Imputation of Missing Streamflow Data at Multiple Gauging Stations in Benin Republic

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Abstract

Streamflow observation data is vital for flood monitoring, agricultural, and settlement planning. However, such streamflow data are commonly plagued with missing observations due to various causes such as harsh environmental conditions and constrained operational resources. This problem is often more pervasive in under-resourced areas such as Sub-Saharan Africa. In this work, we reconstruct streamflow time series data through bias correction of the GEOGloWS ECMWF streamflow service (GESS) forecasts at ten river gauging stations in Benin Republic. We perform bias correction by fitting Quantile Mapping, Gaussian Process, and Elastic Net regression in a constrained training period. We show by simulating missingness in a testing period that GESS forecasts have a significant bias that results in low predictive skill over the ten Beninese stations. Our findings suggest that overall bias correction by Elastic Net and Gaussian Process regression achieves superior skill relative to traditional imputation by Random Forest, k-Nearest Neighbour, and GESS lookup. The findings of this work provide a basis for integrating global GESS streamflow data into operational early-warning decision-making systems (e.g., flood alert) in countries vulnerable to drought and flooding due to extreme weather events.

Introduction

Discharge predictions are critical for decision-making in many areas of climate change adaptation, including flood and drought prevention, agricultural planning, and hydroelectric power system operations (Kratzert et al. 2019). Predictions can be generated by physical and statistical models of the hydrological process within the river basin (Adounkpe et al. 2021). Regardless of the approach, observation data is required to sufficiently calibrate the localised dynamics within catchments. Model-based predictions are even more essential in vulnerable and under-developed regions that are less resilient to extreme weather events such as drought and flooding. However, localised observations for hydrological models are not always available due to physical sensor failure events (Hamzah et al. 2020). Physical sensor systems often endure harsh environmental conditions, destruction and power outages (Tencaliec et al. 2015). These phenomena result in prolonged periods of missing or invalid observation readings. In developing regions such as Benin Republic, the effect of such missing data is further complemented by the already sparse distribution of stream gauging stations (Harigan et al. 2020a). Fitting statistical models based on incomplete observation data results in inaccurate models that do not capture the full dynamics of the underlying hydrological processes (Hamzah et al. 2020). A more complete set of streamflow data allows for greater confidence in the outputs of hydrological models (Pigott 2001). Imputation of missing data therefore leads to much needed improved flood and drought predictions in a climate change context where these events are expected to increase in intensity and frequency (Kalantari et al. 2018). Thus missing data imputation has become a necessary first step in data preprocessing tasks (Pigott 2001). Moreover, missing observations and the estimation of streamflow at ungauged locations are two of the most pervasive problems in the field of hydrology (Hamzah et al. 2020). Since the area of missing data imputation commands a relatively vast amount of statistical literature, a wide variety of techniques have been developed and applied with different data requirements and accuracy (Little and Rubin 2019).

A simple approach to handling missing data is discarding records where any missingness arises. Gill et al. (2007) show that while deletion of missing data is common practice in hydrology, it is not necessarily optimal as significant amounts of predictive information can be lost. On the other hand, single imputation methods attempt to replace missing values one feature at a time with a pre-specified summary statistic (e.g. mean or median) of the complete data (Baraldi and Enders 2010). Regression-based methods such as imputation by Random Forest, k-Nearest Neighbours and Multilayer perceptrons improve upon single imputation by exploiting correlations between variables in complete data (Gao 2017; Pantanowitz and Marwala 2009). Both regression and single
imputation can lead to biases in the resultant analysis when the assumption that data are missing at random is violated (Gao 2017). Multiple imputation methods such as Multivariate Imputation by Chained Equations (MICE) reduce this bias by replacing missing data points with predictions from an ensemble of regressors obtained from multiple subsets of the complete data (Van Buuren 2018).

Each of the imputation techniques above is used extensively in hydrology. Hamzah et al. (2021) compares numerous regression methods to reconstruct streamflow data in the Malaysian Langat River Basin. Norazizi and Deni (2019) employs MICE and expectation maximisation (EM) for the imputation of rainfall data. Adeloye and Rustum (2012) and Mwale, Adeloye, and Rustum (2012) propose the use of self-organising maps (SOMs) for infilling streamflow data at inadequately gauged basins in South West Nigeria and the Shire river basin in Malawi. In this work, we propose further augmenting regression imputation with data from Global streamflow forecasting systems.

Global streamflow prediction systems present a potential solution to missing data and the sparse distribution of stream gauge stations in developing countries. The Global Flood Awareness System (GloFAS) is one such system jointly developed by the European Commission’s Joint Research Center (JRC) and the European Centre for Medium-Range Weather Forecasting (ECMWF) (Harrigan et al. 2020b). GloFAS transforms numerical weather predictions to surface runoff through the hydrology tiled ECMWF scheme for surface exchanges over land (HTESSEL) model (Sanchez Lozano et al. 2021). These surface runoff estimates are then routed to stream networks using the LISFOOD river routing scheme (Snow 2015; Harrigan et al. 2020b). A limitation of the GloFAS system is that streamflow estimates are only available at a low resolution of a 0.1-degree grid cell (10 km²); this limits the applicability of GloFAS to mainly large watersheds (Snow 2015; Souffront Alcantara et al. 2019).

The Group on Earth Observations Global Water and Sustainability Initiative (GEOGloWS) attempts to address the coarse resolution of GloFAS with the GEOGloWS ECMWF streamflow service (GESS) (Ashby et al. 2021). The GESS extends GloFAS to local sites using an updated digital elevation model (DEM) that allows for increased resolutions in areas of the world with narrow watersheds (Ashby et al. 2021). Similar to GloFAS, runoff predictions from the HTESSEL land surface model are further downscaled and routed through a high-resolution stream network using the Muskingum algorithm of the routing application for parallel-discharge computation (RAPID) (Gill 1978).

While GloFAS and GESS provide much-needed streamflow data, localised calibration is still a significant challenge. A global calibration of these systems is biased primarily to developed regions with dense and complete observations data (Ashby et al. 2021). Thus, the utility of streamflow forecasts from these systems can be significantly enhanced by bias and variance correction to minimise systemic biases between model output and gauging station observations. Statistical Learning methods are broadly popular when learning transfer functions between global model forecasts and local observations (Piani et al. 2010; Rischard, Pillai, and McKinnon 2018; Wang, Zhang, and Villarini 2021). Various statistical learning methods have been put forward for bias correction tasks, including penalised regression, Quantile Mapping, Artificial Neural Networks and Gaussian Processes (Xu and Liang 2021; Pastén-Zapata et al. 2020; Hunt et al. 2022).

This paper presents and evaluates the bias correction of GESS river discharge estimates using statistical learning methods on ten hydrological gauging stations in Benin Republic. The proposed bias correction methods can be utilised to impute missing observation data with higher accuracy than standalone GESS and are superior to complete data-based Random Forest and k-Nearest Neighbour imputation.

Figure 1: Benin’s catchments, rivers and hydrological stations missing data rate.

Methods

Study Area

For the purposes of this study, ten hydrological stations located on the outlets of Benin’s major river basins were selected: Athiémé, Beterou, Bonou, Domè, Kaboua, Kompongou, Koubéri, Lanta, Porga and Yakin. Benin’s basins are not limited to only Benin’s administrative boundary but extend to its neighbouring countries: Togo, Burkina Faso and
Nigeria. The Kouffo, Mono, Okpara, Ouémé and Zou rivers originate from central Benin and Togo and generally flow into the Atlantic Ocean. The Alibori, Mékrou and Sota rivers also originate from the centre of Benin but have their outlet up north in the Niger river. The Pendjari river (sometimes referred to as the Oti river) originates from Northern Benin and flows into the Volta river in Togo and Ghana.

Data

*In-situ* hydrological data (daily river discharge record at ten locations from 1980 to 2021) was acquired from Benin’s hydrological service, Direction Générale de l’Eau (DG-Eau). The percentage of missing data for the selected hydrological stations is 27.9%, with the station of Athiémé having the least and the Kompongou station having the most. Figure 2 shows in detail the periods of missing data for each station. On the other hand, the GESS forecasts present no missing data and provide daily river discharge data ranging from 1979 to the present at targeted river sections (Ashby et al. 2021).

**Imputation Methods**

We investigate streamflow imputation by bias-correcting GESS forecasts. We propose an imputation scheme where we replace a missing *in-situ* GESS forecasts. We propose an imputation scheme where

\[
\tilde{x}_t = h(x'_t)
\]

where each of its finite subsets is jointly Gaussian (Rasmussen and Williams 2006). GPs are sufficiently defined by a mean function \(\mu(x')\) and a kernel function \(k(x'_t, x'_t)\).

Given a training dataset \(\{x_t, x'_t\}_{t=1}^T\) with \(t\) noisy observations \(x_t = h(x'_t) + \epsilon\), where \(\epsilon \sim \mathcal{N}(0, \sigma^2_x)\). The GP prior on \(h\) is such that \(h(x') \sim \mathcal{N}(\mu_{x'}, K_{x'} + \sigma^2_x I)\). The mean and variance of the Gaussian posterior predictive distribution of the function \(h(x'*)\) at a test point \(x'_*\), are given by

\[
\mathbb{E}(h_*) = \mu_{x'_*} + k^T_{x*}(K_{x'} + \sigma^2_x I)^{-1}(X - \mu_{x'})
\]

\[
\text{var}(h_*) = k_{x*} - k^T_{x*}(K_{x'} + \sigma^2_x I)^{-1}k_{x*}
\]

where \(k_{x*} = k(x'_*, x'_*)\) and \(k_{x*} = k(x', x'_*)\). The kernel hyperparameters \(\theta\) and the noise parameter \(\sigma_X\) are obtained by maximising the log-marginal likelihood

\[
\log p(X|X') = \log \mathcal{N}(\mu_{x'}, K_{x'} + \sigma^2_X I).
\]

In this work, we use a multi-output formulation of the GP where all ten stations share a squared exponential kernel, thus allowing for implicit inference of connectivity relationships between stations.

**Elastic Net** The elastic net is a penalised linear regression model that employs weighted \(l_1\) and \(l_2\) norm regularisation terms. The regularisation terms serve as conservative priors (bias towards zero) on the coefficients that prevent overfitting to training data. Similar to the GP, we utilised a multi-output formulation of the Elastic Net that allows information sharing between stations. In our imputation formulation;

\[
\tilde{x}_t = h(x'_t) = X'\beta + \epsilon
\]

where \(\beta\) is a matrix of coefficients on the GESS predictions \(x'_t\). The matrix of coefficients is obtained by optimising the posterior:

\[
||X - X'\beta||^2 + \lambda_2||\beta||^2 + \lambda_1||\beta||_1
\]
with the hyperparameters $\lambda_1$ and $\lambda_2$ obtained by cross validation with the constraint $\lambda_1 + \lambda_2 = 1$. Given limited in-situ data, the elastic net has the advantage of limiting over-fitting.

**Quantile Mapping** Quantile Mapping (QM) is a well-known method for bias correction of physical model output (Maraun 2013; Ringard, Seyler, and Linguel 2017). In QM, we seek to learn a mapping between the empirical cumulative distribution functions (CDF) of the in-situ and GESS predictions. In this case, the bias correction transfer function is:

$$\hat{x}_t = h(x'_t) = F_X^{-1}(F_X(x'_t))$$  \hspace{1cm} (7)

Where $F_X^{-1}$ is the inverse empirical CDF of the in-situ data and $F_X$, is the empirical CDF of the GESS data. Both empirical CDFs are obtained during a specified training period.

**Baselines** We compare imputation by bias correction using the abovementioned methods to traditional regression imputation methods that rely only on complete in-situ data. We consider regression-based imputation by Random Forest (RF) (Pantanowitz and Marwala 2009) and k-nearest neighbours (Hamzah et al. 2021) as our baselines.

**Performance Evaluation**

We measure the quality of the imputation using Kling-Gupta Efficiency (KGE) (Gupta et al. 2009), Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970) and Root Mean Square Error (RMSE) (Chai and Draxler 2014).

The KGE metric provides a diagnostically informative decomposition of the NSE and RMSE. It facilitates the analysis of the relative importance of its different components (correlation, bias and variability) in the context of hydrological modelling. The NSE measures the ability to predict variables different from the mean and gives the proportion of the initial variance accounted for by the model. The RMSE is frequently used to evaluate how closely the predicted values match the observed values based on the relative range of the data.

$$KGE = 1 - \sqrt{\left(\frac{r - 1}{1 - r^2}\right) + \left(\frac{\hat{x}_t - \bar{x}_t}{\sigma_{\hat{x}_t} - \sigma_{\bar{x}_t}}\right) + \left(\frac{\pi}{\sigma_{\hat{x}_t}}\right)^2}$$ \hspace{1cm} (8)

$$NSE = 1 - \frac{\sum_{i=1}^{n} (x_t - \hat{x}_t)^2}{\sum_{i=1}^{n} (x_t - \bar{x}_t)^2}$$ \hspace{1cm} (9)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_t - \hat{x}_t)^2}$$ \hspace{1cm} (10)

In the above equations, $x_t$ represents the observed discharge at a time $t$, $\bar{x}_t$ represents the imputed discharge at a time $t$, $\hat{x}_t$ is the mean of the observed discharge, $\bar{x}_t$ is the mean of the imputed discharge, $\sigma_{\bar{x}_t}$ is the variance of the simulated discharge, $\sigma_{\hat{x}_t}$ is the variance of the observed discharge, $r$ is the Pearson correlation coefficient, and $n$ is the number of observations. The KGE values range from $-\infty$ to 1, with values close to 1 indicating good agreement. Similarly to the KGE, the NSE values also range from $-\infty$ to 1, with the perfect model having the value 1. The RMSE values range from 0 to $\infty$, with 0 implying the model has a perfect fit.

**Results and Discussion**

We partition the data such that 60% of the period (1980/01-2004/11) is for training and 40% is for (2004/11-2021/06) testing. We evaluate the performance of the imputation methods by randomly simulating missingness on the complete testing data at rates of 5%, 10%, 20%, 30% and 50%.

Figure 3 shows the mean KGE, NSE and RMSE of the imputation methods across gauging stations and levels of missingness. It can be seen that a simple lookup of the GESS predictions yields the worst imputation performance. The low KGE and high RMSE values detailed in Table II suggest that the GESS predictions have significant bias.

The hypothesis around significant bias in the GESS predictions is reinforced by the outperformance of the GP and
Discharge (m$^3$/s)

Ditions with highly complete data in the Athièmè and Bonou stations with the highest KGE values obtained at stations. The complete data could not sufficiently calibrate the bias correction. GP and Elastic Net imputation methods provide the best performance in eight of the ten stations. QM as bias correction yields KGEs superior to multiple imputations by k-NN and RF, suggesting that bias correction would remain the most efficient approach when constrained by computational resources.

Figure 4 depicts the embedded bias in the GESS forecasts at the Koubéri station. Figure 4 shows the resultant time series by looking up the missing data from the GESS. The positive bias in the GESS manifest in that GESS lookups lead to new discharge extremes that are five times the extremes recorded in the in-situ observations. In operational settings, such significant positive biases can lead to false flood alerts and sub-optimal use of already limited resources. The remedy to this extreme bias is seen in Figure 5 where bias correction removes the significant positive bias while retaining the seasonal periodicity in discharge.

Conclusion

We evaluated state-of-the-art imputation methods for streamflow prediction, demonstrating the need and importance of bias-correcting GEOGloWS ECMWF streamflow service (GESS) streamflow forecast information. Our findings show that the bias introduced by GESS forecasts can be significant and result in possible false flooding alerts. We minimize such bias using QM, GP, and Elastic Net regressions trained in periods where in-situ observations are available. The resultant imputation under simulated missingness shows that GESS bias correction outperforms train k-NN and RF imputation trained on available data alone.

Our findings enhance decision-making based on streamflow model-based forecasts, reducing bias introduced by missing in-situ data. The reliance on such forecasts is high, particularly in areas where data collection is too costly, under-resourced, or not possible across Sub-Saharan Africa. The proposed bias correction methodology integrates into existing operational GESS forecasting and now enables real-time flooding and drought monitoring with lead times of up to 15 days. Continued work aims to enhance and expand on the operational implementation of our bias-correction-based methodology. Specifically, we aim to interpolate and extrapolate the best-performing bias-correction model to ungauged areas. This is anticipated to vastly increase the utility of GESS to large areas across Sub-Saharan Africa and Central America that are currently ungauged. The robustness of our proposed approach will also be further tested at the seasonal scale to ensure that wet seasons and overall seasonal dynamics are captured accurately.

Table 1: Mean KGE, NSE and RMSE of each imputation method at varying levels of missingness across the ten stations.
References

Adeloye, A. J.; and Rustum, R. 2012. Self-organising map rainfall-runoff multivariate modelling for runoff reconstruction in inadequately gauged basins. *Hydrology Research*, 43(5): 603–617.

Adounkpe, P. J. Y.; Alamou, E.; Diallo, B.; and Ali, A. 2021. Predicting Discharge in Catchment Outlet Using Deep Learning: Case Study of the Ansongo-Niamey Basin. In *NeurIPS 2021 Workshop on Tackling Climate Change with Machine Learning*.

Ashby, K. R.; Hales, R. C.; Nelson, J.; Ames, D. P.; and Williams, G. P. 2021. Hydroviewer: A Web Application to Localize Global Hydrologic Forecasts. *Open Water Journal*, 7(1): 9.

Baraldi, A. N.; and Enders, C. K. 2010. An introduction to modern missing data analyses. *Journal of school psychology*, 48(1): 5–37.

Chai, T.; and Draxler, R. R. 2014. Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscientific Model Development*, 7(3): 1247–1250.

Cohen, S.; Mbuvha, R.; Marwala, T.; and Deisenroth, M. 2020. Healing products of Gaussian process experts. In *International Conference on Machine Learning*, 2068–2077. PMLR.

Gao, Y. 2017. *Dealing with missing data in hydrology: Data analysis of discharge and groundwater time-series in Northeast Germany*. Ph.D. thesis, Freie Universität Berlin.

Gill, M. A. 1978. Flood routing by the Muskingum method. *Journal of Hydrology*, 36(3-4): 353–363.

Gill, M. K.; Asefa, T.; Kaheil, Y.; and McKee, M. 2007. Effect of missing data on performance of learning algorithms for hydrologic predictions: Implications to an imputation technique. *Water resources research*, 43(7).

Gupta, H. V.; Kling, H.; Yilmaz, K. K.; and Martinez, G. F. 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, 377(1): 80–91.

Hamzah, F. B.; Hamzah, F. M.; Razali, S. M.; and Samad, H. 2021. A comparison of multiple imputation methods for recovering missing data in hydrological studies. *Civil Engineering Journal*, 7(9): 1608–1619.

Hamzah, F. B.; Mohd Hamzah, F.; Mohd Razali, S. F.; Jaafar, O.; and Abdul Jamil, N. 2020. Imputation methods for recovering streamflow observation: A methodological review. *Cogent Environmental Science*, 6(1): 1745133.

Harrigan, S.; Zsoter, E.; Alfieri, L.; Prudhomme, C.; Salamon, P.; Wetterhall, F.; Barnard, C.; Cloke, H.; and Pappenberger, F. 2020a. GloFAS-ERA5 operational global river discharge reanalysis 1979–present. *Earth System Science Data*, 12(3): 2043–2060.

Harrigan, S.; Zsoter, E.; Alfieri, L.; Prudhomme, C.; Salamon, P.; Wetterhall, F.; Barnard, C.; Cloke, H.; and Pappenberger, F. 2020b. GloFAS-ERA5 operational global river discharge reanalysis 1979–present. *Earth System Science Data*, 12(3): 2043–2060.

Hunt, K. M. R.; Matthews, G. R.; Pappenberger, F.; and Prudhomme, C. 2022. Using a long short-term memory (LSTM) neural network to boost river streamflow forecasts over the western United States. *Hydrology and Earth System Sciences Discussions*, 2022: 1–30.

Kalantari, Z.; Ferreira, C. S. S.; Keesstra, S.; and Destouni, G. 2018. Nature-based solutions for flood-drought risk mitigation in vulnerable urbanizing parts of East-Africa. *Current Opinion in Environmental Science & Health*, 5: 73–78.

Kratzert, F.; Herrnegger, M.; Klotz, D.; Hochreiter, S.; and Klambauer, G. 2019. NeuralHydrology—interpreting LSTMs in hydrology. In *Explainable AI: Interpreting, explaining and visualizing deep learning*, 347–362. Springer.

Little, R. J.; and Rubin, D. B. 2019. *Statistical analysis with missing data*, volume 793. John Wiley & Sons.

Maraun, D. 2013. Bias correction, quantile mapping, and downscaling: Revisiting the inflation issue. *Journal of Climate*, 26(6): 2137–2143.

Mwale, F. D.; Adeloye, A. J.; and Rustum, R. 2012. Infilling of missing rainfall and streamflow data in the Shire River basin, Malawi–A self organizing map approach. *Physics and Chemistry of the Earth, Parts A/B/C*, 50: 34–43.

Nash, J.; and Sutcliffe, J. 1970. River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, 10(3): 282–290.

Norazizi, N. A. A.; and Deni, S. M. 2019. Comparison of artificial neural network (ANN) and other imputation methods in estimating missing rainfall data at Kuantan station. In *International Conference on Soft Computing in Data Science*, 298–306. Springer.

| Method                | Yankin | Lanta | Kompongou | Athiémè | Kaboua | Beterou | Bonou | Porga | Koubéri | Domè |
|-----------------------|--------|-------|------------|----------|--------|---------|-------|-------|---------|-------|
| KNN                   | 0.786  | 0.728 | 0.725      | 0.864    | 0.772  | 0.847   | 0.846 | 0.851 | 0.784   | 0.797 |
| RF                    | 0.821  | 0.784 | 0.780      | 0.859    | 0.841  | 0.807   | 0.832 | 0.839 | 0.626   | 0.822 |
| Gaussian Process      | 0.863  | 0.857 | 0.829      | 0.919    | 0.833  | 0.831   | 0.877 | **0.913** | **0.914** | 0.894 |
| GESS                  | **0.896** | 0.651 | **0.905** | 0.643    | 0.870  | 0.865   | 0.808 | 0.853 | 0.443   | 0.448 |
| Elastic Net           | 0.848  | **0.872** | 0.809      | **0.930** | **0.881** | **0.881** | **0.908** | 0.894 | 0.901   | 0.905 |
| Quantile Mapping      | 0.831  | 0.871 | 0.823      | 0.936    | 0.841  | 0.838   | 0.906 | 0.872 | 0.865   | **0.912** |

Table 2: KGE of each imputation method at 20% missingness at each respective gauging station.
Pantanowitz, A.; and Marwala, T. 2009. Missing data imputation through the use of the random forest algorithm. In Advances in computational intelligence, 53–62. Springer.

Pastén-Zapata, E.; Jones, J. M.; Moggridge, H.; and Widmann, M. 2020. Evaluation of the performance of Euro-CORDEX Regional Climate Models for assessing hydrological climate change impacts in Great Britain: A comparison of different spatial resolutions and quantile mapping bias correction methods. Journal of Hydrology, 584: 124653.

Piani, C.; Weedon, G.; Best, M.; Gomes, S.; Viterbo, P.; Hagemann, S.; and Haerter, J. 2010. Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. Journal of Hydrology, 395(3): 199–215.

Pigott, T. D. 2001. A review of methods for missing data. Educational research and evaluation, 7(4): 353–383.

Rasmussen, C. E.; and Williams, C. K. I. 2006. Gaussian Processes for Machine Learning. The MIT Press.

Ringard, J.; Seyler, F.; and Linguet, L. 2017. A quantile mapping bias correction method based on hydroclimatic classification of the Guiana shield. Sensors, 17(6): 1413.

Risbard, M.; Pillai, N.; and McKinnon, K. A. 2018. Bias correction in daily maximum and minimum temperature measurements through Gaussian process modeling. arXiv preprint arXiv:1805.10214.

Sanchez Lozano, J.; Romero Bustamante, G.; Hales, R. C.; Nelson, E. J.; Williams, G. P.; Ames, D. P.; and Jones, N. L. 2021. A Streamflow Bias Correction and Performance Evaluation Web Application for GEOGloWS ECMWF Streamflow Services. Hydrology, 8(2): 71.

Snow, A. D. 2015. A New Global Forecasting Model to Produce High-Resolution Stream Forecasts. Brigham Young University.

Souffront Alcantara, M. A.; Nelson, E. J.; Shakya, K.; Edwards, C.; Roberts, W.; Krewson, C.; Ames, D. P.; Jones, N. L.; and Gutierrez, A. 2019. Hydrologic modeling as a service (HMaaS): a new approach to address hydroinformatic challenges in developing countries. Frontiers in Environmental Science, 7: 158.

Tencaliec, P.; Favre, A.-C.; Prieur, C.; and Mathevet, T. 2015. Reconstruction of missing daily streamflow data using dynamic regression models. Water Resources Research, 51(12): 9447–9463.

Van Buuren, S. 2018. Flexible imputation of missing data. CRC press.

Wang, C.; Zhang, W.; and Villarini, G. 2021. On the use of convolutional Gaussian processes to improve the seasonal forecasting of precipitation and temperature. Journal of Hydrology, 593: 125862.

Xu, T.; and Liang, F. 2021. Machine learning for hydrologic sciences: An introductory overview. Wiley Interdisciplinary Reviews: Water, 8(5): e1533.