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The Urbanized Area Evolution and Multi-factor Coupling Mechanisms in the Barcelona Metropolitan Region based on Landscape Ecological Indices

La evolución del área urbanizada y los mecanismos de acoplamiento multifactorial en la Región Metropolitana de Barcelona basados en índices ecológicos del paisaje

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Abstract

Keywords:
urbanization; urban fabric;
landscape ecology;
sustainable development

Urban expansion is a multifaceted urbanization process that reflects not only changes in land use patterns but also the complex coupling between human activities and the natural environment. This study focuses on the Barcelona Metropolitan Region (BMR), applying landscape ecological indices to analyze the utilization patterns of continuous and discontinuous urban land between 2006 and 2018. A visual framework was developed to assess the expansion and contraction of urban and built-up areas. Using a multivariable interaction model, we identified NDVI and NDBI as the key factors most strongly associated with urban spatial dynamics. The results show that BMR has maintained a stable urban land scale, with high spatial cohesion and population density, where continuous urban textures dominate the landscape. A non-significant relationship was observed between NDVI and NDBI in promoting urban growth and mitigating decline. In conclusion, BMR has undergone compact development in recent years, supported by effective policy interventions, resulting in a more efficient and coherent urban structure. The strong coupling between NDVI, NDBI, and urban land change highlights their crucial role in guiding sustainable urban development. This study offers a comprehensive evaluation of urban texture evolution from both macro and micro perspectives and reveals the spatial heterogeneity and multi-factor interactions influencing urban distribution. The findings provide a scientific basis for urban planning and contribute to the global understanding of urbanization processes.

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Resumen

Palabras clave:
urbanización; textura
urbana; ecología del
paisaje; desarrollo
sostenible

La expansión urbana es un proceso de urbanización multifacético que refleja no solo los cambios en los patrones de uso del suelo, sino también el complejo acoplamiento entre las actividades humanas y el entorno natural. Este estudio se centra en la Región Metropolitana de Barcelona (BMR), aplicando índices ecológicos del paisaje para analizar los patrones de utilización de tierras urbanas continuas y discontinuas entre 2006 y 2018. Se desarrolló un marco visual para evaluar la expansión y contracción de las áreas urbanas y construidas. Utilizando un modelo de interacción multivariable, se identificaron el NDVI y el NDBI como los factores clave más fuertemente asociados con la dinámica espacial urbana. Los resultados muestran que BMR ha mantenido una escala urbana estable, con alta cohesión espacial y densidad de población, donde las texturas urbanas continuas dominan el paisaje. El NDVI y el NDBI exhiben efectos no significantes en la promoción del crecimiento urbano y la mitigación del declive. En conclusión, BMR ha experimentado un desarrollo compacto en los últimos años, respaldado por intervenciones políticas efectivas, lo que ha resultado en una estructura urbana más eficiente y coherente. El fuerte acoplamiento entre el NDVI, el NDBI y el cambio en el uso del suelo urbano destaca su papel crucial en la orientación del desarrollo urbano sostenible. Este estudio ofrece una evaluación integral de la evolución de la textura urbana desde perspectivas macro y micro y revela la heterogeneidad espacial y las interacciones multifactoriales que influyen en la distribución urbana. Los hallazgos proporcionan una base científica para la planificación urbana y contribuyen a la comprensión global de los procesos de urbanización.



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1. Introduction

Urban expansion has emerged as a dominant form of land transformation in the 21st century, driven by rapid population growth, economic development, and policy changes. This phenomenon not only alters the spatial structure of cities but also profoundly impacts ecological systems, resource distribution, and the sustainability of urban environments. Urban expansion is inherently complex, encompassing not only the outward growth of built-up areas but also the internal restructuring of land use, infrastructure, and socio-economic functions (Huang et al., 2021; Chu et al., 2022).

A key dimension of this process lies in its spatial configuration, which is often categorized into two primary forms: continuous urban fabric (CUF) and discontinuous urban fabric (DUF) (Kasanko et al., 2006). CUF refers to spatially cohesive, high-density urban zones that facilitate efficient transportation, public service provision, and compact urban development. However, high-intensity CUF expansion can also intensify environmental stress and lead to issues such as traffic congestion, heat island effects, and land-use saturation. In contrast, DUF typically represents fragmented, low-density urban patches dispersed across peri-urban and rural landscapes. While DUF may offer flexibility in land development and lower land costs, it often results in urban sprawl, inefficient infrastructure investment, and ecological fragmentation (Wei & Zhang, 2011).

Given the contrasting implications of CUF and DUF on urban function and sustainability, understanding their evolution patterns and underlying driving forces is crucial. However, existing studies tend to treat urban expansion as a uniform process, often overlooking the internal heterogeneity of urban textures and the interactions between spatial form and ecological indicators.

Advances in remote sensing and geographic information system (GIS) technologies has significantly enhanced the capacity for high-resolution, spatiotemporal monitoring of urban dynamics. For example, Curran (1988) utilized Landsat MSS data to classify land use at the urban fringe of the English Highlands. Sudhira et al. (2003) assessed urban expansion in Karnataka, India using IRS imagery from 1971 to 2001. In the European context, Roca et al. (2011) analyzed the spatial structure and environmental implications of urban sprawl in Madrid and Barcelona. More recent studies, such as Al-Bilbisi et al. (2019), have used multi-temporal Landsat imagery to trace the evolution of urban land in Amman, Jordan, while Arellano and Cladera (2010) revealed patterns of convergence between high- and low-density urban growth in Mexico and Spain.

Despite these valuable contributions, there remains a lack of integrated research that simultaneously account for the structural differences between CUF and DUF, the ecological indicators that influence urban morphology, and the interactions among multiple driving forces. Addressing this gap is essential for advancing both theoretical understanding and practical strategies for sustainable urban planning.

European cities, particularly those located along the Mediterranean coast, have developed under distinctive climatic, environmental, and institutional contexts. The Mediterranean urban system is generally characterized by compact urban forms, high population densities, and strong interactions between urban development and natural ecosystems, shaped by limited land resources and long-term human-environment relationships (Salvati et al., 2018; Batty, 2013).

In parallel, European urban planning traditions place strong emphasis on land-use regulation, environmental protection, and sustainable development, which have played a crucial role in constraining urban sprawl and promoting more efficient and compact land-use patterns (European Commission, 2011; Newman and Kenworthy, 1999). Within this broader European and Mediterranean context, the Barcelona Metropolitan Region represents a typical case, reflecting both the spatial characteristics of Mediterranean cities and the long-standing influence of European planning frameworks.

This study focuses on the Barcelona Metropolitan Region (BMR), a representative polycentric urban system in Southern Europe, to investigate the spatiotemporal evolution of CUF and DUF from 2006 to 2018. By integrating landscape ecological indices, remote sensing data, and multivariable interaction modeling, we aim to quantify the dynamics of urban form and uncover the coupled mechanisms between urban expansion and ecological indicators, such as NDVI and NDBI. The findings are expected to offer new insights into the spatial heterogeneity of urban growth and provide a scientific foundation for evidence-based planning and policy development.

2. Literature review

In recent years, landscape metrics have also been increasingly utilized to study of urban expansion. Lin et al. (2017) integrated landscape ecology principles to develop a regional landscape stress analysis index, comparing the landscape pattern characteristics of rapidly expanding urban areas during urbanization and examining the stress effects of artificial landscapes on the ecological security pattern of natural landscapes. Das and Angadi (2020) employed landscape metrics, including the Shannon entropy index, combined with remote sensing data and GIS technology, to assess the spatial growth dynamics of urban areas in 16 municipalities of West Bengal during two periods: 1972-2001 and 2001-2016. Sarif & Gupta (2021) evaluated urban morphological changes in Prayagraj, India, using Shannon entropy, relative entropy, density index, and multiple spatial indicators, revealing the progression of urban sprawl. Similarly, Shukla and Jain (2019) developed an ecosystem resilience assessment model from both a landscape background perspective and an “exposure-adaptation” perspective, comprehensively evaluating the urban expansion patterns of Changchun, China, and analyzing their driving factors.

Furthermore, the spatial distribution of urban land is strongly influenced by a variety of external natural and anthropogenic factors. For instance, Jat et al., (2017) conducted a case study in Ajmer, Rajasthan, India, using Landsat and LISS-III satellite imagery to delineate the extent of built-up areas from 1977 to 2002 via supervised classification. They observed that while the population increased by only 50.1%, the urban built-up area grew by 160.8%, suggesting that urban expansion was driven by factors other than demographic growth. Similarly, Masek et al. (2000) investigated the Washington D.C. region, highlighting a strong inverse correlation between NDVI values and urban areas. By integrating spatial texture analysis, they effectively excluded agricultural land transitions and precisely mapped urban growth between 1973 and 1996. Sarvestani et al., (2011) using a combination of Landsat and SPOT-4 data, categorized land use types in Shiraz, Iran. Their analysis, incorporating population dynamics, revealed a decoupling between vegetation development and urban growth, accompanied by a marked reduction in green coverage. On a broader scale, Angel et al. (2021) examined the global patterns of urban land expansion, underscoring the fundamental influence of environmental conditions on urban form and distribution. Seto et al. (2009) further assessed how climate and topography shape urban growth trajectories, particularly under the pressure of climate change. Verburg et al., (2004) focused on socioeconomic drivers, constructing quantitative models to capture the effects of economic development and population rise on urban expansion. More recently, Zhang & Arellano in 2022 utilized a multi-variable regression framework to evaluate the interplay between urban expansion and climate variables across China’s four municipalities, highlighting the differential impacts of various indices.

Although existing studies have explored the spatiotemporal characteristics and driving mechanisms of urban expansion from multiple perspectives, such as landscape patterns, urban morphology, and natural and anthropogenic factors, several limitations remain. Most current research is conducted at the level of administrative units or entire cities, lacking fine-scale spatial analysis, making it difficult to reveal the spatial heterogeneity of urban expansion. In addition, landscape metrics are mostly used for pattern description rather than being quantitatively integrated into models of driving factors, which limits their explanatory and predictive capabilities.

3. Materials and Methods

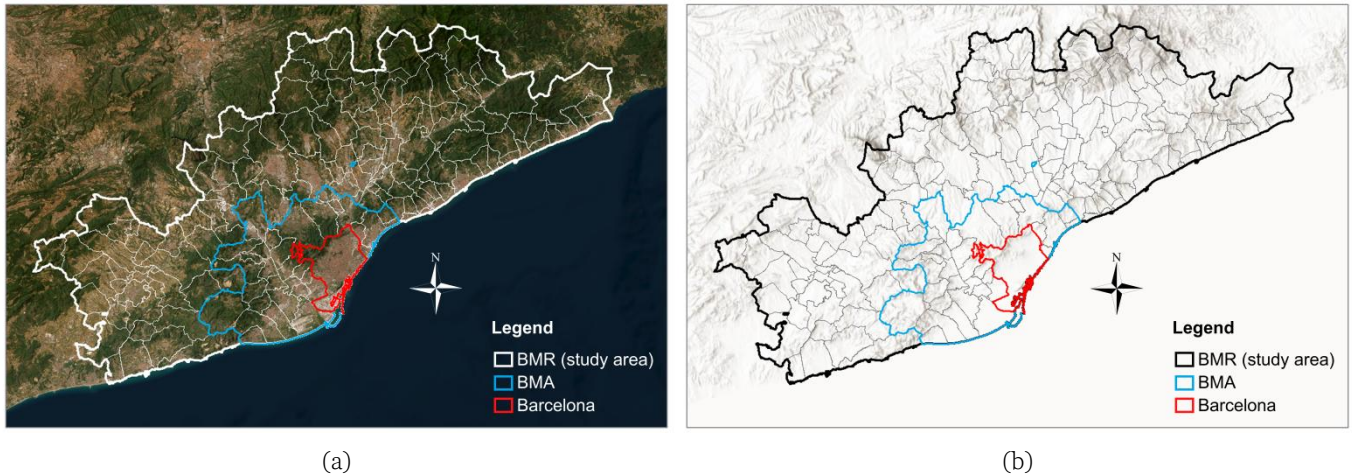
3.1. *The Field of Study*

The Barcelona Metropolitan Region (BMR) (Figure 1), as an important economic center in Spain and one of the most economically and socially active regions in Europe (Catalan Economy, 2023), plays a significant role in understanding the urbanization process in Europe and optimizing urban planning. It is located in the northeastern part of the Iberian Peninsula, at the center of the Mediterranean corridor connecting Spain to other parts of the European continent, characterized by a typical Mediterranean climate. The region is traversed by two major rivers, the Llobregat and Besòs, while the coastal and pre-coastal mountain ranges frame the coastal and pre-coastal depressions where most population centers are situated. The Collserola Serralada, located in the center of the metropolitan area, is a key component of the coastal mountain range and serves as the “green lung” of the region, providing a natural buffer zone for urban development.

The BMR covers an area of approximately 3,224.7 km², consisting of 164 municipalities, with a population of around 5.4 million, making it the most densely populated metropolitan area in the European Union (Cebollada & Miralles-Guasch, 2012). The Barcelona Metropolitan Area (BMA), a subset of the BMR, spans 636 km², including the city of Barcelona and 35 neighboring towns, with a permanent population of approximately 4.7 million. The central area of Barcelona covers about 100 km², with a population of over 1.65 million and a population density exceeding 16,500 people/km² (ORNL).

The BMR has long been influenced by urban planning and regional policies, experiencing significant urban expansion and spatial structural evolution (Busto & Arellano, 2018). The region includes both highly concentrated continuous urban areas and large expanses of discontinuous urban land, making it an ideal case for studying different types of urban expansion patterns (Pla territorial metropolitana de Barcelona).

Figure 1. Barcelona Metropolitan Region (BMR, with municipalities). (a) BMR satellite aerial photography; (b) BMR mountain elevation map



Source: Prepared by the authors based on regional ArcGIS 10.8 basemap data.

3.2. Materials

1. Corine Land Cover (CLC) provides us with relatively accurate European land cover data (Zhang et al., 2024a) with a resolution of 100 m in 2006, 2012, and 2018 (<https://land.copernicus.eu/en/products/corine-land-cover>, accessed on 15 February 2025), which records in detail two different types of urban land systems and nine other types of construction land.
2. The MODIS_MOD13Q1 (<https://lpdaac.usgs.gov/products/mod13q1v006/>, accessed on 20 February 2025) dataset provides remote sensing image data related to NDVI and NDBI calculation with a resolution of 250 m.
3. The daytime and nighttime land surface temperature (LST) can be obtained from MODIS_MOD11A2 (<https://lpdaac.usgs.gov/products/mod11a2v006/>, accessed on 20 February 2025) with a resolution of 1 km. The LST data used in this study were obtained by extracting the most stable image for each month of each study year and calculating the annual average.
4. DEM terrain data come from SRTM (<https://www.earthdata.nasa.gov/sensors/srtm>, accessed on 14 February 2025), with a resolution of 30 m.
5. E-OBS can provide annual European precipitation grid data, but the resolution is 1° (approximately 9 kilometers latitude in Spain), which is very large (https://surfobs.climate.copernicus.eu/dataaccess/access_eobs.php, accessed on 16 February 2025). Therefore, we used the kriging interpolation method based on the E-OBS data to reconstruct the relevant climate map of the BMR with a resolution of 1 km (Boer et al., 2001). Ordinary Kriging is a geostatistical interpolation method that estimates unknown values based on the spatial autocorrelation structure of observed data (Meng et al., 2013). It assumes that spatially closer observations are more similar than those farther apart and uses a variogram to model this spatial dependence (Bostan, 2017). By weighting surrounding observations, Kriging produces a continuous surface that reflects the underlying spatial pattern of precipitation (Ozturk & Kilic, 2016).

6. The road network vector data for BMR comes from Centro de DescargasOrganismo, the Spanish Autonomous National Center for Geographic Information (<https://centrodedescargas.cnig.es/CentroDescargas/resultados-busqueda>, accessed on 12 January 2025).
7. Population data comes from the LandScan 1km Global Population Grid dataset developed by the U.S. Department of Energy Oak Ridge National Laboratory (ORNL) (<https://landscan.ornl.gov/>, accessed on 12 January 2025).
8. The Statistical Institute of Catalonia can provide the per capita GDP and total population for the Catalonia region (<https://www.idescat.cat/pub/?id=pibc&n=13830&geo=mun:080193&lang=en>, accessed on 12 January 2025). Based on the total population and the population distribution in the region from LandScan, the spatial distribution of GDP is calculated (Hanberry, 2022).

All the image data and illustrations are compiled in Appendix A.

3.3. Methodology

This study aims to achieve the following objectives: first, to quantitatively assess the urban change patterns in the Barcelona Metropolitan Region from multiple perspectives using landscape ecology analysis methods. Second, we will visualize the urbanization changes in the RMB urbanized areas between 2006 and 2018. Finally, we will explore various potential integrated factors related to urban land distribution and expansion, identifying the main factors associated with urban change and examining their underlying mechanisms. To achieve the above, we will proceed according to the following steps:

1. First of all, in addition to analyzing the two basic indicators reflecting urban human economic activities-population and GDP in the BMR urban area (Seto et al., 2011; Jiao, 2015), we also need to assess the growth and evolution of urban land use from 2006 to 2018. For the spatial and morphological changes of the two types of urban fabric, continuous and discontinuous, in the study area, we introduced relevant landscape ecological metrics for measurement (Bai, 2004; Hu, 2009; Lu et al., 2014; E-erdun, 2015). The main metrics include:

(a) Landscape Proportion (PLAND) reflects the proportion of each type of urban land relative to the total area of the BMR.

$$PLAND = \frac{\sum_{j=1}^n a_{ij}}{A} \times 100\%, \quad (1)$$

Where:

a_{ij} represents the area of the j^{th} plaque in the i^{th} type of urban land;

A is the total area of all landscapes.

When the plaque area percentage value is close to 0, it indicates that the plaque type is rare in the landscape; when the value equals 1, it means the entire landscape consists of only one type of plaque.

Plaque Density (PD) reflects the fragmentation of urban land as a whole or of a single type, and the heterogeneity per unit area.

$$PD = \frac{n_i}{A} \times 100\%, \quad (2)$$

Where:

n_i is the number of plaques of the i^{th} type of urban land;

A is the total area of all landscapes.

(c) Largest Plaque Index (LPI) is used to determine the dominant plaque type in the landscape.

$$LPI = \frac{a_{\max}}{A} \times 100\%, \quad (3)$$

Where:

$a_{\max}$ refers to the area of the largest plaque in a specific urban land type;

A is the total area of the landscape.

The value of this index helps determine the dominant plaque type in urban land, indirectly reflecting the direction and magnitude of human activity interference.

(d) Based on LPI, we believe it is also necessary to calculate the minimum plaque area during the analysis of urban land expansion, even though this index is not specifically defined in landscape indices. The value of this index helps determine the smallest plaque type in urban land, which often reflects the fragmentation and complexity of the urban structure.

(e) Shannon Entropy (ENT) measures urban land heterogeneity and structural complexity based on information theory. Sensitive to the uneven distribution of plaque types, it emphasizes the role of rare types. A higher ENT value indicates greater landscape fragmentation and disorder, often reflecting negative impacts on urban structure and planning.

$$ENT = -\sum_{i=1}^n (p_i) \times (\log_2 p_i), \quad (4)$$

Where:

n refers to the total number of plaques in urban land,

P_i refers to the area ratio of urban land type i in the entire landscape.

The larger the index, the greater the fragmentation of urban land in the area, the more complex the structure, and the higher the negative impact.

(f) Perimeter-Area Fractal Dimension (PAFRAC) refers to the non-integer dimension of the irregular geometric shape of urban land, reflecting the complexity of the urban shape. The values range from 1 to 2.

$$PAFRAC = \frac{2}{\frac{[n_{ij} \sum_{j=1}^n \ln p_{ij} - \ln a_{ij}] - [(\sum_{j=1}^n p_{ij})(\sum_{j=1}^n a_{ij})]}{(n_i \sum_{j=1}^n \ln p_{ij}^2) - (\sum_{j=1}^n \ln p_{ij})^2}}, \quad (5)$$

Where:

a_{ij} refers to the area of the jth plaque in the ith urban land type;

p_{ij} represents the perimeter of the jth plaque in the ith urban land type;

n_i is the number of plaques.

The closer the result is to 1, the more regular or compact the urban shape is; conversely, the closer it is to 2, the more complex the shape is, indicating a more severe case of disordered sprawl.

(g) Compactness reflects the compactness of the urban land in the BMR.

$$Compactness = \frac{P_i}{A_i}, \quad (6)$$

Where:

P_i is the perimeter of the ith urban land type;

A_i is the area of the ith urban land type.

The smaller the index result, the more compact the urban land type is; the larger the result, the more dispersed the urban land is.

(h) Cohesion reflects the aggregation and dispersion of urban land in the landscape, with values ranging from -1 to 1.

$$COHESION = [1 - \frac{\sum_{j=1}^n p_{ij}}{\sum_{j=1}^n p_{ij} \sqrt{a_{ij}}}] [1 - \frac{1}{\sqrt{A}}]^{-1} \times 0.01, \quad (7)$$

Where:

a_{ij} refers to the area of the jth plaque in the ith urban land type;

p_{ij} represents the perimeter of the jth plaque in the ith urban land type;

A is the total area of the urban land type.

When the index result is -1, the urban land is in a completely dispersed state; when the result is 0, it is randomly distributed; and when the result is 1, it is in a clustered distribution.

2. Secondly, to more intuitively and accurately reveal the long-term growth and changes in urban land within the BMR and to identify expansion trends at different stages, urban land change maps were constructed, following approaches commonly adopted in urban expansion and spatial growth analyses (Herold et al., 2004). By incorporating directional reference lines, the spatial distribution of urban expansion and its dominant growth directions can be clearly visualized, which has been shown to be

effective in capturing directional heterogeneity and stage-specific urban growth patterns (Xu et al., 2019). This visual framework facilitates a deeper understanding of the dynamic processes underlying urban expansion.

3. Finally, we aim to gain a deeper understanding of how different natural and human factors interact with the evolution of the spatial patterns of urbanized areas. Establishing an Ordinary Least Squares (OLS) interaction model with multiple explanatory variables will help investigate the relationship between various potential factors and urban distribution changes (Zhang et al., 2019). Referring to several relevant studies, we have listed the various datasets related to urban land distribution in Table 1 (Baker et al., 2003; Wang & Lu, 2011; Y. Wang et al., 2021; Arellano & Roca, 2022; X. Zhang & Han, 2024). After obtaining the data from the table, we established a 1km grid within the BMR and extracted the increment and decrement of the proportion of urbanized land area between 2018 and 2006 as dependent variables. Multiple models were then built to analyze the degree of association and the mechanisms of influence.

Table 1. List of factors that potentially affect the distribution of urbanized land

Type	Factors
Natural factors	Longitude
	Latitude
	Distance from coastline
	Orientation
	Altitude
	Slope
	NDVI_Mean
	Precipitation
	LST
Human activity	NDBI
	Road length
	Population density
	GDP

Source: Prepared by the authors based on literature summary.

4. Results

4.1. Analysis of the urban expansion pattern in BMR

Table 2. Rezoning and allotment of BMR land to major categories

Code	Reclassification	Categories	Description
1	Continuous built-up area	Urban land	Land within the urban planning area that has been assigned a specific use and function.
2	Discontinuous built-up area		
3	Industrial land	Construction land	Land that has undergone development and construction, and is used for building structures. To distinguish this, urban land is specifically classified in this study.
4	Transportation land		
5	Construction sites		
6	Leisure land	Green area	Vegetated spaces such as parks, gardens, and other managed or natural greenery.
7	Cropland		
8	Woodland		
9	Grassland	Water bodies	Rivers, lakes, reservoirs, and other surface water features.
10	Water bodies		
11	Barren land	Barren land	Areas with minimal or no vegetation cover, such as bare soil, rocks, or degraded land.

Source: Prepared by the authors based on the CLC land classification table.

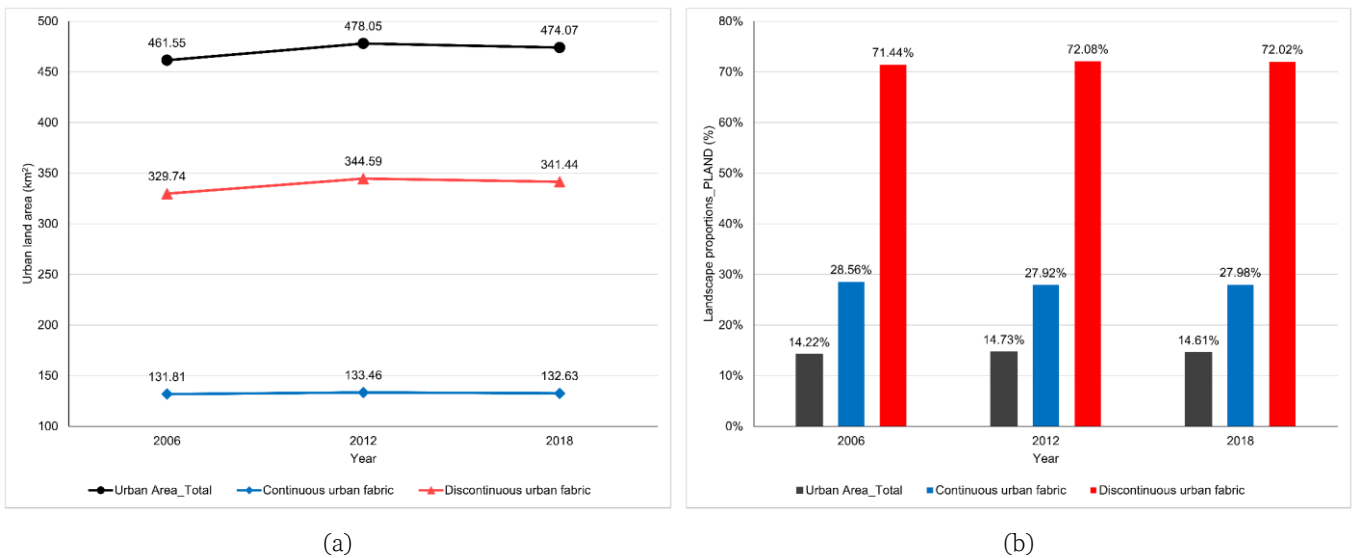
To assess and analyze the pattern and process of urban expansion in the BMR from 2006 to 2018, we first need to extract the urban land in the BMR based on the land cover descriptions provided by CLC (Corine Land Cover, 2018). Urban land is classified into two types based on its form and distribution density characteristics: continuous urban fabric and non-continuous

urban fabric. This section will analyze the two development forms of urban land. Additionally, for easier differentiation between urban land, built-up areas, and other non-urbanized regions, we categorize the 11 detailed land use types into 5 main categories (Table 2).

4.1.1 The urban land development scale and utilization pattern of BMR are relatively stable

To further examine the changes in the urban land area of the BMR and its evolution characteristics under two different urban fabric patterns, we calculated the total area and proportion of each type of urban land (figure 2). Overall, urban land in BMR experienced some growth between 2006 and 2012, with an increase of approximately 17 km², reaching a total area of 478 km². However, in the following six years (2012–2018), urban land not only failed to continue expanding but actually decreased by about 3 km². Overall, throughout the research period from 2006 to 2018, the scale of urban land in BMR remained relatively stable, consistently covering just over 14% of the total land area. Among the different types of urban land, the proportion of non-continuous urban fabric was always the highest. In 2006, it accounted for about 71.4%, and this proportion remained above 72%, peaking at 2012. This indicates that urban development pattern of BMR largely relies on low-density, dispersed expansion. On the other hand, the total area of continuous urban fabric also reached its peak in 2012, at around 133 km². However, after 2012, the scale of all types of urban land in BMR showed a declining trend, suggesting that the pace of urban expansion in the region has slowed, potentially influenced by land use policies, changes in the economic environment, or urban renewal factors.

Figure 2. Land Occupation of Urban Land in BMR. (a) Trend of Urban Land Area Change in BMR; (b) Changes in Urban Land Proportion in BMR

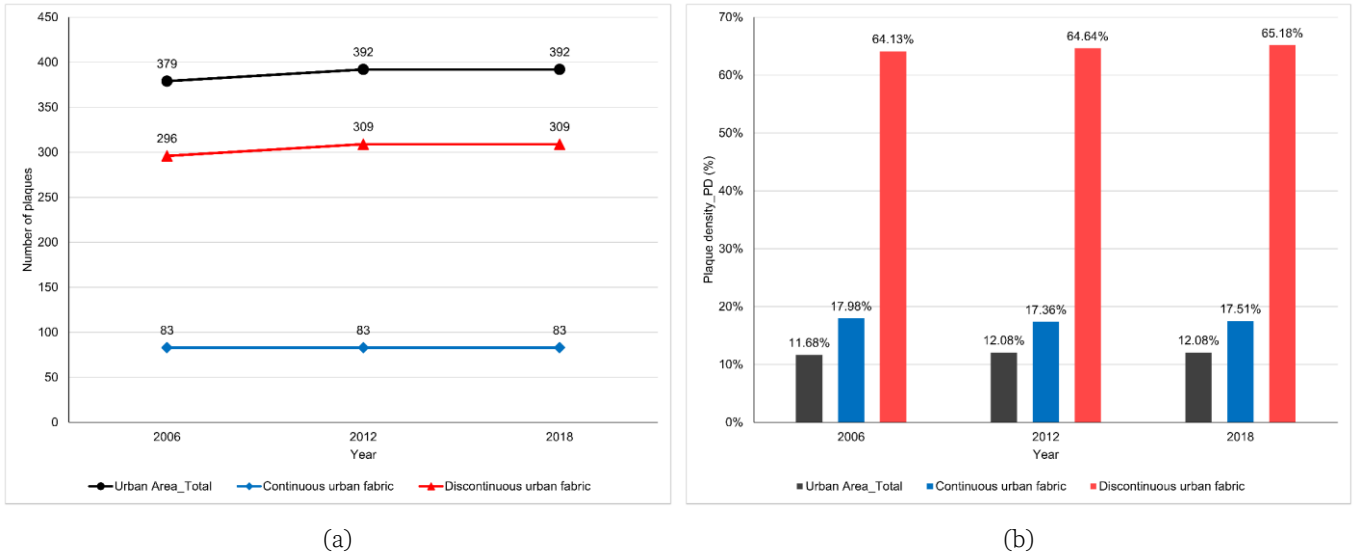


Source: Prepared by the authors based on the analysis results.

4.1.2 The number of urban land fragments no longer increases

Figure 3 visually demonstrates the trend of changes in the number of plaques and plaque density of BMR urban land from 2006 to 2018. The data shows that in 2012, BMR urban land had a total of 379 plaques, which then slightly increased to 392 plaques and remained stable in subsequent years. Overall, the plaque density of BMR urban land remained relatively low, gradually increasing from 11.68% to 12%. From the internal structure of urban land, the number of plaques of discontinuous urban fabric is the highest, exhibiting a high degree of spatial fragmentation. In 2006, there were 296 such plaques, which remained stable at 309 plaques for the following two years. The plaque density of this land type remained high, initially exceeding 64%, gradually increasing each year, and surpassing 65% by 2018. This trend indicates that the urban development in BMR is primarily characterized by discontinuous and scattered expansion. In contrast, the number of plaques of continuous urban fabric was the smallest, remaining at 83 plaques in all three years, showing higher spatial stability. The plaque density reached its highest value in 2006, close to 18%, and then decreased to 17.36%, with a slight increase of 0.15% in 2018. This change suggests that, although the spatial structure of continuous urban land remains relatively stable, its density is still influenced by urban expansion and land use adjustments.

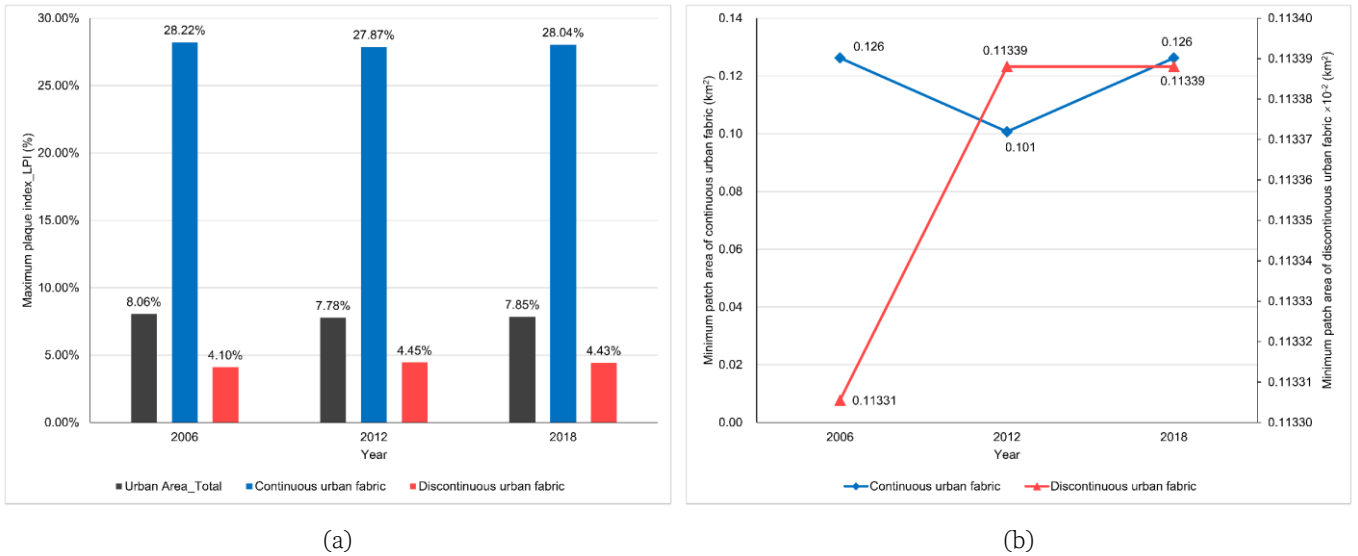
Figure 3. BMR urban land plaque situation. (a) Trend of changes in the number of BMR urban land plaques; (b) changes in the plaque density of BMR urban land



Source: Prepared by the authors based on the analysis results.

4.1.3 Continuous urban fabric is the dominant land use type in BMR urban areas

Figure 4. Extreme Plaque Situation of BMR Urban Land. (a) Maximum plaque Index of Urban Land; (b) Minimum plaque Area of Urban Land



Source: Prepared by the authors based on the analysis results.

Figure 4 illustrates that, in the urban land use of BMR, continuous urban fabric dominates through its largest single plaque, despite having a smaller total area than the other type of urban fabric. It is evident that the largest plaque occurs in the continuous urban fabric, with an area of 37.2 km². In 2006, this largest plaque accounted for 28.22% of the total urban area of Barcelona. Although its area slightly decreased thereafter, it remained around 27.87% in the following years and eventually stabilized at over 28%. The largest single plaque in the continuous urban fabric accounted for about 4% of the total urban area, and while this proportion increased over the years, it never exceeded 4.45%. From the perspective of the Barcelona metropolitan area, about 8% of the land area is occupied by this largest plaque.

Analyzing the area of the smallest plaques can measure the degree of urban fragmentation and development details. In Barcelona, the smallest plaque area in the discontinuous urban fabric has been only 0.001 km² in all years, indicating that this type of land use is highly scattered, possibly related to low-density development or leapfrog development. In contrast, the smallest plaque area in the continuous urban fabric can reach 0.1 km², reflecting a more compact spatial pattern and higher land use intensity.

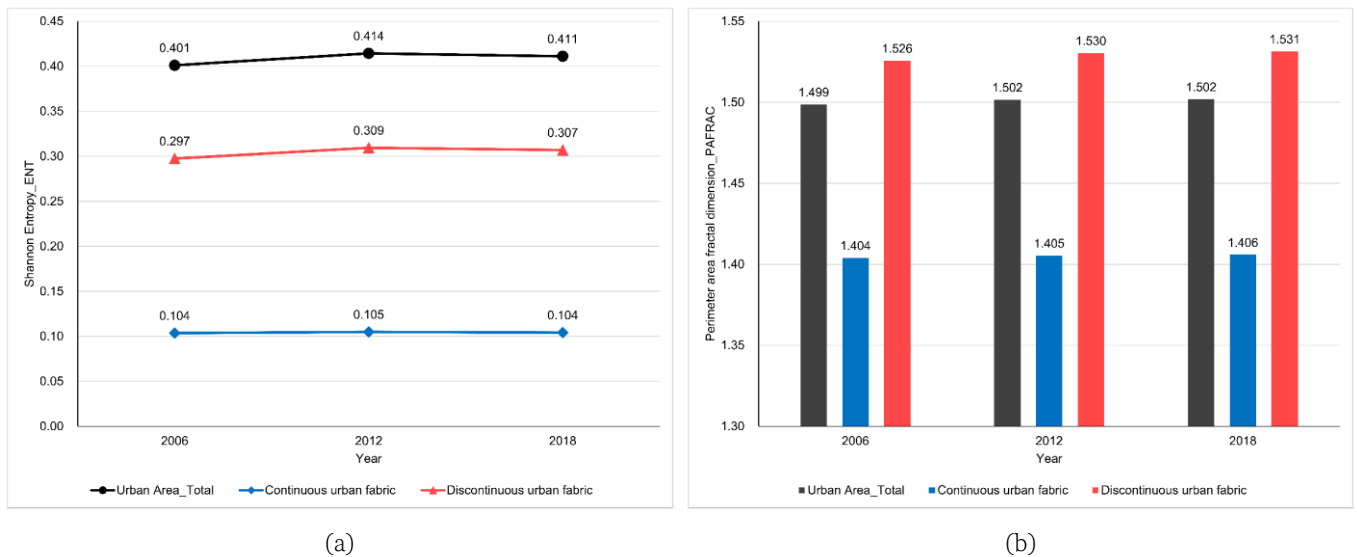
4.1.4 The structure of urban plaques in BMR is stable, with a moderate form

The Shannon entropy index is used to measure the heterogeneity and complexity of the spatial structure of urban land, while the perimeter-area fractal dimension reflects the complexity of urban morphology and the degree of human interference. From Figure 5, it can be observed that, compared to 2006, the complexity of the BMR urban land plaque structure slightly increased by 0.1 in 2018, reaching its peak of 0.41 in 2012. However, the overall trend shows that the changes between years are minimal, with the index consistently staying around 0.4, indicating that the urban land structure remained relatively stable.

Among different types of urban land, the heterogeneity of continuous urban morphology is significantly lower than that of non-continuous urban morphology, with its ENT index consistently maintaining around 0.1. In contrast, the spatial distribution of non-continuous urban land is more complex, with the ENT index being lowest in 2006 at 0.297, and then consistently exceeding 0.3, indicating that non-continuous urban morphology is more dispersed, heterogeneous, and about three times as complex as continuous urban morphology.

From the perspective of urban morphology, the urban space of Barcelona does not exhibit a highly compact development model but rather shows a certain degree of sprawl. Overall, the PAFRAC index for BMR urban land has remained around 1.5, suggesting a development pattern that is between organized growth and disordered sprawl. Non-continuous urban land consistently had a PAFRAC index above 1.5, showing an increasing trend year by year, indicating that this type of land has a looser spatial form. In contrast, the PAFRAC index for continuous urban land has remained stable at 1.4, indicating a more compact form with minimal change and stricter planning controls.

Figure 5. Complexity of Urban Space in BMR. (a) Trend of Shannon entropy index for urban land use; (b) Trend of perimeter area fractal dimension for urban land use



Source: Prepared by the authors based on the analysis results.

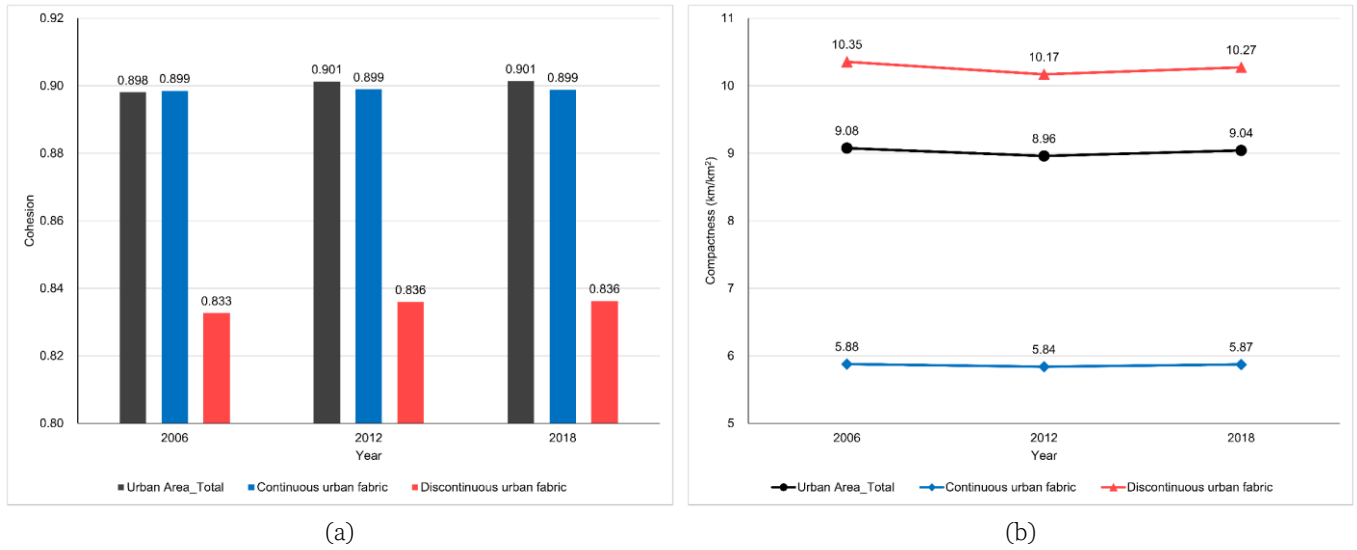
4.1.5 BMR urban area is highly compact

The compactness and cohesion indices are important indicators of the degree of aggregation of urban plaques. Figure 6 shows the trend of these two indices in the BMR region. Unlike the cohesion index, the smaller the compactness index, the more compact the urban land distribution. Analyzing the cohesion index, it is evident that Barcelona's urban land overall exhibits a high level of cohesion. In 2006, the index was close to 0.9 and remained at this high level in the following years, indicating that the distribution of urban plaques was relatively concentrated. Especially in continuous urban areas, the cohesion index remained at 0.899 without significant change, reflecting highly intensive land use in these areas. In contrast, the cohesion index for non-continuous urban land was lower, but it remained above 0.83 since 2006 and showed a slight increase in subsequent years.

Among the three years of comparison, Barcelona's urban land was most compact in 2012, with a compactness index of 0.896. In comparison, the compactness indices in 2006 and 2018 were slightly higher, but the changes were minor, indicating the stability of the overall trend. Among

non-continuous urban land, the compactness was most dispersed, with the lowest index in 2012 at 10.17, the highest in 2006 at 10.35, and 10.27 in 2018. In contrast, the compactness index for continuous urban land remained stable at 5.85, much lower than that of non-continuous urban land, indicating a more compact spatial form with almost no changes.

Figure 6. Compactness and cohesion of urban land in BMR. (a) Trend of urban land compactness; (b) Trend of urban land cohesion

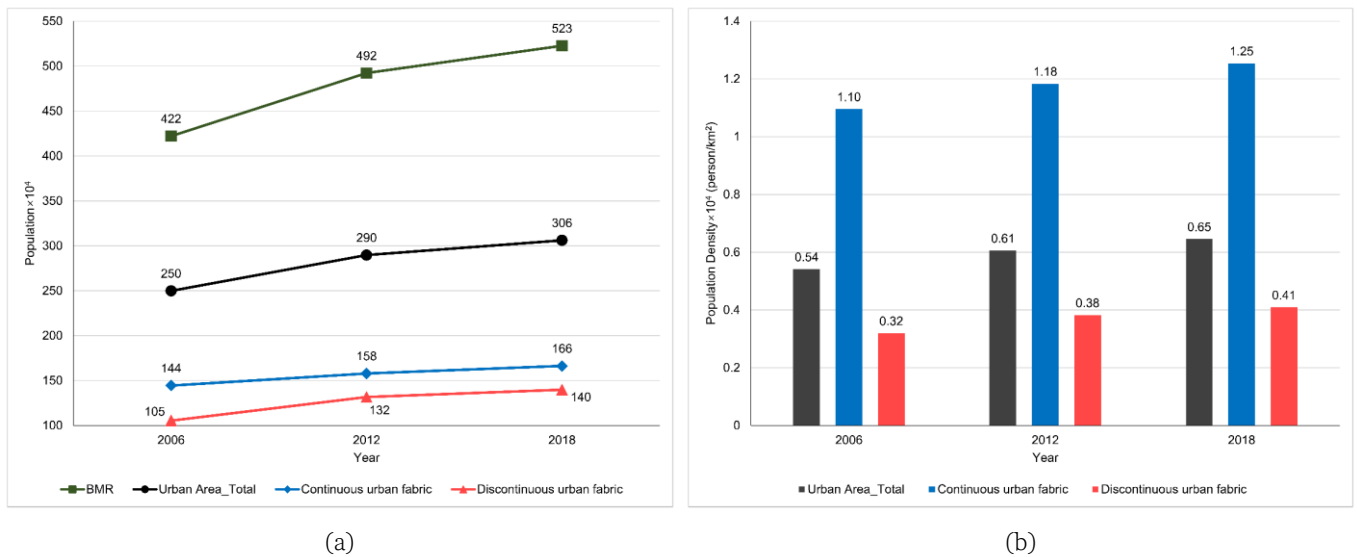


Source: Prepared by the authors based on the analysis results.

4.1.6 The urban population has steadily increased

We have compiled the total population data for the BMR area (Figure 7) and observed a significant population growth over the years, especially during the first phase, where the population increased by 700,000, from 4.22 million to 4.92 million. Afterward, the growth rate slowed down, and the population eventually reached 5.23 million. The population changes in urban areas follow a similar trend to the overall BMR pattern, with rapid growth occurring between 2006 and 2012, from 2.5 million to 2.9 million, after which the population continued to increase but at a slower pace, attracting more than 1 million new residents.

Figure 7. Changes in BMR and Urban Population. (a) Trend of BMR and urban population changes; (b) Urban population density changes



Source: Prepared by the authors based on the analysis results.

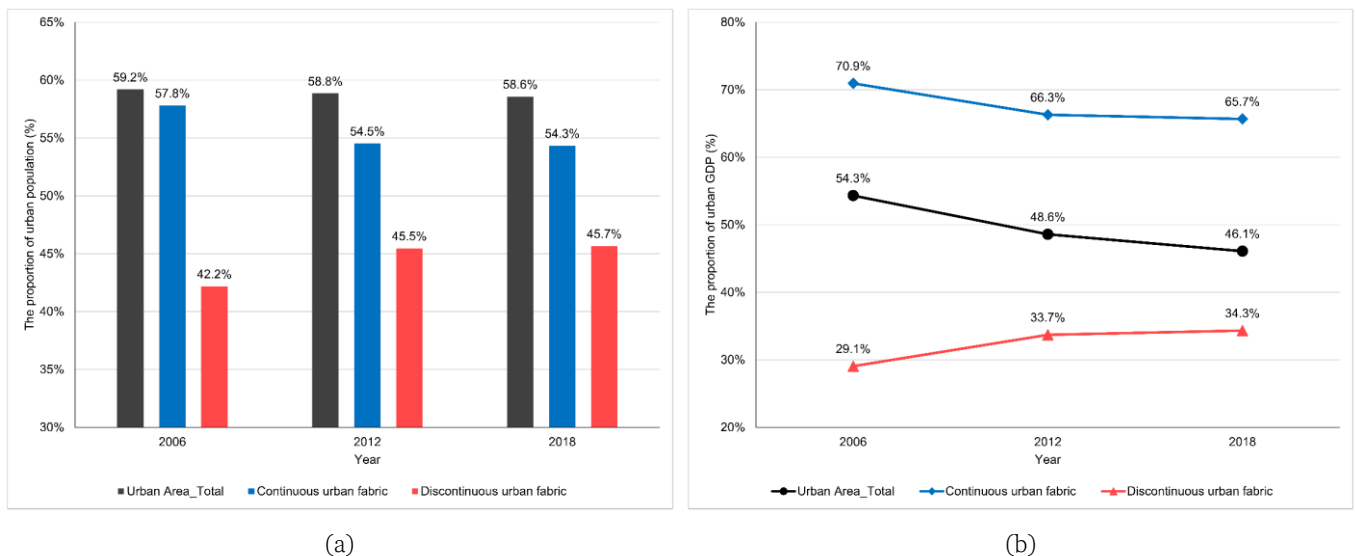
In terms of land use types, population density in continuous urban areas is significantly higher than in non-continuous urban areas, with a steady growth trend. The population in continuous urban land increased from 1.44 million to 1.66 million, demonstrating a stable growth pattern. In contrast, non-continuous urban areas also saw rapid population growth, with an increase of 400,000 people in six years. By 2018, the population in non-continuous urban areas was 200,000 lower than in continuous urban areas.

From the perspective of population density, although the expansion of urban space was not drastic, the rapid population increase led to a gradual rise in overall city density. The population density in continuous urban land is much higher than in non-continuous urban land and the entire city area. The density rose steadily from 11,000 people/km² to 12,500 people/km², nearly three times that of non-continuous urban areas. While the population density in non-continuous urban areas also increased, the growth rate was slower compared to continuous urban areas.

4.1.7 The human economic activity is shifting from urban areas to the outskirts

Analyzing the urban population and GDP proportions helps understand the changing trends in human economic activity in the BMR region. From Figure 8, it is evident that although the urban population in the BMR region is growing, the proportion of urban population relative to the total population in BMR has been steadily decreasing, although at a slow rate. In 2006, the urban population accounted for over 59% of the total population, but this proportion decreased annually, reaching 58.6% in 2018. Particularly in continuous urban areas, the decline in the urban population proportion is more significant. Specifically, in the first six years, the proportion of the urban population in continuous urban areas decreased from 57.8% to 54.5%, continuing to decline slightly in the last year. In contrast, the proportion of the population in non-continuous urban areas showed an increase. From 2006 to 2012, the population share in non-continuous urban areas increased by 3.3%, reaching 45.5%, and further increased by 2018, ultimately accounting for 45.7% of the total urban population. Similarly, the proportion of urban areas in the total GDP of BMR also showed a decreasing trend. In 2006, urban areas contributed 54.3% of the total GDP of BMR, but over time, this contribution decreased annually, dropping to 46.1% by 2018. Specifically, within continuous urban land, the proportion of urban GDP also decreased, falling by nearly 10% from the initial 71%. However, economic activity in non-continuous urban areas gradually increased. Initially contributing only 29% to the urban GDP, this proportion grew over twelve years, reaching 34.3% in 2018. This change indicates that economic activity is gradually shifting from the urban core to the peripheral areas, and the economic functions of fragmented urban land are also becoming increasingly significant.

Figure 8. Proportion of human activity in BMR cities. (a) Proportion of urban population; (b) Proportion of urban GDP



Source: Prepared by the authors based on the analysis results.

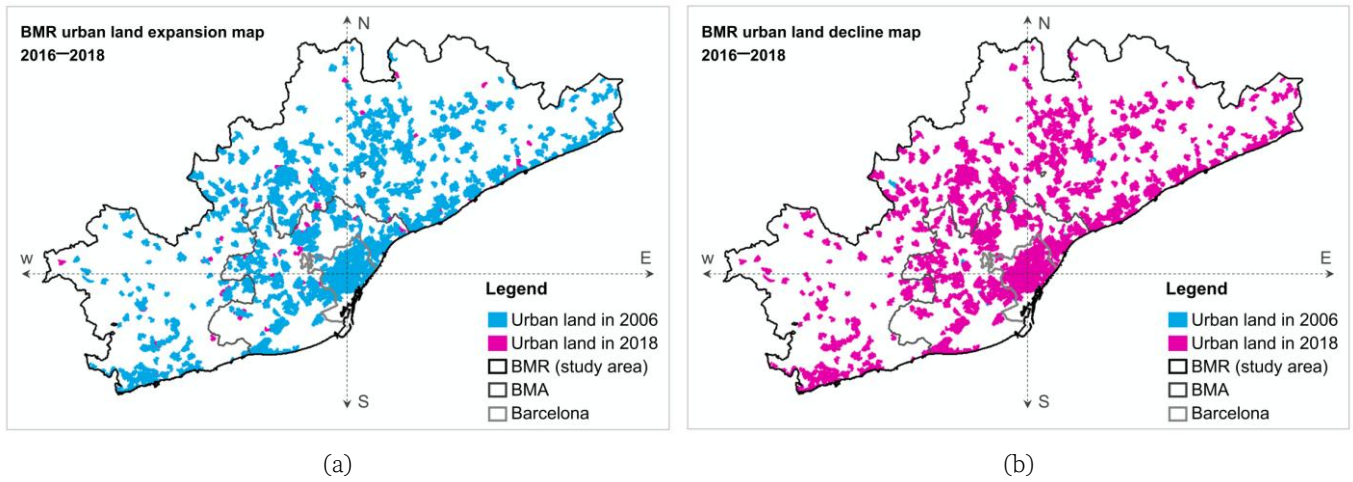
4.2. Spatial analysis of the urbanized area in the BMR

4.2.1 The urban land changes in the central and eastern regions of BMR are active

The urban land change maps provide a more intuitive and accurate way to identify the long-term evolution characteristics of BMR urban land. To facilitate the observation of land increase and decrease, during the creation of the map set in ArcGIS 10.8, the study magnified the urban land boundaries by two times and added directional auxiliary lines centered around the

centroid of Barcelona to enhance the readability of the spatial distribution pattern, as shown in Figure 9.

Figure 9. BMR urban land change maps. (a) Urban land expansion map; (b) Urban land decline map

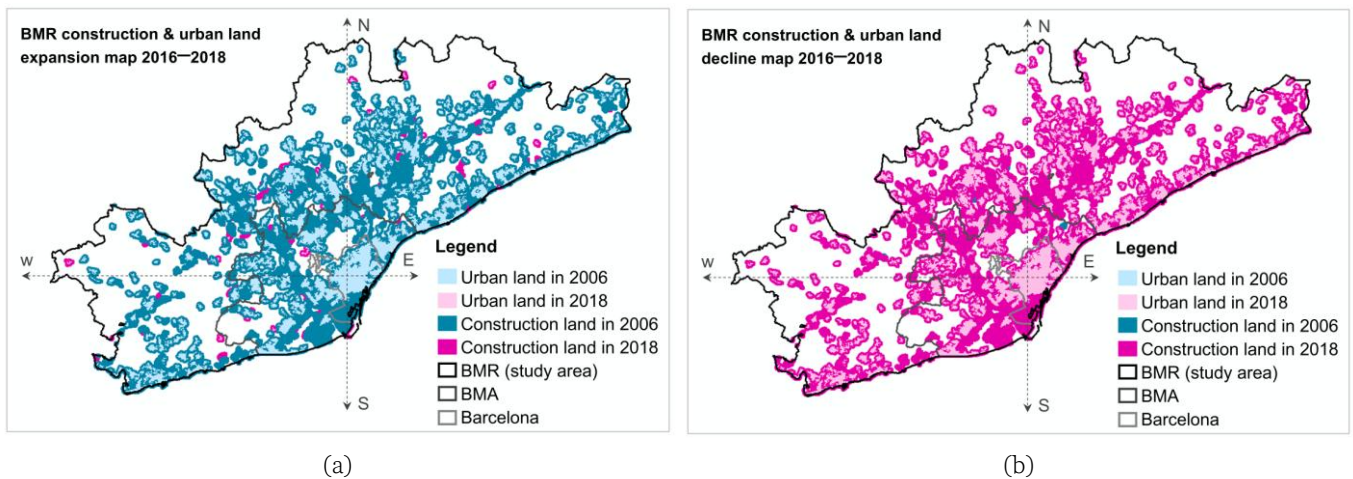


Source: Prepared by the authors based on the analysis results.

4.2.2 The urban construction land expansion in the BMR is significant

In general, urbanized areas within metropolitan regions not only encompass core urban land but also include other non-agricultural construction lands. These construction lands are closely linked with urban lands and jointly support the development of municipal functions (Yan et al., 2019). Therefore, based on the classification in Table 2, this study presents a map collection of BMR construction land changes, including urban land, in Figure 10 to further explore the evolution of the urbanization spatial structure.

Figure 10. BMR construction & urban land change maps. (a) Construction land expansion map; (b) Construction land decay map



Source: Prepared by the authors based on the analysis results.

Compared to the fragmented distribution of urban land, construction land has enhanced the connectivity between urban land plaques, optimizing the overall structure of the urban system. The spatial distribution of construction land resembles that of urban land but with more gaps filled, making the urban form more coherent. The city of Barcelona is almost fully covered by construction land, extending toward the southwestern and northeastern peripheral areas. Additionally, the construction land in the BMA occupies over half of the space, reflecting the further advancement of urbanization in the region.

Similar to urban land, the expansion of construction land is also concentrated in the northeastern part of the BMR, the periphery and interior of the BMA, and a few plaques of construction land in the western part of the BMR. Some construction land in the northwest of the BMR and the northeast of the BMA has undergone decay. No significant changes have occurred in the construction land of Barcelona.

To further explore the relationship between construction land and urban land in the BMR, as well as their development patterns, this study conducted a statistical analysis of human and economic activity data in Table 3. The results indicate that the area of construction land in the BMR has shown a continuous growth trend. Although the growth rate slowed between 2012 and 2018, the scale of construction land has consistently remained nearly twice that of urban land. Furthermore, the population density in the area has been rising; however, compared to the core urban areas, the population density in the construction land remains relatively low.

Table 3. BMR urban land and construction land area human activity data.

Year	Area (km ²)	Population density (person/km ²)	Population contribution rate (%)	GDP contribution rate (%)
2006	724.97	4626.25	79.46%	58.74%
2012	753.21	5213.32	79.77%	52.82%
2018	756.72	5487.09	79.45%	50.00%

Source: Prepared by the authors based on the analysis results.

Analysis shows that about 80% of the population in the BMR has long resided in construction land. This area not only supports a significant amount of population activity but also contributes more than half of the economic output. However, despite the importance of construction land in economic activities, its GDP contribution rate has been declining annually.

This suggests that while the expansion of construction land has somewhat driven regional development, the growth of its economic vitality may have been constrained by other factors. It is noteworthy that the major population and economic activities in urban construction land are still highly concentrated in the core urban areas, highlighting the dominant role of the urban center in the regional economic structure.

4.3. Analysis of factors associated with the increase and decrease of BMR urbanization area distribution

By constructing an Ordinary Least Squares (OLS) interaction model with multiple explanatory variables, this study enables a direct analysis of the relationships between various potential factors and the changes in urban and built-up land distribution in the BMR (Bun & Harrison, 2018). Based on a review of multiple relevant studies, 14 types of natural and human activity factors were selected as explanatory variables (Baker et al., 2003; Wang & Lu, 2011; Y. Wang et al., 2021; Arellano & Roca, 2022; X. Zhang & Han, 2024).

The study area was divided into 2,985 grids with a side length of 1 km. The change in the proportion of urban and built-up land within each grid, calculated as the difference between 2018 and 2006, was used as the dependent variable. To facilitate comparison, we separately analyzed grids with increasing and decreasing urbanized areas, resulting in a total of four OLS regression models. In the models, B represents the unstandardized regression coefficient, Beta the standardized regression coefficient, t the student's t statistic, and Sig. the significance level (p-value).

Prior to interpreting the results, the multivariable interaction model was assessed for its statistical assumptions. Specifically, we checked for multicollinearity, autocorrelation, and residual normality. No significant multicollinearity or autocorrelation was detected, and the residuals were approximately normally distributed, indicating that the model assumptions were satisfactorily met.

4.3.1 Analysis of factors associated with BMR urban expansion

Table 4 presents the variables associated with the expansion of urbanized areas in the BMR between 2006 and 2018, along with their respective effects. The analysis indicates that NDVI and NDBI show positive associations with urban expansion, although these relationships do not reach statistical significance ($p > 0.05$). Specifically, NDBI appears to be more closely associated with the increase in urban land, whereas NDVI shows a relatively stronger relationship with the expansion of construction land. The combined effects of these variables suggest a potential interaction in explaining urban expansion patterns.

In addition, annual precipitation appears to be associated with urban expansion patterns. While it is positively associated with the expansion of urban land, it tends to show a negative relationship with the growth of construction land. This suggests a potentially complex and unresolved relationship between precipitation and urban expansion, which warrants further investigation. Although Kriging interpolation may introduce some uncertainty and affect the

accuracy of the precipitation data, precipitation is used in this study only as a reference variable to examine its general trends in relation to urbanized areas. It is not treated as a direct driving factor, and causal relationships between precipitation and urban expansion or decline are not inferred. Therefore, while the interpolation may slightly influence absolute values, the observed associations with urban patterns remain useful for understanding general trends.

Table 4. OLS model of land distribution expansion in BMR urbanization.

Independent variable	Model_Urban land ^a				Model_Construction land ^b			
	B	Beta	t	Sig.	B	Beta	t	Sig.
Constant	-596.46		-0.08	0.94	11827.41		1.76	0.08
Longitude	0.00	0.28	0.32	0.75	0.00	1.89	3.00	0.00
Latitude	0.00	0.22	0.18	0.86	0.00	-1.22	-1.65	0.10
Distance from coastline	0.00	-0.14	-0.14	0.89	0.00	1.24	1.97	0.05
Orientation	0.02	0.09	0.71	0.48	0.06	0.18	1.82	0.07
Altitude	0.01	0.09	0.34	0.73	0.00	0.02	0.09	0.93
Slope	-9.09	-0.52	-2.81	0.01	-6.79	-0.35	-1.99	0.05
NDVI_MEAN	11.69	0.25	0.52	0.60	15.45	0.24	0.68	0.50
Precipitation	6.65	0.21	0.64	0.53	-20.03	-0.44	-1.94	0.06
LST_DAY	-2.30	-0.53	-2.06	0.04	-3.44	-0.69	-3.07	0.00
LST_NIGHT	-1.13	-0.21	-0.59	0.56	-1.74	-0.23	-0.87	0.39
NDBI	13.55	0.26	0.63	0.53	11.16	0.15	0.49	0.63
Road_KM	-0.30	-0.43	-1.15	0.26	-0.31	-0.30	-0.98	0.33
Population density	0.00	-0.14	-0.23	0.82	0.00	0.17	0.40	0.69
GDP	0.00	0.18	0.31	0.76	0.00	-0.08	-0.21	0.83

Source: Prepared by the authors based on the analysis results. a The independent variable is the increase in urban land between 2006 and 2018. b The independent variable is the increase in construction land between 2006 and 2018.

Slope was identified as a statistically significant inhibitory factor for urban expansion, particularly in the urban land model. LST also exhibited a negative relationship with urban growth, especially in the construction land model. By contrast, the effects of road network density, orientation, altitude, population density, and GDP were comparatively weak and did not show statistical significance in the models. Collectively, NDVI, NDBI, precipitation, and slope may contribute to explaining urban expansion patterns, although only Slope demonstrated clear statistical significance in the analysis.

4.3.2 Analysis of factors associated with BMR urban attenuation

Table 5. OLS model of land distribution attenuation in BMR urbanization.

Independent variable	Model_Urban land ^a				Model_Construction land ^b			
	B	Beta	t	Sig.	B	Beta	t	Sig.
Constant	223.45		3.235	0.003	2091.93		1.923	0.06
Longitude	0.00	-1.59	-1.59	0.122	0.00	-1.72	-1.38	0.175
Latitude	0.00	3.19	3.00	0.005	0.00	3.13	1.92	0.061
Distance from coastline	0.00	-2.13	-2.53	0.017	0.00	-2.65	-1.74	0.088
Orientation	0.00	-0.03	-0.28	0.783	0.00	0.03	0.25	0.804
Altitude	0.00	0.07	0.25	0.801	0.00	0.05	0.19	0.854
Slope	0.09	0.37	1.60	0.121	0.02	0.01	0.07	0.941
NDVI_MEAN	-0.19	-0.37	-0.84	0.406	-3.25	-0.66	-1.96	0.055
Precipitation	-0.07	-0.22	-0.93	0.36	-1.71	-0.63	-2.62	0.012
LST_DAY	0.01	0.28	0.85	0.403	-0.12	-0.28	-1.20	0.234
LST_NIGHT	0.00	-0.04	-0.12	0.908	0.24	0.42	1.39	0.171
NDBI	-0.12	-0.20	-0.67	0.507	-1.67	-0.30	-1.06	0.293
Road_KM	-0.01	-0.58	-1.17	0.25	0.00	0.00	0.01	0.996
Population density	0.00	1.34	1.98	0.056	0.00	-0.76	-1.30	0.199
GDP	0.00	-1.38	-2.07	0.047	0.00	0.57	0.96	0.343

Source: Prepared by the authors based on the analysis results. A. The independent variable is the absolute value of reduction in urban land between 2006 and 2018. B. The independent variable is the absolute value of reduction in construction land between 2006 and 2018.

In the model analyzing factors associated with urban decline in the BMR, the dependent variable represents the absolute value of the reduction in construction land, ensuring that all declines are treated as positive quantities for comparison purposes.

NDVI and NDBI both show negative associations with the decline of urbanized areas, with NDVI exhibiting a relatively stronger relationship than NDBI (Table 5). However, these relationships do not reach statistical significance ($p > 0.05$). The combined effects of these variables may indicate a potential association with the reduction in urban land distribution in the BMR. Precipitation also shows a negative association in both models, suggesting a possible relationship with urban decline patterns. In the urban land model, slope exhibits a comparatively stronger association than precipitation and LST. However, the influence of slope in the construction land model appears to be limited. Overall, NDVI, NDBI, precipitation, and slope may collectively contribute to explaining urban decline patterns, although their non statistical significance varies across models.

Daytime LST and nighttime LST exhibit different relationships with urban land reduction, although their individual effects remain relatively weak. Their associations become more apparent when considering the overall urbanized area. Specifically, reductions in construction land tend to be associated with decreases in daytime LST and increases in nighttime LST.

5. Discussion

Based on these findings, we can strongly affirm that the urbanized space of the Barcelona Metropolitan Region has not undergone significant expansion over the past two decades. Instead, it has developed in a compact manner, with some urban plaques even shrinking. The structural organization of the urbanized area has been well-planned, urban functions have gradually improved, and scattered urban fragments have evolved into a more sustainable whole. This is largely attributed to the "40-Year Metropolitan Urban Planning", which has regulated and coordinated the land use and morphology of the BMR (Pla territorial metropolitana de Barcelona; 40 Years of Urban Planning - Metròpolis Barcelona - Àrea Metropolitana De Barcelona, 2025). This evolution pathway, oriented toward structural optimization rather than large-scale expansion, is characteristic of many European and Mediterranean cities. In cities such as London, Paris, and Amsterdam, urban expansion primarily manifests through internal redevelopment, functional reorganization, and spatial integration, rather than through large-scale additions of built-up land (Urban Sprawl in Europe - Joint EEA-FOEN Report, 2016; Guastella et al., 2019). In Mediterranean coastal cities, constrained by topography, historical urban structures, and strict planning policies, urban form generally exhibits a high degree of compactness, and growth relies more on the optimization and redevelopment of existing built-up areas (Díaz-Pacheco & García-Palomares, 2014; Salvati, 2021). These patterns reflect a general trend in mature urban systems, shifting from "outward expansion" toward "structural optimization" and "quality improvement." In contrast, rapidly urbanizing cities in Asia and other developing regions, such as Beijing and Delhi, have generally experienced significant outward expansion, with rapid increases in built-up land area, continuous outward growth of urban patches, and increasing fragmentation of urban space (Angel, 2023; Liu et al., 2014).

The results of this study indicate that the driving mechanisms of urbanized area evolution are complex and vary considerably across factors, with NDVI and NDBI having the most significant influence. Similarly, in rapidly developing cities such as Beijing and Guangzhou, the growth of built-up areas is closely linked to spectral indices such as NDVI and NDBI, suggesting analogous landscape transformation mechanisms driven by anthropogenic land conversion (Zheng et al., 2020; Khan et al., 2021). Moreover, studies of some European and North American cities have also highlighted that urban expansion exhibits spatial patterns consistent with ecological gradients (Oueslati et al., 2015; Seto et al., 2011). Taken together, these studies indicate that, although specific drivers may vary according to geographic and planning contexts, the overall association between vegetation indices, built-up land dynamics, and urban growth remains consistent.

In addition, precipitation is a non-negligible natural factor in this study. It shows a significant positive correlation with urban expansion in the Barcelona Metropolitan Region, while exhibiting a negative correlation with urban decline, which is consistent with findings reported in previous studies. Higher precipitation levels generally contribute to improved ecological conditions, promote vegetation growth, and support the maintenance of green spaces, thereby enhancing urban livability and the overall carrying capacity of land development, and providing a relatively favorable natural background for urban expansion (Wei et al., 2014). Meanwhile, stable precipitation conditions help reduce the risks of ecological degradation and land retreat, thus restraining the decline of construction land to a certain extent (Lal, 2012). In the case of the Barcelona Metropolitan Region, precipitation is not a direct driving force of urban expansion; however, by influencing environmental quality, land suitability, and urban green systems, it indirectly regulates the processes of urban expansion and contraction, highlighting the supportive role of natural environmental factors in urban evolution (Alberti et al., 2020; Zheng et al., 2023).

This study assessed the internal correlation strengths between various potential natural and human activities factors and urban land distribution. NDVI and NDBI were ultimately identified as the two key variables that exhibit interactive relationships with both the increase and decrease of urban spatial distribution. However, during the analysis, precipitation and slope were also found to play important roles. In our previous work, we employed a spatial triangular framework to explore the complex mechanisms between precipitation and NDVI, which partially clarified their relationship (Zhang & Han, 2024). Based on the current findings, the connection between precipitation and urban land distribution is also complex, and using NDVI as a mediating indicator to analyze this relationship appears to be a promising approach. Furthermore, in some cases, the relationship between LST and urbanized areas warrants deeper investigation. Therefore, this aspect will be a key focus of our future research.

In the analysis of urbanized region evolution in the BMR, although continuous and discontinuous urban land as well as directional expansion analyses were applied to systematically investigate urban evolution patterns, certain limitations remain. First, the temporal resolution of the data (2006, 2012, and 2018) may not fully capture short-term or annual variations in urban change. Second, the analysis of urban expansion patterns primarily relies on remote sensing and landscape ecological indices, without fully considering socio-economic factors or policy interventions, which may limit the interpretation of complex urban evolution processes. Future studies could integrate higher temporal resolution data and multiple driving factors to further enhance the understanding of urban evolution patterns.

On the other hand, due to limitations in technology and data accessibility, certain spatial datasets used in this study remain inadequate. The spatialized GDP data were estimated by the authors using LandScan population distribution data in combination with total population and per capita GDP statistics from the Statistical Institute of Catalonia. However, this approach introduces a high degree of inaccuracy; thus, GDP data were only used as a supplementary reference and were not included in precise quantitative analyses. Additionally, due to the complex feedback mechanisms within the climate system, remote sensing for climate monitoring still faces many challenges (Henson et al., 2016). Problems such as the coarse resolution of precipitation data and the inconsistent spatial resolution among LST and other remote sensing variables still exist. Therefore, efforts to develop high-precision spatial GDP databases and improve the accuracy of climate data are essential to overcome the current limitations.

6. Conclusions

This study, utilizing landscape ecological metrics, conducted a comprehensive evaluation and visualization of the dynamic evolution of two types of urban land in the Barcelona Metropolitan Region (BMR) from 2006 to 2018, ranging from a global to a local scale. It also analyzed the interactions between various potential external factors and changes in the distribution of urbanized areas. The results reveal that among the urban land types in BMR, discontinuous urban fabric covers a significantly larger area than continuous urban fabric, exhibiting higher levels of fragmentation and complexity, but lower cohesion and compactness. In contrast, the continuous urban fabric represents a more advantageous urban development model. Overall, during the study period, the scale of urban land in BMR remained relatively stable, characterized by high cohesion and moderate morphological patterns, with no significant changes. Meanwhile, the population steadily increased, but economic activities showed a tendency to disperse toward the urban periphery.

In addition, the study identifies NDVI and NDBI as the most critical variables influencing both the expansion and contraction of urban areas, while precipitation and slope also play notable roles. In summary, urban land in the BMR has entered a relatively stable developmental phase, with NDVI and NDBI showing the strongest correlations with spatial changes in urban distribution.

Principally, the urban land area in BMR has remained stable, with a rational internal structure, high spatial cohesion, and a high population density. Continuous urban fabric holds a dominant position in the urban spatial pattern.

- From 2006 to 2012, urban land exhibited a slight outward expansion and an increase in plaque numbers. However, between 2012 and 2018, the overall pattern stabilized. The complexity of plaque structures remained nearly unchanged and stayed at a reasonable level, with excellent compactness and cohesion.
- The largest urban plaques were primarily contributed by continuous urban fabric, while discontinuous urban fabric was the main driver of fragmentation and increased spatial complexity. The compactness of the latter was also significantly lower.

- Although the number of BMR residents grew significantly, the growth rate slowed down while population density continued to increase. Meanwhile, economic activity weakened and showed a tendency to shift toward peripheral and fragmented urban areas.
- Spatially, urban and construction land change was most active in the central and eastern parts of BMR, with limited land reduction observed. The gaps between urban plaques were gradually filled, and Barcelona city itself became almost entirely covered by built-up land.

By constructing multivariate OLS interaction models, the study confirmed that NDVI and NDBI are the two most influential variables associated with both the increase and decrease of urbanized areas in BMR.

- Among all the variables, NDVI and NDBI consistently demonstrated the strongest intrinsic relationships with changes in urbanized areas. Both variables were significantly positively correlated with expansion and negatively correlated with contraction.
- The models also indicated that the two climatic variables—land surface temperature (LST) and precipitation were noticeably associated with the dependent variables. However, their explanatory power was considerably lower than that of the top two covariates, and their mechanisms of influence appeared more complex (Zhang et al., 2024a; Zhang et al., 2024b), suggesting a need for further in-depth research and analysis.

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8. Authorship

Conceptualization, Xu Zhang, Blanca Arellano Ramos and Josep Roca Cladera; methodology, Xu Zhang; software, Xu Zhang; validation, Blanca Arellano Ramos and Josep Roca Cladera; formal analysis, Xu Zhang; resources, Xu Zhang; data curation, Xu Zhang; writing—original draft preparation, Xu Zhang, Josep Roca Cladera and Blanca Arellano Ramos; writing—review and editing, Blanca Arellano Ramos and Josep Roca Cladera; visualization, Xu Zhang; supervision, Blanca Arellano Ramos and Josep Roca Cladera; project administration, Josep Roca Cladera and Blanca Arellano Ramos; funding acquisition, Josep Roca Cladera and Blanca Arellano Ramos. All authors have read the manuscript and made some official changes. All authors have read and agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript.

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9. References

- 40 years of urban planning - Metròpolis Barcelona - Àrea Metropolitana de Barcelona. Available online: <https://urbanisme.amb.cat/en/visions/40-anys-de-planejament-urbanistic> (accessed on 13 March 2025).
- Alberti, M., Palkovacs, E. P., Roches, S. D., De Meester, L., Brans, K. I., Govaert, L., Grimm, N. B., Harris, N. C., Hendry, A. P., Schell, C. J., Szulkin, M., Munshi-South, J., Urban, M. C., & Verrelli, B. C. (2020). The complexity of urban eco-evolutionary dynamics. *BioScience*, 70(9), 772 - 793. <https://doi.org/10.1093/biosci/biaa079>
- Al-Bilbisi, H. (2019). Spatial Monitoring of Urban Expansion Using Satellite Remote Sensing Images: A Case Study of Amman City, Jordan. *Sustainability*, 11(8), 2260. <https://doi.org/10.3390/su11082260>
- Angel S; Sheppard S; Civco D L. (2021, October 1). The Dynamics of global urban expansion. Cities Alliance. Cities Alliance. <https://www.citiesalliance.org/resources/publications/case-study/dynamics-global-urban-expansion>

- Angel, S. (2023). Urban expansion: theory, evidence and practice. *Buildings and Cities*, 4(1), 124-138. <https://doi.org/10.5334/bc.348>
- Arellano, B., & Cladera, J. R. (2010). El urban sprawl, ¿un fenómeno de alcance planetario? Los ejemplos de México y España. *ACE Arquitectura Ciudad Y Entorno*, 4(12), 115 - 148. <https://doi.org/10.5821/ace.v4i12.2489>
- Arellano, B., & Roca, J. (2022). Effects of Urban Greenery on Health. A Study from Remote Sensing. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences/International Archives of the Photogrammetry, *Remote Sensing and Spatial Information Sciences*, XLIII-B3-2022, 17-24. <https://doi.org/10.5194/isprs-archives-xliii-b3-2022-17-2022>
- Bai, J. (2004). *Study on the Spatial Pattern and Dynamics of Vegetation Landscape in Wenlue River Basin of Guandi Mountain Forest Area*. Master's Thesis, Shanxi Agricultural University, Taiyuan, China.
- Baker, P. J., Ansell, R. J., Dodds, P. a. A., Webber, C. E., & Harris, S. (2003). Factors affecting the distribution of small mammals in an urban area. *Mammal Review*, 33(1), 95 - 100. <https://doi.org/10.1046/j.1365-2907.2003.00003.x>
- Batty, M. (2013). Big data, smart cities and city planning. *Dialogues in Human Geography*, 3(3), 274-279. <https://doi.org/10.1177/2043820613513390>
- Boer, E. P., De Beurs, K. M., & Hartkamp, A. D. (2001). Kriging and thin plate splines for mapping climate variables. *International Journal of Applied Earth Observation and Geoinformation*, 3(2), 146-154. [https://doi.org/10.1016/s0303-2434\(01\)85006-6](https://doi.org/10.1016/s0303-2434(01)85006-6)
- Bostan, P. (2017). Jeo-İstatistik'te kullanılan temel kriging yöntemleri. *Yüzüncü Yıl Üniversitesi Tarım Bilimleri Dergisi*, 27(1), 10-20. <https://doi.org/10.29133/yyutbd.305093>
- Busto, A. L., & Arellano, B. (2018). Shrinking cities. El caso aplicado de Ferrol. *ACE Arquitectura Ciudad Y Entorno*, 13(38), 263-286. <https://doi.org/10.5821/ace.13.38.6479>
- Bun, M. J. G., & Harrison, T. D. (2018). OLS and IV estimation of regression models including endogenous interaction terms. *Econometric Reviews*, 38(7), 814 - 827. <https://doi.org/10.1080/07474938.2018.1427486>
- Catalan Economy. (2023). Available online: <https://catalonia.com/w/barcelona-catalonia-s-capital-ranks-4th-as-europe-s-best-city> (accessed on 15 February 2024).
- Cebollada, A., & Miralles-Guasch, C. (2012). La movilidad en la región metropolitana de Barcelona: entre los nuevos retos y las viejas prácticas. *Finisterra*, 45(90). <https://doi.org/10.18055/finis1339>
- Chu, N., Wu, X., Zhang, P., Xu, S., Shi, X., & Jiang, B. (2022). Spatial Distribution Pattern Evolution of the Population and Economy in Russia since the 21st Century. *International Journal of Environmental Research and Public Health*, 20(1), 684. <https://doi.org/10.3390/ijerph20010684>
- CORINE Land Cover 2018 (vector/raster 100 m), Europe, 6-yearly. Available online: <https://land.copernicus.eu/en/products/corine-land-cover/clc2018> (accessed on 15 February 2025).
- CORINE Land Cover classification definitions. Available online: <https://land.copernicus.eu/content/corine-land-cover-nomenclature-guidelines/html/index-clc-111.html> (accessed on 15 February 2025).
- Curran, P. J., & Ojeda, B. (1988). Airborne mss for land cover classification. *Geocarto International*, 3(4), 67-72. <https://doi.org/10.1080/10106048809354182>
- Das, S., & Angadi, D. P. (2020). Assessment of urban sprawl using landscape metrics and Shannon's entropy model approach in town level of Barrackpore sub-divisional region, India. *Modeling Earth Systems and Environment*, 7(2), 1071-1095. <https://doi.org/10.1007/s40808-020-00990-9>
- Díaz-Pacheco, J., & García-Palomares, J. C. (2014). Urban sprawl in the Mediterranean urban regions in Europe and the crisis effect on the urban land development: Madrid as study case. *Urban Studies Research*, 2014, 1-13. <https://doi.org/10.1155/2014/807381>
- E-erdun. (2015). *Impact of Land Use and Landscape Pattern Changes on Watershed Erosion and Sediment Production*. Master's Thesis, North China Electric Power University, Beijing, China.
- European Commission (2011). A Renewed EU Strategy 2011-14 for Corporate Social Responsibility. Brussels. [http://www.europarl.europa.eu/meetdocs/2009_2014/documents/com/com_com\(2011\)0681/_com_com\(2011\)0681_en.pdf](http://www.europarl.europa.eu/meetdocs/2009_2014/documents/com/com_com(2011)0681/_com_com(2011)0681_en.pdf)
- Guastella, G., Oueslati, W., & Pareglio, S. (2019). Patterns of urban spatial expansion in European cities. *Sustainability*, 11(8), 2247. <https://doi.org/10.3390/su11082247>

- Hanberry, B. B. (2022). Imposing consistent global definitions of urban populations with gridded population density models: Irreconcilable differences at the national scale. *Landscape and Urban Planning*, 226, 104493. <https://doi.org/10.1016/j.landurbplan.2022.104493>
- Henson, S. A., Beaulieu, C., & Lampitt, R. (2016). Observing climate change trends in ocean biogeochemistry: when and where. *Global Change Biology*, 22(4), 1561 - 1571. <https://doi.org/10.1111/gcb.13152>
- Herold, M., Couclelis, H., & Clarke, K. C. (2004). The role of spatial metrics in the analysis and modeling of urban land use change. *Computers Environment and Urban Systems*, 29(4), 369 - 399. <https://doi.org/10.1016/j.compenvurbsys.2003.12.001>
- Hu, W. (2009). *Study on Landscape Pattern and Stability of Hani Terraces in Yuanyang*. Ph.D. Thesis, Kunming University of Science and Technology, Kunming, China.
- Huang, D., Lang, Y., & Liu, T. (2021). The Evolving Structure of Rural Construction Land in Urbanizing China: Case Study of Tai'an Prefecture. *Land*, 10(1), 65. <https://doi.org/10.3390/land10010065>
- Jat, M. K., Garg, P., & Khare, D. (2007). Monitoring and modelling of urban sprawl using remote sensing and GIS techniques. *International Journal of Applied Earth Observation and Geoinformation*, 10(1), 26-43. <https://doi.org/10.1016/j.jag.2007.04.002>
- Jiao, L. (2015). Urban land density function: A new method to characterize urban expansion. *Landscape and Urban Planning*, 139, 26-39. <https://doi.org/10.1016/j.landurbplan.2015.02.017>
- Kasanko, M., Barredo, C. J., Lavalle, C., McCormick, N., Demicheli, L., Sagris, V., & Brezger, A. (2006). *Are European cities becoming dispersed? A comparative analysis of 15 European urban areas*. JRC Publications Repository. <https://publications.jrc.ec.europa.eu/repository/handle/JRC33924>
- Khan, M. S., Ullah, S., & Chen, L. (2021). Comparison on Land-Use/Land-Cover indices in explaining land surface temperature variations in the city of Beijing, China. *Land*, 10(10), 1018. <https://doi.org/10.3390/land10101018>
- Lal, R. (2012). Climate change and soil degradation mitigation by sustainable management of soils and other natural resources. *Agricultural Research*, 1(3), 199-212. <https://doi.org/10.1007/s40003-012-0031-9>
- Lin, M. X., Lin, T., Qiu, Q. Y., Sun, C. G., Deng, F. L., & Zhang, G. Q. (2017). Comparison of ecological security stress effects of artificial landscapes on natural landscapes in different rapid urban sprawl areas. *Chinese Journal of Applied Ecology*, 28(4), 1326 - 1336. <https://doi.org/10.13287/j.1001-9332.201704.007>
- Liu, X., Ma, L., Li, X., Ai, B., Li, S., & He, Z. (2014). Simulating urban growth by integrating landscape expansion index (LEI) and cellular automata. *International Journal of Geographical Information Science*, 28(1), 148-163. <https://doi.org/10.1080/13658816.2013.831097>
- Lu, S., Guan, X., He, C., & Zhang, J. (2014). Spatio-Temporal Patterns and Policy Implications of Urban Land Expansion in Metropolitan Areas: A Case Study of Wuhan Urban Agglomeration, Central China. *Sustainability*, 6(8), 4723-4748. <https://doi.org/10.3390/su6084723>
- Masek, J. G., Lindsay, F. E., & Goward, S. N. (2000). Dynamics of urban growth in the Washington DC metropolitan area, 1973-1996, from Landsat observations. *International Journal of Remote Sensing*, 21(18), 3473-3486. <https://doi.org/10.1080/014311600750037507>
- Meng, Q., Liu, Z., & Borders, B. E. (2013). Assessment of regression kriging for spatial interpolation - comparisons of seven GIS interpolation methods. *Cartography and Geographic Information Science*, 40(1), 28-39. <https://doi.org/10.1080/15230406.2013.762138>
- Newman, P., & Kenworthy, J. (1999). Costs of automobile dependence: Global Survey of Cities. *Transportation Research Record Journal of the Transportation Research Board*, 1670(1), 17-26. <https://doi.org/10.3141/1670-04>
- Oak Ridge National Laboratory. Available online: <https://landscan.ornl.gov/> (accessed on 20 February 2025).
- Oueslati, W., Alvanides, S., & Garrod, G. (2015). Determinants of urban sprawl in European cities. *Urban Studies*, 52(9), 1594-1614. <https://doi.org/10.1177/0042098015577773>
- Ozturk, D., & Kilic, F. (2016). Geostatistical approach for spatial interpolation of meteorological data. *Anais Da Academia Brasileira De Ciências*, 88(4), 2121 - 2136. <https://doi.org/10.1590/0001-3765201620150103>
- Pla territorial metropolitana de Barcelona. Available online: https://territori.gencat.cat/ca/01_departament/05_plans/01_planificacio_territorial/plans_territorials_nou/territorials_parciais/ptp_metropolitana_de_barcelona/ (accessed on 20 February 2025).

- Roca, J., Arellano, B., Moix, M. (2011). Urban Structure, Sprawl and Polycentrism: the Examples of Madrid and Barcelona. *Ciudad Y Territorio Estudios Territoriales*, 43(168), 299 - 321. <https://recyt.fecyt.es/index.php/CyTET/article/view/76055>
- Salvati, A., Coch, H. (2021). Urban Climate and Building Energy Performance in Compact Cities in Mediterranean Climate. In: Palme, M., Salvati, A. (eds) *Urban Microclimate Modelling for Comfort and Energy Studies*. Springer, Cham. https://doi.org/10.1007/978-3-030-65421-4_6
- Salvati, L., Zambon, I., Chelli, F. M., & Serra, P. (2018). Do spatial patterns of urbanization and land consumption reflect different socioeconomic contexts in Europe? *The Science of the Total Environment*, 625, 722-730. <https://doi.org/10.1016/j.scitotenv.2017.12.341>
- Sarif, M. O., & Gupta, R. D. (2021). Comparative evaluation between Shannon's entropy and spatial metrics in exploring the spatiotemporal dynamics of urban morphology: a case study of Prayagraj City, India (1988-2018). *Spatial Information Research*, 29(6), 961-979. <https://doi.org/10.1007/s41324-021-00406-5>
- Sarvestani, M. S., Ibrahim, A. L., & Kanaroglou, P. (2011). Three decades of urban growth in the city of Shiraz, Iran: A remote sensing and geographic information systems application. *Cities*, 28(4), 320-329. <https://doi.org/10.1016/j.cities.2011.03.002>
- Seto, K. C., & Shepherd, J. M. (2009). Global urban land-use trends and climate impacts. *Current Opinion in Environmental Sustainability*, 1(1), 89-95. <https://doi.org/10.1016/j.cosust.2009.07.012>
- Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A Meta-Analysis of Global urban land expansion. *PLoS ONE*, 6(8), e23777. <https://doi.org/10.1371/journal.pone.0023777>
- Shukla, A., & Jain, K. (2019). Critical analysis of spatial-temporal morphological characteristic of urban landscape. *Arabian Journal of Geosciences*, 12(4). <https://doi.org/10.1007/s12517-019-4270-y>
- Sudhira, H., Ramachandra, T., & Jagadish, K. (2003). Urban sprawl: metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation*, 5(1), 29-39. <https://doi.org/10.1016/j.jag.2003.08.002>
- Urban sprawl in Europe - joint EEA-FOEN report. (2016, June 8). Publications | European Environment Agency (EEA). <https://www.eea.europa.eu/en/analysis/publications/urban-sprawl-in-europe?utm>
- Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: current practice and research priorities. *GeoJournal*, 61(4), 309-324. <https://doi.org/10.1007/s10708-004-4946-y>
- Wang, H., & Lu, S. (2011). Spatial distribution, source identification and affecting factors of heavy metals contamination in urban-suburban soils of Lishui city, China. *Environmental Earth Sciences*, 64(7), 1921-1929. <https://doi.org/10.1007/s12665-011-1005-0>
- Wang, Y., Yi, G., Zhou, X., Zhang, T., Bie, X., Li, J., & Ji, B. (2021). Spatial distribution and influencing factors on urban land surface temperature of twelve megacities in China from 2000 to 2017. *Ecological Indicators*, 125, 107533. <https://doi.org/10.1016/j.ecolind.2021.107533>
- Wei, Y., & Zhang, Z. (2011). Assessing the fragmentation of construction land in urban areas: An index method and case study in Shunde, China. *Land Use Policy*, 29(2), 417 - 428. <https://doi.org/10.1016/j.landusepol.2011.08.006>
- Wei, Y., Huang, C., Lam, P. T., & Yuan, Z. (2014). Sustainable urban development: A review on urban carrying capacity assessment. *Habitat International*, 46, 64 - 71. <https://doi.org/10.1016/j.habitatint.2014.10.015>
- World Cities Report 2024: Cities and climate Action. UN-Habitat. <https://unhabitat.org/world-cities-report-2024-cities-and-climate-action>
- Xu, G., Jiao, L., Liu, J., Shi, Z., Zeng, C., & Liu, Y. (2019). Understanding urban expansion combining macro patterns and micro dynamics in three Southeast Asian megacities. *The Science of the Total Environment*, 660, 375-383. <https://doi.org/10.1016/j.scitotenv.2019.01.039>
- Yan, Y., Ju, H., Zhang, S., & Jiang, W. (2019). Spatiotemporal Patterns and Driving Forces of Urban Expansion in Coastal Areas: A Study on Urban Agglomeration in the Pearl River Delta, China. *Sustainability*, 12(1), 191. <https://doi.org/10.3390/su12010191>
- Zhang, L., Cheng, J., & Jin, C. (2019). Spatial Interaction Modeling of OD Flow Data: Comparing Geographically Weighted Negative Binomial Regression (GWNBR) and OLS (GWOLSR). *ISPRS International Journal of Geo-Information*, 8(5), 220. <https://doi.org/10.3390/ijgi8050220>
- Zhang, X., & Han, H. (2024). Characteristics and factors influencing the expansion of urban construction land in China. *Scientific Reports*, 14(1). <https://doi.org/10.1038/s41598-024-67015-8>
- Zhang, X., & Arellano, B. (2022). Urban Sprawl and Warming – Research on the Evolution of the Urban Sprawl of Chinese Municipalities and its Relationship with Climate Warming in the Past Three Decades. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information*

Zhang, X., Arellano, B. & Roca, J. (2024b). Study on factors influencing forest distribution in Barcelona Metropolitan Region. *Sustainability*, 16(13), 5449. <https://doi.org/10.3390/su16135449>

Zhang, X., Arellano, B. & Cladera, J. R. (2024a). Research on Key Influencing Factors of Ecological Environment Quality in Barcelona Metropolitan Region Based on Remote Sensing. *Remote Sensing*, 16(24), 4735. <https://doi.org/10.3390/rs16244735>

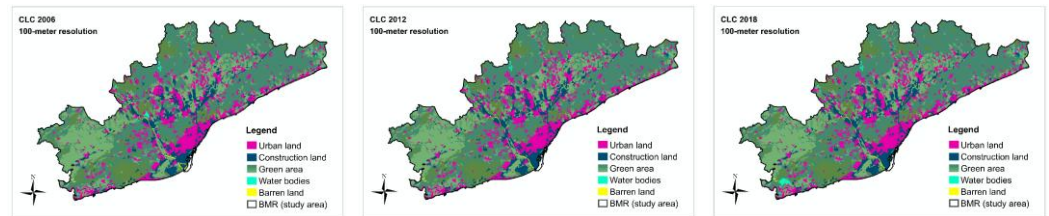
Zheng, Q., Arellano, B., & Cladera, J. R. (2023). Redefiniendo las zonas climáticas de España: una nueva clasificación climática para la eficiencia energética de edificios. *ACE Arquitectura Ciudad Y Entorno*, 18(53). <https://doi.org/10.5821/ace.18.53.12087>

Zheng, Z., Wu, Z., Chen, Y., Yang, Z., & Marinello, F. (2020). Detection of city integration processes in rapidly urbanizing areas based on remote sensing imagery. *Land*, 9(10), 378. <https://doi.org/10.3390/land9100378>

10. Appendix

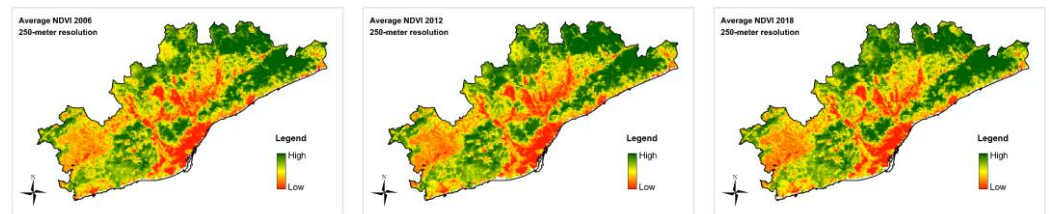
Appendix A

Figure A1. Corine Land Cover (CLC) annual data.



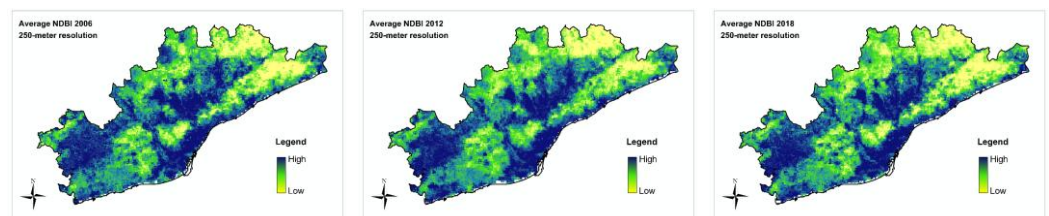
Source: Prepared by the authors.

Figure A2. Annual average NDVI.



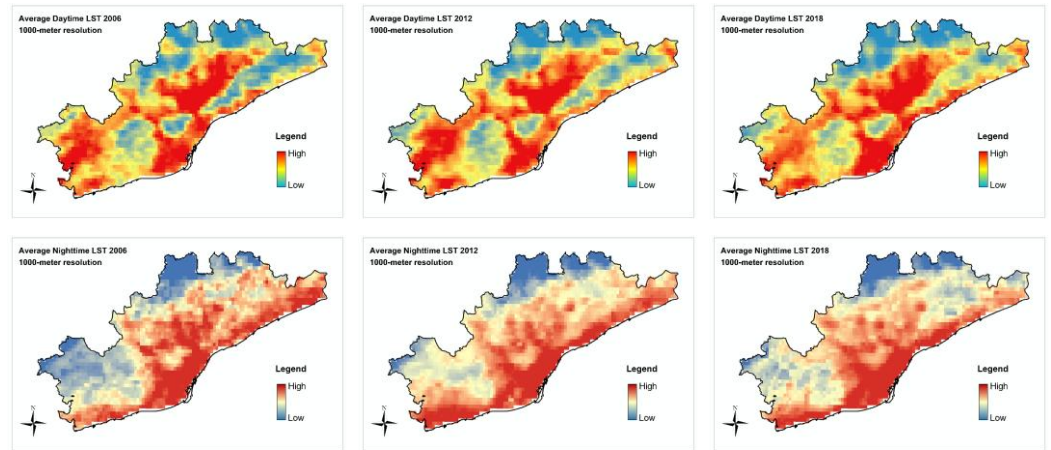
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Figure A3. Annual average NDBI.



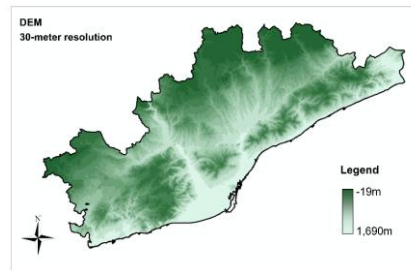
Source: Prepared by the authors.

Figure A4. Annual daytime and nighttime surface temperature (LST).



Source: Prepared by the authors.

Figure A5. DEM terrain data



Source: Prepared by the authors.

Figure A6. Annual precipitation.

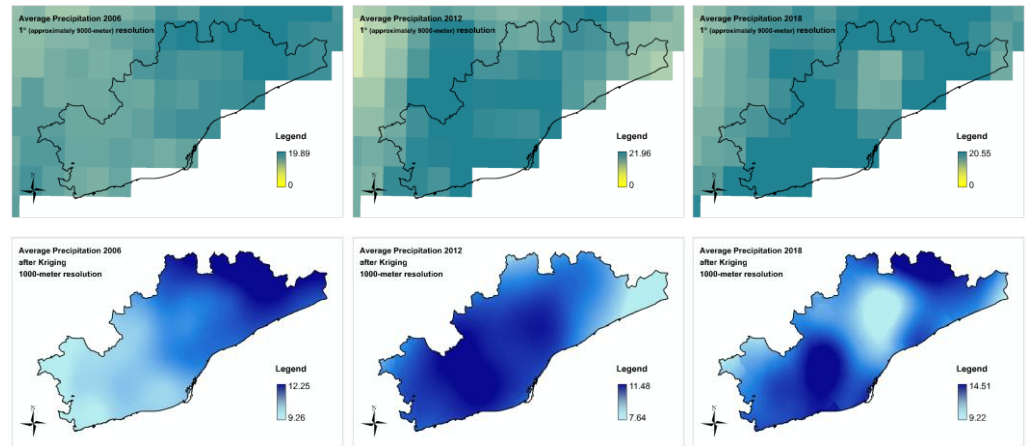
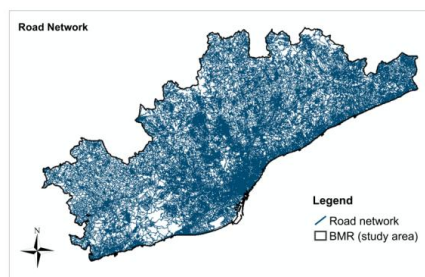
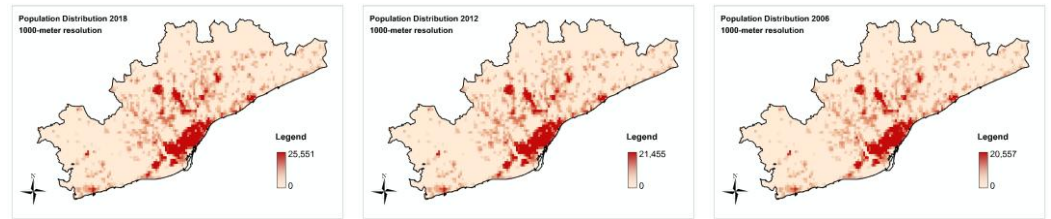


Figure A7. BMR road network vector data.



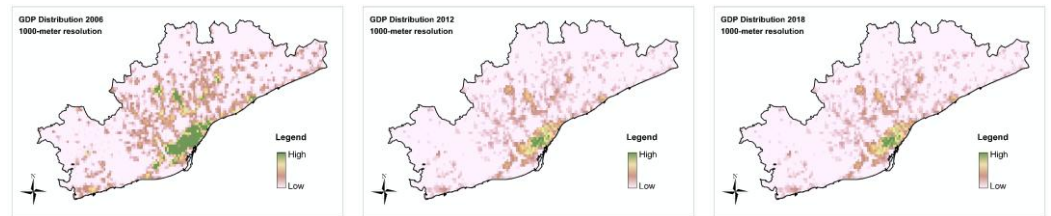
Source: Prepared by the authors.

Figure A8. Annual population distribution data.



Source: Prepared by the authors.

Figure A9. Annual GDP distribution data.



Source: Prepared by the authors.