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Enhancing monthly streamflow forecasting for Brazilian hydropower plants through climate index integration with stochastic methods

Previsões mensais de vazões para as usinas hidrelétricas brasileiras utilizando métodos estocásticos e informação climática

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ABSTRACT

This study demonstrates the potential for enhancing monthly streamflow forecasting in Brazil through the incorporation of climatic indices. It extends the conventional periodic autoregressive model (PAR) for streamflow forecasts by integrating climate information, represented by three key climate indices reflecting sea surface temperatures in the Pacific and Atlantic Oceans, as well as zonal wind patterns in southeastern Brazil. Using the Kling-Gupta Efficiency (KGE) skill metric, our findings reveal that the inclusion of climate data consistently outperforms existing PAR models in numerous scenarios. Notably, during May, the proposed model enhances forecasts for 79% of the reservoirs (124 out of 157), while in January, it reduces forecast variance for up to 90% of the reservoirs (141 out of 157).

Keywords: Monthly streamflow forecasts; PAR models; Climate information.

RESUMO

Esse estudo demonstra o potencial de aperfeiçoamento das previsões mensais de vazão ao sistema hidroelétrico brasileiro por meio da incorporação de índices climáticos. A modelagem proposta amplia o modelo periódico autoregressivo (PAR) convencional para previsões de vazão a partir da inclusão de informações climáticas, representadas por três índices climáticos-chave que refletem as temperaturas da superfície do mar nos Oceanos Pacífico e Atlântico, bem como padrões de vento zonal no sudeste do Brasil. Usando a métrica de *Kling-Gupta Efficiency* (KGE), os resultados obtidos revelam que a inclusão de informação climática supera consistentemente os modelos PAR existentes em inúmeras situações. Em particular, durante o mês de maio, o modelo proposto melhora as previsões para 79% dos reservatórios (124 de 157), enquanto em janeiro, reduz a variância das previsões em até 90% dos reservatórios (141 de 157).

Palavras-chave: Previsões mensais de vazões; Modelos PAR; Informação climática.

INTRODUCTION

The Brazilian electrical grid relies heavily on hydropower plants, accounting for nearly 65% of the country's electricity production (Brasil, 2020). The operational protocols for these hydropower plants, interconnected through transmission lines within the National Interconnected System (SIN), are established and overseen by the Brazilian National Operator (ONS). The overall efficiency of the SIN, influenced by various factors, critically hinges on the capability of streamflow forecast models to generate dependable simulations across various time scales.

At the monthly scale, autoregressive stochastic models are frequently employed (Maceiral et al., 2018; Centro de Pesquisas de Energia Elétrica, 2018, 2019). In recent research efforts (e.g., Pham et al., 2021; Li et al., 2020; Moradi et al., 2020; Silveira et al., 2017; Lima & Lall, 2010a, 2010b), attempts have been made to enhance such forecasts by incorporating exogenous indices alongside the inherent autoregressive components. While rainfall data is commonly utilized at shorter time scales (daily or weekly), for monthly streamflow predictions, it is more customary to employ climate predictors associated with large-scale processes and climate teleconnections.

Incorporating climate information into streamflow forecasts can be achieved through various methods. When working with empirical autoregressive models, one straightforward approach involves extending the conventional Periodic Autoregressive Model (PAR) by introducing additional covariates, namely climate predictors. This modification gives rise to the Periodic Autoregressive Exogenous Model (PARX). In this study, we assess both models, utilizing the PAR as a baseline to replicate the existing practices of ONS.

In the existing literature, it's also common to encounter machine learning techniques capable of integrating climate data into streamflow forecasts (Pham et al., 2021; Li et al., 2020; Ribeiro et al., 2020; Fu et al., 2019; Botsisa et al., 2018; Schick et al., 2016). However, many of these models are often labeled as "black box" due to their reduced interpretability compared to other methods. One machine learning approach that maintains its interpretability is ridge regression (Berk, 2020; James et al., 2013; Lima & Lall, 2010a), which is also assessed in this study.

Regarding climate data, we have selected three climate indices to incorporate into our forecasting models. These indices capture large-scale climate processes that influence rainfall variability (and consequently streamflow) across Brazil. Specifically, these indices are derived from sea surface temperature (SST) data in parts of the Atlantic and Pacific Oceans, as well as the zonal wind field in Southeastern Brazil. The efficacy of these indices in enhancing streamflow forecasts for certain hydropower plants across Brazil has been previously demonstrated in prior studies (Oliveira & Lima, 2016; Lima & Lall, 2010a, 2010b).

The streamflow time series employed in this study consist of monthly natural incremental streamflow data collected from the majority of hydropower plants within the SIN, spanning from 1949 to 2022 (coinciding with the period covered by the climatic indices). The only hydropower plants omitted from this analysis are those with consistently null monthly natural incremental streamflow, a common occurrence for reservoirs configured in cascade arrangements. To assess the goodness of fit, we employ the Kling-Gupta Efficiency criteria, denoted as KGE, as our chosen evaluation metric (Gupta et al., 2009).

METHODOLOGY

Monthly streamflow forecasts up to six months in advance were generated employing three distinct models: i) A Periodic Autoregressive Model (PAR), which relies solely on historical streamflow data as input; ii) A Periodic Autoregressive Exogenous Model (PARX), incorporating climate indices as additional predictors; iii) A Ridge Regression Model, also utilizing the climate indices as part of its input features.

To evaluate the goodness of fit, the Kling-Gupta efficiency coefficient (Gupta et al., 2009) is used (Equation 1). The coefficient itself (KGE) along with each of the three components (α, β and *r*) that are needed to create it are evaluated. The *r* component is for the correlation between the observed streamflow and the model used, α stands for the division of the simulated and observed standard deviation ($\alpha = \sigma_S / \sigma_O$) and β is the division of the simulated and observed mean ($\beta = \mu_s / \mu_o$).

$$\mathrm{KGE} = 1 - \sqrt[2]{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad (1)$$

Out of the 167 operational hydropower plants in Brazil within the SIN, this analysis included 157 of them, as illustrated in Figure 1. The selection criteria excluded hydropower plants with a null naturalized incremental monthly streamflow, which is a common characteristic of cascade reservoirs. Figure 1 also provides information about the subsystem (North, South, Northeast, and Southeast) to which each reservoir belongs, with the centroid of each subsystem indicated on the map.

Streamflow data

The dataset utilized encompasses 73 years of monthly incremental and naturalized streamflow data for each hydropower plant, spanning from 1949 to 2022. This data is readily accessible, courtesy of the national operator (Operador Nacional do Sistema Elétrico, 2022). The term "incremental" is employed because it involves subtracting the upstream station's streamflow from the observed value. Furthermore, it is referred to as "naturalized" as it incorporates additional factors, such as water withdrawals upstream for various purposes, into the observed fluviometric station data.

Climate indices

To assist in the monthly streamflow forecasting for Brazil, we have incorporated three climate indices, also referred to as predictors. These specific indices were selected based on prior research, which has demonstrated their effectiveness in enhancing predictions for certain reservoirs (Lima & Lall, 2010a). Notably, all three indices cover the same time frame as our streamflow data, ranging from 1949 to 2022. One of these indices focuses on zonal winds at 700mb, situated between 10°S to 20°S and

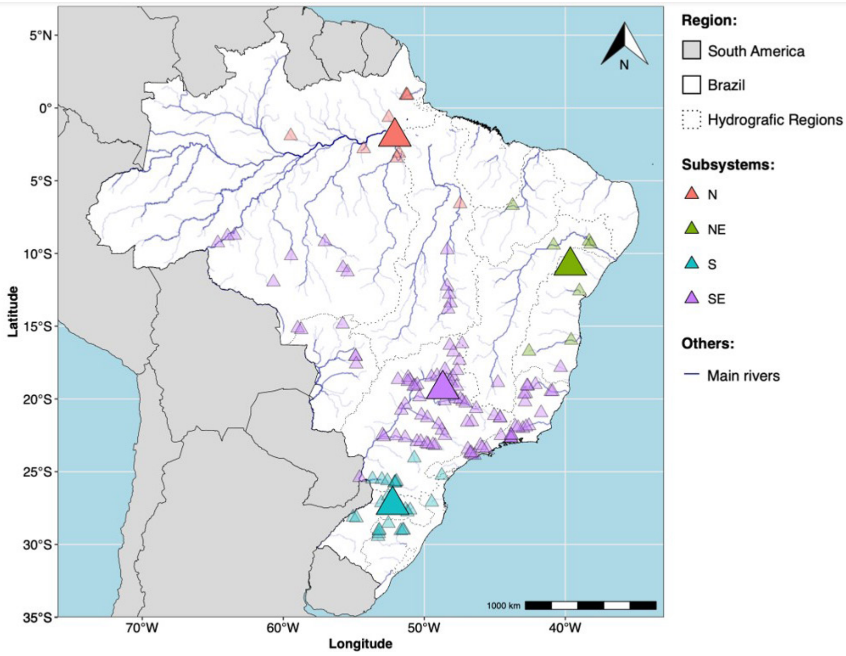

Figure 1. Location of the hydropower plants used by subsystem, with its subsystem centroid.

35°W to 50°W, and is denoted as U1 within this study. This data is available at Columbia University (2023a).

The remaining two indices are derived from anomalies in sea surface temperature (SST). The first of these, referred to as SST2 in this study, pertains to the Atlantic Ocean and covers the region between 12°S to 30°S and 20°W to 40°W. The second index, labeled as NINO3, is associated with the Pacific Ocean and encompasses the area between 5°S to 5°N and 150°W to 90°W. These indices (SST2 and NINO3) are available at, respectively, Columbia University (2023b, 2023c).

Autoregressive Periodic Model (PAR)

Periodic Autoregressive Models belong to the category of stochastic models, relying solely on past streamflow time series data for forecasting. These models are extensively applied in the context of monthly streamflow prediction. The Brazilian National Operator for the electric system (ONS) employs various models that internally incorporate such stochastic models, including the PREVIVAZM model. Therefore, in this study, we adopt a simplified PAR model to simulate the forecasting capabilities of ONS for up to 6 months in advance.

A generic PAR model to forecast a monthly streamflow (*Q*) for a given year (*v*) and month (τ) is mathematically represented in Equation 2. As it is designed, only the last observed monthly streamflow is used, based on the on the lag used (*h*) – so for a prediction six months ahead, only the streamflow from six months prior is used. It is a periodic model, due to the existence of a different coefficient (φ_0) for each month/period (τ), hence there are 12 models for each reservoirs evaluated. To calculate the value of each φ, the least square method is used. If $\tau - h < 1$, then $Q_{v-1,.\tau-h+12}$ is used instead of $Q_{v,.\tau-h}$. The calibration of such model (values of φ0) was done with data from 1949-2010, using 2011-2021 for validation.

$$Q_{v,\tau} = \varphi_{0,\tau} * Q_{v,\tau-h} \tag{2}$$

Autoregressive Periodic Exogenous Model (PARX)

An Autoregressive Periodic Exogenous Model closely resembles a PAR model, with the key distinction lying in its consideration of climatic indices alongside previous streamflow values. These climatic indices, as previously mentioned, include the three climate indices previously defined. The model is mathematically represented by Equation 3, and it employs the least squares method to determine the coefficients (φ) for each month (τ) and reservoir. The coefficients were calibrated with data from 1949-1990, being tested between 1991-2010, where the best values (with highest KGE) were chosen for validation (2011-2021).

Notably, the lag applied to the climate index corresponds to the same lag utilized for the autoregressive component. For instance, when predicting streamflow four months into the future, the model incorporates the monthly streamflow data from the preceding four months as well as the climate index value for the same month.

$$Q_{v,\tau} = \varphi_{0,\,\tau} * Q_{v,\,\tau-h} + \sum_{i=1}^{3} \varphi_{i,\,\tau} * Xi_{v,\,\tau-h} \tag{3}$$

RIDGE regression

Ridge regression, a form of L2 regularization, shares the same equation structure as the PARX model (Equation 3). The primary distinction lies in the method used to estimate the coefficients (φ), as depicted by Equation 4. This approach operates on the principle of the bias-variance tradeoff, introducing a controlled level of bias to reduce the model's variance (Berk, 2020; James et al., 2013). While categorized as a machine learning technique, ridge regression remains interpretable and yields results in a manner akin to the models currently employed by ONS in Brazil.

$$\min\left\{\sum_{i=1}^{N}\left[Y_{v,\tau}-Q_{v,\tau}\right]^{2}+\lambda\sum_{i=0}^{3}\varphi_{i,\tau}^{2}\right\} \tag{4}$$

In this Equation 4, $Y_{v,\tau}$ stands for the actual streamflow, with $Q_{v,\tau}$ being represented by Equation 3 (as the PARX model). The shrinkage is made by the λ parameter, where it penalizes higher values of each coefficient. It is worth noting that when λ = 0, the ridge regression calculates the coefficients by the least square method, similar to the PAR and PARX models. Values ranging from 0 to 1000, with 0.01 steps, were tested for λ, with data from 1949-2010, with the optimum λ being used for validation (2011-2021).

RESULTS AND DISCUSSIONS

One of the initial findings pertains to identifying which model yields the highest KGE value (or the values of its three individual components), as illustrated in Figure 2. This figure indicates the superior model for each forecasted month (where all lead times are combined into a single time series for a given month), without quantifying the extent of its superiority. The rationale behind this approach is that, from an operational standpoint, what matters most is determining which model performs best. In this context, it is worth noting that PREVIVAZM, an ONS-utilized model, explores multiple variations of several models but selects only the most effective one for forecasting the desired values.

This figure distinctly highlights the advantages of incorporating climatic indices in monthly streamflow forecasting. It is evident that the KGE values have seen improvements in as many as 79% of the evaluated hydropower plants (124 out of 157 in May). The benefits brought by each of these components are visually represented for each month, potentially paving the way for future research to focus on improving specific components rather than the entire model. For instance, in January, the α values were superior for climatic models (PARX or Ridge) in 90% of the reservoirs. Moreover, in March, there was a noteworthy enhancement of 82% and 71% in the β and r components, respectively.

While the binary assessment of model performance is operationally crucial, gaining insight into the magnitude of these values is equally important. This insight is provided by Figure 3, which features density plots for each component and KGE. Below each density plot, we present at least the middle quantiles via a boxplot, as the density is an approximation of the data points. In cases where the boxplot contains points beyond the visible plot range, a red asterisk is placed near the boxplot boundary (*). The red dashed line represents the optimal value for each component.

This visualization makes it evident that the most significant improvement (in absolute terms) is observed in the α component. This is particularly noteworthy as it underscores how the incorporation of climatic indices in the PARX model can enhance the standard deviation of the simulated series (given that $\alpha = \sigma_s / \sigma_o$, where σ represents standard deviation).

Lastly, it is of significant interest to gain a spatial understanding of where the primary benefits of employing these climate indices lie. Given the large number of hydropower plants

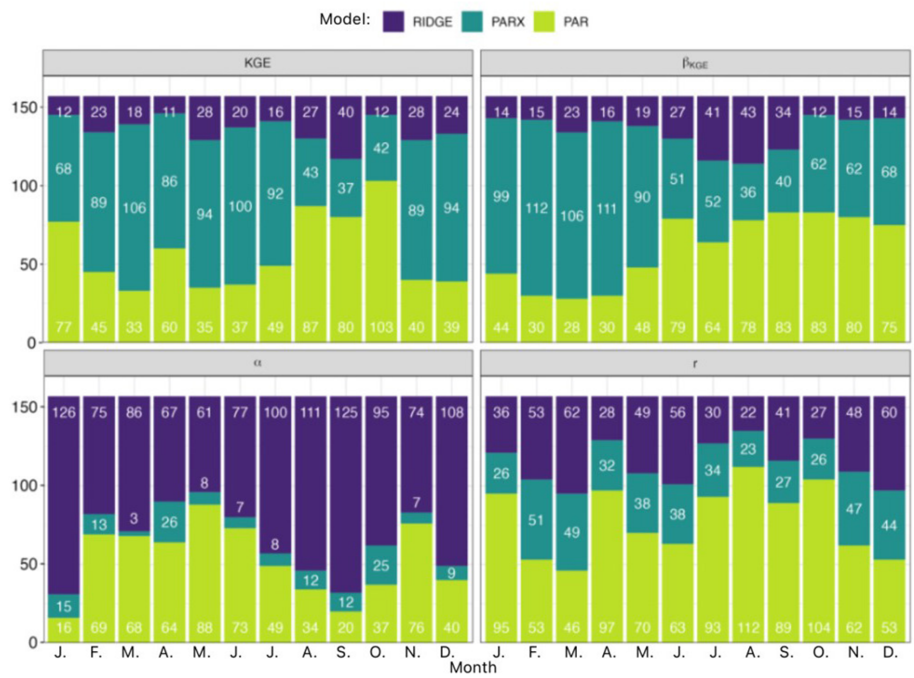

Figure 2. Best model for each month for each hydropower evaluated.

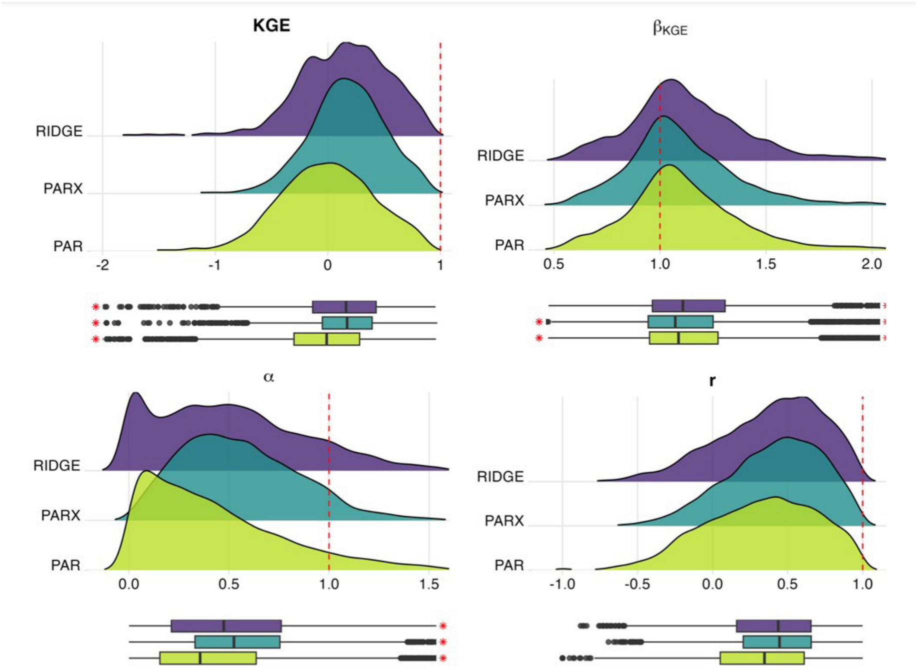

Figure 3. Density plot and a boxplot for the value of each component for the three models used.

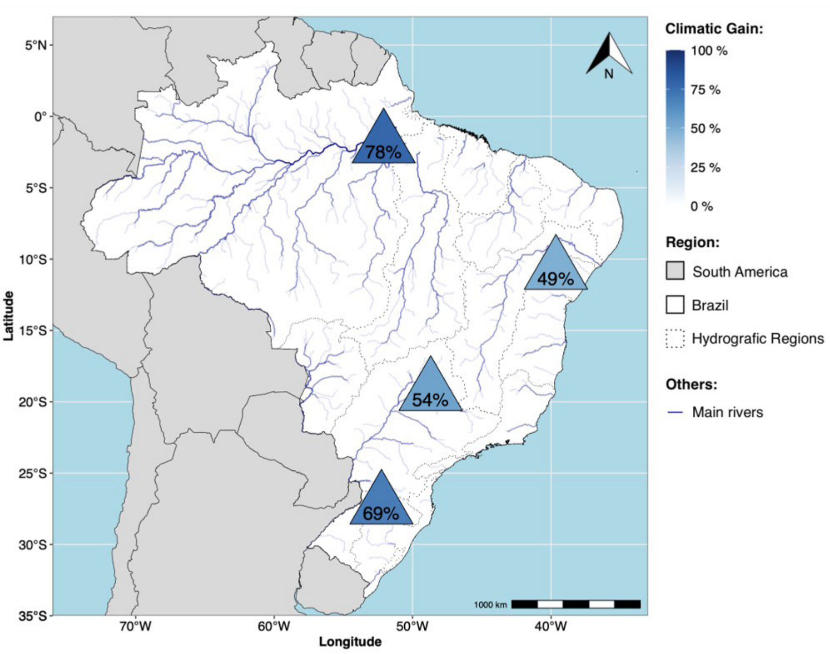

Figure 4. Map for the climatic gain for each Brazilian subsystem.

considered (157), for visual clarity, we've grouped the reservoirs into the four subsystems depicted in Figure 1, using the concept of Equivalent Energy Reservoir (REE) (Arvanitidits & Rosing, 1970). In Figure 4, the intensity of the blue shading within each subsystem centroid illustrates the percentage of cases where the proposed model (PARX or RIDGE) outperforms the base PAR model, denoting the "climatic gain." This percentage value is also explicitly indicated within each centroid, providing a clear representation of the spatial distribution of benefits.

The map presented in Figure 4 clearly illustrates the regions where the climate indices prove to be most beneficial, notably in the Northern and Southern parts of Brazil. In the Northern region, a striking 78% of all forecasts (which encompass 6-month ahead predictions for each of the 12 months, totaling 72 forecasts for each subsystem) showed improved performance when the climate indices (U1, SST2, and NINO3) were incorporated. Even in the Northeast, which represents the least favorable case for Brazil, a noteworthy 49% of the forecasts exhibited higher KGE values — an outcome of significance. As previously mentioned, the primary objective in operational scenarios is to attain models with enhanced forecasting capabilities. While the precise numerical value of this improvement is essential, the paramount significance lies in the existence of any improvement at all.

CONCLUSIONS

This study has demonstrated the superior performance of models incorporating the three climate indices (U1, SST2, and NINO3), namely PARX and RIDGE, in numerous instances of monthly streamflow forecasting. Employing the KGE metric, the climatic models managed to outperform the non-climatic model in as many as 79% of the hydropower plants (124 out of 157) during a particular month (May). This superiority persisted across 8 out of the 12 months, with the remaining 4 months still witnessing improvements in some reservoirs through the utilization of climate indices, albeit not consistently across the majority.

A closer examination of the individual components of the KGE visually illustrated how the incorporation of climatic information effectively aligned the standard deviation of the forecasted time series with the observed data, particularly evident in the α component. While the gains in the other two components were not as substantial, they were still evident in the majority of reservoirs, underscoring the overall effectiveness of the PARX and RIDGE forecast models.

The Northern and Southern regions of Brazil emerge as the primary beneficiaries of incorporating these climate indices into the forecast models, as evidenced by the climatic gains observed within each subsystem. Nevertheless, the advantages extend to other regions as well, including the seemingly less favorable Northeast, where better results were achieved in 49% of scenarios employing the climatic models.

In operational settings where the primary objective is to attain the most accurate forecasts while retaining a certain level of interpretability, this study provides compelling evidence for the inclusion of these three climate indices in monthly forecasting. It is worth noting that the models employed in this study were not optimized to their full potential, and there may be additional climatic information not utilized that could further enhance monthly forecasts.

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Thiago Lappicy: Writing, Models development, Images.

Carlos H. R. Lima: Writing, Revision, Models development.

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