RECENZIRANI ČLANKI | PEER-REVIEWED ARTICLES

Kronološki pregled rabe zemljišč v mestu Ali Mendjeli v provinci Constantine (Alžirija)

Diachronic study of land use in the city of Ali Mendjeli, Constantine (Algeria)

Ammar Lakhdar, Toufik Ferhad, Souad Haouari, Mohamed Baadeche

UDK: 528.8:349.414(091)(652)
Klasifikacija prispevka po COBISS.SI: 1.01
Prispelo: 14. 11. 2025
Sprejeto: 2. 3. 2026

DOI: https://doi.org/10.15292/geodetski-vestnik.2026.02.230-247
SCIENTIFIC ARTICLE
Received: 14. 11. 2025
Accepted: 2. 3. 2026

SI | EN

IZVLEČEK

Zaznavanje sprememb je proces, ki temelji na identifikaciji in kvantifikaciji prostorskih sprememb skozi čas na podlagi primerjave kart rabe zemljišč, izdelanih iz satelitskih posnetkov istega preučevanega območja z različnimi datumi. Cilj našega dela je pokazati pomen orodij daljinskega zaznavanja za dolgoročno spremljanje urbanih sprememb ter kvantificirati prostorski in časovni razvoj rabe zemljišč v mestu Ali Mendjeli v 37 letih. Rezultati, pridobljeni s tehniko zaznavanja sprememb, ki temelji na nadzorovani klasifikaciji največje verjetnosti z uporabo posnetkov Landsat za leta 1985, 2006, 2015 in 2022, so pokazali precejšnjo fragmentacijo mest v škodo drugih talnih enot, zlasti enote golih tal, in kmetijskih zemljišč, ki postanejo degradirana. Ugotovitve študije poudarjajo pomen vključevanja daljinskega zaznavanja in GIS-a z diahrono analizo v procese ocenjevanja urbanističnega načrtovanja ter zagotavljanja dragocenih povratnih informacij za izboljšanje prihodnjih strategij načrtovanja, zlasti v kontekstu razvoja novih mest in trajnostne rasti mest.

ABSTRACT

Change detection is a process based on the identification and quantification of spatial changes over time based on the comparison of land use maps produced from satellite images of the same study area with different dates. The aim of our work is to show the importance of remote sensing tools for the long-term monitoring of urban changes and to quantify the spatial and temporal evolution of land use in the city of Ali Mendjeli during 37 years. By applying a change detection technique based on supervised Maximum Likelihood classification using Landsat images for the years 1985, 2006, 2015 and 2022, the results obtained showed that a significant urban fragmentation has occurred to the detriment of the other soil units, particularly the bare soil unit and the degradation of agricultural land. The findings of this study underline the importance of integrating remote sensing and GIS with a diachronic analysis into urban planning evaluation processes and providing valuable feedback for improving future planning strategies, particularly in the context of new city development and sustainable urban growth.

KLJUČNE BESEDE

prostorsko-časovna evolucija, daljinsko zaznavanje, klasifikacija največjega verjetja, zaznavanje sprememb, načrtovanje vrednotenja

KEY WORDS

spatio-temporal evolution, remote sensing and GIS, maximum likelihood classification, change detection, planning evaluation

1 Introduction

Urban land-use change has become one of the most critical issues in contemporary urban studies. Accelerated urbanization, demographic pressure, and increasing demand for housing and infrastructure have profoundly transformed urban landscapes, often generating spatial imbalances, environmental degradation, and challenges for urban governance. Understanding the dynamics of land-use change is therefore essential not only for environmental monitoring but also for evaluating the effectiveness of urban planning policies and development strategies (Aghaloo & Sharifi, 2025; Bikis et al., 2025)

In this context, remote sensing and Geographic Information Systems (GIS) have emerged as powerful tools for monitoring spatio-temporal changes in land use. Multi-temporal satellite imagery enables the identification, quantification, and mapping of land-use transformations over long periods, offering an objective and consistent basis for spatial analysis. Numerous studies have demonstrated the relevance of these tools for analyzing urban expansion, landscape fragmentation, and land conversion processes (Xiuwan, 2002; Souici & Zouak, 2024; Maity & Mishra, 2024).

The study of land use evolution is crucial for understanding and addressing environmental problems and their link to human activities. It reveals how human communities change land use patterns in response to evolving needs, driven by factors like population growth, urbanization, and economic pressure. Research and analyses carried out on land cover and land use form an information base necessary for planners and developers to create informed policies and sustainable management strategies and opt for the best possible decision-making (Van Lier, 1998; Cheshire & Sheppard, 2005; Marchamalo & Romero, 2007; Mosadeghi, 2015).

Spatio-temporal change monitoring studies are possible mainly through the use of remote sensing data and GIS which are widely used to perform change detection and identification. These techniques analyze images of the same area taken at different dates to quantify and identify changes allowing for the monitoring of land use (Dewan & Yamaguchi, 2009; Hegazy, I. R., & Kaloop, 2015; Dechaicha & Alkama, 2020; Das & Angadi, 2022).

The study of the evolution of land occupation and its use is interesting to emphasize environmental problems in general. It is necessary to determine the nature and the mode of intervention of human communities that modify the forms of overall land use according to the evolution of needs. Research and analyses carried out on land cover and land use form an information base necessary for planners and developers (Soto et al., 2024).

Remote sensing makes it possible to monitor spatial changes over large areas, to make comparisons in time and space in order to better understand our space. A multi-temporal analysis of the evolution of the phenomenon from multi-date satellite images, i.e. a diachronic study, makes it possible to better understand the evolution of the surface state and to better interpret the phenomena linked to the modification of this environment (Oussedik *et al.*, 2003; Bouiadjra *et al.*, 2011; Koumassi *et al.*, 2014; Jaziri and Baccouche, 2020; SSH and KA, 2021).

In Algeria, rapid urban growth has posed major challenges to existing cities, particularly large metropolitan areas such as the city of Constantine. During the period 1977-1987, Constantine, metropolis and capital of eastern Algeria, experienced intense demographic growth and urban densification, leading to saturation of its urban fabric and the emergence of socio-spatial dysfunctions, includes congestion, informal housing, and degradation of living conditions (Rebbah, 2014).

The urban expansion of the city of Constantine is a natural reflection of the sharp increase in the number of inhabitants and their needs, which leads to an increase in the demand for land, resulting in enormous and serious problems: socio-economic segregation, difficult car traffic, deterioration of the road network, insecurity, pollution, precarious housing and the proliferation of shanty towns. And for this purpose, the alternative was to create a new urbanization pole designed to alleviate this pressure on the city of Constantine aimed at redistributing population, controlling urban sprawl, and ensuring more structured and sustainable urban development. This is what happened in the city of Ali Mendjeli.

Against this background, the present study adopts a diachronic analysis of land-use change in the city of Ali Mendjeli over a 37-year period (1985–2022), using multi-date Landsat imagery and supervised classification techniques. Beyond simple change detection, this research seeks to interpret observed land-use dynamics in relation to urban planning intentions and development strategies, thereby contributing to a more integrated understanding of urban growth processes in new towns.

2 Materials and Methods

2.1 Study Area

The city of Constantine is part of the North East of Algeria, it is roughly bounded to the North and the South respectively by the latitudes 36 ° 27” 35 “N and 36 ° 16” 30 “ N, as to the East and the West by longitudes 6 ° 49’30 “E and 6 ° 37 “30” E. The city of Constantine is one of the largest cities in the country; known for its bridges and rich history, and covers an area of approximately 2297 km².

The city of Ali Mendjeli is located on the Ain el Bey plateau. It is located about fifteen kilometers south of the city of Constantine, a twelve kilometers west of the city of Khroub, and about ten kilometers east of the city of Ain Smara with an area of 2946 ha (Figure 1).

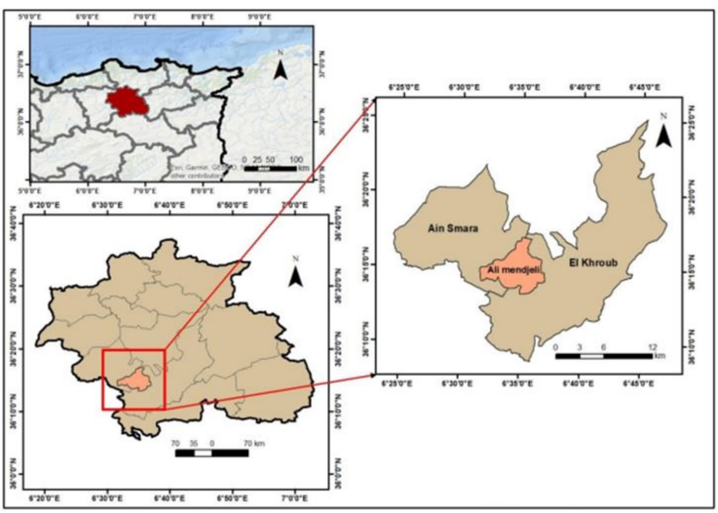

Figure 1: Situation map of the city of Ali Mendjeli

The town of Ali Mendjeli is located on the Ain El Bey plateau with a calm but varied topography, which rises between 692 m and 864 m with a dominant altitude (41.11%) between 780m and 820m (Figure 2).

The physical space of the city Ali Mendjeli is modeled according to four classes of slopes (Figure 3) where more than 95% of the slopes are less than 15%. The dominant class of slopes is between 5% and 10% with a percentage of 47.59%.

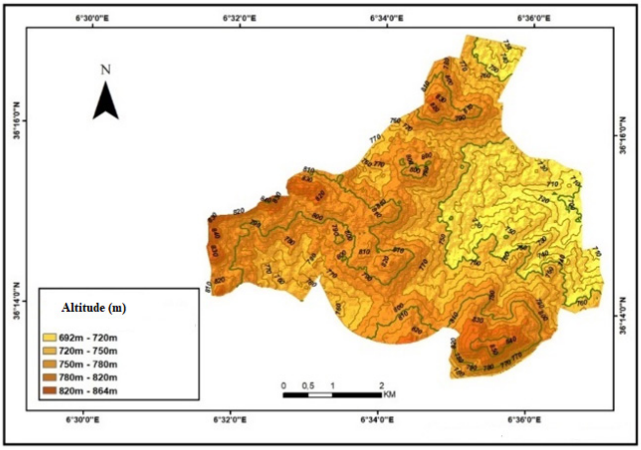

Figure 2: Altitude map of the city of Ali Mendjeli

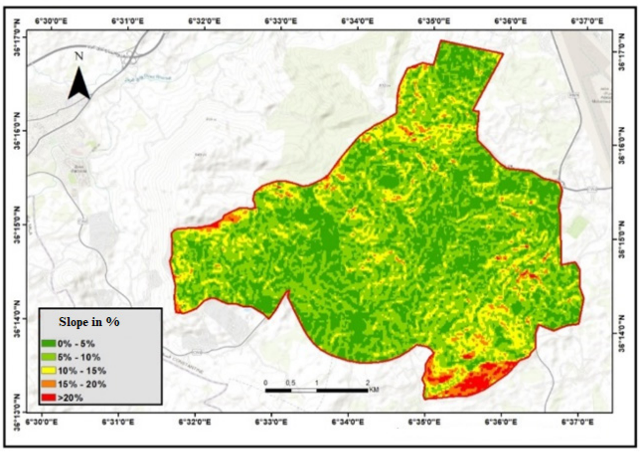

Figure 3: Slope map of the city of Ali Mendjeli

The Ain El Bey plateau is made up, almost essentially, of backfill material from topographic depressions characterized by the abundance of coarsely detrital elements, in the first levels appearing to belong to the Upper Miocene (Bouguebrine *et al.*, 2022). According to the geological map of Oued Athmenia at 1/50,000, this backfill material is made up of hard or cavernous red, pinkish or brownish travertine limestones and lacustrine marls, breccias, conglomerates, sandstones and continental sands (Figure 4).

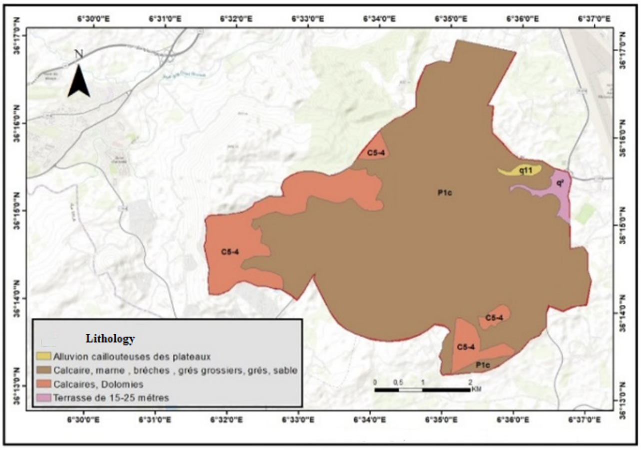

Figure 4: Lithological map of the city of Ali Mendjeli

2.2 Methodology

Data sources

Monitoring landscape changes through land use analysis in the study area during the period [1985-2022] is based on the analysis of multi-date satellite images acquired from two sources: Landsat 5 TM satellite images for the years 1985 and 2006 and Landsat 8 OLI for the years 2015 and 2022; hence, four scenes were downloaded from earthexplorer.usgs.gov. All images have a spatial resolution of 30 m and were acquired during comparable seasonal periods in order to ensure consistency for change detection and land cover mapping. The Landsat data were chosen for their long temporal continuity, radiometric consistency, and suitability for long-term urban change analysis. The satellite data characteristics are shown in Table 1.

Table 1: Satellite data characteristics

Year	1985	2006	2015	2022
Acquisition date	09 May 1985	10 May 2006	17April 2015	14 May 2022
Sensor	Landsat 5 TM	Landsat 5 TM	Landsat 8 OLI	Landsat 8 OLI
Resolution	30m	30m	30m	30m

Supervised classification

To carry out our study, we adopted a method based on the Maximum Likelihood classification (Bolstad and Lillesand, 1991) which is a parametric supervised classification and one of the most widely applied and statistically robust classification methods in urban remote sensing studies (Patil et al., 2013; Liang et al., 2021). This algorithm assumes a normal distribution of spectral values and assigns each pixel to the class for which it has the highest probability of membership. In which the objective is to study the evolution of land use (quantitative and qualitative change) in the city Ali Mendjeli during 37 years, Land-use maps for each reference year were produced using the ML classification method and Three main land-use classes were identified based on the characteristics of the study area: Built-up areas, Vegetation and Bare ground. Two phases are generally used in a supervised classification; training phase and validation phase.

- **Training and sample extraction**

In the training phase (learning), the extraction of training samples, to improve the discrimination of land-use classes, two widely used spectral indices were used:

- Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), which highlights vegetated areas and provides information on vegetation density and health. The NDVI is given by

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

- Normalized Difference Built-up Index (NDBI) (Zha et al., 2003), which enhances built-up surfaces and facilitates the identification of urban areas. The NDBI is given by

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{2}$$

Where, NIR is the near infrared band, RED is the red band and SWIR is the short wave infrared band.

The NDVI values are between -1 and +1, with positive values close to 1 indicating a plant formation rich in chlorophyll. The NDBI index also takes its values between -1 and +1, a value closer to 1 of this index indicates a high density of built-up land.

In addition, true-color and false-color composites were generated to support visual interpretation and training sample selection. The combined use of spectral indices and color composites improved class separability and reduced confusion between spectrally similar surfaces.

For each reference year, a stratified random sampling strategy was adopted to ensure a balanced and representative selection of training samples for each land-use class. Training samples are distributed across the entire image and a minimum of 30 training polygons per class were selected for 1985 and 2006, and at least 20 polygons per class for 2015 and 2022, depending on landscape heterogeneity and image quality. All steps of the classification procedure was carried out using the Arcgis 10.3 software.

- **Accuracy Assessment and Validation**

Evaluating data accuracy is an essential step in remote sensing which determine the informational value of a resulting data processing to a user (Rwanga and Ndambuki 2017).

In the validation phase, the accuracy of each classified map was evaluated using a confusion matrix, which compares classified pixels with reference data extracted from **Google Earth Pro** high-resolution imagery as the «ground truth».

For each classified map, independent validation points were generated using a stratified random approach. A total of 80 validation points were used for 1985, 85 for 2006, 42 for 2015, and 65 for 2022, proportionally distributed among land-use classes.

For earlier years (1985 and 2006), historical imagery archives were consulted to ensure temporal consistency. Although Google Earth Pro imagery may not provide complete temporal coverage for older dates, it remains widely used in land-use validation studies due to its high spatial resolution and accessibility.

In addition to the overall accuracy (OA), the following accuracy metrics were calculated:

- Manufacturer accuracy (MA), indicating the probability that a reference pixel is correctly classified;
- User accuracy (UA), indicating the probability that a pixel which has been classified in a class actually belongs (in the real world) to that class;
- Kappa coefficient (Landis and Koch, 1977), used to assess the level of agreement between the classified maps and reference data (ground truth) beyond chance. This index indicates that the classification is good and we can move on to the change detection stage or a return to the training phase is necessary (Table 2).

The accuracy formulas are given by

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixels}}{\text{Total number of reference pixels}} * 100 \tag{3}$$

$$\text{Manufacturer accuracy} = \frac{\text{Number of correct pixels in that class}}{\text{Total number of reference pixels for that class}} * 100 \tag{4}$$

$$\text{User accuracy} = \frac{\text{Number of correct pixels in that class}}{\text{Total number of classified pixels into that class}} * 100 \tag{5}$$

$$\text{kappa coeffecient} = \frac{TS * TCS - \Sigma(\text{colum total } * \text{ row total})}{TS^2 - \Sigma(\text{colum total } * \text{ row total})} * 100 \tag{6}$$

TS: Total Samples.

TCS: Total Corrected Samples.

Table 2: Interpretation of the Kappa index values (Landis and Koch, 1977)

Kappa index values	Classification Accuracy Interpretation
0,81 - 1,00	Excellent
0,61 - 0,80	Good
0,41 - 0,60	Moderate
0,21 - 0,40	Poor
0,00 - 0,20	Bad
<0.0	Very Bad

An overall accuracy of 100% (1.0) and a Kappa coefficient of +1.0 indicate Perfect Agreement between the classification and the ground truth.

- **Change detection analysis**

Land-use change detection was carried out by overlaying classified maps from successive dates and analyzing pixel-by-pixel transitions between land-use classes. This approach allows the identification, quantification, and spatial localization of land-use transformations over time.

In the change detection step, a land use change rate is calculated. This change rate is a measure that allows us to assess the intensity and speed at which land use classes change over time. It indicates the percentage change between two specific time periods and is given by the following formula:

$$\text{Rate of Change} = \frac{\text{final Value - initial Value}}{\text{initial Value}} * 100 \tag{7}$$

In our study, this indicator facilitates comparison between different development phases of the city Ali Mendjeli and supports interpretation of urban growth dynamics in relation to planning objectives.

3 Results and Discussion

3.1 Results

In this section we present the results obtained by the classification method (land use maps) as well as the different changes between the thematic classes (change maps) for the different dates used in this study. The flowchart of the adopted method is given in Figure 5.

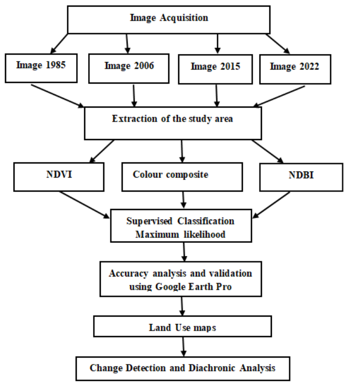

Figure 5: Methodology flowchart.

3.1.1 Spatio-temporal Evolution of Land Use

The land-use classification results reveal a profound transformation of the urban landscape of Ali Mendjeli between 1985 and 2022, reflecting successive phases of urban development associated with the implementation of the new city project.

Year 1985

The confusion matrix established from the reference data and the classified image for the year 1985 is given by Table. 3. The Kappa index and the overall accuracy calculated from this matrix are equal to 0.7301 and 82.5% respectively which means that the classification is good and the land use map of this year in which three main classes are distinguished is given by Figure 6.

Table 3: Confusion matrix for the classification of the image of 1985.

	Built	Bare Ground	Vegetation	Total	Kappa	UA
Built	23	7	0	30		23/30 (76.7%)
Bare Ground	2	28	0	30		28/30 (93.3%)
Vegetation	1	4	15	20		15/20 (75%)
Total	26	39	15	80		
Kappa					**0.7301**	
MA	23/26 (88.5%)	28/39 (71.8%)	15/15 (100%)			OA 66/80 (**82.5%**)

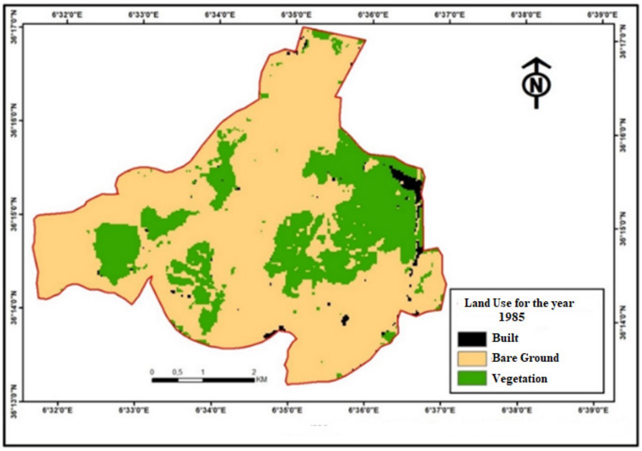

Figure 6: Land use map of the city of Ali Mendjeli for the year 1985.

In 1985, the new city Ali Mendjeli was almost an empty area, the bare ground is the dominant class which it occupies a very large area of about 2127 ha (72.19% of the total area), the area covered by the vegetation class is 780.55 ha (26.49% of the total area), and concerning the built class it represents a very small area compared to the other classes 38.77 ha (1.32% of the total area) (Table. 4).

This configuration corresponds to the pre-urbanization stage of the site, prior to the effective launch of urban development programs. At this stage, land use was dominated by undeveloped land, indicating the availability of extensive land reserves intended for future urban expansion.

Table 4: Areas of thematic classes of the year 1985.

Occupation Classes	Surface (ha)	Percentage (%)
Bare Ground	2127,00	72,19%
Vegetation	780,23	26,49%
Built	38,77	1,32%
Total	2946	100%

Year 2006

From the confusion matrix of the classification for the year 2006 given in Table 5, the Kappa index and the overall accuracy calculated from this matrix are equal to 0.6674 and 77.6% which means also that the classification is good and the land use map of this year is given by Figure 7.

Table 5: Confusion matrix for the classification of the image of 2006.

	Built	Bare Ground	Vegetation	Total	Kappa	UA
Built	29	0	1	30		29/30 (96.7%)
Bare Ground	2	15	13	30		15/30 (50%)
Vegetation	1	2	22	25		22/25 (88%)
Total	32	17	36	85		
Kappa					**0.6674**	
MA	29/32 (90.6%)	15/17 (88.2%)	22/36 (61.1%)			OA 66/85 (**77.6%**)

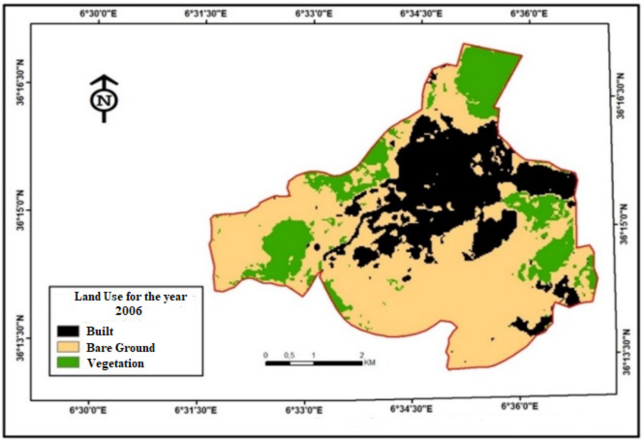

Figure 7: Land use map of the city of Ali Mendjeli for the year 2006.

In 2006, the dominant class is also the bare land, which occupies a significant area of approximately 1676.48 ha (57% of the total area), followed by the built class with an area of 768.75 ha (26% of the total area) and finally the vegetation class with an area of 501.03 ha (17% of the total area) (Table 6).

Table 6: Areas of thematic classes of the year 2006.

Occupation Classes	Surface (ha)	Percentage (%)
Bare Ground	1676.48	56,90%
Vegetation	768.75	26.09%
Built	501.03	17,01%
Total	2946	100%

Despite the sharp increase in urban areas at the expense of agricultural land, which is considered to be low-fertility land in the new city, the area of agricultural land has not decreased significantly because the northern region was bare ground in 1985 and became vegetated ground in 2006.

Year 2015

The confusion matrix of the classification for the year 2015 is given in Table 7. The Kappa index and the overall accuracy calculated from this matrix are equal to 0.926 and 95.2% which means that the classification is excellent and the land use map of this year is given by Figure 8.

Table 7: Confusion matrix for the classification of the image of 2015.

	Built	Bare Ground	Vegetation	Total	Kappa	UA
Built	14	1	0	15		14/15 (93.3%)
Bare Ground	0	15	0	15		15/15 (100%)
Vegetation	0	1	11	12		11/12 (91.7%)
Total	14	17	11	42		
Kappa					**0.926**	
MA	14/14 (100%)	15/17 (88.2%)	11/11 (100%)			OA 40/42 (**95.2%**)

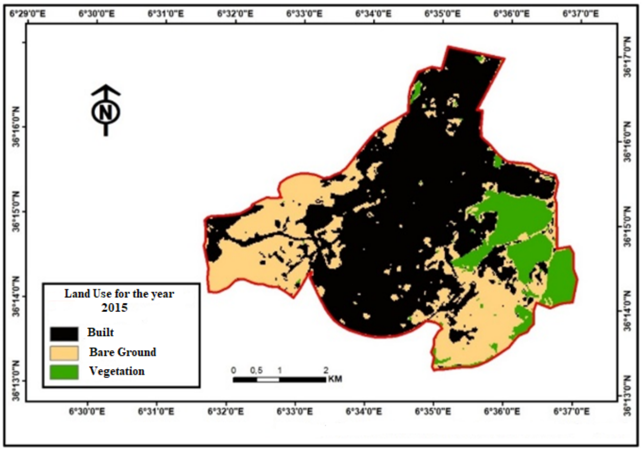

Figure 8: Land use map of the city of Ali Mendjeli for the year 2015.

According to this figure, the most dominant class is the built class with an area of 1807 ha (59% of the total area), the bare ground class occupies 837 ha (30% of the total area) and the vegetation covers 302 ha (11% of the area) (Table 8).

Table 8: Areas of thematic classes of the year 2015.

Occupation Classes	**Surface (ha)**	**Percentage (%)**
Built	1807	58,69
Bare Ground	837	29,94
Vegetation	302	11,37
Total	2946	100%

In 2015, we observed a significant urban sprawl in the city of Ali Mendjeli, which confirms the continuation of the implementation of the new city program to the detriment of bare land (the creation of all neighborhood units).

Year 2022

The confusion matrix of the classification for the year 2022 is given in Table 9. The Kappa index and the overall accuracy calculated from this matrix are equal to 0.8309 and 89.2% respectively which indicates a good to excellent level of agreement according to the interpretation scale of Landis and Koch (1977). The land use map of this year is given in Figure 9.

Table 9: Confusion matrix for the classification of the image of 2022.

	Built	**Bare Ground**	**Vegetation**	**Total**	**Kappa**	**UA**
Built	29	1	0	30		29/30 (96.7%)
Bare Ground	2	15	3	20		15/20 (75%)
Vegetation	1	0	14	15		14/15 (93.3%)
Total	32	16	17	65		
Kappa					**0.8309**	
MA	29/32 (90.6%)	15/16 (93.8%)	14/17 (82.3%)			OA 58/65 (**89.2%**)

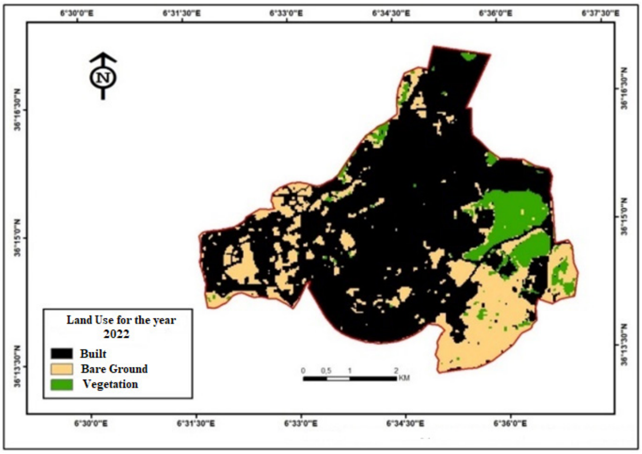

Figure 9: Land use map of the city of Ali Mendjeli for the year 2022.

According to figure 9, the most dominant class is the built class with an area of 2111 ha (72% of the total area), the bare ground class occupies 603 ha (20% of the total area) and the vegetation covers 232 ha (8% of the area) (Table 10).

Table 10: Areas of thematic classes of the year 2022.

Occupation Classes	Surface (ha)	Percentage (%)
Built	2111	71.66%
Bare Ground	603	20.47%
Vegetation	232	7.87%
Total	2946	100%

In 2022, built-up areas further increased (realization of UV 21, the South extension and the West extension), although at a relatively slower rate compared to the previous phase. This trend suggests a transition toward a more mature stage of urban development, characterized by consolidation and densification rather than extensive spatial expansion. The persistence of urban growth reflects continued demographic demand, while the reduction of available bare land indicates a progressive saturation of developable space within the planned perimeter of the new city.

Overall, Kappa values ranging between 0.667 and 0.926 indicate good to excellent agreement levels, confirming the reliability of the classification results for subsequent change detection analysis.

3.1.2 Land-Use Change Detection and Urban Dynamics

This technique allows us to follow the changes in land use in chronological order between different dates; it consists of comparing the values of the pixels of each classified image, to determine the type, the surface, and the location of the changes in the city of Ali Mendjeli, which can be anthropogenic or natural.

a- The change between 1985 and 2006

The operation of the intersection between the land use maps of the two years 1985 and 2006 gives the identification and the quantification of the changes between these two dates (Figure 10) and the surfaces of the different changes are given in Table 11.

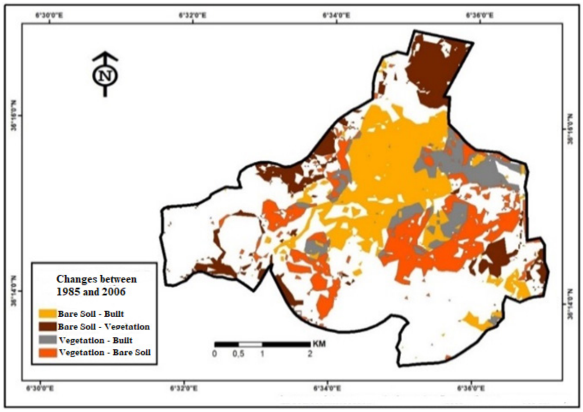

Figure 10: Map of changes between 1985 and 2006.

Table 11: Change surfaces between 1985 and 2006.

	Land use 1985	Land use 2006	Change surface (ha)	(%)
1	Vegetation	Built	201	14.05%
2	Bare Ground	Built	530	37.04%
3	Bare ground	Vegetation	310	21.66%
4	Vegetation	Bare Ground	390	27.25%
Total	-	-	1431	100%

According to the map of changes and the Table of areas, the change in land use between the two years 1985 and 2006 presents a deep dynamic of land use in the studied area.

By 2006, a significant increase in built-up areas is observed, marking the first major phase of urbanization. This expansion corresponds to the initial implementation of the new city policy, aimed at accommodating population overflow from the saturated urban core of Constantine. Urban growth during this period primarily occurred at the expense of bare land, reflecting a planned conversion process consistent with the objectives of structured urban development.

The results reveal a trend towards increasing buildings (731 ha), which can be seen that the East and North East of the new city were the subject of new urbanization areas, where 530 ha of bare land and 201 ha of vegetation areas are urbanized.

b- The change between 2006 and 2015

The operation of the intersection between the land use maps of the two years 2006 and 2015 gives the identification and the quantification of the changes between these two dates (Figure 11) and the surfaces of the different changes are given in Table 12.

Table 12: Change surfaces between 2006 and 2015.

	Land use 2006	Land use 2015	Change surface (ha)	(%)
1	Vegetation	Built	218	15.59%
2	Vegetation	Bare Ground	162	11,59%
3	Bare ground	Built	836	59,80%
4	Bare Ground	Vegetation	182	13,02%
Total	-	-	1550	100%

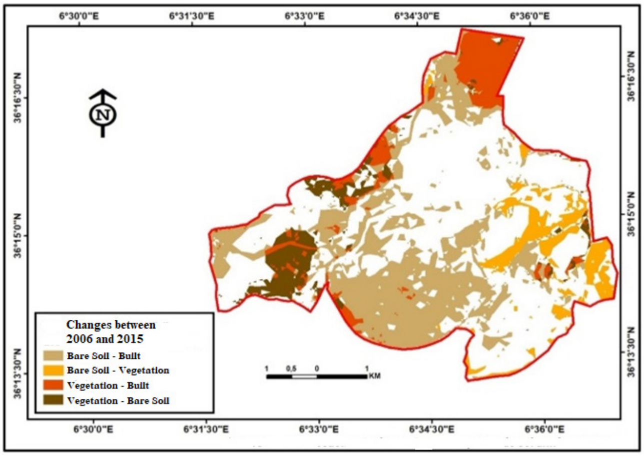

Figure 11: Map of changes between 2006 and 2015.

The period 2006–2015 represents the most dynamic phase of land-use change. Built-up areas expanded rapidly, becoming the dominant land-use class; a large area of bare and vegetated soils were transformed into buildings (836ha and 218ha). This acceleration coincides with the intensification of housing programs and the construction of neighborhood units (UVs), confirming the central role of Ali Mendjeli as a strategic growth pole within the metropolitan system of Constantine. The magnitude of land conversion during this period highlights both the effectiveness of the new town in absorbing urban growth and the strong spatial pressure exerted on non-built surfaces.

c- The change between 2015 and 2022

The operation of the intersection between the land use maps of the two years 2015 and 2022 gives the identification and quantification of the changes between these two dates (Figure. 12) and the areas of the different changes are given in Table 13.

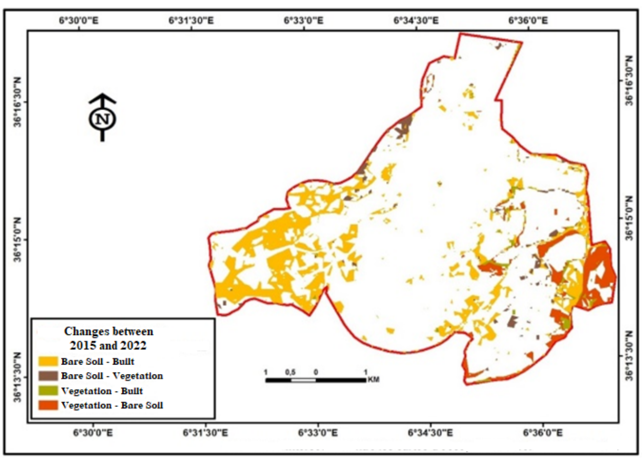

Figure 12: Map of changes between 2015 and 2022.

Table 13: Change surfaces between 2015 and 2022.

	Land use 2015	Land use 2022	Change surface (ha)	(%)
1	Vegetation	Built	30	5.16%
2	Vegetation	Bare Ground	112	19.28%
3	Bare ground	Built	398	68,50%
4	Bare Ground	Vegetation	41	7.06%
Total	-	-	581	100%

The same types of changes occurred during the period 2015 - 2022 in the city of Ali Mendjeli; the urban sprawl in favor of the bare and vegetated soils and the degradation of agricultural land (112ha). A large area of bare and vegetated soils were transformed into buildings (398ha and 30ha).

In this period, land-use changes remained significant but showed a relative slowdown. Urban growth continued mainly through the extension of existing urban sectors, notably in the southern and western extensions of the new city. This spatial configuration suggests a shift from extensive expansion toward infill development and the completion of previously planned urban zones.

Overall, during the period 1985 – 2022 (37 years), fundamental changes occurred in the city of Ali Mendjeli, where the most significant were the urban sprawl and the degradation of agricultural land.

d- Rate of change

After detecting changes between different dates, the rates of change between the areas of the land use classes in the time interval [1985-2022] are calculated (Table 14). Positive values represent a progression of the area of the class during the analyzed period and negative values indicate a regression of the area of a class between the two years.

Table 14: Rate of change in land use in the city Ali Mendjeli between 1985 and 2022.

	Rate of change 1985-2006	Rate of change 2006-2015	Rate of change 2015-2022
Built	1882,85	135.05	16.83
Vegetation	-35,78	-33.13	-23.17
Bare Ground	-21,19	-50.06	-27.95

According to Table 13, we notice that the rate of change of buildings in the three periods is very high, this shows that there is a very significant urban progression especially between the years 1985 and 2006, with a slowdown in the evolution in the second and third periods because of the implementation of the majority of housing programs in the city of Ali Mendjeli. On the other hand, a negative rate of change shows a significant regression for the bare ground and vegetation classes in the three periods.

3.2 Discussion: Planning Effectiveness and Spatial Implications

The observed land-use transitions can be directly linked to successive planning phases of the Ali Mendjeli new town project. The period 1985–2006 corresponds to the initial implementation phase, during which the first neighborhood units (UVs) were developed following the strategic objective of relieving demographic pressure from Constantine.

The accelerated transformation observed between 2006 and 2015 coincides with the large-scale national housing programs launched by the Algerian government, particularly social housing and AADL schemes, which significantly increased the built-up footprint of the city.

The 2015–2022 phase reflects a consolidation stage, marked by southern and western extensions (including UV 21 and peripheral sectors), indicating a transition from expansion toward spatial completion and densification within the planned urban perimeter.

Beyond the quantitative assessment of land-use change, the results provide important insights into the effectiveness of planned urban development in the city of Ali Mendjeli. The observed land-use dynamics indicate that, unlike many cases of uncontrolled urban sprawl, urban expansion in the city of Ali Mendjeli has largely occurred within the framework of a planned new city, following a spatial logic defined by planning instruments and development programs.

However, the results also reveal certain spatial imbalances. The progressive reduction of vegetated areas and the dominance of built-up land raise questions regarding environmental sustainability and the integration of green spaces within the urban fabric. While the conversion of bare land was an expected outcome of the new city strategy, the long-term implications of limited vegetation cover deserve further attention from urban planners.

From a planning perspective, the case of city Ali Mendjeli demonstrates that remote sensing-based diachronic land-use analysis can serve as an effective tool for evaluating the spatial outcomes of urban policies. By comparing intended land-use allocations with actual spatial transformations, such analyses provide valuable feedback for improving future planning strategies, particularly in the context of new town development and sustainable urban growth.

Given that the long-term sustainability of the urban system depends on a more balanced land-use structure that preserves environmental functions and enhances urban livability, Future planning efforts should therefore prioritize the protection and integration of green spaces, as well as the monitoring of land-use change as a continuous decision-support process rather than a purely descriptive exercise.

4 Conclusion

This study provided a diachronic analysis of land-use change in the new city of Ali Mendjeli over a 37-year period (1985–2022) using multi-temporal Landsat imagery and supervised classification method. The results reveal a profound transformation of the study area, characterized by a progressive dominance of built-up land at the expense of bare and vegetated surfaces, reflecting successive phases of planned urban development.

Beyond documenting spatial change, the analysis highlights the strong relationship between land-use dynamics and urban planning policies. The most intense phase of urban expansion coincides with the acceleration of state-led housing programs, confirming the central role of Ali Mendjeli as a strategic planning instrument aimed at relieving demographic and spatial pressure on the city of Constantine. The relative slowdown observed after 2015 suggests a transition toward a more mature stage of urban development, marked by consolidation rather than extensive expansion.

Overall, the findings demonstrate that remote sensing and GIS-based change detection are not merely descriptive tools, but effective analytical instruments for evaluating the spatial outcomes of planned urbanization. The case of the city of Ali Mendjeli illustrates both the capacity of the new town model to structure urban growth and the need for continuous monitoring to ensure long-term spatial balance and sustainability.

Policy Implications

From a policy and planning perspective, the results of this study carry several important implications. First, the effectiveness of new towns as tools for managing metropolitan growth depends on regular spatial evaluation using objective and quantitative methods. Integrating remote sensing and GIS into planning monitoring frameworks would enable decision-makers to assess whether land-use evolution remains consistent with initial planning objectives.

Second, the progressive reduction of vegetated areas highlights the need to strengthen environmental considerations within urban development strategies. Urban planning policies should place greater emphasis on the preservation and integration of green spaces in order to enhance environmental quality and urban livability.

Finally, this research underscores the value of diachronic spatial analysis as a decision-support tool for future urban projects. By linking observed land-use changes to planning strategies, such approaches can inform adaptive planning practices, improve the management of new town development, and contribute to more sustainable and resilient urban growth models in rapidly urbanizing contexts.

References

Aghaloo, K., & Sharifi, A. (2025). Balancing priorities for a sustainable future in cities: Land use change and urban ecosystem service dynamics. Journal of Environmental Management, 382, 125460.

Bensaid, A., Mostephaoui, T., & Nedjai, R. (2021). Apport des images ETM+ et du SIG dans la détection des changements dynamiques de l'espace steppique de Naâma, Algérie. Revue Marocaine des Sciences Agronomiques et Vétérinaires, 9(4), 629-642.

Bikis, A., Engdaw, M., Pandey, D., & Pandey, B. K. (2025). The impact of urbanization on land use land cover change using geographic information system and remote sensing: a case of Mizan Aman City Southwest Ethiopia. Scientific Reports, 15(1), 12014.

Bolstad, P. & Lillesand, T. M., (1991). Rapid maximum likelihood classification. Photogrammetric engineering and remote sensing, 57(1) : 67-74.

Bouguebrine, M., Alkama, D., & Bouadam, R. (2022). La Hiérarchie fonctionnelle du système urbain de la ville nouvelle Ali Mendjeli. Journal of Humen Sciences, 9(1), 850-861.

Bouiadjra, S. E. B., Zerey, W. E. & Benabdeli, K., (2011). Étude diachronique des changements du couvert végétal dans un écosystème montagneux par télédétection spatiale : cas des monts du Tessala (Algérie occidentale). Physio-Géo. Géographie physique et environnement, 5, 211-225.

Cheshire, P., & Sheppard, S. (2005). The introduction of price signals into land use planning decision-making: a proposal. Urban studies, 42(4), 647-663.

Das, S., & Angadi, D. P. (2022). Land use land cover change detection and monitoring of urban growth using remote sensing and GIS techniques: A micro-level study. GeoJournal, 87(3), 2101-2123.

Dechaicha, A., & Alkama, D. (2020). Détection du changement de l'étalement urbain au Bas-Sahara algérien: apport de la télédétection spatiale et des SIG. Cas de la ville de Biskra (Algérie). Revue Française de Photogrammétrie et de Télédétection, (222), 43-51.

Dewan, A. M., & Yamaguchi, Y. (2009). Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka Metropolitan of Bangladesh during 1960–2005. Environmental monitoring and assessment, 150(1), 237-249.

Hegazy, I. R., & Kaloop, M. R. (2015). Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. International journal of sustainable built environment, 4(1), 117-124.

Jaziri, B. & Baccouche, N., (2020). Suivi par télédétection de la dynamique de la végétation de Jbel Bil Lahrish un an après l'incendie de 2017 (Bizerte-Beja, Tunisie septentrionale). Geo-Eco-Trop, 44(1), 65-82.

Koumassi, D. H., Tchibozo, A. E., Vissin, E. W. & Houssou, C. S., (2014). SIG et télédétection pour l'optimisation de la cartographie des risques d'inondation dans le bassin de la Sota au Bénin. Rev. Ivoir. Sci. Technol, 23, 137-152.

Landis, J. R. & Koch, G. G., (1977). An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. Biometrics, 33(2), 363-374.

Liang, F., Zhang, X., Li, H., Yu, H., Lin, Q., Jiang, M., & Zhang, J. (2021, November). Land use classification based on maximum likelihood method. In Advances in Intelligent Data Analysis and Applications: Proceeding of the Sixth Euro-China Conference on Intelligent Data Analysis and Applications, 15–18 October 2019, Arad, Romania (pp. 133-139). Singapore: Springer Singapore.

Maity, N., & Mishra, V. N. (2024). Urban Growth Analysis Using Multi-Temporal Remote Sensing Image and Landscape Metrics for Smart City Planning of Lucknow District, India. Engineering Proceedings, 82(1), 59.

Marchamalo, M., & Romero, C. (2007). Participatory decision-making in land use planning: An application in Costa Rica. Ecological Economics, 63(4), 740-748.

Mosadeghi, R., Warnken, J., Tomlinson, R., & Mirfenderesk, H. (2015). Comparison of Fuzzy-AHP and AHP in a spatial multi-criteria decision making model for urban land-use planning. Computers, Environment and Urban Systems, 49, 54-65.

Oussedik, A., Iftene, T. & Zegrar, A., (2003). Réalisation par télédétection de la carte d'Algérie de sensibilité à la désertification. Science et changements planétaires/ Sécheresse, 14(2), 121-127.

Patil, M. B., Desai, C. G., & Umrikar, B. N. (2012). Image classification tool for land use/ land cover analysis: A comparative study of maximum likelihood and minimum distance method. International Journal of Geology, Earth and Environmental Sciences, 2(3), 189-196.

Rebbah, I. (2014). Croissance et étalement urbain de la ville de Constantine « La planification urbaine à L'épreuve », Thèse de Doctorat, Université d'Oum el Bouaghi, Algérie.

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. Third ERTS Symposium, NASA SP-351 I, 309-317.

Rwanga S.S., Ndambuki J.M. 2017. Accuracy assessment of land use/land cover classification using remote sensing and GIS. International Journal of Geosciences, 8(4), 611.

Soto, S., Hamouda, A., & Rebah, H. (2024). Monitoring and quantification of rural urbanisation: Case of Arris and Theniet Elabed, Algeria. Glasnik Srpskog geografskog drustva, 104(2), 95-108.

Souici, I., & Zouak, Z. (2024). Land Use/Land-Cover changes and their impacts on ecosystem services values: a spatio-temporal analysis in Mila, Algeria from 1994-2024. Indonesian Journal of Social Science Research, 5(2), 471-483.

SSH, B., & KA, N. (2021). Dynamique spatio-temporelle de l'occupation du sol et du couvert forestier dans les Hautes Terres Fraîches de Lubero (RD Congo). Geo-Eco-Trop, 45(4), 641-658.

Van Lier, H. N. (1998). The role of land use planning in sustainable rural systems. Landscape and Urban Planning, 41(2), 83-91.

Xiuwan, C. (2002). Using remote sensing and GIS to analyse land cover change and its impacts on regional sustainable development. International journal of remote sensing, 23(1), 107-124.

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. International Journal of Remote Sensing, 24(3), 583-594.

Lakhdar A., Ferhad T., Haouari S., Baadeche M. (2026). Diachronic study of land use in the city of Ali Mendjeli, Constantine (Algeria). Geodetski vestnik, 70 (2), 230-247.
DOI: https://doi.org/geodetski-vestnik.2026.02.230-247

Ammar Lakhdar, Ph.D. in Territorial Planning
Faculty of Earth Sciences, Geography and Territorial Planning
Constantine, Algeria
E-mail: lakhdar.amar@yahoo.fr

Toufik Ferhad, Ph.D. in Territorial Planning
Faculty of Earth Sciences, Geography and Territorial Planning
Constantine, Algeria
E-mail: toufikferhad90@gmail.com

Souad Haouari, Ph.D. in Territorial Planning
Faculty of Earth Sciences, Geography and Territorial Planning
Constantine, Algeria
E-mail : souadhou95@gmail.com

Mohamed Baadeche, Prof. in Computer Science
Faculty of Earth Sciences, Geography and Territorial Planning
Constantine, Algeria
E-mail: baadechemohamed@yahoo.fr