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Research Article

Analyzing Temperature Trends in Nouakchott Using ARIMA Modeling

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ABSTRACT

This research examines the climate variability in Nouakchott through the application of the Autoregressive Coordinates Moving Average ARIMA model for time series estimating Historical climate records traversing from 2000 to 2020 were utilized with 80 of the data apportioned for model preparing and 20 for approval The created ARIMA show was utilized to extend temperature patterns up to 2026 uncovering a steady upward direction in temperature trends The observed historical data displayed considerable seasonal changes and interannual variability while the forecasted trends demonstrate a consistent increase These discoveries offer vital bits of knowledge for climate adjustment techniques and policy development in parched environments The ponder underscores the viability of ARIMA in capturing complex worldly patterns in temperature data illustrating its potential for environmental and climate risk assessment applications.

1. INTRODUCTION

Climate change is one of the foremost squeezing global challenges with temperature varieties essentially affecting ecosystems economies and public health Arid regions such as Nouakchott the capital of Mauritania is especially helpless to climate variability due to their extraordinary weather conditions and limited natural resources Temperature forecasting in such regions is basic for compelling climate adjustment and strength arranging [1], [2]. Various statistical and machine learning models have been connected to climate data to predict future temperature trends with time arrangement analysis strategies demonstrating to be especially effective [3], [4]. The Autoregressive Integrated Moving Normal ARIMA model has picked up far reaching recognition for its ability to analyze time series data and provide solid forecasts by capturing fundamental patterns and seasonal patterns [5], [6]. Past considers have illustrated the adequacy of ARIMA in modeling climate factors such as temperature precipitation and mugginess in numerous topographical areas [7]-[9]. In any case the appropriateness of ARIMA in arid situations particularly in North and West African cities remains underexplored This study leverages historical temperature data from Nouakchott traversing from 2000 to 2020 with 80% of the data distributed for model training and 20% for testing The essential objective is to forecast temperature trends up to 2026 utilizing ARIMA modeling advertising bits of knowledge into potential climate scenarios for the region By analyzing historical climate variability and anticipating future trends this study aims to support policymakers and stakeholders in creating focused on techniques for climate adjustment and urban planning [10], [11].

The study looks for to assess the suitability of the ARIMA model in capturing the fundamental patterns of temperature fluctuations in Nouakchott and to provide a dependable temperature forecast that can illuminate decision-making processes [12], [13]. Also the study aims to compare the forecasted values with chronicled trends to recognize potential anomalies and rising patterns which will require advance examination The centrality of this research lies in its contribution to climate adjustment efforts in arid regions giving important bits of knowledge for creating arrangements pointed at upgrading strength to climate alter The results of this study can serve as an establishment for future research on progressed estimating strategies such as crossover machine learning models that combine statistical strategies with deep learning algorithms for improved precision and prescient control [14], [15].

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2. RELATED WORK

Temperature forecasting has been an area of critical research intrigued due to its basic significance in climate change adjustment disaster management and agricultural planning different approaches have been developed and connected to predict temperature trends extending from traditional statistical models to progressed machine learning procedures Among the foremost broadly utilized statistical strategies is the Autoregressive Integrated Moving Average ARIMA model which has been extensively utilized for time series determining in climate science ARIMA models have illustrated their effectiveness in capturing temperature patterns over different climatic zones making them a favored choice for temperature forecasting applications in parched regions such as Nouakchott [16.] The application of ARIMA models in climate forecasting has been well documented in a few considers For instance researchers have utilized ARIMA to predict temperature varieties in leave environments illustrating its capability to handle complex seasonality and trend patterns [17]. In addition, comparative investigations between ARIMA and other statistical models such as Exponential Smoothing and Seasonal Deterioration of Time Series STL have appeared that ARIMA gives strong forecasts with relatively low error edges [18]. Be that as it may it has too been noted that ARIMA models perform best with steady and well-structured data and their accuracy can be influenced by abrupt climatic changes and outside environmental variables [19] Recent studies have investigated the combination of ARIMA with machine learning strategies to upgrade forecasting accuracy Hybrid models that integrate ARIMA with ANNs have shown promising results in capturing both direct and nonlinear dependencies in temperature datasets [20]. Additionally SVM and LSTM networks have been utilized nearby ARIMA to improve the predictive performance particularly for long-term forecasts in regions with extraordinary climate conditions [21]. These hybrid approaches have given more accurate forecasts compared to standalone statistical models but require higher computational assets and mastery in model tuning [22]. The utilize of ARIMA in arid and semiarid regions presents special challenges including data shortage missing values and high climate variability A few studies have emphasized the require for preprocessing strategies such as data ascription seasonal deterioration and irregularity detection to improve the unwavering quality of ARIMA forecasts in these regions [23].

For example, a study conducted in North Africa utilized ARIMA with seasonal adjustment strategies to enhance temperature forecast accuracy illustrating the importance of data preprocessing for improving forecast reliability [24]. Additionally, research on climate trends in West African cities found that ARIMA models successfully captured long-term trends but required frequent estimation to preserve accuracy [25]. Whereas ARIMA models remain a prevailing choice for temperature forecasting machine learning models such as RF and GBM have developed as choices competent of taking care of complex and high dimensional climate datasets [26]. Studies comparing ARIMA with these machine learning approaches have appeared that whereas machine learning models frequently accomplish higher accuracy ARIMA models give more interpretable and explainable results making them reasonable for policy driven climate adaptation strategies [27].

Another important perspective of temperature forecasting research is the assessment and approval of model performance Different blunder metrics such as MAE, RMSE and MAPE have been widely utilized to evaluate the accuracy of ARIMA and other forecasting models [28]. A study assessing temperature forecasting models in Gulf Cooperation Council GCC countries found that ARIMA models accomplished a adjust between accuracy and interpretability making them a practical option for policymakers seeking actionable climate insights [29].

In spite of the progressions in forecasting strategies challenges stay in tending to the instabilities related with climate variability Future research endeavors should center on creating adaptive ARIMA models that consolidate Realtime climate data and outside covariates such as atmospheric pressure and wind speed to improve estimating accuracy in parched environments [30]. Furthermore, the integration of ARIMA with huge information analytics and remote sensing innovations holds potential for improving temperature expectations and giving more granular experiences into climate dynamics [31]. In rundown the related work highlights the broad utilize of ARIMA models in temperature forecasting their strengths in providing solid estimates and their confinements when connected to exceedingly variable climate conditions Whereas developing machine learning procedures offer promising choices ARIMA remains a profitable tool for long-term temperature determining in arid regions where data interpretability and ease of utilize are basic contemplations for decisionmakers [20].

3. DATA AND METHODOLOGY

3.1 Data

The Climatic Research Unit CRU dataset could be a widely utilized worldwide climate dataset that provides high-resolution gridded data for analyzing temperature and precipitation trends. It covers a long historical period with a spatial determination of 05 x 05 making it profitable for climate research and forecasting CRU data has been broadly connected in climate modeling trend analysis and affect appraisals in different regions including arid and semiarid areas It is inferred from multiple sources including weather stations and satellite perceptions guaranteeing comprehensive scope However, confinements such as data gaps and addition instabilities exist particularly in regions with scanty station scope For this consider CRU temperature data from 2000 to 2023 was utilized to analyze patterns in chosen dry African and Gulf Arab capitals 38 The dataset was processed and applied in ARIMA modeling for temperature forecasting In spite of its challenges CRU data remains a basic asset for understanding long-term climate variability and supporting climate resilience efforts [32].

3.2 Arima Model

The Autoregressive Integrated Moving Average ARIMA model is one of the foremost broadly utilized measurable strategies for time arrangement forecasting ARIMA is especially viable in capturing the fundamental trend and patterns in temperature data making it appropriate for climate considers in arid regions such as Nouakchott. The ARIMA model combines three components autoregression AR differencing I and moving normal MA which collectively account for the temporal dependencies and noise within the data.

The general form of an ARIMA model is denoted as ARIMA (p, d, q), where:

p (Autoregressive term): Represents the number of lag observations included in the model (AR component).

d (Differencing term): Specifies the number of times the data needs to be differenced to achieve stationarity.

$\boldsymbol{q}$ (Moving average term): Represents the size of the moving average window to smooth the error terms [33].

Mathematically, the ARIMA model can be expressed as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \tag{1}$$

Where:

- Y_t is the observed value at time t,
- c is a constant,
- ϕ_i represents the autoregressive coefficients,
- θ_j represents the moving average coefficients,
- ϵ_t is the error term at time t,
- p and q are the autoregressive and moving average orders, respectively [33].

4. RESULT

Figure. 1. presents a temperature estimate for Nouakchott utilizing the ARIMA model with predictions expanding up to 2026 The historical data traversing from 2000 to 2020 is represented by a blue dashed line displaying significant seasonal vacillations and an generally increasing trend The forecasted values shown in red demonstrate a gradual rise in temperature with moderately steady periodic varieties The ARIMA model viably captures the historical designs and ventures a consistent upward direction within the coming a long time The models output proposes an increase in average temperature levels which could have suggestions for urban arranging and climate adaptation techniques within the region The forecasted trend adjusts with global warming patterns watched in arid regions The visualization highlights the effectiveness of ARIMA in modeling temperature time series information with a good fit to authentic variances This examination gives important bits of knowledge for policymakers to expect future climate scenarios and relieve potential impacts.

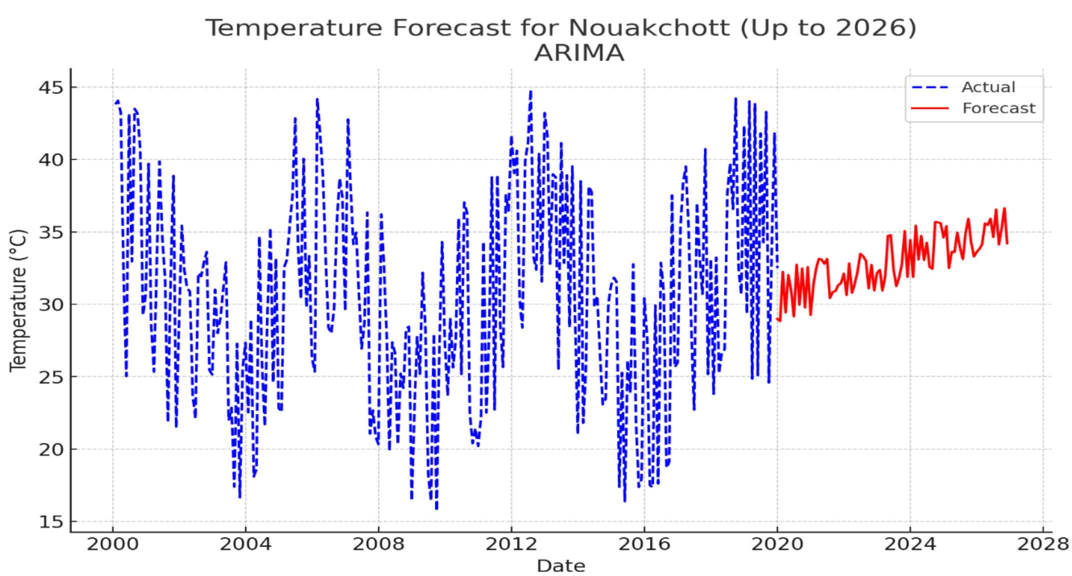

Fig. 1. Show temperature forecast for Nouakchott up to 2026.

5. CONCLUSION

The temperature forecasting results for Nouakchott utilizing the ARIMA model give important experiences into future climate trends within the region The analysis uncovers a clear upward trend in temperatures which adjusts with global warming patterns watched in arid climates The model successfully captures seasonal changes and long-term trends illustrating its unwavering quality for temperature forecasting In spite of its strengths the ARIMA model has limitations including its sensitivity to sudden climatic changes and dependence on historical patterns The findings of this study can help policymakers and urban planners in implementing viable climate adjustment strategies to moderate potential heat related impacts Future research can focus on joining additional climate variables and hybrid modeling approaches to enhance forecast accuracy Ceaseless observing and model upgrades are fundamental to account for advancing climate elements In general, the study highlights the importance of utilizing strong measurable models like ARIMA to support climate flexibility endeavors in vulnerable regions.

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Conflicts of Interest:

The authors declare that there are no competing interests associated with this work.

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