ANALYSIS OF SEASONAL STREAMFLOW FORECASTS BASED ON THE ECMWF SEAS5 SYSTEM FOR THE 1983 SOUTH AMERICAN HISTORICAL FLOOD AT ITAIPU DAM

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ABSTRACT - Seasonal forecasting is the process of making predictions of streamflow months in advance and is a powerful tool for planning and management of water resources. A Hydrologic Ensemble Prediction System (H-EPS) uses precipitation ensemble forecast data as input to hydrological models. In South America, seasonal forecast finds demand in the hydroelectric sector, responsible for 65% of the energy produced in countries such as Brazil. In this work we analyzed seasonal streamflow forecasts issued by a H-EPS for Itaipu Dam specifically for the years 1982 and 1983, when a strong El Niño caused extreme floods in several South American regions, especially in the La Plata Basin. For the experiment, we used a continental-scale hydrological model forced with seasonal precipitation hindcast data from the ECMWF model (SEAS5) after bias correction. The hindcast data consist of 25 members with lead times up to 215 days and are available for every first day of the month. The resulting forecasts were compared with those produced by the Ensemble Streamflow Prediction method (ESP), commonly used as benchmark. Results show that the H-EPS method was able to predict the occurrence of the February peak approximately one month before its occurrence, although the predictive skill was reduced with the increase in lead time. The H-EPS performed better than the ESP, resulting in predicted discharges closer to the observed values over the forecast lead times.

Keywords – Seasonal streamflow forecast; Itaipu dam; 1983 historical flood.

INTRODUCTION

Seasonal or long-term streamflow forecasting is the process of making predictions of rivers streamflow months in advance. In a world where conflicts over water use, floods and droughts are increasingly frequent, seasonal forecasting becomes a powerful tool for planning and management of water resources.

The Hydrologic Ensemble Prediction System (H-EPS) method is considered the state of the art to predict seasonal streamflow (Troin et al., 2021). This method typically combines the use of hydrological models with ensemble Quantitative Precipitation Forecasts (QPF), resulting in probabilistic streamflow forecasts (Cloke; Pappenberger, 2009) that represent the chance of occurrence of high and low flow events. The use of ensemble instead deterministic precipitation forecast has been shown to be more suitable for hydrological forecasting (Boucher et al., 2011), once it considers the uncertainty of the forecast.

Even though the uncertainty on initial and boundary conditions of the atmosphere is the greater obstacle for seasonal forecasting, the modeling process also face systematic errors, or bias,

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inherited from the meteorological model (Crochemore; Ramos; Pappenberger, 2016; Pechlivanidis et al., 2020) and errors from the hydrological model, for instance the parametrization (Lan et al., 2020) and initialization (Crochemore; Ramos; Pappenberger, 2016).

In Brazil, seasonal forecasts find special demand in the hydroelectric sector, which accounts for 65% of the energy produced (EPE, 2021). The dams, in addition to energy production, supply water to the population, irrigation, and mitigate the impacts of droughts and floods, recurrent phenomena throughout the territory. A few studies have been investigating the seasonal streamflow predictability in Brazil (Collischonn Et Al., 2005; De Paiva; Montenegro; Cataldi, 2020; Tucci et al., 2003), however, all of them were issued for different locations, hydrological models and precipitation forecast data, generating fragmented knowledge about the seasonal predictability.

In this context, this work presents some preliminary outcomes from a H-EPS currently under development, which aims to produce seasonal streamflow forecasts for the reservoirs of the Brazilian National Interconnected System (SIN). The H-EPS uses the MGB-SA (Siqueira et al., 2018), a continental-scale hydrodynamic model version from the conceptual semi-distributed hydrological model MGB, which has been applied and consolidated in large tropical basins in South America. To run the model, we used the seasonal precipitation hindcast data from the ECMWF model (SEAS5), after a bias removal process. The SEAS5 is one of the best models capable of predicting ENSO phenomena (Barnston et al., 2012), one of the major sources of seasonal predictability in South America (Weisheimer et al., 2020).

Here we aim to analyze the seasonal predictability of a specific event, the extreme 1983 flood at the Itaipu Dam, located in the Paraná River Basin. This event was caused by a strong El Niño period that produced floods at various locations in the years 1982 and 1983.

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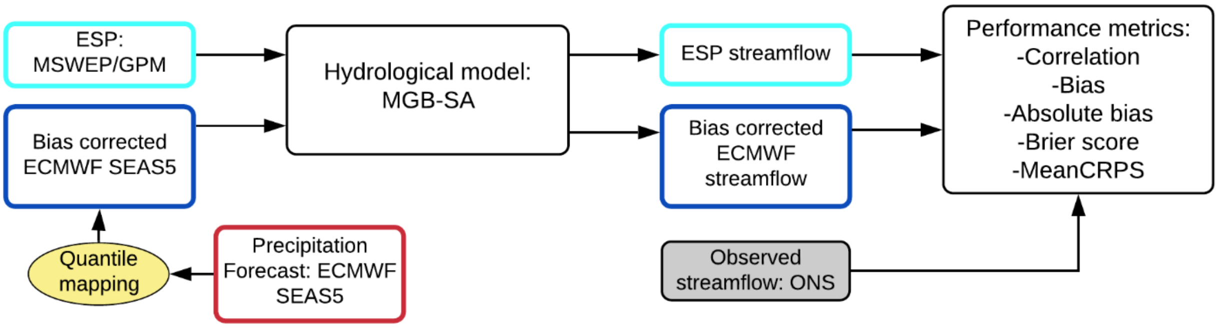
MATERIAL AND METHODS

The 1983 extreme flood that occurred in large South American rivers, reached around ~40 000 m^3s^{-1} at the Itaipu dam and had two main peaks, one in February and another in June. The year of 1983 was associated with a strong El Niño event that caused many extreme floods in different regions and months in South America (Fleischmann et al., 2020).

The procedure applied to produce and analyze seasonal streamflow forecasts at the Itaipu dam during this event is shown in Figure 1.

The H-ESP results were compared with seasonal forecasts resulting from the Ensemble Streamflow Prediction method (ESP), which produces ensemble forecasts by forcing the hydrological model with precipitation scenarios resampled from historical observations, commonly used as benchmark.

Figure 1 – Methodology flowchart



Precipitation data

As the rainfall forcing, the MGB-SA model uses a combination of the following precipitation products: the Multi-Source Weighted Ensemble Precipitation v1.1 (MSWEP) (Beck et al., 2017), and the Global Precipitation Measurement (GPM-NASA). For the ESP benchmark, we produced a precipitation forecast ensemble by resampling the historical rainfall data from years 1979 to 2018 for a given calendar day (i.e., same day and month) but excluding the years of 1982 and 1983, which correspond to the flood period. This resulted in an ensemble precipitation composed by 38 members.

Regarding the H-EPS, the precipitation forecast used are the ensemble products from the fifth generation of the ECMWF seasonal forecasting system, SEAS5. The data is made available by the Copernicus Climate Change Service (C3S), a platform implemented by ECMWF, on behalf of the European Commission, with the aim of providing unrestricted access controlled and quality data, as well as free data (Buontempo; Thépaut; Bergeron, 2020).

The SEAS5 system has a forecast horizon of 215 days (~7 months) and a spatial resolution of approximately 36 km, and predicted precipitation data are provided with a 24-h accumulation interval. Forecasts are always issued on the first day of each month, for a given year. For the current study period, SEAS5 provides reforecast, or hindcast data. The latter correspond to historical forecasts issued with a model version that is similar to the operational one, allowing the comparison with historical observations (Johnson et al., 2019). The hindcast data are available from 1981 to 2016, with 25 members (Johnson et al., 2019). Daily predicted precipitation data with a spatial resolution of 1° was used.

In order to reduce the existing systematic errors in the SEAS5 precipitation product (Pechlivanidis et al., 2020), the forecast data were bias-corrected using the Quantile Mapping method (Bárdossy; Pegram, 2011) as shown in the Equation 1:

$$Z_C(x,t) = F_O{}^{-1}(F_R(Z_R(x,t),x),x) \qquad (1)$$

where *Zc* is the bias-corrected precipitation at location *x* and day *t* simulated by ECMWF, *Fo* is the inverse form of the cumulative distribution function (CDF) of the observed precipitation, *Fr* is the CDF of the ECWMF raw precipitation, and *Zr* is the raw precipitation at location *x* and day *t*.

The parameters were obtained for each lead time and month of the year, totalizing 84 groups of parameters.

Model initial conditions were saved for the years of 1982 and 1983 by using a reference run of MGB-SA. The model was then forced with the ensembles of historical precipitation (ESP) and also the bias-corrected ECMWF forecasts to produce daily seasonal streamflow forecasts up to 7 months in advance. ESP forecasts were produced for the same ECMWF available dates.

Streamflow forecast performance indicators

The analyses were carried out by comparing the streamflow predicted by the MGB-SA using bias-corrected ECMWF data (H-EPS) and the ESP method to observed data. For this study, observed streamflow data for Itaipu dam correspond to naturalized flows, which are regularly produced and made available by the Brazilian National Electric System Operator (ONS).

The performance indicators applied for the ensemble mean were, correlation (from -1 to 1, where 1 is the perfect association), bias (m³/s) and absolute bias (%). For the full ensemble, we calculated two indicators. The first one is the mean continuous ranked probability score (CRPS) in terms of m³/s (Equation 2):

$$CRPS_{h,n} = \int_{-\infty}^{+\infty} \left[F_P\left(QP_{h,n}\right) - F_O(QP_{h,n})\right]^2 dQP_{h,n} \qquad (2)$$

where Fp is the CDF of the ensemble forecast $QP_{h,n}$, Fo is a step function that assumes probability equal to one for $QP_{h,n}$ values greater than or equal to the observation, and zero otherwise. CRPS is finally calculated as a mean value by averaging the individual CRPS computed for each forecast n and a given lead time h.

The second performance indicator for the ensemble is the brier score (BS) (Equation 3):

$$BS_h(L) = \frac{1}{N}\sum_{n=1}^{N} \left(F_{QP_{h,n}}(L) - \imath(Q_{O_{h,n}} \geq L)\right)^2 \qquad (3)$$

where N is the total number of issued forecasts n is a given evaluated forecast. h is the evaluated forecast horizon; L is a threshold that represents the occurrence of a hydrological event; $F_{Qph,n}$ is the probability of flood exceedance, calculated by the proportion of the ensemble members that exceeds the evaluated threshold, and $\imath()$ is a function that equals one when the observed streamflow $Qo_{h,n}$ exceeds the evaluated threshold and is zero otherwise.

For the analysis, the observed streamflow that is exceeded only 10% of the time (Q_{10}) was used as the threshold to compute BS.

RESULTS AND DISCUSSIONS

The MGB-SA simulation results were accumulated into monthly timestep, in order to better analyze the seasonal predictability. Thus, the seasonal streamflow forecast turned from 215 days to seven lead times (one to seven months).

Figure 2 shows the comparison between the observed streamflow with the ensemble mean of the ESP and bias-corrected ECMWF, for each of the 7 lead times. It is possible to see that both ESP and H-EPS methods have greater predictability in the first month, losing skill at longer lead times. In terms of ensemble mean, the first peak was better predicted by the ECMWF simulations, for all lead times, and the signal of occurrence of a second flood peak was only visible in the first month of forecast.

Figure 2 - Streamflow forecast at Itaipu (ensemble means) for the different horizons.

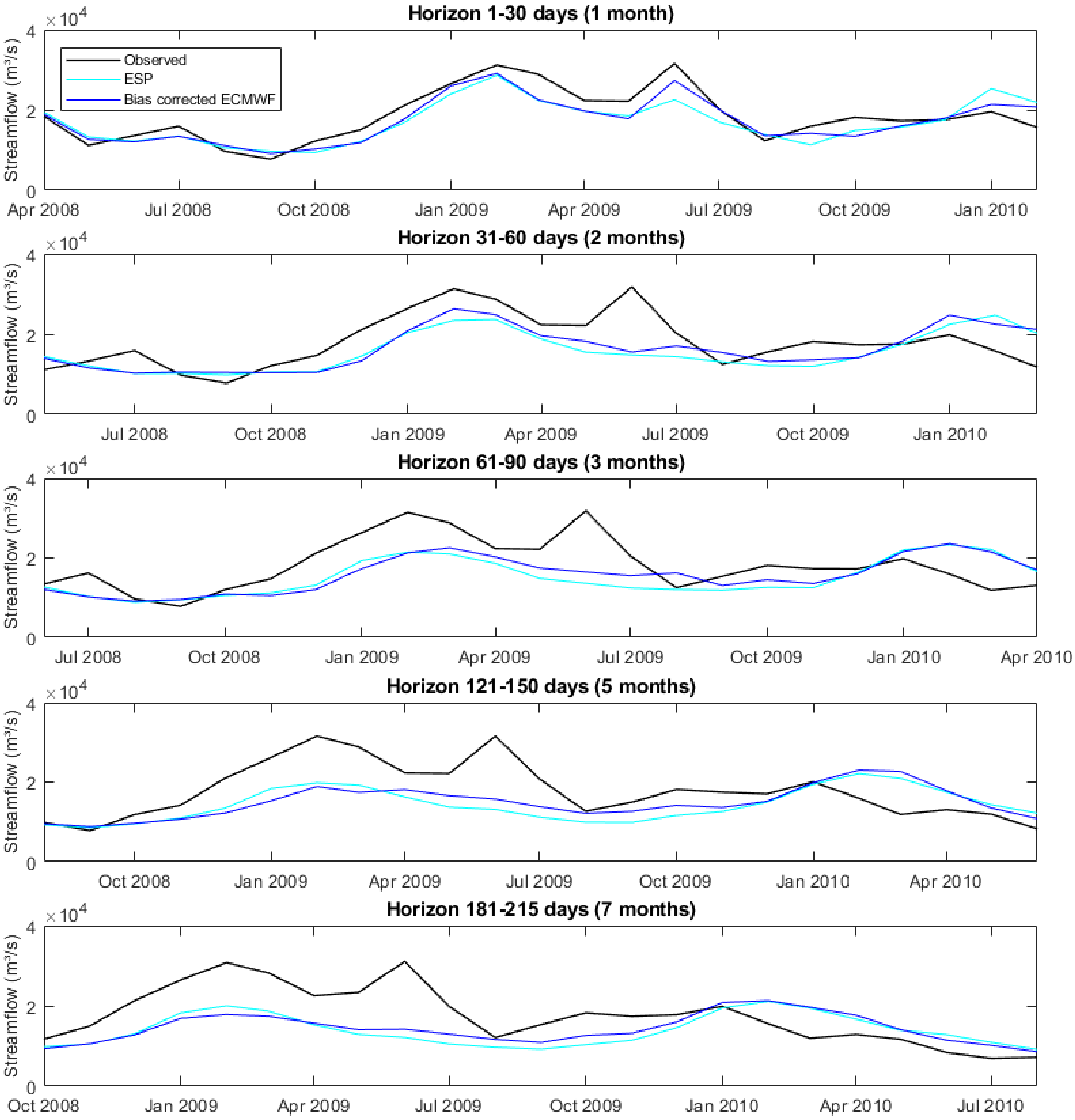
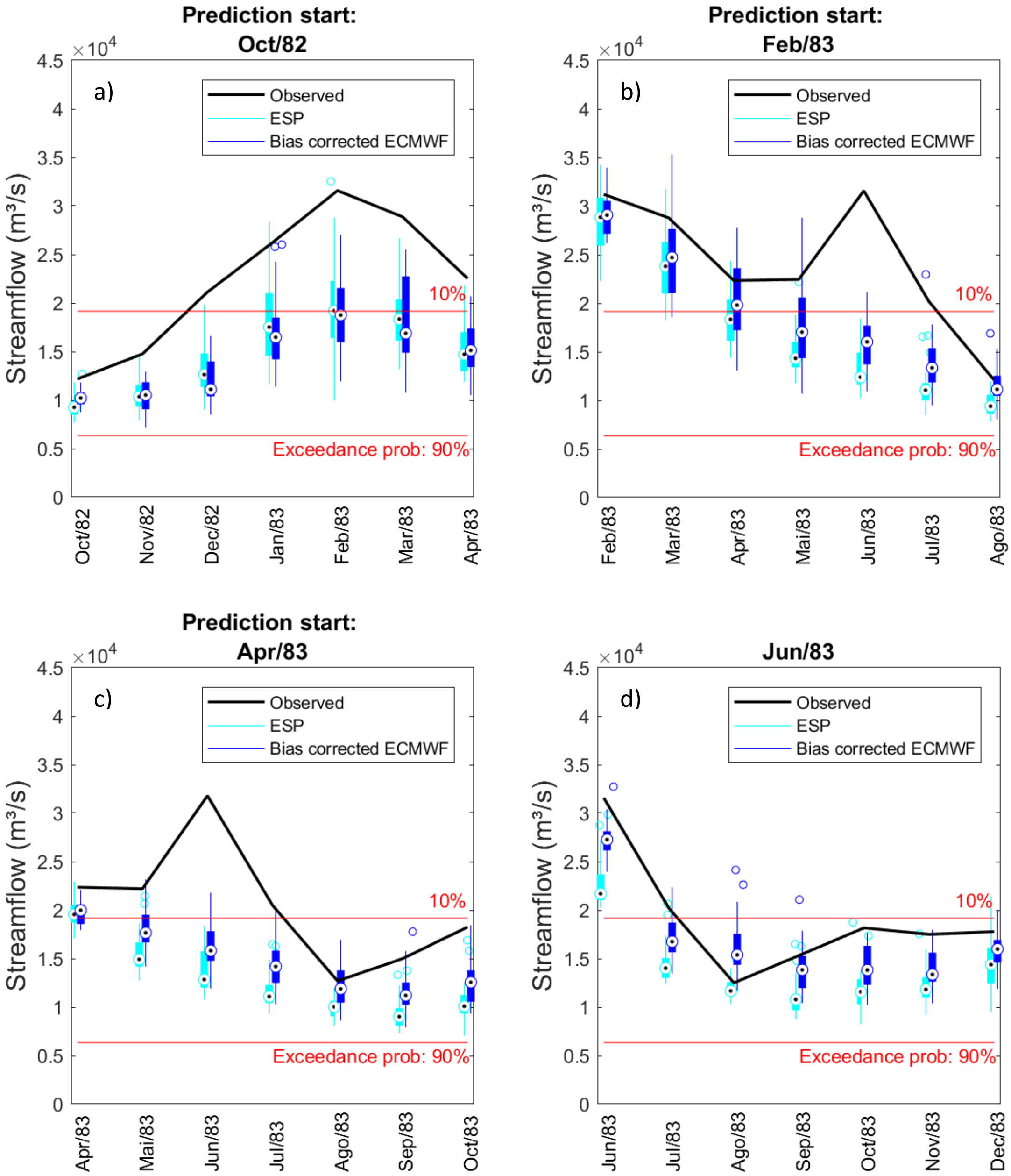


Figure 3 shows sequences of forecasts with boxplots to summarize the ensemble members for both methods. Four forecasts were chosen to represent the predictability of the flood, the ones starting in Oct/1982, Feb/1983, Apr/1983 and Jun/1983 were plotted. Figure 3a shows that, five months in advance of the first peak, it was better predicted by the ESP, while the second peak was better predicted by the H-EPS (Figure 3b), also five months in advance. As closer to the second peak, more consistent the ECMWF members were, shown in the Figures 3c and 3d.

Figure 3 - ESP and ECMWF bias-corrected streamflow forecasts for Itaipu dam. The boxplots are composed by the ensemble members of each forecast system.

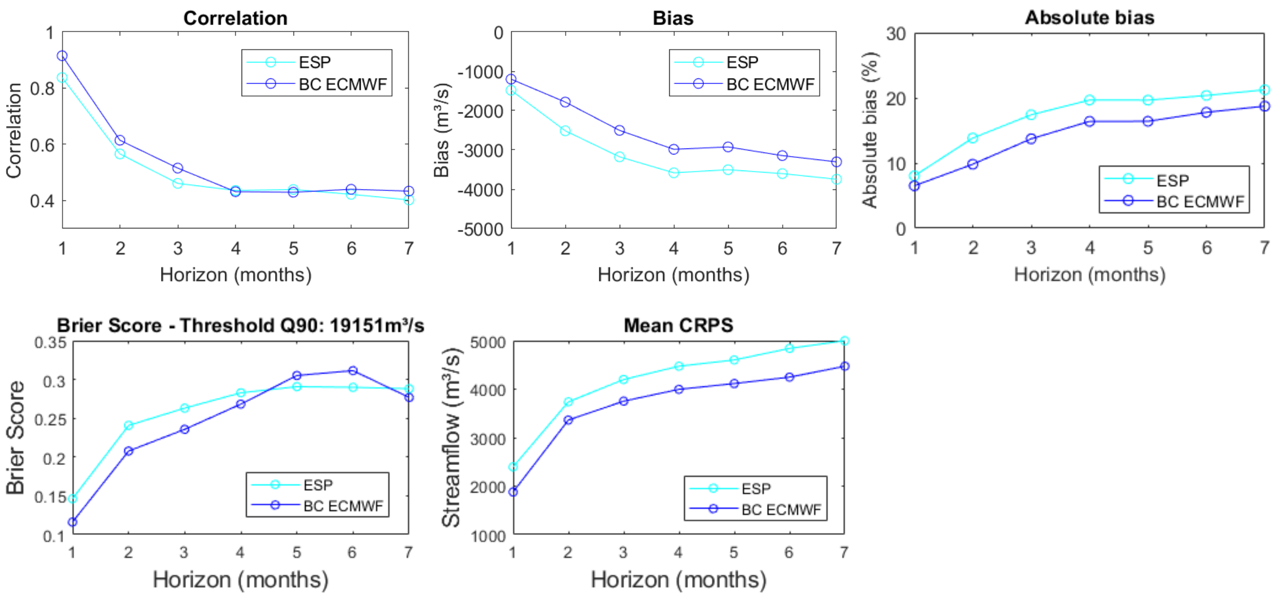


The performance indicators are shown in Figure 4. The ECMWF correlation coefficient is slightly better than the ESP from the first to the fourth lead time month, ranging from values around 0.85 to 0.4. In terms of streamflow error, the ECMWF ensemble mean performs better than the ESP, with a constant difference between them of 800 m^3/s from the second to seventh lead time. The absolute bias ranges from 8% to 20% from the first to the last horizon, increasing with lead time.

The ensemble coefficient Mean CRPS, show H-EPS have a higher ensemble performance than ESP. The brier score is indicating that bias corrected ECMWF is more accurate in predicting whether the Q10 threshold will be exceeded.

All of the indicators, bias, absolute bias, correlation, brier score and mean CRPS decrease along the lead times. Besides, compared to ESP, ECMWF had a better predictability skill for all lead times.

Figure 4 –Streamflow forecast performance indicators



The spread of ECMWF ensemble members in relation to the observed streamflow is shown in the Figure 5 and Figure 6. It can be noted that the ensemble spread for the 1-month lead is narrower than those observed for longer lead times, and both observed flood peaks are contained in the range of the members. For the other forecast horizons (2–7 months in advance), the first peak is always inside the ensemble coverage (i.e., the range between the upper and lower member), while the second peak is not being indicated by the ensemble. In addition, in most forecasts and lead times the observed streamflow is lying outside the 50% ensemble prediction interval.

Figure 5 - H-EPS ensemble spread for the first lead time

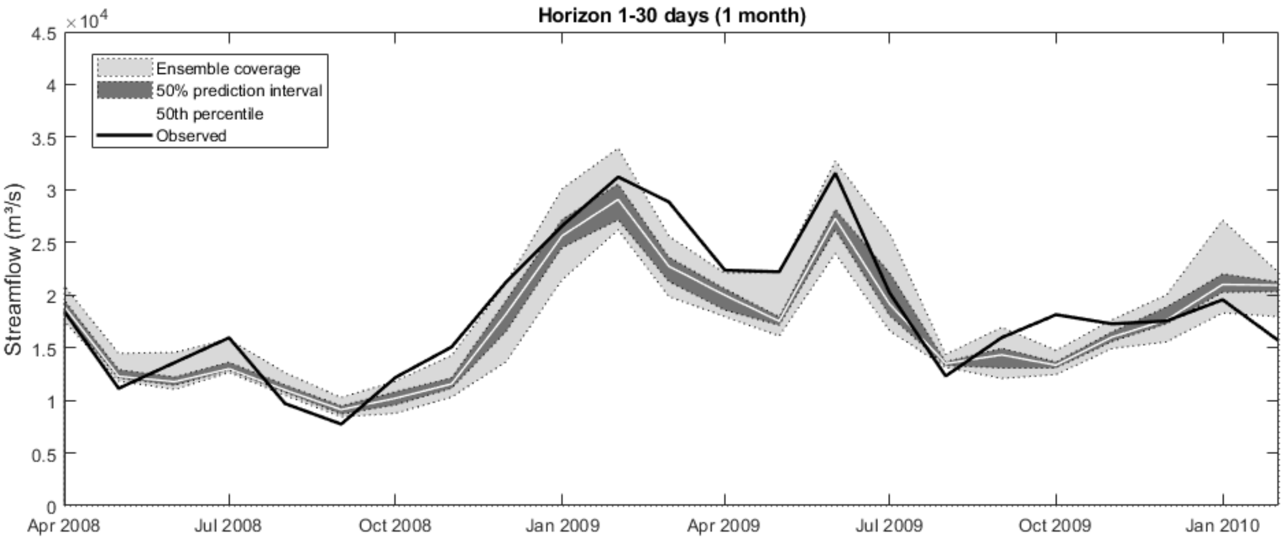
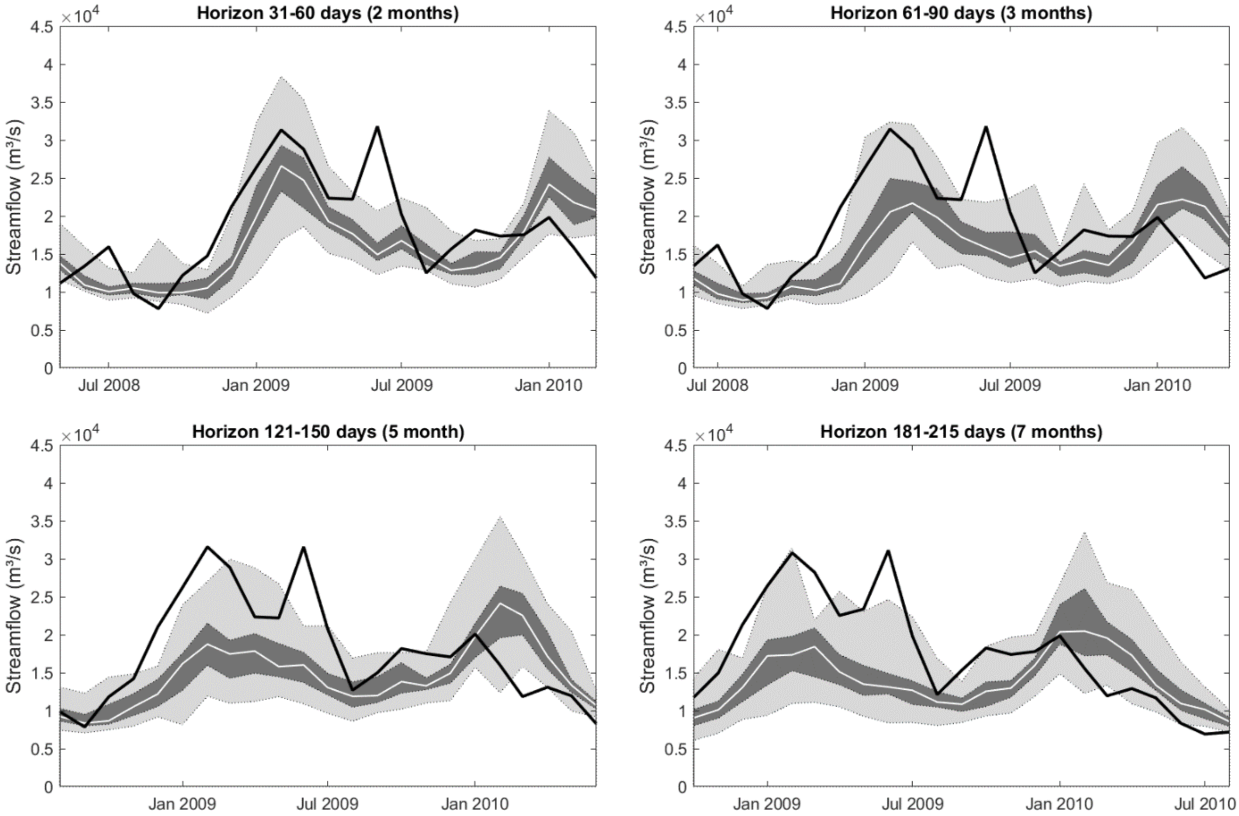


Figure 6 - H-EPS ensemble spread for the second, third, fifth and seventh lead time



FINAL CONSIDERATIONS

Results show that the streamflow forecasts based on the ECMWF SEAS5 were able to predict the occurrence of the February peak approximately one month in advance, reducing the performance with the increase in lead time. In relation to the ensemble mean, the seasonal ECMWF based forecasts perform better than the ESP, resulting in discharges closer to the observed over the lead times.

Despite of the greater complexity, seasonal forecasts produced by coupling the continental hydrological model to the ECMWF SEAS5 showed skill in the prediction of the extreme 1983 flood event at Itaipu Dam, demonstrating potential for improving water resources management in the basin, especially in comparison to the traditionally used ESP approach

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