Predicting Discharge in Catchment Outlet Using Deep Learning: Case Study of the Ansongo-Niamey Basin

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Abstract

Hydrological models are one of the key challenges in hydrology. Their goal is to understand, predict and manage water resources. Most of the hydrological models so far were either physical or conceptual models. But in the past two decades, fully data-driven (empirical) models started to emerge with the breakthroughs of novel deep learning methods in runoff prediction. These breakthroughs were mostly favored by the large volume, variety and velocity of water-related data. Long Short-Term Memory and Gated Recurrent Unit neural networks, particularly achieved the outstanding milestone of outperforming classic hydrological models in less than a decade. Moreover, they have the potential to change the way hydrological modeling is performed. In this study, precipitation, minimal and maximum temperature at the Ansongo-Niamey basin combined with the discharge at Ansongo and Kandadji were used to predict the discharge at Niamey using artificial neural networks. After data preprocessing and hyperparameter optimization, the deep learning models performed well with the LSTM and GRU respectively scoring a Nash-Sutcliffe Efficiency of 0.933 and 0.935. This performance matches those of well-known physically-based models used to simulate Niamey's discharge and therefore demonstrates the efficiency of deep learning methods in a West African context, especially in Niamey which has been facing severe floods due to climate change.

Keywords: Ansongo-Niamey basin, deep learning, gated recurrent unit, hydrological model, hyperparameter optimization, long short-term memory

1   Introduction

According to Aich et al. (2016), in the Niger Basin (particularly in the Middle Niger Basin), extensive catastrophic flooding has increased drastically during the last two decades, with a high frequency and at large extent in the city of Niamey. As part of possible mitigation solutions, finding means to improve hydrological models could alleviate the suffering of the population by improving the existing early warning systems. Many hydrological models have been deployed to predict the discharge in Niamey. The models studied were physically-based hydrological models such as the Niger-HYdrological Predictions for the Environment (Niger-HYPE) by Andersson et al. (2017), Interaction between Soil Biosphere and Atmosphere-Total Runoff Integrating Pathway (ISBA-TRIP) by Casse (2015), Soil and Water Assessment Tool (SWAT) by Pomeon et al. (2018) and HydroGeoSphere (HGS) by Boko et al. (2020). Few hydrological models have performed well in Niamey at discharge prediction

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Codes related to article on GitHub: `https://github.com/pyaj0/DL-hydrological-model`

(section 5). Artificial intelligence (AI) AI based models which are fully data driven appear to be able to overcome deficiencies of physically-based hydrological models (Shen (2018)).

In hydrology, deep learning (DL) is a subset of machine learning well known for predicting and estimating floods, monitoring drought accurately, analyzing atmospheric imaging, estimating tropical cyclones and their precursors, and predicting other hydrological processes (Ardabili et al. (2019)). Hochreiter and Schmidhuber (1997), the creators of the Long Short-Term Memory (LSTM) neural networks, proved that their recurrent neural network structure was an innovative DL method for achieving high accuracy time series prediction and reducing CPU cost. Due to their cell state, LSTMs can learn and store long-term dependencies of the input-output relationship. The Gated Recurrent Unit (GRU) is an improved version of the LSTM proposed by Chung et al. (2014) and able to outperform its predecessor. Furthermore, Shen (2018) demonstrates that DL can help address several major new and old challenges facing research in water science, and hydrological modeling is no exception.

Intending to look for alternative hydrological models to better face climate change damages, this study focuses on simulating efficiently the Niger river discharge in the city of Niamey using artificial neural networks. The methodology followed includes (i) preprocessing climate and hydrological data, (ii) optimizing LSTM and GRU hyperparameters, and (iii) training and testing the DL models. The following sections progressively explore the study conducted by depicting the area of study, describing the data used, sharing the methods and techniques deployed and discussing the results obtained.

2   Study Area

The Ansongo-Niamey basin is a transborder catchment located in the middle region of the Niger basin between Burkina Faso, Mali and Niger. Ansongo (Mali) - the outlet of the upper Niger basin - was considered the upstream of this study area. The Ansongo-Niamey basin was chosen as study area because it would prove challenging to collect data of the upper Niger basin.

This basin's runoff regime is affected by recurring floods which flow from different geographic locations with distinct characteristics. The first flood is the annual peak during the rainy season (July to November) in the Ansongo-Niamey basin called the "Red Flood" or "Sahelian Flood". The second one is the Guinean Flood, which originates from the headwaters of the Niger in the Guinean highlands during the rainy season between July and November (Aich et al. (2016)). Check appendix 6 for figures illustrating study area.

3   Data

Precipitation, minimum and maximum temperature data were provided by AGRHYMET Regional Centre (ARC). The river discharge data of the Ansongo, Kandadji and Niamey were provided by ARC and Niger Basin Authority (NBA). These observation datasets are daily records dating from June 1981 to December 2010. A digital elevation model of West Africa was obtained from the Consortium for Spatial Information (CGIAR-CSI).

4   Methods and Techniques

This work was executed using open-source tools such as QGIS for delineation and mapping of the Ansongo-Niamey basin, Anaconda for package management and deployment, Jupyter Notebook as programming interface and Python modules (Numpy, Pandas, TensorFlow, Matplotlib, Scikit-Optimize, ...).

The data processing was done in 5 steps: delineation of the Ansongo-Niamey basin, transformation of the climate data, transformation of the hydrological data, analysis of the hydrological data and merging climate and hydrological data. The final output used is a dataframe of 10806 rows and 7 columns with the number of rows representing the number of days of observation and the number of columns representing the date, input and output variables (precipitation, maximum temperature, minimum temperature, discharge at Ansongo, discharge at Kandadji and discharge at Niamey).

Hyperparameter optimization refers to performing a search to discover the set of specific model configuration arguments that result in the best performance of the model on a specific dataset. In this case, the goal was to minimize the cost function of the LSTM and GRU models after 40 iterations on the validation sets. The selected neural networks parameters to optimize were the learning rate, the number of unit, the number of epoch and the batch size.

Before loading the data into the DL models, a few transformations were applied such as data normalization, transformation from time series to supervised learning series and data splitting into training, validation and testing sets. The optimizer used was the Adam optimizer and its learning rate was obtained from the hyperparameter optimization process. The chosen loss function was the mean square error. For the training phase of the DL models, the number of epochs was set to 100 epochs to have the same scale of comparison between models. The batch size corresponded to the value obtained after hyperparameter optimization. The evaluation of the models was done using the test dataset. We evaluated the models by analyzing the curve of the loss function over the number of epochs (appendix 6). To evaluate the performance of river flow forecasting models, the Nash-Sutcliffe Efficiency (NSE) was used as a statistical method.

5 Results and Discussion

The table below presents values of the selected parameters after hyperparameter optimization.

Table 1: Optimized hyperparameters obtained

Model	Learning rate	Number of unit	Number of epoch	Batch size
LSTM	0.0156	30	500	128
GRU	0.0100	100	100	100

Both DL models performed better with lower learning rates (between 10^{-3} and 3.10^{-2}) and smaller number of units (not more than 300). The number of epoch and the batch size have lower influence on the model although higher number of epochs generally slightly improves the predictions.

The DL models performed well with the testing data ranging from June 2006 to December 2010. The LSTM and the GRU scored respectively 0.933 and 0.935 for the NSE test. The GRU performed a little better than the LSTM at predicting discharges (Figure 1). The downside was that the discharge peaks were underestimated by the models.

Few studies were published on surface discharge prediction in Niamey. However, four classical/physical hydrological models were identified to be compared to the DL models' performance. Below is a table of the studies found which presents the model name, its input data (excluding precipitation, temperature and discharge) and its performance during a validation period.

Table 2: Performance of hydrological models in Niamey

| Model	Paper	Input data	Validation period	Performance
Niger-HYPE	Andersson et al. (2017)	Topography, land use, soil, lakes, reservoirs	1995-2010	NSE: 0.72
ISBA-TRIP	Casse (2015)	Radiation, wind speed, air pressure, air humidity	2003-2012	NSE: 0.93
SWAT	Pomeon et al. (2018)	Topography, land use, soil	2008-2013	KGE: 0-0.5
HGS	Boko et al. (2020)	Soil moisture, surface water depth, land use, evaporation	1980-2005	Good

KGE: Kling Gupta Efficiency
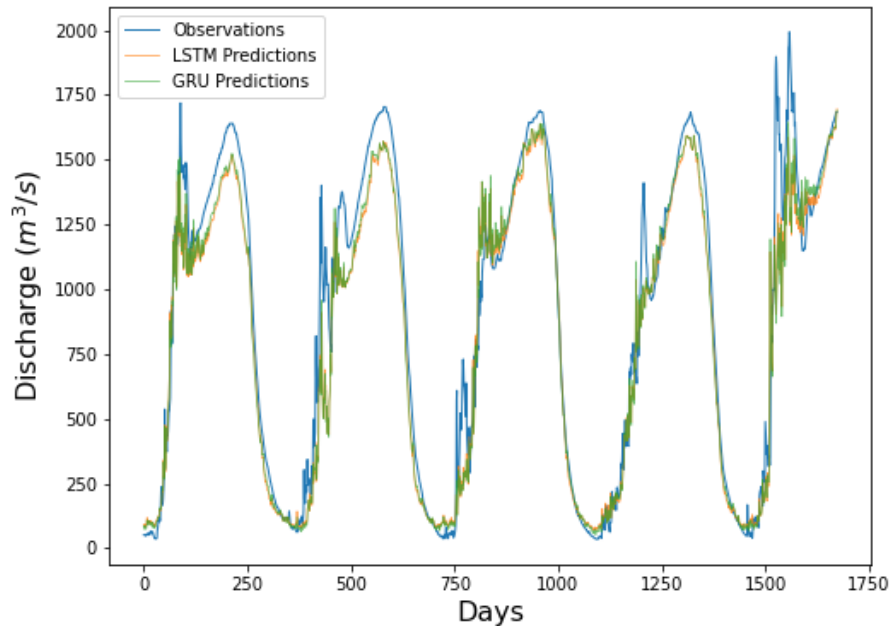
Figure 1: Discharge predictions of LSTM and GRU models in Niamey from June 2006 to December 2010

Physically-based models predicting Niamey's discharge had a good performance. Generally, the more data is fed into these models, the better the results. The DL models match the performance of their predecessor with fewer input data. The execution of the DL models required low computational resources (was run on a CPU in less than five minutes). Only the hyperparameter optimization process was time-consuming (up to one day of runtime) because of the number of epoch set as a hyperparameter. Artificial neural networks are indeed promising in the field of hydrology.

6 Conclusion

This research investigated the potential of using LSTM and GRU neural networks for simulating discharge from precipitation, temperature and upstream discharge observations. The work confirms that the DL models trained and tested were able to achieve high accuracy and efficiency while maintaining a low computational cost and using fewer data. As expected, the GRU performed slightly better than the LSTM. The trained DL models matched and even outperformed classical hydrological models at predicting historical surface discharge in Niamey. These results represent a new milestone towards the development of AI-based hydrological models as alternatives to classical/physical models.

Meanwhile, better performance could have been obtained if we replaced the number of epochs and the batch size with other hyperparameters in the optimization phase. The extreme discharge could have been better simulated if additional variables were added to the model (data-centric approach) or if the model was tweaked in a manner that predicts extreme events easier (model-centric approach). The next step would be to exploit DL models to their extent by studying their regionalization in the Niger basin by integrating catchments' physical characteristics.

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Appendix

Study Area

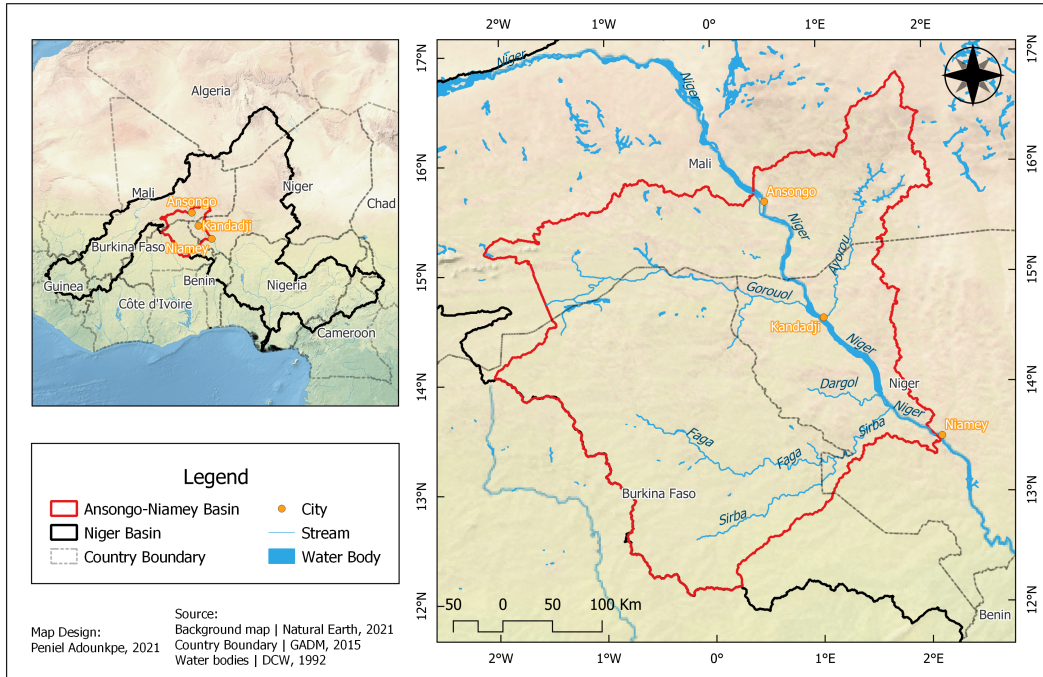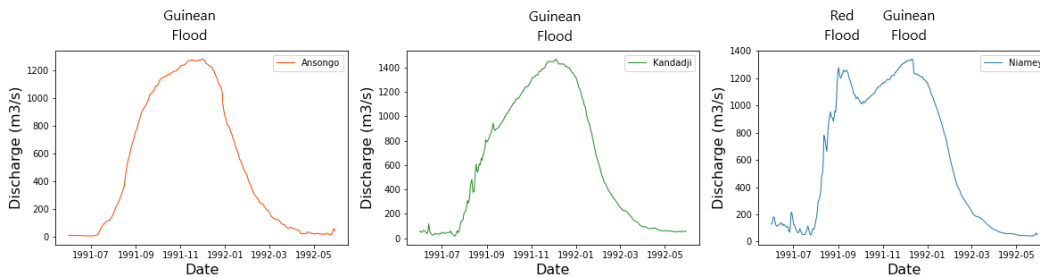Figure 2: Map of Ansongo-Niamey basin

Figure 3: Hydrographs of Ansongo, Kandadji and Niamey for June 1991 to Mai 1992

Statistical Method

The Nash-Sutcliffe Efficiency (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 NSE values ranges from $-\infty$ to 1 with the perfect model having the value 1.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

In the equations, y_i represents the observed discharge at a time t, $\hat{y}_i$ represents the simulated discharge at a time t, $\bar{y}_i$ is the mean of the observed discharge and n is the number of observations.

Loss Fonction

The loss curve trend shows that the DL models converged reasonably quickly and both train and validation performance remained equivalent. The performance and convergence behavior of the model suggest that mean squared error is a good match for a neural network learning this problem.
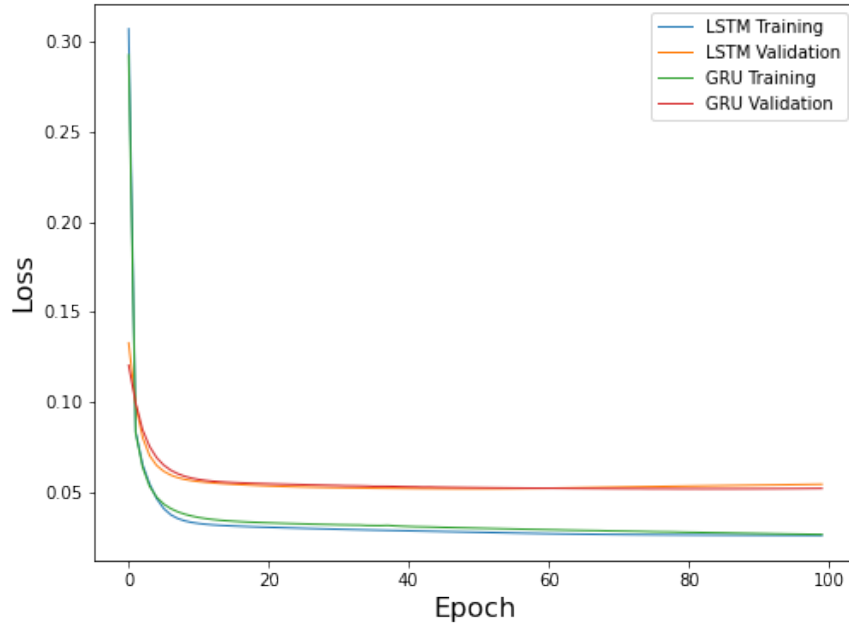

Figure 4: Loss function of LSTM and GRU models