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Assessing the Effect of Spatial Proximity on Urban Growth

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Abstract: Land-Use/Cover Change (LUCC) reacts to demographic pressures, economic trends, or improved transport networks. Urban growth with implications on LUCC patterns can be measured using a diversity of methods. Our study derives from Tobler's first law of geography: 'everything is related to everything else, but near things are more related than distant ones'. We identified and measured the influence of neighbouring distance on urban growth from the edge of existing urban areas. For that, we have developed a method, built using the NetLogo software tool, which we called Land-use chAnge and Neighbouring Distance (LAND). We selected Torres Vedras (Portugal) to conduct our case study due to its increasing urban development in the past few years. The periods of analysis were 1995–2010, 1995–2007, and 2007–2010. The results have shown the influence and the effect of strong spatial correlation between the proximity of existing artificial surfaces and the emergence of new ones. The understanding of the patterns of urban growth is helpful to plan forward land developments. This method can be used to write guidelines for decision makers to monitor urban expansion and define spatial planning priorities.

Keywords: Land-Use/Cover Change; transition matrix; neighbouring distance; urban growth; peri-urban

1. Introduction

Land-Use/Cover Change (LUCC) is the result of a complex system intertwined with interactions of environmental, social and economic factors [1], which involves biota, soil, topography, surface and groundwater, human structures [2], and employment [3].

The driving forces behind LUCC can be classified into economy, demography, transport, and policy. Eiter and Potthoff [4] identified three main causes for LUCC: (a) extrinsic (socioeconomic, technology, recreational, protection legislation); (b) intrinsic indirect forces (transport infrastructure, seasonal farming, vegetation, tourism and outdoor recreation, and nature and landscape protection); and (c) intrinsic direct forces (working force, population, drought, and grazing forces).

Urbanisation is one of the most critical consequences of LUCC at the local level [2,5–8], and has evolved over the years due to social, economic, historical, and cultural factors. As a complex phenomenon, urbanisation has socioeconomic and environmental impacts [9], often evolving in the form of urban sprawl. There are different definitions of urban sprawl; however, as a common definition, urban sprawl occurs in the fringe of large cities, and is defined by its compactness and dispersion. Urban sprawl is also identified as the urban expansion into the suburban areas and is categorised by unplanned [10], uneven growth [11], contiguous suburban growth [12], mixed uses [13], scattered and leapfrog development [14], strip or linear development, poly-nucleated nodal development [15], and both as a state, and a process. [16]. The consequences of urban sprawl can be both negative and positive. On the one hand, it has undesirable impacts on public health and quality of life [17], loss of farmlands [9], increased urban pollution [18], greater dependence on cars [19], or social fragmentation [20]. On the other hand, however, it also has positive impacts on the sense of community between the inhabitants [21], more living space [9], decreasing crime rates [19]—and fragmented urban growth has been perceived as economic expansion [11].

In the past few years, different reviews on urban growth modelling have been made e.g., [22–25]. In the research carried out by Antrop and Van Eetvelde [24], White and Engelen [25], White [26], Batty et al. [27], Batty and Longley [22], Jaeger et al. [16], and Ewing et al. [28], the spatial dimension of urban growth was measured and analysed using different methods, such as fractal analysis and landscape metrics.

Patterns of urban growth can be detected, mapped, and analysed integrating Geographic Information Systems and spatial statistics approaches, such as the percentage of built-up areas [29]; dispersion, which quantifies the spatial distribution of built-up areas [30]; urban permeation, which measures how far the built-up areas have extended through a given territory [30]; or the proximity index, which quantifies the degree of isolation and fragmentation of the urban areas [14,31].

Analysing and understanding how urban growth has been developing is a fundamental principle for spatial planning. New tools are needed to monitor urban sprawl, measuring the landscape characteristics and distribution, and the extent of urban sprawl. Decision makers need to measure urban expansion to integrate it in the planning processes by using updated, accurate data, and reduce time activities.

The purpose and innovation of this study is to create a method to measure, analyse, and identify the existence of spatial dependence and influence of neighbouring distance from the edge of existing urban areas for the emergence of new urban areas (at each 10 m). In the case study we conducted, we assessed whether the urban growth trend is more or less discontinuous, and verified the greater or smaller urban containment. The periods of analysis are between 1995–2010 (year 0–year 1), 1995–2007, and 2007–2010. For this analysis, we created a method in Netlogo, which we called Land-use chAnge and Neighbouring Distance—LAND. The ultimate goal of the LAND method is to provide guidelines for decision makers. The results from this study demonstrated the high influence (spatial dependence) of existing artificial surfaces on the emergence of new ones.

This paper is organised as follows: first, we make a literature review. Then, we describe the study area and the data acquisition process, as well as the purpose of the LAND method. Finally, we discuss the outcomes obtained and we outline future work that can be done.

2. Materials and Methods

2.1. Study Area

Torres Vedras municipalityis located roughly 50 km north of Lisbon (Figure 1), and it was selected as the study area to conduct this research. The population density in 2011 was 195 inhabitants per sq. km [32]. Torres Vedras is mainly covered by agricultural and forest land, and has been driven by urban pressure over the past two decades. Between 1995 and 2010, artificial surfaces increased by 41% [33].

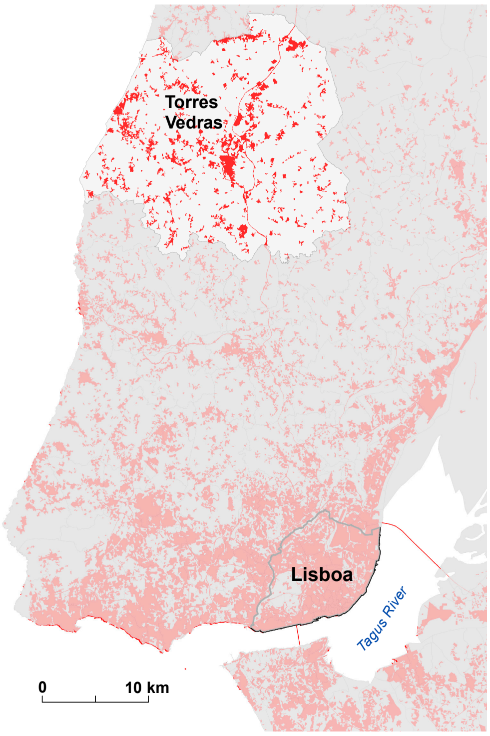


Figure 1. Location of Torres Vedras (Portugal).

2.2. Land Use Data

Land cover maps for 1995, 2007, and 2010 at the 1:25,000 scale (the most updated and detailed data for the study area) were selected for this research. This data was validated by Direção-Geral do Território [33]. We regrouped these land cover maps into 7 classes: 1—artificial surfaces; 2—non-irrigated arable land; 3—permanently irrigated land; 4—permanent crops; 5—pastures; 6—heterogeneous agricultural land; and 7—forest. The artificial land use class was the focus of this study and it comprises the urban fabric, industrial, commercial and transport units, mines, dumps and construction sites, sport and leisure facilities, and green urban areas when contiguous to an urban area.

This data is in the ETRS89/PT–TM06 projection system and it was converted into raster format (*ASCII*) with a 10 m resolution. The choice of the spatial resolution resulted from a trade-off between data costs, computer processing time, reliability, feasibility, and ecological fallacy. A small 10 m spatial resolution has the advantage of providing detailed land-use data, and facilitates the identification of land use relationships [34,35].

2.3. LAND Method

2.3.1. Definition of the Method

LAND—a method used to measure sprawl between existing land use classes and new ones of the same category—was written in the Logo programming language and developed in NetLogo (Figure 2). NetLogo is one of the most widely used software tools to model the environment [36].

The LAND method allows us to:

(1) quantify LUCC in area and % from year 0 to year 1 at different distances, ranging from 1 patch (10 m) to 50 patches (500 m), and from the land use class x to the land use class y;
(2) identify the distribution of class frequencies for the neighbourhood of remaining (not selected) land use classes; and

(3) detect stable land use classes between two periods (Figures 2 and 3).

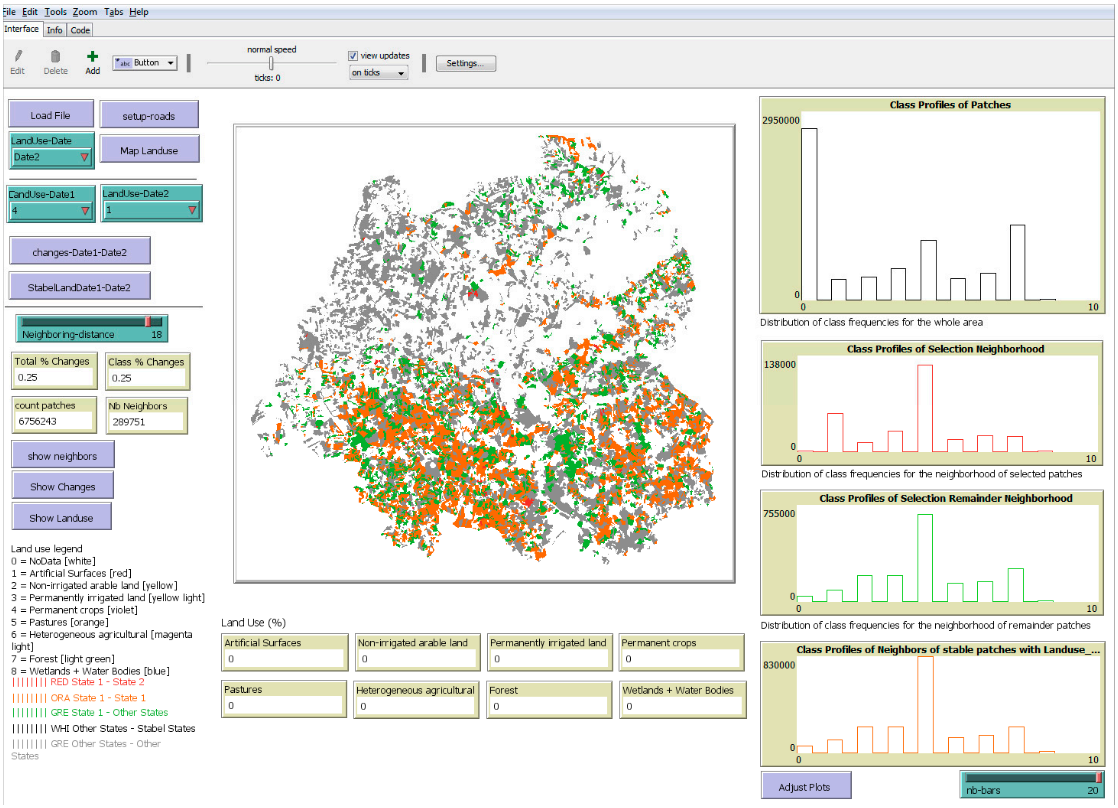


Figure 2. Land-use chAnge and Neighbouring Distance (LAND) method interface.

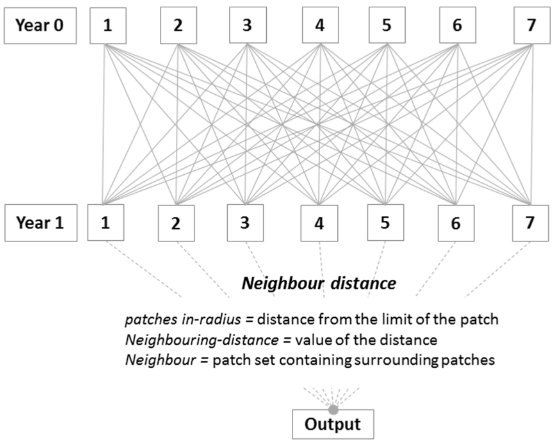
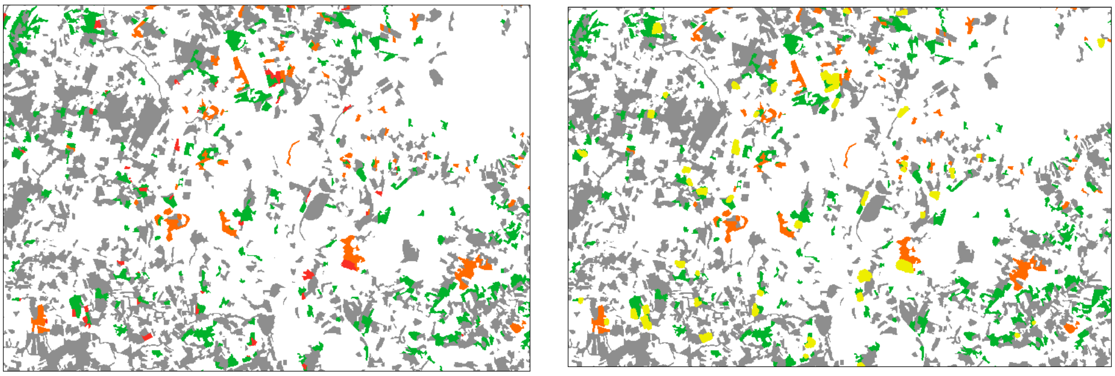


Figure 3. LAND method mechanism: 1. define the land use class in year 0 and in the year 1; 2. define the neighbour distance.

In each running process (the step from state 1 to state 2), the LUCC output can be visualised graphically in the interface, and in a .txt table. Figure 4 illustrates an extract of how the LAND method is represented after each running process, where we can visualise the state of each cell in different colours.



(**a**) (**b**)

Figure 4. (**a**) Extract of the LAND method running. Example Figure (**a**): LUCC between pastures-1995 (year 0-state 1) and artificial surfaces–2010 (year 1-state 2). Each colour represents one state. Red means: changed state 1 to state 2; orange: maintained state 1 as state 1; green: changed state 1 to other states; white: other states that have maintained their class and become stable states; and grey means: changed other states to other states; (**b**) shows the neighbours (50 m distance) in LUCC between pastures-1995 (state 1) and artificial surfaces–2010 (state 2).

2.3.2. The LAND Method Applied to Our Study

In our research, we measured the influence of neighbouring distance for new artificial surfaces in year 1 counted from the edge of artificial surfaces that had existed in year 0; we then verified in which non-artificial areas of year 0 (non–irrigated arable land, permanently irrigated land, permanent crops, pastures, heterogeneous agricultural land, and forest) these changes had occurred. Neighbouring distance was estimated for each 10 m, and up to 200 m.

To analyse our object of study, firstly in year 0, we identified the land use classes that changed to artificial surfaces in year 1. This land use classes were reclassified as follows: class 2, non-irrigated arable land to 2b; class 3, permanently irrigated land to 3b; class 4, permanent crops to 4b; class 5, pastures to 5b; class 6, heterogeneous agricultural land to 6b; and class 7, forest to 7b (the wetlands and water bodies land use class was not included due to the inexistence of LUCC from this land use class to artificial surfaces in the periods analysed).

Secondly, after this land use reclassification, we used this land use data as year 1. Since we already knew that these non-artificial land use classes were artificial surfaces in year 1, we could identify and quantify the artificial surfaces that emerged at each 10 m from the edge of the artificial land use classes that had existed in year 0.

3. Results

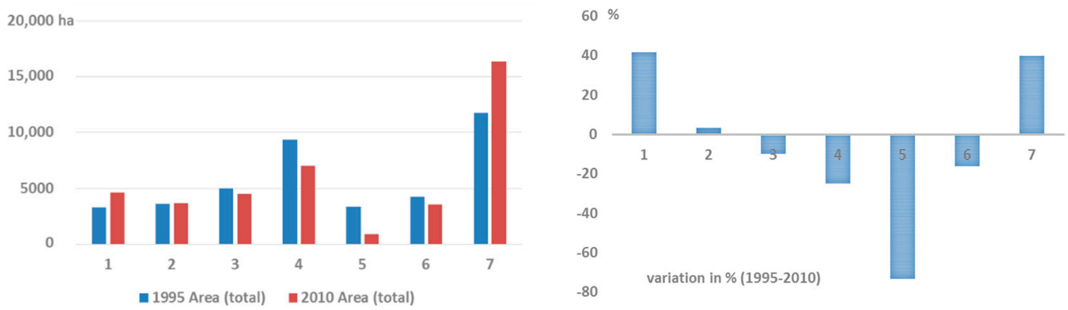
3.1. Transition Matrix LUCC Analysis (1995–2007–2010)

Land cover transitions express a change of state. A state changes if a land use class is in state 1 at a given time and later in state 2 at another given time. The transition matrix process was employed to track the land use past of each raster pixel in the 1995–2010 period (Figure 5) [33].

The total area of the studied area is 407 sq. km. In 2010, artificial surfaces covered 11.44%; non-irrigated arable land, 9.09%; permanently irrigated land, 11%; permanent crops, 17.2%; pastures, 2.17%; heterogeneous agricultural land, 8.7%; 40.25% of forest; and wetlands and water bodies, 0.15% (Figure 5).

The transition analysis between 1995 and 2010 demonstrates that LUCC were significantly higher in some land use classes. 52.5 ha of forest area in 1995 had been converted into artificial surfaces by 2010. During the same period, 214.9 ha of pastures had been converted into forest. Moreover, between

1995 and 2010, 92 ha that had been permanent crops in 1995 had been converted into non-irrigated arable land in that period (Figure 6).



(**a**) (**b**)

Figure 5. (**a**) Total area (in hectares) by land use class in 1995 and 2010; (**b**) variation (in %) by land use class between 1995 and 2010. Land use classes: 1—artificial surfaces; 2—non-irrigated arable land; 3—permanently irrigated land; 4—permanent crops; 5—pastures; 6—heterogeneous agricultural land; and 7—forest.

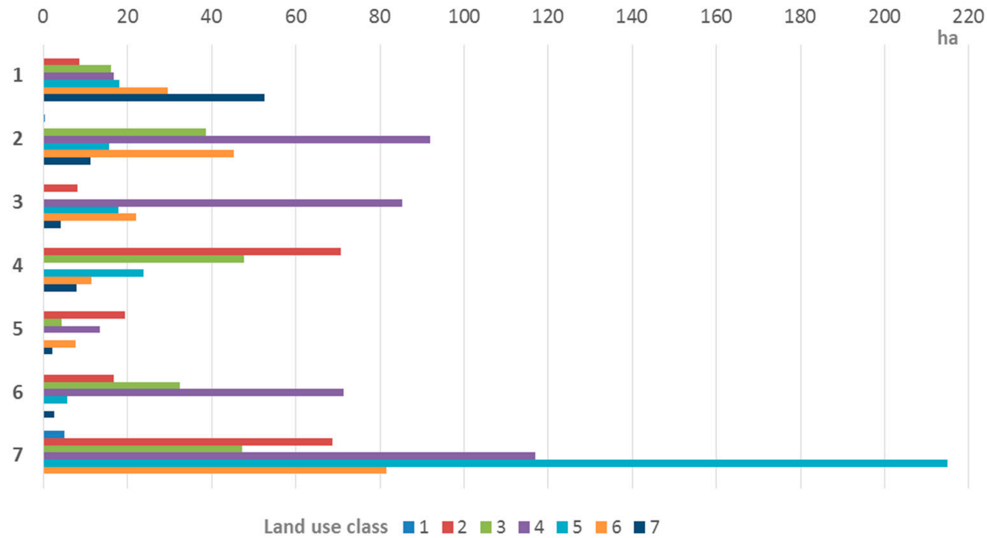


Figure 6. Land use transitions between 1995 and 2010 (by each land use class–in ha). Land use classes: 1—artificial surfaces; 2—non-irrigated arable land; 3—permanently irrigated land; 4—permanent crops; 5—pastures; 6—heterogeneous agricultural land; and 7—forest.

This land use trends indicate that human activities had a significant toll on the land use types in this period, with negative impacts for the environment [37,38].

3.2. Neighbouring Distance and Spatial Autocorrelation

LUCC is not spatially independent [39,40]. In our analysis, the neighbourhood–local state was not ignored. We measured the influence of existing artificial surfaces in year 0, connecting the neighbouring distance with the emergence of new artificial surfaces in year 1. Figure 7 illustrates the percentage of land use classes that changed from non-artificial surfaces to artificial surfaces at each 10 m interval (from 1995 to 2010).

As shown in Figure 8, we have demonstrated the spatial continuity that links the new urban areas with the existing ones and an increasing trend towards the compactness of built up areas (patches) with the 10 m section zone. Every 10 m, from 0 to 200 m, the proportion of new artificial surfaces always decreased with distance. We had to estimate the new built up areas every 10 m up to 500 m from the existing ones to identify a 'return point' (albeit a slight one), i.e., an area (in distance) where the new built up areas were more than in the previous ones. This was verified at 460 m in the stabilisation phase (Figure 8).

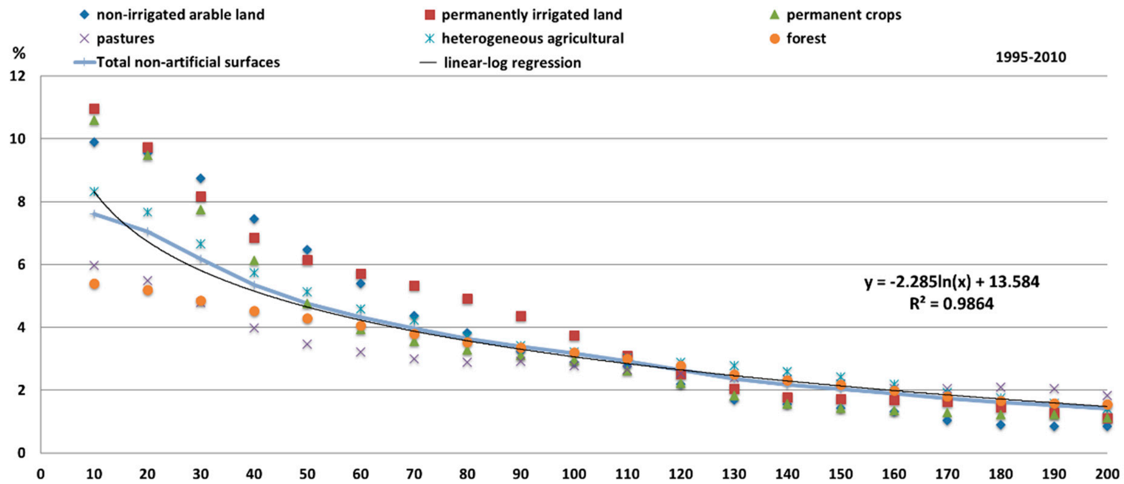


Figure 7. LUCC (in %) from non-artificial surfaces to artificial surfaces, and linear-log regression in the areas of urban growth from 1995 to 2010 according to distance from existing built-up areas.

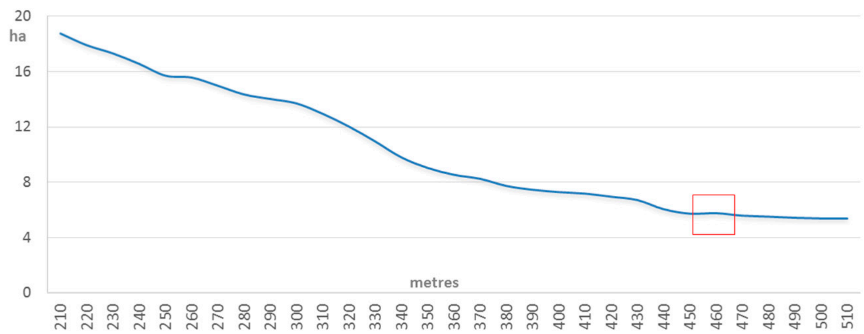


Figure 8. New artificial surfaces (2010) (in ha) every 10 m, from 210 m to 510 m, in relation to the edge of existing artificial surfaces in 1995.

The spatial relationships between the new artificial surfaces in year 1 (2010), from the distance in metres of artificial surfaces in year 0 (1995) every 10 m (from 10 m to 200 m) can be seen in Figure 8. The relationships were tested statistically through the estimation of a linear-log regression, where an r^2 of 0.9864 (strong correlation) was obtained between the distance and the new artificial surfaces. The spatial autocorrelation analysis using the Moran's–Rook's Case (4 × 4 and 8 × 8 neighbourhood) [41] showed values of 0.9612 and 0.9543, respectively, which indicates that the emergence of new artificial surfaces has a strong spatial correlation with the existing artificial surfaces in 1995.

The analysis of cumulated values has shown that 7.6% of the total new artificial surfaces in year 1 (2010) emerged 10 m from the artificial surfaces that had already existed in year 0 (1995); 14.7% at 20 m; 30.9% at 50 m; and 49.4% in the first 100 m. Additionally, 20.2% of the total new artificial surfaces emerged between 100 m and 200 m of existing artificial surfaces, while 30.4% emerged more than 200 m from existing artificial surfaces.

Figure 8 also shows the percentage of all non–artificial land use classes that changed to artificial surfaces from 1995 to 2010. Permanently irrigated land lost the highest percentage 200 m from the edge of urban areas (84%). Comparatively, pastures and forest lost less land, respectively 60% and 64%.

However, when we looked closely at the total area lost, forest had the highest numbers. Conversely, non–irrigated arable land lost less land, followed by permanently irrigated land (Figure 8).

To analyse the evolution of non–artificial surfaces to artificial surfaces, we compared the situation in the three time periods: 1995–2010, 1995–2007, and 2007–2010. Figure 9 shows that the urban growth trend is similar, with the highest growth rate occurring closer to existing urban areas.

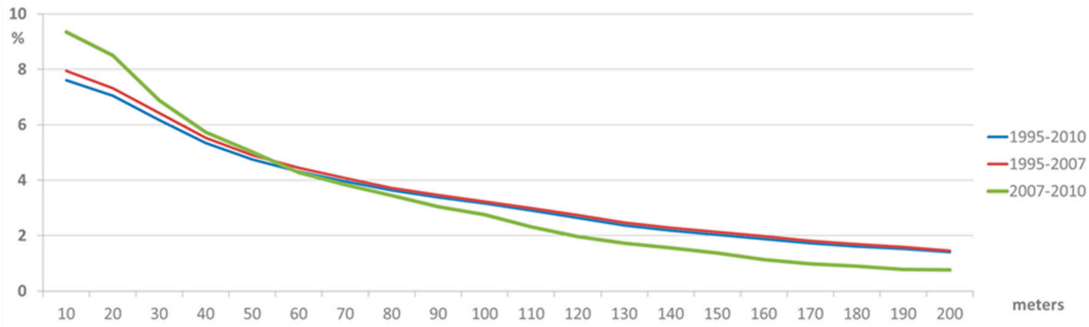


Figure 9. LUCC (in %) of non-artificial surfaces to artificial surfaces in urban growth areas in the three time periods: 1995–2010, 1995–2007, and 2007–2010 (from the edge of artificial surfaces in 1995 for the 1995–2010 and 1995–2007 periods, and from the edge of artificial surfaces in 2007 for the 2007–2010 period).

In the 1995–2007 time period, the highest percentage of new urban areas was found less than 200 m from existing ones, when compared to the 2007–2010 period (72.2% and 64.4%, respectively). However, when we analysed new artificial areas closer to the edge of artificial surfaces that had already existed in year 0, we saw greater urban contiguity in the 2007–2010 period. In the 1995–2007 time period, 32% of new urban areas emerged in the first 50 m of existing urban areas, and 35% in the 2007–2010 period (Figure 10).

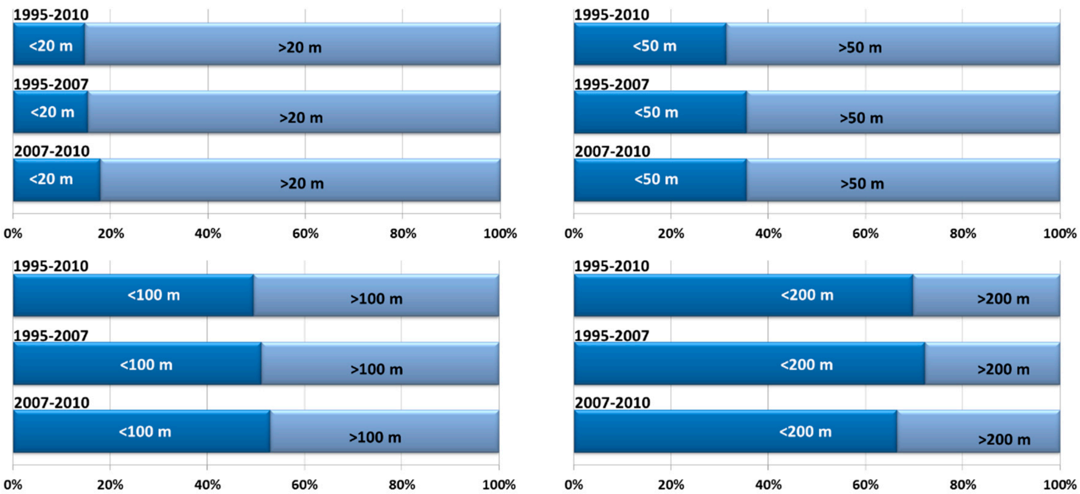


Figure 10. Total weight (%) of new artificial surfaces from the edge of existing urban areas less and more than 20 m, 50 m, 100 m, and 200 m, for the three time periods: 1995–2010, 1995–2007, and 2007–2010. Land use class used: 1—artificial surfaces.

Figure 11 illustrates the percentage of land use classes that changed from forest land to artificial surfaces. Permanently irrigated land lost more ha in the area that was less than 200 m from existing artificial surfaces. Permanent crops lost 26.3% in 2007–2010 in the areas that were less than 200 m. However, in the 1995–2010 period, permanent crops lost 73.7%.

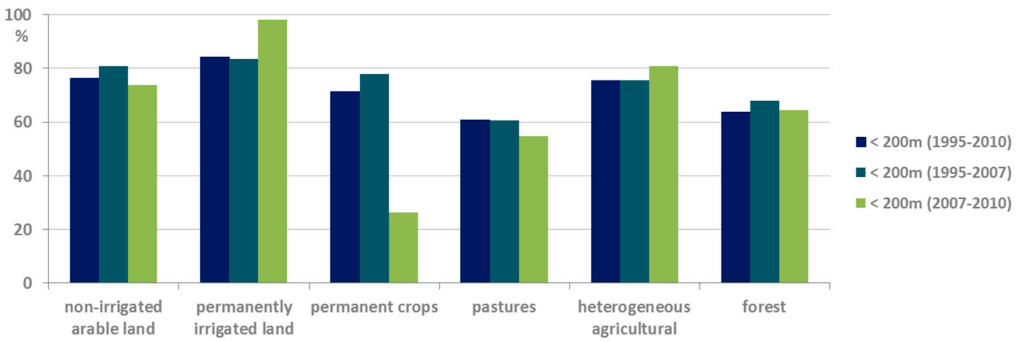


Figure 11. LUCC (in %) by each non-artificial land use class less than 200 m from existing artificial surfaces (when compared to the total loss of each land use class) that changed to artificial surfaces in the three time periods: 1995–2010, 1995–2007, and 2007–2010.

3.3. Proximity Index for Artificial Surfaces in 1995, 2007, and 2010

To compare the results obtained using the LAND method, we estimated the proximity index. This landscape metric is one of the most widely used metrics to calculate the distance between patches [11,31,42–44]. Both analyses allow us to measure urban dynamics depending on the distance to urban areas. The proximity index was established by Gustafson [44], and is defined as the size and proximity of all patches. In our analysis, the proximity index corresponds to the sum of artificial surfaces (sq. m) divided by the nearest edge-to-edge squared distance (sq. m) between artificial surfaces and the artificial surface of all the single artificial surfaces of the equivalent land use class whose edges are within a specified distance (m) of the land use class. The proximity index is 0 if the artificial surface has no neighbours, and it increases as the neighbourhood is increasingly occupied by artificial surfaces, becoming less fragmented areas. The proximity index is expressed by the following Formula (1):

$$PX_i \sum \frac{S_k}{n_k} \tag{1}$$

where S_k is equal to the area (sq m) of k patch, n_k is equal to the nearest-neighbour distance between focal patch and the nearest cell of the same type of patch. We used the statistical package FRAGSTATS to estimate this index, using as input data the artificial surfaces that existed in 1995, 2007, and 2010 (Figure 12).

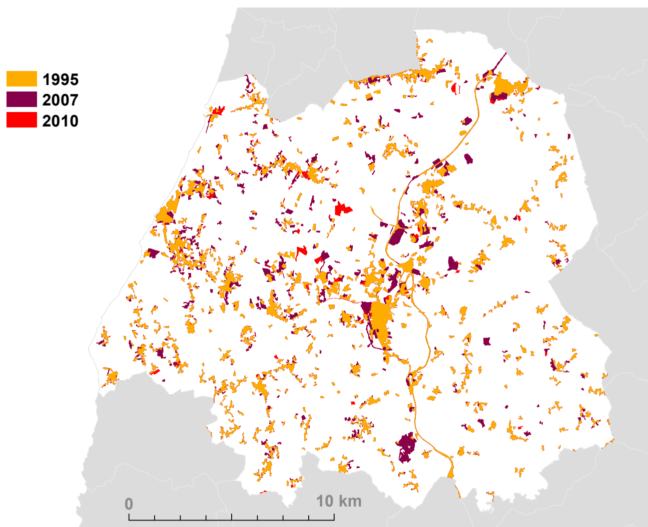


Figure 12. Artificial surfaces in 1995, 2007, and 2010 in Torres Vedras municipality (data source: [33]).

Artificial surfaces in 1995 had 530 patches; in 2007, 805; and in 2010, 826 patches. The mean proximity obtained at landscape level was 95.42 for 1995, 113.21 for 2007, and 114.16 for 2010. These results have shown an increase of the proximity index between 1995 and 2010, which means that artificial surfaces have become less fragmented and discontinued [44] in the study area.

3.4. Impacts on Non-Artificial Land Use/Cover

Impacts on LUCC and their implications have been studied by a series of authors in the past few years [45–48]. Figure 13 shows the social and land use regulation impacts of urban growth. The National Agricultural Reserve (RAN)—defined as the best soils for agriculture and imposing a constraint to urban development [5]—lost a total of 180 ha: 123 ha less than 20 m from existing artificial surfaces and 57 ha more than 200 m from the edge of existing areas (this corresponds to 1.21% of the total RAN area defined in the Master Plan of Torres Vedras). Moreover, we have identified the transgressions to non aedificandi areas, i.e., areas where construction is forbidden. These non aedificandi areas include the National Ecological Reserve (REN), groundwater, flood areas, railway station, quarries, spring water, cultural heritage, coastal planning, and the Natura 2000 network. We established that a total of 207 ha were consumed by urban development between 1995 and 2010.

Developable areas defined as future urban development in the Master Plan were classified as urban areas between 1995 and 2010, 168 ha less than 200 m, and 56 ha more than 200 m from the edge of existing urban areas (which corresponds to 8.5% of the total developable areas as defined in the Master Plan) (Figure 13).

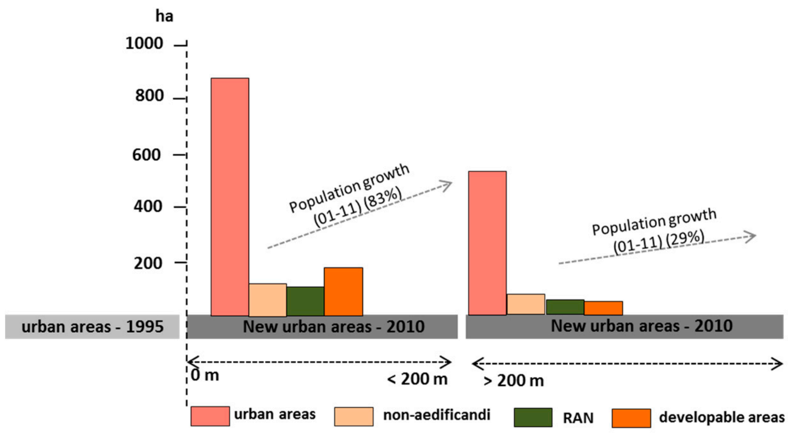


Figure 13. Impacts of urban growth on non aedificandi areas, RAN, and developable areas (above and below 200 m).

Comparing the resident population between 2001 and 2011 at subsection level in the urban areas that emerged between 1995 and 2010, we saw that population increased by 83% in the new urban areas less than 200 m from the edge of existing urban areas (in 1995), and 29% in areas more than 200 m away.

Lastly, as demonstrated in the previous section, the conversion to urban development led to the decrease of agricultural areas. Consequently, in the 1989–2009 time period , farmers' population at municipality level decreased from 7185 in 1989 to 2201 in 2009, and farms also reduced in number in the same period from 7245 to 2337 [49].

4. Discussion and Conclusions

Measuring urban growth is fundamental to anticipate and understand future land use transformations. Sprawl measurement techniques quantify spatial patterns and structures of land use cover patches [11,31,50]. To measure spatial configuration of urban areas, several metrics have been studied and analysed. Accordingly, two statistical approaches can be used: first–order and second–order statistics. First-order statistics, e.g., patch area, patch density [51], number of patches [52], define the variation at individual locations [53]. However, second-order statistics identify the spatial dependence between two areas [54], e.g., proximity index [42], nearest neighbour distance [51], landscape division index [55].

Sprawl measurement can be presented in relative and absolute values [31]. The LAND method is performed at both scales. The main advantage of expressing it at relative level is that it can be used in different case studies, and the results can be compared. Relating the LAND method with the 13 suitability criteria to measure urban sprawl, following Jaeger et al. (2010) [16], we can ascertain that the LAND method meets all 13 criteria. These criteria are related to patch structure, and other elements, such as intuitive interpretation, mathematical simplicity, and modest data requirements.

While the LAND method fails to provide a spatial-geometry analysis, an important issue to measure sprawl [56,57], this method—unlike other urban sprawl measures, e.g., [58,59]—gives evidence on the dynamics of land use change, provides detailed information on urban sprawl in space and in time, offers easy mapping, and shows urban sprawl monitoring capabilities.

The statistical analysis we performed has led to the following findings:

- Between 1995 and 2010, there were progressively less fragmented urban areas. We demonstrated this by means of an analysis supported by the LAND method in different time periods, and at different neighbouring distances from the edge of existing artificial surfaces. The proximity index calculated using the statistical package FRAGSTATS also supported the results we obtained in our case study;
- We demonstrated the high influence of existing artificial surfaces in year 0 on the emergence of new artificial surfaces in year 1. During the 1995–2010 period, 70% of new artificial surfaces appeared more than 200 m from existing artificial surfaces;
- The LAND method can be used and adapted for different scales, replicable for other case studies, land use resolution data, and land use classes, and at different neighbouring distances;
- The LAND method has the ability to examine data not only from the urban growth perspective but also based on other land use classes, such as agricultural or forest areas;
- Longer time periods of land use coverage and equal intervals would be an advantage in this work, although a comparative analysis was performed in terms of percentage. This would help to check if the lower fragmentation of urban areas we saw is a long-term or a temporary trend;
- The results obtained with the LAND method can also be used as inputs in studies to evaluate the negative and positive impacts of sprawl, such as urban pollution, social fragmentation, water overconsumption, or loss of wildlife habitat.

The research findings corroborate the 'first law' of geography [60] and the theory of spatial dependence. We saw high urban containment, coalescence, and reducing discontinuity—results that are in line with He et al. [61], and Couch and Karecha [62].

Different policies may have different effects on a territory. Land use planning measures to reduce urban sprawl and protect and preserve natural areas are needed [13,63,64]. The LAND method can help decision makers to develop instruments for implementation of urban containment policies to limit, monitor, and regulate sprawl, e.g., [13,65–67], preserve natural areas [13], and convert vacant plots or redevelop low–density inner–city areas, e.g., [13,19,64].

Author Contributions: Eduardo Gomes and Arnaud Banos conceived, designed the experiments, and performed the experiments; Eduardo Gomes and Patrícia Abrantes analysed the data; Eduardo Gomes, Arnaud Banos, Patrícia Abrantes, and Jorge Rocha contributed materials/analysis tools; Eduardo Gomes wrote the paper.

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