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MONITORING AND QUANTIFICATION OF RURAL URBANISATION. CASE OF ARRIS AND THENIET ELABED, ALGERIA

Abstract: In recent decades, rural agglomerations in the Aurès (Algeria) have undergone an to increasing human pressure and major transformations within an uncontrolled urbanization leading not only to a loss of natural and agricultural areas but an intensive artificialization of ecosystems as well. Regular monitoring of urban growth and updated data of the present state of land use are key steps for any action striving for sustainability in the Aurès region. The main objective of this research is to assess and quantify the spatial growth of two rural communities of the Aurès: Arris and Teniet El Abed during the period 1992 – 2022, through a quantitative approach based on the use of multi- date satellite images and the application of landscape metrics. The results reveal a clear unevenly expansion of the urban fabric, with varying rates depending on the period considered, but a bit faster during the period (2002 – 2013). In addition, it appears that development of the urban patch followed at first a continuous mode of spatial growth, then transitioned to a more scattered and fragmented urban form. The study conclusions are not only useful for developing and implementing national policies and programs, but also for assessing and monitoring progress seeking achievement towards Sustainable Development Goals.

Key words: urban expansion, remote sensing, landscapes metrics, rural area, Aurès, sustainable development

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Introduction

In recent years, there has been a strong focus on the challenges of urban sprawl and the crucial role of cities in the implementation of sustainable development. While these issues are of great importance, it is essential to recognize that rural territories are also a key pillar of sustainable development. Rapid urban growth has led to significant transformations in rural landscapes. During the urbanization process, many villages become cities or become part of a city due to urban expansion (Wang et al., 2011).

In Algeria, rural areas are undergoing very significant changes due to accelerated urbanization, generating many small urban centres and a new spatial organization with an increasing competition in land use. Depending on regions, these changes illustrate the evolution of land use resulting from a long-term interaction between humans and the environment, and policies adopted.

The rural regions of Aurès have undergone increasing human pressure and major transformations during the last decades, whether on their proliferating peripheries or their old historical centre (Barrou, 2019). Consequently, an uncontrolled urbanization took place to the detriment of natural and agricultural land combined to an intensive artificialization of ecosystems. As a result, regular monitoring of urban growth and updated knowledge of situation of land use are key steps for any sustainability project in Aurès (Aguejdad & Hubert-Moy, 2016).

The main objective of this research is to evaluate and quantify the spatial growth of two rural communities of the Aurès: Arris and Teniet El Abed (Algeria) during the period 1992 – 2022, through a quantitative approach based on the use of multi-date satellite images and the application of landscape metrics.

Remote sensing and geographic information systems (GIS) have been widely used to understand spatiotemporal patterns of urbanization (Jenerette et al., 2011). These tools are powerful and cost-effective for assessing spatial dynamics and temporal urbanization and land cover use (LULC). They can also help to identify laws violations and regulations and support the development of appropriate plans for sustainable urban growth (Geymen & Baz, 2008). Change sensing is one of the key innovations brought by these new technologies. This method is based on a comparison of multi-date satellite scenes, while the result is the identification of the biophysical change in land cover during a specific period. The change can be illustrated by calculating the change in radiance of the same pixels, measured at two different times (Singh, 1989; Mas, 2000; Daikh & Debache-Benzegouta, 2022).

Landscape metrics are also appropriate indicators for assessing land use change in a specific time period. They are applied to characterize the process of urban expansion (Barnsley & Barr, 1997; Alberti & Waddell, 2000; Herold et al., 2002) and to describe the ways in which the urban and rural landscape are organized (Lehmkul & Ruggiero, 1991; Cissel et al., 1999; Fu & Chen, 2001; Daikh, 2022). These landscape indices represent algorithms that quantify specific features of the spatial structure of parcels/polygons. They are calculated in relation to defined spatial units (Gulinck & Wagendorp, 2002).

Materials and Methods

Study area

The communities of Arris and Teniet El Abed are two neighbouring communes located in the wilaya of Batna, they are part of the Aures region, a mountainous region in northeastern Algeria. Arris is located on the right bank of the valley of oued El Abiod, at a distance of 60 km south-east of the Wilaya of Batna, along the national road N° 31 which connects Batna to Biskra. On the other hand, Teniet El Abed is located in the valley of the oued Abdi, south of the capital of the wilaya, along the national road N° 87 (Fig. 1).

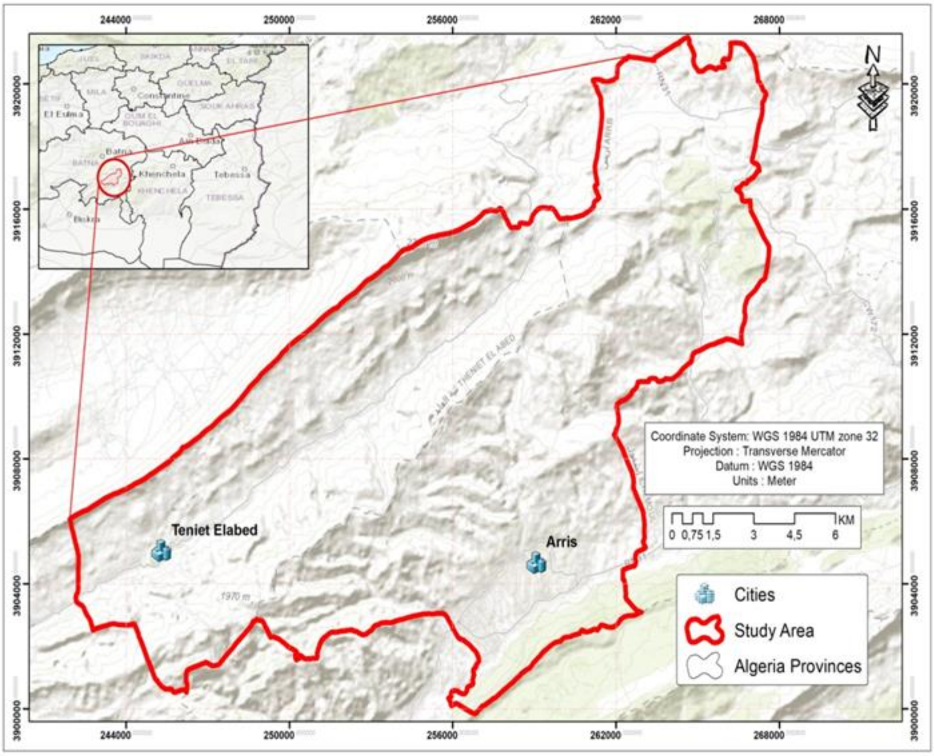

Fig. 1. The study area (Source: Map made on QGIS by authors)

Arris and Teniet El Abed belong to a very rugged physical environment divided into two distinct sub-areas: The first area includes mountains and escarpments, with very high altitudes reaching up to 1970 meters. These massifs are interspersed with several intramontane basins. The second zone includes plains with alluvial soils with high agricultural potential. The slopes are gentle and do not exceed 25% (Barrou, 2019). The hydrographic network is mainly endorheic, with irregular and temporary flows. The forests cover an area of 9819 ha they consist of Atlas Cedar, Aleppo Pine and Holm oak and Juniper.

The climate of the study area belongs to the semi-arid Mediterranean climate, characterized by a dry and hot summer and a cool winter on the reliefs and mild on the plain.

These municipalities stand out as the main agglomerations of the valleys of the oued El Abiod and the oued Abdi, playing a very important role in the structuring of the space of these two valleys. They stand out from their both traditional and modern characters, while the ancient nuclei still active (Barrou, 2019).According to the German Soil Texture Classification System soil can be divided by its sand, silt and clay content into main texture classes (sand, loam, silt and clay) and into more detailed texture sub-sections (Sponagel et al., 2005) (p. 142). The main texture classes can be used for estimating heat extractions from VDI 4640, whereas the thermal conductivity calculations are based on more specific information.

Data and materials used

For the spatio-temporal analysis of the evolution of urban expansion in the study area, four chronological series of Landsat images with a spatial resolution of 30 meters, from 1992 to 2022 were obtained from the United States Geological Survey (USGS) website. A period during which urban sprawl seems to be more significant. These four satellite scenes are selected according to their temporal similarity in order to ensure better consistency in terms of atmospheric and phenological conditions (Coppin et al., 2004; Lu & Weng, 2007; Daikh & Debache-Benzegouta, 2022).

Methodological approach

The method adopted in this study consists of five steps: pre-processing and normalization of the acquired images; classification and post-processing of the images; evaluation of the classification performance; post-classification comparison of the resulting thematic maps (Lu & Weng, 2007; Ban & Yousif, 2016; Dechaicha et al., 2004); modelling and quantification of landscape metrics (Aguejdad, 2016).

Image preprocessing and normalization

The images chosen for this study are of the L1TP category. This type of image is geometrically self-corrected and geocoded prior to release by the USGS, according to the WGS 84 Georeferencing System, Area 31 North. The overlay of images is visually verified after aligning the four images within the same geographic system. The study area is defined by extracting the current administrative division using the shapefile, obtained via a free computer program for mapping and geographic data analysis (DIVA-GIS). Since raw Landsat images are provided in radiance with digital number (DN), radiometric calibration was achieved by performing a TOA (Top of Atmospheric) correction and applying the DOS1 (Dark Object Subtraction) model (Congedo, 2016) to remove dark noise from the image.

Supervised classification and post-processing of maps

There are two categories of automatic classification: supervised (or directed) and unsupervised (or undirected). The first one consists of assigning each of the n observations {x1, ..., xn} to one of the k classes known a priori, while the second aims to group these data into k homogeneous groups (Charles & Stéphane, 2009). A supervised classification type was initiated through the selection of training plots (ROIs) which are groupings of distinct pixels that represent a specific land cover. Next, the Maximum Likelihood Estimation (MLE) algorithm was used to classify images that are based on the principle of calculating the probability of a pixel belonging to a given class or not (Oreste, et al. 2019). This algorithm offers a good generalization capability.

Based on reference documents and field knowledge, three land use classes are defined:1-Build-up (Residential buildings, industrial fabrics, mechanical tracks, equipment, commerce, railways), 2-Vegetation (Tree plant, low vegetation and forest), 3-Bare-soil. Each of these classes or macro-classes represents a similar group of land uses (Dechaicha et al., 2021). It should be noted that the dry rivers oued Abdi and oued El Abiod are considered bare land.

Performance Evaluation: The Confusion Matrix

A confusion matrix was generated to assess the quality of the classification in its overall accuracy. This technique is the most widespread across previous LULC & GIS studies (Congalton, 1991). A synthetic index derived from the confounding matrix is also used in the assessment of accuracy. This is the Kappa coefficient (Khat), a quality indicator used to measure the performance of a classification through the examination of the elements of the matrix (Congalton, 1991; Stehman, 1996). For a Khat value greater than or equal to 0.8, the classification is considered statistically acceptable; whereas if Khat varies between 0.4 and 0.8, the classification is considered to be of average quality (Congalton & Green, 2008; Landis & Koch, 1977). This assessment was complemented by field visits to validate the classification carried out upon the images.

Change Detection and Calculation

The aim of this study is to visualize and quantitatively describe the spatiotemporal trends that characterize the urban growth of the municipalities of Arris and Teniet El Abed during the study period. The thematic maps obtained at the end of the classification seem to be subjected to a post-classification comparison operation. These maps are accompanied by a detailed report that meticulously describes the various changes observed on the surfaces, indicating the nature of the alterations.

Calculating Landscape Metrics

To measure the spatio-temporal changes, five metrics that correspond to the level of class metrics were selected: Number of Patches (NP); Percentage of landscape (PLAND); Average parcel size (AREA_MN); Largest Patch Index (LPI); Aggregation index (AI) (Hérold et al., 2005; McGarigal et al., 2012). All of these spatial metrics were calculated at a level of analysis corresponding to the "Urban Spot" class using the FRAGSTAT program (Version 4.2). To achieve this, the land cover was converted to ASCII (American Standard Code for Information Interchange) rasters, which led to the selection of metrics that are suitable for this study.

Following the complexity of the landscapes studied and the analysis of the results, we undertook a correlation of these metrics to develop a synthetic interpretation taking into account the overall behaviour of the different metrics analysed.

Metric	Description	Range
NP (Units)	$NP = n_i$ n_i: number of patches in the landscape of patch type (class) i	NP ≥ 1
PLAND (%)	$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$ P_i: proportion of the landscape occupied by patch type (class) i. a_{ij}: area (m²) of patch ij. A: total landscape area (m²).	0 < PLAND ≤ 100
AREA_MN (ha)	$AREA\_MN = \frac{\sum_{j=1}^{n} x_{ij}}{n_i}$ x_{ij}: total class area (m²) of patch ij. n_i: number of patches in the landscape of patch type (class) i	AREA_MN ≥ 0
LPI (%)	$LPI = \frac{\max(a_{ij})}{A}(100)$ a_{ij}: area (m²) of patch ij. A: total landscape area (m²).	0 < LPI ≤ 100
AI (%)	$AI = \left[\frac{g_{ii}}{max^{-}g_{ii}}\right](100)$ g_{ii}: number of like adjacencies (joins) between pixels of patch type (class) i. max-g_{ii}: maximum number of like adjacencies (joins) between pixels of patch type (class) i.	0 ≤ AI ≤ 100

Fig. 2. Landscape metrics used According to (Aguejdad & Hubert-Moy, 2016; McGarigal et al., 2012; Skupinski et al., 2009; Dechaicha & Alkama, 2020)

Results and discussion

Validation of the classification

As a result of the various processing of the remote sensing and GIS data, four land cover maps were produced. The resulting thematic maps are shown in (Fig. 3), corresponding respectively to the years 1992, 2002, 2013 and 2022 respectively. The confusion matrices generated for these maps showed a satisfactory level of accuracy, both for overall accuracy and class accuracy. The Kappa index (Khat) thus showed an acceptable level of accuracy. The summary of this assessment is illustrated in (Tab. 1).

Tab. 2. Classification accuracy of the four images 1992, 2002, 2013 and 2022, source: authors

Type of assessment	1992	2002	2013	2022
Overall accuracy (%)	96.99	98.47	94.93	94.23
Accuracy of "Build-up" class (%)	98.52	93.92	90.71	90.53
Accuracy of the "Vegetation" class (%)	99.18	98.36	99.40	98.80
Accuracy of the "Bare-soil" class (%)	92.56	100.00	98.03	96.98
Khat index	0.95	0.97	0.92	0.90

Study of changes in LULC 1992–2022: a distinct expansion of built-up areas

The first diachronic reading of the four maps shows a significant growth in the Build-up class, against a significant regression in the vegetation class (Fig. 3, Fig. 4, Fig. 5, Fig. 6).

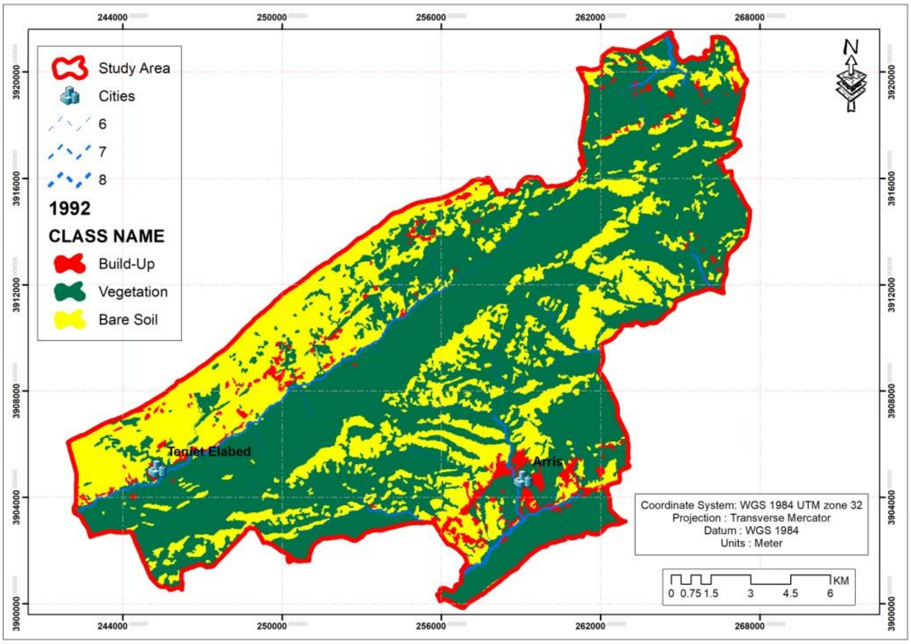

Fig.3. QGIS map with land use and land cover classes (1992), source: authors

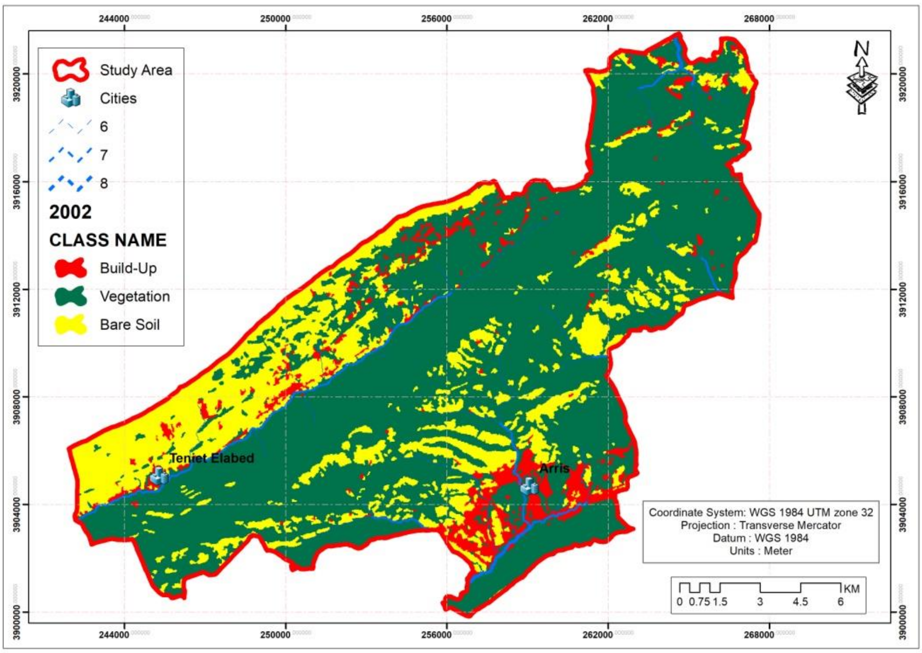

Fig.4. QGIS map with land use and land cover classes (2002), source: authors

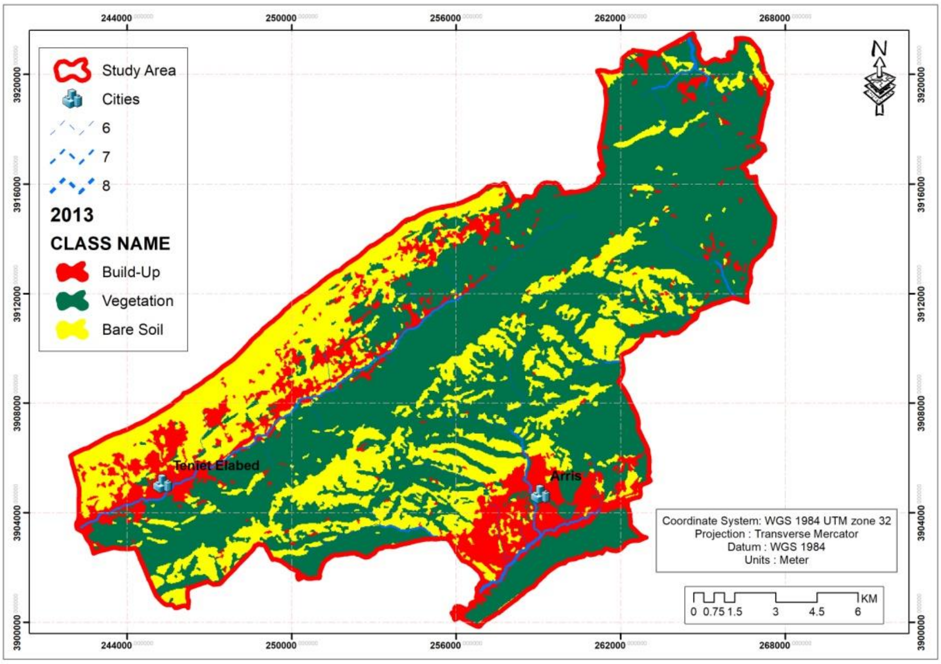

Fig.5. QGIS map with land use and land cover classes (2013), source: authors

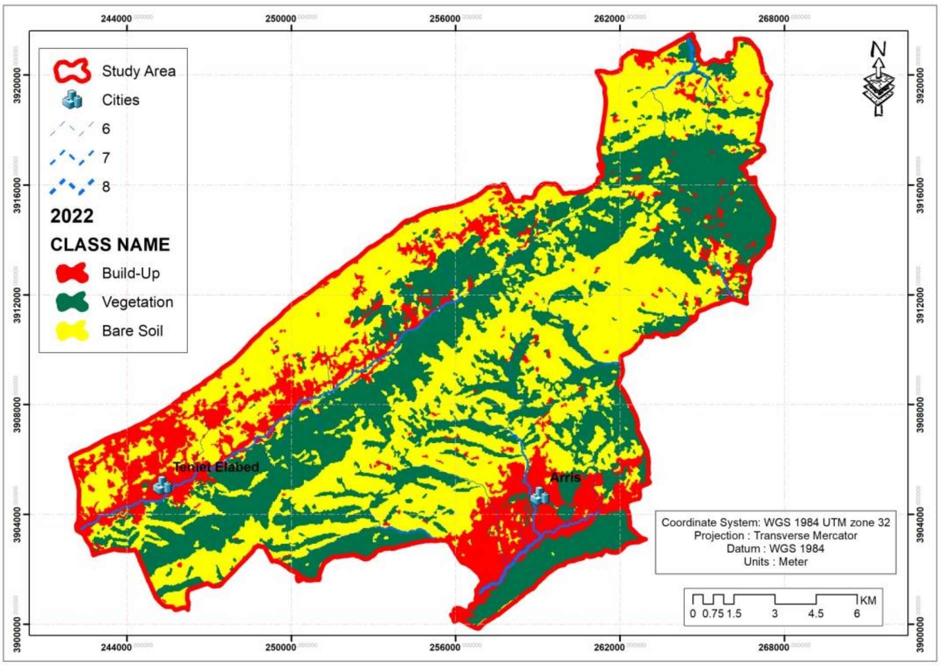

Fig.6. QGIS map with land use and land cover classes (2022), source: authors

Tab.2. Quantification of class evolution, source: authors

Land use class	Area (ha)				Change (+/-) Ha		
	1992	*2002*	*2013*	*2022*	1992-2002	2002-2013	2013-2022
Build-up	1289.97	1632.48	2245.45	2655.84	+342.51	+612.97	+410.39
Vegetation	16666.58	16913.31	12560.77	10105.98	+246.73	-4352.54	-2454.79
Bare-soil	8099.01	7109.76	10818.64	13704.13	-989.25	+3708.88	+2885.49

During the first period, the spatial growth of the study area was characterized by linear extensions in three directions to the northeast, north and southwest along the main roads, including the RN° 87 in the agglomeration of Teniet El Abed and along the RN° 31 in the agglomeration of Arris (Fig. 3, Fig. 4). This growth is characterized by spatial growth that is generally in continuity with existing urban fabric. During this period, the built class recorded an increase in its surface area. It increased from 1289.97 ha in 1992 to 1632.48 ha in 2002 with an increase of +342.51 ha (Tab.2). The vegetation recorded an estimated area gain of +246.73 ha. This class increased from 16666.58 ha in 1992 to 16913.31 ha in 2002. As a result, the bare soil class has lost some of its surface area, including -989.25 ha converted by the other classes (Tab. 2).

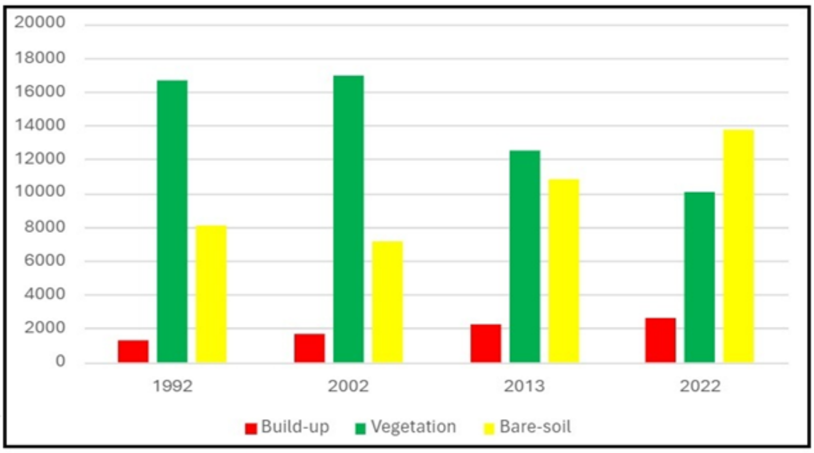

Fig.7. Evolution of the surface portions of land cover classes (1992 -2022), source: authors

In the second period, in situ urbanization developed in the Dechra (historical centre), along the national road no. 31 and along the southern bypass. This spontaneous urbanization has densified and extended the old urban fabrics located to the north of the Arris agglomeration, especially those of the Dechras, it has created new neighborhoods such as Sanef. Along route 87, the growth of the Teniet elabed municipality has followed two types of development. Continuous one, densification of the old core to the north and another discontinuous to the northeast (Fig. 5). This is due to the scarcity of land and the configuration of the mountainous site, which is crossed by a set of rivers. During the second period, the urbanized areas continued to grow to reach the threshold of 2245.45 ha in 2013, with an estimated surface gain of +612.97 ha (Tab.2). A speedy growth compared to the first period should therefore be noted. This period is also marked by a clear decrease in vegetated areas compared to the first period, which lost its surface area up to 12560.77 ha in 2013 (Fig. 7).

The third period 2013-2022 is characterized by a northward sprawl of the built class in the two agglomerations (Fig. 6). This class gained an estimated total area of +410.39 to reach an area share of 2655.84 ha in 2022. The vegetation continued to lose space. Its surface area has decreased to a value of 2,454.79 ha. The Bare Soil class recorded an estimated surface gain of +2,885.49 ha. This class increased from 10818.64 ha in 2013 to 13704.13 ha in 2022 (Fig. 7).

Quantification of landscape metrics -Landscape-ecological indexes- and assessment of spatial changes

The diagrams of the surface indicators show that the class of buildings has followed two opposite trends (Fig. 8). A slight decrease in the number of urbanized fragments is marked over the period 1992-2002 with a decrease of (-19) fragments. The urban expansion observed in this period occurred without the creation of new fragments far from the already existing urban areas. During the last two periods a continuous increase is observed, but with a more accelerated pace during the period 2013 - 2022 with an increase of (+84) fragments (Fig. 8). It is marked by a diffusion model in which urban expansion has occurred through the emergence of new fragments away from already existing urban areas.

Between 1992 and 2002, with the relative decrease in the number of NP fragments, PLAND and LPI show an increase in values (Fig. 8). PLAND increased from 64.92.81% to 71.26.68% while LPI increased slightly from 63.08% to 69.47%. While NP is increasing between 2002 and 2022, both PLAND and LPI metrics are decreasing. The portion occupied by urbanized fragments represented by PLAND decreased from 71.26% to 39.45%; the index for the largest urban fragment also decreased from 69.47% to 22.64%. These results from these spatial indicators corroborate previous results from the detection of land use change.

The average size of fragments in the built class shows two different trends (Fig. 9): an increase characterizing the first period, from 183.33 ha in 1992 to 254.38 ha in 2013. This means that the extension of the urban fabric during this period was mainly in continuity with the existing one, the remarkable growth of the LPI index seen above consolidates this interpretation. These results also show a decrease in connectivity between the components of the agglomeration accompanied by a decrease in fragmentation between (1992-2002). The slight increase in the AI aggregation index reflects a trend towards the densification of the urban macroform. This period is followed by a decrease in the average size of fragments of the built class, which has fallen from 254.38 ha to 56.14 ha in recent periods (Fig. 9). This shows an increase in connectivity owing to the appearance of new urban fragmented plots spread towards other directions and closer to the centers of the urban area. Subsequently, a tendency towards morphological fragmentation became a characteristic during the second study period. This is well illustrated by the decrease the AI aggregation index reaching 82.77% in 2022.

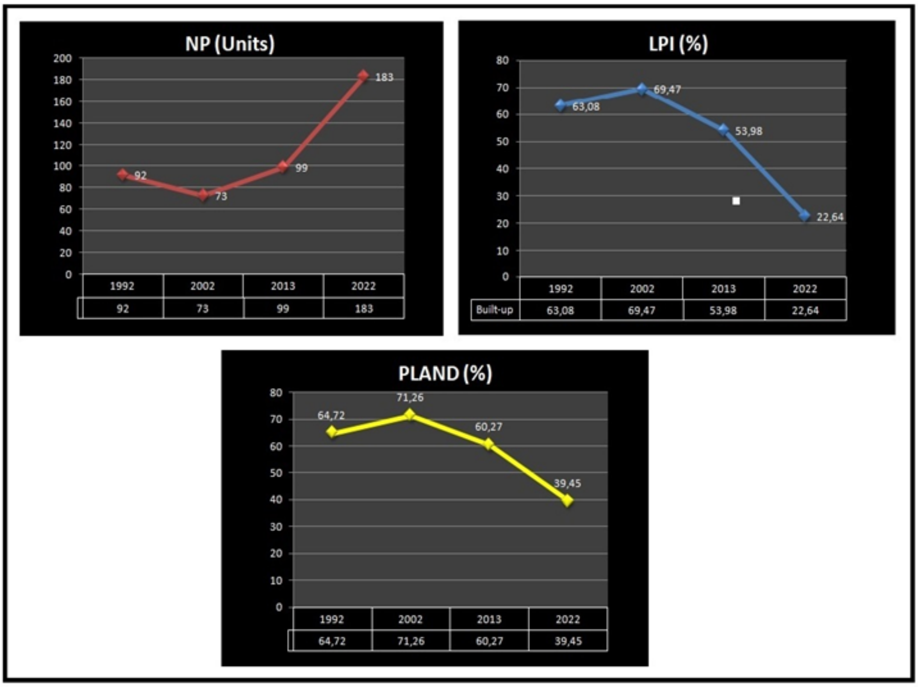

Fig.8. Evolution of landscape area metrics (1992 - 2022), source: authors

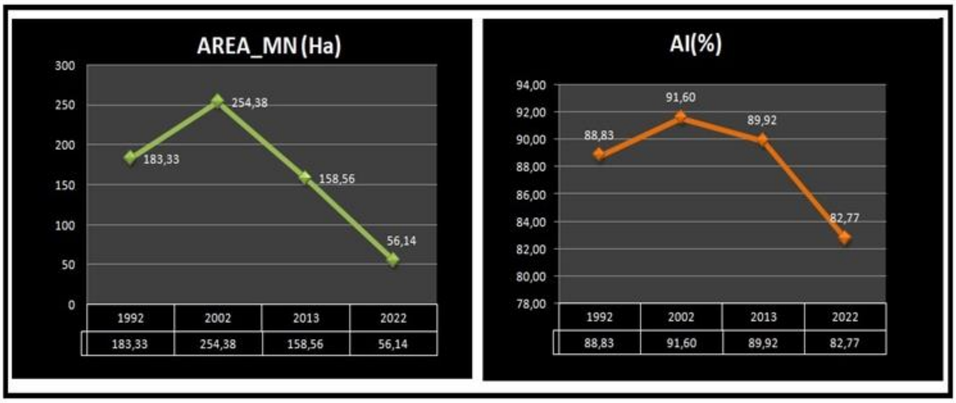

Fig. 9. Evolution of landscape distance metrics and configuration metrics (1992-2022), source: authors

Conclusion

Taking into consideration how spatial structure of land cover and dynamics of urban growth evolve over time, it is crucial that effective land management and sustainable urban planning in rural areas of Aures, must take place. The combination of earth observation data and geographic information systems (GIS) with the application of landscape metrics has proven to be a useful tool for analyzing spatio-temporal dynamics and changes in land use.

This study examined the spatio-temporal urban growth of two rural municipalities in the Aurès, Arris and Teniet El Abed (Algeria) during the period 1992 – 2022, through a quantitative approach based on the use of multi-date satellite images and the application of landscape metrics. It appears that these municipalities have recorded significant growth in their urban fabric in recent decades. The quantification of land cover and land use change revealed variations of the spatial growth rate of the urban area, which is more rapid during the period (2002 – 2013).

If the urban patch was initially continuous, results finally show a second fragmented step making the entire fabric loose. This is due to the scarcity of land and the configuration of the mountainous site, which is crossed by a set of rivers. Transport axes, especially the RN° 87 and RN° 31, have influenced the direction of current urbanization, since urban extensions took place far from the centers of urban areas and along these axes.

Although the overall objectives of this study were achieved, some limitations should be noted. Most of the indicators applied emanate from land use and cover data. So we need to improve the accuracy of image classification. In addition, this study mainly relies on Earth observation data, which to some extent may be insufficient to assess urban growth and spatial structure in its complexity. Therefore, the inclusion of socio-economic variables is crucial to obtain more reliable results.

Conflicts of Interest: The authors declare no conflict of interest.

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