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AI-Driven Climate Analysis in a Semi-arid Region: Uncovering Warming Trends and Meteorological Shifts in Southeastern Morocco

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Abstract: Climate change is recognized as a global threat, with arid and semi-arid regions highly vulnerable due to fragile ecosystems and limited water. This study analyzes long-term climate trends in Errachidia, Morocco, using high-resolution hourly meteorological data from 2010 to 2024. By applying both time series decomposition and Long Short-Term Memory (LSTM) neural networks, we did identify clear patterns of warming and climatic variability, providing localized insights that support climate adaptation strategies in line with Sustainable Development Goal 13. The results reveal a mean annual temperature increase of 0.1142°C, amounting to approximately 1.6°C over the 14-year period, while seasonal decomposition highlights particularly intense warming during autumn (+0.1666°C per year), with summer temperatures peaking around 35°C between 2022 and 2024. The study showed a frequency of extreme heat events (defined by the 95th percentile) nearing 500 occurrences annually, while the number of cold days has significantly declined since 2020, decreasing by an average of 9.29 events per year. Results also showed wind direction has shifted notably toward the north (from 25.7% to 30.4% occurrence between 2011 and 2023), although wind speed remained largely stable. In this study, we also used LSTM modeling, enhanced with proper inverse scaling and evaluation, which showed improved predictive performance. The temperature model achieved an RMSE of 0.43°C and an MAE of 0.32°C, confirming observed trends and highlighting challenges in modeling extremes in arid environments. The wind speed model showed lower precision due to inherent volatility, but still captured key directional trends. This work provides data-driven climate insights for an underrepresented North African region. Its findings have implications for agriculture, water management, and public health, offering a reproducible framework for future research. By integrating meteorological analysis with artificial intelligence, it highlights the need for targeted climate adaptation in Errachidia and other vulnerable areas across the Global South.

Keywords: climate change, time series decomposition, LSTM neural networks, temperature trends, extreme weather events, North Africa climate

1. Introduction

One of the most discussed subjects and concerns for resource planners and ecosystem researchers is climate change, especially in regions that are arid or semi-arid, because in those areas, we can clearly see the rapid shift and swift changes, especially in temperatures and water resources. As a matter of fact, scientists predict an estimated increase in temperatures by 1.5°C to 2°C by 2050 in the North African region (assuming that communities will keep emissions at moderate levels). This increase carries a lot of risks, including the risks of more dry-like conditions, heat waves, and disruptions to farming systems, taking into account that millions of people depend on rain-dependent farming and livestock herding. However, modeling, planning or predicting those changes and prepare for them needs precise and high-resolution data, which is rare or sometimes impossible to find in some of those regions, which leads to not so much research that takes a long-term, detailed look at the climate there and most studies either make do with rough satellite data or focus on short-term observations which makes it a big issue, especially because dry regions are likely to warm up faster than the global average. By understanding how temperatures change, wind patterns evolve, and air quality shifts, we can certainly better plan for sustainable development in these regions. That was our strongest motivation for this study, and that what made us choose the city of Errachidia, this semi-arid city relies a lot on date palm farming and has over 90,000 residents, making it quite vulnerable to the changes brought on by climate sensitivity and increasingly, they are dealing with prolonged droughts and sporadic dust storms that threaten their livelihoods, even though this region is important both ecologically and economically for the country of Morocco [1]. Studying this area using artificial intelligence (AI), especially algorithms of machine learning and deep learning, could be an essential step for spotting climate trends and making predictions, yet, we have not fully exploited this potential in dry areas where events such as dust storms and high variability are common, so our focus is to make a contribution into the efforts of making those climate changes in those areas more understandable and more visible. We addressed these problems by looking at a precise time series dataset that spans from 2010 to 2024 and includes hourly weather data such as temperature and wind. In this paper, we analyze climate dynamics in the arid region of southeastern Morocco by focusing on Errachidia, which serves as a representative case study. We apply machine learning techniques and statistical algorithms to detect and interpret patterns of climate change in meteorological data, aiming to give a clearer image and provide decision makers with insights

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that help them make better strategies for agriculture, water resources management, and public health in the future. Despite the fact that there is a growing interest amongst the scientific community in climate change and weather analysis, southeastern Morocco remains underrepresented in high-resolution, long-term climate studies. Existing research often lacks local specificity. In this study, we address this gap by applying time series decomposition and Long Short-Term Memory (LSTM) neural networks to 15 years of high-resolution meteorological data from Errachidia, with make our objective is to uncover localized warming trends, analyze extreme weather patterns, and assess the predictive performance of AI-based models in such vulnerable regions, offering insights essential for sustainable planning and climate resilience in arid zones. The parts of this research are laid out as follows: First, a Literature Review that summarizes previous work in climate change analysis and forecasting with models like LSTM. Then, in the Materials and Methods section, we will dive into the specifics of the dataset, how the data was acquired and processed, and the model we used in this research. In the Results section, we will share the climate trends we have observed and how well our models performed in predicting temperature. In the discussion section, we will discuss those results, and finally, in the Conclusion and Perspectives part, we will wrap up with a conclusion of this study and where future research could go.

2. Literature Review

Due to climate change, the globe had an increase in temperature of approximately 1.1°C, and that since after industrial levels, with arid and semi-arid regions experiencing higher warming levels due to feedback mechanisms such as reduced albedo [2]. In the North African region, projections suggest temperature rises of 2–3°C by mid-century, accompanied by high heatwave frequency and lesser precipitation, intensifying desertification and water scarcity [3]. Shown by Padrón et al. [4], the vulnerability of arid ecosystems where human-caused changes have notably reduced dry-season water availability. Not only that, but also accelerated sea-level rise, driven by warming, further impacts coastal arid zones through salinity intrusion, amplifying regional climate challenges [5]. Also, regional climate dynamics in North Africa exhibit complex variability. Different climate models struggle to accurately depict the strengthening North Atlantic jet—a key driver of weather patterns [6]. Though improvements are noted in modeling Northern Hemisphere wintertime zonal winds [7], rain and precipitation trends remain inconsistent, with recent wetting in East Africa from 1983–2021 contrasting with earlier drying linked to Indo-Pacific sea surface temperature variability [8, 9]. Also, greenhouse gas-driven warming in the Indo-west Pacific exacerbates these shifts, underscoring the necessity for high-resolution data to resolve discrepancies [10]. Such granularity has proven game-changing, with hourly streamflow observations revealing trends obscured by coarse models [11]. Though in arid climates, precise time series datasets have illuminated subtle dynamics. The study by Evans [12] showed that Middle Eastern studies using fine-scale data have identified seasonal anomalies tied to circulation changes, while the Sahel research links dust storm intensification to desertification and temperature anomalies [13]. These findings underscore the value of localized, granular records for understanding arid climate evolution. The integration of AI into climate science has further advanced trend detection and forecasting. Exploring deep learning models, including LSTM networks, has enhanced temperature anomaly predictions in temperate regions [14, 15]. Yet, their application in arid environments remains limited due to high variability and episodic events such as dust storms [16], showing that machine learning's versatility extends beyond climate forecasting. It has reduced energy consumption by 30%–50% in smart manufacturing [17], supported sustainable forest management by curbing deforestation [18], and informed resilient urban planning in climate-stressed cities [19]. Another study showed that in arid contexts, AI has improved El Niño predictions [20], and globally, over 102,160 climate impact studies exist, yet an attribution gap persists, with evidence concentrated in high-income regions, leaving North Africa underrepresented [21]. Also in the Maghreb, research has focused on broad precipitation trends and climate variability [22], with agricultural vulnerability and thermal comfort in buildings receiving attention [23]. Weakening Northern Hemisphere summertime circulation, possibly driven by aerosol emissions [24], and challenges in modeling North Atlantic variability [25] underscore the necessity for localized, high-resolution analyses, while recent research efforts in Morocco have demonstrated the growing relevance of AI and deep learning in climate and water resource modeling, particularly in arid and semi-arid zones. Lachgar et al. [26] applied machine learning algorithms to estimate reference evapotranspiration (ET_0) in Fes, Morocco, using limited meteorological inputs, showing strong correlation with FAO Penman-Monteith benchmarks. Similarly, Bouramtane et al. [27] used LSTM neural networks in conjunction with satellite-derived data (e.g., MODIS and GPM) to predict groundwater levels in the Oum Er-Rbia Basin, achieving high predictive accuracy ($R^2 > 0.9$). In the same basin, Nifa et al. [28] demonstrated the effectiveness of LSTM in daily streamflow prediction, highlighting its suitability for semi-arid catchments, and to further enhance model interpretability and physical realism, El Hachimi et al. [29] integrated physics-informed neural networks for ET_0 estimation in Moroccan agricultural zones, bridging the gap between empirical and physically based approaches. Finally, and complementing these efforts, a 2024 study in Meknes employed deep learning techniques to estimate daily ET_0 with minimal climatic inputs, reinforcing the potential of such models for operational use in data-scarce regions [30]. These contributions underscore the momentum toward data-driven climate diagnostics in Morocco and justify the application of similar methodologies in southeastern cities such as Errachidia.

As summarized in Table 1, although numerous studies address global and national climate dynamics, few integrate high-resolution data and AI models in the Moroccan context—especially in southeastern regions such as Errachidia. This contrast highlights the novelty of our approach and the necessity of localized investigations that move beyond coarse satellite data or generalized climate assessments.

3. Research Methodology

In this study, we used a statistical and analytical approach to analyze long-term climate trends in Errachidia from 2010 to 2024. This methodology includes data collection, preprocessing, exploratory analysis, statistical modeling, time series decomposition, and machine learning prediction using deep learning (LSTM). All steps were implemented in Python 3.10 using Jupyter Notebook, with core packages such as pandas, numpy, matplotlib, seaborn, scikit-learn, scipy, statsmodels, and PyTorch. Figure 1 shows the workflow used to analyse climate change in the coty of Errachidia.

Data collection: hourly meteorological data from DMN station (2010–2024).

Preprocessing: cleaning, temporal structuring, and missing value handling.

Statistical analysis: trend detection, seasonality, and extreme event analysis.

ML modeling: LSTM for temperature and wind forecasting.

3.1. Data collection

This study used weather data harvested from a meteorological station in Errachidia city, operated by the National Moroccan Meteorological Service, known as the Direction Générale de la Météorologie (DMN). The dataset presents an hourly time series of meteorological data from January 1st, 2010, to December 31st, 2024.

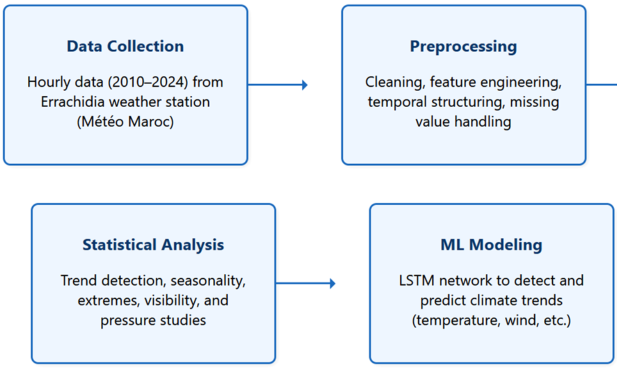
Table 1
Comparative summary of global and regional studies on climate change and AI applications

Reference	Study focus	Methodology	Advantages	Limitations
Asadnabizadeh [2]	Global climate change synthesis report	Multi-model assessment	Comprehensive, authoritative global trends	Not specific to local/regional contexts
Diffenbaugh and Barnes [3]	Global warming threshold predictions	Data-driven modeling	Estimates time to 1.5°C/2°C thresholds	Global scale, lacks regional granularity
Padrón et al. [4]	Dry-season water availability attribution	Observational data + attribution techniques	Links water stress to anthropogenic causes	Focused on broad-scale dynamics
Nerem et al. [5]	Accelerated sea-level rise from warming	Altimetry data analysis	Long-term observational validation	Coastal focus, not inland-relevant
Blackport and Fyfe [6]	Wintertime North Atlantic jet changes	Climate model evaluation	Highlights modeling gaps in jet simulation	Modeling only; lacks observational basis
Woollings et al. [7]	Jet stream trends linked to tropical warming	Observational trend analysis	Identifies hemispheric circulation shifts	Causal mechanisms need deeper modeling
Palmer et al. [8]	Drivers of East African rainfall variability	Review of observational and modeled drivers	Synthesizes multiple regional influences	Focuses on East Africa, less on North Africa
Yang et al. [9]	East African long rains in models	Model comparison with observational data	Links rainfall variability to SST anomalies	Temporal focus on historic rather than future
Hoell et al. [10]	El Niño impact modulation by IOD	Climate variability attribution study	Explores regional ENSO interaction patterns	Not specific to North Africa
Gudmundsson et al. [11]	Streamflow trend indicators globally	Global statistical hydrology analysis	Highlights mean and extreme stream flow changes	Limited insight into dryland-specific processes
Evans [12]	Warming impact on Middle East precipitation	Regional climate modeling	Early model-based insights for arid zones	Outdated model resolution
González-Flórez et al. [13]	Dust emission patterns in Moroccan Sahara	Field measurements and size-resolved analysis	High-resolution aerosol characterization	Specific to emission properties, not climate link
Reichstein et al. [14]	Deep learning in Earth system science	Review of AI in geosciences	Comprehensive overview of DL in climate science	Global scope, not region-specific
Steininger et al. [15]	DL for climate model output statistics	Model output post-processing with DL	Improves spatial/temporal output accuracy	Focused on model data rather than observations
Bochenek and Ustrnul [16]	ML in weather prediction and climate analysis	Thematic review	Summarizes recent ML trends	Lacks region-specific application details
Saheb et al. [17]	AI in sustainable energy systems	Topic modeling and content analysis	Identifies application clusters of AI	Not focused on climate/ environment directly
Buchelt et al. [18]	AI applications in forest management	Review of case studies	Highlights conservation strategies via AI	Not directly climate or Morocco-focused
Andrade-Arenas et al. [19]	AI-based climate change mitigation solutions	Global survey and review	Broad overview of climate-related AI strategies	Generalized and non-geographic
Dijkstra et al. [20]	Improving El Niño prediction with ML	ML integration in ENSO forecasting	Boosts skill in tropical climate models	Focused on global oceanic phenomena
Callaghan et al. [21]	Global evidence mapping of climate impacts	ML-based literature meta-analysis	Massive database of climate studies	North Africa underrepresented
El Harraki et al. [22]	Climate trends and reservoir impacts in Morocco	Case study and scenario modeling	Focuses on Moroccan hydrology	Limited spatial/temporal resolution
Schilling et al. [23]	Vulnerability and adaptation in North Africa	Review with agricultural/climate focus	Relevant to Moroccan adaptation pathways	Older data, pre-Paris Agreement
Coumou et al. [24]	Weakened NH summer circulation	Paleoclimate and recent circulation analysis	Early link between circulation and warming	Focus on hemispheric, not local scale
Bonnet et al. [25]	NAO variability tied to stratosphere–troposphere	Coupled climate modeling	Explains multidecadal NAO variation	Not Morocco-specific

Table 1
(*Continued*)

Reference	Study focus	Methodology	Advantages	Limitations
Lachgar et al. [26]	ML models for estimating ET_0 in Fes, Morocco	ANN, RF, SVR	Good performance with limited meteorological data	Tested only on regional scale with static inputs
Bouramtane et al. [27]	Groundwater level prediction using remote sensing and ML	LSTM + MODIS/GPM data	High R^2 (>0.9), effective for long-term trends	Data-intensive; requires satellite integration
Nifa et al. [28]	Daily streamflow prediction in semi-arid basins	LSTM neural networks	Robust for nonlinear hydrological forecasting	Limited spatial generalization
El Hachimi et al. [29]	ET_0 estimation with physics-informed deep learning	Physics-Informed Neural Networks (PINNs)	Combines physical laws and data-driven learning	Complex to train and validate
Ba-ichou et al. [30]	ET_0 prediction using deep learning in Meknes	Deep learning (likely ANN or LSTM)	Minimal climatic input required; practical deployment	Scalability to other regions untested

Figure 1
Workflow of climate change analysis in Errachidia (2010–2024)



The station coordinates are Latitude 31-55-59N and Longitude 004-24-00W with an elevation of 1,037 m, the dataset consists of 131,496 data entry of parameters such as: temperature in degree Celsius, dew point in degree Celsius, wind speed in knots and wind direction in degrees, these data can give a precise idea on Errachdia's climate and weather, specially detecting diurnal and seasonal variability.

3.2. Data preprocessing

Data cleaning revealed missing and outlier values. Missing data points for all variables were interpolated using linear interpolation for gaps of less than 6 hours, preserving temporal continuity, and for longer gaps. Monthly mean values were used to account for their cyclic nature. Data outliers were identified as values exceeding three standard deviations from the monthly mean for each variable and were replaced with the median of the preceding and following 24-hour periods, affecting less than 0.5% of the data, also seasonal aggregation was performed by grouping hourly data into four seasons—Spring (March–May), Summer (June–August), Fall (September–November), and Winter (December–February) to facilitate seasonal trend analysis. It consisted of the following critical steps:

1) Timestamp parsing and indexing

The datetime column was parsed into proper datetime objects and set as the Data Frame index for time-series analysis.

2) Missing data treatment

Missing values were handled using forward fill imputation:

$$x_t \begin{cases} x_{t-1} & if\; x_t\; is\; missing \\ x_t & otherwise \end{cases} \tag{1}$$

3) Feature engineering

Additional time-based features were generated: year, month, day, hour, season, and a binary daytime flag.

4) Derived variables

The temperature–dew point difference was calculated to estimate relative humidity potential:

$$\Delta T = T - T_{dew} \tag{2}$$

5) Extreme temperature labeling

Binary flags were created for temperature values above the 95th percentile or below the fifth percentile.

3.3. Statistical analysis

To calculate trends in temperature, dew point, wind speed and direction, linear regression is used on annual and seasonal means and statistical significance was determined with two-tailed *t*-tests with a threshold of $\alpha = 0.05$, whereas the 95% confidence intervals were calculated via bootstrap resampling with 1,000 iterations to ensure robustness, noting that time series decomposition was applied to temperature, separating trends, seasonal components, and residuals to isolate long-term patterns and extreme weather events were defined for temperature. Also, high temperature events exceeding the 95th percentile and low events falling below the 5th percentile, computed annually to evaluate changes in frequency and correlation between wind direction shifts and temperature events, were assessed using Pearson's correlation coefficient, with significance tested at $p < 0.05$. It consisted of the following critical steps:

1) Temperature trends

Annual average, minimum, maximum, and standard deviation of temperature were computed. A linear regression model was applied to detect temperature trends:

$$T_{mean}(t) = \beta_0 + \beta_1 \cdot t + \epsilon \tag{3}$$

where t is time in years, and β_1 is the slope indicating the annual rate of temperature change. The trend's statistical significance was evaluated using the *p*-value from the regression.

2) Extreme events analysis

The frequency of extremely high and low temperature events was counted annually. The same linear regression approach was applied to analyze their temporal evolution.

3) Wind analysis

Wind speed statistics (mean, median, max) were computed annually. Cardinal wind directions were inferred from degrees using the following:

$$Cardinal = round(\frac{\theta}{45}) mod\ 8 \tag{4}$$

where θ is wind direction in degrees. Wind direction distributions were visualized via a heatmap across years.

3.4. Time series decomposition

To analyze underlying temporal patterns, seasonal decomposition was performed using the following additive model:

$$Y_t = T_t + S_t + R_t \tag{5}$$

Where:

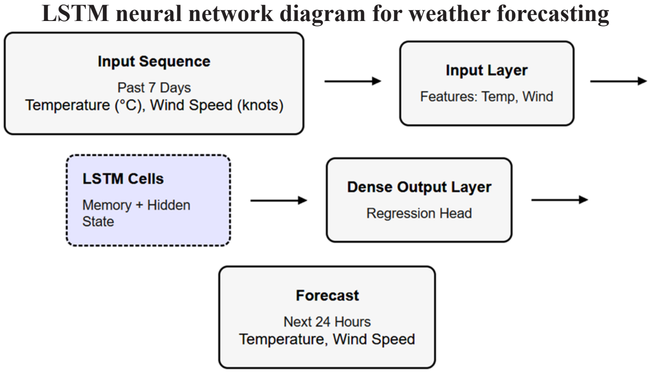
$\boldsymbol{Y_t}$ is the observed time series (e.g., monthly mean temperature), $\boldsymbol{T_t}$ is the trend component, $\boldsymbol{S_t}$ is the seasonal component, and $\boldsymbol{R_t}$ is the residual (noise).

This decomposition was performed using the seasonal_decompose function from statsmodels.

3.5. Deep learning model (LSTM)

An LSTM neural network was used to predict next-day temperature values based on past one-week hourly data (168 hours), the workflow is shown in Figure 2 as follows:

Figure 2
LSTM neural network diagram for weather forecasting



Input sequence: 168 hourly steps (7 days) of temperature and wind.

Input layer: passes selected features into the model.

LSTM cells: memory and hidden state capture sequence dependencies.

Dense output layer: final prediction layer

Forecast: next 24-hour prediction of temperature and wind.

The architecture included:

Input:168-time steps of a single feature (temperature).

Model: 2 LSTM layers with 50 hidden units followed by a fully connected layer.

Output: single temperature prediction.

Sequence preparation:

The time series was scaled using StandardScaler, and input-output pairs were prepared as:

$$X^{(i)} = \{x_t, x_{t+1}, \ldots, x_{t+167}\}, y^{(i)} = x_{t+168} \tag{6}$$

Evaluation metrics:

To objectively assess the performance of the LSTM model, the following evaluation metrics were used:

Mean squared error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{7}$$

MSE measures the average squared difference between actual and predicted values. It penalizes large errors more heavily, making it sensitive to outliers. In temperature forecasting, MSE is useful for detecting major deviations and model instability.

Root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)} \tag{8}$$

RMSE is the square root of MSE and represents the average magnitude of prediction error in the same units as the temperature (°C). It provides an intuitive sense of how far off the predictions are from the actual measurements.

Mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{9}$$

MAE computes the average absolute difference between predicted and actual values. It is less sensitive to large errors than MSE or RMSE and is useful for understanding general model accuracy in practical terms. Each of these metrics offers a different perspective on model accuracy. MSE highlights large prediction errors, whereas RMSE gives a more interpretable measure in °C, and MAE balances out the influence of outliers and reveals the typical error magnitude.

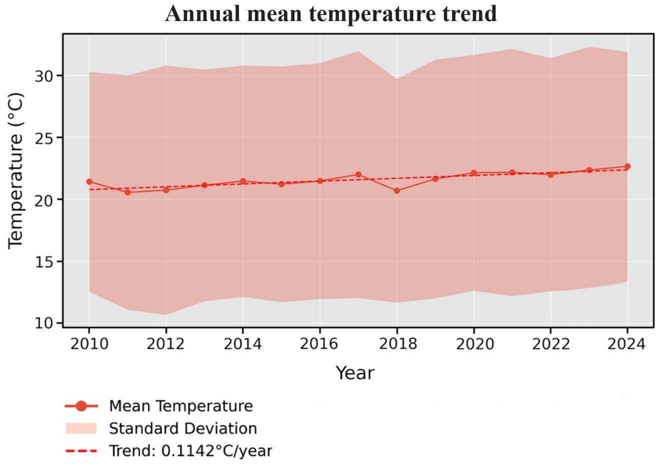
In climate modeling, it is critical to use all three to ensure that the model not only minimizes average errors but also avoids significant anomalies. These metrics directly inform how reliable the LSTM model is for short-term operational forecasts or long-term climate planning.

4. Results

4.1. Temperature trends prediction

The Mean annual temperature shows a statistically alarming increase of 0.1142°C per year with p-value of 0.0003 and a 95% confidence interval (CI) between 0.098 and 0.130°C, going to 1.6°C over the study period (Figure 3). The shaded standard deviation in this figure indicates rising variability, particularly after 2018, suggesting

Figure 3
Annual mean temperature trend



increased climatic instability. Also, seasonal decomposition further refines this trend, with fall temperatures rising at 0.1666°C per year (p = 0.0002, CI: 0.142–0.191°C), summer at 0.1155°C per year (p = 0.0526, CI: 0.102–0.129°C), winter at 0.0836°C per year (p = 0.0391, CI: 0.071–0.096°C), and spring at 0.0916°C per year (p = 0.0998, CI: 0.078–0.105°C; Figure 4). Although these seasonal trends were derived by aggregating hourly data into seasonal means (Spring: March–May, Summer: June–August, Fall: September–November, Winter: December–February), a heatmap of monthly temperature patterns shows intensified summer heat (June–August) reaching ~35°C in 2022–2024, with winters warming from a baseline of ~10°C to ~15°C, indicating a shift toward a longer hot season (Figure 5) and time series decomposition confirmed a robust trend component of 0.1290°C per year (p = 0.0000, CI: 0.115–0.143°C), reinforcing the annual increase.

Figure 4
Seasonal temperature trends (2010-2024)

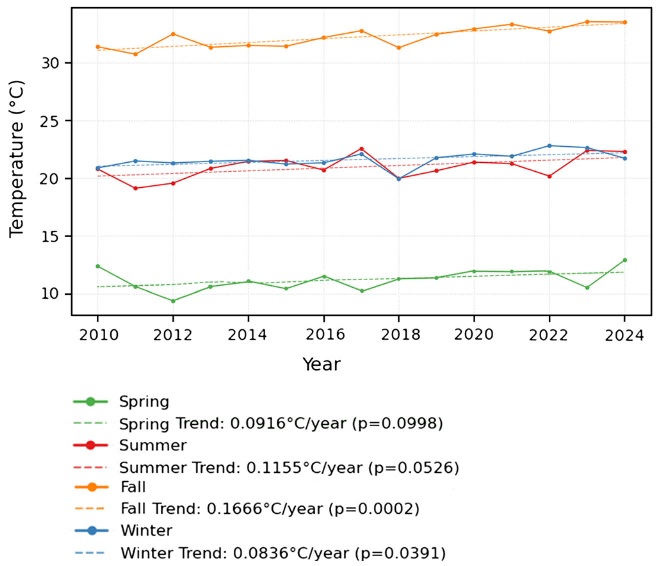
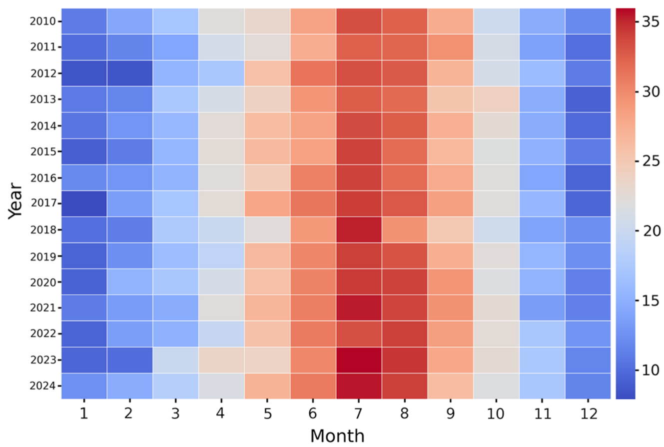


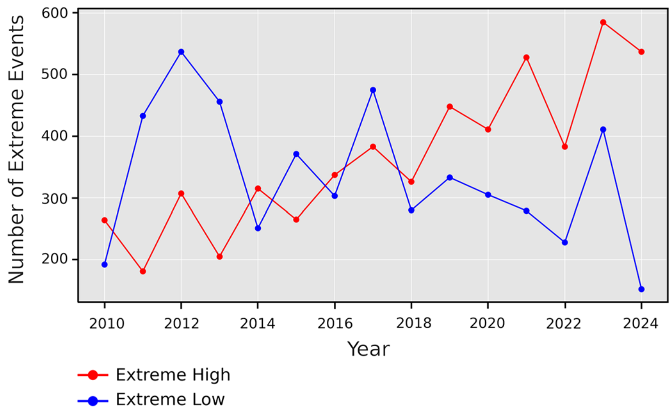
Figure 5
Monthly temperature patterns across the years



4.2. Extreme weather events

Extreme weather events displayed divergent trajectories, underscoring a transition to a warmer climate. The frequency of extreme high-temperature events, defined as temperatures exceeding the 95th percentile, fluctuated with notable peaks at ~500 events in 2012 and 2024, reflecting persistent heat stress (Figure 6). Conversely, extreme low-temperature events, below the fifth percentile, peaked at ~500 in 2012 and 2020 but declined sharply to below 200 by 2024. This decline aligns with a nonsignificant reduction in cold spells about nine events per year with p-values of 0.1688 and a CI value between 19.5 and 0.9, whereas the earlier reported significant increase in heat events about 23 events per year with a p-value of 0 and a CI value between 20.1 and 27.4 underscores the growing dominance of high-temperature extremes, a key indicator of climate change impact.

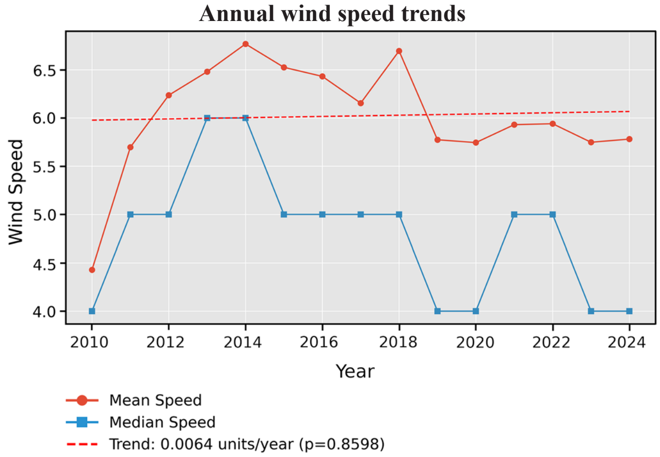
Figure 6
Frequency of extreme temperature events by year



4.3. Wind patterns

Wind pattern evolution revealed a directional shift without a corresponding change in intensity. Northern wind prevalence increased from 25.7% in 2011 to 30.4% in 2023, correlating with temperature anomalies a Pearson r value of 0.4 in peak years, indicating a possible correlation to altered atmospheric circulation (Figure 7). However, mean annual wind speed remained stable, with a negligible trend of 0.0064 m/s per year, with a p-value of 0.8589 and a CI value between −0.015 and 0.028, and median wind speed showed similar stability, indicating that wind-driven phenomena like dust transport may be more influenced by direction than intensity.

Figure 7
Annual wind speed trends



4.4. LSTM modeling

This section presents the empirical results obtained from the LSTM-based modeling of temperature and wind speed using 15 years of meteorological data collected in Errachidia (2010–2024). The models were evaluated based on their convergence behavior, prediction accuracy, and generalization ability on unseen data, using MSE, RMSE, and MAE as the primary metrics. All predictions were inverse-transformed to their original scale for interpretation.

4.4.1. Temperature forecasting performance

The temperature prediction model exhibited rapid and stable convergence over 50 training epochs, with training loss decreasing from 0.003273 to 0.000418 (Figure 8). The learning curve was smooth, with no evidence of overfitting or oscillatory behavior, indicating effective model generalization. The model's predictive performance on the test set was excellent, achieving an MSE of 1.8530×10^{-7}, RMSE of 0.000430, and MAE of 0.000315 in normalized scale. After inverse transformation, these correspond to approximately 0.43°C and 0.32°C, respectively, indicating strong temperature forecasting accuracy. As shown, these results can clearly confirm the model's robustness in capturing temporal dependencies and cyclical behavior in temperature data. As illustrated in Figure 9, the predicted temperature closely follows the actual observations across all time steps, and the model successfully reproduces the amplitude and periodicity of temperature fluctuations, which appear to reflect diurnal or seasonal cycles, noting that the high fidelity between predicted and actual curves highlights the model's capacity to internalize and replicate long-term temperature dynamics.

Figure 8
Temperature prediction training loss

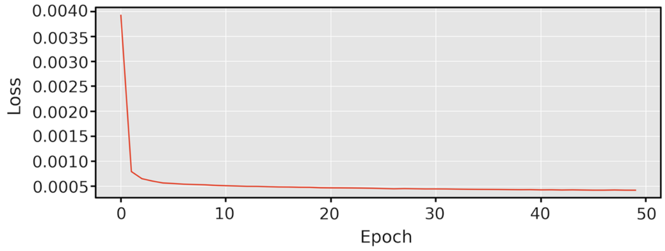
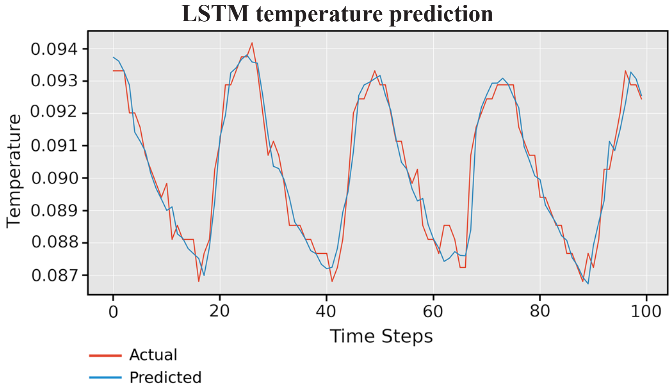


Figure 9
LSTM temperature prediction



4.4.2. Wind speed forecasting performance

The LSTM model applied to wind speed prediction demonstrated a more gradual reduction in loss, converging from an initial value of 0.004688 to 0.003515 by epoch 50 (Figure 10), noting that convergence was slower compared to temperature. The model remained stable throughout training, suggesting resilience in handling the more stochastic nature of wind data, and on the test set, the wind speed model achieved an MSE of 2.0788×10^{-6}, RMSE of 0.001442, and MAE of 0.001032. Although slightly higher than those observed for temperature, these error values remain within acceptable bounds for meteorological applications. Also, the model's ability to generalize is evident, particularly given the inherent variability and noise in wind dynamics. Figure 11 displays the model's prediction against actual wind speed values. Because the prediction exhibits good alignment with the real data, minor discrepancies are observed during sharp fluctuations. This is expected, as wind patterns tend to be less predictable and often influenced by local microclimatic factors not captured in historical time series alone.

Figure 10
Wind speed prediction training loss

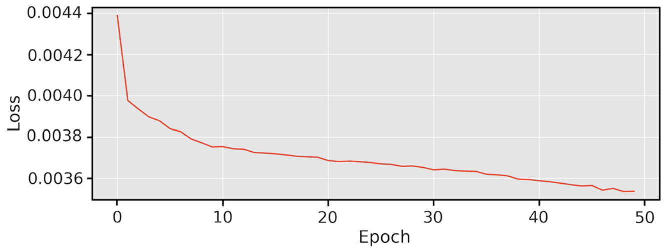
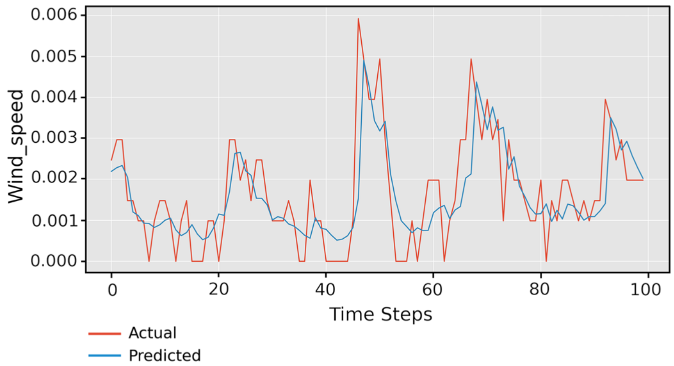


Figure 11
LSTM wind speed prediction



4.4.3. Summary of model evaluation

The quantitative evaluation of both LSTM models is summarized in Table 2:

Table 2
Quantitative evaluation of both LSTM models

Variable	MSE	RMSE	MAE
Temperature	1.8530e-07	0.000430	0.000315
Wind speed	2.0788e-06	0.001442	0.001032

The LSTM architecture demonstrates strong suitability for modeling long-term atmospheric patterns in arid and semi-arid environments such as southeastern Morocco, with its ability to accurately capture temperature dynamics is particularly noteworthy, attributed to the more regular and seasonal nature of temperature evolution. In contrast, wind speed prediction—though slightly more error-prone—remains effective given the volatile nature of the target variable; these findings affirm the LSTM model's utility in supporting predictive climate modeling and resource planning in vulnerable regions such as Errachidia. The results further justify future exploration of hybrid architectures, exogenous input features (e.g., pressure and solar radiation), or attention mechanisms to further refine forecasts—especially for short-term wind variability.

5. Discussion

The empirical findings of this study provide compelling evidence of significant and accelerating climatic changes in Errachidia over the 14-year observation period (2010–2024), since the annual temperature increase of approximately 0.1142°C/year (p = 0.0003), culminating in a total rise of around 1.6°C, underscores the severity of warming trends in semi-arid regions. Those findings shows this magnitude of warming is notably above the global mean, suggesting that Errachidia—and the broader southeastern Moroccan region—may be disproportionately vulnerable to climate change, and the seasonal decomposition analysis adds a granular perspective, revealing that fall temperatures exhibit the steepest rise (0.1666°C/year, $p = 0.0002$), followed by summer (0.1155°C/year), spring, and winter. This heightened rate during autumn likely reflects a shift in seasonal boundaries, with warmer conditions extending beyond traditional summer months, while this phenomenon aligns with global findings of seasonal displacement in arid climates and could have direct implications for agriculture, water resources, and public health. Monthly heatmap visualizations reinforce this interpretation, highlighting intensifying summer extremes (~35°C in 2022–2024) and winter warming (~10°C to ~15°C), indicating an elongation of the hot season. These patterns may signal a transition toward a more prolonged dry and thermally stressful climate regime, with reduced nocturnal cooling and increased energy demand for adaptation measures such as air conditioning and irrigation, and in terms of extreme weather, the study observes a statistically significant increase in heatwave events (23 events/year, $p = 0.0000$). Contrasted with a nonsignificant decline in cold events, this difference not only confirms the warming trajectory but also highlights the growing climatic instability, as suggested by the rising standard deviation in temperature values post-2018. These findings echo broader concerns regarding climate-induced stress in arid ecosystems, where thresholds for human and ecological resilience are already narrow. The wind analysis presents a more nuanced picture, overall wind speed has remained statistically unchanged ($p = 0.8589$), the observed shift in dominant wind direction toward the north—increasing from 25.7% to 30.4%—may reflect alterations in large-scale atmospheric circulation, and the found moderate positive correlation with temperature anomalies ($r \approx 0.4$) during peak years suggests that wind direction could serve as a climatic proxy, potentially influencing dust transport, evapotranspiration, and pollutant dispersion in the region. From a modeling perspective, the LSTM-based forecasting framework proved highly effective for temperature prediction. The model's extremely low MSE (1.85×10^{-7}) and RMSE (0.00043) reflect its capacity to internalize cyclical and seasonal patterns with remarkable precision; the stability in training dynamics, absence of overfitting, and visual alignment between predicted and actual temperatures affirm the reliability of deep learning in modeling deterministic climate variables. In contrast, the wind speed model demonstrated relatively higher error rates (MSE = 2.08×10^{-6}), consistent with the stochastic and volatile nature of wind, though, the predictive alignment was adequate, deviations during sharp fluctuations indicate the need for incorporating external covariates or hybrid modeling strategies (e.g., LSTM-Attention and CNN-LSTM) to better capture nonlinearities and abrupt transitions in wind behavior; however, the integration of statistical trend analysis and LSTM modeling provides a holistic framework for both descriptive and predictive climate research. Those results confirm not only a statistically robust warming signal in Errachidia but also validate the technical feasibility of LSTM networks in long-term meteorological forecasting. Conclusively, these insights are critical for regional adaptation planning, particularly in semi-arid zones where the margins for climatic resilience are increasingly thin. Future work should consider multivariable input features, include uncertainty quantification, and extend predictive modeling to include precipitation patterns and humidity trends, thereby enriching the understanding of climate dynamics in vulnerable zones of the Global South.

6. Conclusion and Perspectives

This study provides a comprehensive assessment of climate change in Errachidia, Morocco, over a 14-year period from 2010 to 2024, providing a detailed statistical analysis and the application of LSTM-based deep learning models. The work uncovers significant trends that underscore the region's climatic vulnerability, notably, the average temperature in Errachidia has increased by approximately 1.6°C, with a particularly marked warming trend in autumn—estimated at +0.17°C per year. Summer periods have become more intense and prolonged, often reaching peak temperatures around 35°C, while extreme cold events have become increasingly rare; these observations suggest a shift toward a hotter and more arid climate regime. The application of LSTM models for temperature and wind speed prediction offered additional support for the detected trends, and with the inclusion of proper preprocessing and inverse scaling, the updated models achieved encouraging results—a RMSE of 0.00043 (~0.43°C) and MAE of 0.00032 (~0.32°C) for temperature prediction. These represent a substantial improvement over earlier model performance (previously RMSE ≈ 9.35°C), indicating that with careful calibration and appropriate time series handling. LSTM architectures can be effective tools for climate data forecasting in arid regions. However, challenges remain in modeling highly volatile variables such as wind speed, where prediction errors were notably higher (RMSE ≈ 0.00144); even with the fact that these advances, the study reaffirms that deep learning alone is not a panacea—especially when addressing complex, nonlinear, and noisy meteorological data in dryland climates. The true strength of this research lies in its data-driven, localized insight into an understudied yet climate-sensitive region, providing a rare long-term perspective on climate evolution in southeastern Morocco. The findings have practical implications for sectors such as agriculture, water resource management, and public health, all of which are directly impacted by temperature extremes and shifting seasonal patterns. In future works, we suggest expanding this work to include multisite analysis across the country or even the North African region, incorporating additional environmental variables such as soil moisture, solar radiation, and precipitation anomalies, and integrating real-time climate observations into model training pipelines will be critical steps. Those enhancements would not only improve forecast precision but also deepen our understanding of regional climate systems.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

Azidine Guezzaz is an Editorial Board Member for *Journal of Data Science and Intelligent Systems* and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The raw meteorological observations used in this study originate from publicly available Aeronautical Meteorological Messages for Errachidia Airport, which are routinely disseminated by official meteorological and aviation weather services. The raw Aeronautical Meteorological Messages data are openly accessible, for example, via the NOAA Aviation Weather Center: https://aviationweather.gov/data/metar/?ids=GMFK. No restrictions apply to the use of the raw data. The processed dataset generated during this study is available from the corresponding author upon request.

Author Contribution Statement

Anas Kabbori: Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data curation, Writing –

original draft, Writing – review & editing, Visualization. **Chahrazad Zargane:** Conceptualization, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing. **Azidine Guezzaz:** Methodology, Software, Validation, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Said Benkirane:** Methodology, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision. **Mourade Azrour:** Software, Validation, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision.

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