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MAPPING AND DETECTING LAND USE LAND COVER (LULC) CHANGES DYNAMICS OF PER-URBAN SPACES IN CONSTANTINE CONTEMPORARY STATES (NORTHEAST OF ALGERIA) A GEO-SPATIAL METHODS BY USING GIS, REMOTE SENSING, LCM AND GEE PLATFORM FROM 1984 TO 2020

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ABSTRACT

Cities through his urbanizations strongly distort the land use to divergent spaces and casing a change in the natural land cover. This impact makes it necessary to provide municipalities with land use maps and information relating to their condition and dynamics. This study aims to map changes and effects of human activities in a Per-urban space area of Constantine contemporary states CCS (North East of Algeria). Within sixty tree years and experiment the suitability of Google earth Engine platform data's and remote sensing techniques for lands protection as an effort to preserve it following urban planning. For that reason, a multi temporal satellite Landsat 5TM (in 1984, 1991, 1998, 2005, 2012) and Landsat 8 OLI (in 2020) was investigated from 1984 to 2020 (5 periods) and a spatial resolution of 30 meters. a supervised classification with random forest algorithm with accuracy test by means of the confusion matrix and kappa index are applied. Moreover, local ground information allowed uncovering the dynamic of land-cover shape in the study area. The results of LUCL class changes in Constantine states North East of Algeria Region from 1984 to 2020 indicates that the agricultural land in per-urban spaces has the potential to be urbanized. In addition, the water land, forests land and built up land classes are increasing respectively by +0.23%, +2.06% and +57.98% in the period study. Unlike, the agricultural land and bare land classes wich are experiencing a remarquable reduction respectively by -29.70% and -30.58% over the whole study area. Where the main causes are: the massive rural exodus; population growth, the increasing demand for constructive land and type of agriculture practiced by the population.These results could serve as a basis for defining priority intervention areas for the restoration of degraded areas and the management of agricultural and natural per urban spaces.

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1. Introduction.

The LUCL pattern and its spatial distribution are the major fundamentals for the foundation of an effective land use strategy required for appropriate development of an area (Cherutoet *al.*2016). Its transformation has serious impacts on human well-being. Recently; both of natural conditions (climate change, ,…) and human activities (rural exodus, population growth …….) are widely transforming and menacing per urban spaces existences around the world. These transformations have led to changes in the distribution and dynamics of different types of terrestrial ecosystems (Gonzalez *et al.,* 2012; Niang*et al.,* 2014; Ofori*et al.,* 2021). hence; the active increase in human needs and high anthropogenic pressure on land use / cover land were resulted in intensive land changes dynamics. Where, the frequency and intensity of these changes influence the status of ecological systems impacting vegetation composition, biodiversity, biogeochemical cycles, and soil degradation (Lambin et al., 2003; Osvaldo E. Sala et al., 2000; B. L. L. Turner et al., 2007; Vitousek et al., 1997). if; Land use/land cover spaces, distinguish several biophysical categories Vegetation zones (trees, shrubs, fields, and lawns), bare soils (even if it is a lack of cover), hard surfaces (rocks, buildings), wetlands and water bodies (aquifers and streams, floodplains). It is à physical description of space - the observed (bio) physical cover of the earth's surface (DI GREGORIO & JANSEN 1997), i.e. what covers the ground. The mapping and monitoring of land use and cover land classes are certain in order to understand the different changes that are happening to this space.

More then the complexity and dynamics of per urban landscapes is also a challenge for geospatial applications. It is an unwieldly task to integrate multi-source data especially in the case of temporal studies on per urban spaces dynamics. LUCL classification plays a crucial role in the detection of LUCL changes dynamics; extraction and analysis of its information's.

However, traditional LUCL classification methods always spend a lot of time on data processing, which leads to inefficient production of classified products. Furthermore, most of the existing methods rarely consider the application of the sample in time, especially the lack of basic data for constructing long time series.

Recently, to understanding, the effects of land use/land cover changes and natural factors in the past, managing the current situation with modern GIS tools and modelling the future, it is possible to develop plans for various uses of natural resources and conservation (Zamani*et al.,* 2012). The trajectory of land cover change can give as the real image of difference between two times; spatial situations or process. Because, reconstructing past LULC change and for predicting future changes that will help in expanding sustainable management practices meant for preserving vital landscape functions (Hietel *et al.,* 2004; Masese *et al.,* 2012).

In order to map the earth's surface, a wide range of satellites is available with different spectral, spatial and temporal characteristics (Kennedy et al., 2009; Stow et al., 2004). Furthermore; Landsat program provides the largest temporal record of space-based land observations, with more than 40 years of multispectral imagery (Hansen and Loveland, 2012; Ju and Roy, 2008). The spatial resolution (30 meters) of the Landsat sensors together with its sample frequency of 16 days and the availability of relatively homogeneous measurements over a long period, make it a crucial dataset for monitoring dynamic landscapes (Goodwin et al., 2013; Wulder et al., 2008).

Moreover, this technics and tools will be immensely beneficial to developing countries such as Algeria where there are restricted funding and little data on per urban space characteristics and their reforms over time. The valuable information gained from this new technics can contribute much in the domains of monitoring, quantifying, modeling and ultimately predicting the LUCL changes dynamics.

In Algerian as one of the important developing counties which has the second largest area in North Africa (Lambi*et al.,* 2003) . Per urban spaces, suffer from dramatic agricultural and natural lands changes at a wide range of spatial and temporal scales. They acquired, rapid and uncontrolled urbanization witch considered as one of important human activities that forced cities to make inappropriate use of its lands and cause changes in the land cover, which ultimately leads to its impact on its general environment.

More particularly ,in Constantine contemporary states CCS as the third metropolitan area in north east of Algeria – the urban center is surrounding by an important agricultural and natural per urban spaces (80% at species level) . Despite its high agricultural importance, the states has undergone a strong land use/cover transformation similar to most regions in the country. Since 1984; Agricultural conversion and the political events are main processes that shaped the large natural and agricultural per urban conversion spaces.it has been characterized by rapid urbanization phenomena sins 1980d (PDAU[1], 1998). The area has undergone a strong land use/cover transformation similar to most large cities in Algeria (Marc cote, 2010).

Also; the process of urban development from a proactive policy which forced people to leave the big city for residing in there peripheral localities and for good reason, Constantine, circumscribed within its municipal limits, was faced with many management problems, which 'it could only settle with neighbouring municipalities. One of the consequences of this option is the transfer of certain problems from the center agglomeration to the host neighbourhoods that in turn experience the multiple tensions resulting from this delay of growth. Today, there is a need to integrate multiple periods to identify slow and rapid LUCL transformations over time.

This study focuses on the remote sensing of LUCL changes (agricultural land class) in Constantine per urban spaces and the observation of there spatial-temporal change dynamics over the period (1984-2020). It allows observation using geospatial data from the Landsat satellite program, which passes over the same places on the Earth every sixteen days.

With the integrated remote sensing and GIS and Google Earth Engine technologies and LCMs models can contribute much to the generation of digital maps with detailed data on LUCL change and the evolution of natural or agricultural per urban space in some states over this country. So all a preprocessing and processing chain of the multi-temporal series: landsat5 (TM[2]) and landsat8 (OLI[3]) images in1984; 1991; 1998; 2005; 2012 and 2020 are completed by GEE platforms until the validation of the results obtained. As well, the transformation that are happening to forest and agricultural land features are used as a proxy to quantify the nature and extent of changes dynamics using geospatial tools. The gain and losses of per urban surface, the various forms of extension and its spatial reality etc. can be easily identified using this innovative tools and techniques. Our objectives are:

- the classification and analyze of land use/land cover change on per urban spaces in the contemporary states of Constantine with modern technology tools: GEE platform; remote sensing RS; geographic information system GIS and land change muddler LCMs) to better appreciate and occur in lands resource management.

- detecting and quantifying the LUCL change dynamics by showing the location and condition of both feature within different date.

At the end, this study will help to get an easy understanding on the identification and preservation of unspoiled natural environmental resources, natural open space, environmentally sensitive areas like forests, natural parks; agricultural land; …. etc. then , it will help local collectivities in expanding sustainable management practices meant for protective vital landscape functions.

2. Tools and methods.

2.1. Study area: location and characterizations.

Our study area is Constantine Contemporary States (CCS) witch is the capital of the northeast Algerian region, it is located in the geometrics center of Constantine province. It is located between the range of 36° 22 ’North and 6°37’ East of the Greenwich meridian. It is far from the Tunisian border with about 245 km in the East, from Algiers capital with 431 km, from Annaba city with 159 km in the North, and from Biskra city with 235 km in the south. Constantine states (CCS) covers an area of 2297.77 km², that is to say 0.09% of the whole of the national surface from the last administrative decoupage of 2018. Different states bound it: to the north by Skikda states, to the East by Guelma states, to the West by Mila states, and to the South by Oum El Bouaghi states. However, it enjoys a remarkable

[1] Urban Development and Planning Plan"
[2] TM: Thematic Mapper)
[3] OLI: Operational Land Image

central and geographical position in this region, at the crossroads of two major axes: East-West axis of the Tell-height Plaines contact (Serif-Annaba), at the crossroads North-South axes (Skikda-Biskra) to constitute a communication node and a place of exchange between North and South. Fig. 1.

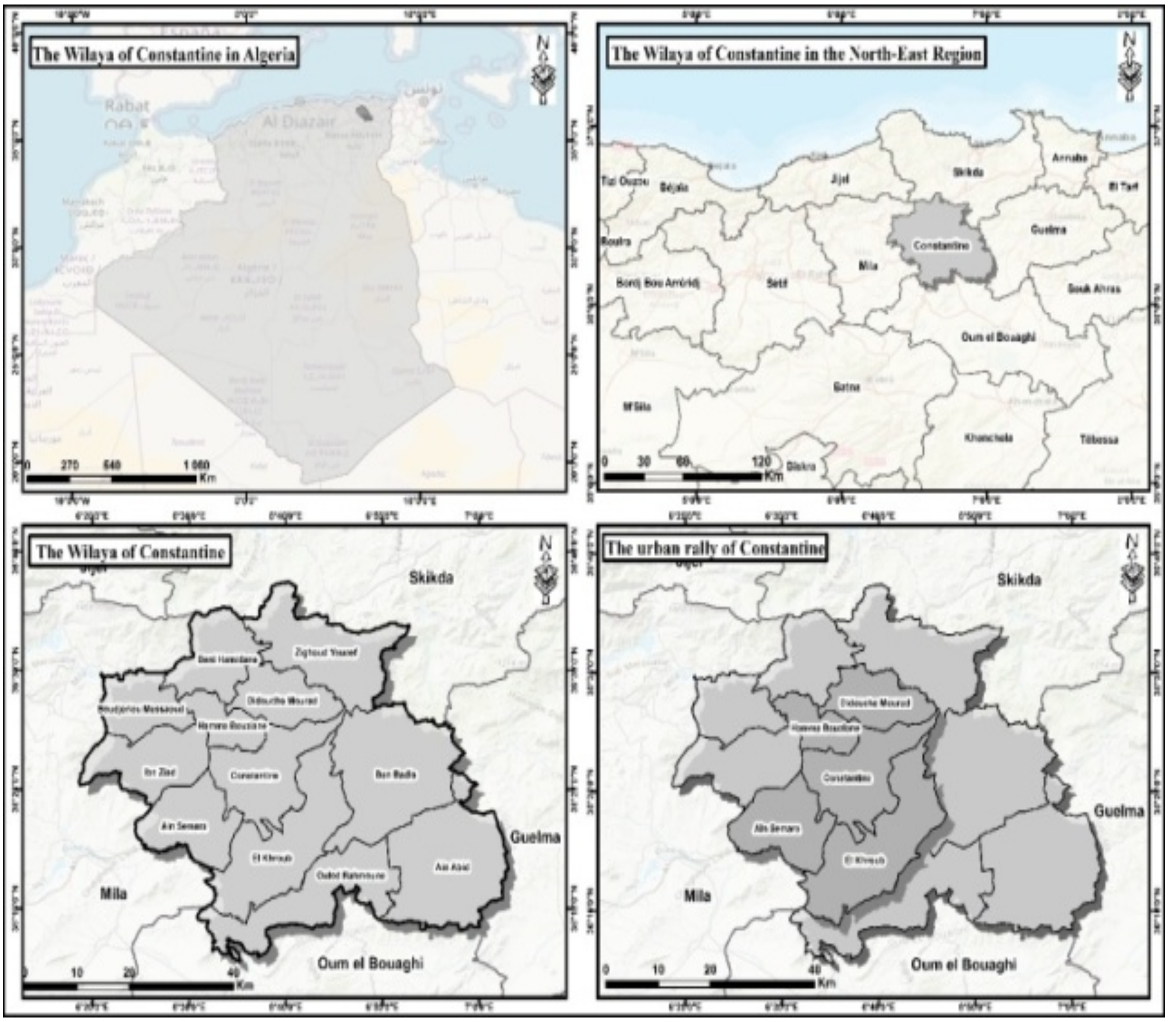

Figure 1. Geographical location of Constantine metropolis.

Source: author, September 2022.

Geographically, it is composed of twelve 12 municipalities which cover different population and surface. One of its most important topographical features is the presence of mountains (djbal Al-Wahsh, 1202 meters, Chettaba Mountain, 1316 meters high above sea level) and highlands such as (Sidi Mecid's highland 725 meters, Ain El-Bey's highland between 700-800 meters above sea level).The climate of this city is in the range of tropical to subtropical with four seasons. The mean annual temperature is 20.9 °C with a yearly precipitation record of 1323.4 mm. In addition, CCS is the third metropolitan area in the country that's why performs higher functions: administrative, cultural and industrial ones.

2.2. Data and materials.

The difficulty of building a geographical database with a wide coverage and the simulation of spatiotemporal transformations deserves the combination of data of different nature. Therefore, in this study, different types of data and techniques are used to evaluate historical land use /cover land change dynamics in Constantine per urban spaces as like it illustrate below:

-1-A series of six satellite images from Landsat5 (TM) of 1984, 1991, 1998, 2005, 2012 and Landsat8 (OLI) of 2020 sensors spaced seven to eight years apart constitute the main data used to reconstruct the trajectory of the land use and cover land form in the metropolis of Constantine. The characteristics of the images obtained are shown in Tab 1.

Tab 1. The Characteristics of the Landsat systems selected for processing in the study.

Images features	**1984**	**1991**	**1998**	**2005**	**2012**	**2020**
Satellite	Landsat 5	Landsat 5	Landsat 5	Landsat 5	Landsat 5	Landsat 8
Sensor	TM Multi spectral	TM Multi spectral	TM Multi spectral	TM Multi spectral	TM Multi spectral	OLI Multi spectral
Spectral bands (µm)	0.45-0.52µm 0.52-0.60µm 0.63-0.69µm 0.76-0.90µm 1.55-1.75µm 10.40-12.5µm 2.08-2.35µm	0.45-0.52µm 0.52-0.60µm 0.63-0.69µm 0.76-0.90µm 1.55-1.75µm 10.4-12.5µm 2.08-2.35µm	0.45-0.52µm 0.52-0.60µm 0.63-0.69µm 0.76-0.90µm 1.55-1.75µm 10.4-12.5µm 2.08-2.35µm	0.45-0.52µm 0.52-0.60µm 0.63-0.69µm 0.76-0.90µm 1.55-1.75µm 10.4-12.5µm 2.08-2.35µm	0.45-0.52µm 0.52-0.60µm 0.63-0.69µm 0.76-0.90µm 1.55-1.75µm 10.4-12.5µm 2.08-2.35µm	0.43-0.45µm 0.45-0.51µm 0.53 -0.59 µm 0.64 -0.67µm 0.85 -0.88 µm 1.57-1.65µm 2.11-2.29µm 0.52-0.90µm 1.36-1.38µm 10.60-1.19µm 11.5-12.51µm
Acquisition Date	1984/01/01 – 1984/12/30	1991/01/01 – 1991/12/30	1998/01/01 - 1998/12/30	2005/01/01 – 2005/12/30	2012/01/01 – 2012/12/30	2020/01/01 – 2020/12/30
Spatial resolution	projection system Mercator WGS 84 / UTM zone 32N					
Pre-treatment	Atmospheric correction by dark					

Source: author, December 2022.

-2- More called auxiliary data is made up of two old land use maps of Constantine province from 1982 and 2011 provided successively by BNEDER[1] and INCT[2].

-3- Field survey data (duration from September 2016 to December 2018) which allowed us to better distinguish the different types of land use and cover land in the study area.

-4- Other tools and software are used in this study such as: the creation of an account on the GEE platform (Google earth engine) and the employ of a grid-Based geographic analysis system (IDRISI) or (TerrSat) software to analyze and quantify the Land Use Change Modeling (LCM) of land cover class's studied from 1984 to 2020.

-5- The use of a Geographic Information System (GIS) by means of Arc GIS software (version 10.8) which allowed us to: automate and generate maps, calculate landscape indices as well as visualize, process and map the databases already incorporated.

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[1]BNEDR: Bureau National des Etude et de Development Rurales.
[2]INCT: Institut National de la Cartographies et de la Tele detection.

2.3. Global approach and methodological steps to follow. The objective of this work is to verify the hypothesis of per urban spaces front of LUCL change dynamics in CCS using a geospatial method basis on a processing multi-date satellite images in order to evaluate the agricultural area changes through time. Essentially, we are based on the visual analysis of images in coloured composition through an analytical approach and supervised classification founded on a machine learning approach through the application of random forests classifier. Moreover, we can share the study methods globally on five steps as shown below.

2.3.1 Registration, under (GEE) platform mtreatments and collect of data's. To acquiring data's of interests we must start by accessing to the GEE platform and carrying out the registration process, that is, opening an account for the user (Figure.2).

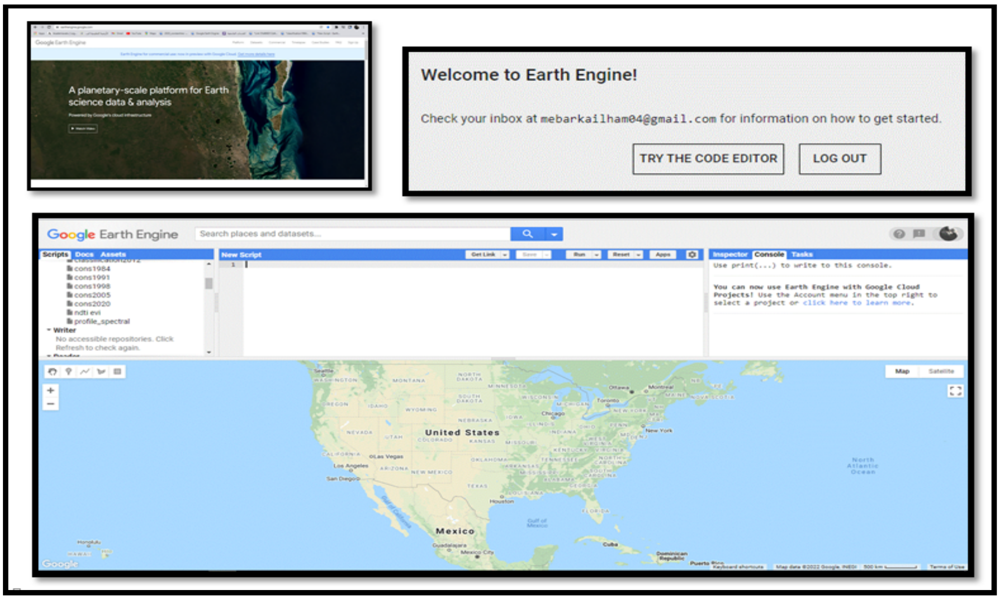


Fig.2. Registration under GEEP.

Source: author, September 2022.

Then, the treatments sequence carried out on the satellite images with GEE, just after we added information about the administrative boundaries of the study area as *Shape file*. In this time, we collected all the information about the study area and named it in the form of a table. (Fig. 3).

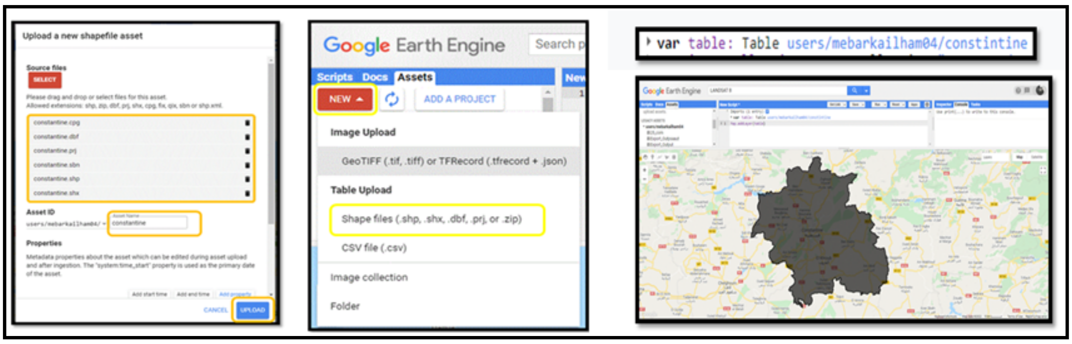


Fig 3. Added administrative information under GEEP.

Source: author, September 2022.

In this research, the area of interest is the contemporary city of Constantine or Constantine province. The geometry point will automatically be defined as a variable and put as an imported asset at the top of the code window pane. (Fig. 4).

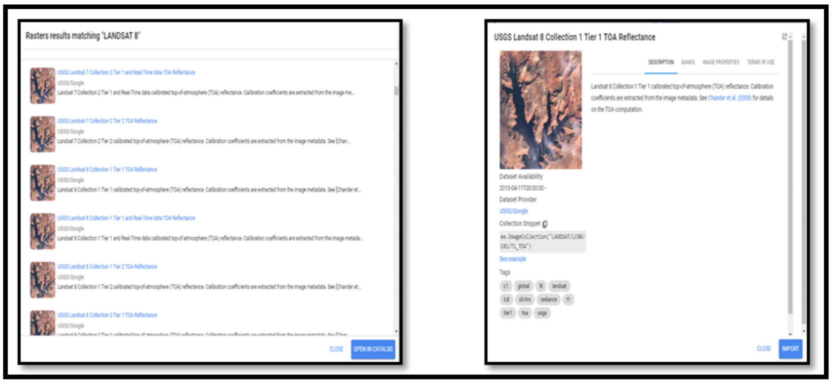


Fig.4. Data's acquisition from LANDSAT 5 and LANDSAT8 collection's.

Source: author, September 2023.

At this time, we depended on the two collections LANDSAT 5 and LANDSAT8 SR, each of them has its proper identifier which can be derived from the GEE platform. Therefore, we will load Landsat imagery and choose the area and dates of interest. By way of exhausting type to filter the Image Collection by % cloud cover from the GEE platform, a property included with the Landsat Top of Atmosphere (TOA) collection.

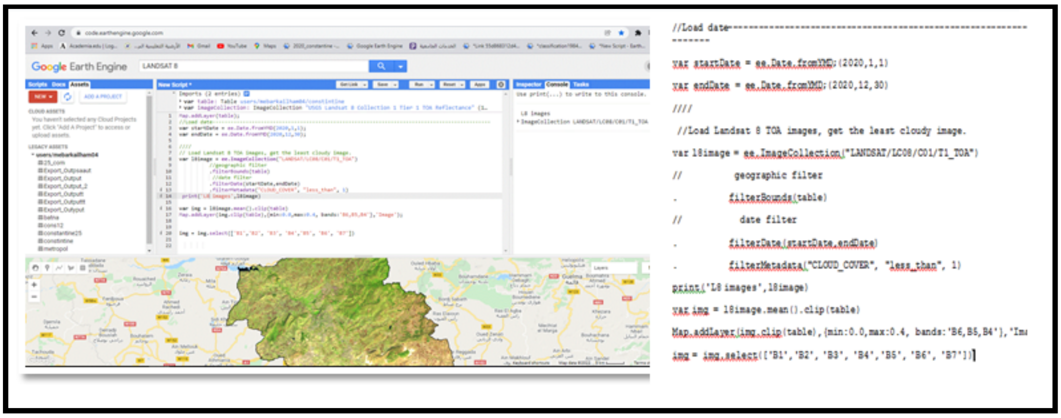


Fig 5. Faltering and select of good images quality's.

Source: author, September 2023.

We then select the first (least cloudy) Image from the sorted Image Collection. (Fig.5) Other way, we are loading an Image Collection then filtering them to a single image.

2.3.2 Landsat Satellites imagery and there pre-processing.

Such as confirmed by (Chen 2007), the initial step for properly accomplishing change detection comparison for unprocessed images and classified images is image pre-processing techniques. Where Image pre-processingis an operation widely used prior to the principal analysis of remotely sensed data (Campbell and Wynne 2011). So to achieve the objectives of this study, we accomplished the necessary image preprocessing (i.e., atmospherically, geometric correction, and radiometric calibration) at the six selected LANDSAT 5 Images of for1984, 1991, 1998, 2005, 2012 and LANDSAT 8 Images of 2020. (Fig.6).

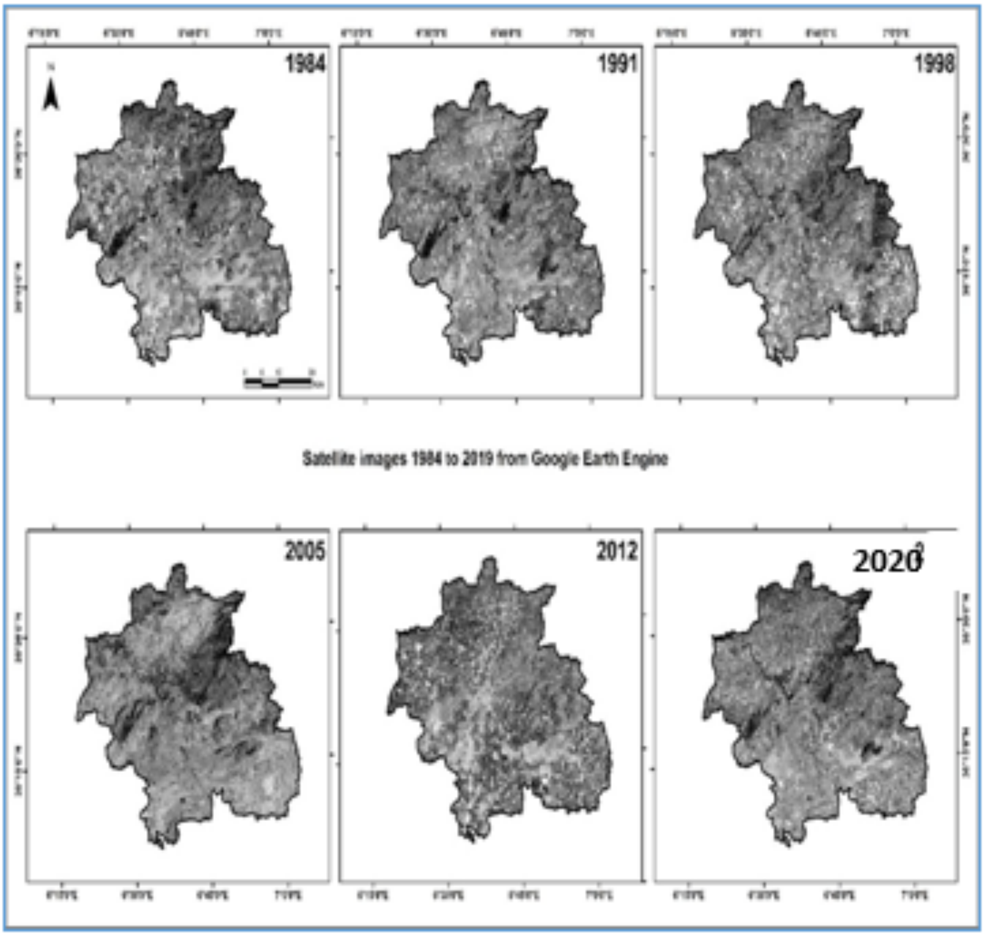


Fig.6. The six selected Landsat imagery: (TM) for1984, 1991, 1998, 2005, 2012 and (OLI) for 2020, respectively, used in this study.

Source: author, September 2022.

- **Atmospherically and Geometric correction:** first, we employed the atmospherically corrected Landsat-8 optical imagery available in GEE (Tier 1 product, ee. Image Collection (LANDSAT/LC08/C01/T1_SR). These products are atmospherically corrected using the Landsat-8 Surface Reflectance Code (La SRC) and contain cloud, shadow, water, and snow masks, which are generated using the C Function of Mask (CF Mask) algorithm (Foga et al., 2017). The (LaSRC) algorithm applies a modified version of the 6SV relative transfer code along with an accurate method for aerosol estimation. Therefore, adopting an efficient method for cloud and snow removal from Landsat-8 images is challenging. Since multi-date images over six years were used in this research, cloud- and snow-contaminated areas were effectively removed from the images. To do so, a JavaScript code in GEE was applied to all Landsat-8 and Landsat-5 imagery chosen in which a median ee. Reducer function was used.

Second, correcting geometric distortions due to variations in the Earth-sensor geometry the goal is to transform data into true coordinates on the Earth's surface to conform to the desired map projection, and to resample to a standard size square pixel. Each pixel is then positioned in this projection. (Moquet, 2003)Thus reducing the geometric distortions that occur during the recording of the scene. Hence, we used the image-to-image registration method accordingly; the images can be overlapped with vector data in a geographic information system (GIS) and used for change detection.

- Radiometric calibration: here, we used methods presented by (Chander, Markham, and Helder 2009) as a prerequisite for creating high-quality image data. All the preprocessing and analysis data have been carried out using GEE platform.

Fig.7. Satellite images after correction.

Source: author, September 2022.

This single image for which the pixel values represented the median of the image pixels containing no or minimum snow/cloud. In an effort to create a composite image, a series (a stack) of six satellite scenes covering the study area were called up and composited. (Fig.7)

2.3.3 Image classification with random forests classifier.

The image obtained is not very clear; therefore, we will clarify them by applied the supervised classification approach to classify the selected image into a number of known and homogenous groups of pixel class. That is based on the occurrence of a pixel's membership in a particular class with a supervised image classification using random forest machine learning approach (Breiman, 2001). The algorithm was trained based on the land cover reference data (previously described) to discriminate between different LUCL classes. The analysis was carried out using random Forest package (Liaw and Wiener, 2002). It is builds on classification and regression trees but overcomes their sensitivity towards noise in the data as an alternative of relying on a single decision tree, using the majority vote of a forest of decision trees fit to bootstrap samples from the original data.

While individual decision trees suffer from a high variance of estimates, the averaging across the bootstrap sample leads to a significant variance reduction (Hastie et al., 2009; James et al., 2013).In addition to catching approaches, random forests decor relate the trees by using only a random sample of the variables (i.e., spectral bands) for each split.

- Class determination or selecting and signing samples: five layers or classes are selected; of which each layer represents a specific class. The identified classes represent agricultural land, forests class, built-up land, bare land and water surfaces class (tab.2) then each new layer represents one class within the training data.

Tab 2. Category of completed land cover and land use classes.

Class	**Description**
Built-up land	All artificialized land where built (housing, administration, industrial equipment
Bare land	Land that contains no construction or vegetation cover
Agricultural land	All types of agriculture: serial cultivation, arboriculture; market gardening, gardens, farms
Forests	Trees, Park, Urban Forest.
Water laces	Ouadis and laks

Source: Author, 2022.

-From sample Imagery to Drawing Training sites. In the supervised classification, training sites are selected (ROI[1]), that is to say areas where we know the land use, and where we tell the software to take these areas as a reference to classify and generalize to the full image (Fig.8).

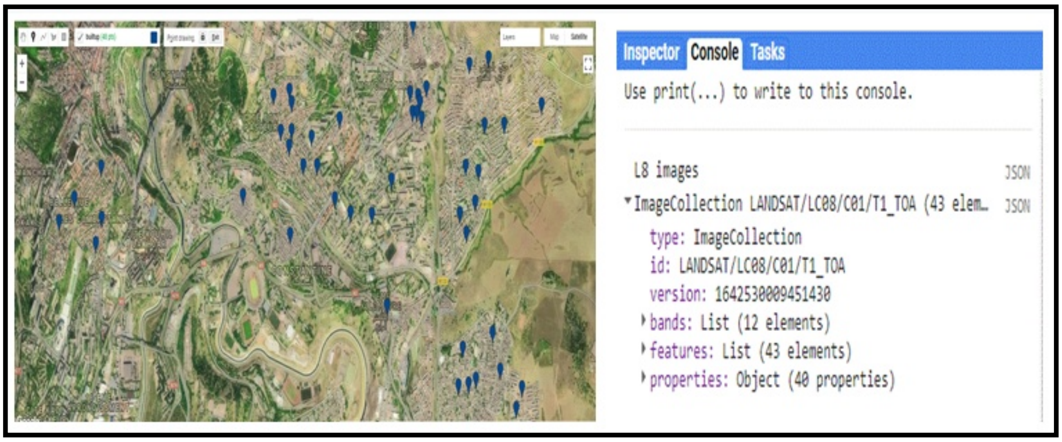
Subsequently we have created the points and labels; we need to sample the Landsat 8 imagery using Image Sample Regions.

This command will extract the reflectance in the designated bands for each of the points we have created. We will use reflectance from the optical, NIR, and SWIR bands ('B4', 'B3', and 'B2'). Here, decision rule applied for classification with Random forests algorithm are based on the occurrence of a pixel's membership in a particular class. This algorithm assumes that these probabilities of occurrence are equal for all classes, and that the input bands have a normal distribution.

Fig 8.Drawing Training Data.

Source: author, September 2022.

After taking the samples that we will work on, we enlarge the satellite visuals and set them in the form of points on them. Then, we use the third code; which enables us to use the classifier algorithm from a multispectral perspective. The samples that were selected by the user "supervised classification" are applied to the rest of the images as shown in Figur 9.



Figur 9. Applied a supervised classification to Images.

Source: author, September 2022.

In the latter, we use the third code; which enables us to use the classifier algorithm from a multispectral perspective. After that, the samples that were selected by the user "supervised classification" are applied to the rest of the images as shown in the Fig 10.

[1] ROI: Region of Interest.

Fig 10. Supervised classification results.

Source: author, September 2022.

2.3.4 Land cover change analysis by LCM muddler.

Accuracy assessment was necessary to recognize the level of agreement between classified images with a set of reference data and to gather valuable information for spatial change detection and further analysis.

They were accomplished during the post-supervised classification stage.it was carried out by collecting ground truth samples for 1984, 1991, 1998 2005, 2012 and 2020 imageries based on the visualization of the imageries, indigenous information, and *Google Earth*'s archived imageries.

To assess the spatial change LCM muddler was applied with IDRISI TerrSet Lab Kit. The TerrSet system incorporates the IDRISI GIS Analysis and IDRISI Image Processing tools along with a constellation of vertical applications, Land Change Modular, and many more applications for in-depth research and analysis. It is an integrated geospatial software system developed by Clark Labs at Clark University for the analysis and display of digital geospatial information. One of the TerrSet advantages is the offers the most extensive set of geospatial tools in the industry in a single, affordable package. (Fig. 11)

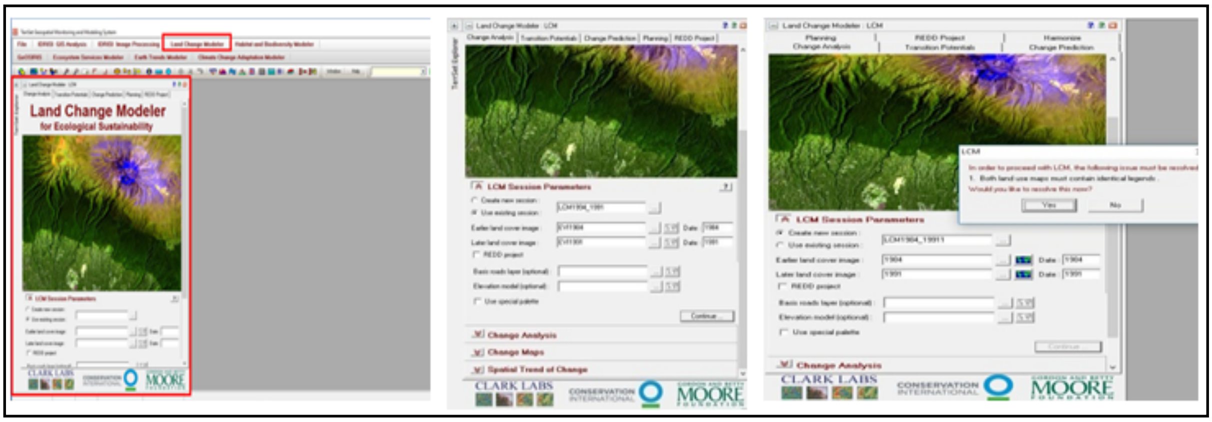
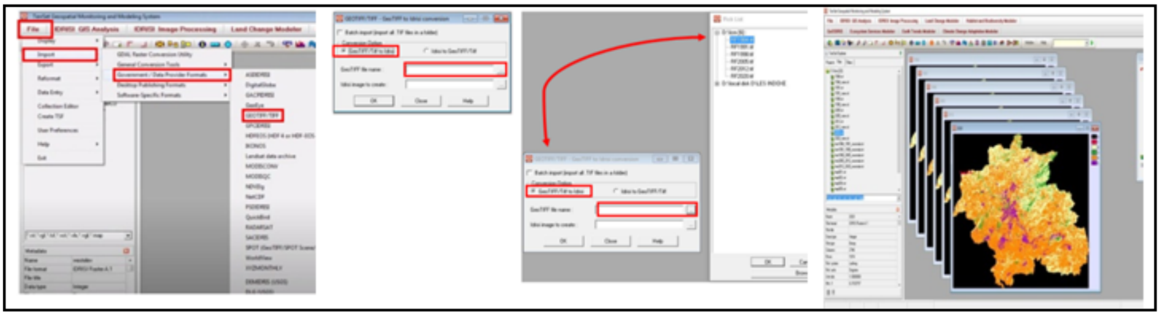


Figure. 11LCMs model select and TerrSet software connection.

Source: author, September 2022.

After the downloading then installing TerrSet 17.0 software, we begin the operation of preparing the six land use layers (raster format) produced in the first phase under the GEE platform and importing them into the TerrSet software. Fig.12



To achieve LULC change analysis, we combined land cover information from two consecutive years to avoid large areas without information due to clouds and cloud shadows. This resulted in six combined land cover maps for the following periods: T1=1984-1991; T2=1991-1998; T3=1998-2005; T4=2005-2012; T5=2012-2020.

To analyze the land cover information, we calculated the extent, net change, gain and losses of each land cover class between consecutive periods over time. We generated cross-tabulation matrixes using IDRISI SELVA (Eastman, 2012) to derive and analyze the different land cover trajectories. The frequency of land cover change was identified by combining binary maps of change/no change events between the six combined LULC maps.

The change can be in the type of feature in a place for example, the different categories of land cover/use in a study area compared to 36 years ago. Or, the change can be in a quantity associated with each feature, for example, the aggregate of feature class has increased or decreased in each area over the past 36 years.fig.13.

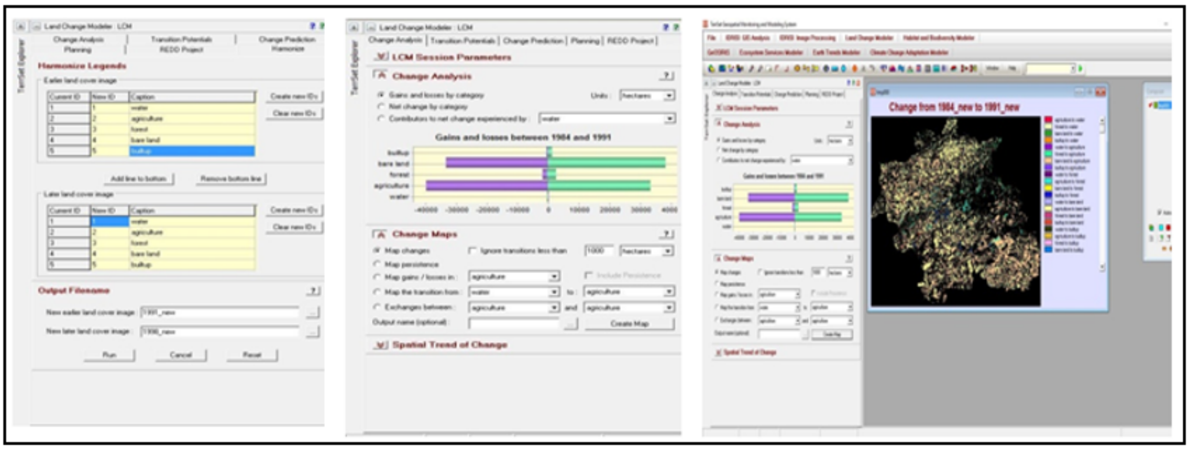


Fig 13. Figur.13 LCM change detection and distribution of resultants.

Source: author, September 2022.

2.3.5 Validation and accuracy assessment.

Once the images classification and spatial change detection phases are completed. There is a validation stage by carrying out different tests as: train Accuracy, test Accuracy, confusion matrix and the KAPPA coefficient of each satellite image from the case study in order to present a very precise classification. The goal behind this step is to quantitatively assess the degree of efficiency with which pixels were sampled in the correct land cover classes (Rwanga & Ndambuki, 2017). According to the summary of this validation measurement shows in fig.14. The land cover classification global accuracy ranged from 0.93 to 0.95 (figure 14), with the minimum values in 1984 and 2012 in addition the maximum value in 2020, respectively. In addition, the Kappa coefficient thus showed an acceptable level of precision. With the values of 0.81, 0.84, 0.84, 0.85, 0.79 and 0.86 for the years 1984, 1991, 1998, 2005, 2012 and 2020 respectively.

Land classes	classification map of 1984					Total
	water surface	Agricultural land	forest	Bare land	Built up land	
water surface	307	15	1	15	2	340
Agricultural land	1	214	2	98	0	315
forest	0	18	181	13	16	228
Bare land	6	25	6	4746	95	4878
Built up land	0	3	0	65	308	376
Total	314	275	190	4937	421	6137
global precision of maps						0.93
Kappa Indices						0.81

Land classes	classification map of 1991					Total
	water surface	Agricultural land	forest	Bare land	Built up land	
water surface	322	0	0	0	2	324
Agricultural land	0	199	1	105	0	305
forest	0	6	173	10	35	224
Bare land	5	16	8	4762	65	4856
Built up	0	5	0	70	298	373
Total	327	226	182	4947	400	6082
global precision of maps						0.94
Kappa Indices						0.84

Land classes	classification map of 1998					Total
	water surface	Agricultural land	forest	Bare land	Built up land	
Water surface	322	0	0	3	1	326
Agricultural land	0	164	1	138	2	305
forest	0	7	176	10	33	226
Bare land	14	16	6	4777	67	4880
Built- up land	2	2	0	51	419	474
Total	338	189	183	4979	522	6211
global precision of maps						0.94
Kappa Indices						0.84

Land classes	classification map of 2005					Total
	water surface	Agricultural land	forest	Bare land	Built up land	
water surface	324	0	0	0	2	326
Agricultural land	0	198	0	112	2	312
forest	1	5	183	6	34	229
Bare land	6	29	2	4806	60	4903
Built up land	0	0	0	59	389	448
Total	331	232	185	4983	487	6218
global precision of maps						0.94
Kappa Indices						0.85

Land classes	classification map of 2012					Total
	water surface	Agricultural land	forest	Bare land	Built up land	
water surface	337	0	3	4	4	348
Agricultural land	0	45	1	274	3	323
forest	0	0	192	5	41	238
Bare land	5	19	1	4802	43	4870
Built up land	0	0	0	29	428	457
Total	342	64	197	5114	519	6236
global precision of maps						0.93
Kappa Indices						0.79

Land classes	classification map of 2020					Total
	Water surface	Agricultural land	forest	Bare land	Built up land	
water	337	2	1	1	1	342
Agricultural land	0	178	7	129	0	314
forest	1	0	205	4	0	210
Bare land	2	24	9	4708	61	4804
Built up land	2	0	1	32	303	338
Total	342	204	223	4874	365	6008
global precision of maps						0.95
Kappa Indices						0.86

Fig 14. Distribution of the spatial reflectance in class area between 1984 and 2020 from Landsat TM /OLI data.

Source: author, September 2022.

Nevertheless, in this study, we refer to the KAPPA coefficient results as a more accurate estimation of the classification quality; it takes into account well-classified pixels. It is always between -1 and 1.

Usually, the following scale is used to interpret the value obtained: K < 0 disagree, 0 to 0.20 none to slight, 0.21 to 0.60 moderate, 0.61 to 0.80 substantial, and K0.81 near perfect agreement.

Generally, the results of the classifications accuracy estimation obtained are in their majority excellent (K0.81) apart from that of 2012 (0.79%) which was considered substantial.

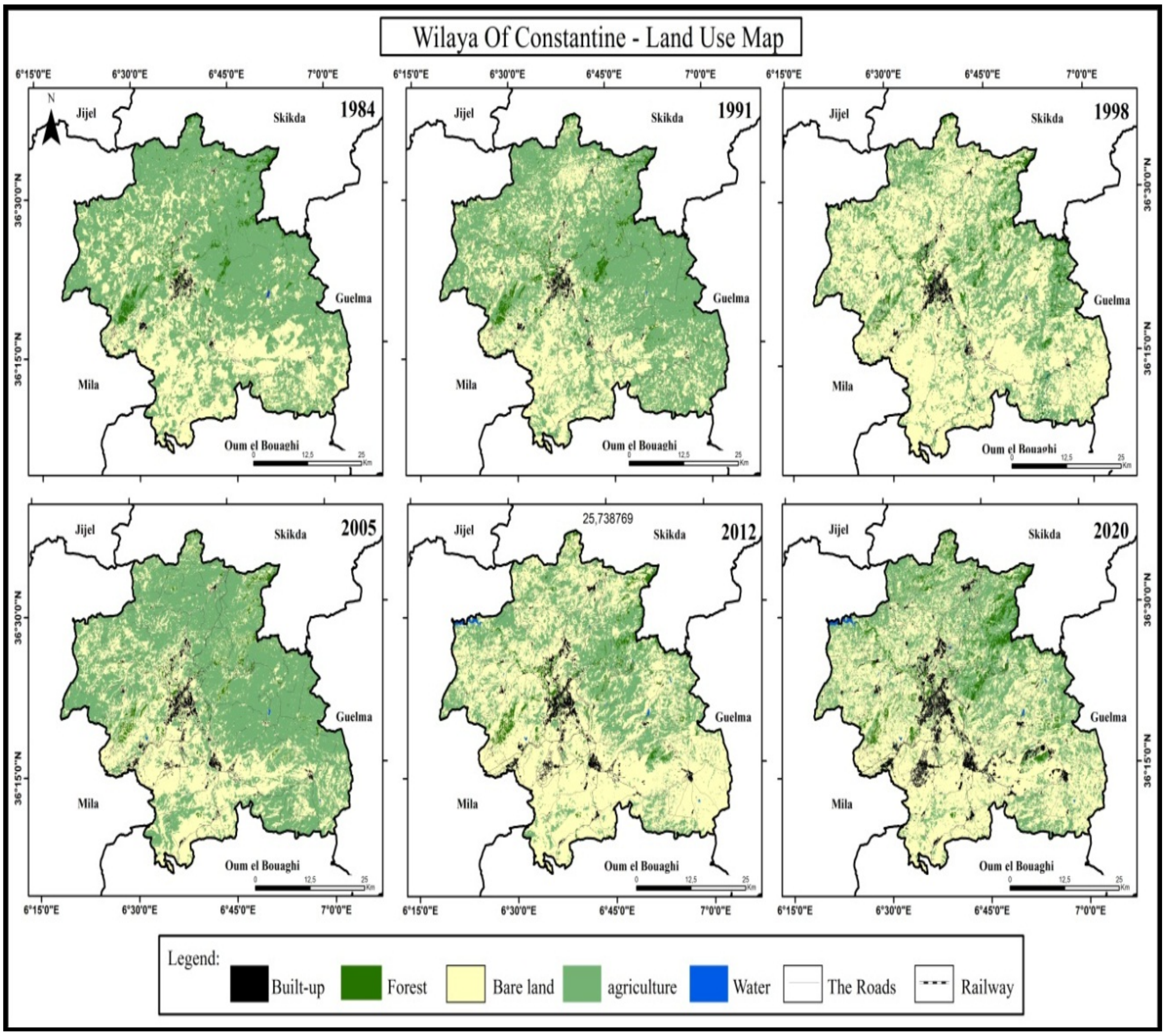
3. Study results.

3.1 new LUCL thematic maps of Constantine Contemporary states.

The results obtained through this temporal spatial study based on data from the GEE platform and the rates of spatial change in each LUCL class's on all the study area (12 municipalities) offer us very interesting information on the spatial reality of the state and dynamics of LUCL over the last 36 years in the contemporary states of Constantine. Including, the state of occupation and land use classes in the study area will be analyzed on the basis of cartographic and tabular data constructed after the supervised classification of Landsat 5 TM and Landsat 8 OLI images under the GEE platform.

The visual analysis of Figure.15, presented that the five LUCL class analyzed in Constantine per urban space are transformed in the time and in the space as it is mentioned below.

The agricultural land class is regress over all the municipalities of the CCS, but in different degrees and areas that are not homogeneous from one municipality to another. It also witnesses fluctuations and declines in its area over time.



Figur 15. Constantine contemporary states: land use/cover land classification maps in 1984, 1991,1998, 2005, 2012 and 2020.

Source: author, September 2022.

The forest class presents a concentrated distribution in the northeastern and northwestern parts of CCS, especially due to the presence of mountains and high plateaus, noting that the contemporary city of Constantine is located within a geographical area with a complex and severe topography.

The built up land class (urban class) is focused in the geometric center of the city and in the centers of its constituent municipalities, giving the image of an oil spot. The area of this class increases from year to year and in different directions, the most important of which is the southwestern direction.

The bare lands class is concentrated in the southern and southwestern part of the state. It, in turn, witnesses a general decline in its area from year to year.

The lands covered by the water network class is characterized by its small presence in the contemporary city, however, it records a relative increase from year to year.

3.2. Status LULC classes in Constantine contemporary states.

The trajectories of LULC classes in Constantine stats over time were analyzed; and more than exposed in (fig.16). Thus; in 1984, we note that there is regional dominance of the agricultural land class in the distribution of LUCL pattern in the contemporary states of Constantine, with an area of 138 098.60 hectares, or (61.28%), followed by the bare land class with 79608.26 hectares that is (35.33%). Then the forest class is 5596.05 hectares, that is (2.48%), and the built-up land class is 1959.03 hectares that is (0.86%). Finally, we find the land covered by water class, which is the least, represented type, with an area of 61.44 hectares, or (0.02%) successively and during the same year.

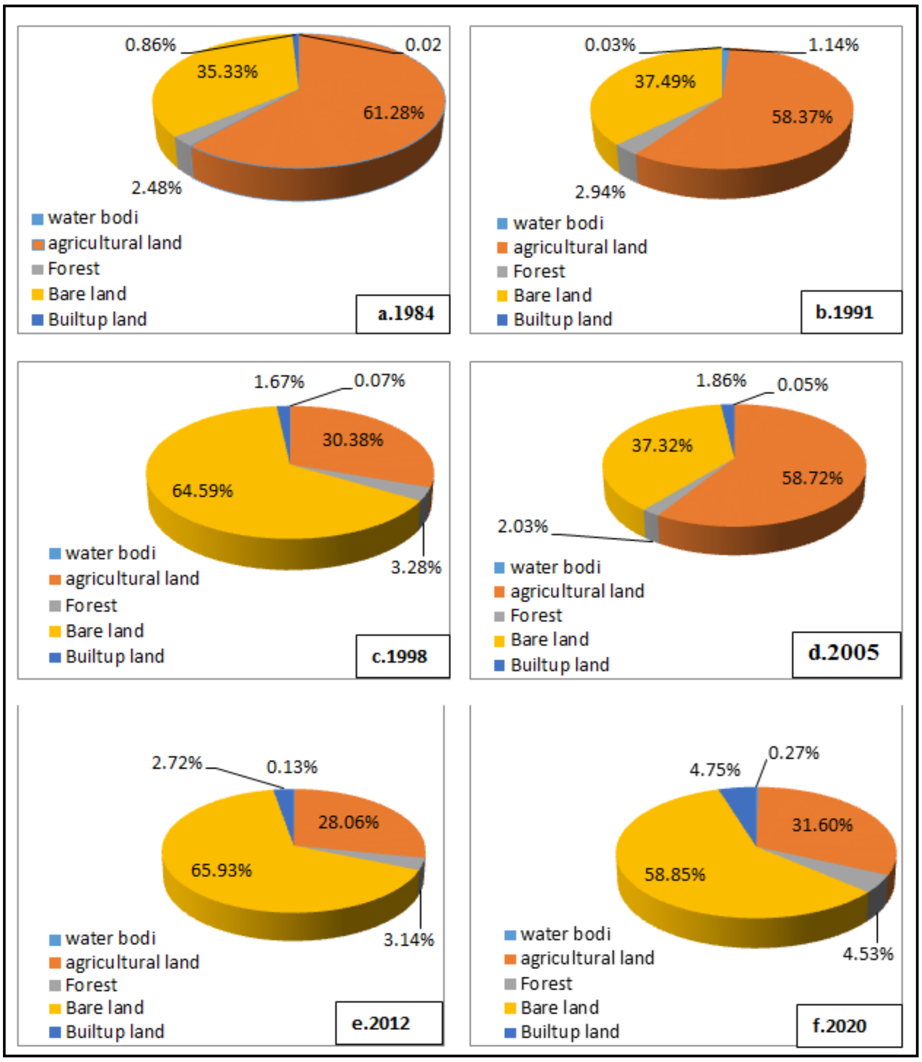


Fig 16. Constantine contemporary states:
LULC classification results from 1984, 1991, 1998, 2005, 2012 and 2020.

Source: author, September 2022.

In 1991, the (Fig.16 b.1991) presented an accumulative order of LUCL classes as follows: an area of 35701.46 hectare that is (58.37%) for agricultural land class, an area of 37041.16 hectare (37.32%) for bare land class; an area of 3230.27 hectare or (2.03%) for the forestland class. In other way, an increase in the two classes remain water class with 33.15 hectare (0.03%) and built land class with 2157.01 hectare (1.14%) compared to the previous year.

More then, ***in 1998*** bare land class occupied the first place in Constantine states class land distribution with an area of 145236.3 hectares (64.59%); followed by the agricultural land class with 68,306.4 hectares (30.37%). Then, the forest class recorded a small increase in this year with an area of 68306.4 hectare or (3.28%). so, both of land covered by water class and built up class were showing added augmentation in this year also with an percentage area of 0.07 % and 1.67% successively as it is detailed in (Fig.16 c.1998).

However, in 2005, all of agricultural land class, built up class and water body class were augmented successively with a percentage area of 58.72 %, 1.86% and 0.05% as it is observed in (Fig.16 d.2005). In the other why; bare land class and forests class were reduced and presented a percentage area of 37.32% and 2.02%.

In 2012, the (Fig.16 e.2012) presented a derived classment of the LUCL classes studied. First; a percentage area 65.93%) for bare land class. Second, a percentage area 28.06% for agricultural land class. Third, an area of 3.14% for the forests land class. Fourth, a percentage area of 2.72% for the built land class. At the end, a percentage area of 1.14% for the land covered by water class compared to the previous year.

Finally, in 2020, a continuous enlargement of the built up land classes with a percentage area of 4.75%. In addition; at agricultural lands with a percentage area of 31.60%, a percentage area 0.27% covered by water class and a percentage area 4.53% for forests land class compared to the previous year. In addition, bare land class unregistered a small's decrease with a percentage area 58.85%, as it is presented in (Fig.16 f.1991).

4. Discussions.

The present study aims Analysis of Remotely Sensed Data for Detecting and Mapping the Changes of Agricultural land, which happened in Constantine per-urban space between 1984 and 2020. Using GEEP, LCM muddlers, GIS and Image Processing Software. results of Land use /cover land classification of images from 1984,1991 ,1998 ,2005, 2012 and 2020 with an supervised classification method with random forest algorithm; presented the change of each LUCL class from the five classes chosen: Agricultural lands, Urban lands, forests land ,Barren lands and water lands.

The LUCL change observed in Fig17 and (Tab.9) can be analyzed in the type of feature in a place for example, the different classes of LUCL compared to 36 years ago. Alternatively, in a quantity associated with each feature, for example, the extent of feature class has increased or decreased in each area over the study period.

Tab 9. Land use / land cover change detection in Constantine contemporary states between 1984-2020.

	T1		T2		T3		T4		T5		TOTAL	
soil (BDI)	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)
Water	23.2+	0.01+	89.81+	0.04+	45.3-	0.02-	172.45+	0.08+	321.06+	0.14+	561.22+	0.23+
Agricultural land	6546.87-	2.92-	62968.25-	28.01-	63736.5+	28.35+	68929.37-	30.66-	7941.09+	3.54+	-66767	-29.7
Forest	1050.93+	0.47+	752.36+	0.34+	2799.56-	1.25-	2504.67+	1.11+	3108.46	1.39+	4614.86+	2.06+
Built up land	626.65+	0.27+	1183.28+	0.53+	417.14+	0.19+	1935.37+	0.86+	126195.84+	56.13+	130358+	57.98+
Bare land	4845.9+	27.84+	60945.12+	27.1+	61308.78-	27.27-	64316.88+	28.61+	137567	61.18-	-68767	-30.58
Total	-	-	-	-	-	-	-	-	-	-	-	-

Source: author with excelle, december 2020.

Therfore; change dynamics results of LUCL classes in Constantine states from 1984 to 2020 are represented in Figu.17. In addition, differentiation between LUCL classes area delivered important information needed to identify spatial LUCL change dynamics (tab.9). The analysis of these one reveals the following observations:

First, water land class expose exceptionnelle gain of land area with 561.22 hectare (+0.23%) comparing to the other class. Then; forests land class experienced a gain of land area of 4614.86 hectare (+2.06%) over the study period. Also; Bare land class experienced the greatest loss of land area, with over 68767 hectare (-30.58%) converted to other classes. This makes bare land the biggest loser during this period. This significant changes in LUCL class reflect the growing demand for constructive land distining for urban development, agriculture, and other purposes in the Constantine states over the past 36 years.

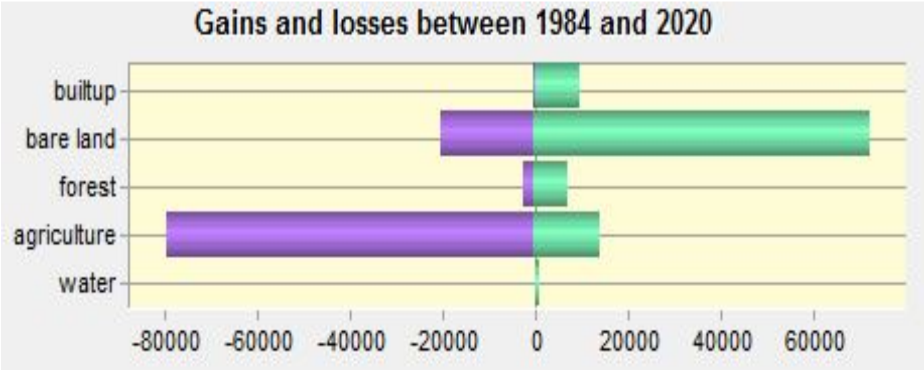


Fig 17. Gains and losses in Constantine contemporary states LUCL between 1984-2020.

Source: author with excelle, December 2020.

The agricultural land underwent significant deterioration with 66767 hectare (-29.7), but in return, it regained significant areas, allowing it to recover its losses and even record a net gain of land over in the same period. Since 1962, the proportion of agricultural land allocated for the construction and equipment sector has been increasing at an accelerated rate from year to year, reaching 10427 hectares in 2008, or 14.67% of the total agricultural area in Constantine states, estimated at 71082 hectares, with varying degrees of fertility (very fertile 33.46%, fertile 14.16%, and medium to low fertility13.16%). This is according to the estimates of the Office of Rural Studies [BNEDER,1989]. Some field investigations have confirmed that construction and development activities on agricultural land, which have spread through real estate transactions used for non-agricultural purposes but exploiting agricultural land, have reached an area of over 78000 hectares during the period from 1980 to 1996. Also, the application of Law 29-90 of land use planning and its spatial consequences (Abdi. N, 2023). Hence ; Built up land (artificiel lands) were always progressing and without any loss (0 hectares), experienced a slight increase of 130358 hectare (+57.98%). The urban use extended south of the states from the municipality of El khroub, to the south west of Ain Smara municipality. With speed, sprawling phenomena involved in the bare lands class, for the reason to a Built up land expansion wich is justified by the important population growth and infrastructure development in this third Algerian metropolitan area. For example, the commune of El Khroub no longer needs land for its future expansion, as its municipal reserves exceed 258 hectares. However, it is receiving housing programs from the commune of Constantine, wich was already saturated by 1980 (PDAU, 2008). This growing demand for built-up land is leading to environmental degradation through lands erosion.

That's why; the LUCL change dynamics class in CCS expose an réduction of peri-urban agricultural spaces wich be explained by several policies (urban, economic and social) as well as different spatial stratégies practiced in the country during each analysis period. We cite as an example:

A continuous increase in the population since the first RGPH[1] in 1966 in the metropolis, as confirmed by (R. boussof, 2006).

A type of agriculture practiced by the populations. Indeed, after one or two years of food crops, farmers abandon the cultivated plots to colonize new, more fertile forest lands, leaving the former fallow to restore their fertility.

A massive rural exodus (sakhraoui; 2013), the cultivation of fallow land and the extension of cultivated areas and buildings (DAS[2]; 2017).

[1] RGPH: General Population and Housing Census.
[2]DAS: Land Use Planning Directorate.

Fanally; the increasing demand for constructive land puch the locales communities to taken some steps to solve this problem, but more needs to be done. this locales communities can play a vital role in addressing this environmental conflits and creating a more sustainable future city.

5.Conclusion.

The study has provided a clearer picture of the spatial commonalities of large Algerian cities, particularly the major regional metropolises. It is focus on analysis of land use changes dynamics in the Constantine states, from 1984 to 2020. Our analysis shows that the reduction of peri-urban agricultural spaces due to shifting cultivation practices requires a multifaceted approach that considers both the underlying causes and the specific context of each region. In general, **the expansion of urban areas at the expense of agricultural land:** driven by population growth and the demand for housing, infrastructure, and other urban services**. In addition; the deterioration of peri-urban agricultural land:** due to a number of factors, including the encroachment of urban development, the conversion of land to other uses, and unsustainable agricultural practices.

Therefore; the integration of landscape research into local planning processes adds base knowledge to balance economic, social and environmental dimensions in the per urban space. By adopting these study recommendations, decision-makers in Constantine wilaya and other large Algerian cities can effectively address the environmental challenges and ensure a more sustainable future for their communities.

For the better understanding of current LUCL configuration integrate SIG; GEE platform, LCM muddler, remote sensing techniques and high temporal resolution satellite images (Landsat5 TM and Landsat8 OLI) were very demanded and useful. Because it helps to maps different transformations trajectory that happened in our cities. This technichs allowed us to identify strong relations between the different LUCL classifications and the dynamic change calculated. Because; detailed trajectories of spatial change provide crucial information that would otherwise be, absent such as the peaks of change from agricultural/natural area to build up area (artificial area) in per urban spaces.The conversion of agricultural land in per urban spaces to built up land purposes is a major issue in Constantine state and in Alegria.This conversion has a number of négative consequences, including: A decrease in agricultural production. An increase in food prices and Environmental degradation.

At the end, Understanding the change in the spatial pattern of LULC and the revolution of the per urban area over a period study is very much important for better sustainable urban planning and better land management. More than; we recommended that future research should aim at assessing the value of different landscape parts for local and global cities environment in developing countries.

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