Strategy paper
Instruments for monitoring and analysis of urban change

Alex Hagen-Zanker
ahagen@riks.nl

Urban Planning group
TU Eindhoven, Department of Building and Architecture
PO Box 513, 5600 MB Eindhoven, the Netherlands
phone: +31(40)2472861

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Contents

1 Research context

Urban planners realize that the development of urban areas is subject to hidden forces. Large scale programs that initially appear water tight can later turn out to function differently than expected. There are many examples to the contrary, neglected neighbourhoods or abandoned industrial areas that seemingly spontaneously develop into thriving commercial, residential or nightlife areas.

Successful and efficient planning requires a good understanding of the city and its many interactions and spatial structures. Researchers seek regularities in spatial structure and causal relations to explain them. Where traditionally simple equilibrium models were used, now geographers recognize the complex nature of urban areas and seek metrics, models and methods that account for this complexity.

A distinction that underlies our strategy is between descriptive models and explanatory models. Descriptive models summarize data. Therefore they are always correct, but the summary may be of little relevance when it does not help understanding the underlying processes. Explanatory models on the other hand are elaboration on hypotheses about processes. They offer an interpretation of reality and analysis of model results can lead to increased confidence in, or rejection of, hypotheses.

Descriptive models of urban patterns are, by large, based on static situations i.e. single moments in time. They may present us with surprising regularities in space and time, such as the rank size distribution of city populations (Ioannides & Overman, 2003; Chen & Zhou, in press), the cluster size distributions of urban areas (Benguigui *et al*, 2006) and fractal relations in urban form (Batty & Longley 1996). Furthermore there are many metrics of spatial clustering and diffusion such as enrichment factors (Verburg *et al.* 2004) and transiograms (Li 2006). Patterns are recognized, but due to the static nature the relation with processes and understanding of causal relations remains low.

Descriptive 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 and benefits of scale or negative externalities that lead to buffers, segregation and diffusion. Modern computing makes it possible to simulate virtual cities which are composed of many small elements and relatively simple interaction rules. Two much used techniques are Cellular Automata modelling (White & Engelen 1993, Couclelis 1997, Clarke *et al*. 1997) and Agent Based Modelling (Parker *et al*. 2003). Model results are promising and build confidence in the hypothesis of urban dynamics as a self-organizing process (White & Engelen 1993, Irwin & Geoghegan 2001).

Irwin & Geoghegan (2001) not only point to the potential of self-organising models, but also to the lack of theory and empirical support. Lambin *et al*. (2001) identify a number of myths (popular but false assumptions). Calibration procedures have been applied to fit models to historical data (Silva & Clarke 2004, Straatman *et al*. 2004) and the predictive capacity of models is investigated (Hagen-Zanker *et al*. 2005, Pontius, 2004), but the poor fit between descriptive and explanatory models leaves many questions of validity unanswered.

Starting point for this project is the notion that the current generation of descriptive models is not sufficiently aligned with the hypotheses that underlie the current generation of explanatory models. This limits the relevance of the descriptive models and also leaves the validity of many hypotheses unexplored. This project seeks to develop a methodology to describe urban change in a manner that is relevant to the explanatory models. A focus on change rather than condition will be achieved by means of a state-space approach.

Recently methods from landscape ecology (Turner, 1989) have been applied to describe the change of urban patterns (Luck & Wu, 2002; Herold *et al*, 2005; Tao *et al*, 2004; Seto & Fragkias, 2005). These descriptions are based on metrics that summarize landscape structure, and their development through time is analysed. It appears that the interpretation of these trajectories through time is problematic, as quite different change patterns can cause the same trajectory for individual metrics. The methodology of first summarizing spatial data to structure metrics and than analysing their changes implies that the spatial distribution of changes is not considered at all. In essence the methods of these papers chronicle the changes in structure over time, instead of the structure in the changes.

This brings a more fundamental problem, because as we aim for an empirical approach we have to acknowledge that change itself cannot be observed. We can observe differences from one moment in time to the next, but it is impossible to say what happened in between. This may be a trivial consideration when clear objects are present, but presents real challenges when a spatial field based approach is followed. Therefore, to be more precise the objective of the project is to recognize patterns in differences over time and summarize those in ways that are likely to reflect the changes that took place.

The integrated approach on the basis of a state-space representation, cluster analysis and elements from landscape ecology is intended to lead to an instrument that takes spatial information and extracts the information relevant to understanding of the underlying processes. It will be a tool for the monitoring and analysis of spatial change.

1.1 Research questions

We will seek to answer the following questions

- How can spatial changes of urban areas be classified?
    - Which spatial attributes need to be measured?

    - What methodology is suited to incorporate different spatial and temporal scales in the analysis?
- How can cluster techniques be helpful in the classification of change patterns?
    - What analytical techniques are available to give an interpretation to the classes that are found?
- Which classes of urban dynamics can be recognized at European, Dutch and municipality level?
- Which socio-economic and physical factors can explain the differences in patterns of urban change?

2 Methodological elaboration: Comparing and classifying temporal change in pairs of raster maps

2.1 Introduction

This paper investigates the potential of a method for the comparison of urban dynamics on the basis of a state-space representation. Two experiments investigate different applications of the methodology. The first application is the validation of simulation results and the second application is classification of different forms urban dynamics.

2.1.1 Model validation by map comparison

Simulation models of spatial processes, and in particular land use change, often follow a dynamic approach. This means that given an initial situation the models describe the transitions that take place over time. Examples of such models are cellular automata models and multi-agent models.

In the past different strategies have been followed for validation of model performance. A typical approach is operational validation (Rykiel 1996); the model is run for a period in the past, after which results are compared to the actual situation at the end year of the simulation. When independent calibration (training) and validation (testing) datasets are used this approach is appropriate for assessing the predictive quality of models. When different criteria and scales are considered, it is even possible to obtain rich information on the strengths and weaknesses of the model (Hagen-Zanker & Lajoie in prep.).

By only assessing the end situation, a defining characteristic of the spatial model is left unexplored, being the nature of the changes that the model imposes. We speculate that better understanding of model performance and the validity of model hypotheses can be gained if we assess them on the basis of the transitions that they invoke. The direct advantage of the transition based approach is that the models are evaluated on patterns of change rather than patterns of the end state. In that sense models are evaluated on a criterion that lies closer to the processes than before.

The model that is evaluated in this paper is a cellular automata model of the island La Réunion. The performance of the model is compared to that of several ‘neutral models of landscape change’.

2.1.2 Classification of urban dynamics

The state-space approach loses the notion of location along the way. To be specific, the approach evaluates whether units with a similar set of characteristics change according to similar patterns. It therefore becomes possible to compare the change patterns of regions that do not overlap, or only partly overlap. In effect the approach links a time period and region to a certain change pattern. In that sense it is a descriptive model of urban change.

There seems to be scope for a classification system of spatial dynamics. Would it not be interesting – and useful - if we could recognize the fingerprint of urbanisation of different regions and times? To know, for instance, if an urban region is developing more like LA in the 1990's or NY in the 1920's. Or to evaluate in an urban planning context, whether the patterns of urbanisation indeed follows the objectives laid out by planners.

Such a change based classification is a deviation from existing descriptive models that summarize static urban patterns in one or more variables. Those variables can be simple, e.g. the total build up area, or more complex, e.g. fractal dimension or the slope of a cluster-size distribution plot.

This paper does not intend to provide the definite classification or methodology. Instead it explores the use of the state-space approach in an urban context. The experiment classifies urban change patterns in the Netherlands over the period 1989-2000. It is limited to the change in urban area at a coarse and fine scale.

2.2 Methods

In a categorical raster map every location (cell) is primarily defined by its category. However, there is more information contained in a map, namely the geographic relation between locations. Other attributes that characterize a location are implied and need to be derived. On the basis of different attributes a location on the map is linked to a location in state-space. Over the course of time the characteristics of a location change and therefore the location in state-space changes (not the geographical location). The comparison of changes is based on the comparison of trajectories is state-space.

In this application a simple approach to the comparison of trajectories is followed. In first instance the location in state-space is summarized by a single class. The transition from one state-space class to another state-space class summarizes the state-space transition.

The following section explains the approach step-by-step by an artificial example. In the example there are two attributes that comprise state-space; housing density within 500 m radius and distance to natural land. These two attributes are also the axes against which the state-space plot is drawn. **Figure 2.1** illustrates how a location changes attributes and thus moves through state-space in two time steps. Transitions in state-space are made at all locations and can be summarized in a single plot (**Figure 2.2**). All transitions together may be further summarized in a transition matrix (**Table 2.1**) on the basis of a classification (**Figure 2.3**).

Note that the transition matrix has the same structure as those applied in Markov Chain analysis. However, there is lack of independence between observations (because geographical relationships are mutual). Some combinations of transitions are more likely than others and some combinations are plainly impossible. In future we will investigate to what extent Markov Chain analysis is applicable and can lead to more insight or formal induction.

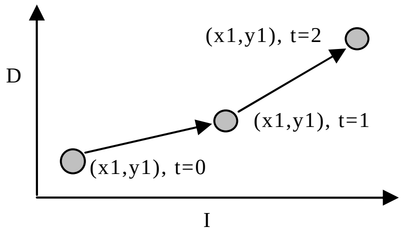


Figure 2.1 *The geographical location (x1,y1) changes location in state-space over time. The two axes represent distance to nature (vertical) and inhabitants within a 500 m radius (horizontal). Through time the locations gains inhabitants and becomes further away from nature.*

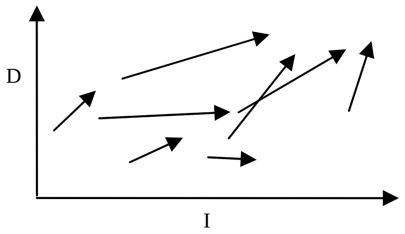


Figure 2.2 *All locations combined provide a summary of the changes in the map.*

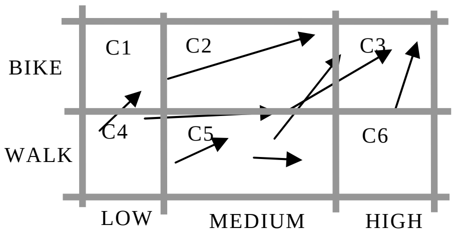


Figure 2.3 *A simple classification yields six categories. Distance to nature is expressed in two bins for biking and walking distance. Number of inhabitant ranges is classified as {low, medium, high}*

Table 2.1 *The normalized transition matrix tabulates all changes that occurred.*

		t+1						
		C1	C2	C3	C4	C5	C6	SUM
t	C1	$T_{1,1}$	$T_{1,2}$	etc.				100%
	C2	$T_{2,1}$	$T_{2,2}$					100%
	C3	etc.						100%
	C4							100%
	C5							100%
	C6							100%

The transition matrices of two regions or time periods can be compared on the basis of a straightforward cell-by-cell comparison, according to **Equation 1.1**.

$$d(A,B) = \sum_{i,j} \left| A_{i,j} - B_{i,j} \right| \qquad \text{Equation 1.1}$$

Where
A, B two compared transition matrices
$A_{i,j}$ fraction of locations originally in state i that changes to state j.

The possibility exists that a class does not occur at all in the initial situation in one of the maps. In that case the method is underspecified since it is not possible to normalize (division by zero). Therefore, a weight adjustment is made to the cell-by-cell comparison (**Equation 1.2**). If not a single class is present in both initial maps then the dynamics can not be compared.

$$d(A,B) = \frac{\sum_{i,j} \left(\left| A_{i,j} - B_{i,j} \right| * T_{i,A,B} \right)}{\sum_{i} T_{i,A,B}} \qquad \text{Equation 1.2}$$

Where
$T_{i,A,B}$ presence indicator, it takes value 1 if class i is present in the initial map of both pairs A and B, and 0 otherwise.

A classification of patterns of change is achieved by means of cluster analysis. In this approach we divide a map into n regions ($R_1,\ldots,R_n$) and compare them mutually, yielding a regional distance matrix D.

A level of spatial coherence can be imposed by invoking a ‘neighbour bonus’ i.e. by considering neighbouring regions more similar to each other. Thus the elements of the regional similarity matrix are calculated as follows:

$$D_{i,j} = \begin{cases} \text{if } R_i \text{ neighbours } R_j: & \beta * d(R_i, R_j) \\ \text{else}: & d(R_i, R_j) \end{cases} \qquad \text{Equation 1.3}$$

where

β neighbourhood factor, $0<\beta<=1$

$D_{i,j}$ the distance between regions i and j as applied in the cluster analysis

The cluster analysis if based on a nearest neighbour approach. This approach iteratively merges the two most similar regions and then reassesses the distances that involving the merged region. Regions are considered neighbours when one or more of their cells border each other.

2.3 Results

2.3.1 Experiment 1 – Land use model calibration and validation

The first experiment to assess the use and potential of a transition based comparison is the evaluation of performance of a land use model. We will compare the performance of one model under different parameter settings and also compare the performance to that of several 'neutral models of landscape change'. The model is a Constraint Cellular Automata model of land use change in La Réunion. Results from the same model with two different parameter sets are compared. The first parameter set is based on a quick calibration and the second on a more thorough calibration. It is expected that the second calibration will produce results more similar to reality than the first calibration. Furthermore, the results from two neutral models of landscape change are evaluated. These neutral models are simple models that are subject to the same constraints as the cellular automata model, but otherwise do not represent any system knowledge. Their only premise is a minimization of the level of change given the initial situation. It is expected that the neutral models of landscape change are outperformed by both calibrated versions of the CA model.

The first neutral model of landscape change is a random constraint match model (Hagen-Zanker & Lajoie 2007 in prep). This model changes the original map as little as possible, but where it has to change (because of the constraints, that prescribe a total area per cell) it finds locations randomly.

The second neutral model of landscape change is a growing clusters model (Hagen-Zanker & Lajoie 2007 in prep). This model, like the random constraint mathc model, changes the original map as little as possible, but where it has to change it finds locations for categories at locations that are adjacent to a a cell of that category.

A last neutral model is a random location model, this model does not take the initial situation into account and randomly allocates the area constraints over the map. This model is expected to perform worst of all.

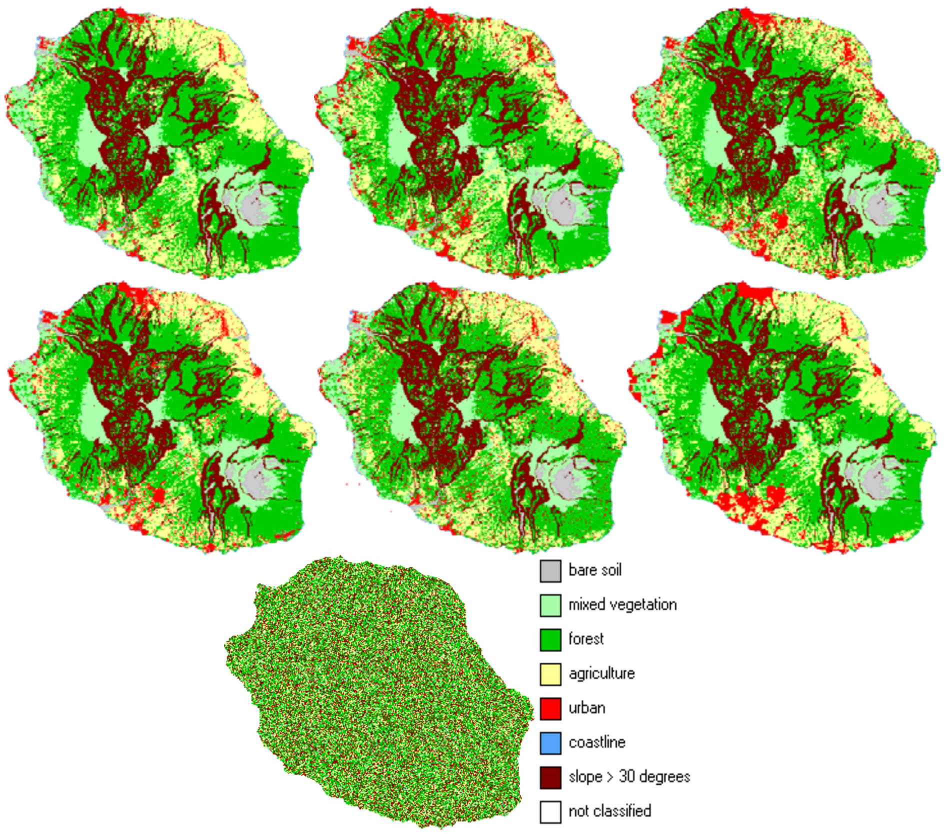
In summary, we have 5 land use models. In order of expected similarity to ground truth, these are the following:

1. Constraint Cellular Automata model with thorough calibration
2. Constraint Cellular Automata model with quick calibration

3. Neutral models of landscape change
    a. Random constraint match
    b. Growing clusters
4. Random location

The maps that are available for this experiment and the related case have been documented elsewhere (Hagen-Zanker & Lajoie, 2007 submitted). This information will not be repeated here, but the maps are visualized in **Figure 2.4**. The maps are categorical raster maps with a resolution of 200 meter.

Figure 2.4 *Seven land use maps of La Réunion*
a. Ground truth 1989
b. Ground truth 2000
c. Thorough calibration 2002
d. Quick calibration 2002
e. Random constraint match 2002
f. Growing clusters 2002
g. Random location 2002



To reduce the dimensionality of the problem the maps have been reclassified to only four classes: Natural vegetation, Agriculture, Urban and Unused land. The categories on the original maps that referred to coastline and ocean are treated as nodata values and are ignored in the analysis. The reclassification scheme of **Table 2.2** has been applied.

Table 2.2 *Reclassification of land use types*

Reclass category	**Original category**
Natural vegetation	Mixed vegetation
Natural vegetation	Forest
Agriculture	Agriculture
Urban	Urban
Unused land	Slope
Unused land	Bare soil

Each dimension in the state space comparison refers to a single category. Of that category the prevalence (fraction of occurrence) within a circular neighbourhood is registered and is divided into 6 bins. Thus, in a moving windows analysis the percentage of occurrence for each of the four classes is calculated and a classification is made on the basis of 6^4=1296 classes. In first instance the analysis is performed on the basis of a circular neighbourhood with a radius of 10 cells.

The results (**Table 2.3**) indicate as expected that the intensively calibrated model is most similar to the ground truth data. Also according to expectation, the neutral models that take into account the initial situation (random constraint match and growing clusters) perform much better than the random location model that generates a landscape from scratch. It is surprising however that the extensive calibration, the earlier version of the model, does not outperform both neutral models of landscape change. Even though beforehand it was clear that this calibration is of less quality than the intensive calibration, the predicate ‘worse than random’ indicates that the quality of the calibration was overestimated.

Table 2.3 *Difference in transition pattern, based on land use fractions within a 10 cell radius.*

	Score	Normalized
Thorough calibration	43.0	0.42
Quick calibration	79.4	0.78
Random constraint match	73.1	0.72
Growing clusters	74.6	0.73
Random location	130.5	1.28
No change	102.0	1

The choice of a 10 cell radius is trivial, and therefore different radii are evaluated, establishing a multi-scale analysis. Hagen-Zanker & Lajoie (2007, in press) indicated that models can be expected to predict non-change better than change. In this moving window approach fine scales by definition change more than coarse scales, therefore there is a bias that considers maps at coarse scales more similar than at fine scales. To overcome this bias the difference metrics are normalized to the level of actual change. This level is found by calculating the difference between a model of no-change and the actual change evident in the ground truth maps. The multi-scale results after this normalization are found in **Table 2.4.**

The multi-scale results are surprising because they indicate that the model is performing best at the finest scales. This is unexpected because earlier analysis (Hagen-Zanker & Lajoie 2007) pointed to the opposite. It is tempting to conclude that a realistic representation of fine-scale dynamics is responsible for coarse scale structural similarity. If this was the case however the best results should be present at the radius of spatial interaction of the CA model (max 8 cells) and not at a radius of 0. Note that the setting with a radius of 0 is special in the sense that the land use fractions for all location is either 0 or 1. Instead of 1296 there are only 5. This may have impacted the analysis. Further research should indicate whether the normalization procedure or the weighting of presence in **Equation 1.2** introduce new biases to the analysis.

Table 2.4 *Normalized differences in transition pattern based on land use fractions within 4 different radii.*

	R = 0	R = 5	R = 10	R = 20
Intensive calibration	0.25	0.51	0.42	0.38
Extensive calibration	0.84	0.80	0.78	0.70
Random constraint match	0.80	0.74	0.72	0.70
Growing clusters	0.83	0.79	0.73	0.67
Random location	3.07	1.23	1.28	1.42

2.3.2 Experiment 2 – Classification of urbanization patterns

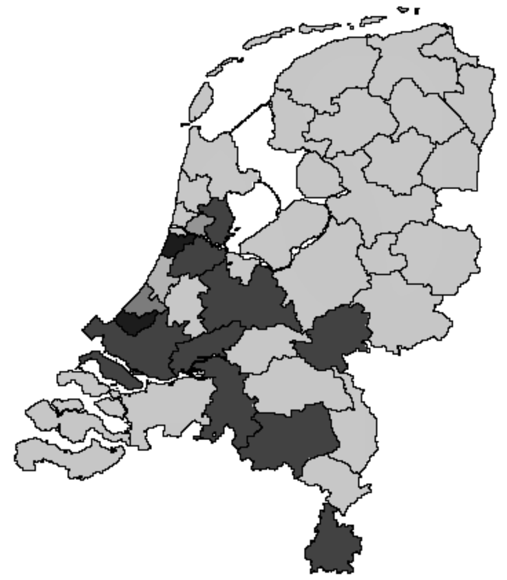
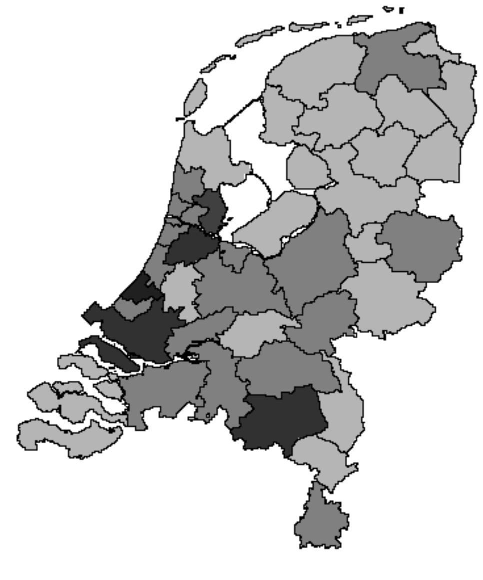
The second experiment aims at a classification of urbanization patterns in the Netherlands. The attributes that are taken into account in this experiment are presence of urban area within two different radii. The fractions of presence are classified into 5 bins of equal size. Thus, there are 5^2=25 different classes.

The map pair consists of the land use maps of 1989 and 1996. In a pre-processing step, these maps have been reclassified to only contain the classes urban and non-urban. The maps are categorical raster maps with a resolution of 500 m. The analysis is performed for 40 regions, in European context called NUTS2 regions. To test the robustness of the results the analysis is performed for several setting (radii) and also for a second map of regions that divides the Netherlands in square 15*15 km^2 regions.

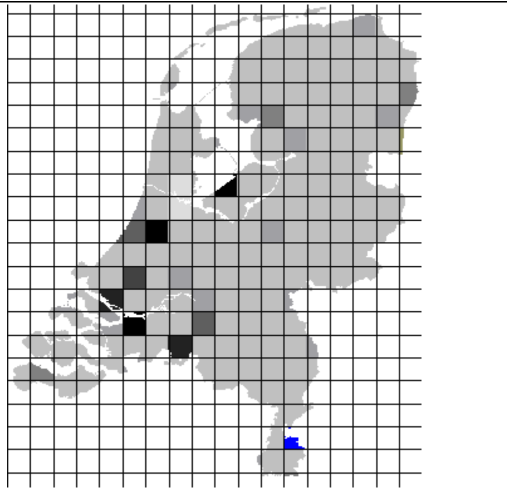
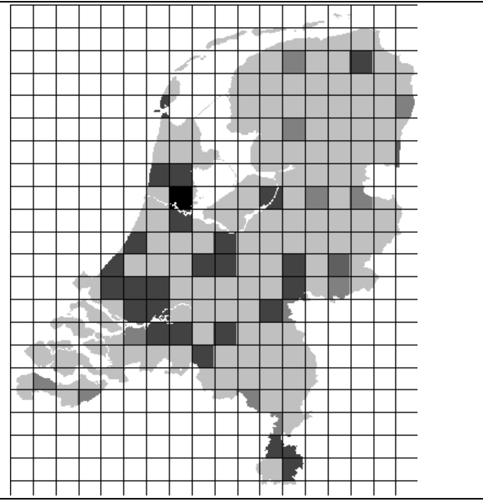
The results are considered robust if for similar settings we find similar results. The method finds robust results for the NUTS2 regions when no neighbour-bonus is applied. The results for the 40 regions are robust, but those for 15 km grid regions not. Only when the neighbour-bonus is applied (β in **Equation 1.3),** a pattern similar to that of the 40 regions is found, and then only in some of the settings. This lack of robustness may be caused by the small size of the regions, which makes the analysis more susceptible to noise in the data (e.g. classification errors or highly localised change events).

A familiar pattern emerges (**Figure 2.5**). It highlights the Randstad, the ring of major cities including Amsterdam, Rotterdam, Utrecht and the Hague together with some other highly urbanized areas. In the middle of the Randstad lies the Green Heart, a large natural/agricultural area subject shielded from urbanization by strict planning,. This Green Heart forms a cluster with the more rural areas of the Netherlands. Depending on the precise settings some separate clusters are found at the coast in the highly urbanized areas. A possible explanation is that these high density areas are saturated and do not allow for much growth.

A full explanation of these results is not within the reach of this paper. We suffice by pointing some striking correlations. There is a strong similarity in pattern with population distribution (**Figure 2.6**) as well as planning status both before and after the analysed period (**Figure 2.7**).

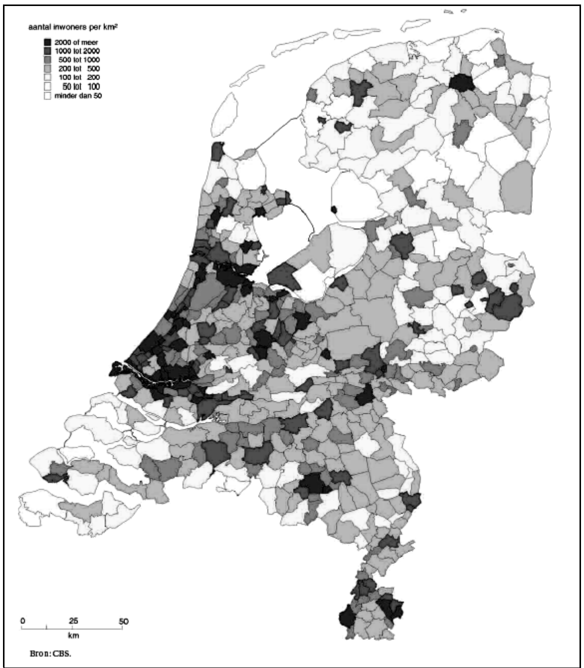
	

const double r1 = 2;
const double r2 = 16;
const double nbhFactor = 1;
const int nBins = 4;
	const double r1 = 4;
	const double r2 = 15;
	const double nbhFactor = 1;
	const int nBins = 5;

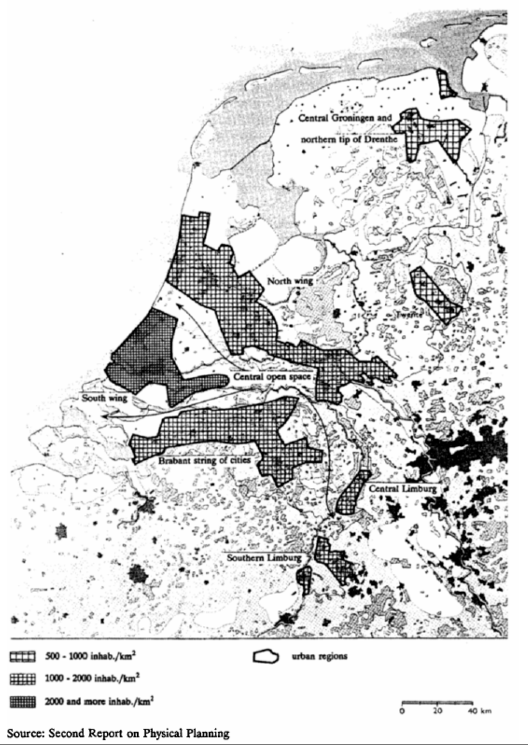
const double r1 = 2;
const double r2 = 16;
const double nbhFactor = 0.8;
const int nBins = 4;
	const double r1 = 4;
	const double r2 = 15;
	const double nbhFactor = 0.8;
	const int nBins = 5;

Figure 2.5 *Clusters of similar patterns of urban change in the Netherland. The robustness of the method is investigated by applying it under slightly different settings*

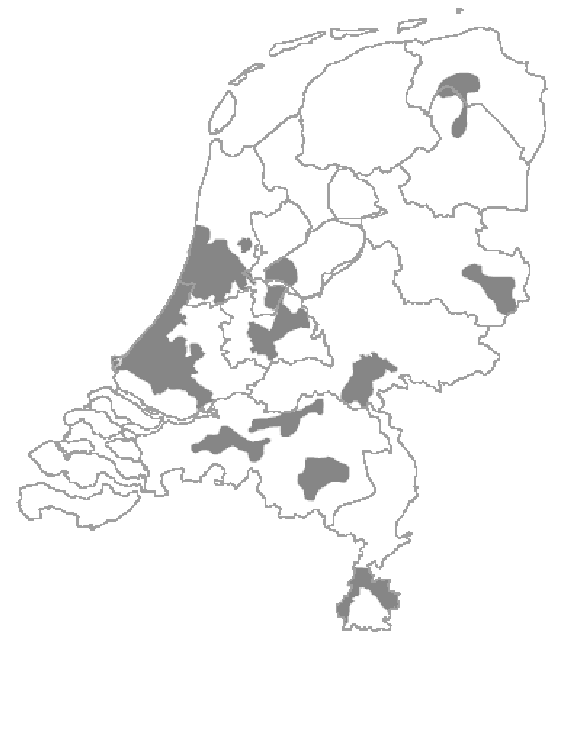


Population density in the Netherlands 2000 (source: Ekamper et al. 2003)

Figure 2.6 *Population density*



Second report of physical planning (1966) Urban regions and planned densities for 2000. (source Buijs 1992)



National Spatial Strategy (2004), combination areas (source Snellen et al. 2006)

Figure 2.7 *Spatial policy at the national level*

2.4 Conclusion

This paper introduces a methodology for summarizing urban change. As a proof of concept the application of the method is demonstrated by two experiments. The first experiment demonstrates how the comparison of changes over time can be a measure of model performance. In this case of models that predict change over time it evaluates models precisely on their essence. The ranking of the different models of the experiment are largely according to expectations. The exception is the extensively calibrated version of a spatial land use model, which performed poorer than models of random change.

In the second experiment a robust classification of urbanization patterns was made. The results indicate that highly urbanized areas change differently over time than less urbanized areas. This may not be a surprising result, but it indicates a consistency of the methodology. The results present questions that warrant further research. For instance the relation between population density and urban change and the impact of urban planning at the national level can be further investigated on the basis of this approach. A question of particular interest is to what extent spatial planning prescribes or follows patterns of urban change.

In summary the experiments indicate good prospects for transition based descriptive modelling of urban change. Some weaknesses, however, are revealed as well.

The classification application with small regions did not bring the same robust results of the large region application. The results from the multi-scale analysis raise questions; possibly the corrections for non-occurrence of classes and the normalization to the level of historical change introduce biases to the analysis. A suggested line of research that may settle these questions is a formal elaboration on the basis of Markov Chains. In that work, a central topic would be account for the lack of independence between observations.

Other drawbacks of the methodology are the loss of information due to classification of continuous data into a small number of bins, and related, the curse of dimensionality. This curse holds that the number of classes grows exponentially with the number of dimensions and the number of observations per class reduces accordingly. Therefore, even though theoretically the number of characteristics and classes to distinguish is unlimited, in practice it is imperative to reduce to the essentials.

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