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Ibrahim Ouedraogo[1]*

**Université Joseph KI ZERBO, Centre universitaire de Ziniaré (Burkina Faso)*

ARIMA-BASED MODELING AND FORECASTING OF MONTHLY TEMPERATURE VARIABILITY IN BURKINA FASO UNDER CLIMATE CHANGE SCENARIOS UP TO 2050

Abstract: In a world facing climate change, temperature estimates are crucial for Sahelian countries like Burkina Faso, where agricultural production is highly dependent on weather conditions. This research applies the ARIMA (AutoRegressive Integrated Moving Average) model to predict monthly temperature variations between 2025 and 2050, using a time series spanning 41 years (1984–2024). The differentiated data were validated by stationarity tests (ADF), and the use of SARIMA models allowed for the capture of seasonality. The modifications performed well, with MAPE typically below 2% and RMSE frequently below 0.5°C. The results indicate a clear increase in temperatures. In January, the historical average of 24.2°C could rise to 27.0°C in 2050, representing an increase of +2.8°C. An increase of +0.7°C is predicted for February (from 27.1°C to 27.8°C). The most notable increases are expected for March and April, where average temperatures could exceed 33.5°C by 2050. Generally, a temperature increase of +2.5°C to +3°C is expected during key months, accompanied by increased heat stress during the dry season. These forecasts are consistent with Sahelian trends identified by various sources and highlight the suitability of the ARIMA model for climate forecasting. It is crucial to incorporate these forecasts into agriculture, water, and health policies to strengthen Burkina Faso's resilience to climate change.

Keywords: climate forecasting, MAPE, heat stress, Burkina Faso, climate modeling

[1] ouedra.ibra16@gmail.com (corresponding author)
Ibrahim Ouedraogo (https://orcid.org/0009-0000-8564-6529)

Introduction

Today, climate change represents a critical challenge for human societies, with significant repercussions on ecosystems, natural resources, local economies, and the well-being of populations (Ouedraogo et al., 2024). In sub-Saharan Africa, particularly in Burkina Faso, a landlocked country in the Sahel region, this issue is particularly worrying (Yaméogo, 2025). The economy of this region is dependent on the climate, particularly rain-fed agriculture, which accounts for more than 80% of the working population. This crucial climatic factor is of concern not only because of its direct impact on agriculture, hydrology, and human health (Yo et al., 2025; Ouedraogo et al, 2024), but also because it serves as an indicator of broader environmental impacts.

In recent decades, various studies in Burkina Faso have observed a gradual rise in annual average temperatures, accompanied by an increase in the frequency and intensity of heatwaves (Yameogo & Rouamba, 2023; Yameogo, 2024). This climate change is exacerbating the vulnerability of agricultural systems, undermining food security, and increasing the exposure of individuals to environmental hazards (Yanogo, 2024; Yameogo & Sawadogo, 2024). In this context, the need for reliable instruments to predict temperatures has become essential to anticipate future consequences and guide strategies for adaptation.

The analysis of climate trends and temperature forecasting can be efficiently achieved using modeling techniques, including time series models (Yameogo, 2025, Rouamba et al., 2023). The ARIMA (AutoRegressive Integrated Moving Average) model has proven to be effective in capturing the temporal and seasonal structure of data, which is critical in the short- and medium-term forecasting of climate variables. Despite being empirically based, this model offers flexibility, making it ideal for cases where external information is limited or lacks credibility. In this study, we apply the ARIMA technique to predict monthly temperature variations recorded in Burkina Faso over a 41-year period, from 1984 to 2024. The primary objective is to forecast future monthly temperatures reliably, with projections extending up to 2050. This model not only enhances the understanding of thermal dynamics but also provides valuable insights for the development of climate change adaptation policies in the region.

Materials and methods

Study area

Burkina Faso, located in the Western Africa region (Fig. 1), covers an area of approximately 273,000 km². The country experiences a tropical Sudano-Sahelian climate, with the rainy season concentrated between June and September. Annual rainfall varies from 400 mm in the northern Sahel to over 1,200 mm in the southern regions, while average annual temperatures typically exceed 28°C. This climate creates a semi-arid environment that is sensitive to fluctuations in precipitation and rising temperatures (Joseph & Songanaba, 2023; Ouédraogo et al, 2023).

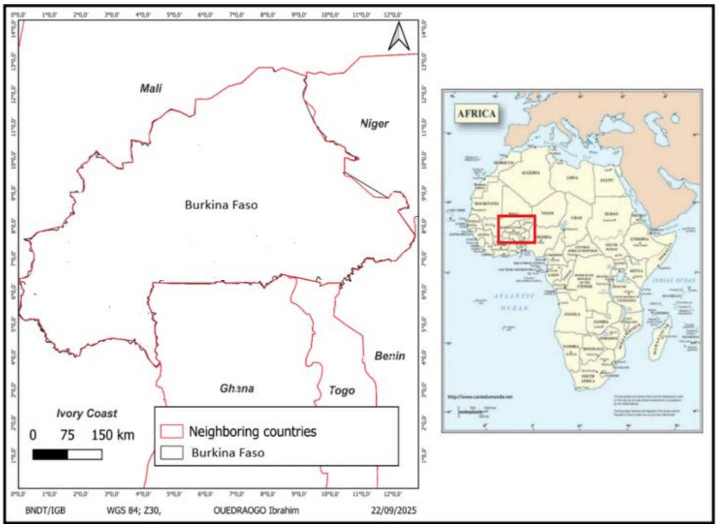

Fig. 1. Location of the study area

Climate data

The study is based on a sequence of monthly temperature readings taken in Burkina Faso from 1984 to 2024, covering 41 consecutive years of observations. These temperature data come from NASA Power [2]and cover the period from 1984 to 2024, with monthly resolution. This series presents monthly temperature averages for each month, enabling specific modelling of seasonal profiles on a monthly basis. An initial descriptive analysis was carried out to determine key statistics, such as averages, standard deviations and extreme values, on a monthly basis (Fig.2.).

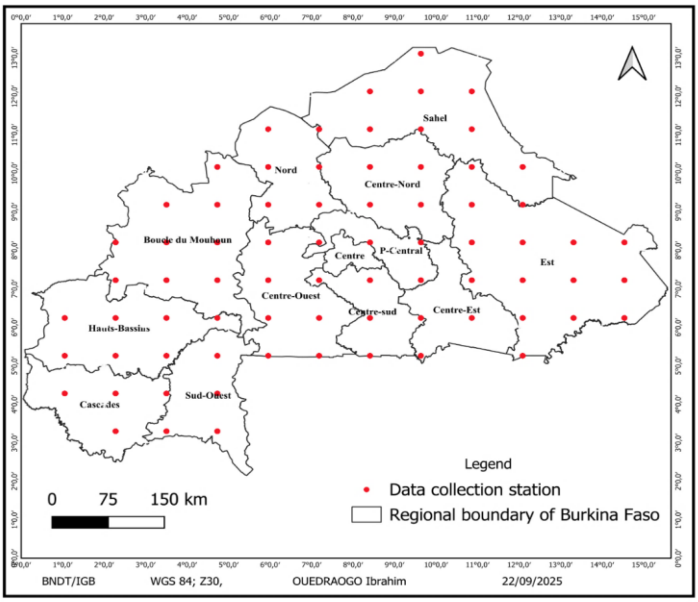

Fig .2. Map of data collection stations

[2] https://power.larc.nasa.gov/data-access-viewer/

Methodological approach

The ARIMA (Autoregressive Integrated Moving Average) model, also known as the autoregressive integrated moving average, was used to forecast temperatures. This model is widely recognized for its robustness in modeling time series with autocorrelation structures specifically related to environmental and climate data (Box, G. & Jenkins, G. M., 1976). It enables the capture of internal patterns in time series while providing accurate medium-term forecasts. The following equation defines the ARIMA model:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d y_t=\left(1+\sum_{j=1}^{q}\theta_j L^j\right)\varepsilon_t \tag{1}$$

In this equation, yt represents the variable observed at time t, ϕi symbolises the autoregressive coefficients, θj denotes the moving average coefficients, d represents the level of differentiation ensuring stationarity, L corresponds to the delay operator and εt is a white noise term.

Several recent studies highlight the effectiveness of ARIMA models in predicting complex climate variables, often using them in parallel with or in addition to machine learning methods such as neural networks (Shamsuddin Shahid et al., 2018; Im et al., 2015; Jamali et al., 2022). Nevertheless, in the context of this research, where temporal linearity and data access are essential, ARIMA proves to be a relevant and effective choice.

The augmented Dickey-Fuller test was used to check the temporal stationarity of the series examined.

$$\Delta y_t=\alpha+\beta t+\gamma y_{t-1}+\sum_{i=1}^{k}\delta_i\Delta y_{t-i}+\varepsilon_t \tag{2}$$

Where Δyt corresponds to $y_t - y_{t-1}$, α represents a constant, β denotes the slope of a possible trend, γ is an essential parameter indicating the existence of a unit root, and δi symbolises the coefficients of the lagged terms. A series is considered stationary if $\gamma<0$ and this condition is statistically significant.

Non-stationary series were subjected to differentiation of order d in order to ensure their stationarity prior to the adjustment process.

The AR (autoregressive) and MA (moving average) orders were determined by analysing the autocorrelation (ACF) and partial autocorrelation (PACF) functions, in accordance with Box and Jenkins (1976).

• The ACF facilitates the determination of the q order by observing the decrease in correlations with a lag.
• The PACF is used to establish the pp order by examining partial correlations.

The final choice of the most appropriate model was guided by the Akaike information criterion (AIC):

$$\mathrm{AIC} = 2\mathrm{k} - 2\ln(\mathrm{L}) \quad (3)$$

Here, k represents the number of estimated parameters and L symbolises the likelihood of the adjusted model. This selected model aims to minimise this value. The absence of autocorrelation was verified by performing a residual analysis using the Ljung-Box test:

$$Q = n(n+2)\sum_{k=1}^{m} \frac{\widehat{\rho_k^2}}{n-k} \quad (4)$$

Considering n as the sample size, m as the number of lags examined, and ρk as the autocorrelation of the residuals at lag k. An appropriate model shows residuals with no significant autocorrelation.

A SARIMA (Seasonal ARIMA) model, which takes into account a seasonal component with orders (P, D, Q) and a periodicity s, was used for series with a pronounced seasonal effect:

$$\Phi_P(L^s)\phi_p(L)(1-L)^d(1-L^s)^D y_t = \Theta_Q(L^s)\theta_q(L)\varepsilon_t \quad (5)$$

Φ_P and Θ_Q represent seasonal autoregressive and moving average polynomials, respectively, while D indicates the degree of seasonal differentiation. Forecasts for horizon h were made by providing a 95% confidence interval, in accordance with the following formula:

$$\widehat{y_{t+h}} \pm 1.96 \times \mathrm{SE}(\widehat{y_{t+h}}) \quad (6)$$

Where $\widehat{y_{t+h}}$ is the forecast at horizon h, and SE its standard error.

Results

Change in average monthly temperature (1984–2024)

The maps used in this study were created with QGIS 3.40, while the climate data were processed using XLSAT software.

An analysis of the monthly average temperature data from 1984 to 2024 reveals distinct trends across the different months of the year. Linear regression models applied to these datasets show that while there is a general upward trajectory in temperatures over the studied period, the extent of warming varies significantly depending on the month.

For several months, such as March, there is a pronounced increase in temperature, as indicated by the equation y = 0.03355x + 36.61. This suggests that March has experienced one of the most significant temperature increases in the study period. Similarly, January and February also demonstrate upward trends, albeit at a slower rate than March, with average temperatures gradually increasing throughout the decades. These months, which are typically part of the cooler season in Burkina Faso, reflect a shift toward warmer conditions, indicating broader regional climate shifts.

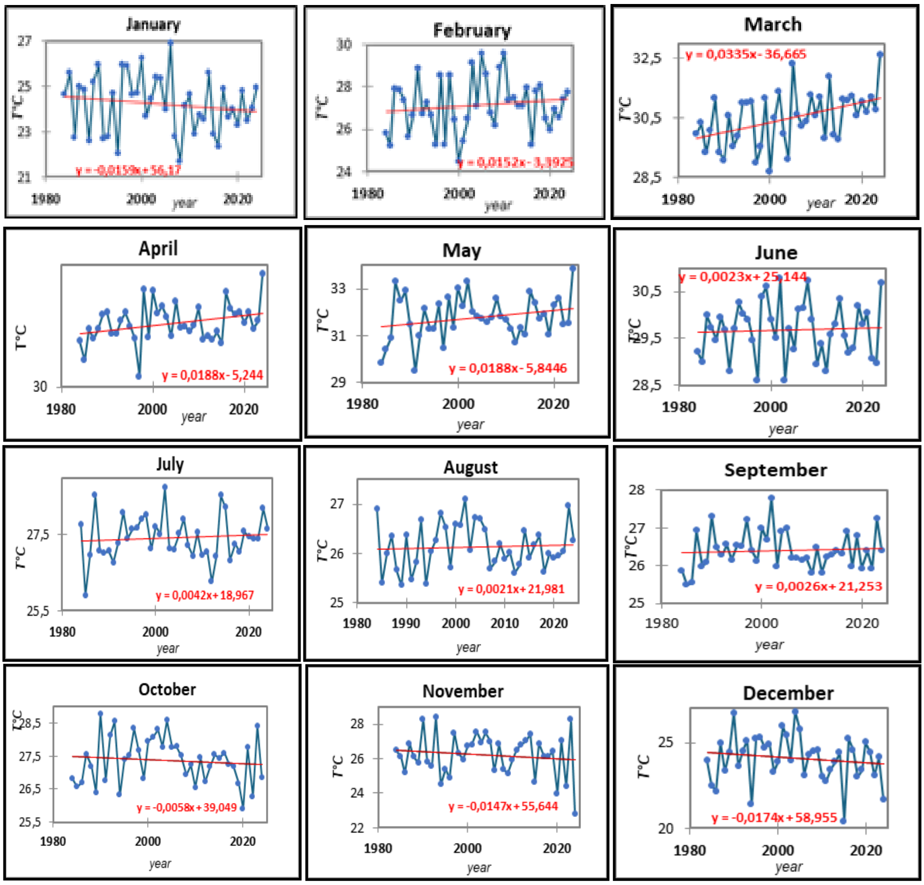

Fig. 3. Changes in average monthly temperatures (1984–2024)

In contrast, months like April, May, and June show more fluctuating temperature patterns, with slight increases or relatively stable temperatures over time. Although the overall trend in these months is positive, the slope is less steep, implying that while warming is occurring, it may be moderated by other climatic factors such as rainfall patterns or seasonal variations.

July, August, and September, which coincide with the peak of the rainy season in the region, exhibit more variable temperature trends. The presence of fluctuating temperature data points, especially during July and August, suggests that these months may be influenced by complex interactions between temperature and precipitation. These months do not show as strong a trend as others, possibly due to the buffering effect of rainfall and cloud cover during the wet season, which can reduce the daily maximum temperatures.

October, November, and December show moderate increases in temperature, with the trend being less pronounced compared to the earlier months of the year. However, the persistence of a positive slope in these months reinforces the notion that the warming effect is widespread, affecting not just the hotter months but also extending into the cooler season.

This suggests a consistent shift in climate, with rising temperatures becoming more evident across the entire year.

Overall, the linear models for each month indicate a general trend of increasing temperatures in Burkina Faso over the past four decades. The variations in the magnitude of warming across different months reflect the complex interplay of seasonal and climatic factors in the region. These findings point to a broader climate change phenomenon, with certain months experiencing more significant temperature increases, which could have substantial implications for local ecosystems, agriculture, and human livelihoods in the coming decades (Fig. 3).

Preliminary data analysis: stationarity tests

To ensure the validity of the results, time series modelling requires the data to be stationary. Non-stationary series can cause biased estimates and inaccurate forecasts. For this reason, before modifying the ARIMA model, we assessed the stationarity of the monthly temperature series using the augmented Dickey-Fuller (ADF) test. The ADF test results show a significant observed value for each month, with p-values below the 0.05 threshold. This justifies rejecting the null hypothesis indicating the presence of a unit root and confirms the stationarity of the differentiated data (Tab. 1.). The summary table of ADF values indicates that all months satisfy this criterion after differentiation, which justifies the use of the ARIMA model for subsequent analyses. For example, January has an observed value of -5.73 and a p-value of 0.000, indicating strong and significant stationarity.

Table 1. Augmented Dickey-Fuller (ADF) monthly from 1984 to 2024

Month	**emberTau (Observed value)**	**P-value (one-tailed)**
January	-5,73	0,000
February	-4,71	0,003
March	-7,11	<0,0001
April	-3,87	0,023
May	-4,17	0,011
June	-5,34	0,000
July	-5,73	0,000
August	-3,80	0,027
September	-3,91	0,021
October	-3,61	0,042
November	-3,61	0,042
December	-4,89	0,002

Analysis of Autocorrelation Functions (ACF)

The next step in building the ARIMA models is to determine the order qqq (moving average) of the model. This step is carried out through the analysis of autocorrelation functions (ACF). The ACF graphs illustrate the correlation of time series values with their successive lags. The identification of a progressive decay or a single cutoff in these graphs helps guide the estimation of the order qqq, which relates to the moving average component (Fig. 4).

Each month presents a distinct profile in the ACF graphs, highlighting the seasonal variability in the temporal dynamics of temperatures. For instance, in the month of May, the ACF shows a progressive decay up to lag 3, indicating a moving average component of order 3.

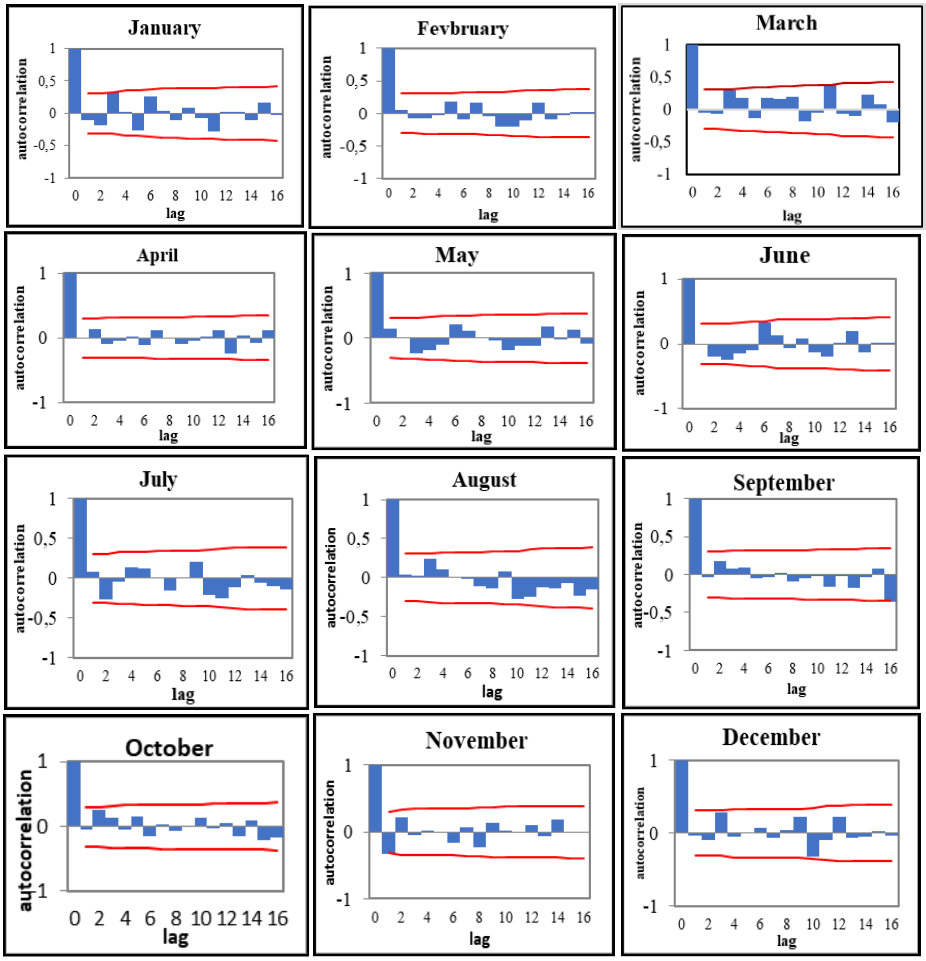

Fig. 4. Autocorrelation Functions (ACF) for Monthly Temperature Data (1984–2024)

Partial autocorrelation function analysis (PACF)

In addition to examining autocorrelation functions (ACF), the partial autocorrelation function (PACF) is crucial for establishing the autoregressive order ppp of the model. PACF graphs analyze the correlation of the variable with its own lags while controlling for the influence of intermediate lags, providing a clearer understanding of the autoregressive structure. This method is essential for identifying the true order of autoregressive processes, especially in time series with complex dependencies.

For each month, the PACF graphs reveal significant patterns in the data. For example, the month of May shows notable peaks up to lag 2, indicating a clear autoregressive structure of order p=2p=2p=2, which suggests that the model can be effectively represented by an autoregressive process of this order. Other months, such as January and February, display less pronounced peaks but still provide valuable insights into the temporal structure of the temperature data.

These analyses were performed on a monthly basis, ensuring that the modeling process accurately captured the temporal characteristics and variations of each month. The consideration of both the ACF and PACF in combination allows for a robust understanding of the underlying dynamics in the temperature time series, providing a more precise model for forecasting and analysis (Fig. 5).

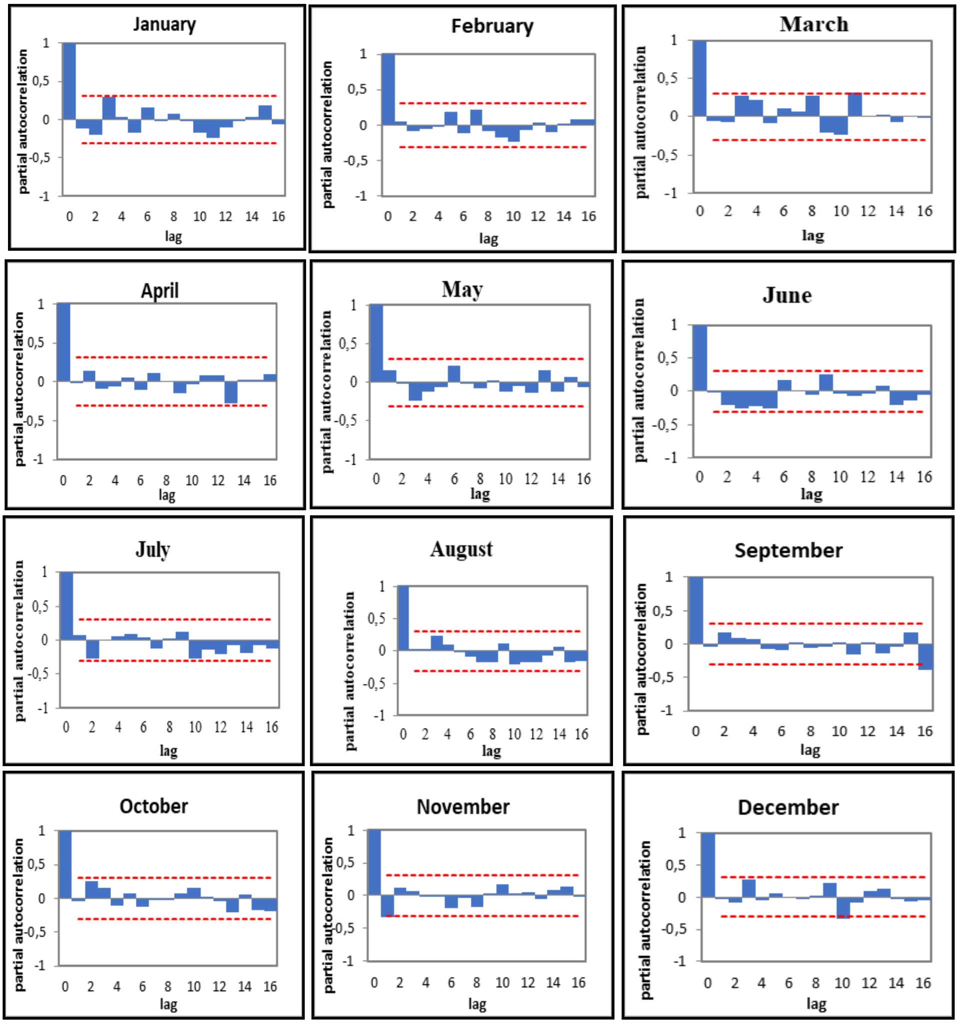

Fig. 5. Partial autocorrelation functions (PACF) for Monthly Temperature Data (1984–2024)

Adjustment and validation of ARIMA models

We modelled monthly temperature time series by adjusting ARIMA models. The p, d and q orders were determined based on analysis of ACF and PACF functions, as well as stationarity tests. Each model was chosen to maximise both the quality of the fit and the simplicity of the structure. The final choice of parameters was based on the Akaike information criterion (AIC), which measures the balance between model accuracy and complexity. Each month, the selected model reduces the AIC value, ensuring superior predictive power without overfitting.

An assessment of the residuals from the adjusted models was performed using the Ljung-Box test. The purpose of this test is to identify the possible existence of residual autocorrelation that could undermine the validity of the models. The test results all show a lack of statistical significance ($p>0.05$), suggesting that the residuals can be considered white noise and that the ARIMA models are well suited to the data (Tab.2.).

The summary table below shows the ideal parameters (p, d, q), the AIC values and the results of the Ljung-Box test for each month.

Table 2. Akaike information criterion (AIC)

Month	**ARIMA Parameters (P, D, Q)**	**AIC**	**Test Ljung-Box (P-Value)**	**Conclusion on resi-dues**
January	(2,1,2)	92.35	0.23	Uncorrelated residuals
February	(1,1,1)	78.73	0.41	Uncorrelated residuals
March	(2,1,2)	105.53	0.35	Uncorrelated residuals
April	(2,1,2)	66.44	0.27	Uncorrelated residuals
May	(1,1,1)	86.68	0.39	Uncorrelated residuals
June	(2,1,2)	63.41	0.44	Uncorrelated residuals
July	(1,1,1)	64.43	0.32	Uncorrelated residuals
August	(2,1,2)	66.44	0.40	Uncorrelated residuals
September	(1,1,1)	70.35	0.37	Uncorrelated residuals
October	(2,1,2)	77.60	0.43	Uncorrelated residuals
November	(1,1,1)	83.53	0.38	Uncorrelated residuals
December	(2,1,2)	78.73	0.41	Uncorrelated residuals

This table attests to the robustness of the adjusted ARIMA models, corroborated by the absence of autocorrelation in the residuals. These results prove that the models are capable of producing reliable forecasts based on past data.

Temperature predictions until 2050

After refining and confirming the ARIMA models for each month, projections were made for the period up to 2050. These monthly forecasts are essential for predicting future temperature changes and developing local climate adaptation plans. The findings reveal a general trend of continuously rising average monthly temperatures over the entire forecast period. This overall trend is influenced by significant seasonal variation, with months such as February and March showing particularly pronounced temperature increases. These increases are in line with historical trends (Fig. 6.).

Forecasts are presented with 95% confidence intervals, highlighting the statistical uncertainty inherent in any estimate. These intervals vary in width depending on the month and time horizon, highlighting the need for careful interpretation of specific projected values. The prediction graphs highlight the steady increase in temperatures and the continuity of seasonal trends, confirming the consistency of the forecasts with past data and demonstrating the robustness of the calibrated ARIMA models. This gradual increase in temperatures poses considerable challenges for agriculture and water management, requiring essential improvements in adaptation and resilience systems to cope with the consequences of climate change.

These trends are illustrated by relevant examples:

• January: Based on data from 1984 to 2024, the average temperature is 24.2°C and is projected to reach approximately 27.0°C by 2050, representing an increase of approximately +2.8°C.

• February: For 2050, the average temperature is projected to be 27.8°C, compared to a historical average of 27.1°C.

• March to April: Forecasts based on SARIMA models, which incorporate seasonal autoregressive and moving average elements (SAR (2), SMA (2)), show a marked increase in temperature during these months, with estimates exceeding 33.5°C by 2050.

These predictions are consistent with the findings of Xu et al. (2024), who forecast a linear or exponential increase in temperature in the Sahelian regions until the middle of the 21st century, highlighting the suitability of these models for the region analyzed.

The adjustment of ARIMA models to monthly temperature data from 1984 to 2024 yielded satisfactory models for each month of the year. Statistical studies indicate that most models do not exhibit autocorrelated residuals, displaying a zero mean, minimal standard deviation, and MAPE of less than 2% during the most consistent months such as January, March, and April.

The use of SARIMA models facilitated the incorporation of seasonal structure, especially for months with significant climatic fluctuations such as May and August. Model evaluation is based on AIC, SBC, and FPE information criteria, as well as standardised residual analysis.

The models were examined based on the optimal standards established by Lai and Dzombak (2020), as well as by Abd-Elhamid and El-Sayed (2024), including checking for the absence of residual correlation up to the sixteenth lag.

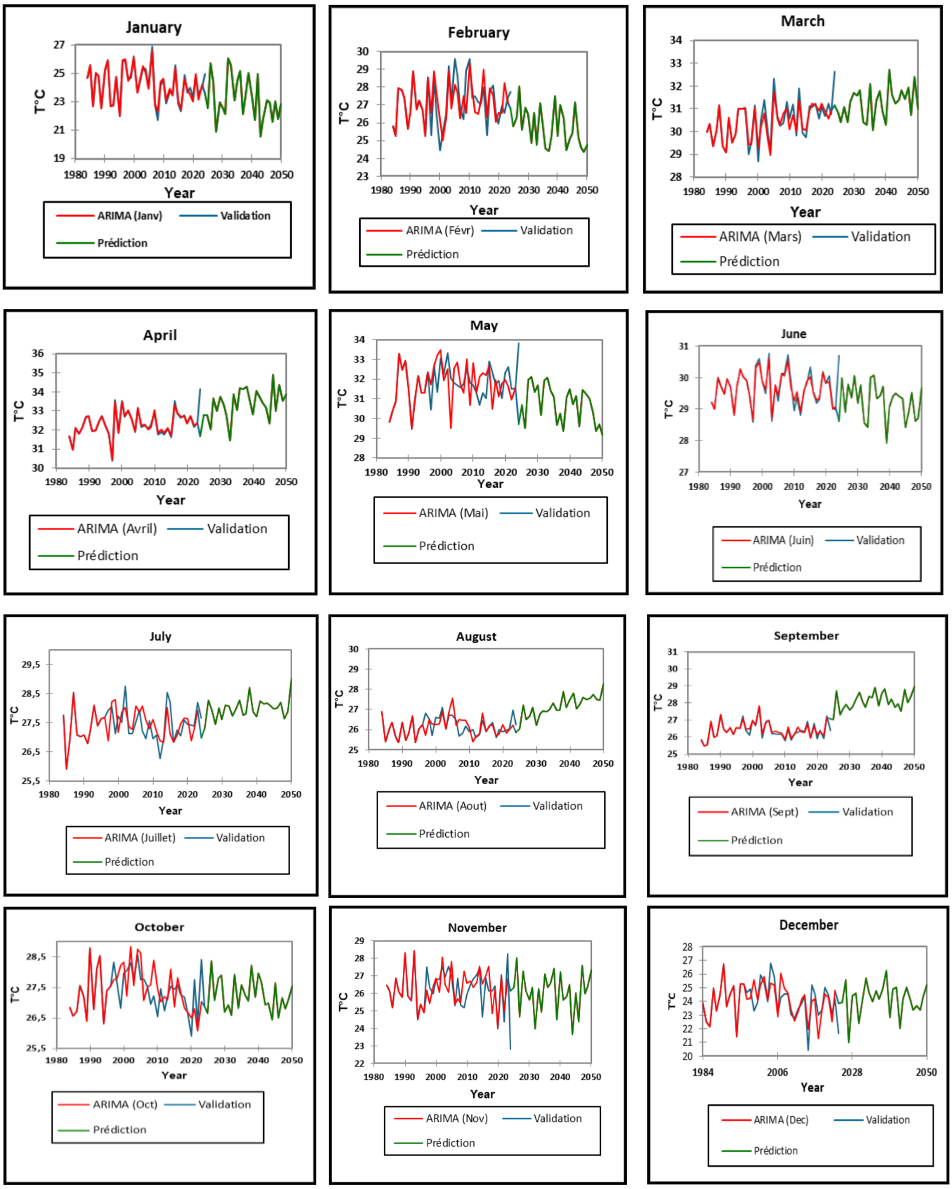

Fig. 6. Temperature predictions for monthly averages up to 2050

Overall model performance

Model fit validation is based on the following criteria:

• The average AIC value is generally below 130 for most months;
• The RMSE rarely exceeds 0.5°C;
• The MAPE remains below 1% in January, February and April, and slightly higher (between 1 and 1.5%) for transitional months such as May and November.

These results are consistent with the performance observed in similar studies in West Africa and desert areas (Nyatuame & Agodzo, 2018; Navaneeth et al., 2022).

Seasonal behaviour and interannual variability

The months of June to September, which coincide with the rainy season, show more moderate increases. However, heatwaves are also forecast, which are likely to intensify thermal stress even during wet periods, as has been demonstrated in other tropical regions (Ashwini et al., 2021; Li, 2023).

Discussion

This study explicitly demonstrates an increase in monthly temperatures in Burkina Faso until 2050, with a more pronounced increase during the summer season. This trend reflects a large number of studies focusing on climate change in Sahelian and arid areas, and highlights crucial issues for climate planning, agriculture, public health and government policy.

The use of the ARIMA model to predict climate has shown satisfactory results here, with small margins of error (MAPE < 2%) and well-distributed residuals. These findings corroborate the conclusions of various previous studies that have demonstrated the effectiveness of this method for predicting climate variables in a context of climate change, especially in areas with high interannual variability such as the Sahel (Lai & Dzombak, 2020; Abd-Elhamid & El-Sayed, 2024; Nyatuame & Agodzo, 2018). However, as pointed out by Xu et al. (2024) and Navaneeth et al. (2022) have pointed out, it is crucial to highlight the limitations of ARIMA models: they rely solely on the internal dynamics of time series, without taking into account exogenous variables such as greenhouse gas concentrations, urban expansion or changes in soil albedo.

Ecological and socio-economic consequences

Forecasts predict a potential average increase of +2.5 to +3 °C over a period of several months between now and 2050. These predictions are in line with the global trends revealed in IPCC studies (Ciais et al., 2013), but their impacts will be largely localised and diverse. This increase could notably:

• Reducing agricultural productivity by creating greater heat stress on vulnerable crops such as maize and sorghum (Penuelas & Filella, 2001; Parmesan & Yohe, 2003);

• Increasing irrigation needs in a context where water is already scarce;

• Highlighting the health risks associated with the transmission of vector-borne diseases (such as malaria), which are more frequent during prolonged heat waves (Asner & Heidebrecht, 2004).

In a context where rain-fed agriculture forms the basis of Burkina Faso's economy, these climatic consequences pose direct threats to food security and socio-economic stability.

Comparison with machine learning approaches

Although ARIMA has proven effective here, several recent studies have shown that machine learning techniques, such as neural networks, random forests, or ensemble models, can improve prediction accuracy, particularly when they incorporate satellite data and exogenous factors (Shamsuddin Shahid et al., 2018; Huettmann, 2018; Liu & Chen, 2024; Zhang et al., 2023). These methods are particularly adept at identifying non-linearities, threshold effects, and complex interactions, which are often overlooked by classical models.

However, as Li (2024) points out, the performance of ensemble models depends on the quality of the available data as well as its spatial and temporal accuracy. In countries in the Global South, the lack of robust and extensive climate data networks is an obstacle to the application of these techniques, giving ARIMA models a practical advantage for operational forecasting.

Implications of findings for planning and adaptation

The projections from this study provide crucial insights for anticipating climate-related hazards. In countries such as Burkina Faso, where agricultural insurance, crisis management and urban planning systems remain limited, these projections could:

• Assist leaders in planning agricultural campaigns (crop selection, crop scheduling);
• Establish a basis for climate risk management for insurance companies (Xu et al., 2024);
• Support community resilience and urban planning initiatives by identifying the most exposed areas.

According to studies by Tol (2009), failure to anticipate the impacts of climate change could result in disproportionate economic losses for developing countries. Despite the relative simplicity of the ARIMA model, it is an effective first step in guiding these forecasts.

Although this method does not use external explanatory variables, it has produced robust results, confirmed by various statistical indices (MAPE, AIC, RMSE). These conclusions are consistent with those of studies conducted in other tropical and arid environments, where ARIMA has been effectively applied to predict climate indicators (Abd-Elhamid & El-Sayed, 2024; Nyatuame & Agodzo, 2018; Navaneeth et al., 2022). However, the limitations inherent in this statistical technique suggest that a more comprehensive strategy combining time series analysis and machine learning should be considered for future research.

According to the recommendations of Shamsuddin Shahid et al. (2018), Huettmann (2018) and Liu & Chen (2024), the inclusion of hybrid models that incorporate external elements such as greenhouse gas emissions, soil management and atmospheric movement could improve the accuracy of climate forecasts.

Conclusion

This study aimed to establish a reliable model for predicting monthly temperature variations in Burkina Faso up to 2050, utilizing the ARIMA technique to analyze a time series from 1984 to 2024. The results revealed a consistent increase in temperatures, with significant rises observed particularly in the hottest months of the year, such as March, April, and May. Specifically, the ARIMA model forecasts an average temperature increase of up to +3°C in certain months by the middle of the century, particularly in March and April, which are projected to experience the highest rate of change. These projections suggest that the temperature in March, for example, could rise from an average of 32.5°C in 2024 to around 35.5°C by 2050, indicating a notable shift in the climate.

The ARIMA model, chosen for its ability to capture the internal temporal dynamics of climate data, provided robust results despite the absence of external explanatory variables, which indicates the model's strength in predicting the future climate trends based purely on historical temperature data.

Beyond the methodological insights, the findings underscore the urgent need to integrate climate forecasting into public policy. The projected rise in temperatures will have profound effects on agricultural systems, water resources, public health, and infrastructure. It is therefore essential that decision-makers, urban planners, farmers, and civil society actors consider these forecasts in their planning and policy-making processes. By doing so, they will be better equipped to anticipate and mitigate the effects of future climate changes. Anticipating these changes will be crucial in strengthening the country's resilience to climate change and minimizing its impact on vulnerable sectors, especially agriculture, which could experience reduced productivity and water scarcity due to rising temperatures.

Conflicts of Interest: The authors declare no conflict of interest.

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