



Urban sprawl characterization and its impact on peri-urban agriculture in Sidi Bel Abbes, Algeria, using multi-date landsat imagery

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Abstract Identifying and characterizing the spatiotemporal dynamics of urban areas is mandatory in many disciplines, e.g., in environmental studies, infrastructure, and agriculture. The current research work investigates the overall trends of urban development and agricultural land changes of Sidi Bel Abbes city, for the years 1987, 1999, 2009 and 2019. To this end, Landsat archives have been considered due to its excellent temporal coverage, appropriate spatial dimension for urban characterization, and free data access. Multiple classifiers decision fusion technique was performed to characterize the spatial distribution of the built-up areas followed by agricultural land changes estimation through the Normalized Difference Vegetation Index. The results reveal that over the last three decades, a significant increase of built-up lands has been settled at the expense of peri-urban agriculture where the net-growth rate (%) of built-up areas and agricultural land per year between 1987 to 1999, 1999 to 2009 and 2009 to 2019 were +4.2, +2.83, +2.11 and -1.66, -0.94, -0.69

respectively. The multi-temporal assessment of urban change and orientation permitted the identification of slow (southeast) and fast (north-east) sprawling areas. In addition, to understand the built-up expansion effects on the agricultural land-cover, urban sprawl was analyzed and the results show that the settlement areas generally increased in the whole study period, which was around 39.01% of the total area (7077 ha) and similarly, peri-urban agriculture areas decreased by approximately 32% from the arable lands (4648 ha).

Keywords Landsat · Multi-classifiers · Late fusion · Urban sprawl · Peri-urban agriculture

Introduction

Motivation

Under the constraint of global population growth, the planet is being rapidly urbanized and much of natural landscapes have been artificialized (Leeson, 2018). The spatiotemporal dynamics of urban areas play an important role in global environmental changes. Policymakers and modern urban theory agree that consumer-leisure amenities attract population, particularly, the highly skilled and their employers (Debru & Brand, 2019). This caused the migration from rural regions to big and moderate cities, which generates many problems such as vegetation degradation,

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climatic change, etc. (Ayambire et al., 2019; Serra et al., 2018; Simon, 2008).

Urban sprawl studies include their detection, identification of their nature, measurement of the surfaces affected and the characterization of their spatial arrangement (Ismael, 2021). Thus, to correctly interpret the change type, it is necessary to determine the actual evolution of urban sprawl over the agricultural areas. The Algerian agricultural territory extends over 8 million hectares of useful agricultural land (Mendas et al., 2021). It represents a fragile ecosystem that is constantly threatened by degradation due to the concentration of the population, economic activities and infrastructure on the periphery of the big cities. The proportion of urbanization is 72% and the rural population is now decreasing even in absolute terms – 0.4%/year (Bessaoud, 2019). In fact, the Algerian population counts approximately 42.4 million inhabitants, with a growth rate of 2.1% of its population, which are concentrated with, 87% in the north of the country (Benabdelkader et al., 2021).

The concentration of industrial activities in the north of the country, has accentuated the migration attractiveness of the populations to the large cities causing a strong urban expansion. Sidi Bel Abbes has transformed from a small town and strong of a diversified agricultural territory, to a large city saturated by urbanization where public authorities remain in difficulty to manage population mobility and protection of agricultural land. As a result, SBA population has increased from 154,745 to 283,100 inhabitants between 1987 and 2021 with 68 people/km² of population density according to the General Census of Population and Housing (ONS, 2011, 2013).

Although contrary to the law of agricultural land, this growth supervised by the authorities or illegal spreads “linearly” in the periphery of the city. The rate of urbanization of the Sidi Bel Abbes has increased from 41.45% in 1987 to 57.49% in 2008 (ONS, 2011). Large cities such as Algiers and Oran, its peri urban lands currently constitute a single urban mass, this finding, it is not far for the case of the peri urban agricultural land of Sidi Bel Abbes to become urban areas.

Urban networks are a complex disposition not only in terms of their composition (type of construction, roof area) (Safia et al., 2015), but also in terms of geometry and distribution in geographic areas (planned habitat, slum housing), currently the spatial

monitoring of urban areas has become a progressive necessity both for the monitoring of human activities (growth of cities, monitoring of industrial areas, etc.) and for the protection of the agricultural territory from possible transgressions (household and industrial pollution, reducing of agricultural land etc.) (Nemouchi & Zeghiche, 2021). This continuous spatial statement requires the use of remote sensing and mapping tools, joined with a detailed consideration of the geographical area, in this case the urban sprawl takes a focus attention, according to the complex environment, including crops land identification (fallow land, arboriculture, cereal growing), as well as its spatiotemporal evolution (Dhanaraj & Angadi, 2020).

Based on the above discussion, The goal of this work is to identify the urban sprawl of Sidi Bel Abbes, via remote sensing tools, then, from the crops land maps, characterize the multi-date trend of urban sprawl during the last three decades (1987–2019) and to identify the most relevant areas of change in favor of urban growth.

Related work

Urban sprawl is an attractive research topic that interests researchers and decision makers from different fields; geography, land use planning, urbanism, ecology, economics, etc., where RS plays a dominant role as a tool to evaluate and analyze the urban sprawl and to monitor the evolution of territories. A literature review was conducted, which included searching bibliographic databases on Google Scholar, Web of Science (WoS) and Scopus, querying these databases using a few keywords such as: “urban sprawl”, “urban mapping”, “land use change” and “RS” (Das & Angadi, 2022; Demaze, 2010; Dhanaraj & Angadi, 2020; Herold et al., 2003; Maity et al., 2020; Shah et al., 2022).

According to many authors, the birth of ‘urban sprawl’ term was firstly appeared with the establishment of the first urban cores (Franz et al., 2007; Ismael, 2021). In this context, the concept of protecting agricultural land from urban sprawl goes back into the history of urbanization. Furthermore, this phenomenon has affected the United Kingdom that goes back to the thirteenth, and to protect the farmland against the advance of the urban built in 1935, the British urbanist initiated the green belt (Ismael, 2021).

Between 1950 and 1960, Europe has experienced significant urban areas growth with an annual growth rate of 3.3%. In Eastern Europe, specialists in urban geography have expressed explanations for the causes and consequences of urban sprawl. Consequently, politics has always been influenced by the organization of social groups, which generates power relations between the actors involved in land-use policies (Ismael, 2021). The built-up areas are not the only factor responsible for urban sprawl; there are other types of artificialization such as infrastructure, road networks and business parks, which take up a lot of land and contribute to urban sprawl. This urban sprawl has caused many development issues, including pressure on housing, a proliferation of informal housing and the rise of crime in neighborhoods, water supply, sanitation problems, traffic congestion, loss of agricultural land, etc. (Shah et al., 2021).

In Algeria, according to different official censuses, the number of urban agglomerations increased from 211 to 751 between 1977 and 2008, with the appearance of new agglomerations, including 236 between 1977 and 1987, 132 between 1987 and 1998, and 172 in the last decade (ONS, 2011).

In recent years, spatial data archives have become freely available on a large scale by providers including the USGS Global land cover and ESA GlobCover (Inglada et al., 2017; Olofsson et al., 2012), operational high-resolution land cover map creation on the country scale using satellite image time series (Inglada et al., 2017) and Global Human Settlement Layer (GHSL) (Florczyk et al., 2019).

To this end, this mass of archived data has supported research on the analysis of built-up areas, and the development of treatment processes in the case of Algerian cities began to attract attention. There have also been recent advances in our understanding of the process of urban sprawl using satellite remote sensing. Missoumi et al. (2018) have used Landsat images of different periods of time, covering 1987 to 2016 and using the cuirass index to analyze the changes urban development in Oran area. Rabehi (2018) discussed the change analysis based on the statistics extracted from the four LU/LC maps of the Algiers Metropolitan using remote sensing and GIS. Rendering to him, land use statistics and transition metrics are important information to analyze the changes of land use in coastal area. Kadri and Khalfallah (2022) evaluated the

impact of urban expansion using remote sensing on the urban transport of east region in Bordj Bouariridj. Khallef and Brahamia (2019) have applied remote sensing indices, The Normalized Difference Built-up Index (NDBI) (Zha et al., 2003) the urban index (UI), Normalized Difference Bareness Index (NDBaI) and Enhanced Built-Up and Bareness Index (EBBI) (As-Syakur et al., 2012) by using a Sentinel 2 image (2018). Dridi et al. (2015) have used different time periods (1987, 1999, 2009 and 2019) freely available satellite data of Landsat to estimate and qualify urban sprawl in Batna by Support Vector Machine (Radio Basis Function classifier RBFC). Saouli et al. (2020) offered an integrated approach of remote sensing and GIS based urban sprawl change detection using supervised classification of a time series of Landsat for 1987, 2013 and 2017. Abdaoui et al. (2020) reported the application steps of geospatial technologies and Landsat remote sensing methodology from 1972 to 2016. This study computes the changes in LULC from 1972 to 2016 of Saharan context in Oued Souf region. Bouhata et al. (2016) showed analysis of the dynamics of urban extensions of sub-Saharan in Biskra region by multi-temporal Landsat image-ries (TM 1987, TM 2009 and 2014) to describe the growth in the urban area. Bentekhici and Yousfi (2013) provided an integrated approach of supervised classification and the cuirass index for the study diachronic study of urban area in Mostaganem (Coastal area) over the period 1984–2007. Diaf et al. (2007) describes a methodology to obtain built-up area changes from Sidi Bel Abbes area using optical remote sensing Landsat (1987 and 2001) and Aster (2003) by Normalized Difference Vegetation Index (NDVI). Ardjoum (2015) demonstrated study on the peri-urban area of Sidi Bel Abbes city, using Landsat satellite data to evaluate the urban area changes over the period from 2008 to 2014. Hamza et al. (2022) supported the vectorization and digitalization operations using Landsat and Google-Pro images of urban areas. This work enhances the influence of human activities in time and space on the environment in two periods from 1987 to 1998, and 2010 to 2018. Akram et al. (2019) elaborated a land information system, this system integrates land ownership and land use data for urban planning purposes using high spatial resolution satellite imagery (Ortho-image QuickBird 2015 and Alsat 2017). In

the present study, we intend to investigate machine learning classifiers the built-up area in peri-urban of the SBA city during 1987, 1999, 2009 and 2019 using Landsat TM, ETM+ and OLI images. In this regard, our work reveals the impact of sprawl on the peri-urban agricultural lands surrounding SBA city. When dealing with lands through complex dynamics such as peri-urban agricultural environments, it is necessary to improve methods that take into account all characteristics that makes for better identifying and analyzing all transformation' types, and that does not focus on a particular type of change (Dube et al., 2022). Thus, it is necessary to combine approaches that rely on image processing, which take into account the data heterogeneity used to detect and analyze changes since they are usually acquired several years apart, in different seasons, and using sensors with different spatial and spectral properties (Lin et al., 2022). Data heterogeneity is one of the main sources of error in interpreting

changes. Finally, they must consider changes' types of objects that is likely need to know over time.

Study area and data

The study context includes the SBA's periphery, which is situated in the western region of the Algeria' anterior plain. The north and east borders are shared with the provinces of Oran Mascara and Saida, the west borders are shared with the provinces of Tlemcen and Ain Timouchnet, the south with the province of Naâma as shown in Fig. 1. On the regional level, SBA is limited to the North by the Mediterranean Sea, 90 km from the metropolis of Oran. The province of SBA is endowed with several infrastructures of an economic nature (industrial zone), scientific (universities), etc., which makes this the province an attractive pole for the populations for the surrounding regions.

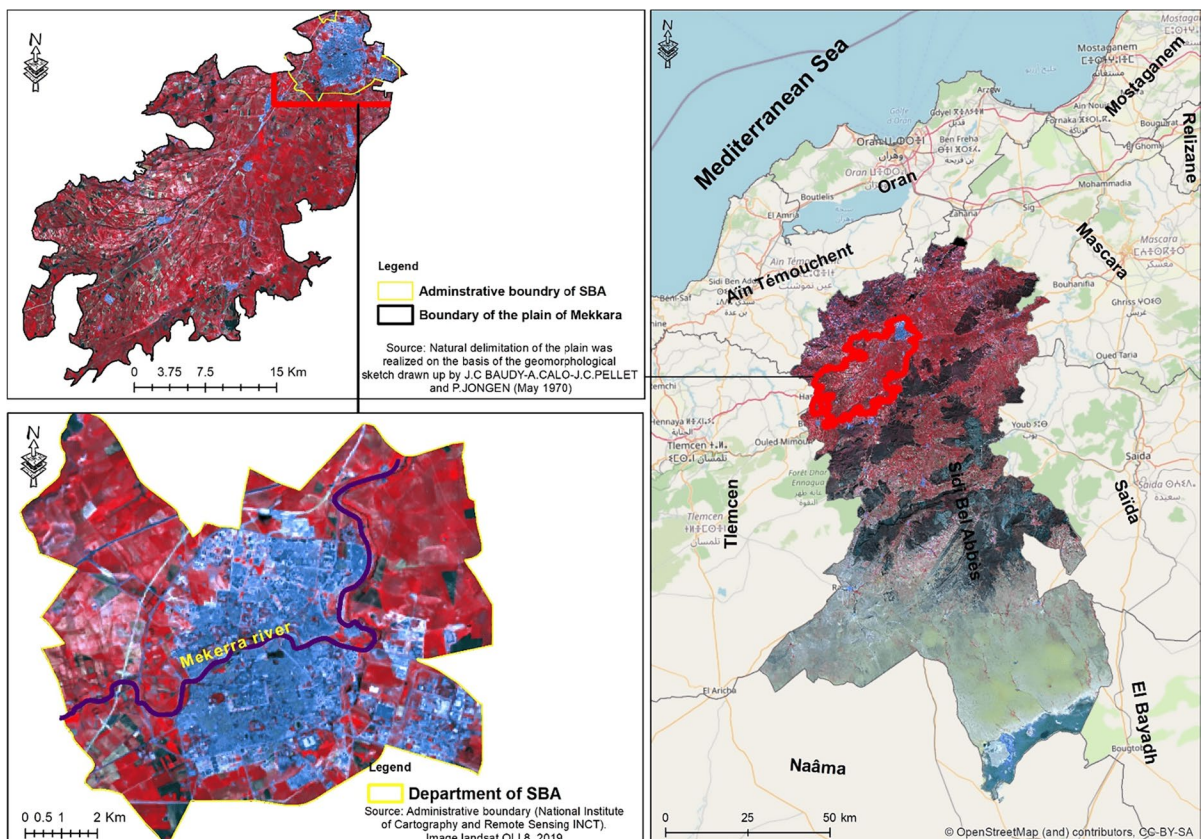


Fig. 1 The extended regional of SBA department

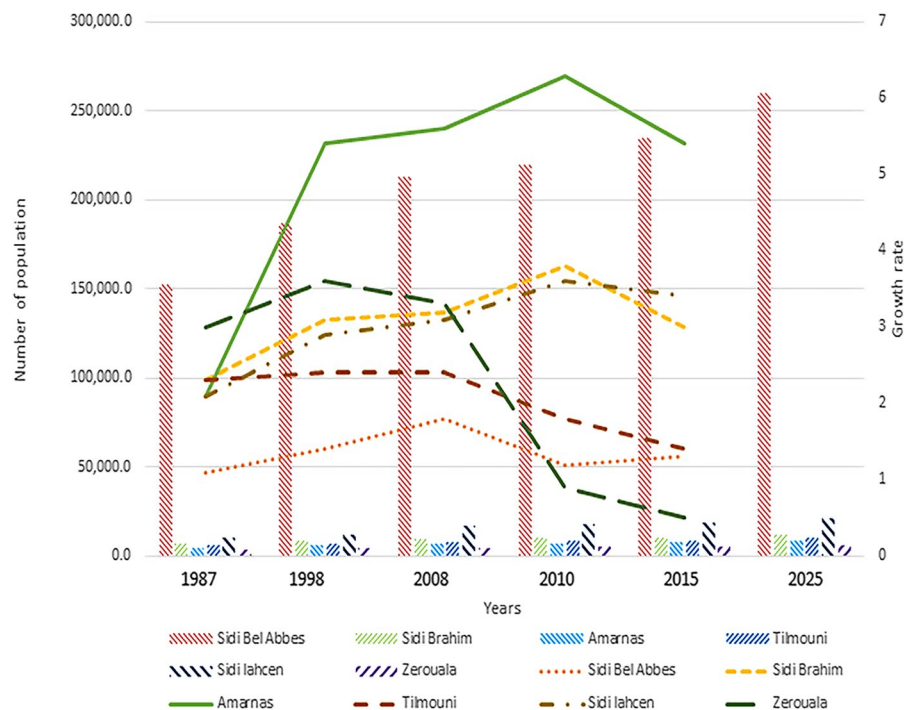
In order to detect and delineate urban sprawl, in this paper, a multi-classifiers decision fusion approach using three decades of the freely available multi-spectral Landsat satellite data is developed, which has achieved the desired goals of urban detection and agricultural land conversion to highlight the urban extent over time. The proposed approach is validated on SBA city and accuracies judgments were assessed through different statistical metrics. The remainder of this paper is organized as follows; statistical demographic of SBA city is given in “Demographic background of the study area”, then, data selection and preprocessing are justified in “Data source and preprocessing”. Section “Method” explains the established method for urban extension and “Experimental results” presents the experimental results for built-up detection, whereas the urban dynamic over agricultural land results are given in “Urban dynamic over agricultural land transformation”. In “Perspectives and discussions”, perspectives and future work are shared for further improvements on our results, and finally this work is concluded in “Conclusion and future work”.

Demographic background of the study area

SBA district covers an area of 7775 ha and had 237,400 inhabitants referencing to the GCPH, National Statistics Office (NSO) in 2015 as shown in Fig. 2. It is characterized by an emerging economy and a rapidly growing demography, with a population that increases according to the three periods surveyed by NSO in an uneven way notably; +3.06% in 1977–1987, 1.7% in 1987–1998, and 1.4% in 1998–2008, which attract important population for local migration. This population growth leads to pressure on urban areas of SBA city and a heavy extension of built-up areas in the periphery. The latter is related to residential mobility (Bendjelid, 1997). Certainly, population growth in SBA peripheral is a consequence of moving from other provinces to the city (Safia et al., 2015). This can explain the reason behind the decreasing natural growth rate of SBA and the increasing population number according to the demographic contributions linked to the rural exodus (see Fig. 2).

On January, 2015, the SBA’ population was 251,670 inhabitants, half of whom are under 25 years old, and extrapolations of the NSO predict 283,100 inhabitants and more than 300,000 inhabitants

Fig. 2 Population growth in the study area



respectively in 2030 and by 2050. In half a century, SBA' population has increased by a factor of 2 with a growth rate exceeding 3% annually in the various municipalities between 1987 and 2010, and fell to 1.4% in the 2010s, announcing a phase of demographic transition with rate drops by 2.1% (ONS, 2011, 2013). By observing the rural exodus period experienced by regions, either we can observe the exponential rate of population growth due to the high birth rate or because of the attractiveness of the city (employment, standard of living) compared to the outlying rural municipalities.

Data source and preprocessing

Multi-spectral Landsat satellite data has been selected as the data source. Here, a complete workflow is developed for urban classification and change detection. The pre-processing procedures are briefly listed for creating the analysis-ready data for atmospheric/radiometric correction and Region of Interest (ROI) substitution. Color composite images were employed to identify different types of LULC classes (urban/non-urban) for the manual annotation task. In addition, one of the main challenges is the creation of a cloud-free mosaic, which is achieved by pixel-wise cloud detection and the combination of multi-temporal images within short time periods (Schmitt et al., 2019). The Landsat top of atmosphere reflectance data, and all spectral bands were used as listed in Table 1, which are collected in the different seasons (Fig. 3).

Landsat satellite has the required spatial and spectral resolutions to successfully classify and monitor the land changes (Chen et al., 2017; Estoque & Murayama, 2017). For this study, three decades of Landsat images

time series from 1987 to 2019 are used with ten years of temporal step between each consecutive pair. Indeed, with over 40 years of operation [since its inaugural launch (Landsat MSS) in the summer of 1972], the Landsat data program is the world's oldest continuous recording of land surface imagery, allowing scientists to observe, monitor, and investigate how the land surface has been transforming over time (Chen et al., 2017; Howarth & Boasson, 1983). In addition, the free availability of more than three million imageries, provides the most preferable option for researchers, scientists, and real-world applications.

Cloud-free multi-temporal composites

The multi-temporal composites are theoretically based on the previous studies by Müller (Müller et al., 2015) where temporal metrics corresponding to each pixel have been extracted from a dense stack of Landsat time series. The missing values due to clouds and incomplete coverages were excluded from these calculations. Consequently, all related scenes for each period are stacked. Using this data cube, the mean, median and standard deviation (Eqs. 1, 2, 3) were calculated:

$$\text{Mean} = \frac{1}{n} \sum_{i=1}^n x_i, \quad (1)$$

$$\text{Median} = \left(\frac{n+1}{2} \right)^{\text{th}} \text{Observation}, \quad (2)$$

$$\text{Standard deviation} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2. \quad (3)$$

To detect the cloud coverage, Landsat images were atmospherically corrected, then clouds are masked

Table 1 Technical characteristics of Landsat imageries

	Landsat data							
	20/06/1987		20/06/1999		03/09/2009		13/07/2019	
Years	20/06/1987		20/06/1999		03/09/2009		13/07/2019	
Size	4186×5387		4186×5387		4186×5387		4186×5387	
Bands/Resolution	Bleu (B)	B1/30m	Bleu (B)	B1/30m	Bleu (B)	B1/30m	Bleu (B)	B2/30m
	Green (G)	B2/30m	Green (G)	B2/30m	Green (G)	B2/30m	Green (G)	B3/30m
	Red (R)	B3/30m	Red (R)	B3/30m	Red (R)	B3/30m	Red (R)	B4/30m
	(NIR)	B4/30m	(NIR)	B4/30m	(NIR)	B4/30m	(NIR)	B5/30m
Samples building/no building	10,000/10000							

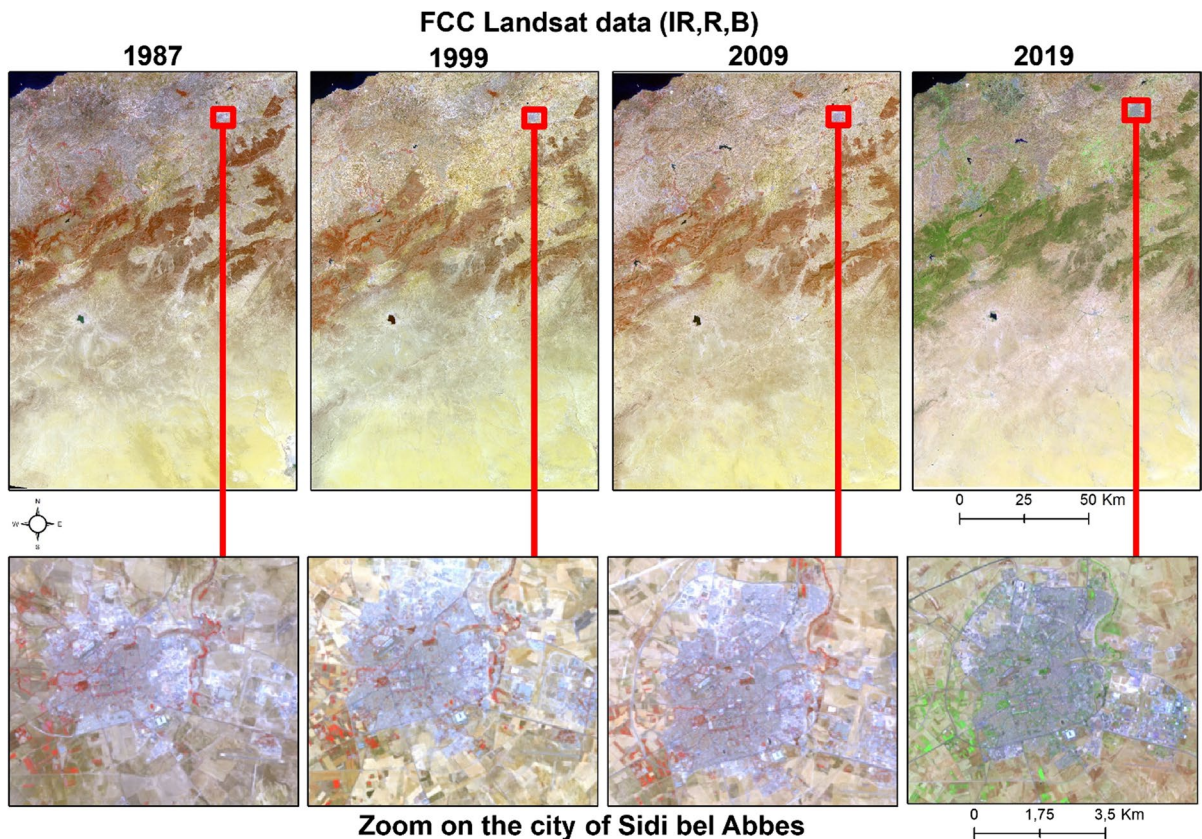


Fig. 3 Multi-date Landsat imagery

using an open-source framework (Hostert et al., 2015) where all bands were used for subsequent analysis. The original spatial resolution of 30 m was chosen to avoid information loss caused by pan-sharpening.

Training dataset sampling

In order to train multiple classifiers with good generalization abilities, a large-scale and representative annotated dataset is important and crucial. For this purpose, labeled samples are carefully created as reference datasets. The dataset consists of randomly distributed 10,000 image patches of urban labels over SBA city, manually assigned by domain experts that are uniformly distributed within the study area. To minimize the spatial autocorrelation effect, a minimum distance of 1000 m to the training areas has been assured. A detailed description of samples preparation is given in the next section. A comparatively medium amount of labeled data is required for

classifiers training, as some models require more, and others require less. To ensure precise and sharp urban extensions delineations capabilities of supervised classifiers, it is important to cover all potential class transitions as negative (non-building) classes when collecting the training polygons.

Figure 4 provides a meaningful picture of the spatial patterns where 10,000 training samples per class were created. In addition, it is straightforward to collect negative training samples (no-building) while it is not the case for the positive samples (building) due to the varying prevalence of the classes. This processing step includes two main stages, conceptualized and adopted as supervised classification and fusion steps. Thus, four images (1987, 1999, 2009, and 2019) were employed to test multiple classifiers' approaches. The intersection of the classifications allows us to determine the areas of change using fusion techniques.

Our methodological approach is outlined in three parts, including the binary classification scheme,

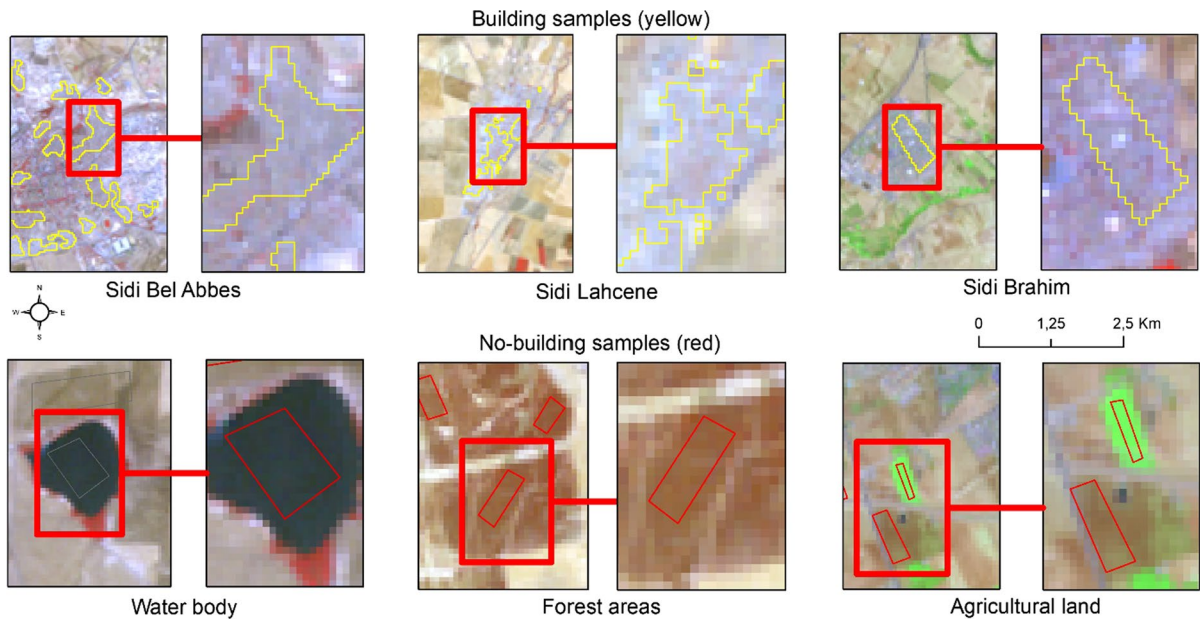


Fig. 4 Training and validation data sampling

decision fusion, and change detection to quantify the dynamic of urban/peri-urban areas (Complete workflow is shown in Fig. 5). The multi-bands images of different dates are classified following multiple supervised classifiers with a focus on built-up areas characterization. The spatial distribution of the built-up areas is constituted of several different types of housing including principal houses built with local materials. As well, the non-building class includes all other classes including all vegetation type as forests, agricultural land, grassland, bare soils, and waterbody.

Method

Using multiple classifiers is a hot trend that offers more opportunities and better accuracies compared to single classifiers. Usually, among diverse candidate classifiers, the best performing one should be selected, that fits the specific needs. However, classifiers may get a failure to correctly classify diverse patterns, even the best performing one on some patterns may fail on others whereas weak classifiers succeed. In this research, a mixture of supervised classifiers was built to take advantage of the entire ensemble. Five state-of-art classification algorithms named; Random forests (RF), Maximum Likelihood

Classifier (MLC), support vector machine (SVM), neural networks (NN), KD-tree (KDTKNN) were selected for performance comparison. By doing this, complementary information from various classifiers maybe exploited.

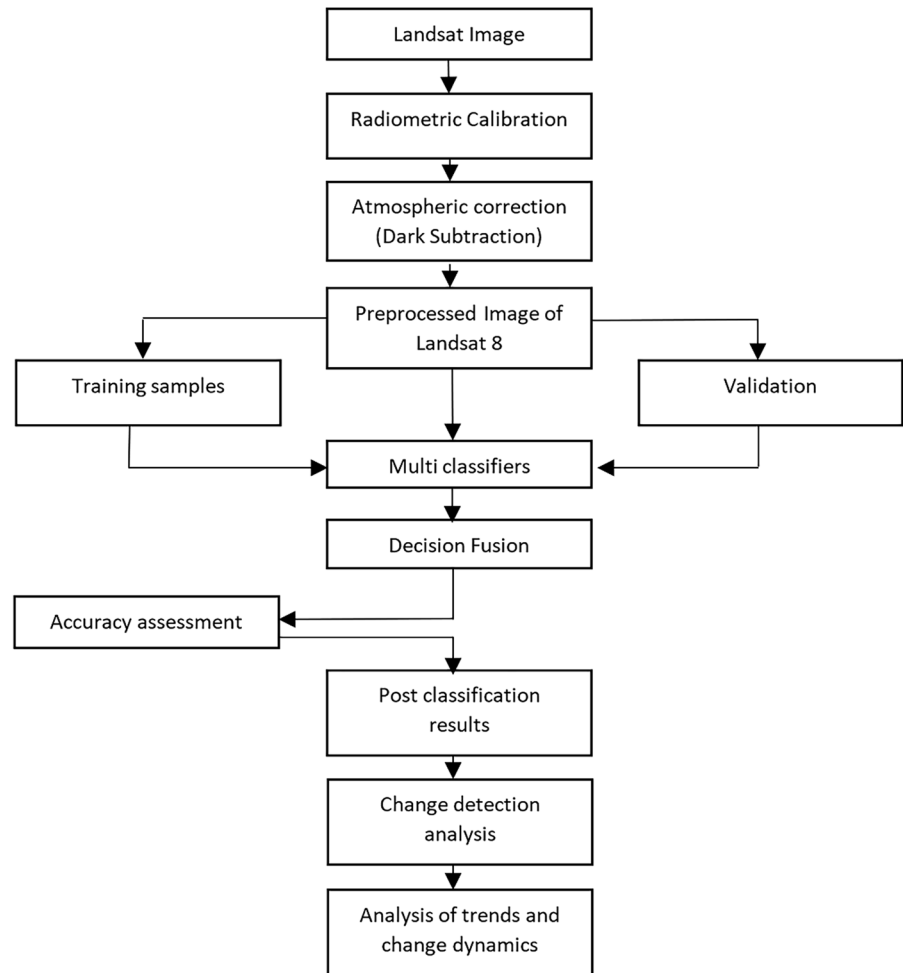
Recently, deep learning (DL) approaches have achieved new records in RS related tasks. However, this comes with non-negligible inconvenient for real worlds automatic applications as it requires intensive computing power and large amount of expert's labor training datasets, which is not preferable for near real-time real-world applications. And thus, DL algorithms have been excluded from this work.

Many interesting design questions appear; what is the best combination strategy that can be selected in order to reach the desired accuracy? Should we combine the results following sample arithmetic operations (sum, product, min, max, mean, median, etc.), majority voting (MV), which means superior to half of the whole must be positive, k-means clustering, automatic thresholding (Otsu), elimination, etc.

Decision fusion

Multiple classifiers combination is one of the most robust and accurate approaches, these methods have been proposed to handle different real problems

Fig. 5 Complete workflow for mapping the urban extent based on cloud-free Landsat composites including subsequent performance analysis

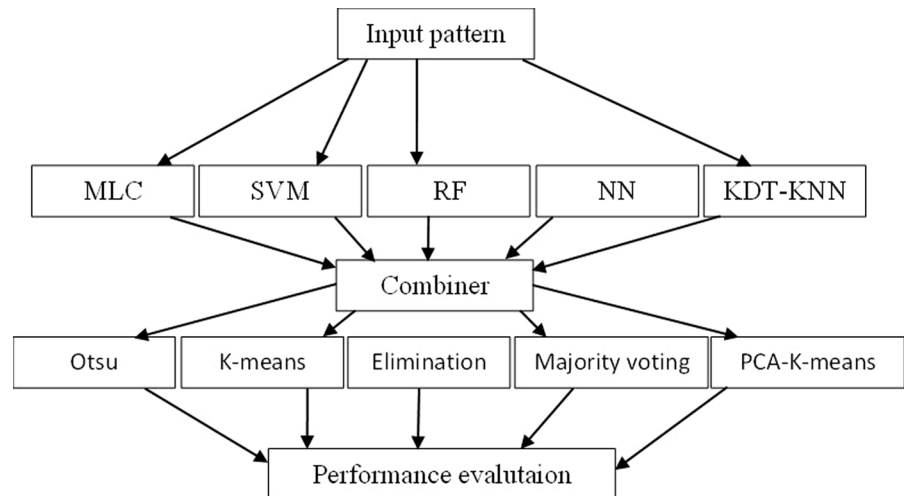


and to improve unstable performance or classifiers' weakness. Combining classifiers is a methodology of creating an ensemble of classifiers in order to produce a new architecture (Lefebvre et al., 2011). This approach seeks different opinions before making a decision as output (see Fig. 6). Several hybrids' techniques have been proposed in the literature to address the pattern recognition tasks including combination, aggregation, classifiers fusion and mixture of experts. Dietterich (Mountrakis et al., 2011) has illustrated that a combination of classifiers achieved good performances for different applications.

Assuming that classifiers are complementary, a theoretical framework was proposed by Kittler et al. (Thanh Noi & Kappas, 2017) that includes the sum, product, max, min, average and median rules.

Change detection

Change detection aims at identifying changes between scenes of the same location acquired at different time's periods. Ranging from simple arithmetic differencing to ML, change detection techniques can be applied directly to raw images, intermediate representation (features), or classified images. This later is highly dependent on classified NDVI values in a changing order of vegetation, which will be considered in this work with a computing difference map technique (Das & Angadi, 2022; Lefebvre et al., 2011). The NDVI values clearly illustrated in the Table 2, The NDVI images (1987, 1999 and 2009) was examined for distinctive NDVI values for changed features (Rizvi et al., 2009).

Fig. 6 Decision fusion

Vegetation area changes estimation

Agricultural land is one of the vital parts of land cover. A crop area always helps to satisfy the height demand for food. It also helps to balance the oxygen and carbon dioxide cycle and fight against climate change. In the current day's rapid technological development, human lifestyles changes are the causes of agricultural areas' loss. Many national programs related to habitation, companies, or industries, are depending on the availability of agricultural areas.

According to the literature, many spectral vegetation indices (VIs) have been formulated to evaluate biophysical characteristics of vegetation including Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI) and Modified Soil-Adjusted Vegetation Index (MSAVI) (Bannari et al., 1995; Xue & Su, 2017). These indices have been strongly contributed to the characterization of vegetation

especially for the quantification of the properties of the vegetation to detect the green vegetation in relation to other types of land cover in mountainous areas (Kokhan & Vostokov, 2020; Kou et al., 2017). It is a worth noting to say that NDVI is the most-used VI by scientists and has not been chosen fortuitously (Glenn et al., 2008; Li et al., 2010). Accordingly, in this work, crop types distinction has been achieved through Normalized Difference Vegetation Index (NDVI) thresholding into distinct ranges (Akbar et al., 2019; Rizvi et al., 2009) as revealed in Table 2, and confirmed via terrain knowledge of the study area (Akbar et al., 2019; Rizvi et al., 2009). The resulting classes have been employed to characterize the crops types consumed by the artificialization phenomenon:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (4)$$

Table 2 NDVI ranges for land cover types classification

Land use types	NDVI values
Water (deep and shallow)	−0.41379 to −0.10401
Built-ups/river sand	−0.10401 to 0.055727
Fallow/wasteland	0.055727 to 0.14
Bare soil	0.14 to 0.20579
Crop, grass	0.20579 to 0.37035
Agroforestry, plantation	0.37036 to 0.51073
Forest	0.51074 to 0.82051

Experimental results

Performance assessment

The last step consists of computing statistical indices over fusion results called respectively Kappa index, F1 score, precision, and recall. These indices are used to validate the classification results. They are calculated through the confusion matrix whose rows correspond to the observation data (or field) and columns to the classification data (see Table 3). Therefore, a “quality estimator considers errors in rows and

Table 3 Statistical metrics

	Total population	True condition	
		Condition positive	Condition negative
Predicted condition	Predicted condition positive	True positive (TP)	False Positive (FP) Type I error
	Predicted condition negative	False Negative (TN) Type II error	True negative (TN)

columns”. Its value is between 0 and 1. The Kappa metric (5) is an accuracy metric that compensates for the chance agreement between classes. The F1-score (6) is the average of the harmonic means between precision (7) and recall (8) for the built-up class. This measure is sensitive to class accuracy, but additionally considers the number of correctly classified pixels over the number of predicted labels:

$$Accuracy\ assessment = \frac{FP + FN}{FP + FN + TP + TN}, \tag{5}$$

$$Precision = \frac{TP}{TP + FP}, \tag{6}$$

$$Recall = \frac{TP}{FP + FN}, \tag{7}$$

$$F1\ Score = 2 \frac{Precision * Recall}{Precision + Recall} \tag{8}$$

The attained results are shown in Fig. 7 where the first evaluation illustrates that multi-classifiers supervised learning method responds well to urban built-up area extraction visually and highlights the advantages of classifiers ensemble. From 1987 to 2019, the MCL classifier performs slightly better as compared to RF, SVM, NN and KDTKNN with kappa values of 0.53, 0.59, 0.63 and 0.66 for the years 1987, 1999, 2009 and 2019 respectively as shown in Table 4. The widely used supervised classification algorithm RF (0.19) and KDTKNN (0.21) classifiers provide the lowest accuracies in 1987 (see Table 4). This can be explained by the difficulty of discriminating built-up areas from other classes like barren soil and the particularity of Landsat 5 images. Even though, RF algorithm is outperformed by other classifiers for built-up areas extraction, its results still promising for such challenging task. According to the statistics in Table 4, we argue that the obtained results are greatly

dependent on images qualities, which in turn depend on the capture conditions (season, atmospheric condition, etc.).

For validation purposes and to assess the quality of classification results, the above-mentioned indices are calculated where several polygons that contains all housing types identifiable at the satellite image spatial resolution, distributed over the entire study area and corresponding to each class are manually selected based on the preliminary acknowledge of the research field. Then, intersected with the resulting classification map. The summarized results of the assessment were plotted in Table 4. The overall accuracy (OA) values of different classifiers were achieved from classified images of 1987, 1999, 2009, and 2019. The qualitative results from the built-up classification of four respective years; 1987, 1999, 2009 and 2019, are shown in Fig. 6. Each classified map contains binary classification (built-up and no built-up) and illustrated the quality of different classification results (Fig. 7).

The eliminate fusion decision provides the best statistical metrics improvements for recall, precision, F1-score, and kappa compared to all the methods used in this study over different Landsat images from 1999 to 2019 (Table 5). Qualitative results of different decision fusion approaches are visualized in Fig. 8. Visually, urban area delimitation quality of different fusion-based techniques was enhanced in comparison to individual classifiers. In addition, it is clear that the eliminate fusion has well-characterized the built surfaces of SBA against all other techniques. The validation accuracies signify the agreement between digital classification and ground truths (reference points) which have a strong relationship. This was sensibly good overall accuracy as well as accepted to meet the requirement of change detection analysis (Anderson, 1976; Butt et al., 2015).

According to the kappa coefficient, the eliminate technique shows higher kappa as compared to different fusion methods. Figures 9 and 10 clearly show

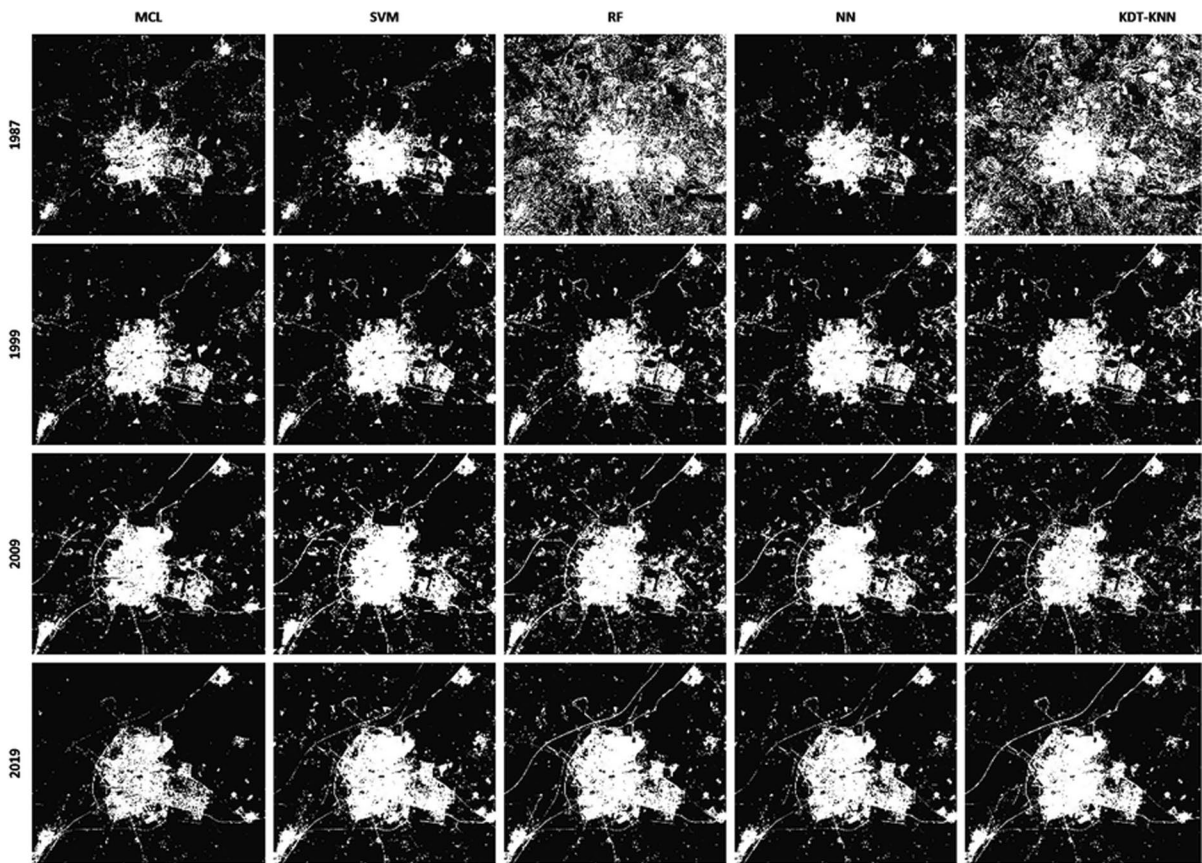


Fig. 7 Classification results from individual classifiers

Table 4 Kappa coefficient for individual classifiers

Classifier	1987		1999		2009		2019	
	OA	kappa	OA	kappa	OA	kappa	OA	kappa
MLE	86.85	0.53	86.58	0.59	85.28	0.61	87.13	0.66
SVM	86.66	0.52	85.63	0.57	85.74	0.62	83.34	0.61
RF	59.52	0.19	84.49	0.55	82.61	0.57	83.96	0.62
NN	87.08	0.53	84.45	0.55	82.98	0.57	85.51	0.65
KDTKNN	62.20	0.21	84.51	0.55	84.72	0.60	85.04	0.64

The bold text makes the table easier to read and highlights a quick comparison between the statistics for the different types of classification

that the eliminate is the best technique in terms of statistical results where the kappa coefficient exceeded the other fusion techniques (+0.70 for the all-voting technique). On the other hand, the other fusion techniques presented satisfactory statistical results and can compete with the eliminate technique.

Visually, comparing the binary classification maps of each classifier apart and the eliminated

fusion techniques, it is clearly shown that the later has best capability of classifying urban areas. The eliminate fusion approaches can map urban almost correctly and can delineate the built-up areas. As well, it provides the best mapping results while other decision fusion methods show promising and acceptable delineation according to statistical metrics as shown in Fig. 10 and Tables 4 and 5.

Table 5 Statistical results of different decision fusion

	1987				1999			
	Recall	Precision	F1 score	kappa	Recall	Precision	F1 score	kappa
Eliminate	0.80	0.69	0.74	0.70	0.93	0.75	0.83	0.79
Max-vot	0.96	0.51	0.67	0.61	0.97	0.67	0.79	0.73
K-means	0.98	0.25	0.40	0.25	0.98	0.64	0.77	0.70
Ostu	0.95	0.51	0.66	0.59	0.98	0.63	0.76	0.69
PCA-K-means	0.98	0.25	0.40	0.25	0.98	0.63	0.77	0.69
	2009				2019			
Eliminate	0.93	0.66	0.77	0.71	0.81	0.78	0.80	0.72
Max-vot	0.98	0.61	0.75	0.66	0.93	0.71	0.81	0.72
K-means	0.99	0.54	0.70	0.59	0.95	0.69	0.80	0.71
Ostu	0.96	0.57	0.72	0.63	0.92	0.69	0.79	0.69
PCA-K-means	0.99	0.54	0.70	0.60	0.95	0.69	0.80	0.71

The statistical results in bold signify a brief connection between statistical metrics based on the types of fusion methods. The value in bold is the type of decision fusion that was well appreciated

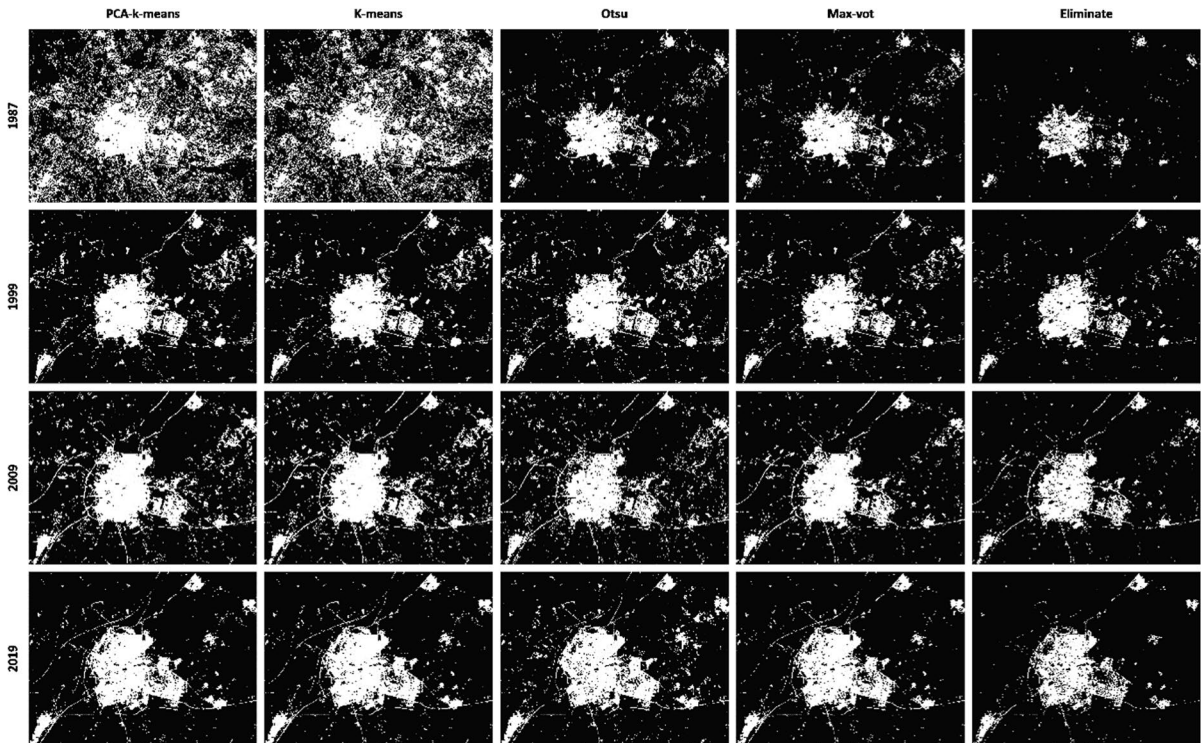


Fig. 8 Classification results from fusion techniques

Built-up area extraction

The quantitative results of built-up areas in the principal’s localities are reported in the Table 6. SBA city is the largest in terms of surface, which is partly explained by the importance of economic activities in this city (Fig. 11 and Table 6). The

urbanized areas represent 15.37% of the total area in 1987, reaching 27.36% in 1999 (Table 3), 34.22% in 2009, and 39.01% in 2019. These results highlight a clear progression of the urban areas with an average of 47.77 ha/year (see Table 6). This is an important information that can guide decision makers to straighten out their planning policies. The

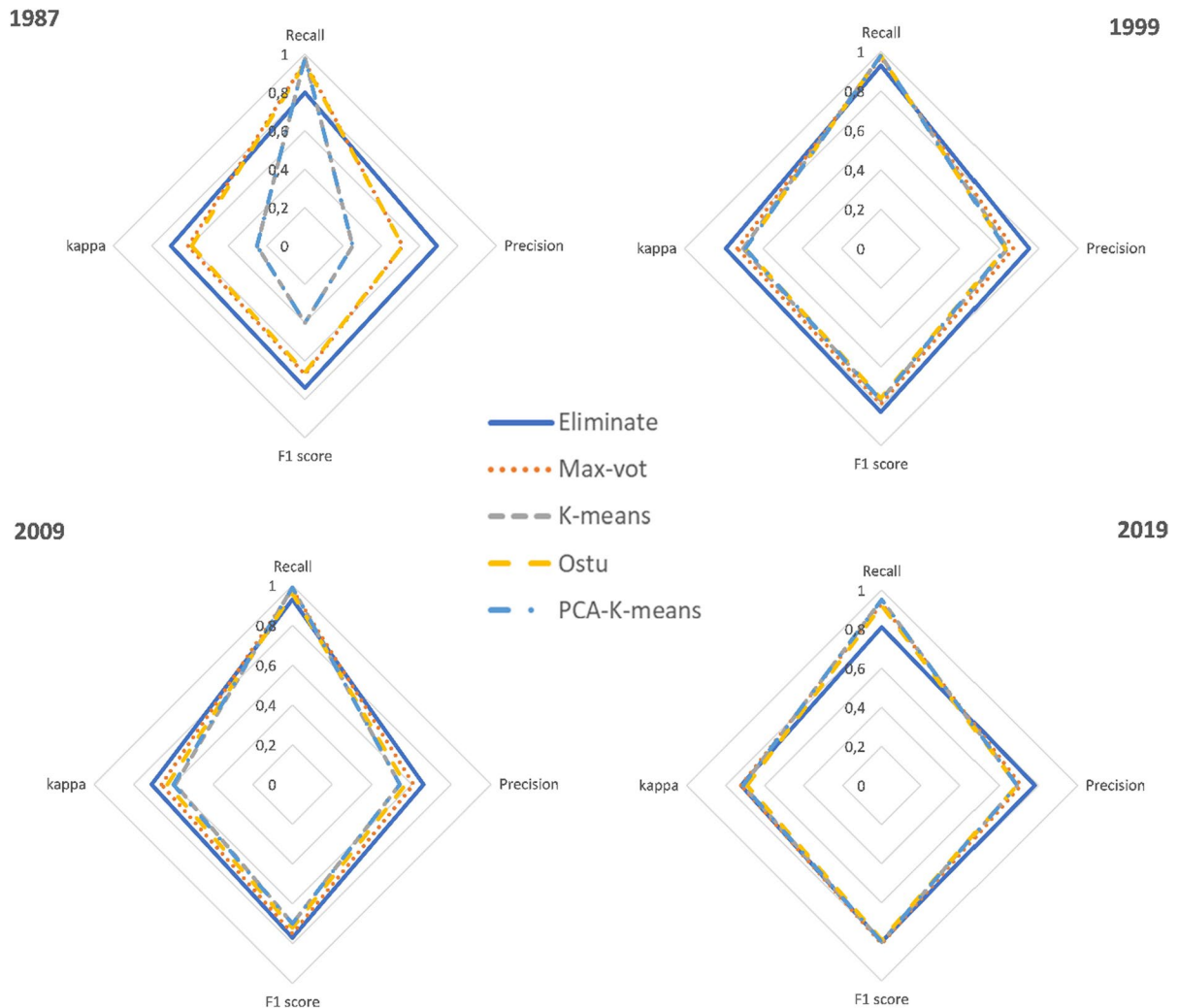


Fig. 9 Representation of statistical metrics results

urban sprawl of SBA is in the form of morphological sprawl, through the growth of peri-urban areas (inter-agglomeration expansion). This has resulted in a demographic spillover into the peri-urban areas, which was remarkable between 1987 and 1999 through the creation of new urbanization region (see Table 6 and Fig. 12). In total, 2616.99 hectares of urban areas of SBA city were mapped.

According to urban sprawl results shown in Fig. 11 and Table 6, the villages close to SBA border were converted into small towns i.e., Sidi Lahssen, Sidi Brahim, Zerouala, Amaranas and, Tilmouni. It plays an important role in re-housing

over of the population of SBA within the framework of housing programs. SBA' built-up area has experienced a gradual increase during the first decade of 1987–1999 (50.5%) at an average rate of 4.2% per year equivalence of 64.33 ha per 12 years. This trend continued during 1999–2009 as the increase was 28.38% for 10 years, showing an average increase of 2.83% that is around 43.39 ha in the same period. However, during 2009–2019, there was a moderate increase in the built-up areas by 21.11% as compared to the first period and almost with the average rate of 32.28% per year (see Fig. 12, Table 7).

Fig. 10 Variation of kappa coefficient over fusion decision techniques

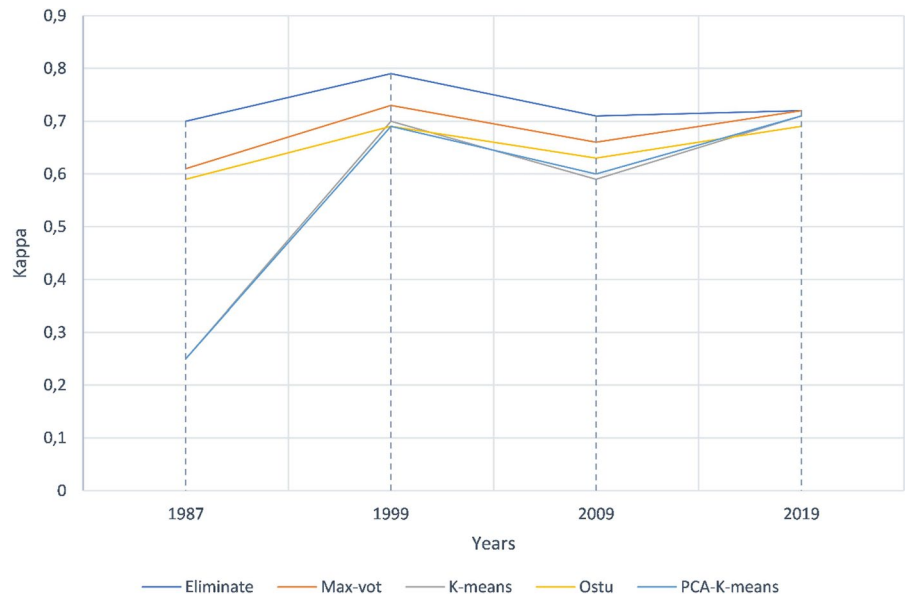


Table 6 Statistical results of urbanized surfaces in SBA

Department	Area per hectare				Total area/Department (hectare)	Urbanization rate (%)			
	1987	1999	2009	2019		1987	1999	2009	2019
Amaranas	63.35	143.34	271.06	322.15	9480.97	0.67	1.51	2.86	3.40
Sidi lahssen	85.27	307.11	487.57	548.32	9078.02	0.94	3.38	5.37	6.04
SBA	1 088.17	1 860.24	2 294.18	2 616.99	7077.63	15.37	27.36	34.22	39.01
Sidi Brahim	48.72	99.78	164.46	179.28	3908.95	1.25	2.55	4.21	4.59
Tilmouni	46.39	167.54	274.78	324.51	7708.31	0.60	2.17	3.56	4.21
Zerouala	60.23	205.50	268.83	273.32	13,396.94	0.45	1.53	2.01	2.04

Urban dynamic over agricultural land transformation

Land cover has shown a remarkable loss of agricultural surface (around 1527) ha during the whole study period (1987–2019). The huge amount of migration population from rural areas had come and settled down in different parts of the city. Meanwhile, the total built-up growth rate was around 772.3 ha during 1987–1999 where the crop and fallow lands have converted rapidly to built-up land as shown in Fig. 13 and Table 8.

Later, from 1999 to 2009 period, it is shown that the proportion of vegetation lost was more than 191.9 ha of fallow land simultaneously with 28.28 ha of plantation and 5.17 ha of crop. Five peripheral departments have grown in the study area over the

past 30 years, demonstrating the impact of urban development on rural transformation as demonstrated in Fig. 13. Landsat images have clearly revealed that the urban sprawl of the SBA has been made at the cost of exploiting the barren lands, fallow lands, plantations, and crops. The extensive concentration of built areas during these three decades has exhausted the carrying capacity and sustainability of the city remains a major challenge. Urban areas for different periods have spread over the agricultural area consumed in built-up areas. Much of this land was taken from the suburbs of the city.

The built-up area thus has consumed about 1528.07 ha spread over three periods. This surface initially represents the agricultural domain intended for fallow land, crop, and plantations. The land considered, as bare soil is generally the land left in

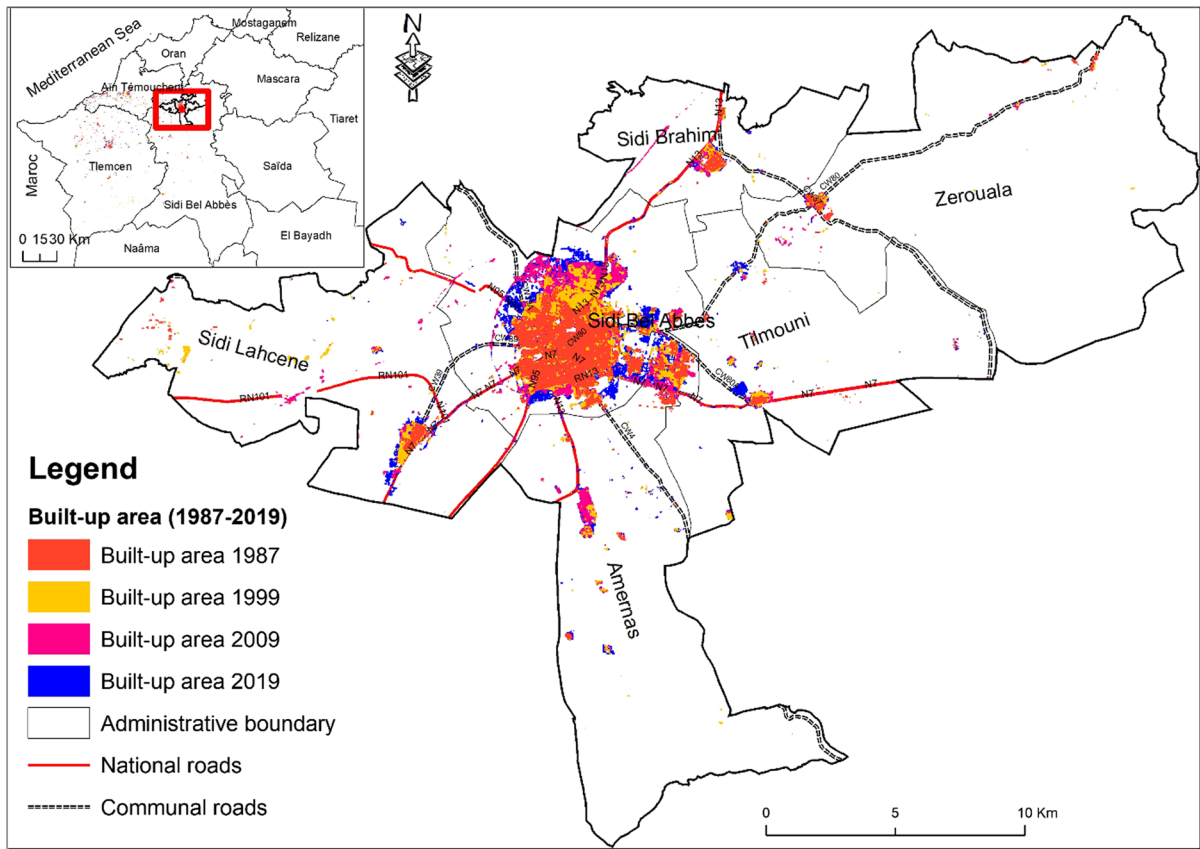


Fig. 11 Spatial distribution of built-up areas over the studied period

rest or not cultivated. The fallow land has recorded extraordinary areas around 645.86 ha in the period of 32 years, which has been reconverted to built-up areas and has also consumed the land under plantation and crop (see Table 8).

1987 to 1999 period

The results in Fig. 13 demonstrate how the pressure is progressively occur over crop and fallow land. It is clear that the fallow land is the most converting area at the suburban of SBA city, which are facing a rapid conversion into built-up areas. The most leading changes were found in built-up lands gain with 772 ha during 12 years of urban setting up, due to the emerging of private business sectors in SBA.

According to statistical values in Table 8, it is shown that the first period took over 16% of the useful agricultural land during 12 years, which is distributed much more in the fallow area with 9.7 and

4.2% of lands occupied by other crops. Similarly, the agricultural areas have endured a well-conflicted situation (operation of the uprooting of the vineyard). Moreover, the vineyards land converted to fallow land or crops (cereal) have shown a weakness towards this disproportionate urbanization due to the failure of agricultural policies during this period and the ineffectiveness of planning instruments in the protection of land stock (Bauouche, 2014).

1999 to 2009 period

Urban area extension shows a strong revival of land artificialization between 1999 and 2009 with about an area of 434.62 ha. This urban sprawl at the expense of other land uses is due to not only housing but also other infrastructure (East–West Highway, platforms, and business parks, etc.) developments approved by the MPDU. In this period, we notice that the urbanized surfaces have taken 209 ha bare lands, 191 ha

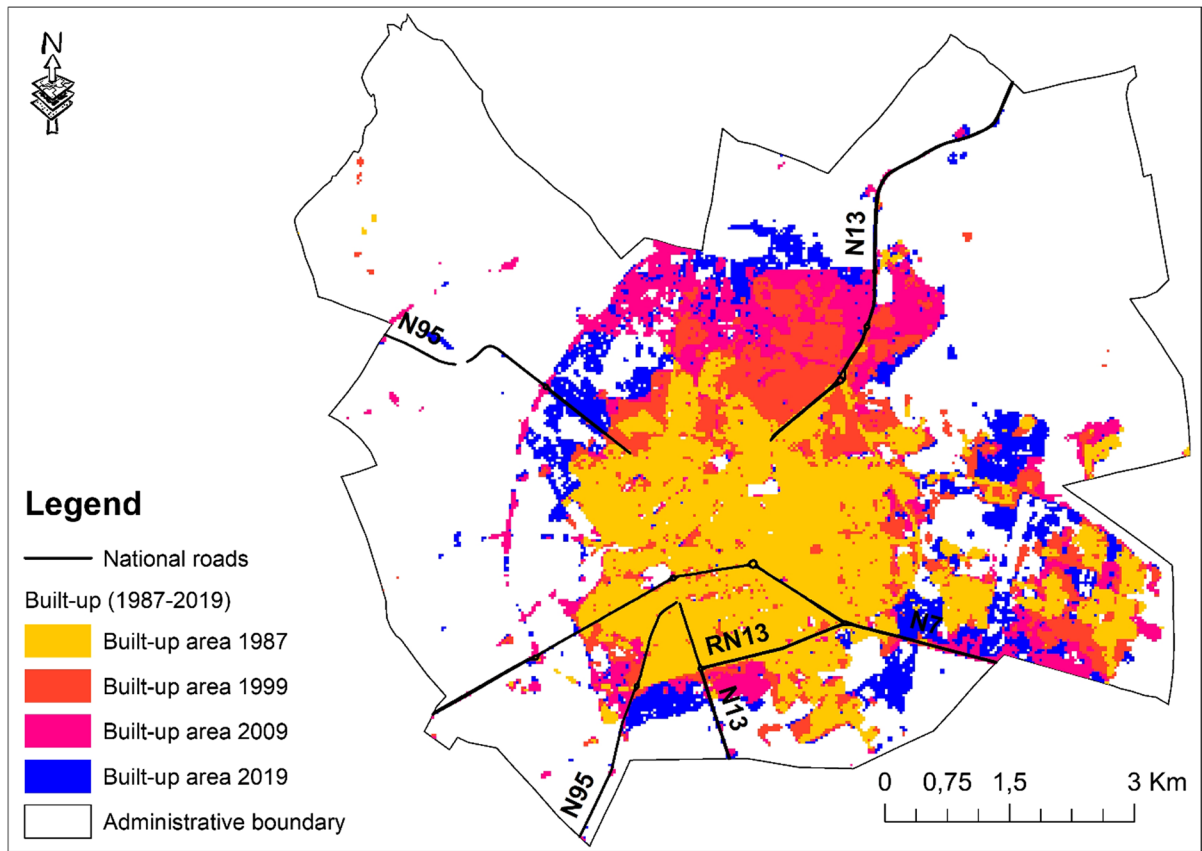


Fig. 12 Spatial distribution of built-up areas in Sidi Bel Abbas

Table 7 Urbanization rate in different time periods (ha)

Time periods	1987, 1999	1999, 2009	2009, 2019	Total period
Surface per period	772.07	433.94	322.81	1528.82
rate of growth	64.33	43.39	32.28	47.77
percentage per period (%)	4.20	2.83	2.11	3.12
Percentage rate per period	50.50	28.38	21.11	100

fallow lands and 28 ha of plantation. Therefore, we are witnessing a consumption oriented much more towards bare agricultural land and a progressive taking out of plantation land. In addition, during this period, Algeria has experienced a decade of national insecurity and leads to generating a serious exodus toward the city. Consequently, to meet the needs in terms of housing, excessive pressure was conducted on useful agricultural lands where the bare soil areas were the most degraded with more than 4.5% of the total area converted into buildings, succeeding by fallow land with 4.1% (see Table 8 and Fig. 14).

2009 to 2019 period

In this period, there is no preservation of useful agricultural land, which reflects the progressive consumption of 1% of plantations, as compared to the first period (1987–1999), which has taken around 0.5%, where all the useful agricultural lands have lost many surfaces on all the crops (see Fig. 14). There is a decline in cereal areas by the neglect of land around 3.9% left bare.

According to our fieldwork and discussions with local decision-makers (June 2019 and May 2021),

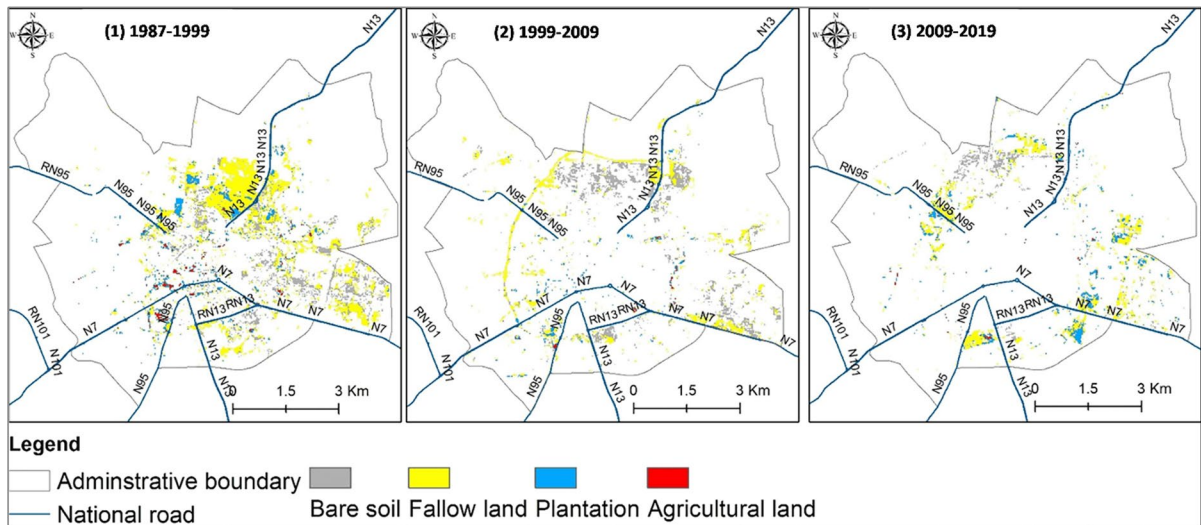


Fig. 13 Built-up growing over vegetation areas

Table 8 Agricultural lands deterioration in favor of urban sprawl

	1987–1999	% (Arable land)	1999–2009	% (Arable land)	2009–2019	% (Arable land)	1987–2019	% (Arable land)	Arable land per ha
Bare soil	102.4	2.2	209.0	4.5	182.2	3.9	493.6	10.6	4648.0
Fallow land	449.1	9.7	191.9	4.1	4.8	0.1	645.9	13.9	
Plantation	23.9	0.5	28.5	0.6	71.4	1.5	123.9	2.7	
Crop	196.8	4.2	5.2	0.1	62.7	1.3	264.7	5.7	
	772.3	16.6	434.6	9.4	321.2	6.9	1528.1	32.9	

arboriculture is better recomposed within the framework of urbanization. This explains why farmers have opted for these practices, such as the reconversion of the cereal zones towards arboriculture in the peri-urban area of SBA city. These strategies have become more frequent to preserve land for a long period in order to have more recomposed-on behalf of urbanization. The results of urban dynamics during the period studied for the benefit of urbanization allowed us to examine their directions.

Spatial orientation of urban expansion

Results from the changes maps from 1987 to 2019 are given in Fig. 13 and show significant changes in the peripheral agricultural land of the city. Typically, its northeastern part has recorded an increased loss of

agricultural land as presented in Fig. 15a leading to a sharp declining of areas intended for agriculture (see Fig. 15b). The evolution continued from the built-up of three urban suburbs towards the North and North-east (Fig. 15) with a parallel extension of the peripheral districts towards the East until 1987, at a rate of 64.33 ha / year. SBA city is thus very dynamic where its urban area spreads out completely over about 10 km from the center of the city to the outlying suburbs and overlapped with the peripheral municipalities (see Fig. 12). In this regard, the nature of land prices is significant about fallow land, cultivated land, and plantations. This agricultural decline benefits mainly the artificial spaces that have increased during the three study periods, especially with regard to crops located in the eastern sector of the city. In the same way, we witness seasonal variations and

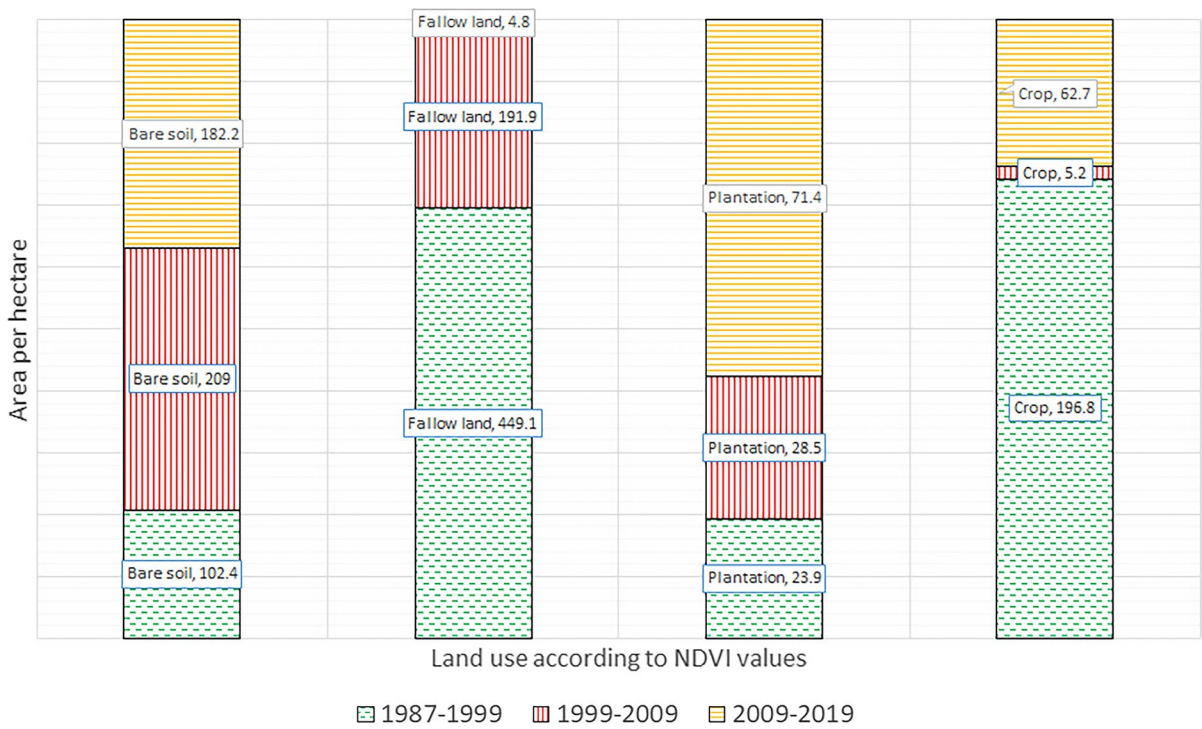


Fig. 14 Distribution of agricultural land consumed by urbanization

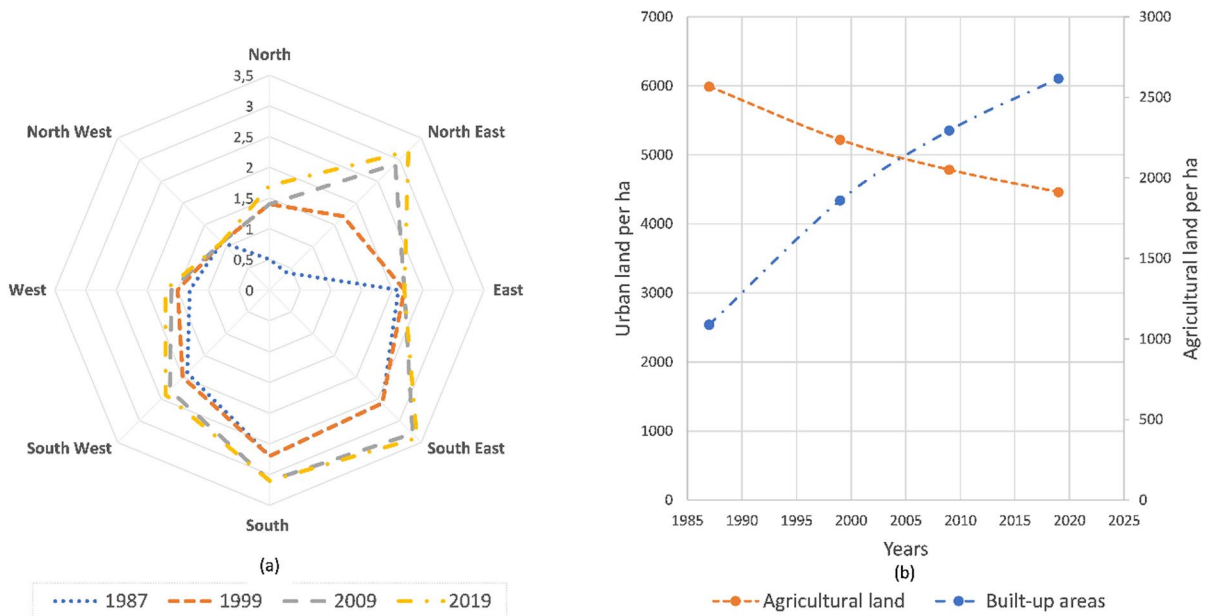


Fig. 15 The trend of urbanization at the expense of agricultural land: **a** urban area orientation, **b** urban areas vs. agricultural land

reconversion of agricultural practices oriented to satisfy individual interests on the peri-urban agricultural area. Then, these lands constitute an agricultural potential frozen by agricultural practices such as fruit trees, where the surface consumption intended for plantations is gradually increasing in the peripheral zone of SBA from where the conflicts start between rural and urban areas. At this moment, conflicts of interest arise between actors (decision-makers, promoters, and farmers or agricultural companies).

Finally, we noted a greater fragility of the system cereal-fallow land belt in the face of consumption via new urban expansion programs. Cereal growing being in a semi-arid climate, the yield has fluctuated much more, pushing farmers to abandon the land (fallow land), thus making these areas under threat, and more easily allocated to urbanization. The plantation is much more stable between 1987 and 2009 and shows a low resistance up to 2009 facing urban pressure, and moderate consumption of arable lands during this period.

Perspectives and discussions

The MPDU specify a regulatory framework for the forthcoming urban extension. On the legislative level, the first development plan for SBA city was in 1961, during the colonial era, and several areas were programmed for future urbanization on the eve of independence after 1962 (Ardjoum, 2015). In this regard, the SBA Master Plan has been modified to meet the needs of the local community. The law on development and urban planning of December 1990 decided to replace the urban planning plans with the master plan that defines the main urbanization guidelines at the local level. This planning failed in achieving its objectives due to the political and security crisis that the country was experiencing, which are the consequence of the strong housing needs on behalf a significant population number coming from rural areas (Yamani & Trache, 2020).

In the nineteen eighties, Algeria went through a situation marked by a regression of the urban economy, the opening of markets, urban squaring, and the rise of the informal sector, which coincided with a bloody decade of terrorism (1990–2000), the fall of oil and gas prices and structural reforms (Nemouchi & Zeghiche, 2021). These events affected medium cities like SBA. It is in this circumstance due to the

decline of oil reserve, urban and peri-urban became a major issue (Baouche, 2014). Initially, the peri-urban area of SBA was planned as follow:

Proposals for the development and urbanization of the cluster: Submitted on July 02, 2007 in the executive council of the province, communicated on July 24, 2007 to the local provincial council with the presence of technical services, the services of agriculture and urbanism accompanied by the national agency of the territory development proceeded on March 13, 2007 to retain the proposals of urban extension of phase II.

Orientation report and regulations: Posted on August 04, 2007 and awarded on September 26, 2007 to the local provincial council and with the presence of technical services, 2nd handing over on December 29, 2007: lift of reserves following the meeting of December 1, 2007. It was mandatory to revise the master plan every 10 years based on the changes in physical and socio-economic conditions.

Despite the fact that the last three decades (from 1998) have witnessed several procedures of urbanism' instruments revision (master plan and land use plan), modification and complement of certain laws, texts and decrees. These instruments remain far from being concretizing a harmonious and sustainable development for the city and are unable to produce viable and sustainable urban spaces. The local authorities, unfortunately, failed to implement the orientations instructions of the master plan. After its approval at local level, which have found difficulties in its implementation. They are linked mainly to the problem of land; this problem is related to the conflicting situation in terms of public management between agricultural policies (the legal framework for land) and the allocation of land in the framework of development policies. In this situation, local decision-makers have become unable to carry out management programs properly, which results in anarchy in the achievement of projects and generates threats to agricultural land.

The actual program of the master plan for SBA is following the same practices for the choice of land supply in the peripheries of the city. Likewise, farmers have also developed their strategies to protect their land from the advance of the building by plantations (based on our results and even from the fieldwork (June, 2019 and May, 2021)). In the long term, the master plan must carefully integrate the principles of sustainable urbanism in order to protect the land resources against urbanization and artificialization.

Conclusion and future work

In this paper, we evaluate the built-up extensions over agricultural lands based on remote sensing Landsat archive that cover the study period (1987–2019). More precisely, supervised classifiers is trained separately, and then, the results maps are merged. Through this study, it is revealed that the actual urbanization rate and the weak urban management strategies have a negative impact on the peri urban agricultural land, the main indicator to highlight the transformations occurred in the last three decades through a case study (agglomeration of Sidi Bel Abbes), is the process of overflow of this city on its peripheral agricultural land, which represents opportunities for urban expansion without natural constraints. Indeed, Sidi Bel Abbes at present must cope with economic constraints that consist in the preservation of agricultural resources around the city. For further research, especially in the Algerian context, this work is seen as a way to draw attention to the issue of preserving agricultural resources around cities, through serious economic studies that could determine the need to entrust some land on behalf of urbanization, and therefore, present serious jeopardized for future generation and sustainable development goals.

In this context, decision makers and stakeholders should take urgent measurements to protect the remaining peri urban agricultural lands (4460.63 ha). For this purpose, this study can be used to assess the amount of land that has been urbanized at the expense of agriculture. Agricultural land has always been affected by anarchic and planned urban development. To this end, Algerian urbanism has not ensured the applicability of local urban planning laws. The challenge then lies in the ability of the legislative framework to frame urban planning, by making available to local actor's geospatial tools via our results to achieve the objectives of sustainability. The integration of our results lies in the continuation of the planning in the new extensions, see their needs in terms of transport, schooling, and healthcare. This can be used for future planning of the city and revision of the master plan due to spatio-temporal changes of urban sprawl. The data will support the existing database about the built-up area changes over peri urban agricultural land for comparative assessment and future legislation about the land use planning in Sidi Bel Abbes, and then provide novel information about the clustering density of the building and the population living in these new extensions to guide urban management.

Urban sprawl leads to land artificialization, according to the present study, every year 47 hectares of agricultural land disappear in Sidi Bel Abbes as a result of urbanization, or 3.2% of the municipality's territory, the overall rate of decline not varying much over the last 30 years. The results obtained show that the artificialized surfaces covered 40% of the 7077 hectares of the department of SBA against 15% 30 years ago, an increase of more than 47 ha/year. This work is limited to revealing consumption rates for agricultural areas in suburban areas. Of course, that urban sprawl is not the only fact of residential habitat because the zones of activities, technopoles, parking lots, artificial land not built (gardens, lawns, sites, waste sites, urban, landfills, quarries) are considered as building typology which have not been mentioned in this work. This opens a search trail to see satellite data with better resolution than Landsat (30 m) like Algerian satellite Alsat (2.5 m) in order to characterize the construction typology as a perspective.

The process performed in this study via ML classifiers is conducting by a good sample collected and tested on building types (building/no-building samples). However, the procedures to have more details on the typology of the building, it is a work which requires a good sampling plan on all the types of the building, at this time the unsupervised classification can be an interesting test to have relationships between the built classes and to perform clustering in the near-term works.

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Declarations

Conflict of interests The authors have no competing interests to declare that are relevant to the content of this article.

Ethical statement I would like to inform you, that this work is part of my doctoral thesis. Doctoral training (LMD) is currently governed by the texts following regulations: (1) Executive Decree No. 08-265 of August 19 2008 scheme carrying studies with a view to obtaining a bachelor's degree, master's degree and the diploma of doctorate. (2) Executive Decree No. 10-231 of October 2 2010 on the status of the doctoral student. (3) Order No. 191 of July 16, 2012 setting the organization of third-grade training course for obtaining the diploma of doctorate, amended and supplemented by the order No. 345 of October 17, 2012.

Appendix

Classification Algorithm

Random forest

RF algorithm defined as the most well-known ensembles learning methodology that can be used in different tasks such as prediction out-of-sample rapidly and ranking capably of the importance of features (Belgiu & Drăguț, 2016; Breiman, 2001). Generally, RF is created by randomly selected samples (bootstrap sampling). As output classification, the results are obtained by selecting the MV technique from all the used Decision Trees (DT).

Support vector machine

SVM is one of the most ML techniques used in RS data classification tasks that can generalize with limited training samples (Mountrakis et al., 2011). The benefits of using SVM come from two aspects such as the discovery of a large margin linear boundary in the new space and converting the original training set' space into a new very high-dimensional new space. In addition to this, SVM can optimize the non-separable using 'kernel stick'.

k-nearest neighbor

The k-NN is defined as a Machine Learning (ML) classifier used for memory-based and nonparametric learning, as well as instance-based learning for regression and classification tasks (Thanh Noi & Kappas, 2017). In the classification process, k-NN classifies a given pixel employing the MV of its neighbors in the feature space.

Maximum likelihood classifier

MLC is a well-known algorithm for the RS community and is commonly used for classification tasks. Individual pixels are assigned to the class, which can maximize the likelihoods of the data set. As a pixel-based technique, this approach does not take contextual information about the classes of neighboring

classes into account in labeling a pixel (Turker & Ozdarici, 2011).

Neural networks

NN is one of the best performing ML techniques. Since NN is non-parametric (meaning they do not assume a Gaussian distribution), it has been successfully applied to RS data sets. For this research, a Multi-Layer Perceptron (MLP) with one hidden layer was applied (Qian et al., 2020).

Decision fusion

All these rules can be used to combine classifiers on measurement level:

- **Minimum:** Select the minimum score of each class provided by each classifier and allocates the input pattern to that class with the maximum score.
- **Maximum:** Select the maximum score of each class provided by each classifier and allocates the input pattern to the class with the maximum score.
- **Product:** Multiplies the score from each classifier and allocates the class label with the maximum score to the specified input pattern.
- **Sum:** Adds the score provided by each base classifier and assigns the class label with the maximum score to the specified input pattern.
- **Average:** Select the mean of the scores of each class between the classifiers and allocates the input pattern to the class with the maximum score.
- **Median:** Calculate the scores' median of each class from the classifiers and assigns the input pattern to the class with the maximum score.
- **Majority voting:** It is an elementary combiner, together with the average and the product rules, majority vote is the most used one. As mentioned beforehand, for several ML methods, the majority voting is selected as the optimal combiner.
- **Elimination:** To combine classifiers, all of them must produce the same result, else rejected. This mechanism can be reformulated as voting where all of them vote for the same class.
- **Otsu:** An automatic thresholding method.
- **K-means:** Automatic clustering method. There are different ways of classifiers combination.

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