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Analysis of Climatic Variables on the Water Resources of the Ouémé River Using the Seasonal ARIMA Approach

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Abstract One of today's research challenges is to predict and anticipate the continuing effects of climate change, so as to be able to react and adapt to future developments. Global warming and weather forecasts indicate a growing risk of climate change-related events, which are not without consequences for ecosystems, including the Ouémé river basin. Water availability is strongly influenced by the variability of meteorological parameters. Precipitation and temperature are important parameters that have been side-lined in many water resource management projects. Daily rainfall and temperature data from 1982 to 2022 were collected at three representative sites in the Ouémé river basin: Bétérou, Savè and Kétou. Time series analysis, and more specifically trend analysis, was used as a first approach to describe the evolution of the various parameters over time. In this study, the ARIMA seasonal model (SARIMA) was used and forecasts were made for the next 30 years (2015-2045). The auto-regressive (p) integrated (d) moving average (q) model (ARIMA) is based on the Box Jenkins approach, which predicts future trends by making the data stationary and removing seasonality. The results of the study show that temperatures are high during the dry season, when precipitation is low. In addition, the multiplicative seasonal models that best fit precipitation and temperature are represented by ARIMA (5, 1, 0)(2, 0, 0)$_{12}$ and ARIMA (2, 1, 1)(1, 0, 1)$_{12}$ respectively. The information on patterns and trends can be used as a forecasting tool for the planning and procurement of water resource projects, as well as for the development of better water management practices in the study area.

Keywords: *ARIMA Models, forecasting, precipitation, temperature, Ouémé river*

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1. Introduction

Environmental degradation and climate change are among the challenges the world has been facing in recent decades [1]. Water resources management either long-term involving planning, design and construction, or short-term involving maintenance of new and existing facilities is sensitive to climate variability. Modelling and forecasting of hydro meteorological variables have proved to be a thought-provoking chore in water resources management.

However, it has been established that climate change will affect water resources [2]. In Benin, we are witnessing more and more extreme weather events: disruption of seasons alternation, temperature rise and changes in hydrological regimes [3,4]. The first studies carried out concerning the hydro-climatic variability and the hydrological flow of the Ouémé catchment in Bétérou have clearly shown a rainfall deficit at the inter-annual scale of nearly 20% and an inter-annual variability of the rainfall flow ratio since the 70s [5]. This combination of temperature rises and fall in rainfall would result, according to several studies, in lower flows, leading to a decrease in hydropower energy generating capacity [6]. The extent of changes affecting hydrological cycle can vary from one basin to another [7].

Forecasts of hydro meteorological parameters are useful in making decision on both short and long-term bases for managing extremes such as floods and drought. Stochastic and time series models have been used for predictions, which are usually related to the data that are not independent and are consecutively interrelated [8]. Majority of the literatures on climate change used variations in atmospheric temperature and rainfall as indicators.

For prediction of weather at regional and national levels, various precipitation forecasting methods are available. Regression analysis, Auto Regression Integrated Moving Average (ARIMA), genetic algorithm, Adaptive Splines Threshold Autoregressive (ASTAR), Support Vector Machines (SVMs), K-nearest neighbour (K-NN) are among the best methods available for weather forecasting. Regression analysis determines the strength of relation between a dependent variable and a series of independent predictor variables by fitting a regression model. The regression analysis is called multiple regression analysis, if it caters to more than two predictor variables. However, this regression analysis is not recommended for most of the practical problems as it tends to oversimplify the real-world situations.

ARIMA model forecasts weather variables which are kind of time series data by linearly combining their historic values. ARIMA model as a tool deals with all the aspects related to univariate time series model identification and its parameter estimation and forecasting. ARIMA model has the chances of over-fitting and misidentification if not used carefully [9].

In the light of above-mentioned weather forecasting models in the recent times and especially in the last decades there is a wide use of ARIMA model in water resources by various scientists. They have found Auto Regression Integrated Moving Average (ARIMA) and Seasonal Auto Regression Integrated Moving Average (SARIMA) to be the best fit model to understand the climatic variables (precipitation and temperature) [9,10,11,12,13,14,16,17]. [15] had applied ARIMA model in Brong Ahafo Region of Ghana for forecasting of monthly average surface temperature and found a decreasing trend. [18,19] had used seasonal ARIMA model for agricultural irrigation and found that it has good model fitting degree in decision making. [20] had used ARIMA model on weekly rainfall data and had found a decreasing trend in it for semi-arid Sinjar District of Iraq. [21] had done a comparative study of SARIMA and ARIMA for runoff in United States and found that SARIMA is better fitted and a better forecaster compared to ARIMA model. All these studies have been successful in understanding the climate parameters (precipitation and temperature) by using ARIMA and SARIMA models and have given a better insight into understanding the hydrological regime of the watersheds. In this paper, we study the time series of temperature and precipitation data and perform seasonal analysis of the monthly mean temperature and precipitation for three different locations (Béterou, Kétou and Savè) in Ouémé river basin situated in republic of Benin, from the year 1982–2022 using SARIMA model. The model is also further used for forecasting for next 30 years, i.e. 2015–2045.

2. Data used and Study Area

2.1. Study Area

The Ouémé river basin (Figure 1) covers an area of 47,000 km^2, about 43% of the country's area [22]. Located between 6.8 and 10.2° Latitude North, the Ouémé basin is characterized by a transition from the Sudannean climate in the North with an average year precipitation of 900 to 1000 mm, to the Beninese climate in southern with an average year rainfall of 1200 mm.

About 89% of the Ouémé river basin is located in Benin, 10% in Nigeria and 1% in Togo [23]. The Ouémé river basin records a mean annual temperature of 26 ° C to 30 ° C [23]. From a hydrological perspective, this river basin is characterized by lower and lower flows and the early drying up of seasonal courses [24]. The Ouémé River, which is 510 km long and has the two largest tributaries, flows to Lake Nokoué (150 km^2) and ends up into the sea through the coastal lagoon [25].

Precipitation water, which flows into the basin, is subdivided into water intercepted by plants, water retained by the soil, infiltrated water and water flowing at soil surface [26].

All of the water intercepted and some of the water retained by the soil are lost through evaporation and transpiration [27]. Surface water is an important part of the flow at the outlet.

The Ouémé basin is subdivided into three sub-basins known as valleys:

- The Upper Valley, whose representative site is Bétérou;
- The Middle Valley, whose representative site is Savè;
- The lower valley, whose Kétou is the representative site.

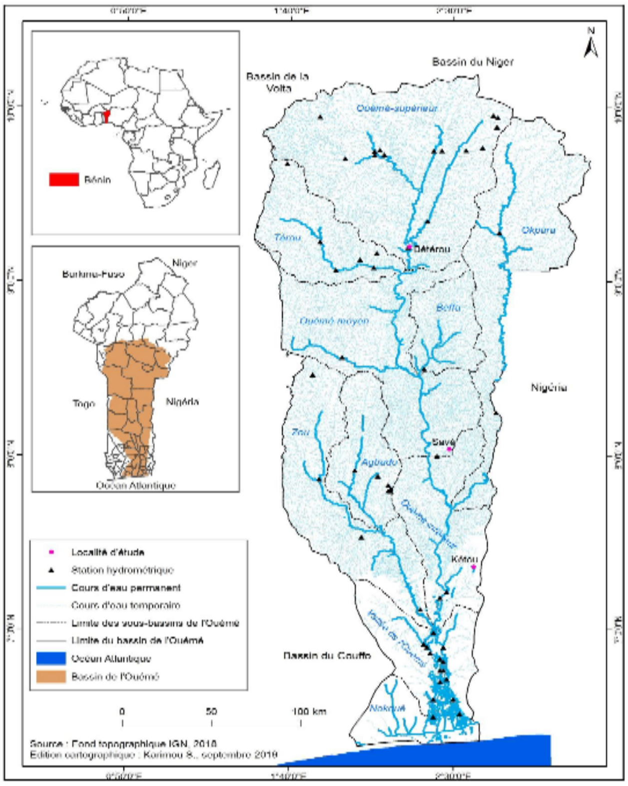


Figure 1. Presentation of the Ouémé River watershed and location of 3 representative sites

Table 1. Basins and location

Sub-basin	Latitude	Longitude
Bétérou	9°08'N	2°17'E
Savè	8°05'N	2°21'E
Kétou	7°37'N	2°28'E

2.2. Data Used

The data used in this work are satellite data obtained from the NASA database. The main characteristics are presented below:

- Database: POWER LARC NASA [28]
- Data frequency: Daily
- Data types:
  - Precipitation

- Temperature
- Period: from January 1, 1982 to December 31, 2022

3. Model Description

In time series analysis, to better understand the data and for future forecasting, auto-regressive (p) integrated (d) moving average (q) (ARIMA) model is used. The basic idea of using ARIMA model is to remove trend of the series by differencing so that a stationary series is obtained by transforming a non-stationary series [9].

This ARIMA model is based on Box–Jenkins approach. The AR part of the ARIMA model shows that the variable under concern is regressed on its own prior values. The MA part of the ARIMA model shows that the regression error is a linear combination of error values occurring at various time intervals in the past. The I part shows the number of times differencing has been performed. The entire objective of finding an adequate AR, I and MA terms is to make the model to fit the data in the best possible way. The model assumes data to be a non-seasonal series which needs to de-seasonalize before modelling. A non-seasonal ARIMA model is generally denoted as ARIMA (p, d, q), where p is the lag order, d is the order of differencing, and q is the order of moving average. A seasonal ARIMA model is denoted as ARIMA (p, d, q) (P, D, Q) $_m$, where m is the number of periods in each season, and the uppercase P, D, Q refer to the autoregressive (AR), differencing (I), and moving average (MA) terms respectively, for the seasonal part of the ARIMA model. ARIMA methodology has its own limitations of relying on past values; however, it works best for long and stable time series. It does not explain the structure of the underlying data mechanism but simply approximates the historical patterns [9,26].

- An AR (p) model can be describe as:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + Z_t \qquad (1)$$

Where $Z_t \sim \left(0, \sigma^2\right)$, c is an unknown constant term, and equal to 1, are the parameters of the AR model.

- A MA(q) model can be described as:

$$Y_t = c + Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \cdots + \theta_q Z_{t-q} \qquad (2)$$

Where $Z_t \sim \left(0, \sigma^2\right)$, c is an unknown constant term, and θ_1, θ_q are the parameters of MA model.

- A stationary time series Y_t is called autoregressive moving average of order (p), ARMA (p,), if for every t.

$$\begin{aligned} & Y_t - \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} \\ & = c + Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} \end{aligned} \qquad (3)$$

$$Z_t \sim \left(0, \sigma^2\right)$$

The generating polynomials $(z) = 1 - \varphi_1 z - \cdots - \varphi_p z^p$ and $(z) = 1 - \theta_1 z - \cdots - \theta_q z^q$ have no common roots.

If we combine the differencing with ARMA model, we get the autoregressive integrated moving average model, i.e., the ARIMA (p,d,q), where d is the order of differencing. So, an ARIMA model correspond to an ARMA after differencing Y_t, d times. This means that Y_t satisfies the difference equation:

$$\begin{aligned} & \left(1 - \varphi_1 B - \cdots - \varphi_p B^p\right)(1-B)^d Y_t \\ & = c + \left(1 + \theta_1 B - \cdots + \theta_q B^q\right) Z_t \end{aligned} \qquad (4)$$

$$\varphi(B)(1-B)^d Y_t = c + \theta(B) Z_t, Z_t \sim \left(0, \sigma^2\right) \qquad (5)$$

For d and D are non-negative integers, the time series is a seasonal ARIMA, SARIMA $((p,d,q),(P,D,Q)_m$ process with period m if the differenced time series $X_t = (1-B)^d (1-B^m)^{DY_t}$ is a causal ARMA process. $\{X_t\}$ is causal, if there exist constant $\{\psi_j\}$ such that:

$$\sum_{j=0}^{\infty} \left|\psi_j\right| < \infty \textit{ and } X_t = \sum_{j=0}^{\infty} \left|\psi_j\right| Z_{t-j} \qquad (6)$$

$$\varphi(B)\phi\left(B^m\right)X_t = \theta(B)\Theta\left(B^m\right)Z_t, Z_t \sim WN\left(0,\sigma^2\right), Z_t \sim \left(0,\sigma^2\right) \qquad (7)$$

Where

$$\varphi(z) = 1 - \varphi_1 z - \cdots - \varphi_p z^p, \phi(z) = 1 - \phi_1 z - \cdots - \phi_P z^P$$

$$\theta(z) = 1 - \theta_1 z - \cdots - \theta_q z^q, \Theta(z) = 1 - \Theta_1 z - \cdots - \Theta_Q z^Q.$$

$\{X_t\}$ is causal, which is equivalent to the condition that $(z) \neq 0, \Theta(z) \neq 0, \text{for} |z| \leq 1 \text{for complex } z$.

4. Methodology

The methodology used for the study is summarised in Figure 2. The precipitation and temperature data considered for the study are for the years 1982-2022. They are prepared for the analysis as daily data. Once the data files are prepared, the ARIMA model has to be identified. In this study, there has been an attempt to fit separate SARIMA models to the precipitation and temperature time series. So we have a SARIMA model that fits the precipitation time series and one that fits the temperature time series. Identifying the appropriate SARIMA model involves the following steps.

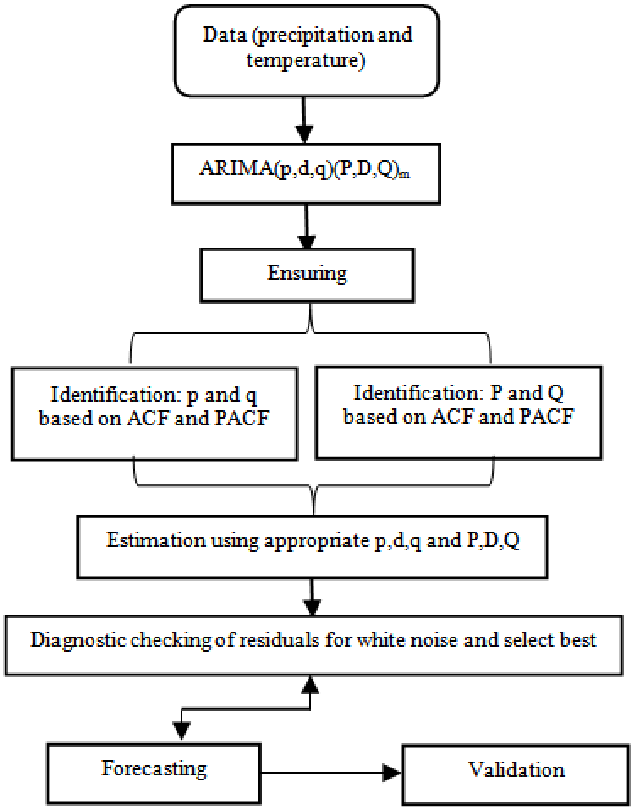


Figure 2. Research flowchart

Table. 2. Stationarity test

		ADF Test			
		Test statistic	Critical Value 1%	Critical Value 5%	Critical Value 10%
Precipitation	Bétérou	-3.800385	-3.444047	-2.867580	-2.569987
	Savè	-3.617526	-3.444163	-2.867631	-2.570014
	Kétou	-4.599666	-3.444047	-2.867580	-2.569987
Temperature	Bétérou	-11.13831903	-3.43078728	-2.86173325	-2.56687286
	Savè	-10.87011274	-3.43078731	-2.56687287	-2.56687287
	Kétou	-9.93854931	-3.43078731	-2.86173327	-2.56687287

4.1. Check for data stationarity

Since our data are time series, it is important to ensure the conformity of some of their properties. An important property of the time series is its stationarity. If a process is stationary, it means that its statistical properties do not vary over time, namely its mean, its variance (homoscedasticity) or its covariance. This notion of stationarity represents a crucial point in the analysis of time series, where the estimation of non-stationary series leads to spurious or illusory regressions. A stationarity study of the data is therefore important to ensure that the structure of the process that generated these series does not change over time: this is a very important condition for the time series forecast. The Augmented Dickey–Fuller test (ADF) is an appropriate statistical tool. The time series considered is stationary if the p value is low (according to the null hypothesis).

4.2. Performance Criteria

The performance of various models during calibration and validation were evaluated by using the statistical indices: The Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and coefficient of determination (R^2).

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N} y_t - \hat{y}_t \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{N}(y_t - \bar{y})^2} \text{ for } \bar{y} = \frac{1}{N}\sum_{t=1}^{N} y_t \tag{10}$$

4.3. Identification of AR(p) and MA(q) Components

The plots of the sample ACF and PACF are used for the selection of the order of an ARIMA model, specifically when the data are generated by an ARMA (p, 0) model or from an ARMA (0, q) model. If the ACF and PACF have large (positive) values that decrease very slowly with time, this indicates that d is greater than zero, i.e. differencing should be performed. The autocorrelation function ACF and the partial autocorrelation function (PACF) can be used to select p, d and q. If there is a sharp cut-off in the

PACF of the differenced series and the series shows mild 'under-differencing', then an AR term is added to the model. If there is a sharp cut-off in the ACF of the differenced series and the series is mildly 'over-differenced', an MA term is added to the model.

The ACF plot helps to identify the moving average (MA) component of the model, while the PACF plot helps to identify the autoregressive (AR) component of the model for the data. Table. 3.

5. Results and Discussions

Precipitation and temperature in Ouémé basin river of Bénin has been assessed. The time series variation of precipitation for Bétérou, Kétou and Savè stations is shown in Figure 3, Figure 4 and Figure 5, respectively. The precipitation data shows that the maximum rainfall occurs during the month of August (113.67 mm) at Bétérou, the months of july and September (109.46 mm) at Kétou, and the month of july (82.24 mm) at Savè, and almost no or scanty rainfall in the months of November and December for all three basins.

Variations in the temperature time series are shown in Figure 6, Figure 7 and Figure 8 for temperatures in the Bétérou, Kétou and Savè basins, respectively. Temperatures range from 19.08 to 33.21°C in Béterou, from 18.87 to 32.80°C in Kétou and from 19.37 to 32.20°C in Savè.

The study revealed that temperature was high in the dry season, while precipitation was high in the wet season. It was also revealed that there are systematic changes known as trend in the variables studied. Precipitation shows a non-significant negative trend, while temperature shows a non-significant positive trend. In addition, it was observed that multiplicative seasonal models best fit precipitation and temperature represented by ARIMA (5, 1, 0)(2, 0, 0)$_{12}$ and ARIMA (2, 1, 1)(1, 0, 1)$_{12}$ respectively, while the p-value shows the parameters of the models are significant.

The forecast trends for the selected SARIMA model are shown in Figure 9 Figure 10 Figure 11 Figure 12 Figure 13 Figure 14 and model fit, and model statistics are shown in Table 5 Table 6 for Bétérou, Kétou and Savè.

Model forecasts for precipitation and temperature resemble the local trend and seasonal trend at the end of the series, but are slightly smoother in appearance because the trend and seasonal trend are effectively averaged over

the seasons. Precipitation forecast results show a downward trend in values. Temperature forecasts show a

constant trend in Bétérou, an upward trend in Kétou and a downward trend in Savè. Although the RMSE, MAE and R^2 values are quite low for precipitation and temperature at all three basins, it can be seen that the model overestimates temperature data.

Table 3. AIC-BIC criterion for SARIMA models

	Parameters	Sarima model	AIC	BIC	RMSE	MAE	R^2
Bétérou	Precipitation	$(5,1,0)(2,0,0)_{12}$	1851.891	1885.462	2.098	1.407	0.488
	Temperature	$(2,1,1)(1,0,1)_{12}$	1174.422	1199.601	0.695	0.535	0.106
Kétou	Precipitation	$(5,1,0)(2,0,0)_{12}$	1971.291	2004.862	1.937	1.399	0.221
	Temperature	$(2,1,1)(1,0,1)_{12}$	939.668	964.846	0.721	0.567	0.251
Savè	Precipitation	$(5,1,0)(2,0,0)_{12}$	1967.555	2001.127	2.992	2.0265	0.406
	Temperature	$(2,1,1)(1,0,1)_{12}$	1052.026	1077.205	0.710	0.562	0.134

Table 4. Descriptive statistics of Precipitation and Temperature

		Min	Max	Mean	Std	25%	50%	75%
Precipitation	Bétérou	0.00	113.67	3.37	5.06	0.01	1.55	4.84
	Savè	0.00	109.46	3.68	5.45	0.10	1.83	5.26
	Kétou	0.00	82.24	3.34	4.74	0.28	1.78	4.60
Temperature	Bétérou	19.08	33.21	25.89	1.95	24.56	25.56	27.07
	Savè	18.87	32.80	26.04	1.68	24.91	25.83	27.06
	Kétou	19.37	32.10	26.23	1.56	25.09	26.07	27.30

Mean, Min, Max and standard deviation (Std) have the units corresponding to the units of meteorological variables.

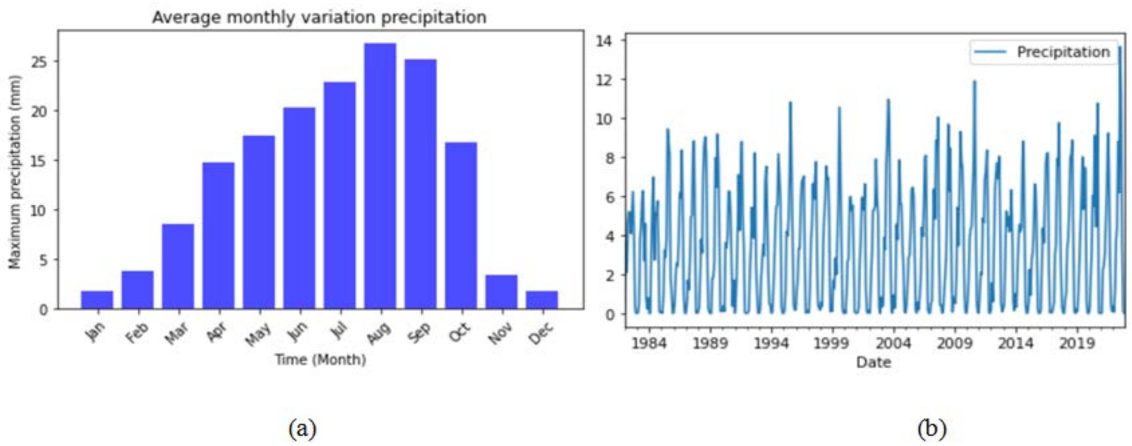
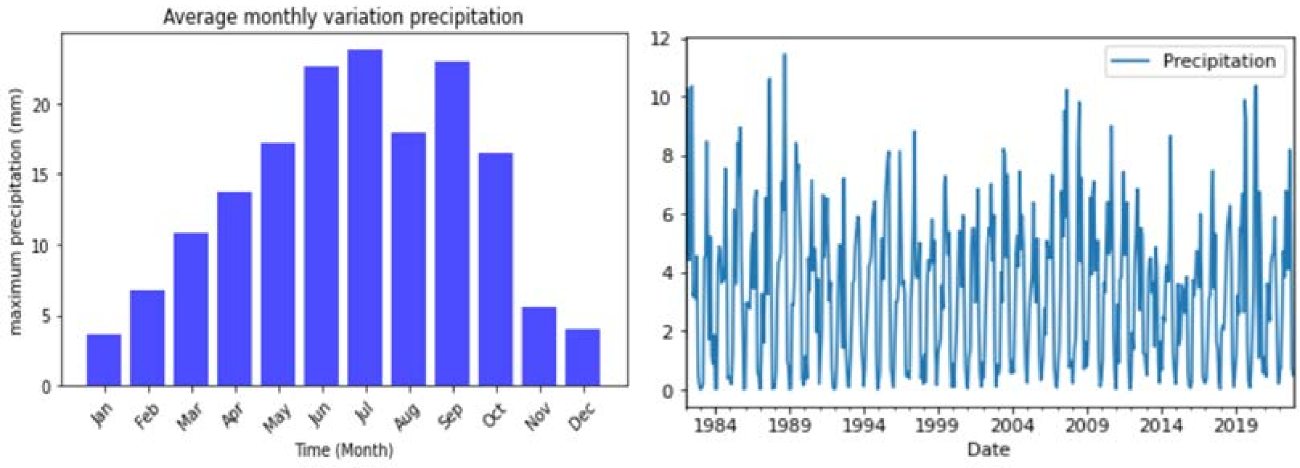
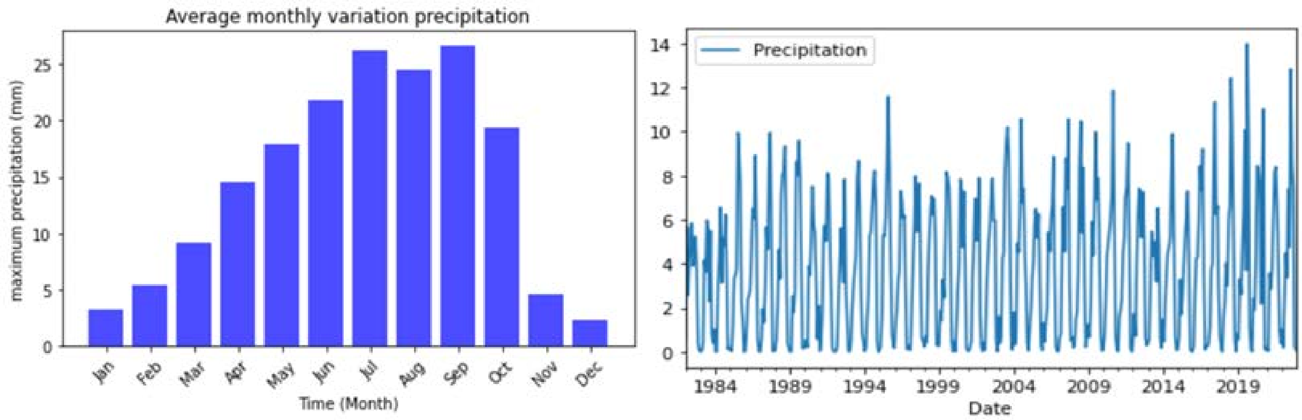


Figure 3. Monthly (a) and annual (b) precipitation variation over the years at Bétérou



(a) (b)

Figure 4. Monthly (a) and annual (b) precipitation variation over the years at Kétou



(a) (b)

Figure 5. Monthly (a) and annual (b) precipitation variation over the years at Savè

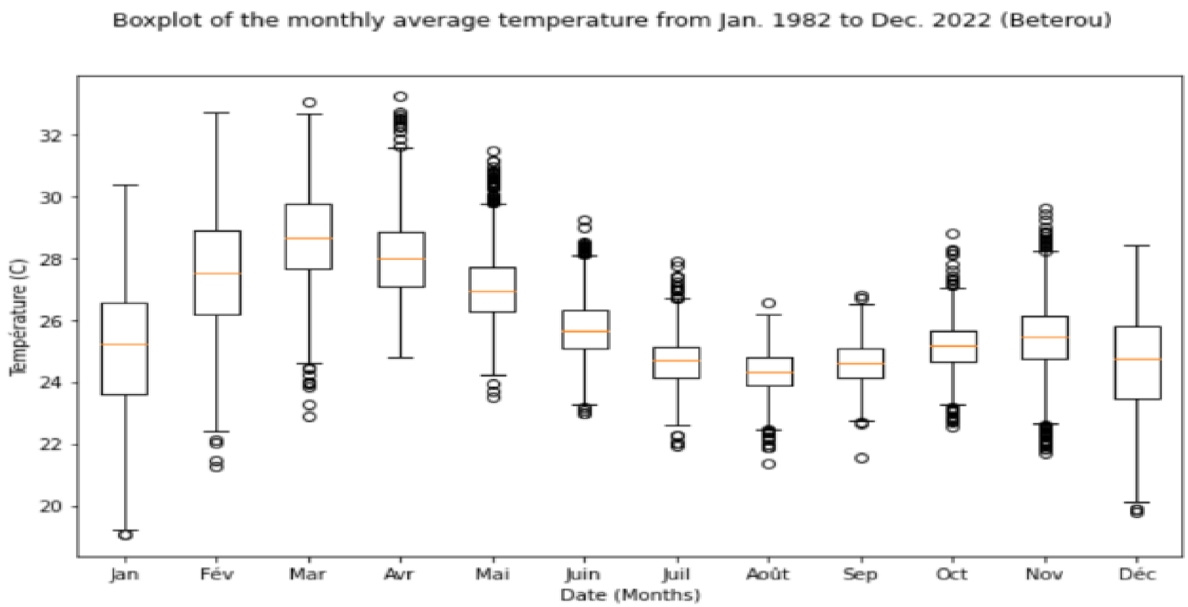


Figure 6. Monthly average temperature variation over the years at Bétérou

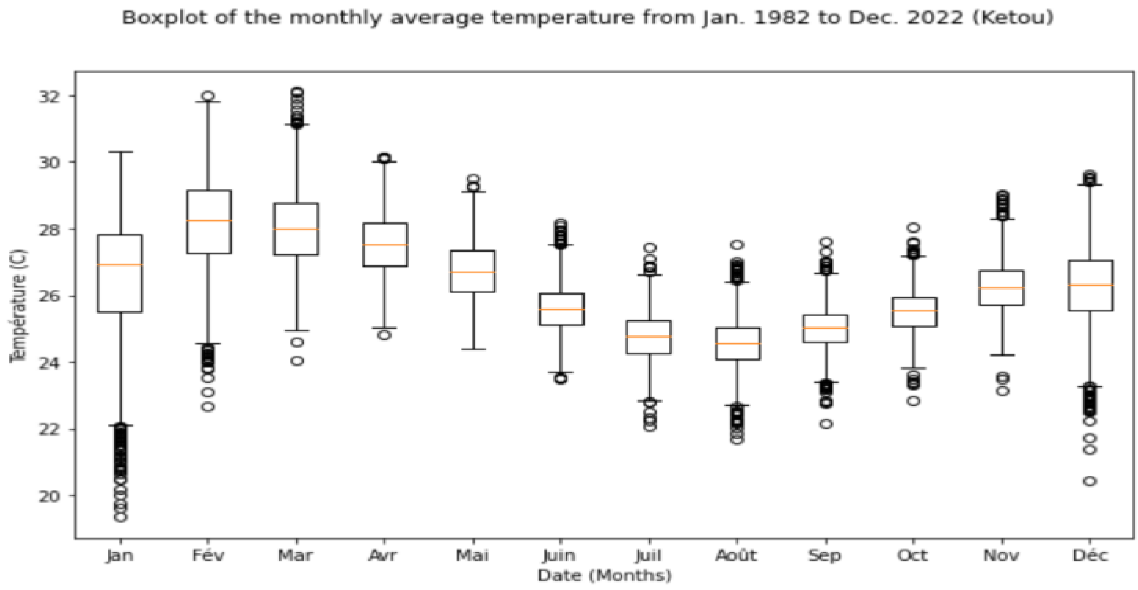


Figure 7. Monthly average temperature variation over the years at Kétou

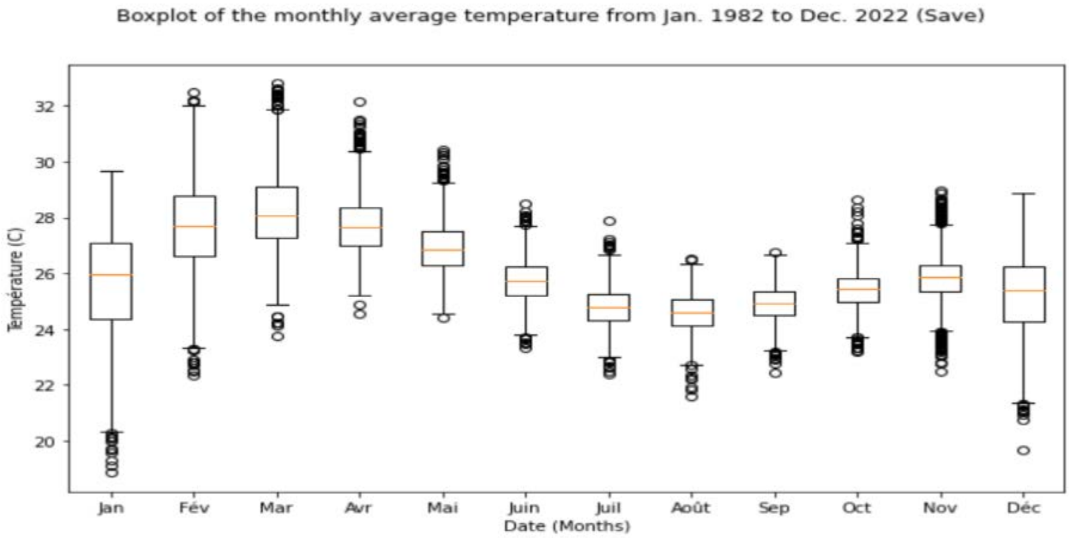


Figure 8. Monthly average temperature variation over the year at Savè

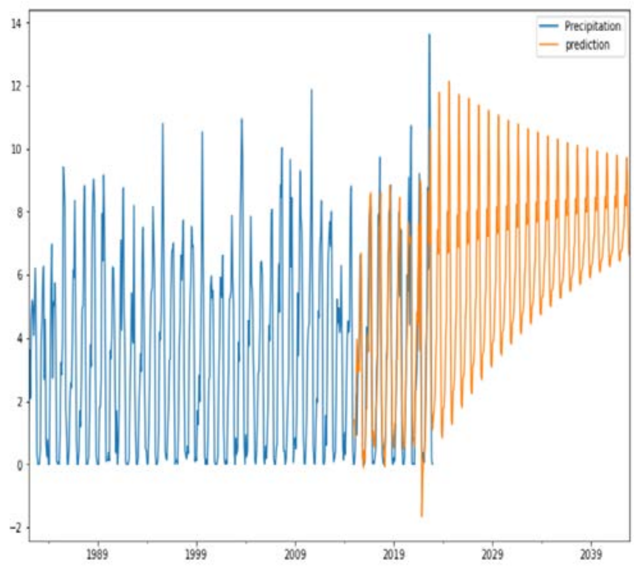


Figure 9. Forecast of Precipitation at Bétérou

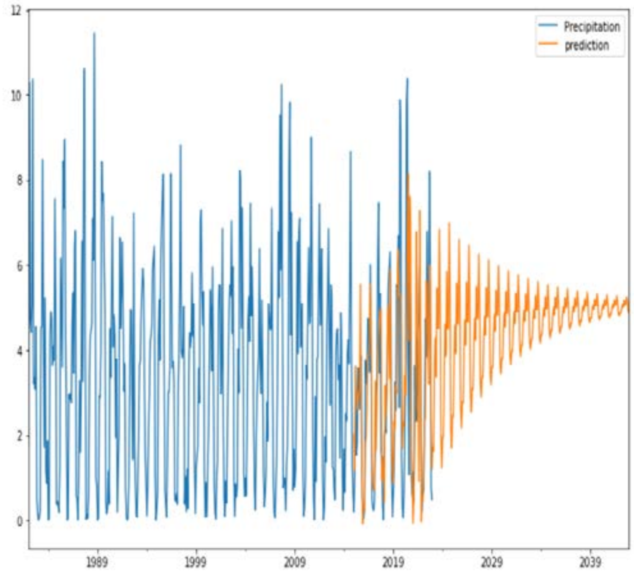


Figure 10. Forecast of Precipitation at Kétou

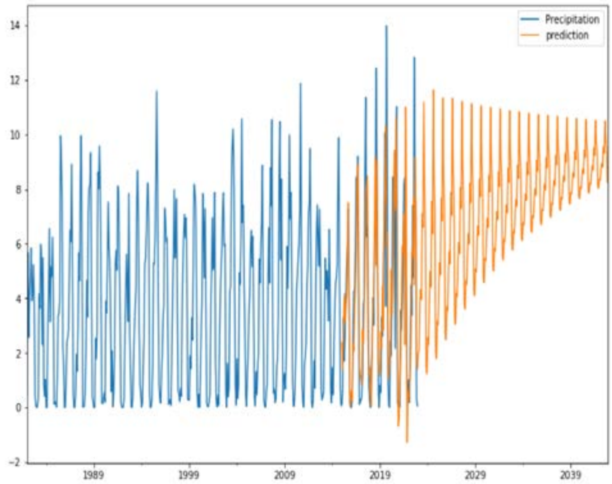


Figure 11. Forecast of Precipitation at Savè

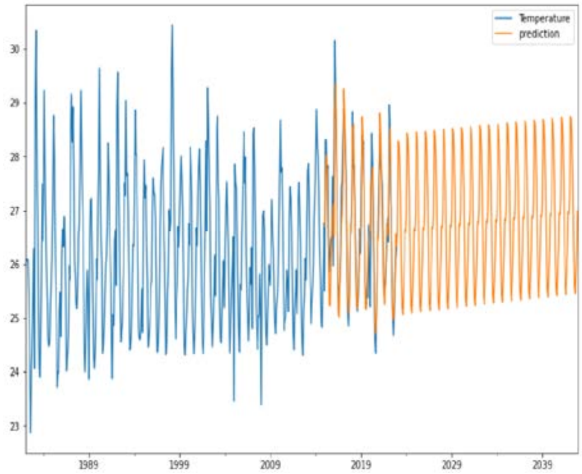


Figure 13. Forecast of Temperature at Kétou

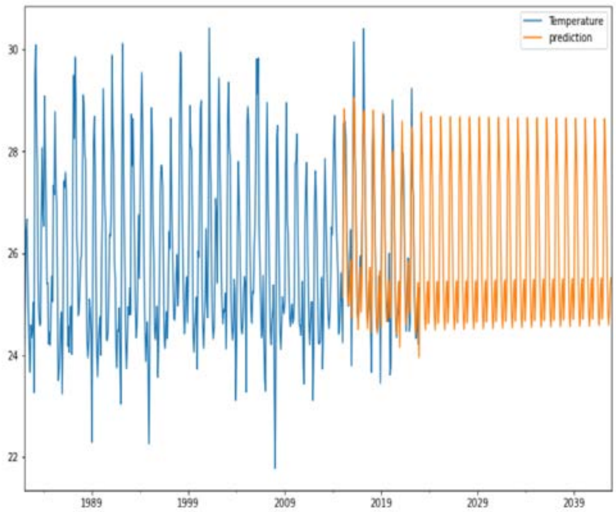


Figure 12. Forecast of Temperature at Bétérou

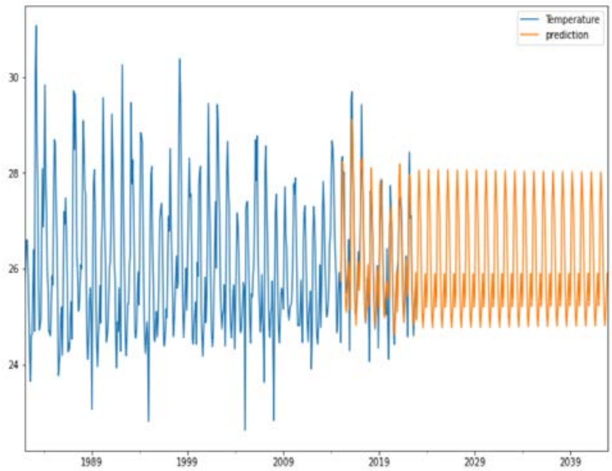


Figure 14. Forecast of Temperature at SaTable 5. Summary of estimated parameters of ARIMA(5,1,0)$(2,0,0)_{12}$ (with constant) model fit for precipitation

Table 5. Summary of estimated parameters of ARIMA(5,1,0)$(2,0,0)_{12}$ (with constant) model fit for precipitation

		ar.L1	ar.L2	ar.L3	ar.L4	ar.L5	ar.S.L12	ar.S.L24	Sigma2
Bétérou	Coefficients	-0.5977	-0.4960	-0.3526	-0.2794	-0.0859	0.5713	0.3388	2.3638
	Std error	0.042	0.049	0.059	0.065	0.063	0.032	0.034	0.118
	z	-14.251	-10.175	-5.973	-4.300	-1.373	17.730	9.941	19.976
Ketou	Coefficients	-0.5940	-0.5247	-0.3805	-0.2361	-0.1843	0.4634	0.3508	3.0615
	Std error	0.040	0.048	0.052	0.055	0.050	0.039	0.044	0.177
	z	-14.998	-10.925	-7.300	-4.269	-3.672	11.750	7.980	17.259
Savè	Coefficients	-0.6271	-0.5689	-0.4424	-0.2858	-0.1233	0.5591	0.3366	3.0009
	Std error	0.035	0.050	0.058	0.063	0.057	0.029	0.030	0.146
	z	-17.751	-11.357	-7.609	-4.533	-2.158	19.541	11.044	20.570

Table 6. Summary of estimated parameters of ARIMA(2,1,1)$(1,0,1)_{12}$ (with constant) model fit for temperature

		ar.L1	ar.L2	ma.L1	ar.S.L12	ma.S.L12	Sigma2
Bétérou	Coefficients	0.4309	0.1146	-0.9908	0.9984	-0.9290	0.5854
	Std error	0.031	0.003	0.021	0.002	0.034	0.030
	z	13.787	45.547	-46.264	601.710	-27.082	19.458
Kétou	Coefficients	0.4686	0.1344	-0.9863	0.9991	-0.9482	0.3613
	Std error	0.027	0.040	0.012	0.001	0.020	0.008
	z	17.057	3.367	-84.278	1507.622	-47.528	42.622
Savè	Coefficients	0.4485	0.1058	-0.9879	0.9984	-0.9252	0.4589
	Std error	0.031	0.006	0.017	0.001	0.024	0.018
	z	14.691	16.768	-59.238	928.582	-38.878	25.038

Lack of information to meet the challenges resulting from climate variability is common in developing countries. Water resource management is sensitive to the variability of hydrometeorological parameters; the results presented in the study could therefore complement other water resource management tools for the study area. The variability of precipitation and temperature in the study area over the next decade will have a profound effect on water resource management plans, as well as on agriculture and GDP.

6. Conclusion

Statistical analysis of temperature data collected between 1982 and 2022 points to an average temperature increase of more than 1.1°C between now and 2045 on the Ouémé River. Meanwhile, forecasts indicate a substantial decrease in precipitation, which could exceed 7% of the current value.

The prediction of atmospheric parameters is essential for climate monitoring, drought detection, severe weather prediction, agriculture and production planning in energy and industry, communication, pollution dispersal etc.

Precipitation and temperature are the main factors governing the dynamic structure of the climate, leading to climatic changes. In the present study, time series of precipitation and temperature data were investigated and the most suitable ARIMA model was found, and forecasting was carried out using the same model.

The study concludes that the results obtained from SARIMA modelling for precipitation (ARIMA(5,1,0)(2,0,0)$_{12}$) and temperature (ARIMA(2,1,1)(1,0,1)$_{12}$) forecasting will help scientists and decision-makers to establish priorities in terms of water demand management.

Declaration of Interests

Authors have declared that no competing interests exist.

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