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Research Article

QUANTIFYING LULC CHANGES IN CONSTANTINE, ALGERIA USING GOOGLE EARTH ENGINE

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ABSTRACT

The objective of this research is to analyze land use changes in the municipality of Constantine over a thirty year period (1993 – 2023) using Landsat satellite data provided through the Google Earth Engine (GEE) platform and a supervised classification approach. Five land cover classes were mapped at six key dates: water bodies, green spaces, built-up areas, bare soil and agricultural land. The quantified changes highlight a considerable reduction in bare soil in favor of an increase in cultivated land, as well as an expansion of artificial surfaces during certain periods (2008 to 2023). These dynamics reflect the processes of urban sprawl and peri-urbanization at work in this territory. The results obtained demonstrate the potential of remote sensing through GEE for detailed spatio-temporal monitoring of land use. Coupled with other data, this approach contributes to a better understanding of territorial evolutions and provides valuable information for sustainable land use planning.

Keywords: *Classification, Constantine, GEE, Land use, Remote sensing*

Introduction

Remote sensing data is utilized to analyze environmental processes across various scales, from local to global levels. It also enables the detection of changes that have occurred over decades. Satellites such as Landsat, Sentinel, Spot, etc. provide remote sensing data that is highly useful for visualizing, classifying, and analyzing a given area (El Garouani & Aharik, 2021). Google Earth Engine is a cloud-based computing platform that allows for storage and processing of vast amounts of data (Benoumeldjadj, Bouarroudj, et al., 2023).

It makes available all of this remote sensing data, as well as other data sources like GIS data, social, demographic, meteorological, digital elevation model, and climate data. Remote sensing imagery is extremely valuable for understanding the spatio-temporal evolution of land cover. Image classification is one of the key activities in remote sensing (Seeberg et al., 2022). Classification procedures aim to interpret a digital image by leveraging computational power (Aksoy et al., 2022). Supervised classification is the most common of these procedures. Classifying an image in remote sensing involves

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grouping all the pixels in an image into a reduced number of classes corresponding to the main landscapes observed, in order to obtain a thematic map (El Garouani & Aharik, 2021). Classification requires manual sampling by the user, which allows for differentiating thematic classes in an area (El Garouani & Nabunya, n.d.). This operation facilitates and simplifies the understanding of natural phenomena as well as spatio-temporal evolution (Diédhiou et al., 2020a). Over the years, several supervised classification algorithms have been developed, for example neural networks, Bayesian approaches, decision trees (Bellanger et al., 2021). Our main objective is to produce land cover maps using supervised classification at different dates (1993 to 2003, 2003 to 2008, 2008 to 2013, 2013 to 2018 and 2018 to 2023), to analyze spatio-temporal variations over a 30-year period. We believe this type of analysis is an essential tool for development planning and sustainability land management.

Material and Methods

Study area

Remote sensing data is utilized to analyze environmental processes across various scales, from local to global levels. It also enables the detection of changes that have occurred over decades. Satellites such as Landsat, Sentinel, Spot, etc. provide remote sensing data that is highly useful for visualizing, classifying, and analyzing a given area (El Garouani et al., 2020). Google Earth Engine is a cloud-based computing platform that allows for storage and processing of vast amounts of data (Benoumeldjadj et al., 2024). It makes available all of this remote sensing data, as well as other data sources like GIS data, social, demographic, meteorological, digital elevation model, and climate data. Remote sensing imagery is extremely valuable for understanding the spatio-temporal evolution of land cover. Image classification is one of the key activities in remote sensing (Seeberg et al., 2022). Classification procedures aim to interpret a digital image by leveraging computational power (Aksoy et al., 2022). Supervised classification is the most common of these procedures. Classifying an image in remote sensing involves grouping all the pixels in an image into a reduced number of classes corresponding to the main landscapes observed, in order to obtain a thematic map (El Garouani et al., 2020). Classification requires manual sampling by the user, which allows for differentiating thematic classes in an area [5]. This operation facilitates and simplifies the understanding of natural phenomena as well as spatio-temporal evolution (Diédhiou et al., 2020a). Over the years, several supervised classification algorithms have been developed, for example neural networks, Bayesian approaches, decision trees (Bellanger et al., 2021). Our main objective is to produce land cover maps using supervised classification at different dates (1993 to 2003, 2003 to 2008, 2008 to 2013, 2013 to 2018 and 2018 to 2023), to analyze spatio-temporal variations over a 30-year period. We believe this type of analysis is an essential tool for development planning and sustainable land management.

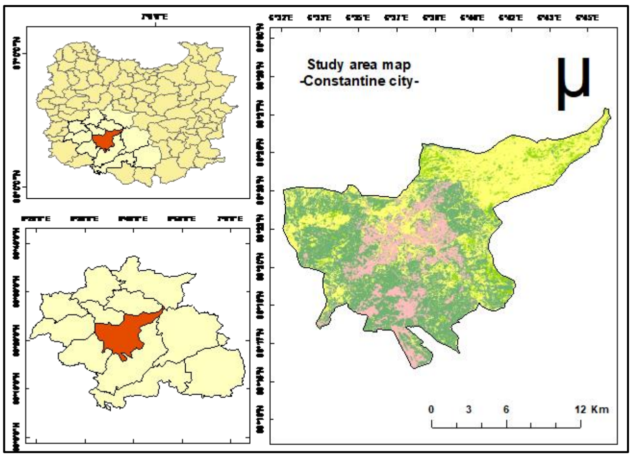

Figure 1. Study area of Constantine

Data Landsdat

We utilized Landsat 5 and Landsat 8 imagery for land cover and vegetation mapping. The analysis involves six scenes every five years; 1993 to 2003, 2003 to 2008, 2008 to 2013, 2013 to 2018 and 2018 to 2023. These images were acquired from the GEE platform (Table 1). We assigned a zero value for vegetation cover.

Table 1. Landsat images used (USGS)

Satellite	Period	Bands
Landsat 5 LANDSAT/LT05/C01/T1	1993 to 1998 /1998 to 2003 2003 to 2008 /2008 to 2012	B1, B2, B3, B4, B5, B6, B7, QA
Landsat 8 LANDSAT/LC08/C02/T1_RT_TOA	2013 to 2018 /2018 to 2023	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, QA, SAA

The Landsat-5 and 8 satellite data used correspond to 30 m resolution multispectral and multitemporal images with on-the-fly rendering and indices for visualization and analysis. The Landsat 5 and 8 images in this layer are updated daily and come directly from the USGS Landsat collection on AWS (Table 2).

Table 2. Multispectral bands (Interior & Survey, 2020)

Description	Wavelength (μm)	Spatial resolution (M)
Coastal aerosol (Band1)	0.43 – 0.45	30
Blue (Band2)	0.45 – 0.51	30
Green (Band3)	0.53 – 0.59	30
Red (Band4)	0.64 – 0.67	30
Near Infrared (NIR) (Band5)	0.85 – 0.88	30
SWIR 1 (Band6)	1.57 – 1.65	30
SWIR 2 (Band7)	2.11 – 2.29	30
Cirrus (Band9)	1.36 – 1.38	30
QA Band8 (Collection2)*	0.500 – 0.680	30
VHSR 1 (no band)	10.60 – 11.19	100 * (30)
TIRS2 (Band10 and 9)	11.50 – 12.51	100 * (30)

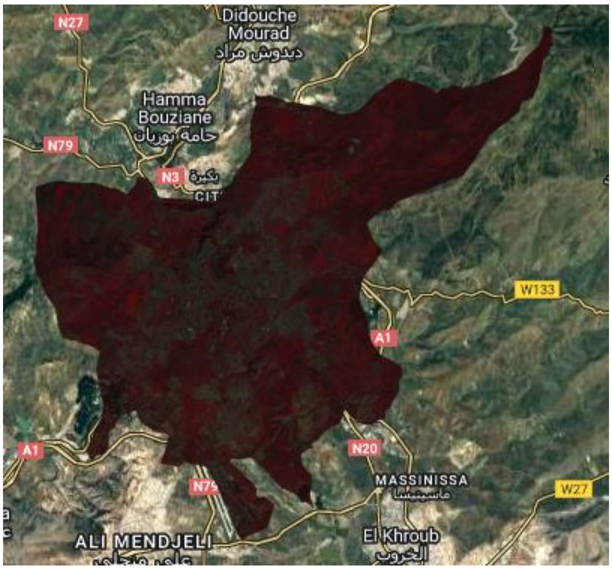

Figure 2. Scene covring Constantine city (2018 Landsat8, Gee)

These layers are time-enabled and include a number of on-demand rendered band combinations and indices. The effective classification of high spatial resolution remote sensing imagery brings significant value for land cover. classification. Advances in remote sensing and deep learning have facilitated the extraction of spatio-temporal information for this classification (Figure 2).

Methodology

A retrospective ground study using Google Earth Pro, which provides us with actual images since 1984, multivariate analysis and thematic analysis preceded the present study, the results of which were exploited and facilitated the choice of land cover classes (Ujaval Gandhi, 2022). Ground data allowed validation of changes in the study area (Seeberg et al., 2022) and evaluation of the classification result in this study.

Figure 3 illustrates the methodology adopted in this work. Indeed, it is based on the main steps which are: data collection, data pre-processing with scripts in GEE, data processing and analysis of the results obtained. The maps are imported and then processed in Arcmap and after that we proceeded with the correlation of variables using Minitab Statistical Software (version 20.3).

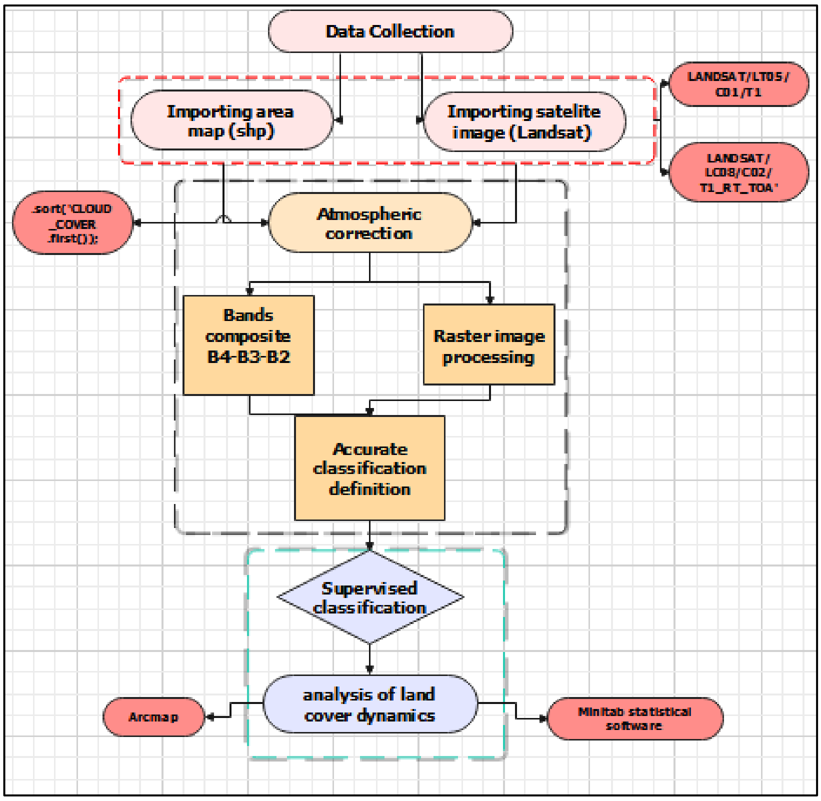

Figure 3. Methodological workflow

Images preprocessing

Thanks to the GEE platform, preprocessing is done using scripts indexed in the platform's catalog (da Silva et al., 2022). Once the collection is made, we proceed to select Landsat satellite images according to the period. LANDSAT/LT05/C01/T1 (collection 1 and level 1) was used to capture images from 1993 to March 2013. LANDSAT/LC08/C02/T1_RT_TOA (collection 2 level 1) for the years 2013 to 2023. We proceeded with an almost zero cloud cover. Radiometric corrections are adjustments applied to the radiometric pixel values of an image to make them as close as possible to actual ground measurements. This improves the quality and accuracy of the radiometric data used in land cover analysis and other remote sensing applications [(Ujaval Gandhi, 2022). They allow compensation for sensor calibration errors, effects of atmospheric differences, and also illumination differences between images (Diédhiou et al., 2020b). And to support the distinction of land cover types and training zones, we performed a color composite by combining the three spectral bands: red, green and blue (RGB) (Jabbar & Yusoff, 2022).

Data processing

In order to achieve an accurate and correct supervised classification, we defined a similar number of points for each land cover class. For previous years, we relied on Google Earth Pro and old images. We defined five classes: water, vegetation, built area, bareland and crops. The scripts and precision codes available on the platform were used to extract previous and current images. The quality of the classification is evaluated using two measures: overall accuracy and Cohen's Kappa coefficient. When the Kappa coefficient is between 0.61 and 1, it indicates that the classification is of good quality(Benoumeldjadj et al., 2024)

Results and Discussion

The analysis of images taken in 1993, 1998, 2003, 2008, 2013 and 2023 made it possible to map the evolution of land cover in the municipality of Constantine. Before proceeding with the analysis and interpretation of these maps, it is recommended to evaluate the classification results. This validation was performed by visually comparing the classification results with external data (Google Earth Pro images, aerial photos and field observations), as well as by analyzing the confusion matrix (Benoumeldjadj, Kanouni, et al., 2023). The definition of the samples was random in the area. Approximately 250 samples for the five classes were defined based on GEE and are proportionally distributed according to the variability of the classes and dispersed throughout the study area. These sampling points were used as support points in the choice of "ROI" (Regions of Interest) training sites. The percentage of overall accuracy and the Kappa coefficient for the four classifications exceed 93% and 0.90 respectively (Test accuracy = 93% and Consummers accuracy = 0.9); so the accuracy test for all classes is 0.93. The classifications are therefore considered reliable and usable for our areas of interest, which are development planning and land management. Table 3 illustrates the distribution of the five classes (water-vegetation-built area-bareland-crops) over 30 years. The area of uncultivated land (barelands) has decreased substantially, while the area of cultivated land has increased significantly, from 41,29 hectares during the 2008-2013 period to 82,453 hectares for the 2018-2023 period.

Between 1993 and 1998, the area of barelands was 84,277 m2, while for the 2003 to 2008 period, the area reached 48,388, almost half. The area of crops also nearly doubled over fifteen years; for vegetation, the change is minimal, we can say that the lost lands have been planted and cultivated in recent years. This evolution reflects the increasing urbanization process observed during these last two decades in the studied region.

Table 3. Evolution of land use from 2008 to 2023

	Water (%)		**Vegetation (%)**		**Built area (%)**		**Bareland (%)**		**Crops (%)**	
1993-1998	8540	**4%**	55974	**28%**	28538	**14%**	84277	**14%**	24452	**12%**
1998-2003	12684	**6%**	59753	**30%**	25696	**13%**	60506	**13%**	43142	**21%**
2003-2008	8865	**4%**	50242	**25%**	23961	**12%**	48388	**12%**	70325	**35%**
2008-2013	9571	**5%**	65378	**32%**	40763	**20%**	44773	**20%**	41296	**20%**
2013-1018	17330	**9%**	33462	**17%**	22556	**11%**	28689	**11%**	99744	**49%**
2018-2023	11435	**6%**	34958	**17%**	31578	**16%**	41357	**16%**	82453	**41%**

This evolution can be explained in particular by the freezing of urban extensions in the city of Constantine decreed by the Master Plan for Planning and Urbanism (P.D.A.U.), leading to a shift of populations from the city center to the outskirts. We also observe a degradation and dilapidation of buildings in some central and historic neighborhoods, as well as a political will to reabsorb shantytowns and rehouse them in new agglomerations such as Ali

Mendjeli, Massinissa and other satellite cities (Benoumeldjadj Maya, 2022). The increase in built-up area over the 2008-2013 period can be interpreted as the development of individual residential and commercial construction, encouraged by the 2008 law aimed at regularizing and completing ongoing construction. This incentive measure led residents to build new buildings or expand existing surfaces. The maps in Figure 5 illustrate land use from 1993 to 2023; each map represents a five-year period, produced in GEE and imported into Arcmap with its classes and layers as well as the attribute tables. In order to produce the layout, the maps with the assigned colors are very clear and meaningful supporting the already calculated surface areas.

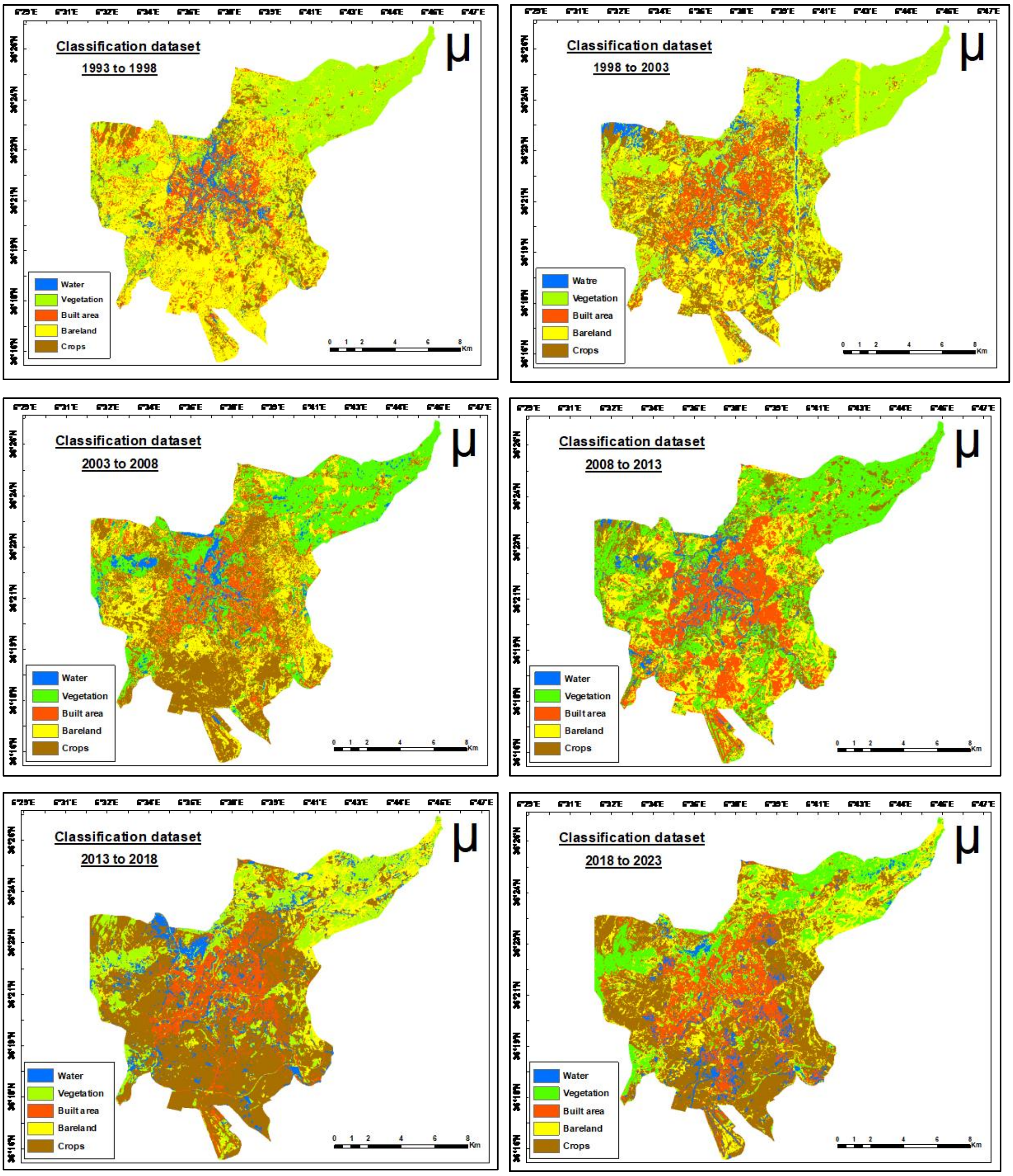

Figure 4. Landcover classification of the sixth datasets (1993 to 2023)

Conclusion

This study made it possible to map and analyze the evolution of land use in the municipality of Constantine over a 30-year period (1993 - 2023), divided into six five-year periods, based on Landsat 8 and Landsat 5 satellite data, each with its appropriate bands, and a supervised classification performed on the Google Earth Engine platform. The results obtained show that the area of uncultivated land decreased significantly while the area of cultivated land increased significantly between 2008 and 2023. This evolution reflects the increasing urbanization process of the study area, characterized in particular by the freezing of urban extensions, the shifting of populations towards the periphery and the degradation of old buildings. The increase in built-up areas observed over certain time intervals can be explained by the development of individual constructions, encouraged by political and regulatory measures.

It highlights the relevance of satellite remote sensing data and supervised classification methods for mapping land use in detail and analyzing its spatio-temporal evolutions. It provides valuable information to support sustainable land use planning and management. The diachronic land use maps produced can serve as a decision-making tool for managers. Future work based on these results could enrich the analysis by integrating additional data (demographics, transportation networks, cadastre, etc.) from different sources. This would help refine the understanding of the territorial dynamics at work and allow a more detailed assessment of the impacts of planning policies. More broadly, this research contributes to methodological thinking on the usefulness of remote sensing for multi-date monitoring of land use and land cover. It underlines the importance of combining cartographic approaches with in-depth statistical and spatial analyses to derive lessons that are useful for sustainable land management.

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