QUANTIFYING URBAN EXPANSION AND ITS DRIVING FORCES IN THE CITY OF MILA

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Abstract: Urban sprawl is a description of the uncontrolled urban development that results from the suburbanization process. Thus, the need to identify the driving factor of urban sprawl is crucial to understand the urban expansion of Mila city and overcome the severe challenges of rapid urbanization. A list of eight driving factors was identified from the literature review after interviews with local urban experts and consideration of data availability. Therefore, a logistic regression analysis was applied to investigate those factors with data extracted from remotely sensed data for 1998–2008. The evaluation of the LR model results is conducted by the operating characteristic curve (ROC). The outputs gave high accuracy rates for the entire study area. The results revealed that during the study period, Mila city experienced a highly intense built-up expansion reflected in an area increase from 285h to 582h. The analysis of driving factors has demonstrated a decreasing significance of the population density, slope, distance to industrial enterprises, and elevation as drivers of urban expansion. Meanwhile, the most significant factors corresponding to the study were the proximity (accessibility) factors of distances to urban roads, distance to CBD, and educational facilities. The research results have shown that the city of Mila expanded into the suburban area along the road network, leading to more informal urban settlements and a more sprawled pattern. However, these findings should be integrated into urban planning policies and development regulations to control future urban expansion.

Keywords: urban expansion, urban sprawl, urbanization, land use, determinants, logistic regression, Mila

1 INTRODUCTION

After the 1950s, the degree of urbanization in the world has undergone significant changes, with the urban population exceeding 50%. This demographic growth is reflected in the increasing number of urban agglomerations and their expansion in physical size, whose total urban land quadrupled between 1970 and 2000 on a global scale (Li et al., 2013). Accordingly, these rapid changes posed a challenge for local authorities in meeting the needs of the urban population. The development of the cities and the changing patterns of land use imposed many spatial, economic, social, and environmental consequences, including the consumption of the natural land area, traffic congestion, the effect of heat islands, pollution, and the modification of the land shape and water quality (Traore and Watanabe, 2017).

It is frequently predicted that the urban expansion process is identified by its driving factors (Rifat and Liu, 2019). It varies according to the natural condition of cities, the social and economic situation of the population, and the legal guidance of each region (Li et al., 2018). Thus, a good understanding of the expansion process, its patterns, and its determinants is the decisive challenge in the management process and the planning of the city's future growth. For example, the main determinants of urban expansion in China are economic and social factors (Chen et al., 2018; Hu et al., 2015; Yang et al., 2015), and their impact is more significant than natural factors (Li et al., 2019). In most Eastern European cities, the increasing income per capita and population growth represented the key drivers of urban expansion (Oueslati et al., 2015). In Western Europe, economic development and population migration are the main driving factors of urban expansion (Korec et al., 2020; Špačková et al., 2016). To list the most important determinants we relied on previous studies (Table 1), which summarized the driving factors for urban expansion into four groups: Socio-economic factors (Batisani and Yarnal, 2009; Jiang et al., 2013; Seto et al., 2011), topographical factors (Chen, 2007; Dewan and Yamaguchi, 2009; Monteiro et al., 2011; Luo and Wei, 2009), proximity factors (Huang et al., 2009; Rui and Ban, 2011; Zhao et al., 2017), as well as urban policies (Cheng and Masser, 2003; Tian et al., 2005; Xiao et al., 2006). In most of the studies related to the determinants of urban expansion, researchers focus on metropolitan areas. Small and medium-sized cities were abandoned, even though their critical function was to reach regional balance, particularly in Algeria (Mila, northeast of Algeria). (Small-sized cities: population between 20000 to 50000/ medium-sized cities: 50000 to 100000. Law No. 06 – 06 of 20 February 2006 on the City’s Orientation, www.-joradp.dz, Algeria)

Since its independence in 1962, Algeria witnessed rapid urbanization. The proportion of the urban population increased from 31.4% in 1966 to 65.94% in 2008. Accordingly, the urban agglomerations were augmented from 95 to 751 agglomerations (National Office of Statistics, 2011). This was due to the demographic explosion resulting from the natural increase in population and the internal population migration, which characterized the period from 1966 to 2008. As a result, intensification in the urban network of various city sizes and urban fabric exceeded the limits drawn by the master plan. Hence, the urban expansion of Algerian cities was characterized by irrational consumption of agricultural land, real estate, and resources. This made us wonder about the pace of urban expansion of the city of Mila and its determinants in the period between 1998–2008. The term “urban fabric” describes the physical characteristics of urban areas: cities and towns. This includes the streetscapes, buildings, soft and hard landscaping, signage, lighting, roads and other infrastructure. Urban fabric can be considered an urban area’s physical texture.

This study will attempt to answer this question by quantifying the pace and identifying the determinants of urban expansion in Mila between 1998 and 2008 using quantitative indicators, GIS techniques, and a logistic regression model. We chose that precise period for its coincidence with the political changes in the country by pursuing a new urban policy based on planning development according to a master plan. However, the city's expansion in this period was chaotic and requested a re-examination of the urbanization strategy. These results should provide valuable information about urban land use management and planning.

The objective is to map, quantify, and explore the relationship between urban expansion and its driving factors.

1. Measure and map the urban expansion of the city of Mila from 1998 to 2008, using quantitative indicators such as expansion intensity index, annual expansion rate, urban land proportion, and GIS techniques.
2. Apply a logistic regression model to measure the strength and nature of the relationship between urban expansion and its determinants.

2 THEORETICAL BACKGROUND

Urban expansion is related to the socio-economic, spatial, and institutional context. As a result, it can produce various types of urban forms. It can be defined according to several aspects: density, proximity, compactness, nuclearity, centralization, concentration, continuity, and mixed uses (Zhang and Su, 2016). Urban expansion is a three-dimensional process combining vertical and horizontal expansion (Shi et al., 2009), but in recent years the extended horizontal form, or as it is called "urban sprawl", has been the primary form of urban expansion (Rao et al., 2020). The emergence of the concept of urban sprawl was linked to the consequences of the industrial revolution in both the United Kingdom and the United States of America. The significant development of infrastructure and transportation (individual cars, trains) and high income have contributed to the transition of urban development from city centres to suburbs in the USA after World War 2. The structure of the American urban population changed dramatically between 1960 and 2000 from 60% of the nation's metropolitan population (New York, Boston, Chicago and others) living in the city core to more than 60% of the metropolitan population living in suburban areas outside of the city (Gillham, 2002). European cities have experienced a more compact pattern than US cities (Nechyba and Walsh, 2002).

The urban sprawl is a description of the uncontrolled urban development that results from the suburbanization process. The term "suburbanization" refers to the migration of the population, the displacement of dwelling places, and commercial and industrial activity from the compact urban core to the suburbs (Pieretti, 2014). Therefore, urban sprawl as a concept suffers from ambiguity and difficulties in definition (Wilson et al., 2003). Urban sprawl is generally defined as uncontrolled urban development characterized by low-density, single-use zoning, open spaces, and individual car dependence for transportation (Abdullahi et al., 2017). However, the term “sprawl” first emerged in the USA during the national conference of planners in the Tensei Valley in 1937, where Earle Draper recognized that the sprawling city distorts the countryside, in addition to being a pattern of non-incremental expansion of services and affecting social connectivity (Wassmer, 2002). After 1950, academic concern about the impact of urban sprawl has grown rapidly. As a result, relevant research emerged, mainly involving patterns, processes, causes, consequences, and countermeasures (Bhatta, 2010).

Urban expansion has been studied in various aspects and trends, through scale (Batty, 2005; Hennig et al., 2015; Siedentop and Fina, 2012), pace (intensity) (Al-Sharif et al., 2014), pattern and its impact on the environment (Camagni et al., 2002; McGarigal et al., 2018; Trinder and Liu, 2020), in addition to demographic transformations and economic development (Correia Filho et al., 2022; Salvati and Lamonica, 2020; Zhang and Xie, 2019), researchers have addressed the study of spatial differences, background and causes of urban expansion (Liu et al., 2015), based on a set of indicators, which are: the index of increasing magnitude, the intensity of expansion (annual), the percentage of urban land and the rate of expansion (annual) (Kantakumar et al., 2016; Zhang and Su, 2016).

Urban expansion analysis facilitates the conception of the changes in the urban landscape over time by observing its shape concerning the current and expected variation in time and space to see whether the expansion is extended or compact. This analysis can be conducted for the past, present, and future (Bhatta, 2010). The importance of the spatiotemporal studies of urban expansion has been emphasized through accurate and detailed information that helps urban managers make decisions and allows searchers to develop and update urban theories (Arsanjani et al., 2013). By using a set of methodologies and techniques represented in four types: the use of remote sensing techniques to extract the spatial boundaries of urban expansion, the use of dynamic models to understand spatial and temporal patterns of urban expansion, the use of statistical models to help understand the mechanisms, effects, and determinants of urban expansion with future expansion simulations using some models such as the cellular automat model (Shi et al., 2019). Where remote sensing and GIS are one of the most critical tools in urban studies, the analytical processes of data that most GIS software and remote sensing are available, such as monitoring changes in land use through spatial analysis and statistical models, which help to understand the process of urban expansion and determine its patterns (Fan et al., 2009; Traore and Watanabe, 2017).

Many studies have investigated the determinants of urban expansion, focusing on a metropolitan area or regional scale. For example, Salem et al. (2021) argued that the proximity to roads, the city centre, and medical facilities are the most influential factors in urban expansion in Delhi, India. Guangjin et al. (2016) stated that population growth and proximity to roads are among the factors affecting urban expansion in Eastern China, while industrialization and economic development are the most influential factors in its midst, and economic development is the factor influencing urban expansion in western China. Moreover, another study conducted by Rifat and Liu (2019) showed that population growth, proximity to the coast, proximity to roads, and per capita income are the most critical factors affecting urbanization in Miami, USA. Salem et al. (2019) confirmed that population density and proximity to roads are the factors affecting the urban expansion of a city in Cairo, Egypt. Gielen et al. (2018) claimed that proximity to the city centre and urban density are the main causes of urban expansion in Valencia, Spain. In contrast, a few studies have investigated small and medium-sized cities in Algeria, especially Mila.

Our study is based on a quantitative method to examine the relationship between urban expansion and its driving factors for improving understanding of the urban expansion process to better future management and planning (Table 1).

Table 1 Summary of urban expansion determinants based on previous studies

Determinants	variables	literature
Topographic factors	Slope, elevation	(Chen, 2007; Dewan et Yamaguchi, 2009; Monteiro et al., 2011)
	Distance to river	(Batisani et Yarnal, 2009; Braimoh et Onishi, 2007; Luo et Wei, 2009)
Socio-economic factors	Gross product domestic	(Dewan et Yamaguchi, 2009; Jiang et al., 2013; Wu et , 2012)
	Population	(Batisani et Yarnal, 2009; Braimoh et Onishi, 2007; Seto et al., 2011)
Proximity factors	Distance to roads	(Huang et al., 2009; Li et al., 2013; Ye et al., 2013)
	Distance to city centre	(Batisani et Yarnal, 2009; Rui et Ban, 2011; Vermeiren et al., 2012)
	Distance to educational facilities	(Sarkar et Chouhan, 2020; Xu et al., 2018)
	Distance to industrial facilities	(Braimoh et Onishi, 2007; Zhang et al., 2017; Zhao et al., 2017)
Urban policy	Master plan	(Cheng et Masser, 2003; Tian et al., 2005; Xiao et al., 2006)
	Land use planning and guideline	

Source: Own elaboration

It can be concluded that the topographic factors (slope and elevation) are significant factors that determine the expansion of areas, patterns, and obstacles that limit it. Moreover, it is critical to define the land's suitability and construction cost (Poelmans and Van Rompaey, 2010; Ustaoglu and Williams, 2017; Wu et al., 2019).

The socio-economic factors (population, income level etc.), in addition to the proximity factor that is related to the economic factors (proximity to main roads, proximity to the centre etc.), are the two key factors of urban expansion represented in various previous studies (Liu et al., 2015; Wu et al., 2021).

The urban policy factor catalyzes urban development through political decisions or a constraint to urban development through juridical restrictions related to land use and urban plans (Feng et al., 2015; Braimoh and Onishi, 2007; Turnbull, 2005).

3 MATERIALS AND METHODS

3.1 Study area

The city of Mila represents the study area in this paper, which is the headquarters of the state, and the antique city in the middle of it is a historical witness that reflects the succession of civilizations that the region has witnessed since its founding by the Romans in 47 BC (Master plan of Mila approved in 1997).

The city of Mila located in the northeast of the state, occupies an area of 1500 hectares (Figure 1) (The master plan of Mila was approved in 1997); it is considered one of the most important cities of the state due to its administrative and demographic weight, with a population of 63251 in 2008 and high urbanization rates of 91% in 1998 (NOS, 2011).

In addition to the economic role of the city, due to its strategic location, it is the link between the north and the south, as it represents a crossing for goods and products coming from the province of Jijel (Port of Djin-Djin, the industrial zone of Belara) towards the highway that is located south of the city. It also had outstanding economic qualifications in the agricultural field (80% of the municipal area), several other services, and the industrial activity represented by an industrial zone.

Furthermore, the city suffers from several obstacles that hinder its development, including natural challenges such as the topographic characteristics and geological components (soil characteristics). Firstly, Mila is located in a basin with an elevation between 1040 m south and 150 m north (meters above sea level), with a slope ranging between 5% and 50%. Secondly, soil fragility causes many landslides, affecting the urban fabric's continuity. Thirdly, the high-quality agricultural land represents an obstacle to the expansion of the city of Mila.

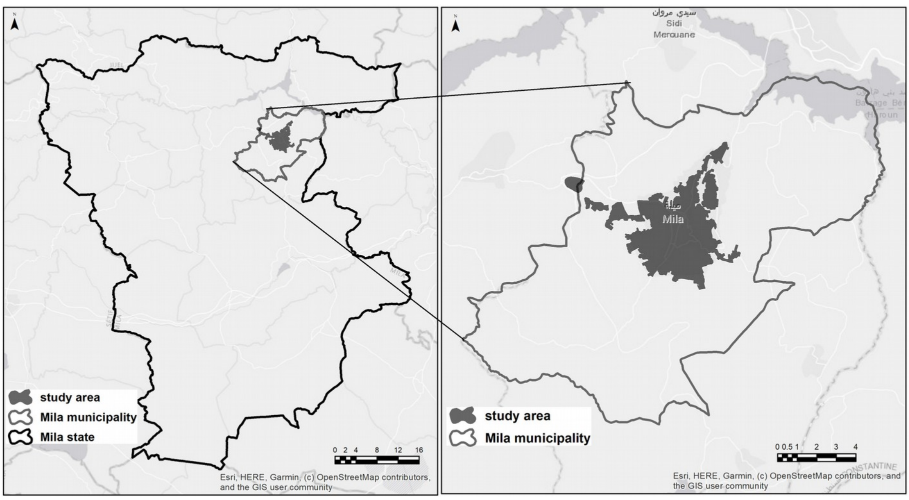

Figure 1 Location and administrative districts of Mila. Source: Esri imagery OSM

3.2 Data sources

Information for this study was collected from several sources.

Land satellite imagery from various sensors (TM) and (OLI) for 1998, 2008, and 2020, uploaded from the USGS website, were used as primary data sources.

The topographic map of 1998 was used as the main reference for following urban expansion.

Statistical data such as population density were collected from the National Office of Statistics.

Roads, industrial enterprises, and educational facilities were extracted from the open street map and master plan of Mila.

3.3 Data processing

In the initial processing of satellite images, we used ENVI 5.3 to perform a geometric and radiometric correction, a necessary process that enables us to obtain good land cover/land use classification (LCLU) results.

For the classification process, the Maximum Likelihood supervised classification method was used to classify all satellite images by selecting homogeneous samples from the study area by identifying the training sites. We identified four land-use categories for each space visual: 1- Built-up land; 2- Water; 3- Agricultural land; and 4- Barren land.

As for the classification accuracy, it was derived from matching the classification result with reference data. As a result of this process, the overall accuracy is 85%. All data used in this study are geographically referenced on the WGS 84 UTM zone N32 projection system. The results were demonstrated as raster images with a spatial resolution of 30 m × 30 m based on ArcGIS 10.3 as a processing and output tool.

3.4 Measuring Urban Expansion

Based on the indicators that we discussed in the literature review, we measured the urban expansion of Mila City mathematically through the values extracted from the completed database, which represent the years 1998 and 2008, using the following equations:

The urban expansion intensity index (Eq: 1) shows the expansion intensity. Annual expansion rate (Eq: 2), which describes its speed, and urban land proportion (Eq: 3), which shows us the extent of urban expansion (Rifat and Liu, 2019):

$$UEII = \frac{area_{t_2} - area_{t_1}}{(t_2 - t_1) \times TA} \times 100 \tag{1}$$

Where UEII represents the expansion intensity, area t2 and area t1 refer to the urban core area in t2 (2008) and t1 (1998). TA in this study represents the urban area limits identified by the master plan. The urban expansion intensities were classified into five groups: <0.28, 0.28-0.59, 0.59-1.05, 1.05-1.92, and >1.92, which refer to the urban expansion intensity level of very low, low, moderate, rapid, and highly rapid, respectively.

$$AER = \frac{area_{t_2} - area_{t_1}}{t_2 - t_1} \quad (2)$$

$$ULP = \frac{area_t}{area_{total}} \times 100 \quad (3)$$

AER represents the annual expansion rate, and ULP represents the proportion of urban land. (Area) is the area of urban land, (area total) describes the municipality area, (t) is the period, t2 refers to 2008, and t1 refers to 1998.

3.5 Selection of Determinants of urban expansion for the Study

The selection of determinants of urban expansion is a complex topic, as they are related to urban growth, urban expansion, and the urbanization process, which are complex and intertwined dynamic processes and are influenced by a set of dynamic determinants that change temporally and spatially (Sarkar and Chouhan, 2020). Reviewing the previous literature, we found four fundamental determinants: topographical, accessibility, socio-economic, and urban policies. As a result, the point of view we chose in our study consists of variables related to the previously mentioned determinants, which are determined according to the data availability. Therefore, we excluded the urban policy factor from this study due to insufficient data.

3.5.1 Topographic determinants

Identifying influencing factors that determine the location of urban expansion is a critical part of this study. To achieve this, two independent variables were selected: elevation and slope extracted from the digital elevation model (DEM) with a resolution of 30 m. The slope is calculated in percentage.

3.5.2 Proximity determinants

Five independent variables were chosen as determinants of proximity: distance to main roads, distance to tertiary roads, distance to the city centre, distance to educational facilities, and distance to industrial enterprises. The database was downloaded from the OSM platform and modified through the field investigation and master plan of Mila. The distances in this study were measured by calculating the Euclidean distances through the spatial analysis tool in ArcGIS 10.3.

3.5.3 Socio-economic determinants

Due to the lack of statistical data on the social and economic aspects, this study is satisfied with the population density variable. The population data for 2008 were collected from the National Office of Statistics (NOS) to create the population density map (urban area only).

To build a suitable model, it is necessary to verify the multicollinearity between the independent variables, as we used the linear regression model to detect it, where we relied on the study carried out by (Dahal and Lindquist, 2018), through which the excluded values of each variable whose variance inflation factor (VIF) exceeds the value of 5.1 were determined. (Table 2)

Table 2 Testing the existence of the multicollinearity between variables

Variables		tolerance	vif
X1	Slope	0,972	1,029
X2	Elevation	0,707	1,415
X3	Distance to main roads	0,334	2,990
X4	Distance to tertiary roads	0,204	4,910
X5	Distance to city centre	0,217	4,611
X6	Distance to educational facilities	0,174	4,975
X7	Distance to industrial facilities	0,213	4,688
X8	Population density	0,652	1,534

Source: The researchers used software

Finally, all maps of variables that passed the test through ArcGIS were converted to ASCII format and included in the IDRISI terrset to build a logistic regression model using the Land Change Modeler (LCM).

3.6 Logistic regression

Many studies have used logistic regression to analyze the determinants of urban expansion (Cheng and Masser, 2003; Hu et Lo, 2007; Sarkar and Chouhan, 2020; Zhang et al., 2017). The benefit of the LR model is its ability to predict the link between continuous or categorical variables and the dichotomous dependent variable (Sarkar and Chouhan, 2020). Our study used this statistical model to examine the relationship between urban expansion and its determinants based on spatial data.

Based on the bilateral logistic regression model, the determinants of urban expansion in Mila city between 1998-2008 were studied, and the model's validity was evaluated based on the 2020 land cover map. We relied on physical, accessibility, and socio-economic factors as determinants of the urban expansion of Mila in the period 1998-2008, with a total of 08 independent variables.

Logistic regression is used to determine the relationship between independent variables and a dichotomous dependent variable that expresses the occurrence or non-occurrence of transformation (Traore and Watanabe, 2017), predicting the probability of urban expansion (dependent variable) based on independent variables (X), and dependent variable (Y).

In this work, we considered the pixel as the smallest unit. We have followed the change from non-urban to urban expressed in a binary raster through it. The occurrence of urban expansion is represented by the value 1. The value 0 indicates that non-change occurred between 1998-2008.

The LR model is based on the probability that the relationship between the independent variables (X) and the dependent variable (Y) is nonlinear, where the values are confined between 0 (negative response) and 1 (positive response). We can define it using the following equations (4):

$$P=(Y=1|X)=\frac{\exp\sum_{k=0}^{k} b_k x_{ik}}{1+\exp\sum_{k=0}^{k} b_k x_{ik}} \quad , \tag{4}$$

where P indicates the probability of the dependent variable (urban transformation) from 0 to 1, X expresses the independent variables $X=(X_0, X_1, X_2, X_3 \ldots X_k)$, $X_0=1$ are the estimated parameters, $b=(b_0, b_1, b_2 \ldots b_k)$ represents the coefficient of variables.

The coefficients of independent variables are estimated based on the maximum likelihood method, which helps to find the most suitable coefficient for the model, and the logistic regression model provides the property of predicting the probability of change for the dependent variable (Y), which is suitable for using the maximum likelihood method.

If we consider that each pixel graph (*Xi*) is a vector, and (*yi*) viewers. So, the probability of the target variable is P, if *yi*=1 or 1-P if *yi*=0. In this case, the maximum likelihood equation is as follows eq (5):

$$the\, L(\beta 0, \beta)=\prod_{i=1}^{n} P(X_i)^{yi}(1-PX_i)^{1-y} \quad . \tag{5}$$

In binary logistic regression, the odds ratio for a phenomenon occurring is defined as the probability or likelihood of an event occurring. It is expressed as a proportion of the probability that an event occurs or does not occur. Therefore, if ρ is the probability of occurrence and p∼ is the probability of non-occurrence, then the odds will be p⁄p∼ for logistic regression. The odds that Y = 1 is calculated using the following equation (6):

$$\Omega=e^{\alpha}\sum_{i=1}^{k} \beta_i X_i \quad . \tag{6}$$

The odds ratio of a binary variable is defined as the relationship between independent variables (*Xi*), with the dependent variable (*Y*) representing urban expansion. Therefore, the probability of changing from a non-urban pixel to an urban pixel is expressed by the following equation (7):

$$P = \frac{\exp\left(\alpha + \beta, x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n\right)}{1 + \exp\left(\alpha + \beta, x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n\right)} \quad , \tag{7}$$

where P represents the probability of the response of the variable, α constant value, exp is the constant basis of the natural logarithms of the equation and β is the coefficient of the standard variables (xi).

The LR measures the probability of urban pixels based on their driving factors by quantifying their interaction. It produces a map of the potential for expansion based on the specific period we chose to be 2020. To verify the model's validity, a comparison is critical with the land use map for the same year.

The ROC curve was used in the validation section. It is one of the best methods to evaluate the model. It expressed the results of comparing the probability of the expansion prediction map and the land use map as a binary image for the same period (Hu and Lo, 2007). The results are expressed in a graph (Figure 2). This study compared the probability of the expansion map of the LR model with the actual urban expansion map 2020 to measure the model's predictability with a threshold value of 0.5. Here, we plotted a true positive probability of determination as an urban cell against a false positive probability determined as an urban cell for a set of thresholds 0.5-1. The result shows that the model is suitable with an ROC value of 0.91, indicating that the urban expansion probability map is valid for a follow-up study.

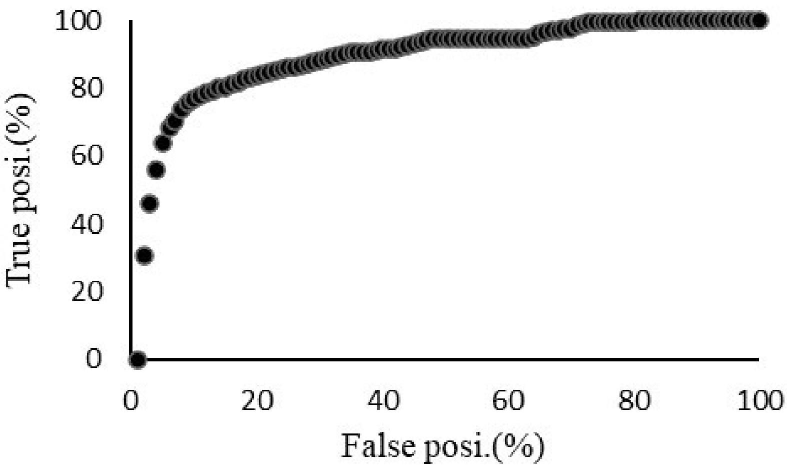

Figure 2 Testing the suitability of the model by using the Receiver Operating Characteristic curve. Source: by the researchers using software

4 RESULTS

4.1 Development of the urban area

The urban area of the city of Mila recorded a significant increase between 1998-2008. It developed from 285h in 1998 to 582h in 2008, an increase of 297h over ten years. The expansion intensity index was 1,98 during the study period, which means that Mila city's expansion is highly intense, with an annual rate of 29,7h/year. The proportion of urban land doubled from 2.18% to 4.45% in the same period (Figure 3).

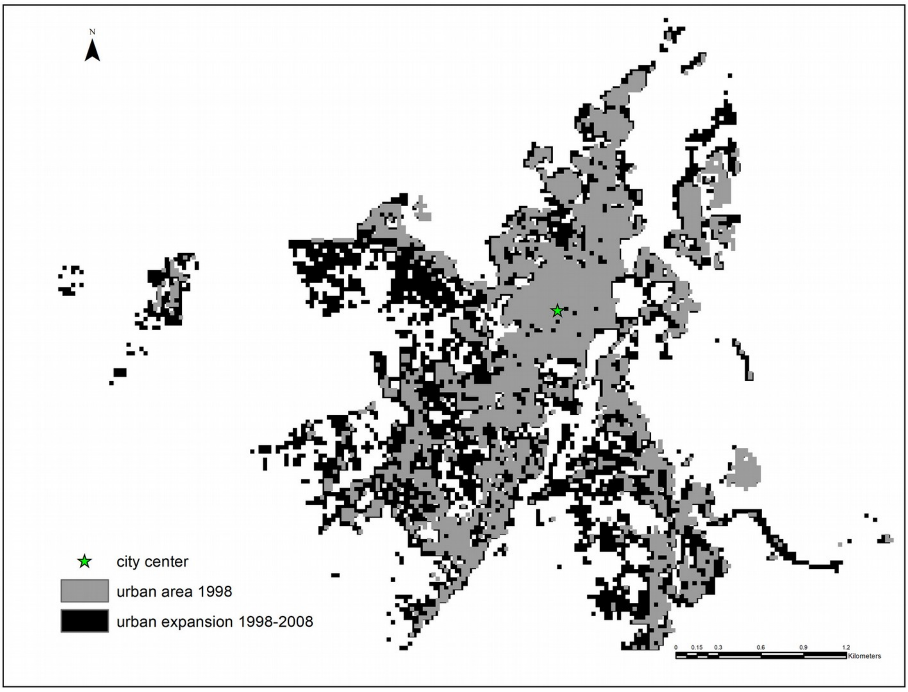

Figure 3 Evolution of the urban area of Mila 1998-2008. Source: USGs Landsat image

The interval from 1990 to 2008 is considered the most substance period during which Algerian cities witnessed major transformations at the level of their urban fabric. Through the analysis of the land cover maps of Mila for the years 1998-2008, we found that the built-up area of Mila developed significantly and at a rapid pace, as its urban area doubled over ten years. (Figure 4). This growth rate is high for a medium-sized city that was newly upgraded to the capital of a state during the administrative division in 1984. This promotion is considered one of the most critical factors that contributed to the high rates of urbanization of Algerian cities, especially the capitals of the provinces, which benefited from public investments to upgrade their administrative and local role in organizing the region and curbing the urban growth of major cities, such as Chiman and Wuhan (Li et al., 2011; Luo et al., 2019).

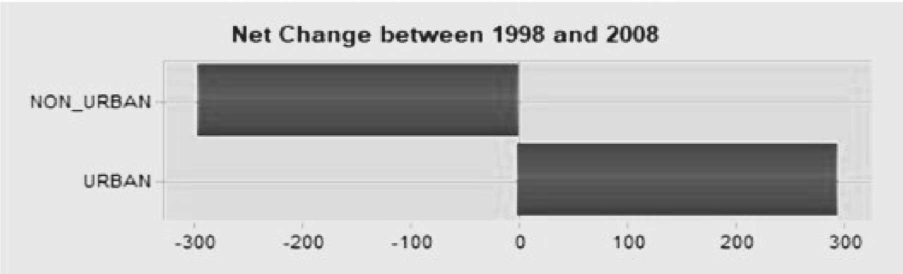

Figure 4 Development of the urban area of Mila 1998-2008. Source: by the researchers using software

The urban policy implemented by the state to face the problems resulting from the urbanization process, especially in major cities, led to the expansion of the built-up area of Algerian cities of all sizes. Residential allocations represented the most crucial housing patterns that guided the expansion process of Mila, especially the western side. Further-more, the chaotic construction constituted most of the city's urban area, reflecting the worsening housing crisis in Mila in particular and Algerian cities in general.

The spread of the single-family house in the city was caused by the inability of the capacity of soil to resist high-rise buildings. In addition, the lack of state-owned land to provide collective housing and the control of private individuals over most of the vacant spaces provided an alternative for the middle class to obtain private housing at a reasonable price compared to housing prices in the real estate market. Previous studies confirm the role of urbanization and housing policy in the expansion of cities, as low-density horizontal development leads to the consumption of urban real estate suitable for construction at a rapid pace and produces what is known as sprawled cities (Diafat and Madani, 2016; Kateb, 2003).

4.2 Logistic Regression Analysis

We have done statistical calculations related to the model illustrated in (Table 3): Chi-square, Goodness of fit, Pseudo R^2, and the operating characteristics of the receiver ROC/AUC, through which we can verify the model's suitability. In our study, we can test the significance of the logistic regression model based on the Pseudo R^2 expressed by the equation $(1-(\ln L/ \ln Lo))$, where its value indicates the fit of the model with the dataset, which is limited between value (1) representing the ideal fit, and value (0) expresses no relationship (Menard, 2002).

The value of the Pseudo R² (0.3898) indicates the excellent fit of the model. Based on Hensher and Johnson's (2018) study, the Pseudo R² value ranged between 0.2 and 0.4 and was considered a good fit for the model.

Table 3 Model statistics

type	statistics
2logLo-	734.8638
2log(likelihood)-	448.3989
Pseudo R2	0.3898
Goodness of Fit	7052.6208
Chi-Square	286.4649
ROC	0.90

Source: The researchers used software

The finding described the relationship between urban expansion with its determinants in the study area (Figure 5). The regression coefficient explained the cause-effect relationship between independent variables and dependent variable. However, the increase in coefficient value increases the change probability of pixels near to independent variables. The value 0 indicates that the likelihood of occurring or no-occurring change is 0,5. The positive and the negative signs represent the direction of the relationship between urban expansion and its driving factors. In the case that the value of the correlation coefficient is positive and the relationship is positive. At the same time, the negative value expresses an inverse relationship between the dependent and the independent variables (Menard, 2011). The factors of distance to tertiary roads, distance to educational facilities, distance to the main roads, distance to educational facilities, slope, and elevation negatively correlated with urban expansion. In contrast, the correlation was negative for other factors: distance to the city centre, distance to industrial enterprises, and population density (Table 4).

The research results show that the eight factors affected the urban expansion to different degrees, as indicated by odds ratios. The odds ratio for tertiary roads is (0.57), meaning that the predicted urban expansion in an area close to a road is estimated as 215% more than the predicted urban expansion 300 m further away from tertiary roads. The odds ratio for the main road is (0.66), which means that the probability of urban expansion will decrease by 170% in an area 300 m further away from the main roads. The odds ratio for distance to educational facilities is (0.65), which means that urban expansion odds increase in the area near educational facilities by 175% more than urban expansion in an area 300 m farther away. The odds ratio for distance to the city centre is (1.23), which means that urban expansion probability will increase by 115% in an area 300 m farther away from the city centre. The slope odds is (0.96), which means that the decrease in 1 unit of slope increases the probability of expansion by 4%. The odds ratio for distance to industrial enter

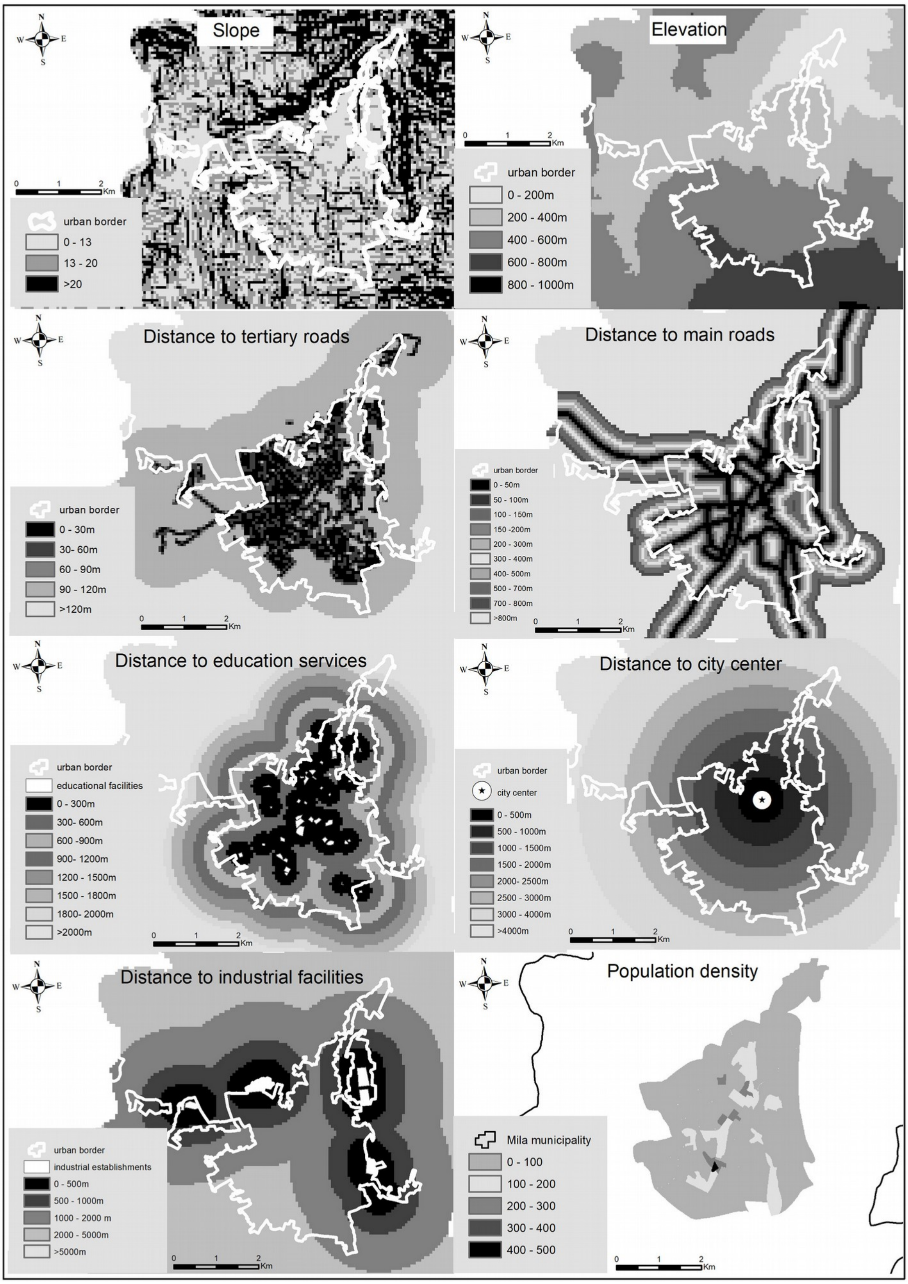

Figure 5 Independent variables (driving factors) in the logistic regression model.
Source: Own elaboration

prises is (0.93), meaning that the predicted urban expansion in an area close to a road is 35% more than the predicted urban expansion 300 m farther away from industrial enterprises. The odds ratio was 1 for elevation and population density), which means these factors have no impact on the urban expansion process within the study area.

Table 4 The relationship between the independent variables with the dependent variable

variables	regression coefficient	odd ratio
X1	-0.0460	0,96
X2	-0.0015	1,00
X3	-0.4161	0,66
X4	-0.5579	0,57
X5	0.2084	1,23
X6	-0.4335	0,65
X7	-0.0677	0,93
X8	0.0106	1,00
intercept	5.1551	174,16

Source: The researchers used software

5 DISCUSSION

The results showed that proximity factors had the most significant influence on urban expansion, with a moderate negative correlation with urban expansion. The urban expansion of Mila depends on the basic structure of roads and transportation networks that characterize the sprawled city, which relies on the increasing rates of car dependency, similar to previous studies in north African cities such as Batna (Algeria), Giza governorate (Egypt), and Monastir (Tunisia) (Fekkous et al., 2023; Osman et al., 2016; Rejeb Bouzgarrou et al., 2019). Furthermore, the distance to educational facilities is strongly linked to urban expansion because urban expansion occurs in areas with various services, especially educational ones (Sarkar and Chouhan, 2020). Thus, the distance between the city centre and suburbs increased continually caused of the expansion process. That increase in distance is compensated by the availability of public transport, the individual car, and the road network that connects to the city centre.

The topographical determinants (slope and elevation) have a weak (negative) relationship with urban expansion. An expected result given the absence of significant topographical obstacles in the city of Mila, this result confirms that a low slope is preferable for city expansion (Alkhuzamy Aziz and Alghais, 2021; Liao and Wei, 2014). While the population density also had a weak (positive) relationship with urban expansion, which is an expected result. The city of Mila was expanding in the form of new sprawling, random, and unplanned expansions in the periurban area of the city, as the same cases in many studies (Achmad et al., 2015; Salem et al., 2019).

6 CONCLUSIONS

Through this research paper, we measured the urban expansion of the city of Mila and identified its driving factors between 1998 and 2008. By combining remote sensing and GIS techniques, we monitored the urban expansion of Mila. The result shows that its urban area has doubled in ten years, with an annual rate of 29,7 h/year. The economic, political, urban, and social transformations that the country witnessed during this period were directly reflected in the size of cities and their urban composition, which stands in the way of applying the principles of sustainable development. The residential allocations are the most crucial housing patterns that guided the expansion process, especially on the western side. In addition, the chaotic construction represents most of the urban area of Mila.

To better understand the urban expansion of Mila, we selected a set of determinants based on previous studies. We analyzed their relationship with urban expansion based on a logistic regression model. The results showed in the order of effect that the proximity factors as the distance to tertiary roads, distance to educational facilities, distance to main roads, and distance to the city centre are the most influential on the urban expansion process of Mila. The study results are logical and acceptable because the proximity of roads and public facilities such as schools ensures accessibility and reduces costs and transportation efforts. Conversely, urban expansion in the suburbs has translated into a sprawling urban form, which has imposed many social, economic, and environmental consequences.

Although this study is consistent with others, the use of a logistic regression model presents several disadvantages, including the problem of multicollinearity, which has a powerful impact on model outcomes. However, it is one of the best models for helping us to understand the relationship between urban expansion and its drivers. The logistic regression model can deal with a wide range of variables. Still, it cannot introduce some critical variables into the analysis process (urban policy and real estate speculation) that represent the most critical factors controlling urban expansion. We also refer to the expansion probability map that does not provide timely data for the occurrence of expansion. It can also be said that the model cannot predict different scenarios for expansion but only one possibility based on the results of the variables entered into it.

Through our study, we can propose to future researchers to combine the logistic regression model with some models that cover its shortcomings, such as the cellular automat model, and we also recommend the inclusion of the state's urban policies.

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Kvantifikácia mestského rastu a jeho hnacie sily v meste Mila

Súhrn

Väčšina svetových miest zažíva od obdobia priemyselnej revolúcie masívny nárast počtu obyvateľov. V dôsledku vnútornej migrácie obyvateľstva pri hľadaní lepších životných podmienok nebola väčšina týchto miest pripravená prispôsobiť sa kontinuálnym vlnám migrácie. Mestá sa rýchlo šírili v rámci svojho zázemia a ich rast bol často neregulovaný, čo viedlo k mnohým sociálnym, hospodárskym a environmentálnym problémom.

Po získaní nezávislosti Alžírska v roku 1962 sa počet obyvateľov a veľkosť alžírskych miest dramaticky zvýšili. Pretrvávajúce potreby obyvateľov kladú veľký tlak na rozhodujúcich politických činiteľov. Podnietenie naliehavej reakcie štátu prostredníctvom masívnych a zle zvažovaných rozvojových programov viedlo k rýchlemu a neregulovanému rozšíreniu alžírskych miest a spôsobilo mnoho problémov. To motivovalo výskumníkov a tvorcov politík, aby preskúmali faktory, ktoré stoja za rozvojom miest, s cieľom ich identifikácie, riešenia súčasných problémov miest a plánovania ich budúceho územného rozvoja.

Cieľom štúdie je kvantifikovať priestorovú expanziu mesta Mila a identifikovať jej kľúčové faktory. Na meranie mestskej expanzie boli použité tri ukazovatele, konkrétne rýchlosť expanzie, ktorá vyjadruje intenzitu expanzie, miera ročnej expanzie, ktorá opisuje jej rýchlosť a podiel zastavanej plochy, ktorý ukazuje rozsah jej rozšírenia. Na základe predchádzajúcich štúdií, ako aj dostupných údajov boli skúmané viaceré skupiny faktorov, konkrétne topografické faktory, dostupnosť a sociálno-ekonomické faktory, a to za účelom hodnotenia ich vplyvu na rozširovanie miest.

Mesto Mila je jedným z alžírskych miest nachádzajúcich sa na severovýchode štátu s rozlohou približne 15 štvorcových kilometrov. Je považované za jedno z najdôležitejších miest krajiny. Vďaka svojej administratívnemu a demografickému významu je mesto okrem svojej strategickej polohy aj dôležitým severo-južným dopravným uzlom v rámci Alžírska. Má tiež významnú ekonomickú úlohu v poľnohospodárskej produkcii (80 % mestskej oblasti) a vyznačuje sa variabilnou geomorfológiou. Nachádza sa v nadmorskej výške od 150 do 1040 m n. m., s exponovaným sklonom reliéfu v rozmedzí od 5 % do 50 %. Mesto z toho dôvodu trpí aj rizikom pôdnych zosuvov. Tieto faktory spôsobujú prirodzené ohrozenie života jeho obyvateľov a ovplyvňujú kontinuitu mestskej štruktúry, ako aj plánovanie mestských projektov v rôznych oblastiach.

Pomocou GIS ako nástroja na realizáciu štúdie boli aplikované rôzne merania na Mila Urban Expansion Map od roku 1998 do roku 2008. Výsledky ukázali zdvojnásobenie zastavanej oblasti mesta. Celková transformácia krajiny viedla v 90. rokoch minulého storočia k zavedeniu právneho systému a zmene mestskej politiky, ktorá sa opierala o kvóty na bývanie na uspokojenie potrieb miestnych obyvateľov, ako aj právo zasahovania do procesu plánovania výstavby v rámci územia mesta.

Na štúdium vzťahu medzi mestskou expanziou a jej determinantmi na identifikáciu jej hnacích síl bol použitý binárny regresný model. Mila sa vyznačuje rozsiahlou mestskou štruktúrou s prevažne individuálnym bývaním, ktorá si vyžaduje hustú cestnú sieť na uľahčenie prístupu k rôznym službám lokalizovaným najmä v centre mesta.

Táto štúdia je z aplikačného hľadiska určená výskumným pracovníkom a subjektom s rozhodovacou právomocou s cieľom pochopenia procesu a hnacích faktorov rozširovania miest a nevyhnutnosti prijatia potrebných opatrení na usmerňovanie a plánovanie budúceho územného rozširovania mesta.