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Investigating Land Use Changes and Environmental Drivers in Aures region

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Abstract

This study aims to study the spatio-temporal dynamics of natural resources using geomatic techniques by exploiting multispectral data. The study consists of the use of Landsat 5 TM and 8 OLI satellite images of three dates, 2000, 2009 and 2023, which are subjected to pre-processing techniques in order to eliminate errors and distortions affecting the reliability of radiometric values. The analysis of the obtained images is carried out based on digital processing, namely, Supervised classification by maximum likelihood and calculation of spectral indices NDVI NDMI. The results revealed that significant changes occurred over the 23 years, recording a considerable shift in land use units. The analysis of the NDVI and NDMI indices revealed a deterioration in vegetation health and a depletion of water reserves in wetlands of around 98%, which provides information on the extent of the changes in this region.

This study provides informative and decision-making support for planning the conservation of natural resources and establishing successful intervention strategies.

Keywords: Land use, Wetlands, geomatics. Spectral indices, Aures region, Algeria.

1- Introduction

Global changes, including global warming and degradation of natural resources, have reached unprecedented records in recent decades, dominated by increasing global temperatures, irregular precipitation and an intensified repetition of extreme climatic events, constituting a real threat to natural ecosystems (Vitousek, 1994; Seneviratne et al., 2012; Stocker et al., 2014). According to IPCC (2014), an increase in global average temperatures of around 0.85°C was recorded in the last decade between 1880 and 2012 and is expected to continue increasing to reach 4.8°C by the year 2100 (Hansen et al., 2010; Hoerling et al., 2012). Therefore, climate aridification and drought are causing the most visible global changes, such as ecosystem degradation, biodiversity decline, habitat destruction and species extinction worldwide (Arar et al., 2020).

The world's natural resources are subject to changes over time; these changes are mainly due to pressures exerted by human activities and aggravated by climate change. These dynamics have gradually emerged as a major global concern and a hot topic of leading research since they are essential elements for the study and understanding of the environment (Foody, 2002). This issue is now of paramount importance in most cartographic inventories and monitoring systems for environmental phenomena (Ouattara et al., 2006).

Among the most sensitive ecosystems to global changes are forests and wetlands; these ecosystems are a shelter for the most important biodiversity on Earth and play a key role in climate regulation and the provision of crucial ecosystem services. Forests, unanimously recognized as the first reservoir of carbon sequestration, constitute a stabilizing force of the climate and contribute to the mitigation of the climate change effects; they are home to about 80% of the Earth's species (Saponaro et al., 2024; Peñuelas and Sardans, 2021). Likewise, wetlands cover about 6% of the Earth's surface and are home to the most important biodiversity on the planet (Tockner, 2021); they are essential for water resource management and maintenance of the water cycle, mitigation of cures and natural water purification. However, both types of ecosystems are under increasing pressure from deforestation, drainage, urbanization, and climate change (Mao et al., 2020; Xu et al., 2020).

In this context, geomatics is positioned as a privileged tool, offering the possibility of regularly acquiring spatio-temporal data to characterize land use evolution, including that of wetlands. This information is essential for establishing spatial models to understand the functioning and dynamics of ecosystems. For more than four decades, satellite images and aerial photographs have been valuable sources of information for mapping land cover and analyzing the changes that occur there (Gressin et al., 2014; Lambin et al., 2003; Serra et al., 2008). The analysis of satellite images covering different periods will make it possible to monitor changes in spaces (forests, wetlands, etc.) and a given region, thus facilitating the mapping of the spatio-temporal evolution of land use (El Halim, 2015).

In this study, the analysis of satellite images from different periods (multi-dates) allowed us to monitor the evolution of natural resource changes in the Aures region over a period of 23 years (2000-2023), using geomatics tools (GIS and remote sensing). This study aims to achieve several objectives:

- Identify land use classes at three different periods between 2000 and 2023 using remote sensing data.
- Quantify changes in land use, particularly for forests and wetlands, which are the most sensitive.
- Analyze the ecological status of different ecosystems by analyzing spectral indices and explore possible reasons for changes.

2- Materials and methods

2-1- Study area

The Aures region is located in the North-Eastern of Algeria within the Saharan Atlas between the geographical coordinates' latitudes of 34°60" and 35°30" North and longitudes of 6°11" and 7°10" East, covering an area of 5200 km^2 (Figure 1). This area constitutes a mountain ecosystem that is characterized by a rugged relief and a diversified geomorphology. This area is distributed between three wilayas: The wilaya of Khenchela, Biskra and the wilaya of Batna. The geomorphological diversity of this area has given it ecological variability, which is particularly reflected in its remarkable floristic biodiversity. This area is dominated by Mount Chelia, whose highest point reaches 2,328 m, which contains a mosaic of habitats between Atlas Cedar (*Cedrus atlantica*) forest, Holm Oak (*Quercus ilex*) scrubland, Phoenician juniper mattorales and semi-arid Alfa (*Stippa tinacissima*) and white mugwort steppes (*Artemisia herba alba*) (Aissi et al., 2020).

The geomorphological complexity and continentality of the Aures region have given it a remarkable climatic diversity, with irregular rainfall and significant temperature differences between seasons and between day and night, with average annual precipitation ranging from 400 mm to 800 mm and temperatures ranging from 0 to 35°C.

The Aures region has experienced multiple ecological and anthropogenic constraints over the last decade, including deforestation, overgrazing and increasing aridity. The combined effect of these factors compromises ecosystem functions and exacerbates challenges for agriculture and local populations.

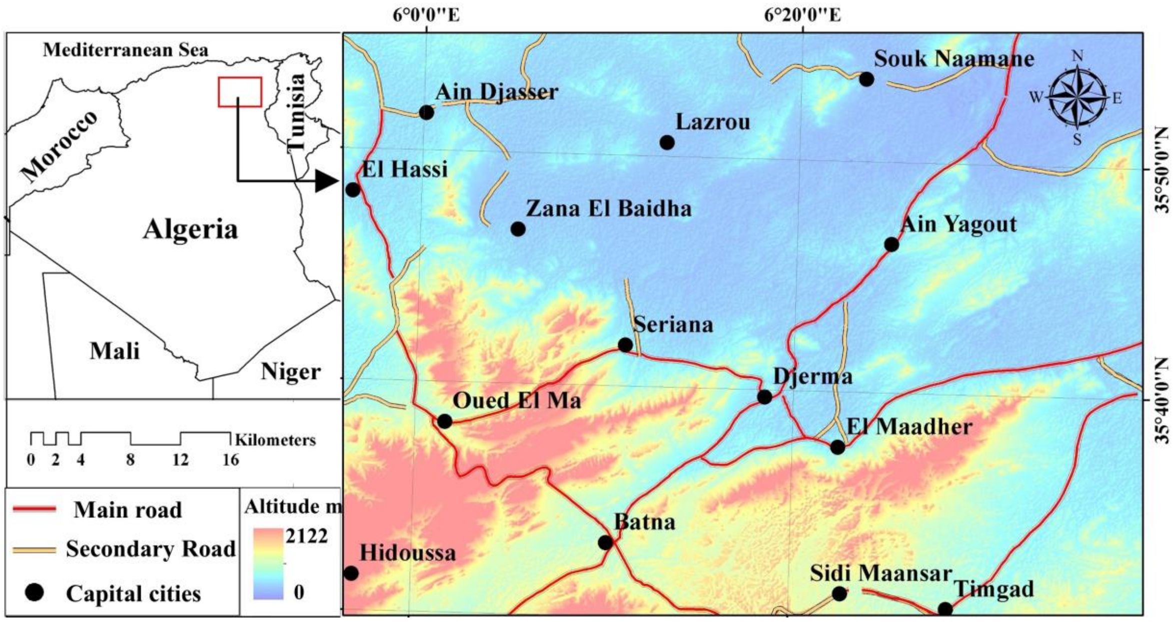

Figure 1. Geographical Localisation of the study area (Aures region).

2-2- Methodological approach

2-2-1- Data collection

Three satellite images of the Landsat 8 OLI and Landsat 5 TM were obtained from the United States Geological Survey (USGS) platform (www.usgs.gov) and were used to map and quantify spatio-temporal changes by synthesizing and observing the evolution of natural resources.

The choice of images used in this study was based on several essential criteria, namely, The extent of the image scene that encompasses the entire area, the clarity of the images in terms of atmospheric distortion, such as the presence of clouds, etc., the free availability on the USGS website, the Satellite image capture date that corresponds to the period conducive to the optimal state of the vegetation and the detection of humidity availability and water resources. This multi-temporal image series spans a period of 23 years, with acquisitions made in March of the years 2000, 2009 and 2023. The images were selected according to similarity criteria in terms of atmospheric and phenological conditions (Coppin et al., 2004; Lu and Weng, 2007). The table 1 gives an overview of the technical characteristics of the obtained images.

Table 1: An overview of the technical characteristics of the obtained images.

Images	**Satellite sensors**	**Dates**	**Bands**	**Spatial résolution (m)**
Image 1	Landsat 5 TM	06/03/2000	1-2-3-4-5-6-7	30 m
Image 2	Landsat 5 TM	15/03/2009	1-2-3-4-5-6-7	30 m
Image 3	Landsat 8 OLI-TIRS	22/03/2023	2-3-4-5-6-7	30 m

Before proceeding with the classification treatments of satellite images, their pre-processing is a crucial step to ensure the quality and reliability of subsequent analyses and expected results. These steps allow for the improvement of image quality by reducing errors and distortions, eliminating imperfections, and improving data accuracy. This is done through radiometric and atmospheric corrections, noise reduction, artifact removal, cloud and shadow removal, distortion rectification and image matching.

Before proceeding with the processing of satellite images, it is important to apply a Mask by removing the rest of the unstudied areas in order to work on the part of the images that correspond to the study area.

2-2-2- Field Survey

The study area chosen to carry out this study is a diversified region in terms of natural resources, such as forest areas, wetlands, crop areas, topographic diversification, etc. Therefore, field surveying is a crucial step in collecting the necessary information to classify satellite images. Before any field survey, a bibliographic search was carried out through the literature and existing maps and plans in order to position the important areas that are part of our study and to draw the most suitable route in order to optimize resources in terms of time and effort.

Field survey missions were carried out by choosing control points according to the distribution of the various land use units and accessibility to the land. The objective is to recognize and define the different landscape elements (entities) constituting all the classes of objects existing on the ground in the entire study area. While carrying out surveys of GPS points representative of each class of land use, for each point, information was collected such as longitude, latitude, altitude, nature of the objects existing on site (dominant species, bare soil, crops, etc.) (figure 2)

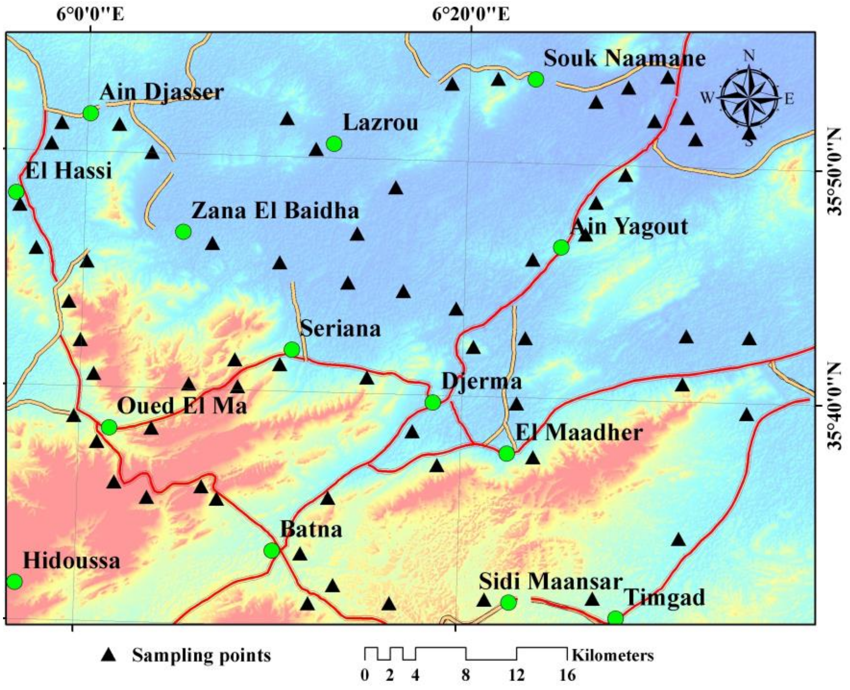

Figure 2: Map of sampling points

2-2-3- Supervised classification of satellite images

Image classification consists of assigning to each group of pixels of the same category a definition of its land use unit type (Training area) so that it is classified according to its spectral value in order to obtain a generalized classification of all land use classes. Technically, several polygons were established for the particular pixel classes using one or more polygons. The training area were chosen according to the classes uniformity and the way in which each class is represented consistently across the entire image. Based on the pixel values in all the spectral bands used, an estimation of the mean and covariances is carried out for each class by the classifier algorithm to assign particular classes to the pixels generalized across the entire processed image (Ahmad and Quegan, 2012). The classifier used in this study is the maximum likelihood classifier (MLC); this method is one of the best-known parametric classifications. In MLC, each pixel is assigned to a class based on the probability that it belongs to that class; the mean and covariance are modeled following a normal distribution in the multispectral variable space (Sisodia et al., 2014). Five spectral signature classes were selected to classify the images, namely Forests, crop areas, wetlands, bare soils and urban areas.

According to Congalton (1991), it is essential to assess the accuracy of the classification in order to carry out a thematic analysis. The Kappa index is an indicator derived from the confusion matrix and is used to assess the classification performance. According to Landis and Koch (1977), for a kappa index greater than or equal to 0.8, the classification is statistically considered acceptable, while for values between 0.4 and 0.8, the classification is considered to be of average quality, and values greater than 0.8 indicate a classification with high accuracy.

2-2-4- Spectral indices assessing

In order to ensure continuous and consistent monitoring of the environment and analysis of the earth's surface biophysical properties, spectral indices are developed by the scientific community by combining specific spectral bands to explore various aspects of ecosystems. In this context, two indices have been calculated, namely NDVI and NDMI, whose details and corresponding formulas are mentioned in Table 2.

Table 2: Normalized Indices and Their Formulas

Indices	Indice Name	Formula
NDVI	Normalized Difference Vegetation Index	NDVI= (NIR-RED) / (NIR+RED)
NDMI	Normalized Difference Moisture Index	NDMI=(NIR-SWIR) / (NIR+SWIR)

NDVI (Normalized Difference Vegetation Index) is closely related to the plant's photosynthetic activity and allows the generation of images representing the density of vegetation, also called relative biomass (Tucker, 1979). The red spectral band (Red) is sensitive to the chlorophyll pigments of the vegetation class, while the near-infrared band (NIR) is sensitive to the high reflectivity of plant materials. The values of the NDVI index vary from -1 to +1. Sellers (1985) considers that plant formations generally present positive values , which are usually between 0.2 and 0.8. The highest values are associated with the densest canopies (maximum vegetation cover). NDMI is used to monitor soil moisture and vegetation stress (Wilson & Sader, 2002). High values are indicative of high soil or vegetation moisture, while low values are indicative of low moisture content.

2-2-5- Land Use, Land Cover Change Detection

Change detection is an approach used to analyze the changes that have occurred in a given area between two or more periods (Singh, 1989). The thematic mapping obtained is subjected to a post-classification comparison procedure. The main objective of this step is to generate a map that highlights the spatio-temporal changes while quantifying the areas that have changed and those that have remained unchanged by the object analysis method. The purpose of this operation is to visualize and describe in a quantitative way the spatio-temporal trends that represent the expansion of land cover classes. However, the pixel analysis method is used for the quantification and changes in the biophysical properties of the studied ecosystems during the specified study period using spectral indices.

3- Results

The accuracy evaluation results were obtained to show an excellent level of agreement between the field data and classes modeled by the maximum likelihood algorithm. The obtained results indicate a notable separation level between the classes, indicating satisfactory accuracy, the results of which are mentioned in Table 3.

Table 3: Evaluation Metrics for Supervised Classification

Image	Overall precision	Kappa coefficient
Image 1 (2000)	99,9709 %	0,9988
Image 2 (2009)	99,9600 %	0,9991
Image 3 (2023)	99.2970 %	0.9871

3-1- Analysis of land use, land cover dynamics

Over time, land use has undergone significant changes. A cartographic analysis of the results illustrated in figure 3 highlighted a marked increase in forest areas, bare soils, and especially urban areas, while a significant decrease was observed in cultivated areas and wetlands.

The results reveal that for the period between 2000 and 2009, forests declined by 60.11 km², representing a decrease of 10.899% of the total forest area. On the other hand, crop lands experienced a notable increase of 45.44 km² (8.623%). It is also important to note that there was an increase of 1.44 km² for wetlands and 13.23 km² for bare land, corresponding to a rise of 2.665% and 3.99%, respectively. In contrast, urban areas recorded a growth of 2,133 km², equivalent to 0.072% of the total area (table 4).

During the extended period from 2009 to 2023, the trends continued to evolve. Forest areas increased considerably, with an increase of 108.25 km², representing an increase of 22.028%. However, crop lands suffered a considerable loss of 202.31 km², resulting in a decrease of 35.347%. Similarly, wetlands, including Gadaine, Ezzemoul and Tinsilt located in north of study area, experienced a notable reduction of 54.71 km², estimated at 98.632%. Bare land increased to 148.77 km², equivalent to an increase of 8.209%. Furthermore, urban areas recorded a development of 24.5 km² (table 4).

Table 4: Spatial evolution of land use, land cover classes (2000 – 2023).

	Area Km²			**Changes Km²**		**Changes %**	
	2000	**2009**	**2023**	**2000/2009**	**2009/2023**	**2000/2009**	**2009/2023**
Forests	551.50	491,39	599,64	-60,11	108,25	-10,89	22,02
Agriculture	526,91	572,35	370,04	45,44	-202,31	8,62	-35,34
Wetlands	54,03	55,47	0,76	1,44	-54,71	2,66	-98,63
Bare lands	1799,1	1812,3	1961,1	13,23	148,77	0,73	8,20
Urban zones	52,94	55,05	79,55	2,11	24,50	3,99	44.5

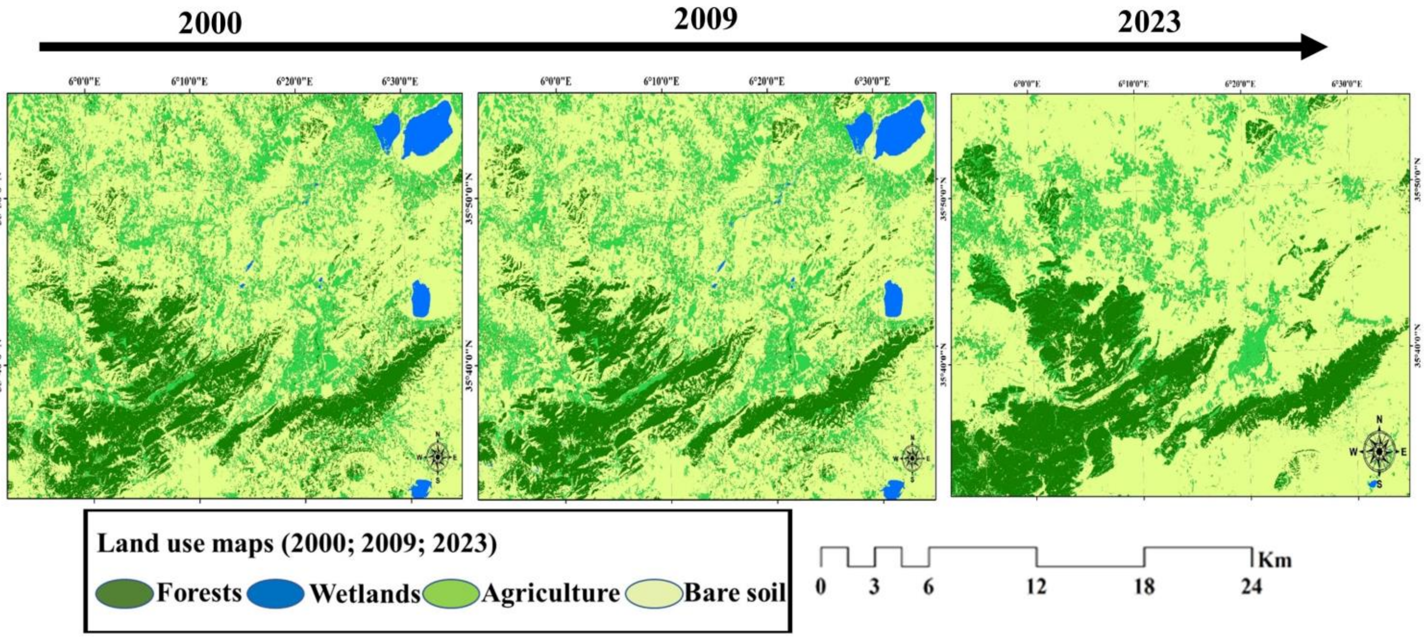

Figure 3: Spatio-temporal change in land use over 23 years

2-2- Spatio-temporal analysis of NDVI and NDMI indices: Changes in vegetation and moister conditions

The figure 4 illustrates the evolution of the vegetation state between 2000 and 2023, which reveals significant changes in health. In order to better understand these changes, NDVI evolution rates are presented in the table 5.

Table 5: Spatio-temporal variation of NDVI between 2000 and 2023

	NDVI classes	***(-1 ; - 0,07)***	***(-0.07 ; +0,025)***	***(+0,025 ; 0,09)***	***(0,09 ; 0,14)***	***(0,14 ; 0,5)***	***(0,5 ;1)***
Changes km²	**2000-2009**	58,95	16,16	-31,36	-22,68	-21,06	0
	2009-2023	-60,61	-23,57	41,23	22,26	19,91	0,06

In the first decade between 2000 and 2009, the NDVI classes between -1 and 0.025, representing wetlands and water bodies, experienced a significant increase in area of 75.11 km². In addition, an area decrease was recorded for the NDVI classes: (0.025; 0.09), (0.09; 0.14), and (0.14; 0.5) representing bare soil, Sparse leafy vegetation and medium dense leafy vegetation, respectively, with decreases of 31.36 km², 22.68 km² and 21.06 km2. At the same time, the class (0.5;1) representing dense leafy vegetation has completely disappeared.

For the second period between 2009 and 2023, an increased regression of wetlands and water bodies was recorded, with decreases reaching 84.18 km². However, areas increases were recorded for the classes of bare soil, medium dense deciduous vegetation, and, to a lesser extent, dense deciduous vegetation, reaching respectively 41.23 km², 22.26 km², 19.91 km² and 0.065 km².

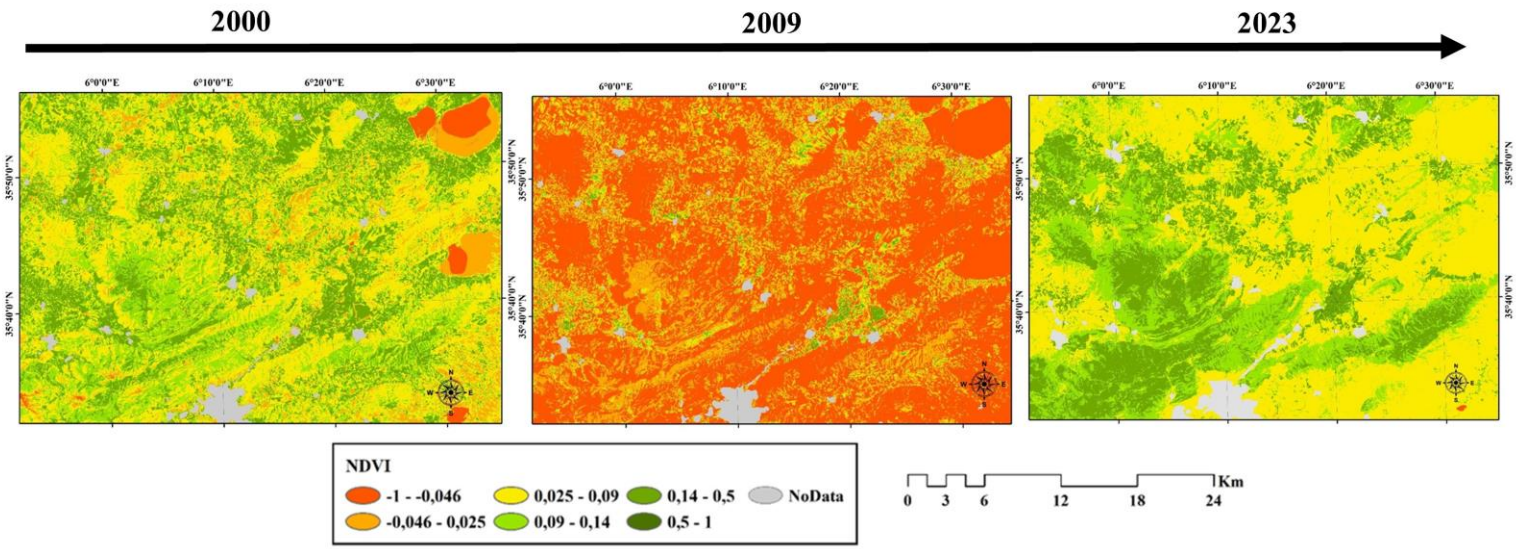

Figure 4: Spatio-temporal variation of NDVI between 2000 and 2023

The results of the NDMI class analysis presented in the table 6 and figure 5, highlight significant variations in hydrologic conditions and vegetation moisture levels.

For the first period between 2000-2009, the areas represented by the NDMI class (-1;0) experienced a sharp decrease of 82.19 km² indicating a severe lack of moisture and very severe drought, while for the classes (0;0.2) and (0.2;0.3) experienced a decrease of 12.26 km² and 0.72 km² respectively, indicating a strong and moderate drought state. However, a remarkable increase of order 95.82 is recorded for the class (<0.7), representing a very high moisture rate.

The second period between 2009-2023 experienced moderate variability. The NDMI classes (-1; 0), (0; 0.2), (0.2; 0.3) and (0.3; 0.4) marked by severe drought experienced stability without significant changes. On the other hand, classes (0.5;0.6) and (0.6; 0.7) experienced a considerable increase with 0.3 km² and 75.31 km² respectively, indicating high humidity levels. The NDMI class (> 0.7), represented by very high humidity areas, experienced a decrease of 75.66 km².

Table 6: Evolution of humidity levels according to the NDMI index (2000-2023)

	NDMI classes	(≤0)	(0 ; 0,2)	(0,2 ; 0,3)	(0,3 ; 0,4)	(0,4 : 0,5)	(0,5 ; 0,6)	(0,6 ; 0,7)	(≥ 0,7)
Changes km²	**2000-2009**	-82,18	-12,26	-0,72	-0,14	0	0	0,19	95,82
	2009-2023	0	0	0	0	0	0,35	75,30	-75,6

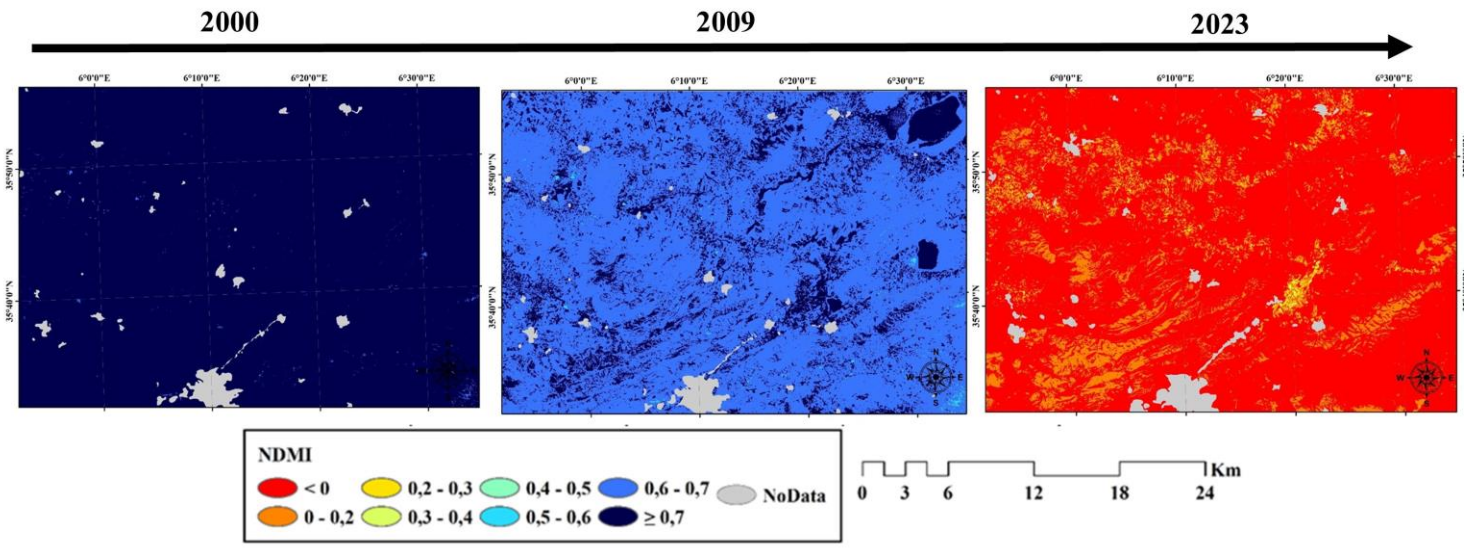

Figure 5: Variability of NDMI over 23 years

4- Discussion

The results of land use changes constitute essential support for identifying the impacts of global changes and establishing a classification of terrestrial ecosystems according to the intensity of their degradation.

Among the natural resources most affected by progressive degradation are forest ecosystems, which have suffered a decrease during the period 2000-2009, estimated at -10.89% of total forest cover. These results are in agreement with studies by many researchers, such as Bouazza and Benabadji, (1998) and Rebbah (2019), according to which more than 90% of Mediterranean forests are vulnerable or actually affected by degradation. These ecosystems play a crucial role as an essential source to meet the needs of the local population, such as food, timber and ecosystem services (Orékan et al., 2014); the degradation of the vegetation cover is the result of several combined factors of which the anthropogenic ones are the most accentuated, through the excessive exploitation of natural resources driven by the growing demand for raw materials, resulting from global population growth, various destructive practices have emerged, such as deforestation, overgrazing, land clearing, pollution, and industrial exploitation of natural heritage (Rebbah, 2019). This situation has further worsened due to the decrease in rainfall, the irregularity of precipitation and the resurgence of severe drought periods (Abdessemed, 1985; Bensaid, 2006; Berkane, 2007). These results are consistent with NDVI results showing degradation of classes representing forest areas, indicating a state of stress in response to severe drought factors confirmed by very low NDMI values. These factors, together with forest fires, have disrupted the environmental balance, creating conditions conducive to the onset of desertification (Rahmani, 2022). During the period 2009-2023, NDVI values detected a slight improvement in forest vegetation cover, probably due to successful natural regeneration as well as stable moisture conditions as indicated by NDMI values; however, these gains remain marginal compared to previous losses, confirming the vulnerability of these ecosystems (Lambin et al., 2003; Hansen et al., 2013).

The findings of this study clearly reveal that the wetlands, have undergone an alarming decline in the quantities of stored water of the order 98.632% of all wetlands in the study region in recent years; thus, these results are in line with the low NDMI values indicating a very severe drought. According to Bouras (2019), the fragile wetlands ecosystems of the Sebkhet of Aures wetlands complex (SAWC) have undergone significant alterations in their habitat quality and water regime due to recent global warming, to which are added anthropogenic practices that aggravate the situation such as pollution, habitat fragmentation, agriculture, hunting and pumping (Benslimane et al., 2019; Samraoui and Samraoui, 2013).

Agricultural areas have experienced a marked regression of order 35.347% in recent years, 2009-2023, in favor of bare soils and urban areas, which have increased considerably with 8.2% and 44.5%, respectively, confirming the emergence of a new situation of degradation. The decrease in agricultural areas is driven by climate change, leading to the appearance of conditions conducive to desertification (Hannachi, 2018) marked by a decline and severe irregularity of rainfall and an increase in the drought frequency periods, to which are added the rapid and unplanned expansion of urban areas (Hannachi, 2018). Similarly, Aliat and

Belaidi (2019) stated that in future climatic conditions, agricultural yields will decrease due to the rise in the severity of water stress.

The current state of natural resources and their evolution trends highlight the need to emphasize the urgency of establishing sustainable management plans in order to reduce the impacts of anthropogenic pressures and environmental forcing on natural habitats. The integration of satellite data is an essential asset in the decision-making process in order to monitor areas vulnerable to degradation better.

5- Conclusion

Through this study, geomatics technologies have offered a reliable and efficient approach that highlights significant changes in natural habitats by analyzing land use changes, NDVI and NDMI, in order to explore the combined impacts of climate change and anthropogenic pressures.

The results of this study showed a regressive evolution of wetlands and agricultural areas in favor of bare soils and urban areas. However, the dynamics of soil moisture and the health of plant populations have experienced significant fluctuations. These dynamics highlight the increasing vulnerability of ecosystems, exacerbated by unsustainable human practices that compromise the integrity of natural resources.

Faced with these challenges, it is crucial to establish sustainable management strategies that combine integrated territorial planning, strict regulation of urban expansion, and measures to adapt to the impacts of climate change. These efforts must be supported by increased awareness and involvement of local communities, with a view to preserving the resilience of ecosystems and the services they provide to current and future generations.

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