APPLICATIONS OF RECURRENT NEURAL NETWORKS FOR FLOW FORECASTING IN THE SENEGAL RIVER VALLEY

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ABSTRACT-The prediction of the hydraulic regimes of rivers has always been of great importance insofar as it allows to prevent certain phenomena such as floods, drought on the one hand, and to improve agricultural productions and river navigations on the other hand.

Consequently, the increase of floods and the economic stakes constitute particularly the motivations of this work.

In our paper we developed an application with Streamlit capable of predicting the daily hydraulic regime at the stations of Bakel, Matam and Podor. The predictive algorithm that was used is a model based on artificial intelligence. It is precisely a variant of recurrent neural networks called LSTM (Long Sort Term Memomry).

In addition, we evaluated the results of our forecasts using the following metrics : the MAE (Mean Absolute Error) and the Nash criterion (R^2). At the end of this study, we found that the LSTM model performed very well.

Keywords : forecasts, recurrent neural networks, Long Sort Term Memory (LSTM), ratings, flows, Senegal River basin

1. I NTRODUCTION

At present, the changes in climatic conditions observed in the tropical zone since the late 1960s and early 1970s indicate a trend toward decreasing rainfall in quantity and duration in many watersheds, more specifically in the Senegal River.

Thus, the interest of our study is based on ecological and economic considerations, particularly the literature review, which provides objective information.

Today, data science is a discipline that can play a key role in the analysis and prediction of river levels in any territory. It complements the work of hydrologists, geographers, and statisticians whose focus is on explaining certain phenomena related to rising and falling water levels.

Moreover, the interest in measuring and predicting water levels is now reinforced by the current challenges of global warming (floods, drought), new demands for sharing water between different uses (energy, irrigation, drinking water), the restoration or preservation of natural environments and their biodiversity, the social demand for knowledge and the increased vulnerabilities of society.

Indeed, the measurement of the flows of a river answers several purposes: operational management of hydraulic works (hydroelectric developments, irrigation systems, reservoirs for flood control or low water support...), dimensioning of these works, by the knowledge of the characteristics of these watercourses, regulatory control for the verification of the obligations of restitution of flow downstream of works (minimum flow to ensure the survival of fish, the maintenance of other uses; the non-aggravation of floods), the declaration of state of disaster (droughts...), the protection of goods and people, by the announcement of floods; of heritage, by the constitution of series of long-term observations, essential to know the evolutions of the regimes of the rivers, to sensitize the populations to the natural risks, to assign a probability to the extreme events (floods, low water).

Thus, our research is anchored in the Senegal River basin with three stations in the river valley (in the Sahelian zone), located on the course of the river between the two dams, mainly the stations of Bakel, Matam and Podor.

In this approach, we aim to develop and deploy a web application based on a deep learning model such as LSMT capable of predicting daily water levels measured between 1960 and 2008 at the Senegal River.

2. FORECASTING ON TIME SERIES : STATE OF THE ART

Until the end of the 1990s, stochastic models were the most widely used for river flow forecasting. Among these models we distinguish the ARIMA class (Auto Regressive Integrated Moving Average) proposed by Box and Jenkins in 1976 **[1]** and taken up in 1990 by Mujumdar and Nagesh Kumar in the article Stochastic models of streamflow- Some case studies **[2].**

However, in recent years, many methods based on artificial intelligence have become popular in time series forecasting, replacing traditional techniques. This is due to their ability to handle large volumes of data in various domains.

Thus the adaptability of recurrent neural networks in hydrology has been well illustrated in ASCE (2000a) **[3]** and a reference list of ANN applications in hydrology is given in ASCE (2000b) **[4]**.

In 2004, D. Nagesh Kumar et al **[5]**, after a comparative study on networks, recommended using recurrent neural networks as a tool for river forecasting.

In 2018, at the 17th IEEE International Conference on Machine Learning and its Applications, Sima Siami-Namini et al **[6]** demonstrated the effectiveness of predictions made by artificial intelligence-based algorithms especially LSTMs vis-à-vis the classical model namely Arima.

In 2020, Youchuan Hu et al **[7]** showed the importance of LSTMs in their work on the prediction of the flow of small rivers based on a comparative study between the following three models : LSTM (Long Sort Term Memory), SVR (Support Vector Regression) and MLP (Multilayer Perceptions). Indeed, based on the RMSE, R^2, MAE and STA-LSTM, the LSTM model obtained the best predictive performance. The LSTM was able to predict the future water level in 6 hours by combining the following parameters: the previous water level and the rainfall.

In 1999, Awadallah, Ayman Geaorges, in his Ph.D. thesis **[8]**, set up two models for predicting the cumulative volume of natural inflow to the Nile. The first one is based on transfer functions with noise (TFN) and the second on artificial neural networks (ANN). The inputs to the models are the ocean surface temperatures (OST) in specific regions and the cumulative volumes of natural supplies in previous years. The results obtained by the two models are quite satisfactory because they explain 63% of the variability of flows with correlation coefficients that exceed 0.85 between the predicted and observed flows.

Thus, the comparison between the TFN and the ANN allowed us to draw the following two conclusions. The first is that the relationship between OST in the Eastern Pacific and the Nile flood can be approximated by a linear relationship to an acceptable degree of accuracy, given that the results of the TFN and RNN models are similar. The second is that TFN models are more appropriate for addressing the problem of medium-term flow forecasting using climate information.

In 2004, within the framework of the "Flood Risk" program (RIO2), Sandrine Jenni et al **[9]** carried out a comparative study and improvement of forecasting tools in the upper Loire basin. In this paper, about fifteen catchment areas, ranging from 30 to 5000 km^2 in total, were studied. On the one hand, an approach based on artificial neural networks was used to advance the conceptual models and propose a direct assimilation version. The results of this approach were considered satisfactory. On the other hand, a multi-model approach was done but was not as successful as expected. The latter just allowed for an uncertainty calculation.

In 2009, Yonaba Harouna, in his PhD thesis **[10]**, replaced the BV3C (Balance Vertical 3-Layer) module of the HYDROTEL distributed model by a set of neural networks. The conclusions drawn from the different tests performed show first of all that the substitution gives satisfactory results and a slight time saving in the process execution. Moreover, the balance criterion and the mean absolute error indicate that neural networks outperform the BV3C module.

In 2014, Johanet et al **[11]** addressed hydrodynamic modeling of karsts using artificial neural networks. In this paper, they demonstrated the effectiveness of mathematical models derived from artificial intelligence in their ability to perfectly model the hydrodynamics of karst aquifers.

In 2018, Yaseen et al **[12]** developed a data-driven machine learning model, namely the Extreme Learning Machine (ELM). It was implemented in the flow forecast of the Johor River in Malaysia. It was then compared with another learning machine model: the ANN (Artificial Neural Network). The R^2, RMSE and MAE metrics thus showed that ELM performs better than ANNs in terms of accuracy and time.

In 2019, Bastien NONY, as part of his internship at the European Center for Research and Advanced Training in Scientific Computing (CERFACS) **[13]** participated in the design of a model capable of predicting the height of water at the level of Toulouse on a 6-hour time frame. Firstly, the statistical models that were trained on the whole database gave poor results, leading to a reduction in the amount of data. Secondly, models such as linear regression, SVM (Support Vector Machine), gradient boosting, ε-SVR and a neural network of MLP (Multilayer Perceptron) type were implemented to make predictions from 4h to 6h. In this case, the results obtained are quite satisfactory.

In 2020, Syed Kabir et al **[14]** developed a modeling approach based on a deep convolution neural network (DCN) method for rapid prediction of river flooding in Carlisle, UK. To evaluate the performance of this model, it was compared to the Support Vector Machine (SVR). In the end, the results showed that the CNN significantly outperformed SVR.

In 2020, Yuka Ding et al **[15]** proposed an interpretable model of short-term memory and spatio-temporal attention (STA-LSTM) based on the LSTM and the attention mechanism. This method was developed to overcome the limitations of existing solutions for hydrological prediction. The results of experiments conducted on three small and medium-sized basins in China suggest that the STA-LSTM model outperforms the historical average (HA), graphical convolutional networks (GCN), original LSTM (LSTM), spatial attention LSTM (SA-LSTM) and temporal attention LSTM (TA-LSTM) in most cases.

3. MATERIALS AND METHODS

3.1. Study area

The Senegal River is 1,086 km long and covers an area of approximately 300,000 km^2. It flows through Senegal, Mauritania, Mali and Guinea. It is the second most important river in West Africa after the Niger.

The basin comprises three main regions : the Upper Basin, the Valley and the Delta. These regions are strongly differentiated by their topographic and climatological conditions.

This watershed, which extends from humid tropical zones (1500 mm/year in the Guinean part) to dry tropical zones (200-250 mm/year in the northern part of the basin), crosses diversified biophysical environments from the upper basin located in the Fouta Djallon mountains (still called the water tower of Africa) to the delta, passing through sub-desert zones. In this watershed live about 3.5 million people who derive most of their income from the resources of the environment **[16]**.

In 1972, these States, through which the river flows, created the OMVS (Organization for the Development of the Senegal River) with the aim of making the best use of the resources and opportunities offered by the river. As a result, development programs focusing on irrigation, hydroelectric power production and navigation were launched. Thus, the Diama and Manantali dams have been built. As a result, the agricultural sector and riverside towns have developed.

The study area extends over the downstream basin of the Senegal River and concerns particularly the stations of Bakel, Matam and Podor. The data used are the daily water levels measured between 1960 and 2008.

3.2. Data processing software

We performed the data processing with the help of Jupyter Notebook which is a web-based interactive development environment for notebooks, code and data. As for the application, it was built using the Streamlit framework.

3.3. Models

In our work, we have chosen a model based on artificial intelligence. It is a variant of the recurrent neural networks called the Long Sort Term Memory (LSTM).

A. Long Sort Term Memory (LSTM) networks

First developed around the 1980s, recurrent neural networks are networks in which information can propagate in both directions, including from deep layers to early layers **[7]**. These networks have recurrent connections in the sense that they store information in memory : they can take into account a certain number of past states at a given moment.

The basic and classical logic of RNN is presented below :

$$h_t = f_h(x_t, h_{t-1}) = \phi_h(W^T h_{t-1} + U^T x_t) \quad \textbf{(1)}$$

$$y_t = f_0(h_t, x_t) = \phi_0(V^T h_t) \quad \textbf{(2)}$$

Where x_t is the input, ht represents the hidden state and y_t is the output, the index t represents the time.

First the output of the last hidden state is combined with the current input (each with the weights W_T and U_T), the result of which is transformed by a nonlinear tanh or sigmoid function, and then is introduced into the hidden state. Then the hidden state takes its weight V_T, it is transformed by another nonlinear function and the result is finally assigned to y_t. In this way, the current output y_t is assigned to the last hidden state, resulting in a short memory.

Although RNNs are very convenient for sequential data processing, it turns out that they are extremely difficult to train to handle long-term dependency due to the gradient vanishing problem.

To overcome the gradient vanishing problem, Long Sort Term memory (LSTM) neural networks were introduced by Hochreiter, Schmidhuber et al. in 1997 **[17]** and improved in the paper by F. Gers and j. Schmidhuber **[18]**.

LSTMs use memory cells and gates to control the information stored in the network **[19]**. In other words, it is a series of gates and cells that cooperate to produce a final result. A forward pass of an LSTM neural network is modeled by equations (3-8).

$$f_t = \sigma(W_f.xt + U_f.h_{t-1} + b_f) \quad \textbf{(3)}$$

$$i_t = \sigma(W_f.x_t + U_i h_{t-1} + b_i) \quad \textbf{(4)}$$

$$\check{c} = tanh(W_e.xt + U_e.h_{t-1} + b_e) \quad \textbf{(5)}$$

$$c_t = f_t * c_{t-1} + i_t + \check{c}_t) \quad \textbf{(6)}$$

$$o_t = \sigma(W_o.xt + U_o.h_{t-1} + b_o) \quad \textbf{(7)}$$

$$h_t = o_t * tanh(c_t) \quad \textbf{(8)}$$

Where U and W are the weights of the inputs to the different gates: the input gate (i_t), the input modulation gate (c_t), the forgetting gate(g_t) and the output gate (ot).

b is the bias vector, c_t is the cell state and h_t is the hidden state.

All these parameters determine how much information to receive from the last loop and how much to transmit to the new state. By actively choosing which useful information to store and discard, LSTMs provide a solution to the gradient explosion and vanishing problem faced by RNNs.

2.4 *Modelling methods*

A. Data acquisition

The data for the study were collected from the ODSR (Organization for the development of the Senegal River) and DMPWRS (Direction of the Management and Planning of Water Resources of Senegal) databases.

They consist of daily water levels recorded between 1960 and 2008 at the stations of Bakel, Matam and Podor. Each station has 366 records distributed in 49 columns.

B. Data pre-processing

In this section, we transformed the initial data from each station into tables consisting of only two columns : the date and the water level. This allowed us to obtain exactly for each day the water level that was recorded. Thus we go from tables of 366 records and 49 columns to dataframes consisting of 17,532 records distributed in 2 columns.

The missing data were treated with the interpolation method which consists in estimating unknown data points between two known data points.

Then we checked the stationarity of the data which describes the fact that the time series has a constant mean, variance and covariance and that they are not time dependent. The Dickey Fuller test was used and the results are shown graphically in Figure 2. Thus, we notice that the values of the p-values of each of the stations are lower than 5% so we reject the null hypothesis which means that our data are stationary.

With the seasonnal decompose package from the python statsmodels library, we performed a seasonal decomposition. This led us to observe the presence of seasonality, trend and residuals in Figure 3.

In general, we observe an almost similar trend in the stations. It highlights three periods : a succession of wet years noted between 1960 and 1970, followed by a succession of dry years, from the early 1970s to the mid-1990s. Finally, a return of wet years is noted in the 1990s **[16]**. We can therefore say that our series show seasonality.

As a result, the data were divided into two sets, one for the training data and the other for the test data. We thus took 85% of the observations as training data and 15% as test data.

However, since LSTM neural networks are sensitive to the scale of the input data, we had to resize them using the MinMaxScaler function of the Scikit Learn library. Indeed, this estimator scales and translates each feature individually so that it lies within a range of data on the training set, in our case between 0 and 1. Its mathematical formula is defined below :

$$x' = \frac{x - min\,(x)}{max(x) - min\,(x)} \qquad \textbf{(9)}$$

In addition, we have defined a function that takes as argument the dataset and the look_back which is the number of previous time steps to use as input variables to predict the next time period by default it is equal to 1.

This default value will create a dataset where X is the water height at a given time (t) and Y is the water height at the next time (t + 1).

In addition, LSTMs expect the X input data to be provided with a specific array structure in the form of : [samples, time step, features] because the input data is in the form of [samples, features]. Since we frame the problem at one time step for each sample, it was necessary to transform the input data into the expected structure using the reshaping function available in the notebook.

C. Model training

Our LSTM model operates using multiple layers of stacked networks. We know that an LSTM layer requires a three-dimensional input and that LSTMs will by default produce a two-dimensional output as an interpretation from the end of the sequence. To solve this problem we generate with the LSTM a value for each time step in the input data by setting return_sequences to True on the layer. This will allow us to have a 3-dimensional output of the hidden LSTM layer as input for the next one. By experiment, the sigmoid activation function was chosen for the LSTM blocks.

At the input_shape level, the model takes as argument the number of time steps and the number of features. As we work with a univariate series the number of time steps is x_train.shape[1] and the number of input steps is x_train.shape[2].

At the first level of the last hidden layer, we have 128 units in each layer and the dense layer of size 1 is the output layer.

The model is fitted using Adam and optimized using the mean square error, or loss function (mse).

With batches, the model updates several times before processing the entire data set. A small batch size significantly slows down the learning speed and a large batch size causes overlearning **[7]**. In our experiment the batch size was set to 32.

Once the model is fitted, we first estimate the performance of the model on the training data sets and then on the test values.

D. Evaluation criteria

In this article, two metrics were used as evaluation criteria. These are the Nash criteria and the Mean Absolute Error (MAE).

MAE is a common metric to show the difference between the predicted value and the observed value and its error is linear. Moreover, a lower MAE means a better prediction. Its mathematical formula is the following:

$$MAE = \frac{1}{m} \sum_{1}^{m} |y_i - \widehat{y_i}| \quad \textbf{(10)}$$

Where m is the total number of values, y_i is the observed value and $\hat{y}_i$ is the predicted value.

The Nash-Sutcliffe criterion is based on the sum of the squares of the differences between the observed and simulated values **[20]**. It was constructed to allow comparison between events with different orders of magnitude of flow rates. It differs from the previous measurement in that the scale of the result does not depend on the scale of the input. In most cases, its value is between 0 and 1.

A high positive value means a better prediction, while the opposite effect is a sign of model inadequacy, and a zero value means that the model gives no better result than a basic model giving at each time step a constant flow equal to the average of the observed flows. Its mathematical formula is the following:

$$Nash = 1 - \frac{\sum_{i}^{m}(y_i - \widehat{y_i})^2}{\sum_{i}^{m}(y_i - \overline{y_i})^2} \qquad \textbf{(11)}$$

Where m is the total number in the sample, y_i is the observed flow, $\hat{y}_i$ is the predicted flow, and $\bar{y}$ is the average of the observed flows.

3. RESULTS

Once the data from the different stations were pre-processed and then divided into two samples, one for training and one for testing, they were finally passed to our three models which made predictions on them. The metrics of this process are recorded in Table 2 and the predictions have been visualized in Figure 4.

Thus, we can see that the LSTM model performed very well. Moreover, Figure 4 shows that the predictions made on the test flows almost perfectly match the real situations. In addition to this, these results prove that the forgetting memory capability of LSTM greatly helps it to predict nonlinear and time series data **[7]**.

Regarding the prediction technique used with the LSTM model, it is based on the moving window method which consists of selecting a well-defined set of test data. Then, it makes a prediction of one unit and then moves one unit and makes another prediction. It continues this operation until a fixed term of the number of days to predict.

In our work, we used the last year's readings to make the predictions in the future. An example of the visualization of the predicted water level in 5 days at each station is available in Figure 5.

Table 2. Metrics Table

	Métriques	
Stations	MAE	NASH
Bakel	14.13	0.98
Matam	8.18	0.99
Podor	2.38	0.99

4. DISCUSSION

The results prove that the historical flow data play an important role in the prediction accuracy of our model. According to Table 2, LSTM achieved largely satisfactory predictive performance as the values of MAE and Nash criteria are close to 0 and close to 1 respectively.

In addition to that, this remarkable efficiency is explained by an approach based on an iterative optimization algorithm. By iterative, we mean obtaining results several times and then selecting the most optimal one, i.e. the iteration that minimizes the errors. Therefore, the iterations and the setting of the other hyperparameters, namely among others the batch size, the chosen Adam optimizer, allowed our LSTM model to adapt to the data. To this, we must also add the pre-processing work that has been done beforehand, it is of paramount importance insofar as it has strongly impacted on the final product i.e. the output of our data.

5. CONCLUSION

River forecasting is still of paramount importance for the preservation of human lives, property and natural disasters.

In this paper, we have developed an application capable of predicting the hydraulic regime of the Senegal River using the LSTM model. At the end of this study, the results of the MAE and the R^2 allowed us to draw satisfactory conclusions on the predictive capacity of the method used.

However, there is still room for improvement with the prediction method. The results show some errors in the prediction peaks that cannot be ignored. It is sufficient to continue to adjust the hyperparameters of the model, to train and to compare the performances in order to obtain the optimum model, i.e. the one that minimizes the errors as well as possible.

Moreover, we will aim in our next work to develop its performances by making comparative studies with artificial intelligence and statistical models.

Table 1. Characterization of the hydrometric stations of the Senegal River bassin [16]

Stations studied	Lower basin (influenced by dams)		
	Bakel	**Matam**	**Podor**
Longitude	*12°27 W*	*13°15'W*	*14°57'W*
Latitude	*14°54' N*	*15°39'N*	*16°39'N*
Altitude (Scale zero in m IGN)	*11,16*	*6 ,32*	*-0,44*
Upstream watershed area (km^2)	*218 000*	*230 000*	*266 000*
Years of installation station	*1901*	*1903*	*1903*
Measured parameters	*Débit et cotes*	*Débit et cotes*	*cotes*
Monitoring period	*1904-2011*	*1903-2011*	*1903-2011*
Study period	*1960-2008*	*1960-2008*	*1960-2008*

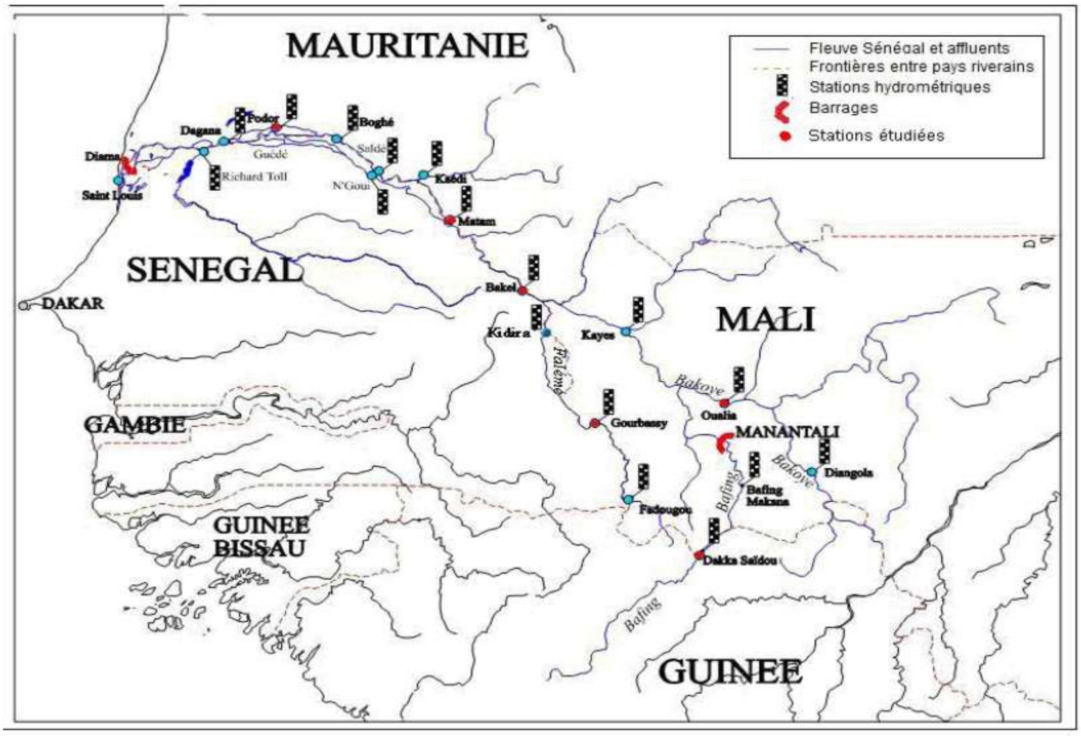


Figure 1. Hydrological monitoring network of the Senegal River [16]

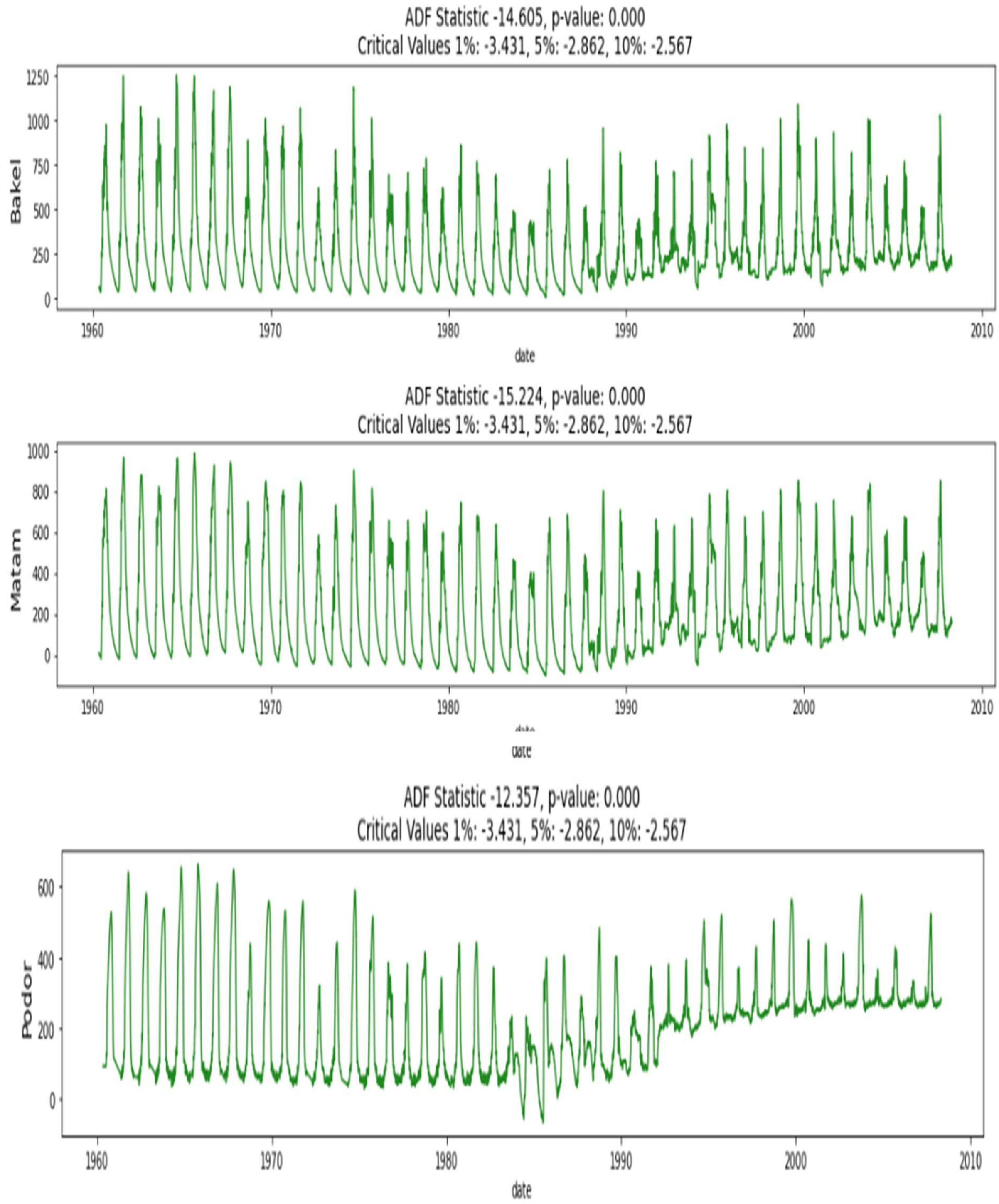


Figure 2 : Verification of the stationarity

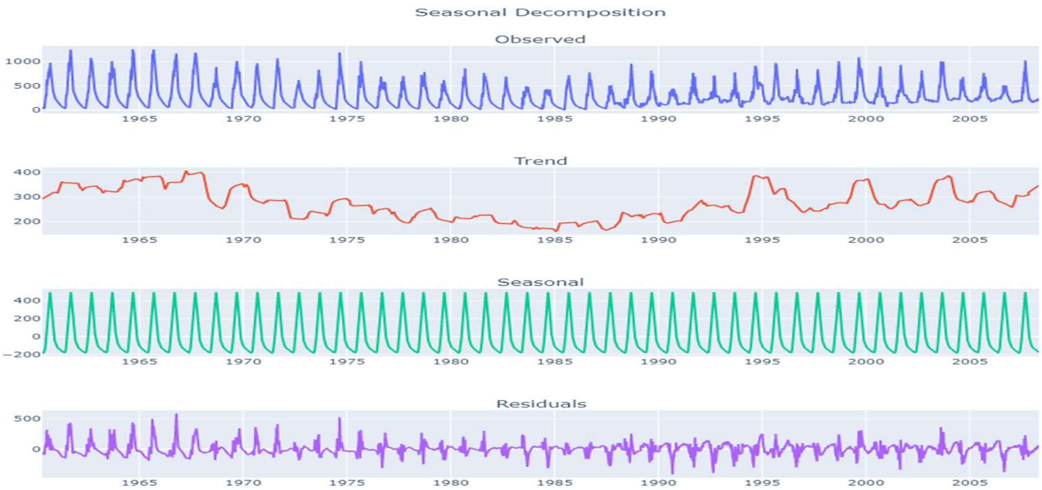


***Figure 3a* : Seasonal breakdown for the Bakel station**

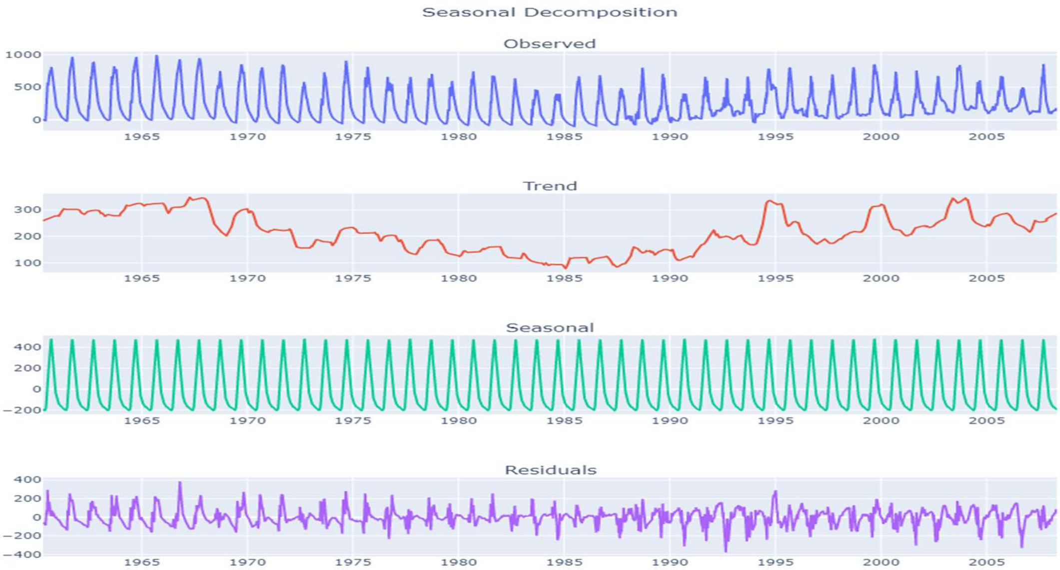


***Figure 3b* : Seasonal breakdown for the Matam station**

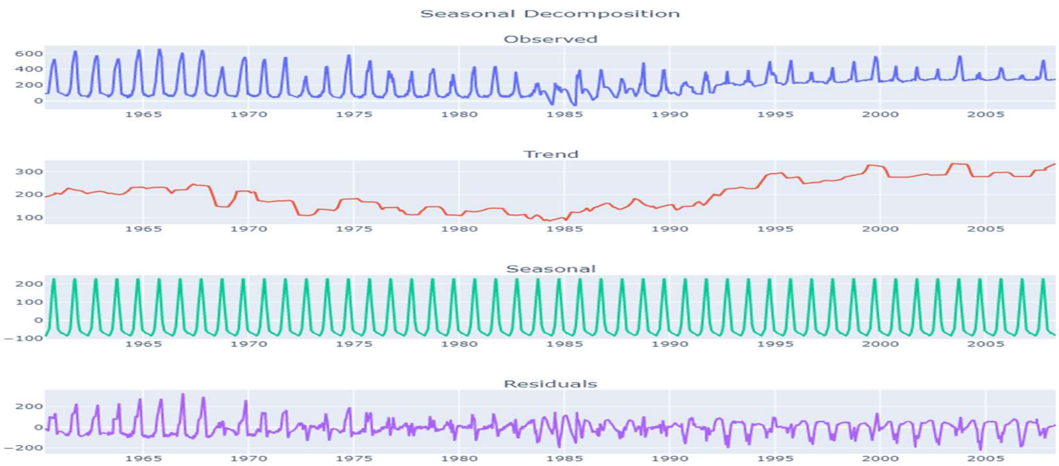


***Figure 3c* : Seasonal breakdown for the podor station**

Figure 3 : Seasonal decomposition

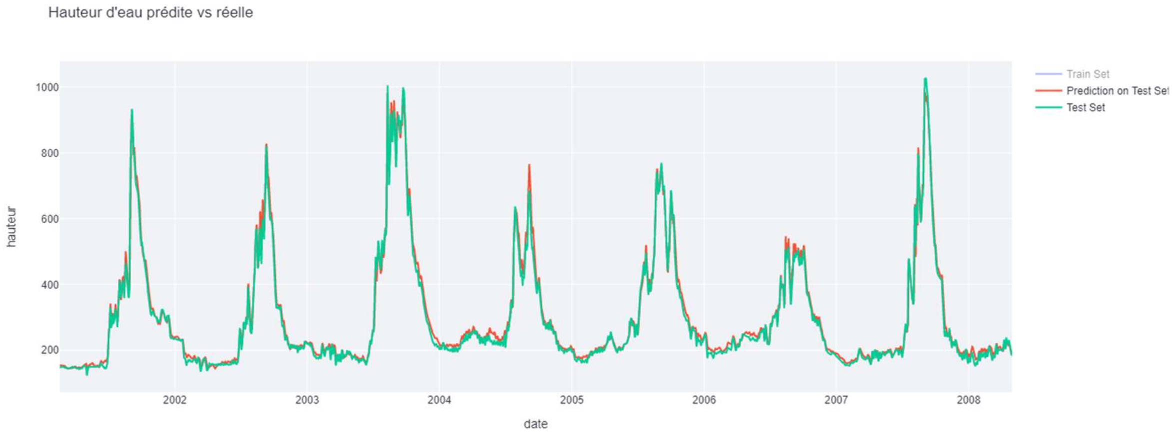


***Figure 4a*. PREDICTION ON TEST DATA FOR THE BAKEL STATION**

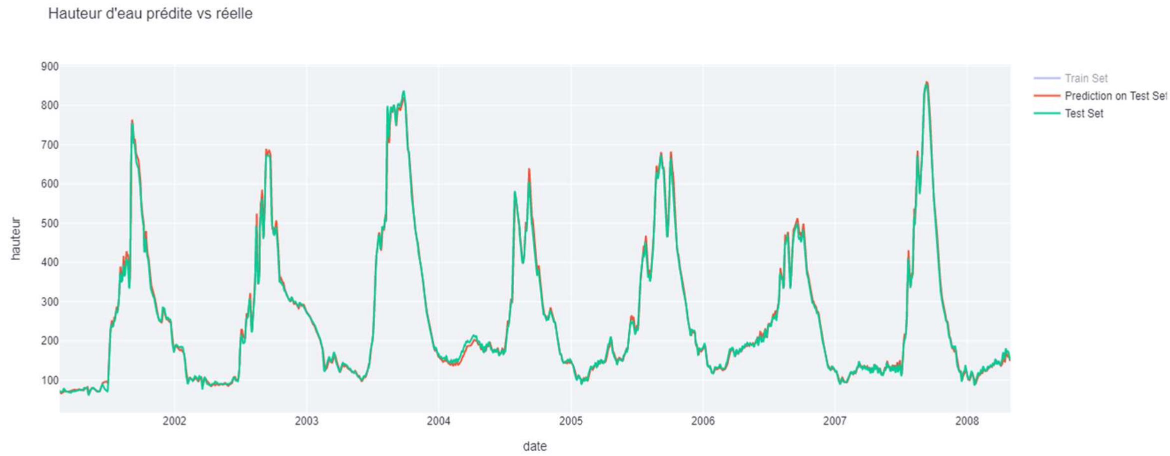


Figure 4b :* *Prediction on test data for the Matam station

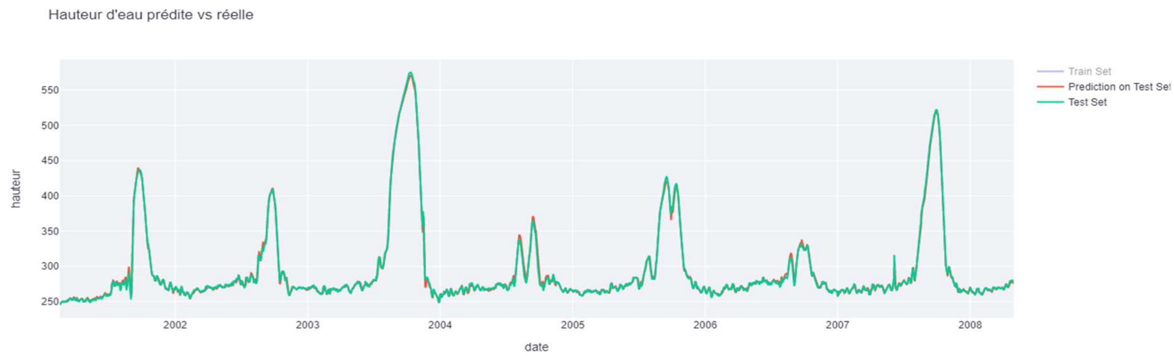
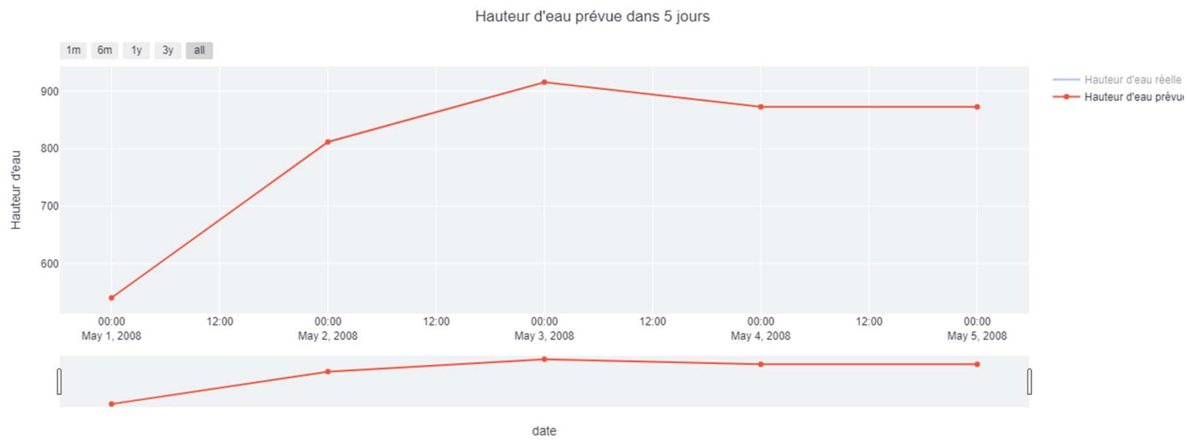
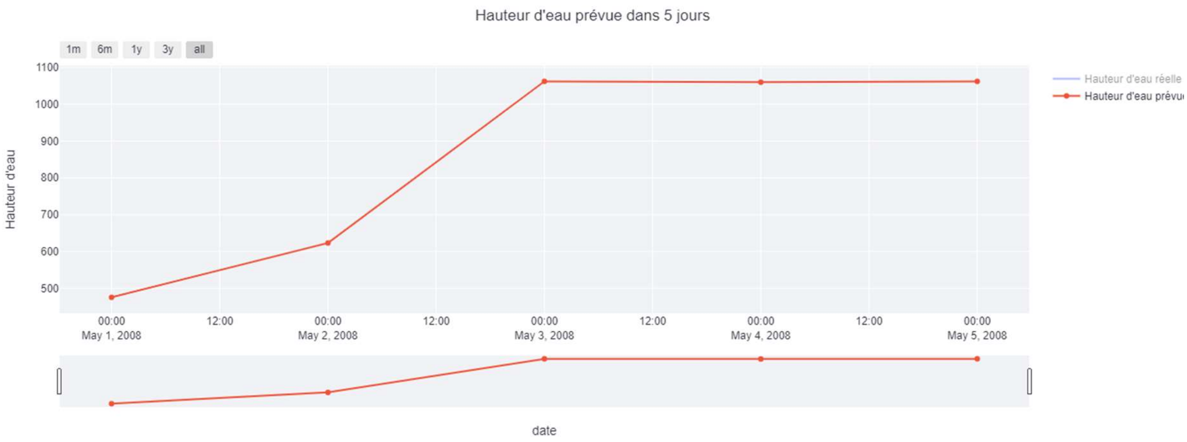


Figure 4c*. P*rediction on test data for the Podor station

Figure 4 : Prediction on test data at the three stations using the lstm model



<u>Figure 5a.</u>* *Water level expected in 5 days at Bakel station



<u>Figure 5b.</u>* *Water level expected in 5 days at Matam station

<u>Figure 5c.</u>* *Water level expected in 5 days at podor station

Figure 5. Water level expected in 5 days at each of the 3 stations

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