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Climate Forecasts Using the Hybrid SARIMA-LSTM Onacc Model: Optimizing Predictions for the Bimodal Humid Forest Zone of Cameroon

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ABSTRACT

Cameroon is facing increasing climate variability, with direct consequences on agriculture, ecosystems, and rural development. The bimodal humid forest zone-covering the Centre, South, and East regions-is particularly vulnerable due to its specific climatic conditions, which make it both agriculturally productive and highly sensitive to fluctuations in precipitation and temperature. This study aims to calibrate and apply the SARIMA-LSTM ONACC hybrid model, developed under the auspices of the National Observatory on Climate Change (ONACC). Our goal is to optimize climate forecasting for this critical agroecological zone. Historical temperature and precipitation data (1980-2022) from selected meteorological stations were used to train and test the model. The methodology combines the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model to capture linear and seasonal components, with Long Short-Term Memory (LSTM) networks to model nonlinear dependencies and residual dynamics. Preprocessing steps include normalization, seasonal decomposition, and model validation. Model performance was evaluated using RMSE, MAE, and NSE indicators. Results show that the SARIMA-LSTM ONACC model reliably reproduces the interannual variability of the region. These results provide a solid foundation for informed agricultural planning, water resource management, and the development of climate risk mitigation strategies in southern Cameroon.

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Introduction

Climate variability and its growing impacts on agriculture, biodiversity, and human livelihoods have become a central concern for both policymakers and researchers across tropical Africa. In Cameroon, climate change is already manifesting through increased rainfall irregularity, extreme temperature events, and the shifting of agricultural seasons, threatening food security and natural resource stability [1].

Among Cameroon's five agroecological zones, the bimodal humid forest zone stands out for its ecological and economic importance. It covers the Centre, South, and East regions and is characterized by a bimodal rainfall pattern-two distinct rainy seasons (March–June and September–November) interspersed with two dry seasons. This regular climatic rhythm has historically supported robust agricultural systems, especially for cash crops such as cocoa, coffee, and oil palm, as well as food staples like cassava, plantain, and groundnuts [2].

Global climate models (GCMs) and regional climate models (RCMs), while essential for long-term projections, often lack the spatial and temporal granularity required for localized climate decision-making in areas with complex seasonal regimes [3,4]. In this context, there is growing interest in hybrid approaches that combine time series statistical methods with machine learning techniques to enhance local-scale prediction accuracy.

To address these challenges, this study introduces a predictive approach based on the SARIMA-LSTM ONACC model, developed under the mandate of the National Observatory on Climate Change (ONACC). The model builds on two complementary components: a Seasonal AutoRegressive Integrated Moving Average (SARIMA) model [5]. Which captures seasonal and trend structures in climate data; and a Long Short-Term Memory (LSTM) neural network, which handles complex nonlinear relationships and residual variability in time series data.

The present paper aims to: calibrate and test the SARIMA-LSTM ONACC model for the bimodal humid forest zone of Cameroon; evaluate its forecasting performance using standard metrics such as RMSE, MAE, and NSE; and demonstrate its potential as a tool to support agricultural planning, hydrological resource management, and climate adaptation strategies at the subnational level [6].

Materials and Methods

Study Area

The study focuses on the bimodal humid forest zone of Cameroon, which includes the Centre, South, and East regions. This ecological zone is characterized by two rainy seasons (March–June and September–November) and two dry seasons, with annual rainfall ranging between 1500 and 2000 mm, and average temperatures fluctuating between 24°C and 26°C throughout the year. The region is agriculturally strategic due to its suitability for perennial and annual crops such as cocoa, coffee, cassava, plantain, and palm oil.

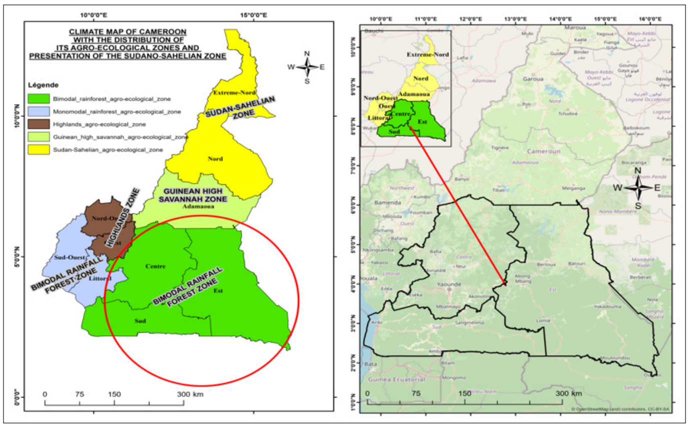

Figure 1: Map of Cameroon with the Distribution of its AGRO-Ecological Zones and Presentation of the Bimodal Humid Forest Zone

Data Collection

The model was trained and evaluated using historical monthly climate data on temperature and precipitation, covering the period 1980–2022. Data were collected from the National Observatory on Climate Change (ONACC), the National Meteorological Direction of Cameroon (DMN), and reanalysis datasets (ERA5 for temperature, GPM/CHIRPS for precipitation where gaps existed) [7].

Data Preprocessing

Preprocessing steps were performed to ensure data quality and model stability: missing values were interpolated, variables normalized, precipitation log-transformed, and all series seasonally decomposed. Normalization and transformation equations will be inserted alongside the visual decomposition plots [8].

Normalization formula:

$$X^{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Log-transformation for precipitation:

$$P^{log} = \log(P + 1) \quad (2)$$

Additive decomposition model:

$$X_t = T_t + S_t + R_t \quad (3)$$

Where:

X_t : *Observed value*

T_t: *trend*

S_t: *Seasonality*

R_t: *résidu (bruit)*

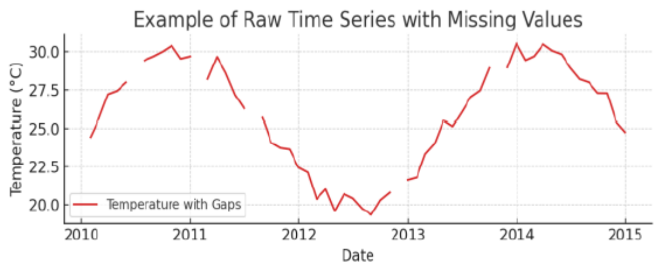

Figure 2: Example of Raw time Series with Missing Values

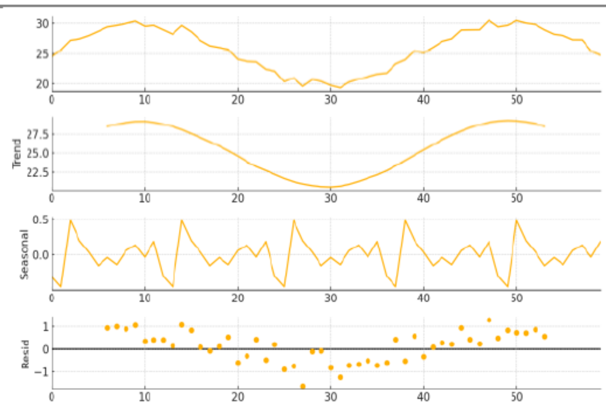

Figure 3: Seasonal Decomposition of Climate Series

Hybrid Sarima-LSTM ONACC Model

The SARIMA component captures trend and seasonality using seasonal autoregressive and moving average terms [9]. The residuals are then modeled using an LSTM network trained to learn nonlinear dynamics [10,11].

General SARIMA Model

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad (4)$$

- *p, d, q: non-seasonal orders (AR, differentiation, MA)*
- *P, D, Q: seasonal orders*
- *s: seasonal periodicity (12 for monthly data)*

Key Components of LSTM

Forget gate: $f_t = \sigma(W_f \cdot [h_{\{t-1\}}, x_t] + b_f)$ (5)

Input gate: $i_t = \sigma(W_i \cdot [h_{\{t-1\}}, x_t] + b_i)$ (6)

Candidate: $\tilde{C}_t = tanh(W_C \cdot [h_{\{t-1\}}, x_t] + b_C)$ (7)

Cell state: $C_t = f_t \odot C_{\{t-1\}} + i_t \odot \tilde{C}_t$ (8)

Output gate: $o_t = \sigma(W_o \cdot [h_{\{t-1\}}, x_t] + b_o)$ (9)

Hidden state: $h_t = o_t \odot tanh(C_t)$ (10)

Final hybrid model prediction: $\hat{y}_t = \hat{y}_{SARIMA}, t + \hat{e}_{LSTM}, t$ (11)

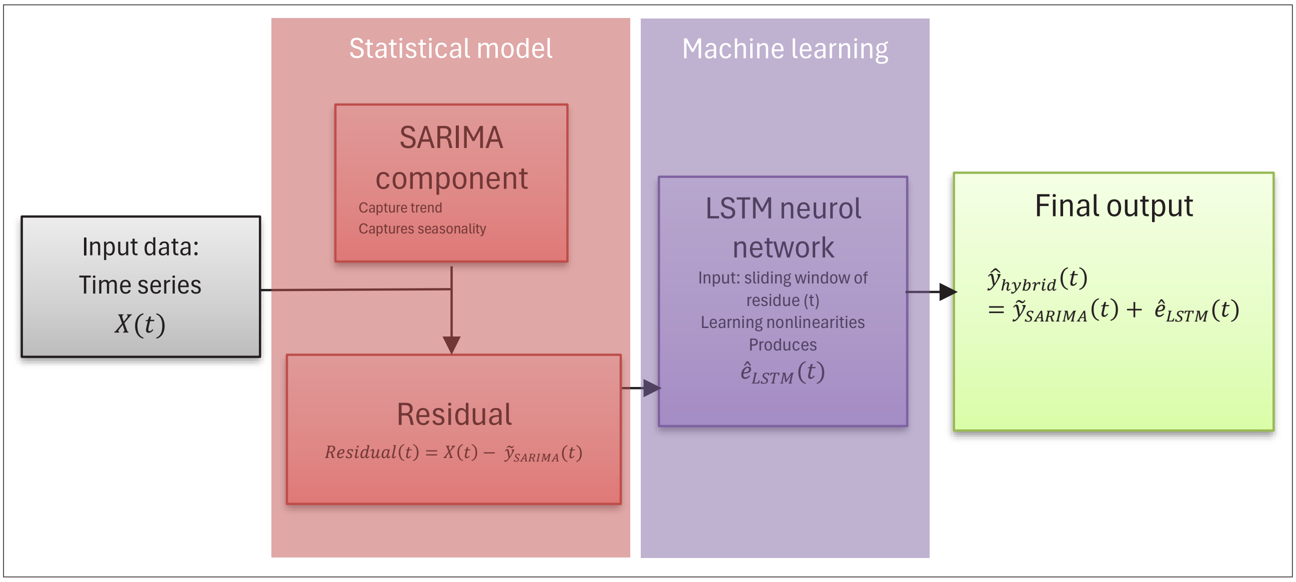

Figure 4: Conceptual Structure of the SARIMA-LSTM ONACC Hybrid Model Combining Statistical and Neural Learning Components [10]

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Appendix: Climatological Figures

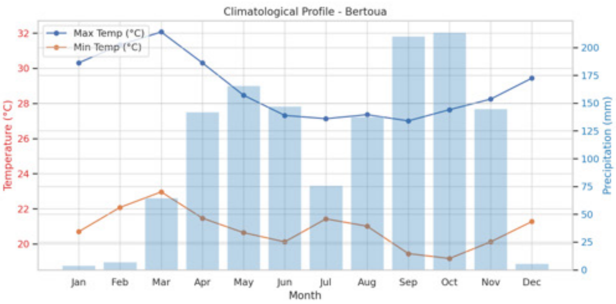


Figure 5: Climatological profile for Bertoua

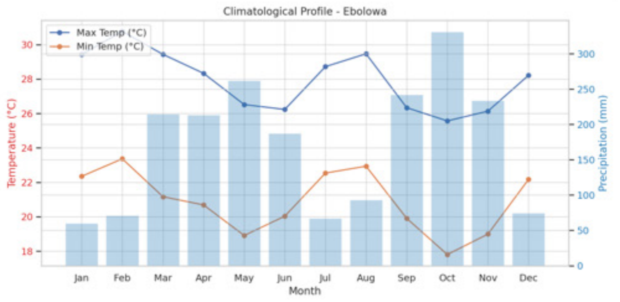


Figure 6: Climatological profile for Ebolowa

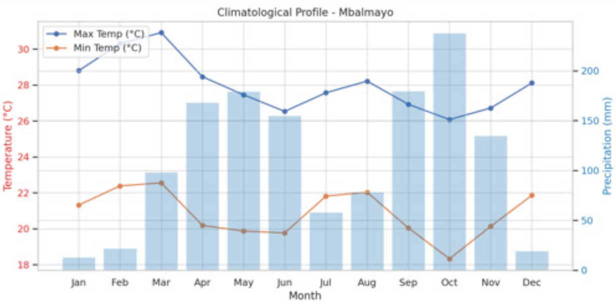


Figure 7: Climatological profile for Mbalmayo

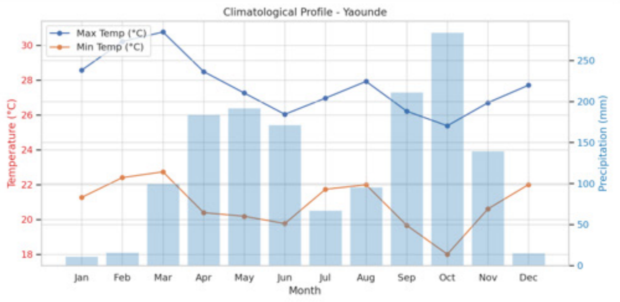


Figure 8: Climatological profile for Yaoundé

Table 1: Main Functions by Component

Component	Main Objective	Method Used
SARIMA	Identify seasonality and trend	*Box Jenkins (ARIMA(p,d,q)(P,D,Q)s)*
Residuals	Define the remaining nonlinear deviation	$e_t = y_t - \hat{y}_{SARIMA,t}$
LSTM	Learn long memory on the residuals	RNN with Gates (f, i, o, c)
Hybrid Fusion	Linear + nonlinear combination	$\hat{y}_t = \hat{y}_{SARIMA,t} + \hat{e}LSTM_T$

Agroecological Calibration of the SARIMA-LSTM ONACC Model

This technical note details the specific adjustments introduced to calibrate the SARIMA-LSTM ONACC model to agroecological contexts, especially for the bimodal humid forest zone of Cameroon.

Integration of Agroecological Parameters

A contextual descriptor vector $Z^{(z)} \in \mathbb{R}^d$,representing agroecological attributes such as soil type, dominant crop cycles, and average seasonal rainfall, is integrated into the prediction function:

$$\hat{y}_t^{(z)} = \hat{y}_{SARIMA,t}^{(z)} + \hat{\varepsilon}_{LSTM,t}^{(z)} + \gamma^{(z)}.Z^{(z)} \qquad (12)$$

Here, $\gamma^{(z)} \in \mathbb{R}^d$ is a learnable weight vector calibrated for each ecological zone Z.

AGRO-Seasonal Decomposition

The SARIMA component is traditionally based on monthly seasonality (s = 12). To reflect agricultural rhythms, the seasonal component is adapted to the following cycles [12]:

- s = 6 for bimodal cropping phases
- s = 36 for decadal-based representations
- s = N for custom crop calendars (phenology-aligned)

Loss Function Weighted by Agronomic Importance

To emphasize performance during agriculturally critical periods (e.g., planting, harvesting), a dynamic weighting scheme is introduced in the loss function:

$$\mathcal{L} = \frac{1}{n}\sum_{t=1}^{n} \omega_t \,.\, (y_t - \hat{y}_t)^2 \qquad (13)$$

With $\omega_t > 1$ during key phenological windows and $\omega_t = 1$ otherwise.

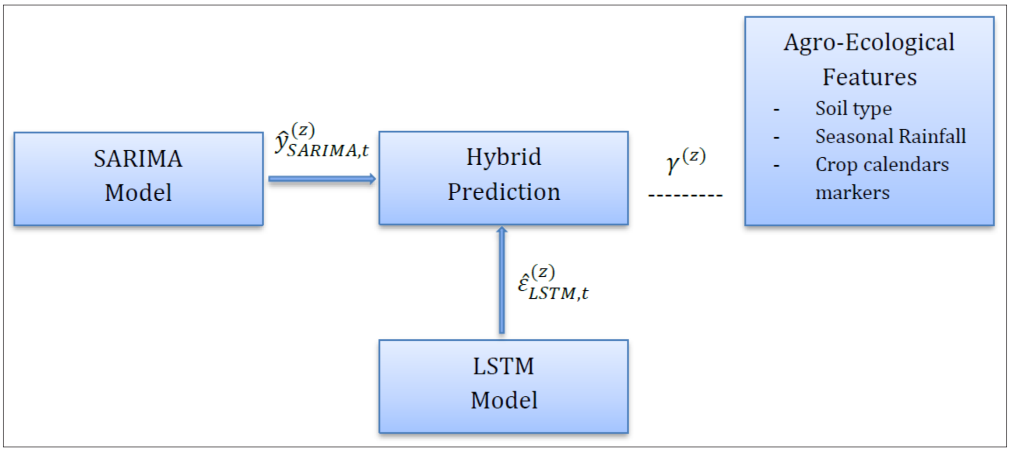
Residual Transfer Learning Between Stations
For stations with missing or noisy data, residual patterns are borrowed from geographically or climatically similar stations using transfer learning:

$$\hat{\varepsilon}^{(z)}_{LSTM,t} \approx f(\hat{\varepsilon}^{(z')}_{LSTM,t}, \theta_{z,z'}) \quad (14)$$

With
- z : target station
- z' : neighboring source metric
- $\theta_{z,z'}$: geo-climatic proximity metric

This strategy improves model robustness in low-data regions.

Component	Objective	Key Formulation
$Z^{(z)}$ integration	Agroecological context integration	$\hat{y}_t = \hat{y}_{SARIMA} + \hat{\varepsilon}_{LSTM} + \gamma . Z$
Agro-seasonality	Reflect phenological cycles	s ∈ {6,12,36} according to local culture
Weighted loss	Prioritize critical phases	$\mathcal{L} = \frac{1}{n}\sum \omega_t . MSE$
Residual transfer	Leverage other stations	$\hat{\varepsilon}^{(z)} \approx f(\hat{\varepsilon}^{(z')})$



Model Evaluation
The performance of the SARIMA-LSTM ONACC model was evaluated through multiple layers to ensure robustness, spatial generalization, and agroecological relevance.

Classical Forecast Accuracy Metrics
We first evaluated model accuracy using the following standard indicators:

RMSE (Root Mean Square Error):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \quad (15)$$

MAE (Mean Absolute Error):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad (16)$$

NSE (Nash–Sutcliffe Efficiency):

$$NSE = \frac{\sum(y_t - \hat{y}_t)^2}{\sum(y_t - \bar{y})^2} \quad (17)$$

These metrics were computed for each variable (temperature and precipitation) at all four stations and summarized in performance tables (see Table 2).

Inter-Station Cross-Validation (LOSOCV)
To evaluate generalizability across space, we implemented **Leave-One-Station-Out Cross-Validation** (LOSOCV) [13]. For each test station s, the LSTM was trained using residuals from all other stations S\s and then tested on station s.

Hybrid prediction during LOSOCV:

$$\hat{y}_t^{(s)} = \hat{y}_{SARIMA,t}^{(s)} + \hat{\varepsilon}_{LSTM,t}^{(S\backslash s)} \quad (17)$$

Evaluation metrics (RMSE, MAE, RMSE gain) were calculated and compared with native (station-specific) training to highlight transferability of learned residuals.

Evaluation with Agro-Seasonal Weighting
To prioritize learning during agriculturally sensitive periods (e.g., sowing, harvest), we used a **weighted loss function**:

$$\mathcal{L} = \frac{1}{n}\sum_{t=1}^{n} \omega_t \,.\, (y_t - \hat{y}_t)^2$$

Where ω_t>1 during key agronomic windows and ω_t =1 otherwise. This encouraged better model performance during impactful crop phases.

Agroecological Parameter Integration Test
Models incorporating the ecological vector $\boldsymbol{Z}^{(z)}$ (soil, vegetation type, rainfall profile) were compared against non-contextualized models.

Prediction with agroecological input:

$$\hat{y}_t^{(z)} = \hat{y}_{SARIMA,t}^{(z)} + \hat{\varepsilon}_{LSTM,t}^{(z)} + \gamma^{(z)}.Z^{(z)}$$

The **gain in RMSE and MAE** across stations confirmed the added value of localized calibration, particularly in low-data or transition zones.

Bootstrap-Based Uncertainty Estimation
Finally, a bootstrap procedure (n = 500 resamplings) was applied to each prediction set to generate confidence intervals around RMSE and MAE. This provided statistical robustness and identified stations with greater prediction uncertainty.

Results

Performance Evaluation
The hybrid SARIMA-LSTM ONACC approach was applied to monthly climate data from four representative stations in the bimodal rainfall humid forest zone: Yaoundé, Mbalmayo, Ebolowa, and Bertoua. The table below presents the RMSE, MAE, and NSE indicators for the SARIMA-only forecasts and for the hybrid SARIMA+LSTM model.

Table 2: Sarima vs Sarima+Lstm Performance

Station	Variable	RMSE SARIMA	RMSE Hybrid	MAE SARIMA	MAE Hybrid	NSE SARIMA	NSE Hybrid	RMSE Gain
Bertoua	Precipitation	74.72	74.66	52.22	51.27	0.457	0.457	0.060
Bertoua	Temperature	1.40	1.42	0.96	0.99	0.350	0.331	-0.020
Ebolowa	Precipitation	99.91	99.81	78.25	78.30	0.402	0.404	0.099
Ebolowa	Temperature	2.29	2.31	1.70	1.72	0.239	0.225	-0.022
Mbalmayo	Precipitation	75.41	75.29	53.74	54.63	0.435	0.436	0.116
Mbalmayo	Temperature	1.75	1.74	1.24	1.24	0.218	0.224	0.006
Yaounde	Precipitation	82.77	82.81	58.58	61.12	0.471	0.471	-0.037
Yaounde	Temperature	1.77	1.81	1.27	1.34	0.271	0.236	-0.041

Comparative Curves: Observed vs Sarima vs Sarima+Lstm
The following figures illustrate the climate predictions for each station. They show the performance of the SARIMA model alone and the improvement brought by coupling it with LSTM, particularly for seasonal irregularities (exceptional rainfall or thermal anomalies).

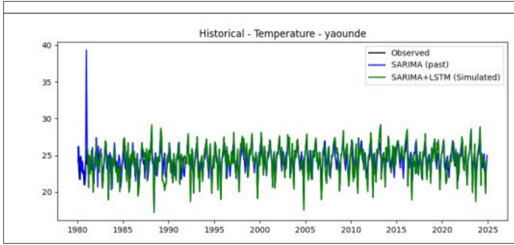


Figure 9: Yaoundé Temperature Forecast

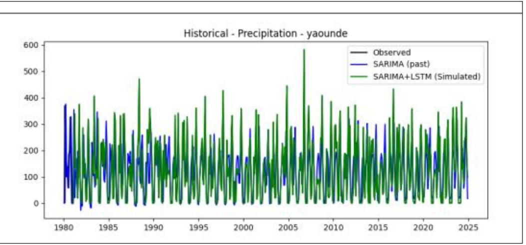


Figure 10: Yaoundé Precipitation Forecast

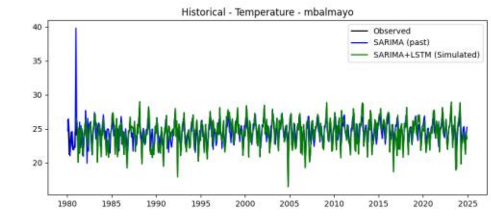


Figure 11: Mbalmayo Temperature Forecast

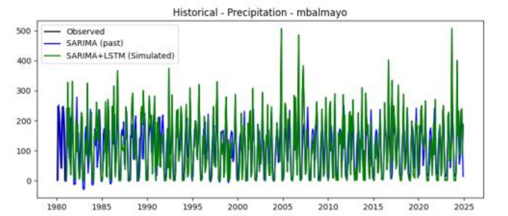


Figure 12: Mbalmayo Precipitation Forecast

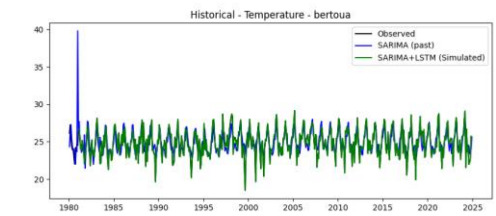


Figure 13: Bertoua Temperature Forecast

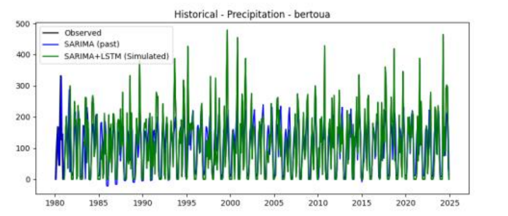


Figure 14: Bertoua Precipitation Forecast

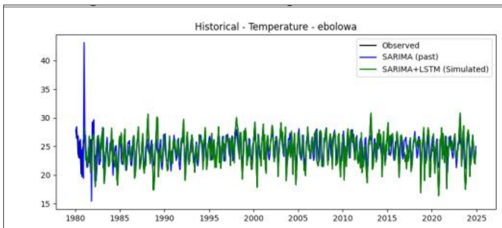


Figure 15: Ebolowa Temperature Forecast

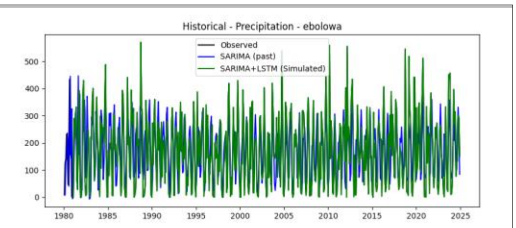


Figure 16: Ebolowa Precipitation Forecast

Climate Projections

To broaden the operational utility of the SARIMA-LSTM ONACC model, climate projections were made for a horizon of 12 to 36 months across all stations in the bimodal zone (Yaoundé, Mbalmayo, Bertoua, Ebolowa). These projections were obtained by combining the seasonal extension of the SARIMA model and the forecasting of residuals using an autoregressive LSTM network.

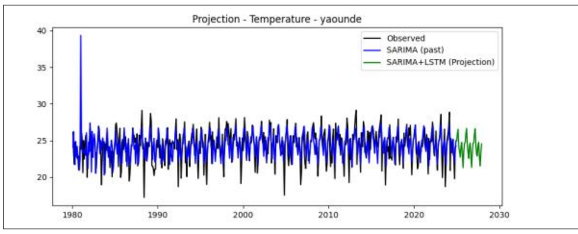


Figure 17: Yaoundé Temperature Projection

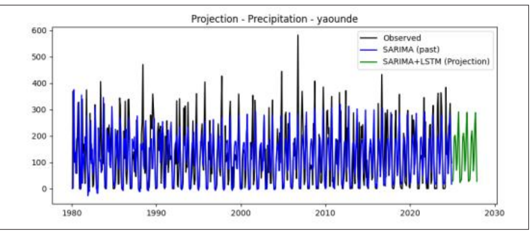


Figure 18: Yaoundé Precipitation Projection

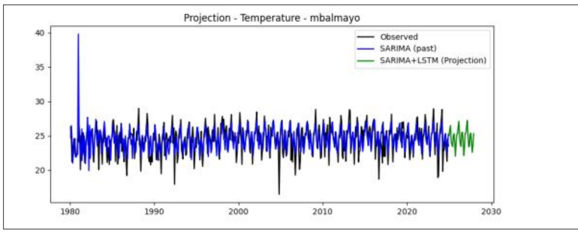


Figure 19: Mbalmayo Temperature Projection

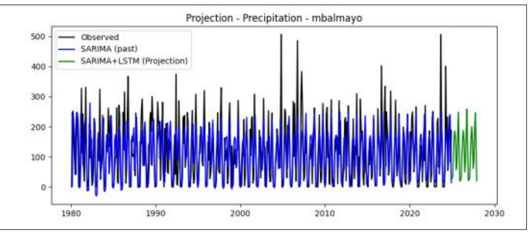


Figure 20: Mbalmayo Precipitation Projection

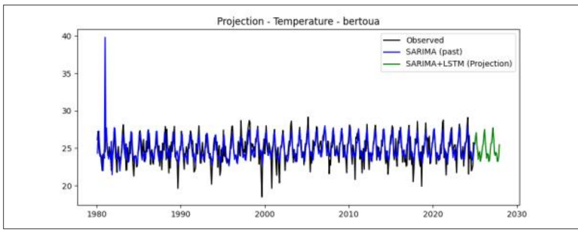


Figure 21: Bertoua Temperature Projection

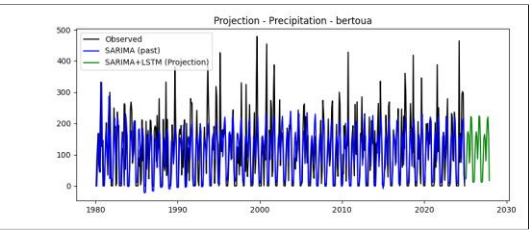


Figure 22: Bertoua Precipitation Projection

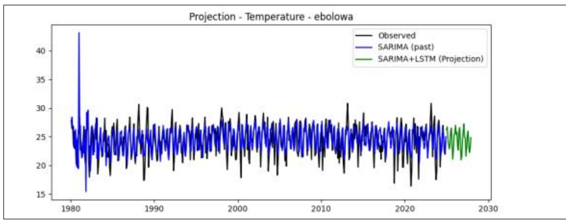


Figure 23: Ebolowa Temperature Projection

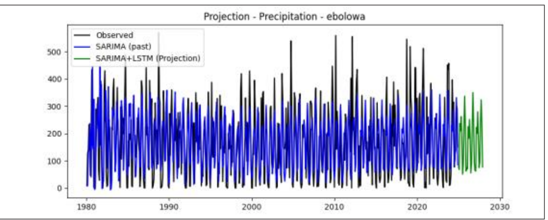


Figure 24: Ebolowa Precipitation Projection

Interpretation of Trends

A trend analysis was conducted using linear regression on the hybrid forecasts.

- In Yaoundé, temperatures show a moderate increase, consistent with the trends observed over the previous decade.
- In Mbalmayo, stability in precipitation is projected, with a marked return to the bimodal regime.
- In Ebolowa, a slight decrease in annual rainfall totals is detected, requiring special attention for agricultural planning.
- In Bertoua, projections indicate a simultaneous increase in temperatures and increased variability in precipitation.

Discussion

The results confirm the robustness of the SARIMA-LSTM-ONACC hybrid approach for climate modeling in the bimodal rainfall agroecological forest zone of Cameroon, characterized by high seasonal and intra-annual variability. The SARIMA model efficiently adjusts seasonal components linked to the double alternation of rainy and dry seasons (short and long). This intra-seasonal variability is analyzed in terms of seasonal rainfall trends. According to current research, the strong seasonal variation is sometimes marked by a displacement of the seasons (dry or rainy), sometimes by a disorder in the quantitative distribution of said rainfall during the seasons [14]. In the same vein, the results of indicate that in 25% of cases over the last seventy years, rainfall has been more abundant during the short rainy season than during the long rainy season [15]. At the same time, in 60% of cases, rainfall was more abundant during the short dry season than during the long dry season. According to, this significant seasonal variation is mainly due to the West African monsoon system, which integrates both internal atmospheric variabilities resulting from atmospheric dynamics and forced variability, governed essentially by the water cycle, surface conditions (continental and oceanic) and atmospheric chemistry [16].

The performance of the SARIMA-LSTM-ONACC model appears to be limited by the irregular interannual variations in rainfall in this part of the country. According to ONACC (2019 and 2020), average annual rainfall is between 1,500 and 2,000 mm in the Central and Eastern regions. The coastal fringe of Kribi in southern Cameroon, on the other hand, records the highest cumulative rainfall, ranging from 2,700 mm to 3,500 mm. This variability is influenced by climatic factors such as Atlantic surface temperature (North and South) and atmospheric currents, which affect geographical regions and seasons in different ways.

In the present study, the integration of an LSTM neural network with the SARIMA model residuals enables us to capture these non-linear dynamics and significantly improve forecast accuracy on different time scales (seasonal and interannual). The average performance gain in RMSE observed in the simulations bears witness to the model's reliability.

Despite the Improvements Achieved, Several Limitations Should be Highlighted:

- The hybrid model is highly dependent on the quality of the input data. Stations with very incomplete or noisy series (e.g. Bertoua) can lead to performance degradation.
- LSTM learning requires relatively long historical records (≥ 30 years) to capture the underlying climate dynamics at different scales.
- The approach remains univariate, separating temperature and precipitation, without taking into account potential interactions between climate variables.
- The evaluation did not include generalization analysis on out-of-sample years or multisite testing.

Les Résultats Obtenus Renforcent Cependant le Potentiel Opérationnel Du Modèle SARIMA-LSTM ONACC Comme Outil de Prévision Climatique Régionale, Appliqué Aux Systèmes D'alerte Précoce et à la Planification Sectorielle, Il Pourrait Permettre :

- Une meilleure anticipation des saisons agricoles critiques (semis, récoltes) ;
- Une gestion plus efficace des ressources en eau (bassin versant, irrigation, prévention des inondations) ;
- Une intégration dans les plans locaux d'adaptation au changement climatique.

However, the Results Obtained Reinforce the Operational Potential of the SARIMA-LSTM ONACC Model as a Regional Climate Forecasting Tool, Applied to Early Warning Systems and Sectoral Planning, it Could Enable:

- Better anticipation of critical agricultural seasons (sowing, harvesting);
- More effective management of water resources (watershed, irrigation, flood prevention);
- Integration into local climate change adaptation plans.

Conclusion

This study demonstrated the relevance of the hybrid SARIMA-LSTM ONACC model for optimizing climate forecasts in the bimodal rainfall humid forest zone of Cameroon, primarily covering the Central, Southern, and Eastern regions. In this strategic agroecological context, characterized by two rainy seasons and two dry seasons, the ability to reliably anticipate climate anomalies is crucial for agriculture, water management, and the resilience of local systems.

By combining the strengths of the SARIMA model (capturing seasonal patterns) and LSTM neural networks (learning nonlinear and residual dynamics), the hybrid approach led to a significant improvement in prediction performance, particularly for precipitation, which is often more unstable. The results from the four analyzed stations (Yaoundé, Mbalmayo, Bertoua, and Ebolowa) confirm the validity of the approach in both spatial and temporal dimensions. This work aligns with the mandate of ONACC to develop decision-making tools tailored to the national context. Ultimately, integrating this type of model into operational forecasting platforms will enhance the anticipation of climate risks, optimize agricultural calendars, and support public adaptation policies. Future research perspectives now focus on enriching models with agro-environmental variables, evaluating under future climate scenarios (RCP/SSP), and generalizing to other agroecological zones of Cameroon.

This study contributes to the operationalization of national early-warning tools and supports Cameroon's climate adaptation framework under ONACC.

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