



Use of Remote Sensing and GIS to Study the Expansion of Sands and Vegetation in the Draa Region (Morocco) From Landsat Satellite Images

Otman Tamri^{1*} , Allal Labriki² , Soukaina el Idrissi³ , Mohammed Amine Zerdeb⁴ ,
Saïd Chakiri⁵

^{1,4,5}Geosciences and Natural Resources Laboratory, University of Ibn Tofail, Kenitra, Morocco.

²Department of Geology, College of Geosciences and Applications, University of Sciences Ben M'Sik, Casablanca, Morocco.

³ Department of Geology, College of Geosciences, University of Ibn Tofail, Kenitra, Morocco.

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Correspondence:

Name: Otman Tamri

Email: otman.tamri5@gmail.com

ABSTRACT

The Draa region, located in the southern part of Morocco, has been faced with a significant increase in desertified surfaces, sand deposits, and a decrease in vegetation cover. The region's ability to develop is hampered by this issue. Through a spatio-temporal study, this project aims to contribute to the comprehension and quantitative assessment of these potential risks. Understanding the dynamics of land use is made possible by the merging of remote sensing and geographic information systems techniques. For this diachronic analysis, two multitemporal satellite images are employed (Landsat 7 ETM+ 2001 and Landsat 9 OLI 2023). After all the necessary processing of these images, a map of changes is generated by the difference between the two land use maps, which correspond to the two dates of the time interval considered in the project. This allows us to make a diachronic analysis and highlight the change in each component of the studied environment. The obtained results are validated by contrast with other climatic data and by examining the correlations between the remote sensing parameters. The changes are important, especially for the vegetation cover and the migration of sands in the considered area. This is due to the influence of climatic factors. After digitization, it is evident that in comparison to 2001, there was a 43.46% decline in vegetation in 2023. By 2023, living sand will have taken over 20.90% of the area that was covered by vegetation in 2001, posing the biggest threat to the palm oasis.

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استخدام الاستشعار عن بُعد ونظم المعلومات الجغرافية لدراسة توسع الرمال والغطاء النباتي في منطقة درعة (المغرب) من مرئيات الأقمار الصناعية لاندسات

عثمان التامري^{1*}، علال لبريكي²، سكينة الإدريسي³، محمد أمين زردب⁴، سعيد شكيري⁵

^{1,4,5} مختبر علوم الأرض والموارد الطبيعية، جامعة ابن طفيل، القنيطرة، المغرب.

² قسم علوم الأرض وتطبيقاتها، كلية العلوم بن مسيك، جامعة الحسن الثاني، الدار البيضاء، المغرب.

³ قسم علوم الأرض، كلية العلوم، جامعة ابن طفيل، القنيطرة، المغرب.

معلومات الارشفة	الملخص
تاريخ الاستلام: 14- اغسطس-2024	على مدى العقود القليلة الماضية شهدت منطقة درعة في جنوب المغرب زيادة كبيرة في المناطق المتصحرة والترسبات الرملية وانخفاض الغطاء النباتي. وقد أعاققت هذه المشكلة قدرة المنطقة على التنمية. ويهدف هذا المشروع من خلال دراسة مكانية وزمانية إلى المساهمة في فهم هذه المخاطر المحتملة وتقييمها كمياً. وقد أصبح ممكناً فهم ديناميكيات استخدام الأراضي من خلال دمج الاستشعار عن بعد ونظم المعلومات الجغرافية. وقد استُخدمت مرئيتان من مرئيات الأقمار الصناعية متعددة التواريخ لهذا التحليل الزمني (لاندسات 7 2001 + ETM+ ولاندسات 9 2023 OLI). وبعد إجراء جميع المعالجات اللازمة لهذه المرئيات، تم إنشاء خريطة للتغيرات من خلال الفرق بين خريطتي الغطاء الأرضي المطابقة للتاريخين في الفترة الزمنية التي تم أخذها في الاعتبار في المشروع. يمكننا ذلك من إجراء تحليل زمني وتسليط الضوء على التغيرات في كل مكون من مكونات البيئة المدروسة. يتم التحقق من صحة النتائج التي تم الحصول عليها من خلال مقارنتها ببيانات مناخية أخرى ومن خلال فحص الارتباطات بين معاملات الاستشعار عن بعد. كانت التغيرات كبيرة خاصة بالنسبة للغطاء النباتي وهجرة الرمال في المنطقة قيد الدراسة. ويرجع ذلك إلى تأثير العوامل المناخية. بعد ترقيم وحدات استخدام الأراضي المختلفة في عامي 2001 و2023، يمكن ملاحظة أن الغطاء النباتي قد تناقص بنسبة 43.46% في عام 2023 مقارنة بعام 2001. إن أخطر ما يهدد واحة النخيل هو أن 20.90% من المساحة التي كان يغطيها الغطاء النباتي في عام 2001 قد استعمرتها الرمال الحية بحلول عام 2023 مما يشكل تهديداً لواحة النخيل.
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الاسم: عثمان التامري Email: otman.tamri5@gmail.com	

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Introduction

Observing the Earth from space increasingly becomes an indispensable tool in the development of a multitude of scientific disciplines. This technique allows us to track the dynamic changes and metamorphoses undergone by the globe through diachronic analysis (Kieffer and Serradj, 2013). As a corollary, the launch of several satellite constellations has been observed, taking continuous images to predict catastrophes and occurrences and to plan appropriate and sustainable territorial development (Ahmed, 2022).

Due to the prolonged periods of drought that have affected the Draa region over the past few decades, it is currently experiencing enormous difficulties (Ben Salem and El Alami El Filali, 2024).

This area is currently experiencing a process of desertification that manifests as the degradation of the vegetative cover, which mostly occurs in the oasis where the majority of the population derives its primary economic support. This degradation is primarily the result of sand migration and a decrease in water storage (Karmouji *et al.*, 2022; Oussedik *et al.*, 2003).

This study has two main goals. On the one hand, it attempts to demonstrate the potential of the employment of remote sensing and GIS for monitoring the evolution of the major components of land use between 2001 and 2023. In contrast, the creation of spatial information layers and cartographic supports provides local representatives, leaders, and decision-makers with accurate information on the state of the environment and resources of the area (Al-Zahraa *et al.*, 2021). In the framework of the conservation and integrated management of the ecosystem in the region.

Presentation of the study area

The study area addressed in this work is located in southern Morocco, covering an area of 14,767 km², representing 2.08% of the national territory (Fig. 1). It is limited to:

- at the north by the region of Beni Mellal-Khenifra
- at the south by Algeria
- at the east by the region of Tafilalet
- at the west by the region of Souss-Massa

This study zone is diversified, including plateaus in the desert, acacia forests, mountains, and valleys. One of the largest palm plantations in Africa and Wadi Drâa in the middle can be seen to the east of the sand dunes.

Draa has long, heated summers and extremely moderate winters during the daytime but freezing winters at night, which is typical of the Moroccan desert. With an average annual rainfall of just 61 mm, the climate is extremely arid throughout the year. Summer temperatures are intense and persistently hot, usually exceeding 40°C (Sefiani and Kettab, 2018).

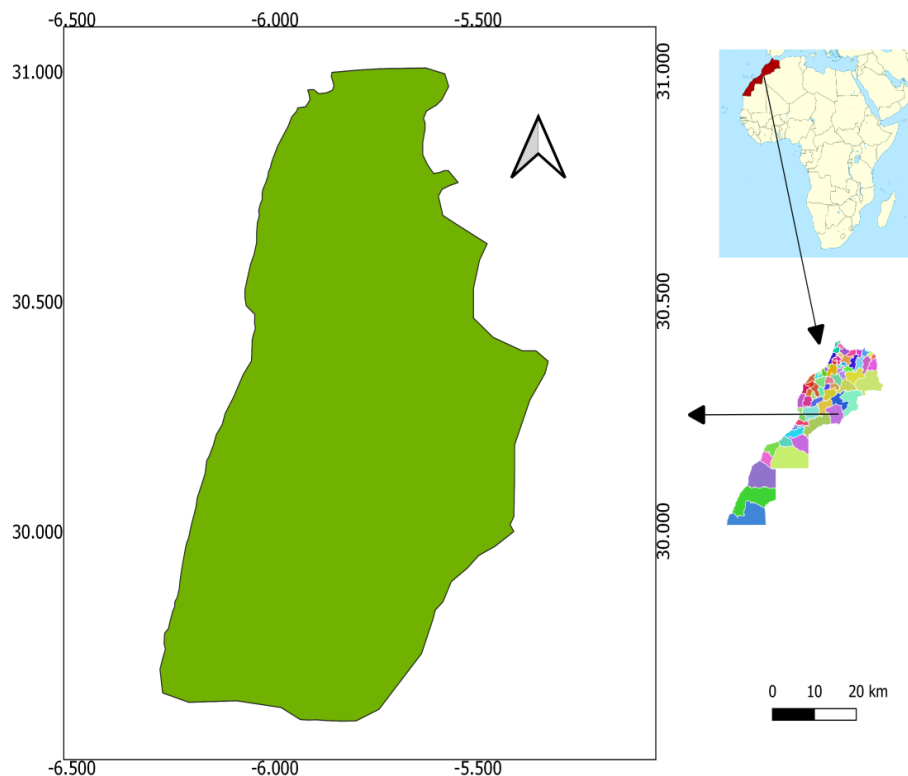


Fig. 1. Geographic Location of Study Area.

Materials and Methods

Data Selection and Acquisition

• On two different dates, datasets of two Landsat satellite acquisitions were collected, both in the years 2023 and 2001, available for free download on the USGS website (<https://earthexplorer.usgs.gov/>).

However, using Landsat satellite images for long-term studies has several advantages compared to other satellite data. This archive allows for the analysis of land changes over decades, making it ideal for monitoring long-term trends like in our case, such as climate change.

Landsat's consistent data stream over many years ensures comparability across time, but the disadvantage is that the resolution is low. As our study does not involve the classification of fine objects, we have accepted this type of resolution by introducing a panchromatic layer with a resolution of 15 m (Roy and Boschetti, 2016).

The (Landsat Collection 1 Level-1 data) (L1T) are freely available (Ghobadi *et al.*, 2012). However, the primary issue with optical images is the existence of clouds, which is ignored at this level of processing. This explains our decision to only acquire data during the summer or when the sky is often clear. In order to obtain photographs of the region with the lowest percentage of clouds, the cloud coverage percentage has been set at 10%.

To fully cover the study region, two scenes were acquired for each acquisition. The following Table 1 lists the characteristics that describe two acquisitions.

Table 1: Characteristics of the Images.

Image 2001	Image 2023
Landsat 7 ETM+ C1 Level-1	Landsat 9 OLI/ TIRS C2 Level-1
ETM+ (Enhanced Thematic Mapper Plus)	OLI (Operational Land Imager)
Resolution: 30 m	Resolution: 30 m
Panchromatic band: 15 m	Panchromatic band: 15 m

- Land use maps
- The climatic data of the region (temperature, rainfall, humidity, wind ...) come from the High Commission for Water and Forests and the fight against desertification in Zagora: <http://www.eauxetforets.gov.ma/SitePages/Index.aspx>

Software

The satellite data are processed, and the land use maps are created using two software programs (ENVI and QGIS).

- Image data are processed using the ENVI (Environment for Visualizing Images) software. It enables the analysis and visualization of big data sets in a variety of forms. Its primary benefit is its capacity to manipulate several multispectral images.
- QGIS is a GNU General Public License-compliant Geographic Information System (GIS) that is simple to use. It supports various uses that exploit geographic data and is frequently used.
- Google Earth is a software application that enables any user to fly over the Earth and zoom in on a specific location. The information is more or less precise depending on the geographic zone (Gore and Hu, 2012).

Using ENVI and QGIS together allows for a more robust and complete approach to remote sensing projects. While ENVI excels at advanced analysis and processing of raw satellite data, QGIS provides the flexibility to combine and visualize that data in a geographic context, making it ideal for spatial analysis and map creation (Lillesand *et al.*, 2015).

Working method

This section will describe the steps used, from data collection to final results confirmation, to create a cartography of the components of the occupation of our interested land using Landsat data (Bachir and El Zerey, 2014). The methodology used is shown in the organizational structure in Fig. 2.

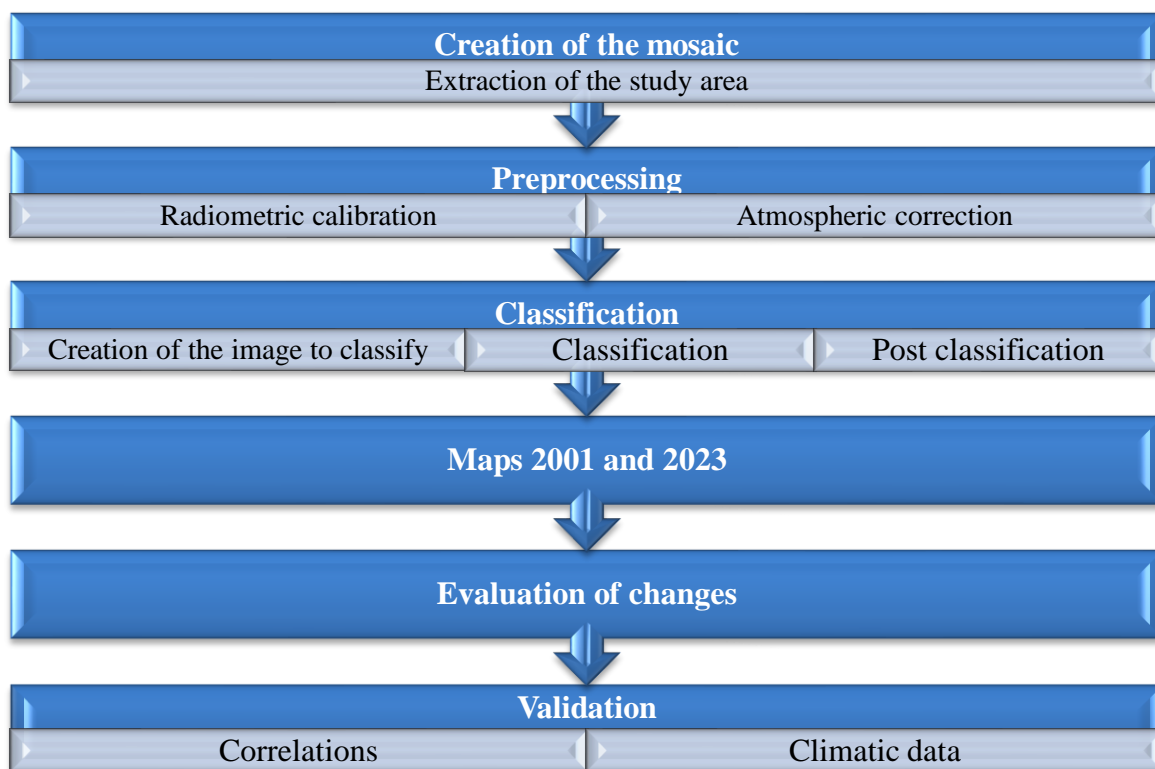


Fig. 2. General outline of the methodology.

Extraction of the Study Area

The creation of satellite image mosaics is a method for putting together scenes that were captured continuously from the same orbit or from two parallel orbits whose paths overlap. To cover the entire research area, a mosaic is created using the two scenes from each acquisition.

In this instance, the projection was used: Projection: UTM Zone 30 North; Datum: WGS 84

The desired study area is extracted using a georeferenced shapefile projected onto the mosaic of scenes.

Preprocessing

Landsat satellite images must first be pre-processed to remove possible faults before they can be used successfully. These images are pre-processed mostly through radiometric calibration and atmospheric correction procedures.

Radiometric calibration

This process involves converting the pixel numerical counts into radiance values and subsequently into the apparent reflectance at the atmosphere's top (Bildgen *et al.*, 1990).

Atmospheric correction

It is carried out because the two shooting dates did not have the same atmospheric conditions.

The relative approach of atmospheric correction, on the other hand, is applied based on the choice of a priori invariant objects in the image. The relationship between the numerical counts of the two images on the two dates is straightforward to explain (Teferi *et al.*, 2010).

Spectral sharpening

Using a high spatial resolution panchromatic band, the PC spectral sharpening model is employed to modify a low spatial resolution multi-band image (in our case, 30m). The technique assumes that the panchromatic band with a high spatial resolution (in our case 15m) corresponds to the low spatial resolution spectral bands. Since our images are georeferenced, both datasets may be co-registered instantly by ENVI by resampling (Baker and Williams, 2014).

Classification

Creation of the image to classify

The strategy based on the calculation of neo bands is used to reduce class confusion. This basic technique's idea is to create new bands using the pre-processed image's original bands as a starting point. Two new bands, corresponding to the two primary classifications of land cover vegetation (through the calculation of the normalized difference vegetation index (NDVI) and sand by the gloss index (IB) were established, as the goal of our study is to produce land cover maps. While Principal Component Analysis is used to create the other bands' sound (PCA).

- IB is the index of brightness that represents the image's average brightness. It is sensitive to the brightness of the soil, which is related to its moisture and salt content. The following formula generates this index:

$$IB = (PIR \times PIR + R \times R)^{1/2} \quad (1)$$

- NDVI is the most famous and extensively utilized vegetation index. It is a metric that describes the chlorophyll greenness, relative density, and vegetation health of each pixel in a satellite image (Yu *et al.*, 2017; Zhou *et al.*, 2015). This index has been defined using the following basic variant:

$$NDVI = \frac{PIR - R}{PIR + R} \quad (2)$$

where:

- R – red band.
- PIR – near infrared band.

After the establishment of the neo-bands in the preceding step, they must be combined into a single image with QGIS for classification. The result of this processing is an image made up of the NDVI, IB, and PCA bands (Fig. 3). The reason for combining the NDVI, IB, and PCA bands is to create a more informative multi-dimensional representation of the landscape, which enhances the classification process. To merge multiple bands, a “Build Virtual Raster” in QGIS can be used (Jensen, 2007).

NDVI, IB, and PCA play a crucial role before classification.

The NDVI is used to:

- enhance class separability: This helps in differentiating bare soil, water, and vegetation.
- improve supervised classification by distinguishing forests from agricultural lands.
- feature selection: It is used as an additional band to improve classification accuracy.

The Brightness Index (IB) can help in separating built-up areas from natural landscapes.

The PCA is used to:

- reduce redundancy: It removes correlations between spectral bands.
- improve computational efficiency: i.e., fewer dimensions mean faster processing.
- enhance class discrimination: That is, the first components contain the most relevant information.

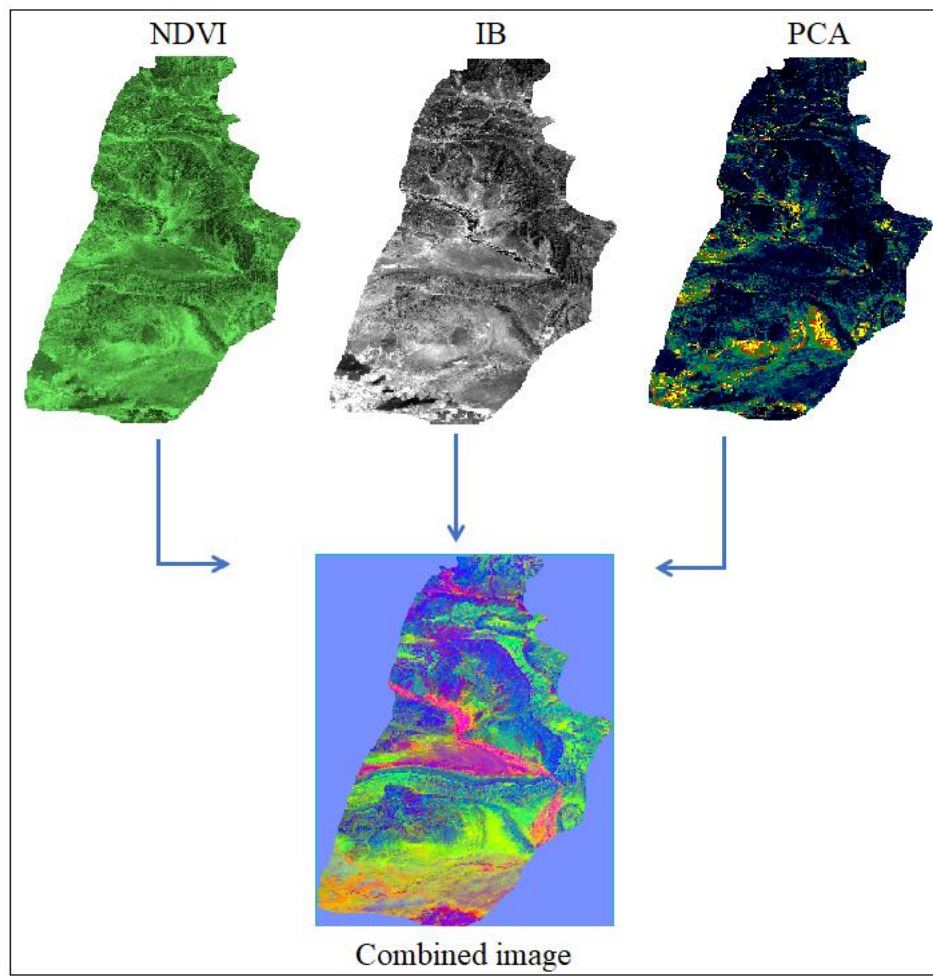


Fig. 3. Creation of the image to classify.

Classification

A **comprehensive** and accurate classification of land cover in this study area is achieved through the application of supervised classification. Before initiating the classification process, a thorough understanding of the land under investigation was developed using various data sources. Google Earth imagery provided high-resolution satellite images, allowing for an initial visual inspection of the area. Additionally, field trips were conducted to collect ground-truth data, which ensured that the classifications would be based on accurate real-world observations. These combined efforts helped to refine the boundaries and characteristics of different land cover types within the study area.

With this foundational understanding, we proceeded to supervised classification based on the Maximum Likelihood Classification (MLC) algorithm, a commonly used technique in remote sensing (Jemberie et al., 2016). Supervised classification involves manually selecting training samples **from** specific regions in the image that are representative of the different land cover classes you wish to identify. These training samples serve as the basis for the classification algorithm, which uses them to “learn” how to categorize the pixels in the entire image.

The MLC algorithm assigns each pixel in the image to a specific class based on the probability that it belongs to that class. It does so by analyzing the spectral signatures of the training samples. Each land cover class is associated with a set of statistical parameters, such as the mean and variance of pixel values within the training samples. These parameters describe how the spectral values of a given class are distributed across different image bands (red, green, blue, and near-infrared). Once the statistical properties of each class have been established, the

MLC algorithm assigns each pixel in the image to the class that has the highest probability given in its spectral values (Li *et al.*, 2016).

This method is especially effective for working with multispectral satellite imagery, where multiple bands provide different types of information. It is particularly useful in cases of low-resolution images like those used in our study, which have a spatial resolution of 15 meters. Although low-resolution data may have a reduced ability to capture fine spatial details. The MLC algorithm compensates for this by analyzing the statistical relationships between the spectral bands and making class assignments based on overall patterns in the data rather than on fine-scale spatial features. This makes MLC an appropriate choice for datasets with relatively coarse spatial resolution.

One of the key advantages of using the MLC algorithm in this context is that it accounts for the variability of each class's spectral signature. This means that even if some pixels exhibit mixed characteristics or fall on the boundaries between different classes, the algorithm can still assign them to the most likely class based on the statistical likelihood.

After the classification process, the results are evaluated for accuracy. This is done through an accuracy assessment, like the global precision and kappa coefficient, used to quantify the accuracy and reliability of the classification results (Lillesand *et al.*, 2015).

Global Precision is a simple and direct measure of the correct classification rate in the results. It compares the number of correctly classified pixels to the total number of pixels in the confusion matrix.

$$\text{Global precision} = \frac{\text{Number of Correctly Classified Pixels}}{\text{Total Number of Pixels}} \quad (3)$$

Kappa Coefficient is a more advanced measure that accounts for the possibility of random chance agreement. It compares the observed accuracy to the expected accuracy.

The kappa statistic is especially useful when dealing with imbalanced data (where some classes dominate the classification) (Congalton, 1991).

$$\text{Kappa coefficient} = \frac{P_0 - P_e}{1 - P_e} \quad (4)$$

where P_0 is the observed accuracy, and P_e is the expected accuracy by chance.

Table 2: Confusion Matrix (2001).

Actual Class \ Predicted Class	Sand	Vegetation	Dune	Other	Total
Sand	2800	250	200	125	3375
Vegetation	200	1150	80	70	1500
Dune	250	120	1100	155	1625
Other	125	90	150	5637	6002
Total	3375	1500	1625	6002	12502

Table 3: Confusion Matrix (2023).

Actual Class \ Predicted Class	Sand	Vegetation	Dune	Other	Total
Sand	3180	70	80	45	3375
Vegetation	60	775	20	20	875
Dune	140	40	1390	55	1625
Other	80	30	110	5782	6002
Total	3460	875	1600	5902	12502

Table 4: Results of classification.

Classification	Global Precision	Kappa coefficient
2001	(11302/12502) =89 %	(0,89-0,31)/ (1-0,31) =0.84
2023	(11560/12502) =92.45 %	(0,92-0,125)/ (1-0,125) =0.91

Post classification

Following the classification procedure, a small number of isolated pixels are usually left, usually misclassified or unclassified, and frequently located at the boundary of two distinct assignment ranges (Moutaz and Hussain, 2016). These give the image a "pointillist" appearance, which can be embarrassing for a cartographic representation. The classification should then be homogenized by reassigning these pixels to one of two classes. Filtering techniques are also used to accomplish this.

- **Classification aggregation**

This tool connects smaller adjacent class regions to a larger region. Aggregation is a useful cleaning process when the classification result includes a large number of small regions (this is the case for our classification) (Jensen, 2016).

The aggregation equation is typically:

$$\text{Aggregated value} = \sum_{i=1}^n C_i \times A_i \quad (5)$$

Where: C_i : Classification value (class label, such as forest, water, or urban); A_i : Area or pixel count of class; n : Total number of classes in the classification.

- **Clumping classes**

Our classification images suffer from a lack of spatial coherence (spots and holes in the classified areas). Similarly, clumping classes will be used to group adjacent areas using morphological operators (Prakasam, 2010).

To mathematically express clumping or reclassification, we can use the following equation:

$$C_i^{new} = \sum_{K \in G_i} C_K \quad (6)$$

Where:

C_i^{new} : The new merged class label; G_i : The group of original classes that are clumped into a new class; C_K : The original class labels.

- **Majority Analysis**

The majority analysis will be used to modify the spurious pixels within a single large class. A kernel size is selected, and the center pixel in the kernel is replaced by the class value that has the majority of pixels in the kernel (Lillesand *et al.*, 2015).

The majority rule equation can be expressed mathematically as:

$$C_{i,j} = \arg \max_k \left(\sum_{m,n \in N(i,j)} \delta(C_{m,n}, k) \right) \quad (7)$$

Where:

$C_{i,j}$: The new class assigned to the central pixel (i, j); k : Possible class values; $N(i, j)$: The neighborhood (usually a 3×3, 5×5, or 7×7 window) centered on pixel (i, j); $C_{m,n}$: The class label of the pixel at location (m, n) within the neighborhood; $\delta(C_{m,n}, k)$: Indicator function, defined as:

$$\delta(C_{m,n}, k) = \begin{cases} 1, & \text{if } C_{m,n} = k \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

The argmax function selects the class k that appears most frequently in the neighborhood.

Results and Discussion

The results announcement is presented in the form of 2 maps of desired land use components which are vegetation and sands in 2001 and 2023 (Fig. 4).

Furthermore, a visual comparison of the two classifications to clearly show the changes in the Draa area.

The quantitative calculation of land use changes was established by the difference between the two classified maps.

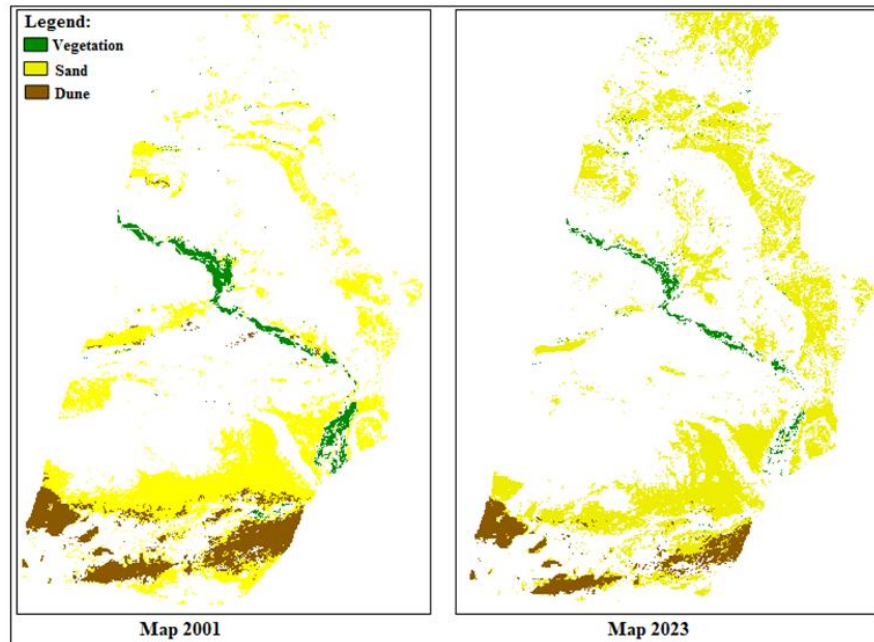


Fig. 4. Land use maps in 2001 and 2023.

Vegetation Dynamics

Following the digitization of the various land use units in 2001 and 2023. It can be seen that the vegetation has decreased by 43.46% in 2023 compared to 2001 (Fig. 4).

The most dangerous threat to the palm oasis is that 20.90 % of the space covered by vegetation in 2001 has been colonized by living sand by 2023 (Fig. 5).

The NDVI classes indicate a decrease in vegetation production, which is mainly made up of date palms. This decrease is related to the distribution of rainfall in the treated years. The rainiest year, 2001, has the highest chlorophyll activity with a value of NDVI max of about 0.26; on the other hand, the driest year, 2023, has the lowest activity, justified by its maximum NDVI of 0.17. Also, the negative impact of the long periods of severe drought that affected it between the two treated dates. The spectral signatures are also used to validate these results.

It can be concluded that there is a retreat of vegetation space, which is already very limited in a desert environment dominated by soils and dunes that feed the living sand. Also, by calculating the NDVI index from a satellite image, a sustainable development can be valued as a nation's indicator of sustainable development. Rainfall and NDVI have a powerful link. Many authors have already noted the strong relationship between these two variables (Pal, 2005).

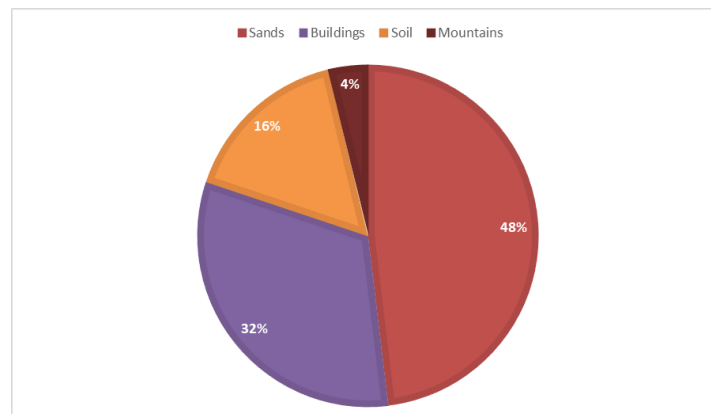


Fig. 5. Percent of vegetation colonized by other soil components between 2001 and 2023.

Silting Dynamics

The mobile sands are a persistent threat to Draa's oasis. This research allows for mapping the evolution of silting from an image archive (Landsat 7 ETM+ and Landsat 9 OLI) to the red sands that are the final product of soil stripping. The recognition of the sands by supervised classifications is enabled by the iron index image, which allows us to precisely locate them due to their ferric nature (Karnieli *et al.*, 2002).

The land use change map shows that there is a 19.1 % increase in sand between 2001 and 2023. Sand dunes precisely feed these massive amounts of sand (Fig. 4).

Large quantities of these displaced live sands have taken the place of vegetation cover, making the problem more dangerous (Fig. 5).

It has been demonstrated that sand distribution and migration are affected by climatic conditions such as humidity, wind speed, and precipitation. The year 2023, which was the driest in terms of precipitation, saw a greater migration of sands; whereas the year 2001, which was the wettest, saw a less significant movement.

According to Coude-Gaussen and Rognon (1993); Wang and Liu (2013), the problem of silting has become very acute in semi-arid and arid countries, particularly in Morocco, where the effect is developing particularly in the south and southeast of the country: in the east of the High Atlas, in the basin of the middle and lower Ziz, around Errachidia, Goulmima, Erfoud, and southward in the Tafilalet and the Draa basin, particularly in the province of Zagora.

It should be noted that the work of Lemsanni (1999) about the monitoring of desertification in Morocco from NOAA AVHRR images, and Desjardins (2005), who highlighted the advance of dunes in several locations in southeastern Morocco using remote sensing data for the characterization of the desertification phenomenon. This is achieved because of the free availability of satellite data and open-source processing software.

Correlation Between Remote Sensing Parameters

In this regard, and to assist surveyors in better interpreting remote sensing variables, and to validate our results, we developed a correlation method that allows us to investigate the relationships between the following parameters: normalized difference vegetation index (NDVI), brightness index (IB), and land surface temperature (LST) (Wan and Li, 1997).

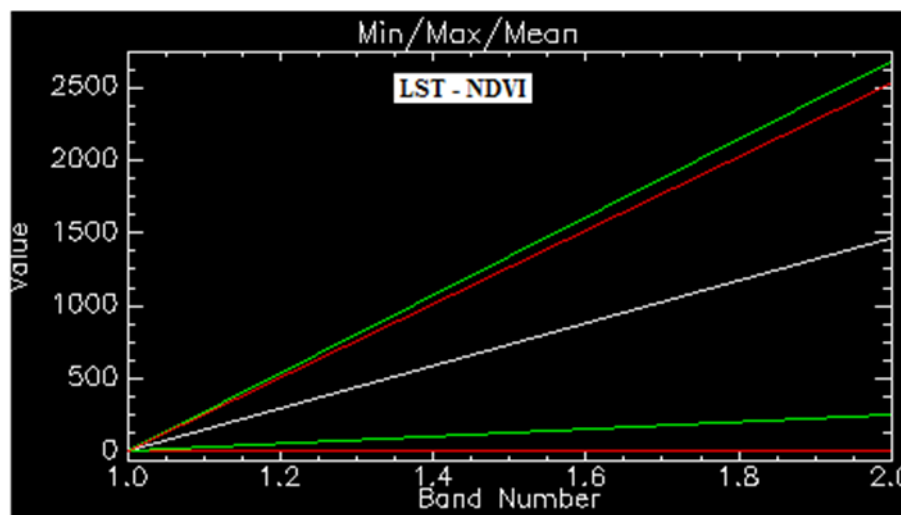


Fig. 6. Correlation between NDVI and LST.

An inverse correlation between surface temperature and vegetation index is obtained in the year 2023 (Fig. 6), especially for areas with high vegetation cover, which is -0.85.

The results reveal that the environment's chlorophyll activity is strongly related to the land surface temperature.

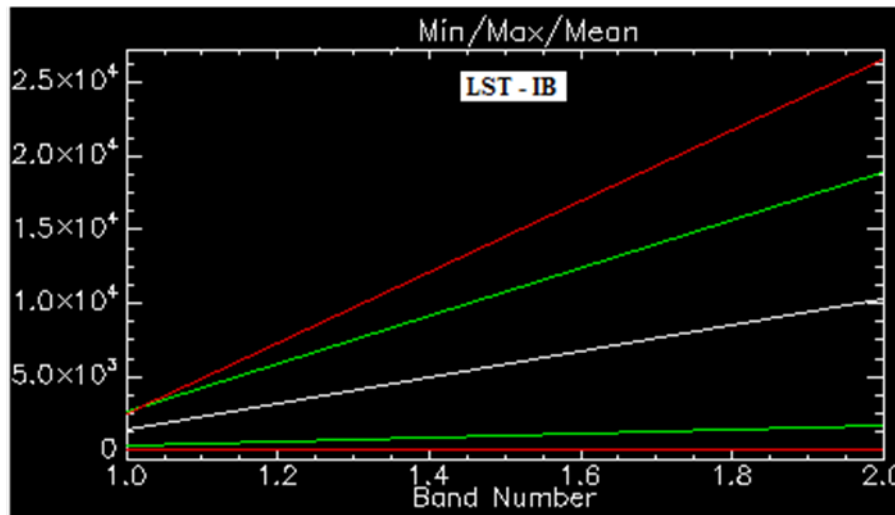


Fig. 7. Correlation between LST and IB.

Fig. 7 illustrates the correlation result for the year 2023 image as an example, showing a significant link between LST and IB of 0.96, especially in areas with low vegetation cover, soil, and sand, which provides optimal conditions for sand migration.

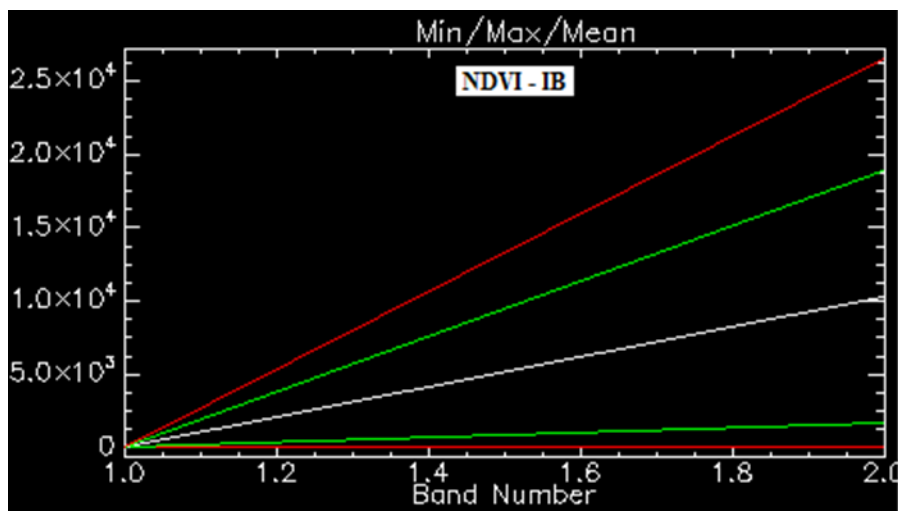


Fig. 8. Correlation between NDVI and IB.

The analysis of 2 bands of NDVI and IB shows that there is a strong negative correlation of -0.83 between these bands (Fig. 8), which explains the dominance of vegetation cover with low chlorophyll activity, as well as the large spaces occupied by the soil and the salty sands that have a high brightness value.

The analysis of remote sensing data (NDVI, LST, and IB) through the GIS for this study allows to conclude that the Draa area is characterized by a dominance of bare soil, sand, low vegetation cover, and high-temperature values.

These resource distributions create favorable conditions for desertification and silting, and have a negative influence on the Draa oasis.

Conclusion

With the increasing frequency of recurrent droughts and growing demographic pressure, it is crucial to monitor the natural resources of the Draa region for sustainable and rational

management. In this context, remote sensing serves as a powerful tool for data collection, resource monitoring, and decision-making in long-term environmental management.

This study employed diachronic analysis using Landsat ETM+ (2001) and Landsat 9 OLI/TIRS (2023) imagery to assess land-use changes over 22 years. The results reveal a 43.46% decline in vegetation cover and a 19.1% increase in sand migration, highlighting the expansion of desertification. These findings underscore the importance of integrating Geographic Information Systems (GIS) for a more detailed analysis of spatial and temporal changes.

The study further confirms the vulnerability of the oasis ecosystem to climate change, where reduced rainfall and prolonged dry periods significantly impact both agricultural productivity and sand encroachment. While Landsat imagery provides valuable insights for land cover mapping and decision-making, the use of Sentinel-2 images (not available for the year 2001) with a higher spatial resolution (<10 m) and free accessibility could enhance classification accuracy. However, given the study's objective of analyzing long-term changes, Landsat data remain indispensable for historical assessments (Sekertekin et al., 2017).

While remote sensing is undeniably a powerful tool for large-scale environmental monitoring, it is important to recognize that its effective use depends on the context, resources, and technical expertise available. Remote sensing excels in applications like urban planning and environmental monitoring, offering large-scale insights and enabling efficient data collection over time. However, it can be more challenging to adopt for small-scale projects or in resource-constrained settings, where high costs and specialized technical expertise may limit its effectiveness. In such cases, improving the accessibility of remote sensing tools such as using freely available Sentinel-2 imagery, can help overcome these challenges, especially for smaller-scale studies in developing regions.

Future research should explore a comparative study of optical and radar remote sensing for land use and land cover mapping in the Draa region, where such analyses remain limited (Wang et al., 2012). This approach could improve classification accuracy and provide deeper insights into environmental changes in arid regions. By balancing the advantages of remote sensing with its limitations, future studies can maximize its potential while addressing resource constraints and ensuring its effective use in different contexts.

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The authors would like to acknowledge the insightful study on the topic of desertification. Their thorough investigation into the factors contributing to desertification in the Draa region has shed light on the complex interactions between climate change, human activities, and ecological resilience.

The findings presented in their study highlight the urgent need for sustainable land management practices and effective policy interventions to mitigate the adverse effects of desertification. By identifying key indicators and mapping vulnerable areas, their research provides a valuable foundation for developing targeted strategies to conserve and restore ecosystems affected by desertification.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript

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