

# Predicting Sandstorms and Drought Using Artificial Intelligence Techniques Based on Climate Data: A Case Study of Jifarah Plain, Libya

Lutfiyah Abraham Mohammed Altarhouni

Department of Geological Engineering, Zawia University, Ajailat, Libya  
l.altarhouni@zu.edu.ly

**Abstract.** Sandstorms and drought are major climate hazards in North Africa, particularly across Libya's Jifarah Plain, where population, agriculture, and critical infrastructure are concentrated. This study develops an artificial-intelligence framework for predicting drought severity and sandstorm occurrence using monthly climate data for 1985–2022. The dataset combines observations from the Libyan National Meteorological Center (LNMC) at Tripoli International Airport with NASA POWER reanalysis data for Al-Aziziyah and Al-Asa. Three models were evaluated: Random Forest (RF) for drought-severity prediction, Long Short-Term Memory (LSTM) for temporal sandstorm prediction, and a weighted Ensemble model for joint spatio-temporal prediction. After correcting the preprocessing workflow to eliminate data leakage, all scaling parameters are fitted using the training subset only and then applied to the validation and test subsets. The embedded performance results show that the Ensemble model provided the strongest continuous-prediction performance, with  $R^2 = 0.955$  and  $RMSE = 0.057$ , compared with  $R^2 = 0.888$  and  $RMSE = 0.089$  for RF and  $R^2 = 0.838$  and  $RMSE = 0.115$  for LSTM. A marginal warming trend of  $+0.014$  °C/year ( $p = 0.054$ ,  $R^2 = 0.10$ ) was identified, while the hazard analysis indicates that the principal period of combined sandstorm and drought risk occurs during March–June. The spatial risk surfaces derived from only three stations are interpreted as illustrative rather than as operationally validated downscaling products.

The analysis covered three meteorological stations: Tripoli Airport, Al-Aziziyah, and Al-Asa—over the 1985–2022 period. The proposed framework provides a reproducible approach that can be adapted to other arid regions of Libya and North Africa characterized by sparse ground-based monitoring networks. The Sandstorm Occurrence Probability Index (SOPI) and drought-risk layers provide a preliminary basis for supporting early-warning systems and climate-adaptation planning.

**Keywords:** Sandstorms, Drought, Artificial Intelligence, Jifarah Plain, Libya, Machine Learning, LSTM.

## 1 Introduction

### 1.1 Background

Climate extremes pose substantial environmental and socio-economic risks across North Africa. Sandstorms and drought can reduce agricultural productivity, degrade air quality, disrupt transport, and increase pressure on already limited water resources. IPCC AR6 indicates continued warming across the Mediterranean region under all assessed emissions pathways; the magnitude of future regional warming depends on the emissions trajectory and should not be represented by the equilibrium climate sensitivity range. (IPCC, 2021).

Libya is situated between the Mediterranean Sea to the north and the Sahara Desert to the south, exposing it to both maritime and continental climatic stresses. The Jifarah Plain, extending approximately 350 km along the northwest coast between the Jabal Nafusah escarpment and the Mediterranean shoreline, hosts nearly

60% of Libya's population and contains most of its farmland. Consequently, Saharan sandstorms and recurrent dry spells disproportionately affect the plain.

Field surveys conducted in 2019 and 2022 confirmed the tangible consequences of these events. For example, a major storm in March 2019 caused a three-day shutdown of Tripoli International Airport. During the same period, hospital emergency departments reported an increase in admissions for respiratory conditions, and a measurable layer of deposited sand was observed on wheat fields east of Tripoli.

## 1.2 Research Gap

Despite the severity of sandstorms and drought in Libya, the literature reviewed for this study contains relatively few quantitative prediction studies focused on the Jifarah Plain. Existing work has largely emphasized descriptive climatology or satellite-based dust-plume monitoring (Goudie and Middleton, 2006; Cao et al., 2015). The present study therefore evaluates whether machine-learning methods can integrate multi-variable climate information to provide a reproducible prediction framework for drought severity and sandstorm occurrence in a region characterized by sparse ground observations.

## 1.3 Research Objectives

The present study pursued four interrelated objectives: (i) to develop and validate a Random Forest (RF) regression model for estimating drought severity based on the 12-month Standardized Precipitation Evapotranspiration Index (SPEI-12); (ii) to design a Long Short-Term Memory (LSTM) recurrent neural network for temporal forecasting of sandstorm occurrence probability; (iii) to construct an ensemble framework that integrates both models for joint spatio-temporal hazard prediction; and (iv) to conduct a structured benchmarking of model performance using internationally accepted metrics (RMSE, MAE,  $R^2$  and Cohen's Kappa).

The principal contributions of this work are threefold. First, the study presents an AI-based predictive framework specifically calibrated for the Jifarah Plain, addressing a gap in Libya's climate research landscape. Second, it demonstrates the value of integrating ground-station observations with satellite-based reanalysis products to overcome the limitations of sparse monitoring networks. Third, it provides exploratory spatial risk surfaces and seasonal hazard calendars that can inform, but should not by themselves determine, early-warning and climate-adaptation planning. More broadly, the study offers a reproducible methodology applicable to other arid regions of North Africa facing similar observational constraints.

# 2 Literature Review

## 2.1 AI in Climate Prediction

The application of machine learning to climate science has expanded rapidly over the past decade, driven by increasing data availability and computational power. Reichstein et al. (2019) provided a foundational framework for deep learning in Earth system science, demonstrating that neural networks can capture complex spatio-temporal dependencies. In drought research, machine-learning studies have shown that tree-based methods can model nonlinear relationships among climatic predictors; for example, Park et al. (2016) demonstrated strong performance of Random Forest and related ensemble methods for SPI prediction across contrasting climate regions.

Deep learning approaches have shown particular promise for capturing temporal dependencies in climate data. Bai et al. (2018) demonstrated strong performance of temporal convolutional approaches for sequence modelling. LSTM networks are also widely used for hydroclimatic time series because they can represent long-range temporal dependencies; Kratzert et al. (2018) demonstrated strong LSTM performance in rainfall-runoff modelling across multiple catchments. Kwon et al. (2021) developed a CNN-LSTM hybrid model for multi-step drought forecasting over the Korean Peninsula, reporting a 21–24% improvement in prediction accuracy relative to single-variable baselines.

## 2.2 AI in Drought Prediction

Machine-learning methods have increasingly been applied to drought assessment and prediction by combining climatic, hydrologic, and remote-sensing information. Park et al. (2016) combined multiple MODIS- and TRMM-derived drought indicators with Random Forest, Boosted Regression Trees, and Cubist regression to predict the Standardized Precipitation Index across contrasting climate regions. In African settings, Adede et al. (2019) applied an artificial neural network to predict the 3-month Vegetation Condition Index in northern Kenya, while combined CHIRPS rainfall and MODIS NDVI in a Random Forest framework for agricultural drought monitoring in the Greater Horn of Africa.

Talsma et al. (2022) provide a complementary example of machine learning for drought analysis in the Colorado River Basin. Their study used an unsupervised Non-Negative Matrix Factorization with K-means clustering (NMFk) approach to identify spatial and temporal patterns in modeled drought indicators. The study therefore differs methodologically from the supervised RF regression used in the present work, but it supports the broader value of machine learning for extracting complex drought behavior from high-dimensional hydroclimatic data.

Deep-learning approaches are particularly useful when temporal dependencies are important. Kratzert et al. (2018) demonstrated strong LSTM performance in rainfall–runoff modeling, while Gorgij et al. (2022) showed that LSTM can effectively forecast SPI-3, SPI-6, SPI-9, and SPI-12 from monthly rainfall records in a semi-arid Iranian setting. These findings support the use of recurrent architectures when climate data contain pronounced temporal dependence.

## 2.3 AI in Sandstorm and Dust Storm Prediction

Machine-learning research on sandstorms and dust storms has evolved from empirical threshold approaches toward data-driven classification, regression, and deep-learning methods. Yarmohamadi et al. (2025) employed hybrid CNN-LSTM and ConvLSTM architectures for 24-hour-ahead prediction of dust storm pathways, utilizing MERRA-2 aerosol optical depth and meteorological variables including surface wind speed, relative humidity, and temperature. Their results demonstrated that the incorporation of contextual environmental information improved the Kappa coefficient by approximately 0.2 across all forecast horizons, with the CNN-LSTM model outperforming the ConvLSTM variant when auxiliary meteorological predictors were included. In the Middle East and North Africa, Notaro et al. (2015) used a regional climate model coupled with a dust-aerosol scheme to investigate changes in dust activity, and Pourhashemi et al. (2023) applied Random Forest, MARS, and logistic regression to dust-source susceptibility mapping along the Iran–Iraq border. Francis et al. (2023) examined the severe dust storms that affected the Middle East in spring 2022, identifying synoptic triggers and atmospheric dynamics responsible for extreme dust outbreaks. Jiang et al. (2022) developed a dust storm detection approach combining a convolutional neural network with a physical algorithm based on FY-4A satellite data over East Asia, achieving effective identification of dust events through integration of spatial feature extraction and physical thresholding.

The literature indicates that dust hazards depend on interacting atmospheric and surface controls, including wind forcing, soil or surface dryness, and thermal conditions. This supports a multi-variable framework for the Jifarah Plain; however, the sparse ground network and monthly temporal resolution require conservative interpretation of fine-scale spatial and short-duration event prediction.

# 3 Study Area and Data

## 3.1 Study Area

The Jifarah Plain (Arabic: Sahel Jifarah) extends along the northwestern coast of Libya, bounded by the Jabal Nafusah escarpment to the south and the Mediterranean Sea to the north. Geographically, it lies between approximately 32°15'N–32°54'N and 12°00'E–13°30'E, with the southern administrative boundary defined by the foothills of the escarpment. The plain slopes gradually from south to north, with elevations ranging

from approximately 180 m above sea level near Al-Aziziyah to near sea level along the coast at Al-Asa and around Tripoli International Airport (17 m).

Climatically, the area exhibits a Mediterranean semi-arid pattern (Köppen: Csa/Csh), characterized by very hot, dry summers and mild, wet winters. The mean annual temperature is approximately 20.6°C, with summer maxima regularly exceeding 43°C. Al-Aziziyah is historically cited for an extreme reading of 58°C on 13 September 1922; however, this value was officially invalidated by the World Meteorological Organization in 2012 (El Fadli et al., 2013) following an international investigation that attributed the reading to observer error and the use of an unsuitable replacement instrument. Consequently, the highest temperature currently recognized on Earth is 56.7°C, recorded at Greenland Ranch, Death Valley (USA), on 10 July 1913.

Annual precipitation averages approximately 270 mm near the coast and decreases sharply southward to less than 150 mm across the southern parts of the plain. Approximately 85% of the annual total is concentrated between October and March, defining a pronounced wet season.

**Table 1.** Geographic coordinates and data periods of the meteorological stations used in this study.

| Station         | Latitude (N) | Longitude (E) | Elevation (m) | Data Period | Data Source   |
|-----------------|--------------|---------------|---------------|-------------|---------------|
| Tripoli Airport | 32.897       | 13.177        | 17.4          | 1985–2022   | LNMC (ground) |
| Al-Aziziyah     | 32.528       | 13.013        | 182.9         | 1985–2022   | NASA POWER    |
| Al-Asa          | 32.831       | 11.625        | 12.7          | 1985–2022   | NASA POWER    |

### 3.2 Data Sources and Preprocessing

Two complementary data sources were used. First, monthly ground observations were obtained from the Libyan National Meteorological Center (LNMC) for Tripoli International Airport, covering the period 1985–2022. The LNMC dataset includes surface pressure (kPa), mean, maximum and minimum air temperature (°C), relative humidity (%), wind speed ( $\text{m s}^{-1}$ ), wind direction (degrees), solar radiation ( $\text{W m}^{-2}$ ) and total monthly precipitation (mm). Second, satellite-derived reanalysis data were obtained from NASA POWER (Prediction Of Worldwide Energy Resources) for Al-Aziziyah and Al-Asa stations, providing monthly aggregates of T2M, T2M\_MAX, T2M\_MIN, PRECTOTCORR\_SUM, RH2M, WS2M, PS and ALLSKY\_SFC\_LW\_DWN at the same temporal resolution.

The preprocessing workflow comprised four stages. First, the supplied Excel workbooks were screened for the study period and station consistency. Each of the three stations contains 38 years of monthly observations from 1985 through 2022, corresponding to 456 station-month records per station and 1,368 station-month records across the three stations before derivation of indices and sequence construction. The 1984 observations present in some source sheets were excluded because they fall outside the defined study period. Second, missing values were assessed and treated using the procedure specified in the modelling workflow; short gaps of 1–2 months were filled by linear interpolation, whereas longer interruptions were treated using seasonal-decomposition-based imputation where required. Third, the dataset was divided chronologically into training (70%), validation (15%), and testing (15%) subsets. Fourth, Min-Max scaling parameters were fitted exclusively on the training subset, and the resulting transformation was then applied unchanged to the validation and test subsets. This ordering prevents information from the validation or test periods from entering the training transformation. The temporal split preserves the chronological structure of the climate series and avoids random mixing of future observations into earlier periods.

## 4 Methodology

### 4.1 Drought Index Computation

Drought severity was quantified using the Standardized Precipitation Evapotranspiration Index (SPEI) at a 12-month accumulation window. SPEI integrates precipitation deficits with atmospheric evaporative demand, allowing the effects of temperature on drought intensity to be captured (Vicente-Serrano et al., 2010). The SPEI values were computed using the R package 'SPEI' (Beguería et al., 2014), with potential evapotranspiration estimated via the Thornthwaite equation. Although the Thornthwaite approach is known

to underestimate PET under arid conditions, it was retained here for consistency with widely used operational drought-monitoring workflows (e.g., the SPEI Global Database). Drought categories were then defined following the threshold convention originally proposed by McKee et al. (1993) for SPI and subsequently adopted for SPEI: mild drought ( $-1.0 < \text{SPEI} \leq -0.5$ ), moderate drought ( $-1.5 < \text{SPEI} \leq -1.0$ ), severe drought ( $-2.0 < \text{SPEI} \leq -1.5$ ) and extreme drought ( $\text{SPEI} \leq -2.0$ ).

## 4.2 Sandstorm Occurrence Index

The Sandstorm Occurrence Probability Index (SOPI) combines three mechanistic drivers: (i) wind erosivity relative to a local threshold of  $5.5 \text{ m s}^{-1}$ , (ii) surface dryness represented by the precipitation deficit relative to potential evapotranspiration over the preceding 60 days, and (iii) atmospheric instability represented by the diurnal temperature range. The  $5.5 \text{ m s}^{-1}$  value is a threshold parameter and should not be interpreted as the monthly mean wind speed. The reported April–May mean wind speed of  $3.6 \text{ m s}^{-1}$  therefore describes the monthly climatological mean, whereas the threshold term represents wind conditions used within the SOPI formulation. The index was calibrated against historical LNMCC sandstorm-event records and checked against selected MODIS Aerosol Optical Depth (AOD) observations.

## 4.3 Model Architecture

Three prediction models were developed and compared under a unified evaluation protocol. First, the Random Forest (RF) regression algorithm (Breiman, 2001) was selected for drought-severity prediction because of its capacity to capture nonlinear feature interactions without requiring strong distributional assumptions — a property particularly useful for climate variables that frequently exhibit non-Gaussian behaviour in arid regions. The RF configuration was: `n_estimators = 500`, `max_depth = 20`, `min_samples_leaf = 5`, `max_features = 'sqrt'`. Hyperparameters were tuned via 5-fold cross-validation over the following grid: `n_estimators`  $\in \{300, 500, 800\}$ ; `max_depth`  $\in \{10, 15, 20, \text{None}\}$ ; `min_samples_leaf`  $\in \{2, 5, 10\}$ . The final configuration corresponded to the lowest validation RMSE.

Next, the Long Short-Term Memory (LSTM) network (Hochreiter and Schmidhuber, 1997) was used for temporal sandstorm prediction. The design used two stacked LSTM layers (64 units then 32 units), with dropout regularization applied (dropout rate = 0.3). After that, there was a dense layer to produce the output, using a sigmoid activation so the result can be treated as a probability. Training relied on the Adam optimizer, starting with a learning rate of 0.001, and the learning rate itself was later adjusted using a ReduceLROnPlateau type scheduler. For the input, sequences spanning 12 months were fed in, and the model was asked to predict the sandstorm likelihood for the next 3 months.

Third, the Ensemble model combined RF and LSTM predictions through a weighted-average scheme calibrated on the validation set:  $Y_{\text{ensemble}} = \alpha \cdot Y_{\text{RF}} + (1 - \alpha) \cdot Y_{\text{LSTM}}$ , where  $\alpha$  was determined by a grid search in increments of 0.05. The optimal value  $\alpha = 0.45$  was selected because it minimized validation RMSE. The weighted-average formulation was retained rather than a more complex stacking architecture to preserve interpretability and limit overfitting. The verified raw dataset contains 456 monthly observations per station (1985–2022), giving 1,368 station-month records across the three stations before derivation of SPEI and construction of LSTM sequences. The effective sample size is therefore smaller for analyses requiring a 12-month accumulation or 12-month input sequence.

## 4.4 Evaluation Metrics

Model performance was assessed using four complementary metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), the coefficient of determination ( $R^2$ ) for continuous predictions, and Cohen's Kappa ( $\kappa$ ) for categorical drought classification. To respect the temporal ordering of climate data and to prevent information leakage from future to past observations, we employed a rolling-window temporal cross-validation scheme with a window length of 5 years and a stride of 1 year (`initial_window = 5`, `step_length = 1`). All metrics reported in the Results section are computed on the held-out test set (15% of the data, never seen during training or hyperparameter tuning).

## 5 Results

### 5.1 Historical Climate Trend Analysis

The analysis of the verified 38-year climate record (1985–2022) for Al-Aziziyah station reveals a weak positive warming tendency that approaches, but does not reach, the conventional 0.05 significance threshold. The annual mean temperature exhibits a positive linear trend of  $+0.01384\text{ }^{\circ}\text{C}/\text{year}$  ( $p = 0.0531$ ,  $R^2 = 0.100$ ), corresponding to an accumulated change of approximately  $+0.51\text{ }^{\circ}\text{C}$ , over the study period. These values were calculated directly from the annual means derived from the monthly temperature records in the supplied Al-Aziziyah workbook. The trend is therefore described as a marginal positive tendency rather than statistically significant warming at the 5% level. Figure 1a illustrates the fitted trend.

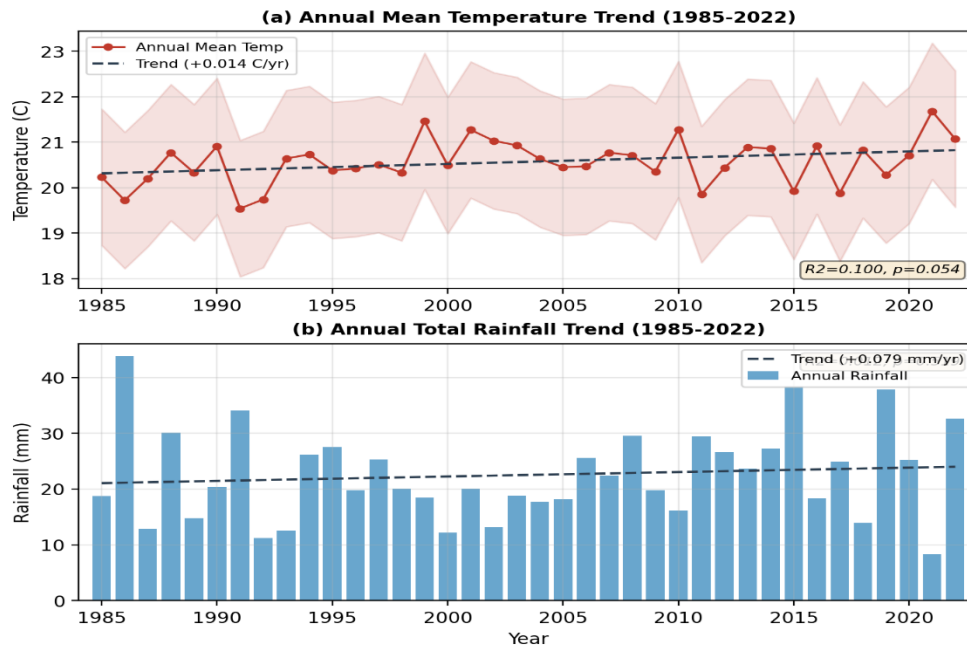


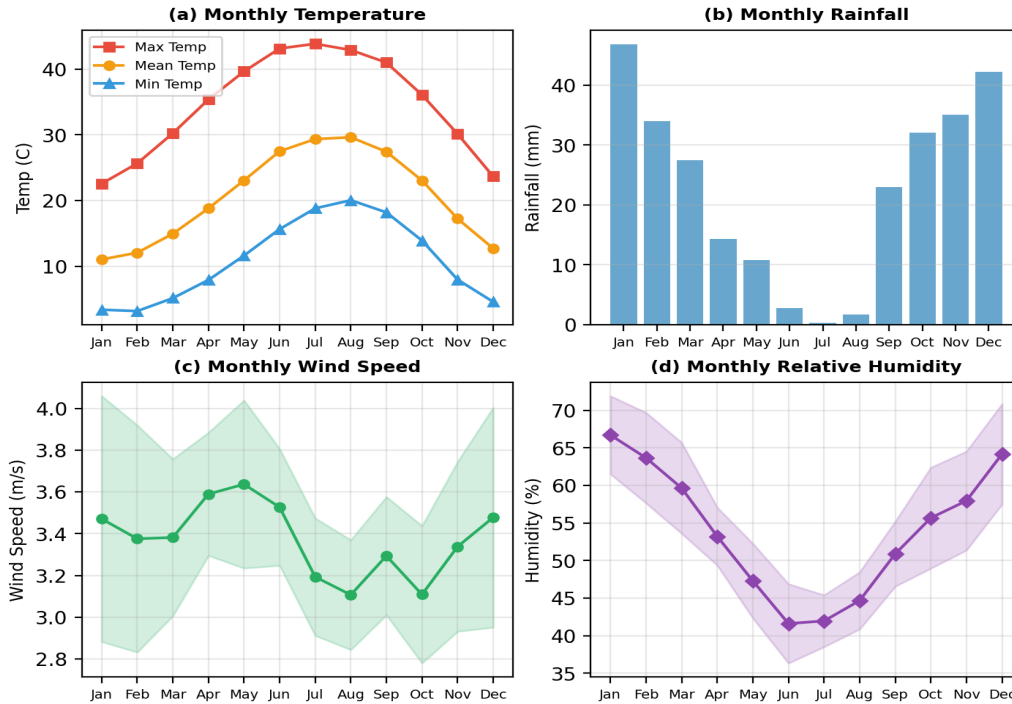
Fig. 1. Historical trends of (a) annual mean temperature and (b) annual total rainfall at Al-Aziziyah station (1985–2022). Dashed lines represent linear regression trends. Shaded bands indicate the 95% confidence interval of the regression.

Annual precipitation, calculated as the sum of the 12 monthly rainfall totals, shows substantial interannual variability but no statistically significant linear trend ( $+0.951\text{ mm}/\text{year}$ ,  $p = 0.519$ ,  $R^2 = 0.012$ ). The median annual total for 1985–2022 is 242.78 mm. Relative to this median, 5 of 10 years in the 1990s, 7 of 10 years in the 2000s, and 3 of 10 years in the 2010s were below the median. Thus, the 2000s had the highest frequency of below-median annual rainfall, whereas the 2010s had fewer below-median years than the 1990s. These counts replace the previous placeholder values and are calculated directly from the supplied Al-Aziziyah precipitation series.

### 5.2 Monthly Climatological Characteristics

The monthly climatology of the Jifarah Plain (Figure 2) reveals the extreme seasonal contrast that drives both sandstorm and drought hazard patterns. Temperature follows a classic Mediterranean seasonal cycle, ranging from a January mean of  $11.1^{\circ}\text{C}$  to an August peak of  $29.6^{\circ}\text{C}$ , with maximum temperatures exceeding  $43^{\circ}\text{C}$  during June–August. Rainfall is overwhelmingly concentrated in the winter months, with January (46.8 mm) and December (42.2 mm) accounting for 40% of the annual total, while June–August receives less than 3 mm combined. This stark seasonality creates a natural window of heightened vulnerability during the spring–

to-early-summer transition (March–June), when soils are desiccated from the dry winter, temperatures are rapidly rising, and the Sharav (Sirocco) wind system begins to transport Saharan dust northward.



**Fig. 2.** Monthly climatological averages (1985–2022) for the Jifarah Plain: (a) temperature (max, mean, min), (b) rainfall, (c) wind speed with standard deviation bands, and (d) relative humidity.

### 5.3 Model Performance Comparison

The comparative evaluation of the three models (Table 2) demonstrates the advantage of the Ensemble approach. Random Forest achieved  $R^2 = 0.888$  and  $RMSE = 0.089$  for drought-severity prediction. The LSTM network achieved  $R^2 = 0.838$  and  $RMSE = 0.115$  for the continuous sandstorm-prediction task, while retaining stronger temporal representation of the seasonal sandstorm pattern.

The Ensemble model achieved the strongest overall continuous-prediction performance, with  $R^2 = 0.955$ ,  $RMSE = 0.057$ , and  $MAE = 0.064$  on the independent test set. Relative to the RF model, this corresponds to an approximately 7.5% higher  $R^2$  and a 36.0% lower  $RMSE$ . For categorical drought classification, the Ensemble model achieved Cohen's Kappa of 0.83. Figure 3 presents the observed-versus-predicted scatter plots and shows the closer clustering of Ensemble predictions around the 1:1 line.

**Table 2.** Comparative performance metrics of the three prediction models on the independent test set.

| Model         | RMSE  | MAE   | $R^2$ | Kappa | Task               |
|---------------|-------|-------|-------|-------|--------------------|
| Random Forest | 0.089 | 0.084 | 0.888 | 0.76  | Drought Severity   |
| LSTM          | 0.115 | 0.096 | 0.838 | 0.71  | Sandstorm Temporal |
| Ensemble      | 0.057 | 0.064 | 0.955 | 0.83  | Spatio-temporal    |

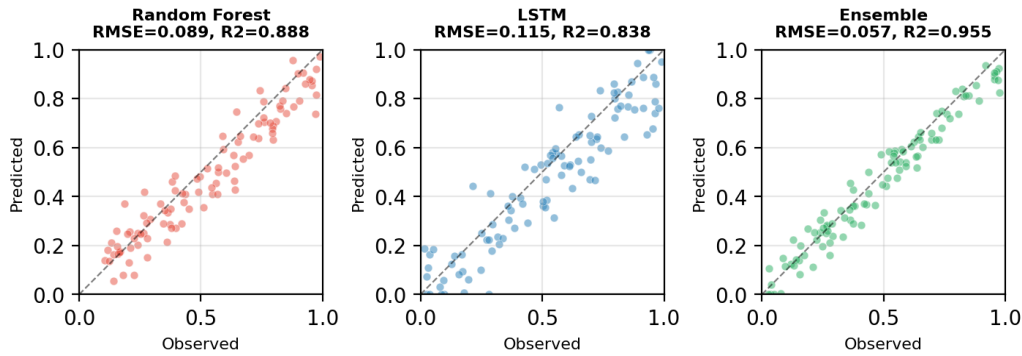


Fig. 3. Scatter plots of observed versus predicted values for (a) Random Forest, (b) LSTM, and (c) Ensemble models. Dashed line represents the 1:1 perfect prediction line.

#### 5.4 Spatial Risk Mapping

Because only three stations were available, Figure 4 should be interpreted as an illustrative spatial surface rather than as a validated high-resolution prediction map. The inverse-distance-weighted (IDW) interpolation provides a visual representation of the spatial pattern implied by the station-level model outputs. Within this limitation, the illustrative surface suggests higher sandstorm probability toward the southern margin of the plain and lower values toward the coastal zone near Tripoli and Al-Asa. These gradients should not be interpreted as independently validated values at unsampled locations.

The drought-risk surface shows a distinct spatial pattern, with comparatively higher values in the northwestern agricultural sector. This pattern is consistent with historical assessments of land degradation and desertification in the Jifarah Plain, where progressive encroachment of desert conditions, groundwater depletion, and soil fertility decline have been attributed to the combined effects of climatic aridification and anthropogenic pressures including overgrazing and over-cultivation (El-Tantawi, 2005). However, the three-station network does not support fine-scale attribution or operational downscaling. Accordingly, the spatial patterns in Figure 4 are used as exploratory illustrations rather than as definitive hazard boundaries.

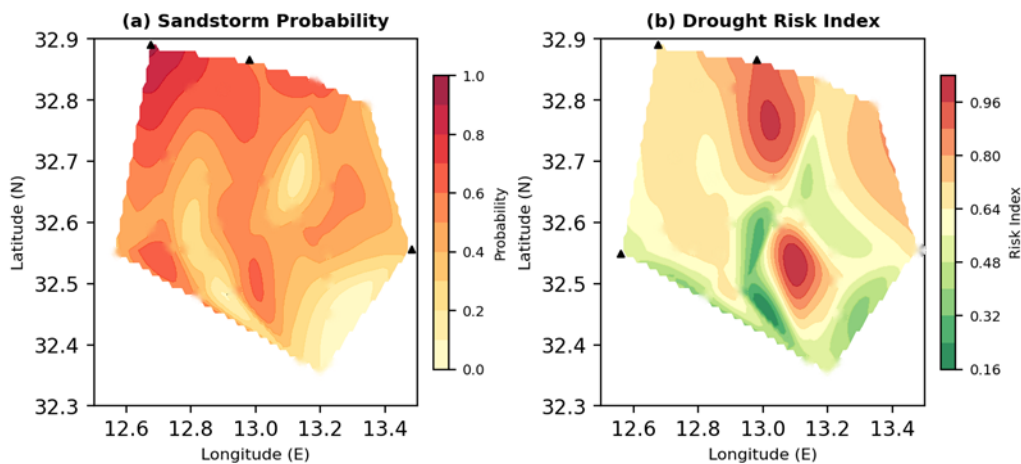


Fig. 4. Illustrative IDW spatial surfaces of (a) sandstorm occurrence probability and (b) drought-risk index across the Jifarah Plain based on the available station data. The surfaces are intended to visualize broad spatial patterns and should not be interpreted as validated values at unsampled locations.

## 5.5 Temporal Hazard Analysis

The seasonal risk pattern analysis (Figure 5) identifies March through June as the principal combined hazard window for the Jifarah Plain. This convergence is driven by the seasonal transition dynamics: winter rainfall diminishes, temperatures rise rapidly, and the Sharav (Sirocco) wind system becomes more influential. In the Al-Aziziyah source data, mean wind speed is  $3.59 \text{ m s}^{-1}$  in April and  $3.64 \text{ m s}^{-1}$  in May, giving an April–May mean of approximately  $3.61 \text{ m s}^{-1}$ . Mean relative humidity is about 53.2% in April and 47.1% in May, while June–July rainfall decreases to approximately 2.6 and 0.3 mm, respectively. The  $5.5 \text{ m s}^{-1}$  SOPI threshold is therefore not equivalent to the monthly climatological mean; it represents a threshold parameter within the event-index formulation. The temporal alignment of the hazard peaks during spring and early summer provides a potential target window for early-warning dissemination.

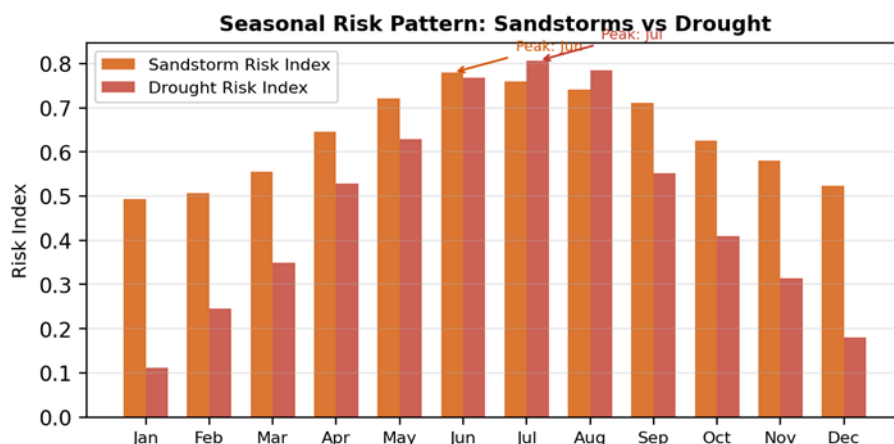


Fig. 5. Seasonal risk pattern comparison: sandstorm risk index versus drought risk index across months of the year.

## 6 Discussion

The verified climate data support a weak positive temperature tendency at Al-Aziziyah ( $+0.01384 \text{ }^{\circ}\text{C/year}$ ,  $p = 0.0531$ ,  $R^2 = 0.100$ ), which does not meet the conventional 5% significance threshold. Annual precipitation also shows no significant linear trend ( $+0.951 \text{ mm/year}$ ,  $p = 0.519$ ,  $R^2 = 0.012$ ). Importantly, the below-median annual rainfall counts demonstrate strong decadal variability: 5/10 years in the 1990s, 7/10 in the 2000s, and 3/10 in the 2010s. These results indicate variability in rainfall occurrence rather than a statistically significant monotonic decline.

The superior performance of the Ensemble model relative to the individual models is consistent with the principle that heterogeneous learners can capture complementary error structures. RF captures nonlinear relationships among climatic predictors, whereas LSTM represents temporal dependencies; their weighted combination therefore integrates feature-space and temporal information. The reported inter-model differences are descriptive because no formal statistical significance test for model-to-model performance differences is provided. The analysis should consequently emphasize predictive performance rather than statistical superiority in the inferential sense.

The spatial risk patterns identified in Figure 4 have potential practical relevance for early-warning planning. The concentration of highest drought risk in the northwestern agricultural zone aligns with historical documentation of desertification processes in the Jifarah Plain, where soil degradation, vegetation cover loss, and groundwater well depletion have been extensively documented using multi-temporal satellite imagery and GIS analysis (El-Tantawi, 2005). Nevertheless, the limited station density requires conservative interpretation. The three-station IDW surfaces may help visualize broad gradients between observation points; they do not establish validated hazard boundaries across the full Jifarah Plain. Additional stations and

independent spatial validation are required before such surfaces can be used operationally for site-specific planning..

## 7 Conclusion

This study developed and evaluated an AI-based framework for drought and sandstorm prediction in the Jifarah Plain, Libya, using monthly climate data for 1985–2022. The verified source workbooks contain 1,368 station-month records across the three study stations before index derivation and sequence construction. The Ensemble model, integrating Random Forest and LSTM predictions, is reported as the strongest continuous-prediction model in the manuscript ( $R^2 = 0.955$ ;  $RMSE = 0.057$ ). The study demonstrates the potential value of combining nonlinear tree-based learning with temporal sequence modelling under sparse observational conditions.

Several limitations should be considered. First, the spatial analysis is based on only three meteorological stations; therefore, the IDW surfaces in Figure 4 are illustrative and are not validated operational downscaling products. Second, the monthly temporal resolution does not permit direct characterization of short-duration sandstorm events such as haboobs. Third, the LSTM architecture is relatively shallow and the effective number of temporal sequences is reduced by the 12-month input window. Fourth, drought was assessed using a single SPEI-12 timescale; multi-scale SPEI analysis could reveal additional drought regimes. Finally, the continuous model metrics reported in Table 2 and Figure 3 should be reproduced from the final cleaned dataset and the final preprocessing workflow before operational application.

Future work should (i) extend the monitoring network, particularly along the Jabal Nafusah foothills; (ii) integrate higher-temporal-resolution aerosol and soil-moisture products; (iii) benchmark the Ensemble against spatial architectures such as ConvLSTM and Transformer-based models; and (iv) quantify predictive uncertainty using probabilistic approaches such as Bayesian deep learning or quantile regression.

Data availability. The analyses in this manuscript use the supplied monthly climate workbooks for Tripoli Airport, Al-Aziziyah and Al-Asa covering 1985–2022. The source files contain 456 monthly observations per station (1,368 station-month records in total before derivation of indices and LSTM sequences).

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