Monitoring the Health Status of Ghouts in El Oued Region (Southeast Algeria) Using Support Vector Machine Models

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Abstract

El Oued, located in the Souf region (southeastern Algeria), is characterized by its unique architecture and palm groves. These are cultivated in depressions excavated into the sandy soil to access the water table, thereby enabling date palm cultivation. These depressions, known as ‘Ghouts’, constitute an exceptional agricultural innovation. In 2011, the Food and Agriculture Organization of the United Nations (FAO) recognized the Ghout system as a Globally Important Agricultural Heritage System (GIAHS) due to its profound historical, socio-economic, and cultural significance. However, this valuable agricultural heritage, essential for the livelihoods of the inhabitants, is currently threatened by various factors of degradation, including the rising or lowering of the water table, extreme climatic conditions, rural exodus, groundwater pollution, urban expansion, and more. This article examines the contribution of artificial intelligence to the monitoring of Ghout health status in the municipality of El Oued, employing the Support Vector Machine (SVM) model. The research focuses particularly on these agricultural systems that are currently threatened by severe degradation. The results reveal a steady decline in the Ghouts’ area, shrinking from 61.79 hectares in 2015 to 23.90 hectares by 2023. A significant degradation was observed between 2018 and 2019, with a loss of 17.65 hectares documented within a single year. The factors contributing to this degradation include climate change, increasing urbanization, and the evolution of agricultural practices that have altered the structure and function of these essential agricultural systems. Furthermore, this comprehensive analysis expands upon the initial findings by providing detailed SVM methodology documentation, enhancing uncertainty quantification, presenting a comparative analysis with alternative machine learning methods, and integrating a socio-economic analysis with policy implications and long-term monitoring recommendations for the GIAHS conservation.

1. Introduction

The use of Support Vector Machines (SVMs) in plant monitoring has several advantages, including their effectiveness for small datasets and their ability to handle complex nonlinear relationships (Savalkar & Patil, 2023). Indeed, SVMs are particularly suitable for small to medium-sized datasets, which is often the case in ecological studies where data acquisition can be expensive or difficult (Mountrakis et al., 2011). Thanks to kernel functions, SVMs can capture nonlinear relationships between plant traits and their health status, which is crucial in natural systems where interactions are rarely linear (Lodhi et al., 2000). SVMs are also robust to high-dimensional data, making them suitable for handling datasets where each plant sample is described by a large number of features, such as vegetation indices or spectral measurements (Huang et al., 2002). Additionally, SVM excels at binary classification tasks, such as distinguishing between healthy and degraded vegetation (Boser et al., 1992). However, there are also limitations to using SVMs. SVM performance is highly dependent on the choice of parameters, such as kernel type and error penalty, often requiring cross-validation to optimize these parameters (Hsu et al., 2003). Furthermore, SVMs can be less intuitive to interpret than other models, and their scalability becomes a challenge when datasets are very large, as computational time increases quadratically with the number of samples (Burges, 1998). For multi-class scenarios, although extensions of SVM exist, other models such as convolutional neural networks (CNNs), YOLO or random forests may be more appropriate (Girshick, 2015; Redmon et al., 2016; Ahangarha et al., 2021; Boser et al., 1992). In Algeria, the SVM model is used for crop classification and detection of agricultural areas from satellite images. Mountrakis et al. (2011) and Zheng et al. (2015) applied SVM to distinguish crop types, assess vegetation conditions, and monitor land use changes, particularly in regions such as the Sahara where extreme climatic conditions make agriculture vulnerable. Azzouzi et al. (2017) used SVM for soil classification and detection of areas prone to desertification. By analyzing satellite images and climate data, SVM models can help predict risk areas and plan interventions to combat desert encroachment (Abdelhakim et al., 2024). Lin et al. (2006) modeled and predicted water levels in reservoirs, groundwater, and rivers. For example, SVM models can be used to predict water flow based on historical data and climate parameters, to improve water resource management (Jamshidzadeh et al., 2024). SVM is also used for health data analysis in Algeria. Guido et al. (2024) and Duraisamy et al. (2023) used SVM for epidemic prediction or medical image analysis. They classified medical images for the diagnosis of cardiovascular diseases, which is crucial in regions where access to medical experts is limited. The use of Support Vector Machines (SVM) in the study of palm grove health is an interesting area, especially in arid and semi-arid regions such as the El Oued region, where ecosystems play a crucial role. Zheng et al. (2021) successfully classified various health conditions of palm groves from satellite and aerial imagery through the application of vegetation indices, notably the Normalized Difference Vegetation Index (NDVI), and other spectral characteristics. Their SVM model contributed to the identification of areas affected by diseases or environmental stresses. Zhang et al. (2022) conducted image classification based on the presence of disease symptoms, including Banana fusarium wilt or root rot, thereby facilitating proactive and targeted treatment management. Shaharum et al. (2020) employed SVM with spectral data and field measurements to model palm grove biomass and estimate productivity.

2. Materials and methods

2.1. Study area

The study area covers 77 km^2, representing the main commune of the Wilaya of El Oued, with a population of 169345 inhabitants, according to the 2018 census (PSD, 2018). The geographic coordinates of the study area lie between latitudes 33° 12′ 01″ - 33°13′ 02″N, and longitudes 6° 40′ 03″ - 6°41′ 02″ E.

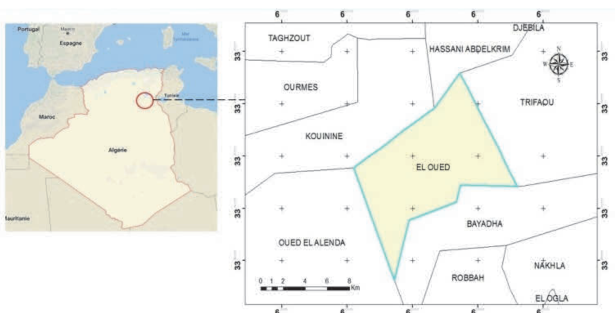

Figure 1 Study area.

The study area is bordered by the following communes (Fig. 1):

- Kouinine and HassaniAbdelkerim to the north;
- Oued El Alenda to the west;
- Bayadha to the south;
- Trifaoui to the east.

2.2. Geographic description

Based on previous research (Cornet, 1964; Voisin, 2004; Remini, 2006; Bensaâd, 2011; Zahi et al., 2011; Bouchahm et al., 2013; Miloudi & Remini, 2016; Remini & Souaci, 2019; Eid et al. 2024), it has been shown that the study area comprises three multi-layered geological formations that are considered permeable, and are alternated by other heterogeneous and impermeable formations. Within the study area, three aquifers have been identified, from top to bottom: an unconfined aquifer (phreatic), and two confined aquifers (terminal complex aquifer and intercalary continental aquifer). Climatic analysis confirms that the El Oued region has a hyper-arid climate, with an average annual precipitation of around 73.75 mm, and average annual temperatures being around 22.42 °C (NWS, 2018).

2.3. Universal heritage

In 2011, the Ghout was classified as a universal agricultural heritage site by the Food and Agriculture Organization (FAO) of the United Nations. This was due to its historical, socio-economic, and cultural significance on a global scale (FAO, 2011). The Ghout, also known as the inverted pyramid, serves not only as an affective cultivation method, but also as a popular tourist destination for both domestic and international visitors. Its unique design showcasing the ingenuity of its creators, has allowed lush palm groves and food sources to thrive in harsh, arid Saharan environment. Additionally, the Ghout has facilitated the cultivation of a high-quality date variety known as "Baâli" (FAO, 2011; Betrouni, 2020).

2.4. Ghout architecture

Generally speaking, the main factors influencing the shape of Ghouts are the type of soil and the direction of the sand wind. Ghout shapes can be organized into three categories:

a) Circular Ghouts: This type of Ghout is found throughout the south-western Souf region (Mih Ouensa, Oued Turk, etc.). According to Bisson (1990) Kadri & Chaouche (2018), if the excavation depth exceeds 7 meters and the slope height exceeds 15 meters, the construction of a new chasm becomes impossible. The characteristics and conditions of the south-western Souf region are slightly different. The water table is 5 to 10 meters shallower, the sandy soils are not deeply encrusted, but the material is highly mobile and sensitive to all types of wind, which explains the presence of small driving dunes. Access to water is less of a problem than the management of wind flows (Fig. 2).

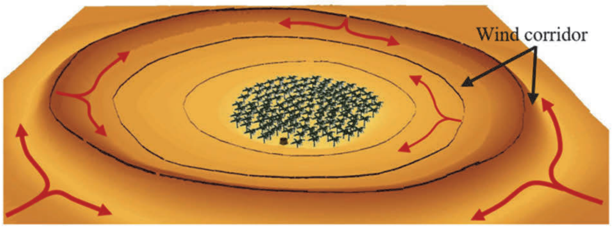

Figure 2 Circular Ghout (Miloudi & Remini, 2018).

b) Lying Ghouts: The Sufi devotes himself to the hoe, with the assistance of a donkey for transportation. He looks for very loose, sandy soils, free from gypsum encrustation, in order to excavate the site of his palm trees (Fig. 3). The sand is relatively homogeneous in the southern and southeastern parts of the region (El Oued, Nakhla, Robbah, etc.), where the crusts are thin and friable (Miloudi & Remini, 2018).

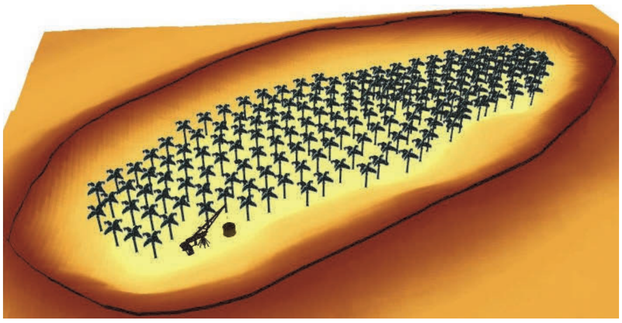

Figure 3 Elongated Ghout (Miloudi & Remini, 2018).

c) Rectangular Ghouts: This type of Ghout is found in the northern Souf region: Hassi Khalifa, Magrane, Hassani A-Kerim, Reguiba. They are more numerous than deep Ghouts, and probably have a brighter future, as they can be modernized. The landscapes of the northern half of the Souf are marked by shallow craters and escarpments, which are bright reddish (Fig. 4).

Figure 4 Rectangular Ghout (Miloudi & Remini, 2018).

Figure 5 is a photo taken in the municipality of Ourmes (El Oued region) showing palm trees in an advanced state of degradation, probably due to desertification, insufficient irrigation and the effects of climate change in the El Oued region (municipality of Ourmes, El Oued region). Drought and dwindling water resources, combined with potentially inappropriate agricultural practices, have led to the death of palm trees, which directly affects the local ecosystem (Lacheheb et al., 2025). In addition, the presence of visible waste on the ground also suggests pollution that contributes to the deterioration of environmental conditions. This situation compromises agricultural production and the livelihoods of local populations dependent on date palm crops.

2.5. Methodology

The main objective of this research is to analyze the degradation of Ghouts in El Oued within the framework of remote sensing, utilizing Support Vector Machines (SVMs). This approach is based on the use of high-resolution satellite images, and SVMs are used for supervised classification of land cover changes over time.

Figure 5 A degraded Ghout.

2.5.1. Data acquisition and preparation

The satellite data used are from two main sources; the first is from the Copernicus Data Space Browser platform, containing Sentinel-2A images for the 2015–2024 period; the second is SPOT-5 images for the 2002–2010 period, available through the CNES REGARDS portal. These images correspond to the period of exceptionally low spatial resolution, which were selected to cover the study area of El Oued Ghouts.

2.5.2. Image processing

ENVI 5.3 commercial geospatial image processing software (Exelis Visual Information Solutions, USA) was used to conduct preprocessing, including georeferencing of the images. The images were segmented into regions of interest, and many of the multiple image layers were overlaid to form multispectral composites allowing the monitoring of the changes in vegetation cover and the water content of the Ghouts.

2.5.3. Selection of spectral indices

To evaluate vegetation cover and Ghouts water availability, several spectral indices were used, including the NDVI (Normalized Difference Vegetation Index), which detects those with dense versus sparse vegetation. The NDWI (Normalized

Difference Water Index) was also calculated to monitor variations in soil water content showing areas where the water increased or decreased. Finally, the soil brightness index (BI), which is sensitive to salts and humidity, was used to characterize soil brightness to provide results on environmental changes in the Ghouts.

2.5.4. Supervised classification with SVM

SVM, a supervised learning algorithm, was used for supervised classification. It classifies the pixels in the satellite image into different categories based on the spectra signatures extracted from selected regions of interests (ROI). These ROIs, describing patterns representative of vegetation, sand, water, or urbanization were manually defined over the images. The SVM model was trained with a training dataset and validated with a test set to represent the predicted classification accuracy corresponding to change and no-change areas, between the images obtained in 2015 and 2024, respectively.

2.5.5. Validation and evaluation of results

In order to check and validate the results, the classifications of the processed images were compared with real data from the test set. The model was constructed using a training set, whilst the test set is then applied to evaluate its average out-of-sample performance for generalization and predicting classes well to unseen data. The results were analyzed using metrics including the confusion matrix, Cohen's kappa, and overall accuracy, which enabled the identification of classification errors and verified the performance of the SVM model in detecting environmental changes in the Ghouts of El Oued.

2.5.6. Change detection and time tracking

Using Thematic Change Workflow tool in ENVI 5.3, Ghouts were compared with satellite images for years 2015 and 2024 to perform change detection and temporal monitoring to develop the thematic change map. This allows for the visualization and identification of changes in the region, such as urban growth and the gradual disappearance of Ghouts. Simultaneously, monitoring the temporal evolution of the vegetation cover of Ghout areas using the NDVI index allowed quantifying their changes over time with precision, and exploring the environmental and socio-economic dynamics affecting territorial development through these traditional agrarian systems.

Figure 6 presents the methodology diagram for Ghout detection and analysis based on remote sensing and spatial analytics. The first stage is data preparation, which includes downloading and collecting satellite images (Sentinel-2A and SPOT-5) and describing them according to their spatial, spectral, and temporal resolutions. Next, a number of spectral indices were calculated, including NDVI, NDWI and BI, to analyze vegetation, water content, and soil brightness, with subsequent image classification based on these indices. In supervised classification (SVM), regions of interest ROIs are selected, a machine learning model SVM is trained to classify pixels, and the model's accuracy is evaluated using metrics such as confusion matrices. The last step, area tracking, is calculating NDVI in time, reclassifying the images to make Ghout areas standalone, exporting the results as shape files and calculating Ghout areas with spatial analysis tools in ArcGIS. This methodology monitors Ghout vegetation and water resource dynamics, which can present information for sustainable land management and conservation strategies.

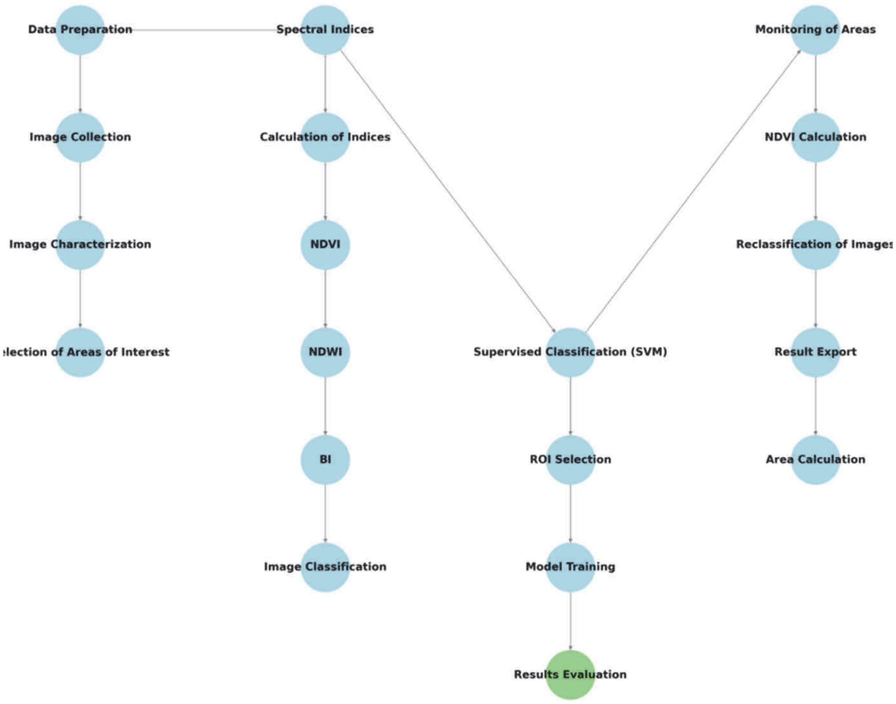

Figure 6 Approach to monitoring the health status of Ghouts

3. Results and Discussion

3.1. NDVI

The analysis of the evolution of Ghouts in the El Oued region, South-East of Algeria, over the period from 2015 to 2024, reveals a significant decrease in their areas. From Sentinel-2A and SPOT-5 satellite images and using processing and analysis tools such as ENVI 5.3 and ArcGIS 10.8, the areas of Ghouts were calculated annually after reclassification of NDVI, NDWI and BI indices. The NDVI map from 2024 (Fig. 7) reveals a predominance of low values, represented by dark tones, in the study region. This pattern indicates a substantial reduction in vegetation cover when compared to 2002 data. While the NDVI of the year 2002 presented more extensive areas of high values in yellow, corresponding to a significant vegetation density in the Ghouts. Figure 7 reveals a significant decrease in these areas, with an expansion of dark tones (values close to 0 or negative). The area decreased from 61.79 hectares in 2015 to 23.90 hectares in 2023. The remaining high-NDVI areas in 2024 likely correspond to residual pockets of still-functional Ghouts or regions where conservation efforts have been implemented, though these areas remain significantly smaller than in 2002.

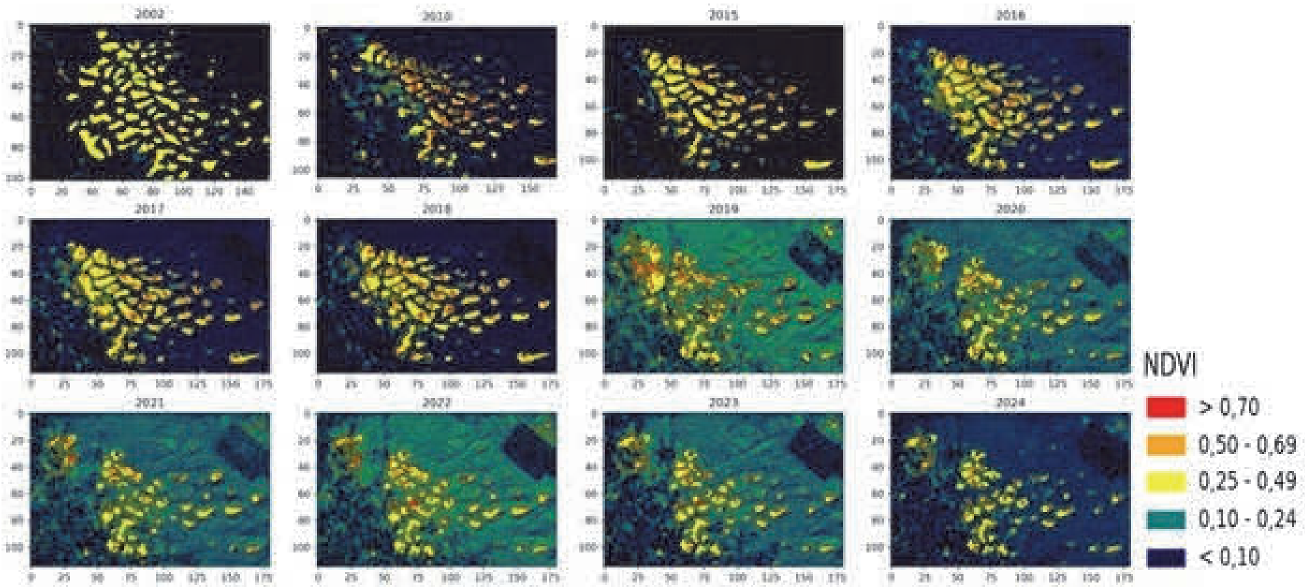

Figure 7 NDVI of Ghouts (from 2002 to 2024).

3.2. NDWI

The graph in Figure 8 illustrates the evolution of the NDVI vegetation index in the El Oued region, obtained from the *Google Earth Engine* (GEE) platform, between 2016 and 2024. There is a high variability in NDVI values, particularly between 2016 and 2020, with several peaks indicating periods of intense vegetation. However, from 2020 onwards, a general downward trend is noticeable, suggesting a gradual reduction in vegetation cover, possibly due to environmental factors such as drought or changes in land use (Sietz et al., 2017). By 2024, NDVI values approach zero, indicating substantial vegetation degradation or loss in the region.

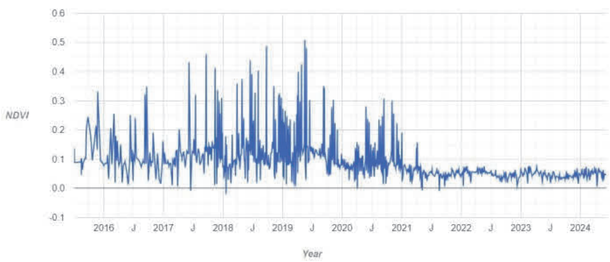

Figure 8 Evolution of NDVI (from 2016 to 2024) (Source: GEE).

The 2019 NDWI map (Fig. 9) shows overall positive values, represented by light tones, indicating a marked presence of humidity in the Ghouts that year. This observation corresponds to the peak observed in the NDWI time curve (Fig. 10), which shows high humidity in 2019 compared to other years. A direct correlation between water availability and vegetation density was observed, indicating that the decline in NDVI values is closely linked to the reduction in NDWI. Areas of high NDWI values are likely associated with still-functional Ghouts, where access to groundwater remains sufficient to support vegetation. However, the spatial distribution of high values is heterogeneous, with concentrations in specific areas, which could reflect local variations in the depth of the water table or agricultural practices. In 2024, NDWI values drop considerably. Water degradation is observed, probably due to overexploitation of water resources and prolonged droughts after 2019.

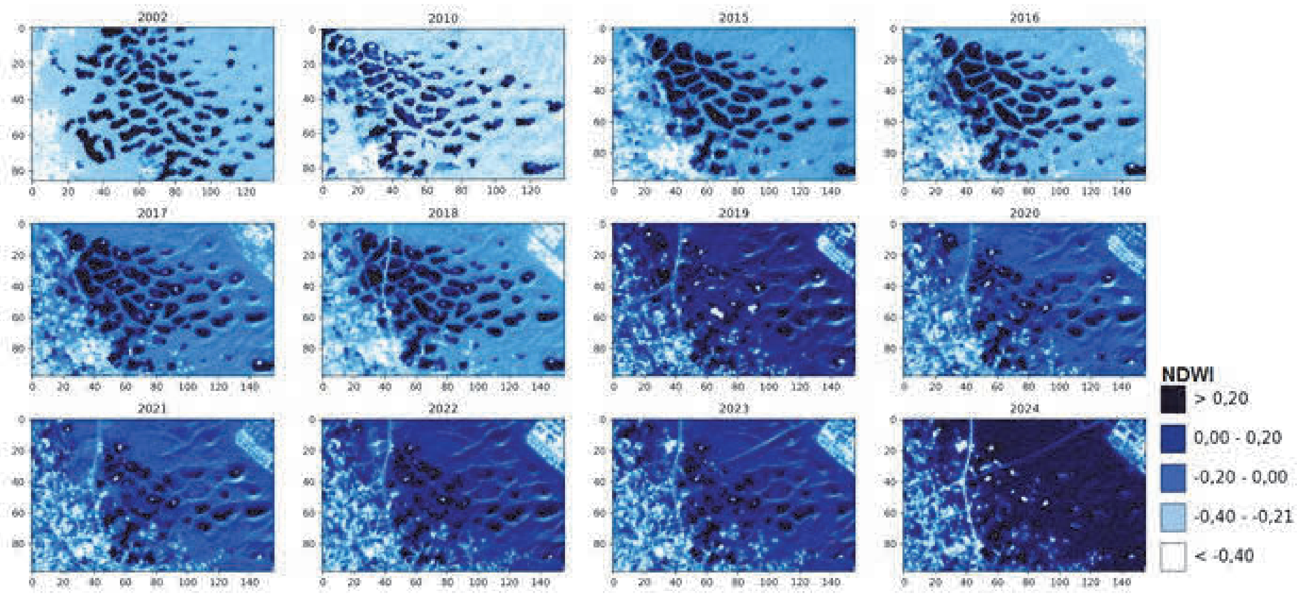

Figure 9 Evolution of the water index in the El Oued region (from 2002 to 2024).

The graph in Figure 10 shows the evolution of the NDWI water index, obtained from the *Google Earth Engine* (GEE) platform, between 2016 and 2024 in the El Oued region. The NDWI values vary significantly, regularly oscillating around the value of -0.20, with several marked peaks and troughs. These fluctuations could indicate seasonal variations in the presence of water in the region, perhaps related to rainfall or changes in agricultural or irrigation practices. Negative values dominate the observed period, indicating low water presence or prolonged periods of drought. However, it is possible to observe some periods of relatively high values, which indicate an increase in humidity or water in the region, probably after rainfall or periods of irrigation. This increase is also due to the upwelling that the region presents, which contributes to the temporary increase in humidity levels.

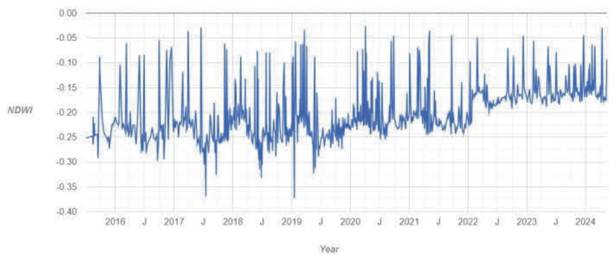

Figure 10 Evolution of the NDWI (from 2016 to 2024) (Source: GEE).

3.3. SVM Classification by indices

The brightness index (BI) is not discussed in this article. The supervised classification map presented in Figure 11 summarizes its evolution. Figure 11 illustrates the evolution of land use in El Oued between 2015 and 2024 by combining the spectral indices NDVI, NDWI and BI, calculated from Sentinel-2A and SPOT-5 data, in ENVI 5.3. Each index being assigned a distinct color to visualize the changes, revealing a notable reduction in vegetation cover (Ghouts). With extensive green areas in 2015 (61.79 ha) against a marked decrease in 2024 (23.90 ha in 2024, Fig. 11), a parallel increase is seen in humidity (NDWI). Going from low values in 2015 (-0.24) to high in 2024 (-0.05, Figure 10). These changes reflect the impact of recurrent droughts, water scarcity and intense urbanization across the entire study region (Fig. 11). Although limitations such as spatial resolution and possible confounding (urban/wetlands) require validation, this multi-index analysis highlights the urgency of conservation strategies to preserve the Ghouts in the face of observed environmental degradation.

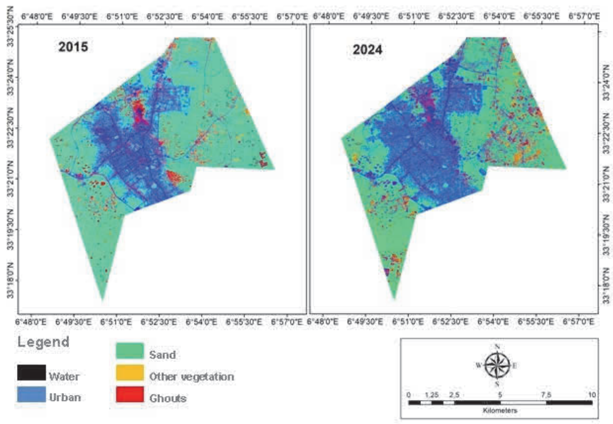

Figure 11 Change detection (SVM Classification by indices).

3.4. SVM Classification by region of interest (ROI)

The comparison of the 2015 and 2024 maps reveals significant changes in land use. In 2015, the Ghout areas (in green) are larger, corresponding to the still functional Ghouts, with a total area of 61.79 hectares (Fig. 12). On the other hand, in 2024 these areas have shrunk considerably (23.90 hectares), in favor of urban areas (in gray) that are expanding towards the south and east. This indicates a dense and rapid urbanization in the region. Sandy areas (in yellow) also increase in 2024, indicating an alarming situation of recurrent droughts. The water lake (in blue) shows an increased presence in 2024, suggesting hydrological changes, perhaps related to salt accumulation or water stagnation in some areas after periods of drought. The results of this classification illustrate consistency with the results obtained in the sections above (4.1, 4.2 and 4.3). These results highlight the combined impact of urbanization and environmental degradation on the Ghouts. A marked conversion of agricultural land to urban or desert areas, highlighting the need for sustainable management to preserve these traditional agricultural systems.

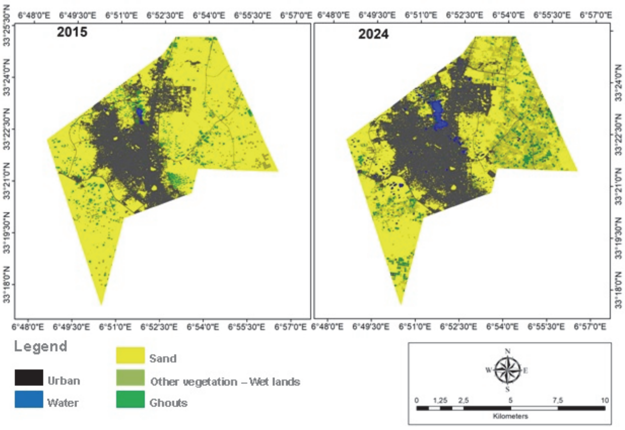

Figure 12 Change detection (SVM Classification by ROI).

3.5. Confusion matrix

Tables 1 and 2 present the confusion matrices of the supervised SVM classification, performed on both images of 2015 and 2024. For the 2015 image (Table 1), shows an overall accuracy of 98.87% (1314/1329 pixels correctly classified), which indicates a very high performance to identify land use classes such as vegetation (Ghouts), sand or urban areas, with only 15 misclassified pixels probably due to minor confusions between similar classes (e.g., sparse vegetation and sand). Regarding Table 2 (confusion matrix for the 2024 image), shows an overall accuracy of 89.77% (1650/1838 pixels correctly classified), indicating a slightly lower but still acceptable performance, reflecting changes in the distribution of classes (increase in urban and sandy areas, decrease in the Ghouts class). Tables 1 and 2 demonstrate overall good reliability for detecting changes in land use, although potential confoundments and the lack of details on specific classes limit more detailed analysis.

3.6. Mapping changes

Figure 13 illustrates land use transformations in the El Oued region between 2015 and 2024 using the Thematic Change Workflow tool of the ENVI software. This tool compares supervised SVM classifications of the 2015 and 2024 images to identify areas of change and immutability. Mapping land use changes can likely reveal specific transitions, such as the conversion of vegetation areas (Ghouts) to urban or sandy areas (as shown in Figure 13, where urban areas in gray expand to the south and east, and sandy areas in yellow increase). A notable reduction in the areas of Ghouts can be observed (from 61.79 ha in 2015 to 23.90 ha in 2024, Table 3). An increase in water and humidity surfaces is seen (Fig. 13) due to hydrological changes. This mapping highlights environmental and socio-economic dynamics such as rapid urbanization, desertification and local water changes, although the lack of specific details on exact colors or classes in the text limits more precise interpretation, nevertheless highlighting the significant impact of these factors on the degradation of the Ghouts over time.

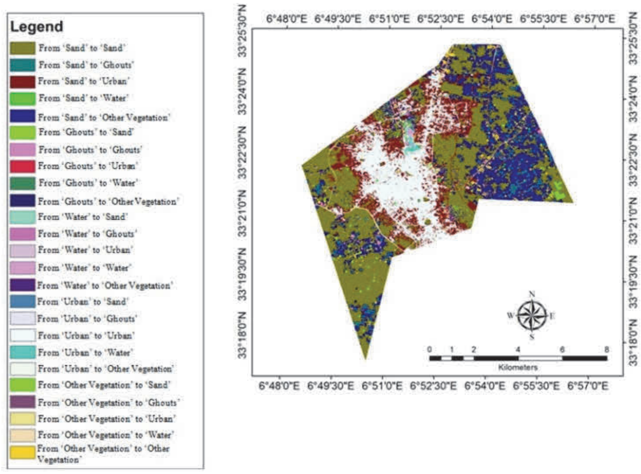

Figure 13 Change detection (SVM Classification by ROI).

3.7. Ghout Statistics

Table 3 shows the total annual areas of Ghouts in the commune of El Oued between 2015 and 2024. A gradual decrease can be seen from 61.79 ha in 2015 to 23.90 ha in 2024, i.e. a loss of 37.89 ha over nine years, with annual decreases ranging from -1.36 ha (2021-2022) to a marked drop of -17.65 ha between 2018 and 2019 (from 55.87 ha to 38.22 ha, i.e. a reduction of 31.6% in one year). This significant decline likely coincides with adverse climatic conditions such as prolonged droughts or overexploitation of groundwater (Mega & Khechana, 2021), as well as anthropogenic pressures such as urbanization (illustrated in Figure 13), while more moderate losses such as -2.05 ha (2015-2016) or -2.75 ha (2022-2023) suggest continued but less abrupt degradation. These results confirm the vulnerability of the Ghouts and the urgency of conservation strategies to counter this trend towards the gradual disappearance of traditional agricultural systems in the El Oued region.

Table 1. Confusion matrix result (supervised classification of 2015 data).

Ground Truth (Pixels)	(1314/1329)
Overall Accuracy:	98.87%
Kappa Coefficient:	0.9838

Ground Truth (Pixels)

Class	Sand	Ghouts	Other vegetation	Water	Urban	*Total*
Unclassified	0	0	0	0	0	*0*
Sand	608	0	13	0	0	*621*
Ghouts	0	206	0	0	0	*206*
Other vegetation	2	0	214	0	0	*216*
Water	0	0	0	30	0	*30*
Urban	0	0	0	0	256	*256*
Total	*610*	*206*	*227*	*30*	*256*	*1329*

Ground Truth (Percentages)

Class	Sand	Ghouts	Other vegetation	Water	Urban	*Total*
Unclassified	0	0	0	0	0	*0.00*
Sand	99.67	0	5.73	0	0	*100.00*
Ghouts	0	100	0	0	0	*100.00*
Other vegetation	0.33	0	94.27	0	0	*100.00*
Water	0	0	0	100	0	*100.00*
Urban	0	0	0	0	100	*100.00*
Total	*100*	*100*	*100*	*100*	*100*	*100.00*

Commission/Omission Error

Class	Omission (%)	Commission (%)	Omission (Pixels)	Commission (Pixels)
Sand	2.09	1.33	13/621	2/610
Ghouts	0.00	0.00	0/206	0/206
Other vegetation	0.93	5.73	2/216	13/227
Water	0.00	0.00	0/30	0/30
Urban	0.00	0.00	0/256	0/256

Accuracy (Producer/User)

Class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sand	99.67	97.91	608/610	608/621
Ghouts	100.00	100.00	206/206	206/206
Other vegetation	94.27	99.07	214/227	214/216
Water	100.00	100.00	31/31	30/30
Urban	100.00	100.00	256/256	256/256

Table 2. Confusion matrix result (supervised classification of 2024 data).

Ground Truth (Pixels)	(1650/1838)
Overall Accuracy:	89.77%
Kappa Coefficient:	0.8397

Ground Truth (Pixels)

Class	Sand	Ghouts	Other vegetation	Water	Urban	*Total*
Unclassified	0	0	0	0	0	*0*
Sand	928	0	0	0	185	*1113*
Ghouts	0	89	0	0	0	*89*
Other vegetation	0	0	270	0	0	*270*
Water	0	0	0	297	0	*297*
Urban	3	0	0	0	66	*69*
Total	*931*	*89*	*270*	*297*	*251*	*1838*

Ground Truth (Percentages)

Class	Sand	Ghouts	Other vegetation	Water	Urban	*Total*
Unclassified	0	0	0	0	0	*0.00*
Sand	99.68	0	0	0	73.71	*100.00*
Ghouts	0	100	0	0	0	*100.00*
Other vegetation	0	0	100	0	0	*100.00*
Water	0	0	0	100	0	*100.00*
Urban	0.32	0	0	0	26.29	*100.00*
Total	*100*	*100*	*100*	*100*	*100*	*100.00*

Commission/Omission Error

Class	Omission (%)	Commission (%)	Omission (Pixels)	Commission (Pixels)
Sand	16.62	0.32	185/1113	3/931
Ghouts	1.00	1.00	0/89	0/89
Other vegetation	0.00	0.00	0/270	0/270
Water	0.00	1.00	0/297	1/297
Urban	4.35	73.71	3/69	185/251

Accuracy (Producer/User)

Class	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (Pixels)	User Accuracy (Pixels)
Sand	99.68	83.38	928/931	928/1113
Ghouts	100.00	100.00	89/89	89/89
Other vegetation	100.00	100.00	270/270	270/270
Water	100.00	100.00	297/297	297/297
Urban	26.29	95.65	66/251	66/69

Table 3 Ghouts statistics (from 2015 to 2023).

Year	*Total area (ha)*	*Annual decrease (ha)*
2015	61.79	-
2016	59.73	-2.05
2017	57.82	-1.92
2018	55.87	-1.94
2019	38.22	-17.65
2020	30.51	-7.70
2021	28.01	-2.51
2022	26.65	-1.36
2023	23.90	-2.75

3.8. Discussion

The obtained results confirm the findings of many studies concerning the degeneration of classical agricultural systems spread throughout the Saharan area, particularly under the two-fold stress of climate change and anthropogenic pressures (Lu et al., 2004) The Ghout areas were decreasing mainly between 2018 and 2019, owing to multiple causes. Firstly, the rapid urbanization of the El Oued region, which is seen in the urban areas growth in the classification maps (Figures 11, 12 and 13), has resulted in the burial or abandonment of many Ghouts in favor of construction. This trend parallels Januel (2009), who reports the deleterious effect of urbanization on traditional oasis systems. Secondly, the downward trend in NDVI and NDWI indices after 2019 indicates a worsened environmental situation, namely less water supply thus smaller vegetation cover. These observations are in line with the work of Gorelick et al. (2017) who surveyed environmental trends in arid regions using Google Earth Engine with estimates of agriculture water, droughts, and groundwater overexploitation. However, because of the water depth (the water table) that in these Ghouts of El Oued, these crops are more sensitive to the aforementioned water variations. The high strength of the NDWI index from 2019 to 2024 indicates the rise of high humidity, likely influenced by agricultural activity, and the absence of the sanitation network (sustainable management of water resources). In conclusion, it was confirmed that the SVM method was effective for supervised classification for the detection of land change with an overall accuracy of 89.77%. Results fall in line with those obtained by Bruzzone and Prieto (2000), who exploited similar mechanisms to identify change within complex environments. However, some caveats are to be considered for example, confusion between urban areas and wetlands in NDWI images (Fig. 9), but it needs further visual verification in the field or through tools like Google Earth Pro. Ghouts provide important functions in mitigating desertification and maintaining regional biodiversity; and the results highlight the need to implement conservation measures to protect them. One possible solution to help mitigate these observed impacts is through the application of integrated water resources management and the adherence and respect of traditional agricultural systems with urban planning policies to safeguard the Ghouts from unsustainable pressure in the El Oued region.

4. Conclusion

This research, which presents a comparative spatio-temporal purpose to monitor the health status of Ghouts in the El Oued region of southeastern Algeria, has managed to quantify and analyze temporal spatial changes between 2015 to 2023. Data generated through remote sensing methods were based on SVMs used in this methodology. The results revealed a significant decrease in the area of Ghouts, which measured 61.79 hectares in 2015 and 23.90 hectares in 2023, a more than 61% decrease within nine years. Many of these factors are also linked to the environmental impacts of climate change, including reduced water availability and longer drought seasons; anthropogenic pressures, such as urbanization and changes in agricultural practices; and a growing global population. The analysis of spectral indices like NDVI, NDWI and BI combined with supervised classification through SVM were potent tools to elucidate and diagnose these changes. Confirming the robustness of the adopted methodology has an overall accuracy of 89.77%. Nevertheless, the findings also demonstrate the susceptibility of Ghouts to climate and socio-economic pressures, indicating the necessity of immediate actions for their conservation. Overall, the research presented in this study is a vital contribution to the comprehension of the enormous dynamics impacting traditional agricultural systems across the Saharan region. These include the sustainable management of water and land resources, and the need for greater integration of traditional practices as components of regional development plans. Predictive models (Cortes & Vapnik, 1995; Gorelick et al., 2017) may now be applied to predict how Ghouts would evolve, and gauge how effective the conservation recommendations would be. However, the Ghout degradation detection in El Oued using SVMs methodology proposed holds some main advantages. It combines high-resolution satellite data (Sentinel-2A and SPOT-5) for broad and precise monitoring of impacted areas and enabling the monitoring of the evolution of Ghouts during several years. The use of SVMs for the classification of spectral data (NDVI, NDWI, BI) provides high accuracy for environmental change detection, along with the ability to predict areas prone to degradation. Not only is this a new, practical method for assessing long-term changes in an objective and repeatable manner, but the framework can be applied to other ecosystems as well. It therefore brings together the strength of remote sensing as well as Artificial Intelligence and spatial analysis to provide a faster, more reliable and proactive approach than the conventional methods hence supporting sustainable management of Ghouts and natural resources in vulnerable regions.

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