Buildings & Cities

Urban growth in peri-urban, rural and urban areas: Mexico City

SPECIAL COLLECTION: URBAN EXPANSION

RESEARCH

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ABSTRACT

This remote sensing study compares growth occurring in three urban types between 2005 and 2014: peri-urban, rural and urban, in a fast-growing metropolitan region west of Mexico City. Future urban growth for the period 2014–24 is modelled using the land-use/cover change (LUCC) model Geomod. Urban expansion is correlated with some socio-territorial factors and the impacts are assessed for the loss of biomass. In both periods, the urban zone differed the most from the other two in terms of urban expansion. The Geomod predictions overestimate the urban expansion in the urban zone and underestimate it in the peri-urban and rural zones. Significant differences exist in the average urban expansion between zones. The main urban growth drivers were elevation, population density, distance to previous urban land and distance to roads. A substantial loss of biomass is due to urban growth, including expansion and infill. The research reveals significant differences in growth between peri-urban, rural and urban areas, and contributes spatial information for designing focused land-use policies in dynamic urban contexts.

POLICY RELEVANCE

This article contributes to understanding the differentiated urban growth of urban, peri-urban and rural areas, which can translate into more precise and effective public policies. Urban expansion and infill patterns differ. For peri-urban and rural areas, the main growth is infill, so actions should be implemented to sustainably manage the vacant or undeveloped land within an existing human settlement to prevent further expansion, but also to avoid the loss of priority areas for the provision of ecosystem services. In urban areas where the main urban increment is expansion, sensible consolidation decisions need to be taken to avoid further urban expansion and the incorporation of urban green space.

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1. INTRODUCTION

Urban areas have experienced rapid growth in the last century. In 1900, approximately 10% of the world's population lived in urban settlements. This increased to more than 50% in the first decade of the 2000s, and it is expected to continue increasing (Grimm *et al*. 2008). Population growth also drives urban expansion (Seto *et al*. 2011). By 2030 the urban area is expected to expand by 1.2 million km^2 and will be triple the size compared with the year 2000 (Seto *et al*. 2012). This accelerated expansion of the urban settlements in many parts of the world frequently occurs in a disorderly and dispersed way, which increases the consumption of resources and generates environmental problems (Arha *et al*. 2014; Seto *et al*. 2012; Zijlstra 2011). A large proportion of this urban expansion generally occurs in peri-urban areas, which are transition zones where urban and rural activities overlap and where rural landscape characteristics are quickly modified by industrial, commercial or residential land uses (Heider *et al*. 2018; Pribadi & Pauleit 2015; Tian 2015; Winarso *et al*. 2015). This land-use transformation is known as peri-urbanisation, and over time the land uses of these areas are converted to residential, commercial or service uses, until they completely lose their rurality (Aguilar *et al*. 2022; Coq-Huelva & Asián-Chaves 2019; Geneletti *et al*. 2017).

These peri-urban areas are essential to the sustainability of the cities since they still contain natural ecosystems that provide biodiversity and ecosystem services (Dobbs *et al*. 2018). These spaces are heterogeneous from the social, environmental and economic points of view. In the case of cities in the Global South, including Mexico City, peri-urban areas represent spaces of social conflict, governance problems and challenges to the conservation of natural land (Aguilar *et al*. 2022).

Urban growth can also take place in purely rural and urban environments. As conditions that influence land-use change can vary among these zones, it is pertinent to analyse and quantify the differences in the urban growth dynamics and its environmental impacts. This can then help to generate and implement focused sustainable land-use policies for each environment (Ortiz-Báez *et al*. 2021).

Several studies have reported the successful use of remote sensing methods to quantify urban change (Daudt *et al*. 2018; Dou & Han 2022; Liu *et al*. 2020; Reba & Seto 2020; Wellmann *et al*. 2020), and many models have been used to project future urban growth (Karimi *et al*. 2021; Lyu *et al*. 2019; Poelmans & van Rompaey 2010; Yang *et al*. 2019). Some of these spatiotemporal studies also consider the environmental effects and driving forces of urban growth (Huang *et al*. 2018; Zhang *et al*. 2018). For example, Seto *et al.* (2012) assessed the direct impact of urban expansion on carbon pools around the world, and Hernández-Flores *et al.* (2017) studied the urbanisation driving forces in the periphery of north Mexico City reporting as main factors the welfare population, population working in the third sector, distance to schools, distance to urban areas, distance to roads, population growth rate, precipitation, and the immigrated population growth rate.

This periphery in Mexico City, as in many other cities of developing countries, is characterised by high urban growth rates and informal settlements of poor residents in precarious living conditions, where rural–urban and urban–urban immigration plays a crucial role (Heider *et al*. 2018). In fact, the urbanisation process in Mexico, particularly in its capital city, began in the 1940s during the industrialisation and institutionalisation of the country characterised by a chaotic migration from the countryside to the city. It has been distinguished by a rapid urban expansion, diffuse and fragmented growth, and a conurbation with small and medium peripheral settlements. The urban growth pattern of the Mexican megalopolis corresponds to that observed in other megacities and can be synthesised into five types: infill, extension, linear development, expansion and large-scale projects (Camagnia *et al*. 2002).

The present study uses remote sensing techniques and the spatially explicit land-use model Geomod to analyse the historical and future urban growth in a fast-growing region west of Mexico City. This growth was compared between three development zones: urban, rural and peri-urban. Statistical tests were applied to assess the differences in urban growth between zones. Urban expansion is correlated with some socio-territorial factors. Urban growth is also assessed for its impact on the loss of biomass.

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2. MATERIAL AND METHODS

2.1 STUDY AREA

The study area encompassed 30,802 ha in three municipalities west of Mexico City: Huixquilucan de Degollado, Cuajimalpa de Morelos and Álvaro Obregón (Figure 1). The significance of this area lies in the fact that it encloses the Santa Fe mega-project created in the early 1980s to establish an urban centre that would promote economic activity and development of the real estate sector (Moreno-Carranco 2014). This mega-project has triggered the urban sprawl and a mix of land uses (financial, commercial, housing and services), with a high-income population established mainly in the centre of the mega-project surrounded by low-income communities lacking services and infrastructure. The rapid expansion of Santa Fe has brought several social, economic and environmental consequences to both rural and urban areas to the west of Mexico City, which already faces multiple problems. Some of these problems are air pollution, solid waste accumulation, land subsidence, landslides, floods and health risks (Romero-Lankao *et al.* 2014). The urban growth in rural and peri-urban regions of the study area by unplanned or illegal settlements has increased these problems and caused the loss of ecosystem services of the surrounding natural and rural systems (Calderon-Contreras & Quiroz-Rosas 2017).

The study area was divided into three zone types: urban, rural and peri-urban. The individual polygons that comprise the urban and rural areas were the basic geostatistical areas (Spanish: AGEB), which are the smallest geographical unit used by the Mexican government's geographical and statistics agency to generate statistics and which cover all Mexico (INEGI 2014). An urban AGEB is an:

> area occupied by a group of blocks, generally ranging from 1 to 50, perfectly delimited by streets, avenues, walkways or any other easily identifiable feature in the terrain and whose land use is mainly residential, industrial, service, commercial, *etc.*
>
> (INEGI 2010)

A rural AGEB is an:

> area located in rural regions, whose territorial extension is variable and characterised by agricultural or forestry land use. It contains rural localities and natural features (e.g. swamps, lakes, deserts, etc.), and engineered features (railroad tracks, power lines, roads, etc.).
>
> (INEGI 2010)

The peri-urban areas were delimited following González-Arellano *et al.* (2021), who applied Shannon's entropy index to identify peri-urban spaces based on the degree of land-use diversity and their spatial contiguity with urban boundaries (Table 1). The land-use layer was obtained from CONABIO (2015).

The urban zone, where the land use is mainly residential, industrial, services and commercial, with little land-use diversity, covered 12,224 ha, containing 269 AGEB. The rural zone, where land use is mainly agriculture and forest, comprises 16,291 ha in five AGEB. Finally, the peri-urban zone, where there is urban growth in the fringe with either natural vegetation or a rural environment, with a high diversity of land uses, encompasses 2287 ha including 22 AGEB (Figure 1).

The three zones show significant differences in population, business and road densities (Table 1). As expected, the urban areas present higher values in these variables than the peri-urban and rural areas. These socio-territorial indicators and education years and single women percentage show a centre–periphery gradient. In contrast, the variables occupants per dwelling, percentage of indigenous households and fertility rate show a periphery–centre gradient. These statistics show that, in general, peri-urban areas present both similarities with the urban (built environment) and the rural areas (natural environment). This mixed condition of the peri-urban areas (both urban and rural) explains their high value in the land-use entropy index.

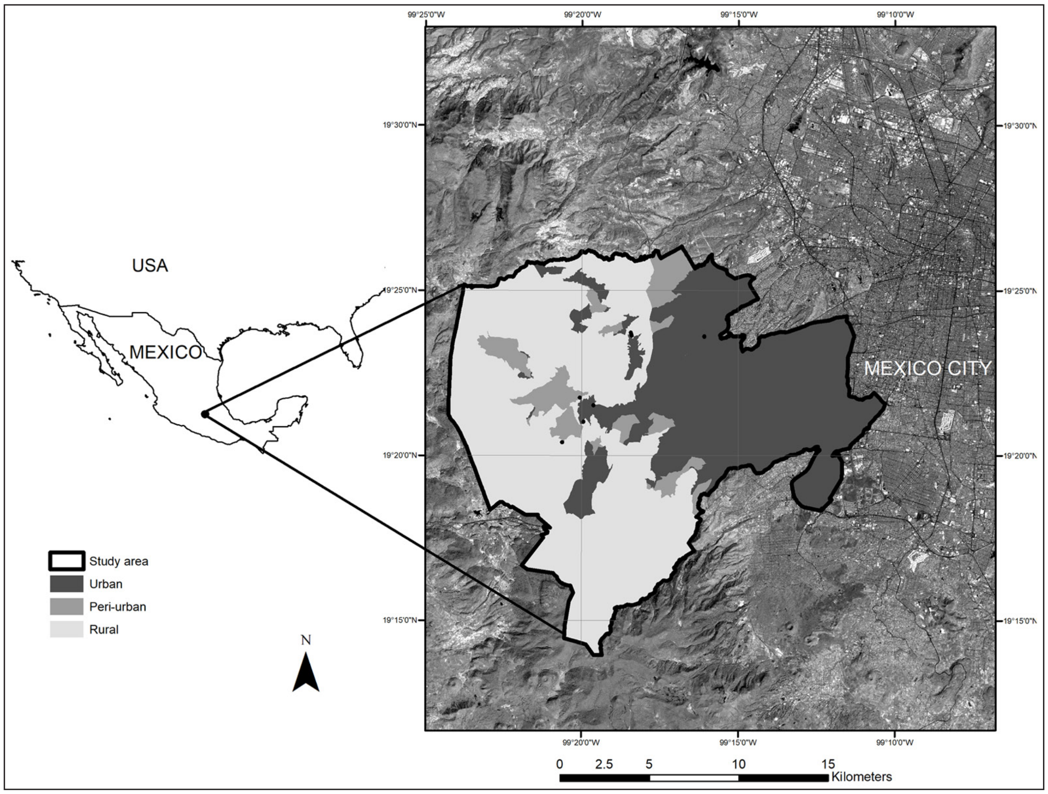

Figure 1: Study area: urban, rural and peri-urban zones to the west of Mexico City.

SOCIO TERRITORIAL INDICATORS	URBAN	PERI-URBAN	RURAL
Population density (/ha)	159.8	43.5	2.1
Business density (business/ha)	4.4	1.8	0.01
Road density (m/ha)	284.5	217.7	27.5
Education years	10.6	9.1	8.0
Occupants per dwelling	3.7	3.9	4.2
Percentage of the dependent population	34.9%	34.3%	36.5%
Percentage of indigenous households	2.2%	2.9%	3.9%
Percentage of single women	30.0%	26.6%	27.3%
Fertility rate (children per woman)	1.8	2.0	2.4
Build land percentage	91.8%	74.7%	2.4%
Cultivated land percentage	4.3%	5.3%	3.5%
Natural land percentage	4.1%	16.6%	19.5%
Entropy of land use (bits)	0.3	0.8	0.5

Table 1: Socio territorial indicators for the three zone types: urban, peri-urban and rural.

2.2 METHODS

2.2.1 LAND-USE CHANGE ANALYSIS

The land-use change from non-urban to urban was analysed using an accepted classification with the maximum likelihood method. SPOT 5 satellite images of the dry season (November–December) of 2005, 2010 and 2014 were used. These images were obtained from the Mexican Reception Station (ERMEX). They were radiometrically corrected using the black body subtraction method and orthorectified. To comply with Jensen (2007) and McCoy (2005), who proposed to use several pixels of at least 10 times the total of bands included in the classification, 209 training sites for 2005, 225 for 2010 and 159 for 2014 were used.

All land-use categories used in the classification were finally reclassified into urban and non-urban. An accuracy assessment procedure was carried out for each year's classification. More than 50 accuracy assessment sites for each category were used. These sites were taken from QuickBird satellite images from 2005, 2010 and 2014. An error matrix was generated for each date, which is the most accepted measure to represent the thematic accuracy (Congalton & Green 2009). All image processing was accomplished in ENVI, and all spatial analysis processes were developed in ArcGIS.

2.2.2 LAND-USE CHANGE MODELLING

The model Geomod, available in TerrSet, was used to predict the transformation from non-urban to urban. This model is one of the most extensively used worldwide (Mirzapour *et al.* 2020; Nahib *et al.* 2018; Shade & Kremer 2019; Yesuf *et al.* 2021). It can only predict the transition from one category to another (*e.g.* urban and non-urban), extrapolating the land-use change from date 1 to a given time 2. It allows the user to set the amount of change obtained in time 2. A linear model was generated with data from 2005 and 2014 to estimate the urban area in 2024:

$$y = -453631.602 + 228.084\,x,$$

where y is the urban area and x is the year.

Geomod selects the change locations based on three decision rules: nearest neighbours, stratification by subregions and suitability maps. The model then simulates future change by selecting areas with the highest suitability values (Hall *et al.* 1995; Pontius *et al.* 2001; Pontius & Malanson 2005). The present study followed the specialised literature to generate the layer of land suitability for urbanisation that has reported several urban growth drivers (Hall *et al.* 1995; Pontius & Schneider 2001). Seven drivers with a categorical scale were used (Table 2). In this layer, high suitability values are assigned to those places with similar biophysical attributes to those places that have changed to urban, and low suitability values are given to sites where biophysical attributes are similar to non-urban areas. Equal weights were allocated to all drivers.

Table 2: Driver categories used to generate the layer of land suitability for urbanisation.

DRIVER	CATEGORIES
Terrain slope (%)	< 5, 5.1–10, 10.1–15, 15.1–20, > 20
Altitude (masl)	< 2500, 2500.1–2800, 2800.1–3100, 3100.1–3400, > 3400
Distance to roads (m)	< 500, 500.1–1000, 1000.1–2000, 2000.1–5000, > 5000
Distance to urban areas (m)	< 500, 500.1–1000, 1000.1–2000, 2000.1–5000, > 5000
Natural protected areas	Yes, No
Population density (/km^2)	< 10, 10.1–50, 50.1–100, 100.1–300, > 300
Land use	Agriculture, forest, urban

A Geomod output validation was conducted, evaluating the concordance between the predicted and the reference map of the same date. It was carried out for 2014 using the satellite image classification as a reference map for that year. Since most pixels preserve their same category from one date to another (persistence), analysing the percentage of agreement between prediction and reference layers will give low percentages of disagreement in the amount and location of pixel categories (Pontius *et al.* 2004). To solve this, the study used a pattern validation through a map overlay of the observed earlier land cover image, the observed reference image of the later land cover and the predicted image of the later land cover. Since it was impossible to validate the prediction for 2024, the model prediction and the validation were run for the period 2010–14. It was implemented using the verification tool of the Land Change Modeler, also available in the software TerrSet. This tool generated an output layer with four validation categories: (1) correct rejections: the model predicted persistence, and it persisted; (2) hits: the model predicted change, and it changed; (3) false alarm: the model predicted change, and it persisted; and (4) misses: the model predicted persistence, and it changed.

2.2.3 URBAN GROWTH COMPARISON IN THE THREE ZONE TYPES

For each individual polygon (AGEB) comprising each zone, the net and relative urban growth were obtained. The urban growth was differentiated between urban expansion and urban infill. Urban infill was conceptualised as the urban growth happening in non-urban areas surrounded by the urban category, and urban expansion as the urban growth happening in non-urban areas that were not entirely enclosed by the urban category. The actual selection of urban expansion and urban infill was performed by converting the urban growth raster layer to vector format and selecting separately the polygon containing all the outer growth (expansion) from the individual polygons that were surrounded by urban areas (infill).

The average urban expansion (AUE) for each zone was calculated based on the corresponding individual AGEB's relative increment. A Kruskal–Wallis test was implemented to assess the independence between zones and the AUE for the periods 2005–14 and 2014–24, to see if there were statistically significant differences. Besides, Mann–Whitney tests were computed to locate in which pair of zones the AUE statically differs for the two periods. These analyses were carried out in the statistical software SPSS.

2.2.4 DRIVING SOCIO-ECONOMIC FACTORS

To correlate urban expansion with specific driving socio-economic and territorial factors, Cramer's *V* statistics were used. This statistic is based on the chi-squared and measures the relative (strength) of an association between two variables. It ranges from 0 (no association) to 1 (perfect association). Values close to 0.4 show an association between variables, and values less than 0.15 indicate a low association (Akintuyi *et al*. 2021; Fathizad *et al*. 2019; Subiyanto *et al*. 2019). The independent factors used were elevation, distance to previous urban land, distance to roads, population density, education years, occupants per dwelling, percentage of the dependent population, percentage of indigenous households and land use.

2.2.5 BIOMASS LOSS ESTIMATION

To estimate the *biomass* (here the term *biomass* refers to only above-ground carbon biomass), the data from the forest inventory carried out between 2008 and 2010 by Mexico City's Environmental and Land Planning Authority (Spanish: PAOT) were used. The sampling design consisted of conglomerates comprised of four circular sampling plots of 400 m^2 distributed in an inverted 'Y' shape (CONAFOR 2012). Per tree biomass was estimated using the allometric equations developed by Acosta-Mireles *et al*. (2002) and Avendaño-Hernández *et al*. (2009) for the species established in the region.

To convert biomass from conglomerate to hectares, the 'ratio of means' was used (Šmelko & Merganič 2008):

$$\hat{R} = \frac{\sum_i^n Y_i}{\sum_i^n X_i}$$

where Y_i is the total biomass in all plots of 400 m^2 and X_i is the total area sampled, in *i* plots. A Regression–Kriging (RK) model was then used to generate a spatial layer of biomass distribution in all the study area. The RK method is a hybrid interpolation model that uses the combination of linear regression methods with ordinary Kriging, where the application of ordinary Kriging is carried out on the residuals of the regression (Galeana *et al*. 2021). In this case, the drift and residual predictions are made separately and then integrated (Galeana-Pizaña *et al*. 2014), as follows:

$$\hat{z}RK(S_0) = \sum_{k=0}^{p} \hat{\beta}_k * q_k(S_0) + (\sum_{i=1}^{n} \omega_i \varepsilon(S_0) + \sum_{i=1}^{n} \omega_{2j} Z_2(S_i)$$

where $zRK(S_0)$ is the point estimate of the variable at an unknown spatial location, β_k is the coefficients of the drift model, q_k is the number of auxiliary variables, $\varpi i(S_0)$ is the weights determined by the semi-variogram, and *e* is the regression residuals.

To model the biomass, as a secondary variable, (r^2_{adj} = 0.4026), the Enhanced Vegetation Index (EVI) generated from the SPOT-5 used in the study was employed. Afterward, 50% of the conglomerates were randomly selected to calibrate the RK; the remaining percentage was taken to verify the models. The verification was made by the root mean square error (root mean square error—RMSE). Finally, the biomass loss due to urban growth was estimated by identifying those forest areas that were urbanised in each period and calculating the corresponding loss by urban expansion and urban infill.

3. RESULTS

Accuracies of the SPOT images classifications were at least 90%, which complied with the standards established in the specialised literature (de Jong & van der Meer 2004; McCoy 2005). The most significant omission errors were in the non-urban category for 2005 and 2010. In contrast, the most extensive commission errors were in the urban category for the same years (Table 3).

VALIDATION IMAGE	CLASSIFICATION			OMISSION ERROR (%)	COMMISSION ERROR (%)	TOTAL ACCURACY (%)
	URBAN	NON-URBAN	TOTAL			
2005						
Urban	47	8	55	4%	15%	91%
Non-urban	2	53	55	13%	4%	
Total	49	61	110			
2010						
Urban	47	8	55	6%	15%	90%
Non-urban	3	52	55	13%	5%	
Total	50	60	110			
2014						
Urban	51	4	55	6%	7%	94%
Non-urban	3	52	55	7%	5%	
Total	54	56	110			

Table 3: Confusion matrix: commission and omission errors and total accuracy for 2005, 2010 and 2014 classifications.

In the three zone types: urban, rural and peri-urban, there were increments of the urban category at the expense of the non-urban category. For the period 2005–14, the most significant net increment happened in the urban zone with a gain of 21%, followed by the increment in the peri-urban zone with a gain of 19%. The smallest increment was in the rural zone with a gain of 7% (Table 4 and Figure 2).

YEAR	ZONE											
	URBAN				RURAL				PERI-URBAN			
	URBAN (HA)	%	NON-URBAN (HA)	%	URBAN (HA)	%	NON-URBAN (HA)	%	URBAN (HA)	%	NON-URBAN (HA)	%
2005	5,206	43	7,018	57	202	1	16,089	99	230	10	2,056	90
2010	5,923	48	6,300	52	391	2	15,900	98	365	16	1,922	84
2014	7,815	64	4,409	36	1,281	8	15,010	92	656	29	1,631	71

Table 4: Area of the urban and non-urban categories for the urban, peri-urban and rural zones.

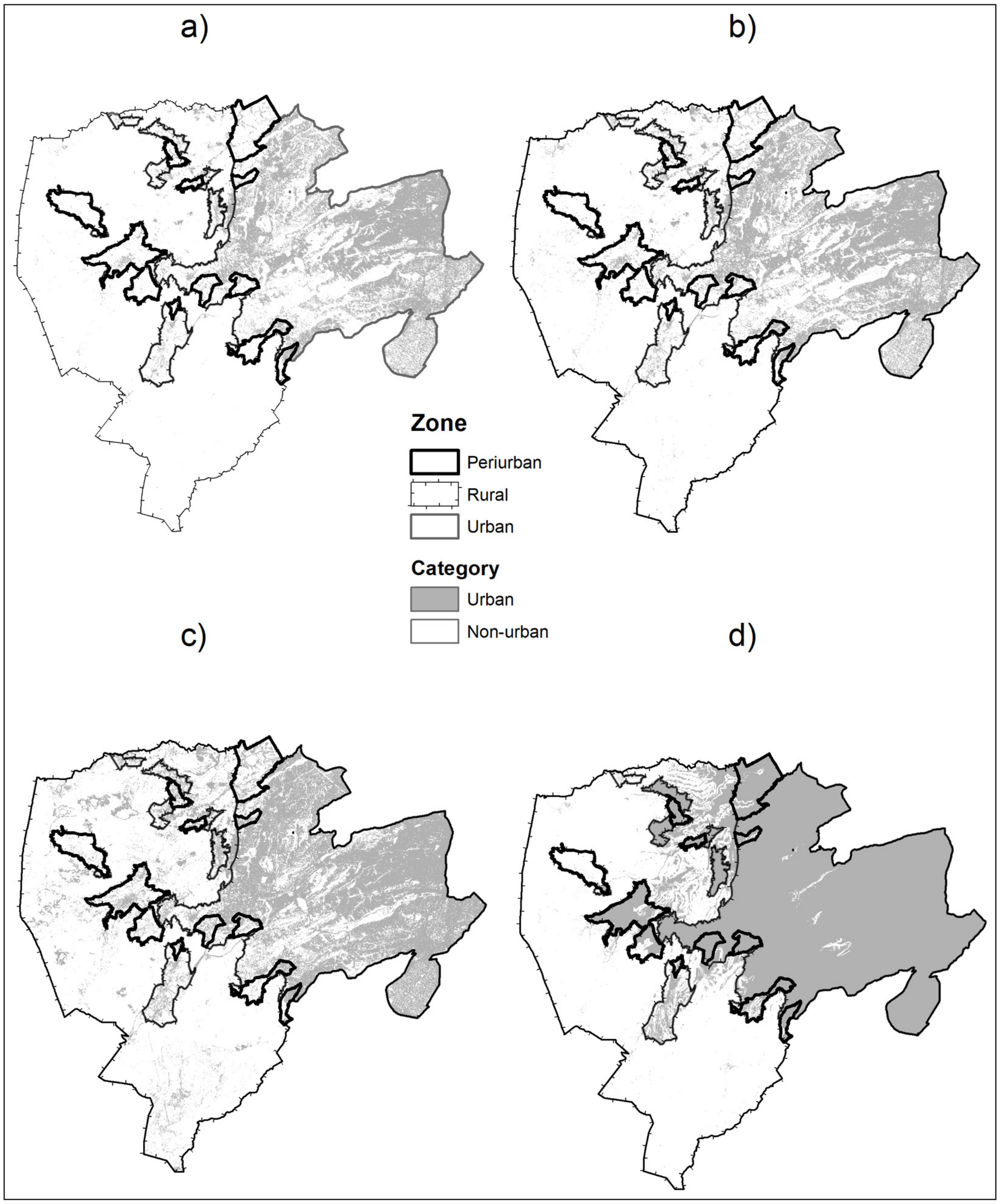

Figure 2: Land use in urban, rural and peri-urban zones: **(a)** 2005, **(b)** 2010, **(c)** 2014 and **(d)** 2024.

Of this urban growth between 2005 and 2014, the urban expansion represented 56% in the urban zone, 8% in the peri-urban zone and only 1% in the rural zone. It means that in the rural and peri-urban areas, more than 90% of the urban growth in this period was infill (Table 5).

PERIOD	ZONE	GROWTH (HA)	EXPANSION (HA)	INFILL (HA)
2005–10	Peri-urban	134	9	125
	Rural	194	5	189
	Urban	717	289	428
2010–14	Peri-urban	291	25	266
	Rural	890	10	880
	Urban	1,892	1,174	718
2014–24	Peri-urban	1,131	499	631
	Rural	956	69	888
	Urban	3,989	2,794	1,195

Table 5: Areas of urban growth, urban expansion and urban infill.

Comparing the Geomod output with the SPOT classification for 2014, in the urban zone the model overestimated in almost 5% the area of the urban category. In the rural and peri-urban zones, Geomod underestimated the area of this category by 6% and 11%, respectively (see the areas for 2014 in Tables 4 and 6).

YEAR	ZONE											
	URBAN				RURAL				PERI-URBAN			
	URBAN (HA)	%	NON-URBAN (HA)	%	URBAN (HA)	%	NON-URBAN (HA)	%	URBAN (HA)	%	NON-URBAN (HA)	%
2014	8,394	69	3,830	31	252	2	16,038	98	414	18	1,873	82
2024	11,696	96	528	4	1,353	8	14,938	92	1,722	75	564	25

Table 6: Predicted urban and non-urban areas for the urban, rural and peri-urban zones (2014 and 2024).

Geomod's land-use prediction for 2024 indicated that the urban category would occupy almost all the area in the urban zone, with an increment of 27% in 10 years (2014–2024). The urban category will only increment 6% in the rural zone, while in the peri-urban zone, the urban category will increase by 57% (Table 6 and Figure 2).

The Geomod validation showed 83.9% of correct rejections (model predicted persistence, and it persisted) (15,362 ha), 3.7% of hits (model predicted change, and it changed), 6.3% of misses (model predicted persistence, and it changed) and 6.1% of false alarms (model predicted change, and it persisted). This yields an accuracy of almost 90%.

Regarding the individual AGEBs, the average percentage of urban growth (comprising urban expansion and infill) was more considerable in the peri-urban zones, followed by the urban and rural zones. However, the average percentage of urban expansion was more prominent in the urban zone, followed by the peri-urban and the rural. In contrast, the infill average was more significant in the peri-urban followed by rural (Table 7).

PERIOD	ZONE	GROWTH (%)	EXPANSION (%)	INFILL (%)
2005–10	Peri-urban	6%	1%	6%
	Rural	1%	0%	1%
	Urban	4%	2%	2%
2010–14	Peri-urban	13%	1%	12%
	Rural	5%	0%	5%
	Urban	12%	9%	3%
2014–24	Peri-urban	43%	14%	29%
	Rural	7%	0%	6%
	Urban	22%	17%	5%

Table 7: Percentage average urban growth, expansion and infill in the peri-urban, rural and urban zones.

For the period 2005–14, the Kruskal–Wallis test showed a dependency between zones and the AUE ($p < 0.0001$). In other words, zone types significantly differ in their urban expansion. The Mann–Whitney test indicated the major differences in AUE between the peri-urban and urban zones and the rural and urban zones ($p < 0.0001$). In contrast, there were no significant differences in AUE between the peri-urban and rural zones ($p > 0.05$), which means that the zone that differed the most from the other two was the urban. For 2014–24 (the modelling period), the Kruskal–Wallis test also showed that zone types significantly differ in their urban expansion ($p < 0.0001$). However, the Mann–Whitney showed major differences in AUE between the urban and rural zones ($p < 0.0001$), followed by the peri-urban and urban zones ($p = 0.18$), and by the peri-urban and rural zones ($p = 0.47$). Again, the zone that differed the most from the other two was the urban in terms of urban expansion.

The socio-economic and territorial factors that correlated the most with urban growth in the study area with an overall Cramer's coefficient close to 0.40 or higher were elevation, population density, distance to previous urban land and distance to roads (Table 8).

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FACTOR	V
Elevation	0.5613
Population density	0.5436
Distance to previous urban land	0.3676
Distance to roads	0.3564
Percentage of the dependent population	0.1891
Slope	0.1592
Percentage of indigenous households	0.0695
Land Use	0.0032
Education years	0.0000
Occupants per dwelling	0.0000

Table 8: Cramer's *V*-values for socio-economic and territorial factors.

The environmental impact of urban growth (infill and expansion), illustrated by the loss of carbon storage, revealed a total loss of biomass of 93,835 carbon megagrams (MgC) for the period 2005–10, 204,590 MgC for 2010–14, and 1,596,780 MgC for 2014–4 (Table 9 and Figure 3). The mean square error of the spatial modelling was 43 MgC/ha.

	BIOMASS LOSS					
	2005–10 (MGC)		2010–14 (MGC)		2014–24 (MGC)	
	EXPANSION	INFILL	EXPANSION	INFILL	EXPANSION	INFILL
Urban	8,108	66,684	73,019	47,447	1,166,289	82,100
Peri-urban	188	7,232	1,298	15,668	196,264	37,580
Rural	135	11,488	524	66,634	51,878	62,669

Table 9: Biomass loss due to urban infill and urban expansion in the urban, peri-urban and rural zones.

Note: MgC = carbon megagrams.

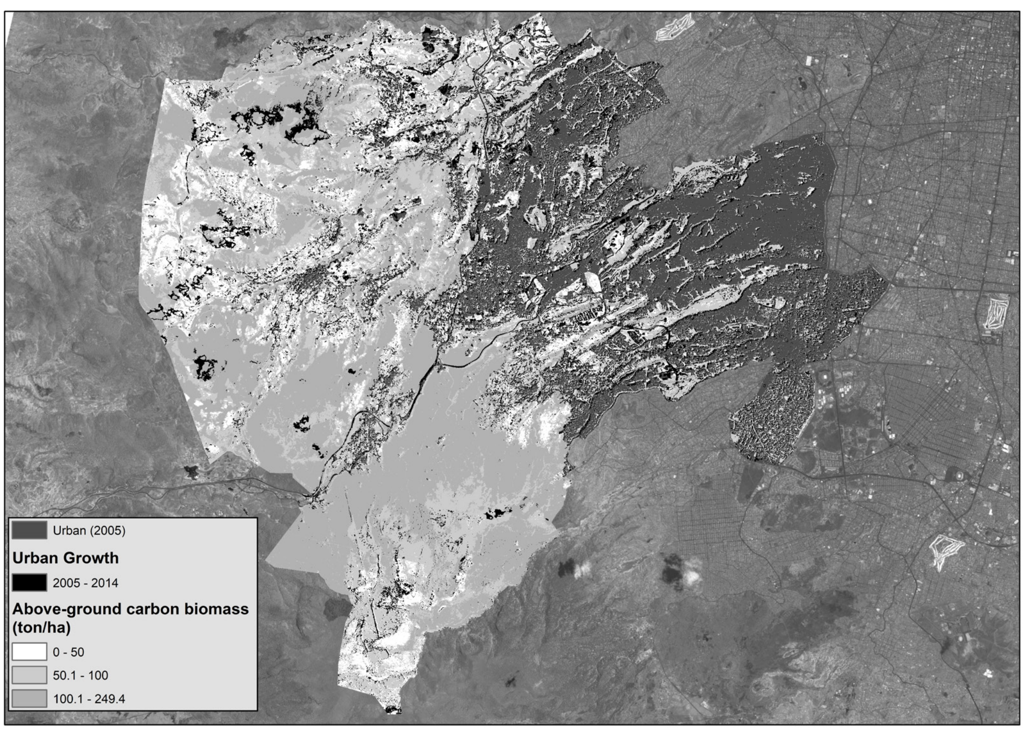

Figure 3 Spatial distribution of biomass and urban growth.

4. DISCUSSION

Urban areas have been spreading in the past and will continue to do so in future. It has been reported that much of this increment occurs in peri-urban areas, which are transition zones where urban and rural activities overlap and rural landscape characteristics are quickly modified by industrial, commercial or residential land uses. However, it also can take place in purely rural and urban areas. Since conditions that influence land-use change can broadly vary among these zones, the differences in urban growth were analysed and quantified to understand their behaviour and give elements to support sustainable land-use policies appropriate for each zone to reduce their environmental impact.

Urban growth between 2005 and 2014 was found in all three zones (urban, rural and peri-urban), which is also observed in other worldwide studies (Dou & Han 2022; Li *et al.* 2022). This net increase was higher in the urban zone, followed by the one present in the peri-urban and rural zones; this agrees with the urban expansion reported by Li *et al.* (2022) for cities in Brazil, who state that this increment takes place in a polycentric way. Consequently, more than 90% of the urban growth in the peri-urban and rural zones in this period was infill of the gaps left by this fragmented and scattered urban form. This land-use fragmentation was also found by Ortiz-Báez *et al.* (2021) in peri-urban areas of Ecuador. Although urban infill reduces the use of natural and rural areas for urban expansion there are also disadvantages, such as reducing open green spaces suitable for natural flood protection or increasing land-use conflicts due to space limitations (Eichhorn *et al.* 2021). In a more consolidated urban form such as the one in the urban zone, more than half of the urban growth corresponded to expansion.

The relative urban growth in the individual AGEB relating to their total area happened mainly in the peri-urban zones, as reported by several authors worldwide (Pribadi & Pauleit 2015; Tian 2015; Winarso *et al.* 2015). It is related to the population increment due to vegetative growth of the urban population and rural–urban migrations (Coq-Huelva & Asián-Chaves 2019) mainly of low-income people creating irregular settlements (Heider *et al.* 2018; Wigle 2010). In addition, the local government has failed to control urban sprawl in areas of high ecological value (Aguilar *et al.* 2022).

Significant differences arose in the AUE between the three zone types for the multitemporal analysis and the modelling exercise. Urban zones differed the most from the other two in the AUE. It is partially explained due to the relative similarity between the peri-urban and the rural zones in population density which is one of the primary drivers of urban expansion (Li *et al.* 2022). This was one of the main urban growth drivers along with elevation, distance to previous urban land and distance to roads. This agrees with Heider *et al.* (2018) and Hernández-Flores *et al.* (2017) who reported among the main urban driving forces distance to urban areas, distance to roads and population growth rate. But they did not agree with the findings of Akintuyi *et al.* (2021), Fathizad *et al.* (2019) and Subiyanto *et al.* (2019), perhaps because they analysed other land-use changes in addition to urbanisation in countries with very different conditions from the study area.

Forests and green spaces provide different ecosystem services that can be of local, regional and global importance (Alexander & DePratto 2014; Dobbs *et al.* 2018; Livesley *et al.* 2016). Among the regulating ecosystem services is carbon sequestration, which mitigates climate change and air quality problems (Vos *et al.* 2013). However, as revealed in this study, urbanisation has provoked the reduction of carbon sequestration causing the liberation of more than 298,000 MgC into the atmosphere between 2005 and 2014. So, if forest and green spaces continue to be lost by urbanisation there will be a decrement in the provision of this and other ecosystem services and in biodiversity, reducing cultural diversity and diminishing urban resilience to environmental shocks and stresses (Colding & Barthel 2013). Furthermore, if forests and green spaces are properly managed, they can make valuable contributions to the quality of life of the people, who are increasingly concentrated in large cities (Conway *et al.* 2019) such as Mexico City. Therefore, understanding, the particular characteristics of the urban growth for each area type, rural, urban and peri-urban, will help to generate and implement specific sustainable land-use policies.

For peri-urban and rural areas the main growth is infill, so actions should be implemented to sustainably manage the vacant or undeveloped land within an existing human settlement to prevent expansion, but also to avoid the loss of priority areas for the provision of ecosystem

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services. This issue is relevant for those cities in Mexico and around the world that present an increasingly fragmented and scattered urban form. In urban areas, where the main urban increment is expansion, sensible consolidation decisions need to be taken to avoid further urban expansion and the incorporation of urban green space.

Some recommendations to improve further studies are as follows. It is advisable to test multi-temporal time series of free images such as Landsat or Sentinel, sacrificing spatial resolution but gaining temporal resolution (Deng *et al.* 2019; Li *et al.* 2018). To decrease the over- and underestimation in urban growth predictions by cellular automata models such as Geomod, models that consider the interactions of social actors can be used, *e.g.* through the use of agent-based models and dynamical systems to make modelling more flexible and consider individual variations in behavioural rules and random variations (Degenne & Lo Seen 2016; Helbing & Balietti 2013).

5. CONCLUSIONS

This study demonstrates the urban growth differences in peri-urban, rural and urban areas, making an explicit distinction between urban expansion and urban infill, revealing the socio-territorial factors driving urban growth, and estimating the effect of urban expansion on the loss of biomass. This spatial information is useful for designing focused land-use policies in dynamic urban contexts. The remote sensing approach showed its applicability to the study of urban growth. The findings comply with the standards but use the simplest classification methods.

The modelling exercise predicted urban growth, with high accuracy of nearly 90%, if hits and persistence are considered. It opens the possibility for future research to highlight possible interventions to control urban sprawl. However, predictions should be carefully used since they tend to overestimate urban expansion in the urban zone and underestimate it in the peri-urban and rural zones.

There was continuous urban growth in the study area. Nevertheless, this increase differed for the three zone types, urban, peri-urban and rural. The zone with more net growth was urban, followed by peri-urban and rural. However, the relative urban growth in the individual polygons that comprise each zone happened mainly in the peri-urban zones. This could be related to the population increment due to vegetative growth and rural–urban migrations mainly of low-income people creating irregular settlements. Differentiating between urban expansion and urban infill, urban expansion dominated the urban zone, while urban infill represented more than 90% of the urban increment in the rural and peri-urban areas. These differences imply the need for focused management strategies aimed at peri-urban and rural areas to prevent further expansion and maintain the ecosystem services provision. In urban areas, sensible consolidation decisions need to be taken to avoid further urban expansion and maintain urban green space.

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The authors have no competing interests to declare.

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