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Monitoring and observing the movement of sand dunes and their impact on urban centers, engineering facilities, and agricultural lands in Al-Ahsa governorate using geo- AI and GIS for environmental sustainability

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Abstract

The study emphasizes the significance of geographic information systems (GIS) and geospatial artificial intelligence (GeoAI) in monitoring and predicting sand movement within Al-Ahsa Governorate. This is accomplished through the analysis of satellite imagery, field measurements, and artificial intelligence models to identify sand sources, determine annual movement rates, and assess their impact on urban areas, agricultural lands, and transportation infrastructure. By extrapolating the data, the Redness Rating results indicated that approximately 40% of the sand sources are continental, while 60% are marine, providing valuable insights for decision-makers to implement appropriate sand stabilization technologies. Additionally, the rates of sand encroachment are influenced by various geographical factors. The vegetation change detection index (NDVI) analysis from 2000 to 2020 revealed an increase in vegetation density from 0.12 to 0.52 in certain regions, attributed to afforestation, windbreaks, and agricultural activities. The terrain is characterized by flat, gently sloping plains ranging from 57 to 218 meters above sea level, with some isolated hills. Sand movement is predominantly driven by winds from the north, northeast, and northwest, resulting in higher sand concentrations in the northern parts of the study area. Regarding the performance of artificial intelligence models, the Random Forest (RF) model demonstrated superior accuracy compared to Support Vector Machine (SVM) and Artificial Neural Network (ANN) models when integrated with GIS indicators to monitor sand dune movement and predict their severity. The RF model achieved an accuracy of 0.937, with a strong Area Under the Receiver Operating Characteristic curve (AUCROC) of 0.982 and an Area Under the Precision-Recall curve (AUCPR) of 0.963. The study produced a predictive sand encroachment map indicating an average annual movement rate of 13 meters, with hazard zones classified as high, medium, or low for urban areas, agricultural lands, and roads. It recommends the application of deep learning models within GeoAI and GIS to enhance the accuracy of sand movement predictions. Furthermore, the study highlights the importance of utilizing predictive models and maps in selecting sand stabilization techniques such as afforestation, tree belts, and engineering methods. It also underscores the necessity of integrating GeoAI models and GIS indicators into environmental impact assessments to promote sustainable development planning.

Keywords: Geospatial artificial intelligence, GIS, Sustainable development, Prediction, Sand encroachment rate, Sand stabilization.

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1. Introduction

Sand dune movement is a major environmental issue in arid and semi-arid regions, threatening livelihoods and rural communities with sand inundation. Sand dunes are a major environmental problem globally, affecting urban areas, transportation, and people [1]. It also contributes to land degradation, causing poverty and food insecurity. Sand movement can be observed at different scales: individual dune movement, dune field changes, or sandstorms. Understanding dune movement is key to mitigating these risks. Sand dunes are also found in coastal areas, where sea waves and winds carry sediments to beaches. Coastal dunes play an important role in managing coastal erosion risks, acting as a dynamic natural sea defense. In addition, they provide habitats that enrich coastal biodiversity and enhance ecosystem resilience. The world's sandy beaches are undergoing significant changes, with 24% subject to erosion and 28% to material accumulation, while the remaining 48% remain stable. Therefore, there is an urgent need for a comprehensive understanding of sand dune activity. This requires more accurate measurement techniques that are compatible with the frequency of observation and the rapid dynamic movement of sand dunes [2].

The rapid development of artificial intelligence has contributed to improving the performance of various fields in the humanities and applied sciences, including innovations in highly sophisticated computational methods that mimic the workings of the human brain. The application of artificial intelligence aims to overcome the challenges of environmental degradation. With the availability of a vast amount of quantitative and qualitative data and artificial intelligence in this digital age, it has become possible to address these concerns more efficiently and effectively [3]. This study aims to employ geospatial artificial intelligence and modern technologies, such as remote sensing and geographic information systems, to develop a system to monitor and track sand movement (sand encroachment and erosion) in Al-Ahsa Governorate, located in the Eastern Province of the Kingdom of Saudi Arabia. Al-Ahsa Governorate is one of the areas most affected by this phenomenon due to its geographical location, leading to the emergence of desertification. The study also focuses on developing an early warning system to predict sand movement in order to mitigate its environmental, economic, and social impacts, and proposes appropriate techniques for its stabilization. The study has broader regional and international significance, as it falls within the overall framework of the Sustainable Development Goals (SDGs 13-17) in addressing environmental issues and their economic and social challenges in arid regions, particularly since some communities rely on agricultural and pastoral activities for their economies. Linking the problem of sand encroachment to climate change underscores the importance of regional partnerships in addressing it, as it extends beyond the Kingdom of Saudi Arabia to include neighboring countries facing similar environmental challenges. The study is also linked to the Action Lines Matrix of the World Summit on the Information Society (WSIS +20) (AL C1. Applications of Information and Communication Technology: Benefits in All Aspects of Life - E-Environment). The following are the project's main objectives and outcomes:

1. Sand Movement Monitoring: The primary objective is to track and monitor the movement of sand dunes in the Eastern Province, which is directly linked to desertification and the impact of climate change. The project will use remote sensing tools and artificial intelligence algorithms to identify and map the geographical distribution of moving sand dunes and their encroachment paths.
2. Environmental Sustainability: The project aims to enhance environmental sustainability by understanding the extent of sand movement and its impact on the environment. This includes reducing encroachment on agricultural land, urban areas, and infrastructure, and implementing measures to stabilize sand dunes.
3. Supporting agricultural production: The Eastern Province is a vital agricultural center in Saudi Arabia, and sand encroachment threatens food security. The project will focus on enhancing food security by protecting agricultural land from the negative effects of sand movement.
4. Regional cooperation and knowledge sharing: Neighboring countries, such as Bahrain, Qatar, the United Arab Emirates, Kuwait, Oman, and Iraq, will benefit from this research. The project proposes the establishment of a regional early warning center to monitor and control sand movement, and to enhance cooperation, data sharing, and desertification management strategies.

2. Literature Review

Drought destroys vegetation, dries out soil, and releases previously stable sand into the wind, forming sand dunes that move across roads, gardens, pastures, homes, and solar panel installations [4]. Numerous applied studies have been conducted using scientific and technical methods to understand the nature of sand dune movement, mitigate their environmental, economic, and social impacts, and propose appropriate technologies to stabilize them and mitigate their effects. These studies include:

- Tao, et al. [5] titled: Artificial Intelligence Models for Suspended River Sediment Prediction: State-of-the-Art, Evaluation of Modeling Frameworks, and Proposed Future Research Directions. This study aims to explore the future developments in advanced AI models applied to predicting river sediment transport. Based on the findings, several hydrological and environmental aspects are identified and analyzed. The advantages and limitations of AI models, particularly the latest modeling frameworks and their application-specific evaluation, are discussed, and some key future research directions are proposed. In addition to synthesizing this information to advance a new understanding of models and methodologies related to suspended river sediment prediction, this study provides a future research vision for hydrologists, hydrologists, water resource engineers, oceanographers, and environmental planners [5].
- In a study by Bag, et al. [3] they identified soil erosion-prone zones (SESZs) in the Sobha Basin of West Bengal, India, which suffer from severe soil erosion due to specific geo-ecological conditions and unscientific land management practices. This poses a serious threat to agricultural development and natural resources, leading to land degradation and desertification. The study used remote sensing and geographic information systems (GIS) data in various machine learning algorithms, such as support vector machine (SVM), classification and regression tree (CART), boosted regression tree (BRT), and random forest (RF), considering sixteen soil erosion control factors (SECFs). Additionally, the effectiveness of the selected machine learning models was evaluated using known soil erosion and non-erosion data. The results showed that elevation, drainage density (DD), and normalized mean vegetation cover index (NDVI) are the most significant contributors to soil erosion. Receiver operating curve (ROC) and area under the curve (AUC) were used to compare each model, and the RF model was found to perform best and provide the best predictions. Results based on machine learning algorithms and extensive field visits are used to assess soil erosion risk areas, and this work will provide insight into implementing appropriate policies to mitigate this problem [3].
- Alnafisah, et al. [6] presented a graphical framework for predicting road segments affected by sand encroachment from high-resolution satellite imagery, using a graph embedding approach to predict new road segments affected by sand encroachment and their connections. Sand encroachment prediction on roads is a major problem in the road topography of Saudi Arabia. Recently, artificial intelligence techniques have been used to classify and segment high-resolution satellite images to understand economic development. Deep learning has been used to identify roads in satellite imagery. Several methods have been proposed, such as width, length, curvature angle, pixel color, and travel time between two points. These methods include how to handle noisy and incomplete data, how to model the road network using a graph neural network, and how to obtain a robust loss function less susceptible to noise and outliers, road type, and speed limit. These methods then calculate: Node Hyper shape Embedding (NEH); Node Route Type Embedding (NERT); Node Speed Limit Embedding (NESL); Node Shape and Route Type Embedding (NEHRT); Node Hyper shape and Speed Limit Embedding (NEHSL); Include the road type and speed limit node (NERTSL); and include the super column nodes and road type and speed limit (NEHRTSL). Finally, based on these calculations, we will use the area under the curve (AUC) in the embedding to make predictions [6].
- In Wang, et al. [7] study on predicting sand and dust storm sources in arid Central Asia using machine learning, based on the Google Earth Engine (GEE) platform, four machine learning methods were used to predict sand and dust storm sources. Fourteen meteorological and terrestrial factors were selected as influencing factors controlling the susceptibility of sand and dust storm sources and applied to the modeling process. The results showed that the Random Forest (RF) algorithm performed best, followed by the Gradient Boosting Tree (GBT), Maximum Entropy Model (MaxEnt), and Support Vector Machine (SVM). The Gini Impurity Index (Gini) results of the RF model indicated that wind speed played the most important role in predicting the source of SDS, followed by the Normalized Difference Vegetation Index (NDVI). This study could facilitate the development of programs to reduce SDS risk in arid and semi-arid regions, particularly in arid areas [7].
- van Westen, et al. [8] study demonstrated that the interaction between morphological dynamics resulting from air and sea transport can play an important role in predicting unstable sands. This approach predicts the marine and wind contributions to the evolution of the sand drive using coupled modeling, enabling the design of nature-based solutions, particularly in coastal environments. This approach uses a methodology that combines three process-based models: Delft3D Flexible Mesh, SWAN, and AeoLiS. This framework facilitates the continuous exchange of bed levels, water levels, and wave characteristics between numerical models focused on the wind and sea domains. The coupled model is used to simulate the morphodynamic evolution of the massive sand drive flow [8].
- In a study by Abd El Aal, et al. [9] they examined the geological and environmental risk assessment of sand dune encroachment in arid lands using machine learning techniques. This study presents the integration of machine learning techniques (MLTs) with geographic information systems (GIS) and R software to monitor sand dune movement in Najran City. Using linear support vector machines (SVMs), random forests (RFs), and artificial neural networks (ANNs), this study presents a new drift sand index (DSI) for effectively identifying and mapping sand dune accumulations. The DSI integrates multispectral sensor data and demonstrates a strong ability to monitor dune

dynamics. These models produced a comprehensive dune encroachment risk map that divided the area into five risk zones: very low, low, medium, high, and very high. The study provides valuable insights for sustainable development and environmental protection, enabling decision-makers to prioritize areas for sand dune mitigation techniques [9].

- Cúñez and Franklin [10] study, "Detection and Tracking of Barchan Dunes Using Artificial Intelligence," can be useful for estimating local wind direction and strength, identifying sand transport and accumulation systems, and estimating the effects of global changes on the ground based on sand dune dynamics. By training a CNN on interaction patterns measured in the laboratory, the trained network can predict the same type of interaction in the field based on satellite imagery. This information can also be used to estimate desertification as an effect of climate change and predict whether structures are threatened by sand erosion [10].

Another application is annual monitoring of sand dune movement to estimate sand cover on the ground and test climate models. This enables automatic detection, classification, identification, and tracking of sand dunes in different environments, by conducting experiments and exploring individual and collective images using deep learning. The trained network demonstrated its ability to identify, classify, map, and track interacting sand dunes using various image types (contrast, color, perspective, resolution, etc.), with confidence levels ranging from 70% to 90% and an average accuracy of up to 99%. Trained convolutional neural networks (CNNs) open new avenues for predicting the future of barchan fields. The study represents a step forward in the field of automated barchan monitoring and understanding their dynamics, with important applications for human activities, such as disaster mitigation on Earth.

Among the studies that attempted to employ AI and GIS applications in environmental hazard research is the study by Kudaibergenov, et al. [11] which applied AI to landslide susceptibility assessment [11]. The researchers reviewed the latest research findings in landslide susceptibility mapping (LSM) using AI methods. Among the models used were random forest (RF), support vector machine (SVM), convolutional neural network (CNN), and multilayer perceptron (MLP), as a basis for comparing any new model proposed for developing landslide susceptibility maps. The study results demonstrated the accuracy of the AI models applied in predicting LSM for selected geographical locations. It recommended the importance of conducting further research activities using modern AI methods and the trend toward increasing the use of AI in disaster management, with implications for improving practical applications, such as early warning systems, and guiding policy decisions aimed at reducing risks in vulnerable areas.

3. Technological Application and Methodology

The application of time series analysis using Geographic Information Systems and remote sensing techniques contributes to providing continuous observations of sand dunes over periods of contiguous years over very large areas. Multispectral optical satellite sensors, synthetic aperture radar techniques, and airborne lidar are used to detect, such as monitoring sand dune movement and its impact on urban and agricultural areas, forests, water bodies, and archaeological sites [1, 11].

The project will rely on an inductive approach to collecting and analyzing data through artificial intelligence applications, field surveys, and laboratory analysis. Project outcomes are expected to include:

- Identifying the geographical distribution of sand dunes and their movement directions.
- Measuring the annual rate of sand encroachment.
- Analyzing the factors affecting sand movement activity and their sources.
- Predicting sand movement.
- Proposing appropriate techniques for sand dune stabilization.
- Supporting decision-makers with a spatial database that contributes to sound planning for development projects in the governorate.

Through these objectives, the project seeks to achieve environmental sustainability and enhance food security, as the region is home to the largest agricultural oasis and a source of agricultural production in the eastern part of the Kingdom.

3.1. Research Areas

The Al-Ahsa Oasis, located in the eastern part of the Kingdom of Saudi Arabia, covers an area of 20,000 hectares, of which 8,200 hectares are irrigated, divided into 25,000 farms [12]. Al-Ahsa represents an arid ecosystem, with very low rainfall of less than 73 mm per year. Al-Ahsa is one of the oldest agricultural settlements in the region, dating back to 4000 BC. Currently, Al-Ahsa is the largest agricultural area dominated by palm trees, with over three million trees (Figure 1). It relies on springs from the vast Euphrates-Gulf-Rub' al-Khali basin for its water resources. The Late Cretaceous and Tertiary formations of Aroma, Umm ar-Rudmah, Ar-Rus, Ad-Dammam, and Neogene form a complex multi-layered aquifer system [13]. They are characterized by sandy and sandy loam soils with very low clay and organic matter content, high calcium carbonate ($CaCo3$) content, and sand and silt particle sizes [14].

The region is affected by a continental climate and climate fluctuations resulting from monsoon winds and winter cyclones with little rainfall [15]. These winds cause sandstorms known as "samum," which form when wind speeds reach 40 km/h, stirring dust and sand into the air to an altitude of 3 to 5 kilometers. Their maximum speeds reach 92 km/h in the summer [16].

In winter, the study area is affected by dry, cold northerly winds blowing from the continental air masses in the north (Siberia). Rain falls during the winter, reaching its highest levels in January and March. The average annual rainfall is 6.9

mm. This rainfall is associated with a low above-average atmospheric pressure, which attracts winds coming from the Central Asian high-pressure area. The average relative humidity reaches its highest level in December, reaching 91% [17].

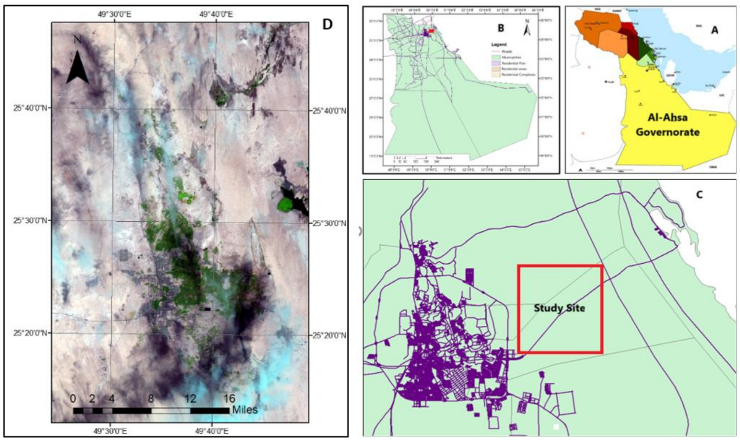

Figure 1.
Location of the Study Area.
Source: Ministry of Municipal and Rural Affairs [18].

3.2. Materials and Methods

To achieve its objectives, the study relied on geospatial artificial intelligence and geographic information systems (GIS) applications to monitor sand dune movement using linear support vector machines (SVMs), random forests (RFs), and artificial neural networks (ANNs), In addition to fieldwork to analyze spatial data, select the study sample, and determine the color of sand dunes.

3.2.1. Geospatial Artificial Intelligence (Geo-AI)

AI applications typically fall into three categories: First information collection and integration and analysis, second practical tools, Third, AI-powered services [19] Through predictive analytics and machine learning, AI-based approaches contribute to building resilient landscapes that are compatible with positive nature management and sustainable land use [20]. Modern AI techniques, such as data mining and evolutionary computing, are useful in many geotechnical applications. In the future, we expect greater integration of data mining, evolutionary computing, and GIS tools to play a key role at the design, construction, and management levels of geotechnical technologies [21]. These algorithms are efficient in handling multidimensional data and provide satisfactory classification results [22].

- *Support Vector Machines (SVMs):* Support vector machines (SVMs) are effective machine learning algorithms for pattern recognition and classification problems [23].
- *Random Forests (RFs)*: is an ensemble learning approach that creates multiple classification trees that are then combined to produce a classification result. RF resists overfitting by growing a large number of random forest trees, each representing an independent random experiment. The risk assessment of sand dune movement on urban areas, agricultural land, and roads is modeled using the Random Forest package [24].
- *Artificial Neural Networks (ANNs):* The complexities of interconnected ecological and human systems across time and space in fragile systems pose challenges for new data-driven approaches. Combining Geographic Information Systems (GIS) and Artificial Neural Networks (ANNs) allows us to design a model that accurately predicts changes in fragile ecosystems, analyzing and presenting the dynamics of "where" and "why" that have occurred or will occur in the future. According to the research, ANNs offer significant advantages over other methods used for prediction and decision-making, including performing a sensitivity analysis of the natural forces of the sand dune system in the study area, understanding the factors influencing erosion changes, and highlighting the importance of an intelligent environmental decision support system to address these risks. This quantitative knowledge of erosion changes and a map-based analytical framework are essential for integrated management of the area and the development of policies that support sustainability [25].

3.2.2. Geographic Information Systems (GIS) and Remote Sensing

Geographic Information Systems (GIS) and remote sensing data will be used to collect, analyze, and present spatial data related to the movement of sand dunes. This includes:

- Satellite imagery and aerial surveys to monitor changes in the landscape over time.
- High-resolution spatial maps to visualize the encroachment of sand dunes on agricultural fields, urban developments, and infrastructure.
- Developing an early warning system using real-time data to provide alerts on impending sand movement and help mitigate the impacts before they become critical.

Sand movement in the study area was measured using cloud-free Landsat images, captured between 2000 and 2020 at a spatial resolution of 30 meters (Table 1), from the USGS website (https://earthexplorer.usgs.gov). Satellite images were processed: Landsat 5, which includes Thematic Mapper (TM) data and Landsat 8 LNB, Operational Land Imager (OLI) using remote sensing and GIS techniques, ERDAS IMAGINE 2014 and ArcMap 10.4, The study also relied on morphometric and morphological measurements of sand dunes in terms of distribution, density and size based on the Digital Elevation Model (DEM) with a horizontal resolution of 90 meters and a vertical resolution of 16 meters, and a confidence level of up to 90%, downloaded from the USGS under the name Shuttle Radar Topographic Mission (SRTM).

Table 1.
Landsat images used to monitor sand movement and its formation factors.

Path	Row	***Sensor and Acquisition Date (Dataset, yyyymmdd)***		
		Master	***Slave***	***Test***
164	42	LT05-20001014	LC08-20200820	LE07-20170209
164	42	DEM: n25_e049_1arc_v3		

It is used in satellite image analysis to extract the morphological characteristics of sand dunes and detect changes to indicate sand movement and its effects on the environment of the region. This is done by applying the following indices: NDVI (Natural Difference Vegetation Index), Change Detection Index, and the NDSI (Natural Dune Concentration Index) as follows:

-*Natural Difference Vegetation Index (NDVI):* The study uses the NDVI to identify the impact of sand movement on agricultural lands in the study area. It is calculated using the following equation:

NDVI = NIR – R / NIR + R

Where:

NDVI: Orthogonal Difference Vegetation Index (NDVI) value.

NIR: Spectral Response in the Infrared Region.

R: Spectral Response in the Red Region.

When calculated, the NDVI ranges between 1 and -1 [26].

- *Change Detection:* refers to the relatively rapid partial or total change that occurs in geographical phenomena. Multi-temporal remote sensing images are used to detect and track changes in the spatial characteristics of geographical phenomena in a specific area. Two satellite images of a dune field recorded at different times are combined and since we have the dates of recording the images we can easily obtain the speed of the dunes [27]. The application of the change detection index requires the availability of satellite images from two different dates that are similar in terms of spectral resolution, radiometric resolution, and spatial resolution. It is important to ensure that the spatial imaging season is close in time to allow for the ranges to be set for change detection [28]. Trends identified by change detection can also be used to predict the evolution of environmental conditions. Images recorded at different times can be consistently compared or combined into a sequence, creating a multi-temporal image that allows us to easily observe local changes. The change detection technique is used to measure the annual sand encroachment on urban centers, engineering facilities, and agricultural lands in the study area during the period between 2000 and 2020.
- *Application of the Normalized Difference Sand Index (NDSI):* The concept of this model is based on examining the spatial distribution of sand dunes and their concentration locations. It is applied in a remote sensing environment by calculating the quotient of the intensity of the short-wave infrared (SWIR2) spectral band and the red band from satellite images. It is used to detect the presence of sand dunes and drifting sands [29]. The following equation is calculated:
- *NDSI = (SWIR2-R)/(SWIR2+R)*

Where:

SWIR2: is the short-wave infrared, which occupies the band (band 7: 2.08-2.35 µm).

R: is the red band (band 3: 0.63-0.069 µm) of the electromagnetic spectrum.

This technique is applied in this study to verify the concentration of encroaching sand dunes on urban centers in the study area, then measure their impact and propose appropriate treatments.

- *Redness Rating*: Mineral magnetism is an effective tool for characterizing magnetic minerals (such as iron oxides), their concentration, and grain size (domain size). This can be studied to determine their sensitivity to environmental processes governed by a variety of factors, including formation [30] transport, deposition, and post-depositional changes. Spectral redness is calculated using the following formula:

  R= BRFr/(BRFr+ BRFg+ BRFb)

  Where:

  R: Spectral redness

  BRFb: Bidirectional reflectance in the blue visible spectrum (400-500 nm)

  BRFg: Bidirectional reflectance in the green visible spectrum (500-600 nm)

  BRFr: Bidirectional reflectance in the red visible spectrum (600-700 nm)

These redness values are correlated with the redness rating derived from the color relationships in the Soil Color Book, and these results are then calibrated to the image using a regression equation. The benefit of applying this technique is to examine the spatial variation in sand dune colors, as redness classification can provide reliable estimates of hematite oxide concentrations. This technique is useful for examining the spatial variation in sand dune colors and classifying them in the study area.

3.2.3. Field Surveys and Laboratory Analysis

Field data collection will play a critical role in understanding the local environmental conditions. These surveys will include measurements of sand drift, wind speed, and temperature in various locations across the region. The laboratory analysis of collected soil and sand samples will help identify factors that influence sand movement, Which included 6 sites covering the subject and objectives of the study (Figure 2, Table 2).

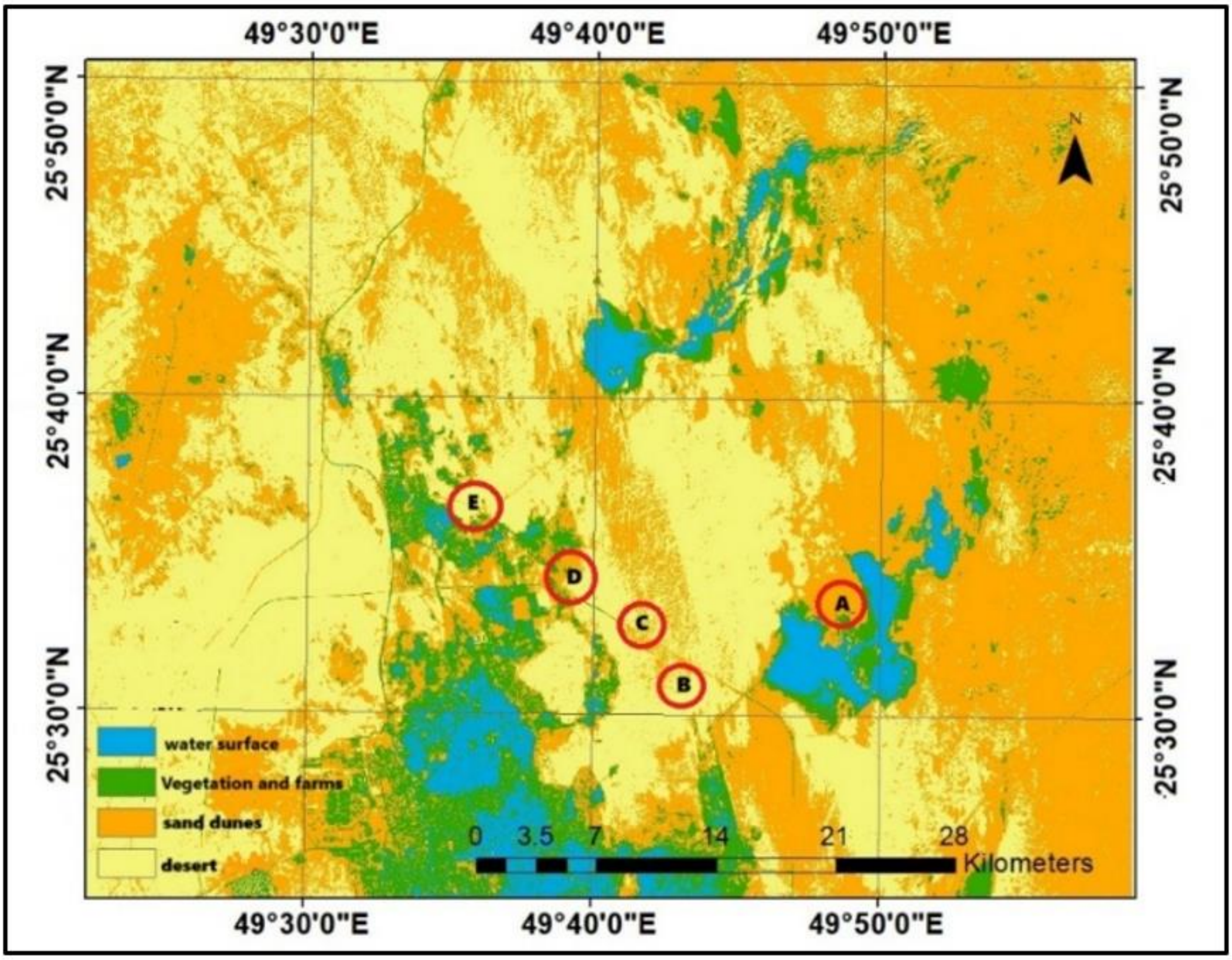

Figure 2.
The geographical location of the study samples is in the north and east of Al-Ahsa Oasis.

Table 2.
Sample of sites affected by sand movement in the study area.

Location	Code	Description
A	SD-25-01	In the northern and eastern parts of the lake, crescent-shaped sand dunes are scattered, most of which are crescent-shaped sand dunes of continental origin.
B	SD-25-02	Sand dunes north of the Al-Ahsa Agricultural Oasis from the northeast of the oasis at the fifth stop in Al-Ahsa National Park.
C	SD-25-03	Sand dunes north of the 6614 ring road of the Al-Ahsa Oasis metropolis in the northeast of the oasis
D	SD-25-04	North of the agricultural and residential lands in the north of the study area where sand dunes are spread near agricultural fields.
E	SD-25-05	Sand dunes north of Al-Uyun city, and Road 612 linking Al-Uyun and Al-Uqair.

Therefore, the applications of GIS and spatial artificial intelligence technology in monitoring and controlling sand movement on urban centers, agricultural lands, and roads in order to mitigate their economic, social, and environmental impacts and to predict the future of the region should these impacts persist, the implementation stages consist primarily of collecting data, processing it, and selecting GIS indicators and artificial intelligence models, as shown in the figure. Data is usually collected using GIS software and field studies. Figure 3 illustrates the stages of achieving the study's objective of monitoring the movement and development of sand dunes in the study area. These stages consist of:

1 .Data collection: from Landsat 7 and Landsat 8 satellite images and a digital elevation model (DEM), in addition to fieldwork and the selection of the study sample using a stratified random sampling method. Seventy percent of the randomly divided spatial blocks were allocated for model training and 30% for validation in each iteration.

2 .Data processing: The factors affecting the formation and development of sand dunes in the study area were identified and extracted from satellite images and the DEM using GIS technology (Elevation, Aspect, curvature, Slope, NDVI, NDSI, Change detection).

3 .Artificial intelligence model building: Four machine learning-based prediction models (RF, SVM, ANN) were built and trained on the training set. A dune source distribution map was created, and the hazard level of the moving sand dunes was predicted.

4. Model performance evaluation: Using training accuracy (TA), validation accuracy (VA), precision, recall, and F1 score to evaluate model performance. Receiver operator characteristic (ROC) and precision-recall (PR) curves are also presented.

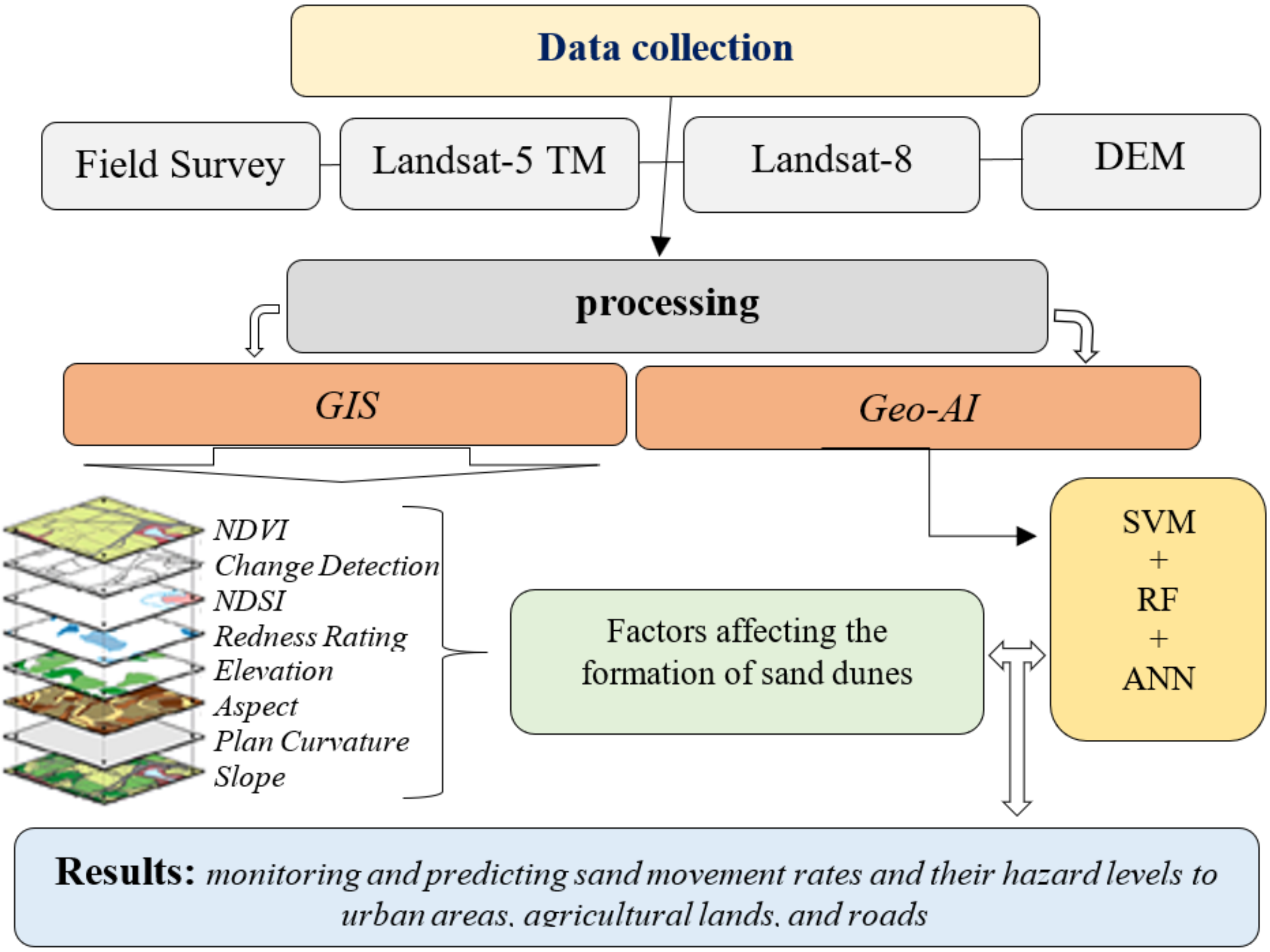

Figure 3.
A study model for the applications of geospatial artificial intelligence and geographic information systems in monitoring and predicting sand movement.

4. Results and Discussion

Monitoring and controlling the movement of sand dunes and their impact on urban centers, engineering facilities, and agricultural lands in the study area using geographic artificial intelligence and geographic information systems (GIS) technology to achieve environmental sustainability is achieved by studying the factors influencing the formation of sand dunes. The shape of sand dunes is determined by the interaction of sand with wind, and thus their characteristics greatly influence their formation [2]. These factors include: variations in wind speed and direction, sand source, vegetation cover, the effect of terrain on sand dunes, and time. Consequently, the ability to predict their movement rates and risk levels can be achieved, which can support decision-makers in planning to protect affected areas by implementing appropriate techniques to stabilize them.

4.1. Variations in Wind Speed and Direction

which play an important role in determining dune type. Wind speed primarily acts as a driving force that determines the amount of dune displacement, while wind direction determines the direction of dune movement, the downward movement of the wind. Wind-induced soil erosion is the most important and widespread type of degradation in the study area, resulting in sand encroachment at a rate of 5–9 meters (Figure 4), with an annual average of 6.8 meters [31].

Northerly, northeasterly, northwesterly, and southerly winds cause the loss of fertile topsoil, which is widespread in Al-Omran, Al-Muqaddam, Al-Juth, Al-Kalabiya, Al-Ka'kab, Wasit, and Abu Al-Has [32]. It is prevalent in flat or river plains and sandy soils. Soil erosion occurs when strong winds blow over unprotected soil, increasing the drying and loosening of the soil. Figure 2-d shows the distribution of lands affected by soil erosion, with a total area of 66.99 square kilometers [33]. The study area is exposed to wind erosion in most seasons of the year, especially since the region is characterized by the presence of three sand seas represented by the Dahna Desert - the Jaforah Desert - the Rub' al Khali Desert, which exposes urban centers, agricultural lands and roads to the risk of sand encroachment that occurs within these deserts [34].

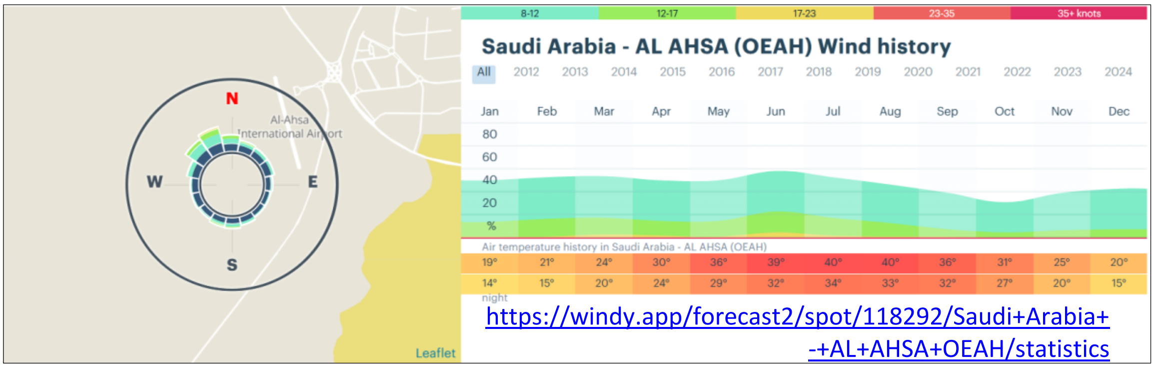

Figure 4.
Wind speed and direction in the study area.

4.2. Sand Source

Sand supply significantly influences dune type, and sand dunes color is an indicator of these fundamental properties [35]. Darker soils are often associated with higher organic matter content, nutrients, and moisture, while lighter-colored soils may indicate sandy conditions or lower fertility, which are unsuitable for plant growth [36]. The size and sorting properties of sand grains also significantly influence the size and spacing of dunes [37]. When studying the color characteristics of moving sand using the Redness Rating technique (Figure 5) and verifying visible colors in the field using the Munsell Soil Color Chart, three colors were identified:

1. Pale Brown (2.5Y 7/3): The pale brown color, indicating a continental origin of the sand, extends as a longitudinal strip from north to south and from northwest to southeast around Al-Asfar Lake at site (SD-25-01) and north of Al-Ahsa National Park at site (SD-25-02), where agricultural lands, residential areas, and the ring road around Al-Ahsa Oasis are located. This indicates the continental origin of the sand.
2. Very Pale Brown (10YR 7/3): Concentrated around Al-Asfar Lake, windbreaks in Al-Ahsa National Park, and north of Al-Uyun City at site (SD-25-05), as well as in the eastern part of the oasis. This is an indication of the presence of sabkhas (salt flats).
3. Yellow (10YR 7/6): The dominance of the yellow color across all parts of the study area indicates the marine origin of the sand, as in the Jafurah Desert.

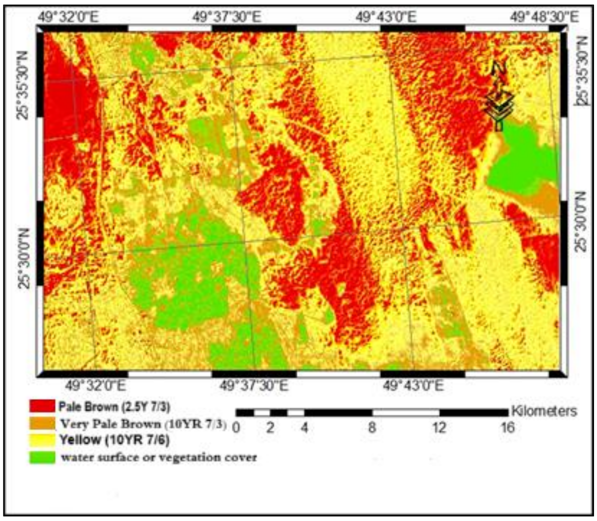

Figure 5.
The benefit of applying this technique lies in examining the spatial variation in sand dune colors and estimating the concentration of hematite oxides. These redness values can be correlated with the redness assessment derived from the color relationships in the Soil Colors book, thus identifying the source of the sand.

4.3. Vegetation

It plays an important role in controlling the movement of sand dunes, and Sand stabilization with plants is considered the most cost-effective and long-lasting of the many sand control measures [38] It also has an effective role in preventing surface soil erosion and sand movement, and improving the surface structure and environment in sandy areas [39]. The study area is home to a variety of plant groups [40] most of which are shrubs and herbs. The most important of these are:

1 .Rhanterium epapposum: This is a shrubby plant found in desert plains and sandy beds.

2 .Haloxylon persicum, Suaeda vermiculata, and Andab: This is predominant on the slopes of fixed sand dunes and in the low areas between dunes.

3 .Calligonum comosum, Comulaca leucacantha, Tribulus, and Andab terrestris: This extends from the northeast of the study area.

4. Suaeda vermiculata and Seidlitzia rosmarinus: This is found in the southeastern part of the study area and is a plant that can tolerate high salinity.

These plant species were widespread around Yellow Lake, north of urban areas near Al-Uyun City, and in villages and towns in Al-Ahsa City to the north, northeast, west, and south in 2000. The Normalized Differential Vegetation Index (NDVI) ranged between -0.48 and 0.12. The (NDVI) increased in 2020, ranging between 0.52 and 0.03. This increase is attributed to the green spaces and agricultural lands in the Yellow Lake Reserve, Al-Ahsa National Park.

The change detection in the geographical distribution of vegetation cover between 2000 and 2020 (Figure 6) indicates that the northeast of the study area, near the Asfar Reserve (SD-25-01), was affected, as were the agricultural lands east of Al-Ahsa National Park (SD-25-02), the ring road east of Al-Uyun City (SD-25-04), and the north of Al-Uyun City (SD-25-05).

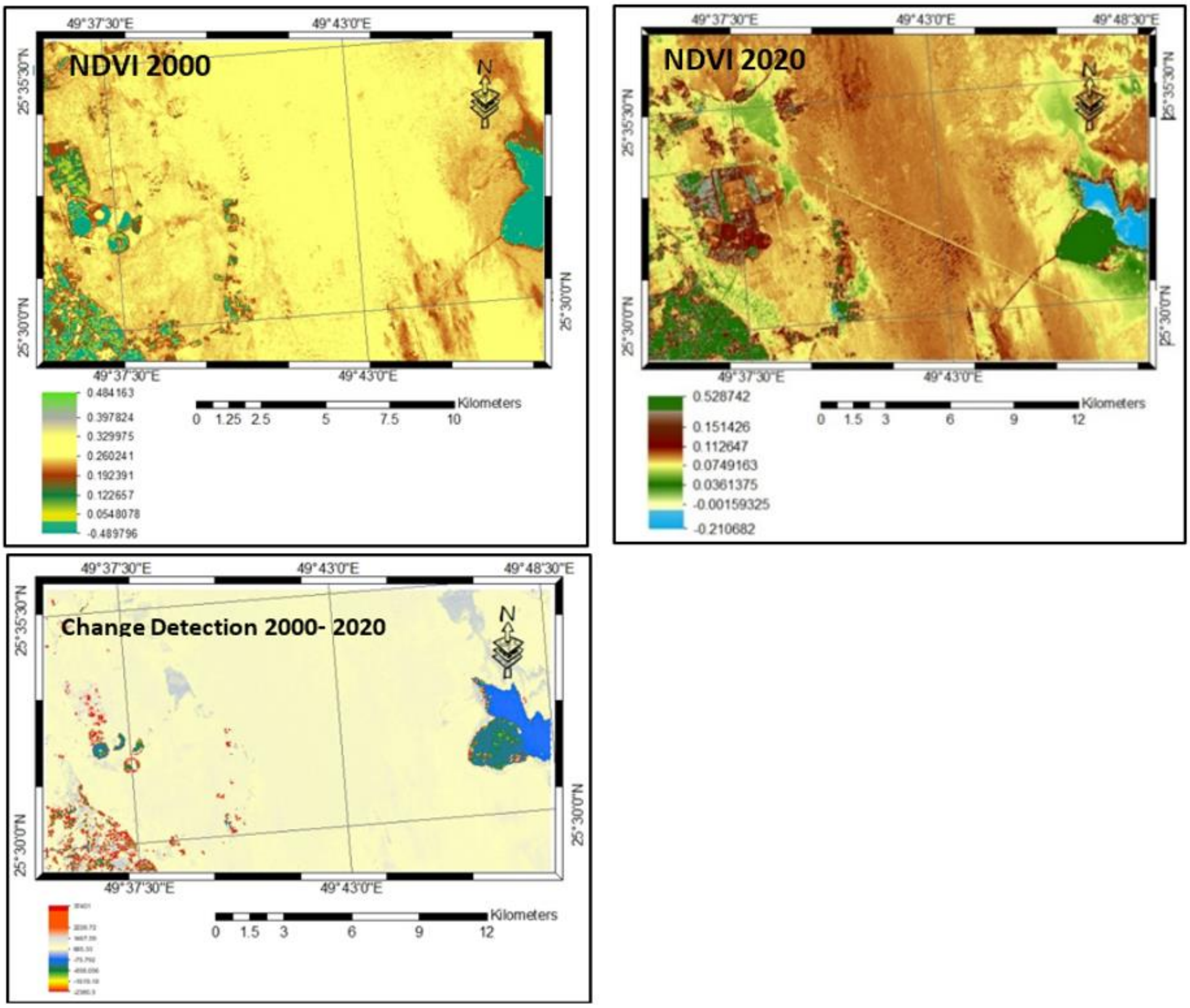

Figure 6.
The NDVI technique was applied in the study to verify the locations of the movement of encroaching sand dunes on urban centers, agricultural lands, and roads in the study area, using the vegetation cover index. This was then used to detect spatial changes over time series, measure their impact, and propose appropriate treatments.

4.4. The Influence of Topography on Sand Dune

This directly affects the processes of abrasion, transport, and deposition by changing wind speed and direction near the ground's surface. It also controls the movement of sand particles, causing a deviation in their transport direction [41]. The topography in the study area varies between isolated hills, plains, sabkhas, crescent-shaped sand dunes (barkhans), desert depressions, and Sand Sheet [42]. The study also relied on the Digital Elevation Model (DEM) to demonstrate the effect of the topography of the study area on the movement of sand dunes in terms of distribution, density and size (Figure 7), as follows:

A. Elevation: The elevations in the study area were derived from the SRTM-DEM digital elevation model. The elevations range from 57 to 218 meters (Figure 7a). Most of the higher elevations are concentrated in the northern and western areas, particularly on the Shadqam Plateau (218 m), as well as in some parts of the southern areas of the study region, while the lowest elevations are found around Al-Asfar Lake in the eastern part of the study area.

B. Aspect: The slope aspects in the study area were extracted from the digital elevation model (Figure 7b). The figure shows a dominance of northern, northeastern, and eastern slope aspects, while other directions are less frequent in the study area. Aspect is an important factor in studies of susceptibility to erosion processes, as the slope face can influence the erosion affecting the slopes. This makes it a significant factor in determining the locations and concentration of sand dunes, as well as in assessing the level of risk to land use in areas exposed to prevailing wind directions.

C. Plan Curvature: The plan curvature, also known as surface curvature, is determined by the curvature of contour lines [43] resulting in two forms of curvature that are directly associated with the occurrence of natural hazards (Figure 7c): convex and concave shapes. Convexity usually has positive values, while concavity is represented by negative values. Sand encroachment is associated with areas of concave slopes [44]. Accordingly, it is observed that all northern and northeastern locations of the study area are exposed to the risk of sand encroachment and a high annual rate of sand drift.

D. Slope: Slope is of great importance in geomorphological studies and has a direct impact on the occurrence and formation of many surface features. The slope percentage of the study area was derived from the digital elevation model (Figure 7d), showing a range from 0 to 20 degrees. It is observed that the central areas of the study region, extending from north to south, as well as the eastern part, are characterized by relatively steep slopes of 10–20 degrees.

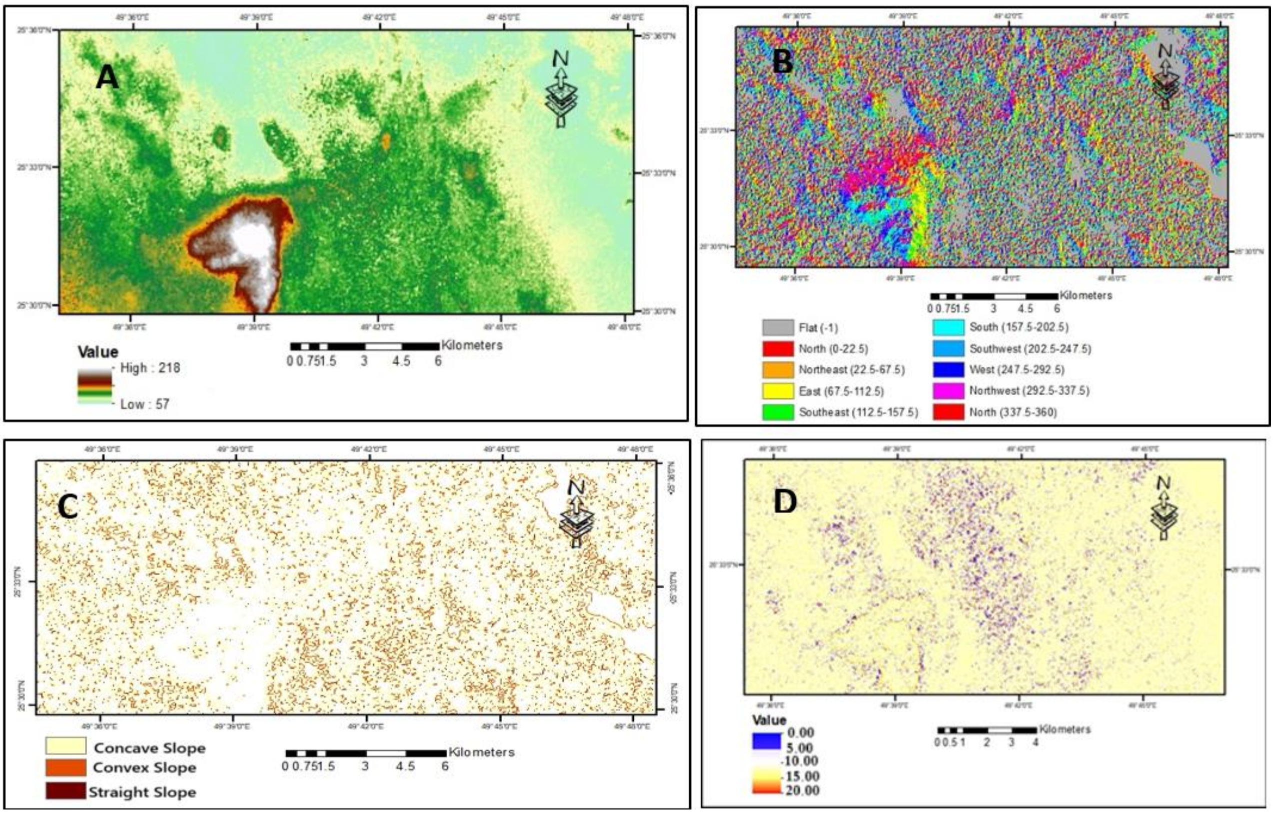

Figure 7.
The influence of topography on sand dune, (A) Elevation (B) Aspect (C) Plan Curvature (D) Slope.

4.5. Time and Prediction

The Time is an important factor in the process of sand dune accumulation, movement, and predicting its annual encroachment rate [45]. This contributes to estimating the duration of its impact on agricultural lands, roads, and urban centers, and determining its level of danger according to the direction of its movement and size after knowing its geographical distribution. To study the effect of the time factor on sand movement in the study area, artificial intelligence algorithms and geographic information systems technology were relied upon, which include: Support Vector Machines (SVMs), Random Forests (RFs), Artificial Neural Networks (ANNs) and Normalized Difference Sand Index (NDSI). Figure 8 shows the concentration of sand dunes and beds in the study area according to the Sand Distribution Index

(NDSI), from which we notice the concentration of sand dunes in the northern, northeastern and western parts of the study area. The percentage of their concentration reached 51% in the northern parts of the agricultural lands at site (SD-25-02) and the ring road of the Ahsa civilization at site (SD-25-03), as well as in the northeastern parts at site (SD-25-01) north of the Asfar Reserve, and a percentage of 41.4% in the northeast of Al-Uyun city at site (SD-25-05), which exposes these sites of the study area to the influence of these sand dunes.

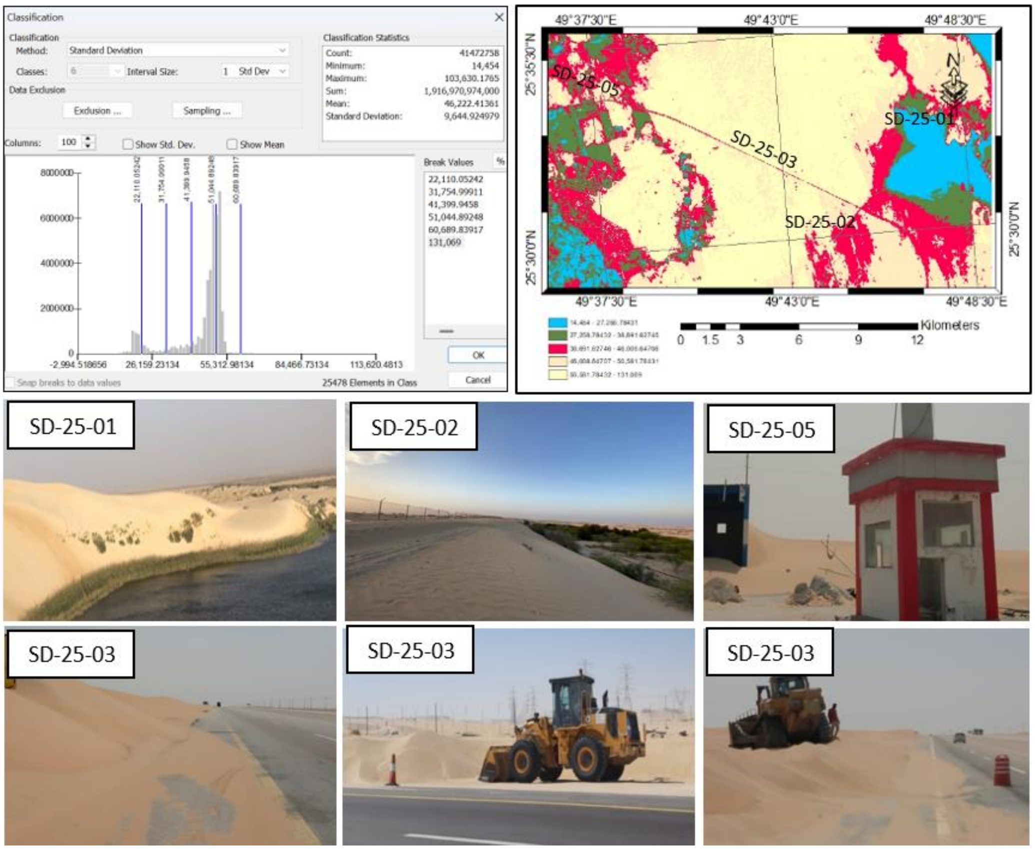

Figure 8.
Spatial distribution of sand dune concentration in the study area according to the Sand Distribution Index (NDSI), satellite imagery (Landsat 8), and field work (21/5 – 14/6/2025).

Table 3 and Figures 9 & 10 show the results of measuring the average performance of Random Forests (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) models in predicting the origin and movement of sand dunes in the study area. We note the following:

1. The performance values of the RF, SVM, and ANN models for the TA training data were 0.988, 0.873, and 0.991, respectively. This was based on 70% of the sample points used in locations affected by sand dune movement, particularly on agricultural lands, roads, and urban centers in the villages of Al-Ahsa Oasis and Al-Uyun City as training data.
2. The VA values were obtained, at approximately 0.738 (RF), 0.846 (SVM), and 0.935 (ANN), based on 30% of the sample points used for sand dunes in the study area as test data, including the north of Al-Asfar Lake, Al-Ahsa National Park, and the ring road around Al-Ahsa City.
3. Estimated accuracy values based on both the training and test datasets indicated that the RF model was the most effective model for predicting the origin, movement, and annual creep rate of sand dunes, depending on their continental and marine sources, geomorphological forms, and morphometric characteristics. This figure was approximately 0.937, compared to the SVM model with a value of 0.891 and the ANN model with a value of 0.864.
4. In terms of accuracy, the ANN model performed best with a value of 0.841, followed by the SVM model (0.838), and the RF model.(0.761)
5. The SVM model achieved the highest average recall rate (0.917), while the RF model achieved an average recall rate of 0.864, followed by the ANN model with an average recall rate of 0.853.
6. Based on the AUC_{ROC} results, RF was confirmed as the best-performing model (0.982), followed by ANN (0.972) and SVM (0.964).
7. AUC_{PR} results indicated that RF (0.963) was more accurate in predicting sand dune source sensitivity and movement compared to ANN (0.874) and SVM(0.847).

Table 3.
Results of the ability of performance models in geospatial artificial intelligence (RS, SVM, ANN) in monitoring the movement and direction of sand in the study area.

ML Models	*TA*	*VA*	*Precision*	*Recall*	*F1 Score*	*AUC_{ROC}*	*AUC_{PR}*
RF	0.988	0.738	0.937	0.761	0.864	0.982	0.963
SVM	0.873	0.846	0.891	0.838	0.917	0.964	0. 847
ANN	0.991	0.935	0.864	0.841	0.853	0.972	0.874

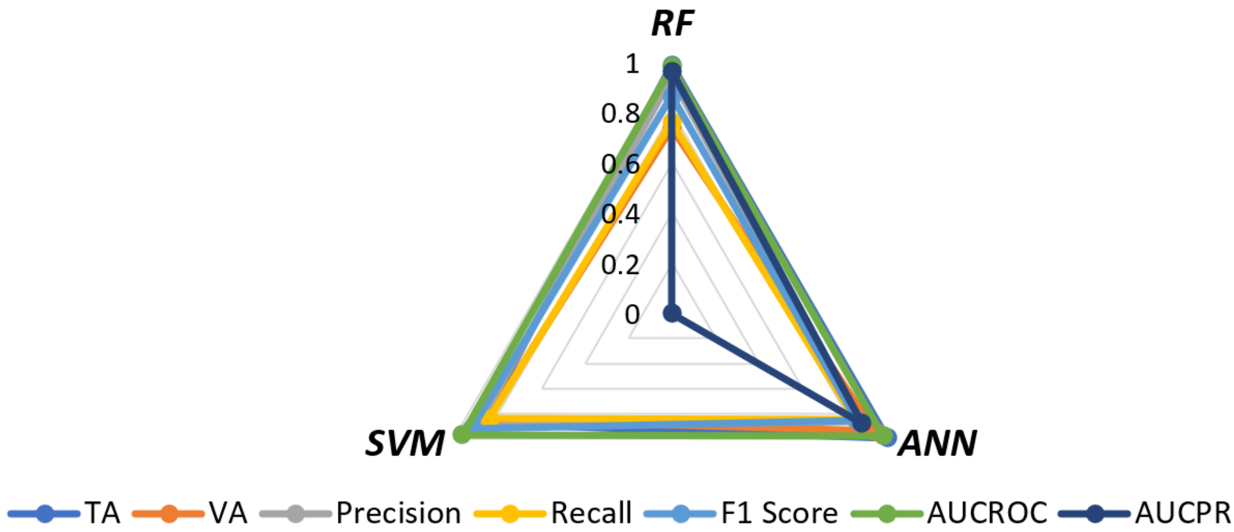

Figure 9.
Evaluation of the ability of performance models in geospatial artificial intelligence (RS, SVM, ANN) in monitoring the movement and direction of sand in the study area.

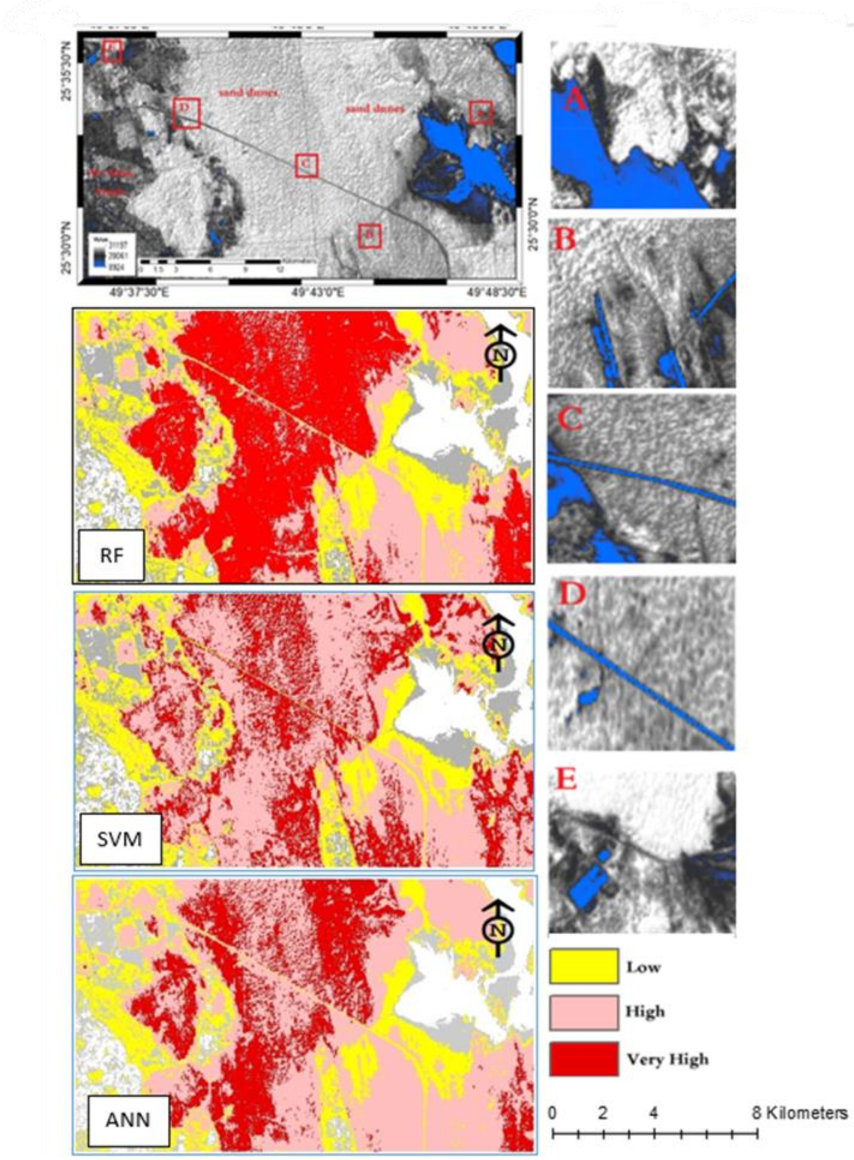

Figure 10.
Sensitivity maps of the source and direction of sand movement in the study area using performance models in geospatial artificial intelligence (RS, SVM, ANN).

The results of the field study and satellite image measurements using GIS and remote sensing techniques for sand dune morphology (Table 4) indicate the following:

1 .The average length of the sand dunes was 73.2 m, with a standard deviation of 29.5 m. The longest dune was 129.2 m long at Site (3), north of the agricultural lands, while the shortest dune was 45.3 m long at Site (2), north of the Al-Ahsa ring road.

2 .The average width of the sand dunes was 40.8 m, with a standard deviation of 18.6 m. The largest dune width was 63.8 m at Site (5), near the agricultural lands north of the oasis, while the smallest dune width was 14.6 m at Site (2), north of the Al-Ahsa oasis.

3. The average area of the sand dunes was 3.1 km2, with a standard deviation of 1.4 km2. The smallest area was dune (2), at 0.7 km2, while the largest was dune (3), at 7.7 km2.

4 .There was limited variation in the height of the sand dunes above the surrounding ground surface, with an average of 3 m and a standard deviation of 0.6 m. The highest was dune (4), at 4 m, and the lowest was dune (2), at 2 m.

5. The general direction of the sand dune axis was northwest-southeast, except for site (3), which had a northeast-southwest axis, indicating the influence of northwesterly winds in directing the movement of the sand dunes. 6. The average annual sand encroachment rate was 16.2 meters/year, with a standard deviation of 1.6 meters/year, where the highest annual encroachment rate was 21 meters/year for sand dune (5), and the lowest with an annual encroachment rate of 13 meters for sand dune No. (2).

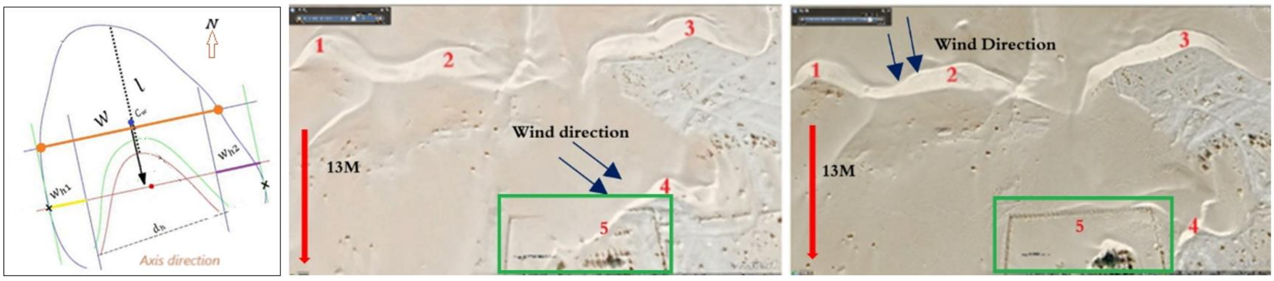

Figure 11.
Measuring the annual encroachment rate of some moving sand dunes at site SD-25-02 for the period 2020–2024 (satellite image from Google Earth).

Table 4.
Morphological characteristics of the moving sand dunes in the study area.

Annual creep rate/m	Axis direction	Height/m	Area/km2	Width/m	Length/m	Sand dune number
16	SW- SE	3	2.4	37.4	64.3	1
13	SW- SE	2	0.7	14.6	45.3	2
17	SE- SW	3	7.7	59.6	129.2	3
14	SW- SE	4	1.6	28.5	54.4	4
21	SW- SE	3	4.6	63.8	72.7	5
16.2	-	3	3.1	40.8	73.2	*Mean*
1.6	-	0.6	1.4	18.6	29.5	*Standard deviation*

Overall, the performance of RF was consistently significantly higher than that of other models based on both the area under the curve (AUC) and other performance metrics (Figure 9). Therefore, the RF classifier is suitable and can be used to map the sensitivity of the source and direction of sand movement at larger scales in the study area.

The Random Forest (RF) model in geospatial artificial intelligence was combined with the Dune Concentration Spatial Index (NDSI) in GIS technology to map the direction of sand movement and the annual encroachment rate and predict the hazard levels for residential, agricultural, and road areas in the study area. This revealed that the sand source is continental and influenced by northwesterly wind speeds, with three hazard levels: very high in the north of the Yellow Lake and the northern parts of the Al-Ahsa Agricultural Oasis, as well as on the Al-Ahsa Metropolitan Ring Road and Al-Ahsa National Park (Figure 10).

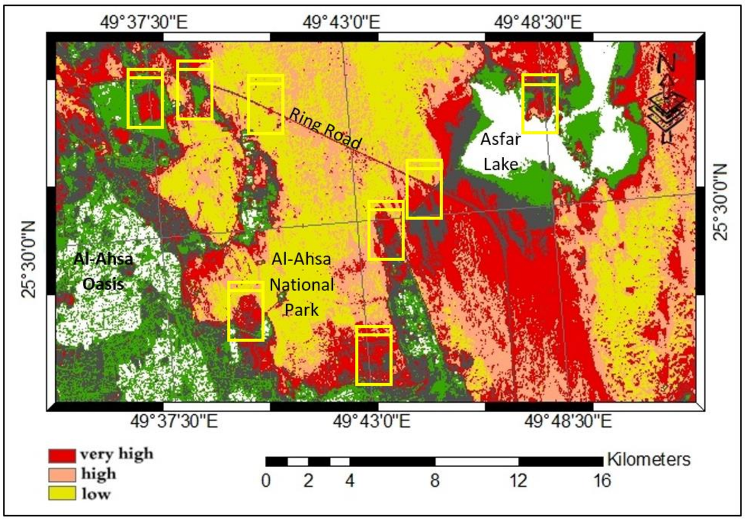

Figure 12.
Sand movement monitoring map and prediction of hazard levels for urban areas, agricultural lands, and roads in the study area.

5. Conclusion

The study demonstrated the potential of GIS and geospatial artificial intelligence technologies in monitoring sand movement, predicting annual movement rates, and determining the extent of their impact on land uses, particularly urban, agricultural, and service uses. This was achieved by processing data derived from satellite imagery and fieldwork applied to training samples (70%) and test samples. Through redness rate applications, the study was able to identify the continental source of sand at 40%. Fieldwork measurements to determine the color of the sand indicate the presence of hematite, which can help in adopting sand stabilization techniques by planting tree belts and green spaces. Marine sand, estimated at 60%, can be stabilized using engineering stabilization techniques. The results of the vegetation change detection indicated a variation in the density and distribution of vegetation cover between 2000 and 2020, particularly in the northwestern and northeastern regions and at Al-Ahsa National Park, ranging from 0.12 to 0.52. This is a result of the adoption of sand stabilization techniques by planting trees around roads and residential areas, and the cultivation of the Yellow Lake Reserve and windbreaks in Al-Ahsa National Park. Regarding the topography of the study area, the digital elevation model indicators indicated a lack of surface ruggedness and a slope, with the area being devoid of mountains and a few isolated hills. The elevation of the area ranges from 57 meters in the plains to 218 meters above sea level. These results represent important geographical factors in the annual sand encroachment rate and its geographical distribution. Since the study area falls within the arid climate zone and is influenced by northerly, northeastern, and northwestern winds for most months of the year, we find sand concentrations throughout the northern part of the study area, as indicated by the NDSI.

The results of measuring the average performance of the Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) models showed high values for the training data, 0.988, 0.873, and 0.991, respectively, and for the test data, approximately 0.738, 0.846, and 0.935. The estimated accuracy values for the training and test datasets indicated that the Random Forest (RF) model was the most effective model for predicting the origin, movement, and annual creep rate of sand dunes, with an accuracy of approximately 0.937. The AUCROC results also indicated that the RF model was the best performing model (0.982), followed by ANN (0.972) and SVM (0.964). In addition, the AUCPR results, with an accuracy of approximately 0.963, showed that it was more accurate in predicting the sensitivity and movement of the sand dune source compared to ANN (0.874) and SVM (0.847). By extrapolating the results of geospatial artificial intelligence performance models (), applying GIS technology, and field morphological measurements of sand dunes, a map was extracted to predict the annual sand encroachment rate (13 meters) and the risk levels for urban areas, agricultural lands, and roads in the study area, ranging from high, medium, and low risk. This can contribute to supporting decision-makers in properly planning the implementation of sand stabilization projects and protecting the region from the environmental, economic, and social impacts of sand movement, thus achieving sustainable development goals in addressing climate change issues. Accordingly, the study recommends the following:

1. The importance of utilizing deep machine learning models in geospatial artificial intelligence and GIS technology indicators in building models to achieve more accurate results when studying sand movement across continental and coastal environments.

2 .Adopting models and maps that predict the source and movement of sand when selecting sand stabilization techniques, especially afforestation and tree belt techniques.

3. Adopting performance models in geospatial artificial intelligence and GIS technology indicators in research teams when assessing the environmental impact of development projects with the aim of achieving sustainable projects.

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