A metric of compactness of urban change illustrated to 22 European countries

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Abstract

Most metrics of urban spatial structure are snapshots, summarizing spatial structure at one particular moment in time. They are therefore not ideal for the analysis of urban change patterns. This paper presents a new spatio-temporal analytical method for raster maps that explicitly registers *changes* in patterns. The main contribution is a transition matrix which cross-tabulates the distance to the nearest urbanized location at the beginning and end of the analyzed period. The transition matrix by itself offers a powerful description of urban change patterns from which further metrics can be derived. In particular, a metric that is an indicator of the compactness of urban change is derived. The new metric is applied first to a synthetic dataset demonstrating consistency with existing classifications of urban change patterns. Next, the metric is applied country by country on the European CORINE land cover dataset. The results indicate a striking contrast in change patterns between Western and Eastern European counties. The method can be further elaborated in many different ways and can therefore be the first in a family of spatio-temporal descriptive statistics.

1 Introduction

Over the years, a variety of models of urban patterns and urban dynamics has been suggested. In this context, a distinction between descriptive models and explanatory models is highly relevant. Descriptive models summarize data. Well-known examples are the rank size distribution of city populations (Ioannides and Overman, 2003; Chen and Zhou, 2008), the cluster size distributions of urban areas (Benguigui et al., 2006) and fractal relations in urban form (Batty and Longley, 1996; Shen, 2002; Thomas et al., 2008). Furthermore, several metrics of spatial clustering and diffusion such as enrichment factors (Verburg et al., 2004) and transiograms (Li, 2006) have been proposed.

In contrast, explanatory models go beyond mere description by focusing on processes underlying spatial patterns, thereby offering an interpretation of reality. Explanatory models of urban areas are typically based on the dynamic interactions between actors and their relative geographic position. Such relations can include for instance network effects, benefits of scale and spatial externalities, and lead for instance to buffers, segregation, agglomeration and sprawl effects. Especially, Cellular Automata modeling (White and Engelen, 1993; Clarke et al., 1997; Couclelis, 1997) and Agent Based Modeling (Parker et al., 2003), based on the assumed process of self-organization (White and Engelen, 1993; Irwin and Geoghegan, 2001) have become quite popular.

Because of this difference in focus, a gap can be identified between descriptive models and the inherent dynamic nature of urban change. Dynamic descriptive models would constitute a building block in the sense that such models support empirical evidence of dynamic processes and could also serve as a basis for theory development. An examination of the existing literature however suggests that such descriptive models have been used in rather limiting ways. First, explanatory models have been fit to historical data (Silva and Clarke, 2004; Straatman et al., 2004) and their predictive capacity has been investigated (Pontius, 2004; Hagen-Zanker et al., 2005), these studies have evaluated dynamic models only in terms of the static end-situation of a simulation run as opposed to focusing on the dynamic process. Secondly, although there is some recent evidence of spatio-temporal analysis of urban form (e.g., Tao et al., 2004; Herold et al., 2005; Seto and Fragkias, 2005; Xiao et al., 2006), mirroring earlier developments in the field of landscape ecology (Turner, 1989), these studies first apply a spatial analysis to summarize the structure of maps in multiple metrics for multiple moments in time and then conduct a temporal analysis to summarize the trajectories in time. Although this is a valid approach, it does have some clear disadvantages. The most important of these is the fact that already in the first step of the analysis all spatial information is lost, making it problematic to interpret the trajectory of individual metrics over time in terms of processes or patterns of change. For instance, one of the most commonly used metrics is patch size. Increasing patch size over time can be the consequence of disappearing small patches, but also of appearing large patches or of expansion of existing patches. Which of these change patterns occurred can only be conjured from other metrics, for instance the number of patches. If mixed change patterns occur (e.g. some patches appearing and some disappearing), it becomes impossible to untangle different change patterns.

A notable exception to this approach can be found in Wilson et al. (2003) whose spatial analysis is based on patterns of change in spatial structure. They identified five different patterns of urban change, presented in an urban change map: *Infill, Expansion, Isolated growth, Linear branch*, and *Clustered branch*. Xu et al. (2007) used a similar classification of *Infill*, *Edge-expansion* and *Spontaneous growth*.

Other spatio-temporal analyses describing land use change are based on the land use transition matrix (Debussche et al., 1977; Muller and Middleton, 1994). This matrix cross-tabulates land use categories of locations (cells) at the beginning and end of the analyzed period. However, these land use transition matrices typically do not consider spatial structure, except for cell-to-cell overlap, and therefore are of limited interest when investigating the link between pattern and process.

The goal of the present paper therefore is to suggest a new method to alleviate these limitations of existing approaches. More specifically, a distance class transition matrix is suggested to capture descriptively processes of land use change. The method can be viewed as an extension of the traditional land use transition matrix for only two classes; *Urban* and *Non-urban*, and builds on the concept of urban change maps (Wilson et al., 2003; Xu et al., 2007). It does not arbitrarily break down the spatial and temporal analysis and is also not based on the spatial configuration of land use pertaining to the end situation only, as in the calibration process.

The paper is organized as follows. First, we will introduce the method that we propose. Next, we will illustrate and apply the method to two data sets: synthetic data and European land cover data. The paper is completed by discussing the results of the analysis and reflecting on possible elaborations of the suggested method.

2 Method

2.1 Distance to urban

Input is a pair of binary (*Urban*, *Non-urban*) raster maps that delineates the urban area at the beginning and end of the study period. From these two maps, indicator maps are derived that express for every cell the distance to the nearest cell of class *Urban*.

To allow cross-tabulation, distance classes are defined. These distance classes are simple bins with a lower (included) and upper (excluded) boundary. The upper boundary of one distance class is the lower boundary of the next. In the equations that follow, the distribution over distance classes is used as an approximation of the distribution over distances. The precision of this approximation depends on the number and size of the bins. In the current application, increasingly broader bins are applied to larger distances. The rationale for this choice is that at larger distances the required (absolute) precision is lower.

The first bin is always for the cells at distance 0 to *Urban*, i.e. cells that are *Urban* themselves. Table 1 gives the general form of a transition matrix for two classes *Urban* and *Non-urban*; it illustrates that the distance classes are a further specification of the class *Non-urban,* and that the class *Urban* is identical to the first distance class (D_1).

Table 1. Generic distance class transition matrix.

<table>
<tr><td colspan="3" rowspan="3"></td><td colspan="6">Final</td></tr>
<tr><td>Urban</td><td colspan="4">Non-urban</td><td rowspan="2">Sum</td></tr>
<tr><td>D_1</td><td>D_2</td><td>D_3</td><td>…</td><td>D_n</td></tr>
<tr><td rowspan="6">Initial</td><td>Urban</td><td>D_1</td><td>$t_{1,1}$</td><td>$t_{1,2}$</td><td>$t_{1,3}$</td><td>…</td><td>$t_{1,n}$</td><td>$t_{1,+}$</td></tr>
<tr><td rowspan="4">Non-urban</td><td>D_2</td><td>$t_{2,1}$</td><td>$t_{2,2}$</td><td>$t_{2,3}$</td><td>…</td><td>$t_{2,n}$</td><td>$t_{2,+}$</td></tr>
<tr><td>D_3</td><td>$t_{3,1}$</td><td>$t_{3,2}$</td><td>$t_{3,3}$</td><td>…</td><td>$t_{3,n}$</td><td>$t_{3,+}$</td></tr>
<tr><td>:</td><td>:</td><td>:</td><td>:</td><td></td><td>:</td><td>:</td></tr>
<tr><td>D_n</td><td>$t_{n,1}$</td><td>$t_{n,2}$</td><td>$t_{n,3}$</td><td>…</td><td>$t_{n,n}$</td><td>$t_{n,+}$</td></tr>
<tr><td></td><td>Sum</td><td>$t_{+,1}$</td><td>$t_{+,2}$</td><td>$t_{+,3}$</td><td>…</td><td>$t_{+,n}$</td><td>$t_{+,+}$</td></tr>
</table>

Urban and *Non-urban* are land use classes. D_1, D_2, $D_3 \ldots D_n$ are distance classes. $t_{i,j}$ is the number of cells changing from class D_i to D_j. $t_{i,+}$ is the number of cells originally in class D_i. $t_{+,i}$ is the number of cells finally in class D_j. $t_{+,+}$ is the number of cells in the map.

Even though the distance to cells with an urban land use class is a simple concept, the calculation of these distances is not straightforward. Naive implementations will demand prohibitively long calculation times on substantial datasets. This problem is known in computer science as the Euclidean Distance Transform and over the years many algorithms have been proposed. Typically, these algorithms trade accuracy of the distance estimates for calculation time. We settled for the exact algorithm of Felzenszwalb and Huttenlocher (2003) which is reasonably fast and does not introduce errors into the analysis. The algorithm approaches the Euclidean Distance Transform as a minimization problem and applies dynamic programming to solve it. The execution time of the algorithm is proportional to the number of cells and it manages 18 million cells in 5 seconds on a 1.6 GHz AMD Turion processor.

Fig. 1 illustrates the relation between urban land use, distance to urban and distance classes for the case of Luxembourg. Note that for legibility less distance classes are displayed than in the results section. The distance classes that are used and their total presence on the maps are tabulated in table 2. The distance class transition matrix is given as table 3.

Table 2. Distance classes of the Luxembourg example

Class	From	To	Area in 1991	Area in 1991, cumulative	Area in 2000
D_1	0	1	20839	20839	22591
D_2	1	6	70634	91473	73331
D_3	6	20	130649	222122	128802
D_4	20	82	37439	259561	34837

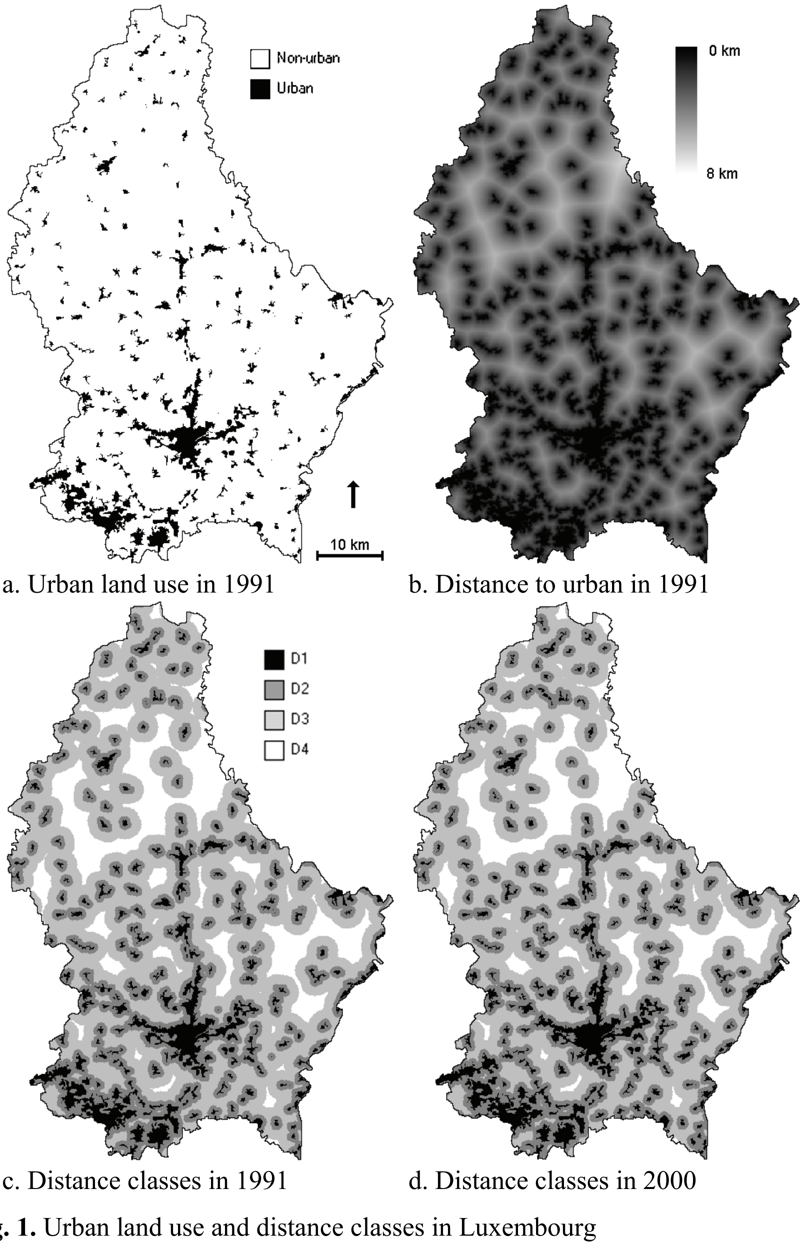
Distance and area are measured in cell units; the cell size is 100 m

Table 3. Transition matrix of the Luxembourg example

	D_1	D_2	D_3	D_4
D_1	20810	29	0	0
D_2	1303	69305	26	0
D_3	458	3687	126504	0
D_4	20	310	2272	34837

2.2 Summary metric

The distance class transition matrix itself can be interpreted in terms of change patterns by visual inspection. It is clear that when urban growth takes place (and no shrinking) all non-zero values are found below or on the diagonal of the matrix. If the growth pattern is compact, transitions are found close to the diagonal (indicating that urban areas are only encroaching slowly) and towards the upper left corner (indicating that cells close to urban areas are affected, but those far away from urban areas are not). If loss of urban area takes place, which is not common given the irreversible nature of urbanization, the transitions are registered above the diagonal. In this case, compactness is gained when transitions are found away from the diagonal (creating large non-urban areas) and in the upper right corner (affecting those areas at great distances from urban cells).



a. Urban land use in 1991 b. Distance to urban in 1991

c. Distance classes in 1991 d. Distance classes in 2000

Fig. 1. Urban land use and distance classes in Luxembourg

Different summary metrics can be envisioned on the basis of the transition matrix. We will introduce only one here, focusing on the relative loss of compactness, normalized to the total area of change.

The relative loss in compactness of a cell on the map is calculated as the drop in the cumulative distribution of distance to urban areas on the map, using the following equation:

$$L\left(d_{before,cell}, d_{after,cell}\right) = \frac{F_{before}\left(d_{after,cell}\right) - F_{before}\left(d_{before,cell}\right)}{\frac{1}{2}\left(F_{before}\left(d_{after,cell}\right) + F_{before}\left(d_{before,cell}\right)\right)} \tag{1}$$

where the function $L(d_{before,cell}, d_{after,cell})$ yields the loss of compactness associated to the transition from distance $d_{before,cell}$ to $d_{after,\ cell}$ at the location of *cell*. F_{before} is the cumulative distribution of distance to urban area of all *nCells* cells, it is defined as follows:

$$F_{before}\left(d^*\right) = \frac{\sum_{cell=1}^{nCells}\left[d_{cell,before} \le d^*\right]}{nCells} \tag{2}$$

where square brackets are Iverson brackets; [*P*] returns 1 if proposition *P* is true and 0 otherwise. Thus, $F_{before}(d^*)$ is the proportion of all cells that lie at distance d^* or closer to urban areas in the initial situation.

Using distance classes means that information on the precise distance is lost. Therefore, the loss of compactness cannot be calculated exactly on the basis of the transition matrix. However an approximation can be made following:

$$F_{before}\left(d^*\right) \approx \frac{\sum_{ii=1}^{i} t_{ii,+}}{t_{+,+}} \tag{3}$$

where distance d^* is within distance class D_i. Yielding the following for each pair of distance classes:

$$l_{i,j} = \frac{\sum_{ii=1}^{i} t_{ii,+} - \sum_{jj=1}^{j} t_{jj,+}}{\frac{1}{2}\left(\sum_{ii=1}^{i} t_{ii,+} + \sum_{jj=1}^{j} t_{jj,+}\right)} \tag{4}$$

where $l_{i,j}$ expresses the loss of compactness related to cells that are originally in distance class *i* and finally in distance class *j*. The indices *ii* and *jj* iterate over all distance classes equal to or smaller than *i* resp. *j*. Note that the value $l_{i,j}$ solely depends on the distribution over distance classes in the initial situation.

Using the cumulative areas per distance class of table 2 the loss of compactness associated to each element of the transition table of the Luxembourg example can be calculated. For instance the loss associated to the transition from D_3 to D_1 is calculated according to eq. 5. The outcomes for all combinations of distance classes are presented in table 4. The spatial distribution of the different degrees of loss is presented in fig. 2.

$$l_{3,1} = \frac{(222122 - 20839)}{\frac{1}{2}(222122 + 20839)} \approx 1.7 \tag{5}$$

Table 4. Loss of compactness ($l_{i,j}$) for the Luxembourg example

	D_1	D_2	D_3	D_4
D_1	0	-1.3	-1.7	-1.7
D_2	1.3	0	-0.8	-1.0
D_3	1.7	0.8	0	-0.2
D_4	1.7	1.0	0.2	0

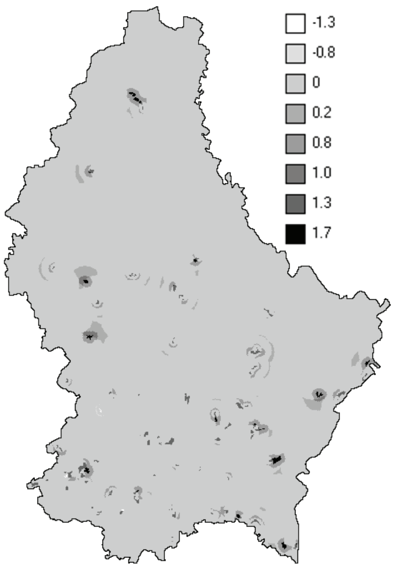


Fig. 2. Spatial distribution of loss of compactness (1991-2000) in the Luxembourg example. Most cells display no loss of compactness.

As indicated, the effect of this formulation is that the change in compactness is weighted relative to the distribution of distances to urban areas in the initial situation. This introduces a scale-independency which means that a loss in cells lying within (say) 5 km of urban areas is registered as a strong loss in compactness in densely and scattered built-up countries (e.g., Belgium), and as only a mild loss in countries with vast open areas (e.g., Spain). Likewise, a change pattern that is considered compact relative to the whole country may not be compact relative to a region.

The overall loss of compactness is calculated as the area weighted mean. Therefore it is equivalent to the mean over the map presented in fig. 2 and it is calculated as follows:

$$l_{mean} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} t_{i,j} * l_{i.j}}{t_{+,+}} \tag{6}$$

The metric presented here is a measure of spatial structure, but there are also non-spatial metrics of compactness of urban change, such as the overall increase in urban area and the increase in population density. In order to express the spatial structure component independently of the other non-spatial metrics of compactness of change, the total loss in compactness is normalized in such fashion that the resulting metric can be interpreted as a measure of elasticity: the relative loss in compactness per relative increase in urban area. It is calculated as follows:

$$l_{region} = \frac{l_{mean}}{\dfrac{u_{after} - u_{before}}{\frac{1}{2}\left(u_{after} + u_{before}\right)}} \tag{7}$$

where l_{region} is the normalized loss in compactness of the studied region; u_{before} and u_{after} are the total urban area in the initial and final situation and can be read from the transition matrix, since distance class D_1 corresponds to *Urban*.

$$\begin{aligned} u_{before} &= t_{1,+} \\ u_{after} &= t_{+,1} \end{aligned} \tag{8}$$

Eq. 9 integrates eqs. 4, 6, 7 and 8; it expresses the loss of compactness as a function of the transition matrix only.

$$l_{region} = \frac{t_{1,+} + t_{+,1}}{t_{1,+} - t_{+,1}} * \frac{1}{t_{+,+}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(t_{i,j} * \frac{\sum_{ii=1}^{i} t_{ii,+} - \sum_{jj=1}^{j} t_{jj,+}}{\sum_{ii=1}^{i} t_{ii,+} + \sum_{jj=1}^{j} t_{jj,+}} \right) \tag{9}$$

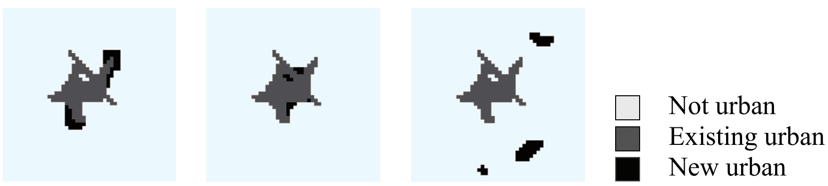
For the Luxembourg example, this yields: $l_{Luxembourg} = 0.29$. This number differs from the result presented further on, because the number of classes in the example is (too) small.

3 Data

The method is tested on two datasets. First, it is applied to a synthetic dataset of which the loss in compactness is well understood. The results for that dataset serve as a verification of the method. Secondly, the method is used to analyze Pan-European land cover data. The interpretation of the results of this application uses the first dataset as reference levels.

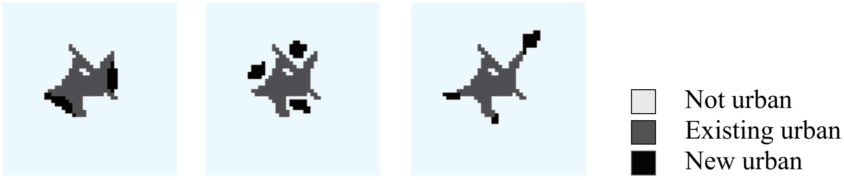
3.1 Synthetic dataset

The synthetic dataset (fig. 3) consists of six maps. The first three maps represent urban growth patterns as identified by Wilson et al. (2003) and Xu et al. (2007). These are *Infill*, *Expansion* (also called *Edge-expansion*) and *Isolated* also called *Spontaneous growth*). In reality, urban areas will not develop exclusively according to one of these patterns, but in fact there may be combinations or in-between forms. Three more maps (fig. 4) give in-between patterns of *Infill-expansion*, *Infill-isolated* and *Expansion-isolated*. The maps do not refer to an actual situation and have no particular scale. The map size is 50 by 50 pixels.



a. Expansion b. Infill c. Isolated

Fig. 3. Archetypical growth patterns



a. Infill-expansion b. Infill-isolated c. Expansion-isolated

Fig. 4. Mixed type growth patterns

3.2 CORINE land cover

CORINE is a Pan-European land cover map produced by the Environmental Assessment Agency (EEA) It recognizes 44 types of land cover, however we only consider one main category and its complement. This category is Artificial Surfaces and includes the following sub-classes:

- Continuous urban fabric
- Discontinuous urban fabric
- Industrial or commercial units
- Road and rail networks and associated land
- Port areas
- Airports
- Mineral extraction sites
- Dump sites
- Construction sites
- Green urban areas
- Sport and leisure facilities

There are some particularities to the CORINE dataset; it is available as a 100m raster dataset, but the classification procedure in fact is based on recognition of objects rather than fields. Homogenous objects are functional objects (i.e. the garden belonging to a house is classified as *Urban fabric* and a farmhouse may be classified as *Arable land*). The objects are recognized with a minimum mapping unit of 15 ha, thus one must be careful not to interpret resolution as precision.

The CORINE dataset is available for two moments in time: 1990 and 2000. The map of 2000 is actually based on imagery of 2000, but the 1990 map in fact is based on imagery ranging from 1985 to 1996. The year 1990 is only the median of the dataset. Individual countries are based on data from one year only and when we present the results further on, we will also indicate the period between the initial and final year. The mapping procedure, and in particular application of the minimal mapping unit, implies that differences between the 1990 and 2000 dataset do not all represent changes that took place in reality. Therefore, EEA has performed an elaborate analysis and produced an additional data layer which is the layer of land cover changes. This layer is the most reliable source of spatially explicit pan-European land use/ land cover change.

The dataset that we have is CORINE 2000 overlaid with the 1990 and 2000 exponent of changes to obtain consistent maps for 1990 (median) and 2000. The two CORINE land cover maps are not available for all countries. The CORINE project is ongoing however and over time more countries may become available. A release of 2005 data is pending.

The data has been cleaned by EEA before releasing it to the public. Nevertheless, visual inspection of the maps indicated several differences between 1990 and 2000 that should possibly be attributed to data errors. It is beyond the scope of this project to redo the data cleaning work of EEA. Instead we assume that over time artificial surfaces do not change to non-artificial. This is put into effect by only considering those values in the transition matrix below or on the diagonal.

4 Results

4.1 Synthetic examples

The distance class transition matrices are given in table 5. The visual interpretation of the transition matrices confirms our expectations. The *Infill* pattern affects only the smaller distance classes, the cells in distance class D_7 or further are unaffected, i.e. lay at the diagonal. The *Expansion* pattern affects cells in all distance classes (off-diagonal values are found for all distance classes), but the magnitude of the effect is small (the off-diagonal values are found close to the diagonal). The *Isolated* pattern only affects cells at larger distances and these distance classes are severely affected.

The transition matrices of the mixed change patterns present a balance of the mixed patterns. *Infill-expansion* has positive values in the same cells as *Expansion*, but the values in the further distance classes are smaller. The matrix of *Infill-isolated* shows that the distance classes at the mid-range are most affected (D_4 to D_6). It thereby takes the middle of the *Infill* and *Isolated* patterns. The *Expansion-isolated* pattern affects the small as well as the mid-range distances. The larger numbers in the matrix are found in the mid-range (D_4 to D_7).

The results for the metric of compactness of urban change are listed in table 7. The results are ordered by compactness. The ranking of the change patterns in terms of compactness is fully according to our a priori expectations: *Infill* is the most compact, *Isolated* the least compact and mixed patterns are ranked in between the two patterns that they mix. Only for the mutual ranking of the patterns *Infill-isolated* and *Expansion* we had no a priori expectation.

Table 5. Distance class transition matrices for the synthetic dataset

Table 5a. Infill

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
D_1	164										
D_2	15	61									
D_3	1	4	31								
D_4	1	3	1	74							
D_5			1	2	115						
D_6					1	216					
D_7							219				
D_8								437			
D_9									606		
D_{10}										479	
D_{11}											69

Table 5b. Expansion

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
D_1	164										
D_2	20	56									
D_3	8	3	25								
D_4	16	8	2	53							
D_5	4	23	3	11	77						
D_6			4	29	44	140					
D_7					7	79	133				
D_8						14	99	324			
D_9								141	465		
D_{10}									134	345	
D_{11}										21	48

Table 5c. Isolated

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
D_1	164										
D_2		76									
D_3			36								
D_4				79							
D_5					118						
D_6		3	3	5	5	201					
D_7	9	4		4	6	34	162				
D_8	13	18	8	26	38	56	31	247			
D_9	36	21	11	27	41	77	61	66	266		
D_{10}		2	4	10	21	52	70	120	79	121	
D_{11}							1	12	37	19	

Table 5d. Infill-expansion

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
D_1	164										
D_2	19	57									
D_3	6	4	26								
D_4	13	4	3	59							
D_5	7	9	4	10	88						
D_6		3	2	11	26	175					
D_7					2	40	177				
D_8						1	43	393			
D_9								55	551		
D_{10}									37	442	
D_{11}										15	54

Table 5e. Infill-isolated

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
D_1	164										
D_2		76									
D_3		8	28								
D_4	12	10	1	56							
D_5	24	8	4	7	75						
D_6	18	14	5	13	18	149					
D_7		3	2	10	15	36	153				
D_8					5	29	58	345			
D_9							6	97	503		
D_{10}									54	425	
D_{11}										14	55

Table 5f. Expansion-isolated

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}
D_1	164										
D_2	4	72									
D_3	4		32								
D_4	5	8	3	63							
D_5	7	8	2	12	89						
D_6	11	9	4	15	29	149					
D_7	5	5	3	10	20	49	127				
D_8		3	1	8	16	60	94	255			
D_9					2	18	49	179	358		
D_{10}								33	149	297	
D_{11}									1	22	46

Table 6. Distance classes in cell units

	From(included)	To(excluded)
D_1	0	1
D_2	1	$\sqrt{2}$
D_3	$\sqrt{2}$	2
D_4	2	$2\sqrt{2}$
D_5	$2\sqrt{2}$	4
D_6	4	$4\sqrt{2}$
D_7	$4\sqrt{2}$	8
D_8	8	$8\sqrt{2}$
D_9	$8\sqrt{2}$	16
D_{10}	16	$16\sqrt{2}$
D_{11}	$16\sqrt{2}$	32

Table 7. Compactness of change of the synthetic dataset

Change pattern	Loss of compactness	A priori expected rank
Infill	0.046	1
Infill-expansion	0.19	2
Infill-isolated	0.31	3 or 4
Expansion	0.38	3 or 4
Expansion-isolated	0.80	5
Isolated	1.1	6

4.2 Patterns of urban change across Europe

The transition matrices and the derived loss of compactness metric are calculated for all countries in the CORINE dataset. The results are presented in table 8. The results of the synthetic dataset are used as reference levels.

The results indicate that the loss of compactness for all countries has been in between that of the *Infill* change pattern and the *Expansion-isolated* pattern.

The analysis is performed twice, once with and once without the filter that ignores loss of urban area. The filter corrects one outlier (Slovakia) that without filtering registers a growth even less compact than *Isolated growth*.

Table 8. Loss of compactness

			Without filtering		
Rank	Country	Loss of C.	Loss of C.	Rank	Period (years)
***	*Infill*	*0.05*	***	***	***
1	**Estonia**	**0.10**	**0.13**	**1**	**6**
2	**Slovenia**	**0.11**	**0.13**	**2**	**5**
3	**Bulgaria**	**0.16**	**0.16**	**3**	**10**
4	**Romania**	**0.18**	**0.18**	**4**	**8**
***	*Infill-expansion*	*0.19*	***	***	***
5	**Lithuania**	**0.20**	**0.18**	**5**	**5**
6	**Poland**	**0.21**	**0.23**	**8**	**8**
7	The United Kingdom	0.21	0.21	7	10
8	Austria	0.22	0.21	6	15
9	Belgium	0.25	0.25	9	10
10	Spain	0.26	0.26	10	14
11	Portugal	0.27	0.27	11	14
12	France	0.29	0.28	12	10
***	*Infill-isolated*	*0.31*	***	***	***
13	**Slovakia**	**0.31**	**3.71**	**22**	**8**
14	Ireland	0.33	0.33	13	10
15	The Netherlands	0.35	0.36	14	14
16	Luxembourg	0.36	0.36	15	11
17	Greece	0.37	0.37	16	10
***	*Expansion*	*0.38*	***	***	***
18	**Hungary**	**0.39**	**0.41**	**17**	**8**
19	Germany	0.41	0.47	20	10
20	Denmark	0.41	0.42	18	10
21	Italy	0.46	0.46	19	10
22	**Latvia**	**0.72**	**0.72**	**21**	**5**
***	*Expansion-isolated*	*0.80*	***	***	***
***	*Isolated*	*1.11*	***	***	***

Eastern European countries in **bold**

5 Discussion

The six urban growth patterns of the synthetic dataset fit well with our intuitive understanding of compactness of urban change. It is therefore comforting that the value of the metric confirms expectations. Moreover, the range of values found on the basis of the CORINE dataset is similar to that of the synthetic dataset. This means that the synthetic dataset provides a useful frame of reference and the results can be well interpreted.

A striking distinction emerges between Western and Eastern European countries. It appears that Eastern countries as a whole have more compact urban change patterns. It is difficult to attribute this difference to one or the other process, particularly because these two regions are distinct in so many aspects. Nevertheless, we like to speculate that in the young Eastern European economies social and economic opportunities primarily occur in the (large) cities. Spatial developments in the countryside are limited and as a consequence there is limited fragmentation. In the Western European countries, rural and peri-urban development is taking place, the contrast between rural and urban areas diminishes, and so does the compactness of the urban areas. Note that the United Kingdom, with London as its strong urban magnet, is the most compact of Western European countries.

One avenue of further investigating the hypothesis that the contrast between rural and urban development explains the distinction between Western and Eastern European countries is to apply the proposed method at a finer scale, for instance European NUTS3 administrative regions. The expectation would then be that in Eastern Europe the compactness at the regional level will be higher, since the regional urban-rural contrast will not longer contribute to the compactness.

Another somehow surprising result is the lack of any clear evidence of the effect of national spatial planning strategy. In particular, the well-known contrast between Belgian (liberal) and Dutch (strict) spatial planning does not materialize. A possible explanation may be that the urban landscape of these countries is the effect of a longer history of spatial planning. It may well be that the recent history breaks that trend. Another explanation may be the role of the initial situation in the sense that in a highly fragmented landscape there may be more possibilities for compact development than in a more compact landscape.

6 Conclusion

This paper set out to develop a method for the description of urban change patterns. The method that is introduced centers on a distance class transition matrix and a metric of compactness of urban change is derived from this matrix. Application of the newly developed method to a synthetic dataset confirms the descriptive power of the transition matrix as well as the derived statistic. It could there be applied with confidence on a real dataset of land use / land cover patterns in Europe.

The results of this analysis present a strong contrast between Eastern and Western European countries, and perhaps surprisingly do not demonstrate a clear link between spatial planning practice and patterns of change. We speculate that this may be the effect of the scale of the analysis and plan to investigate urbanization patterns at finer scales in particular European NUTS3 regions.

The metric and transition matrix presented in this paper are not the ultimate tool of describing urban areas. Instead, they offer a novel approach that may be extended and modified in many ways. Even though the link is not explicit, the analysis of transitions in distance to urban areas relates to fractal analysis. There are several methods to calculate the fractal dimension of urban areas. A common approach is based on (erosion-)dilation. The urban area with a dilation of radius r, is identical to the area of all locations where distance to urban area is smaller or equal to r. This line has not been pursued in the present paper, but the distance class transition matrix may be a useful instrument to derive metrics of fractal change.

The inclusion of other structure indicators than distance to urban area can be readily implemented. A straightforward extension of the transition matrix would be to include distance to non-urban areas in a similar fashion. Other likely candidates are patch size, built up density, population density and edge. Multidimensional transition matrices would allow the evaluation of multiple indicators in a single metric. Further summary metrics can refer to other aspects of urban structure, such as specialization, segregation, accessibility, self-sufficiency, disturbance, and exposure.

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