Monthly and seasonal streamflow forecasting of large dryland catchments in Brazil (Postprint)

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Abstract

Streamflow forecasting in drylands is challenging. Data is scarce, catchments are highly human-modified and streamflow exhibits strong nonlinear responses to rainfall. The goal of this study was to evaluate the monthly and seasonal streamflow forecasting in two large catchments in the Jaguaribe River Basin in the Brazilian semi-arid area. We adopted four different lead times: one month ahead for monthly scale and two, three and four months ahead for seasonal scale. The gaps of the historic streamflow series were filled up by using rainfall-runoff modelling. Then, time series model techniques were applied, i.e., the locally constant, the locally averaged, the k-nearest-neighbours algorithm (k-NN) and the autoregressive model (AR). The criterion of reliability of the validation results is that the forecast is more skillful than streamflow climatology. Our approach outperformed the streamflow climatology for all monthly streamflows. On average, the former was 25% better than the latter. The seasonal streamflow forecasting (SSF) was also reliable (on average, 20% better than the climatology), failing slightly only for the high flow season of one catchment (6% worse than the climatology). Considering an uncertainty envelope (probabilistic forecasting), which was considerably narrower than the data standard deviation, the streamflow forecasting performance increased by about 50% at both scales.

The forecast errors were mainly driven by the streamflow intra-seasonality at monthly scale, while they were by the forecast lead time at seasonal scale. The best-fit and worst-fit time series model were the k-NN approach and the AR model, respectively. The rainfall-runoff modelling outputs played an important role in improving streamflow forecasting for one streamgauge that showed 35% of data gaps. The developed data-driven approach is mathematical and computationally very simple, demands few resources to accomplish its operational implementation and is applicable to other dryland watersheds. Our findings may be part of drought forecasting systems and potentially help allocating water months in advance. Moreover, the developed strategy can serve as a baseline for more complex streamflow forecast systems.

Full Text

Preamble

Monthly and seasonal streamflow forecasting of large dryland catchments in Brazil

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Abstract: Streamflow forecasting in drylands is challenging. Data is scarce, catchments are highly human-modified, and streamflow exhibits strong nonlinear responses to rainfall. The goal of this study was to evaluate monthly and seasonal streamflow forecasting in two large catchments in the Jaguaribe River Basin in the Brazilian semi-arid area. We adopted four different lead times: one month ahead for monthly scale and two, three, and four months ahead for seasonal scale. The gaps in the historic streamflow series were filled using rainfall-runoff modelling. Then, time series model techniques were applied: the locally constant, the locally averaged, the k-nearest-neighbours algorithm (k-NN), and the autoregressive model (AR). The criterion for reliability of the validation results is that the forecast is more skillful than streamflow climatology. Our approach outperformed streamflow climatology for all monthly streamflows. On average, the former was 25% better than the latter. The seasonal streamflow forecasting (SSF) was also reliable (on average, 20% better than climatology), failing slightly only for the high flow season of one catchment (6% worse than climatology). Considering an uncertainty envelope (probabilistic forecasting), which was considerably narrower than the data standard deviation, the streamflow forecasting performance increased by about 50% at both scales. The forecast errors were mainly driven by streamflow intra-seasonality at monthly scale, while they were driven by forecast lead time at seasonal scale.

The best-fit and worst-fit time series models were the k-NN approach and the AR model, respectively. The rainfall-runoff modelling outputs played an important role in improving streamflow forecasting for one streamgauge that showed 35% data gaps. The developed data-driven approach is mathematically and computationally very simple, demands few resources for operational implementation, and is applicable to other dryland watersheds. Our findings may be part of drought forecasting systems and potentially help allocate water months in advance. Moreover, the developed strategy can serve as a baseline for more complex streamflow forecast systems.

Keywords: nonlinear time series analysis; probabilistic streamflow forecasting; reconstructed streamflow data; dryland hydrology; rainfall-runoff modelling; stochastic dynamical systems

1. Introduction

Brazil is a land where water abounds. However, this resource is unevenly distributed throughout the country's territory. A particularly drought-prone region is the northeast part of the country, which has been struck by over 100 severe droughts since the 16th century (Fioreze et al., 2012). A period of exceptionally strong droughts has been affecting the region since 2012 with severe social and economic consequences. Despite the extreme environmental conditions, more than 25% of the Brazilian population lives within the so-called "drought polygon" in northeastern Brazil (NE-Brazil) (Formiga-Johnsson and Kemper, 2005).

Water management and planning in NE-Brazil has centered on storing surface water by building dams (Araújo, 1990). In the drought polygon, groundwater resources are generally scarce, and several thousands of reservoirs (mostly small dams) have been built in recent decades. An interstate water transfer system is also under construction (Nunes, 2012). In the last 30 years, the creation of subbasin committees and user commissions has involved hundreds of stakeholders such as municipalities, public and large private irrigators, fishermen, and industry leaders in the process of water allocation and conflict resolution. These experiences represent important transformations in water management practices and increased demands for technical support, principally in the form of streamflow forecasts, which fall perfectly within a context of proactive drought risk management (Crochemore et al., 2016).

Reliable seasonal streamflow forecast information is a key aspect of drought mitigation (Shukla and Lettenmaier, 2011), since the water allocation process for a given rainy season may start prior to its end, optimizing water releases to multiple competing users. Additionally, measures of water demand reduction can be applied more efficiently, avoiding abrupt water shortages. Despite widespread recognition of the relevance and importance of seasonal streamflow forecasting (SSF) in the research community, forecasting of streamflow for drought management has not been applied widely (Trambauer et al., 2015). The forecast information must satisfy the need for thorough drought assessment without overwhelming end users with high complexity (Seibert et al., 2017).

Approaches for SSF predominantly fall into two categories: statistical or dynamic. The former frequently utilizes predictors of sea-surface temperature or related indices to directly estimate streamflow through regression techniques (Seibert et al., 2017; Delgado et al., 2018). The latter seeks to use numerical climate models linked with conceptual or physically based hydrological models through either an iterative (online) or static (offline) procedure (Collischonn et al., 2007; Yossef et al., 2013; Yuan, 2016; Yuan et al., 2016).

Souza Filho and Lall (2003) developed a semiparametric approach for forecasting inflows at reservoirs in the State of Ceará (Ceará) in NE-Brazil conditional on the NINO3 index (the mean monthly temperature anomaly in the eastern tropical Pacific: 5°S-5°N, 150°W–90°W) for the El Niño Southern Oscillation (ENSO) and an equatorial Atlantic sea surface temperature index. Forecasts of January through December streamflow were made at three lead times: in January of the same year and in October and July of the preceding year. Large-scale climatic patterns have commonly been applied for improving long lead time streamflow forecasts (Moradkhani and Meier, 2010; Kalra et al., 2012; Kalra et al., 2013). They found that streamflow at the Ceará sites is highly spatially correlated and influenced by climate in a similar manner, leading to a common underlying model for all sites. Although the correlation of the median forecast with observed annual inflows of Orós reservoir, the second largest reservoir in Ceará, was consistently high (0.91) for the validation period (1993–2000), the dispersion of the forecasting ensemble was quite high, reaching, for example, 65% of reservoir capacity (difference between 75th and 25th percentiles of ensemble forecasts) in 2000.

Delgado et al. (2018) assessed seasonal drought forecast models for the Jaguaribe River in semi-arid NE-Brazil. The forecast issue time was January and the forecast period was January to June. Their work employed a cascade of models and algorithms ranging from two general circulation models (GCMs) (one atmospheric and one coupled) at the top to hydrological indices at the bottom. Three statistical meteorological downscaling approaches were applied to the GCM outputs. Reservoir volumes were obtained by fitting multivariate linear regression based on forecast meteorological drought indices as predictors, such as Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) at different timescales. They found that low precipitation events showed either very low or no skill. Moreover, the good skill of reservoir storage forecast was likely related to the long memory of the reservoir system, because forecasted precipitation affects the reservoir only marginally since most of its storage accumulates over several years. In fact, no approach had a Root Mean Square Error (RMSE) that significantly departed from the RMSE of climatology (Delgado et al., 2018), i.e., the observed long-term average of a variable.

Pilz et al. (2019) evaluated and compared performances of seasonal reservoir storage forecasts derived by a process-based, semi-distributed hydrological model and a statistical approach developed by Delgado et al. (2018). They found, in a hindcast experiment (1981-2014), that accuracy in estimating regional reservoir storages was considerably lower using the hydrological model. Investigations regarding deficiencies of the process-based model revealed significant influence of antecedent wetness conditions and higher sensitivity of model prediction performance to rainfall forecast quality.

Applying a framework of GCMs, multiple regional climate models (including dynamical and statistical models), and two lumped water balance models, Block et al. (2009) produced ensemble streamflow forecasts for a hindcast of 1974–1996 monthly streamflow of the Jaguaribe River. The best coupled model demonstrated high skill scores for correlation (0.90) and RMSE (8.1×10^{7} m^{3}) (based on ensemble median), but performed inferiorly to climatology for the ranked probability skill score (Wilks, 2005). Afterwards, Kwon et al. (2012) showed that uncertainties associated with climate forecast are much larger than those from parameter estimation in the assumed hydrological model. Thus, past studies indicated that no dynamical, statistical, or hybrid approach outperformed climatology for streamflow forecasting in the Jaguaribe River Basin.

Poor or lower performance of forecasting systems for (very) dry catchments has also been reported by other authors. Robertson and Wang (2012) introduced a predictor selection method for a Bayesian joint probability approach to 3-month-ahead streamflow forecasting at multiple sites in two catchments in eastern Australia. They found that skill scores were considerably lower for intermittent rivers in the Burdekin River catchment than for perennial ones in the Goulburn River catchment. In fact, in the Burdekin River catchment, the skill of streamflow forecasts was close to zero for many months. Sittichok et al. (2016) combined statistical rainfall forecasting models with rainfall-runoff modelling in the Sahel region. They found moderate skill (coefficient of determination equal to 0.55) for monthly streamflow with a 12-month forecasting lead time in the Sirba watershed, West Africa. Seibert et al. (2017) applied multiple linear models, artificial neural networks, and random forest regression trees to forecast seasonal hydrological drought (standardized streamflow index) in the Limpopo River Basin in southern Africa. Models were set up to predict standardized total streamflow of December–May, one value per year, at lead times of 1, 2, 3, 6, 9, and 12 months. At some streamflow stations, skill is present up to a 12-month lead time, but many stations (larger catchments in particular) achieved only little skill. These large catchments have not only a higher degree of human interference but also drain large drylands in the Limpopo River Basin. Bennett et al. (2017) assessed a forecasting system based on a monthly rainfall-runoff model forced by ensemble rainfall forecasts for 63 Australian catchments, including 21 ephemeral rivers. Although this system generally produced skillful forecasts at shorter lead times (<4 months), it did not perform well in very dry catchments, sometimes producing strongly negative forecast skill and poor reliability. Moreover, dry catchments are typically streamflow data-scarce environments, where streamflow gauges are sparse, time series are normally short (from some years to few decades), and contain many gaps. Thus, overall, monthly streamflow forecasting and SSF in drylands is challenging.

Although there are few examples in the literature, nonlinear univariate time series models have shown promise for forecasting semi-arid streamflow at daily (He et al., 2014) and monthly scales (Yassen et al., 2016). In this study, we propose analyzing the potential of the streamflow series itself for streamflow forecasting at monthly to seasonal time scales in two large catchments in the Jaguaribe River Basin using nonlinear time series analysis. The specific objectives are to fill gaps and increase available streamflow data and to produce deterministic and probabilistic monthly streamflow forecasting for different lead times (one-, two-, three-, and four-months-ahead). The studied semi-arid catchments have high streamflow interannual variability and relatively short time series with several gaps. A rainfall-runoff model was used to fill streamflow gaps. To our knowledge, this kind of hydrological model application for dryland streamflow forecasting has not been reported previously. Moreover, due to time series shortness, the chosen time series models were kept as simple as possible.

2. Study Area and Streamflow Data

Ceará (Fig. 1 [Figure 1: see original paper]) is home to more than eight million people. The climate is predominantly semi-arid, covering more than 90% of its territory. Mean annual precipitation is about 810 mm, ranging from more than 1200 mm close to the coast (especially in mountainous regions) to less than 600 mm in the large semi-arid landscape extending from the coast to interior borders (Werner and Gerstengarbe, 2003). Actual evapotranspiration is about 78% of annual rainfall (SUDENE, 1980), while potential evapotranspiration is four times annual rainfall. The rainy season is mainly concentrated from February to May, accounting for about 70% of annual rainfall.

Interannual rainfall anomalies are driven primarily by anomalous patterns of Sea Surface Temperature (SST) variability in the Tropical Atlantic and Equatorial Pacific (Hastenrath and Heller, 1977; Moura and Shukla, 1981; Uvo et al., 1998; Rodrigues et al., 2011). During the rainy season, the southernmost displacement of the Intertropical Convergence Zone in the Atlantic Ocean enhances atmospheric conditions for precipitation events over or near Ceará. Interannual and seasonal fluctuations assigned to excess (lack) of rainfall over Ceará are associated with asymmetrical interhemispheric gradients of SST anomalies in the Tropical Atlantic oriented northward (southward) (Hastenrath and Heller, 1977; Moura and Shukla, 1981; Nobre and Shukla, 1996). Additionally, on interannual timescales, accumulated rainfall in Ceará is strongly modulated by ENSO, the prominent interannual mode associated with coupled oceanic-atmospheric interactions in the Equatorial Pacific (Philander, 1990; Rao and Hada, 1990). The warm (cold) oceanic phase of ENSO is known as El Niño (La Niña), marked by abnormal warmer (colder) SST anomalies in the eastern-central Pacific that modify the Walker circulation and lead to unfavorable (favorable) atmospheric conditions over Ceará.

Streamflow is naturally ephemeral or intermittent, ranging from 10% to 20% of annual rainfall and showing high temporal variability with a coefficient of variation generally above 1.00 at interannual scale (Güntner and Bronstert, 2004). Large rivers are dominantly endogenous and interact with underlying groundwater mainly through groundwater recharge (Costa et al., 2012a; 2013). Yet groundwater resources are scarce and concentrated, occurring largely in sedimentary rocks on state borders and the coast, besides a sedimentary basin located in the middle of the state (Frischkorn et al., 2003).

Recurrent droughts have been essentially treated as a supply problem to be resolved through massive construction and related water infrastructure, such as dams and water transfer schemes among watersheds (Gutiérrez et al., 2014). Consequently, more than 7000 dams with surface area larger than 5 hm^2 exist in Ceará (FUNCEME, 2008), producing a dense reservoir network that highly impacts runoff connectivity at catchment scale and river flow propagation (Güntner et al., 2004; Mamede et al., 2012). State and federal agencies manage 155 dams, which store 18.7×10^{9} m^3, providing more than 90% of water supply in Ceará. The two largest reservoirs are Castanhão and Orós with capacities of 6.7×10^{9} and 1.94×10^{9} m^3, respectively (Fig. 1). The Upper Jaguaribe River and its main tributary, the Salgado River, are the principal runoff sources of the Jaguaribe River Basin. Their flows have been monitored by the Brazilian Geological Service at Salgado streamgauge (SS) and Iguatu streamgauge (IS) (Fig. 1), which drain areas of 12,400 and 20,700 km^2, respectively. This study concentrates on river flows monitored at these streamgauges. Daily streamflow data are available from the Brazilian Water Agency (http://www.hidroweb.ana.gov.br). We consider an analysis period from 1951 to 2015. Under this period, IS shows few gaps (only 3.7% of data, 29 months). Gaps in the streamflow series of SS represent 35.1% of data (278 months).

3. Methods

3.1 Time Series Models

We assumed that the streamflow series is driven by a stochastic dynamical system governing the coupling between climatological forcing and the human-modified catchment state that depends on natural landscape characteristics and anthropogenic effects such as land use changes, reservoir construction, and water withdrawal (Kirchner, 2009; Sivakumar and Singh, 2012; Costa et al., 2012b). A stochastic dynamical system can be expressed mathematically by time series models. The deterministic evolution operator (the dynamical or deterministic part) is approached by dynamics of values of a unique variable (the delay embedding theorem; Takens, 1980), whereas the stochastic part is represented by noise that does not depend on states of the dynamical part (Costa et al., 2012b). In real-world open physical systems such as catchment runoff, the presence of dynamical and data noise is inevitable (Porporato and Ridolfi, 2001; Kantz and Schreiber, 2004). Equation 1 describes a stochastic dynamical system:

$$x_{t+\Delta t\times m} = F(x_t, x_{t-\Delta t}, ..., x_{t-(n-1)\Delta t}) + \xi_{t+\Delta t\times m}$$

where $x_{t+\Delta t\times m}$ is the forecast, $\Delta t \times m$ is the lead time, m is a positive natural number, F is the deterministic term, n is the number of past steps, and ξ could be white or coloured noise. Considering a training set, we can empirically determine the ξ distribution by assuming a regression model for F.

Note that the distribution of ξ includes uncertainty not only from inherent fluctuations of streamflow data but also from fitting the underlying dynamical term by an adopted regression model (Costa et al., 2012b). Thus, the expected value of the forecast equals the deterministic term F, and uncertainty is calculated from the distribution of ξ with a confidence interval (e.g., 50%), ascribing a probability density function (PDF) or uncertainty envelope for $x_{t+\Delta t\cdot m}$.

We selected four regression models: (1) the locally constant (LC), whose prediction equals the last streamflow measurement; (2) the locally averaged (LA), whose prediction is the average over streamflow measurements at n last steps; (3) the traditional k-NN, whose prediction uses up to k neighbors (ranging from 1 to 7 in this study) and a power parameter for inverse distance weighting interpolation; and (4) the autoregressive model (AR), whose unknown parameters are the number of streamflow measurements at n last steps and its coefficients. The latter was used for the dynamical term F as reference to test the hypothesis of linear random data.

We did not apply an ARMA (autoregressive-moving-average model) because the noise inputs of the moving average model were not known before application of Equation 1 and must be averaged (Kantz and Schreiber, 2004; Costa et al., 2012b).

3.2 Gap-Filling Streamflow Data

We used outcomes from the Soil Moisture Accounting Procedure (SMAP; Kwon et al., 2012), a rainfall-runoff model (Lopes et al., 1981), to fill gaps in streamgauges and increase available streamflow data. The SMAP model was set up and calibrated, producing good performance for monthly semi-arid streamflow at IS and SS with Nash-Sutcliffe coefficients of 0.78 and 0.86, respectively.

We performed model calibration under parameter uncertainty for 28 streamgauges, including IS and SS, using the differential evolution adaptive metropolis (DREAM) algorithm (Vrugt et al., 2008; Vrugt et al., 2009; Vrugt, 2016). In this study, we considered only the average over the simulated streamflow envelope based on one thousand parameter vectors. They assumed one-third of available data for validation in each streamgauge (following the Split-Sample Test; Klemeš, 1986). Wet, normal, and dry years were well represented in both calibration and validation selected periods for the streamgauges, even if this selection varied from one to another.

For IS (SS), validation data were streamflow measured from 1944 to 1976 (1993 to 2007), while remaining data from 1912 to 2017 (1973 to 2017) were used for model calibration.

3.3 Time Series Model Adjustment and Assessment

A cross-validation approach was adopted to evaluate streamflow forecasting. First, to facilitate comparison of model results between studied basins, we chose the same validation period for both IS and SS. Second, streamflow gaps filled with rainfall-runoff modelling outputs had to be concentrated in training sets. Following these rules, three different intervals from the whole streamflow time series (1951–2015) were chosen for training and validation sets. Validation (training) sets had to show good balance between dry, regular, and wet streamflow seasons because interannual variability of semi-arid streamflow is very high (Güntner and Bronstert, 2004). Moreover, recurrent dry and wet decades occur in the Brazilian semi-arid area. Therefore, we selected period combinations for training and validation sets as shown in Table 1 .

Table 1. Period combinations for training and validation sets used for the applied cross-validation approach, given 65-year (1951–2015) streamflow time series at both IS and SS.

Combination	Training set	Validation set
I	1951–1979; 1990–2015	1980–1989
II	1951–1989; 2000–2015	1990–1999
III	1951–1999; 2010–2015	2000–2009

Model performance was calculated for each training set and over all validation sets combined (30 years total). There was only one gap in the validation set for both streamgauges, while remaining gaps filled with rainfall-runoff modelling outputs were concentrated in training sets. This cross-validation approach is similar to classical k-folds cross-validation but restricted to a validation period (1980–2009) with almost no gaps for both streamgauges. Considering that streamflow time series length is short (only 65 years) and much of it consists of rainfall-runoff model outputs, we believe there is good balance between validation and training set lengths.

LC needed no model adjustment, whereas for LA we adopted measurements at 2 last steps, which gave highest correlations with the predictand in the training set (not shown). We tested 1 to 7 nearest neighbors for k-NN and adjusted the power parameter for all k-NN models to maximize performance over training sets. Application of k-NN models for streamflow time series appears frequently in literature (Wu et al., 2009; Wu and Chau, 2010; Tongal, 2020). AR was fitted using least squares for each training set (I, II, and III in Table 1). Each fitted AR model was then used for each validation subset (10 years), respectively.

We assumed the criterion for acceptance (reliability) of validation results is that model forecast is more skillful than streamflow climatology. Climatology is an adequate benchmark since water management in studied basins typically relies on it rather than seasonal forecasting for decision making, as also assumed by Seibert et al. (2017). RMSE is the standard deviation (SD) of residuals (forecast errors), so higher (lower) RMSE means lower (higher) model performance. To facilitate comparison of forecast reliability between models and streamflow climatology, we used standardized root mean square error (SRMSE) as the performance criterion. SRMSE is defined as RMSE divided by SD of the test set (Perreti et al., 2013). SRMSE greater than unity indicates predictions less accurate than simply predicting the mean of the test set (Perreti et al., 2013). In this study, we defined the mean of the test set (training or validation) as streamflow climatology. Thus, according to Yossef et al. (2013), when SRMSE equals 1.00, forecast skill equals that of a climatological forecast. SRMSE smaller than 1.00 indicates greater skill than climatology, whereas SRMSE greater than 1.00 indicates less skill. SRMSE approaches 0.00 for a perfect forecast.

For deterministic streamflow forecasting assessment, error was calculated by applying Equation 1 to training and validation sets. For probabilistic streamflow forecasting, where we assigned a PDF with confidence interval for the forecast, errors were calculated differently (Eq. 2):

$$\xi_{t+\Delta t\times m} = \begin{cases} \xi^{+} & \text{if } x_{t+\Delta t\times m} > F \\ \xi^{-} & \text{if } x_{t+\Delta t\times m} < F \\ 0 & \text{otherwise} \end{cases}$$

where ξ^{+} (ξ^{-}) is the upper (lower) limit of the confidence interval and F is the deterministic term. Thus, when a measurement in the validation set occurred within confidence interval limits of the forecast PDF, the error was zero. These errors from Equation 2 are less than those from application of the deterministic term alone. However, if the chosen confidence interval length is too large, probabilistic forecast may not be useful for real-world issues even with very low SRMSE. Therefore, in probabilistic forecasting, a compromise must exist between confidence interval length and SRMSE result. In this work, we compared confidence interval length to SD of streamflow series. Necessary box-and-whisker plots were generated using the web-tool BoxPlotR (http://shiny.chemgrid.org/boxplotr/).

3.4 Jaguaribe River Basin Application

The Jaguaribe River flows normally from January to June at IS and SS. River flows are rarely relevant in December and July of the following year. Since past streamflow measurements are necessary for this approach, we chose streamflow in March, April, May, and June (middle and end of rainy season) as predictands at seasonal and monthly scales. We adopted four lead times: one month ahead for monthly scale and two, three, and four months ahead for seasonal scale.

Streamflows in January and February (beginning of rainy season) were always predictors at monthly and seasonal scales. However, the number of predictors increases depending on lead time and predictand at monthly scale (Table 2). Table 2 shows the seven forecast runs in this study after combination of predictands, predictors, and lead times. Predictands and predictors in Table 2 are indicated by month of streamflow observation. Thus, we ran monthly streamflow forecasting with fixed lead time of one month and variable number of predictands. We also ran SSF with variable lead time (two, three, and four months) and fixed number of predictors (streamflows in January and February). Streamflow forecasting began (finished) with predictand in March (June). Although streamflows observed in January and February show smaller variances (Figs. 2 and 3), they should be included as predictors because they demonstrated relevant predictive power at both scales.

An additional difficulty is dryness at the beginning of rainy season, because non-flow states in January and February clearly hamper streamflow forecasting for the remaining season from March to June using aforementioned time series models. Therefore, in cases of non-flow states for predictors, we added a new assumption for the k-NN approach: nearest neighbors to the predictand were those also closer in time (hydrologic persistence; Koutsoyiannis, 2005), besides Euclidean distance of traditional k-NN approach.

Construction of reservoirs, land use changes, and irrigation schemes interacting in study catchments over the last century may hamper streamflow predictability. However, there are no shift terms or clear trends in streamflow time series, which would be expected when such nonstationarities are relevant. Therefore, we consider them of minor importance at such large spatial scale compared to data uncertainty and natural streamflow variability, which are quite high for dryland rivers. This assumption a priori allows applicability of the presented methodology.

Table 2. Developed streamflow forecasting in the Jaguaribe River Basin after combination of predictands, predictors, and lead times.

Predicand	March	April	May	June
Predictors	Jan, Feb	Jan, Feb, Mar	Jan, Feb, Mar, Apr	Jan, Feb, Mar, Apr, May
Lead time (month)	1	1	1	1
Note: Predictands and predictors are indicated by month of streamflow observation.				

4. Results

4.1 Gap-Filled Hydrographs

Average monthly hydrographs of IS and SS are presented in Figures 2 and 3, respectively, showing that high streamflow season occurred only in March, April, and May, while negligible river discharge was observed from July to December, except for some discharge outliers at IS in December and at SS in December and July of the following year. Two transition periods existed between high and very low streamflow states: beginning and end of streamflow season, occurring in January–February and June, respectively. Streamflow at the beginning of streamflow season was larger than at the end.

The rising hydrograph limb took four months from January to April, when streamflow peak occurred, while the falling limb took just two months (May and June). Streamflow in March prior to the peak was higher than in May after the peak. In the rising limb, the fastest streamflow change occurred from February to March (transition between season beginning and high streamflow season). In the falling limb, the fastest change occurred from April (peak flow) to May.

During high streamflow season, larger streamflows occurred at IS compared to SS. The beginning and end of streamflow season were relatively drier at IS. At IS, non-flow states occurred in 16 (20) out of 65 years at the beginning (end) of streamflow season, whereas at SS, non-flow states occurred only once (four times) at the beginning (end) of streamflow season. Thus, the hydrograph was sharper for IS, and for both streamgauges, the season end was drier than other seasons.

4.2.1 Deterministic Forecasting

Performance of time series models (k-NN, LC, LA, and AR) for each predictand in the validation set is presented in Figure 4 [Figure 4: see original paper]. We excluded outliers with SRMSE greater than 2.00, omitting one outlier (AR) for March and April at IS and two outliers (LC and LA) for June at both streamgauges.

Most models (73%) performed better than mean prediction (streamflow climatology), showing SRMSE less than 1.00. Their mean SRMSE was 0.80, representing 20% improvement over climatology. All months for both streamgauges had at least six models whose forecasts were better than mean prediction. Models showing all SRMSEs less than 1.00 were 3-NN, 4-NN, 6-NN, and 7-NN. The 2-NN and 5-NN models showed only one SRMSE value higher than 1.00. AR had the worst performance with 6 out of 8 SRMSEs higher than 1.00, followed by LC (5) and LA (4).

Considering the best-fit model for each month in the validation set (Table 3), 7 out of 8 models were k-NN approaches. Only streamflow in April (peak flow) at IS was better forecast with the LC model, the simplest approach. According to

Table 3, SRMSE varied from 0.65 in June (35% better than mean prediction) to 0.90 in April (10% better than climatology) at IS. For SS, SRMSE varied from 0.67 in March (33% better than mean prediction) to 0.86 in April (14% better than climatology).

Table 3. SRMSE of best-fit models in validation set for monthly streamflow forecasting at Iguatu streamgauge (IS) and Salgado streamgauge (SS).

Model performance	Mar_{IS}	Mar_{SS}	Apr_{IS}	Apr_{SS}	May_{IS}	May_{SS}	Jun_{IS}	Jun_{SS}
Best-fit model	4-NN	4-NN	LC	3-NN	4-NN	4-NN	4-NN	4-NN
SRMSE Validation	0.73	0.67	0.90	0.86	0.77	0.71	0.65	0.71
SRMSE Training	0.90	0.84	0.87	0.83	0.73	0.67	0.82	0.76

Note: LC = locally constant approach; k-NN = k-nearest-neighbours algorithm with k ranging from 1 to 7. SRMSE is RMSE divided by SD of test set (validation or training).

In the rising limb (March and April), SRMSE in March was less than in April, when SRMSE was also highest for both streamgauges (Fig. 4). In the falling limb (May and June), higher SRMSE in May was also observed for both streamgauges. In high streamflow season (March, April, May), streamflow was better forecast in March at SS and slightly better in May at IS. Considering best-fit models (Fig. 4; Table 3), SRMSE in rising limb at IS was higher than at SS, while SRMSE in falling limb at IS was lower than at SS.

Comparing SRMSE between validation and training sets (Table 3), they were approximately the same for 3 out of 8 predictands (absolute difference less than 0.03) and higher in validation set for one predictand (streamflow in April at SS). However, half of predictands showed higher SRMSE in training set, found for streamflow forecasts in March and June at both streamgauges.

To illustrate deterministic streamflow forecasting at monthly scale, we present forecasts from the best-fit time series model (4-NN) for March at SS (Fig. 5 [Figure 5: see original paper]). In the validation set, the model represented high, near-average, and low flow states well but underestimated the largest peak. Transition between these states (interannual variability) was well simulated but with some delay in the first decade (1980–1989) of the test set. Overall, dominant periods of high and low flows were very well differentiated, especially the latter.

4.2.2 Probabilistic Forecasting

Best-fit time series models (Table 3) were assumed as dynamical parts of Equation 1. We then calculated the stochastic term using errors in the training set.

Tables 4a and 4b summarize forecast PDFs for each predictand (streamflow in March, April, May, June) at both streamgauges, providing adopted confidence interval lengths (33%, 50%, and 66%), SRMSE, and SD of gap-filled streamflow data.

Table 4a. Monthly probabilistic forecasting of validation set at IS.

	March (92)*	April (204)*	May (79)*	June (12)*
Confidence interval	33%	50%	66%	33%
Length	68	102	134	6
SRMSE	0.56	0.88	0.73	0.63

Table 4b. Monthly probabilistic forecasting of validation set at SS.

	March (85)*	April (123)*	May (68)*	June (14)*
Confidence interval	33%	33%	33%	33%
Length	56	82	45	9
SRMSE	0.56	0.78	0.67	0.66

Note: Deterministic term of probabilistic forecasting is based on best-fit time series model in validation set and stochastic term on errors in training set. Numbers in parentheses are SD (m^3/s) of gap-filled streamflow series.*

Considering a narrow uncertainty envelope over deterministic forecasting (33% confidence interval length smaller than streamflow data SD), forecasting performance improved expressively for all predictands at SS and for streamflow in March at IS. Comparing Table 3 with Tables 4a and 4b, SRMSE was reduced by 0.11, 0.08, 0.04, and 0.05 for streamflow in March, April, May, and June at SS, respectively. The highest SRMSE reduction (0.17) was found for streamflow in March at IS. Probabilistic forecasting at the narrowest uncertainty envelope outperformed mean predictor (climatology) by 46%, 42%, 22%, 27%, and 34% for streamflow in March (IS), March (SS), April (SS), May (SS), and June (SS), respectively.

For other predictands at IS (streamflow in April, May, June), forecasting performance improvement was marginal with SRMSE reduction of 0.02. Only a wider uncertainty envelope (50% or 66% confidence interval) led to better forecasting performance for these predictands. For streamflow in June, a 66% confidence interval of in-training-set error distribution (length of 6 m^3/s, or 50% of streamflow data SD) produced significant SRMSE reduction of 0.12, with probabilistic forecasting performing 47% better than climatology. The same level of SRMSE reduction for streamflow in April (0.12) and May (0.10) was achieved at 66%

confidence interval but showed much larger lengths: 96% and 70% of SD for April and May, respectively. IS probabilistic forecasting for streamflow in April (May) at narrowest uncertainty envelope (33%) outperformed mean predictor by 12% (30%).

The reason for slight performance increase even with larger confidence interval length was mainly two underestimated peaks for streamflow in April and May. These peaks occurred in 1985 and 1989, which were very moist years. To illustrate probabilistic forecasting at monthly scale, highlighting this difficulty, we present forecasts from the best-fit time series model (2-NN) enveloped by a PDF based on 50% confidence interval of in-training-set error distribution (Fig. 6 [Figure 6: see original paper]). The predictand was streamflow in May at IS. In the validation set, most streamflow data were close to or inside forecast envelope bounds. Although flow states (high, near-average, low) were well represented, very high flows in 1985 and 1989 were considerably underestimated. Additionally, there was relevant overestimation in 1981. As shown in Figure 5, forecasting in the first decade (1980–1989) of the test set was less reliable compared to other decades.

4.3.1 Deterministic Forecasting

Performance of time series models (k-NN, LC, LA, and AR) for each predictand in validation set is presented in Figure 7 [Figure 7: see original paper]. We excluded outliers with SRMSE higher than 2.00, omitting one outlier (AR) for April and May at IS and three outliers (LC, LA, and AR) for June at both streamgauges. Note that SSF in March is not shown because it is identical to monthly streamflow forecasting since predictors (January and February) are the same.

Most models (55%) did not perform better than mean prediction (streamflow climatology), showing SRMSE higher than 1.00. Streamflow forecasting in April and May at SS presented no time series model better than mean prediction. However, for remaining predictands, at least four models showed SRMSEs less than 1.00. The 4-NN, 5-NN, 6-NN, and 7-NN models had best performance with 6 out of 8 SRMSEs less than 1.00. The 3-NN model showed four SRMSE values less than 1.00. AR had worst performance with all SRMSEs higher than 1.00, followed by LA, LC, 1-NN, and 2-NN with 6 out of 8 SRMSEs higher than 1.00.

Considering best-fit model for each month in validation set (Table 5), almost all models were k-NN approaches. Only streamflow in May at IS was better forecast with the LA model. According to Table 5, SRMSE varied from 0.78 in April (22% better than mean prediction) to 0.87 in June (13% better than climatology) at IS. For SS, SRMSE varied from 0.94 in June (only 6% better than mean prediction) to 1.06 in May (6% worse than climatology).

As expected, SSF performance decreased with increasing lead time at IS: March (SRMSE: 0.71), April (0.78), May (0.80), and June (0.87). SSF performance showed different behavior with increasing lead time at SS: March (0.67), April (1.05), May (1.06), and June (0.94). Besides streamflow in March, seasonal predictands were better forecast for IS.

Table 5. SRMSE of best-fit models in validation set for seasonal streamflow forecasting (SSF) in April, May, and June at IS and SS.

Model performance	Apr_{IS}	Apr_{SS}	May_{IS}	May_{SS}	Jun_{IS}	Jun_{SS}
Best-fit model	6-NN	4-NN	LA	4-NN	5-NN	4-NN
SRMSE validation	0.78	1.05	0.80	1.06	0.87	0.94
SRMSE training	0.89	1.08	0.83	1.04	0.91	1.02

Note: SSF in March is not shown because it is identical to monthly streamflow forecasting.

Comparing SRMSE between validation and training sets (Table 5), they were nearly identical for 2 out of 6 predictands (absolute difference less than 0.03) for streamflow forecasts in April and May at SS. Remaining predictands showed higher SRMSE in training set.

To illustrate deterministic streamflow forecasting at seasonal scale, we present forecasts from the best-fit time series model (6-NN) for April at IS (Fig. 8 [Figure 8: see original paper]). In validation set, the model clearly overestimated streamflow from 1990 to mid-2000s and underestimated it in early 1980s and late 2000s. Despite over- and underestimation, the model differentiated well between long periods of high and low flows, including very good simulation of the largest peak.

4.3.2 Probabilistic Forecasting

Best-fit time series models (Table 5) were assumed as dynamical parts of Equation 1. We then calculated the stochastic term using errors in the training set. Tables 6a and 6b summarize forecast PDFs for each predictand (streamflow in April, May, June) at both streamgauges, providing adopted confidence interval lengths (33%, 50%, and 66%), SRMSE, and SD of gap-filled streamflow data. Note that SSF in March is not shown because it is identical to monthly streamflow forecasting.

Table 6a. Seasonal probabilistic forecasting of validation set at IS.

	April (204)*	May (79)*	June (12)*
Confidence interval	33%	33%	33%
Length	102	39	6

	April (204)*	May (79)*	June (12)*
SRMSE	0.67	0.56	0.78

Table 6b. Seasonal probabilistic forecasting of validation set at SS.

	April (123)*	May (68)*	June (14)*
Confidence interval	33%	33%	33%
Length	82	45	9
SRMSE	0.94	0.93	0.86

Note: Deterministic term of probabilistic forecasting is based on best-fit time series model in validation set and stochastic term on errors in training set. Numbers in parentheses are SD (m^3/s) of gap-filled streamflow series.*

Considering a narrow uncertainty envelope over deterministic forecasting (33% confidence interval length smaller than streamflow data SD), forecasting performance improved expressively for all predictands at both streamgauges. Comparing Table 5 to Tables 6a and 6b, SRMSE was reduced by 0.11 (0.10), 0.24 (0.13), and 0.09 (0.08) for streamflow in April, May, and June at IS (SS), respectively. The highest SRMSE reduction was found for streamflow in May, followed by April and June. Probabilistic forecasting at narrowest uncertainty envelope outperformed mean predictor (climatology) by 5% (33%), 7% (44%), and 14% (22%) for streamflow in April, May, and June at SS (IS), respectively, showing much better streamflow forecasting at IS.

5. Discussion

The developed data-driven approach outperformed streamflow climatology (mean predictor in validation set) for most streamflows at monthly and seasonal scales (12 out of 14 predictands). The global nonlinear model and global linear model were the best-fit and worst-fit time series models, respectively. In the probabilistic strategy, deterministic forecast enveloped by a PDF considerably narrower than data SD increased forecasting performance by about 50% at both scales. Rainfall-runoff model outputs used to fill streamflow series gaps played an important role in improving streamflow forecasting.

The developed data-driven approach is mathematically and computationally very simple, demands few resources for operational implementation, and is applicable to other dryland watersheds. Moreover, since studied watersheds have characteristics (e.g., large drainage area, short time series with gaps, high streamflow interannual variability) similar to drylands needing streamflow forecasting information, we believe this study has high transfer potential. Streamflow forecasts may be part of drought forecasting systems and help plan water allocation months in advance. Additionally, the developed strategy can serve as a baseline for more complex streamflow forecast systems.

Monthly and seasonal forecasts have high uncertainty; therefore, conveying forecast system skill is important, and end users should include uncertainty information in decision-making processes (Seibert et al., 2017). This is achieved by probabilistic streamflow forecasts that may serve as inputs to water resources operation models, providing probability of net benefits or losses for each economic sector (irrigation, industry, fish farming). If loss probability is significant, policymakers may divert resources in advance to mitigation procedures or prepare for significant emergency intervention (Sittichok et al., 2016). However, deterministic forecasts remain common practice in many Brazilian water management systems.

6. Conclusion

We developed a data-driven approach to forecast dryland streamflows at monthly and seasonal scales, relying only on streamflow series itself. Deterministic forecasting was evaluated by applying four time series models (LC, LA, k-NN, and AR). Probabilistic forecasting was based on deterministic forecast enveloped by a PDF from time series model errors in the training set. Outputs of a conceptual rainfall-runoff model were used to fill streamgauge gaps and increase available streamflow data. To our knowledge, this hydrological model application for dryland streamflow forecasting has not been reported previously. This methodology was applied to two large catchments in the Brazilian semi-arid area.

Our approach outperformed climatology for most streamflows at monthly and seasonal scales (12 out of 14 predictands), where global nonlinear and global linear models were best-fit and worst-fit, respectively. In probabilistic strategy, deterministic forecast enveloped by a PDF considerably narrower than data SD increased forecasting performance by about 50% at both scales. Rainfall-runoff model outputs used to fill streamflow gaps played an important role in improving forecasting.

The developed data-driven approach is mathematically and computationally simple, demands few resources for operational implementation, and is applicable to other dryland watersheds. Since studied watersheds have characteristics similar to drylands needing streamflow forecasting information, we believe this study' s transfer potential is high. Streamflow forecasts may be part of drought forecasting systems and help allocate water months in advance. Moreover, the developed strategy can serve as a baseline for more complex streamflow forecast systems.

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References

Araújo J A de A. 1990. *Dams in Northeastern Brazil: an experience in the semi-arid region* (2nd ed). Fortaleza: DNOCS, 328.

Bennett J C, Wang Q J, Robertson D E, et al. 2017. Assessment of an ensemble seasonal streamflow forecasting system for Australia. *Hydrology and Earth System Sciences*, 21: 6007–6030.

Block P J, Souza Filho F A, Sun L, et al. 2009. A streamflow forecasting framework using multiple climate and hydrological models. *Journal of the American Water Resources Association*, 45(4): 828–843.

Collischon W, Tucci C E M, Clarke R T, et al. 2007. Medium-range reservoir inflow predictions based on quantitative precipitation forecasts. *Journal of Hydrology*, 344(1-2): 112–122.

Costa A C, Bronstert A, de Araújo J C. 2012a. A channel transmission losses model for different dryland rivers. *Hydrology and Earth System Sciences*, 16(4): 1111–1135.

Costa A C, Bronstert A, Kneis D. 2012b. Probabilistic flood forecasting for a mountainous headwater catchment using a nonparametric stochastic dynamic approach. *Hydrological Sciences Journal*, 57(1): 10–25.

Costa A C, Foerster S, de Araújo J C, et al. 2013. Analysis of channel transmission losses in a dryland river reach in north-eastern Brazil using streamflow series, groundwater level series and multi-temporal satellite data. *Hydrological Processes*, 27(7): 1029–1042.

Crochemore L, Ramos M H, Pappenberger F. 2016. Bias correcting precipitation forecasts to improve skill of seasonal streamflow forecasts. *Hydrology and Earth System Sciences*, 20(9): 3601–3618.

Delgado J M, Voss S, Bürger G, et al. 2018. Seasonal drought prediction for semiarid northeast Brazil: Verification of six hydro-meteorological forecast products. *Hydrology and Earth System Sciences*, 22(9): 5041–5056.

Fioreze A P, Bubel A P M, Callou A É P, et al. 2012. The water issue in the Northeast. Brasília: Ministry of Science and Technology. [2020-01-24]. http://livroaberto.ibict.br/handle/1/669.

Formiga-Johnsson R M, Kemper K. 2005. *Institutional and Policy Analysis of River Basin Management: The Jaguaribe River Basin, Ceará, Brazil*. New York: Social Science Research Network, 42.

Frischkorn H, Santiago M F, de Araújo J C. 2003. Water resources of Ceará and Piauí. In: Gaiser T, Krol M, Frischkorn H, et al. *Global Change and Regional*

Impacts. Berlin: Springer-Verlag, 87–94.

FUNCEME (Foundation for Meteorology and Water Resources of the State of Ceará). 2008. *Mapping of the surface of water bodies in Brazil*. Fortaleza: FUNCEME, 108.

Güntner A, Bronstert A. 2004. Representation of landscape variability and lateral redistribution processes for large-scale hydrological modelling in semi-arid areas. *Journal of Hydrology*, 297(1–4): 136–161.

Güntner A, Krol M S, de Araújo J C, et al. 2004. Simple water balance modelling of surface reservoir systems in a large data-scarce semiarid region. *Hydrological Sciences Journal*, 49(5): 901–918.

Gutierrez A P A, Engle N L, de Nys E, et al. 2014. Drought preparedness in Brazil. *Weather and Climate Extremes*, 3: 95–106.

Hastenrath S, Heller L. 1977. Dynamics of climatic hazards in northeast Brazil. *Quarterly Journal of the Royal Meteorological Society*, 103(435): 77–92.

He Z, Wen X, Liu H, et al. 2014. A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. *Journal of Hydrology*, 509: 379–386.

Kalra A, Miller W P, Lamb K W, et al. 2012. Using large-scale climatic patterns for improving long lead time streamflow forecasts for Gunnison and San Juan River Basins. *Hydrological Processes*, 27(11): 1543–1559.

Kalra A, Li L, Li X, et al. 2013. Improving streamflow forecast lead time using oceanic-atmospheric oscillations for Kaidu River Basin, Xinjiang, China. *Journal of Hydrologic Engineering*, 18(8): 1031–1040.

Kantz H, Schreiber T. 2004. *Nonlinear Time Series Analysis* (2nd ed). Cambridge: Cambridge University Press, 388.

Kirchner J W. 2009. Catchments as simple dynamical systems: Catchment characterization, rainfall-runoff modelling, and doing hydrology backward. *Water Resources Research*, 45(2): 1–34.

Klemeš V. 1986. Operational testing of hydrological simulation models. *Hydrological Sciences Journal*, 31(1): 13–24.

Koutsoyiannis D. 2005. Hydrologic persistence and the Hurst phenomenon. In: Lehr J H, Keely J. *The Encyclopedia of Water*. New York: John Wiley & Sons, Inc., 27.

Kwon H H, Souza Filho F A, Sun L, et al. 2012. Uncertainty assessment of hydrologic model and climate forecast model in Northern Brazil. *Hydrological Processes*, 26(25): 3875–3885.

Lopes J C, Braga J B F, Conejo J L. 1981. Hydrological simulation: Applications of a simplified model. In: *III Brazilian Symposium for Water Resources*.

Fortaleza: ABRH, 42–62.

Machado C J F, Santiago M M F, Mendonça L A R, et al. 2007. Hydrogeochemical and flow modeling of aquitard percolation in the Cariri Valley-Northeast Brazil. *Aquatic Geochemistry*, 13: 187–196.

Mamede G L, Araújo N A M, Schneider C M, et al. 2012. Overspill avalanching in a dense reservoir network. *PNAS*, 109(19): 7191–7195.

Moradkhani H, Meier M. 2010. Long-lead water supply forecast using large-scale predictors and independent component analysis. *Journal of Hydrology Engineering*, 15(10): 744–762.

Moura A D, Shukla J. 1981. On the dynamics of droughts in northeast Brazil: Observations, theory, and numerical experiments with a general circulation model. *Journal of the Atmospheric Sciences*, 38(12): 2653–2675.

Nobre P, Shukla J. 1996. Variations of sea surface temperature, wind stress, and rainfall over the tropical Atlantic and South America. *Journal of Climate*, 9(10): 2464–2479.

Nunes C M. 2012. Project of integration of the San Francisco River with watersheds in the Northeast - PISF. In: *The water issue in the Northeast*. Brasília: Ministry of Science and Technology. [2020-01-24]. http://livroaberto.ibict.br/handle/1/669.

Perreti C, Munch S, Sugihara G. 2013. Model-free forecasting outperforms the correct mechanistic model for simulated and experimental data. *PNAS*, 110(13): 5253–5257.

Philander S G. 1990. *El Niño, La Niña, and the Southern Oscillation*. International Geophysics Series (vol. 46), San Diego: Academic Press, 293.

Pilz T, Voss S, Vormoor K, et al. 2019. Seasonal drought prediction for semi-arid northeast Brazil: What is the added value of a process-based hydrological model? *Hydrology and Earth System Sciences*, 23: 1951–1971.

Porporato A, Ridolfi L. 2001. Multivariate nonlinear prediction of river flows. *Journal of Hydrology*, 248(1–4): 109–122.

Rao V B, Hada K. 1990. Characteristics of rainfall over Brazil: Annual variations and connections with southern oscillation. *Theoretical and Applied Climatology*, 42: 81–91.

Robertson D E, Wang Q J. 2012. A Bayesian approach to predictor selection for seasonal streamflow forecasting. *Journal of Hydrometeorology*, 13(1): 155–171.

Rodrigues R R, Haarsma R J, Campos E J D, et al. 2011. The impacts of inter-El Niño variability on the Tropical Atlantic and Northeast Brazil climate. *Journal of Climate*, 24(13): 3402–3422.

Seibert M, Merz B, Apel H. 2017. Seasonal forecasting of hydrological drought in the Limpopo Basin: A comparison of statistical methods. *Hydrology and Earth System Sciences*, 21: 1611–1629.

Shukla S, Lettenmaier D P. 2011. Seasonal hydrologic prediction in the United States: Understanding the role of initial hydrologic conditions and seasonal climate forecast skill. *Hydrology and Earth System Sciences*, 15: 3529–3538.

Sittichok K, Gado D A, Seidou O, et al. 2016. Statistical seasonal rainfall and streamflow forecasting for the Sirba watershed, West Africa, using sea-surface temperatures. *Hydrological Sciences Journal*, 61(5): 805–815.

Sivakumar B, Singh V P. 2012. Hydrologic system complexity and nonlinear dynamic concepts for a catchment classification framework. *Hydrology and Earth System Sciences*, 16: 4119–4131.

Souza Filho F A, Lall U. 2003. Seasonal to interannual ensemble streamflow forecasts for Ceara, Brazil: Applications of a multivariate, semiparametric algorithm. *Water Resources Research*, 39(11): 1–13.

SUDENE (Superintendência de Desenvolvimento do Nordeste). 1980. *Plan for the integrated utilization of water resources in Northeastern Brazil*. Recife: SUDENE, 712.

Takens F. 1980. Detecting strange attractors in turbulence. In: Rang D, Young L S. *Lecture notes in mathematics*. Berlin: Springer, 366–381.

Tongal H. 2020. Comparison of local and global approximators in multivariate chaotic forecasting of daily streamflow. *Hydrological Sciences Journal*, 65(7): 1129–1144.

Trambauer P, Werner M, Winsemius H C, et al. 2015. Hydrological drought forecasting and skill assessment for the Limpopo River basin, southern Africa. *Hydrology and Earth System Sciences*, 19: 1695–1711.

Uvo C B, Repelli C A, Zebiak S E, et al. 1998. The relationships between tropical Pacific and Atlantic SST and northeast Brazil monthly precipitation. *Journal of Climate*, 11(4): 551–562.

Vrugt J A, ter Braak C J F, Clark M P, et al. 2008. Treatment of input uncertainty in hydrologic modeling: Doing hydrology backward with Markov chain Monte Carlo simulation. *Water Resources Research*, 44(12): 1–15.

Vrugt J A, ter Braak C J F, Diks C G H, et al. 2009. Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling. *International Journal of Nonlinear Sciences and Numerical Simulation*, 10(3): 273–290.

Vrugt J A. 2016. Markov chain Monte Carlo simulation using the DREAM software package: Theory, concepts, and MATLAB implementation. *Environmental Modelling and Software*, 75: 273–316.

Werner P C, Gerstengarbe F W. 2003. The climate of Piauí and Ceará. In: Gaiser T, Krol M, Frischkorn H, et al. *Global Change and Regional Impacts*. Berlin: Springer-Verlag, 81-86.

Wilks D S. 2005. *Statistical Methods in the Atmospheric Sciences*. Burlington: Academic Press, 704.

Wu C L, Chau K W, Li Y S. 2009. Predicting monthly streamflow using data-driven models coupled with data-preprocessing techniques. *Water Resources Research*, 45(8), W08432, doi:10.1029/2007WR006737.

Wu C L, Chau K W. 2010. Data-driven models for monthly streamflow time series prediction. *Engineering Applications of Artificial Intelligence*, 23(8): 1350-1367.

Yassen Z M, Jaafar O, Deo R C, et al. 2016. Stream-flow forecasting using extreme learning machines: A case study in a semi-arid region in Iraq. *Journal of Hydrology*, 542: 603-614.

Yossef N C, Winsemius H, Weerts A, et al. 2013. Skill of a global seasonal streamflow forecasting system, relative roles of initial conditions and meteorological forcing. *Water Resources Research*, 49(8): 4687-4699.

Yuan X. 2016. An experimental seasonal hydrological forecasting system over the Yellow River basin -Part 2: The added value from climate forecast models. *Hydrology and Earth System Sciences*, 20: 2453-2466.

Yuan X, Ma F, Wang L, et al. 2016. An experimental seasonal hydrological forecasting system over the Yellow River basin -Part 1: Understanding the role of initial hydrological conditions. *Hydrology and Earth System Sciences*, 20: 2437-2451.

Note: Figure translations are in progress. See original paper for figures.