Desertification Susceptibility Assessment Using Expert-Based Approach in Al-Khidhir District, Southern Iraq

Yasir Abdulameer Nayyef Aldabbagh, Helmi Zulhaidi Mohd Shafri*, Shattri Mansor, and Mohd Hasmadi Ismail

***Abstract*—Desertification is a serious threat to environment, agriculture, and public health all over the world. Iraq is concerned about desertification, particularly in the southern regions. As a result, this project will use geospatial methodologies to measure desertification susceptibility in Al-Khidhir, Al-Muthanna. The assessment was based on Landsat 5 TM data from 1998, Landsat 7 ETM+ data from 2008, and Landsat 8 OLI data from 2018. A Multicriteria Decision-Making (MCDM) technique based on the Analytic Hierarchy Process (AHP) was developed to assess the spatial distribution of desertification in the research area and the likelihood that it will occur soon. An examination of the geographical distribution of desertification in Al-Khidhir in 1998 indicated that desertification was most prevalent in the southern region, accounting for 25.9% of the total. Desertification spread to neighboring areas and increased (50.8%) in the research region's north in 2008. The findings suggested that using satellite photos, such as Landsat, can be extremely effective for assessing desertification.**

***Index Terms*—Desertification susceptibility, convolutional neural network, analytic hierarchy process, Al-Khidhir district**

I. Introduction

Desertification is a procedure of land corruption and is considered a global phenomenon and a significant challenge for 21st-century development. Desertification has gained some adverse characteristics because of its considerable complexity [1]. Despite concerted international political efforts under UNCCD (United Nations Convention to Combat Desertification) coming into force in 1994, there are few indications of the process and desertification processes. One of the fundamental obstructions to fighting desertification was the absence of robust evaluation techniques to identify priorities for policy and management measures. These assessment methods are also necessary to assess the influences pertaining to actions and programs and to better understand the desertification drivers [2].

Desertification can have several negative environmental impacts, including the loss of vegetation and wildlife habitat, soil erosion, and declines in soil fertility. In addition, desertification can lead to the formation of sand dunes, which can damage infrastructure and restrict the movement of people and goods. This can have negative economic impacts, as well as social and cultural impacts. In some cases, desertification can cause displacement of communities and the loss of traditional livelihoods. Overall, desertification can create significant negative influences on the environment and on the people who depend on it. As a result, desertification research is important to provide sustainable ecosystems by understanding the dynamics of extreme weather and human movements.

Geographic information systems (GIS) along with remote sensing can be utilized to evaluate the severity and degree of desertification in each area. To conduct remote sensing, satellite plus aerial imagery is used to collect information about the earth's surface, including information about vegetation, land use, and soil conditions. GIS acts as a technology that makes it possible for the data to be mapped and analyzed to identify patterns and trends. Together, GIS and remote sensing can both be utilized to observe fluctuations in vegetation as well as land use as time passes. They are important to pinpoint specific regions that are at a high risk of getting affected by desertification. Using this knowledge, prevention or mitigation techniques can be created to combat the effects of desertification in a specific area.

Desertification susceptibility assessment is a process used to evaluate the potential of a specific area to become affected by desertification. This assessment typically involves analyzing various factors that can contribute to desertification, such as climate, soil type, vegetation cover, and land use, to identify areas that are at a high risk of being affected by this process. The results of a desertification susceptibility assessment can be used to help develop strategies for preventing or mitigating the effects of desertification in a specific area.

In the last decades, several methodological issues have been distinguished in desertification studies. Commonly, remote sensing and satellite imaging are effective methods for assessing desertification [1]. Spatial data on the risk of desertification is essential to planners and decision-makers in drawing up plans and in giving priority to initiative-taking activities to protect and preserve debased gainful terrains. The conventional techniques for mapping desertification changes incorporate a test of helpful atmosphere information and changes in precipitation [3]. Furthermore, researchers can use a compelling strategy for desertification study in large regions by developing remote sensor systems, at the point when joined with GIS. Desertification trends can now be assessed more accurately and thus support predicting and managing this problem [4]. They are utilizing remote sensing strategies to delineate degrees of soil disintegration and the

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dry season uncovered huge yields that depict the spatiotemporal size of desertification. These techniques not only reduce time and cost but contribute to a broader spatial field, which can be evaluated regarding wild examples and contributing elements to make informed risk management decisions [3].

By contributing useful information to map land cover and identify areas of desertification, remote sensing, being a time- and cost-effective technology, overcomes the constraints of conventional approaches. According to several studies, important data sources for determining the extent of desertification include remote sensing data like those from the Landsat series. According to ref. [5], Landsat 4–5, Landsat 7, as well as Landsat 8 images offer an excellent analysis. Hu *et al*. [6] examined the spatiotemporal evolution with respect to desertification of land in the Maqu Plateau from 1977 to 2014 using multitemporal Landsat images. Additionally, the classification and evaluation of desertification in Basra, Iraq, employing spectral indices were done using Landsat multispectral satellite images [7].

Djeddaoui *et al*. [8] integrated data centered on Landsat 8 imagery as well as the Shuttle Radar Topographic Mission Digital Elevation Model (SRTM DEM) for desertification susceptibility assessment. Their findings showed that geomorphological parameters had a minor impact on the occurrence of desertification. Sentinel-1A images were utilized in certain studies to oversee Algeria's desertification in Biskra using soil roughness and moisture content as indicators [9]. Desertification in Morocco was also mapped using spectral indices generated from multispectral satellite images (Sentinel-2 MSI) [10]. More recently, from 1990 to 2020, Meng *et al*. [11] used Landsat imagery and Google Earth Engine to monitor desertification in Mongolia.

The AHP has emerged as a useful technique for desertification risk mapping by allowing the integration of diverse climatic, topographical, environmental, and socio-economic factors [12]. AHP facilitates assigning weights to criteria based on expert knowledge while maintaining consistency through pairwise comparisons and mathematical validation. For instance, Dastorani [13] applied AHP to assess desertification sensitivity in an arid part of Iran using factors like vegetation cover, soil texture, and climate. Weights were elicited from a panel of experts. The resulting map delineated zones of very high to very low susceptibility. Similarly, Shihab and Al-hameedawi [12] utilized AHP to model desertification severity in central Iraq based on criteria ranging from rainfall to land use. Comparison with satellite derived indices showed good agreement. Kacem *et al*. [14] also effectively implemented AHP to map desertification proneness in Morocco by integrating biophysical indicators. A key advantage of AHP is the capacity to manage diverse GIS-based factors in a systematic manner. AHP provides a flexible and consistent framework for desertification modeling by enabling expert knowledge integration along with geospatial data on climatic, topographic, environmental, and human factors known to influence dryland degradation. The capacity to refine criteria and weights based on the local context makes AHP well suited for desertification risk assessment.

This research developed a desertification susceptibility assessment predicated on the Analytic Hierarchy Process (AHP) with respect to the Al-Khidhir district, Iraq. In this study, AHP was selected as an appropriate technique because it [15, 16]: (1) Allows inclusion of expert knowledge for factor weighting in a consistent manner; (2) Enables integration of diverse conditioning criteria encompassing terrain, geology, land use, etc.; (3) Provides a flexible framework to refine factor hierarchies and weights based on the local context; (4) Generates susceptibility maps with good accuracy compared to desertification distribution.

The rest of the content of this investigation is divided into the subsequent sections: Sets of data and the case study of this research are described in Section II. Next, Section III presents the methods used to extract land cover pertaining to the study area from Landsat images, desertification conditioning factors and the assessment method (i.e., AHP), and Section IV concludes the research by explaining the main findings from the study and presents research guidelines for subsequent works.

II. Materials and Methods

A. Case Study

Since surface water levels have declined in upstream nations and precipitation has decreased, particularly in central and southern Iraq, desertification has grown faster there. Much has been done to determine and think about its circumstances and effects [17]. Plenty of locations in Iraq have been affected by desertification because of the country's geographic placement between dry and semi-arid regions. The existing state of the economy, climate change, and inadequate development of agriculture are all factors in accelerated desertification. For instance, the sand-covered Al-Muthanna province is situated in one of Iraq's three major belts. Roads, other human endeavors, as well as agricultural economic initiatives are all at risk in sandy areas. Dune movement of all sizes and forms is accelerating in the north-eastern region located in Al-Muthanna province [18].

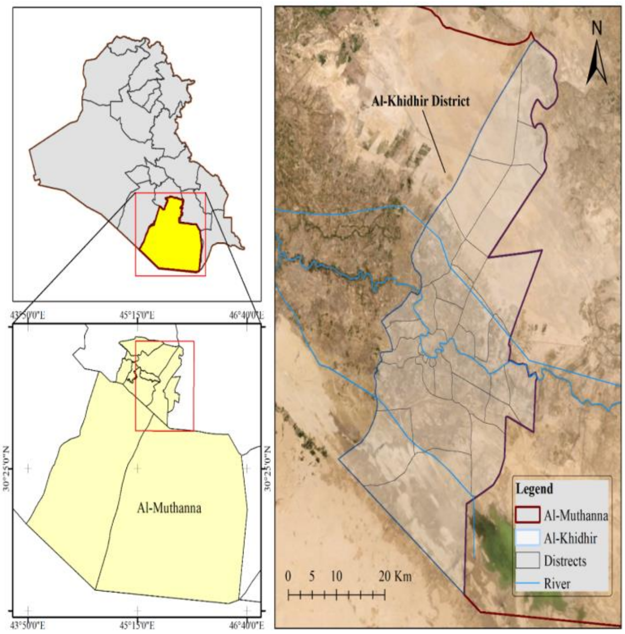


Fig. 1. The research's region map (Khidhir districts, Al-Muthanna).

The study was conducted in the Al-Khidhir district of the southern Iraqi province of Al-Muthanna (Fig. 1). Its 1,702 km^2, of total land area is 3.2% of the province's entire land area. It is located at (31 °12′N, 45 °78′E), 32 kilometers south of Samawah. Due to the district's production of products like wheat, barley, vegetables, as well as dates, Al-Muthanna's economy thrives. Among the primary environmental problems in the area is desertification, which has an impact on social activities, economic development, as well as agricultural land use. Thus, it is essential to conduct environmental studies in this field to prevent difficulties like desertification, agriculture, and additionally social problems.

The region has a classic desert climate. In January, the ambient temperature is 12.1 ℃ whereas, in July, it is 38.5 ℃ in July. The lowest rainfall during the rainy season, which lasts from September to May, was 1.3 mm.

B. Datasets

In this investigation, land cover maps were produced using Landsat TM, ETM+, as well as OLI data dated 1998, 2008, alongside 2018 (Table I). GIS layers for geology, waterways, type of soil, elevation, as well as population density were also added. The United States Geological Survey (USGS) archive (https://earthexplorer.usgs.gov) was used to retrieve the Remote sensing images. These datasets of images are described in Table I. The GIS data were gathered from several sources like free internet resources (https://www.diva-gis.org/gdata), the General Authority for Meteorology, the Central Bureau of Statistics, Seismic Monitoring, the Panning Authority, as well as the Climate Section (Table II).

TABLE I: LANDSAT IMAGES ALONGSIDE THE METADATA EMPLOYED IN THIS INVESTIGATION

#	Landsat Project	Path/Row	Acquisition Date	Spatial Resolution (m)
1	Landsat 5 TM	167/38	1998/3/4	30
2	Landsat 5 TM	167/39	1998/3/4	30
3	Landsat 7 ETM+	167/38	2008/3/7	30
4	Landsat 7 ETM+	167/39	2008/3/7	30
5	Landsat 8 OLI	167/38	2018/3/11	30
6	Landsat 8 OLI	167/39	2018/3/11	30

TABLE II: LIST OF DATASETS USED IN THIS STUDY

Data Name	Purpose	Resolution/Specifications	Source
Landsat 5 TM Images (1998)	Land cover mapping and change detection	30 m spatial resolution, 7 spectral bands	USGS EarthExplorer
Landsat 7 ETM+ Images (2008)	Land cover mapping and change detection	30 m spatial resolution, 7 spectral bands	USGS EarthExplorer
Landsat 8 OLI Images (2018)	Land cover mapping and change detection	30 m spatial resolution, 11 spectral bands	USGS EarthExplorer
SRTM DEM	Extract elevation data	30 m spatial resolution	USGS EarthExplorer
Geology Map	Desertification indicator	Vector dataset at 1:100,000 scale	Local geospatial agency
Soil Map	Desertification indicator	Vector dataset at 1:50,000 scale	Local authorities
Waterways	Desertification indicator	Vector dataset	Local authorities
Population Density	Desertification indicator	Raster dataset at 100 m resolution	Local authorities
NDVI	Desertification indicator	Derived from Landsat images	Computed from Landsat data
Ground Truth Samples	Accuracy assessment	Polygon samples for each land cover type	Visual interpretation

Fig. 2 displays the Landsat images of the research region. The primary prevalent types of land cover in the research region are wet soil, agricultural and bare lands, as well as water bodies. Regions having either bare soil or bare rock on the surface are referred to as bare lands. Agricultural lands are regions that thrive on dryland farming practices and are primarily utilized for primary production. Wet soil or wetlands are regions that are permanently or intermittently covered in fresh, brackish, or salt water that is either static or flowing. A water body is a stationary or moving body of water that is surrounded by land and can be either natural or artificial.

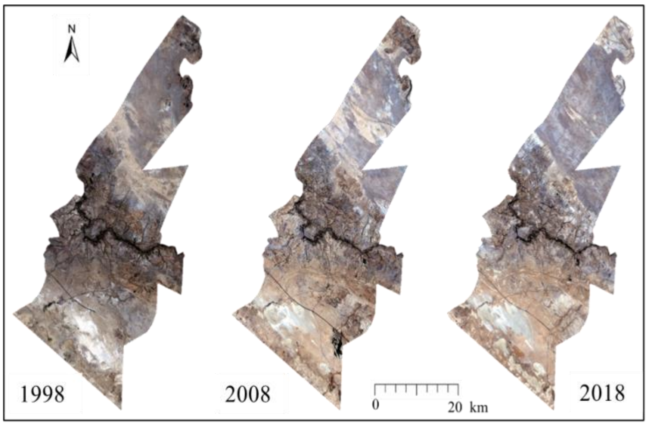


Fig. 2. The research area is depicted by three true color composite Landsat images: (a) 1998's Landsat 5 TM image, (b) 2008's Landsat 7 ETM+ image, as well as (c) 2018's Landsat 8 OLI image.

C. Methodology

1) Landsat preprocessing

Landsat images underwent radiometric modification, atmospheric calibration, as well as geometric adjustment during preprocessing. In the first step, digital images are converted into radiance values to correct sensor malfunction problems. With the use of Ground Control Points (GCPs), which can be manually chosen from images or based on field information like GPS coordinates, the geometric correction modifies the positions of image pixels. Then, these images were converted into the World Geodetic System 84 (WGS84) datum and Universal Transverse Mercator (UTM) projection. In the end, atmospheric calibration changes the radiance values of an image to its reflectance values. The QUAC Atmospheric Correction module of the Exelis Visual Information Solutions software was used to do the atmospheric calibration.

2) Land cover classification

In order to analyze array-like data, for instance, images and movies, convolutional neural networks (CNNs) were generated [19]. According to ref. [20], these models are founded on ideas, including shared weights, local connections, pooling, as well as the usage of numerous layers that reflect characteristics of natural signals.

Artificial neural networks (ANNs) of the CNN variety are extremely effective at image classification projects. A few of the benefits of using CNNs for satellite image classification include the following: (1) CNNs can automatically learn and extract important features from satellite images, which can be used to accurately classify different types of land cover and land use; (2) CNNs can handle large amounts of data, making them well suited for working with large satellite image datasets; (3) CNNs can make use of spatial relationships between pixels in an image, which is important for accurately classifying satellite images; (4) CNNs can be trained to make predictions in real-time, which can be useful for quickly identifying areas of interest in satellite images; (5) CNNs can be used in combination with other machine learning algorithms to improve the satellite image classification's accuracy. Overall, CNNs can be a powerful tool for accurately and efficiently classifying satellite images for a variety of applications.

In this study, CNN was designed as follows. It is encompassed by a single feature stage which contained a pooling layer after a convolutional layer. In the convolutional layer, a 2D convolution with 4 filters was used. In this layer, the kernel size was set as 3, found by randomized search optimization. The activation function in this layer was rectified linear unit or ReLU. The pooling strategy utilized is maximum pooling. The randomized search space recommended that the pool size be 2 × 2. The 2D features were flattened into 1D high-level features that could be utilized as inputs for the classification (SoftMax) layer by adding a dense layer (or completely connected) on top of the pooling and convolutional layers.

CNN has several hyperparameters that need fine-tuning to achieve optimized results. Among these hyperparameters, the variables that need to be optimized the most in this research are the kernel size, activation function, number of convolutional filters, pooling size, optimizer, and its parameters (i.e., learning rate and batch size). A randomized search method that randomly selects parameter sets from the model with uniform distributions was used to conduct the optimization. Table III displays the hyperparameter search space based on the appropriate lower and upper ranges for each parameter. The categorical cross-entropy function shown in Eq. (1) served as the foundation for the optimization.

$$L_{CNN}(W) = -\frac{1}{I}\sum_{i=1}^{I}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] + \lambda_1 \bullet \|W\|^2 \qquad (10)$$

Here, suppose we have a training test with respect to I pixels. Then, L denotes the cross-entropy error function, y_i symbolizes the target label, $\hat{y}_i$ signifies the output of the network, $W = [w_1, w_2]$ resembles the network's weights, as well as λ_1 represents the L2 regularization constant.

TABLE III: SEARCH SPACE PERTAINING TO HYPERPARAMETERS OF CNN

Parameter	Search Space
Number of convolutional filters	2–1024
Kernel size	3–15
Pooling size	(1, 1), (2, 2), (3, 3)
Activation Function	Linear, ReLU, Tanh, Sigmoid
Optimizer	SGD, Adam, Adamax, Adadelta, RMSprop, Nadam
Learning rate	10-5–0.95
Batch size	2–256

Training procedure. Most deep learning algorithms including CNN are commonly trained with gradient descent. This technique has the advantage of the ability to efficiently minimize the objective function by using simple mathematical tricks (e.g., differentiation or chain rules). Several versions of this algorithm are available, and, in this study, Adam was used with a batch size of 32. Other parameters of Adam were set as (learning_rate = 0.0035, beta_1 = 0.9, beta_2 = 0.999).

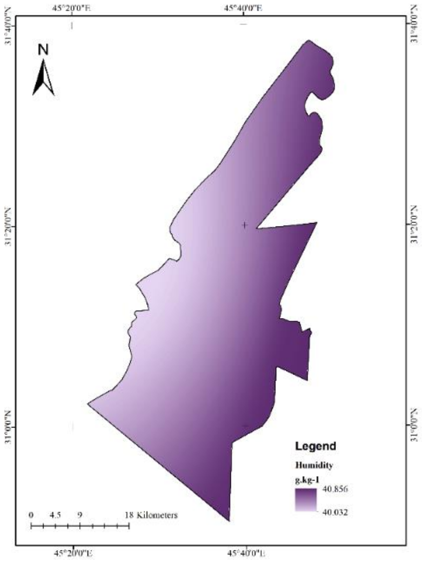
3) Preparing desertification factors

Desertification conditioning factors are the underlying factors that can make an area susceptible to desertification. These factors can include climatic conditions, such as low rainfall and high temperatures, as well as soil characteristics, such as low organic matter and poor drainage. Other factors that can contribute to desertification include land use practices, such as overgrazing and deforestation, and the presence of invasive plant species.

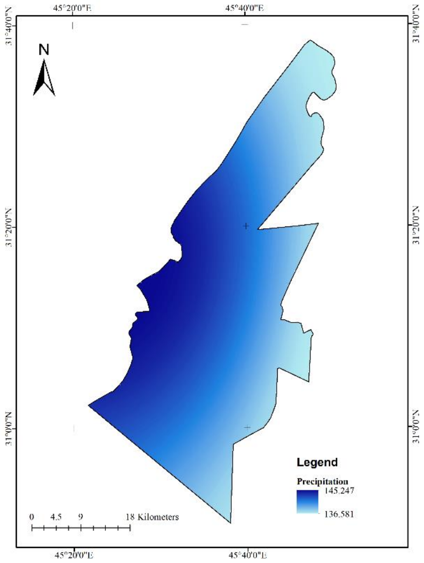
To evaluate desertification conditioning factors, it is necessary to collect information about the relevant factors in a specific area. This can involve conducting field observations, collecting data from remote sensing and GIS technologies, and conducting soil and vegetation surveys. This information can then be analyzed to identify which factors are present and to what extent they may be contributing to desertification in the area.

Once the desertification conditioning factors have been identified, it is important to develop strategies for addressing these factors to prevent or mitigate the effects of desertification. This can involve implementing land use practices that are less likely to contribute to desertification, such as rotational grazing or reforestation, and implementing measures to control or remove invasive plant species. It can also involve implementing strategies to improve soil health and moisture retention, such as using cover crops or building terraces. Overall, evaluating desertification conditioning factors and developing strategies to address them is an important step in preventing and mitigating the effects of desertification.

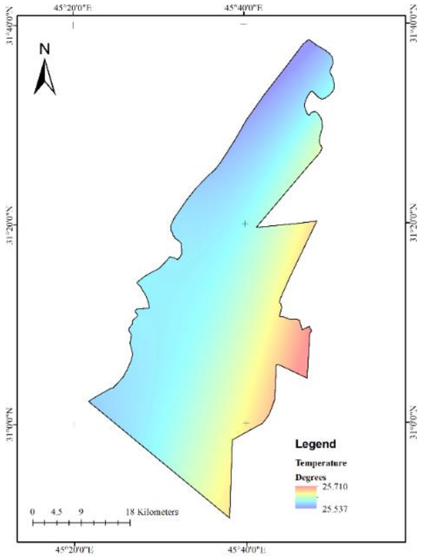
The common controlling parameters distinguished in the desertification procedure are soil, wind and water disintegration, substance, physical, natural corruption, atmosphere, vegetation, geography, and financial elements [1, 21]. The edge wind speed associated with the eolian entrainment of soil particles changes in response to fluctuations in air temperature, precipitation, relative moisture, as well as wind speed. Meanwhile, low rainfall as well as high wind speed and temperature worsen the desertification risk. In addition, human activities including populace development, overgrazing, and overcutting of vegetation may expand desertification. This study established desertification conditioning factors from five main categories including climate, topography, environment, demography, and geology. Fig. 3 presents the hierarchy of the factors used to assess the research area's likelihood of desertification. Temperature, humidity, evaporation, wind speed, as well as precipitation are all considered climatic variables. Elevation and slope were used as topographic conditions. In the environment category, land cover, water ways, and vegetation indices were used. Population density was used to represent the demographic condition related to desertification. Finally, soil types and lithology were included under the geology factors.



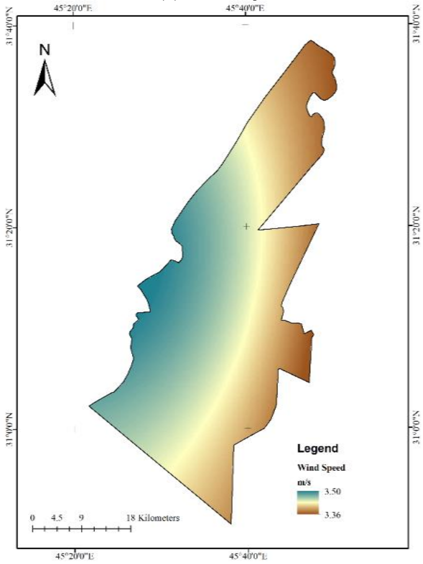
(a) humidity



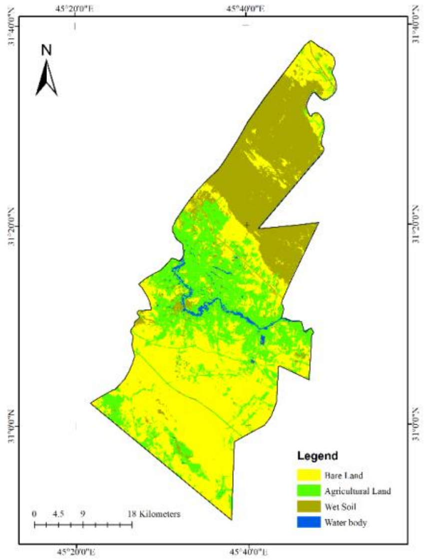
(b) precipitation



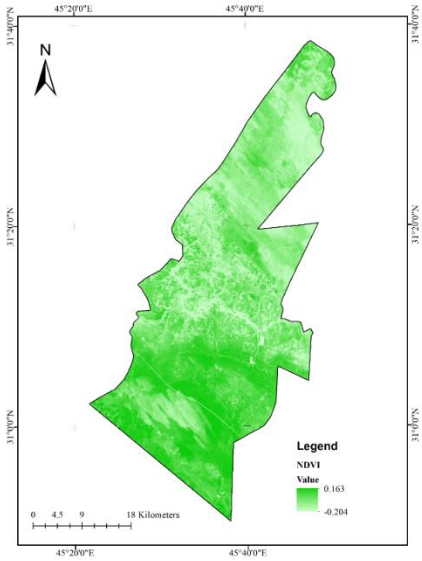
(c) temperature



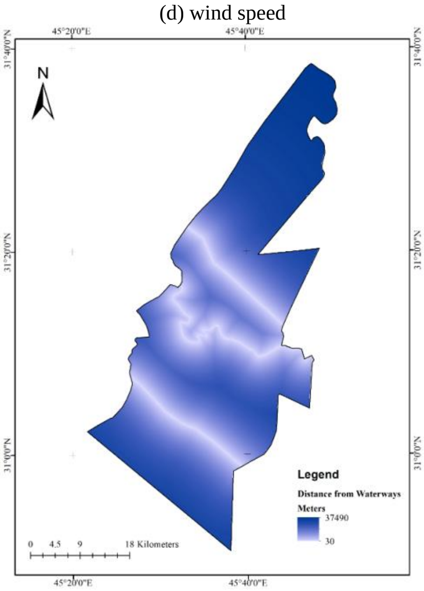
(d) wind speed



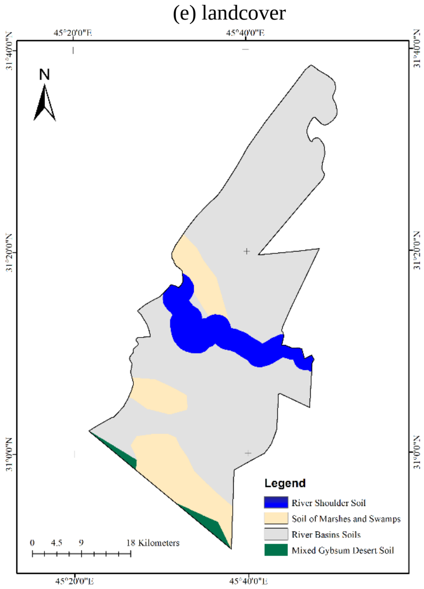
(e) landcover



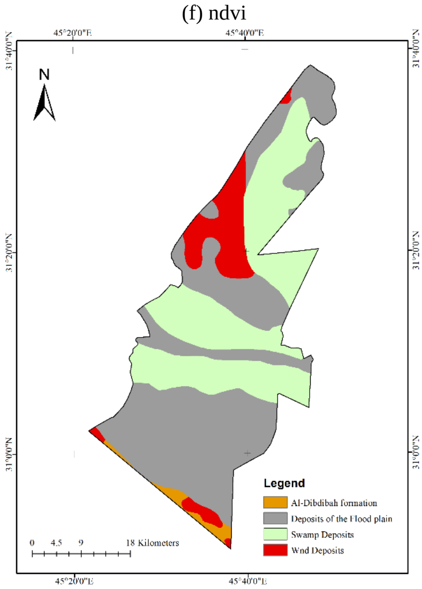
(f) ndvi



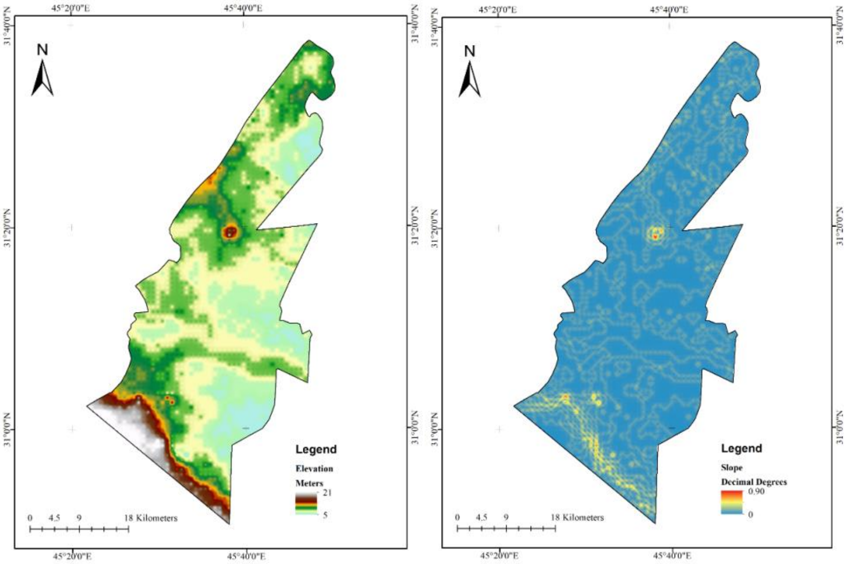
(g) distance from waterways



(h) soil types



(i) geology



(j) elevation (k) slope

Fig. 3. Desertification conditioning factors used in this study.

4) Evaluating conditioning factors using AHP

The AHP is a method for making decisions that assists in evaluating and comparing complex decision options. It is a structured method for assessing and organizing information that is used to make decisions. The AHP involves dividing a decision-making problem into levels of smaller, more manageable sub-problems, and then using mathematical techniques to compare the different options and arrive at a solution. This process can be useful for making complex decisions that involve multiple criteria and multiple options and can assist in decision-making processes to be systematic and in a consistent manner.

AHP was first put up as a multicriteria decision-making (MCDM) strategy by [22]. In this MCDM technique, the factors, such as aims, standards, and plans, are organized hierarchically. The criteria are compared with one another on a pairwise comparison scale. Humans frequently find themselves in predicaments where they must choose based on a range of factors. Through (a) both quantitative and qualitative decision analysis, (b) simple solution evaluation and representation using a hierarchical model, (c) logical argumentation, (d) the decision's quality test, as well as (e) less time needed, the AHP approach may provide optimal responses effectively. Saaty [23] asserts that AHP is the best tool for use when making a decision that involves comparing decision factors and categorizing them in accordance with their shared traits. Throughout the grouping phase, the decision-making factors are rated and then evaluated between each pair in every group using a matrix. The weight and inconsistency ratio of each element will then be calculated. Subsequently, the evaluation of data consistency will be a straightforward one.

The ratio-scale form, which expresses one's perspective when presented with a decision-making situation, is used as input by the AHP technique. The pairwise comparison matrix is then generated using the values of the ratio. The ratio scale is constrained due to the constraints of human brainpower. In the AHP approach, the scale range of 1–9 is thought to effectively reflect human perception [24]. The Standard Preference Scale utilized in the AHP approach is displayed in Table IV.

TABLE IV: PREFERENCE SCALE FOR PAIRWISE COMPARISON

Preference Level	Numerical Value
Equally Preferred	1
Equally to Moderately Preferred	2
Moderately Preferred	3
Moderately to Strong Preferred	4
Strongly Preferred	5
Strongly to Very Strongly Preferred	6
Very Strongly Preferred	7
Very Strongly to Extremely Preferred	8
Extremely Preferred	9

AHP can accept the discrepancy by providing an evaluation with respect to assessment inconsistency. This evaluation is among the most crucial characteristics in the priority decision process, based on the pairwise comparison. Whenever the consistency ratio increases, the evaluation result increases in unpredictability. A consistency ratio having more than 10% is only occasionally acceptable; in most cases, a consistency ratio having less than or equal to 10% can be accepted [25]. The Random Consistency Index (RI) Table V can be utilized to determine the consistency ratio.

Consistency and random index are two concepts utilized in the AHP to assess how logical and coherent the judgments are. The consistency index (CI) is the ratio of the consistency measure (CM) to the random consistency measure (RCM), where CM is the difference between the judgment matrix's greatest eigenvalue and its dimension and RCM is the expected value of CM for a random matrix. The random index (RI) is the average value of RCM acquired through simulations or experiments for matrices of various dimensions. The lower the confidence interval, the more consistent the assessments. A good rule of thumb is that the confidence interval (CI) should be less than 0.1.

TABLE V: RANDOM CONSISTENCY INDEX (RI)

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

In this investigation, five experts were given the task to deliver pairwise comparisons between the conditioning criteria (cut and fill volume, length of paths, agricultural lands, population density, as well as residential areas) that were utilized to establish the fitness function after ranking. These experts had expertise in areas, for instance, civil engineering (1 expert), water resources (2 experts), and GIS (1 expert), alongside remote sensing (1 expert). After gathering pairwise comparisons from experts, the AHP approach was utilized to determine the relative significance pertaining to every indicator and rank them correspondingly.

5) Mapping desertification probability

The pairwise comparison of five primary factors (climate, topography, environment, demography, and geology) as well as the subfactors provided by 14 experts were used to calculate weights of the factors. Then, the raster analysis was performed to overlay the factors with their corresponding weights to establish the research region's spatial probability of desertification.

III. Results

A. Results of Land Cover Mapping

Fig. 4 shows the historical maps of the land cover of 1998, 2008, and 2018, respectively. Based on the model, the dominant classes in the 1998, 2008, and 2018 maps are wet soil, agricultural land, as well as bare land, accordingly. The maps produced by the CNN model at specific times are visually different, especially regarding the most dominant classes i.e., wet soil, agricultural land, as well as bare land. Table VI summarizes the accuracy measures (OA, F1-score) obtained for the CNN classifiers with respect to the images at various times. Furthermore, the results of F1 score of the CNN classifier per class suggest that the classifier could accurately (based on the F1-score) sort the three images' various land cover classes.

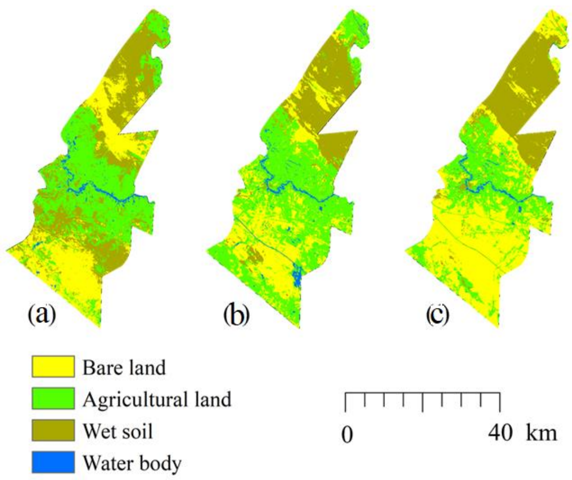


Fig. 4. Land cover maps generated by the default CNN (a, b, and c illustrate the land cover maps of 1998, 2008, and 2018, accordingly) and the optimal CNN land cover maps.

The bare ground shows desertification within the Al-Khidhir district of Al-Muthanna's spatial distribution characteristics of desertification. Desertification was a major issue in the region's south in 1998. Desertification will progress to the neighboring areas in the ensuing ten years. In the northern part of the research's region, desertification advanced in 2008. In addition, the simulated land cover map indicated that the extent of bare land may see a rise in 2028 if the local Al-Khidhir district administration does not implement policies to combat desertification. The results show that in 1998 and 2008, accordingly, 25.9% and 50.8% of the Al-Khidhir were bare ground. The forecasts indicate that bare land will make up 54.1% of the total land area.

TABLE VI: Accuracy Assessment Pertaining to the CNN Classifier with the Default and Optimal Values of the Hyperparameters for the Images at Various Times

Image	OA (training)	OA (validation)	OA (test)	F1-score (training)	F1-score (validation)	F1-score (test)
Landsat 5 TM, 1998	0.975	0.978	0.968	0.980	0.980	0.970
Landsat 7 ETM+, 2008	0.986	0.985	0.985	0.989	0.986	0.987
Landsat 8 OLI, 2018	0.987	0.989	0.989	0.990	0.990	0.990

Fig. 5 displays the area calculated for each land cover class throughout the years 1998, 2008, and 2018. Agricultural land functioned as the center of the economy between 1998 and 2008 (39% and 47.4%, accordingly). Nevertheless, in 2018, agricultural land was factored in just 26.2% of the total, whereas bare land made up 46.6% of the total. The percentage of wet soil decreased from 32.2% in 1998 to 21.3% in 2008, then significantly climbed to 25.9% in 2018. Other than that, the areas reported for the water body class are 2.1%, 2.4%, and 1.3%, accordingly, for 1998, 2008, and 2018.

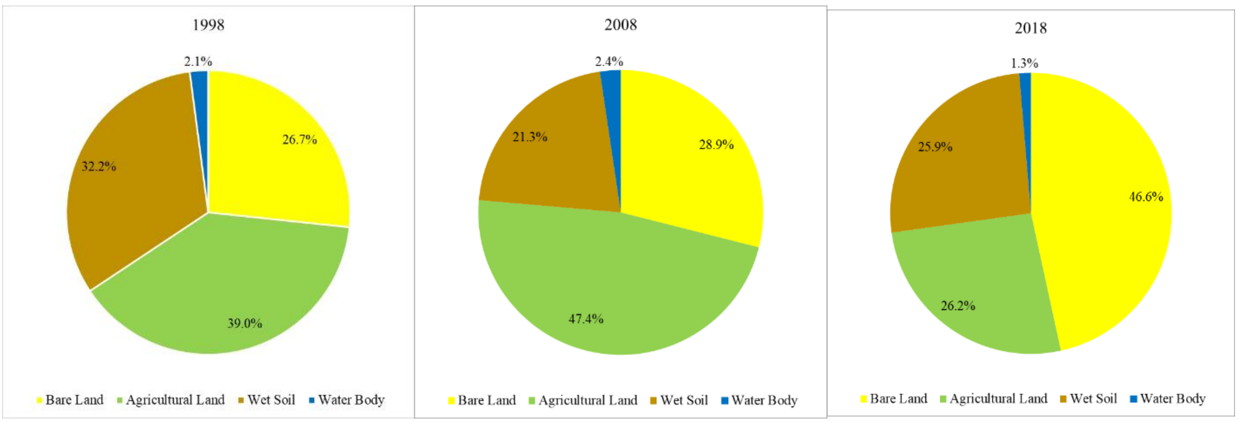


Fig. 5. Each land cover class's percentage of area is computed.

B. Results of Desertification Factors Evaluation

Table VII presents the calculated weights for different desertification conditioning factor based on pairwise comparisons provided by 14 experts. The final weights were calculated based on geometric mean of all the weights from the 14 experts. The results indicate that for the primary factors, the climate has the highest weight (most important) among the five factors. The environment came second followed by topography and demography. Geology has the lowest weight indicating it is the least important for desertification susceptibility assessment in the study area according to the experts. Temperature was the most key factor among the climate factors and humidity was the least important in this group. In addition, land cover was the most important as compared to waterways and vegetation index in the environment category. In the geology category, soil types were more important than lithology. Finally, elevation was found to be more important than slope in the topography category.

TABLE VII: EXPERTS WEIGHTS FOR PRIMARY DESERTIFICATION CONDITIONING FACTORS

Factor	Expert #1	Expert #2	Expert #3	Expert #4	Expert #5	Expert #6	Expert #9	Expert #10	Expert #12	Expert #13	Expert #14	GM
Climate	0.579	0.297	0.600	0.376	0.562	0.307	0.598	0.155	0.185	0.201	0.567	0.360
Topography	0.049	0.375	0.172	0.298	0.258	0.206	0.229	0.399	0.084	0.092	0.052	0.161
Environment	0.139	0.210	0.114	0.145	0.113	0.158	0.096	0.348	0.234	0.261	0.225	0.172
Demography	0.135	0.044	0.065	0.109	0.036	0.188	0.054	0.055	0.374	0.383	0.116	0.103
Geology	0.098	0.075	0.049	0.073	0.031	0.142	0.023	0.042	0.123	0.063	0.041	0.060
Temperature	0.305	0.292	0.592	0.447	0.603	0.194	0.272	0.132	0.289	0.334	0.598	0.334
Evaporation	0.134	0.314	0.227	0.239	0.217	0.288	0.272	0.470	0.109	0.072	0.077	0.189
Wind	0.204	0.174	0.105	0.151	0.115	0.194	0.291	0.161	0.241	0.310	0.039	0.160
Precipitation	0.073	0.118	0.053	0.100	0.044	0.166	0.128	0.131	0.334	0.263	0.250	0.126
Humidity	0.284	0.103	0.024	0.063	0.021	0.157	0.037	0.105	0.027	0.020	0.036	0.054
Land cover	0.594	0.779	0.784	0.648	0.770	0.500	0.702	0.594	0.725	0.752	0.685	0.679
Waterways	0.249	0.180	0.165	0.230	0.185	0.250	0.226	0.249	0.150	0.089	0.206	0.191
Vegetation index	0.157	0.042	0.052	0.122	0.045	0.250	0.073	0.157	0.125	0.159	0.109	0.101
Soil Types	0.667	0.500	0.889	0.750	0.889	0.500	0.900	0.857	0.875	0.889	0.857	0.763
Geology	0.333	0.500	0.111	0.250	0.111	0.500	0.100	0.143	0.125	0.111	0.143	0.182
Elevation	0.857	0.500	0.800	0.750	0.889	0.500	0.857	0.667	0.200	0.143	0.500	0.530
Slope	0.143	0.500	0.200	0.250	0.111	0.500	0.143	0.333	0.800	0.857	0.500	0.317

C. Results of Spatial Distribution of Desertification

The susceptibility of desertification in the research's region was produced by the AHP-based method with several desertification conditioning factors. The susceptibility level was categorized into five groups: very low, low, moderate, high, as well as very high. Fig. 6 presents the susceptibility of desertification developed in this research for the study area. The map shows that the region's north and south both possess high to very high susceptibility levels. The middle parts with regards to the area possess moderate to low susceptibility level.

The findings from this desertification susceptibility assessment in southern Iraq provide important insights that may be applicable to other arid and semi-arid regions facing similar environmental challenges. The factors that were found to be most influential in determining desertification risk in Al-Khidhir district, such as high temperatures, low rainfall, poor soil conditions, and human land use practices, are likely to play significant roles across many dryland environments globally. As such, the modeling approach developed here, utilizing satellite imagery, GIS data, and expert knowledge to map desertification susceptibility at a local scale, could be adapted for risk assessments in other vulnerable regions.

The specific conditioning factors and their weights will need to be validated based on the local context. However, the overall framework for integrating climate, topographical, environmental, demographic, and geological data within an AHP multicriteria analysis provides a robust methodology. In this way, the processes and findings from Al-Khidhir can help guide desertification monitoring and management strategies elsewhere, supporting more sustainable land use planning. Targeted, regional-scale analyses are key to addressing the global desertification challenge.

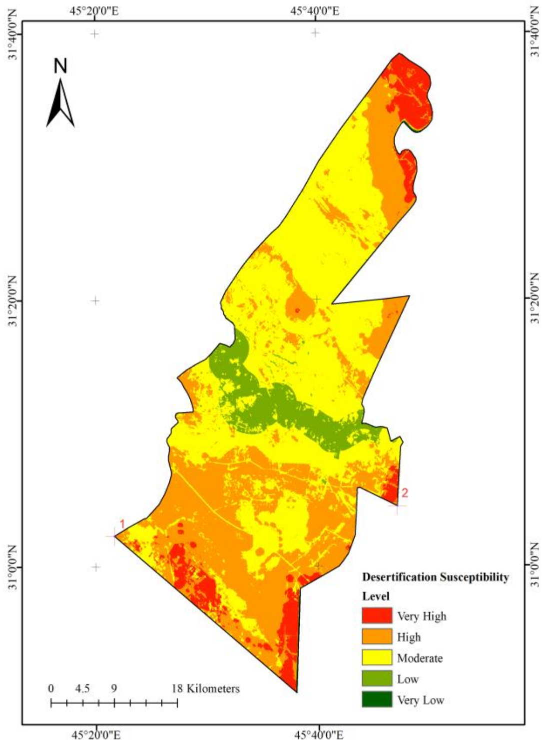


Fig. 6. Spatial susceptibility map of desertification of the study area.

IV. Conclusion

Environmental issues like desertification pose a threat to the global economy, humans, as well as agricultural growth. As a result, a proper assessment of desertification should be conducted in any city to avoid such problems. Iraq's Al-Khidhir district in Al-Muthanna suffers from large areas of desertification which significantly impacts the area's agricultural advancements and human activities. To create improved desertification management strategies, investigations are needed to map, evaluate, and mimic eventualities of desertification in the studied region.

This research examined the desertification of Al-Khidhir in southern Iraq. The region's land cover was generated by the CNN method and based on Landsat images, i.e., Landsat 5 TM captured back in 1998, 2008's Landsat 7 ETM+, as well as Landsat 8 OLI obtained in 2018. The results of evaluating desertification factors indicated that for the primary factors, the climate has the highest weight (most important) among the five factors. Environment came second following by topography and demography. Geology has the lowest weight indicating it is the least important for desertification susceptibility assessment in the study area according to the experts. Temperature was the most key factor among the climate factors and humidity was the least important in this group. In addition, land cover was the most important as compared to waterways and vegetation index in the environment category. In the geology category, soil types were more important than lithology. Finally, elevation was found to be more important than slope in the topography category. The susceptibility of desertification showed that both area's southern and northern parts possess high to very high susceptibility levels. The area's middle parts possess moderate to low susceptibility levels.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yasir, Helmi, Shattri, Mohd conducted the research; Yasir analyzed and collected the data; drafted the paper, conceived, and designed the analysis; all authors approved the final version.

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