STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **13**, March 2025, pp 1063–1075.
Published online in International Academic Press (www.IAPress.org)

Machine learning methods for modelling and predicting dust storms in Iraq

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Abstract Dust storms are a significant problem that impacts humans, the environment, and the economy in Iraq, especially in the Baghdad, Nineveh, and Basra provinces, which have the most vital and substantial urban agglomerations in Iraq. These areas are heavily affected by dust storms. The monthly dust storm data and factors based on temperature, surface pressure, wind speed, wind direction, humidity, and precipitation were sourced from the Iraqi Meteorological Organization and Seismology and NASA from January 1981 to December 2022. In this study, we used the principal components intended to reduce the interrelated variables and capture the components that account for at least 80% of the total variance in the data set. Various supervised machine learning algorithms created a model to analyze and predict the monthly frequency of dust storms in the three provinces until March 2027. Our findings indicate that the Additive Regression model, employing the IBk lazy algorithm for the Basrah and Nineveh regions and the KStar lazy algorithm for Baghdad, outperformed other methods in terms of accuracy. The data suggest a reduction in the occurrence of dust storms in the three provinces, with this downward trend projected to persist over the next 40 months.

Keywords Principal Components, Ensemble Approach, Additive Regression Algorithm, Lazy algorithm, Prediction

AMS 2010 subject classifications 62M20, 68U20

DOI: 10.19139/soic-2310-5070-2122

1. Introduction

Iraq is located in the Middle East, situated within latitude coordinates 29° 5' to 37° 22' north and longitude coordinates 38° 45' to 48° 45' east in the southwestern region of Asia. It shares borders with Iran, Kuwait, Saudi Arabia, Jordan, Syria, and Turkey. Covering an approximate total area of 435,052 square kilometers, Iraq is characterized by four diverse geographical regions, the alluvial plain, and spans approximately a quarter of Iraq's area (about 132,500 square kilometers). The desert plateau comprises less than half of Iraq's territory (approximately 168,552 square kilometers). The mountainous region covers around a quarter of Iraq's landmass (approximately 92,000 square kilometers), and the terrain area occupies about 67,000 square kilometers [1].
Iraq experiences a subtropical continental climate influenced by its proximity to the Mediterranean Sea. Most precipitation occurs during the winter, fall, and spring seasons, with little rainfall in the summer. Throughout the year, northwesterly winds prevail across Iraq, bringing certain weather conditions, especially when air depressions pass from the central and southern regions to hot and humid winds from the Arabian Gulf region [2].
Iraq is situated in the center of the Dust Belt, as a primary source of dust storms [3] (Figure 1). A significant portion of Iraq is the desert (Figure 2), comprising about half of Iraq's total area. This area is Al-Jazeera and the western plateau; Kuwait borders it from the southeast, Saudi Arabia from the southwest, Jordan from the west, and Syria from the northwest [2].

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

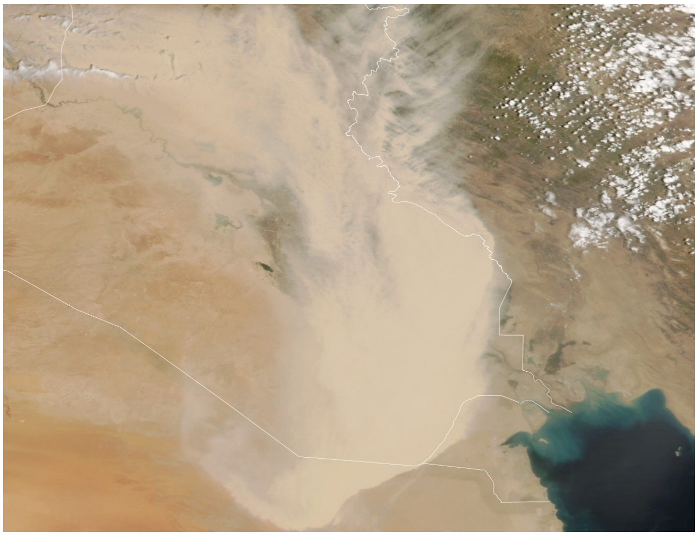

Figure 1. Dust Storm over Iraq [4]

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Figure 2. Map of Iraq [5]

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Iraq stands in the top five countries most severely impacted by global climate change [6]. This reality is evident through rising temperatures and reduced rainfall. Moreover, the increasing frequency and intensity of dust storms over the past few decades highlight a severe environmental concern within the country. These storms from local desert areas and neighbouring countries complicate Iraq's challenges. Consequently, Iraq struggles with the dual dilemma of vulnerability to drought [7] and its ensuing outcomes, including escalating desertification and agricultural land deterioration. These issues significantly shadow food security, the economic sectors, and public health.

Dust storms depict recurrent natural risks ascribable to desertification, low precipitation totals, powerful and unstable winds entraining, low air-pressure environments, and geographical closeness to desert areas. In Iraq, dust storms constitute daunting environmental, economic, social, and health challenges, impacting most Iraqi land, particularly the southern, central, and northwestern regions, covering Basrah, Baghdad, and Nineveh provinces. These provinces, characterized as densely populated, endure the brunt of dust storm phenomena due to their proximity to expansive desert regions and lengthy periods of aridity, exacerbated by energetic winds.

Dust modelling poses a considerable challenge for researchers [8] because of its intricate makeup of meteorological dynamics, its interaction with atmospheric particles [9], and nearby and surrounding environmental interactions.

The broad applications of machine learning in many areas to address intricate issues and problems are well known. The main concept behind machine learning is to recognize and enhance the machine's ability to identify a typical pattern within the problem domain and classify and predict changes [8, 10].

In recent years, studies have effectively utilized machine learning for sand and dust storm modelling and forecasting. Nabavi et al. (2018) employed five machine learning algorithms, artificial neural network, support vector machines, random forest, multiple linear regression, and multivariate adaptive regression spline for dust prediction in West Asia [11]. Harba et al. (2020) utilized a convolutional neural network to design a model to detect dust storms and predict their direction [12]. Gholami et al. (2020) utilized and tested six algorithms for machine learning for predicting dust provenance in southeastern Iran: ANFIS, BMARS, Cforest, Cubist, Elasticnet, and XGBoost [13]. Furthermore, Gholami et al. (2021) applied a novel integrated modelling approach, including deep learning, game theory, Gaussian copula-based multivariate, and leave one feature out method for mapping dust sources in central Asia [14]. Ebrahimi-Khusfi et al. (2021) assessed the suitability of nine machine learning models, named extreme gradient boosting, genetic programming, artificial neural networks, Cubist, k-nearest neighbours, multivariate adaptive regression splines, least absolute shrinkage and selection operator, random forest, and support vector machine for predicting the seasonal dust storm index in arid areas of Iran [15]. Aryal (2022) investigated the performance of five machine learning models, including Bayesian regularized neural networks, Cubist, multiple linear regression, random forests, and support vector machines in predicting aeolian dust over the southwestern United States [16]. Wang et al. (2023) employed four algorithms for machine learning, including gradient boosting trees, random forests, maximum entropy, and support vector machines for sand and dust storm source prediction in the central Asian arid zone [17]. Pourhashemi et al. (2023) used remote sensing methods and machine learning algorithms, including random forest, logistic regression, and multivariate adaptive regression spline to identify dust sources and prepare susceptibility maps for the area in the borders of Iraq and Iran (Maysan and Al-Basrah provinces in Iraq and Khuzestan province in Iran) [18]. Alshammari et al. (2024) employed five machine learning methods: gradient boosting regression tree, long short-term memory, multiple linear regression, support vector machine, and temporal convolutional network to forecast dust storm frequency for three cities of Saudi Arabia (Riyadh, Jeddah, and Dammam) [19].

Numerous studies have concentrated on forecasting dust storms in Iraq using machine learning to improve disaster readiness and mitigate damage. Zamim et al. (2019) implemented an Artificial neural network technique for predicting dust storms in selected cities in Iraq, including Baghdad, Basrah, Samawa, and Nasiriya [20]. Hamidi and Roshani (2023) applied long-short-term memory to investigate dust activity and predict aerosol optical depth [21]. Hassan and Saleh (2023) used five regression algorithm learning (Bayesian ridge, decision tree, linear regressor, gradient boosting regressor, and stochastic gradient descent) to forecast dust in five central Iraqi districts [22]. Additionally, Hassan and Saleh, (2024) applied deep learning long short-term memory-based regression to monitor dust phenomena and dust prediction in Iraq [23].

This paper aims to develop machine learning models for dust storms in three Iraq provinces that characterize different geographical locations. These are Baghdad, Nineveh, and Basrah, which have high population density and therefore predicting occurrences of dust storms from years 2023-2027 as inputs for decision makers for putting in place preventive measures for desertification-prone areas by expanding natural vegetation programs to combat dust storms severity and its associated adverse effects on people living there.

2. Study Area

Our study focuses on Iraq's three provinces: Baghdad, Nineveh, and Basrah. These provinces comprise more than 40% of Iraq's population and are home to over 16,362,695 million people. These regions are particularly prone to frequent dust storms compared to the other parts of Iraq due to their proximity to desert areas, including the island and the western Sahara region, as well as neighbouring desert regions in Syria, Saudi Arabia, and Kuwait. These provinces are as follows:

Baghdad is the capital of Iraq, located in central Iraq, has latitude and longitude coordinates of 33.312805° N and 44.361488° E [24]. It shares borders with Anbar province to the west, where the western desert is located. Covering an area of 5,169 square kilometers. The province of Baghdad is divided into 32 administrative units, which form ten districts. In 2022, the total population of Baghdad province was 9,006,001 [25]. Due to its proximity to the western desert, Baghdad's desert climate is characterized by intense summer temperatures exceeding fifty degrees Celsius and dry atmospheric conditions.

Basrah province, located in southern Iraq, is near the primary source of dust from the south and western deserts. Its latitude and longitude coordinates are 30.5258° N and 47.7738° E, respectively [26]. It shares international borders with Kuwait to the south and Iran to the east. Covering an area of 19,730 square kilometers. Basrah province represents 4.4% of the total area of Iraq. It comprises 16 administrative units (districts), forming seven districts, with a total population of 3,223,158 at 2022 [25]. The climate of Basrah is a hot desert with a wide temperature range, minimal precipitation, and high levels of humidity.

Nineveh province is located in the northern part of Iraq. It encompasses the Al-Jazeera region and is adjacent to the Syrian desert, with latitude coordinates 36.2296° N and 42.2362° E, respectively [27]. Covering an area of 33,313 square kilometers. Nineveh province represents 8.6% of the total area of Iraq. It comprises 31 administrative units (districts), forming ten districts, with a total population of 4,133,536 at 2022 [25]. A semi-arid climate, with dry and hot summers, characterizes Nineveh. Its relatively low elevation, not exceeding 225 meters above sea level, contributes to extreme temperatures. Winter temperatures can drop below freezing, with annual precipitation averaging 375 mm and occasional snowfall [1].

3. Data Collection

Data about dust storms and climate variables for the three provinces of Baghdad, Nineveh, and Basrah were collected from the Iraqi Meteorological Organization and Seismology and NASA. The data set comprises 504 monthly observations that span from January 1981 to December 2022. It encompasses the frequency of dust storms, surface pressure (kPa), wind speed at 10 meters (m/s), wind direction at 10 meters (degrees), minimum and maximum temperature at 2 meters (°C), relative humidity at 2 meters (%), specific humidity at 2 meters (g/kg), precipitation (mm/day).

4. Methods

4.1. Data preprocessing and visualization

Before initiating data analysis, we handled the missing data using Maximum Likelihood parameter estimation with expectation maximization. We employed the Interquartile Range to identify outliers and extreme values. To reduce the number of variables and perform pattern recognition and feature extraction, we employed Principal Component analysis (PCA). This approach intends to minimize the interrelated variables to a few principal components and to capture the components accounting for at least 80% of the total variance in the dataset. Radar plots were constructed for visual comparison and to identify the patterns of the factors. Figure 3 shows the flowchart for data preprocessing, select algorithm, and performance evaluation.

4.2. software tool

We used Weka, an open-source machine learning software that provides tools for data preprocessing, implementation of several machine learning algorithms, and visualization [28]. We utilized Weka's Meta implementation.

4.3. Dataset training

The process comprised two main phases: training and testing to develop the machine learning models. The dataset was partitioned into a training set, which accounted for 67% of the data, and a testing set, which accounted for 33%.

4.4. Statistical Model

For the forecasting process, we utilized machine learning techniques by integrating the meta additive regression algorithm (AR) as an ensemble approach, along with the IBk lazy method as the base learner for Basrah and Nineveh, and the KStar lazy method as the base learner for Baghdad.

4.4.1. Meta classifiers Tukey originated the concept of ensemble learning methods by merging two linear regression models [29]. Since then, other researchers have followed this challenge by using techniques such as splitting the problem space and utilizing single or multiple classifiers [30]. Ensemble modelling aims to perform better by merging multiple learning algorithms [31].

Additive regression models Additive regression is a Meta-learning classifier that enhances the performance of a classifier based on regression. Each iteration fits a model to the residuals left by the classifier on the previous iteration. Prediction is achieved by adding the predictions of each classifier. Reducing the shrinkage (learning rate) parameter helps prevent over-fitting and has a smoothing effect but increases the learning time [32].

Lazy algorithms Lazy consists of algorithms that uphold the edifice in classifiers until the classification time. The KStar and IBk are some approaches of this algorithm.

IBk algorithm The IBk algorithm in Weka software is also called the k-nearest neighbours classifier. It is a lazy learning classification algorithm based on learning by analogy. The training samples are described by N-dimensional numeric attributes. Each sample corresponds to a point in n-dimensional space. The algorithm retains only the training dataset rather than providing a specific discriminative function. An appropriate k value can be selected using cross-validation and can perform distance weighting [33, 34, 35].

KStar algorithm KStar is an easy and efficient method for lazy learning classification. The class of a test instance depends on the class of those similar training instances, as determined by some similarity function in an instance-based classifier. It varies from other instance-based learners through an entropy-based distance function [36, 37].

4.4.2. Performance evaluation criterion We used Mean Square Error (MSE), Relative Absolute Error (RAE), Root Relative Square Error (RRSE), Mean Absolute Error (MAE), and Direction Accuracy (DA) for evaluation metrics.

5. Results and Discussion

Iraq is one of the Arab countries most vulnerable to climate change, manifesting through rising temperatures and diminishing rainfall [38, 39]. These factors culminate in a depletion of water resources, subsequently leading to reduced vegetation cover, agricultural land loss, and heightened desertification. Consequently, the frequency of dust storms escalates, exerting adverse effects on economic, social, and health development and exacerbating the spread

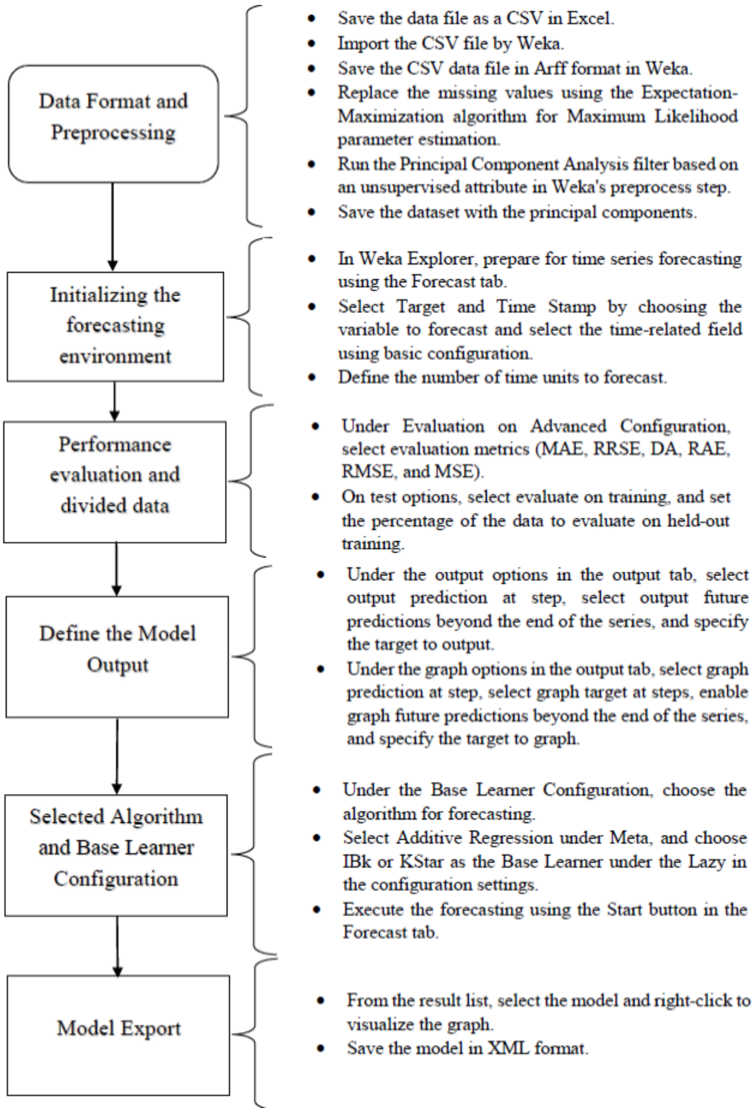
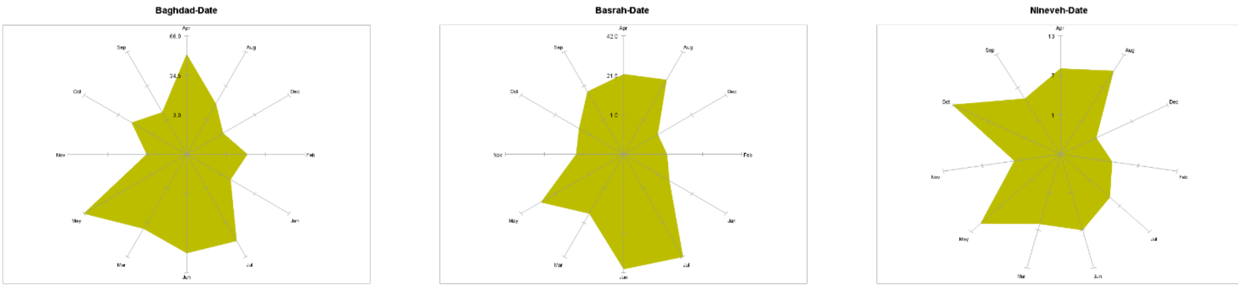


Figure 3. Flowchart for the model selection and configuration in Weka.

of diseases and epidemics. Between 1981 and 2022, Baghdad experienced an average annual temperature increase of 0.067 degrees Celsius, Nineveh 0.043 degrees Celsius, and Basrah 0.032 degrees Celsius. Precipitation levels in Iraq vary according to geographical region, gradually decreasing from northeastern to southwestern areas. In the northeast, annual precipitation exceeds 700 mm and can reach over 1000 mm in certain areas. Conversely, it decreases significantly in the southwest, with an average yearly rainfall of less than 100 mm [1, 40]. The combination of lack of rain, soaring temperatures, and inadequate water management has spurred the expansion of desertification and arid regions. This expansion has affected approximately 70% of irrigated agricultural lands, 72% of rain-fed farmlands, and 90% of pastures due to water scarcity and increased drought [41].

The radar chart displays the variables influencing the frequency of dust storms in the three provinces. The date of the most frequent dust storm events is October in Nineveh, May in Baghdad, and June and July in Basrah (Figure 4). The study results are consistent with previous studies on dust events [42, 43, 44], which found that spring and summer depict the primary dust season in Iraq.



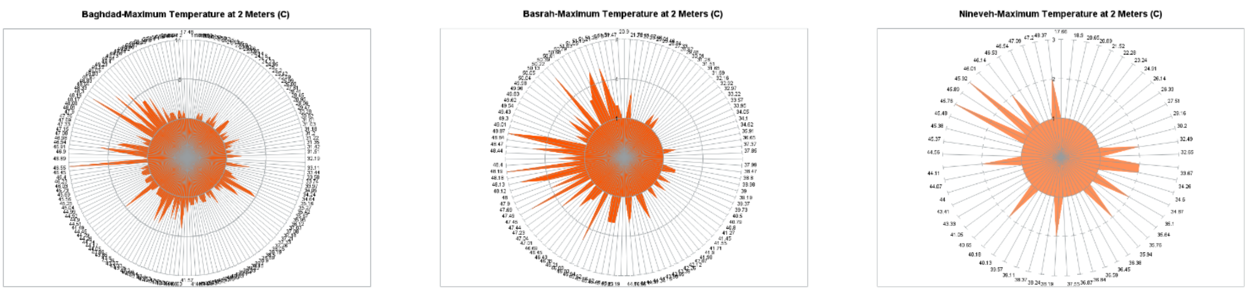
(a) Frequency of the dust storm events by date (in a month) for the Baghdad province.

(b) Frequency of the dust storm events by date (in a month) for the Basrah province.

(c) Frequency of the dust storm events by date (in a month) for the Nenavah province.

Figure 4. Frequency of dust storm events by date in the three provinces.

Iraq is characterized by high summer temperatures, especially in the study area, which may reach 50 degrees Celsius. It is shown from Figure (5) that most dust storms in the three provinces occur when temperatures are high (above 40 degrees Celsius), as the higher the temperature, the greater the frequency of dust storms. High summer temperatures, in addition to extensive seasonal and daily temperature ranges, where The difference between minimum and maximum temperatures ranges from 17 to 20 degrees Celsius, are accompanied by low humidity, which leads to soil fragmentation. Therefore, it is easy to lift with the wind [45].



(a) Maximum temperature relationship with the frequency of dust storm events in the Baghdad province.

(b) Maximum temperature relationship with the frequency of dust storm events in the Basrah province.

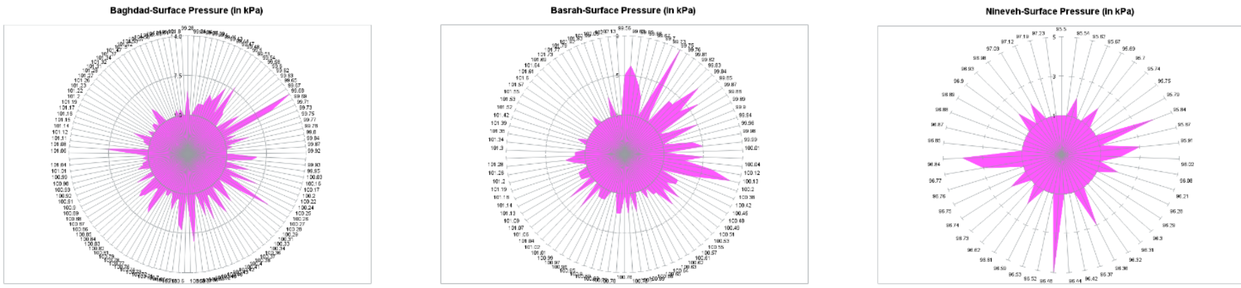
(c) Maximum temperature relationship with the frequency of dust storm events in the Nenavah province.

Figure 5. Maximum temperature relationship with the frequency of dust storm events in the three provinces.

Dust storms have been closely linked to surface pressure, with varying thresholds indicating heightened dust events in the three provinces. In Baghdad, If the surface pressure is less than 101.80 (kPa), at least one dust event is expected. The frequency of dust storms increases with low surface pressure and other contributing factors. In Basrah, If the surface pressure is less than 102.13 (kPa), at least one dust event is expected. In Nineveh, a surface pressure of less than 97.25 (kPa) results in at least one dust event (Figure (6)).

Wind speed at 10 meters (m/s) correlates significantly with dust storm events. In Baghdad, exceeding 5.82 m/s and other contributing factors often result in at least one dust storm event. Basrah sets the threshold at 6.23 m/s, beyond which a dust storm event is expected. In Nineveh, speeds exceeding 6.62 m/s typically lead to at least one dust storm event (Figure (7)).

Dust storms are strongly associated with wind direction. In Baghdad, wind direction from west-northwest to north-northwest and other contributing factors is likely to result in at least one dust storm event, with the likelihood increasing as north-northwest wind direction. Basrah's threshold is west to north-northwest, and at least one dust

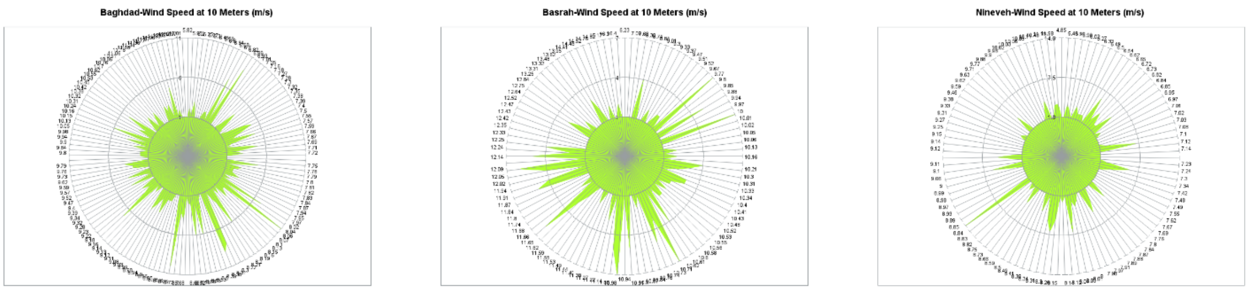


(a) Surface pressure relationship with the frequency of dust storm events in the Baghdad province.

(b) Surface pressure relationship with the frequency of dust storm events in the Basrah province.

(c) Surface pressure relationship with the frequency of dust storm events in the Nenavah province.

Figure 6. Surface pressure relationship with the frequency of dust storm events in the three provinces.



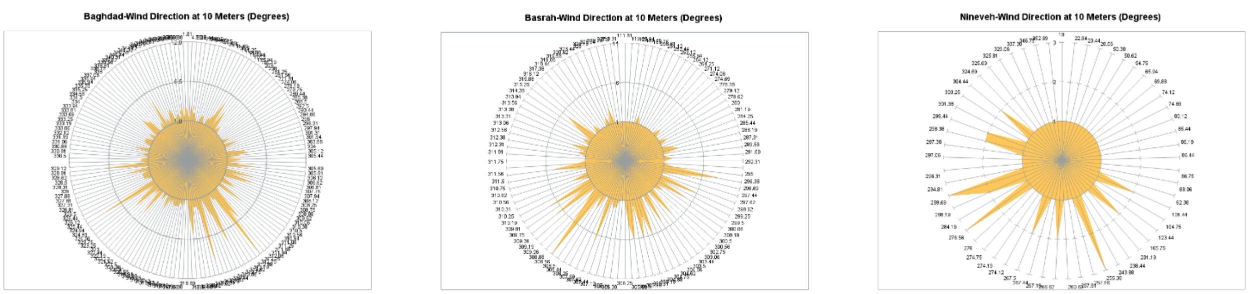
(a) Wind speed relationship with the frequency of dust storm events in the Baghdad province.

(b) Wind speed relationship with the frequency of dust storm events in the Basrah province.

(c) Wind speed relationship with the frequency of dust storm events in the Nenavah province.

Figure 7. Wind speed relationship with the frequency of dust storm events in the three provinces.

storm event is expected. In Nineveh, wind direction from the west-southwest to the north-northwest is likely to lead to at least one dust storm event (Figure (8)).



(a) Wind direction relationship with the frequency of dust storm events in the Baghdad province.

(b) Wind direction relationship with the frequency of dust storm events in the Basrah province.

(c) Wind direction relationship with the frequency of dust storm events in the Nenavah province.

Figure 8. Wind direction relationship with the frequency of dust storm events in the three provinces.

The provinces of Baghdad and Basrah, situated in central and southern Iraq, experience a higher frequency of dust storms compared to Nineveh province in the northwest. This increased frequency can be attributed to combined various factors, including Iraq being affected by several air depressions that move over these areas, usually accompanied by active winds from the northwest or southeast, high temperatures, and low surface pressure.

The study results are consistent with Al-Lami's report that most areas of Iraq are exposed to the dust phenomenon, especially in the area west of Basrah, south of Nasiriyah, Samawah, Salman, and southwest of Baghdad [45]. The peak of this phenomenon occurs due to the nature of its land surface, its geographical location, the loss of vegetation cover, the intensity of the winds, which depend on the nature of the atmospheric pressure systems, the state of instability caused by rising air currents, and the lack of rain, all of which are factors that help in the stirring of dust and sand [45]. Furthermore, the proximity to desert and semi-desert regions and the high population density in urban areas [43]. Al-Khalidi et al. (2021) concluded that drought in the summer, along with northwesterly winds, are the primary factors leading to dust storms and subsequent long-distance dust transport [42]. In a recent study, Khidher (2024) also recorded that dust storms form due to the convergence of two pressure systems over Iraq, two outside Iraq, and a single pressure system affecting Iraq [46]. Furthermore, another study emphasized the regional nature of sand and dust storm events. These events extend beyond Iraqi borders, involving neighbouring countries as well. This regional aspect underscores that such phenomena are not purely local but have broader implications [47].

The first four components explain 85.4% of the dust storm frequency variance for Baghdad province. For the first component, strong associations were identified with minimum temperature, maximum temperature, wind speed, and surface pressure. The second component is precipitation, relative humidity, and specific humidity. The date of the dust storm, Basrah's dust storm frequency for the third component, and wind direction for the fourth component. Similarly, the first four components explain 81.2% of the dust storm frequency variance for Basrah province. For the first component, minimum temperature, maximum temperature, surface pressure, precipitation, and relative humidity. The second component is specific humidity and wind direction. The dust storm frequency of Baghdad and Nineveh is the third component, and the date of the dust storm is the fourth component. Finally, the first four components explain 80.6% of the dust storm frequency variance for Nineveh province. Strong associations were found with minimum temperature, maximum temperature, wind direction, precipitation, and relative humidity for the first component. Dust storm frequency of Baghdad and Basrah for the second component. Wind speed is for the third component, and the date of the dust storm is for the fourth component.

We conducted an exhaustive evaluation of machine learning algorithms to forecast the dust storm frequency data in the three provinces and identify the most suitable methods. The highest accuracy for the Baghdad dust storm frequency data among the algorithms tested was an Additive Regression (AR) with the KStar lazy algorithm, where the number of instances processed is 1000, the number of iterations is 100, and the shrinkage rate is set to 1.0. For the base classifier, the parameter for global blending is 50, the number of instances process is 1000, and the missing mode is average column entropy curves. The AR with the IBk lazy algorithm achieved the highest accuracy for the Basrah dust storm frequency data, where the number of instances processed is 1000, the number of iterations is 100, and the shrinkage rate is set to 1.0. For the base classifier, the number of instances processed is 1000, the number of neighbours used is five, there is no distance weighting, and the nearest neighbour search algorithm is the nearest neighbour search. The highest accuracy for the Nineveh dust storm frequency data was achieved using the AR with the IBk lazy algorithm as the classifier. The number of instances processed is 1000, the number of iterations is 1000, and the shrinkage rate is set to 0.5. For the base classifier, the number of instances processed is 1000, the number of neighbours used is eleven, there is no distance weighting, and the nearest neighbour search algorithm is the nearest neighbour search. Table 1 shows the evaluation metrics for the best methods obtained for the training and testing data. Regarding the results of dust storm frequency for Baghdad province, the evaluation metrics show that the prediction values in both training and testing of dust storm frequency are close to the actual values for the additive regression (KStar as a base learner). The MSE = 0.11, RMSE = 0.33, and DA = 85.6% for training data, while the MSE = 1.33, RMSE = 1.15, and DA = 77.36% for testing data. This illustrates that actual data with predicted values from the used model are aligned. Concerning the results of dust storm frequency for Basrah province, the predicted values in both training and testing of dust storm frequency are very close to the actual values when considering the evaluation metrics (MSE of 0.0, RMSE of 0.0, and DA of 97.22% for training data; MSE = 0.16, RMSE = 0.40, and DA = 82.80% for testing data). This demonstrates that the actual and predicted values from the additive regression with IBk as a base learner are harmonious. For the dust storm frequency for Nineveh province results, the predicted values closely match the actual values considering the evaluation metrics (MSE of 0.0, RMSE of 0.0, and DA of 98.31% for training data; MSE = 0.12, RMSE = 0.35, and DA = 89.30%

for testing data). This confirms that the predicted and frequency dust storm values are harmonious with additive regression (IBk as a base learner).

Table 1. Results of Additive Regression algorithm with base learner methods

	Baghdad		Basrah		Nineveh	
	AR (KStar)	AR (IBk)	AR (IBk)	AR (IBk)	AR (IBk)	AR (IBk)
Evaluation Metrics	Training data	Test data	Training data	Test data	Training data	Test data
MAE	0.04	0.47	0.0	0.102	0.0	0.07
RRSE	20.46	110.78	0.0	77.92	0.0	70.71
DA	85.6	77.36	97.22	82.8	98.31	89.3
RAE	4.45	88.15	0.0	57.96	0.0	50
RMSE	0.33	1.15	0.0	0.40	0.0	0.35
MSE	0.11	1.33	0.0	0.16	0.0	0.12

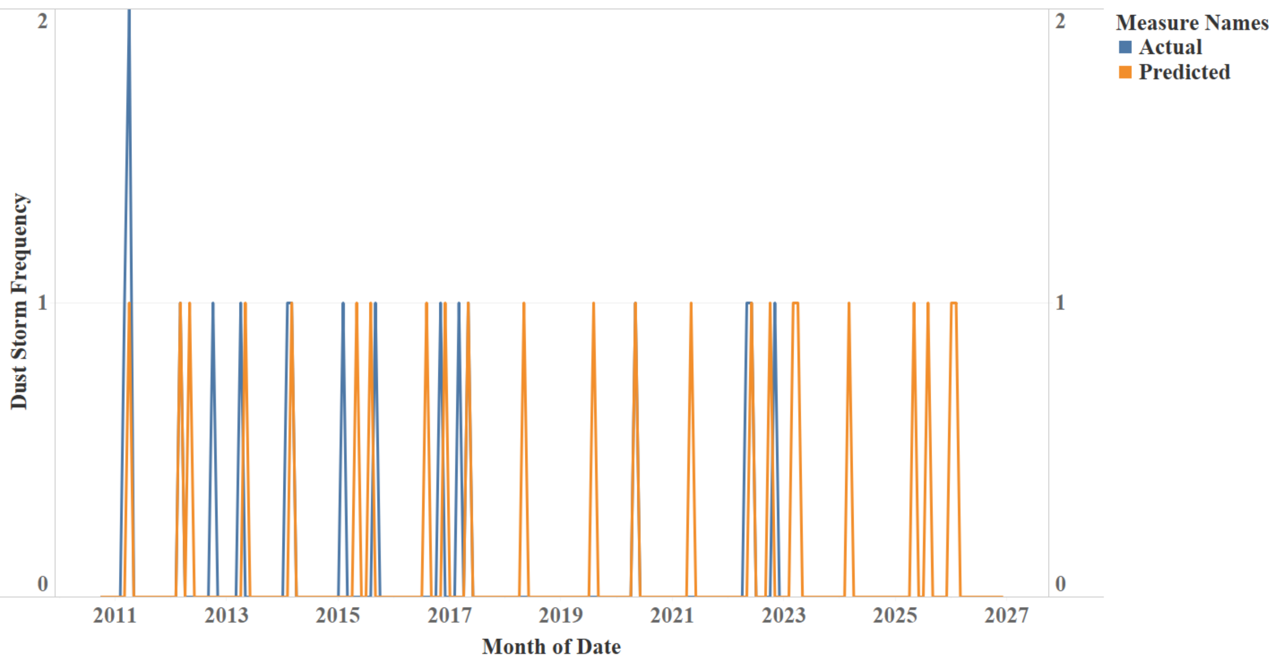


Figure 9. Forecasting of Dust Storm Frequency for Basrah.

Figures 9-11 show the actual versus predicted frequency of dust storms from October 1, 2010, to December 1, 2022, for testing data and a forecast for 40 months to March 1, 2027. The forecasting analysis shows that it produces accurate predictions and performs better. The forecasting analysis shows a slight decrease in the frequency of dust storms in the three provinces, and this decline is expected to continue for the next 40 months.

To reduce the phenomenon of dust storms in Iraq, developing a comprehensive government plan involving a set of steps should be taken by the various state institutions concerned with reducing the phenomenon of dust storms with the participation of society; among these steps is monitoring areas exposed to drought and desertification. Furthermore, early environmental change monitoring uses modern techniques such as remote sensing, geographical information systems, ground-based surveys, climate and weather monitoring, and early warning systems to manage land degradation in arid and semi-arid areas. It also requires reducing overgrazing of natural pastures, plowing

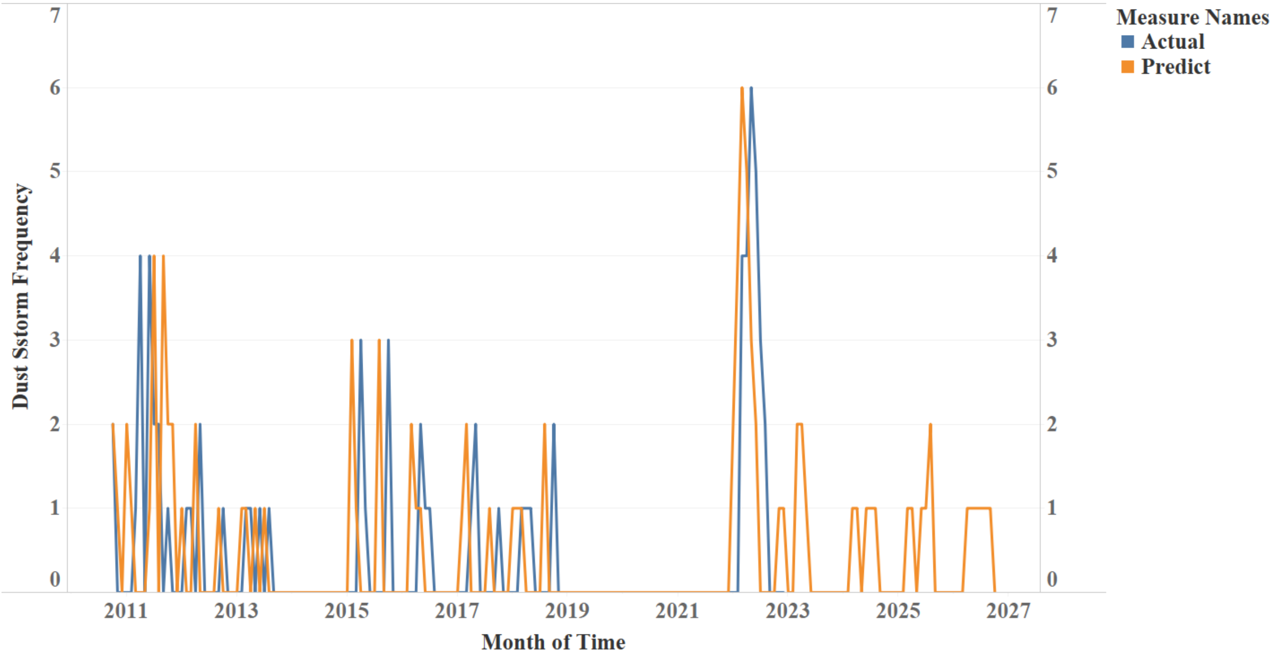


Figure 10. Forecasting of Dust Storm Frequency for Baghdad province.

lands with little rainfall, and restricting the movement of machinery and wheels off paved roads. In addition, desert plants are benefitted as a basic element of vegetation cover in areas exposed to drought and desertification, as well as expanding programs to develop natural vegetation cover through the optimal use of agricultural lands and water resources.

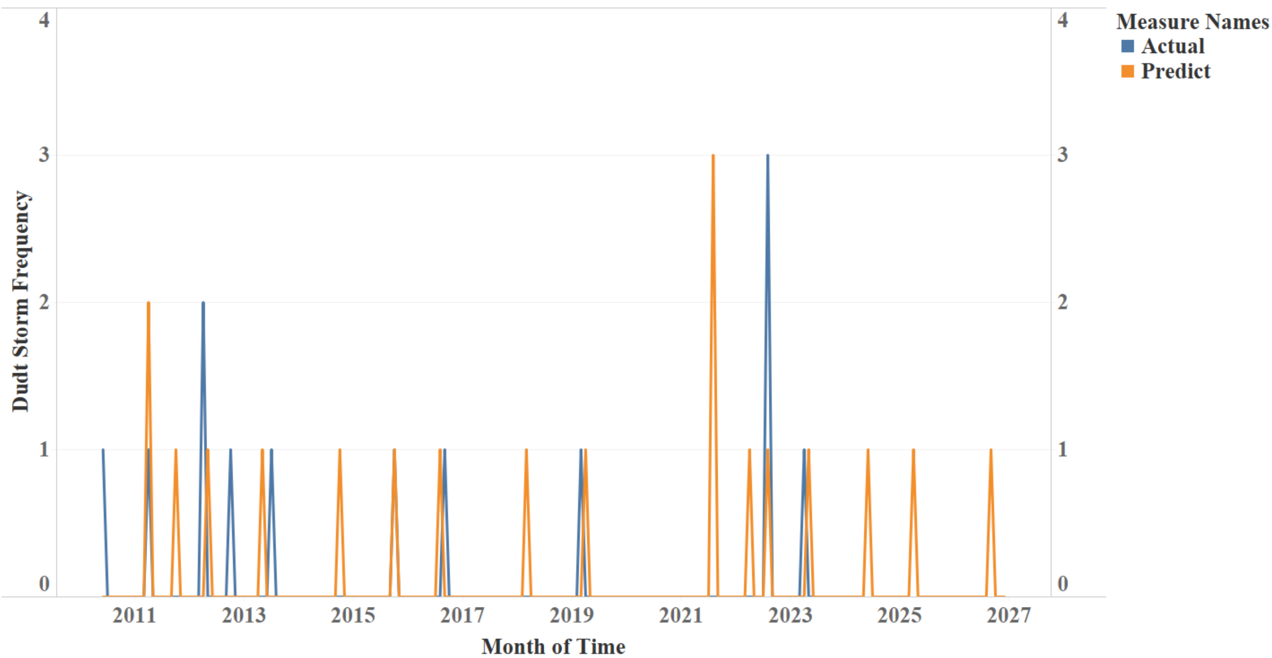


Figure 11. Forecasting of Dust Storm Frequency for Nenavah province.

6. Conclusion

This paper studied the frequency pattern of dust storms in three central provinces: Baghdad, Nineveh, and Basrah, located in central, northern, and southern Iraq, respectively. Principal component analysis revealed that the most critical factors in dust storms are temperature and active winds, followed by low humidity and lack of rain (drought). Third, the propagation of storms from one province to another is influenced by the direction of the wind and the time of the dust storm. Various machine learning algorithms were applied to develop the best models for representing the studied phenomenon and predicting the frequency of dust storms based on historical data for the three provinces until March 2027. We used evaluation metrics, including MSE, RMSE, MAE, PRSE, RAE, and DA. We found that the best models for predicting dust storms in Basrah and Nineveh provinces were AR with the IBk lazy algorithm and AR with the KStar lazy algorithm for Baghdad. These models allow us to measure the frequency of dust storms for the next 40 months. Accurate forecasting models of the frequency of dust storms provide crucial information to the province and decision-makers about predicted events, enabling them to take necessary measures, including developing strategies to counteract desertification, exploring non-traditional sources, and managing water resources. The forecast analysis shows a slight decrease in the frequency of dust storms in the three provinces, and this decline is expected to continue for the next 40 months.

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