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PREDICTABILITY AND POTENTIAL OF SEASONAL STREAMFLOW FORECAST IN SOUTH AMERICA

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Master's Thesis presented to the Institute of Hydraulic Research of the Federal University of Rio Grande do Sul as a partial requirement for obtaining the title of Master in Water Resources and Environmental Sanitation

Advisor: Fernando Mainardi Fan

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ABSTRACT

Seasonal streamflow forecast (SSF) is the process of making predictions of streamflow months in advance and it may be a powerful tool for planning and management of water resources. Variations in river streamflow are mainly driven by meteorological forcing (precipitation, temperature) and initial conditions (ICs), for instance discharge from water storages across the basin. In this sense, the state-of-the-art method for streamflow forecast uses precipitation ensemble forecast data as input to hydrological models and the results are probabilistic streamflow forecasts, the Hydrologic Ensemble Prediction System (H-EPS). On the seasonal horizon, the assertiveness of climatological forecasts is limited by the variability of weather conditions, and the attempts to forecast seasonal streamflow are under development science, with studies showing that SSF present a satisfactory skill up to one month of antecedence. As meteorological forcing is one of the greater sources of streamflow predictability, improvements on the numerical weather predictions are the main driver to advances on SSF. In South America (SA), seasonal forecasts find demand on water planning, spatially on the hydroelectric sector, responsible for 65% of the energy produced in countries such as Brazil. In SA, there are only a few studies that investigated SSF and all of them at basin level. At a continent level, these studies represent fragmented information and do not concede spatial comprehension of the SSF potentials in SA. In this sense, this work aims to assess the current potential of seasonal streamflow forecasts for the natural flows of rivers in large basins (>1000 km^2) in South America from hydrological modelling. For this, two articles are proposed: the first presents an estimate of streamflow predictability with a simple metric, presenting a preliminary overview of streamflow predictability in SA. The second article analyze SSF with a Hydrological Ensemble Prediction System elaborated with the hydrological model MGB-SA and SEAS5 (ECMWF) precipitation products with bias correction. The study shows that streamflow predictability driven by the ICs is relatively high (> 60 days) in the main river reaches of basins with flat relief. The increase in predictability due to climatology-based boundary conditions mostly occur in areas that already have high predictability. Basins with fast response present low streamflow predictability (up to three days). We also observed that ESP remains a hard to beat method for seasonal streamflow forecasting in South America. We highlight the importance of bias correction on the SEAS5 precipitation forecasts so that the H-EPS present positive skill over ESP in many regions of South America. SEAS5-SF skill varies according to season, initialization month, basin and forecast lead time, with greater skill on the initialization month lead time.

Keywords: South America; seasonal streamflow forecast; predictability

RESUMO

A previsão sazonal de vazões (PSV) é o processo de fazer previsões com meses de antecedência e é uma ferramenta poderosa para o planejamento e gestão de recursos hídricos. As variações na vazão dos rios são principalmente impulsionadas pelas forçantes meteorológicas (precipitação) e pelas condições iniciais (CIs), como descarga do armazenamento de água na bacia. Nesse sentido, o método considerado o estado da arte para previsão de vazão usa dados de previsão de conjunto de precipitação como entrada para modelos hidrológicos e os resultados são previsões de vazão probabilísticas, o "Hydrologic Ensemble Prediction System" (H-EPS). No horizonte sazonal, a assertividade das previsões climatológicas é limitada pela variabilidade das condições meteorológicas, e a previsão sazonal de vazões está em fase inicial de desenvolvimento, com alguns estudos mostrando que a PSV apresenta uma habilidade satisfatória até um mês de antecedência. Como as forçantes meteorológicas são uma das maiores fontes de previsibilidade de vazões, melhorias nas previsões numéricas do tempo são um dos principal motivador para os avanços na previsão sazonal de vazões. A recentemente publicada quinta geração do sistema de previsão sazonal ECMWF mostrou ser a melhor previsão de precipitação sazonal atualmente disponível, e seus potenciais estão sendo investigados em estudos de previsão sazonal de vazões em todo o mundo. Na América do Sul (AS), as previsões sazonais possuem demanda no planejamento dos recursos hídricos, especialmente no setor hidrelétrico, responsável por 65% da energia produzida em países como o Brasil. Existem poucos trabalhos que investigaram a previsão sazonal de vazões na América do Sul e todos eles ao nível da bacia. Ao nível continental, esses estudos representam informações fragmentadas e não fornecem uma compreensão espacial da previsão sazonal de vazões na AS. Nesse sentido, este trabalho pretende avaliar o atual potencial de previsões sazonais de vazões naturais de rios em grandes bacias (> 1000 km²) na América do Sul a partir de modelagem hidrológica. Para isso, dois artigos são propostos: o primeiro apresenta uma estimativa de previsibilidade de vazões com uma métrica simples, apresentando um panorama preliminar da previsibilidade de vazões em SA. O segundo artigo analisa a PSV com um Sistema de Previsão Hidrológica por Conjunto (H-EPS) elaborado com o modelo MGB-SA e produtos de precipitação SEAS5 (ECMWF) com correção de viés. Os resultados mostram que a previsibilidade de vazão impulsionada pelos CIs é relativamente alta (> 60 dias) nos principais trechos de rios de bacias com relevo plano. O aumento da previsibilidade devido às condições de contorno baseadas na climatologia ocorre principalmente em áreas que já possuem alta previsibilidade. Bacias com resposta rápida apresentam baixa previsibilidade de vazão (até três dias). Observamos que o ESP continua sendo um método difícil de ser superado para previsão sazonal de vazão na América do Sul. Destacamos a importância da correção de viés nas previsões de precipitação do SEAS5 para que o H-EPS apresente previsibilidade superior ao ESP em diversas regiões da América do Sul. A habilidade SEAS5-SF varia de acordo com a estação do ano, mês de inicialização, bacia e horizonte de previsão, com maior habilidade no horizonte do mês de inicialização.

Palavras-chave: América do Sul; previsão sazonal de vazões; previsibilidade.

PRESENTATION

This dissertation was developed in the Postgraduate Program in Water Resources Engineering and Environmental Sanitation of the Hydraulic Research Institute (IPH) of the Federal University of Rio Grande do Sul (UFRGS) under the guidance of prof. Fernando Mainardi Fan of IPH-UFRGS. The research was funded by a Master's scholarship by the "Coordenação de Aperfeiçoamento de Pessoal de Nível Superior" (CAPES - process 88887.488795/2020-00) from March 2020 to June 2022.

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ACRONYMS LIST

ANA	National Water Agency (Agência Nacional de Águas)
ANN	Artificial Neural Network
BC	Boundary condition
BS	Brier Score
C3S	Copernicus Climate Change Service
CDF	Cumulative distribution function
CFS	Climatic Forecast System
CPTEC	Centro de Previsão de Tempo e Estudos Climáticos
CRPS	Continuous ranked probability score
CRU	Climate Research Unit
DEM	Digital Elevation Model
DGA	Dirección General de Aguas
DJF	December-January-February
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño-Southern Oscillation
EPS	Ensemble Prediction System
ESP	Ensemble Streamflow Prediction
ET	Evapotranspiration
GHM	Global hydrological models
GPM	Global Precipitation Measuremen
GRDC	Global Runoff Data Centre
H-EPS	Hydrologic Ensemble Prediction System
HPP	Hydropower Plant
HRU	Hydrological Response Units
IC	Initial condition
IDEAM	Institute of Hydrology, Meteorology and Environmental Studies
INA	National Water Institute (Instituto Nacional del Agua)
INPE	Instituto Nacional de Pesquisas Espaciais
JJA	June-July-August
KGE	Kling-Gupta Efficiency
LMS	Land surface model
LSM	Land surface model

MAM	March-April-May
MGB-SA	Modelo de Grandes Bacias – South America
MLP	Multi-Layer Perceptron
MOCOM-UA	Multi Objective Complex Evolution
MSWEP	Multi-Source Weighted Ensemble Precipitation
NSE	Nash Sutcliffe Efficiency
NWP	Obtained from Numerical Weather Predictions
ONS	Operador Nacional do Sistema
QPF	Quantitative Precipitation Forecasts
RS	State of Rio Grande do Sul
SA	South America
SEAS5	ECMWF fifth generation seasonal forecasting system
SENAMHI	National Meteorology and Hydrology Service of Peru
SF	Streamflow forecasting
SMAP	Soil Moisture Active Passive
SON	September-October-November
SRTM	Shuttle Radar Topography Mission
SSF	Seasonal streamflow forecast
SSF	Seasonal Streamflow Forecast
SST	Sea Surface Temperature

FIGURES LIST

TABLES LIST

SUMMARY

1. CONTEXTUALIZATION

1.1. STREAMFLOW FORECAST

Streamflow forecasting (SF) is the process of estimating future river flows. In the hydrological forecast context, streamflow is the most frequent variable investigated. However, other hydrological variables can be the forecasting target, such as runoff, soil moisture and evapotranspiration. Some examples of studies related to soil moisture, runoff and evapotranspiration forecast are the ones from Colossi (2020) and Vogel (2021). The focus of the present study is the forecast of streamflow.

According to the forecast antecedence, SF can be classified in four main categories, that can be defined as: short term, from hours to two days of antecedence; medium term, from two days up to two weeks of antecedence; sub seasonal, up to 45 days in advance; and long-term or seasonal, up to 9 months in advance (NASEM, 2016).

The set of techniques used to predict streamflow usually include a model able to simulate river streamflow under different hydrological circumstances. Mathematical models are the most commonly used method because of the computational capabilities offered by affordable computers (WMO, 2008a). They are usually classified as empirical, conceptual and physically-based models. According to Jajarmizadeh, Harun and Salarpour (2012), empirical models represent the hydrological system with mathematical equations elaborated from experimental data, but without the use of physical laws. Conceptual models, on the other hand, assume that the water dynamic in a catchment is a series of interlinked processes and storage (JAJARMIZADEH; HARUN; SALARPOUR, 2012). In this sense, conceptual models use mathematical techniques to simulate the hydrological behavior based on simplified concepts of the physical processes (WMO, 2008a). The physical-base models are the ones that try to represent hydrology only by the laws of physics. As the total comprehension of the processes occurring in a basin is very complex, as well as the full amount of data to represent this dynamic, physical-base models are currently only used to simulate limited physical systems or specific research areas (JAJARMIZADEH; HARUN; SALARPOUR, 2012).

Models can also be classified according to their spatial and temporal characteristics (JAJARMIZADEH; HARUN; SALARPOUR, 2012). About spatial features, models that represent the catchment as a single unit are called lumped; distributed models calculate values for grid cells and can simulate any scale of the catchment; semi distributed models lie between the other two. Temporarily, models can be based on time series or time steps. The time step can vary from minutes to months and can also be divided into continuous or event-based.

Variations in natural river systems streamflow are driven by basin's water storage (i.e., groundwater, snowpack, soil moisture, and channel network) and by meteorological forcing (PECHLIVANIDIS et al., 2020). Thus, hydrological models that transform rainfall into runoff and models that consider the basin's geomorphological characteristics are more realistic representations of the streamflow generation processes and take advantage of this important information (YUAN; WOOD; MA, 2015).

To the short-term forecasts, the use of observed precipitation may result in a satisfactory result. For the longer horizon forecasts (medium and sub seasonal to seasonal ranges), however, it is necessary the use of Quantitative Precipitation Forecasts (QPF) obtained from Numerical Weather Predictions (NWP) models, allowing forecasts with an antecedence greater than the basin concentration time (CLOKE; PAPPENBERGER, 2009).

In the last decades literature, the use of ensemble QPF instead of deterministic precipitations has been shown to be more suitable for hydrological forecasting (BOUCHER et al., 2011), due to the high uncertainties associated with weather forecasting. This is the reason why the Hydrological Ensemble Prediction System (H-EPS) is considered the state of the art method for the streamflow forecast (TROIN et al., 2021): it combines the use of hydrological models with ensemble Quantitative Precipitation Forecasts (QPF), resulting in probabilistic streamflow (CLOKE; PAPPENBERGER, 2009), that represent the chance of occurrence of high and low flow events.

The Ensemble Streamflow Prediction (ESP) method, originally called Extended Streamflow Forecasting, was developed in the mid-1970s for predicting affluent volumes with medium-term to seasonal horizons (DAY, 1985; TWEDT; SCHAAKE; PECK, 1977). This method is still used today in some operational flow forecasting systems due to its relative simplicity and robustness (WOOD, 2016). ESP assumes that meteorological observations in past years represent possible future occurrences of events. Thus, historical data on meteorological variables (such as precipitation and temperature) can be used to generate time series that serve as input to a conceptual hydrological model, but with the condition that the model considers the current state of moisture in the basin. It has been mainly applied as a benchmark in ensemble forecasting studies, mainly for longer horizons such as seasonal and sub-seasonal (ARNAL et al., 2018; CROCHEMORE; RAMOS; PAPPENBERGER, 2016; QUEDI; FAN, 2020).

Hydrological progress has been driven by societal needs and potential understanding given external technological opportunities (SIVAPALAN; BLÖSCHL, 2017). The uncertainty on water availability led humans to build their civilizations near water bodies, aiming to get water security. Their proximity to rivers, however, also increases the risk of being impacted in extreme events such as floods. This led humans to plan strategies and build structures in the attempt to manage water resources. Streamflow forecasting is one of the strategies used as a tool to help on the water management.

According to the horizon, the streamflow forecast finds different demand. Due to increasingly reports about devastating floods around the world, short to medium term forecasts are mostly used on watching and warning systems looking forward to anticipating events that may cause damage to urban areas (CLOKE; PAPPENBERGER, 2009; EMERTON et al., 2016; FAN et al., 2016a; SIQUEIRA et al., 2016; SPECKHANN et al., 2018). Sub seasonal to seasonal forecasts are more suitable for water management, where long-term planning of the water resources is required (CHIEW; ZHOU; MCMAHON, 2003; PEÑUELA; HUTTON; PIANOSI, 2020; QUEDI; FAN, 2020). These situations may be the preparation for a drought period or estimate the future water inflows in reservoirs. Seasonal forecasts find special demand in the hydroelectric sector: dams, in addition to energy production, supply water to the population, irrigation, and mitigate the impacts of droughts and floods.

In the next section, detailed aspects related to seasonal streamflow forecasts will be discussed, the main subject of this study.

1.2. SEASONAL STREAMFLOW FORECASTING

1.2.1. Main concepts and usage

Seasonal streamflow forecast (SSF) comprehends the long-term streamflow forecasts, ranging from one to 9 months in advance (NASEM, 2016). The scientific motivations of SSF are strongly connected to societal needs, once forecast information is directly used on the long-term management of water systems. Furthermore, the longer the antecedence the greater the benefit: antecedence means time to plan management strategies. In this sense, SSF has a great value associated and institutions around the world have been interested in improving SSF.

In 2018, the first operational global-scale seasonal hydro-meteorological forecasting system was released, the GloFAS-Seasonal V1.0 (EMERTON et al., 2018). GloFAS-Seasonal provides forecasts of high or low river flow out to 4 months ahead for the global river network through three new forecast product layers via the openly available GloFAS web interface (EMERTON et al., 2018).

At local scale, there are many studies evaluating SSF, for instance the works from Uvo and Graham (1998), Chiew, Zhou and Mcmahon (2003), Tucci et al. (2003), Demirel, Booij and Hoeskstra (2015), Collischonn et al., Van Hateren, Sutanto and Van Lanen (2019), Kompor, Yoshikawa and Kanae (2020), Peñuela, Hutton and Pianosi (2020), De Paiva, Montenegro and Cataldi (2020).

Besides the interest, SSF faces many challenges. The streamflow predictability through H-EPS method, for instance, is influenced by sources of error such as errors in the parameterization (LAN et al., 2020) and initialization of hydrological models (CROCHEMORE; RAMOS; PAPPENBERGER, 2016) and systematic rainfall errors (bias) (CROCHEMORE; RAMOS; PAPPENBERGER, 2016). Studies have shown that performance of forecasts decreases with the horizon, usually presenting satisfactory performance up to one month (ARNAL et al., 2018; PECHLIVANIDIS et al., 2020; QUEDI; FAN, 2020; SIQUEIRA et al., 2020a). However, due to the non-linearity of hydrological processes, the uncertainty about the catchment's initial conditions (IC) limits the predictability of the system. Furthermore, SSF is also very dependent on the boundary conditions, that is, the ability of the precipitation forecasts to predict precipitation on the long term. As the atmosphere is a chaotic system, it is sensitively dependent on ICs changes (LORENZ, 1993) errors in IC observation or imperfection of the models doesn't allow accurate forecasts beyond a few days (SHUKLA, 1998).

According to Moron (2020), on tropical region precipitation forecast skill is greater where daily rainfall is synchronized by intraseasonal (such as the Madden-Julian Oscillation) as well as interannual ocean-atmosphere modes of variation (such as El Niño-Southern Oscillation), especially over northern Australia and parts of the Maritime Continent, and over parts of eastern, southern Africa and northeast South America. Especially over the open ocean, atmosphere flow patterns are strongly influenced by the sea surface temperature and show little sensitivity to changes in the initial conditions (SHUKLA, 1998). These characteristics may explain the reason why ENSO has been considered the biggest source of precipitation predictability at seasonal scales in South America (WEISHEIMER et al., 2020)

In this sense, evolutions on numerical weather prediction models are great encouragers on SSF studies. In 2019, ECMWF published the ECMWF fifth generation seasonal forecasting system (SEAS5) (JOHNSON et al., 2019). ECMWF is one of the best models capable of predicting ENSO phenomenon (BARNSTON et al., 2012) and works such as Pechlivanidis (2020) and Arnal (2018) have been using this product on SSF.

1.2.2. SSF in South America

In South America, many countries would be benefited by seasonal streamflow forecasts (SSF) systems. In Brazil, the largest country in SA, SSF finds 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 investigated the seasonal streamflow predictability in Brazil. The researchers Uvo and Graham (1998) developed a set of statistical models to estimate seasonal discharge at selected sites within the Amazon Basin on the basis of tropical Atlantic and Pacific sea surface temperature. The models were generated using an extended version of the Canonical correlation analyses. It was observed that the capacity of the models in forecasting discharge varies from site to site and because of the size of the studied basins, the influence of the changes in precipitation could be felt in the discharge of the river with a delay of ~3 months. The models showed that it is possible to forecast seasonal runoff one season in advance, with a certain degree of accuracy.

Tucci, (2003) and Collischon et al. (2005), carried out seasonal flow prediction experiments for the Uruguay River basin using the MGB hydrological model and the CPTEC/INPE climate model (ensemble of 25 members). Their results showed that the climate model underestimates rainfall in almost the entire basin, especially in winter, but its predictions represent relatively well the interannual rainfall variability in the region. After a precipitation bias correction using a statistical method, the flows obtained were significantly higher than those obtained by monthly averages or medians.

On a more recent study, De Paiva et al. (2020) carried out a climatic horizon streamflow forecast study to the Três Marias reservoir (São Francisco river basin), where the generation of runoff scenarios was evaluated from two rainfall-runoff models: one conceptual, based on the SMAP model, and another based on Artificial Neural Networks (ANN), from a Multi-Layer Perceptron (MLP) model. The results were compared to the ones from the model Gevazp (AR(p) model), and the precipitation forecasts from the Climatic Forecast System (CFS) were used, with and without correction. The results were focused on the comparison between the methods.

These studies have in common their basin scale, and were issued for different locations, hydrological models and precipitation forecast data. Besides generating fragmented knowledge about the seasonal streamflow predictability, it represents only the first attempts analyzing seasonal streamflow forecasts in South America. But none of these works evaluated the continent in wide comparative manner.

On the other hand, recently, Siqueira et al. (2020a) developed a study evaluating the potential skill of continental-scale, medium-range ensemble streamflow forecasts for flood prediction in South America. The presented work adopted the original modelling frameworks from Siqueira et al. (2020a) to develop SSF studies to the entire South America Continent. The South American Large Basins Model (MGB-SA) on the forecast context was used to evaluate SSF in South America with the H-EPS method and is further explored in the next session.

1.3. MGB-AS

The South American Large Basins Model (MGB-SA) is a continental and hydrodynamic version of the MGB Model (*Modelo de Grandes Bacias*) (PONTES et al., 2017).

MGB-SA was developed considering the limitations of the global hydrological models (GHMs) and land surface models (LSMs), commonly used on large-scale modelling (SIQUEIRA et al., 2018). According to Siqueira:

> Although global-scale models can provide valuable spatiotemporal estimates of water fluxes and projections of those estimates (Sood and Smakthin, 2015), their ability to reproduce discharge observations at basin scale and to address practical water management issues is still limited (Archfield et al., 2015; Hattermann et al., 2018). Inaccuracies in runoff estimation from GHMs and LSMs may be first attributed to the

> uncertainty in global satellite precipitation products (Tian and Peters-Lidard, 2010; Sperna Weiland et al., 2015), but several studies have shown considerable differences between model outputs even when using the same meteorological forcing, given the lack of knowledge about runoff generation processes and deficiencies in parameter estimation (e.g., Haddeland et al., 2011; Gudmundsson et al., 2012; Zhou et al., 2012; Beck et al., 2017a). In particular, calibration has been found to have the largest impact on storage fluxes, evapotranspiration and discharge in comparison to variations in model structure and forcing data (Müller Schmied et al., 2014), which is a reason to call for efforts on this exercise as many of the GHMs and LSMs are not calibrated (Sood and Smathkin, 2015; Zhang et al., 2016; Beck et al., 2017a).

In this context, expanding catchment models to regional scale is considered a good alternative to overcome some global scale models limitations at the same time that makes a better use of local expert knowledge and country-specific datasets (SIQUEIRA et al., 2018).

The MGB is a conceptual, semi-distributed, large-scale hydrological model (COLLISCHONN et al., 2007; PAIVA et al., 2013) that has been largely applied in South America (COLLISCHONN et al., 2005; FAN et al., 2016a; MELLER; BRAVO; COLLISCHONN, 2012; PAIVA et al., 2013; PONTES et al., 2017; SIQUEIRA et al., 2016) The basins are divided in unit catchments delimited according to the topography and connected to each other by drainage channels. Each unit catchment has a single river reach, and water exchanges throughout the unit catchment occur only through these reaches. The unit catchments are also divided into Hydrological Response Units (HRUs), with the characteristics of vegetation cover, soil type and land use of the basin. Usually with a daily time step, the model uses conceptual and physical equations to simulate the processes:

- Soil water balance;
- Energy balance and evapotranspiration (ET). The ET calculation is based on the equation of Penman-Monteith, using an adjustment factor that takes into account the water deficit from soil;
- Canopy intercept, whose volume is expressed in terms of leaf area index;
- Generation of runoff. Runoff is computed using the Arno model (TODINI, 1996) equation while the subsurface flows and superficial occur, respectively, through linear and not linear according to the volume of water available in the soil;
- Propagation of the flow generated within the unit catchments, through the approach of linear reservoirs;

- Flow propagation along the drainage network. The propagation calculation can be performed through simpler formulations, such as the Muskingum-Cunge method (COLLISCHONN et al., 2007), as well as hydrodynamics, using the complete equations one-dimensional St. VenanT (PAIVA et al., 2013) or an explicit inertial approximation of the latter (Pontes et al., 2017).

Vertical hydrological processes (energy and water balance) occur at the level of the HRUs, while horizontal water exchanges along the drainage network occur between the unit catchments. The model calibration can be performed by defining sub-basins, where each sub-basin has a single set of parameters whose values are assigned to mini-basins. Parameters can be manually calibrated in each sub-basin or can be adjusted automatically through the use of the MOCOM-UA optimization algorithm.

MGB-SA model discretization was performed with an adapted version of IPH-Hydro Tools (SIQUEIRA, et al., 2016) applied to the HydroSHEDS flow directions map for South America with 15 arc second resolution (approximately 500 m on the line of the equator) and a threshold of 1,000 km² of drainage area to define the beginning of the drainage. The floodplain topography in each unit catchment was derived with the processing of the Bare-Earth SRTM DEM (O'LOUGHLIN et al., 2016) after 3-arc-second upscaling (approximately 90 m) for 15 arc seconds (approximately 500 m), aiming at compatibility with other raster files derived from HydroSHEDS (LEHNER; VERDIN; JARVIS, 2008).

The Bare-Earth SRTM plays an important role in estimating with better accuracy the elevation of the terrain and the elevation-area curves in the lowland regions of the Amazon, which are very influenced by the height of trees due to dense vegetation. In the application for the South America, the MGB-SA was segmented into 33479 mini-basins, aiming to obtain stretches of river with a maximum length of 15 km.

Due to the spatial scale of the model, the Multi-Source Weighted Ensemble Precipitation — MSWEP v1.1 (BECK et al., 2017) was used as input precipitation, a global precipitation database with 0.25° grid resolution. MSWEP is a combination of multiple sources of precipitation from their quality, given as a function of scale temporal (monthly, daily and sub-daily) and position in space. The method disaggregates a long-term average precipitation based on a weighted average of anomalies from precipitation of seven products: two based solely on interpolation of in situ observations (CPC Unified and GPCC), three based on satellite precipitation (CMORPH, GsMaP-MVK and TMPA 3B42RT), and two based on atmospheric model reanalysis (ERA-Interim and JRA-55). For each grid point, the weights assigned to the observations are calculated as a function of the density of positions, while the weights assigned to satellite products and reanalysis are calculated to form the performance of these bases in relation to the closest posts. Weather data were obtained from the Climate Research Unit (CRU) database (NEW et al., 2002), in version 2.0. CRU data has a resolution of 10’ and is based on normal climatological data for the period 1961 to 1990, for which data were collected through thousands of stations across the globe. Table 1 shows a summary of the databases used on MGB-SA.

Data	Data description	Reference
Digital Elevatiom Model (DEM)	Bare-Earth SRTM v 1.0 DEM, resampled from 3 to 15 arcsec (~90 m to ~500 m)	O'Loughlin et al. (2016)
Flow directions map	Global HydroSHEDS Flow Direction map, 15 arcsec	Lehner et al. (2008)
Precipitation	Global Multi-Source Weighted Ensemble Precipitation v 1.1 (MSWEP), 0.25º	Beck et al. (2017)
Climate	Monthly climatological averages from *Climate Research Unit* (CRU Dataset v. 2.0)	New et al. (2002)
Streamflow data	In situ observations - ANA (Brasil), Naturalized reservoir streamflow (ONS - Brasil), INA (Argentina), IDEAM (Colômbia), DGA (Chile), SENAMHI (Peru e Bolívia), ORE-HyBAM (Internacional), GRDC (Internacional)	-
Land use / Soil type	South America Hydrological Response Units (HRUs) map	Fan et al. (2015)
Hydrographic regions	Brazilian hydrographic divisions (ANA): https://metadados.snirh.gov.br/geonetwork/srv/por/catalog.search#/home Aquastat map: https://data.apps.fao.org/map/catalog/srv/eng/catalog.search?id=37174#/home	-

Width / Depth of full river channel	Geomorphological relations of regional studies, Amazônia, Prata, bacia da Lagoa dos Patos (RS) Global bankfull width and depth database (other locations)	Andreadis et al. (2013), Paiva et al. (2013), Pontes (2016), Beighley e Gummadi (2011)

Table 1 - MGB-SA databases

In the calibration and validation process, in situ flow data were obtained from institutions from different countries, including ANA/Brazil, IDEAM/Colombia, INA/Argentina, SENAMHI/Peru, SENAMHI/Bolivia, DGA/Chile, ORE-Hybam and GRDC, in addition to flows naturalized from the National Electric Service Operator (ONS) at various controlled points by operation of reservoirs. Only posts with more than 10,000 km² of drainage area, totaling about 600 posts. Information on river geometry, as full gutter width and depth were extracted from the global database of (ANDREADIS; SCHUMANN; PAVELSKY, 2013) and regional studies in the Amazon, Prata and Lagoa dos Patos basins. Manning coefficient values were globally maintained at 0.030, with some adjustments in specific Amazonian tributaries according to (PAIVA et al., 2013).

To avoid an excess of parameterization in the model due to the coarser resolution of the input databases (in relation to those typically used in scale models regional), sub-basins delineated from the intersection of a global map were adopted of lithology/geology and a map of the great hydrographic regions of South America. A traditional “peer-to-peer” type calibration was not performed on the original version of the MGB-SA. The MGB-SA calibration procedure was performed manually, without using an optimization algorithm.

Regarding performance, the continental model simulations resulted in daily flows with similar accuracy to large-basin scale hydrological model applications hydrographic (e.g. Amazonas and Prata). Hydrographs are satisfactorily represented in seasons of large rivers, lagged by flood wave travel for a long time, in addition to hydrographs with rapid peaks of smaller rivers. The KGE coefficient (NSE) was greater than 0.6 in 70% (55%) of the analyzed posts, being better in large rivers and regions moist. The results were also compared to those generated by hydrological models global, concluding that continental modeling with the MGB-

SA improved the accuracy of flow estimates (Siqueira et al., 2018) due to manual calibrations, modeling with physics suitable for the region (large river hydrodynamics) and a priori experience in hydrology of the region.

1.4. RESEARCH STRUCTURE

In this work, MGB-SA streamflow predictability and the current potential of seasonal streamflow forecast in South America are discussed. Figure 1 presents the river places where we will take a closer look at the results, and a summary of the main items of this work.

The present Chapter (Section 1) presents a contextualization of the streamflow forecast concepts and methods. Also, we take a closer look at the seasonal streamflow forecast in South America actual literature found research and at the hydrological model chosen for this study, MGB-SA. Next and last, we present the objectives of this dissertation thesis.

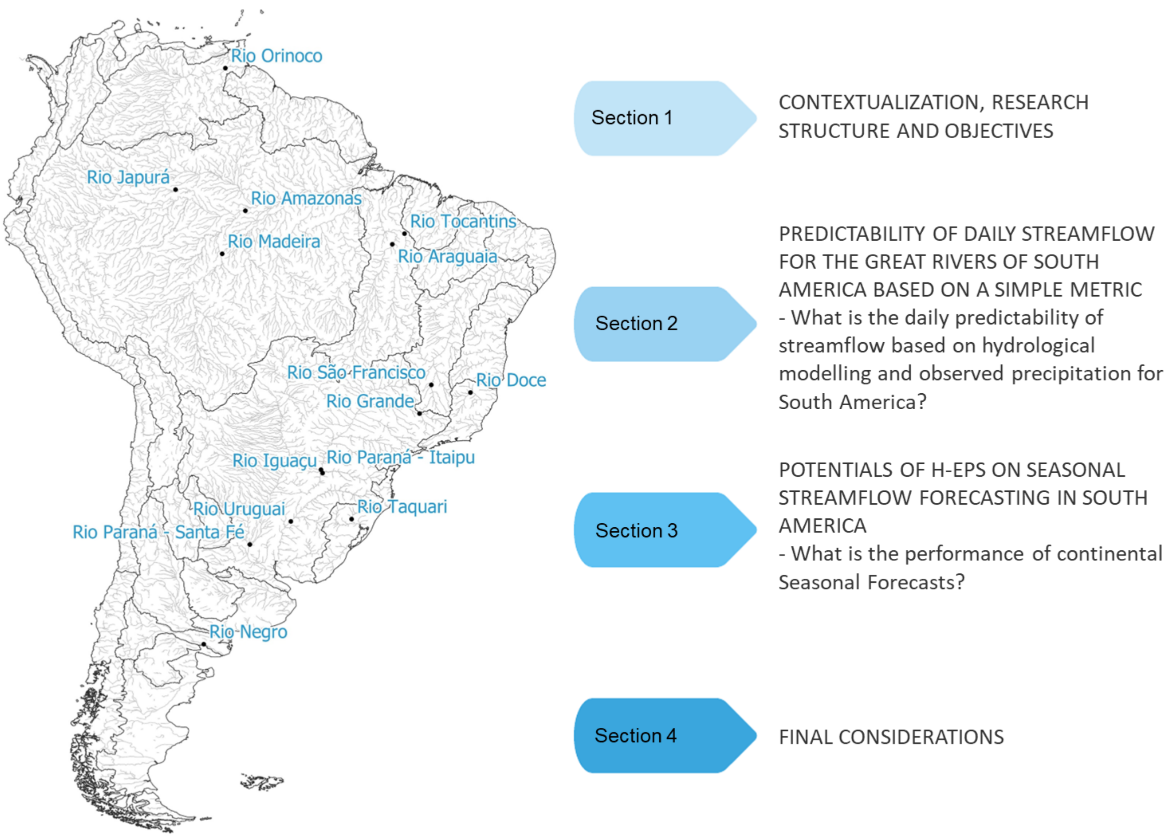


Figure 1 - Research structure flowchart

The results, methodology and main outputs of the present research were developed in the form of two scientific articles. The first, presented in Section 2, evaluates the influence of the initial conditions and meteorological forcing on streamflow forecasting in SA through the estimate of streamflow predictability. Two different SF experiments are performed and predictability is considered as the number of days forecast have NSE (KGE) > 0.95, when compared to the model's simulation. This study brings important insights about the predictability of the MGB-SA main rivers in South America.

The second article counts with a H-EPS for seasonal streamflow forecast in SA combining the MGB-SA model and precipitation forecast data from EMCWF (forecast and hindcast) with precipitation bias correction. The H-EPS skill were compared to an ESP as benchmark. Section 3 presents the results of this study. Section 4 presents the final considerations.

1.5. OBJECTIVES

1.5.1. Main objective

Evaluate streamflow predictability of natural flows of rivers in large basins (>1000 km²) in South America from continental hydrologic modelling; and assess the potentials of seasonal streamflow forecasts in the continent.

1.5.2. Specific objectives

Considering South America as study area, and H-EPS seasonal streamflow forecasts results:

- Quantify streamflow predictability with and without precipitation information;
- Describe streamflow forecasts spatial variability;
- Analyze bias correction effect on precipitation forecast improvement;
- Observe where H-EPS outperforms ESP and where not.

2. PREDICTABILITY OF DAILY STREAMFLOW FOR THE GREAT RIVERS OF SOUTH AMERICA BASED ON A SIMPLE METRIC

This section presents the results of the first article proposed in this dissertation. Many works gave important information about streamflow predictability and its spatial variability (LI et al., 2009; LIU et al., 2021; PAIVA et al., 2012; PECHLIVANIDIS et al., 2020; SHUKLA, 1998; SHUKLA; LETTENMAIER, 2011; YUAN; WOOD; MA, 2015). Among them, the work of Pechlivanidis et al. (2020), developed for Europe, brought many of the most recent insights about seasonal streamflow predictability and the drivers that control its quality. In the South American context, there are two global scale works (SHUKLA et al., 2013; YOSSEF et al., 2013) that contemplate SA and which results could be directly applied to the continent. However, because of its global scale, these works don't give details about predictability at basin scale. To hold the following discussions about streamflow predictability in South America, more spatial details are needed.

From the literature, the spatial comprehension of streamflow predictability in SA is indirectly reported in the works that evaluated streamflow forecasts, with the results and discussions obtained from different basins, design experiments and objectives. In other words, these studies do not draw a general and spatial panorama of predictability in the South America territory.

In this sense, the following scientific article was idealized as a preliminary overview of streamflow predictability in SA. This article is Accepted on the Hydrological Sciences Journal (PETRY et al., 2022).

ABSTRACT – In this work, the role of the initial conditions (ICs) and boundary conditions (BCs) on the predictability of natural flows of rivers in large basins (>1000km²) in SA from the MGB-SA model was investigated. We proposed an analysis based on a simple metric: predictability was estimated by the number of days the streamflow forecasts had a performance greater than a chosen threshold. The role of ICs was assessed through null precipitation experiments and the role of BCs trough climatological rainfall. For the experiments with the metric KGE with threshold of 0.95, the study shows that streamflow predictability from the ICs is relatively high (up to 40 days) in the main river reaches of basins with flat relief. The increase in predictability due to climatology-based BCs mostly occur in areas that already have high

predictability based on ICs. Basins with fast response present low streamflow predictability (up to three days).

Keywords – South America; streamflow forecast; predictability.

2.1. INTRODUCTION

Streamflow forecasting (SF) is the process of anticipating future flows in water bodies. In Hydrology, according to the antecedence, they can be divided into: short / medium term forecast, of hours up to two weeks in advance; sub seasonal, up to 45 days in advance; and long-term or seasonal forecast up to 9 months in advance (NASEM, 2016).

The public/civil defense sector, the agriculture and the hydroelectric sector are usually the main interested in streamflow forecast information, as they help in the management of water resources, mostly during floods and droughts (CHIEW; ZHOU; MCMAHON, 2003; KAUNE et al., 2020; PEÑUELA; HUTTON; PIANOSI, 2020; DEMERITT et al., 2013; FAN et al., 2016, 2017; PAPPENBERGER et al., 2015; SIQUEIRA et al., 2016, 2020; VAN HATEREN; SUTANTO; VAN LANEN, 2019). To the hydroelectric sector forecasts are important not only to improve energy production, but also to determine the best ways to manage the reservoir inputs and outputs among the year (CASSAGNOLE et al., 2020; CROCHEMORE et al., 2017; DE PAIVA; MONTENEGRO; CATALDI, 2020; FAN et al., 2015; KOMPOR; YOSHIKAWA; KANAE, 2020).

In the forecasting context, predictability (the ability to be predicted) is associated with deterministic chaos in which, for certain systems, there is a strong dependence on their initial conditions (ICs) and their boundary conditions (BCs) (LORENZ, 1975; SHUKLA, 1998). On streamflow predictability by hydrological modeling, the initial conditions are, for instance, groundwater, soil moisture, snowpack and floodplains (discharge from water storage across the basin). Some of the boundary conditions are rainfall, snow and temperature (PECHLIVANIDIS et al., 2020; YUAN; WOOD; MA, 2015). In attempts to identify the role of the sources of streamflow predictability the methods Ensemble Streamflow Prediction (ESP) and reverse ESP (revESP) developed by Wood and Lettenmaier (2008), have been the most common methods applied (WOOD; LETTENMAIER, 2008), has been the most common method applied (LI et al., 2009; LIU et al., 2021; PAIVA et al., 2012; SHUKLA et al., 2013; SHUKLA; LETTENMAIER, 2011; YOSSEF et al., 2013). In both methods, a hydrological model is used, forced by ensemble meteorological forcings resampled from historical data on the ESP, and forced by ICs resampled from historical data on the revESP. These methods can identify the primary contributors to hydrological forecasting, however, there isn't always evidence connecting streamflow predictability with physical drivers (PECHLIVANIDIS et al., 2020). Furthermore, the method is computationally heavy and its understanding requires specific technical knowledge, which limits its use by decision makers without all the technical background. Apart from ESP and revESP, hydrological models can be used to understand streamflow predictability though streamflow experiments, as following proposed.

On a basin, the water originated from the initial conditions tends to be the first to reach the outlet. After a few periods of time the water from the boundary conditions starts to contribute on the outlet streamflow. Considering this behavior, in this work we propose a predictability analysis based on hydrological modeling and a simple and widespread performance metric. To illustrate our proposal, let’s consider a daily deterministic streamflow forecast where the precipitation forecast is null. It is expected some skill in the forecast during the first periods of time even with null precipitation, due to the model’s initial conditions. In this sense, the number of days when the forecast presents a satisfactory performance can be treated as an estimate of daily streamflow predictability of initial conditions. If we add some average/climatological precipitation as forecast information, the new skill represents the predictability due to initial conditions and climatological boundary condition. The key to find the predictability value here is determining when the chosen streamflow performance metric will be degraded (below a threshold) in comparison to a perfect streamflow forecast application (equivalent to an observation). Figure 2 illustrates this predictability approach.

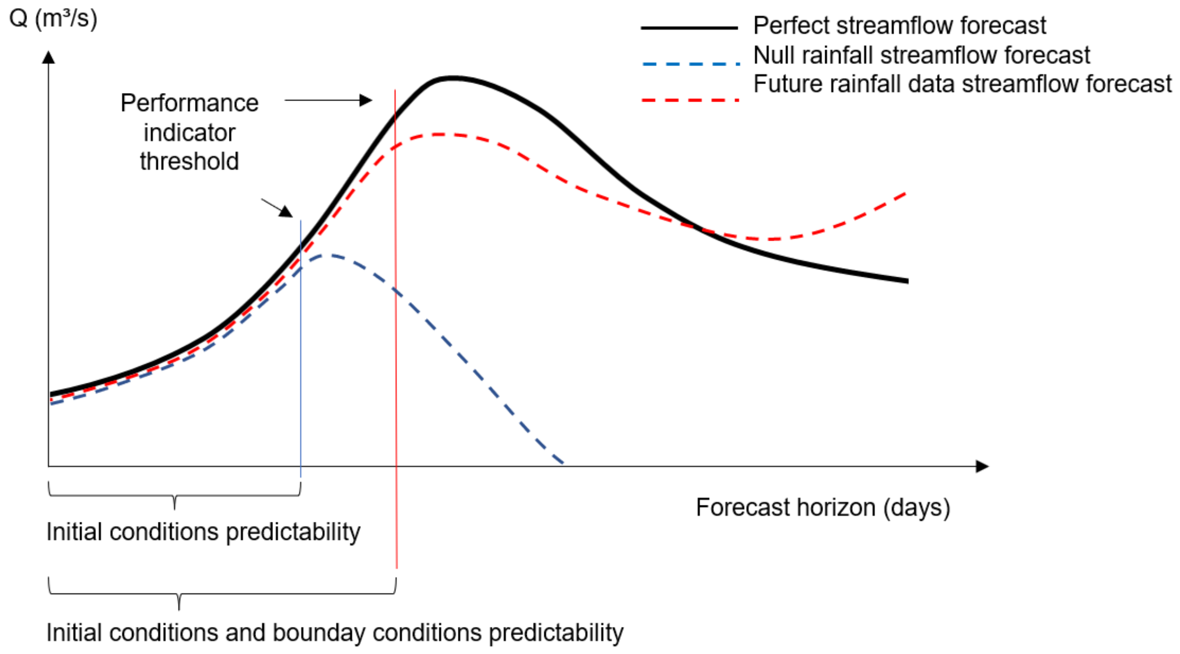


Figure 2 - Predictability approach

The knowledge of the streamflow predictability of rivers from important catchments can contribute to the dimensioning of forecasts systems, an important water management tool. Countries affected by water-related disasters and with hydroelectric sector latent are the ones that would mostly benefit from these systems, for instance Brazil, in South America, which accounts for 65% of the energy produced (EPE, 2021).

In South America (SA), some authors developed studies focused on specific basins that produced important results at the basin level, the works from Uvo and Graham ,1998, Tucci et al., 2003, Collischonn et al., 2005, Siqueira et al. 2016, Fan et al., 2016, 2017 and Quedi and Fan, 2020 and Greuell and Hutjes 2021. These studies, however, produced fragmented information about the streamflow forecast in SA. Large-scale, multi-basin modeling can contribute to a deeper understanding of the dynamics of hydrological processes (PECHLIVANIDIS; ARHEIMER, 2015), due to its ability to cross territorial borders and cover different geographic and climatic regions.

The H-EPS method is considered the state of the art of streamflow prediction (TROIN et al., 2021). This method typically combines the use of hydrological models with ensemble Quantitative Precipitation Forecasts (QPF), resulting in probabilistic streamflow (CLOKE; PAPPENBERGER, 2009). According to Siqueira (SIQUEIRA et al., 2018) expanding catchment models to regional scale is considered a good alternative to overcome some global scale models limitations while making a better use of local expert knowledge and country-specific datasets (SIQUEIRA et al., 2018).

In this context, daily streamflow predictability of great rivers in South America (drainage area greater than 1000km²) was analyzed in this work. For this, the model MGB-SA (SIQUEIRA et al., 2018) was forced with two rainfall products: zero (null) rainfall and climatological rainfall and the experiments were guided by three scientific questions: (i) what is the daily streamflow predictability based on initial hydrologic conditions? The answer to this question is given by the null precipitation experiments and provides an estimate of the importance of initial conditions for predictions across the SA; (ii) when a rainfall corresponding to the climatology in the forecast horizon is adopted, does the predictability increase? The answer to this question provides an estimate of which regions the simple inserting average rainfall information as a boundary condition improves forecasting performance; (iii) what is the predictability given by the climatological rainfall boundary condition? This last question is answered by comparing the forecast results of zero rainfall and climatology and presents the magnitude of predictability increase given by climatological forcings.

The daily deterministic streamflow predictions experiments covered short to seasonal horizons and resulted in continental streamflow predictability maps, that besides answering the scientific questions, guided discussions about variability and spatial patterns of streamflow predictability in South America and serves as technical products of the research.

2.2. STUDY AREA

South America (SA) is a subcontinent of America, with an area of approximately 17.8 million square kilometers. Much of its territory (80%) is under the influence of a tropical climate, where there is a large volume of rainfall distributed in a rainier and hotter season and a drier season. The continent presents a non-homogeneous precipitation regime, spatially and temporally. This is due to the diversified geography, which enables the development and performance of different atmospheric systems (REBOITA et al., 2012). According to Reboita et al. (2012) South America can be divided in eight precipitation regimes areas, described in Table 2.

	Region	Characteristics
R1	Southwest of SA (Central-South of Chile and Far West of Central-Southern Argentina)	Winter precipitation maximums and minimums of Precipitation in summer, except in the southernmost part of the R1, where precipitation is practically homogeneous throughout the year. Annual total varies between 1000 and 1700 mm.
R2	Northern Chile, Northwest and Central-South Argentina	Precipitation is practically homogeneous throughout the year and with a low annual total (less than 350 mm/year). In the Atacama Desert, northern Chile, rainfall is less than 100 mm/year.
R3	West of Peru, West and South of Bolivia, North and Center-East of Argentina and Center-North of Paraguay	Rainfall maximums in summer and minimums in winter. The annual total varies between 350 and 700 mm, except in east-central Argentina and Paraguay, which varies between 700 and 1400 mm.
R4	Southern Brazil, Southern Paraguay and Uruguay	Precipitation is practically homogeneous throughout the year. The annual total is high (1050-1750 mm/year) and is even higher in western southern Brazil on the border with Paraguay (1750-2100 mm/year).
R5	Northwest to Southeast of Brazil including Equator and North of Peru	Rainfall maximums in summer and minimums in winter. The annual total varies along the R5: in the northern sector it is over ~2450 mm, in the Midwest and southeast it is ~1500 mm.
R6	North of the North Region of Brazil and Coast of the Northeast of Brazil	Rainfall maximums in the first half of the year. In the north of the northern region of Brazil the annual total is 2000 mm, while in the coast of northeastern Brazil it is 1500 mm.

R7	Brazil's Northeast Sertão	Rainfall maximums in summer and minimums in winter, but the totals are reduced (between 200 and 500 mm/year).
R8	North of South America (Colombia, Venezuela and Guyana)	Precipitation is abundant year-round, but with higher winter totals. The annual total is over 1500 mm.

Table 2 - Precipitation regimes in South America (REBOITA et al., 2010)

South America has three mountainous regions that draw the subcontinent's outline: the Andes Mountains, the North-Amazonian residual plateaus and plateaus and mountains of the Atlantic-East-Southeast (Figure 3 a). Among these regions are lowland areas where the three main hydrographic basins in South America are located: Amazon, Orinoco and La Plata, and these humid areas can be seen on Figure 3 a (FLEISCHMANN et al., 2021). Important river locations and Hydroelectric Power Plants (HPP), whose predictability will be further discussed, are shown in Figure 3 c.

Figure 3, b shows the drainage area of MGB-SA river reaches and Figure 3, c the baseflow index, a rate between the 10º percentile of the streamflow permanence curve (Q90) and the 50º percentile (Q50). This index is an indicator of the proportion of streamflow originating from groundwater stores, excluding the effects of catchment area (SMAKHTIN, 2001). Rivers where the baseflow has a high contribution to the total flow, present index values close to one. In these rivers, the baseflow acts as a natural flow regulator. Rivers with low base flow contribution present index values close to zero and have greater hydrograph variation during rains and proneness to flood formation.

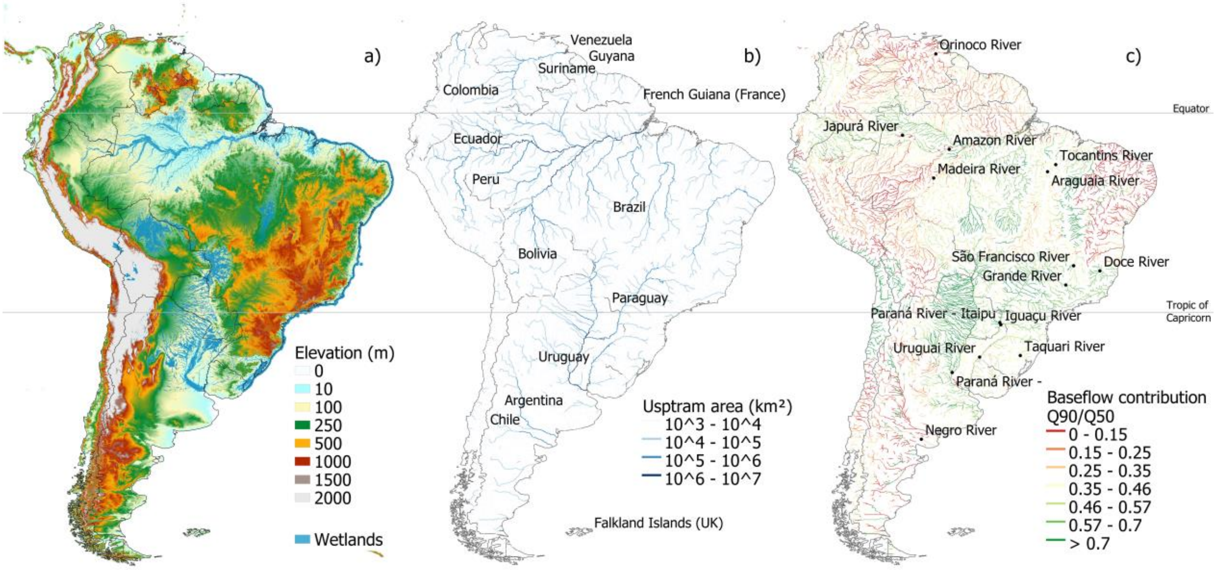


Figure 3 - South America characteristics maps of a) humid areas and elevation map; b) river’s upstream area; c) river’s baseflow index

2.3. METHODOLOGY

The flowchart methodology is shown in Figure 4. The study period was from 1990 to 2010, totalizing 20 years. MSWEP database was used as a proxy of continental rainfall observations, as further explained.

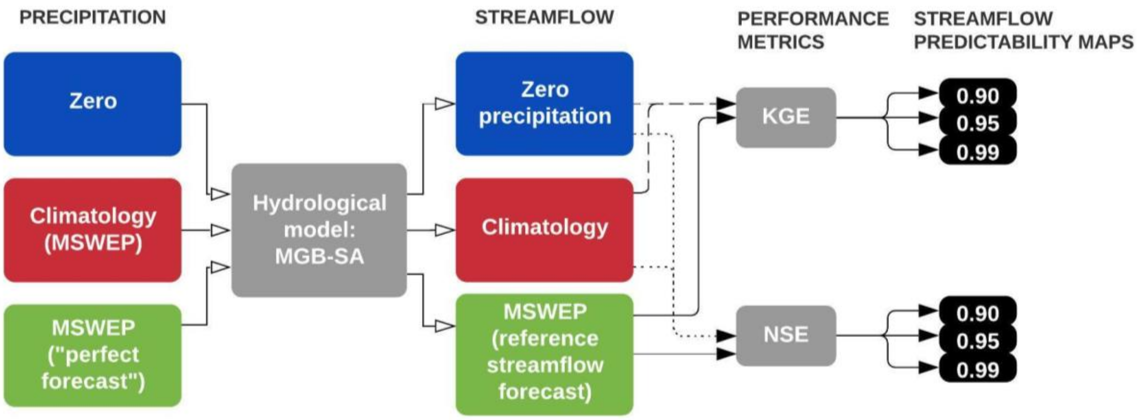


Figure 4 - Methodology flowchart

2.3.1. MGB-SA

The South American Large Basins Model (MGB-SA) (SIQUEIRA et al., 2018) is a continental and hydrodynamic version of the MGB conceptual semi-distributed hydrological model (PONTES et al., 2015), which has been applied and consolidated in large tropical basins in South America (COLLISCHONN et al., 2005, 2007; FAN et al., 2016a; PONTES et al., 2017; QUEDI; FAN, 2020; SIQUEIRA et al., 2016).

Information of land use and soil type are used to compute water budget and energy balance at a daily timestep and are contained in the Hydrological Response Units (HRU). Propagation of surface, subsurface and groundwater runoff to the main channel is computed with linear reservoirs in order to represent catchment delay and attenuation. Flow routing in the river network and associated discharge, water surface elevation and flood extent are simulated using a 1D local inertia hydrodynamic model based.

MGB–SA was manually calibrated with hundreds of in situ observations. For the study period (1990 – 2010) the model showed a good performance (NSE (KGE) > 0.6 in more than 57% (70 %) of the gauges evaluated). Besides, it presented an improvement around 20 days of timing when compared to individual global models (SIQUEIRA et al., 2018). In Figure 5, performance results for 604 streamflow gauges can be seen. More details about MGB-SA can be found in the paper of (SIQUEIRA et al., 2018).

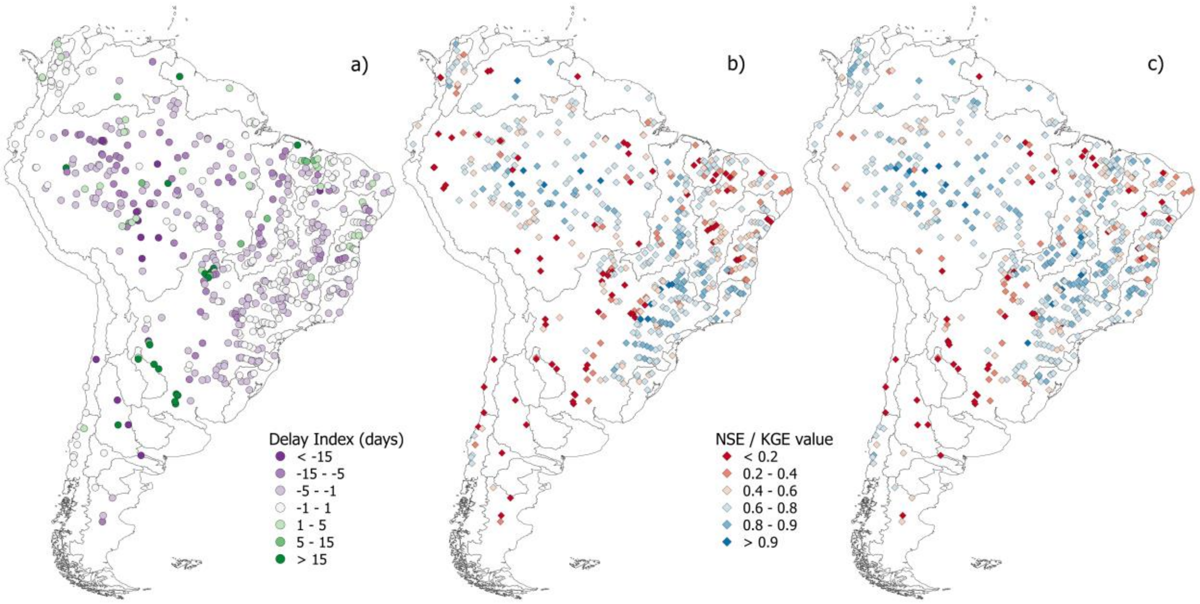


Figure 5 – Performance of MGB-SA from 1990 to 2010, a) presents the delay index (days); b) NSE; and c) KGE

2.3.2. Daily streamflow experiments

For the study period, three different forecasts were simulated. The first with null (zero) rainfall data in the forecasts horizons; the second with a climatological (average) rainfall data in the forecast horizons; and the third with the Multi-Source Weighted Ensemble Precipitation v1.1 (MSWEP) rainfall time series.

MSWEP v1.1 (BECK et al., 2017) is a database that combines observed, satellite and reanalysis data. In grid format, it has a spatial resolution of 0.25º and a daily temporal resolution, with global coverage and data from 1979 to 2015. This is the data used in the MGB-SA as a meteorological forcing of rain. Here, MSWEP is considered as the observed rainfall data, or, what is occasionally claimed as the "perfect forecast"(FAN et al., 2015). In this sense, the experiments using MSWEP historical records are considered here as reference simulations, assuming a perfect model condition. The predictability obtained in this case is a theoretical predictability, which may be greater than the real predictability at each point of interest if observations were used for everywhere. It may occur because the model is a simplified representation of the terrestrial hydrological system and the precipitation information here is assumed to be perfect, which is not true. As observations are not available to all the river reaches, this is the best approach to draw the continental overview.

Climatology represents the daily average of all years of data available by MSWEP. The use of climatology was adopted considering it offers an intermediate skill between null precipitation and precipitation forecasts, once it realistically represents the effect of seasonality on rivers flows, common on tropical watersheds.

To run the experiments, the data were reorganized into files that simulated deterministic rainfall forecast data, in the following format: forecasts with a 215-day horizon, issued on the first day of each month. Considering the experiment period (1990-2010), 240 “precipitation forecast” files were created. The experiments were carried out for the 33749 unit-catchments of the MGB-SA model and their respective river reaches.

2.3.3. Daily streamflow predictability analysis

Two metrics were chosen to evaluate streamflow predictability: Nash Sutcliffe Efficiency (NASH; SUTCLIFFE, 1970) and Kling–Gupta Efficiency (GUPTA et al., 2009). The Nash Sutcliffe Efficiency (NSE) equation is

$$NSE = 1 - \frac{\sum_{i=1}^{n}(OBS_i - SIM_i)^2}{\sum_{i=1}^{n}(OBS_i - \underline{OBS})^2} \qquad (1)$$

in which OBSi are the observation values, SIMi the simulated values and OBS bar is the observation values average. NSE is the absolute difference between observed and simulated, which is then normalized by the variance of the observed discharge to get rid of any bias (KRAUSE; BOYLE; BÄSE, 2005). It ranges between -∞ and 1, with 1 being the perfect fit.

The Kling–Gupta Efficiency (KGE) equation is

$$KGE = 1 - \sqrt{(r-1)^2 + (\frac{\sigma_{sim}}{\sigma_{obs}} - 1)^2 + (\frac{\mu_{sim}}{\mu_{obs}} - 1)^2} \qquad (2)$$

where r is the linear correlation between observations and simulations, σobs is the standard deviation in observations, σsim the standard deviation in simulations, μsim the simulation mean, and μobs the observation mean. KGE ranges from -∞ to 1, and like NSE, KGE = 1 indicates perfect agreement between simulations and observations.

NSE is a statistic coefficient used for assessing the goodness of fit of hydrologic models (MCCUEN; KNIGHT; CUTTER, 2006a). Despite the problems pointed by some studies in relation to the use of NSE (e.g., its sensitivity to peak flows, at the expense of better performance during low flow conditions), Krause, Boyle and Base (2005) highlighted that most of the efficiency coefficients have pros and cons which have to be taken into account during model calibration and evaluation. NSE can be applied to a variety of model types what shows its flexibility as a goodness-of-fit statistic (MCCUEN; KNIGHT; CUTTER, 2006a), remaining a widely used performance metric (ALTHOFF; RODRIGUES, 2021; GUPTA et al., 2009; KRAUSE; BOYLE; BÄSE, 2005; MCCUEN; KNIGHT; CUTTER, 2006b; PONTES et al., 2017; SIQUEIRA et al., 2018). In this sense, NSE was chosen to assess the first large-scale streamflow predictability estimates for South America proposed in this study.

In contrast to NSE, KGE is a balanced solution among the components variability α, bias β, and correlation r measures, decomposed from the NSE by computing the Euclidian distance in the three-dimensional Pareto front of the three components (SEOK LEE; IL CHOI, 2021). Since its formulation, KGE has been increasingly applied for model calibration and evaluation (BECK et al., 2019; CROCHEMORE; RAMOS; PECHLIVANIDIS, 2020; PECHLIVANIDIS; ARHEIMER, 2015; PONTES et al., 2017) once it achieved better variability performance than the NSE calibration results (GUPTA et al., 2009).

The predictability approach of this study considers predictability as the number of days (from 1 to 215) on which the streamflow forecast NSE/KGE is surpassed or equaled to a threshold. As one can have criticism in the adoption of a single value for the proposed methodology, to capture uncertainty limits of the proposed predictability, the chosen thresholds were 0.90, 0,95 and 0.99. As observed by Knoben, Freer and Woods (2019), NSE and KGE values cannot be directly compared, and we clarified here that this is not our goal. The choice of the same threshold for both metrics occurred because they represent similar performances.

NSE and KGE were calculated for each of the antecedence to determine predictability in term of days. For that, time series of streamflow forecasts of each antecedence were assembled from the experiments results and compared to the reference forecast, for each stretch of river MGB-SA.

Maps for the two streamflow experiments (null rainfall and climatology) and the three NSE/KGE thresholds (0.90, 0.95 and 0.99) were elaborated. Also, as in this study it is more important to understand the spatial patterns of streamflow predictability than the value itself, and as there is an uncertainty regarding the adopted thresholds, the predictability values were always presented in a few days' intervals.

2.4. RESULTS AND DISCUSSIONS

2.4.1. Point location analysis

As a first approach to results, a point analysis was performed for 15 selected locations, to illustrate the results generated by the experiments from a hydrograph perspective. Point analysis also included a further view of results for discretized seasons DJF (December-January-February), MAM (March-April-May), JJA (June-July-August) and SON (September-October-November). Figure 6 presents the hydrographs of the experiments.

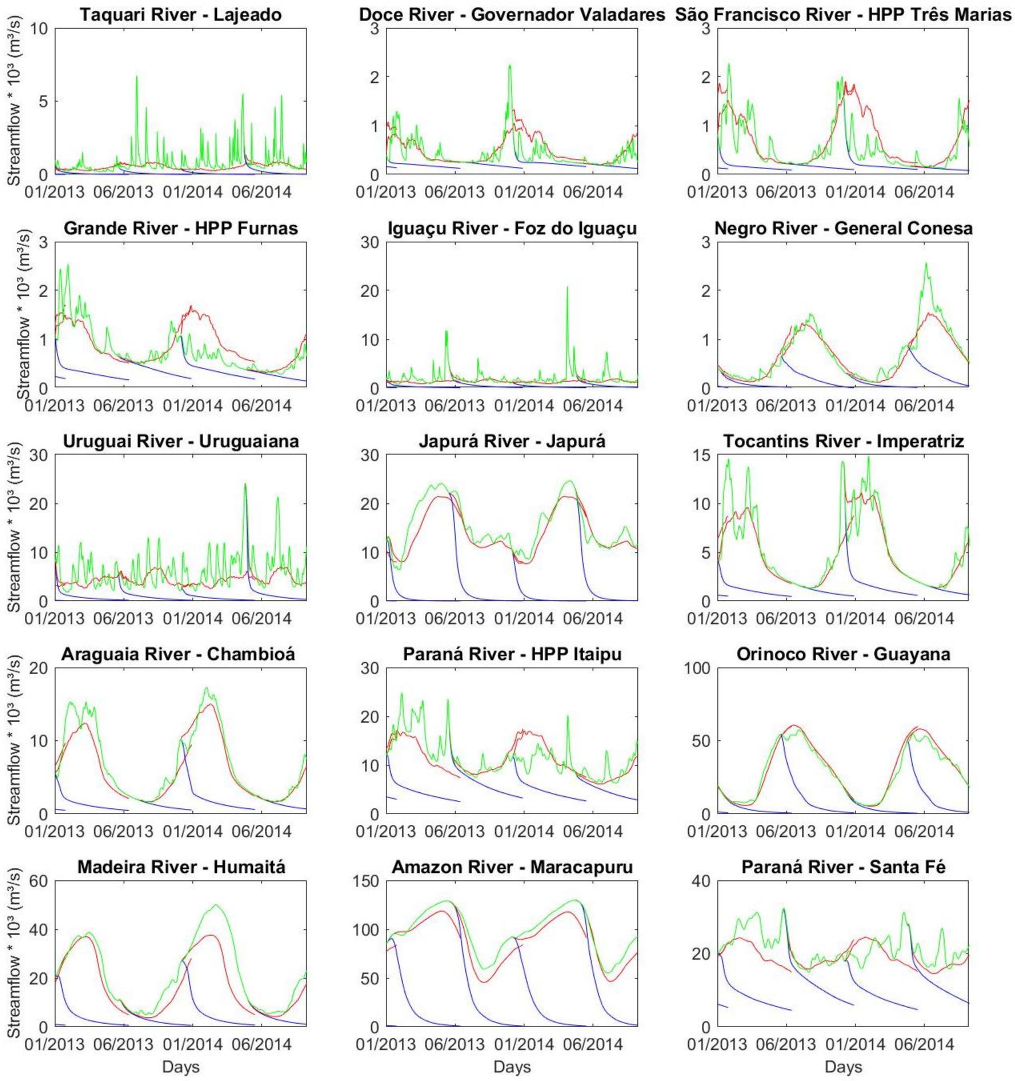


Figure 6 - Hydrographs of simulated streamflow. Green represents the reference experiments, red climatology and blue zero rainfall

The hydrographs have different flow rates. Some rivers, for instance Orinoco, Tocantins, Araguaia and Madeira have a much more expressive seasonal behavior. While these places intersperse periods of high and lower flows, Uruguay and Taquari in the South of Brazil, show streamflow without seasonal pattern. In these places, the streamflow varies within specific events during the year. This behavior is due to the rainfall: while most parts of South America have a rainy season, the South of Brazil experience rains more homogeneously distributed throughout the year.

The Amazon basin has a diverse hydrological behavior. Although it rains all year, in general, the smallest rains are observed between the months of July and September. Periods with more rain can happen from December to May. Due to the flat relief of most part of the basin, floods waves are delayed, and the flood peaks can be observed with months of difference from the rainy season (UVO; GRAHAM; GRAHAM, 1998). Both characteristics working together makes it possible to observe flood peaks in very different parts of the year throughout the Amazon Basin.

Figure 7 shows the KGE of the zero precipitation streamflow experiments for the 15 river points. Figure 8 shows the KGE of climatological streamflow experiments. Annual and seasonal NSE values were plotted. NSE results are very similar and can be found on the APPENDIX I and APPENDIX II. From the figures it is possible to observe that some rivers maintain high and constant KGE values up to about 10 days for zero rainfall, and 20 days or more for climatology (annual values). This behavior may be related to the basin drainage area: greater the area, longer is the travel time of the water across the basin. According to (GHIMIRE et al., 2020), daily streamflow presents strong basin size dependence. Table 3 presents the basin area for the 15 river points sorted from smallest to largest area, and the Figure 7 and Figure 8 are in the same order. The basins with smaller area have KGE values that rapidly decay in the first days of the forecast.

	Name	Drainage area (km²)
1	Taquari River - Lajeado	24034
2	Doce River – Governador Valadares	40924
3	São Francisco River – HPP Três Marias	51159
4	Grande River – HPP Furnas	52144
5	Iguaçu River – Foz do Iguaçu	67574
6	Negro River – General Conesa	109500

7	Uruguay River - Uruguaiana	191274
8	Japurá River - Japurá	249848
9	Tocantins River - Imperatriz	302482
10	Araguaia River - Chambioá	373100
11	Paraná River – HPP Itaipu	826704
12	Orinoco River - Guayana	926943
13	Madeira River - Humaitá	1097248
14	Amazon River - Maracapuru	2202584
15	Paraná River - Santa Fé	2483485

Table 3 - Basins’ drainage area

From Figure 7 and Figure 8 it is observed that predictability vary among the seasons. For the zero rainfall experiments, predictability is greater during the drought periods of the year. In the hydrographs of the rivers Madeira, Amazon, Orinoco, Araguaia, Grande and Negro this behavior is evident. For the climatological experiments, predictability varies less among the seasons, however, predictability is significantly higher from the zero rainfall experiments. The basins with seasonal behavior benefited more from the addition of meteorological forcing in the forecast than areas without seasonal pattern. This happens because rain is the element that gives the seasonal characteristic to the hydrological behavior, thus, when this information is added, all seasons show an increase in predictability.

It is also observed that the performance of forecasts decreases with the horizon, an expected behavior already reported in several studies (ARNAL et al., 2018; PECHLIVANIDIS et al., 2020; QUEDI; FAN, 2020; SIQUEIRA et al., 2020a).

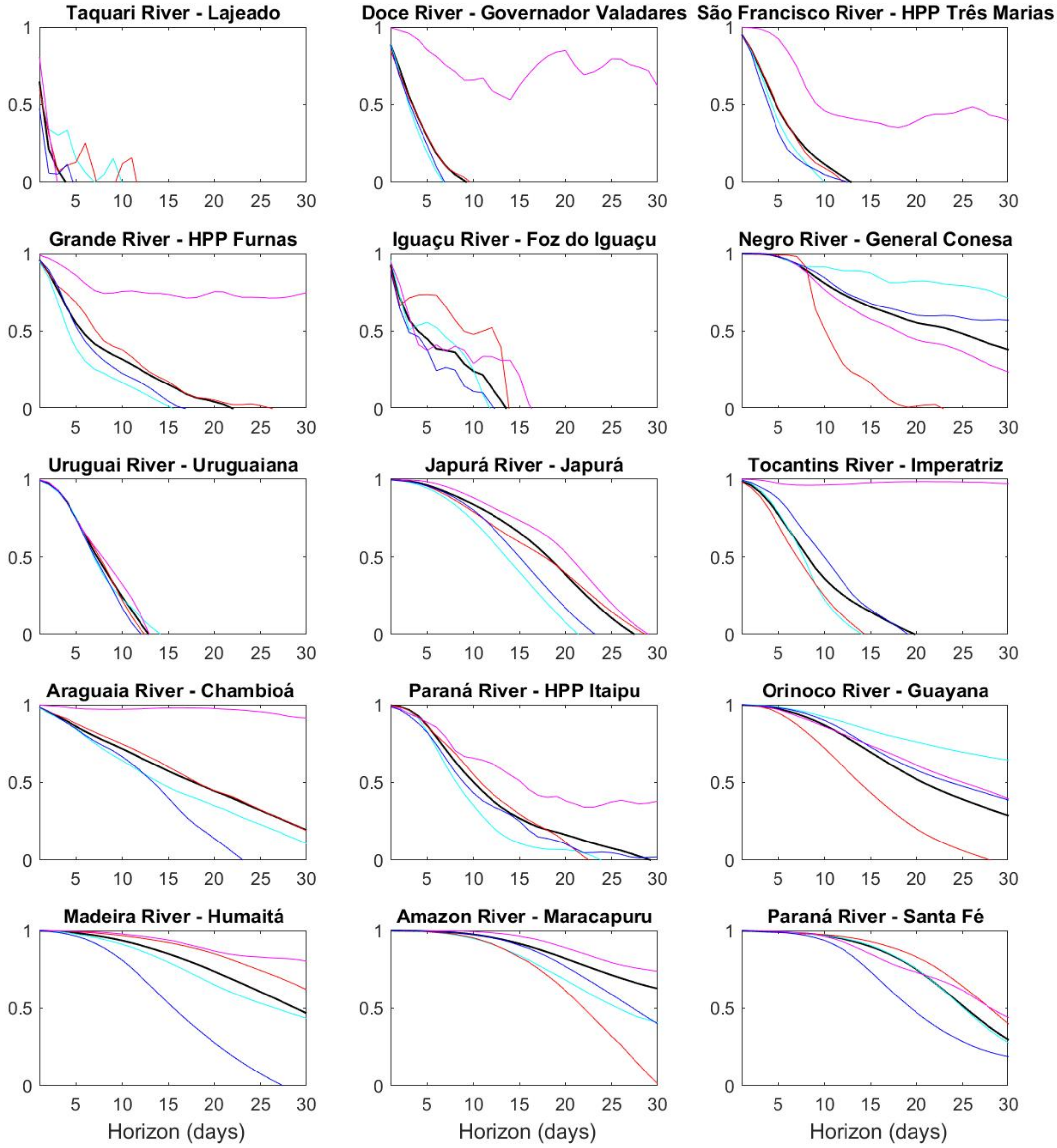


Figure 7 - Performance indicator (KGE) for the zero rainfall experiments up to a 30-day horizon for annual (black), DJF (cyan), MAM (red), JJA (magenta) and SON (blue)

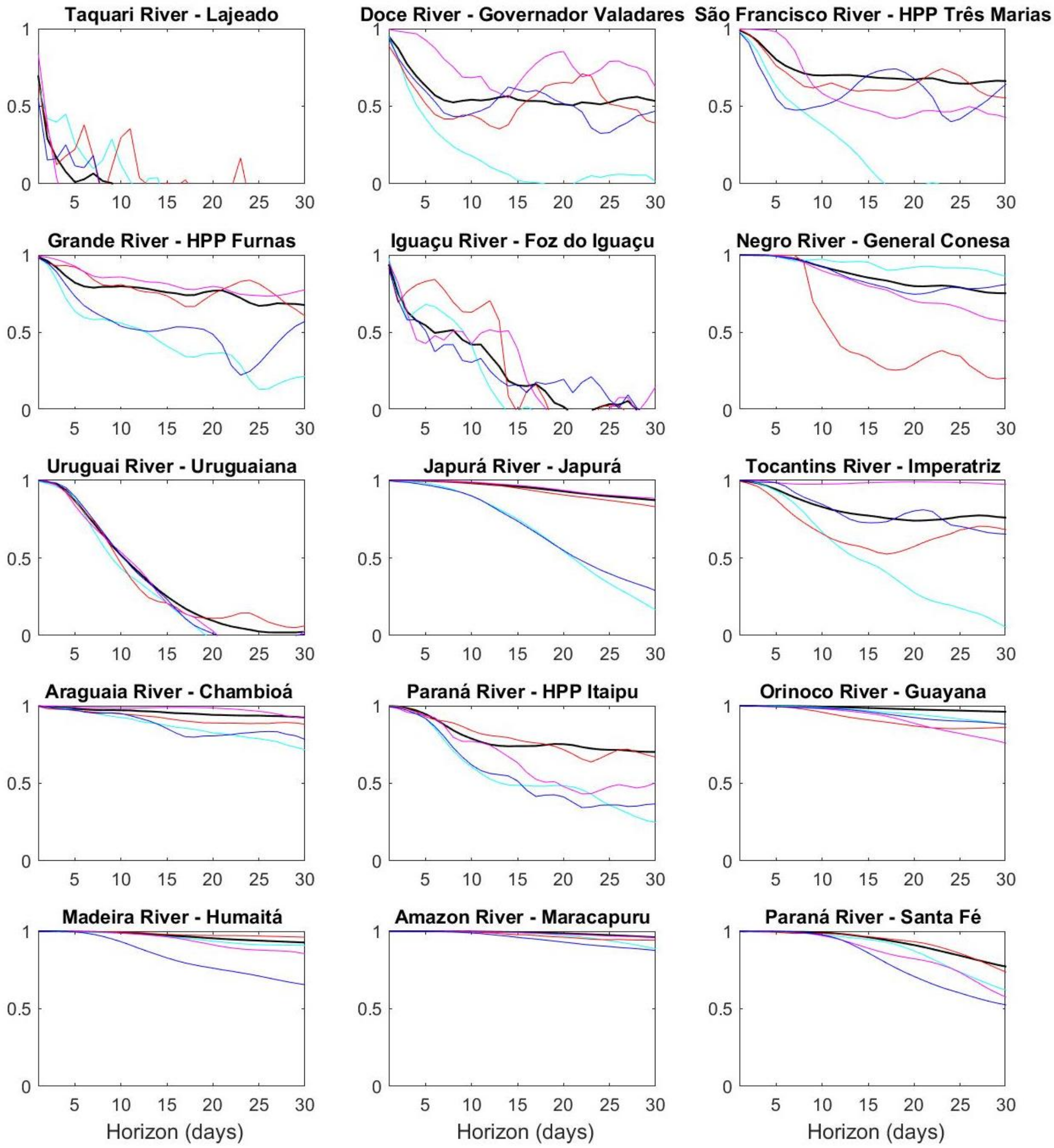


Figure 8 - Performance indicator (KGE) for the climatological rainfall experiments up to a 30-day horizon for annual (black), DJF (cyan), MAM (red), JJA (magenta) and SON (blue)

2.4.2. Spatial patterns

The streamflow predictability maps from zero rainfall and climatology (NSE, KGE, and the three thresholds) are presented in the APPENDIX III and APPENDIX IV. The maps present predictability results calculated for all reaches of South America rivers that have a drainage area greater than 1000 km² in the MGB-SA model and for the entire year. From the results was observed that predictability has a high sensitivity depending on the metric used and the desired performance. In this sense, in order to conduct the following discussion, we defined KGE-0.95 as the reference predictability experiment. The discussions of the three scientific questions proposed in this research and the detailed predictability maps are presented below.

i. What is the daily streamflow predictability based on initial hydrologic conditions?

Figure 9 presents the daily streamflow predictability map from the ICs for the KGE-0.95 experiment. It illustrates that most of the MGB-SA river reaches (79%) have predictability of up to 3 days when there is no precipitation forecast information. Of the other reaches, 17% are predictable from 4 to 10 days, 4% from 11 to 20 days and 1% from 21 to 40 days.

Due to the water propagation time in the basin, the initial conditions tend to have a greater influence on the flow of large basins than small ones, for ground, underground or surface water. Furthermore, lowland areas slow propagation. In this work, most of the river reaches that make up the simulated drainage network for South America (81%) have small unit-catchment area (< 1000 km²), resulting in relatively fast flow generation. It explains the short predictability for most of the analyzed locations (less than 3 days).

The Amazon, Upper Paraguay (La Plata) basins and the east coast of Argentina have the highest predictability values, up to 20 or 40 days. It is believed that this occurs due to the flat relief characteristic of these regions, where flood waves are delayed because floodplains store large volumes of water and release it slowly (PAIVA et al., 2012). These rivers of slow response and long memory are characterized as rivers of superior predictability (PECHLIVANIDIS et al., 2020). In addition, the higher predictability values occur in the main rivers' channels, where the drainage area is greater. The upper catchments have small drainage area and usually present sloping relief.

Regarding the Amazon, these works are compatible with the results from Paiva et al. (2012), where it was found that initial conditions may play an important role for streamflow forecasts even for long lead times (1~3 months) on main Amazon rivers, when Ensemble Streamflow Prediction method was applied (ESP).

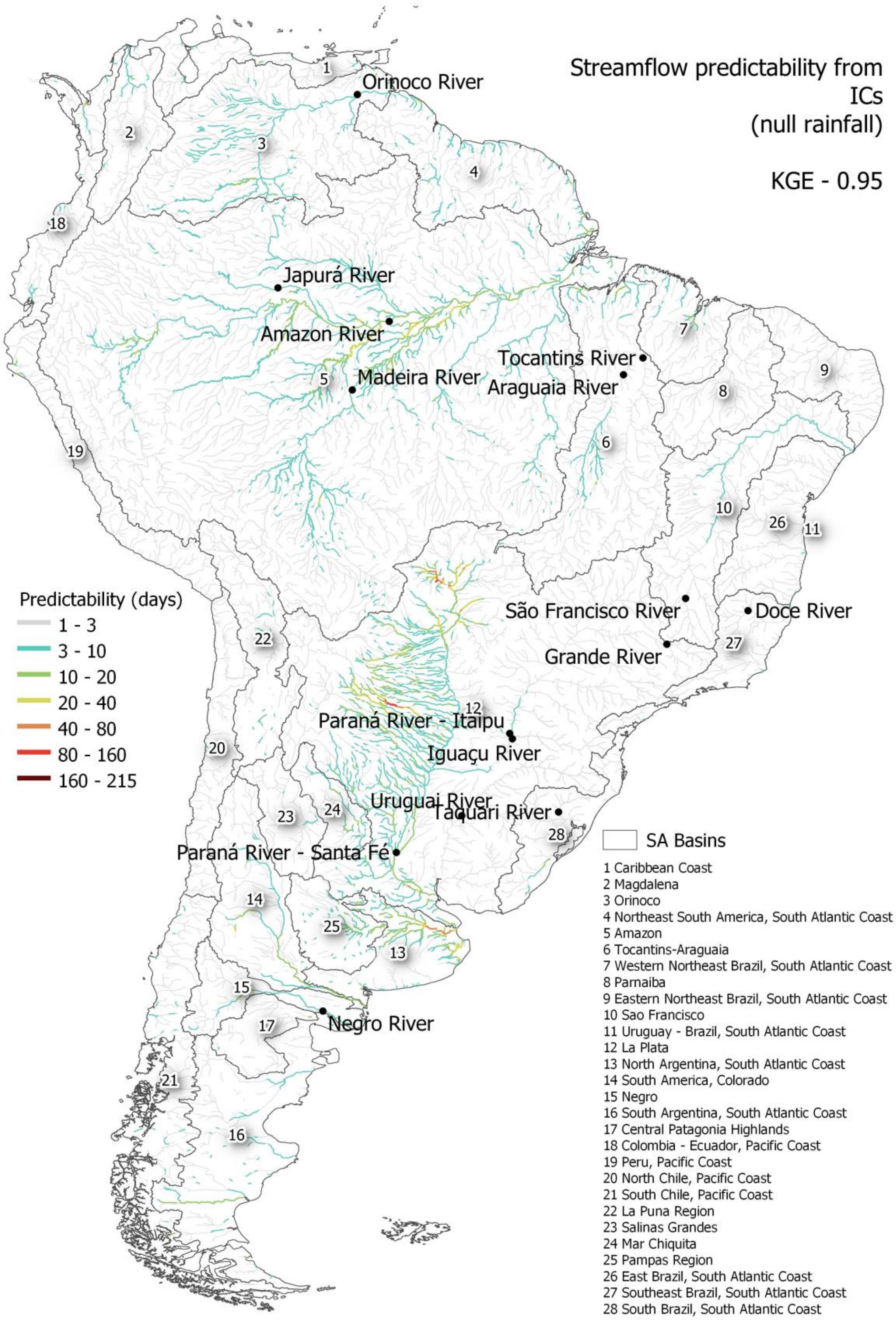


Figure 9 - Daily streamflow predictability map from ICs (null precipitation) for KGE-0.95

In the attempt to trace a relationship between upstream area and predictability, and baseflow index and predictability, Figure 10 presents this information plotted for the unit catchments with upstream area greater than 100,000 km². It is possible to observe a proportional relation between predictability and upstream drainage area for a few unit catchments, however, both factors have a very small correlation to predictability ($R^2 < 0.1$) when analyzed individually.

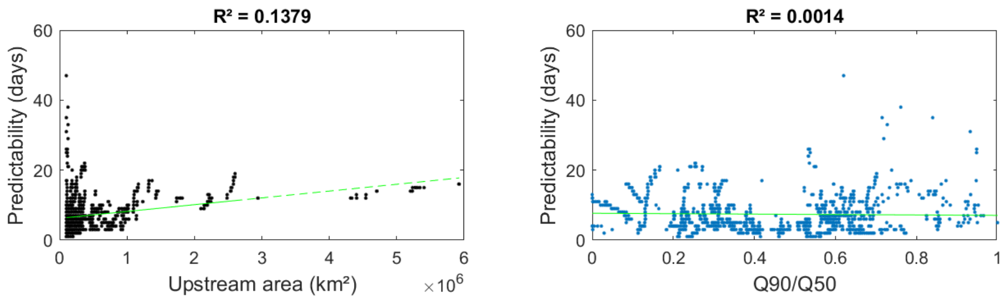


Figure 10 - Graphs of predictability vs upstream area and predictability vs Q90/Q50, for all the unit catchments with upstream area greater than 100,000 km²

Areas with high baseflow contribution index (Figure 3, c) tend to be more dependent on initial conditions once the portion or the streamflow represented by baseflow is a relevant part of the ICs. In this study, however, the increase in predictability due to high baseflow contribution was only noticeable (on the maps) when this characteristic was combined with flat relief. This behavior is noticeable in the Tocantins-Araguaia Basin: both Araguaia and Tocantins River present a baseflow contribution index around 0.4, however, while Tocantins River have a predictability up to three days, an internal portion of the Araguaia River showed a predictability up to thirteen days. This highlighted region is one of the largest wetlands in Brazil, known as Bananal Island (in the Araguaia Basin). In this region, surface water storage is high and cause attenuation and delay of streamflow. Studies that support these claims were made by Lininger and Latrubesse (2016) and Pontes et al. (2017). This indicates that the baseflow index, is not an indicator of predictability by itself, in the current predictability approach, even though, previous studies have shown that it can be an indicator of predictability (GIRONS LOPEZ et al., 2021; HARRIGAN et al., 2018).

In the main axis of Paraná River, São Francisco and Orinoco River predictability reached 10 days. While the tributaries along the length of the great rivers, with their smaller basins, presented predictability of 1 to 3 days. Doce, Iguaçu, Tocantins and Grande rivers presented predictability of up to 3 days. The Uruguay River showed predictability in the order of 1 to 3 days only in its final reaches, just before leaving Brazil and entering Uruguayan territory. These results are compatible with the results of Guimarães (2018), who observed that, despite being a study focused on floods, flows can be predicted with a maximum antecedence of three days without precipitation data in the Uruguay River.

ii. When a rainfall corresponding to the climatology in the forecast horizon is adopted, does the predictability increase?

Figure 11 shows the daily streamflow predictability map from climatological precipitation (KGE-0.95-C), or the predictability due to ICs and BCs. The climatology-forced predictability map illustrates that 57% of the river reaches have a predictability of up to 3 days when there is additional average precipitation information, 24% from 4 to 10 days, 10% from 11 to 20 days, 6% from 21 to 40 days, 2% from 41 to 80 days and 1% from 81 days or more.

When climatology data are used as predicted rainfall, it is noted that the predictability of some places that already have high predictability is increased. This is because in many places, such as the Amazon basin and the upper Paraguay River basin, rainfall has a well-defined seasonality, with the rainy season. In these places, even using climatology as precipitation forecast, the simple addition of a component in the model that includes a forcing behavior of the rain already considerably increases the assertiveness of the forecasts.

In places such as in southern Brazil, in the hydrographic basins of Taquari River, Uruguay River, Iguaçu River, and other basins that drain the region of the lower Paraná River, the use of zero rainfall and climatology resulted in small predictability increase. This happens because in these regions that are transitioning from a tropical climate to a subtropical climate, rainfall does not have a marked seasonal behavior. In other words, it can rain different volumes at any time of the year, and an additional forcing of rainfall seasonality has no effect on predictability in these regions.

In relation to the main axes of large river, with the use of climatological data the rivers São Francisco, Tocantins and Araguaia Rivers presented the largest extension with increase on predictability.

The São Francisco River in its final stretch showed a predictability of 3 to 10 days using zero rainfall. In fact, it is known that the São Francisco River has its sources in a region with a tropical climate, with seasonal rains. However, in the state of Bahia, the São Francisco River starts to flow in a region with a semi-arid climate, with few lateral flow inputs. Thus, the region of the medium to lower São Francisco River is recognized as a portion of flow propagation with few contributions. And it is to be expected that these propagation reaches have just more predictability.

It is also noteworthy that some basins of relevance to Brazil in terms of population and industrial concentration, such as the basins of the Rio Doce, Rio Paranapanema, Rio Paraíba do Sul, among others, always presented predictability in the order of 1 to 2 days. It suggests that these zones have the additional challenge of making assertive short-medium-term forecasts, as these depend more on good weather forecasts, and not just on observed hydrological data.

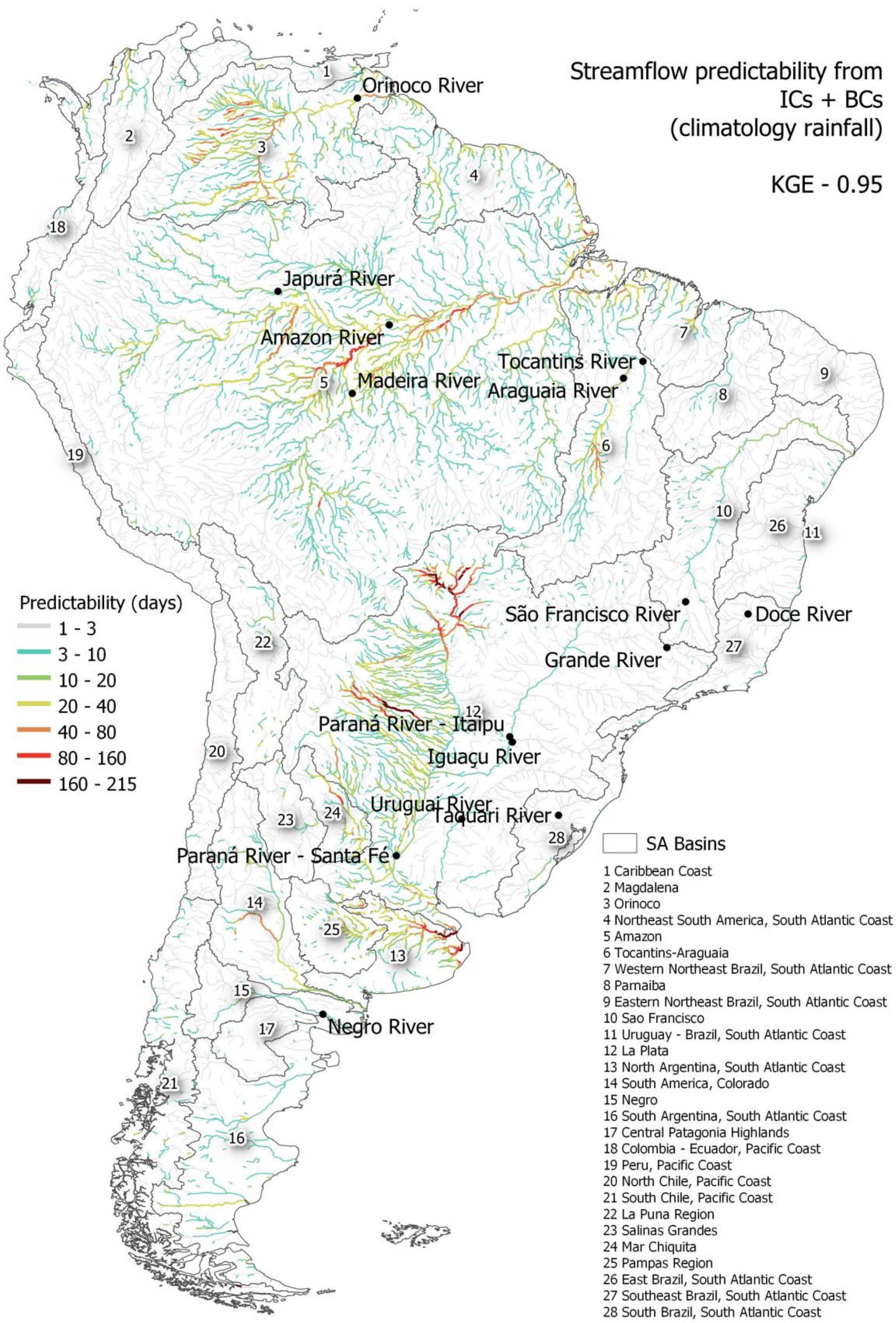


Figure 11 - Daily streamflow predictability map from ICs + BC (climatology rainfall) for KGE-0.95

iii. What is the predictability given by the climatological rainfall boundary condition?

Figure 12 shows the increase in predictability of daily streamflow resulted from the difference between the zero rainfall and climatology experiments. It can also be translated as the predictability due to only boundary conditions, in this case, climatology rainfall.

In South America, the regions where streamflow predictability increased when climatological precipitation data was added were the Orinoco basin, Amazon basin, Upper Paraguay (La Plata basin), Araguaia River (Bananal Island) and the east coast of Argentina. In the main rivers of the basins, where the drainage area is larger, it was possible to observe increases in predictability of up to 40 days or more, decreasing upstream. The common feature of all these regions is their flat relief.

For the Amazon Basin, the results are compatible with the work from Uvo and Graham (1998), whose models shown that it is possible to forecast seasonal discharge one season in advance, with a certain degree of accuracy.

As previously discussed, the addition of a climatological based boundary condition does not always increase streamflow predictability, for instance, basins with fast flow generation and the absence of seasonal precipitation patterns.

As a final consideration, it is necessary to highlight that all these results were obtained from a hydrological-hydrodynamic model calibrated for South America, which has uncertainties. These uncertainties, according to (SIQUEIRA et al., 2018) are related to deficiencies in process representation and simplifications in parameterization, as well as to errors/uncertainties of data used on the model; the model simulates natural flows and does not consider the effect of reservoir operation; and MGB-SA performs better in large rivers and humid regions, and worse in areas with semi-arid to arid climates (SIQUEIRA et al., 2018).

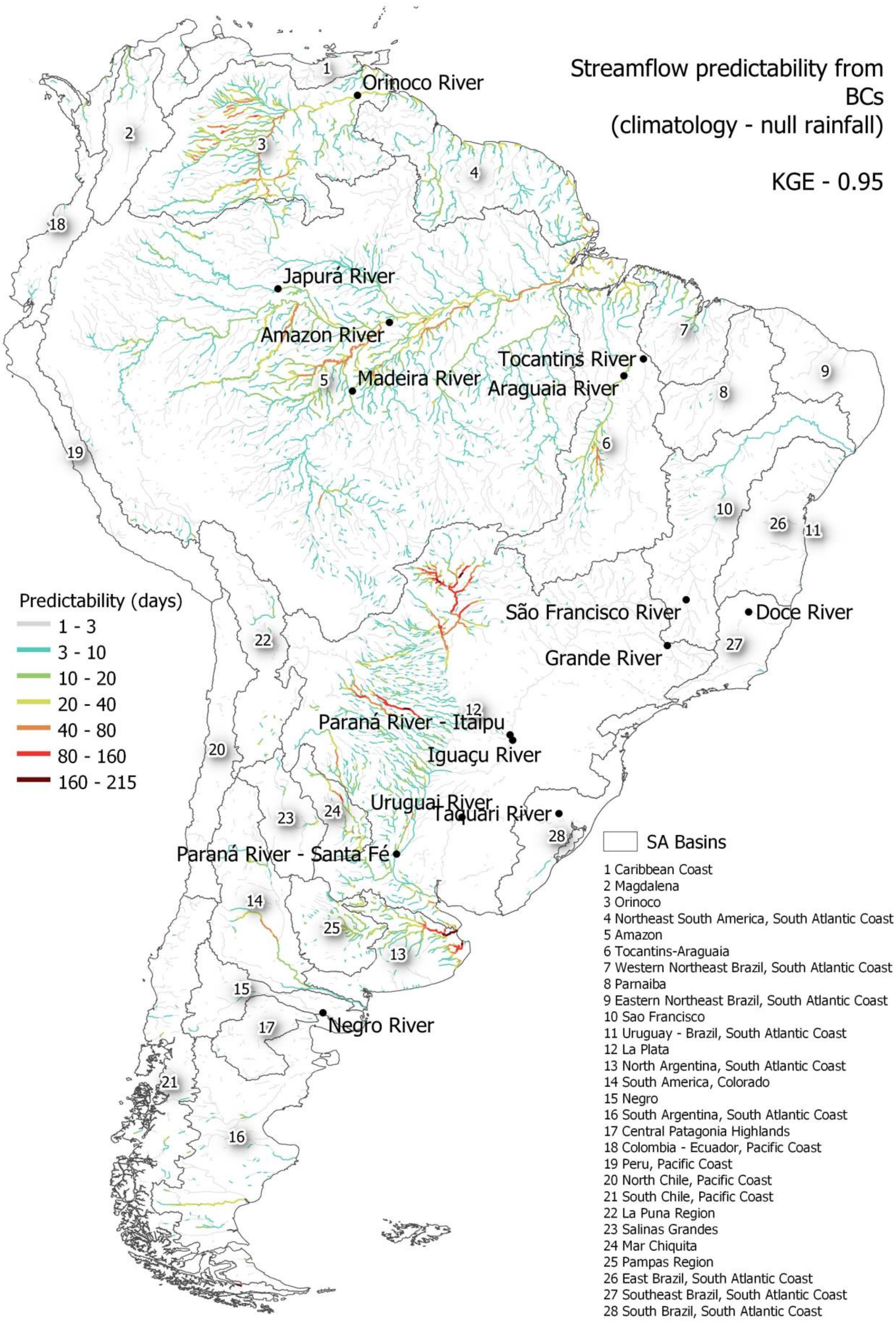


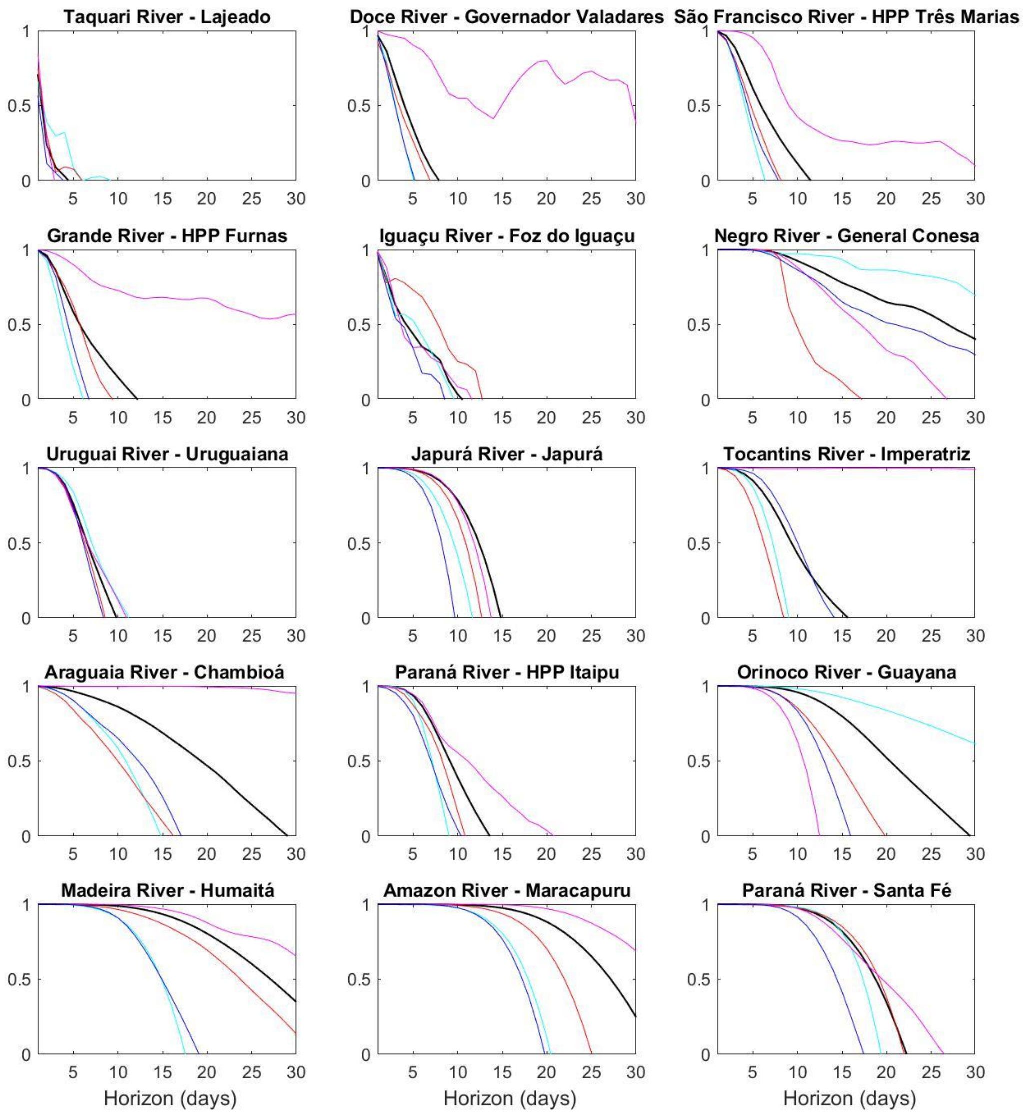
Figure 12 - Daily streamflow predictability map from boundary conditions for KGE-0.95

2.5.CONCLUSIONS

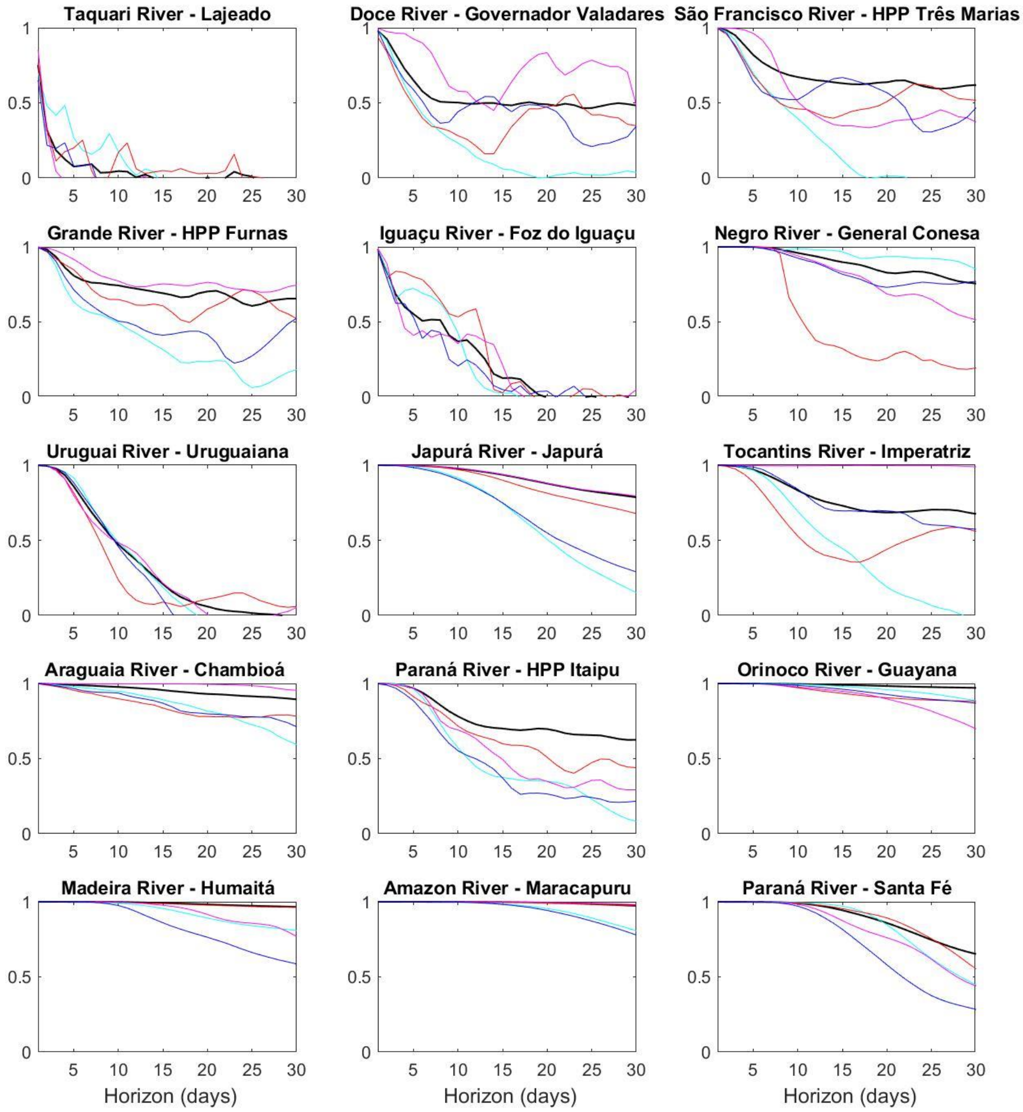
In this work, we investigated the predictability of natural flows of rivers in large basins (>1000km²) in South America from the MGB-SA model. The predictability was estimated by a simple metric based on the number of days the streamflow forecasts had KGE>0.95, when compared to the simulated streamflow with observed precipitation (results using NSE metric and lower and higher thresholds were also available). Two streamflow forecasts experiments were made: the first using null precipitation and the second climatological precipitation as meteorological forcing. Our investigations show that in South America:

- In the absence of precipitation forecast, most river reaches (79%) have predictability of up to 3 days, that is, only with observed precipitation data. Predictability increases near the main reaches of the great rivers of SA, ranging from 4 to 10 days in Iguaçu, Uruguay, São Francisco, Tocantins, Orinoco and Paraná rivers, Bananal Island (Araguaia) and tributaries of the Amazon River; predictability is up to 40 days on the Amazon River, and Atlantic coast of North Argentina and Pantanal plains;
- Streamflow predictability from the initial conditions (null precipitation) is relatively high (> 40 days) in the main river reaches of basins with flat relief. This happens due to their greater drainage area and the slow response time of the basin, what increases the influence on the initial conditions on the flow generation processes, increasing predictability;
- When climatology precipitation is added as precipitation forecast, predictability increase for up to 80 days in rivers Orinoco, Paraná, Bananal Island (Araguaia) and tributaries of the Amazon river; and more than 80 (up to 160) days on the Amazon River, Atlantic coast of North Argentina and Pantanal plains. Areas such as Uruguay, Taquari, São Francisco and Iguaçu rivers keep predictability values of up to 10 days;
- The predictability due to climatology-based boundary conditions mostly occur in areas that already have high predictability with null rainfall, especially where the precipitation seasonal pattern is present;
- Basins with fast response (small drainage area and/or sloping relief) present low streamflow predictability (up to three days).

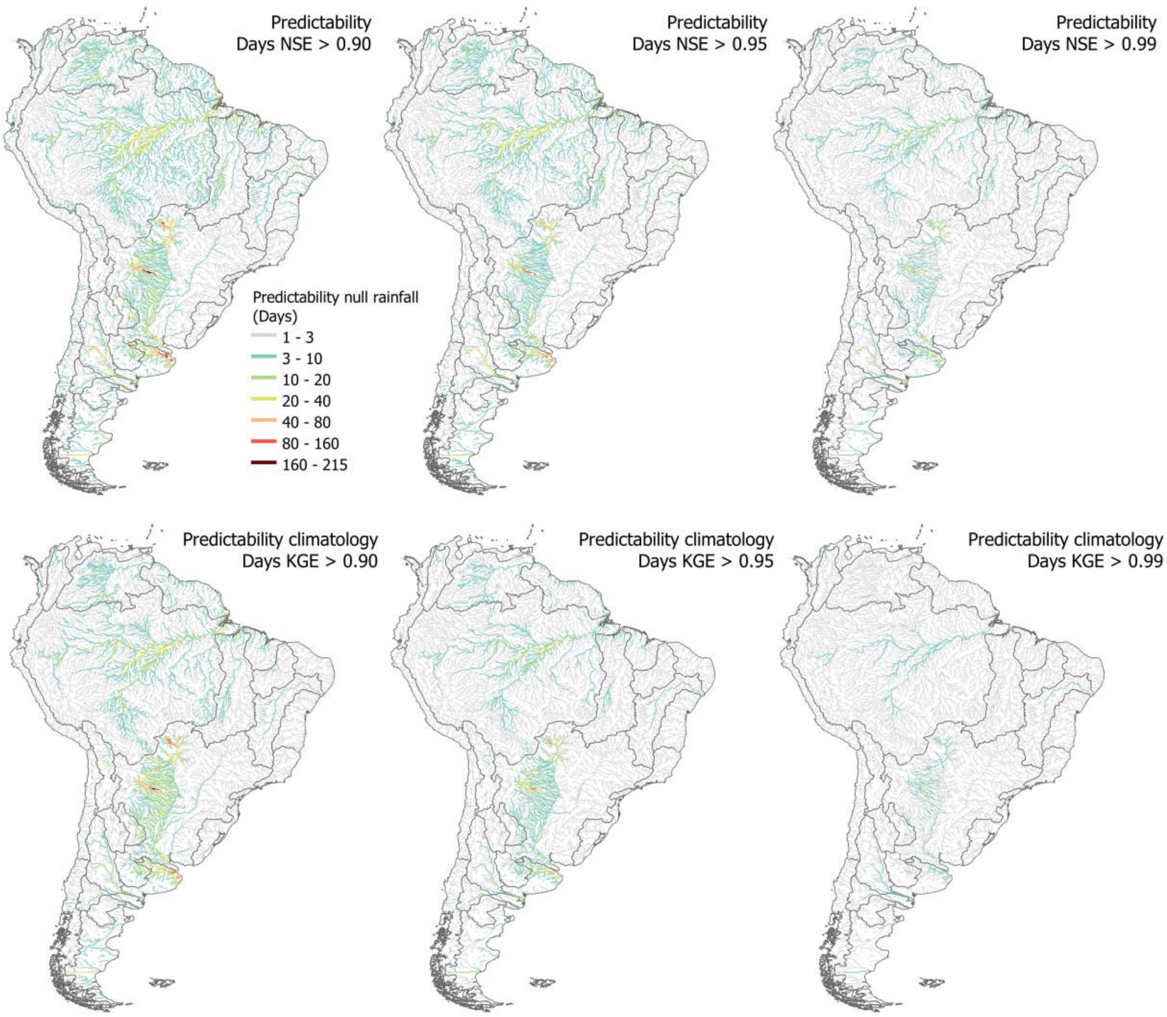
2.6. APPENDIX I -. NSE PERFORMANCE INDICATOR FOR THE ZERO RAINFALL EXPERIMENTS UP TO A 30-DAY HORIZON FOR ANNUAL (BLACK), DJF (CYAN), MAM (RED), JJA (MAGENTA) AND SON (BLUE)



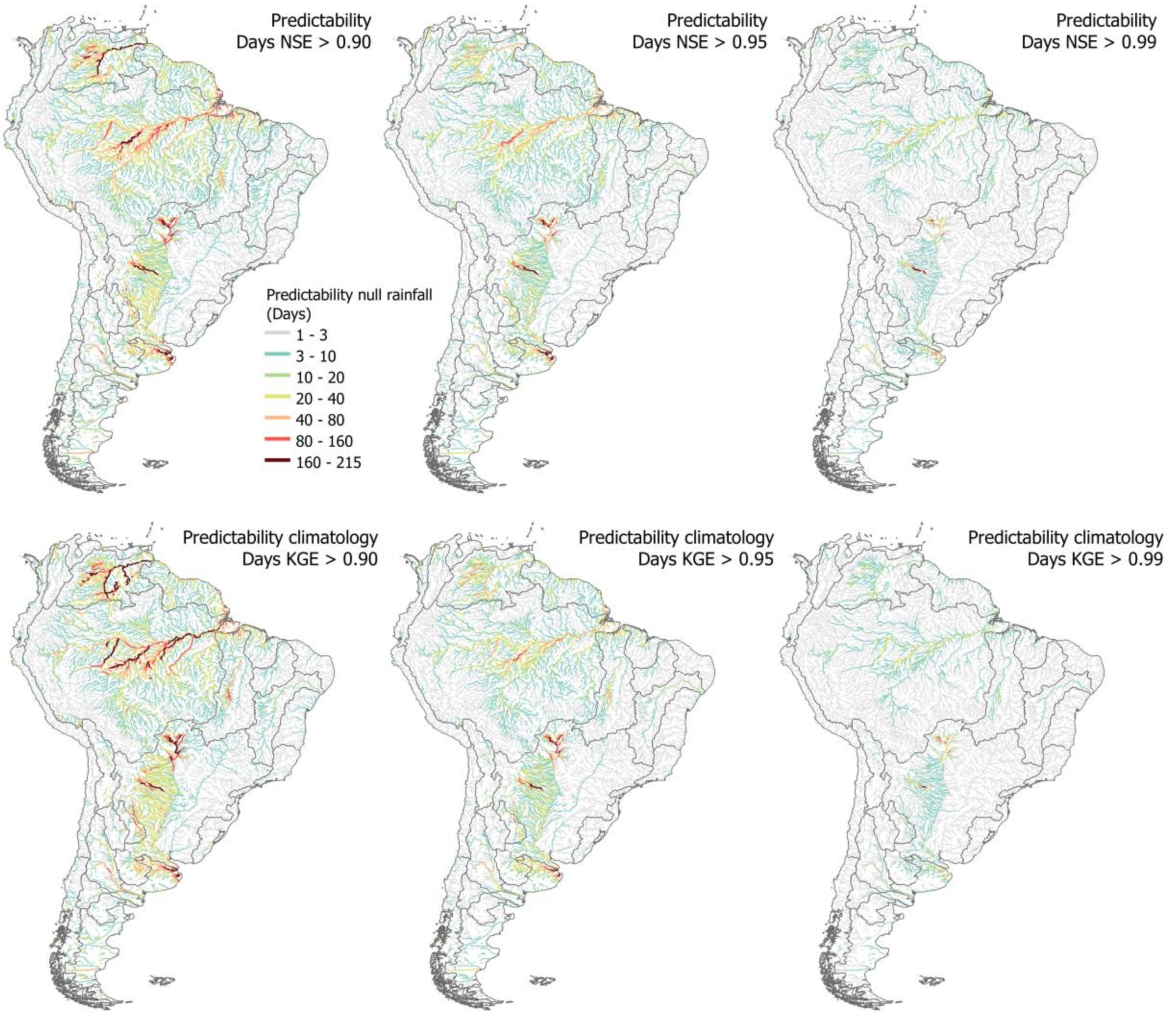
2.7. APPENDIX II - NSE PERFORMANCE INDICATOR FOR THE CLIMATOLOGY RAINFALL EXPERIMENTS UP TO A 30-DAY HORIZON FOR ANNUAL (BLACK), DJF (CYAN), MAM (RED), JJA (MAGENTA) AND SON (BLUE)



2.8. APPENDIX III - DAILY STREAMFLOW PREDICTABILITY MAP FROM ICS (NULL PRECIPITATION)



2.9. APPENDIX IV - DAILY STREAMFLOW PREDICTABILITY MAP FROM ICS (CLIMATOLOGY)



3. POTENTIALS OF H-EPS ON SEASONAL STREAMFLOW FORECASTING IN SOUTH AMERICA

This section presents the second article proposed in this dissertation. The analysis performed in this Section is presented for all the river reaches of MGB-SA, with focus on the locations presented in Figure 1, and for two greater periods of analysis: one for retrospective forecasts and the other for operational forecasts. This article is under review on the Journal of Hydrology: Regional Studies.

ABSTRACT - Society's constant demand for water has generated efforts towards predicting the availability of water resources. Although seasonal climate forecasts are routinely issued in meteorological centers around the world, seasonal streamflow forecasts are at a relative early stage of development. Hydrological Ensemble Prediction Systems (H-EPS), which rely on the combination of dynamic climate and hydrological models, are considered the state-of-the-art in streamflow forecasting, taking advantage of initial land surface conditions and predictions of atmospheric boundary conditions that mostly depend on large-scale climate phenomena. This work represents a first assessment of seasonal streamflow forecasts in South America based on a continental-scale application of a large scale hydrologic-hydrodynamic model and ECMWF's seasonal forecasting system precipitation forecasts (SEAS5-SF) with bias correction. Seasonal streamflow forecasts were evaluated against a reference model run and forecast skill was estimated relative to the Ensemble Streamflow Prediction (ESP) method. We observed that bias correction was essential to obtain positive skill of SEAS5-SF over ESP, which remained a hard to beat benchmark. SEAS5-SF skill was found to be dependent on initialization month, basin and lead time. Rivers where the skill is higher were Amazon, Araguaia, Tocantins and Paraná. The results suggest that seasonal forecasts based on hydrological and climate modelling have potential for water resources planning in South America large rivers.

Keywords – Seasonal streamflow forecast; bias correction; South America.

3.1. INTRODUCTION

Seasonal streamflow forecasts (SSF) provide estimates of river discharges up to 6-7 months in advance. This information finds special demand where long term hydrological planning plays an important role. For instance, it can be used to improve the efficiency of reservoir operation (LEE et al., 2020; PEÑUELA; HUTTON; PIANOSI, 2020), to help water allocation decisions (CHIEW; ZHOU; MCMAHON, 2003; CROCHEMORE et al., 2021; KAUNE et al., 2020), to create flood mitigation strategies (KOMPOR; YOSHIKAWA; KANAE, 2020; PAIVA et al., 2013) and as a drought management tool (CARRÃO et al., 2018; SUTANTO; WETTERHALL; VAN LANEN, 2020).

A Hydrological Ensemble Prediction Systems (H-EPS) is considered the state of the art of rivers streamflow prediction (TROIN et al., 2021). It typically combines hydrological models with ensemble Quantitative Precipitation Forecasts (QPF), resulting in probabilistic estimates of future streamflow (CLOKE; PAPPENBERGER, 2009).

In the seasonal hydrological prediction scale, the traditional approach known as Ensemble Streamflow Prediction (ESP) produces ensemble forecasts by using a hydrological model with appropriated initial conditions forced with future precipitation scenarios resampled from historical observations (DAY, 1985). ESP has been considered a tough to beat streamflow forecast benchmark (HARRIGAN et al., 2018; PEÑUELA; HUTTON; PIANOSI, 2020), therefore being an adequate comparison to evaluate forecasts skill (PAPPENBERGER et al., 2015b).

One of the major sources of streamflow forecasts uncertainty is the precipitation forecast. This is especially true for tropical regions, where the snowfall plays a less important role (FAN et al., 2015). However, rainfall forecasts are strongly dependent on its initial conditions due to the chaotic nature of the atmosphere (LORENZ, 1993), turning precipitation forecasts also a major source of SSF uncertainty. The use of ensembles instead of deterministic precipitation data was one of the advances developed to quantify uncertainty of the forecast (BUIZZA et al., 2005; WMO, 2008b), besides the forecasts remaining systematic errors inherited from the meteorological model (CROCHEMORE; RAMOS; PAPPENBERGER, 2016; PECHLIVANIDIS et al., 2020).

In addition to Lorenz, Shukla (1998) observed that rainfall and tropical atmosphere large scale seasonal circulation are almost completely determined by the sea surface temperature

(SST) conditions. Therefore, the precipitation could be better predicted not only considering the atmospheric initial conditions that produce useful forecasts up to 1 month, but also considering SST as a determining factor. This observation influenced meteorological centers to invest in improving the ability of models to predict large-scale climate phenomena, such as the El Niño Southern Oscillation (ENSO), a phenomenon featured by SST anomalies and one of the major sources of seasonal predictability in South America (WEISHEIMER et al., 2020). In 2019, the European Centre for Medium-Range Weather Forecasts (ECMWF) published the ECMWF fifth generation seasonal forecasting system (SEAS5) (JOHNSON et al., 2019). ECMWF is among the best models capable of predicting ENSO phenomena (BARNSTON et al., 2012; JOHNSON et al., 2019).

One can find in the literature various works that investigate monthly to seasonal streamflow forecasts at basin scales (COLLISCHONN et al., 2005; DE PAIVA; MONTENEGRO; CATALDI, 2020; DELORIT et al., 2017; DEMIREL; BOOIJ; HOEKSTRA, 2015; KOMPOR; YOSHIKAWA; KANAE, 2020; MAHANAMA et al., 2012; PEÑUELA; HUTTON; PIANOSI, 2020; TUCCI et al., 2003; VAN HATEREN; SUTANTO; VAN LANEN, 2019). These works raised important conclusions at the basin level, ranging from 1000 to 1.3 M km². However, at a continental level, generally they represent fragmented information and do not allow a comprehensive and comparative evaluation of forecasts performance. Hydrological events are not necessarily originated outside the catchment borders (EMERTON et al., 2016) and may impact multiple basins and sites (FLEISCHMANN et al., 2020).Thus, it is valuable to have a multi-basin modelling approach to give profound understanding on the dynamics of hydrological processes and to assess the forecasts spatial consistency (PECHLIVANIDIS; ARHEIMER, 2015). Global or continental scale forecasts can contribute to the spatial understanding of hydrological predictabilities while providing information for regions where no other forecasting system exists, due to its ability to cover different geographic and climatic regions (EMERTON et al., 2018; GUPTA et al., 2014).

Scientific and technological advances, as well as the integration of research communities, are required to produce large to global scale forecasts (EMERTON et al., 2016). In 2013, Yossef et al. published a study on the skill of global seasonal streamflow forecasting system. More recently, one of the first attempts in producing and providing seasonal hydro-meteorological forecast products openly at global scale was released, the GloFAS-Seasonal V1.0 (EMERTON et al., 2018). However, global-scale forecasts still face many challenges, such as the lack of available data in the temporal and spatial scales required for application, the communication of forecasts to end users across the globe (EMERTON et al., 2016) and the limited ability of global models to simulate streamflow at local scales (ARCHFIELD et al., 2015). Especially at the continental level, most studies in the topic of seasonal streamflow forecast were developed over Europe, for instance Arnal et al. (2018), Greuell et al. (2019), Pechlivanidis et al. (2020) and Sutanto et al. (2020); and on a country scale with continental dimensions, there are some studies in the United States of America (KOSTER et al., 2010; MAHANAMA et al., 2012; NAJAFI; MORADKHANI; ASCE, 2015) and China (LIU et al., 2021).

In South America (SA), Siqueira et al. (SIQUEIRA et al., 2018) developed a continental-scale version of the MGB (*Modelo de Grandes Bacias*) hydrologic-hydrodynamic model (PONTES et al., 2017), which has been applied and consolidated in large tropical basins in South America (BRÊDA et al., 2020; COLLISCHONN et al., 2005, 2007; FAN et al., 2016a; FLEISCHMANN et al., 2020; LOPES et al., 2018; PETRY et al., 2022; PONTES et al., 2017; QUEDI; FAN, 2020; SIQUEIRA et al., 2016). Expanding regional models to continental scale is considered a viable alternative to overcome some global scale models limitations, bridging gaps between the modelling approach and the better use of local expert knowledge and country-specific datasets (SIQUEIRA et al., 2018). The South American MGB has already been used in medium-range streamflow prediction, through the forecast module that runs Ensemble Streamflow Predictions (ESP) and Hydrological Ensemble Prediction Systems (H-EPS) (SIQUEIRA et al., 2020b, 2021).

Given this scenario and motivated by the recent advances of continental hydro-meteorological modelling in South America, this work aims to assess, for the first time in the published literature as far as author’s knowledge, the current performance and skill of seasonal streamflow forecasts produced with the continental-scale version of MGB (MGB-SA) and SEAS5 precipitation forecasts. With MGB-SA, results are issued for natural flows of rivers in large basins (>5000 km²) with daily time steps and are analyzed at monthly time steps. The skill assessed was the “theoretical skill”, with is the skill considering the hydrologic-hydrodynamic model performance for discharge equivalent to real observations. Streamflow performance thresholds representing low flows are adopted considering that a few months in advance can benefit a variety of sectors in the continent, by allowing sufficient lead time for drought preparedness and mitigation efforts (CARRÃO et al., 2018). The discussion points include precipitation bias correction impact on streamflow forecast; H-EPS performance spatial variability in South America; and H-EPS skill over ESP.

3.2. STUDY AREA: SOUTH AMERICA (SA)

Situated between the Atlantic and Pacific Oceans, South America (SA) is a continent with an area of approximately 17.8 million square kilometers and 90% of its lands are in the Southern Hemisphere. The continent's outline is drawn by the Andes Mountain Range, the North-Amazonian residual plateaus and plateaus and mountains of the Atlantic-East-Southeast. Among them, there are lowland areas where the three main hydrographic basins in South America are located: Amazon, Orinoco and La Plata. The elevation map of South America and its humid areas can be seen in Figure 13 a. Figure 13 b shows rivers' upstream area and other important rivers of South America, such as Araguaia, Tocantins, Paraná, Uruguay and São Francisco.

Most of the territory (~80%) is under the influence of a tropical climate, typically characterized by a rainier (and hotter) season and a drier season. However, the precipitation regime isn't homogeneous.

Precipitation regimes in SA exhibit large spatial variability due to its wide meridional extent (12ºN-55ºS), complex topography (e.g., Andes), particular vegetation features (Amazon rainforest) and influence of the adjacent Atlantic and Pacific oceans (FERREIRA; REBOITA, 2022; GARREAUD, 2009). Seasonal mean precipitation is presented in Figure 13 c. During the austral summer (DJF), the maximum precipitations are concentrated in the central-west region of Brazil, migrating to the north of the equator during the austral winter (JJA). The North of SA is a region of abundant precipitation throughout the year, while the South of SA is much drier. Another exception is the southeastern SA, where one can verify precipitations all over the year.

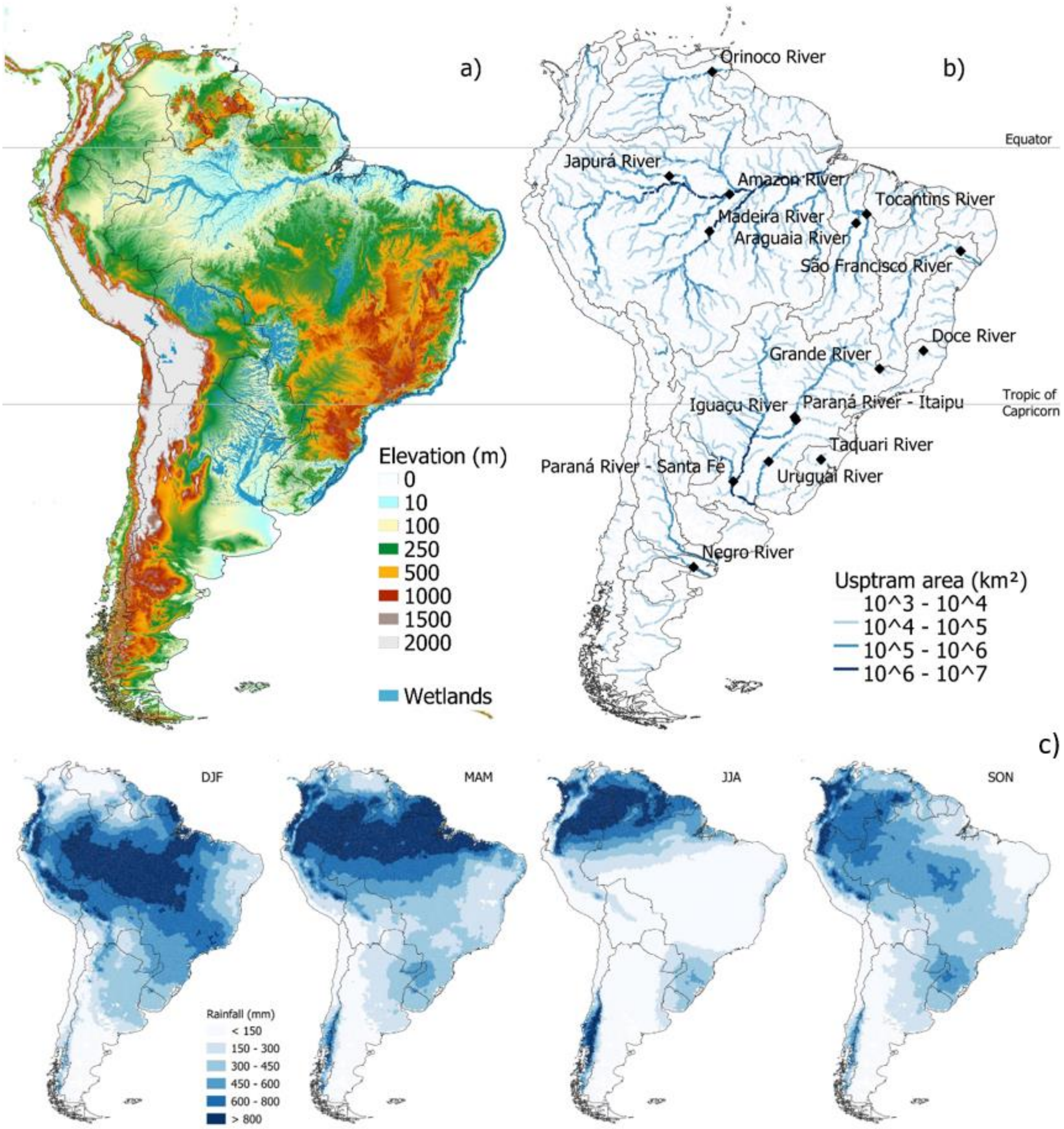


Figure 13 - a) South America elevation map, wetlands and countries' borders; b) SA river's upstream area, important river sites of SA and great SA basins delimitation; c) average annual precipitation in South America according to the season, extracted from the MSWEP database (BECK et al., 2017)

3.3. METHODOLOGY

The methods adopted in this study are summarized in the flowchart of Figure 14. Seasonal streamflow forecasts are obtained by forcing the MGB-SA model with raw and bias-corrected SEAS5 predicted precipitation. Forecast performance is evaluated against a reference MGB-SA run by using deterministic and probabilistic metrics and the Ensemble Streamflow Prediction approach (ESP) is used as a benchmark to evaluate the added skill of SEAS5-based streamflow forecasts (SEAS5-SF). The streamflow forecast analysis was from 2007 to 2016 for the hindcast data and from 2017 to 2022 for precipitation forecast, totalizing 14 years streamflow forecast results. These methods are further detailed in the following sections.

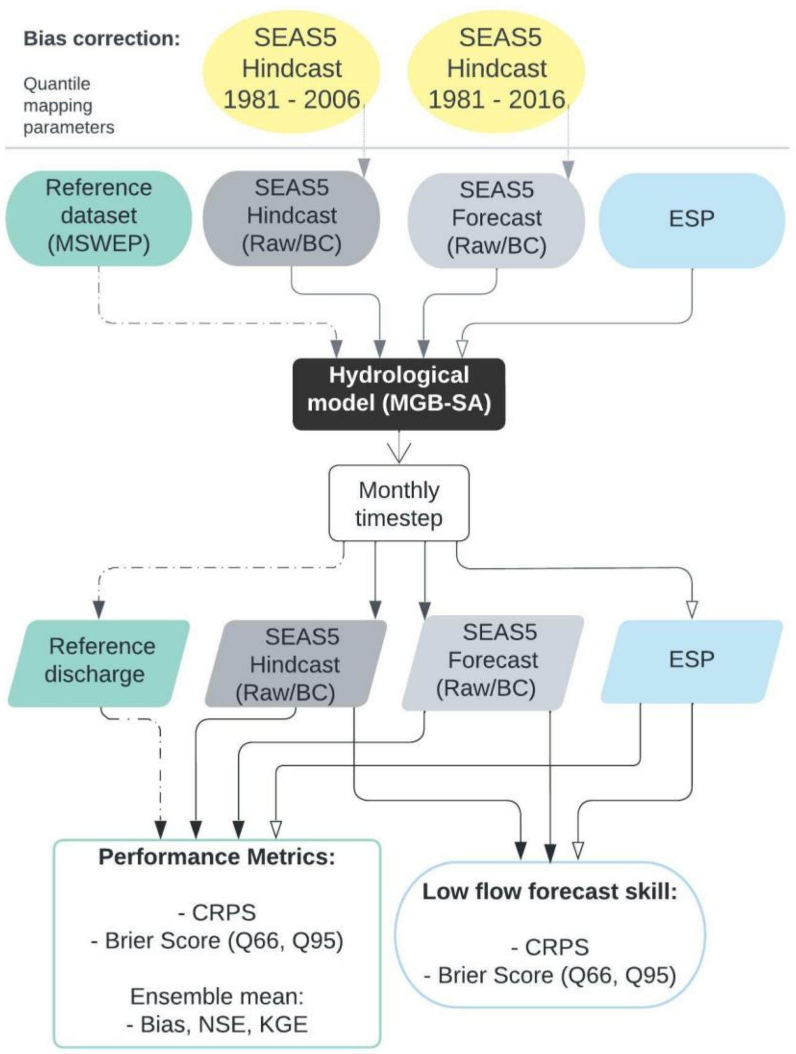


Figure 14 - Methodology flowchart, in green the reference discharge, grey the SEAS5-SF elements and blue ESP.

3.3.1. MGB-SA model

MGB-SA is a continental-scale version of the MGB model (*Modelo de Grandes Bacias*) developed specifically for the South America region (Siqueira et al., 2018). The model was selected as the main tool for continental hydrological-hydrodynamic modelling from its capacity of representing the continent main hydrological process, popularity and added value in producing prognostic results in prior researches in the continent (BRÊDA et al., 2020; FAN et al., 2014, 2016b; FLEISCHMANN; PAIVA; COLLISCHONN, 2019; FLEISCHMANN et al., 2020; PETRY et al., 2021; QUEDI; FAN, 2020; SIQUEIRA et al., 2016, 2020b, 2021).

It is a conceptual, semi-distributed hydrologic-hydrodynamic model that discretizes the spatial domain into unit-catchments and further into Hydrological Response Units (HRUs), which are categorized by combinations of land use and soil type information (PAIVA et al., 2013). Water budget and energy balance are computed at the HRU level with a daily time step. Each unit-catchment has a unique river reach, where the river routing processes are performed. Propagation of surface, subsurface and groundwater runoff resulting from water balance to the main channel is computed with linear reservoirs to represent catchment delay and attenuation. Flow routing in the river network and associated discharge, water surface elevation and flood extent are simulated using a 1D local inertia hydrodynamic model based.

The original MGB-SA model was manually calibrated with hundreds of in situ observations, upstream to downstream of the rivers in large basins (>1000 km²) in SA. For the period of (1990 – 2010) the model showed satisfactory performance (NSE (KGE) > 0.6 in more than 57% (70 %) of the gauges evaluated) and an improvement of around 20 days regarding flood timing in large rivers (e.g., Amazon, Paraguay) when compared to individual global models (SIQUEIRA et al., 2018).

3.3.2. Meteorological inputs

3.3.2.1. Observed precipitation and climate data

We used state of art daily precipitation data from (i) the Multi-Source Weighted Ensemble Precipitation v1.1 (MSWEP) (BECK et al., 2017) until the year of 2014 and (ii) the Integrated Multi-satellite Retrievals for GPM – Global Precipitation Measurement (GPM-IMERG, Version 06) final run from 2015 to 2021, following the same modelling datasets as (ALVES et al., 2022; PETRY et al., 2022). MSWEP (v1.1) is a gridded database with 0.25º spatial resolution and global coverage that combines precipitation from satellite, reanalysis and in situ gauges. IMERG combines data from the GPM satellite constellation and provides gridded precipitation estimates with spatial resolution of 0.1º for the entire globe between latitudes 60ºN and 60ºS (SKOFRONICK-JACKSON et al., 2017). Climate data used to calculate evapotranspiration (temperature, sunshine, relative humidity, pressure and wind speed) were the Climate Research Unit (CRU) v.2 monthly means, which are relative to the 1961-1990 period and are provided at a 10’ resolution (NEW et al., 2002). MSWEP and CRU data were interpolated to the MGB-SA unit-catchments by using the inverse-distance-weighted and nearest neighbor methods, respectively.

3.3.2.2. Precipitation forecasts

We used the fifth generation of the ECMWF seasonal forecasting system (SEAS5) (JOHNSON et al., 2019) as the source of predicted precipitation. The data is made available by the Copernicus Climate Change Service (C3S), a platform that provides unrestricted access to forecast data to its users (BUONTEMPO; THÉPAUT; BERGERON, 2020).

The SEAS5 system has a forecast horizon of 215 days (~7 months), spatial resolution of approximately 36 km (we used 100 km) and temporal resolution of 24-h accumulation interval. Seasonal forecasts are issued on the first day of each month, for a given year (JOHNSON et al., 2019). ECMWF’s SEAS5 provides both retrospective forecasts for multiple years in the past (i.e., reforecasts, also called hindcasts) and real-time operational forecasts. Real-time forecasts have 51 ensemble members for which data is available from 2017 onwards and we obtained real-time precipitation forecasts from the C3S for the period between Jan/2017–Dec/2021. In turn, hindcasts are available from 1981 to 2016 and are produced with a forecast system that is as close as possible to that used operationally, having a reduced ensemble of 25 members. As hindcasts are consistent with the operational forecasts and are available for a longer period (35 years), they were used to correcting biases for both evaluated periods (2007-2016 and 2017-2021, see section 3.2.3).

3.3.2.3. Bias correction of SEAS5 predicted precipitation

Meteorological forecasts may have systematic errors (bias) inherited from meteorological models (CROCHEMORE; RAMOS; PAPPENBERGER, 2016; KIM; WEBSTER; CURRY, 2012). To reduce existing bias in the SEAS5 precipitation product (PECHLIVANIDIS et al., 2020) the widely used Quantile Mapping method (BÁRDOSSY; PEGRAM, 2011) was applied as follows:

$$Z_C(x,t) = F_O{}^{-1}(F_R(Z_R(x,t),x),x) \quad (3)$$

where Zc is the bias-corrected SEAS5 precipitation at location x and day t simulated by ECMWF, Fo^{-1} is the inverse form of the cumulative distribution function (CDF) of the observed precipitation, Fr is the CDF of the SEAS5 raw precipitation and Zr is the raw precipitation at location x and day t.

Parametric gamma distributions were adjusted for both hindcasts and observations to apply the quantile mapping. To obtain the parameters of gamma distributions regarding the predicted precipitation, we created subsets of data by separating SEAS5 daily precipitation hindcasts of each month along the forecast horizon (7) and each forecast initialization month (12). All 25 ensemble members were considered to increase the sample size. The corresponding MSWEP data of each forecast subset were then used to obtain the parameters of gamma distributions for observations. The data used to obtain SEAS5 raw precipitation parameters was the hindcast from 1981 to 2006 for the hindcast experiments and hindcast from 1981 to 2016 for the forecast experiments. Bias correction was performed after the precipitation data (both observed and predicted) had been interpolated to the MGB-SA unit-catchment centroids using the inverse distance weighting method.

3.3.3. Generation of seasonal streamflow forecasts

Seasonal streamflow forecasts were produced with the MGB-SA model by following the steps presented in Siqueira et al., (2020b). First, a long-term simulation run was performed from 1980-2021 and model initial conditions (e.g., soil moisture content, volume of water in rivers and floodplains, etc.), were sequentially saved for the first day of each month along the forecast evaluation periods (between Jan/2007 and Dec/2021, considering both the hindcast and forecast evaluation periods). Next, raw and bias-corrected SEAS5 predictions were used to force the MGB-SA using the updated model states that were saved for each forecast/hindcast initialization day.

For the skill assessment of SEAS5-SF, the ESP approach was used as a benchmark. The ESP builds meteorological forecast scenarios resampled from past observations and uses them as inputs to a hydrological model with updated initial conditions (DAY, 1985; WOOD; LETTENMAIER, 2008). This method has been commonly used to assess the added skill of seasonal streamflow forecasts based on dynamic forecasting systems(e.g., Alfieri et al., 2014; Arnal et al., 2018). To generate the predicted precipitation ensemble for the ESP benchmark, we resampled the historical rainfall data (MSWEP/GPM-IMERG) from all years between 1979–2020 for the same calendar date (i.e., same day and month) of the corresponding hindcast/forecast lead time, excluding the target year. This resulted in a precipitation ensemble composed of 41 members, which was then used as input to MGB-SA (with updated model states) to produce the ESP.

3.3.4. Forecast assessment

For the assessment, seasonal streamflow forecasts were averaged from daily to monthly time step. The performance metrics applied for the ensemble mean were, Relative Mean Error (bias) (%), Nash Sutcliffe Efficiency (NASH; SUTCLIFFE, 1970) and Kling–Gupta Efficiency (GUPTA et al., 2009). For the ensemble, we calculated the continuous ranked probability score (CRPS) (BROWN, 1974; HERSBACH, 2000) in terms of m^3/s and Brier Score (BS) (BRIER, 1950).

NSE is the squared error between observed and simulated streamflow normalized by the variance of the observed discharge (KRAUSE; BOYLE; BÄSE, 2005):

$$NSE = 1 - \frac{\sum_{i=1}^{n}(OBS_i - SIM_i)^2}{\sum_{i=1}^{n}(OBS_i - \underline{OBS})^2} \qquad (4)$$

in which *OBSi* are the observation values, *SIMi* the simulated values and *OBS* bar is the observation values average. It ranges between -∞ and 1, with 1 being the perfect fit.

The Kling–Gupta Efficiency (KGE):

$$KGE = 1 - \sqrt{(r-1)^2 + (\frac{\sigma_{sim}}{\sigma_{obs}} - 1)^2 + (\frac{\mu_{sim}}{\mu_{obs}} - 1)^2} \qquad (5)$$

where r is the linear correlation between observations and simulations, σobs is the standard deviation in observations, σsim the standard deviation in simulations, μsim the simulation mean, and μobs the observation mean. KGE ranges from -∞ to 1, and like NSE, KGE = 1 indicates perfect agreement between simulations and observations.

The continuous ranked probability score (CRPS) is given as:

$$CRPS_h = \frac{1}{N}\sum_{n=1}^{N}\int_{-\infty}^{+\infty}\left[F_P\left(QP_{h,n}\right) - F_O(QP_{h,n})\right]^2 dQP_{h,n} \qquad (6)$$

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

The brier score (BS) is computed according to:

$$BS_h(L) = \frac{1}{N}\sum_{n=1}^{N}\left(F_{QP_{h,n}}(L) - \imath(Q_{O_{h,n}} \leq L)\right)^2 \qquad (7)$$

where *N* is the total number of issued forecasts, *h* is the evaluated forecast horizon; *L* is a threshold that represents the occurrence of a hydrological event; $F_{Qph,n}$ is the proportion of the ensemble members that exceeds the evaluated threshold, and ı() is a function that equals one when the observed streamflow $Qo_{h,n}$ exceeds the evaluated threshold and is zero otherwise. Brier score indicates how good the forecast members are in the detection of a streamflow threshold. The chosen BS threshold aimed to assess the accuracy of the SEAS5-SF in predicting a discharge lower than normal conditions and far below normal conditions. Thus, the threshold was the reference monthly streamflow that is exceeded 66% of the year (the lower tercile) and

95% of the time (Q_{95}), both for the past reference streamflow. These streamflow represent respectively low and very low flows (LIU et al., 2021).

H-EPS skill was calculated by evaluating both BS and CRPS of the SEAS5-SF relative to that of the ESP benchmark:

$$BSS = 1 - \frac{BS_{SEAS5-SF}}{BS_{ESP}} \quad (8)$$

$$CRPSS = 1 - \frac{CRPS_{SEAS5-SF}}{CRPS_{ESP}} \quad (9)$$

Skill scores are calculated upon their previous performance (BS and CRPS). Their interpretation is very similar: results range from -∞ to 1, where positive values indicate that the SEAS5-SF outperforms the ESP, and vice-versa.

MSWEP streamflow simulations were used as reference simulations, since streamflow observations are not available to all the river reaches of South America. In this case, the predictability obtained is a theoretical skill, which may be greater than the actual skill, if observations were used. It occurs because the model and the precipitation are assumed to be perfect, which is not true. However, as in this work we aim to understand the potentials of seasonal streamflow forecast in South America from the MGB-SA model, this approach is acceptable. In the case of a forecast to a hydropower plant, a model bias correction would be applied considering the observed streamflow data.

3.3.5. Conducted Experiments

To accomplish the objective of evaluating the performance and the skill of seasonal streamflow forecasts in the South American large rivers, the following experiments were conducted using the explained framework:

(i) A verification of the impact of the bias correction on seasonal streamflow forecasts.

(ii) An evaluation of the proposed forecasting framework based on SEAS5-SF performance considering deterministic ensemble mean and full ensemble metrics, without comparing with the ESP results.

(iii) As Skill assessment comparing the forecasting framework based on SEAS5-SF performance with the traditional ESP approach as a benchmark.

(iv) A visual more detailed analysis of the forecasting framework based on SEAS5-SF with focus in a specific place during the 2020-2021 drought, to aid the kind of results generated.

3.4. RESULTS

This section is divided in: (i) the impact of bias correction on seasonal streamflow forecast; (ii) the SEAS5-SF performance (ensemble mean and full ensemble); (iii) SEAS5-SF skill; and (iv) detailed analysis of the SEAS5-SF with focus on the Paraná Basin 2020-2021 drought.

3.4.1. Impact of precipitation bias correction on seasonal streamflow forecast

Figure 15 shows boxplots of performance metrics (outliers suppressed) for bias-corrected and raw SEAS5-SF, considering only river segments with drainage area greater than 5000 km2 and results from the Hindcast experiments. When bias correction is applied, the median performance of all evaluated metrics improves in the entire forecast horizon and the interquartile range of the boxplots is largely reduced. In particular, bias correction has a relevant impact on streamflow forecast skill, as CRPSS and BSS mostly change from negative to around zero or positive values.

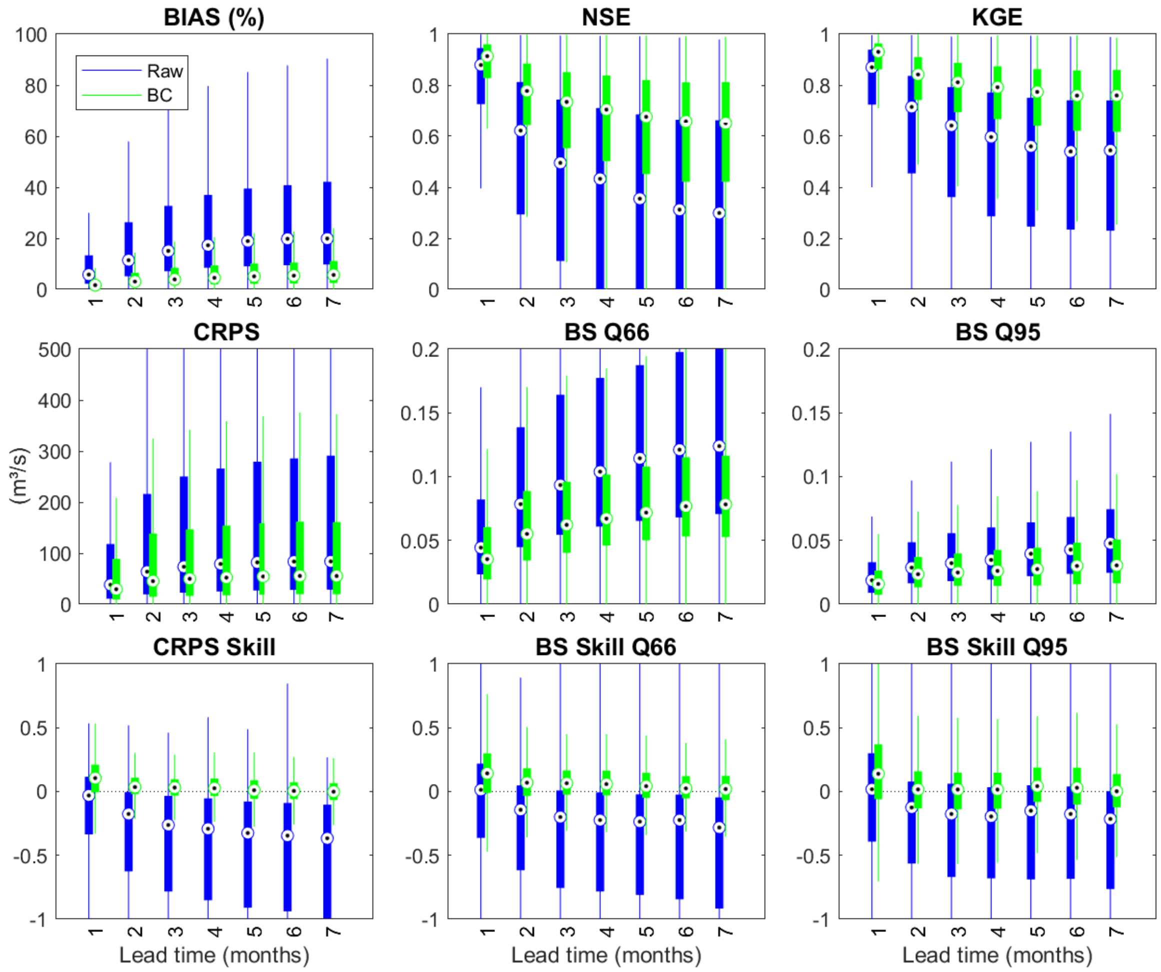


Figure 15 - SEAS5-SF performance metrics for SA rivers with drainage area ≥ 5000 km², for the Hindcast experiments

3.4.2. Evaluation of SEAS5-SF performance in South American rivers

In this section, the performance of bias-corrected SEAS5-SF from both Hindcast and Forecast experiments is presented. Results are given for large SA rivers (drainage area > 5000 km²) and are summarized in (i) boxplots, which refer to the entire data periods (i.e., 2007-2016 for hindcast and 2017-2021 for forecast) and (ii) maps, which display the spatial distribution of SEAS5-SF performance according to the season of the year. Only the Hindcast results are presented in map format due to the longer data availability. Spatial maps were produced by considering January, April, July and October as target months, i.e., results for July with a 2-month lead time refer to hindcasts issued on June 1st, for example.

In general, Hindcasts results present better performance metrics values than Forecasts. We attribute this general behavior to the fact that: hindcasts have a longer sample period; the time series are different; the model versions may be not the same.

3.4.2.1. Ensemble mean metrics

Figure 16 presents the percentage Bias (relative mean error), NSE and KGE for the bias-corrected SEAS5-SF. Median Bias ranges from near zero to 5% for Hindcast and 10% for Forecast, while median NSE and KGE range from around 0.9 to 0.7 over the lead times. In the three boxplots, interquartile range increases with lead time, showing that the SEAS5-SF performance decreases with lead time.

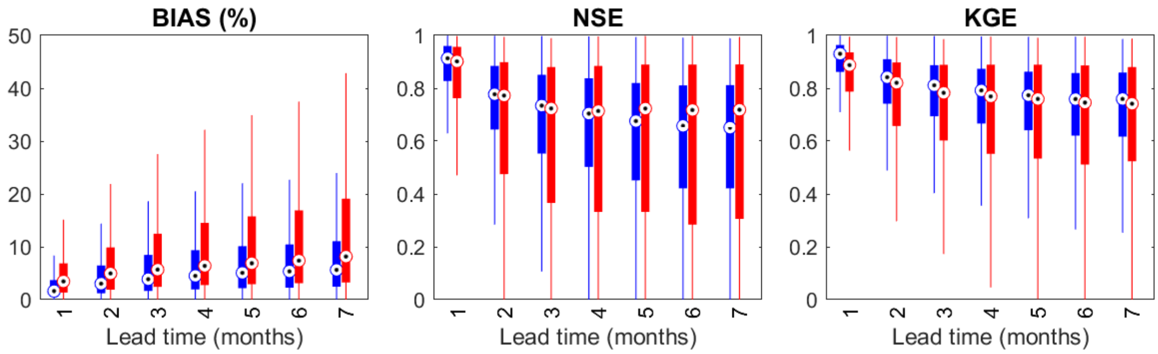


Figure 16 - Percentage bias and KGE for bias-corrected SEAS5-SF according to lead time, considering rivers with drainage area ≥ 5000 km². Blue presents the Hindcast data results and Red the Forecast results

Figure 17 shows the percentage Bias for January, April, July and October for the lead times of one, two, four and six months. Results range from lower bias (yellow) to higher (pink). Streamflow forecast biases are lower in the main river reaches of the great rivers of SA, with a slightly bias increase with lead time. Bias is also very similar for the different seasons, with only a few regions with higher bias, such as the Northeast and Central Brazil for January forecasts issued with a 4 to 7-month lead time, north Amazon basin for the forecasts issued in January.

KGE maps (Figure 18) show that SEAS5-SF performance decreases with lead time. KGE values are close to unity for the lead time of one month in all seasons, except for rivers near the Andes region. For longer lead times, KGE remains close to unity, mainly in extensive floodplain areas of SA: the Pantanal, the Amazon Delta and Tocantins River Delta. NSE maps were suppressed from the main results due to their similarity with the KGE results. However, they can be found in the supplementary material.

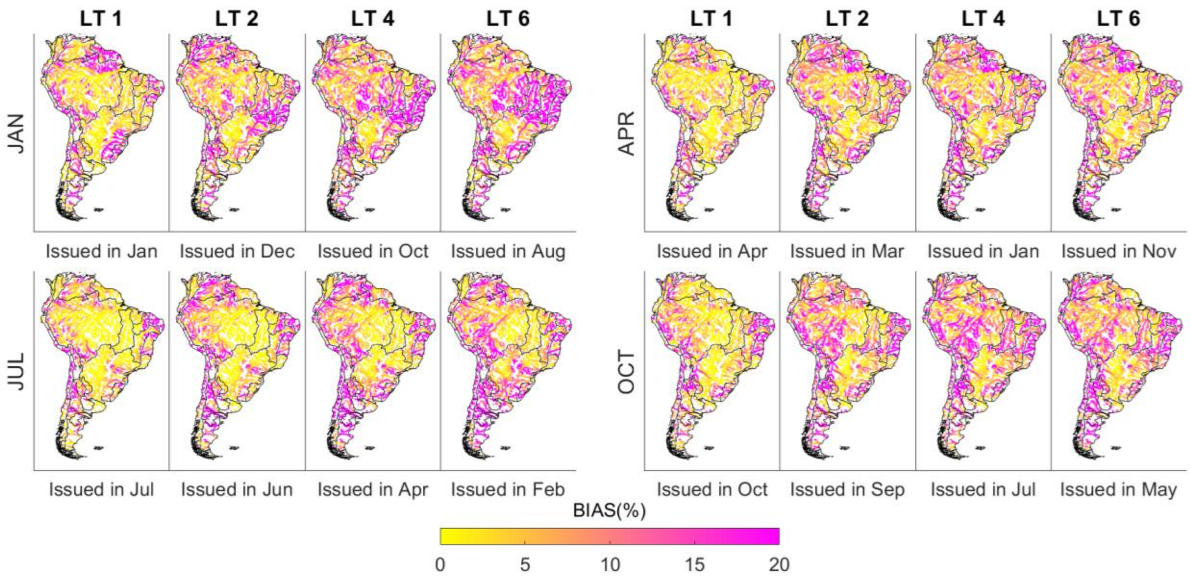


Figure 17 - Bias (%) in SEAS5-SF (bias-corrected) according to season and lead time.

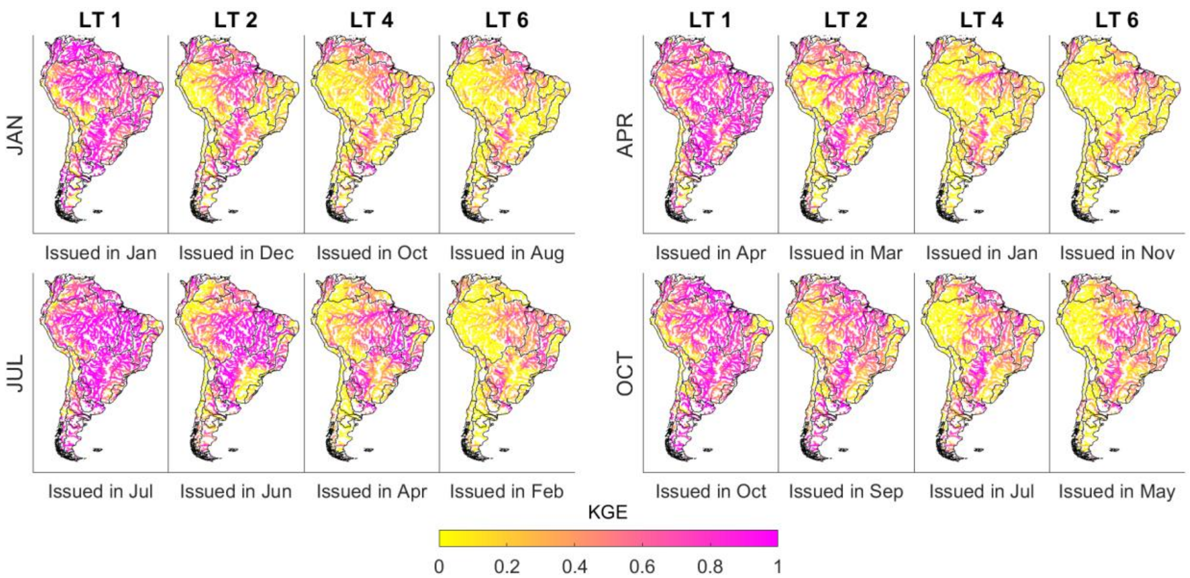


Figure 18 - KGE performance for bias-corrected SEAS5-SF according to season and lead time.

4.4.2.1. Full ensemble metrics

Figure 19 presents the CRPS and Brier Score (Q66 and Q95 thresholds) for the bias-corrected SEAS5-SF. Median CRPS ranges from around 20 to 40 m³/s for both Hindcast and Forecast, from the lead time of 1 to 7 months. The median BS range from around 0.03 to 0.07 throughout the lead times. In all Figure 19 boxplots interquartile range increases with lead time, showing unit-catchment general forecast performance decreases with lead time. Q95 Brier Score is lower than BS Q66, with median values around 0.025.

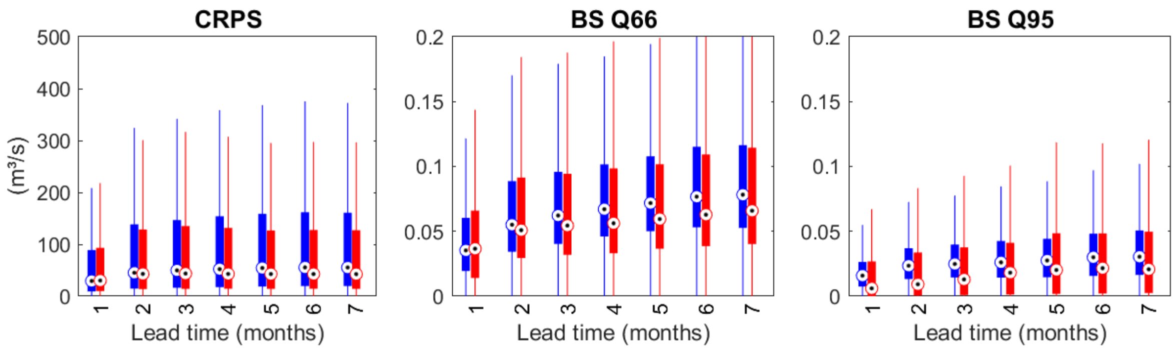


Figure 19 - CRPS and Brier Score (Q66 and Q95) for bias-corrected SEAS5-SF according to lead time, considering rivers with drainage area ≥ 5000 km². Blue presents the Hindcast data results and Red the Forecast results

Figure 20 shows the CRPS (m³/s) for January, April, July and October for the lead times of one, two, four and six months. Results range from lower CRPS (green) to higher (blue). CRPS spatial patterns are visibly similar to the seasonal mean precipitation map in South America (Figure 13), that matches the location of the great rivers of South America. During Summer and Autumn, the Amazon, São Francisco, Uruguay, Paraná, Araguaia, Tocantins and Orinoco rivers present the greatest CRPS (> 200 m³/s). During Winter and Spring, the driest seasons in the intertropical portion of SA, Mean CRPS decrease, while maintain CRPS values greater than 200 m³/s in the extreme North of SA and South of Brazil. In relation to the horizon, it's observed some increase in CRPS values upstream the rivers with high CRPS values throughout the horizons.

Figure 21 shows the lower tercile Brier Score for January, April, July and October for the lead time of one, two, four and six months. The assertiveness of low flow occurrence by forecast members is positive related to the precipitation patterns of South America: greater the precipitation, better the brier score (values close to zero). This is the opposite behavior of the CRPS, that shows that greater the precipitation (and greater the rivers), greater are the streamflow errors. In general, the detection of occurrence of low flows by the 25 hindcast members varies spatially within the seasons, but varies very little spatially and in terms of magnitude within the horizons.

Q95 Brier Score maps results are available at the supplementary material.

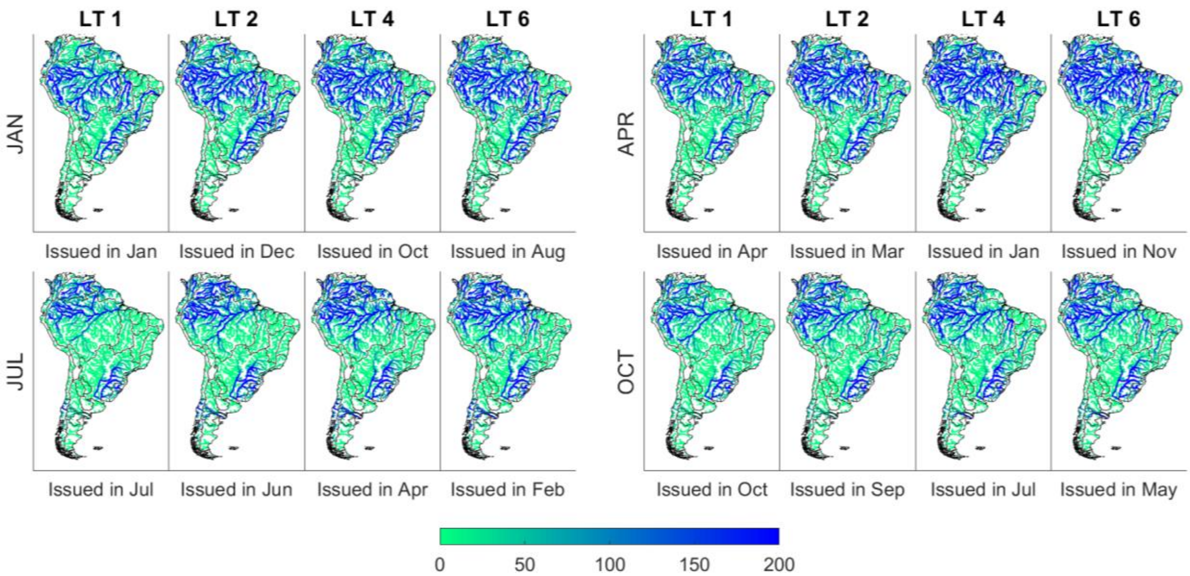


Figure 20 - CRPS (m³/s) for January, April, July and October for the lead time of one, two, four and six months

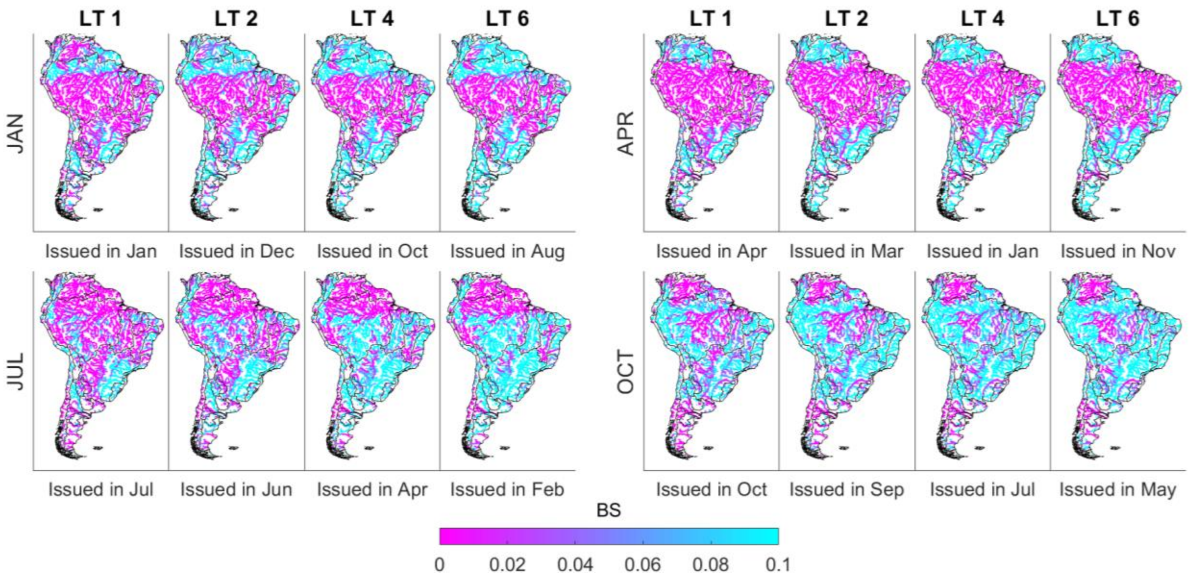


Figure 21 - Brier Score (Q66) for January, April, July and October for the lead time of one, two, four and six months

3.4.3. Assessment of SEAS5-SF skill against ESP

The results presented in this section indicate whether the bias-corrected SEAS5-SF have higher or lower skill than the ESP. Figure 22 presents the results of CRPSS and BSS (Q66 and Q95) for the Hindcast experiment and we observe that all metrics indicate a relatively constant skill over the lead times. In general, the median skill is slightly above zero for the three skill scores, with the lead time of one month showing a higher skill compared with the other lead times. However, the boxplot range indicate that the SEAS5-SF may outperform the ESP in many rivers while in others do not, presenting skill scores above and below zero for both CRPS and BS (Q66 and Q95).

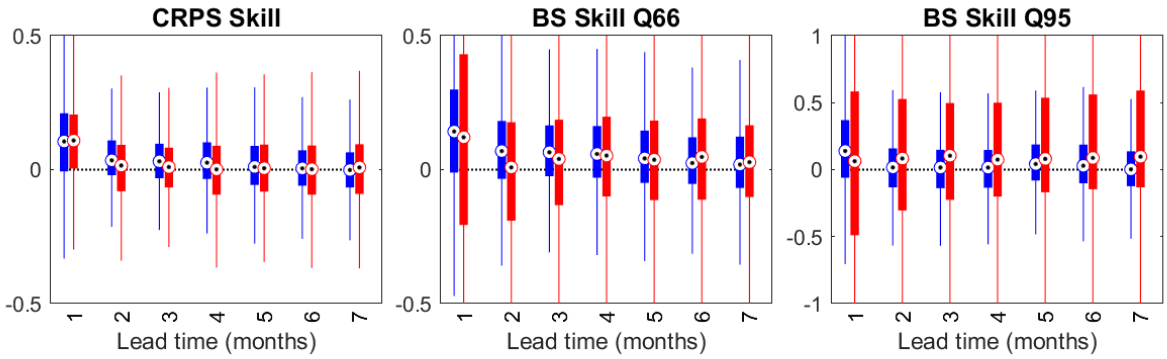


Figure 22 - CRPSS and BSS (Q66 and Q95) for bias-corrected SEAS5-SF SA according to lead time, considering rivers with drainage area ≥ 5000 km². Blue presents the Hindcast data results and Red the Forecast results

Figure 23 shows the spatial distribution of CRPSS in SA rivers. Although patterns of skill are not easily noticeable, in some regions the SEAS5-SF exhibits high (blue) CRPS Skill. SEAS5-SF issued for the austral summer (January) exhibit consistent positive skill for Northeastern and Southeastern Brazil, more specifically in the Araguaia, São Francisco and upper Paraná River for the first lead time. For longer lead times, positive skill values are lower and are observed near the Amazon River mouth. For April, the Northeast of Brazil and the La Plata Basin showed the higher CRPSS for the lead times of one and two months. The 4th to 6th lead time forecasts to January and April showed high CRPSS only in the Amazon River. In the austral winter (July), SEAS5-SF presented better skill for the lead times of four and six months (issued in April and February) for the Northeastern Brazil. Streamflow forecasts issued for October, in turn, showed positive CRPSS only for the 1-month lead time.

Seasonal streamflow forecasts issued in February, March and April (Summer/Autumn) seems to have higher skill than those issued in the austral winter months. This may occur because forecasts issued in the Summer (wet season) are predicting discharges for the dry season. The dry season is consistently easier to predict. Regions such as the Southern Brazil, where precipitation is relatively well distributed throughout the year, consistently showed CRPSS around zero.

Figure 24 and Figure 25 present the BSS maps for the event thresholds of Q66 and Q95, respectively. The white areas on the maps are infinite and not a number BSS results. These BSS values are originated from the division between the H-EPS Brier Score with the ESP BS when

BS ESP is too small (near zero). Besides, these inconclusive BSS results are more frequent in the Q95 results, due to event rarity influence that Q95 commonly represents.

Regarding Figure 25, we can observe that positive values for BSS do not follow a spatial or temporal pattern. The SEAS5-SF is skillful in southern Brazil for all horizons and initialization month, except in the Uruguay River regarding October forecasts (all lead times). Besides, for January forecasts, the lower portion of Amazon basin shows high BSS for the lead time of one month, whereas in the upper Amazon skill is observed for longer lead times. In other parts of South America, skill is positive in some river reaches of SA during July and October from the 4^{th} to the 7^{th} lead time.

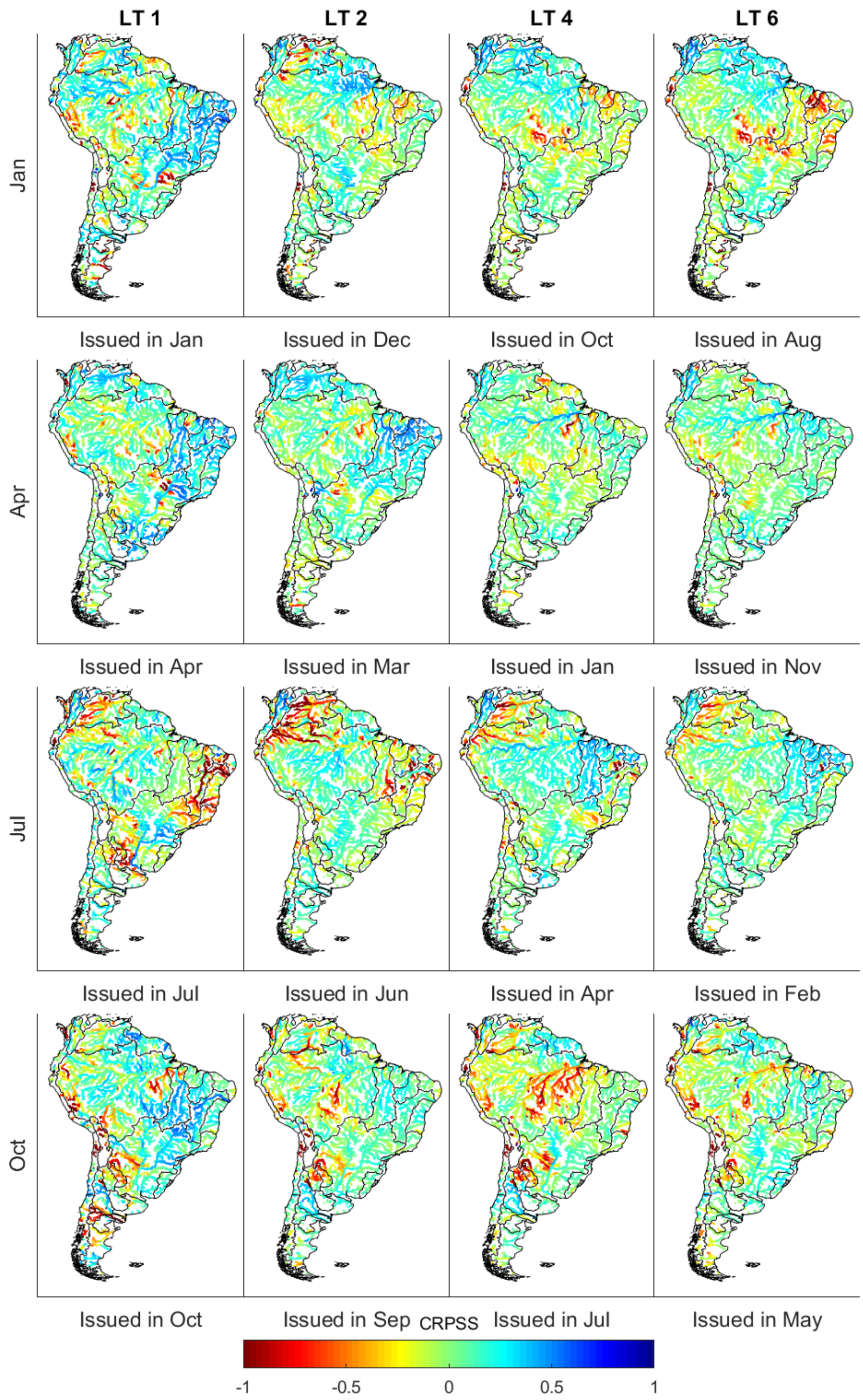


Figure 23 - CRPSS for bias-corrected SEAS5-SF relative to the ESP benchmark, according to season and lead time.

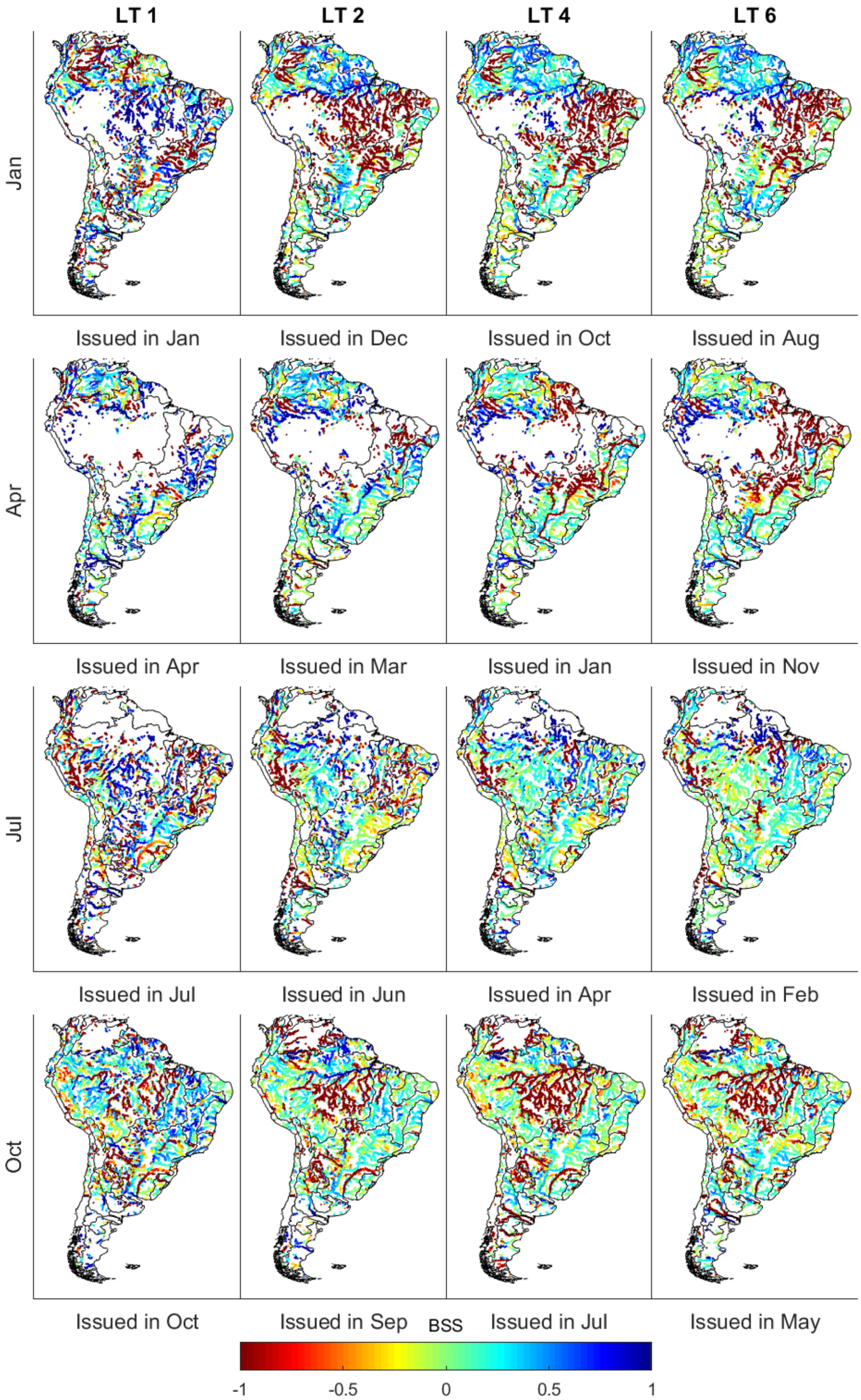


Figure 24 - BSS of bias-corrected SEAS5-SF relative to the ESP benchmark, according to season and lead time. The lower tercile of long-term monthly streamflow (Q66) is used as the event threshold.

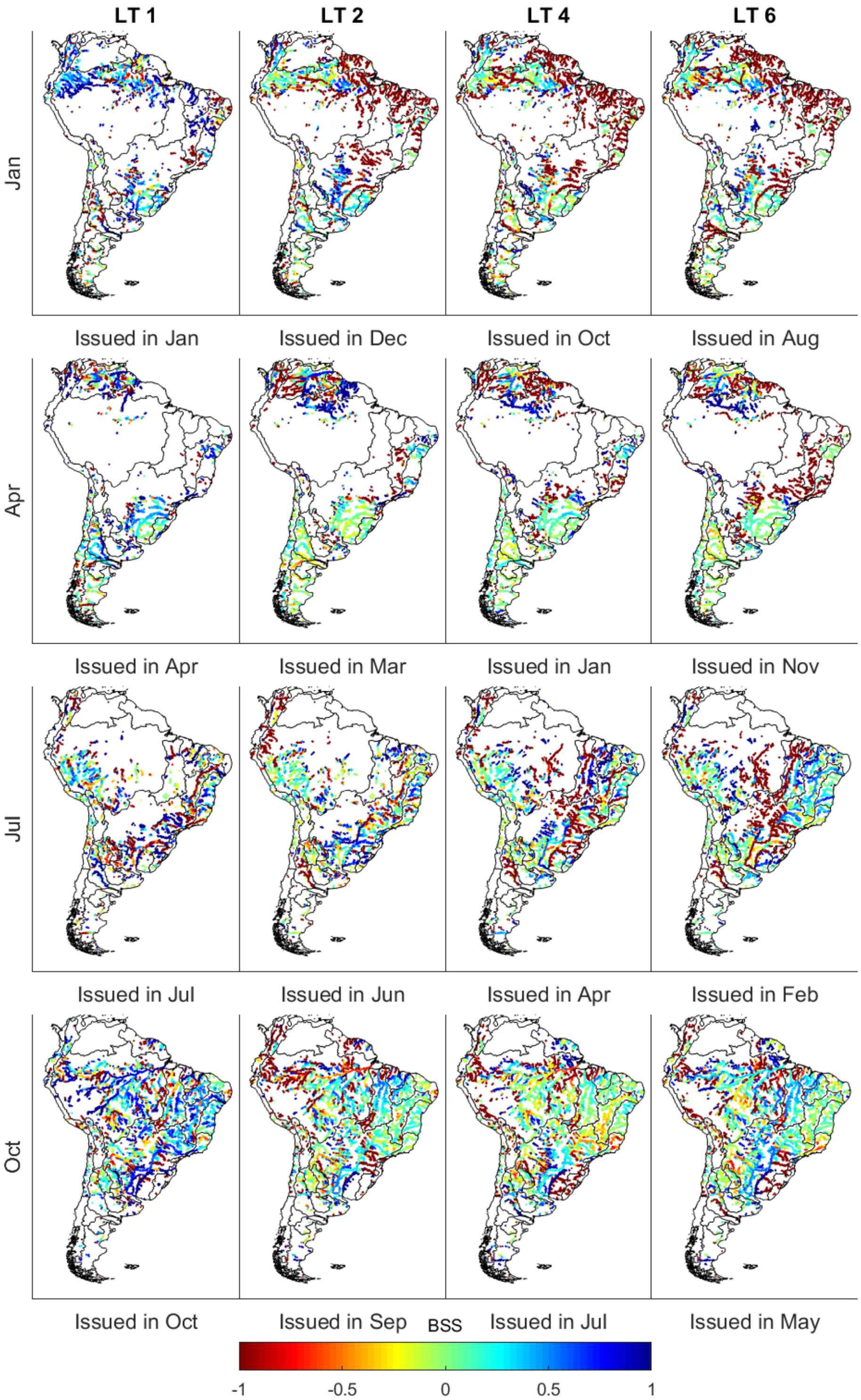


Figure 25 - BSS of bias-corrected SEAS5-SF relative to the ESP benchmark, according to season and lead time. The 95th percentile of long-term monthly streamflow (Q95) is used as the event threshold.

3.4.4. Analysis of SEAS5-SF for the Paraná Basin 2020-2021 drought

Figure 26 shows bias-corrected seasonal streamflow forecasts issued for the Paraná River at the Itaipu Dam in April 2020 and July 2020 at daily timestep (before monthly aggregation) and the Q95 streamflow. By the end of the 2020 and 2021 rainy season, the Brazilian hydropower generation system was under critical regime, with many hydropower plants operating at a fraction of their total capacity (CUARTAS et al., 2022). According to Cuartas (2022), the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) and Standardized Streamflow Index (SSFI) values started to decline in 2019, changing from values around zero and reaching -2 until 2021 (negative values represent streamflow below the climatological average).

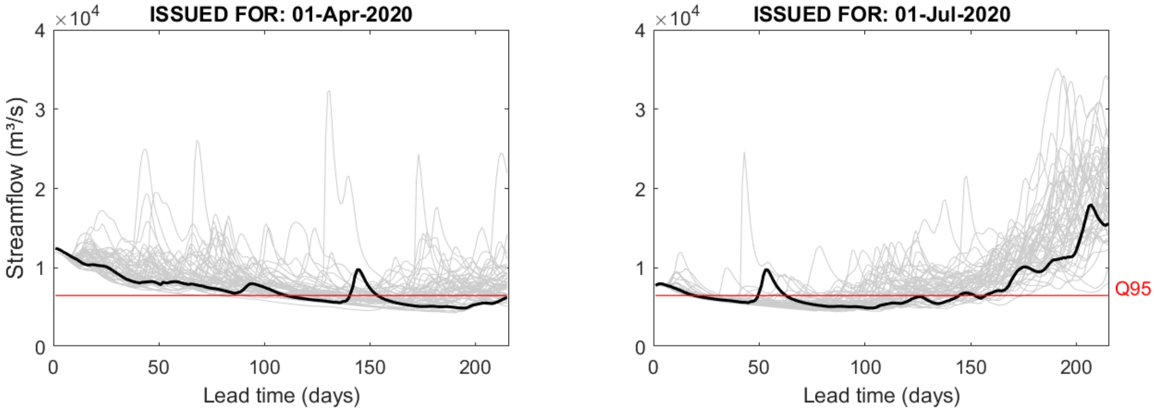


Figure 26 - Bias-corrected SEAS5-SF issued for April 1st 2020 and July 1st 2020. The SEAS5-SF ensemble members, MGB-SA reference simulation, and Q95 discharge threshold are shown in grey, black, and red colors, respectively.

At the Itaipu Dam, April is in the transition between the wet and dry seasons (Autumn) and July is the middle of the dry season (Winter). The forecast members predicted future streamflow below Q95, not only in the forecast issued in July, but also in April, a few months before the dry season (Figure 26). In addition, Figure 27 presents the ensemble coverage (i.e., the interval between the lower and upper member) and the ensemble mean for lead times of one, two, four and six months. We observe that the predicted streamflow for the 2020 dry season is below Q95 and somewhat below the previous year (winter of 2019). We also observe that the ensemble spread is much smaller for the 1-month lead time (i.e., forecasts issued for day 1-30), which reflects the increase in uncertainty of the forecasts for longer lead times.

Figure 28 presents the performance metrics of six different seasonal streamflow forecast experiments for the location of the Itaipu Dam. These include the raw and bias-corrected SEAS5-SF as well as the ESP, considering both forecast and hindcast periods.

The Hindcast experiments present consistently a better performance than those of Forecast for all metrics. Performance decreases with lead time for all metrics and the performance for the 1-month lead time is visibly better. In addition, bias correction improves SEAS5-SF performance in all metrics and results become closer to the ESP performance (Figure 28 continuous line is always near the dotted line). It shows not only the added value of bias correction but also the better performance of ESP in comparison to the raw SEAS5-SF, for this location.

In a closer look at the H-BC results, both CRPSS and BSS are positive for the first lead time, indicating better performance of bias-corrected SEAS5-SF in predicting low and very low flows than the ESP. However, for the other lead times, the skill is around zero. A relatively good performance of the Brier Score (Q95) can be observed for all forecast experiments at the H-BC results. From the BS formula, one can see that itis a metric that is sensitive to the climatological frequency of the event, in that the rarer an event the easier it is to achieve a good BS without having any real forecast skill.

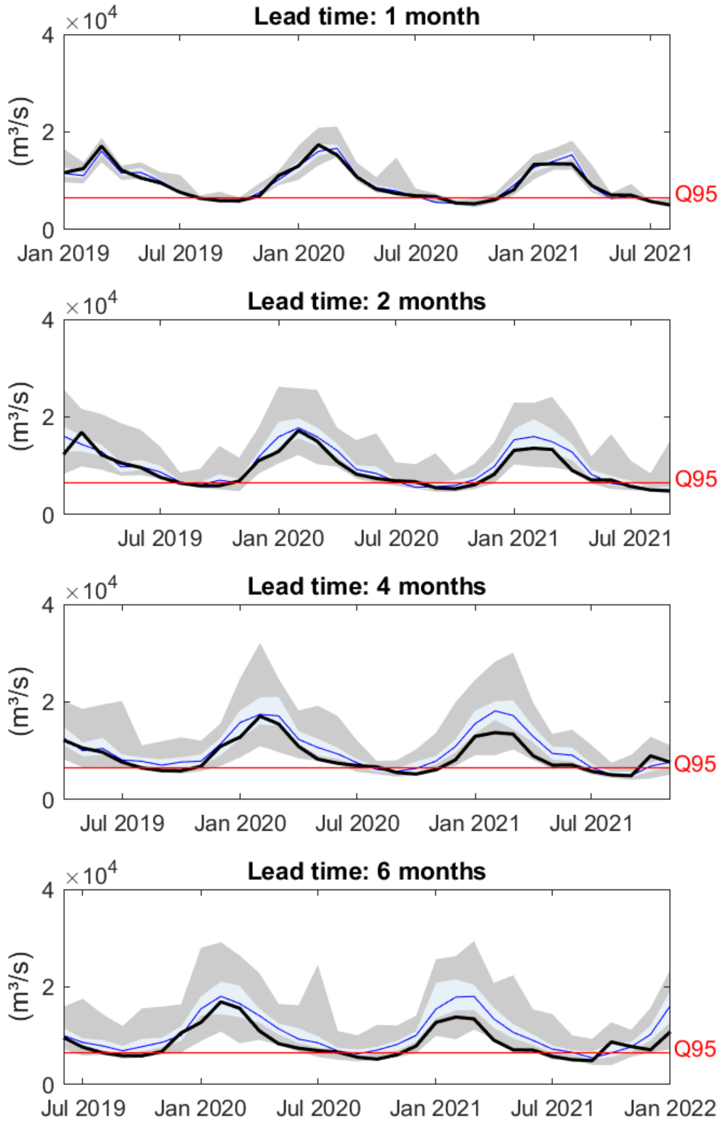


Figure 27 – Bias-corrected SEAS5-SF issued from January 1st 2019 to January 1st 2022. The SEAS5-SF ensemble members, ensemble mean, MGB-SA reference simulation, and Q95 discharge threshold are shown in grey, blue, black, and red colors, respectively. The dark gray areas the total ensemble coverage and light grey area 50% prediction interval

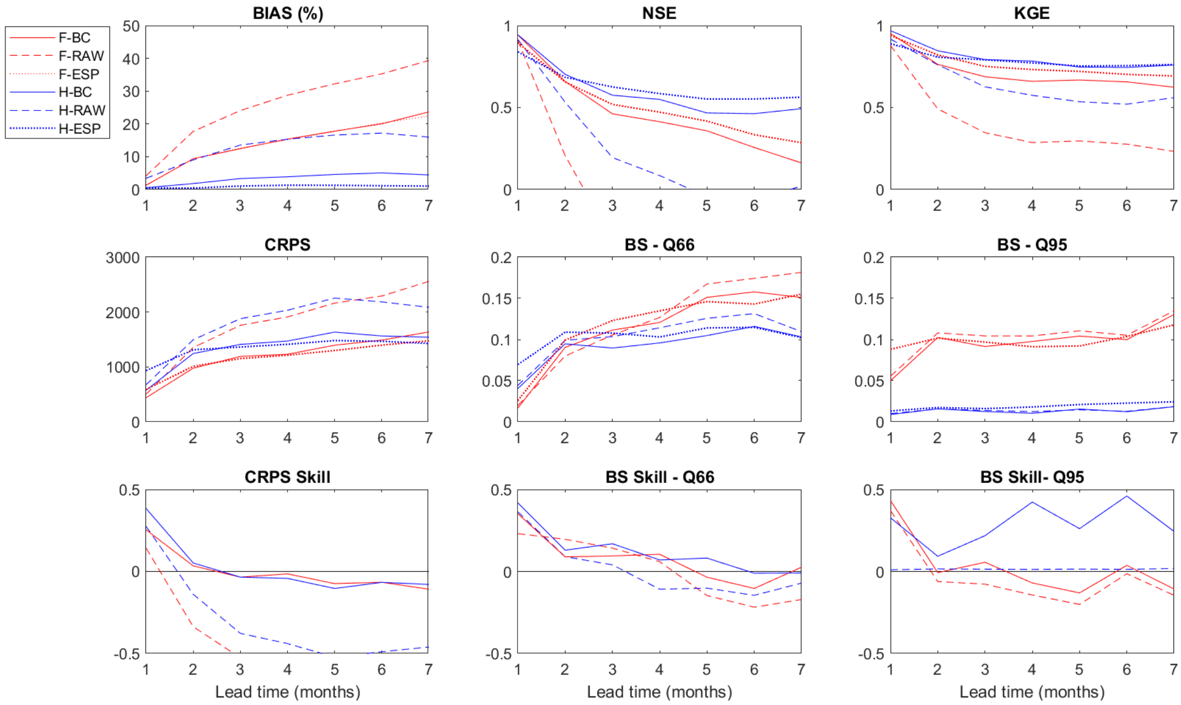


Figure 28 – SEAS5-SF performance metrics for the Paraná River at the Itaipu Dam. F means Forecast data, H means Hindcast and BC means bias corrected.

3.5. DISCUSSIONS

Regarding the importance of bias correction, the verification metrics showed added value in removing ECMWF SEAS5 bias to improve streamflow forecast performance: without bias correction, most of the MGB-SA river segments presented negative skill. After bias correction, the median performance of SEAS5-SF became closer to that of ESP or, in a smaller proportion, outperformed the benchmark.

The proposed framework based on SEAS5-SF performance, calculated by ensemble mean metrics (Bias, NSE and KGE), indicated better forecast performance for the lead time of one month, with similar behavior for the different seasons of the year. The results also suggest a better performance near the main river reaches of SA, i.e., rivers with greater upstream drainage area, commonly showing better predictability due to larger basin size (GHIMIRE et al., 2020; LI et al., 2009). The probabilistic metrics showed that the ability in predicting the occurrence of low flow thresholds (BS) is very similar among the different lead times and seasons and both CRPS and BS have similar spatial patterns to the seasonal average precipitation. The behavior, however, is the opposite. Regions with larger seasonal precipitation presented higher CRPS and lower BS for both the thresholds.

The results from skill statistical verification (CRPSS and BSS) showed that the SEAS5-SF skill over the ESP varies significantly according to the seasons, initialization month, basin and lead time. Our results reinforce that the ESP is a “hard to beat” method (PEÑUELA; HUTTON; PIANOSI, 2020) also in South America, especially after the first month of lead time.

Figure 29 presents the Brier Score Skill (Q95) for annual results and for the lead time of one, two, four and six months. These annual results show a general BSS for the low flow prediction, showing that our H-EPS have a strong positive skill (> 0.5) for the Amazon River and tributaries West tributaries and Paraná River, for the first lead time month. For the lead times of two, four and six months BSS Q95 varies, showing more consistent positive skill on the Tocantins, Araguaia and Parana Rivers.

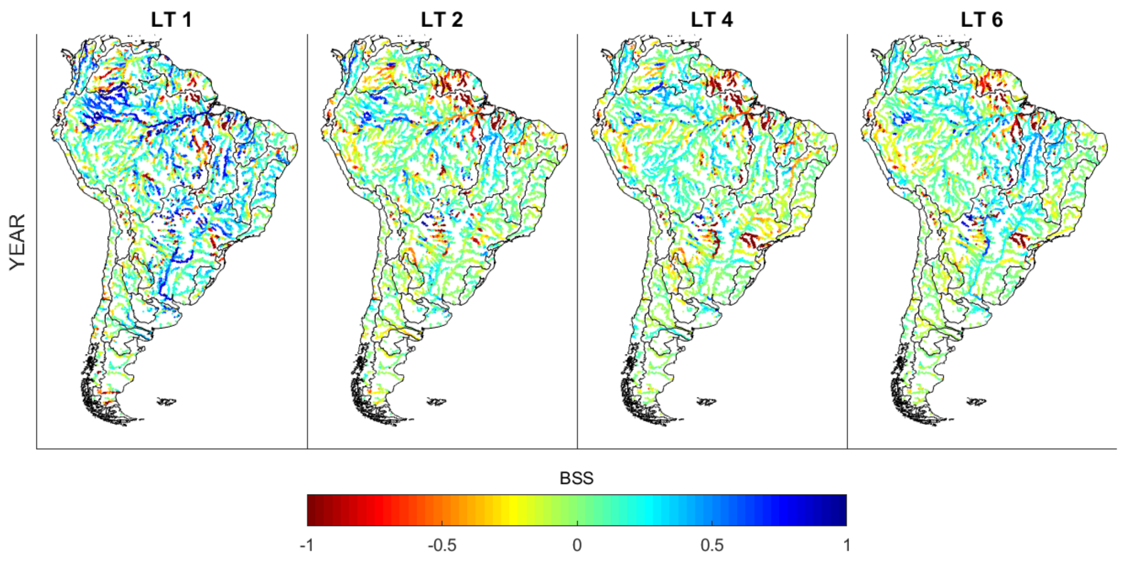


Figure 29 - Brier Score Skill (Q95) for annual results and for the lead time of one, two, four and six months

3.6. CONCLUSIONS

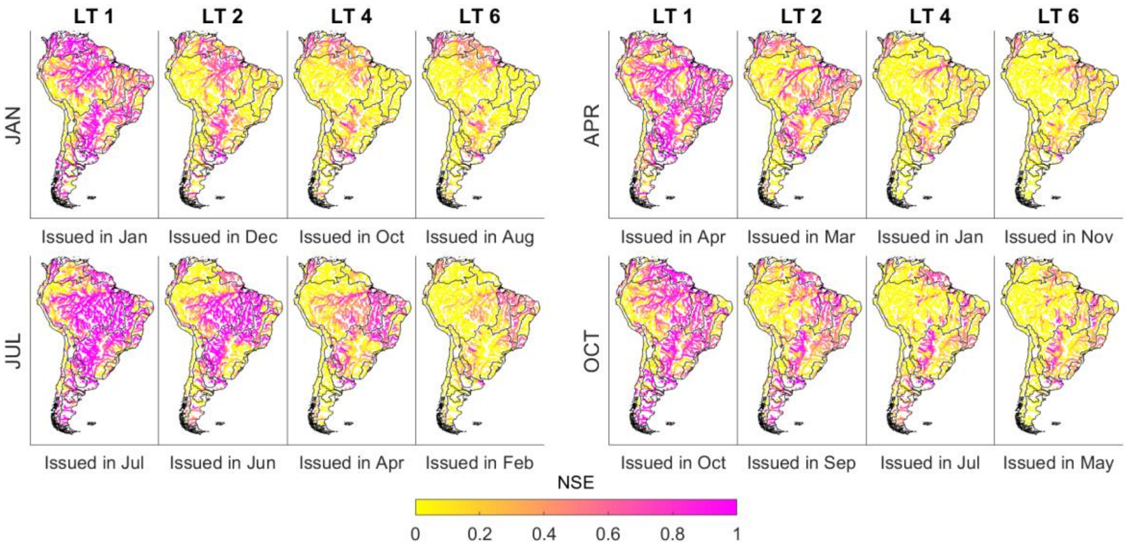
The results presented comprehends a first assessment of continental-scale seasonal streamflow forecasts in South American (SA) large rivers using a continental hydrologic-hydrodynamic approach.

We forced the MGB-SA hydrologic-hydrodynamic model with bias-corrected ECMWF SEAS5 predicted precipitation to produce seasonal streamflow forecasts (SEAS5-SF) and forecast performance was evaluated against a reference simulation run. We also assessed the relative performance of SEAS5-SF using the Ensemble Streamflow Prediction (ESP) as benchmark, thus providing insights on the added skill of using SEAS5 forecasts for predicting monthly discharges (up to 7 months) in large SA basins. Our main findings can be summarized as follows:

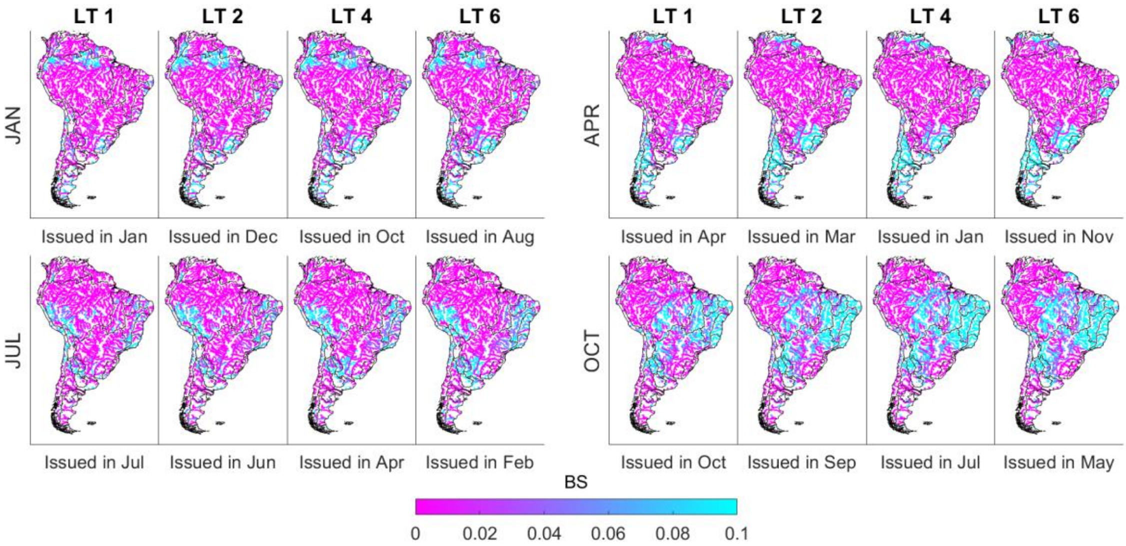
- The bias correction of SEAS5 predicted precipitation improved the performance of the seasonal streamflow forecasts, frequently turning negative skill results into near null to positive skill;
- SEAS5-SF based hydrologic-hydrodynamic forecasts presented the best skill values (for both CRPSS and BSS) on the first month lead time;
- ESP was a hard to beat benchmark for SEAS5-SF in several of South American regions;
- SEAS5-SF based forecasts skill varies according to season, initialization month, basin and forecast lead time. In this sense, we understand that our spatial skill results are suited to be used as a tool in the aid to find the best streamflow forecast method (among ESP and H-EPS) for each study area and objective;
- The rivers where SEAS5-SF presented the best annual BSS over ESP were the Amazon, Araguaia, Tocantins and Paraná.

Those results motivate us to continue working in the search for the best options on seasonal streamflow forecasting in South America. Future works should address the evaluation of the real skill of the forecasts, including comparison with observed discharges distributed over the continent and especially in the hydroelectric power plant’s locations. Also, we aim to investigate techniques on ESP sampling to increase the approach performance based on climatic indicators.

3.7. APPENDIX V - HINDCAST NSE



3.8. APPENDIX VI - HINDCAST BRIER SCORE Q95



4. FINAL CONSIDERATIONS

In this work, the chosen strategies to study the predictability and potential of seasonal streamflow forecasts in South America (SA) were applied and analyzed.

In Section 2, the predictability of streamflow under a null and climatological precipitation experiments was quantified and many aspects of streamflow predictability were discussed. The spatial variability of predictability was presented in map format and the insights obtained are going to support the further discussions.

The study shows that streamflow predictability from the ICs is around 10 days in the main river reaches of basins, such as the Paraná, São Francisco, Orinoco and Araguaia rivers, with even higher predictability in the main river such as Amazon on flat relief basins (> 60 days). The increase in predictability due to climatology-based boundary conditions mostly occur in areas that already have high predictability. Basins with fast response present low streamflow predictability (up to three days), such as the Uruguay Basin.

Section 3 represents the first continental-scale assessment of seasonal streamflow forecasts in SA. Our H-EPS was elaborated with MGB-SA hydrologic-hydrodynamic model with bias-corrected ECMWF SEAS5 predicted precipitation to produce seasonal streamflow forecasts (SEAS5-SF). Forecast performance was evaluated against a reference simulation run and we also assessed the relative performance of SEAS5-SF using the Ensemble Streamflow Prediction (ESP) as benchmark.

Our main finding is that ESP remains a hard to beat method for seasonal streamflow forecasting in South America. We observed the importance of bias correction on the SEAS5 precipitation forecasts so that the H-EPS present positive skill over ESP in many regions of South America. SEAS5-SF skill varies according to season, initialization month, basin and forecast lead time, with greater skill on the initialization month lead time.

Relating both articles, we observed that regions such as the Pantanal and Amazon Basin that have high predictability due the basin slow time response, reflected in higher SEAS5-SF performance up to the same predictability lead time (around two months). Besides, as in these regions ESP also presented better performance, we understand that SEAS5-SF skill does not relates to initial conditions or climatological boundary conditions predictability.

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