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Predictive analytics for urban temperature dynamics in Uganda using Smart Models: An ARIMAX-LSTM and damped local trend approaches

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Abstract
Urban temperature dynamics are increasingly critical to sustainable planning amid rapid population growth and climate variability. This project aims to forecast the urban temperature in a few selected Ugandan cities using smart models such as the Damped Local Trend (DLT) model and ARIMAX-LSTM. The model used monthly temperature, precipitation, and relative humidity datasets (2017–2023) from the Uganda National Meteorological Authority and World Bank annual urban population data (1961–2023). The DLT model fitted with the LBFGS algorithm using Orbit performed better and detected temperature trends more slowly, as evidenced by smaller forecast errors (MAE = 3.239, RMSE = 3.270, BIC = 272.682). The ARIMAX-LSTM model well represented nonlinear interactions, with humidity significantly lowering temperature (Coef = -0.0911, $p < 0.001$) but producing higher error metrics (MAE = 4.07, RMSE = 10.33). Forecasts for 2025 revealed that DLT offered more consistent and plausible temperature trajectories, while ARIMAX-LSTM showed irregularities such as an anomalous drop in January (-4.89°C). These findings underscore the relevance of integrating hybrid deep learning with structural Bayesian methods in urban analytics. The study contributes to intelligent computing by offering data-driven insights for climate-resilient urban policy, highlighting the potential of sensor-augmented forecasting systems as a future research frontier.

Keywords: Urban Temperature, ARIMAX, Long Short-Term Memory, Damped Local Trend, Predictive Analytics.

1. Introduction
Urban centers across Africa are increasingly grappling with the compounded challenges of rapid urbanization and climate change, leading to significant alterations in their thermal environments. Selected cities in Uganda exemplifies this trend, experiencing intensified urban heat island (UHI) effects due to unplanned settlements, infrastructural sprawl, and the encroachment of critical ecological buffers such as wetlands (Li et al., 2022). These environmental transformations have far-reaching implications, not only exacerbating heat stress among urban populations but also overburdening public infrastructure and healthcare systems already under pressure from rapid population growth and resource limitations.

Accurate forecasting of urban temperature dynamics is crucial for effective urban planning, public health preparedness, and climate resilience. In Uganda, elevated temperatures have been linked to increased levels of air pollutants, notably $PM_{2.5}$, which consistently surpasses the World Health Organization's recommended thresholds, posing serious respiratory and cardiovascular risks to residents (Alaran et al., 2024). Moreover, climate-induced hazards such as seasonal flooding, prolonged heatwaves, and shifting rainfall patterns have amplified the city's vulnerability to environmental shocks, further highlighting the need for smart and adaptive forecasting tools (Namuleme, 2024).

Intelligent computing offers promising avenues to enhance the accuracy, robustness, and applicability of urban climate forecasts. Recent advances in deep learning have demonstrated the superior performance of Long Short-Term Memory (LSTM) networks in capturing complex, nonlinear, and temporal dependencies in climate-related data streams (Yu et al., 2021). Complementarily, the Damped Local Trend (DLT) model provides a flexible probabilistic framework for incorporating external covariates and quantifying prediction uncertainty, which is particularly valuable for urban applications characterized by noisy and incomplete dataset (De Saa & Ranathunga, 2020). Together, these models reflect the growing convergence of machine learning, statistical inference, and climate science under the umbrella of intelligent systems.

Despite these technological strides, a substantial gap remains in the application of such models to urban environments in Africa, where localized datasets are often sparse, and climatic behaviors exhibit considerable regional variability. Current forecasting tools are largely calibrated to temperate or data-rich contexts, limiting their transferability and relevance for African cities like Kampala. Addressing this methodological and contextual gap is crucial for developing locally adaptive forecasting solutions that can effectively inform climate-sensitive policy, disaster preparedness, and resource allocation (Mbuvha et al., 2024).

This study aims to develop and compare the predictive capabilities of two intelligent forecasting approaches such as ARIMAX-enhanced LSTM and Damped Local Trend (DLT) models using multivariate meteorological data collected in Uganda. By integrating classical time series techniques with deep learning and Bayesian inference, this research seeks to generate high-resolution temperature forecasts tailored to the Kampala metropolitan context. The findings are expected to contribute to the emerging literature on intelligent environmental modeling in Africa and provide actionable insights for urban planners, environmental health professionals, and climate resilience strategists.

1.1 Objectives of the Study

i. To fit a hybrid ARIMAX-LSTM model capable of capturing both linear and nonlinear patterns in Uganda's historical temperature data.

ii. To implement a Damped Local Trend (DLT) model that incorporates external regressors (humidity, rainfall, urban population) indicators to enhance prediction accuracy.

iii. To compare the forecasting performance of ARIMAX-LSTM and DLT models using key evaluation metrics such as RMSE, MAE, and predictive uncertainty intervals.

iv. To analyze the influence of climate-related and urbanization variables on temperature variability in Uganda using intelligent modeling approaches.

v. To provide evidence-based, actionable insights for urban planners and public health policymakers in Uganda through interpretable temperature forecasting outputs.

2. Literature Review

Urban temperature modelling has evolved significantly over the past decade, driven by growing concerns over climate change, urban heat island effects, and their public health impacts. Traditional statistical models like ARIMA have been widely employed in climate and temperature forecasting due to their ability to capture linear patterns in time series data. However, the advent of deep learning techniques such as Long Short-Term Memory (LSTM) networks has enhanced the modelling of nonlinear and complex temporal dependencies in climate data. Similarly, Damped Local Trend (DLT) models have gained traction for their ability to incorporate uncertainty and external repressors in forecasting frameworks. Despite these advancements, most existing studies have focused on regions with readily available climate data, often overlooking cities in East Africa where urbanization is rapid and data infrastructure is limited. This gap has highlighted the need for hybrid models and Bayesian approaches that can better handle data sparsity and capture both linear and nonlinear dynamics for accurate and context-specific climate forecasting (De Saa & Ranathunga, 2020; Mbuvha et al., 2024).

The study by Simwanda et al. (2019) provides a vital contribution to understanding the spatial dynamics of surface urban heat islands (SUHI) across four rapidly urbanizing African cities—Lusaka, Harare, Addis Ababa, and Kigali using remote sensing techniques and Landsat imagery. Their work reveals how unregulated urban expansion intensifies SUHI effects, urging the need for sustainable urban planning. While the study focuses on spatial analysis and offers a snapshot of SUHI intensity and urban morphology, it does not engage in forecasting or predictive modeling of temperature trends. In contrast, the current study employed intelligent time series models to not only analyze but also predict future temperature variations in selected centres in Uganda. It integrates meteorological data and smart computing (e.g., ARIMAX-LSTM, DLT), offering a forward-looking tool for urban planning and public health preparedness. Thus, while Simwanda et al. offer foundational spatial insights into urban heat effects, the present study expands on this by incorporating temporal forecasting and intelligent analytics tailored to East Africa's urban context.

The study by Yu et al. (2021) presents a compelling approach to urban temperature forecasting by integrating Internet of Things (IoT) data with a Long Short-Term Memory (LSTM) neural network to capture localized and temporally complex variations in surface temperatures across New York City. Their model demonstrated superior accuracy in identifying short-term temperature fluctuations, leveraging the granularity and timeliness of IoT sensor data to enhance predictive performance. This methodology exemplifies the potential of deep learning for environmental modelling in data-rich, technologically advanced urban settings. In comparison, the present study extends this line of research into a data-scarce, climatically distinct urban context in East Africa. Unlike Yu et al.'s exclusive reliance on LSTM, the current study combines ARIMAX-LSTM with the DLT model to capture both deterministic and probabilistic patterns in temperature variation, incorporating external variables such as population growth and urban expansion. This hybrid approach not only compensates for data limitations but also accounts for model uncertainty, making it more suitable for selected cities in Uganda where data quality and infrastructure differ significantly from cities like New York. The present study thus adds contextual innovation and methodological robustness to the growing literature on intelligent forecasting in urban climatology.

The study conducted by Biu et al. (2023) applied the Autoregressive Integrated Moving Average with Exogenous Variables model to examine the effect of inflation rate and unemployment rate on poverty level in Nigeria. The authors followed standard time series modelling procedures by first testing the stationarity of the variables using the Kwiatkowski Phillips Schmidt Shin test and then applying differencing where necessary to achieve stationarity. Several ARIMAX model specifications were evaluated, and the ARMAX (2,0) model was identified as the best fitting model for the dataset. The results indicated that inflation and unemployment have significant influence on poverty dynamics, and the model forecasts suggested a decline in poverty levels between 2022 and 2024 followed by a slight increase in 2025. While the study demonstrates the usefulness of ARIMAX in incorporating external economic variables into time series forecasting, it focuses on socio economic indicators rather than environmental variables. In contrast, the present study applies an ARIMAX based hybrid framework combined with LSTM and Damped Local Trend models to examine urban temperature dynamics in Uganda, thereby extending the application of ARIMAX models to climate related forecasting in an urban African context.

The study by De Saa and Ranathunga (2020) offers a foundational comparison between traditional statistical models and modern deep learning techniques in the context of temperature forecasting. Conducted in Szeged, Hungary, their work demonstrated that Long Short-Term Memory (LSTM) networks consistently outperformed the ARIMA model, especially in modeling non-linear temporal patterns. The study emphasized the limitations of ARIMA in handling complex climatic behaviors and highlighted the potential of deep learning models to offer greater predictive accuracy. In contrast, the present study builds upon and extends this analytical direction by not only integrating LSTM with ARIMAX to account for external variables (like urbanization factors and pollutants) but also introducing the DLT model. This inclusion allows for uncertainty quantification and better handling of structural breaks common in African urban climates. Furthermore, by focusing on selected centres in Uganda —a data-scarce and climatically vulnerable African country—the present study addresses regional modeling gaps that De Saa and Ranathunga's work, limited to a European setting, did not consider. Hence, this study contributes both methodological advancement and regional relevance to the field of smart urban climate forecasting.

The study by Li and Qian (2024) introduces a hybrid CNN-LSTM model for temperature prediction in Delhi, effectively leveraging both spatial and temporal data to improve forecast accuracy. By integrating convolutional neural networks (CNNs) with long short-term memory (LSTM) networks, the study captures intricate spatial-temporal dependencies in weather patterns, outperforming traditional statistical methods such as ARIMA. This demonstrates the power of combining deep learning architectures to handle complex, non-linear time series data commonly observed in urban temperature dynamics. Comparatively, the present study adopts a dual-model strategy by combining ARIMAX-LSTM and Damped Local Trend (DLT) models. While both studies prioritize hybrid modeling, the Uganda-focused research further enriches its methodology by integrating Bayesian frameworks that explicitly quantify uncertainty and incorporate external variables such as rainfall, relative humidity and urban population. Unlike Li et al., who focus on data-rich contexts, this present study addresses challenges related to data scarcity and regional specificity in East Africa, thereby contributing to localized and actionable urban climate forecasting.

3. Methods and Materials

3.1 Data Source and Type

Monthly secondary datasets on maximum Temperature (Degrees Celsius), Rainfall (mm), Relative humidity (Mean R.H 12:00) for selected cities (Arua, Entebbe, Gulu, Kampala, Kasese, Lira, Masindi, Jinja, Mbarara, Kabale, Soroti) in Uganda sourced from the Uganda National Meteorological Authority (2017-2025) gathered on monthly basis, and Urban population growth (1961-2025) gathered on annual basis from World Development Indicators (World Bank) websites were used for this study.

3.2 Model Specification and Mathematical Formulation

ARIMAX Model

The AutoRegressive Integrated Moving Average with Exogenous variables (ARIMAX) model is expressed as

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{r} \beta_k X_{t-k} + \varepsilon_t \quad (1)$$

Where, Y_t is the target variable (urban temperature) at time t

ϕ_i is the autoregressive (AR) coefficients

is the moving average (MA) coefficients

β_k is the coefficients of exogenous predictors

X_{t-k} are the exogenous variables (humidity, rainfall, urban population)

ε_t is the white noise error term

p is the number of AR lags

q is the number of MA lags

r is the number of lags of exogenous variables

LSTM Cell Computation – Forget Gate

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (2)$$

Where,

f_t = forget gate activation at time step t, deciding what information to discard from the cell state.

σ = sigmoid activation function, outputting values between 0 and 1 (0: forget completely, 1: keep fully).

W_f = weight matrix for the forget gate.

h_{t-1} = hidden state from the previous time step.

x_t = current input at time step t.

b_f = bias term for the forget gate.

LSTM Cell Computation – Input and Output Gates

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \quad (3)$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \quad (4)$$

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \quad (5)$$

Where,

i_t = input gate activation at time step t, deciding what new information to store.

o_t = output gate activation at time step t, controlling the final hidden state.

$\tilde{C}_t$ = candidate cell state

W_i , W_o W_C = respective weight matrices.

b_i , b_o b_C = respective bias terms.

LSTM Cell State and Hidden State Updates

$$C_t = f_t \Theta C_{t-1} + i_t \Theta \tilde{C}_t \quad (6)$$

$$h_t = o_t \Theta \tanh(C_t) \quad (7)$$

where

h_t = hidden state at time step t, used as output.

C_t = updated cell state

Θ = element-wise multiplication

ARIMAX-LSTM Hybrid Output Layer

To combine both ARIMAX and LSTM outputs in a hybrid fashion, we define the final temperature prediction $\hat{Y}_t$ as:

$$\hat{Y}_t = \lambda_1 \cdot \hat{Y}_t^{ARIMAX} + \lambda_2 \cdot \hat{Y}_t^{LSTM} \quad (8)$$

with $\lambda_1 + \lambda_2 = 1$

where,

$\hat{Y}_t$ = final predicted temperature at time *t*

$\hat{Y}_t^{ARIMAX}$ = output from ARIMAX model

$\hat{Y}_t^{LSTM}$ = output from LSTM model

λ_1, λ_2 = weights (can be learned or empirically defined)

Damped Local Trend (DLT) model

The observation equation models the observed time series y_t as a combination of the level μ_t, seasonality s_t, regression components r_t, and noise ε_t:

$$y_t = \mu_t + s_t + r_t + \varepsilon_t \quad (9)$$

Where,

y_t = observed value at time *t* (urban temperature)

μ_t = Level component at time *t*

s_t = Seasonal component at time *t*

r_t = Regression component at time *t*

ε_t = Noise term, typically modelled as a student's t-distribution

The level l_t and trend b_t are updated over time to capture the underlying dynamics:

$$l_t = p_l(y_t - g_t - s_t - r_t) + (1 - p_l)(l_{t-1} + \theta b_{t-1}) \quad (10)$$

$$b_t = p_b(l_t - l_{t-1}) + (1 - p_b)\theta b_{t-1} \quad (11)$$

where

l_t = Level at time *t*

b_t = Trend (slope) at time *t*

g_t = Deterministic global trend at time *t*, which can be specified as 'linear', 'loglinear', 'flat', or 'logistic'

θ = Damping parameter that controls the persistence of the trend

p_l , p_b = Smoothing parameters for level and trend

The seasonality s_t and regression components r_t are modelled as follows:

$$s_{t+m} = p_s(y_t - l_t - r_t) + (1 - p_s)s_t \quad (12)$$

$$r_t = \sum_j \beta_j x_{jk} \quad (13)$$

where

s_{t+m} = Seasonal component at time *t* + *m*

r_t = Regression component at time *t*

x_{jk} = Value of the *j-th* regressor at time *t*

β_j = Coefficient for the *j-th* regressor

p_s = Smoothing parameter for seasonality

Root Mean Square Error (RMSE)

RMSE is a widely used metric for evaluating the accuracy of a model's predictions. It gives an idea of the magnitude of the prediction errors and is sensitive to large errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \quad (14)$$

Where,

Y_t = Actual observed value at time *t* (e.g., urban temperature)

$\hat{Y}_t$ = Predicted value at time *t* by the model

n = Number of time points (data points)

4. Results and Discussion

4.1 Descriptive Analytics

Table 1: Summary Statistics of the Study Variables

Statistics	Temperature	Rainfall	Humidity	Urban Population
Count	132.0000	132.0000	132.0000	132.0000
Mena	28.7932	103.0136	54.9629	9.2974
Std.	2.0322	68.4763	9.7262	5.8681
Min.	23.8000	0.0000	29.1000	3.4602
25%	27.7750	48.6000	50.5000	5.6842
50%	28.6000	100.7500	56.9000	6.7597
75%	30.1250	154.5000	62.4000	11.1705
Max.	34.2000	337.7000	72.9000	26.7710

Table 1 presents the summary statistics of the key variables in the dataset, showing that the average temperature is approximately 28.79°C, with a standard deviation of 2.03°C, indicating moderate variability across observations. Rainfall and urban population exhibit high dispersion, as reflected by their large standard deviations (68.48 mm and 5.87 million, respectively), with rainfall values ranging from 0.0 mm to 337.7 mm. Humidity levels are fairly consistent, with a median of 56.9% and an interquartile range between 50.5% and 62.4%, suggesting a relatively stable atmospheric moisture condition.

4.2 Data Visualization

Figure 1 shows the monthly trends of temperature, rainfall, humidity, and urban opulation across selected cities in Uganda. While rainfall exhibits high variability and frequent peaks, temperature, humidity, and urban population remain relatively stable over time, indicating consistent climatic and demographic patterns. Figure 2 illustrates the correlation matrix among the study variables, revealing that temperature is moderately negatively correlated with humidity (r = -0.63) and weakly positively correlated with urban population (r = 0.47). Meanwhile, rainfall shows a moderate positive correlation with humidity (r = 0.53) but has negligible correlation with urban population, suggesting different dynamics in how these factors interact with temperature variations.

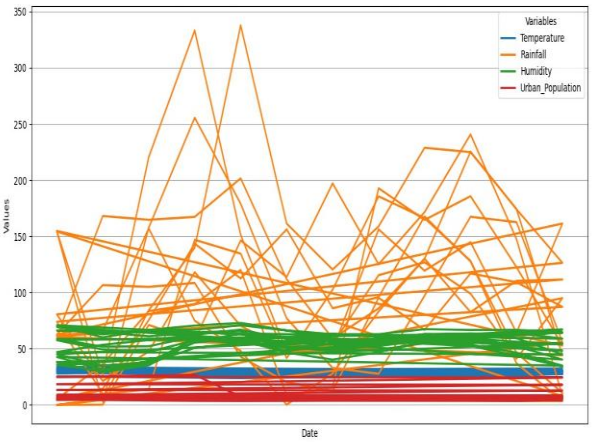

Figure 1: Monthly Trends of the Actual Datasets

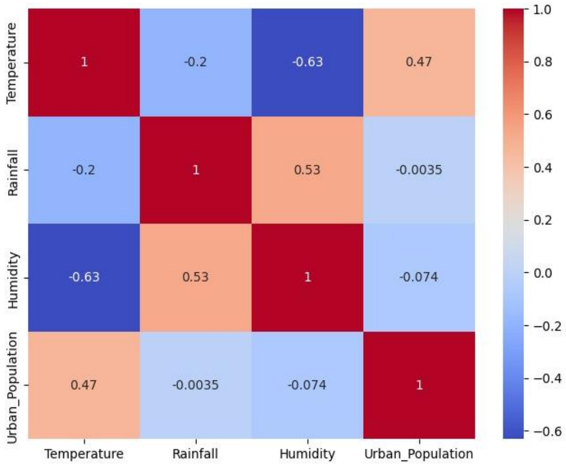

Figure 2: Correlation Matrix Plot

ARIMAX + LSTM Hybrid Model Estimation

Table 2: ARIMAX(5,1,3)-LSTM Model Estimate for Urban Temperature Dynamics

Parameter	Coef	Std. Error	z	P>|z|	[0.025]	[0.975]
Rainfall	0.0003	0.001	0.196	0.845	-0.002	0.003
Humidity	-0.0911	0.009	-9.954	0.000**	-0.109	-0.073
Population	0.0502	0.038	1.335	0.182	-0.023	0.124
ar.L1	-0.2220	6.234	-0.036	0.972	-12.440	11.996
ar.L2	-0.0324	5.899	-0.005	0.996	-11.594	11.529
ar.L3	0.0298	3.914	0.008	0.994	-7.642	7.702
ar.L4	0.0561	1.226	0.046	0.963	-2.347	2.459
ar.L5	-0.0705	0.411	-0.172	0.864	-0.875	0.734
ma.L1	-0.2212	6.270	-0.035	0.972	-12.510	12.068
ma.L2	-0.0878	3.223	-0.027	0.978	-6.404	6.229
ma.L3	0.0680	1.598	0.043	0.966	-3.063	3.199
ar.S.L12	0.5608	0.100	5.607	0.000**	0.365	0.757
sigma2	0.4728	0.072	6.599	0.000**	0.332	0.613
DV:	**Log Likelihood**	**AIC**	**BIC**	**HQIC**	**MAE**	**RMSE**
Temperature	-126.553	279.106	315.234	293.776	4.07	10.33
(L1) (Q)	**(JB)**	**(H)**	**Prob(Q)**	**Prob(JB)**	**Prob(H)**	**Skewness**
0.03	3.70	0.89	0.85	0.16	0.71	0.32
Layer(type)	**Output Shape**	**Param #**	**Total params**	**Trainable params**	**Optimizer params**	**Kurtosis**
lstm_4(LSTM)	(None, 50)	10400	31,355	10,451	20,904	3.58
dense_4(Dense)	(None, 1)	51				

Footnote: *UP = Urban Population, DV = dependent variable, MaxT = Maximum Temperature, H = Heteroskedasticity, JB = Jarque-Bera, L1 = Ljung-Box*

Table 2 presents the ARIMAX(5,1,3)-LSTM model estimates for urban temperature dynamics, indicating that among the exogenous predictors, only *Humidity* has a statistically significant negative impact on temperature (Coef = -0.0911, $p < 0.001$). *Rainfall* and *Population* have positive but statistically insignificant effects on temperature, while most autoregressive (AR) and moving average (MA) components are not significant, except for the seasonal AR term at lag 12 (*ar.S.L12* = 0.5608, $p < 0.001$), suggesting a strong yearly seasonality. The model demonstrates good fit statistics (AIC = 279.106, RMSE = 10.33), with diagnostic tests showing no evidence of autocorrelation (*Prob(Q)* = 0.85), normality of residuals (*Prob(JB)* = 0.71), or heteroskedasticity (*Prob(H)* = 0.32). The LSTM layer adds deep learning strength to the hybrid model with a trainable parameter count of 10,451 and a moderately leptokurtic residual distribution (*Kurtosis* = 3.58), making the model suitable for forecasting urban temperature dynamics.

Damped Local Trend (DLT) Estimate

The Damped Local Trend (DLT) model was fitted using the "LBFGS" optimization algorithm from the Orbit library for the parameters' estimate for analyzing urban temperature dynamics.

Table 3: DLT Model Performance's Summary

Regressor	Regressor_Sign	Coefficient	MAE	RMSE	BIC
Rainfall	Regular	-0.000455	3.239	3.270	272.682
Humidity	Regular	-0.085084			
Population	Regular	0.040965			

Table 3 summarizes the performance of the Damped Local Trend (DLT) model in estimating the effect of key regressors on urban temperature dynamics. Rainfall and humidity both exhibit negative coefficients, indicating an inverse relationship with temperature, while urban population shows a positive association. The model yields a Mean Absolute Error (MAE) of 3.239, Root Mean Square Error (RMSE) of 3.270, and a Bayesian Information Criterion (BIC) value of 272.682, suggesting a relatively good fit with the data.

Figure 3: Plot of the DLT Temperature Forecast

Model Comparison

Table 4: Model Performance's Comparison

Model	MAE	RMSE	BIC
ARIMAX(5,1,3)-LSTM	4.07	10.33	315.234
DLT	**3.239**	**3.270**	**272.682**

Footnote: *LSTM = Long Short-Term Memory, DLT = Damped Local Trend*

Table 4 presents a comparative performance analysis between the ARIMAX(5,1,3)-LSTM and Damped Local Trend (DLT) models for forecasting urban temperature dynamics. The DLT model outperforms the ARIMAX-LSTM model, showing lower Mean Absolute Error (3.239 vs. 4.07), Root Mean Square Error (3.270 vs. 10.33), and Bayesian Information Criterion (272.682 vs. 315.234). These results suggest that the DLT model provides a more accurate and parsimonious fit for the given data.

Forecast

Table 5: Forecasted Urban Temperature of Selected Cities in Uganda

Date	ARIMA-LSTM Forecast	DLT Forecast
Jan-26	-4.8862	26.8608
Feb-26	29.2295	27.9755

Mar-26	29.7914	26.6858
Apr-26	27.9651	25.4502
May-26	28.2705	24.8293
Jun-26	27.6067	24.7658
Jul-26	26.6729	24.0957
Aug-26	26.6564	24.9225
Sep-26	26.6900	24.8379
Oct-26	26.6333	25.4368
Nov-26	27.7277	25.6191
Dec-26	28.5534	26.8538

Table 5 displays the forecasted urban temperature values for Uganda from January to December 2026, comparing outputs from the ARIMA-LSTM and Damped Local Trend (DLT) models. While the DLT model presents a relatively consistent and plausible monthly temperature trend ranging from approximately 24.1°C to 27.98°C, the ARIMA-LSTM model shows an anomalous negative value in January (-4.89°C), suggesting instability or overfitting in extreme conditions. Overall, the DLT forecasts appear more reliable and interpretable for practical use.

Insights

4.3 Value of Hybrid Models (ARIMAX-LSTM): The ARIMAX-LSTM hybrid model combines the strength of linear temporal structures with the nonlinear pattern-recognition ability of deep learning. While the model successfully captures seasonal and dynamic variations in urban temperature across most months, the extreme and unrealistic forecast for January 2026 (-4.89°C) suggests potential overfitting or instability when extrapolating beyond observed values. This highlights that although hybrid models can be powerful for forecasting complex climatic behavior, they require cautious tuning, validation, and interpretability assessment to ensure reliability in policy contexts.

Policy Relevance and Implications of DLT Trend Detection: The Damped Local Trend (DLT) model, implemented via the Bayesian Structural Time Series (BSTS) framework, produced more stable and plausible temperature forecasts, with values ranging between 24.1°C and 27.98°C throughout 2026. This consistent pattern is particularly useful for long-term climate policy planning, as it enables decision-makers to anticipate and mitigate heat-related urban challenges such as energy demand, heat stress, and urban heat islands. The DLT model's transparency and uncertainty quantification make it a valuable tool for environmental monitoring and resilience-building in Uganda's urban centers.

4.4 Limitations and Model Assumptions: Both models are constrained by assumptions inherent in their design. The ARIMAX-LSTM approach assumes that past trends and exogenous variables can sufficiently capture future patterns, which may not hold under climate shocks or policy shifts. The DLT model, while robust, operates under the assumption of gradual trend evolution and may underperform during abrupt structural changes. Additionally, both models depend on the accuracy and completeness of historical data, and missing or biased observations could impact predictive validity. Thus, continuous model validation and the integration of real-time data are essential for improving the accuracy and applicability of forecasts in changing climatic contexts.

5. Conclusion

This study demonstrates the compelling potential of intelligent forecasting models like ARIMAX-LSTM and the Damped Local Trend (DLT) in capturing the nuanced dynamics of urban temperature variations in Uganda. The ARIMAX-LSTM hybrid revealed valuable insights into nonlinear temperature behaviors influenced by exogenous variables, while the DLT model, through its probabilistic structure, offered stable and policy-relevant predictions crucial for climate adaptation planning. Together, these models underscore the growing significance of smart analytics in urban climate surveillance and decision-making, contributing meaningfully to the broader fields of intelligent computing and urban data science. As urban cities face mounting environmental uncertainties, future research should explore the integration of real-time sensor networks, satellite imagery, and edge-AI systems to further enhance the granularity, responsiveness, and ecological intelligence of urban climate modeling frameworks.

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