GeoJournal (2024) 89:72
https://doi.org/10.1007/s10708-024-11078-7

Predicting urban growth and its impact on fragile environment using Land Change Modeler (LCM): a case study of Djelfa City, Algeria

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Accepted: 7 March 2024 / Published online: 14 March 2024

Abstract This study aims at predicting the urban growth of Djelfa, which is the largest Algerian semi-arid city, and assessing its impact on Land Use / Land Cover (LULC). Three satellite datasets (2000, 2010, and 2020) were classified using Maximum Likelihood Classification (MLC). We employed the LULC maps of 2000 and 2010 and integrated four urban growth factors to predict the urban growth of 2020 using Land Change Modeler (LCM) based on Logistic Regression Model (LRM). The predicted urban growth was compared with the observed urban class of 2020 to validate the model. Finally, we predicted future urban growth of 2030, 2040, and 2050. In effect, the urban growth of Djelfa is rapid. Its annual rate was 3.05% from 2000 till 2020 and will be 1.85% between 2020 and 2050. This has caused the loss of 11.88 km^2, 2.01 km^2, and 1.76 km^2 of the steppe, the forest, and the agricultural land respectively, between 2000 and 2020. According to LCM, the steppe, the forest, and the agricultural land will lose 28.33 km^2, 32.54 km^2, and 10.84 km^2 sequentially, between 2020 and 2050.

Keywords Urban growth · Spatio-temporal prediction · Fragile environment · LCM · LRM

Introduction

Rapid and uncontrolled urban growth negatively impacts the environment and people's quality of life (Liu et al., 2019a; Mondal et al., 2020; Yuan, 2010). This makes the urban growth control an essential task that the government's competent services must undertake. On a global scale, urban growth has caused significant changes in LULC and has negatively impacted natural resources. It has been observed, for example, in the USA (Tayyebi et al., 2013), in Germany (Siedentop & Fina, 2010), in Ethiopia (Getu & Bhat, 2021), or in a set of Mediterranean countries (Shalaby et al., 2012; Xystrakis et al., 2017; Ohana-Levi et al., 2018; Abd El-kawy et al., 2019). It turns out that regions characterised by a fragile environment were also exposed to the negative impacts of urban growth, where the consequences on natural resources were alarming (Al-sharif & Pradhan, 2015; Amarsaikhan et al., 2009; Salem et al., 2020).

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Therefore, urban growth spatio-temporal prediction studies are very important for planning agencies and policymakers to develop sustainable urban growth policies that may reduce future environmental impacts (Grigorescu et al., 2019; Petrov & Sugumaran, 2005; Yadav & Ghosh, 2019). In this respect, the analysis of multi-temporal satellite imagery has proven its effectiveness (Aljoufie et al., 2013; Amarsaikhan et al., 2009; Ilyassova et al., 2019; Maithania et al., 2010). However, before that, the satellite dataset must be classified. The comparison between several studies does not give unanimity concerning a better classification method. For example, Srivastava et al. (2012) study has found that Artificial Neural Network (ANN) gives more precision in classification than MLC, while other studies suggest the adoption of MLC, which has proven its excellent accuracy (Patil et al., 2012; Sameen et al., 2016). The supervised classification based on MLC has proven efficient, especially if we know the study area well (Traoré et al., 2013; Zhang et al., 2008). That was why we chose the MLC method widely adopted in studies interested in LULC (Brannstrom & Filippi, 2008; John et al., 2020; Sinha et al., 2015) to classify three LANDSAT satellite images of 2000, 2010, and 2020.

Several studies have successfully adopted many simulation modeling techniques to analyse the environmental impacts of urban growth and make predictions. For instance, empirical and statistical models such as Cellular Automata-Markov (CA-M) (Ahmed & Ahmed, 2012; Losiri et al., 2016); dynamic models such as ANN (Anand & Oinam, 2020; Mohammady et al., 2014); integrated models such as CLUE-S (Grigorescu et al., 2019); and hybrid models such as LCM (Jain et al., 2017; Nor et al., 2017). We opted for the LCM, whose process is less complicated and faster than other models (Altuwaijri et al., 2019; Jain et al., 2017; Jamali & Ghorbani Kalkhajeh, 2019; Nor et al., 2017). LCM provides robust tools for analysing LULC change and creating predictions (Eastman et al., 2005). Based on the change probabilities to the urban class and the urban growth factors, LCM adopts two prediction methods: Multi-layer perceptron (MLP), which gives the possibility of treating in a single analysis all the possible transitions from all the LULC classes to the urban class (Grekousis et al., 2013; Liu & Seto, 2008; Pijanowski et al., 2014), or LRM which analyses the transitions from each LULC class to the urban class independently (Chen et al., 2019; Feng et al., 2018; Lafazani & Lagarias, 2016). Our study determines the change probabilities between the LULC classes between 2000 and 2010. Next, we will move on to the potential transitions to the urban class by selecting and integrating the urban growth factors. Through LRM, we will obtain the potential transitions from each LULC class to the urban class to predict the urban growth of 2020. Finally, the predicted urban growth map will be validated by comparing it to the observed urban class 2020. Once the prediction map is validated, it will be possible to make urban growth predictions by 2050 and quantify its environmental impacts, which will be necessary for urban planning agencies and decision-makers.

Here, we are interested in Djelfa City, which has experienced a significant speed in its demographic growth. Its population accounts for 97% of the overall population of the municipality (NOS, 2008). In other words, nearly the entire population resides in the urban center, and discussing the municipality's population essentially directs us to the city's population. Its population has been multiplied by 2.69 over 21 years, going from 158,679 inhabitants in 1998 (NOS, 1998) to 289,226 inhabitants in 2008 (NOS, 2008), then to 427,491 inhabitants in 2019 (PBMD, 2019). The undeniable fact in Algeria over the past three decades has been the rapid increase in the population, especially in urban areas (Bounoua et al., 2023). Today, Djelfa is among the largest Algerian cities in population and the largest Algerian semi-arid city. To meet the needs of the new residents, new urban areas have been created, particularly on the outskirts of Djelfa City. The incoming population has built illicit constructions throughout the city's outskirts to improve living conditions (PMBD, 2019). It was the case of a set of Algerian cities, such as Oran City (Belbachir & Rahal, 2022), Biskra City (Berghout & Dridi, 2022) or Sidi Bel Abbes City (Mansour et al., 2023). Djelfa City belongs to the central highlands region, characterised by a semi-arid climate and low plant diversity. Forest and steppe lands are threatened by desertification (Bouznad et al., 2020). Its rapid urban growth, combined with the fragility of its ecosystem, imposes the need to control its urbanisation process properly.

For this reason, this study aims to (1) make future predictions of its urban growth and (2) quantify the environmental impacts of its urban growth. The outcomes of this study will be of great importance to urban planning agencies and decision-makers. Based on the results of our study, urban planning agencies will be able to develop urban growth plans that will reduce negative impacts on fragile environments.

Materials and methods

Study area

Djelfa City is 300 km south of the country's capital (Algiers). It belongs administratively to the municipality of Djelfa, which covers an area of 528.13 km^2. Figure 1 shows the administrative location of the study area, including (A: Algeria, B: Djelfa Department, C: The Municipality of Djelfa). The region of Djelfa City is characterised by a semi-arid climate with a rainfall of 300 mm per year and freezing temperatures in winter, accompanied by frequent frosts and snowfall and dry and hot summers (NOM, 2017).

Demographically, Djelfa is the largest Algerian semi-arid city; it has undergone substantial demographic expansion, with its population surging by 2.69 times over 21 years. This growth is evident as the population escalated from 158,679 residents in 1998 (NOS, 1998) to 427,491 inhabitants in 2019 (PBMD, 2019). Owing to its strategically advantageous geographical location, Djelfa City serves as a pivotal junction at a national scale, connecting the Northern and Southern regions, as well as the Eastern and Western areas. Its primary focus lies in commerce directly or indirectly associated with agropastoralism, extending its impact beyond the Algerian highlands to a national scale. Furthermore, Djelfa City boasts an industrial and activity zone accommodating 167 industrial units engaged in various sectors such as agri-food, construction materials, plastic processing, manufacturing, and other industrial domains, providing employment opportunities for 2139 individuals. These elements have driven Djelfa City into a continuous and rapid transformation (PBMD, 2019).

Data used

Three LANDSAT satellite images (LANDSAT 7 ETM+of 2000, LANDSAT 7 ETM+of 2010, and LANDSAT 8 OLI/TIRS of 2020) were downloaded from the U.S. Geological Survey (USGS). The images were taken during the Algerian highlands' spring season, which lasts from March to May, to prevent ambiguity between vegetation and other land use classes. To achieve accurate and reliable results, the preprocessing steps, such as geometric registration, radiometric adjustments, and atmospheric corrections, should be executed as Lu et al. (2004) emphasised to mitigate issues that could lead to inaccurate or unreliable outcomes in remote sensing and image analysis. Regarding our study, all images uploaded were level-1 geometrically and topographically corrected products. All images were converted from digital numbers (DNs) to Top-Of-Atmosphere reflectance. To correct atmospheric effects, Dark Object Subtraction was used (Chang et al., 2008). All the image preprocessing steps were carried out using TerrSet software. To detect the different LULC classes in this study, we primarily opted for the band composition (3, 4, 6) for LANDSAT 7 ETM+and (4, 5, 6) for LANDSAT 8 OLI/TIRS instead of using all the bands (Yu et al., 2019). Two other combinations were explored: natural colour (RGB) by using the combination (3, 2, 1) for LANDSAT 7 ETM+and (4, 3, 2) for LANDSAT 8 OLI/TIRS, and false colour with a specific focus on enhancing the identification of urban areas, (7, 5, 3) for LANDSAT 7 ETM+and (7, 6, 4) for LANDSAT 8 OLI/TIRS. The Algerian Programming and Budget Monitoring Directorate (PBMD, 2000) obtained the road network and the administrative boundary shapefiles. It is important to highlight that shapefiles and satellite images share the same UTM WGS84 projection. (Table 1).

The choice of urban growth factors

There are no previous studies on our study area based on which we can choose the urban growth factors. Thus, the choice was made in light of a study on a semi-arid zone in Algeria (Sehl et al., 2018), where the urban growth factors selected in this study were the distance from roads, the distance from the urban centre, and slopes. In addition, we selected another urban growth factor that we considered important, adopted in previous studies interested in urban growth. This factor is the distance from built-up areas (Aguejdad & Hubert-Moy, 2016; Salem et al., 2020). However, due to a lack of spatial data, we could not select other factors such as land use plans (Aguejdad & Hubert-Moy, 2016; Abd El-kawy et al., 2019) and

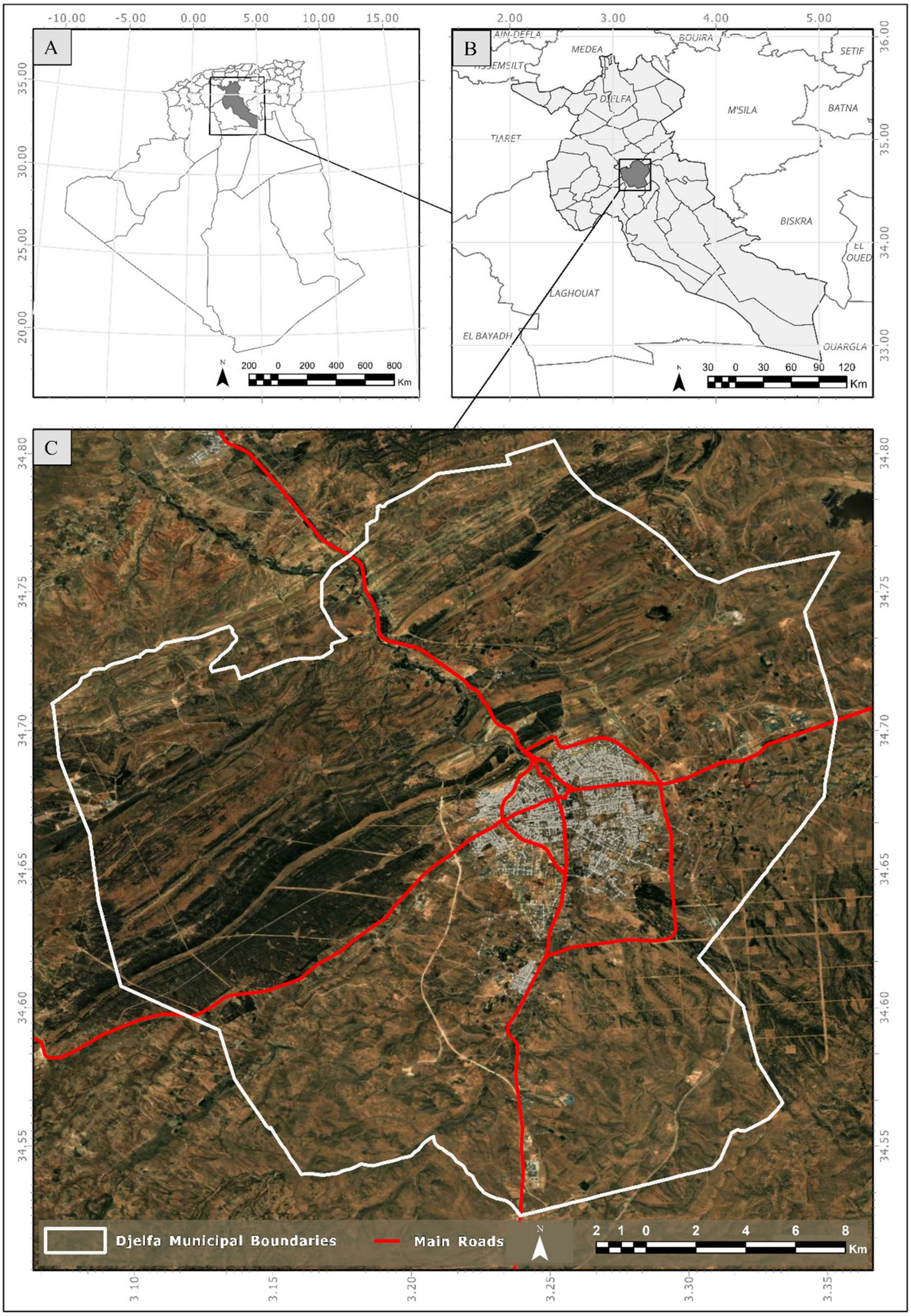

Fig. 1 Location map of the study area (**A**: Algeria, **B**: Djelfa Department, **C**: The Municipality of Djelfa)

Table 1 Data used in the study

Landsat Spacecraft ID	Source	Acquisition Date	Path/Row	Spatial Resolution	Band Combinations
LANDSAT 7 ETM+	https://www.usgs.gov/ Accessed on 20 May 2021	06 April 2000	195/36	30 m	(3,4,6); (3,2,1); (7,5,3)
		04 May 2010			
LANDSAT 8 OLI/TIRS		07 May 2020	195/36	30 m	(4,5,6); (4,3,2); (7,6,4)
Shapefiles	PBMD	2000	-	-	-

Table 2 Urban growth factors selected in the study

Urban growth factors	Type	Source
Distance from roads	Physical	PBMD
Distance from the urban centre	Physical	PBMD
Distance from built-up areas	Physical	https://www.usgs.gov/
Slopes	Physical	https://www.usgs.gov/

land value (Salem et al., 2020). The selected urban growth factors are shown in Table 2.

Methodology

It would be useful to recall the objectives targeted through this study, which are predicting the future urban growth of Djelfa City and quantifying its environmental impacts. To do this, we must first classify the satellite dataset. We adopted the MLC method based on the training zones. For every land use map (2000, 2010, and 2020), 200 samples were assigned randomly across the study area. Among these samples, 70% were allocated for classification, equivalent to 140. While the remaining 30%, equivalent to 60 samples, were reserved for validation. At the end of this stage, we obtained three LULC maps of 2000, 2010, and 2020 representing five LULC classes: urban land, bare land, agricultural land, steppe, and forest. An error classification matrix was produced to calculate the classification's accuracy. The Kappa index showed accuracy rates of 0.92, 095, and 0.94 for 2000, 2010, and 2020, respectively. This means that the classification is accurate, and these maps can be used to analyse the LULC change.

After obtaining an accurate classification of the three LULC maps, we moved on to the prediction of the Djelfa City urban growth using LCM, which is a module integrated into TerrSet software, widely used to analyse the LULC change and predict the future LULC (Anand & Oinam, 2020; Camacho Olmedo et al., 2015; Nagabhatla et al., 2012; Pontius et al., 2004b). LCM requires two LULC maps from two different dates to analyse LULC change. For our study, we used the LULC maps of 2000 and 2010. As for the 2020 LULC map, we will use it at the end of the modeling process to validate the model. LCM allows us to analyse the change between the five LULC classes from the two entry maps. We modelled the potential transitions once we obtained the possible changes between the different classes. For our study, we only considered the sub-model of changes to the urban class to model urban growth. In this sub-model, we have four possible changes: bare land to urban land, agricultural land to urban land, steppe to urban land, and forest to urban land. To integrate the urban growth factors previously chosen, we converted them to a raster format with a resolution of 30 m, and then we analysed them with the Distance function using TerrSet software. To model the maps of potential transitions to the urban class, we chose LRM, which has proven its effectiveness in model-building (Hu & Lo, 2007; Phong et al., 2019; Valdez et al., 2019). LRM requires independent variables and a dependent variable. The urban growth factors represent the independent variables, whereas the dependent variable represents the cells that can be changed to the urban class. The dependent variable follows a binary logic, where 0 indicates no change to the urban class, and 1 indicates a change to the urban class (the urban growth) between 2000–2010. The following formula gives LRM:

$$\mathrm{P} = (\mathrm{Y} = 1\mathrm{Ix}) = \frac{\exp \sum_{k=0}^{k} b_k x_{ix}}{1 + \exp \sum_{k=0}^{k} b_k x_{ix}}$$

where:

P = Probability of Y (the dependent variable) taking 1.

x = $\left(x_0, x_1, x_2, \dots x_k\right)$ representing the urban growth factors.

$b = \left(b_0, b_1, b_2, \dots b_k\right)$ representing regression coefficients.

At the end of this step, four potential transition maps are produced. They will be examined by the Receiver Operating Characteristic (ROC) to compare the highest areas of change probability to the observed change. We have chosen 2020 as the year for predicting urban growth to compare the predicted map with the 2020 reference map. After obtaining the predicted LULC map 2020, we extracted its urban class and the reference LULC map 2020. We looked at the effectiveness of the adopted model using the ROC. We also examined it by inspecting errors in the quantity and the location of the predicted change (Pontius et al., 2004a). Concerning the errors in the quantity of the predicted change (Q), we calculated the difference between the urban class predicted area (PC) and the urban class observed area (OC): $Q = PC - OC$. Regarding the errors in the predicted change location, by comparing the predicted urban class map to that of the observed urban class through the "Cross Tab" function integrated into the TerrSet software, we have highlighted four types of pixels:

a. Pixels correctly predicted as changed: "Hits" (H).
b. Pixels correctly predicted as unchanged: "Null" (N).
c. Pixels falsely predicted as changed: "False alarms" (F).
d. Pixels falsely predicted as not changed: "Misses" (M).

The error in locating the predicted change (A) is the sum of the falsely predicted pixels: $A = F + M$. Then, We calculated the total error (T), which is the sum of the errors in the quantity and the location of the predicted change: $T = Q + A$. If the errors in the quantity and the location of the predicted change are negligible, we can validate the model and predict the future urban growth maps. After that, we can quantify the environmental impacts of the future urban growth of Djelfa City. Figure 2 shows our study flowchart.

Results

LULC change between 2000 and 2020

The study area has experienced a significant LULC change between 2000 and 2020 (Fig. 3). Three LULC classes have experienced an increase in their surfaces between 2000 and 2020: the steppe area has increased from 307.58 Km2 to 334.27 Km^2. This increase occurred over two periods. From 2000 to 2010, the first period, they witnessed a gain of 70.79 km^2, primarily attributed to forest degradation. Subsequently, from 2010 to 2020, the steppe experienced a decrease of 44.10 km^2 in the second period, mainly driven by urbanisation and desertification. Bare land area has also increased from 31.88 km^2 to 35.67 km^2. In the initial period, the bare land area grew 7.68 km^2, followed by a decline of 3.89 km^2 in the second period, primarily caused by urbanisation. Finally, the urban land area has gone from 14.81 km^2 to 38.02 km^2. The urban area represented 2.80% of the municipality's total area in 2000. It increased to 5.41% in 2010, then 7.20% of the total surface of the municipality in 2020. Urban land witnessed uninterrupted expansion throughout both periods, with areas of 13.75 km^2 and 9.46 km^2, respectively. On the other hand, two LULC classes experienced a decrease in their surfaces between 2000 and 2020: the forest area, which decreased from 121.60 km^2 to 100.79 km^2. In the initial period, the forest experienced a reduction of 49.42 km^2 in its area, followed by a subsequent recovery of 28.61 km^2 in the second period. The agricultural land area has also decreased from 52.26 Km^2 to 19.38 Km^2. In the initial period, agricultural land underwent a decrease in area, with a loss of 42.80 km^2. However, a notable rebound in the second period resulted in a gain of 9.92 km^2. (Table 3).

Urban growth modeling

After analysing the LULC change between 2000 and 2010 using LCM, we obtained the LULC change probabilities (Table 4). This matrix displays the probabilities of transitions between the LULC classes and the probability of each class maintaining its current state. Regarding class transitions, the matrix indicates that steppe lands exhibit the highest probability of converting to other land cover types, favouring urban lands, bare land, agricultural land, and forest

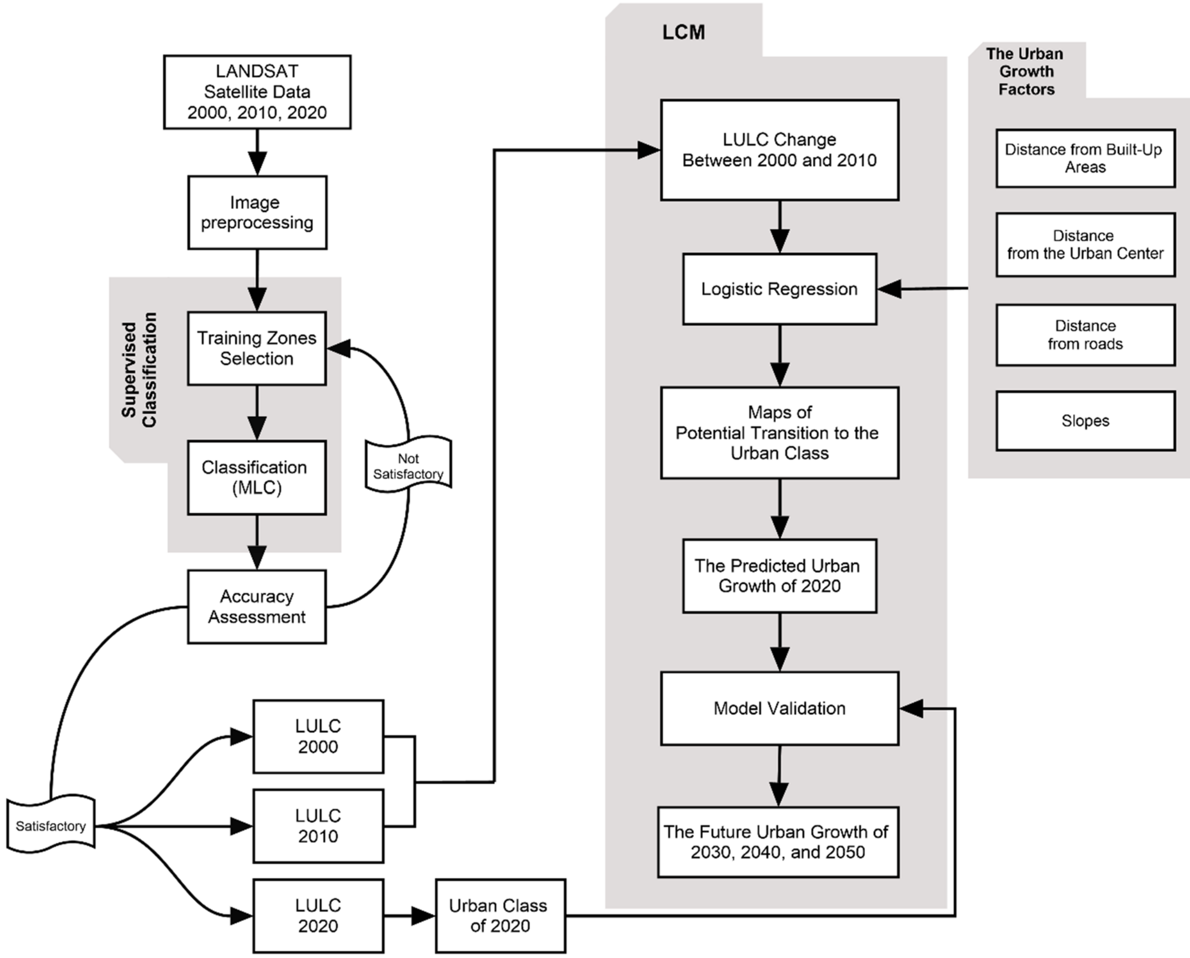

Fig. 2 The Study flowchart

land with probabilities of 05.18%, 47.15%, 78.11%, and 71.90%, respectively. Concerning persistence, the urban class stands out with the highest probability of retaining its surface area at 87.95%, while agricultural land has the lowest persistence probability at 1.03%.

The contribution to net change in urban land came from all the other classes. It should be noted that the urban class gained 0.89 km^2 of agricultural land, 1.17 km^2 of forest, 6.03 km^2 of bare land, and 5.67 km^2 of steppe. On the other hand, bare land gained surfaces to the detriment of all classes except urban land. Finally, agricultural land and forest also lost their areas. The contribution surfaces to the net change in all the LULC classes are shown in Table 5.

To create the potential transition to the urban class maps, we analysed four urban growth factors with the Distance function using TerrSet software: distance from built-up areas, distance from the urban centre, distance from roads, and Slopes (Fig. 4). Subsequently, based on the change probabilities matrix and the urban growth factors, we used LRM to generate the potential transition to the urban class maps (Fig. 5).

Before the generation of the 2020 LULC prediction map, we examined the accuracy of the potential transition to the urban class maps through the ROC, using the observed urban class of 2020 as a reference. The recorded ROC values were 0.87, 0.79, 0.92, and 0.89 for potential transitions to the urban class from bare land, agricultural land, steppe, and forest, respectively.

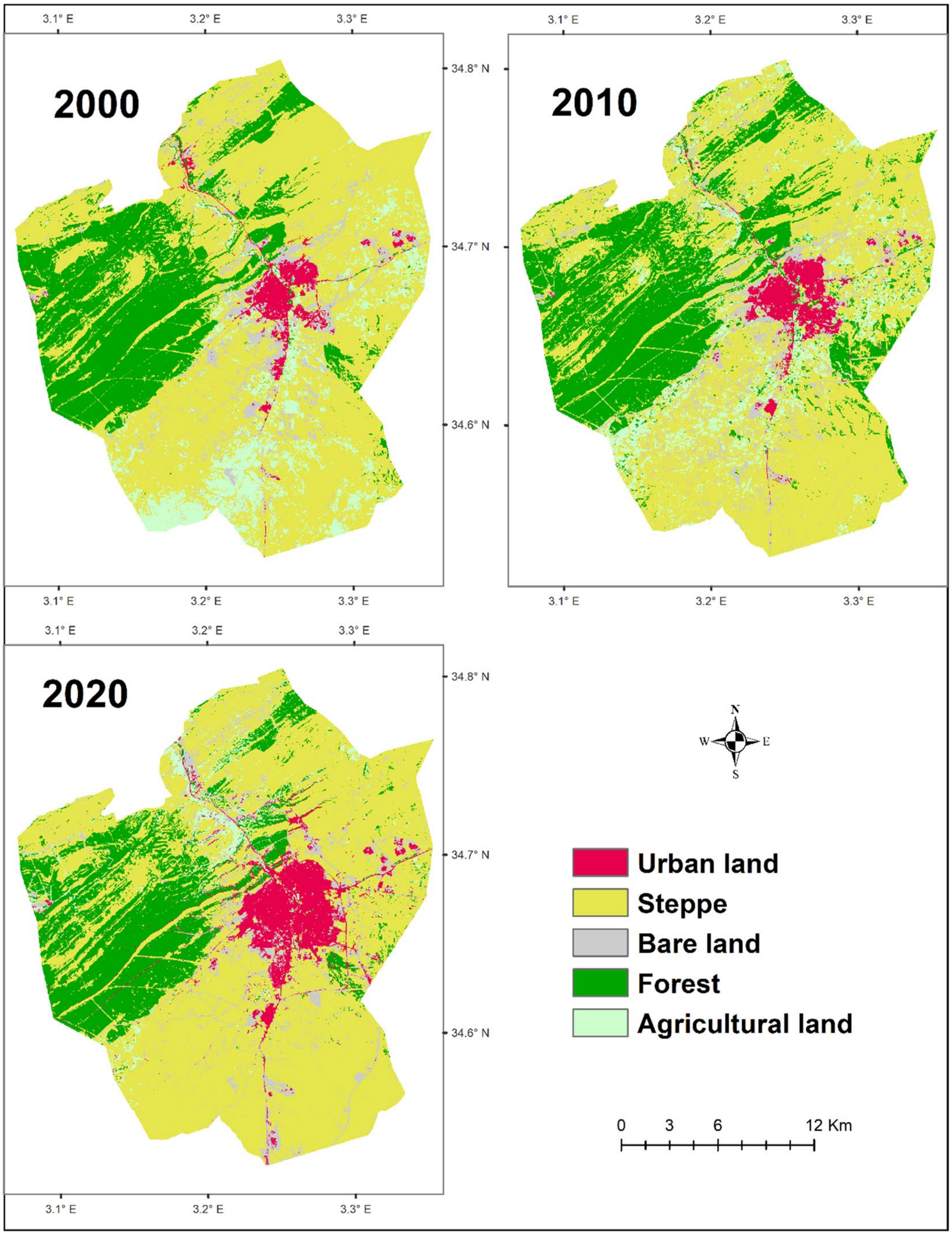

Fig. 3 LULC of The Municipality of Djelfa in 2000, 2010, and 2020

We have produced the 2020 LULC prediction map based on the four potential transition maps.

Table 3 LULC change between 2000 and 2020

LULC classes	2000		2010		area change between 2000 and 2010 (km^2)	2020		Area change between 2010 and 2020 (km^2)	Total area change (km^2)
	Area (km^2)	%	Area (km^2)	%		Area (km^2)	%		
Steppe	307.58	58.24	378.37	71.64	70.79	334.27	63.29	-44.10	26.69
Bare land	31.88	6.04	39.56	7.49	7.68	35.67	6.75	-3.89	3.79
Urban land	14.81	2.80	28.56	5.41	13.75	38.02	7.20	9.46	23.21
Agricultural land	52.26	9.90	9.46	1.79	-42.80	19.38	3.67	9.92	-32.88
Forest	121.60	23.02	72.18	13.67	-49.42	100.79	19.08	28.61	-20.81

Table 4 LULC change probabilities matrix

	Urban land	Bare land	Agricultural land	Steppe	Forest
Urban land	0.8795	0.0584	0.0090	0.0518	0.0014
Bare land	0.3620	0.1538	0.0098	0.4715	0.0030
Agricultural land	0.0964	0.1051	0.0103	0.7811	0.0070
Steppe	0.0990	0.1062	0.0103	0.7780	0.0066
Forest	0.0544	0.0658	0.0136	0.7190	0.1472

Table 5 Contribution to net change in LULC classes between 2000 and 2010 (Km^2)

	Steppe	Bare land	Urban land	Agricultural land	Forest
Steppe		-10.94	-5.67	41.65	45.75
Bare land	10.94		-6.03	2.63	0.14
Urban land	5.67	6.03		0.89	1.17
Agricultural land	-41.65	-2.63	-0.89		2.37
Forest	-45.75	-0.14	-1.17	-2.37	

Subsequently, we extracted the urban class from this map to validate the model based on the observed urban class 2020 (Fig. 6).

The model's validation and the future urban growth

Examining the model's accuracy through the ROC gave a value of 0.84. We also examined errors in quantity and location of the predicted change (Table 6), where the total error (T) recorded was 5.06% of the municipality's total area. The observed quantity of change to the urban class (OC) was 7.2% of the total municipality's area, while the predicted quantity of change (PC) was 7.67%, which gives an error in the quantity (Q) equal to 0.47%. Furthermore, we found that the predicted change that was not produced (F) was 2.53% of the municipality's total area. The observed change that was not predicted (M) was 2.06%, which gave an error in the change location of the urban class (A) of 4.59%.

On the other hand, we found that the urban class change that was correctly predicted (H) represented 5.14% of the municipality's total area. The area predicted correctly as not changed (N) represented 90.27%, which means that the correctly located urban class prediction is 95.41%. Errors/Exactitude in the location of the predicted change are shown in Fig. 7. The results of the ROC and the errors in quantity and location of the predicted urban class have shown that the model can be validated, and future maps can be generated.

At this stage, we moved on to predict the future urban growth of 2030, 2040, and 2050 (Fig. 8). The surface of the city will increase over time. It will be 56.93 km^2, then 71.40 km^2 and 85.18 km^2 in 2030, 2040 and 2050 respectively. The city will gain areas at the expense of all LULC classes, particularly the

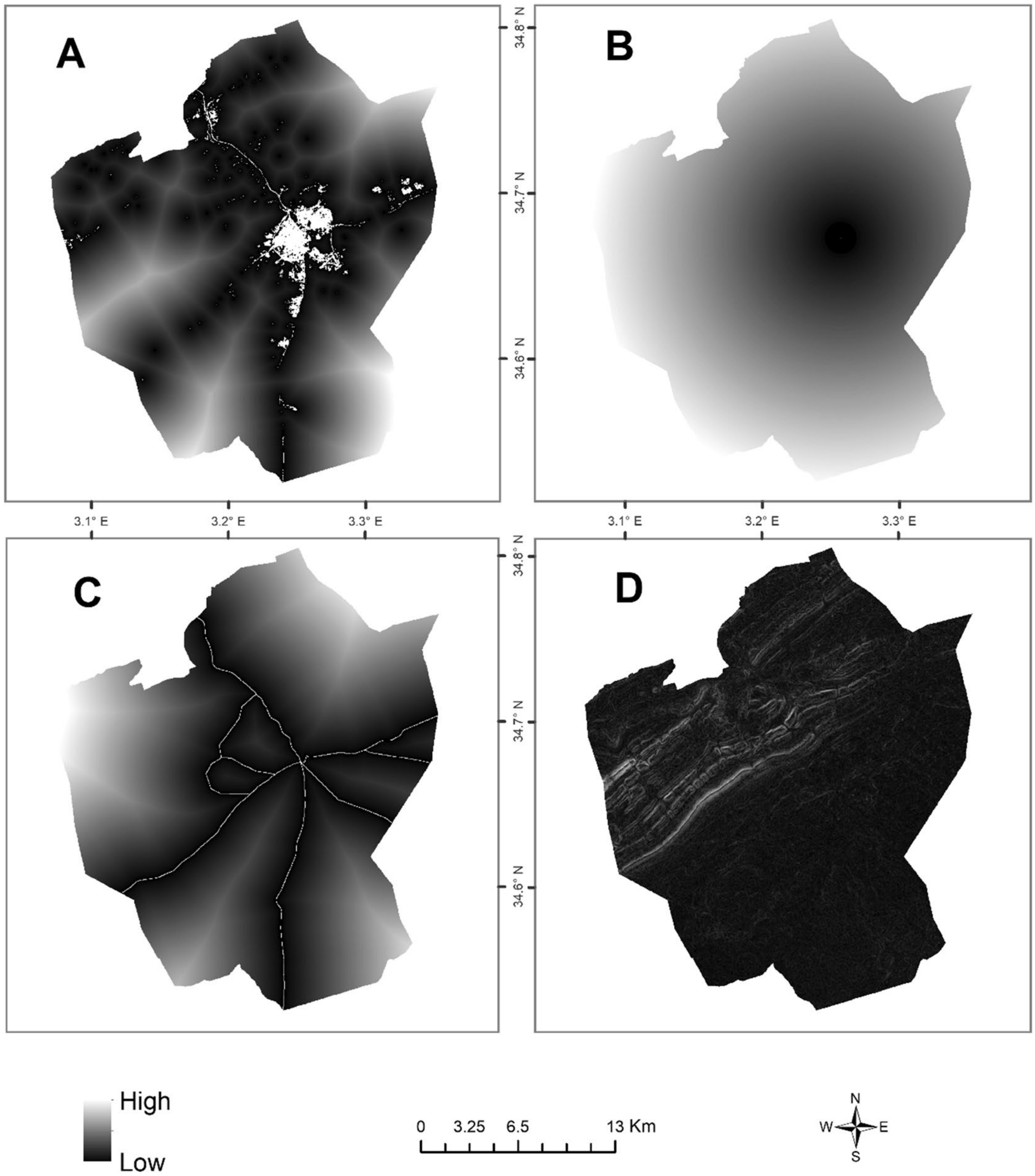

Fig. 4 Urban growth factors in the Municipality of Djelfa (A: Distance from built-up areas, B: Distance from the urban centre, C: Distance from roads, and D: Slopes)

steppe (Table 7). The urban class share gained at the expense of the steppe will be 32.36%, 75.94%, and 81.55% by 2030, 2040, and 2050, respectively. We also note that the urban class share gained at the expense of forest will increase over time; it will be 5.08% by 2030, and then its share will increase to 7.86% by 2040 and 10.6% by 2050. The urban class share gained upon bare soil will decrease over time. It will be 49.13%, then 14.33%, and 5.86% by 2030, 2040, and 2050, respectively.

Discussion

Urban growth modeling using LCM has given good results. The comparison between the predicted urban

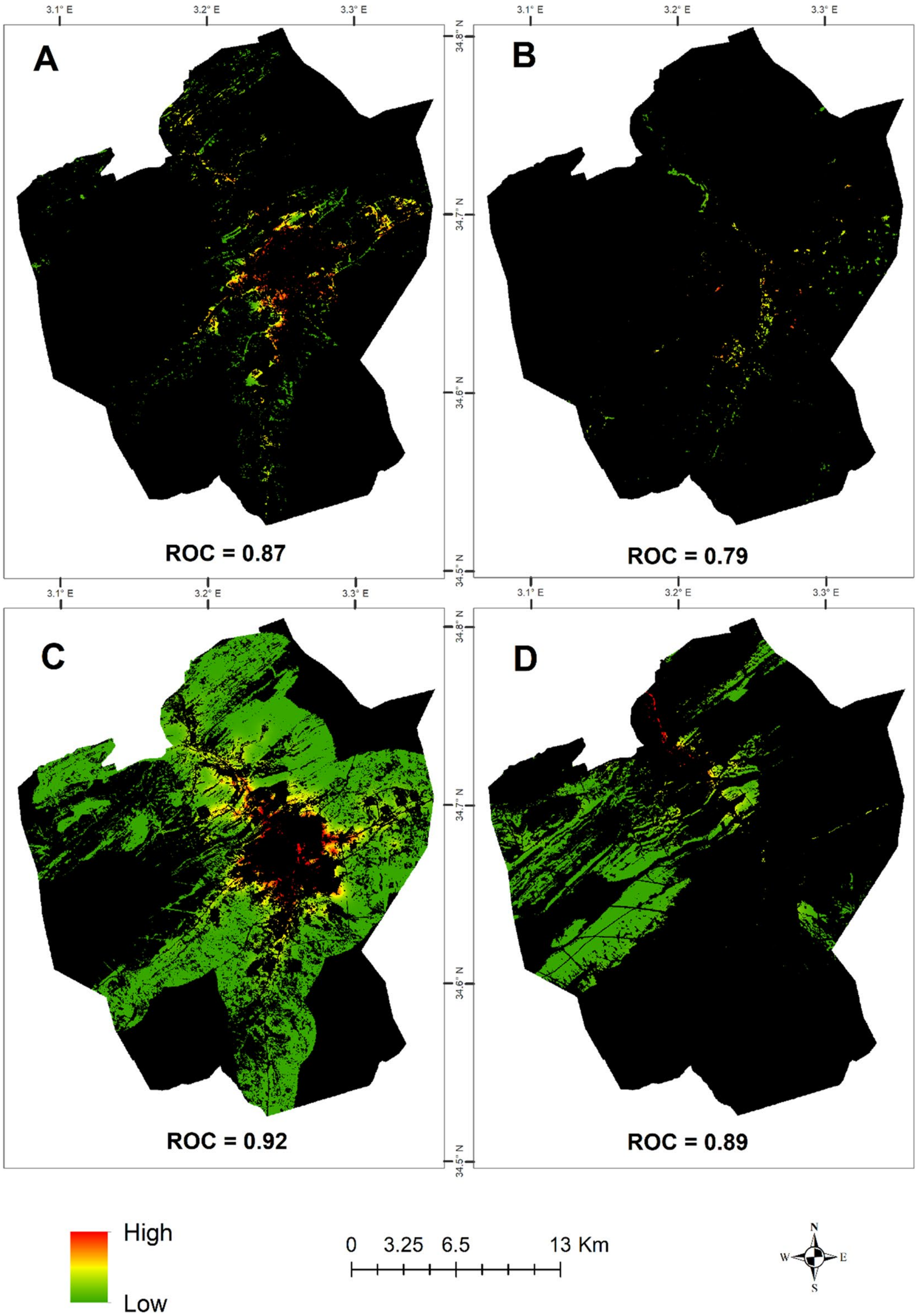

Fig. 5 Potential transition to the urban class in the Municipality of Djelfa (A: From bare land, B: From agricultural land, C: From steppe, D: From forest)

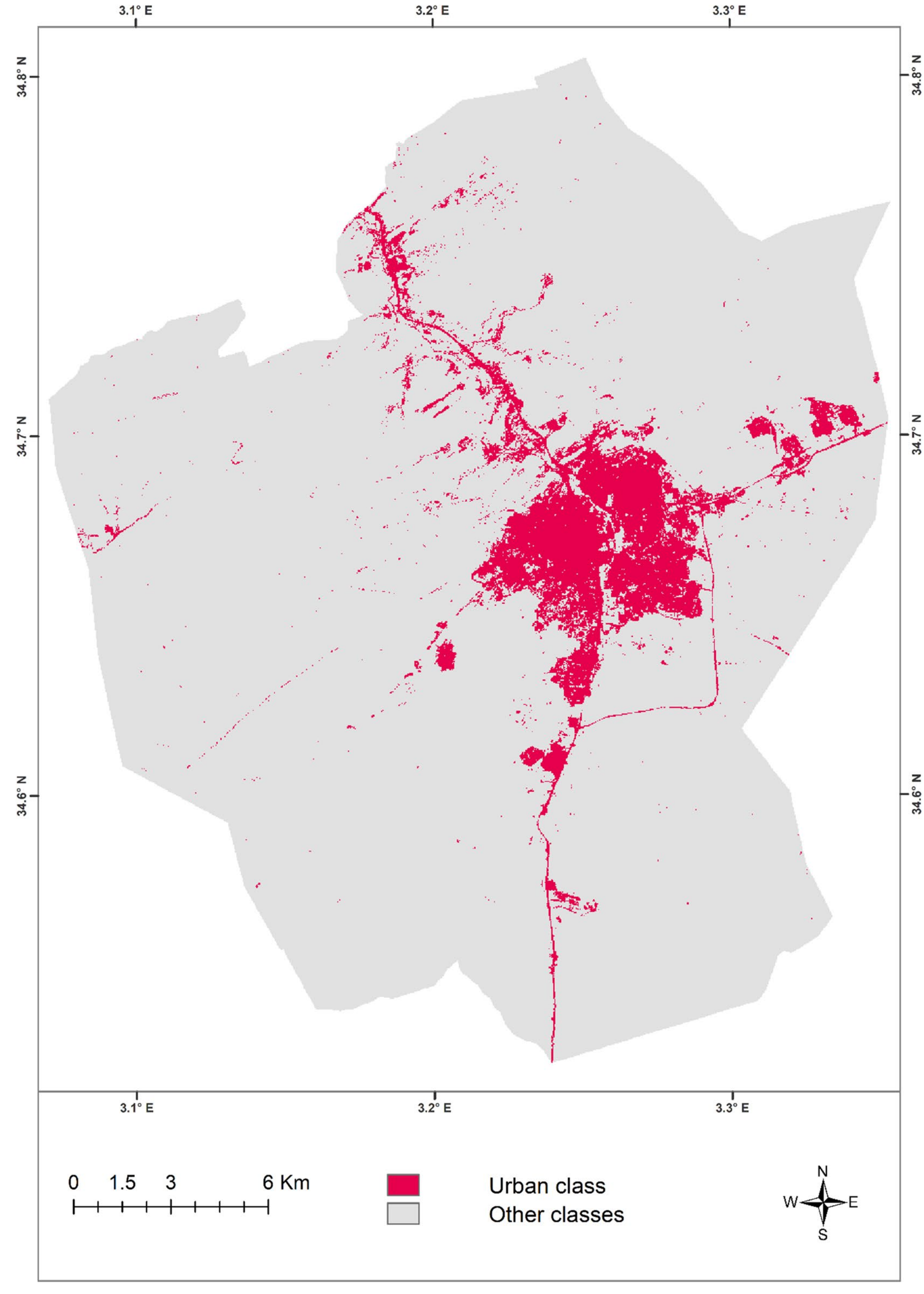

Fig. 6 The predicted urban class (2020) in the Municipality of Djelfa

Table 6 Errors/Exactitude in the quantity and location of the predicted change to the urban class

	Index	Surface (Km^2)	%
Errors/Exactitude in the location of the predicted change	**N**	476.75	90.27
	F	13.37	2.53
	M	10.88	2.06
	H	27.14	5.14
	A	**24.24**	**4.59**
Errors in the quantity of the predicted change	**OC**	38.02	7.20
	PC	40.51	7.67
	Q	**2.49**	**0.47**
Total errors	**T**	**26.73**	**5.06**

class of 2020 and the 2020 LULC map using the ROC gave a value of 0.84. Furthermore, the error in the quantity of the urban class predicted change is 0.47% of the municipality's total area, and the error in the location of the urban class predicted change is 4.59%. These values are negligible, thus demonstrating the effectiveness of LCM in urban growth modeling. LCM has the ability to incorporate various factors, but we have limited the number of factors, strongly recommended to improve the prediction relevance (Arfasa et al., 2023; Djeddaoui et al., 2017). Several studies proved the accuracy of LCM in urban growth modeling (Rodríguez Eraso et al., 2013; Aguejdad & Hubert-Moy, 2016; Abd El-kawy et al., 2019; Salem et al., 2020). LCM is not specially designed for this type of modeling. There are models like SLEUTH (Jantz et al., 2010; Saeidi et al., 2018) and UrbanSim (Waddell & Borning, 2004; Waddell et al., 2003), which are specially designed for urban simulation, but they require input data which is not available in our case.

The study area experienced an important LULC change between 2000 and 2020, characterised by significant urban growth, which is the case for many cities in Mediterranean countries (Couch et al., 2007; Salem et al., 2020; Xystrakis et al., 2017). The urban land area has multiplied by 2.57 in 20 years, going from 14,81 km^2 in 2000 to 38.02 km^2 in 2020. Results close to ours have been recorded in semi-arid regions of Mediterranean countries. The study by Ohana-Levi et al. (2015) found that the urban land area has doubled in 19 years, and the study of Shalaby et al. (2012) showed that the urban land area has multiplied by 2.68 in 17 years. According to LCM, the urban growth speed will decrease over time. It will be 1.90 km^2/year between 2020 and 2030, 1.45 km^2/year between 2030 and 2040, and 1.38 km^2/year between 2040 and 2050. The same result was found by (Yadav & Ghosh, 2019).

Urban growth has negatively impacted the environment, which is evident in numerous cities across Algeria (Bendjemila & Chaouche, 2022; Hamza et al., 2022; Saouli et al., 2023). This also was evident in several semi-arid cities. For instance, 96 km^2 of agricultural land was lost between 2010 and 2018 due to significant urban growth in the peri-urban area of greater Cairo (Salem et al., 2020). In Tripoli (Libya), 13.97 km^2 of agricultural land was converted into urban land from 2002 to 2010 (Al-sharif & Pradhan, 2015). In Ulaanbaatar (Mongolia), 7.52 km^2 and 24.72 km^2 of forest and grassland were lost between 1990 and 2001, respectively. During the same period, 20.41% urban growth was recorded (Amarsaikhan et al., 2009). In our case, if the local authorities do not intervene the decline of the steppe in our investigation area will be considerably substantial. Between 2000 and 2020, this class lost 11.88 km^2 due to urban growth, and it will lose an additional 28.33 km^2 between 2020 and 2050. If this happens, it could negatively influence the regional pastoral activities, and disrupt the ecological and socio-economic systems, hence making our research critical. Therefore, we encourage the authorities to implement necessary measures against this urbanization. The situation is even more alarming as we know that the regional urban population rate has grown steadily, rising from 45% in 1987 to 74% in 2003, according to the Ministry of Territorial Planning (MTP 2014). The built-up areas were also at the expense of agricultural land. It was the case in several cities in Mediterranean countries, such as Barcelona in Spain (Serra et al., 2018) or Attica in Greece (Salvati et al., 2013), or such as Qalubiya Governorate in Egypt (Shalaby et al., 2012). In our study case, 1.76 km^2 of agricultural land was lost between 2000 and 2020 due to urban growth. LCM shows that agricultural land will lose 10.84 km^2 between 2020 and 2050. It should be mentioned that only 1880 of 21,523 illicit constructions located on the outskirts of the city, in particular on agricultural land, were demolished between 2000 and 2020, thus recording a very low rate which does not exceed 8.73% (Municipality of Djelfa, Technical Department, 2020). It is important to highlight that the detrimental

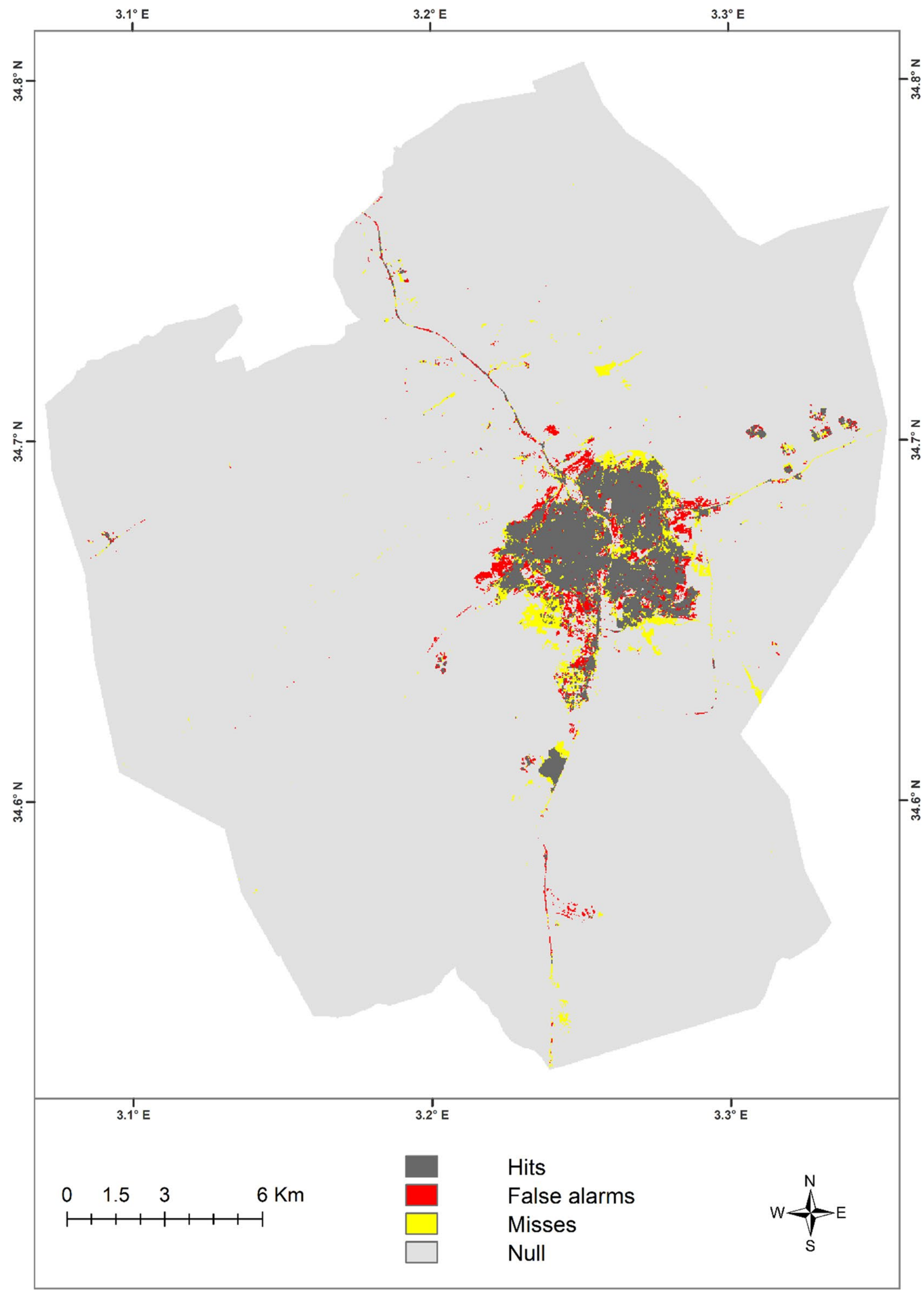

Fig. 7 Errors/Exactitude in the location of the urban class predicted change in the Municipality of Djelfa

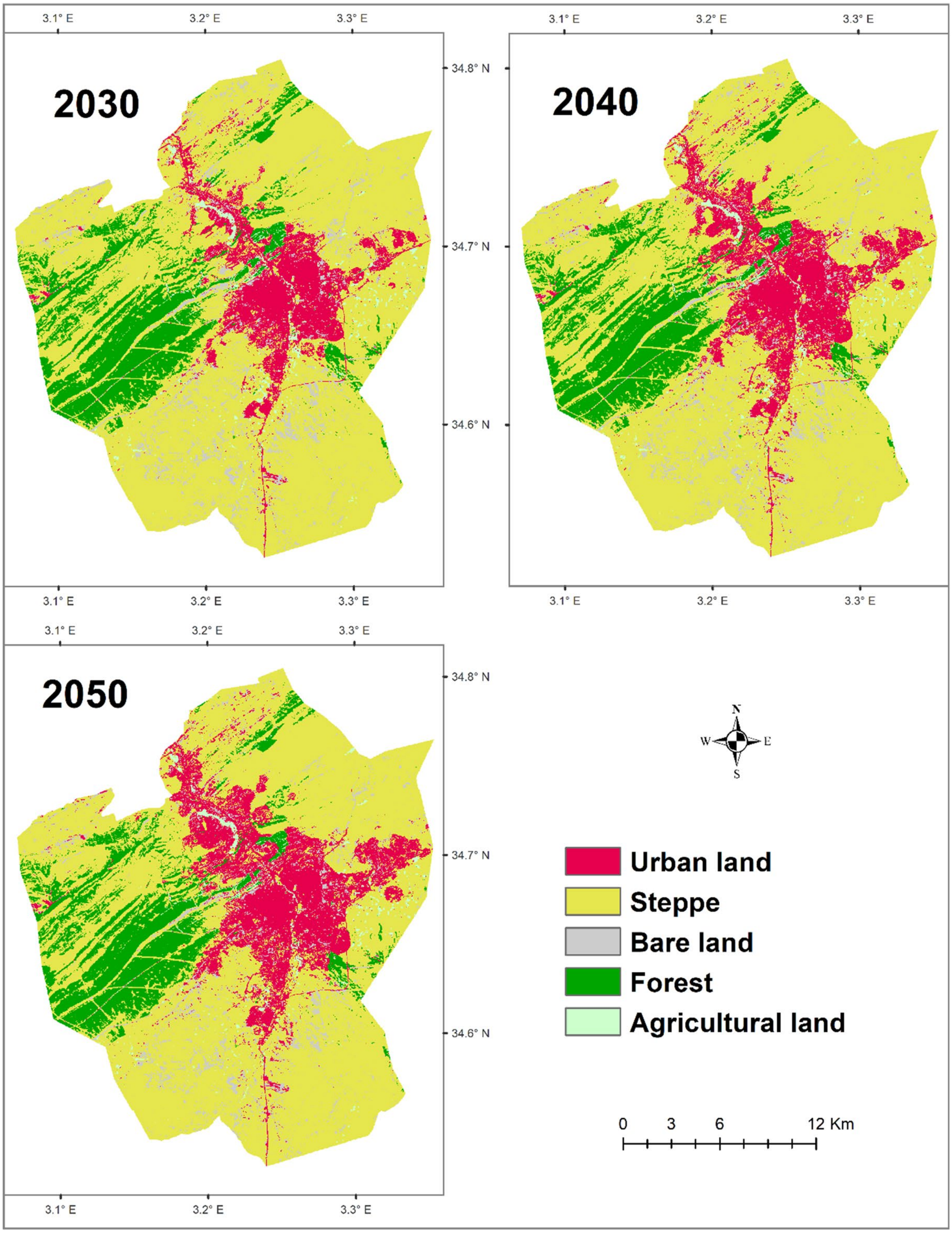

Fig. 8 The Predicted LULC of the Municipality of Djelfa in 2030, 2040, and 2050

Table 7 The Future Urban Growth Evolution (2020 – 2050)

	2020 (Observed)	2030			2040			2050		
	Surface (Km^2)	Surface (Km^2)	Urban growth contribution		Surface (Km^2)	Urban growth contribution		Surface (Km^2)	Urban growth contribution	
			Surface (Km^2)	Rate (%)		Surface (Km^2)	Rate (%)		Surface (Km^2)	Rate (%)
Bare land	35.67	28.38	9.29	49.13	26.30	2.07	14.33	25.50	0.81	5.86
Agricultural land	19.38	9.09	2.54	13.43	8.82	0.27	1.86	8.54	0.27	1.98
Steppe	334.27	362.89	6.12	32.36	351.90	10.99	75.94	340.68	11.22	81.55
Forest	100.79	70.85	0.96	5.08	69.71	1.14	7.86	68.25	1.46	10.60
Urban land	38.02	56.93		71.40		85.18				

effects of urban expansion on the environment were evident in the transformation of 2.01 Km^2 of forest into urban areas from 2000 to 2020. Illicit constructions on forest land have accentuated deforestation in Djelfa, which was probably also due to other factors linked to the aggressiveness of the semi-arid climate. This was the case in Iran, where nearly 50,000 km^2 of forest was converted to farmland and urban areas during the period of 1950 to 2008 because of illicit constructions on forest land and the aggressiveness of the semi-arid climate (Emadodin & Bork, 2012). Our results showed that 32.54 km^2 of forest will be converted into urban land between 2020 and 2050, equivalent to an annual loss of 1.08 km^2/year. Afforestation remains insufficient when we know that only 4.50 km^2 was reforested between 2000 and 2020, with an annual average of 0.23 km^2/year (Forest Directorate of the Djelfa Department, Statistics Department, 2020). In addition, the municipality services must take the demolition of illegal constructions in the forest seriously. Across Algeria, urbanization has impacted agricultural and forest lands, particularly in densely populated Tellian zones. Thus, the authorities at local scale are advised to prioritize residential development in designated new urban extents and on privately-owned agricultural lands to preserve agricultural and forest land on the fringes of major Algerian cities. Many studies can be found in this context, including research conducted in cities such as Algiers (Bellout et al., 2020) and Annaba (Noui et al., 2023). Oppositely, in other Algerian regions, including the central highlands region, to which our study area belongs, loss of agricultural land is primarily driven by illegal construction by individuals (Dechaicha et al., 2021; Slimani & Raham, 2023). This difference exists because authorities in those areas can access suitable non-agricultural land for development. However, forest heritage, including natural forests and afforestation, is highly important throughout Algeria. Consequently, unauthorized construction that ignores the distinction between natural and planted forests was primarily responsible of forest loss in our study area, particularly in near city outskirts areas, similarly to others Algerian cities (Mostari et al., 2021; Slimani & Raham, 2023; Zerouali et al., 2023).

As per LCM, Djelfa City's urban growth will be in all directions. Mountainous areas with steep slopes, primarily located west of Djelfa City, are expected to have the least urban development. The gently sloping land to the east of the city is projected to experience the most significant urbanisation. It should also be noted that during all phases of future urbanisation, the new built-up areas will be adjacent to the old. These geographic features collectively indicate that Djelfa City's future urban growth is expected to be anarchic (Fig. 9).

Djelfa City has experienced very rapid urban growth. Its annual rate is 3.05% between 2000 and 2020. Djelfa City will continue to grow, with an annual urban growth rate of 1.85% between 2020 and 2050. Rapid and uncontrolled urbanisation causes environmental and social problems (Alam et al., 2006; Haas & Ban, 2014; Faysal Ahmed, 2014) Query. It is also considered one of the causes of health problems for city dwellers (Firdaus, 2012; Graham et al., 2004). This study could be succeeded by other studies focusing on environmental degradation due to rapid and uncontrolled urbanisation because rapid urban growth in semi-arid regions could cause degradation of environmental sustainability (Liu et al., 2019b). It could hurt groundwater quality in semi-arid regions (Carlson et al., 2011). Degradation of soil health is also among the consequences of rapid and uncontrolled urban growth in semi-arid regions (Wang et al., 2018). Furthermore, the rising temperatures in semi-arid urbanised areas (Rasul et al., 2017) can lead to multiple ecological changes at the local level, such as early flowering in urbanised areas. This, in turn, results in earlier and extended allergy seasons (Neil & Wu, 2006).

Conclusion

This study predicted the future urban growth of the largest Algerian semi-arid city and then quantified its environmental impacts by 2050. We found that Djelfa City has grown rapidly. It gained 23.21 km^2 between 2000 and 2020 and 47.17 km^2 between 2020 and 2050. In other words, the urban growth between 2000 and 2050 will be 82.61%. Significant areas of steppe, forest, and agricultural land were lost in the urban growth, and according to LCM, more areas will be lost by 2050. Results similar to ours have been found by previous research, particularly in regions characterised by a fragile environment. Based on our results, policymakers must take drastic measures against illegal urban growth, especially on agricultural land and forests. Although the Master Plan's intention aims

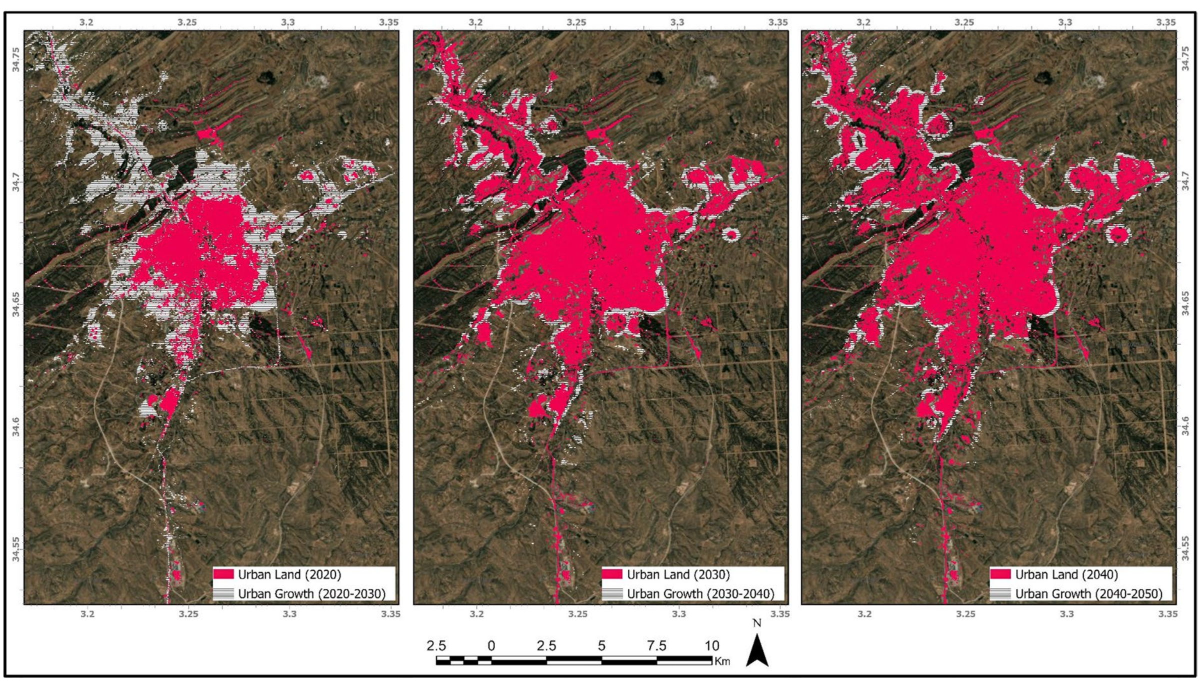

Fig. 9 The predicted urban growth of Djelfa City in 2030, 2040, and 2050

to preserve sensitive areas by prioritizing budget-friendly land, the actual situation is different. We observe alarming agricultural and forest land loss, which often surpasses planned development timelines. This highlights the significance of our model as it serves as an early warning and prediction tool, enabling planners to achieve a sustainable Master Plan. Moreover, regarding the model adopted in this study, we found that LCM was effective; it helped us predict urban growth and quantify its environmental impacts.

The outcomes of this study could be useful for urban planning and environmental agencies. This study could be followed by in-depth studies on the environmental problems caused by rapid and uncontrolled urban growth in fragile environments.

Funding None.

Data availability Not applicable.

Declarations

Conflicts of interest/Competing interests Not applicable.

References

AbdEk-kawy, O. R., Ismail, H. A., Yehia, H. M., & Allam, M. A. (2019). Temporal detection and prediction of agricultural land consumption by urbanisation using remote sensing. *Egyptian Journal of Remote Sensing and Space Science, 22*, 237–246. https://doi.org/10.1016/j.ejrs.2019.05.001

Aguejdad, R., & Hubert-Moy, L. (2016). *Suivi de l'artificialisation du territoire en milieu urbain par télédétection et à l'aide de métriques paysagères. Application à une agglomération de taille moyenne, Rennes Métropole.* Cybergeo. https://doi.org/10.4000/cybergeo.27465

Ahmed, B., & Ahmed, R. (2012). Modeling urban land cover growth dynamics using multi-temporal satellite images: A case study of Dhaka, Bangladesh. *ISPRS International Journal of Geo-Information, 1*(1), 3–31. https://doi.org/10.3390/ijgi1010003

Al-sharif, A. A. A., & Pradhan, B. (2015). A novel approach for predicting the spatial patterns of urban expansion by combining the chi-squared automatic integration detection decision tree, Markov chain, and cellular automata models in GIS. *Geocarto International, 30*, 858–881. https://doi.org/10.1080/10106049.2014.997308

Alam, Md. J. B., Alam, M. J. B., & Rahman, M. H. (2006). Unplanned urbanisation: Assessment through calculation of environmental degradation index. *International Journal of Environmental Science and Technology, 3*, 119–130. https://doi.org/10.1007/BF03325915

Aljoufie, M., Zuidgeest, M., Brussel, M., & van Maarseveen, M. (2013). Spatial-temporal analysis of urban growth and transportation in Jeddah City, Saudi Arabia. *Cities, 31*, 57–68. https://doi.org/10.1016/j.cities.2012.04.008

Altuwaijri, H. A., Alotaibi, M. H., Almudlaj, A. M., & Almalki, F. M. (2019). Predicting urban growth of Arriyadh city, capital of the Kingdom of Saudi Arabia, using Markov cellular automata in TerrSet geospatial system. *Arabian Journal of Geosciences, 12*, 1–15. https://doi.org/10.1007/s12517-019-4261-z

Amarsaikhan, D., Blotevogel, H. H., Ganzorig, M., & Moon, T. H. (2009). Applications of remote sensing and geographic information systems for urban land-cover change studies in Mongolia. *Geocarto International, 24*, 257–271. https://doi.org/10.1080/10106040802556173

Anand, V., & Oinam, B. (2020). Future land uses land cover prediction with special emphasis on urbanisation and wetlands. *Remote Sensing Letters, 11*, 225–234. https://doi.org/10.1080/2150704X.2019.1704304

Arfasa, G. F., Owusu-Sekyere, E., Doke, D. A. (2023). Predictions of land use/land cover change, drivers, and their implications on water availability for irrigation in the Vea catchment, Ghana. *Geocarto International*, 38. https://doi.org/10.1080/10106049.2023.2243093

Belbachir, A. K., & Rahal, D. D. (2022). Study of the urban expansion of the city of Oran using LANDSAT satellite images and local data. *Modeling Earth System and Environment, 8*, 3283–3292. https://doi.org/10.1007/s40808-021-01299-x

Bellout, A., Vaz, E., & Penfound, E. (2020). Rethinking agricultural land use in Algiers: A spatial analysis of the Eastern Mitidja Plain. *Habitat International, 104*, 102239. https://doi.org/10.1016/j.habitatint.2020.102239

Bendjemila, I., & Chaouche, S. (2022). Green City or Urban Countryside? *Prostor*, 30, 56–67. https://doi.org/10.31522/p.30.1(63).6

Berghout, K., & Dridi, H. (2022). Integration of GIS and multicriteria analysis for the assessment of the sensitivity to urbanisation in Biskra and its neighboring oases, Algeria. *GeoJournal, 87*, 4219–4234. https://doi.org/10.1007/s10708-021-10495-2

Bounoua, L., Bachir, N., & Souidi, H. (2023). Sustainable development in Algeria's urban areas: Population growth and land consumption. *Urban Science, 7*, 29. https://doi.org/10.3390/urbansci7010029

Bouznad, I. E., Guastaldi, E., Zirulia, A., et al. (2020). Trend analysis and spatiotemporal prediction of precipitation, temperature, and evapotranspiration values using the ARIMA models: The case of the Algerian Highlands. *Arabian Journal of Geosciences, 13*, 1281. https://doi.org/10.1007/s12517-020-06330-6

Brannstrom, C., & Filippi, A. M. (2008). Remote classification of Cerrado (Savanna) and agricultural land covers in northeastern Brazil. *Geocarto International, 23*, 109–134. https://doi.org/10.1080/10106040701596767

Camacho Olmedo, M. T., Pontius, R. G., Paegelow, M., & Mas, J. F. (2015). Comparison of simulation models in terms of quantity and allocation of land change. *Environmental Modelling and Software, 69*, 214–221. https://doi.org/10.1016/j.envsoft.2015.03.003

Carlson, M. A., Lohse, K. A., McIntosh, J. C., & McLain, J. E. T. (2011). Impacts of urbanisation on groundwater quality and recharge in a semi-arid alluvial basin.

Journal of Hydrology, 409, 196–211. https://doi.org/10.1016/j.jhydrol.2011.08.020
Chang, J., Clay, D. E., Leigh, L., et al. (2008). Evaluating modified atmospheric correction methods for Landsat imagery: Image-based and model-based calibration methods. *Communications in Soil Science and Plant Analysis, 39*, 1532–1545. https://doi.org/10.1080/00103620802006669
Chen, W., Zhao, X., & Shahabi, H. (2019). Spatial prediction of landslide susceptibility by combining evidential belief function, logistic regression, and logistic model tree. *Geocarto International, 34*, 1177–1201. https://doi.org/10.1080/10106049.2019.1588393
Couch, C., Leontidou, L., & Petschel-Held, G. (2007). Urban sprawl in Europe: Landscapes, land-use change & policy. *Blackwell Publishing Ltd*. https://doi.org/10.1002/9780470692066
Dechaicha, A., Daikh, A., Alkama, D. (2021). Monitoring and landscape quantification of uncontrolled urbanisation in Oasis regions: The case of Adrar City in Algeria. *Journal of Contemporary Urban Affairs*, 5:209–219. https://doi.org/10.25034/ijcua.2021.v5n2-5
Djeddaoui, F., Chadli, M., Gloaguen, R. (2017). Desertification susceptibility mapping using logistic regression analysis in the Djelfa Area, Algeria. Remote Sensing, *9*. https://doi.org/10.3390/rs9101031
Eastman, J. R., Solorzano, L., & Van Fossen, M. (2005). Transition potential modeling for land-cover change. In D. J. Maguire, M. Batty, & M. F. Goodchild (Eds.), *GIS, spatial analysis and modeling* (pp. 357–385). ESRI Press.
Emadodin, I., & Bork, H. R. (2012). Degradation of soils as a result of long-term human-induced transformation of the environment in Iran: An overview. *Journal of Land Use Science, 7*, 203–219. https://doi.org/10.1080/1747423X.2011.560292
Faysal Ahmed, Md. (2014). Urbanisation and environmental problems: An empirical study. *International Institute for Science, Technology and Education (IISTE): E-Journals, 4*, 161–172.
Feng, Y., Yang, Q., Hong, Z., & Cui, L. (2018). Modelling coastal land use change by incorporating spatial autocorrelation into cellular automata models. *Geocarto International, 33*, 470–488. https://doi.org/10.1080/10106049.2016.1265597
Firdaus, G. (2012). Urbanisation, emerging slums and increasing health problems: a challenge before the nation: an empirical study with reference to the state of Uttar Pradesh in Nigeria. *E3 Journal of Environmental Research and Management, 3*, 0146–0152.
Forest Directorate of the Djelfa Department, Statistics Department. (2020).
Getu, K., & Bhat, H. G. (2021). Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia. *Land Use Policy, 109*, 105676. https://doi.org/10.1016/j.landusepol.2021.105676
Graham, J., Gurian, P., Corella-Barud, V., & Avitia-Diaz, R. (2004). Peri-urbanisation and in-home environmental health risks: The side effects of planned and unplanned growth. *International Journal of Hygiene and Environmental Health, 207*, 447–454. https://doi.org/10.1078/1438-4639-00314
Grekousis, G., Manetos, P., & Photis, Y. N. (2013). Modeling urban evolution using neural networks, fuzzy logic and GIS: The case of the Athens metropolitan area. *Cities, 30*, 193–203. https://doi.org/10.1016/j.cities.2012.03.006
Grigorescu, I., Kucsicsa, G., & Popovici, E. A. (2019). Modelling land use/cover change to assess future urban sprawl in Romania. *Geocarto Internationa*, *0*, 1–19. https://doi.org/10.1080/10106049.2019.1624981
Haas, J., & Ban, Y. (2014). Urban growth and environmental impacts in Jing-Jin-Ji, the Yangtze, and the Pearl River Delta. *International Journal of Applied Earth Observation and Geoinformation, 30*, 42–55. https://doi.org/10.1016/j.jag.2013.12.012
Hamza, M.B., Abbassia, A., & Mohammed, B. (2022). Urban sprawl and expansion of road networks and its impacts on the environment using sensor and socio-economic data: Macta watershed, western Algeria. *Journal of Geology, Geography and Geoecology*, *31*, 31–44. https://doi.org/10.15421/112204
Hu, Z., & Lo, C. P. (2007). Modeling urban growth in Atlanta using logistic regression. *Computers, Environment and Urban Systems, 31*, 667–688. https://doi.org/10.1016/j.compenvurbsys.2006.11.001
Ilyassova, A., Kantakumar, L.N., & Boyd, D. (2019). Urban growth analysis and simulations using cellular automata and geo-informatics: comparison between Almaty and Astana in Kazakhstan. *Geocarto International*, *0*, 1–20. https://doi.org/10.1080/10106049.2019.1618923
Jain, R. K., Jain, K., & Ali, S. R. (2017). Modeling urban land cover growth dynamics based on Land Change Modeler (LCM) using remote sensing: A case study of Gurgaon, India. *Adv Comput Sci Technol, 10*, 2947–2961.
Jamali, A. A., & Ghorbani Kalkhajeh, R. (2019). Urban environmental and land cover change analysis using the scatter plot, kernel, and neural network methods. *Arabian Journal of Geosciences*, *12*(100). https://doi.org/10.1007/s12517-019-4258-7
Jantz, C. A., Goetz, S. J., Donato, D., & Claggett, P. (2010). Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. *Computers, Environment and Urban Systems, 34*, 1–16. https://doi.org/10.1016/j.compenvurbsys.2009.08.003
John, J., Bindu, G., & Srimuruganandam, B. (2020). Land use/land cover and land surface temperature analysis in Wayanad district, India, using satellite imagery. *Annals of GIS, 00*, 1–18. https://doi.org/10.1080/19475683.2020.1733662
Lafazani, P., & Lagarias, A. (2016). Applying multiple and logistic regression models to investigate periurban processes in Thessaloniki, Greece. *Geocarto International, 31*, 927–942. https://doi.org/10.1080/10106049.2015.1094523
Liu, F., Zhang, Z., & Wang, X. (2019a). Urban expansion in Xiongan New Area since 1975. *Geocarto International, 34*, 1568–1583. https://doi.org/10.1080/10106049.2018.1494758
Liu, W., & Seto, K. C. (2008). Using the ART-MMAP neural network to model and predict urban growth: A

spatiotemporal data mining approach. *Environment and Planning. B, Planning & Design, 35*, 296–317. https://doi.org/10.1068/b3312

Liu, Z., Ding, M., & He, C. (2019b). The impairment of environmental sustainability due to rapid urbanisation in the dryland region of northern China. *Landscape and Urban Planning, 187*, 165–180. https://doi.org/10.1016/j.landurbplan.2018.10.020

Losiri, C., Nagai, M., Ninsawat, S., & Shrestha, R. P. (2016). Modeling urban expansion in Bangkok Metropolitan region using demographic-economic data through cellular Automata-Markov Chain and Multi-Layer Perceptron-Markov Chain models. *Sustain*, 8. https://doi.org/10.3390/su8070686

Lu, D., Mausel, P., Brondizio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing, 25*(12), 2365–2401. https://doi.org/10.1080/0143116031000139863

Maithania, S., Arorab, M. K., & Jain, R. K. (2010). An artificial neural network-based approach for urban growth zonation in Dehradun city, India. *Geocarto International, 25*, 663–681. https://doi.org/10.1080/10106049.2010.524313

Mansour, D., Souiah, S. A., & Larabi, M. E. A. (2023). Urban sprawl characterisation and its impact on peri-urban agriculture in Sidi Bel Abbes, Algeria, using multi-date Landsat imagery. *GeoJournal, 88*, 4671–4695. https://doi.org/10.1007/s10708-023-10875-w

Mohammady, S., Delavar, M. R., & Pahlavani, P. (2014). Urban growth modeling using an Artificial Neural Network a case study of Sanandaj City, Iran. *The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences, 40*, 203–208. https://doi.org/10.5194/isprsarchives-XL-2-W3-203-2014

Mondal, B., Chakraborti, S., & Das, D. N. (2020). Comparison of spatial modelling approaches to simulate urban growth: A case study on Udaipur city, India. *Geocarto International, 35*, 411–433. https://doi.org/10.1080/10106049.2018.1520922

Mostari, A., Benabdeli, K., & Ferah, T. (2021). Assessment of the impact of urbanisation on agricultural and forest areas in the coastal zone of Mostaganem (western Algeria). *Ekol Bratislava, 40*, 230–239. https://doi.org/10.2478/eko-2021-0025

Ministry of Territorial Planning (MTP). (2014). The Regional Plan of the Central Highlands Region.

Municipality of Djelfa, Technical Department, (2020).

Nagabhatla, N., Max Finlayson, C., & Sellamuttu, S. S. (2012). Assessment and change analyses (1987–2002) for tropical wetland ecosystems using earth observation and socio-economic data. *European Journal of Remote Sensing, 45*, 215–232. https://doi.org/10.5721/EuJRS20124520

National Office of Meteorology (NOM). (2017). https://www.meteo.dz/. Accessed 24 May 2021

National Office of Statistics (NOS). (1998). General population and habitat census. Algeria. http://www.ons.dz/-Population-RGPH1998. Accessed 25 May 2021

National Office of Statistics (NOS). (2008). General population and habitat census. Algeria. http://www.ons.dz/-Population-RGPH2008. Accessed 25 May 2021

Neil, K., & Wu, J. (2006). Effects of urbanisation on plant flowering phenology: A review. *Urban Ecosystem, 9*, 243–257. https://doi.org/10.1007/s11252-006-9354-2

Nor, A. N. M., Corstanje, R., Harris, J. A., & Brewer, T. (2017). Impact of rapid urban expansion on green space structure. *Ecological Indicators, 81*, 274–284. https://doi.org/10.1016/j.ecolind.2017.05.031

Noui, N., Rouag Saffeddine, D., Harizi, K. (2023). Detecting changes in land occupation and use (between 1984–2021) using "GEE" and GIS tools: focus on the green structure of the future metropolis of Annaba (north-east Algeria). *Indonesian Journal of Social Science Research*, *4*, 155–170. https://doi.org/10.11594/ijssr.04.02.08

Ohana-Levi, N., Givati, A., & Alfasi, N. (2018). Predicting the effects of urbanisation on runoff after frequent rainfall events. *Journal of Land Use Science, 13*, 81–101. https://doi.org/10.1080/1747423X.2017.1385653

Ohana-Levi, N., Karnieli, A., & Egozi, R. (2015). Modeling the effects of land-cover change on rainfall-runoff relationships in a Semi-arid, Eastern Mediterranean Watershed. *Advances in Meteorology*. https://doi.org/10.1155/2015/838070

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

Petrov, A. N., & Sugumaran, R. (2005). Monitoring and modeling cropland loss in rapidly growing urban and depopulating rural counties using remotely sensed data and GIS. *Geocarto International, 20*, 45–52. https://doi.org/10.1080/10106040508542363

Phong, T. V., Phan, T. T., & Prakash, I. (2019). Landslide susceptibility modeling using different artificial intelligence methods: a case study at Muong Lay district, Vietnam. *Geocarto Intenational*, *0*, 1–24. https://doi.org/10.1080/10106049.2019.1665715

Pijanowski, B. C., Tayyebi, A., & Doucette, J. (2014). A big data urban growth simulation at a national scale: Configuring the GIS and neural network-based Land Transformation Model to run in a High-Performance Computing (HPC) environment. *Environmental Modelling and Software, 51*, 250–268. https://doi.org/10.1016/j.envsoft.2013.09.015

Pontius, R. G., Huffaker, D., & Denman, K. (2004a). Useful validation techniques for spatially explicit land-change models. *Ecological Modelling, 179*, 445–461. https://doi.org/10.1016/j.ecolmodel.2004.05.010

Pontius, R. G., Shusas, E., & McEachern, M. (2004b). Detecting important categorical land changes while accounting for persistence. *Agriculture, Ecosystems & Environment, 101*, 251–268. https://doi.org/10.1016/j.agee.2003.09.008

Programming and Budget Monitoring Directorate (PBMD). (2000). The Djelfa Department Monograph. Djelfa Department: Djelfa, Algeria.

Programming and Budget Monitoring Directorate (PBMD). (2019). The Djelfa Department Monograph. Djelfa Department: Djelfa, Algeria.

Rasul, A., Balzter, H., & Smith, C. (2017). Applying a normalised ratio scale technique to assess influences of urban expansion on the land surface temperature of the semi-arid city of Erbil. *International Journal of Remote*

Sensing, 38, 3960–3980. https://doi.org/10.1080/01431161.2017.1312030
Rodríguez Eraso, N., Armenteras-Pascual, D., & Alumbreros, J. R. (2013). Land use and land cover change in the Colombian Andes: Dynamics and future scenarios. *Journal of Land Use Science, 8*, 154–174. https://doi.org/10.1080/1747423X.2011.650228
Saeidi, S., Mirkarimi, S. H., Mohammadzadeh, M., Salmanmahiny, A., & Arrowsmith, C. (2018). Designing an integrated urban growth prediction model: A scenario-based approach for preserving scenic landscapes. *Geocarto International, 33*(12), 1381–1397. https://doi.org/10.1080/10106049.2017.1353647
Salem, M., Tsurusaki, N., & Divigalpitiya, P. (2020). Land use/land cover change detection and urban sprawl in the peri-urban area of greater Cairo since the Egyptian Revolution in 2011. *Journal of Land Use Science, 15*, 592–606. https://doi.org/10.1080/1747423X.2020.1765425
Salvati, L., Sateriano, A., & Bajocco, S. (2013). To grow or to sprawl? Land cover relationships in a Mediterranean city region and implications for land use management. *Cities, 30*(1), 113–121. https://doi.org/10.1016/j.cities.2012.01.007
Sameen, M. I., Nahhas, F. H., & Buraihi, F. H. (2016). A refined classification approach integrating Landsat Operational Land Imager (OLI) and RADARSAT-2 imagery for land-use and land-cover mapping in a tropical area. *International Journal of Remote Sensing, 37*, 2358–2375. https://doi.org/10.1080/01431161.2016.1176273
Saouli, R. A., Benhassineenhassine, N., & Oularbiularbi, A. (2023). A spatial-temporal retrospective of the urban sprawl of Annaba (Algeria). *Journal of Fundamental and Applied Sciences, 12*, 825–844. https://doi.org/10.4314/jfas.v12i2.20
Sehl, B., Guettouche, M. S., Ait Mouheb, H., & Camacho Olmedo, M. T. (2018). Contribution of consensus methods to resolve sources of uncertainty in suitability maps modeling: application in the Zahrez El Gharbi, Steppe of Algeria. *Arabian Journal of Geosciences*, 11. https://doi.org/10.1007/s12517-018-3495-5
Serra, P., Saurí, D., & Salvati, L. (2018). Peri-urban agriculture in Barcelona: Outlining landscape dynamics vis à vis socioenvironmental functions. *Landscape Research, 43*(5), 613–631. https://doi.org/10.1080/01426397.2017.1336758
Shalaby, A. A., Ali, R. R., & Gad, A. (2012). Urban sprawl impact assessment on the agricultural land in Egypt using remote sensing and GIS: A case study, Qalubiya Governorate. *Journal of Land Use Science, 7*, 261–273. https://doi.org/10.1080/1747423X.2011.562928
Siedentop, S., & Fina, S. (2010). Monitoring urban sprawl in Germany: Towards a GIS-based measurement and assessment approach. *Journal of Land Use Science, 5*, 73–104. https://doi.org/10.1080/1747423X.2010.481075
Sinha, S., Sharma, L. K., & Nathawat, M. S. (2015). Improved Land-use/Land-cover classification of semi-arid deciduous forest landscape using thermal remote sensing. *Egyptian Journal of Remote Sensing and Space Science, 18*, 217–233. https://doi.org/10.1016/j.ejrs.2015.09.005
Slimani, N., & Raham, D. (2023). Urban growth analysis using remote sensing and GIS techniques to support decision-making in Algeria—the Case of the City of Setif. *Journal of the Geographical Institute Jovan Cvijic SASA, 73*, 17–32. https://doi.org/10.2298/IJGI2301017S
Srivastava, P. K., Han, D., & Rico-Ramirez, M. A. (2012). Selection of classification techniques for land use/land cover change investigation. *Advances in Space Research, 50*, 1250–1265. https://doi.org/10.1016/j.asr.2012.06.032
Tayyebi, A., Pekin, B. K., & Pijanowski, B. C. (2013). Hierarchical modeling of urban growth across the conterminous USA: Developing mesoscale quantity drivers for the Land Transformation Model. *Journal of Land Use Science, 8*, 422–442. https://doi.org/10.1080/1747423X.2012.675364
Traoré, F., Cornet, Y., & Denis, A. (2013). Monitoring the evolution of irrigated areas with Landsat images using backward and forward change detection analysis in the Kou watershed, Burkina Faso. *Geocarto International, 28*, 733–752. https://doi.org/10.1080/10106049.2012.744100
Valdez, M., Chen, C. F., & Chiang, S. H. (2019). Illegal land use change assessment using GIS and remote sensing to support sustainable land management strategies in Taiwan. *Geocarto International, 34*, 133–148. https://doi.org/10.1080/10106049.2017.1374474
Waddell, P., Borning, A., Noth, M., Freier, N., Becke, M., & Ulfarsson, G. (2003). Microsimulation of urban development and location choices: Design and implementation of UrbanSim. *Networks and Spatial Economics, 3*, 43–67. https://doi.org/10.1023/A:1022049000877
Waddell, P., & Borning, A. (2004). A case study in digital government: Developing and applying UrbanSim, a system for simulating urban land use, transportation, and environmental impacts. *Social Science Computer Review, 22*, 37–51. https://doi.org/10.1177/0894439303259882
Wang, L., Zhang, S., & Wang, L. (2018). Concentration and risk evaluation of polycyclic aromatic hydrocarbons in urban soil in the typical semi-arid Xi'an in Northwest China. *International Journal of Environmental Research and Public Health*, 15. https://doi.org/10.3390/ijerph15040607
Xystrakis, F., Psarras, T., & Koutsias, N. (2017). A process-based land use/land cover change assessment on a mountainous area of Greece during 1945–2009: Signs of socio-economic drivers. *Science of the Total Environment, 587–588*, 360–370. https://doi.org/10.1016/j.scitotenv.2017.02.161
Yadav, V., & Ghosh, S. K. (2019). Assessment and prediction of urban growth for a mega-city using CA-Markov model. *Geocarto International*, *0*, 1–33. https://doi.org/10.1080/10106049.2019.1690054
Yu, Z., Di, L., Yang, R., Tang, J., Lin, L., Zhang, C., et al. (2019). Selection of landsat 8 OLI band combinations for land use and land cover classification. 2019 8th International Conference on Agro-Geoinformatics. *Agro-Geoinformatics,* 1–5. https://doi.org/10.1109/Agro-Geoinformatics.2019.8820595
Yuan, F. (2010). Urban growth monitoring and projection using remote sensing and geographic information systems: A case study in the Twin Cities Metropolitan Area, Minnesota. *Geocarto International, 25*, 213–230. https://doi.org/10.1080/10106040903108445
Zerouali, B., Santos, C. A. G., do Nascimento, T. V. M., Silva, R. M. da. (2023). A cloud-integrated GIS for

forest cover loss and land use change monitoring using statistical methods and geospatial technology over northern Algeria. *Journal of Environmental Management*, *341*, 3–5.https://doi.org/10.1016/j.jenvman.2023.118029

Zhang, Z., De Clercq, E., & Ou, X. K. (2008). Mapping dominant vegetation communities at Meili Snow Mountain, Yunnan Province, China, using satellite imagery and plant community data. *Geocarto International, 23*, 135–153. https://doi.org/10.1080/10106040701337410

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