CARTOGRAPHY AND ANALYSIS OF THE URBAN GROWTH, CASE STUDY: INTER-COMMUNAL GROUPING OF BATNA, ALGERIA

Nadia Fekkous [1,2], Djamel Alkama [2], Khaoula Fekkous [3]

[1] Department of Architecture, Laboratory of design and Modeling of Architectural and Urban Forms and Ambiances (LACOMOFA), Mohamed Khider University, Biskra, Algeria
[2] Department of Architecture, University 8 May 1945, Guelma, Algeria
[3] Department of Architecture, ABE Laboratory, University of Salah Boubnider Constantine 3, Ali Mendjeli, Constantine, Algeria

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Abstract: This paper focuses on the analysis of the urban macroform in terms of urban compactness and dispersion (urban sprawl) in the inter-communal grouping of Batna, which is composed of four adjacent interconnected communal districts: Batna, Tazoult, Oued Chaaba and Fesdis. First, the urban macroform is examined by mapping the urban areas that are characterised by morphological changes over a period of 36 years utilising remote sensing and geographic information system (GIS) through satellite images taken from Landsat TM and ETM +, Sentinel 2 (1984, 1996, 2008 and 2020). Next, the Shannon entropy method is utilised to determine compactness or dispersion of urban growth over time. In addition, a fractal analysis based on the box-counting method is used to assess the complexity and to explain the morphological reality of the macroform through urban changes. In order to predict the future change scenarios and spatial distributions of land use and land cover in the coming years the hybrid cellular automata (CA) – Markov method is used. The results of the remote sensing, Shannon entropy values and fractal indices demonstrate that Batna inter-municipal grouping has experienced moderate urban development according to the observed urban sprawl between 1984 and 2020. These data are helpful in the urban planning and to provide decision-making tools.

Key words: urban macroform, remote sensing, Shannon entropy, fractal, CA-MARKOV, Batna

Corresponding author: Fekkous Nadia, fekkous.nadia@univ-guelma.dz

Introduction

Urbanisation is presented as a complex and dynamic process and is considered as a very important crucial phenomenon of economic growth and social change (Jimoh et al. 2018). This urbanisation process is one of the primary engines in land cover and uses transformation and change (Al-sharif et al. 2013). It is also the most influential factor in land use and land cover (Deka et al. 2010). Recently, this urbanisation has accelerated tremendously in various developing countries (Jimoh et al. 2018). It is rapid, uncontrolled and causes particular mutations in the landscape (Yeh, Li 2001, Deka et al. 2010, Wu et al. 2013). It also leads to changes in urban macroforms. For this reason, detecting changes in land cover and use is essential to better understand

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the landscape dynamics (Halimi et al. 2017) and to know the urban macroform morphological realities.

For effective urban planning, it is preferable to choose the most reliable means to verify the situation of a landscape and its temporal changes (time series) (Nazarnia et al. 2019). A large number of approaches and techniques have been employed by various researchers and used for knowing, quantifying and tracking the characteristics of urban macroforms through time, and thus predicting their future.

The remote sensing, technology has the potential to be an important tool for monitoring land use (Jensen 1983, Martin 1986, El-Raey et al. 1995). this technique is integrated with geographic information system (GIS), it is admitted as an active tool to observe spatio-temporal metamorphoses and land characteristics at different scales (Makhamreha, Almanasyeha 2011, Amici et al. 2015). Several studies have been published using GIS and remote sensing such as Alharthi, El-Damaty (2022) used it to make a spatial study of the expansion of Taif City in Saudi Arabia during periods of time. Sridhar et al. (2020) employed GIS and remote sensing to track the urbanisation of the city of Surat, India. Robbany et al. (2019) Performed land use change detection and urban sprawl monitoring in Jakarta's metropolitan area (Jabodetabek). Hamad (2019) studied growth and spreading dynamics through land use and cover maps (LULC) in Soran District, Iraqi Kurdistan.

Shannon entropy, another new technique, is a well-known method for calculating the extended urban model (Sudhira et al. 2004). It is a statistic regularly used to study the robustness of urban sprawl (Yeh, Li 2001). Therefore, it is a measurement to know the compactness or sparseness of the built environment in urban areas (Mundhe, Jaybhaye 2015). Different studies using Shannon entropy such as the study of Bhattacharjee (2019) employed Shannon entropy estimation to determine the rate of urban growth in the city of Silchar.

Gyeltshen et al. (2022) have done a study that uses entropy to measure the degree of compactness and dispersion of urban development in the city of Chiang Mai. Serdaroğlu Sağ (2021) assessed the urban development pattern and sprawl using Shannon's entropy: a case study of Konya (Turkey), and Aprillia and Pigawati (2018) used the Shannon entropy to analyse and determine the location of the sprawl in the city of Semarang.

One of the most reliable techniques to solve scale-free problems is fractal geometry (Chen et al. 2017). It is an effective method for assessing urban macroforms over the past two decades.

It could be used to describe the geographical distribution of urban areas and the irregular shape of the urban perimeter (Theiler 1990). Its dimension is recognised as an exceptionally useful indicator of the urban spatial structure (Anas et al. 1998). Several studies have been published that used the fractal method, such as Terzi and Kaya (2008) used fractal geometry to investigate the patterns of urban sprawl in the Istanbul metropolitan area, Ozturk (2017) used fractal analysis to evaluate urban sprawl in the Atakum, Ilkadim, and Canik areas (Samsun, Turkey), and Rastogi and Jain (2018) analysed urban sprawl using the fractal method in the city of Tiruchirappalli, India.

Indeed, the Markov chain and the CA filter, (CA-Markov) modelling have become very prominent in the spatial and geographic areas. In the past two decades. Ghosh et al. (2017) employed it in the majority of studies and research to predict and simulate future growth directions of the city (Nouri et al. 2014). Numerous studies that used CA-Markov, such as Ruwashdi and Khakani (2022), created a simulation and forecast for the urbanisation of Al Najaf. Zhao et al. (2021) used spatial Markov chains and regression-based weighted cellular automata (CA) to combine to simulate urban settlement growth in the Guangdong-Hong Kong-Macau Greater Bay Area. Nasehi et al. (2018) simulated changes in land cover in urban areas using the CA-Markov model (case study: zone 2 in Tehran, Iran).

In the same context of this rapid and alarming urbanisation, the city of Batna, the capital of the Aures, did not escape this reality. Our research has made exceptions, it is going to be switched between four methods to evaluate and analyse the urban growth as well as its urban morphology in the inter-municipal grouping of Batna in the period spread out over 36 years. The objective of this research is to analyse the urban dynamics and the spatio-temporal evolution of land cover and land use (LU/LC) in the inter-municipal grouping of Batna.

Study area

The city of Batna, capital of the Aurès, chief town of wilaya, is located in the Eastern Highlands region, in the middle of the Aurès massif in a valley at the junction of two Atlas Mountain ranges (Tellian and Saharan). According to DRC (2017) this city is located 400 km east of the capital, Algiers, and rises to > 900 m a.s.l. It is bounded in the north, by the wilaya of Mila; In the northeast, by the wilaya of Oum-El-Bouaghi; in the east, by the wilaya of Khenchela; in the south, by the wilaya of Biskra; in the west, by the wilaya of M'Sila; in the northwest, by the wilaya of Sétif. In the WGS 84 coordinate system used by the Global Positioning Satellite, the willaya of Batna is located between the following geographic coordinates: 35°33′21″N, 6°10′26″E.

In this study, we analyse the inter-municipal grouping of the willaya of Batna. It is a grouping of four communes. It is also found that the position of the commune of Batna is in the middle of the communes of Fesdis, Tazoult and Oued Chaaba (Fig. 1). This large urban centre can be considered as a nodal and strategic connection point where major axes converge; it plays a role in reviving the region as a whole and this increases the need to pay attention to this urban entity and its potential for expansion (PDAU 2012). The bordering communes of this inter-communal grouping are in north: Seriana, Oued lma. east: Djerma, Elmadhar, Ouyoun Alassafir. west: Hidoussa and Ain Touta and south: Oued Taga, Bni Fdhala (Fig. 1).

Methods

Remote sensing and analysis of urban transformations

First, we focused on the most adopted approach for urban studies, the remote sensing based on a controlled classification (classification of likelihood or supervised) of satellite multi-dates 1984–1996–2008–2020 images. The main objective of this approach is to assess the urban macroform by monitoring and measuring changes in LU/LC, mapping urban developments and dictate the urban growth spatio-temporal dynamics in the inter-municipal group of Batna.

According to Angel et al. (2005), it is diversely employed for cartographying (to comprehend spatial structure), controlling, evaluating (to understand development), and modelling (to simulate) urban evolution, land use and sprawl. For this purpose, four images covering the study area of inter-communal grouping of Batna were obtained free of charge on United States Geological

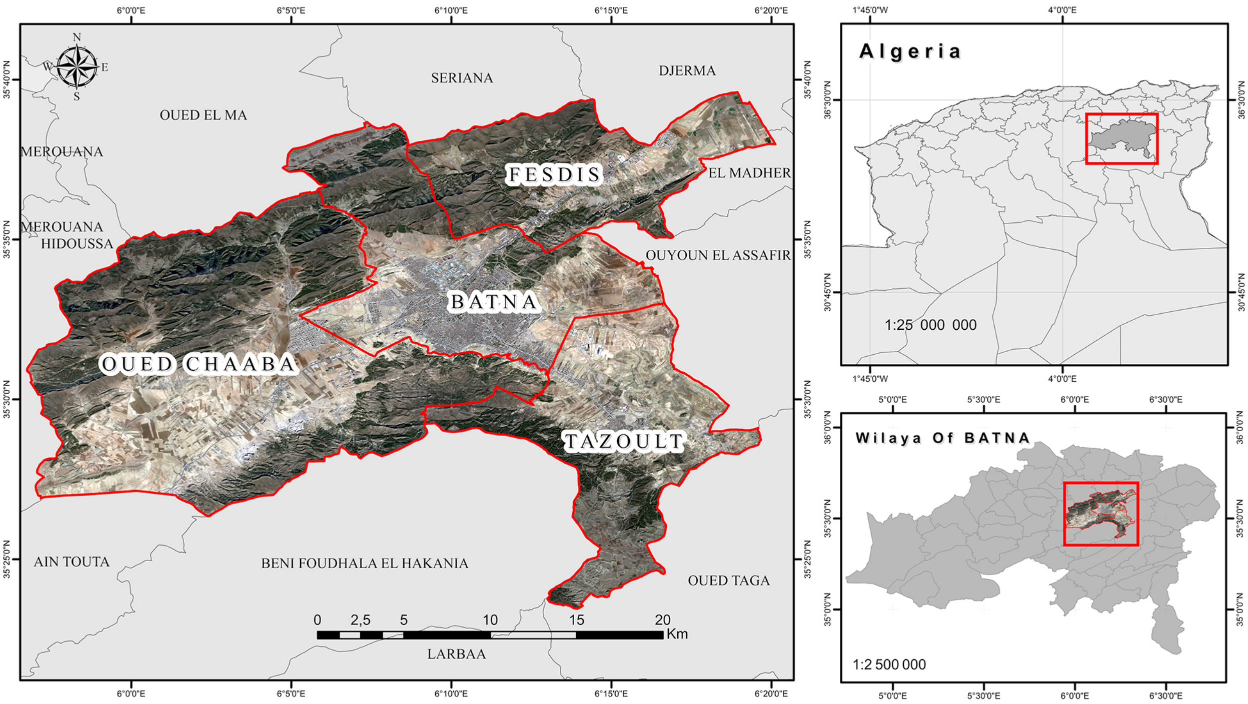

Fig. 1. Location of the inter-municipal grouping of Batna.

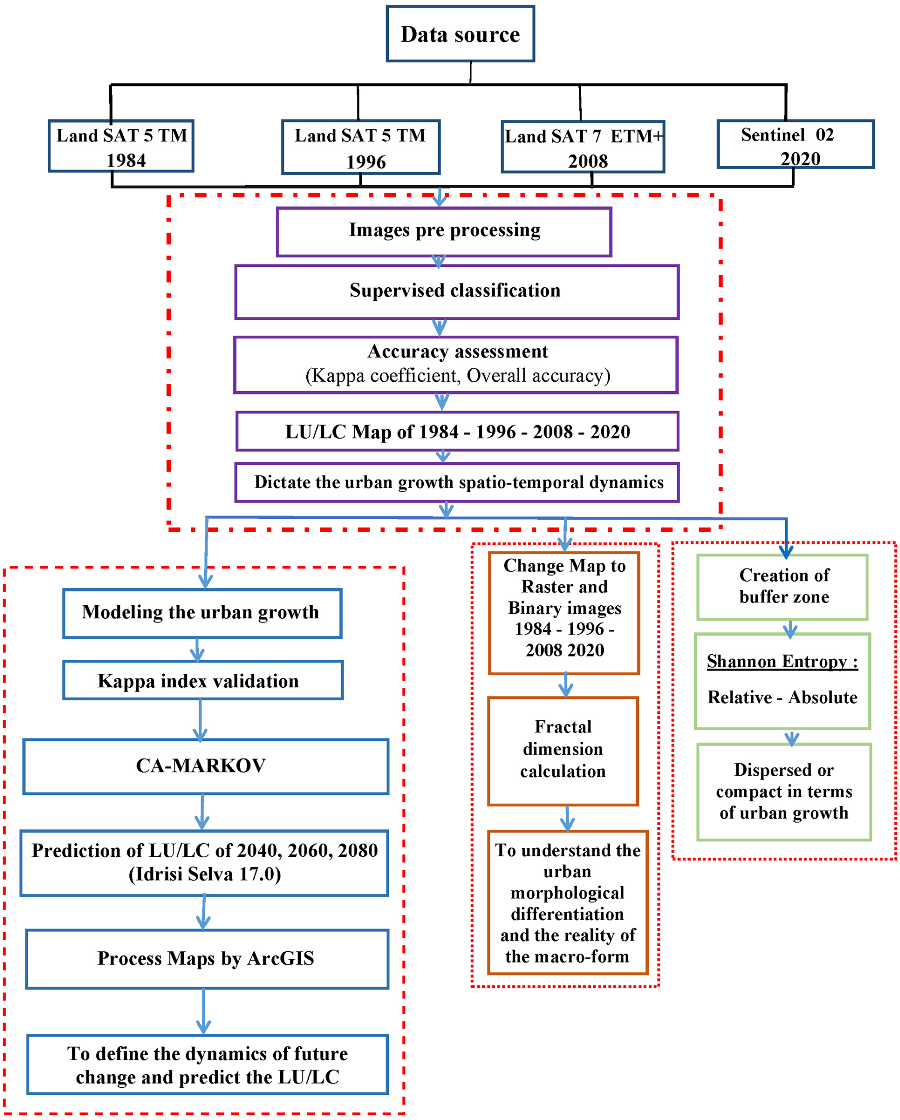

Fig. 2. The methodology flowchart applied in this study.

Survey (USGS) website portal. It is used as main database. These satellite images are of type Landsat TM of the years 1984–1996, Landsat (ETM+) of the year 2008 and the Sentinal 02 satellite of the year 2020 (Fig. 2). These satellite images were taken with a defined constant time interval of 12 years and their selection depends on several criteria such as affordability, availability, spatial resolution, clarity. Detailed information on the images is presented in Table 1.

In our study, a supervised classification algorithm classified into 04 categories is used, it includes the following:

1. **Class 1**: *Built-up area*: Commercial, residential, industrial, mixed use, urban or built-up areas and road network.

Table 1. Detailed information on satellite images.

No	Acquisition date	Satellites	Resolution Scale [m]	Number of bands	Projection
01	30-06-1984	Land SAT 5 TM	30	7	WGS 84 UTM Zone 31 N
02	21-10-1996	Land SAT 5 TM	30	7	WGS 84 UTM Zone 31 N
03	16-06-2008	Land SAT 7 ETM+	30	7	WGS 84 UTM Zone 31 N
04	12-03-2020	Sentinal 02	10	11	WGS 84 UTM Zone 31 N

2. **Class 2:** *Forest*: Forests and shrubs: comprising mainly natural and semi-natural forest lands, mountain, hill and large rough terrain.
3. **Class 3:** *Agricultural land*: Vegetation, wooded agricultural area, vegetated area, agricultural land grassland, natural vegetation, trees, gardens, parks, playgrounds, crop fields, irrigation land and grazing land.
4. **Class 4:** *Bare land (Bare soil)*: open ground, open spaces, excavation sites, areas without vegetation cover, uncultivated agricultural land and landfills.

ARC GIS 10.5 software was used in all stages of image processing such as colour composition, clipping, classification and so on.

Average annual rate of change of urban extension

In order to better clarify the state of urban sprawl, researchers used the annual speed of urban sprawl as a reference in order to know the reality and spatial characteristics of urban sprawl (Ma, Xu 2010) and (Xiao et al. 2006); the annual rate of urban sprawl is presented as an annual rate of change in the built-up area during the study period.

On the other hand, researchers (Ge et al. 2018) also point out that the value of the urbanisation speed index was >0, and this period was expanding. Moreover, if the value <0, a loss was incurred in terms of development. The annual formula for urban sprawl speed is mentioned in the research of Fan et al. (2017) and is designated below in formula (1):

$$VT = \frac{S_B - S_A}{T} \tag{1}$$

where VT is the growth rate of the urban area in the T time period; S_A and S_B show the area of the urban area for times A and B, respectively, where time B follows time A.

Intensity of urban expansion

The urbanisation intensity index (UII) to present the intensity of urbanisation, is used to compare the pace and intensity of urban expansion, show the status of urbanisation and study the changes in urban agglomerations over different time periods (Ge et al. 2018). According to Fan et al. (2017) urbanisation intensification is an indicator (UII) to make a description of the speed and intensity of urban expansion.

The same previous researchers have shown that the large UII values are indicative and the expansion is faster in urban areas, thus indicating that a city has used a large area of non-urban space during its development, while the small UII values show that the lower extension rates in urban areas indicate that less non-urban area was taken. The formula for assessing UII is exposed in formula (2) below:

$$\mathrm{UII} = \frac{U_{ib} - U_{ia}}{TLA} \times \frac{1}{T} \times 100 \tag{2}$$

where UII is the period of urban development intensity index, U_{ib} shows the end point of the urban area, U_{ia} represents the first urban area, TLA is the urban area in the study area and T is the duration of the study period, where the units are in years.

The dynamic degree of urban expansion

The average annual rate of change in urban expansion reveals the change in the increasing urban area only in terms of absolute volume; it introduces the urban area into the average annual rate of change (Fan et al. 2017). The formula for calculating the dynamic degree of urban expansion is given and is shown in formula (3):

$$K = \frac{U_{ib} - U_{ia}}{U_{ia}} \times \frac{1}{T} \times 100\% \tag{3}$$

where K is the dynamic degree of urban expansion in the study period, U_{ib} is the urban area at the end, U_{ia} is the initial urban area and T is the duration of the time interval, where the units are in years.

Shannon entropy as a quantification tool of urban macroform

Shannon entropy is an index based on information theory used to evaluate the urban form and spatial phenomena (Yeh, Li 2001, Sudhira et al. 2004, Joshi et al. 2006). It is an indicator that calculates the distribution of built up according to their area within a certain spatial unit (Jat et al. 2008). Shannon entropy proven technique is used to assess the degree of spatial concentration and dispersion of the surface (Tewolde, Cabral 2011). Currently, it has been inserted to remote sensing and GIS, in order to achieve valuable access that allows measuring the spatial distribution of built areas and indicating the spatial concentration (compactness) and dispersion (urban sprawl) of built areas of urban growth (Nelson 1999, Vanum, Hadgu 2012). The entropy index is divided into two types:

Entropy of Shannon, absolute Hn

$$H_n = -\sum_{i=1}^{n} P_i \log(P_i) \tag{4}$$

P_i = Proportion of built-up areas in the *i th* zone and *n* is the total number of zones since entropy can be used to measure the distribution of a geographical phenomenon. Shannon entropy values vary from 0 to log *n*. When they are closer to zero, this is a very compact distribution, whereas values closer to log *n* indicate a very dispersed distribution. A higher entropy value designates the existence of urban sprawl (Sudhira et al. 2004).

Relative Shannon entropy Hn

The relative entropy is obtained by dividing the calculated absolute Shannon entropy by log *n*. This index can be employed to scale the entropy value to a value between 0 and 1 (Sun et al. 2007, Bhatta et al. 2010). It is calculated by the following relationship (5):

$$H_n = \sum_{i}^{n} P_i \log\left(\frac{1}{P_i}\right) / \log(n) \tag{5}$$

If values are close to 0, the agglomerations are of compact structures (concentrated, aggregated) if values are close to 1, this means spread areas (an unequal dispersed spatial distribution) (Tewolde, Cabral 2011). If the entropy values cross the threshold (0.5), the city is considered as sprawling (Bhatta et al. 2010).

Difference in relative entropy between two-time intervals

The change in entropy between two dissimilar time periods refers to the change in the degree of dispersion of land use or urban sprawl (Sudhira et al. 2004) and this difference as shown in formula (6):

$$\Delta H_n = H_n(t_2) - H_n(t_1) \tag{6}$$

In this part, we will study the compactness or dispersion of the urban macroform of Batna inter-communal grouping over a period of 36 years using the Shannon entropy, based on the previous results of supervised classification that were carried out by remote sensing and (GIS) using the ARC GIS 10.5 software (Fig. 2).

Fractal analysis to determine the urban macroform

Fractal theory has recently gained popularity in urban geography (Tannier, Pumain 2005). It is deeply committed to chaos theory (Hotar, Salac 2014) and was developed in 1977 thanks to the efforts of the mathematician B. Mandelbrot (Tannier, Pumain 2005). Thus, it makes a description of the spatial organisation of built-up areas by taking the hierarchical nature of urbanisation procedure (Thomas, Frankhauser 2013). There are now numerous ways to determine an object's fractal dimension, like the box-counting method, wich is the most used in the scientific field. This is one of the most widely recognised and used methods for assessing fractal dimension (Brown 1995). It is generally used in researches associated with land use, spatial examination and urban study (Shen 2002) and (Kaya, Bolen 2011). It calculates the number of cells to fully cover an object with cell grids of changeable size (Ozturk 2017). It is also done by accumulating regular grids on an object and evaluating the number of cells used (Morency, Chapleau 2003).

Then, we attempt to understand the urban morphological differentiation and the reality of the macro-form of the inter-municipal grouping of Batna between 1984 and 2020 via the fractal dimension of the fractal analysis using boxes counting as a method of urban transformations evaluation. Through this method, we will examine the urban morphological evolution of Batna's inter-communal urban grouping over the last 36 years. Using satellite images of the urban configuration of four dates, 1984, 1996, 2008 and 2020, they are processed by remote sensing and supervised classification previously. After converting the vector images (polygons) obtained from remote sensing to raster images, in binary image format consisting of two types of pixels: black pixels to represent the built-up area and white pixels represent the non-built-up areas with a TIFF or BMP extension. Then, the fractal dimensions of these maps are calculated by means of the box-counting method using Fractalyse, (2.3.1) (Fig. 2). This software has been developed specially to measure the fractality of cities, to calculate the dimension and draw the curves.

Markov chain and cellular automaton for the prediction of the macroform's future

There are various methods for modelling and predicting LU/LC transformations such as Markov model and CA. It is a hybrid model which contains a combination of CA model with Markov chain transition model to define the dynamics of land use change (Jain et al. 2016). According to Nouri et al. (2014), this method consists of two main steps: the first one is Markov chain, which calculates the transition probability matrix, and conditional probability images, then, CA which has the objective of future simulation of land use.

In the present study and to define the dynamics of future change and predict the LU/LC of this cluster, a hybrid model is used.and then we will predict the model and simulate the dynamics of urban growth of the urban macroform of the inter-municipal grouping of Batna by the algorithm of CA based on the Markov chain through the software Idrisi Selva 17.0 (Fig. 2).

Results and discussions

To better understand the morphological reality of the previous urban macroform of the Batna inter-municipal grouping in the years 1984, 1996, 2008 and 2020, the results are interpreted independently using remote sensing, Shannon entropy, fractal analysis, and the CA-Markov model.

Land-use and land cover maps using remote sensing

The maps were made by supervised classification after the extraction of Batna inter-communal grouping on the images of 1984, 1996, 2008 and 2020. The results of this classification are shown in Figure 3.

Evaluation of precision and accuracy

The Kappa value is always ≤ 1. When the Kappa coefficient exceeds 0.8 (80%) (Table 2), the classification is conventionally considered as relevant (Landis, Koch 1977).

Table 2. Overall accuracy index values and kappa coefficient for the years 1984, 1996, 2008 and 2020.

Year	Overall accuracy [%]	Kappa coefficient
1984	88	0.8378
1996	90	0.8671
2008	90	0.8661
2020	86	0.8091

Findings from supervised classification maps

Over the past 36 years, the inter-municipal grouping of Batna has experienced urban dynamics and crucial developments, which lead to many notable changes in LU/LC:

In the classification of the year 1984: the results show that the study site is surrounded by mountain ranges that occupy a very expansive surface. A notable concentration of the mass of built, centralised in the town of Batna, and light in the town of Tazoult, Fesdis or Oued Chaaba, while a significant area of agricultural land spread in all directions of the study area.

In the classification of the year 1996: we noticed always a remarkable concentration of the built space in the central commune Batna, with a continuous growth in all directions oriented towards: south east in Tazoult, East in Fesdis, West in Oued Chaaba. Agricultural land is scarce and consumes the bare soil.

The classification of the year 2008: the results show that a rapid and accelerated urbanisation is characterised by a concentration of buildings in the centre (commune of Batna) with a remarkable dispersed development that is oriented towards the main transport routes which are Tazoult road, Biskra road through Hamla and Constantine Road through Fesdis. To the west, a new urban pole has appeared, Hamla, to support all the new state programmes (housing and equipment) to the detriment of the surrounding agricultural land, adjacent forest areas, devouring the existing

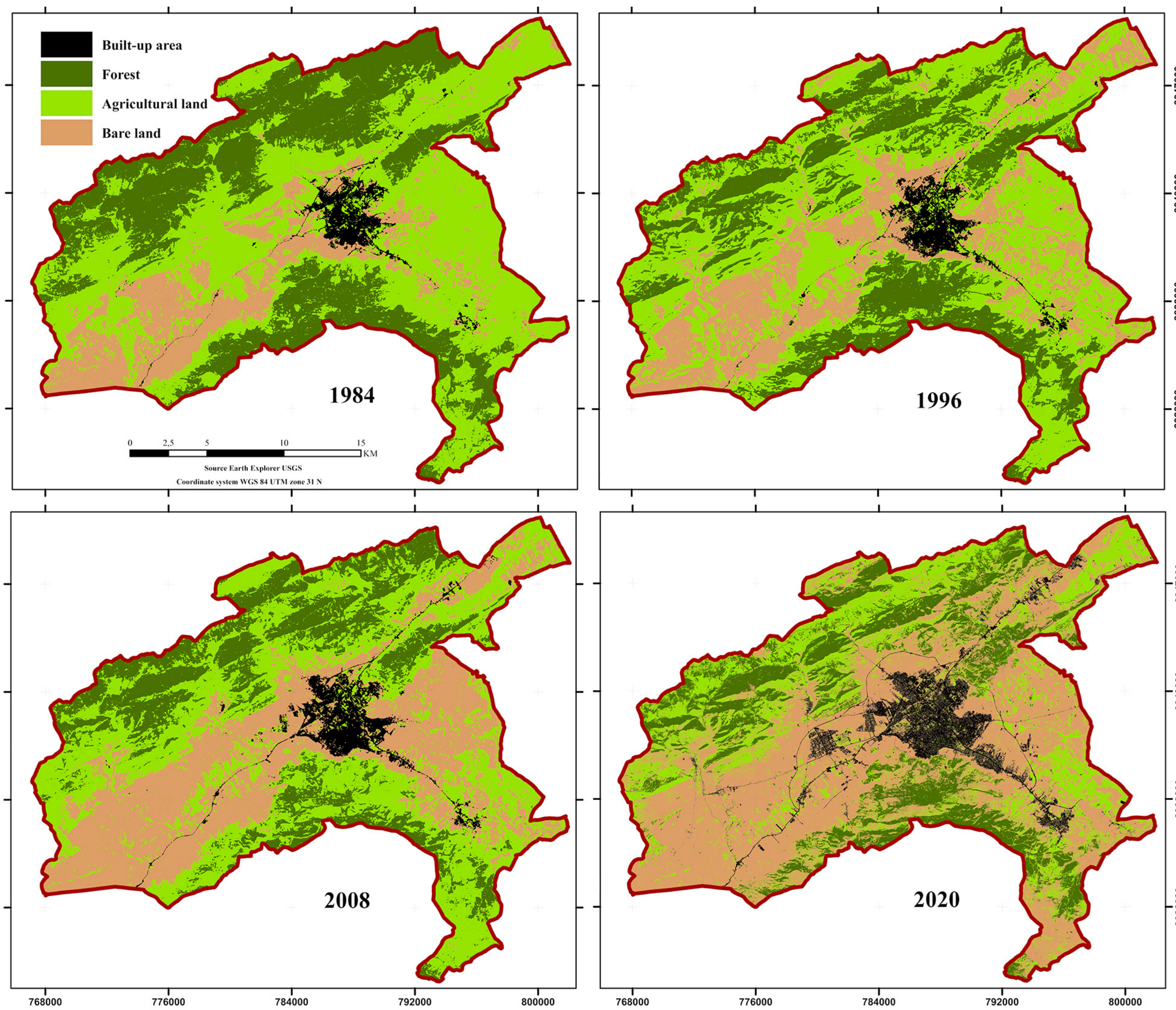

Fig. 3. Supervised classification of the Batna inter-municipal grouping on the images of 1984, 1996, 2008 and 2020.

bare soil. This reality directs us to the possibility of a future conurbation between Batna-Fesdis and Batna-Tazoult.

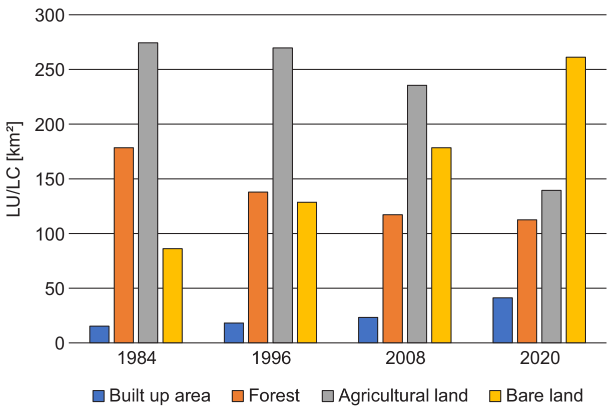

Fig. 4. Graphical representation of the evolution of LU/LC in the Batna intermunicipal area between 1984 and 2020.

The classification of the year 2020: the surface of the communal territory of Batna is occupied by the built-up area the extension of this built-up area is gradually increasing in an amazing way on agricultural land and bare soil. This leads to the development of urban transport systems. A great urban sprawl is oriented along the transportation routes towards three main directions which are, Tazoult Road in the south of the city, on the axis RN31 Road, Biskra Road to the west of the city of Batna, structured by the axis: RN03 Road and Constantine Road through Fesdis in the north of the city of Batna, along the axis RN03 road. The other communes, Oued Chaaba, Fesdis and Tazoult know a remarkable change accompanied by an increase in the built mass, to the detriment of surrounding farmland, and a significant conurbation – between Fesdis-Batna, and Tazoult-Batna.

Evolution of land use and land cover

The graph on Figure 5 clearly shows the change in surface areas between the years 1984 and 2020. Due to the rapid urbanisation, the search for empty plots, vacant land for urbanisation; and the improvement of road networks, there was a subsequent increase in the built-up area from 15,289 to km² to 41,196 Km² between the two dates. On the other hand, there has been remarkable regression in the surface of agricultural land from 274,384 km² to 139,405 km² due to the search for empty pockets for urban expansion, which is detrimental to agricultural land, and an increase in bare soil from 86.172863 km² to 261.217205 km² due to conversion of neglected agricultural and grazing lands to bare soil. On the other hand, forest cover has decreased drastically from 178,472 km² to 112,525 km² due to the timber mafia, frequent fires, degradation and the transformation of agricultural land into grazing areas.

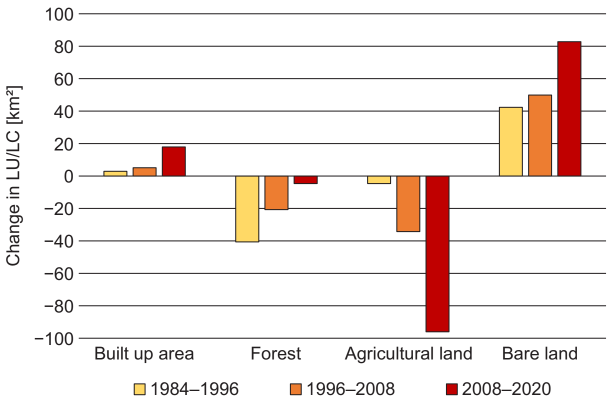

Fig. 5. The change in LU/LC surfaces between 1984 and 2020 of the inter-municipal grouping of Batna.

Evolution of the urban area between 1984 and 2020

The combination of the four urban patches mentioned in the previous (Fig. 6.) provides a thematic map that overlays the built mass in

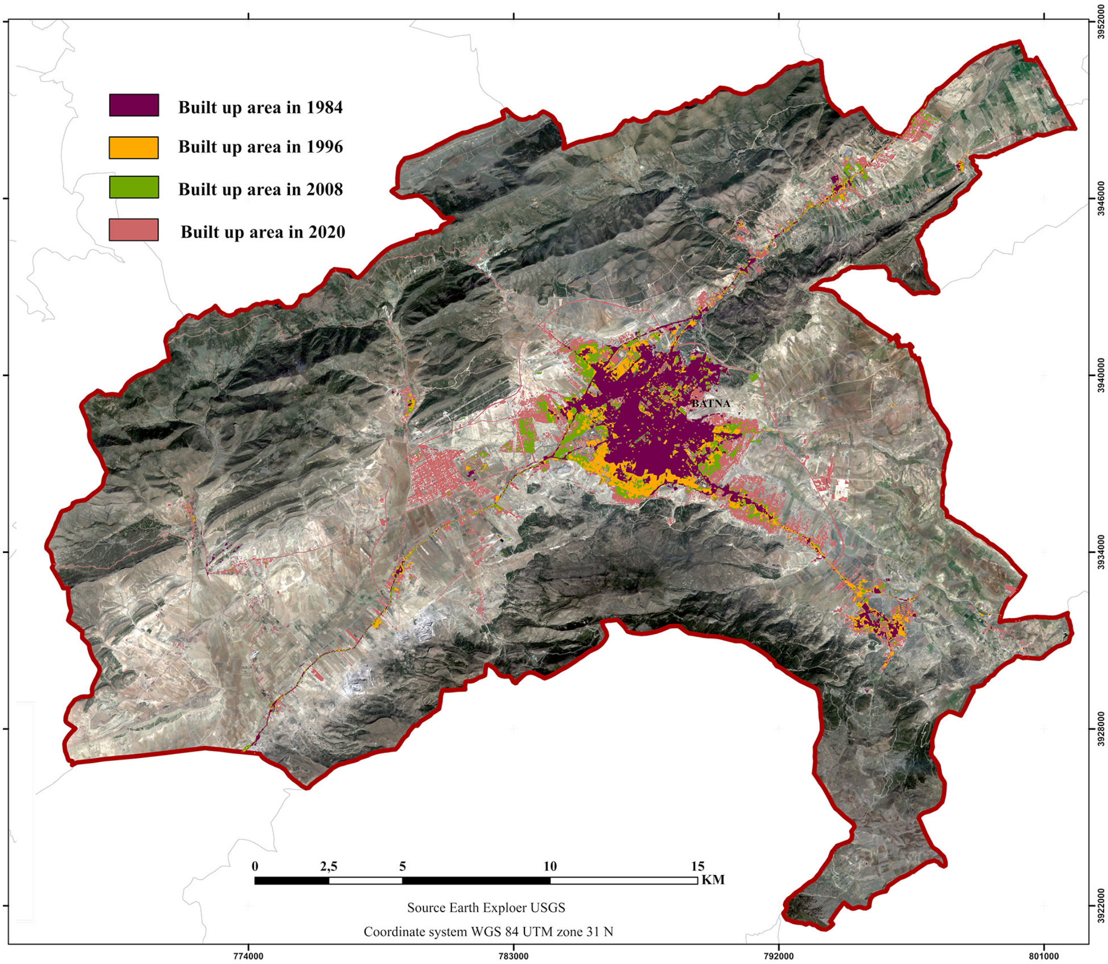

Fig. 6. Evolution of the urban area of the Batna inter-municipal grouping between 1984 and 2020.

1984, 1996, 2008 and 2020. It helps us to make a multi-temporal map of the urban growth of the Batna inter-communal grouping between 1984 and 2020 to observe the changes in LU/LC, to capture the concentration of the urban area within the transportation network, and to delineate the extension of superfluity in the central part of the study area. This will saturate the centre towards the periphery of the city.

Analysis of urban growth between (1984 and 2020)

Annual urban expansion rate

In this study, the results show that the growth of the urban area of inter-municipal grouping of Batna is gradually increasing. According to Ge et al. (2018), the values of urbanisation speed index were >0; these periods of urbanisation were expanding which mainly occurred in two stages of study period is exposed in (Table 3) the first stage was from 1984 to 1996, and the second was from 1996 to 2008 and 2008 to 2020.

During the first stage, urban growth continued at a stabilised rate of expansion with a moderate annual increase. The urban area expanded from 15.29 km^2 of the total area to 18.17 km^2 between 1984 and 1996; so, with an annual rate of urban growth that reaches 0.24 per year. During the second stage, from 1996 to 2008 and from 2008 to 2020, urban growth increased suddenly in 1996 (exponential increase); the urban area expanded by 23.29 km^2 and 41.19 km^2 (or 0.43 km^2 and 1.49 km^2 per year) during the two periods respectively. Generally, the annual growth rates were 0.24 (1984–1996) and 0.43 (1996–2008), 1.49 (2008–2020), which indicates that the city of Batna has experienced a growth that was almost constant and moderate in the first stage and led to a medium growth during the second stage. Due to the increase in urban sprawl, the urban expansion was dominant and created along transportation routes by the effect of road tropism.

Table 3. Average annual rate of change of the urban extension (VT), urbanisation intensity index (UII), dynamic degree of urban expansion (K) of the inter-municipal grouping of Batna between 1984 and 2020.

Dates	VT	UII	K
1984–1996	0.24	0.04	1.56
1996–2008	0.43	0.08	2.35
2008–2020	1.49	0.27	6.40

Urbanisation intensity index

According to Fan et al. (2017), Large UII values are indicative of faster expansion in urban areas and thus suggest that a city has occupied a large amount of non-urban space during

development. Conversely, small UII values indicate lower rates of expansion in urban areas and suggest that less non-urban area has been taken. Table 3 shows the change in UII of inter-communal grouping over time: UII has experienced a process of increase from bottom to top. Between 1984 and 2008, the UII increased from 0.04% to 0.08%, while in 2008–2020 the value plunged to 0.27%, so the value is a slightly increased compared with previous years. All values are small this indicates low or average extension rates in urban areas, which means that less non-urban areas have been taken.

Dynamic degree of urban expansion

Dynamic degree of urban expansion is the intensive urbanisation index (K) allows comparison for urban sprawl that affects diverse durations (Liu et al. 2014). The degree of dynamic expansion of Batna inter-communal grouping in different periods varied considerably. The degree of dynamic expansion (K) reached a low speed expansion of 1.56% between 1984 and 1996, then, plunged slightly to 2.35% between 1996 and 2008; the degree of intensity of dynamic expansion in this period has a relatively moderate speed, the degree of dynamic expansion starts to have a rapid speed of 6.40% between 2008 and 2020.

Analysis of the macroform by Shannon entropy

Shannon's entropy method is also used to designate changes in urban development and to understand the degree of urban macroform in our case study, that is, whether it is dispersed or compact in terms of urban growth, and its spatio-temporal changes. After the classification carried out on the images of 1984–1996–2008–2020, we used Shannon entropy to present the spatio-temporal transformations of urban growth in the inter-municipal grouping of Batna, and to understand the extent of growth, whether it is compact or divergent, and to provide an idea on the reality of urban development of whether it is clustered or disaggregated.

Creation of buffer zones

We use the concentric buffer zones to calculate the Shannon entropy values. This zoning method considers the result of distance from the Central Business District (CBD) of each region and the trend of urban growth (Congalton 1991). The buffer zones have been designed by the use of GIS at a distance of 02–18 km as concentric rings around a point preferred CBD, where there is the concentration of commercial activities, financial and business centre, of our grouping inter-municipal of Batna. The resulting buffer zones created individual built-up areas; they are calculated to determine the Shannon entropy and detect compactness or urban sprawl (Fig. 7).

The values of absolute Shannon entropy are 0.50 in 1984, 0.56 in 1996, while for the year 2008 it is 0.60 and 0.80 in 2020. The values are far from 0 and crossed with the log *n* value that is 0.95. This means that the urban development is oriented more towards dispersion and divergence. Therefore, an urban sprawl is observed. The values of relative Shannon entropy obtained are 0.53 in 1984, and 0.59 in 1996, for the year 2008 it is 0.63. and 0.83 in 2020. The values of the Shannon entropy are close to 1, ≥ 0.5, indicating the presence of propagation. Which confirms an urban sprawl. The values of relative and absolute entropy are of the same trend.

Hence, we can see that the values of absolute and relative entropy have steadily achieved a gradual increase from 1984 to 2020 in a proportional way. This dramatic increase in entropy values indicates that urban development is shifting from compactness to dispersion. This indicates

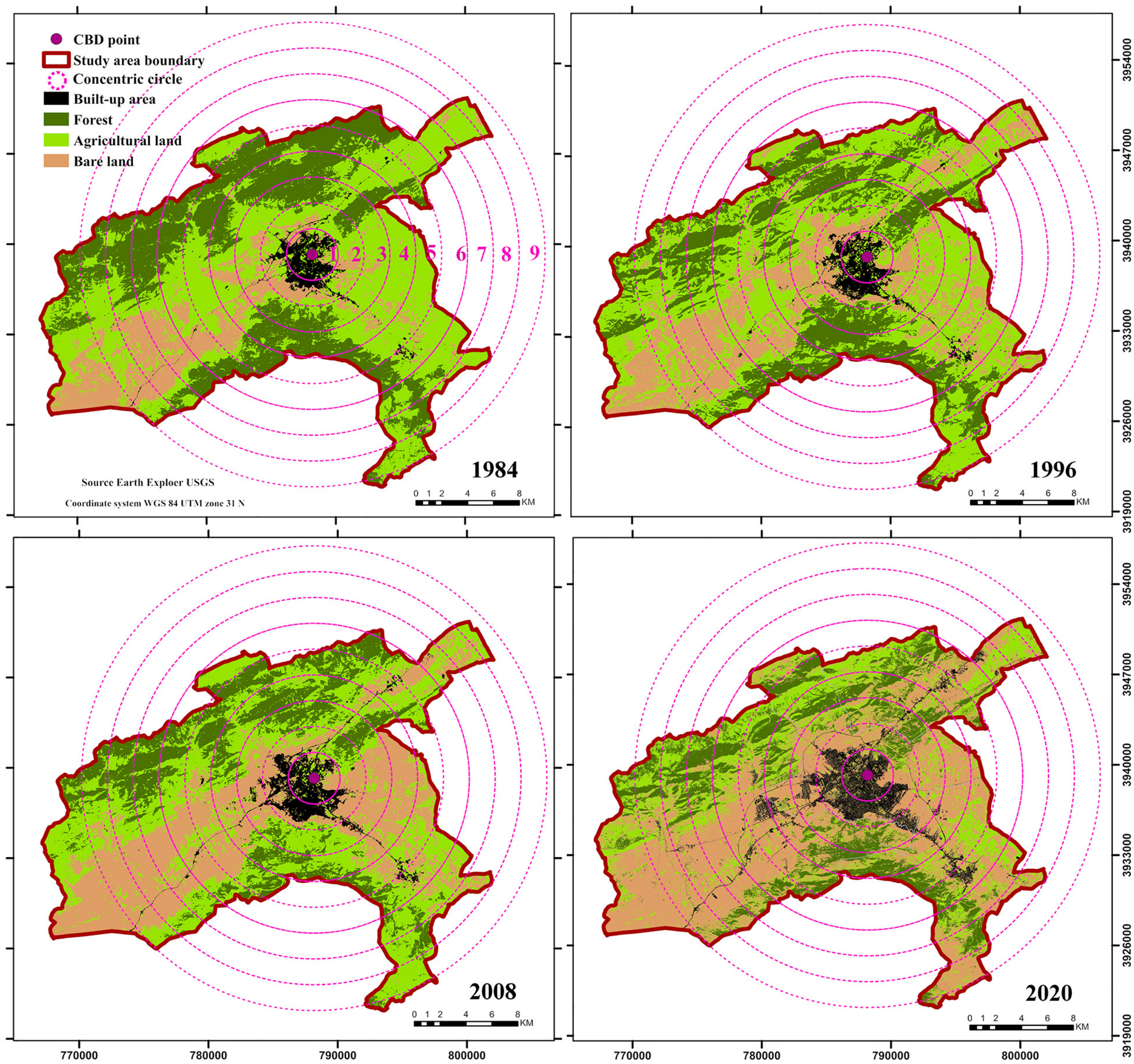

Fig. 7. Circular buffer zones of the Shannon entropy.

spread and urban growth pattern of this inter-municipal grouping that is oriented towards urban sprawl. It is clear that the values of relative and absolute entropy are increasing, which shows that the study area has experienced an increase in urban sprawl between 1984 and 2020; this urban phenomenon has spread over time.

Relative entropy differences

To estimate the change in urban sprawl, the rate of change and urban dispersion (change in urban sprawl) between two time periods was calculated. The results indicate that there is a rather small increase in urban areas between 1984 and 1996 of $\Delta Hn = 0.06$ and successively in 1996–2008 of $\Delta Hn = 0.04$, whith an interesting progression of $\Delta Hn = 0.21$ between 2008 and 2020. This designates that the urban sprawl of Batna inter-municipal grouping is uncontrolled and not taken into consideration in the urbanisation process.

Fractal analysis of the macroform by counting boxes

Fractal analysis is a highly organised approach to explain and evaluate urban growth and urban specimens. Fractal analysis models are very essential and effective ways to examine the urban pattern, the values of fractal dimension with time successions that are useful to know the urban growth (Chen 2013). In order to study the changes in the fractal dimension, box-counting analysis is used with the binary images of the Batna inter-communal grouping over 36 years.

According to Terzi and Kaya (2008), the fractal dimension has a value between 1 and 2. In this regard, the fractal dimensions obtained in the years 1984, 1996 and 2008 are 1.30,1.31 and 1.36, respectively. These values seem to be stagnant and converge between them. In 2020, a higher value is recorded at 1.45. The fractal dimension values have steadily increased in a moderate way from the lowest value of 1.30 in 1984 to a slightly higher value of 1.45 in 2020. This shows that the fractal dimension increases with time and with a progress of the space filling extent of the study area. The fractal dimension is an indispensable factor to describe complexity (De Oliveira et al. 2014). A higher dimension indicates a more complex geometry (Hu et al. 2015). The fractal values show the fractal dimension of the urban form and represent the landscape with complexity. The values, that vary between 1 and 2, indicate an increase in the shape complexity of the built-up area if they approach 2, and show that the built-up area has a simpler shape if they approach 1. Thus, the fractal dimensions are median between the two values even with a gentle increase that tends to 1.5, which explains a less arduous complexity of the built-up area of the urban macroform. Torrens and Alberti (2000) showed that values close to 1 indicate that urban areas are more compact and durable, and values close to 2 indicate that they are less compact or more sprawling and dispersed. Thus, the values of the fractal dimension obtained are slightly higher and pockets to 2, indicating that they are less compact, more sprawling and dispersed. We deduce from the above data that an urban development leads to a moderate urban sprawl is foreseen. So, in general, the morphic description of the fabric of Batna informs that the inter-municipal grouping of Batna has a less arduous urban structure and irregular, dispersed, fragmented macroform, oriented towards sprawl through time.

Prediction and modelling of land use and land cover changes

CA-Markov modelling is a grouping of two methods, where one is a spatially accurate deterministic model and the other is a stochastic model (Parker et al. 2003). The Markov chain supported CA algorithm adopted a bottom-up approach to capture a realistic urban growth pattern and land use dynamics (Liu et al. 2008), using the Idrisi Selva 17.0 software. The LU/LC map in 2020 is taken as the base map, the matrix conversion probabilities (the transition probability matrix) and the conditional probability images of 1996–2008 were taken as input to simulate the future urban land use maps of 2040, 2060 and 2080, and 30 iterations were used.

Validity indices

The use of all Kappa ratings not only leads to the overall success rate, but also provides an understanding of effective factors that assess the reliability or weakness of results (Geri et al. 2011). In our study, the degree of agreement between the 2020 reference map and the 2020 map was simulated by CA-Markov using the statistical Kappa index. If the predictive power value is 80%, then it is considered strong. So, we can say that our simulation model has been validated with a kappa coefficient value that exceeds 80% this shows the validity of the model to predict future projections.

The results of the simulation and modelling of CA-MARKOV

In order to predict future LU/LC changes, a future projection of the urban macroform of the Batna inter-municipal grouping was evaluated using the CA model and Markov chain. The results of the CA-Markov analysis are shown in Figure 8 which processed by Idrisi Selva 17 and in Figure 9 which processed by ArcGIS 10.5 as well as indicated in Figure 10.

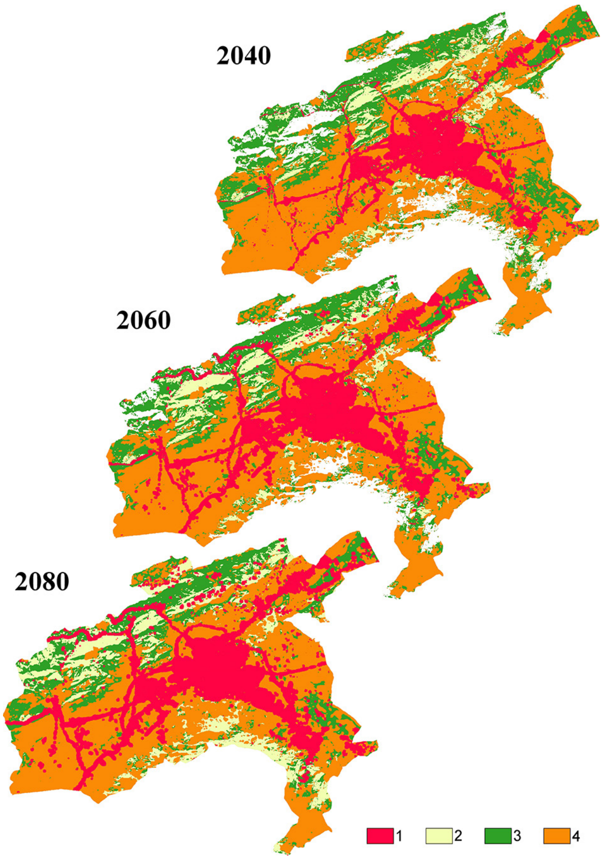

Fig. 8. The future projection of the urban macroform of Batna inter-communal grouping in the years 2040, 2060, and 2080 (processed by Idrisi Selva17).
1 – built up area, 2 – forest, 3 – agricultural land, 4 – bare land.

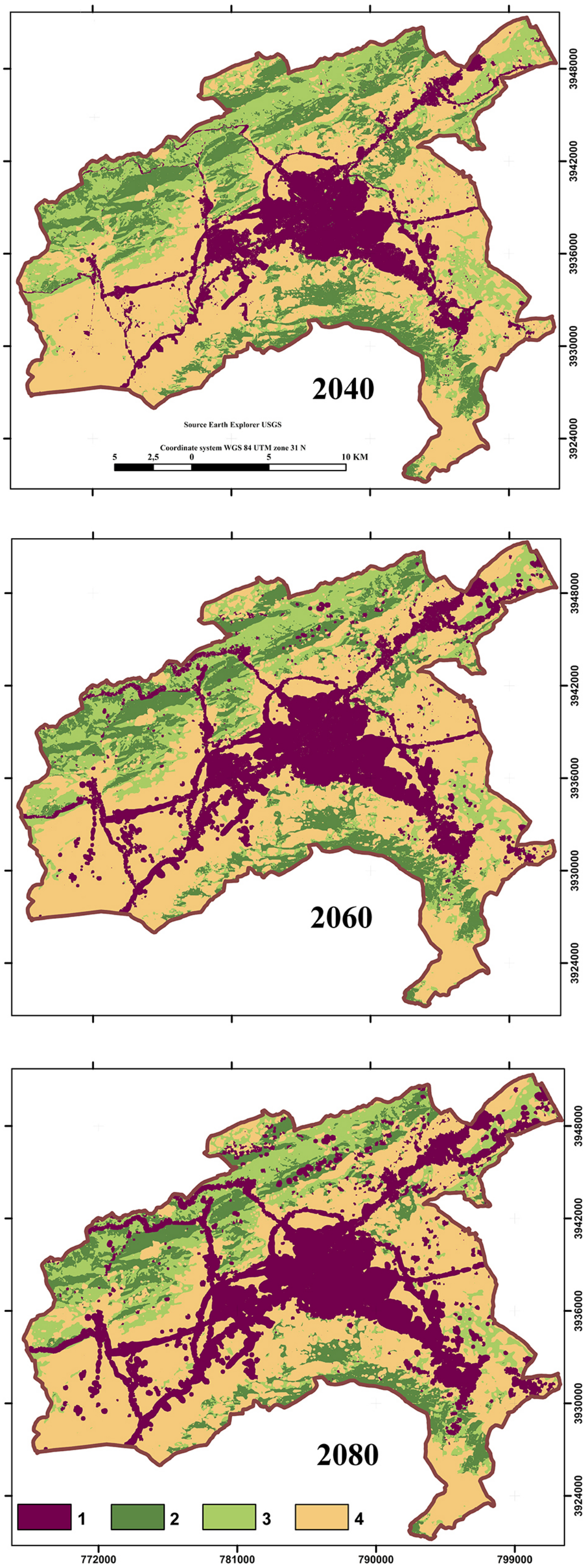

Fig. 9. The future projection of the urban macroform of Batna inter-communal grouping in the years 2040-2060-2080 (processed by ArcGIS 10.5).
1 – built up area, 2 – forest, 3 – agricultural land, 4 – bare land.

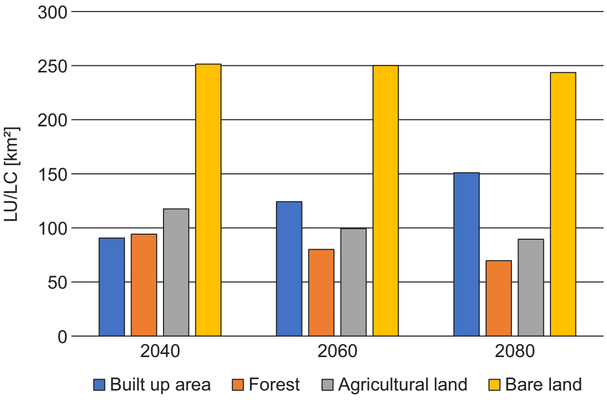

Fig. 10. Comparison graph of the future projection of the urban macroform of Batna the years 2040, 2060, and 2080 (processed by ArcGIS 10.5).

Predictions for future land-use changes based on CA-Markov model in the Batna macroform shows moderate future changes over the study period (2040, 2060, and 2080) as presented in Fig. 9, that due to socio-economic and political factors. These forecasts for future LU/LC changes are characterised by an increase in the built-up area opposite a remarkable decrease in agriculture and forest cover, and thus, a slight reduction in bare soil. This prediction shows an increasing trend of built-up area expected to occur along transportation routes, empty pockets and agricultural land in the study area.

This increase is justified by the reversal of agricultural land to vacant land and fallow land that will be occupied by the built-up area (proposed long-term development projects such as housing and industries). This will increase the built-up rate. The ratio of bare soil has experienced a slight downward trend, which expresses the depletion of land on one hand, which is recovered by a conversion of agricultural land to vacant land, that makes the balance in the land ratio. A decreasing trend in the forest area is due to fires, abandonment and poor protection of forest cover. If such a direction evolves over the next 60 years, most of the agricultural land and forest cover in the study area will be destroyed. This causes environmental problems, which are in opposition to the sustainable urban development.

Conclusion

Remote sensing and GIS are striking, appropriate, necessary and adequate new tools to provide information, to examine urban changes developments and to carry out the urban macroform spatio-temporal analyses of the inter-municipal grouping in Batna during the period 1984–2020. Remarkable changes in LU/LC are characterised by a significant increase in the built-up area and bare soil, against a regression of the agricultural land and forest surface. These transformations lead to an urban development that takes place in all directions; in particular, the transport axes where the various residential, industrial and educational projects are located. Shannon entropy proves to be a reliable indicator, a credible approach that estimates and tracks land arrangement, recognises and examines dispersion and concentration of the built areas in urban macroforms. The spatial measurements in the studied macroform indicate an increase in Shannon entropies values. It shows a dispersed urban development that leads to urban sprawl during the period 1984–2020.

Fractal analysis allowed us to describe the urban morphology, spatial organisation and morphological realities of the urban macroforms through various methods of analysis. The analysis of the urban reality in our study by the method of box counting allowed us to get a real understanding of the spatial development. At this point, urban development show a less arduous urban structure and irregular, dispersed, fragmented macroform, oriented to the sprawl over the time.

The CA-Markov chain approach integrated with remote sensing and GIS are used to predict future transformations. According to the simulated results of this model, considerable degradation of agricultural and forest land will occur due to rapid urban growth that will develop through urban densification in some parts of the studied area. This considerable increase in building will be directed towards empty pockets, agricultural land, vacant land and even at the foot of the surrounding mountains. This hybrid model shows that the urban macroform of Batna tends towards compactness (land saturation) and urban densification in the future. In sum, it appears that all the approaches used confirm that the macroform of Batna is developing in a dispersed manner that tends towards urban compactness in the future.

The lesson drawn from this study is a prospective evaluation of urban growth in the study area to direct it towards sustainability in order to avoid the harmful effects of urban sprawl, a tool to help in the decision for effective planning.

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Founding

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Author's contribution

Nadia Fekkous: Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data, Writing – Original Draft preparation, Writing – Review & Editing, Visualisation; Djamel Alkama: Conceptualization, Methodology, Writing – Original Draft preparation, Writing – Review & Editing, Supervision; Khaoula Fekkous: Formal analysis, Writing – Original Draft preparation, Writing – Review & Editing.

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