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Analysis of land use/land cover spatio-temporal metrics and population dynamics for urban growth characterization

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Abstract

Promoting sustainable urbanization and limiting land consumption is a local and regional priority policy target in Europe. Monitoring and quantifying urban growth supports decision-making processes for the prevention of ecological and socio-economic consequences. In this work, we present a methodology based on spatio-temporal metrics and a new index (PUGI), that quantifies the inequality of growth between population and urban areas, to analyze and compare urban growth patterns at different levels. We computed an exhaustive set of spatio-temporal metrics at local level in a testing sample of six urban areas from the Urban Atlas database, then uncorrelated metrics were selected and the data were interpreted at various levels. Results allow for a differentiation of growing patterns, discriminating between compact and sprawl trends. The index proposed complements the analysis by including demographic dynamics, being also useful for assessing the growing imbalance between the progression on residential areas and the population change at local level. The analysis at various levels contributes to a better understanding of urban growth patterns and its relation to sustainable policies not only within urban areas, but also for the comparison across Europe.

Keywords: urban growth; spatio-temporal metrics; IndiFrag; LULC; Urban Atlas; Population and urban growing imbalance (PUGI)

1. Introduction

Land is a limited resource and cities are continuously growing. The insufficient planning control of fast-growing urban areas may result in ecosystem degradation and loss of quality of life (Kompil et al., 2015). In recent years, new planning initiatives and programmes have been developed to reconsider the urbanization process and promote sustainable land use in Europe. Two examples are the Informal Ministerial Meeting on Urban Development Declaration (2010) and the 7th Environment Action Programme (EC, 2013), which promote urban recycling, compact city planning, improve green infrastructure and soil protection as measures for a more sustainable development of cities. The Urban Agenda for the European Union (EC, 2017) also compiles several policy documents at European and national levels in relation to sustainable land use development.

Urban growth is understood as the expansion of built-up areas that implies changes in Land Use/Land Cover (LULC). Monitoring urban growth trends is important for land managers and decision-making (Patino and Duque, 2013). Generally, urban growth drivers are multi-dimensional forces influenced by local characteristics. According to Inostroza et al. (2010) population growth, income and transport improvements are underlying forces. Other authors included cultural believes in addition to the physical, political and economic drivers (Dale and Kline, 2013), while the EEA (2011) also covered housing preferences and regulations. Quantifying urban growth and its characterization in different spatial patterns is crucial for evaluating its environmental, economic, and social impacts, since the degree of compact or sprawl growth differs both, in causes and in consequences (Bhatta, 2010). Urban growth can be categorized as sprawl or compact according to the spatial arrangement of built-up areas, land uptake per inhabitant and the amount of built-up area in the landscape (EEA, 2016).

The characterization of the spatial configuration and change patterns of LULC is based on methods that allow for multi-temporal assessment. Spatio-temporal metrics, those that combine spatial and multi-temporal metrics, measure landscape characteristics (i.e. spatial configuration, aggregation, diversity, shape, size, etc.) and describe landscape changes (Dale and Kline, 2013), and they are widely used to summarize the complexity of land use patterns into quantitative terms from LULC maps at specific scales (Llausàs and Nogué, 2012). When applied to urban areas, they contribute to characterize the urban growth process (Herold et al., 2005; Uuemaa et al., 2013).

Spatio-temporal metrics do not account for the land uptake per inhabitant, which has been mentioned as a relevant variable to characterize the growth process. A joint analysis of urban growth and population distribution provides an overview of the human use of the landscape and its tendency to sprawl (EEA, 2016; Martinuzzi et al., 2007). Recent studies have combined spatial metrics with population data to categorize urban patterns. For instance, Arribas-Bel et al. (2011) used population density and distribution indices for an inter-city comparison and combined them with spatial metrics for clustering European cities according to their level of sprawl at a single date. Jaeger and Schwick (2014) introduced a metric that integrates urban expansion, dispersion, and the land uptake per inhabitant at intra-city level for a single date. Afterward, it was applied to the built-up area in Europe at various scales: national, regional and 1-km^2-grid (EEA, 2016; Hennig et al., 2015). They found that the application at local scale eased the detection of changes, however, it was hardly comparable with socio-economic data at this level. Other studies revealed that population density combined with other drivers (i.e. spatial characteristics, socio-economic, policies, among others) is suitable for predicting urban growth and its type (Dubovyk et al., 2011; EEA, 2016).

Besides the potential of their combined study, several studies have pointed out the large inequality between the growth pace of built-up areas and population in Europe. Kasanko et al. (2006) analyzed the difference between built-up and population growth rates from the fifties to the nineties at inter-city level, and built-up grew faster in almost all of the 15 cities studied, presenting different growth patterns according to their geographical location. However, they did not propose a way to quantify this inequality. More recent studies obtained similar conclusions studying samples of 29 (Ribeiro-Barranco et al., 2014) and 188 European cities (Haase et al., 2013). They observed that even when population decreased built-up change was positive. This mainly occurred in Southern cities where a faster built-up growth was experienced in the studied periods, while lower rates were found in Eastern cities. However, these results obtained at broader scale (city level) cannot be assumed at local level (intra-city level). The dynamics of urban areas are not homogeneous and they should be quantified independently to characterize the inherent heterogeneity of urban areas, but interpreted and analyzed together at various scales to obtain more accurate conclusions.

Analysis at multiple scales is essential for different reasons. On the one hand, the analysis at broad scale shows an overall value of the actual trends, while detailed scales are more informative (EEA, 2016). On the other hand, policies are applied at national, regional and local levels causing different growth trends (DG REGIO, 2011). Previous studies have reported that the degree of compactness or sprawl of the urban land and its interpretation differs widely depending on the scales employed (Altieri et al., 2014; Hennig et al., 2015). The imbalanced development of population and built-up areas previously detected in European cities may also vary if analyzed at various scales. A concurrent multi-scale analysis of the population and urban growth rates combined with LULC spatio-temporal metrics may help to the characterization of the urban growth process, moreover, the use of several land uses and metrics would be useful for the selection of the most suitable ones to identify growing patterns. In this framework, the main objectives of this study are: to present a methodology based on spatio-temporal metrics that allows to analyze and compare urban growth at inter-city and intra-city levels and to interpret its relation with urban sustainability policies, and to propose a population and urban growing imbalance index, assessing its added value for interpretation of urban growth.

2. **Methods**

2.1 Description of datasets

The study was performed using the Urban Atlas database, which is part of the local component of the Copernicus Land Monitoring Services (EEA, 2010). It provides harmonized, inter-comparable and high-resolution LULC maps from 305 Functional Urban Areas (FUAs) with more than 100,000 inhabitants for the year 2006 (UA2006), and 697 FUAs above 50,000 inhabitants for 2012 (UA2012). The term FUA represents the city and its commuting zone (Poelman and Dijkstra, 2015). The minimum mapping unit is 0.25 ha for urban and 1 ha for rural areas, and the minimum overall accuracy is 85% in urban and 80% in rural areas. Since our purpose was to assess a methodology rather than the in-depth analysis of specific urban areas, a sample testing dataset composed of six FUAs was selected attending to the following criteria: the availability of population data and administrative unit boundary datasets to calculate the metrics, the existence of high LULC change to test temporal indices, and the geographic diversity to cope with different urbanization contexts. As a result, the FUAs selected were Berlin, Paris, Rome, Krakow, Lisbon and Valencia (Figure 1).

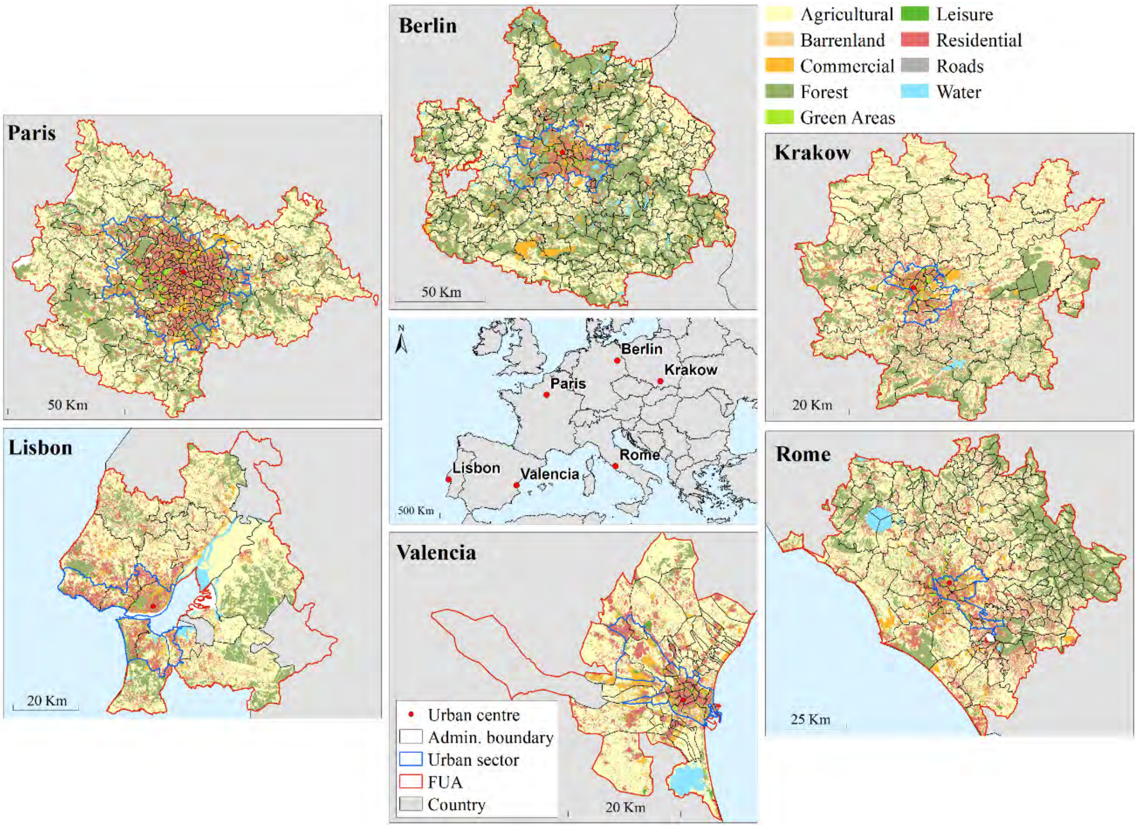

Figure 1. Testing sample areas. Location in Europe (center); UA2012 maps, FUA, urban sector and administrative unit boundaries (municipalities or equivalent local administrative units and city districts), and urban centers.

The UA2006 was initially focused on urban and peri-urban areas represented by twenty classes, seventeen urban and three rural. The UA2012 was extended from three to ten rural classes to allow for a better understanding of the urban fringe. This led us to a legend adaptation before comparing UA2006 and UA2012, harmonizing and simplifying the legend for our urban analysis purpose. We reclassified the legend to nine aggregated land use classes following the criteria of class similarity, thematic coherence and simplification of processing and interpretation tasks. The legend adaptation can be consulted in Appendix A (Table A.1).

Since disparities in urbanization trends within FUAs and cities are expected, according to the EEA (2016) report, more detailed levels were also considered in our analysis. Thus, the FUA level was subdivided into Local Administrative Units (LAU), dividing the territory into municipalities or equivalent units. According to Salvati and De Rosa (2014), this territorial unit is relevant for the purpose of planning and statistical analyses at local level. Cities were also subdivided into districts, which are zones defined according to population criteria (EU, 2016). Both levels are referred henceforth to as administrative units. Administrative unit boundaries were obtained from official institutions, as well as population data from 2006 and 2012 (Appendix A, Table A.2).

Since different growth patterns are expected in urban and peri-urban areas the FUA level was further subdivided into sub-areas or sectors: (i) Urban, and (ii) peri-urban areas, defined as those areas around urban settlements which blend into the rural landscape, where usually low-density urban growth is present (EC, 2012). These sectors were delimited following a dominant land use density criteria in the administrative units of classes forest, agricultural and urban (artificial surfaces, Table A.1). Thus, the urban sector corresponds to those areas where the urban density overpasses agricultural and forest densities, and the peri-urban sector comprises the rest.

2.2 Description and extraction of land use spatio-temporal metrics

The IndiFrag software (Sapena and Ruiz, 2015a, 2015b) was used to compute the spatio-temporal metrics. This software compiles an exhaustive set of indices to quantify urban dynamics from LULC vector maps, allowing to work with different land uses independently and for each territorial unit in the same process, is a suitable tool for comparative urban studies. There are two types of metrics extracted at administrative unit level: those that consider all land uses within the administrative unit (administrative unit metrics), and metrics referred to one land use within an administrative unit (class metrics). A complete list of the computed metrics is included as supplementary material (Appendix A, Table A.3).

In order to analyze and compare LULC changes and to highlight growth patterns in FUAs, administrative units and land use classes, we computed: (i) spatial metrics for two dates (years 2006 and 2012) and their derived changes, and (ii) multi-temporal metrics. As a result, a collection of spatio-temporal metrics was obtained for each administrative unit and class (Figure 2).

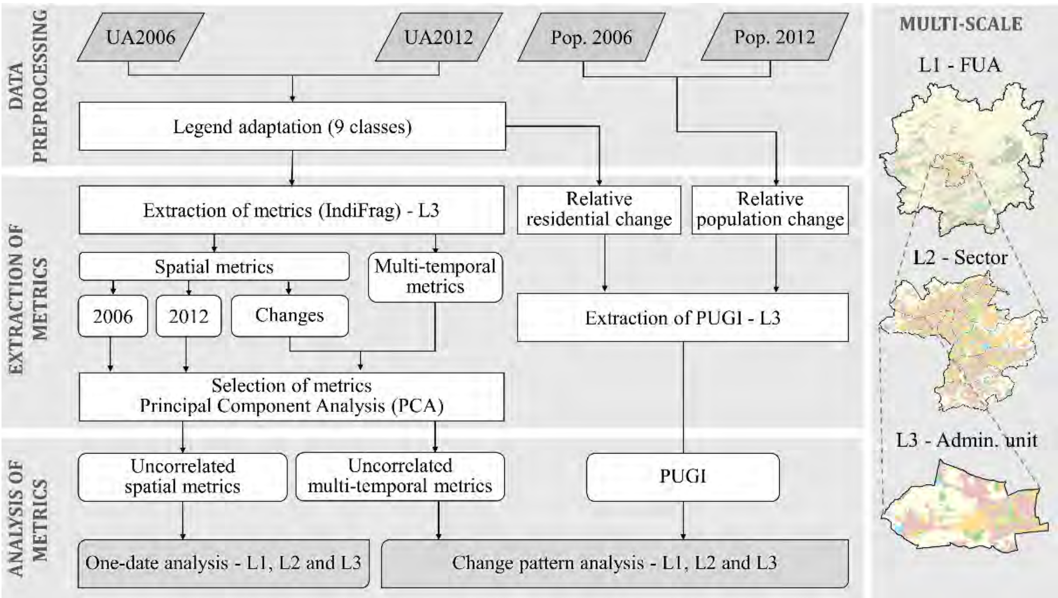

Figure 2. Workflow. Legend adaptation of Urban Atlas; population data and residential areas for 2006 and 2012 and their changes are extracted; spatial metrics for 2006 and 2012, their derived changes, multi-temporal metrics and PUGI index are computed at administrative unit level; uncorrelated metrics are selected using PCA; One-date and change pattern analyses are interpreted at three levels: FUA (L1), sectors (L2) and administrative unit (L3).

Duplicity and redundant information are usually present when working with such a large set of spatial metrics (Cushman et al., 2008), therefore a selection of metrics was applied to avoid redundancies and increase the efficiency of the process. We computed 167 single-date spatial metrics (23 per administrative unit, plus 18 per class, except for roads) and 248 two-date metrics (167 changes from the spatial metrics, plus one per administrative unit and 10 multi-temporal metrics per class) for 833 administrative units. The objective selection of the most relevant metrics was achieved by applying the Principal Component Analysis (PCA) method using R statistical software (R Team Core, 2015). The selection of class metrics was divided into two processes according to the sector. In the urban sector analysis, we focused on the residential class for its particular interest, but also on the most dynamic classes in this sector: commercial and industrial, referred henceforth to as commercial, leisure and green urban areas. The peri-urban sector was focused on forest class and its modification in response to urban growth. Metrics at administrative unit level were included in both sectors.

PCA is a multivariate statistical method allowing for the transformation of a large number of correlated variables into uncorrelated variables (Jolliffe, 2002). Four different PCAs were performed: in urban and peri-urban sectors, and using single-date and two-date metrics. The indices were grouped according to the weights of the first and second components discarding those indices with similar weights in both components and preserving only one per group, ensuring non-correlation between the selected indices. Figure 3 shows the final subsets of indices selected for the analyses.

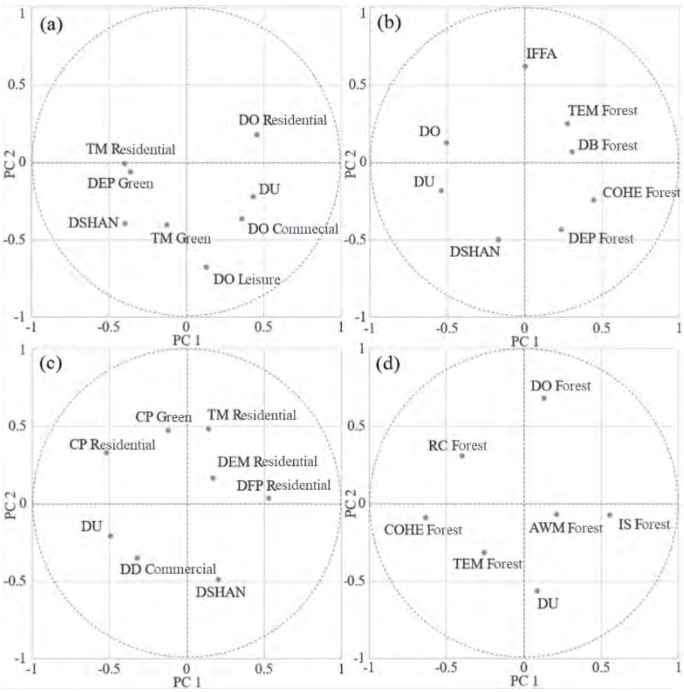

Figure 3. Graphs of spatial distribution of the final uncorrelated metrics selected in the space defined by the first and second principal component weights. Four independent PCAs, where: (a) Single-date metrics for urban and (b) peri-urban sectors, and two-date based metrics for (c) urban and (d) peri-urban sectors. See Table 1 for abbreviation meanings.

Table 1 shows and describes the final set of indices selected for analysis. The results obtained per administrative unit can be found in supplementary material (Appendix A, Table A.4).

Table 1. Description of the spatio-temporal metrics extracted from IndiFrag and selected using PCA. The name, abbreviation, description, units, time: single-date (1t) and two-date (2t), and level of metric: administrative unit or class, are reported. Detailed information on metrics can be consulted in Appendix A (Table A.3).

Name	Definition	Unit	Time	Level
Spatial metrics				
Urban density (DU)	Ratio between urban area and the total admin.unit area.	%	1t	Administrative unit (LAU)
			2t	LAU
Object mean size (TM)	Average of the size of the patches from a class.	ha	1t	Green, residential
			2t	Residential
Edge density (DB)	Sum of lengths of patches from a class divided by its area.	m/m^2	1t	Forest
Area-weighted mean fractal dimension (DFP)	Average of fractal dimension of patches in a class, weighted by patch's area.	None	2t	Residential
Object density (DO)	Number of patches divided by the area of the admin.unit.	n^o/km^2	1t	LAU, commercial, leisure, residential

			2t	Forest
Weighted standard distance (DEP)	Average of distances from patches to the centroid of the class.	km	1t	Green, forest
Euclidean nearest neighbor mean distance (DEM)	Average of the distances between nearest patches of a class	m	2t	Residential
Effective mesh size (TEM)	Size of patches dividing the admin.unit into n areas with the same degree of division.	km^2	1t 2t	Forest Forest
Cohesion (COHE)	Connectedness of the patches from a class. It increases as the class becomes more aggregated.	%	1t 2t	Forest Forest
Splitting index (IS)	Number of patches dividing admin.unit into equal parts, with the same degree of division.	None	2t	Forest
Shannon diversity (DSHAN)	Minus the sum of proportional abundance of each class multiplied by its proportion.	None	1t 2t	LAU LAU
Density-diversity (DD)	Sum of the amount of a class as proportion of the largest class.	None	2t	Commercial
Absolute functional fragmentation index (IFFA)	Ratio between the admin.unit and the sum of every class perimeter.	None	1t	LAU
Multi-temporal metrics				
Change proportion (CP)	Ratio between the change area of a class and the area of the admin.unit.	%	2t	Green, residential
Landscape expansion index (LEI)	Categorizes new patches in: infilling (≥50% adjacent to its class), edge-expansion (0>50%), and outlying (=0%) types by comparing perimeters between new and old patches.	%	2t	Residential, commercial, leisure
Area-weighted mean expansion index (AWM)	Sum across all new patches of the percentages of adjacencies weighted by the area of the new patch.	None	2t	Forest
Change rate (RC)	Annual rate of class change using the compound interest formula.	%	2t	Forest

In order to compare overall results among FUAs, we conducted two sub-analysis. For inter-city analysis and once metrics were calculated for each administrative unit, we computed their mean and coefficient of variation for each FUA and sector (urban and peri-urban) within FUAs. This allows for the comparison of metrics and their homogeneity between different FUAs, which provides useful information when comparing values at broad scales. In addition, we used global growth graphs, concentric circle and sector analysis extracted from IndiFrag software. These graphs are useful to quantify changes and analyze their spatial distribution at different distances and orientations from a central point. We used central points defined by Urban Audit and based on GISCO settlement layer dataset (Data source: GISCO - Eurostat, European Commission).

2.3 Population and urban growing imbalance index (PUGI)

Inequality of urban dynamics regarding the increase of built-up area with respect to population is related to the type of evolution experimented by urban areas over time and it can be especially relevant to monitor the sustainability of urban development (Ribeiro-Barranco et al., 2014). In order to quantify how urban growth outpaces population increase or vice versa and based on the assumption that the distance of the population and urban growth rates -if they are plotted on two axes- to the line of equal growth is related to the imbalance of both rates (Kasanko et al., 2006), we propose a multi-temporal index for a better understanding of the balance in urban growing and population increase in urban dynamic areas: The Population and Urban Growing Imbalance index (PUGI). This index quantifies the inequality between two variables, population and residential land use relative growths extracted at two different dates. We used the area of residential land use, since this is more related and comparable to the actual increase of population, as suggested by Kasanko et al. (2006).

In order to define the index, the increase/decrease of population and the increase of residential area are converted to relative terms as relative change to the first year:

$$\mathrm{rcr} = (\mathrm{r_{t2}} - \mathrm{r_{t1}})/\mathrm{r_{t1}} * 100 \qquad (1)$$

$$\mathrm{rcp} = (\mathrm{p_{t2}} - \mathrm{p_{t1}})/\mathrm{p_{t1}} * 100 \qquad (2)$$

where, $\mathrm{r_{t1}}$ and $\mathrm{r_{t2}}$ represent the areas of residential class, and $\mathrm{p_{t1}}$ and $\mathrm{p_{t2}}$ the population at the beginning and end of the studied period.

Administrative units are plotted in a four-quadrant scatterplot with (1) and (2) in the axes (Figure 4). Similar scatterplots have been previously used to represent urban sprawl by plotting the compactness degree against urban proportion at a single date (Altieri et al., 2014), to analyze the relation between economic development and urban growth (Chen et al., 2013), to compare urbanization and population growth rates (Kasanko et al., 2006), and to classify the development of cities according to their position in the plot (Ribeiro-Barranco et al., 2014). Here, we propose the quantification of the mentioned distance as a measure of the disproportion between rates.

Having the proportion of population change in the abscissas, the proportion of residential increase in the ordinates, and considering the quadrants delineated by the mean values of the two variables, administrative units can be classified into four groups according to the type of change experimented (Ribeiro-Barranco et al., 2014):

– The upper right quadrant indicates a high change (HC) in both variables.
– The lower left quadrant represents a more stable and low change (LC).
– The upper left quadrant corresponds to a high residential growth complemented by a low or negative population change (Partial residential change, PR).
– The lower right quadrant corresponds to a high increase in population followed by a low or null residential growth (Partial population change, PP).

The even growth line represents the same pace of growth rate in both variables, as an ideal or balanced development situation (Figure 4). Administrative units above this line have undergone faster growth of residential areas with respect to population, and in those below the line, the population has exceeded residential growth. The farther the administrative unit is from this line, the larger the difference between the two growth rates. This magnitude is represented by the PUGI index, shown in equation (3), defined as the minimum distance between the location in this bi-variate space and the even growth line. It is computed as the Euclidean distance from a point to a line and measured along a perpendicular line to the even growth line (Figure 4). The sign of the index represents whether the administrative unit is located above or below the line. Thus, a negative value means that the point is below, and the population growth is higher than residential increase. A positive value indicates that the residential area grows faster than population. The administrative unit coordinates are: relative change of population (rcp as x-coordinate) and relative change of residential (rcr as y-coordinate). Considering that the equation of an even growth line is an identity function, and knowing the formula of the Euclidean distance from a point to a line, the PUGI index is obtained as:

$$\mathrm{PUGI} = (\mathrm{rcr} - \mathrm{rcp})/\sqrt{2} \qquad (3)$$

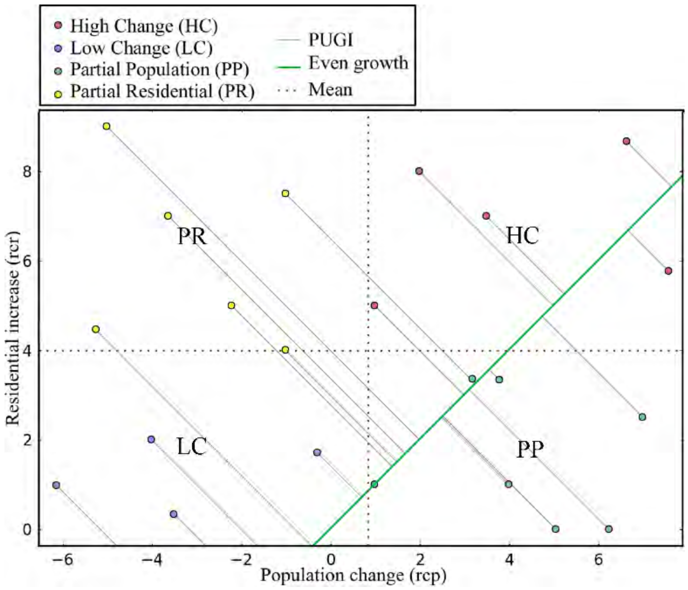

Figure 4. Example of four-quadrant scatterplot. Calculation of the minimum distance from a point to the even growth line (PUGI) and classification of administrative units according to the quadrant delineated by means: high change (HC), low change (LC), partial population (PP), and partial residential (PR).

3. Results

The results of metrics computed in 2012 and from 2006 to 2012 are interpreted at three scales (i.e. FUA, sector and administrative unit). First, we analyze them at FUA and sector levels, then we focus on each FUA at administrative unit level. All metric values can be consulted in Appendix A (Table A.4).

3.1 Analysis at inter-city level

Attending to the spatial metrics from 2012 at FUA level, Paris and Valencia present the highest values of mean Urban density (DU) and the lowest coefficients of variation (CV), showing a compact and homogeneous spatial distribution of built-up areas (Table 2). By contrast, Berlin and Rome present lower mean values and the highest CV, showing a more heterogeneous distribution of urban density than the rest of the FUAs. However, focusing at sector level, the DU in the urban sector is consistently more uniform than in the peri-urban, which presents a higher CV and, as unlike at FUA level, Valencia doubles the density of Paris in the peri-urban sector and has lower CV, while in the urban sectors the values are quite similar.

Analyzing the mean values of Shannon diversity (DSHAN) at FUA level, Lisbon and Paris are significantly more diverse than the rest of the FUAs and present an even distribution (Table 2), while Rome presents low mean DSHAN and CV values. In contrast, when analyzed at sector level, Rome is not the least diverse FUA. Instead, Valencia presents less diversity in both sectors, having an intermediate CV. Berlin and Krakow have similar responses in both sectors.

Class metrics show that Object density of commercial ($DO_{Commercial}$) is variable among FUAs. For instance, Valencia and Paris present high mean values and they are significantly denser than Berlin, Krakow and Rome. However, in the urban sector the differences and CV are much lower, showing uniformity in the distribution of commercial use, especially in Lisbon. Object mean size of residential ($TM_{Residential}$) in urban sectors shows significant differences in buildings size between Berlin and Valencia. Another example of discrepancies among FUAs is the mean values of the effective mesh size index of forest (TEM_{Forest}) in the peri-urban sector, with lower fragmentation values of forest in Berlin and Rome (larger patches and less fragmented) compared to Paris and Krakow, that present more fragmentation (Table 2).

Table 2. Examples of mean values and coefficients of variation (in parentheses) of some spatial metrics for 2012 at FUA and sector levels (urban and peri-urban).

	Urban density			**Shannon diversity**			**Object density of commercial**		**Object mean size of residential**	**Effective mesh size of forest**
	DU			DSHAN			$DO_{Commercial}$		$TM_{Residential}$	TEM_{Forest}
	FUA	Urban	Peri-urban	FUA	Urban	Peri-urban	FUA	Urban	Urban	Peri-urban
Berlin	0.16 (1.23)	0.67 (0.29)	0.1 (0.82)	0.98 (0.3)	1.43 (0.18)	0.93 (0.27)	1.12 (1.26)	4.38 (0.56)	2.13 (0.14)	1.51 (1.11)
Krakow	0.31 (0.92)	0.77 (0.23)	0.17 (0.53)	1.03 (0.34)	1.47 (0.1)	0.9 (0.32)	2.63 (1.29)	7.94 (0.43)	1.64 (0.16)	0.39 (1.83)
Lisbon	0.36 (0.69)	0.63 (0.16)	0.18 (0.5)	1.2 (0.24)	1.48 (0.11)	1.02 (0.17)	3.44 (0.64)	5.7 (0.2)	1 (0.12)	0.82 (1.94)
Paris	0.71 (0.44)	0.84 (0.22)	0.22 (0.7)	1.22 (0.26)	1.25 (0.26)	1.14 (0.23)	7.28 (0.68)	8.78 (0.51)	1.26 (0.29)	0.53 (1.2)
Rome	0.19 (0.94)	0.75 (0.27)	0.16 (0.79)	0.96 (0.25)	1.32 (0.09)	0.94 (0.24)	1.47 (1.38)	7.99 (0.55)	1.25 (0.31)	1.73 (1.67)
Valencia	0.56 (0.51)	0.82 (0.2)	0.39 (0.53)	1.03 (0.28)	1.25 (0.21)	0.89 (0.24)	10 (1.09)	10.7 (0.49)	0.64 (0.26)	0.002 (4.1)

According to the evolution of DU from 2006 to 2012 (Table 3), the FUAs of Krakow, Lisbon and Valencia are very dynamic and homogeneous in terms of built-up surface. Moreover, the population and urban growing imbalance index (PUGI) shows high positive values in Krakow and Lisbon, especially Lisbon in the peri-urban sector and Krakow in the urban sector, evidencing the rapid increase of residential areas with respect to the population growth, probably related with a sprawl development (Table 3). Valencia presents a more balanced development with a negative PUGI value at the FUA level, while the peri-urban sector has a high negative PUGI value, evidencing a densification process in this sector. Berlin and Paris experimented less DU changes but with more spatial variability, accompanied by low and negative PUGI values, meaning that population grew slightly faster than residential land use. Berlin, where the variability of ΔDU is particularly high, increases its CV and has a positive PUGI value in the peri-urban sector. Rome presents an intermediate ΔDU and CV compared to the rest of the FUAs and sectors, with a global negative PUGI that is higher in the peri-urban sector, meaning higher inequality of growth in this sector. Regarding the changes in DSHAN (Table 3), all FUAs increase their diversity except Lisbon. Paris shows a low change in diversity, but this is heterogeneously distributed (high CV value) along the FUA. However, at sector level all, except Lisbon, present two different patterns: Urban areas reduce their diversity, whereas peri-urban interfaces increase it, showing a high variety of land uses with a homogeneous distribution in the peri-urban sectors.

Table 3. Examples of mean values and coefficients of variation (in parentheses) of two spatio-temporal metrics and the PUGI index for the period 2006-2012 at FUA and sector levels (urban and peri-urban).

	Urban density change			**Shannon diversity change**			**Pop. and urban growing imbalance**		
	ΔDU			ΔDSHAN			PUGI		
	FUA	Urban	Peri-urban	FUA	Urban	Peri-urban	FUA	Urban	Peri-urban
Berlin	0.002 (3.34)	0.004 (1.18)	0.002 (3.87)	0.003 (3.71)	-0.008 (1.58)	0.005 (2.5)	-0.982	-1.629	0.993
Krakow	0.01 (0.74)	0.011 (0.95)	0.01 (0.65)	0.013 (1.86)	-0.019 (0.98)	0.022 (0.7)	2.355	3.132	0.678
Lisbon	0.016 (0.72)	0.026 (0.3)	0.009 (0.88)	-0.003 (18.7)	-0.004 (9.33)	-0.002 (30)	3.331	1.050	5.763
Paris	0.003 (1.93)	0.003 (2.33)	0.005 (1.06)	0.001 (38.1)	-0.002 (13.6)	0.01 (1.37)	-1.115	-1.211	-1.883
Rome	0.007 (1.24)	0.005 (1.07)	0.007 (1.25)	0.016 (1.54)	-0.001 (8.28)	0.017 (1.48)	-1.728	0.263	-3.085
Valencia	0.012 (1.47)	0.012 (1.74)	0.013 (1.32)	0.004 (9.57)	-0.013 (2.42)	0.015 (2.86)	-0.697	1.099	-5.083

The global growth graphs of the residential land use close to the city centers present a compact built-up area with permanent land use in some FUAs (Figure 5). In Berlin, Rome, Krakow, Lisbon and Valencia there is a peak in residential land use growth at approximately 16 km away from the urban center, and Rome has a second peak farther from the center. Paris reaches its maxima in the development of residential land use around 35 km away from the center and focused in the West, East and less in the South area. The growth directions in Berlin, Lisbon, Rome and Valencia are different, mainly due to physical and topographic constraints (e.g. the sea or rivers). Furthermore, partial losses of residential areas are present, for example, in Lisbon due to the extension of the road network; or the construction of an airport in Berlin.

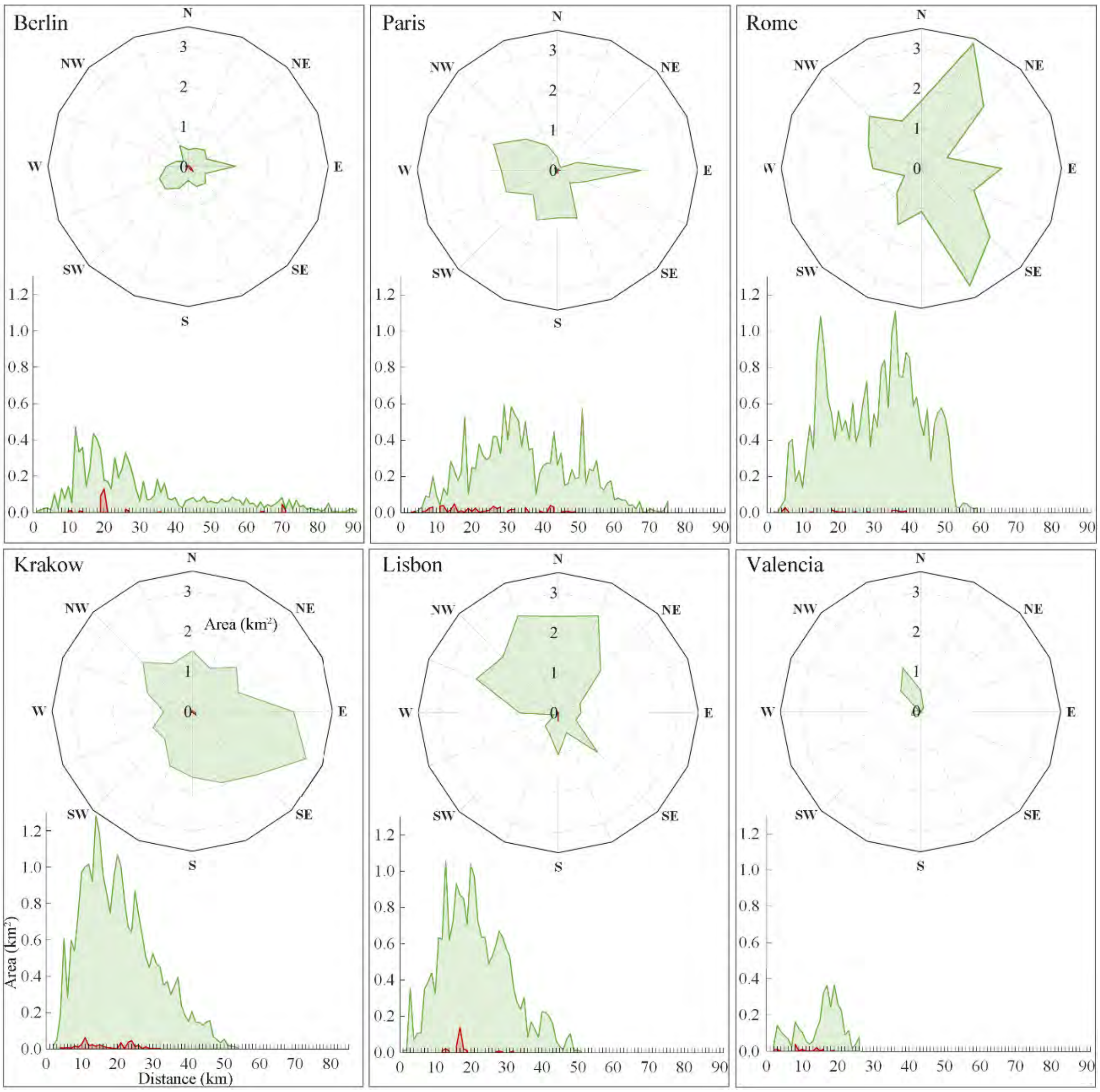

Figure 5. Global growth graphs. (Radar chart above) The sector analysis represents the spatial orientation of residential class changes in the six FUAs, the radius means the change in residential area in square kilometers by orientation, and (area chart below) the concentric circles analysis show the variation of residential area with respect to their central point. Green colour means residential growth, while red shows lost patches.

Analyzing the results of the landscape expansion index (LEI) for residential, commercial and leisure land uses, in general, the expansion process has been mainly edge-expansive and outlying in the six FUAs (Figure 6). Considering the compact growth as a combination of infilling and edge-expansive growths and the dispersed growth as outlying, the urban growth at FUA level in Berlin, Paris, Rome and Krakow tend to be mainly compact, resulting in a more continuous urban cover. However, Lisbon and Valencia have a more disperse growth.

Figure 6 shows the loss of natural and semi-natural vegetation in each FUA as a consequence of urban growth. Despite the double loss of forest in Berlin with respect to Rome, the mean change of the Splitting index in the peri-urban sector in Rome (ΔIS_{Forest}=185, CV=12) is much higher than in the rest of the FUAs (e.g. Berlin, with ΔIS_{Forest}=1, CV=9), showing a stronger trend of forest fragmentation in Rome.

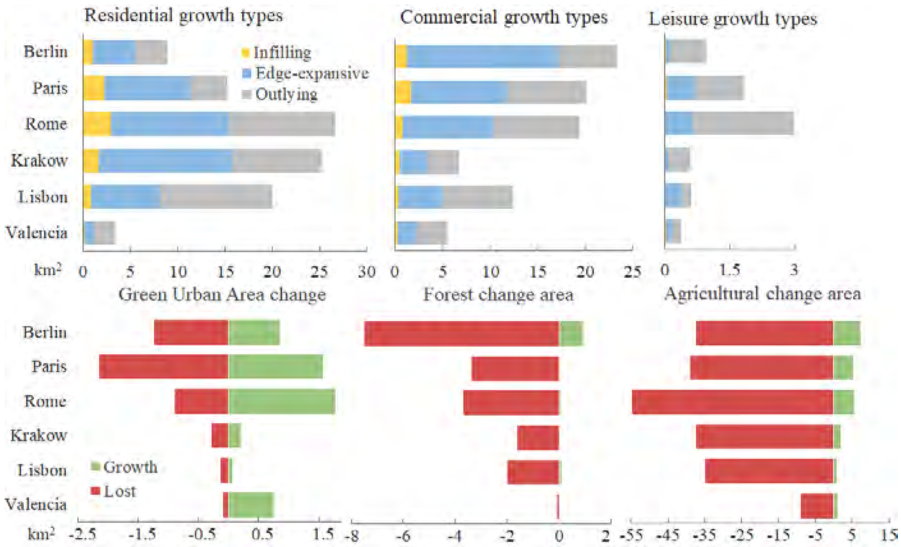

Figure 6. Growth and loss per land use at FUA level. Above, area of growth type in square kilometers (infilling, edge-expansive and outlying) of each FUA by class: residential, commercial and leisure. Below, gain and loss in square kilometers, of each FUA by class: green urban areas, forest and agricultural.

3.2 Analysis at intra-city level

As previously commented in the sector analysis, in 2012 high values of urban density (DU) are mainly located in the urban centers of the FUAs, however, there are variations within FUAs and sectors (Figure 7). For instance, in Berlin, there are some isolated units with high-density values located in the southern half of the FUA. Paris, Rome and Valencia also present scattered administrative units with high DU out of the urban centers in different directions. Krakow and Lisbon show a gradual degradation of DU from the urban sector towards the peri-urban reaching their lowest values in the boundary of the FUA. With regard to Shannon diversity (DSHAN), high and medium values are located not only in the urban sector, but also in the contiguous administrative units, as the mix of land uses is usually higher along the boundary of the urban and peri-urban areas. The lowest values of DSHAN are found in the North-East of several FUAs: Berlin, Rome, Krakow and Valencia.

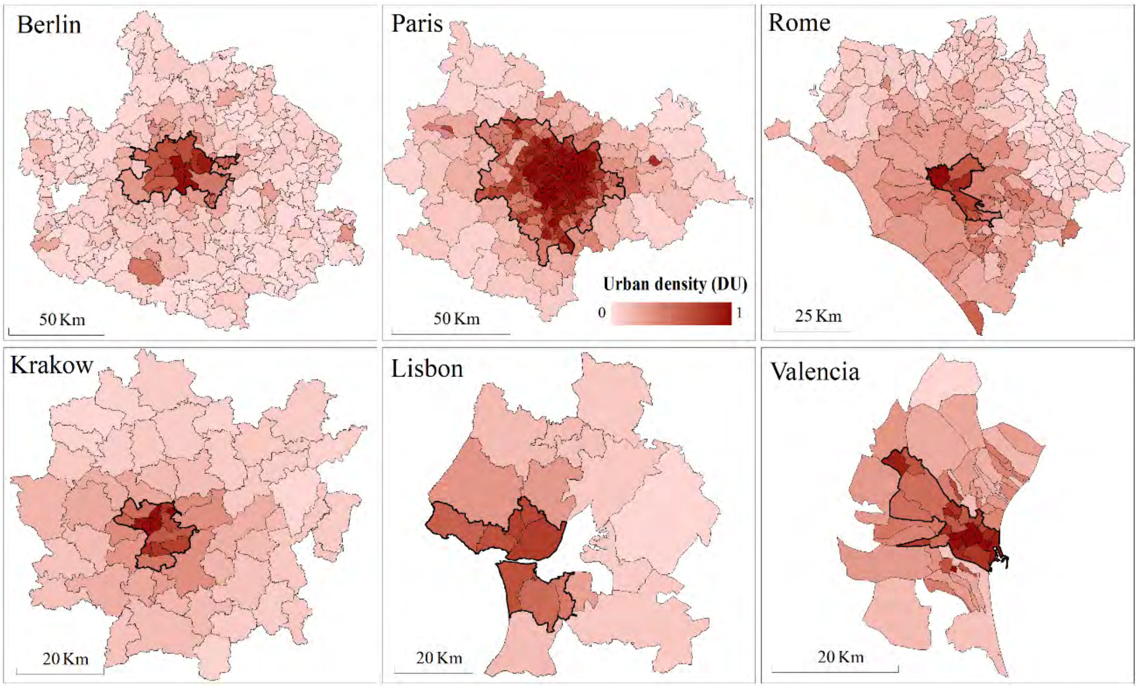

Figure 7. Urban density (DU) in 2012. DU quantitative maps of the administrative units in 2012 for the six FUAs. Bold lines separate urban from peri-urban sectors.

When interpreted together, the object density ($DO_{Residential}$) and object mean size ($TM_{Residential}$) of residential class inform about the quantity and type of the residential patches in each administrative unit. Results show that Berlin, Krakow and Lisbon present more uniform values of $DO_{Residential}$ and $TM_{Residential}$ than the rest of the FUAs. In Paris, Rome and Valencia a more variable response is observed, $DO_{Residential}$ varies along the urban sector, as well as their $TM_{Residential}$. On the other hand, regarding the weighted standard distance of green areas (DEP_{Green}), that shows the aggregation of these elements, different compactness degrees are observed in the urban sector of Berlin, where administrative units differ widely.

The analysis of temporal metrics at administrative unit level revealed significant changes during the analyzed period (2006-2012). In Berlin and Paris, slight increases of DU took place at transition areas between urban and peri-urban sectors. A few administrative units present a slight loss of urban areas, but this effect is mainly due to the transition from barren land (included in artificial land uses in UA legend) to non-urban land uses. Berlin presents also the highest value of ΔDU in the southern part of the urban sector (ΔDU=0.1). Rome and Valencia, in general, increase their artificial surface in specific administrative units, while main changes are located in the peri-urban sector in different directions. DU in Lisbon and Krakow follows a gradient growth pattern from the urban center, reducing its intensity in the periphery, while in the rest of the FUAs presents a more random and scattered distribution (Figure 8).

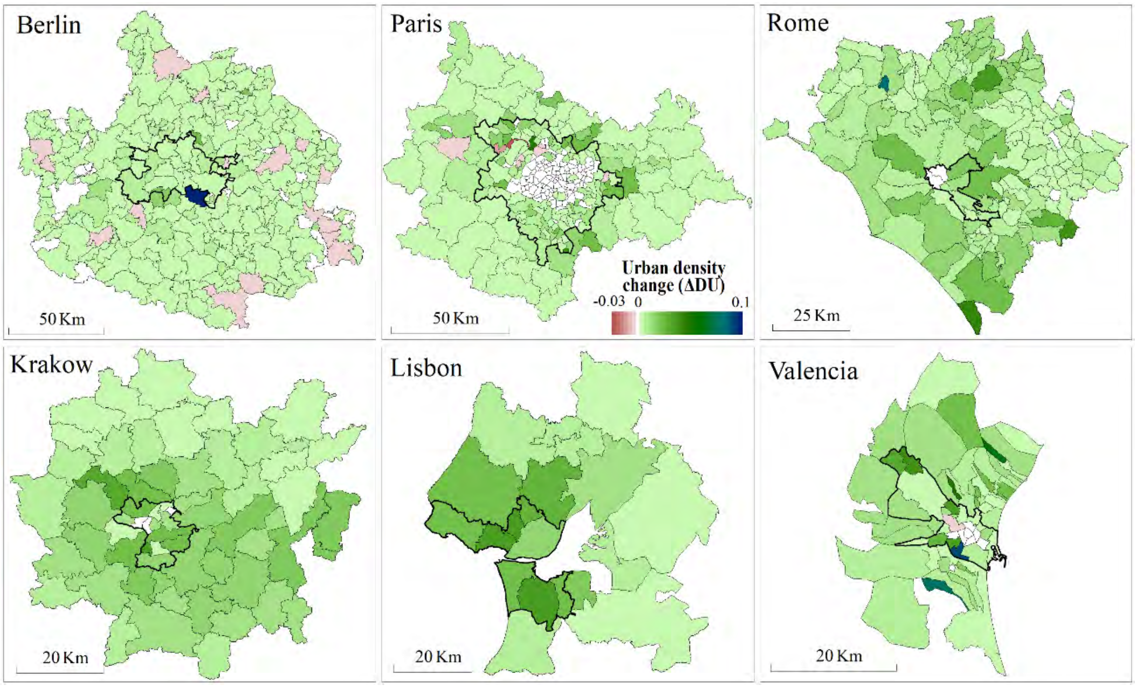

Figure 8. Urban density change (ΔDU). DU change quantitative maps of the administrative units from the six FUAs. Green values mean urban growth in this period, while maroon values show a partial loss of urban areas.

Negative variations of DSHAN are mostly located in the urban sectors of these FUAs, with some exceptions. However, in those areas where there has been an urban growth process, there is an increase of DSHAN and the diversity of land uses. Analyzing the change of per-class indices, we observed a greater occurrence of density-diversity of commercial ($DD_{Commercial}$) in those administrative units along the border between sectors, reaching a maximum in Berlin ($\Delta DD_{Commercial}$= 0.19). The administrative units with an increase of the $DD_{Commercial}$ in Valencia presented a scattered spatial distribution, while in Rome were concentrated along the coast. In addition, the tendency of most FUAs in green areas growth is negative, as in the inter-city analysis, except for Rome, where only one has negative change proportion of green areas (CP_{Green}), and Valencia, with null or positive values (there is a maximum of CP_{Green}=4.35). With respect to residential areas, $TM_{Residential}$ variation shows a tendency to smaller patches, except in some administrative units located on West Rome, South-East Lisbon, and inside and around the urban center of Valencia, where the overall increase of $TM_{Residential}$ implies larger new patches. The residential class in the peri-urban sector of Rome has a compact growth pattern according to the changes of the Euclidean nearest neighbor mean distance of residential class ($DEM_{Residential}$), that reaches the maximum negative change value ($\Delta DEM_{Residential}$ =-51.48 m), meaning that the residential class is more clustered than others, especially in the North. In Krakow, residential patches are more aggregated, mainly in the South-East (maximum negative value of $\Delta DEM_{Residential}$=-9.17m). High positive values of $\Delta DEM_{Residential}$ may evidence that previous residential class is suffering a sprawl process since the mean value of the distances between patches is increasing. Regarding forest class, variations in the TEM_{Forest} show a general reduction of forest patches, decreasing in peri-urban sectors mainly due to the general urban growth dynamics. The most affected FUAs are those with more presence of forest. Berlin, for example, presents a maximum (ΔTEM_{Forest} = -0.9 km^2) but also has a general decrease in the North and South. In Rome, fragmentation increases in the administrative units from the North and North-West (maximum ΔTEM_{Forest} = -0.3 km^2). Paris and Krakow show reduced forest patch sizes in South-West and South-East, respectively.

Administrative units were also classified based on population and residential paces of growth, providing a quantitative measure of their imbalance (PUGI) (values and scatterplots are in Appendix A, Table A.4 and Figure A.1). As an example, administrative units inside and along the border of the urban sector in Berlin are characterized by high change and partial population change, with low and negative PUGI values (Figure 9), accompanied by low and partial residential changes in the limit of the FUA, along with positive PUGI values. There is an exception in the peri-urban sector, where an administrative unit presents a high negative value (PUGI = -30.17), where population grew a 43% and the residential class remained unchanged, meanwhile, spatio-temporal metrics showed a unique slightly positive value of $\Delta DD_{Commercial}$. As opposite, Paris presents low change and partial population changes in the administrative units of the urban sector, with almost no residential increase but a significant population increase. In the peri-urban sector, population increase exceeds residential growth, accompanied mostly by negative $\Delta DEM_{Residential}$, which evidences the densification and transition to more compact administrative units. Rome has a more random distribution of growth classes. Small and balanced changes are located not only in the urban sector but also in the South and East of the peri-urban sector. Partial population change is located at the interface of peri-urban and urban sectors and near the coast, with high negative PUGI values showing a prominent population increase, while spatio-temporal metrics show a slight increase in $DD_{Commercial}$ and CP_{Green}, and a reduction in $DEM_{Residential}$. Partial residential change occurs in the North and North-East, with high and positive PUGI, showing an increase in residential class despite the loss of population in these areas, along with a general decrease of $\Delta DEM_{Residential}$, meaning a more compact distribution. However, there is also an increase of forest fragmentation (maximum ΔIS_{Forest}=12). Lisbon presents a significant residential increase, with positive PUGI and $\Delta DEM_{Residential}$ values in the urban sector and surroundings, evidencing a sprawl trend as previously detected in $LEI_{Residential}$. However, the westernmost administrative unit in the urban sector presents not only negative PUGI and $\Delta DEM_{Residential}$, but also positive $DD_{Commercial}$ and CP_{Green}. Krakow has low change but positive PUGI values in the North, due to the loss of population in these areas. Higher change is focused on the interface of urban and peri-urban sectors, presenting more population increase, while in three administrative units of the urban sector there is a general decrease of $DEM_{Residential}$ and a reduction of CP_{Green}. In general, Valencia has a prominent population increase, particularly in the North. Most of the administrative units in the urban sector suffered low changes (low positive PUGI values, slight or null residential increase accompanied by population loss). However, spatio-temporal metrics in Valencia reveal that negative PUGI values are generally together with a more compact residential growth and the increase of green urban areas (negative $DEM_{Residential}$ and positive CP_{Green}).

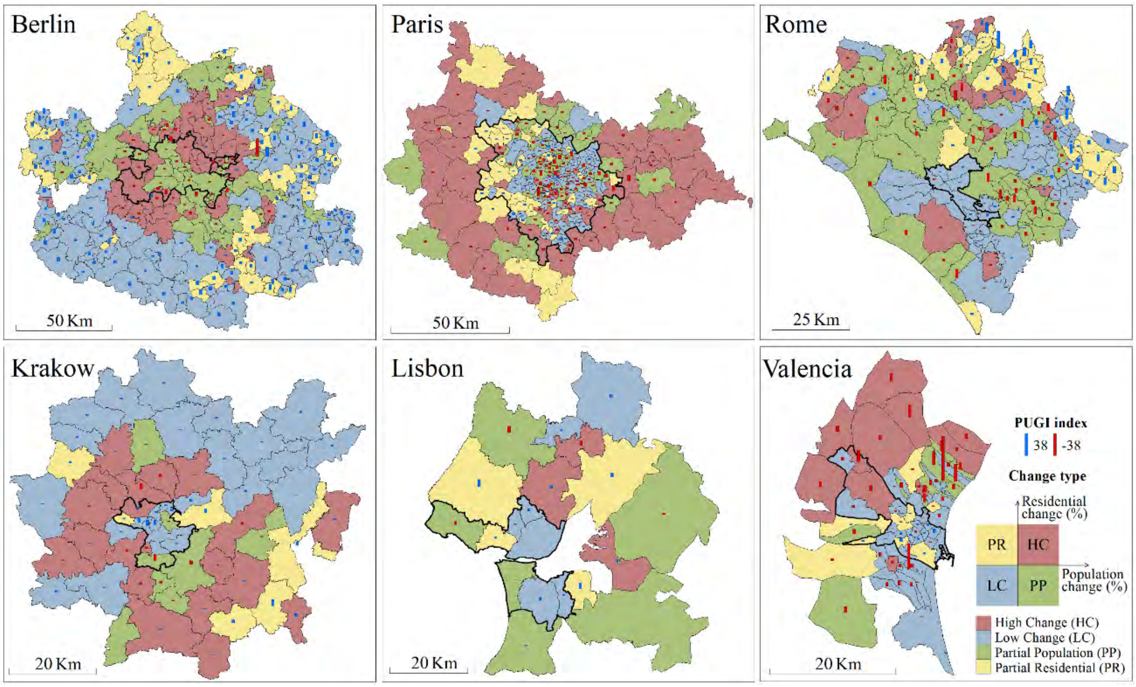

Figure 9. Graphical representation of the administrative units classified in change types and their associated PUGI values. Positive PUGI mean more residential than population increase (blue bar), negative values show the opposite (red bar). The size of the PUGI bar is related to the imbalance between both variables.

4. **Discussion**

The proposed methodology and the metrics analyzed provide useful information of the multi-temporal processes of urban growth between and within FUAs (inter- and intra-city). However, the extrapolation of these tendencies to other urban areas or periods should be taken carefully since only a 6-year interval of a reduced sample of urban areas was considered.

The interpretation of results at FUA level provides an overview of the state of urban areas and their evolution, allowing for the comparison of different FUAs. The analysis of sectors, urban and peri-urban, increases the level of detail and allows for a better differentiation of the type of urban expansion, compact or scattered, and the intra-city analysis complements the spatial distribution of the growth patterns and allows for a local analysis of the evolution of cities. This information is complementary. In some of the examples presented, the analysis provided a uniform response of metrics in a sector, but a variable response at the different administrative units within that sector, reflecting different behavior at different scales of analysis. This is useful for the comparison of FUAs and the analysis of their internal spatial variability. The definition of urban and peri-urban sectors has an evident influence on the results obtained, and this should be properly defined attending to the final aim of each particular study.

The LEI index allows for the classification of the new patches in three growth types, which is useful in order to assign the compactness and sprawl degree of each FUA and land use. Our results are in consonance with a previous report (EEA, 2016) that quantified urban sprawl from 2006 to 2009 in similar urban areas, showing a decrease of the degree of urban sprawl for NUTS-2 (i.e. basic regions for the application of regional policies) of Berlin and Paris, remaining the same in Rome, rising slightly in Krakow and Lisbon regions, and increasing sharply in Valencia. The LEI index might reveal the effect of the compact growth policies supported by the European Communities (1999), encouraging regional authorities to seek the development of sustainable, polycentric, balanced and compact urban systems. When applied at FUA level, this index provides an overview of the growth process, but at the administrative unit level, it allows for the detection of isolated sprawled areas.

On the one hand, in this period only two FUAs presented an increase of green areas in the FUA and urban sector levels. This seems to contradict the current idea of green cities in Europe (DG REGIO, 2011), and the Green Infrastructure Strategy and policies developed by the European Commission (EC, 2016). In this sense, monitoring the change proportion of green areas (CP_{Green}) would allow for the evaluation of the effectiveness of past and present policies. On the other hand, the variation in size of residential patches suggests a change in the typology of new buildings, such as detached houses or large buildings. The Euclidean nearest neighbor mean distance of residential class ($DEM_{Residential}$) represents the restructuring of the class into less or more dispersed, its alteration through the time emphasizes potential areas where residential growth process is being sprawled (a positive variation). This metric may detect, for instance, the variation of distances between residential areas and services. In this sense, the Urban Agenda reports that a compact city model benefits from the reduced distances between services (EC, 2017), and this can be quantified and monitored using this metric.

The classification of administrative units based on population and residential paces of growth, and the values of the PUGI index, provide additional information for the study of growth patterns in the dynamics of urban areas. Similar classification methods have been applied without using population data (Altieri et al., 2014; Chen et al., 2013) and including this variable (Kasanko et al., 2006; Ribeiro-Barranco et al., 2014), but inequality of both variables had not been quantified. The increase in residential class and urban areas do not necessarily have a linear relation with the increase of population at different scales, and the proposed PUGI index quantifies this potential asymmetry. Some authors (EEA, 2011; Haase et al., 2013; Kabisch and Haase, 2013; Ribeiro-Barranco et al., 2014) have stated that, in general, European cities tend to grow faster in built-up than in population when studied at broad scales. However, when this phenomenon is analyzed at local scale, results may vary. According to our results, population relative change outpaced residential relative increase from 2006 to 2012 at FUA level in Berlin, Paris, Rome and Valencia, and higher disparities were found at the intra-city level. In this sense, the PUGI index proposed quantifies the growing imbalance between the progress of the new residential areas and the population, allowing for the identification of differences of growth patterns and such behaviors may reflect differences in local policies or economic models. The PUGI index adds demographic information to the spatial metrics traditionally used in landscape ecology. The high land consumption per inhabitant is considered one of the contributing drivers of urban sprawl (EEA, 2016; Jaeger et al., 2010b; Martinuzzi et al., 2007), thus the use of this metric may assist in the categorization of the urban growth as compact or sprawl, and even estimate the degree of both, being relevant in the context of urban sustainability. Moreover, the combination of this index with changes of spatio-temporal metrics, such as urban density, commercial density-diversity, Euclidean nearest neighbor mean distance of residential, proportion of green areas, and splitting index of forest, allows to identify the type of growth pattern and may help to assess the effect of past or current policies in the development of land uses and the subsequent impact in life quality of urban areas. Furthermore, with detailed information about the urban area and its background, this metric combination may assist in the interpretation of drivers of the urban growth process. For instance, in Valencia, the collapse of the construction and real estate sectors that took place during the studied period had economic consequences. Concurrently, the migration of rural population to coastal and inland municipalities close to urban areas, due to the extension of residential areas as a mean of decongesting the urban core, harmed the territorial and social cohesion (IVIE, 2013). These processes were revealed with local values of PUGI in Valencia (mostly negative in coastal and peri-urban administrative units and low positive in the urban sector), quantifying population movements and a deceleration of housing construction.

The interpretation of the PUGI index is quite intuitive, as the combination of class and magnitude outlines if the change process is balanced at the level of the administrative units. Positive values mean low-dense growth, while negative values reflect the reduction in the land consumption, and hence a densification process. A constraint of this index is the possibility to get a high positive value when there is not relative residential change but population has deeply decreased (since land consumption per inhabitant increases, this case is also a low-dense growth). However, the identification of these cases is straightforward, since the class assigned is usually low change. Another possible limitation is related to the definition of the index. Since the variables involved have relative values its interpretation may lead to confusion, i.e. a slight increase in a small administrative unit will show a great relative change, affecting the mean value used as classification threshold. In this case, different statistics (median, mode, etc.) should be used to avoid possible outliers. The integrated analysis approach based on the use of PUGI, its class and the spatio-temporal metrics is useful to overcome these limitations.

In addition to the potential of the PUGI index itself, analogous indices, obtained by simply modifying its variables, may be applied with different goals and scenarios. For instance, Kabisch and Haase (2013) did not find correlation between population change and the development of new green urban areas, but the application of a modified version of the PUGI index, using the relative population change and the relative green areas change as variables, could provide deeper insight and more specific conclusions at local level. Nowadays, variables related to the dynamics of the landscape (residential areas, green areas, etc.) can be updated using remote sensing techniques (Gil-Yepes et al., 2016).

Finally, some limitations related to the data and methods proposed in this study should be pointed out. The first is related to the scale effect, some spatial metrics vary in response to changes in the spatial extent and scale of the analysis (Šímová and Gdulová, 2012), and hence the conducted metrics might be affected by the minimum mapping unit and the administrative unit size. This constraint could be reduced by including a parameter that specifies the scale, as previously seen in Jaeger et al. (2010a) or by conducting a grid cell based analysis to improve comparability. Another limitation is the quality and thematic accuracy of the dataset, as discussed by Šímová and Gdulová (2012). In our particular test, the overall accuracy of Urban Atlas database was 85% in urban and 80% in rural land uses. However, according to the validation report of the UA2006-2012 change map, the overall accuracy of the transition from artificial to agricultural land uses is 50% in the selected testing sample. Therefore, the decrease of the urban density at local level found in a few administrative units may be related to the poor classification accuracy of these particular classes. Moreover, classification errors are not balanced when working with temporal datasets. For this reason, the interpretation of changes should be done cautiously when working with LULC databases.

5. Conclusions

We explored the application of spatio-temporal metrics and the PUGI index extracted from the Urban Atlas and demographic databases at two dates to compare and analyze urban growth patterns from a testing sample of six FUAs across Europe.

From an objective selection of spatio-temporal metrics quantifying land use variations, we performed a three-fold analysis: an inter-city comparison at FUA level, a sector level analysis between FUAs, and an intra-city analysis at administrative unit level. Discrepancies between patterns observed in the urban and peri-urban sectors were evidenced. Working at administrative unit level presented advantages over the FUA and sector levels since a more specific and spatially explicit identification of urban growth type is feasible. Moreover, it is closer to the boundaries employed by local authorities responsible for spatial planning, and it may be potentially used for monitoring the effect of local and regional policies implemented.

Our results showed that the spatio-temporal metrics are useful for comparison of growth patterns at different scales. Nevertheless, a single metric is not sufficient to properly describe the urban growth process, but the combined analysis of a selection of spatio-temporal metrics and the proposed PUGI index, a qualitative and quantitative metric that relates built-up areas and population dynamics, enables a deeper analysis of urban growth patterns. Its integration into the analysis emphasizes the imbalance between residential land use and population growth rates, providing complementary information related to the per-person land consumption and supporting the characterization of the degree of sprawl in the urbanization process, a relevant issue in the context of urban sustainability. The input data for the PUGI index are affordable and frequently made available by local agencies, and its representation allows for the straightforward interpretation of population and residential dynamics and its balance.

LULC multi-temporal databases allow for more precise urban dynamic studies. Currently, the Urban Atlas dataset has only one period of time available (2006-2012), which is still insufficient for detecting reliable growth trends. Longer and more frequent time-series would allow for more accurate and comprehensive urban dynamic studies. In this sense, Urban Atlas is expected to be updated every six years, progressively increasing possibilities of analysis in the near future.

The present study highlights the suitability of LULC databases for urban growth studies and their potential for analyzing urbanization trends. Future research will be focused on the application of spatio-temporal metrics based on simulated LULC development scenarios, in an attempt to identify and categorize urban sprawl patterns and to preview unsuitable evolution trends.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at (*doi..*)

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