مجلة جامعة أم القرى للعلوم الاجتماعية
الموقع الإلكتروني: https://uqu.edu.sa/jss

Modeling the distribution of coastal sand dunes in western Saudi Arabia between Makkah Al-Mukarramah and Al-Madinah

نمذجة توزيع الكثبان الرملية الساحلية في غرب المملكة العربية السعودية بين منطقتي مكة المكرمة والمدينة المنورة.

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Received:09/06/24 Revised:01/08/24 Accepted: 14/10/24

تاريخ التقديم:09/06/24: تاريخ ارسال التعديلات: 01/08/24 تاريخ القبول:14/10/24

الملخص:

تتناول هذه الدراسة التحديات البيئية التي تفرضها الكثبان الرملية الساحلية الواسعة في المنطقة الغربية الشرقية من المملكة العربية السعودية، والتي تلحق أضرارًا بالمباني والطرق والمناطق الحضرية. تُقترح على وجه التحديد في هذا البحث منهجية لنمذجة توزيع الكثبان الرملية على طول الساحل بين منطقتي مكة والمدينة. الهدف هو التنبؤ بحركة هذه الكثبان الرملية استجابةً للتغيرات الجغرافية والمناخية. لتحقيق ذلك، تم جمع البيانات من مصادر مختلفة، بما في ذلك تقنيات الرصد وقواعد بيانات نظم المعلومات الجغرافية .(GIS) تم كذلك استخلاص البيانات التاريخية المتعلقة بعوامل التحكم مثل الارتفاع وهطول الأمطار واتجاه الرياح وسرعتها، بالإضافة إلى استغلال الأراضي والغطاء، باستخدام تقنيات وأساليب متنوعة. تم تطبيق نموذج MaxEnt كتقنية للتعلم الآلي للتنبؤ بتوزيع حركات الكثبان الرملية المحتملة، مع تقييم العوامل البيئية المؤثرة. تشير خريطة التوزيع الناتجة إلى أن سرعة الرياح هي العامل الأكثر أهمية في حركة الكثبان الرملية، في حين أن هطول الأمطار هو العامل الأقل تأثيراً في منطقة الدراسة.

الكلمات المفتاحية:العوامل المناخية؛ الكثبان الرملية؛ نمذجةMaxEnt ؛ نظم المعلومات الجغرافية؛ التغيرات البيئية.

Abstract:

This study addresses the environmental challenges posed by the extensive coastal sand dunes in the western region of Saudi Arabia, which inflict damage on structures, roads, and urban areas. Specifically, a methodology is proposed for modeling the distribution of sand dunes along the coast between the Makkah and Al-Madinah regions. The objective is to predict the movement of these sand dunes in response to geographic and climatic changes. To achieve this goal, data were collected from various sources, including monitoring techniques and geographic information systems (GIS) databases. Historical data related to controlling factors such as altitude, rainfall, wind direction and speed, as well as land use and cover, were extracted using diverse techniques and methods. The MaxEnt model was implemented as a machine learning technique to predict the distribution of potential sand dunes movements, while assessing environmental impact factors. The resultant map of sand dune movement indicates that wind speed is the most significant controlling factor of sand dunes movement, with precipitation being the least influential factor in the study area.

Keywords: Climatic factors; Sand dunes; MaxEnt modeling; GIS; Environmental changes.

Doi: https://doi.org/10.54940/ss28052076
1658-8169 / © 2024 by the Authors.
Published ***by J. Umm Al-Qura Univ. Soc. Sci.***

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1. Introduction

The movement of coastal sand dunes poses a significant threat, escalating with increasing wind speed and storms (Alkayyadi et al., 2020), leading to the accumulation of drifting sand dunes that present serious hazards in urban areas and road construction in western Saudi Arabia (Al-Harthi, 2002). Approximately 33% of Saudi Arabia territory is covered by various types size and shapes of sand dunes (about 635.000 Km^2) (Alkayyadi et al., 2020). Despite the vast expanse of sand in Saudi Arabia deserts and the growing concern over sandstorms affecting human activities (Alkayyadi et al., 2020), comprehensive research to address this issue is still in its early stages.

Numerous studies have been conducted across various sectors in Saudi Arabia, including Makkah, Jeddah, Riyadh, Al-Qassim, Al-Ahsa, and Al-Jafoura, as well as outside these areas, using multiple data sources such as cartography, satellite imagery, and field surveys. These studies have tackled various aspects of the issue, including desertification, risks associated with moving dune accumulations, sand dune patterns and morphology, dune migration, estimation of sand encroachment, monitoring, geohazard and risk assessment (Al-Mutiry et al., 2016), (Edgell, 1990). Most of these studies used a simple field measurement method.

In recent years, sand movement has become increasingly common (Alkayyadi et al., 2020). Geographical location and climatic elements significantly influence sand movement, especially along coastal roads. Aeolian deposition is the dominant pattern in the coastal area between Makkah and Al-Madinah, where wind and other climatic elements play a crucial role in sand formation and encroachment, hindering regional development (Alkayyadi et al., 2020).

Geomorphological and mathematical modeling studies have contributed for predicting sand encroachment, clarifying its distribution and dynamics, and identifying areas affected to varying degrees (Necsoiu et al., 2009), (Thompson & Amos, 2004), (Willetts & Rice, 1989), (Vincent, 1989), (Anton & Vincent, 1986), (Watson, 1985), (White & Schulz, 1977), (Holm, 1960). Remote sensing and GIS techniques have also been employed for sand dune risk assessment (Pradhan et al., 2018). Additionally, deep learning algorithms have been utilized to model dune motion and predict sand dune morphology evolution with higher accuracy and speed compared to traditional simulation methods (Kochanski et al., 2019). Real-time simulation methods, incorporating GPU (graphics processing unit)-based extensions, have been developed to capture aeolian sand transport and dune propagation, including interactions with obstacles and the formation of echo dunes (Taylor & Keyser, 2023). However, there is a significant lack of studies on sand dune mobility using a machine learning methods (or artificial intelligence techniques in general).
The research gap consisted in adapting an idea from the ecological domain that can be applied as a new technique to predict the sand dune distribution/movement. Among others machine learning methods, some models have been studied (Kochanski et al., 2019), (Taylor & Keyser, 2023). The MaxEnt model was explored in this study, this model hasn't been applied yet in the environmental field concerning sand dune distribution specifically.

Assessing sand dune movement distribution involves susceptibility, hazard, and vulnerability assessments, considering various potential controlling factors such as topography, geography, and climate characteristics. This study aims to highlight the influence of climatic and geographical (see section 2.2) on sand dune movement and identify areas threatened by their hazards, by predicting their spatial movement while identifying the most significant controlling factors.

2. Study area

The western coastal area of Saudi Arabia is selected in this current study, spanning between the regions of Makkah and Al-Madinah, and including the international road adjacent to the Red Sea, along a distance of 720 km, covering an area of 25,676 km² (Figure 1 and Figure 2).

Figure 1. Location map of the study area. Sand dune near road of one astronomical location point.

Climatically, the study area falls within the dry desert range, characterized by minimal rainfall, wide thermal fluctuations, and a significant temperature rise throughout the year, indicative of an arid environment (Alkayyadi et al., 2020). In terms of land use, pastoral areas dominate much of Al-Laith valley (Wadi Al-Laith), primarily utilized for grazing sheep, camels, and goats, making pastures the predominant current land use. Additionally, there are limited areas allocated for agriculture, where fertile soil and irrigation water are accessible, albeit in small and dispersed locations (Alkayyadi et al., 2020). Part of the land is designated for urban purposes, including residential complexes, services, and commercial activities.

Certain regions within this area exhibit a pronounced occurrence of sand movement and dust storm activity, particularly influenced by winds originating from the Red Sea and blowing from southwest to northeast. Residents of urban sectors adjacent to the road (Figure 2), such as Al-Laith valley, experience severe consequences of sand encroachment on their homes and facilities during periods of active sand movement (Alkayyadi et al., 2020), leading to frequent traffic accidents on days with heightened dust activity.

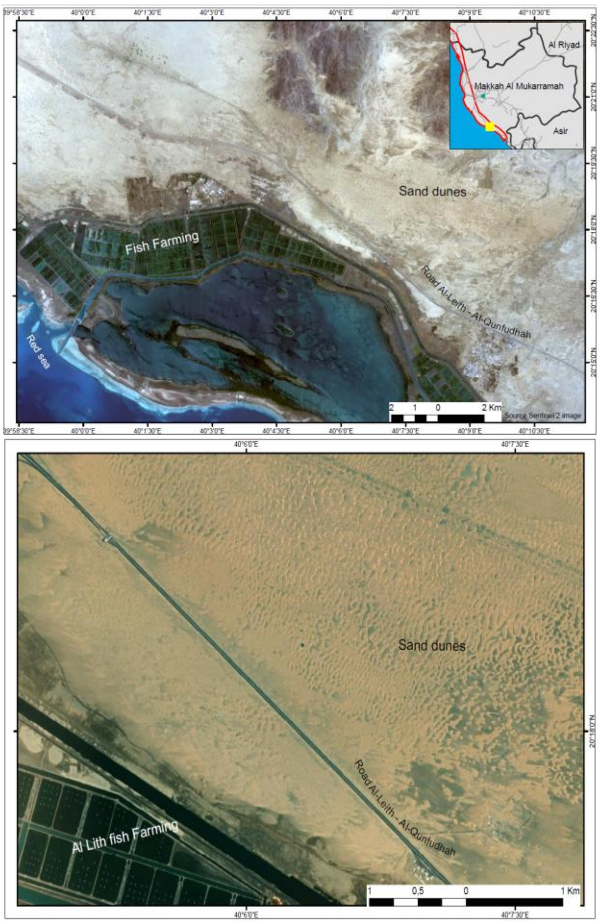

Figure 2. Location map of sand dune in the coastal road Al-Leith – Al-Qunfudhah area (from Sentinel image 18 august 2024 (up) and Google earth image (down).

3. Materials and Methods

Several datasets sourced from various providers are utilized, with some being openly accessible and freely obtainable. Table 1 in Appendix A provides a comprehensive overview of these datasets. All data were acquired, processed, and integrated into GIS database, ensuring uniformity in spatial coordinates.

The available data predominantly comprise dune occurrence records displayed in Figure 3 (thirty presence points), supplemented by background information representing environmental gradients conducive to dune movement. These background data are generated by randomly selecting points within the study area overlapping with dune presence data shown in Figure 3, ensuring the best geographical distribution that fit the surroundings dune movement. By incorporating background data, our aim is to encompass all cells within the potential area susceptible to dune movement, aligning with previous literature findings (Phillips & Dudik, 2008).

a. Sand dune occurrence data

Among approximately fifty control points (presence and background points) in the mapped area of dunes, some are situated within the coastal area, while others are located in fields adjacent to the road. The distribution pattern and ratio of sand measurements may vary between these locations due to the influence of wind movement.

To assess the suitability of the surroundings for dune movement, presence-only and presence-background algorithms were employed (Phillips & Dudik, 2008). These algorithms are designed to determine the suitability of an area for dune movement, irrespective of whether dunes are present or absent. This approach allows us to account for the potential influence of environmental factors on dune dynamics, providing a comprehensive understanding of the landscape's suitability for sand movement.

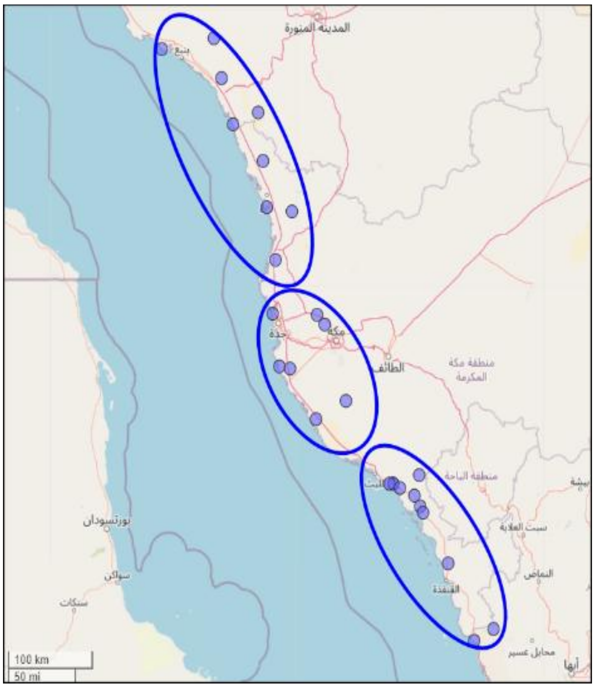

Figure 3. The astronomical location of sand dune (presence-only occurrence data) in three Zones: Zone 1 (High): Yanbu – Rabigh – Asfan – Thuwal; Zone 2 (Medium): Jeddah – Makkah, Zone 3 (Down): Al Lith – Al Qunfudhah.

b. Environmental variables; Sand dune controlling factors

Environmental variables based on representativeness and accessibility were selected to understand the potential adaptations of sand dunes to climatic and geographic pressures influencing their movement. The descriptions of these variables are provided in Table 1 in Appendix A. These variables include:

- Bioclimatic variables: These are commonly utilized in species distribution modeling and ecological niche models. Derived from monthly temperature and rainfall values spanning the period 1970-2000, the 19 bioclimatic variables represent annual trends (e.g., mean annual temperature, annual precipitation), seasonality (e.g., annual range in temperature and precipitation), and extreme environmental factors (e.g., temperature of the coldest and warmest month, precipitation of the wet and dry quarters).

- Monthly climate data: This dataset includes minimum, mean, and maximum temperature, rainfall, solar radiation, wind speed, and water vapor pressure.

- Topography: Altitude, derived from the NASA Shuttle Radar Topography Mission (SRTM) elevation data, is a significant factor influencing erosion processes and sand dune movement. Variations in topography across the study area may impact sediment movement rates.

All these variables were extracted from WorldClim 2.1; Historical climate data — WorldClim 1 documentation (https://www.worldclim.org/data/worldclim21.html) at a spatial resolution of 2.5 arcminutes (approximately 5 km² at the equator).

Additionally, other important controlling factors for sand dune movement were considered:

- Land use and land cover: Derived from the ESRI | Sentinel-2 10-Meter Land Use/Land Cover annual map of Earth's land surface; Esri Land Cover (arcgis.com) (https://livingatlas.arcgis.com/landcover/) from 2017-2023 (with many time snapshots), see more specifically this link: Esri | Sentinel-2 Land Cover Explorer (arcgis.com), https://livingatlas.arcgis.com/landcover-explorer/#mapCenter=10.78696%2C51.66528%2C11&mode=step&timeExtent=2017%2C2023&year=2023, this dataset reflects human activities and environmental development or degradation. It is crucial for sand dune modeling and vulnerability assessments, as it helps assess the potential effects of sand dune events on population and properties (Pradhan et al., 2018).

- Wind speed and direction: Wind is a primary factor in the aeolian erosion processes, significantly influencing sand dune movement. The western region of Saudi Arabia experiences wind activity, with severe winds increasing the potential for sand dune movement. Previous studies (e.g., Al-Ghamidi & Hermas, 2015) have found that prevailing wind directions in this region, particularly from the east and southeast, influence sand dune migration. These sand dunes commonly accumulate near major valleys and move against or into the foothills of escarpments. Consequently, areas with land use elements in close proximity to sand dune accumulations are at risk of dynamic sand movement (Al-Ghamidi & Hermas, 2015). The wind speed variable was derived from WorldClim 2.1; Historical climate data — WorldClim 1 documentation (https://www.worldclim.org/data/worldclim21.html) at a spatial resolution of 2.5 arcminutes (approximately 5 km² at the equator).

c. Sand dune distribution modeling and validation

Presence-only and presence-background data were used in the modeling process for the dune distribution model algorithms. Specifically, the maximum entropy (MaxEnt) algorithm accessed through the R statistical software (Phillips et al., 2006), (Phillips & Dudik, 2008) was performed to model the potential distribution of sand dunes across western Saudi Arabia. MaxEnt is a machine learning model and is the most widely used method in species distribution modeling algorithm. Phillips & Dudík, (2008) described MaxEnt as estimating a distribution across geographic space. Elith et a*l.,* (2011) provide an explanation of the algorithm geared towards ecologists.

The basic formula for a Maximum Entropy (MaxEnt) model, used for probabilistic classification (Berger et al., 1996), is expressed as follows:

$$P(y|\boldsymbol{x}) = \frac{1}{Z(\boldsymbol{x})}\exp\left(\sum_{i=1}^{k}\gamma_i f_i(y,\boldsymbol{x})\right).$$

where, $P(y|\boldsymbol{x})$ is the probability of the outcome (class) y given the observed feature vector $\boldsymbol{x}$. $\boldsymbol{x}$ is the feature vector that contains the information or attributes used to make the prediction. $f_i(y,\boldsymbol{x})$ are the feature functions that encode the relationships and capture various aspects of the input and the output. γ_i are the parameters (weights) learned from the training data and associated with each feature function f_i. $Z(\boldsymbol{x})$ is the normalizing factor or partition function, which ensures that the probabilities sum up to 1 over all possible classes:

$$Z(\boldsymbol{x}) = \sum_{y'}\exp\left(\sum_{i=1}^{k}\gamma_i f_i(y',\boldsymbol{x})\right).$$

The MaxEnt model finds the probability distribution $P(y|\boldsymbol{x})$ that best fits the given constraints (feature functions) while maintaining maximum entropy, meaning it makes the least assumptions beyond what is specified by the features. The model is trained by adjusting the parameters γ_i to match the empirical data (Berger et al., 1996).

The MaxEnt algorithm was adjusted to relate response variables (distribution of occurrences, presence-background) to predictive variables (environmental factors). To address multicollinearity, a Pearson correlation analysis was conducted, and variables with a correlation coefficient greater than 0.75 were removed (Elith et al., 2011). This procedure was performed iteratively during the modeling process to retain only variables significantly affecting model performance. The remaining variables were selected based on their importance for MaxEnt modeling. The distribution model was performed as the average of 10 MaxEnt model replicates. using the random subsampling method for modeling, with 30% of the data reserved for testing and 70% for training (Elith et al., 2011).

Model performance was assessed using two statistics: the Area Under the Receiver Operating Characteristic Curve (AUC) and the True Skill Statistic (TSS), which measures sensitivity and specificity. A robust model was considered to have an AUC greater than or equal to 0.75 (Phillips & Dudik, 2008), (Elith et al., 2011).

These AUC and TSS metrics are commonly used for evaluating classification models (Phillips & Dudik, 2008), (Elith et al., 2011):

- The AUC is a metric used to evaluate the performance of a binary classification model. It represents the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance:
  $\mathrm{AUC} = \int_0^1 \mathrm{ROC}(t)\,dt$, where $\mathrm{ROC}(t)$ is the ROC curve function, which plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.
- The TSS measures the skill of a binary classification model: $\mathrm{TSS} = \mathrm{TPR} - \mathrm{FPR}$, where $\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$ (also known as Sensitivity or Recall) and $\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP+TN}}$ (where TP: True Positives, FP: False Positives, TN: True Negatives and FN: False Negatives).

The same precision metrics (AUC & TSS) were used to evaluate the contribution importance of predictors to the potential distribution of sand dunes and interpret the model output. Finally, the predictions were visualized on a distribution map, providing insights into the potential spatial distribution of sand dunes in the study area.

4. Results and discussion

A comprehensive dataset of sand dune occurrence records (Presence-Background) was compiled and processed for distribution modeling across western Saudi Arabia. The potential distribution of assessed sand dunes spans most coastal regions in the west of Saudi Arabia (Figure 4) This figure illustrates the domain distribution by calculating the Gower distance between environmental variables at any location and those at any known occurrence location ('training sites') (Hijmans & Graham, 2006). The highest potential occurrence is concentrated along the coastal road from Al-Leith to Al-Qunfudhah. The spatial distributions are based on the probability distribution value scale, where black and yellow represent low and high probabilities, respectively.

The decision was made to model dune distribution at the scale of western Saudi Arabia to ensure that a sufficient amount of occurrence data could be utilized, facilitating the production of a high-quality distribution model. This approach is particularly crucial for areas where dune occurrences are rare, such as range land, bare land, and built-up areas.

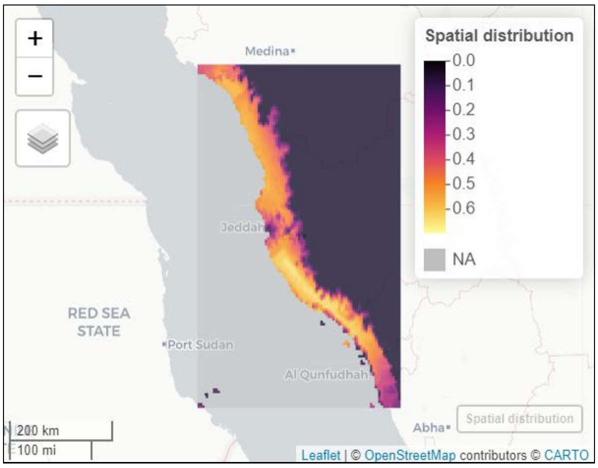

Figure 4. Spatial (domain) distribution map of sand dunes across the western Saudi Arabia using a distance-based approach.

a. Distributions of sand dune

The MaxEnt algorithm model has been deemed robust based on the evaluation criteria. Figure 5 depicts the distribution mapping of sand dune movement generated by the MaxEnt model. This map illustrates sand dune movement as a probability map, where black and yellow colors represent low and high probabilities, respectively.

The entire study area exhibits susceptibility to sand dunes, with the southern portion, particularly the coastal road from Al-Leith to Al-Qunfudhah adjacent to the Red Sea, being more prone. This area covers a distance of 115 km and an area of 437 km^2 (Figure 2).

Sand dunes are anticipated to move as wind speed and direction increase. From Figure 5, regions with high susceptibility are expected to experience high-speed winds, with dune movement likely occurring from west to east across the region, particularly through highly sensitive areas, therefore without contradicting the direction of the winds coming from the Red Sea, which blow from the southwest to the northeast. Additionally, movement from east to southeast is anticipated, aligning with prevailing wind directions in the western region of Saudi Arabia.

The current areas deemed suitable for sand dune mobility cover approximately twice the study area and exhibit a trend towards the east, particularly focusing on mountainous areas along the east-southeast direction.

This distribution modeling integrates susceptibility, vulnerability, and risk assessments of sand dunes. Susceptibility is quantified as a probability (ranging from 0 to 1) of sand dune occurrence. Hazard (or risk) analysis considers spatial and temporal components related to triggering factors such as wind speed and direction. Furthermore, by incorporating land use and cover, the distribution modeling accounts for vulnerability assessment.

Therefore, the potential distribution mapping was prepared as a probability map, combining susceptibility, vulnerability, and risk of sand mobility. Pixel values ranging from 0 to 1 indicate low and high probabilities, respectively. Figure 5 displays the probability of dune movement over the spatial scale of western Saudi Arabia, predicted from values of environmental variables (controlling factors) spanning a historical time period.

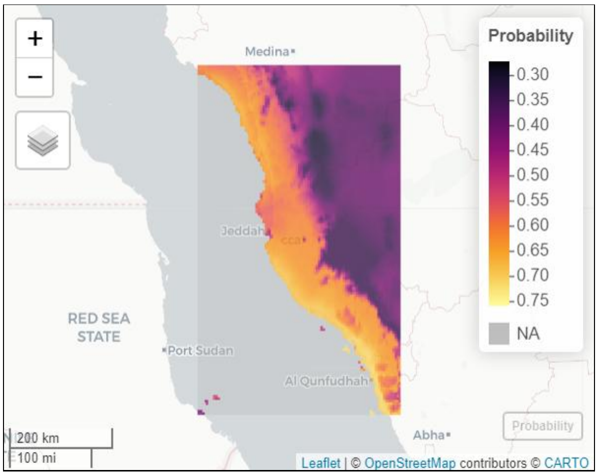

Figure 5. Distribution map of sand dunes movement across the western Saudi Arabia using MaxEnt model.

b. The relative contribution of controlling factors

The relative contribution of each controlling factor to the prediction results was evaluated using the model's AUC and TSS test dependence metrics, and the relative variable importance is depicted in Figure 6. Among the environmental factors, the top five contributors to dune potential distribution, ranked by percent contribution importance, are as follows:

1) Wind speed (wind): This factor emerges as the highest contributor to the potential distribution model, consistent with expectations.
2) Mean diurnal range (bio2): This represents the mean difference between maximum and minimum monthly temperatures.
3) Mean temperature of the driest quarter (bio9).
4) Solar radiation (srad).
5) Mean temperature of the wettest quarter (bio8).

Conversely, the land use and cover factor (LandUC) exhibited relatively less importance in the prediction results. However, when isolating these top five controlling factors, solar radiation (srad) gains more contribution importance, followed by mean diurnal range (bio2) and wind speed (wind). This suggests that wind speed provides the most valuable information when combined with other factors, with the four others having the highest impact. The whiskers in Figure 6 indicate the range of relative importance across the 10 replicate MaxEnt models.

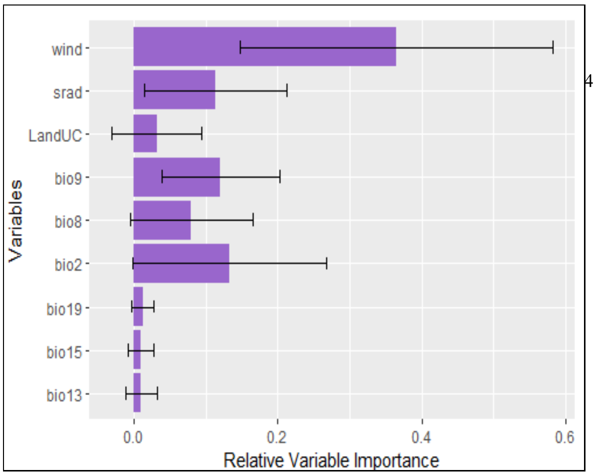

Figure 6. The relative importance of controlling factors.

The results showed the performance of the model in predicting the basic and well-known factors that strongly influence the distribution of sand dunes. The limitations are related to the difficulties in obtaining effective data and the lack of sufficient environmental variables data in sand dune field. Basically, our study shows the feasibility of studying and adapting such a model from the environmental field to predict the distribution of sand dunes.

5. Conclusion

The MaxEnt algorithm was performed for sand dune modeling, facilitating assessments of dune movement and the generation of distribution maps. Our findings indicate that certain geo-environmental factors significantly contribute to sand movement, with wind control emerging as the most influential factor. Key results highlight the importance of wind dynamics as the primary factor affecting sand dune distribution, while precipitation (bio13, bio15, bio19) was identified as less critical. The distribution map illustrates that southern regions are most likely to experience sand dunes. Overall, sand dune movement is a natural process that profoundly shapes coastal and desert landscapes. Understanding the factors influencing dune movement is essential for effectively managing and conserving these dynamic ecosystems, ensuring their sustainability for future generations.

Source of Funding

This research was funded by the Deanship of Scientific Research at King Abdulaziz University, project Number G: 315-125-1443.

Acknowledgement

The research team would like to thank the Deanship of Scientific Research at King Abdulaziz University for its financial support for this investigation (Project Number G: 315-125-1443).

Declarations

Appendix A

Table 1: Controlling environmental variables used in potential distribution modeling.

Data source	Variables	
Bioclimatic variables[1]	Annual mean temperature (ºC)	**bio1**
	Mean diurnal temperature range (ºC)	**bio2**
	Isothermality	**bio3**
	Temperature seasonality (standard deviation) (ºC)	**bio4**
	Maximum temperature of warmest month (ºC)	**bio5**
	Minimum temperature of coldest month (ºC)	**bio6**
	Temperature annual range (ºC)	**bio7**
	Mean temperature of wettest quarter (ºC)	**bio8**
	Mean temperature of driest quarter (ºC)	**bio9**
	Mean temperature of warmest quarter (ºC)	**bio10**
	Mean temperature of coldest quarter (ºC)	**bio11**
	Annual precipitation (mm)	**bio12**
	Precipitation of wettest month (mm)	**bio13**
	Precipitation of driest month (mm)	**bio14**
	Precipitation seasonality (coefficient of variation) (%)	**bio15**
	Precipitation of wettest quarter (mm)	**bio16**
	Precipitation of driest quarter (mm)	**bio17**
	Precipitation of warmest quarter (mm)	**bio18**
	Precipitation of coldest quarter (mm)	**bio19**
Geospatial variables[1,2]	Elevation (m)	**Altitude**
	Solar radiation (kJ m^{-2} day^{-1})	**srad**
	Water vapor pressure (kPa)	**vapr**
	Wind speed (m s^{-1})	**wind**
	Land use & land cover	**LandUC**
	Wind direction	**windD**

[1] WorldClim 2 (ASTER) (https://www.worldclim.org) (https://www.worldclim.org/data/worldclim21.html)
[2] Geospatial Data (https://livingatlas.arcgis.com/landcover) (https://livingatlas.arcgis.com/landcoverexplorer/#mapCenter=10.78696%2C51.66528%2C11&mode=step&timeExtent=2017%2C2023&year=2023)

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