%	49%	58%	17%	9%	21%	12%

Table 7. Successes and errors of forecasts for 6 months lead time.

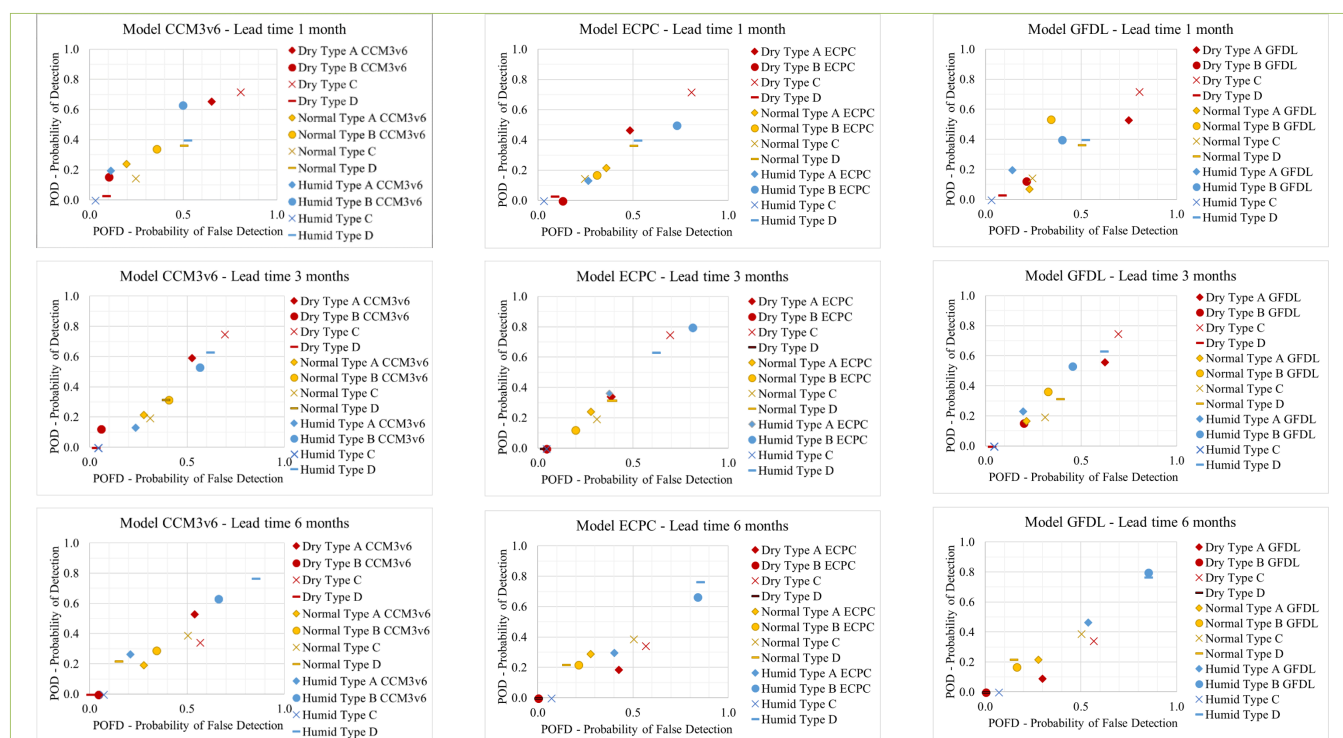| Forecast id	1	2	3	7	4	5	6	8
Error type	Ensemble			Super-ensemble	Mean			Multi-model
	CCM3v6	ECPC	GFDL		CCM3v6	ECPC	GFDL	
Error= 0	32%	26%	25%	26%	30%	28%	30%	32%
+1	16%	24%	33%	21%	37%	34%	37%	33%
-1	33%	20%	15%	33%	12%	10%	6%	7%
+2	7%	15%	17%	2%	20%	28%	27%	28%
-2	13%	15%	11%	17%	1%	0%	0%	0%
Successes: Error= 0	32%	26%	25%	26%	30%	28%	30%	32%
Positive errors	22%	39%	50%	23%	57%	62%	64%	61%
Negative errors	46%	35%	25%	50%	13%	10%	6%	7%

Figure 21. POD and POFD for dry, normal, and humid classes for forecasts. Use Table 3 as reference for forecasts types and ids.
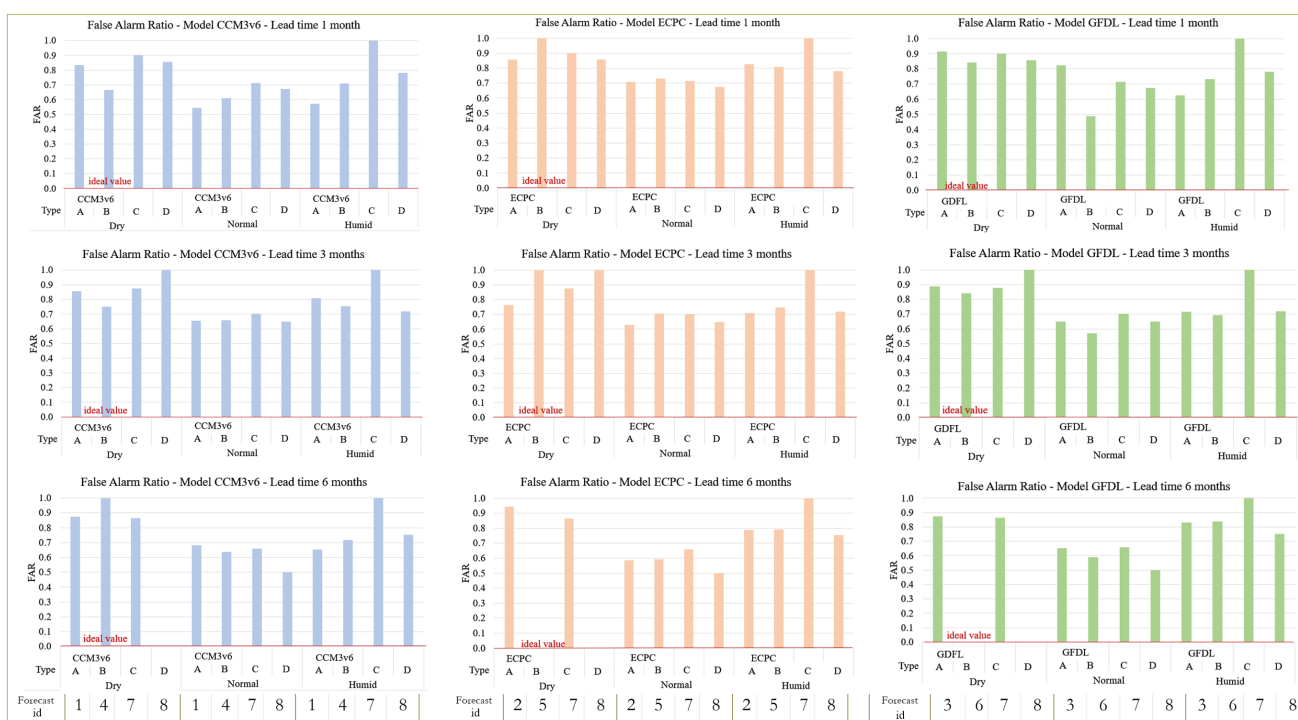
Figure 22. False alarm ratio for dry, normal, and humid classes for different forecasts. Use Table 3 as reference for forecasts types and ids.
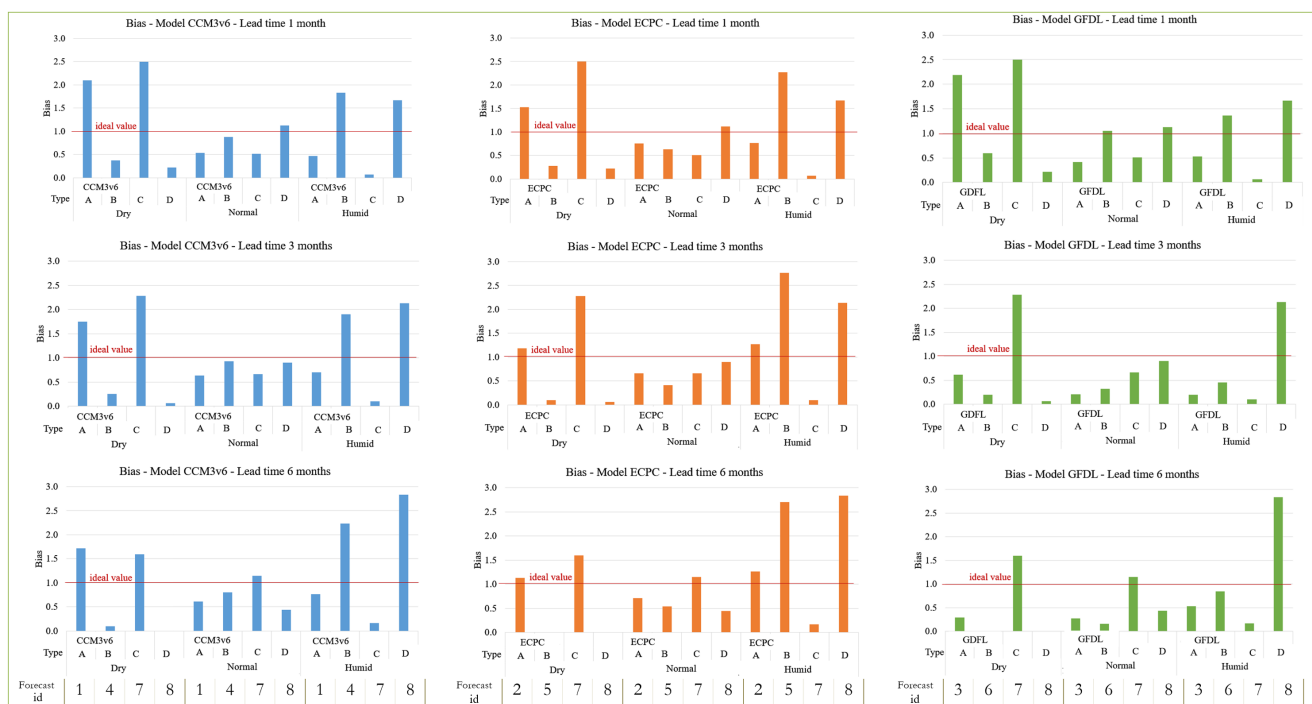

Figure 23. Bias for dry, normal, and humid classes for different forecasts. Use Table 3 as reference for forecasts types and ids.

The multi-model approach (forecast group D) exhibited results that were typically better than any of the predictions made using the members of a model's ensemble, either with the set of members (group A) or the super-ensemble (group C) when analyzing trends, that means, accepting errors +1 or -1, for lead times of one and three months. Soil moisture predictions based on the ensemble of averages (group D) involved less computing time and data management compared to the forecast with the set of members (groups A and C), since it requires less runs of the hydrological model and, consequently, generates a smaller amount of results for processing, and may be an interesting alternative in forecasting. The ensemble of averages (group D), by employing different models, accounts for different physical characteristics, processes, and horizontal and vertical spatial resolutions. For the

ensemble mean of the same model (group B), this may not be true if the members were generated only from perturbations in the model parameters or in the initial conditions.

In the procedure used, the bias of the precipitation forecast was removed from the ensemble mean precipitation. For a large proportion of the models and lead times, the soil moisture prediction with the ensemble mean precipitation of each model (forecasts group B) exhibited similar or moderately better results than the predictions using the complete set of members of each model (group A), or with the super-ensemble (group C). This indicates that, without considering the members dispersion, there was no advantage to using the whole ensemble in the predictions over using the ensemble mean precipitation.

The absence of seasonality in the precipitations of the region under study hinders a possibly better performance of the forecasts. This seasonality would be more easily identifiable by the forecasts, yielding better results. Furthermore, the low performance of the models for precipitation forecast may be influenced by phase errors (for example, a prediction of xx mm predicted one month earlier or later to the observed precipitation). This phase error in the precipitation forecast may impair the performance of the soil moisture prediction. Although the soil acts as a reservoir, the error in the forecast is greater than the soil damping capacity. This error is associated with the temporal resolution of the forecast (monthly) and the process of transformation of the expected monthly totals into daily values, which does not necessarily reflects the observed temporal distribution. Furthermore, the grid of points where the precipitation forecast is available is quite coarse and might represent an important limitation to the forecasted precipitations.

In this study, using ensemble precipitation forecasts, the effect of precipitation forecast uncertainties on the prediction of soil moisture was considered. However, there are other sources of uncertainty that may affect the results.

The observed flow, precipitation, and climate data used for the hydrological model implementation and bias correction of the predicted precipitation may contain errors in the historical series, or even do not have enough density of observation points to represent the basin. Similarly, soil use and type information may not have enough spatial resolution to accurately represent the basin. Furthermore, there are uncertainties when considering that the conditions of land cover and use remained constant in the basin through calibration and simulation periods. Nevertheless, none of the above was identified in this study as a major source of uncertainty.

Finally, the hydrological model, when calibrated, seeks to properly represent the entire hydrological process in the basin. However, a model is a simplification of reality, and does not necessarily accurately reflect what happens in the basin. Thus, the results found herein are linked to the hydrological model used, the MGB.

CONCLUSIONS

Generating soil moisture forecasts for groups B and D uses only the mean precipitation of each model. This way, the hydrological model is run only as much models are been analyzing (in this case, three). Forecasts of groups A and C involve running the hydrological model once for each ensemble member (herein, 66 times for each lead time). Analyzing the set of results, it is perceived that the forecasts made with the average precipitation predicted by the members of each model (group B) involved less computing time and information handling than forecasts made with groups A and C and produced similar or slightly better results in most times. In addition, the multi-model approach (forecasts group D) allowed weighted analysis of the results, accounting for the agreement between the models, and did not require a significant additional processing once the group B predictions were made. For identifying trends (accepting results when the predicted class was at most one class immediately above or below the pseudo-observed soil moisture class), in most cases the average of each model (group B) performed better than the corresponding ensemble (group A), and the ensemble of averages (group D) performed even better. The average of the members of an ensemble softens the forecast by minimizing the effect of details hard to identify. In this sense, the average of the means intensifies this process. However, because of this, the ensemble of means (group D) exhibited better performance for evaluating the soil moisture trends but not necessarily for identifying the exact class, since the average has a decreased capacity to identify extreme events. Accordingly, it tended to have worse performance than the prediction with the average (group B) of the best model when analyzing the exact soil moisture class predicted (humid, normal, or dry) and not trends.

Among the climate models that provided the precipitation forecasts used here, after the bias correction of the precipitations, error, and correlation analysis between the predicted and observed precipitations showed that CCM3v6 model produced better results, although in a very tenuous way. After performing the soil moisture predictions and subsequent analysis of the results, this slightly better performance of the CCM3v6 model can be more clearly verified. However, the use of only one model would eliminate the possibility of the D group forecast. Moreover, the spatial resolution of all three climatic models is very coarse when compared to the studied basin. A precipitation forecast with better spatial and temporal resolution would potentially yield better performance for the soil moisture predictions.

Although the long-term forecast of precipitation and, consequently, of soil moisture still requires great evolution, the available alternative (using the average monthly precipitation) does not allows the identification of anomalies. In other words, the use of precipitation forecasts, even with a low accuracy index for the exact soil moisture class, allows the identification of periods in which soil moisture is higher or lower than normal for the month, which is impossible using the long-term mean monthly rainfall.

The work presented herein aimed to organize and evaluate a methodology for implementing soil moisture ensemble long-term forecasts using free online data and software. This eases the utilization of such methodology, since it requires only internet access to obtain all the data and software necessary. Thus, the main contributions of this study to soil moisture forecasting are the assessment of the forecast generated with different sets of precipitation prediction, the probabilistic element considered in

the forecasting, and the organization of a methodology that is easily reproducible.

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Authors contributions

Bibiana Rodrigues Colossi: Performed all stages of the study, as well as the paper redaction.

Carlos Eduardo Morelli Tucci: Advisor, guided the study elaboration and revised the manuscript.