Computers, Environment and Urban Systems 33 (2009) 35–43

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/compenvurbsys

Modeling urban growth using a variable grid cellular automaton

Jasper van Vliet [a,*], Roger White [a,b], Suzana Dragicevic [c]

[a] Research Institute for Knowledge Systems, P.O. Box 463, 6200 AL Maastricht, The Netherlands
[b] Department of Geography, Memorial University of Newfoundland, St. John's, Canada A1B 3X9
[c] Spatial Analyses and Modeling Laboratory, Department of Geography, Simon Fraser University, Burnaby, Canada V5A 1S6

ARTICLE INFO

Article history:
Received 26 July 2007
Received in revised form 10 June 2008
Accepted 20 June 2008

Keywords:
Cellular automata
Variable grid
Urban growth models
Spatial dynamics

ABSTRACT

Constrained cellular automata (CA) are frequently used for modeling land use change and urban growth. In these models land use dynamics are generated by a set of cell state transition rules that incorporate a neighborhood effect. Generally, neighborhoods are relatively small and therefore only a limited amount of spatial information is included. In this study a variable grid CA is implemented to allow incorporation of more spatial information in a computationally efficient way. This approach aggregates land uses at greater distances, in accordance with a hierarchical concept of space. More remote areas are aggregated into consecutively larger areas. Therefore the variable grid CA is capable of simulating regional as well as local dynamics at the same time. The variable grid CA is used here to model urban growth in the Greater Vancouver Regional District (GVRD) between 1996 and 2001. Calibration results are tested for goodness of fit at the cellular level by means of the kappa statistic and for land use patterns by means of cluster size analysis and radial analysis. Kappa results show that the model performs considerably better than a neutral allocation model. Cluster and radial analysis indicate that the model is capable of producing realistic urban growth patterns.

1. Introduction

Tobler's first law of geography states that "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). Translated to land use this implies that the surroundings of a location are related to the land use at that location, but close surroundings have a stronger influence than more remote surroundings. The notion that land uses are spatially related and that nearby land uses have a stronger relation than land use at a greater distance was confirmed by empirical analysis of neighborhood characteristics (Verburg, Nijs, Ritsema van Eck, Visser, & Jong, 2004a; Verburg, Ritsema van Eck, Nijs, Dijst, & Schot, 2004b). This influence of neighboring land uses is strongly embedded in cellular automata (CA) based land use models by their neighborhood effect.

CA models are used in several ways to model land use changes (Clarke, Hoppen, & Gaydos, 1997; White, Engelen, & Uljee, 1997; Wu, 1998), where they are found to be particularly applicable to simulate urban dynamics (Barredo, Demichelli, Lavalle, Kasanko, & McCormick, 2004; White & Engelen, 1993). The latter is predominantly so for the ability of CA to create complex patterns (Wolfram, 1984) that are not unlike urban patterns (Batty, 2005; Batty & Xie, 1994). More recently, CA land use models have been applied as tools to support land use planning and policy analysis (Geertman & Stillwell, 2004) as well as to explore scenarios for future development (Barredo et al., 2003; Engelen, White, & Nijs, 2003; Nijs, Niet, & Crommentuijn, 2004).

A CA essentially comprises the following elements: (1) a cell space or lattice, (2) a finite set of cell states, (3) a definition of a cell's neighborhood, (4) a set of transition rules to compute a cell's state change and (5) time steps in which all cell states are simultaneously updated (White & Engelen, 2000). To make CA applicable for geographical modeling, the strictly defined CA rules are frequently loosened. These models are therefore referred to as relaxed cellular automata models (Couclelis, 1997). In constrained CA models, the total amount of area per land use is not a function of the transition rules, but determined exogenously instead, while the allocation of these land uses is computed by the CA (White et al., 1997). For example in an urban growth model the total area for residential land use can be derived from historic data or extrapolations thereof. This area demand is then imposed on the CA model that allocates a corresponding number of cells on the map, based on the transition rules.

1.1. On a cell's neighborhood

A cell's neighborhood is the region that serves as an input to calculate the neighborhood effect in the transition rules. This effect is a

* Corresponding author. Tel.: +31 43 3883343; fax: +31 43 3253155.
E-mail addresses: Jvanvliet@riks.nl (J.van Vliet), Roger@mun.nl (R. White), Suzanad@sfu.ca (S. Dragicevic).

0198-9715/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.compenvurbsys.2008.06.006

function of a cell's own state and the state of the cells within its neighborhood. In land use terms, this represents attraction or repulsion of neighboring land uses. Hence, the size of the neighborhood determines the amount of land use information that is considered in the neighborhood effect. Originally, in CA only directly and diagonally adjacent cells were included. In human induced land use change however information at greater distances also influences land use changes, although the effect typically decreases with increasing distance. Hence larger neighborhood configurations are used to model land use change and urban growth (White & Engelen, 1993). In current applications this size ranges up to an 8-cell radius, enclosing 196 cells (Barredo et al., 2004; Engelen et al., 2003). Since larger neighborhoods include more land use information, they allow for better models. The number of cells in a neighborhood is directly related to the radius of the neighborhood. Therefore, increasing this radius would include more land use information. However, the required computation time would increase dramatically, as the number of cell-to-cell relations grow with the square of the radius. At the same time, this approach would use spatial information at larger distances at a higher level of detail then required.

Still, intuitively, more distant areas also influence land use change (Andersson, Lindgren, Rasmussen, & White, 2002a). This notion that information can travel over greater distances and thus have influence further away than just adjacent areas is well established in Hägerstrand's innovation diffusion (1967). To incorporate effects operating over larger distances, it has been necessary to combine two or more models that operate on different spatial levels. In these integrated models, a gravity based regional model calculates regional demands for land uses and a constrained CA model then allocates these demands on the map (White & Engelen, 2000). To overcome this problem, a more complete hierarchical conceptualization of space was introduced in Andersson, Rasmussen, and White (2002b). The assumption is that humans intuitively use a similar indexation to interpret and divide space: A city has several parts, each part consists of several blocks and every block again has a number of houses. The closer a feature is, the more in detail we think of it. Close surroundings, like neighboring houses, are of prime importance in spatial decisions. The more remote environment is considered with respect to its place in a spatial hierarchy: the next block is less important then immediate adjacent houses, but more important than the other side of town (Andersson et al., 2002a). In analogy to this hierarchical notion of space, cells at a greater distance can be aggregated to larger areas, while detailed information is kept for areas close by. This aggregation to area averages of land uses considerably reduces the number of spatial relations and thus the required computation time (White, 2005). Consequently, spatial information over much larger distances can be incorporated in the neighborhood effect and interregional effects need no longer be calculated in a separate model.

The variable grid CA is an implementation of this concept in a CA environment that allows incorporating all available land use information when calculating an individual cell's propensity to change. This is done by enlarging the neighborhood to include cells at all distances by using a hierarchical representation of space in the neighborhood definition. Specifically, this method uses a variable grid to aggregate more remote areas to mean field approximations (White, 2005). More distant cells are aggregated into increasingly bigger fields. This limits the number of spatial relations to be computed while nevertheless incorporating the maximum amount of land use information. Thus the model incorporates long distant relations as well as local effects. In this study the variable grid CA is applied to simulate urban growth in the Metro Vancouver area (former Greater Vancouver Regional District – GVRD). Both its applicability to simulate actual urban growth and its ability to simulate regional dynamics were tested with this application.

Moreover, the variable grid as presented in White (2005) introduces levels of activity for land uses. In the present application these are not incorporated and therefore activities are not considered in this text.

2. The variable grid cellular automata model

For this study the variable grid neighborhood is implemented in a constrained CA model. Hence the demand per land use class is defined exogenously; for every year the demand for constrained land use classes is defined in terms of a number of cells for the whole area (White et al., 1997). The allocation of these cells is determined by the potential of each cell for all land use classes as computed by the CA transition rules and using the variable grid neighborhood configuration. Land uses are assigned to cells with the highest potential, until the demand for this land use is met. Potentials for each cell and for each constrained land use class are calculated as follows (White & Engelen, 2000):

$$P_{il} = v * A_{il} * S_{il} * Z_{il} * N_{il},$$

where P_{il} is the potential for cell i and land use type l; v is a stochastic perturbation term equal to $1 + (-log(random))^{\alpha}$, where α is a scaleable parameter and *random* is a randomly drawn number from a uniform distribution between 0 and 1; A_{il} is the accessibility of cell i for land use l to transport networks; S_{il} is the suitability of cell i for land use l; Z_{il} is the zoning status of cell i for land use l; and N_{il} is the neighborhood effect for cell i for land use l as computed with the variable grid method as explained below. Calculation of variables other than the neighborhood effect is discussed more fully in White and Engelen (2000).

The variable grid CA was implemented using the Geonamica spatial modeling framework. This modeling framework (without the variable grid) has been applied successfully in land use change models, for example the Environment Explorer (Engelen et al., 2003) and the MOLAND project (Barredo, Lavalle, Demichelli, Kasanko, & McCormick, 2003b), and in integrated spatial models, for example MedAction (van Delden, Luja, & Engelen, 2007).

2.1. Definition of the cell neighborhood effect

The basic lattice with the highest resolution is referred to as the level 0 grid. At this level, every cell has only one state that represents its actual land use, formalized as

$$C_k^0(x) = \in \{0, 1\},$$

where $C_k^0(x)$ is 1 if land use k is present at location x and 0 otherwise. Now each successive level (L) then contains $(3^2)^L$ level 0 cells. Thus level 1 cells are an aggregation of $3^2 = 9$ level 0 cells and a level 2 cell of $(3^2)^2 = 81$. As a result, higher level cells are represented with cell counts of level 0 land uses instead of having one single state, and $C_k^L(x)$ is the cell count of land use class k in a square of 3^{2L} cells centered at x. Each level 0 cell has eight adjacent cells, 4 rook adjacent and 4 bishop adjacent. Around this level 0 neighborhood there are eight level 1 aggregated cells, which are again surrounded by eight level 2 cells, etc. More generally every level L contains four rook adjacent cells $D_i^{\text{rook}}(L) = \{(i, i+3^L), (i+3^L, i), (i, i-3^L), (i-3^L, i)\}$ and four bishop adjacent cells $D_i^{\text{bishop}}(L) = \{(i+3^L, i+3^L), (i+3^L, i-3^L), (i-3^L, i+3^L), (i-3^L, i-3^L)\}$. This neighborhood template, as shown in Fig. 1, is relative to each individual cell and therefore moves cell by cell over the entire grid. Each aggregated cell holds cell counts for all land uses $l, k \in \{1, 2, \ldots, \ldots, m\} = K$, where K is the set of all possible land uses states.

Influence of land use is represented by a weight which represents the attraction or repulsion from one land use to another as a function of the distance. Since rook adjacent cells are closer than bishop adjacent cells, this requires two discrete weight values for each consecutive aggregation level. Since the variable grid incorporates the whole area in the neighborhood, the neighborhood effect is the cumulative effect of all weighted cell-to-cell land use relations in all consecutive levels of aggregation

$$N_{il} = \sum_{L} \left[\sum_{x \in D_i^{\mathrm{rook}}(L)} \sum_{k \in K} w_{lk}(3^L) \cdot C_k^L(x) + \sum_{x \in D_i^{\mathrm{bishop}}(L)} \sum_{k \in K} w_{lk}(\sqrt{2} \cdot 3^L) \cdot C_k^L(x) \right],$$

where N_{il} is the neighborhood effect for cell i for land use l, $w_{lk}(d)$ is the weight parameter representing the attraction or repulsion from land use k on land use l at distance d and $C_k^L(x)$ is the number of level 0 cells with land use k aggregated in the cell centered at x. Distance d is measured from the centre of cell i to the centre of each aggregated cell, x.

3. A case study on the Greater Vancouver Regional District

The Greater Vancouver Regional District is a highly urbanized and rapidly growing area located in the Lower Mainland of British Columbia, Canada. In the last century population increased from a little over 230,000 in 1921 to almost 2,000,000 in 2001 (Fig. 2). Projections in the near future show no change in this trend, and population is expected to grow almost linearly to around 2,900,000 in 2031 (BC STATS, 2006). At the same time space for urban expansion is scarce. Greater Vancouver is surrounded by the sea to the west, the United States to the south and mountains to the north. The land that is suitable for urban land use is mainly protected and used for agriculture and natural areas. Hence, to prevent urban sprawl and protect both agricultural and natural areas, the government aims at concentration of population and restricted growth. Formally this is implemented in the Livable Region Strategic Plan (GVRD, 1999).

This plan defines four aims for a sustainable growth strategy: (1) Protect the Green Zone: The Green Zone protects Greater Vancouver's natural assets, including major parks, watersheds, ecologically important areas and resource lands such as farmland. It also establishes a long-term growth boundary. (2) Build complete communities: The plan supports the public's desire for communities with a wider range of opportunities for day-to-day life. Focused on regional and municipal town centers, more complete

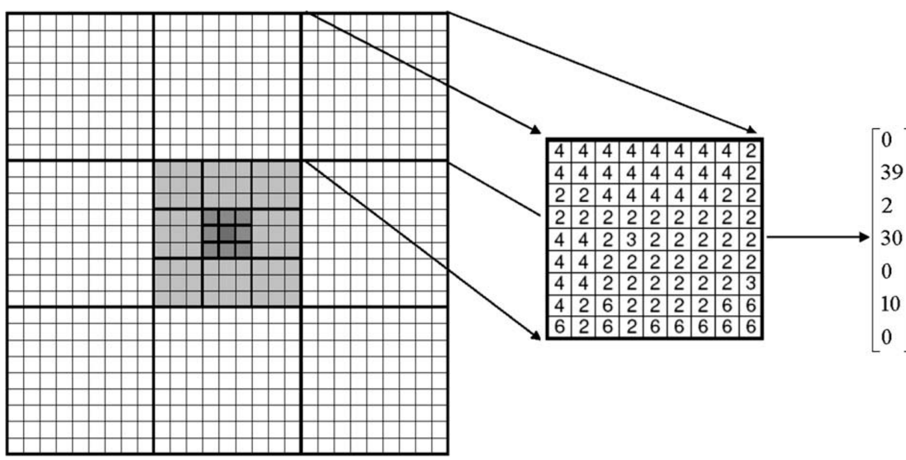

Fig. 1. Three aggregation levels relative to the central cell in the neighborhood. Numbers characterize different land use types. The vector represents the cell counts of level 0 cells per land use type as assigned to the central point of the aggregated level 2 cells.

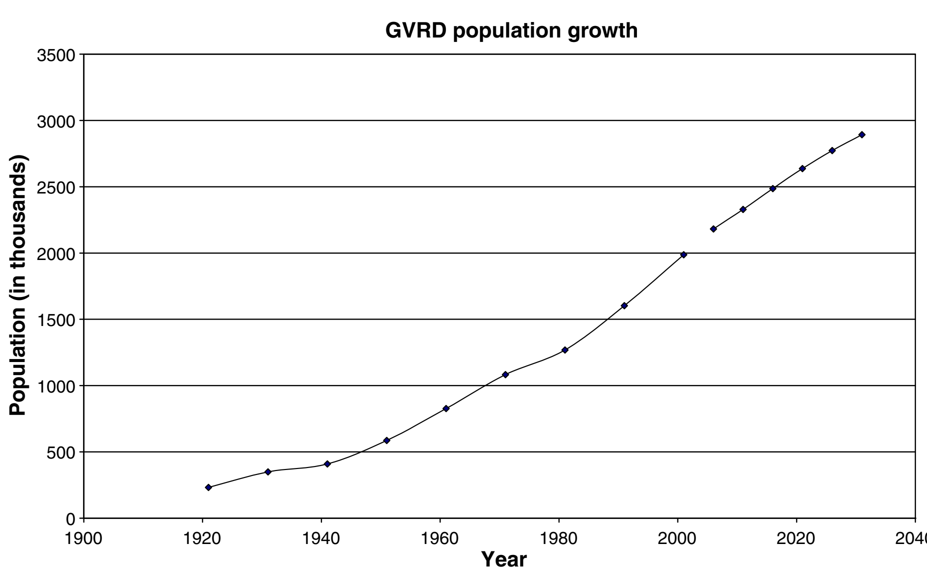

Fig. 2. Historic and projected population numbers in the greater vancouver regional district (GVRD, 1999).

communities would result in more jobs closer to where people live and accessible by transit, shops and services near home, and a wider choice of housing types. (3) Achieve a compact metropolitan region: The plan avoids widely dispersed development and accommodates a significant proportion of population growth within the “growth concentration area” in the central part of the region. (4) Increase transportation choice: The plan supports the increased use of transit, walking and cycling by mini-

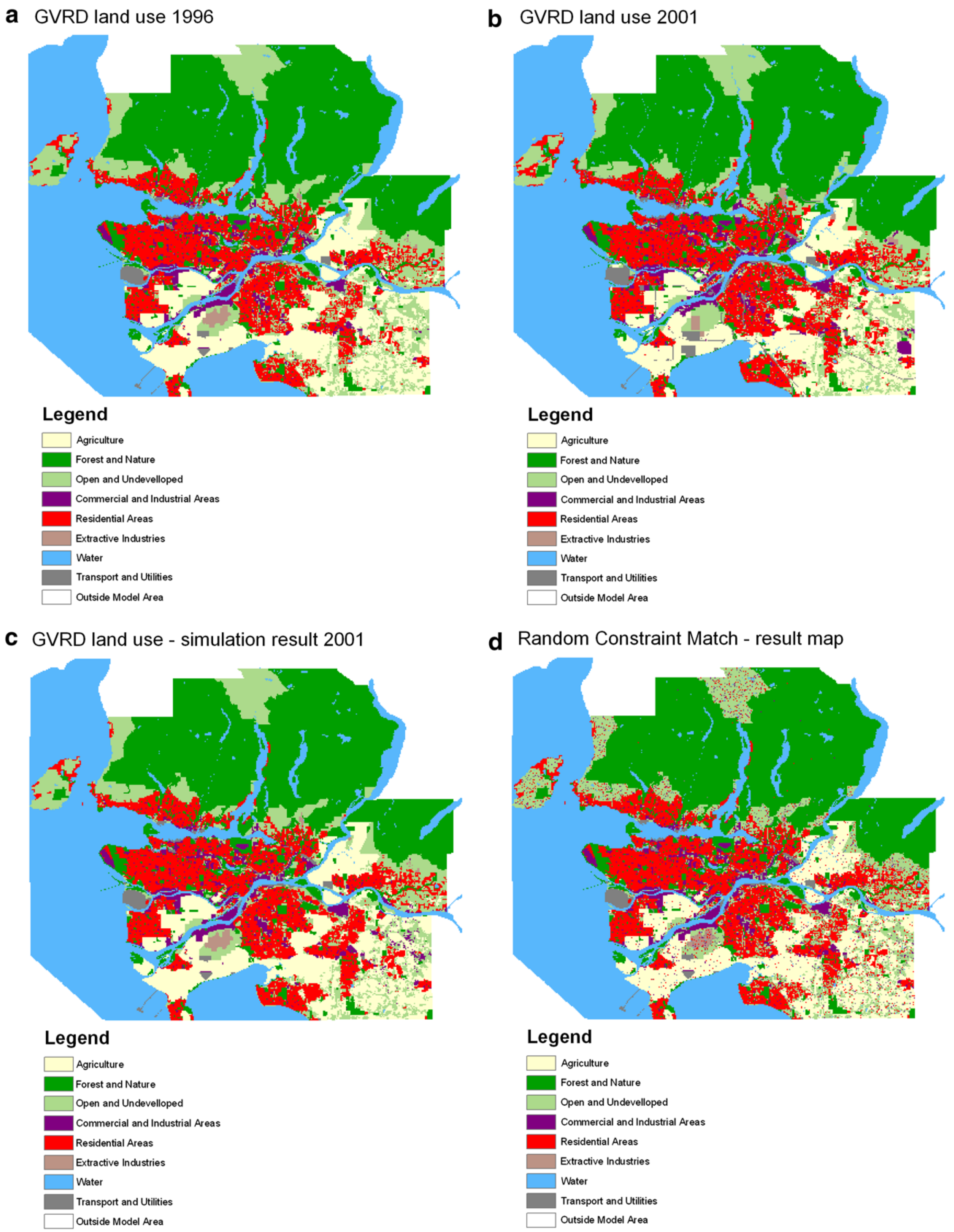

Fig. 3. GVRD land use maps representing (a) the 1996 actual land use, (b) the 2001 actual land use, (c) a simulation result and (d) a random reference result.

mizing the need to travel and by managing transportation supply and demand.

3.1. Datasets

The GVRD area covers 2820 km^2. Raster data layers are represented on a grid of 760 by 635 cells and have a 100 m spatial resolution. Land use data was made available from the Greater Vancouver Regional District for the years 1996 and 2001. Hence land use change was simulated for this period, using time steps of one year. Overall land use change, in terms of number of cells, was derived from the 1996 and 2001 land use data and used as an exogenous constraint to the model. Land use maps were classified in 14 classes in 1996 and 15 classes in 2001. The 14 classes were identical in both maps, which made comparison feasible. The one new class in 2001 is combined residential and commercial land use and is reclassified as commercial. For use in the model, land use was reclassified to seven new classes: (1) *Agriculture*, (2) *Forest and Protected Nature*, (3) *Open and Undeveloped*, (4) *Commercial and Industry*, (5) *Residential*, (6) *Extractive Industry* and (7) *Water*. Of these only (4) and (5) are truly active classes. Their total number is constrained exogenously, but their allocation is completely dependent on the potential as computed with the transition rules. Effectively, at each time step all cells in these classes are allocated again. However, the inertia effect results in only a few actual changes, mainly the increase in these classes. Classes (1), (2) and (3) represent passive land uses, they can only change as a result of change in active classes. Finally, classes (6) and (7) are fixed; they cannot change. However the presence of fixed land uses can influence the allocation of active land uses.

Additional data is used to derive accessibility information, a suitability map and a zoning map. Accessibility is computed in the model as a function of the Euclidean distance to the nearest cell that contains a transport network. Therefore, three transport networks are selected: skytrain, limited access highways and major roads. Information on transport networks was obtained from Greater Vancouver Transportation Authority (TransLink) in BC, Canada. To represent the physical suitability for urban land uses, a slope map is derived from a digital elevation model and aggregated to the appropriate cell size. The Digital elevation model was provided by the Greater Vancouver Regional District. Finally a zoning map is created to represent the restrictions on the development of *residential* and *commercial and industrial* land use in certain areas. This map reflects the GVRD Green Zone policy to preserve natural and agricultural areas (GVRD, 1999).

4. Model calibration and results

Calibration results are derived from properties of the simulated land use maps. Three different aspects of the output maps were measured. These are the goodness of fit on a pixel basis, the capability to produce realistic urban patterns, and the ability to model regional interactions. In the assessment, the simulation results were compared to results from a reference simulation model. A constrained random allocation model was used to create these reference maps. This model computes the amount of actual land use change between two land use maps and allocates this change randomly but with minimal change on the base map, in this case the 1996 land use map. As a result, the random map will have the same land use frequency distribution as the actual 2001 land use map (Hagen-Zanker & Lajoie, 2008).

Generation of both the model results and the reference results involves a random term. Therefore five model runs and five reference results were obtained to assess the quality. Maps a, b, c and d in Fig. 3 represent the 1996 land use map, the 2001 land use map, a simulation result and a random reference map.

4.1. Goodness of fit

Accuracy of simulation results on a pixel by pixel basis was assessed using the Kappa statistic. This statistic measures the goodness of fit between two nominal datasets, corrected for accuracy by chance (Bishop, Fienberg, & Holland, 1975). Since land use maps are categorical maps, Kappa can be used to assess the goodness of fit between the simulation result and the real land use map at the end of the simulation period (Foody, 2002; Pontius, 2002). Because the emphasis of this study is on simulating growth in urban land use classes, i.e. *commercial and industrial* and *residential*, statistics are also derived for these land uses separately.

Kappa values range from 1 to -1, where positive values indicate a better agreement than expected by chance, and negative values a worse agreement. However, the absolute value of Kappa is not an appropriate measure for model results since it is highly dependent on the number of cells that change. A simulation with very few changing pixels will result in high Kappa values, even if all newly allocated pixels are placed incorrectly. Therefore this statistic can only be used to compare different results from the same case study. Hence Kappa values are considered here relative to the results of the random model.

A drawback of using Kappa statistics for model results is that slight displacements are classified as incorrect, whereas from a modeler's perspective they can be considered almost correct. For example new residential land use that is allocated just one cell away from the actual location of this new residential area can be regarded as a good result. Therefore a fuzzy Kappa was used (Hagen, 2003; Hagen-Zanker, Straatman, & Uljee, 2005). This statistic uses a linear distance decay function to account for slightly displaced pixels. Fuzzy Kappa was computed using a slope of 0.2 and a radius of 5 cells. I.e. a residential cell that is dislocated exactly 2 pixels, would count as 0.6 correct.

Model results are presented in Table 1. Although a random perturbation term is necessary to obtain realistic results, and although simulation results differ significantly from each other, Table 1 indicates that simulation results are similar in terms of goodness of fit. Both Kappa and Fuzzy Kappa scores indicate that the model performs considerably better than the random allocation model. The relatively low Kappa scores for commercial and industry are caused by the appearance of a few large patches of this particular land use between 1996 and 2001. These are the results of one single planning decision and as such they cannot be simulated using a bottom up technique like a CA.

Table 1
Kappa and fuzzy Kappa results for the calibration period (1996–2001)

	Kappa			Fuzzy Kappa
	Overall	Residential	Comm & Ind	overall
Simulation 1	0.866	0.871	0.750	0.776
Simulation 2	0.866	0.871	0.752	0.776
Simulation 3	0.866	0.871	0.750	0.776
Simulation 4	0.866	0.872	0.751	0.777
Simulation 5	0.866	0.871	0.752	0.776
Random allocation 1	0.841	0.846	0.738	0.733
Random allocation 2	0.841	0.846	0.738	0.732
Random allocation 3	0.841	0.846	0.738	0.731
Random allocation 4	0.841	0.846	0.737	0.732
Random allocation 5	0.841	0.846	0.738	0.731

Scores are derived by comparing the simulation result map and one of the random reference maps with the actual 2001 land use map.

4.2. Pattern analysis

Since land use models often use randomness to simulate complex processes, some authors argue that accuracy assessment is not the appropriate way at all to measure simulation results (Parker & Meretsky, 2004; Power, Simms, & White, 2000; Remmel & Csillag, 2003). As bifurcation and emergence occur in complex processes like land use dynamics (Batty, 2005), results are generally path dependent and the same model can generate different outcomes (Brown, Page, Riolo, Zellner, & Rand, 2005). Although such outcomes do not match the actual land use change, they may still represent realistic dynamics thus indicating a proper underlying model. Pattern based measurements are a good alternative to assess a model's quality. In recent applications several metrics are used to measure maps, based on patch characteristics (Riitters et al., 1995), polygon matching (Power et al., 2000), or fractal analysis (Frankhauser, 1994, 2004). In this research, two pattern analyses are used to assess simulation results, both associated with fractal properties of urban systems (Batty & Longley, 1994); cluster analysis and radial analysis (White, 2006).

Cluster analysis measures the relation between the size and frequency of urban land use clusters. On a logarithmic scale, this relationship is linear. Hence it can be used to calibrate and validate urban growth models. Radial analysis investigates scaling properties by measuring cumulative area (pixels) against radius on a logarithmic scale. Processes like urban growth that evolve outward from a nucleating centre, show such properties. On a logarithmic scale a linear relation can be observed, with a slope of 1.90 to 1.95 for dense urban centers, and approximately 1.0 in the outer urbanizing zone. A clear bend appears in the plot at the transition points between the urbanized and urbanizing points (White & Engelen, 1993). Because the amount of change over the calibration period is not very large, the simulations were extended to 20 years using the same rate of change. This generates enough spatial dynamics to investigate whether sufficient new clusters of urban land use appear and whether the urban area indeed maintains its characteristic radial dimensions. In this research, cluster analysis was performed on *residential* land use only. Radial analysis was computed for *residential* and *commercial and industrial* land use together.

Results of the cluster analysis for one simulation are presented in Fig. 4. Although the other four simulation results show similar results they are not shown for reasons of visibility. To define clusters, only rook adjacency was considered here. Clusters are aggregated in size classes, and frequencies are of all clusters within the boundaries of that class. The graph indicates that in general the model preserves the characteristic relationship between the cluster size and the frequency. However, from the graph it becomes clear that the simulation generates more small clusters than appear in reality. An explanation for this is the strict planning policy in the GVRD, which prevents these scattered settlements. In reality therefore most newly developed areas are larger patches from the beginning. This is hard to simulate in a CA environment. At the other end of the range of class sizes, an uneven distribution is visible. This uneven distribution is an effect of the local physical constraints. The shape of land patches between the rivers causes some urban patches not to grow any further.

Radial analysis results are presented in Fig. 5. For reasons of visibility, only one simulation result is shown, but the other four results show similar figures. Since urban land use is a combination of *commercial and industrial* and *residential* land uses, this analysis was performed on both land use classes together. The centre for this radial analysis was chosen just southeast of the downtown area, where Vancouver was founded originally. In the graphs for the 1996 land use map and the simulation result, the bend between the inner core and the outer zones is clearly visible. The difference between both graphs shows that new urban land use is mainly allocated at the fringes of the city.

4.3. Regional distributions of land uses

To assess regional land use distributions, the GVRD area was divided in municipalities. For all municipalities the modeled growth or decline in *Commercial and Industrial* and *Residential* land use was compared to the actual change per municipality. The root mean square error (RMSE) is used as a summary statistic for the whole

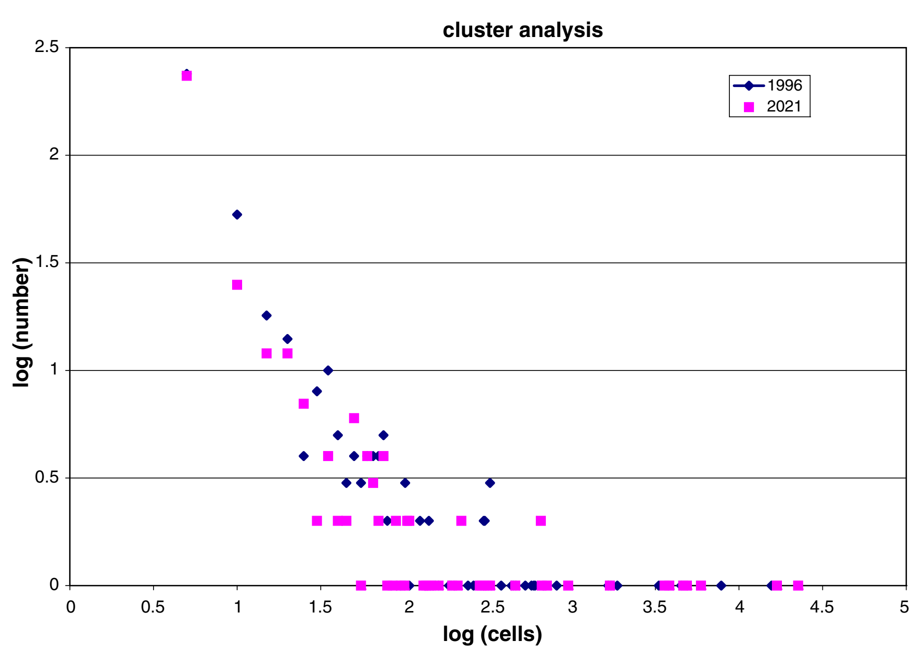

Fig. 4. Cluster size frequency analysis of the 1996 land use map and the result of the simulation extended to 2021. The analysis was performed on clusters with *residential* land use.

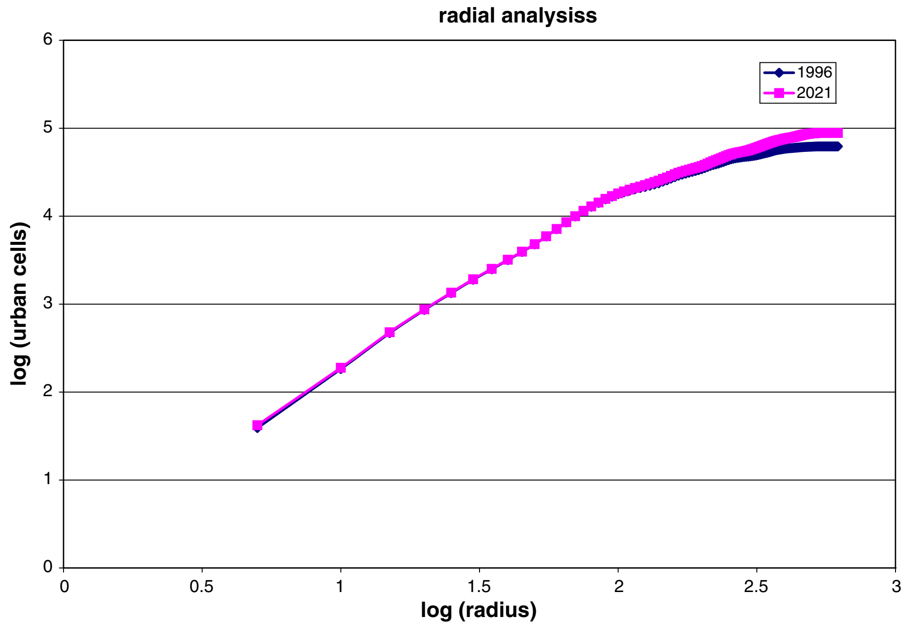

Fig. 5. Radial analysis of the 1996 land use map and the result of the extended simulation. Analysis was performed on a combination of *commercial and industrial* and *residential* cells. The boundary between the inner core and the outer zone of the urban area is visible as the bend at $x = 2$.

map. Results for five simulation runs are presented in Table 2. In this table, model results are compared to the five results from the random allocation model as well as a constant share model. For the constant share model an increase in *residential* and *commercial and industrial* area was distributed over municipalities, proportionally to the existing amount of land use in these classes. This increase was equal to the overall increase in these land use classes. These results indicate that the model performs considerably better than both the random allocation model and the constant share model. Hence this indicates that it is capable of modeling regional interactions.

Table 2
RMSE scores for the simulation and two reference models for both residential and commercial and industrial land uses

RMSE	Residential	Commercial & Industry
Simulation 1	127	80
Simulation 2	127	80
Simulation 3	128	80
Simulation 4	128	79
Simulation 5	128	80
Constant Share	371	170
Random allocation 1	364	144
Random allocation 2	364	137
Random allocation 3	365	139
Random allocation 4	360	138
Random allocation 5	363	137

Results are obtained by comparing the number of cells per municipality for the simulation and reference results with the real 2001 land use map. Results of the random allocation model are the average over five results.

4.4. Model behavior for long range interactions

Model behavior, and specifically sensitivity analysis, is often neglected in land use change models (Kocabas & Dragicevic, 2006). In this study only a qualitative investigation of model behavior was performed to assess the effect of land use interactions over a greater distance. To do so, a very simple scenario was created where only the amount of residential land use increases. This residential land use is allocated using a self-attraction over a limited range, decreasing with the distance. This range of influence roughly coincides with the eight cell radius. All other possible land use interactions are set to zero. No suitability maps, zoning restrictions or transportation network were used in this scenario, only the random perturbation term was included. This model basically creates urban growth at the edge of existing urban areas, which is what occurs in reality (Batty & Longley, 1994).

Then to assess the effect of long distance land use interaction, two alternative scenarios were created, indicating different preferences for new residential areas. The first includes a long range

Table 3
Parameter values for the neighborhood functions in three scenarios for land use change

	Level		0	1	2	3	4	5	6	7	8
	Distance to centre		0	1	3	9	27	81	243	729	2187
	From	On									
Standard	Residential	Residential	1000	10	0	0	0	0	0	0	0
Scenario 1	Residential	Residential	10	10	0	0	0	0	0	0	0
	Water	Residential	0	0	0.005	0.01	0.005	0	0	0	0
Scenario 2	Residential	Residential	10	10	0	0	0	0	0	0	0
	Forest	Residential	0	0	0.005	0.01	0.005	0	0	0	0

Values represent the attraction of a specific land use classes on residential land use as a function of the distance for the respective scenarios. Weight values are defined for discrete distance values. Weights for diagonally adjacent cells are linear interpolations.

attraction from forest and natural areas to residential land use. The second includes a similar relation from water to residential land use. Weight functions used for all three scenarios are presented in Table 3. All three simulations were generated for a period of five years, similar to the simulations in the calibrated model, and result maps were compared with each other. Fig. 6 presents the location of residential land use under the different scenarios. These result maps indicate that the long range interactions make a significant difference in the allocation of new residential cells.

5. Discussions and conclusion

In this study an implementation of a variable grid CA was assessed for its ability to model urban dynamics and long distance land use interactions in particular. Model results indicate that the variable grid CA approach is capable of simulating historic urban growth and that it produces realistic urban patterns. Moreover, the effect of long distance interactions is significant in the allocation of land use change, and simulation results improved consider-

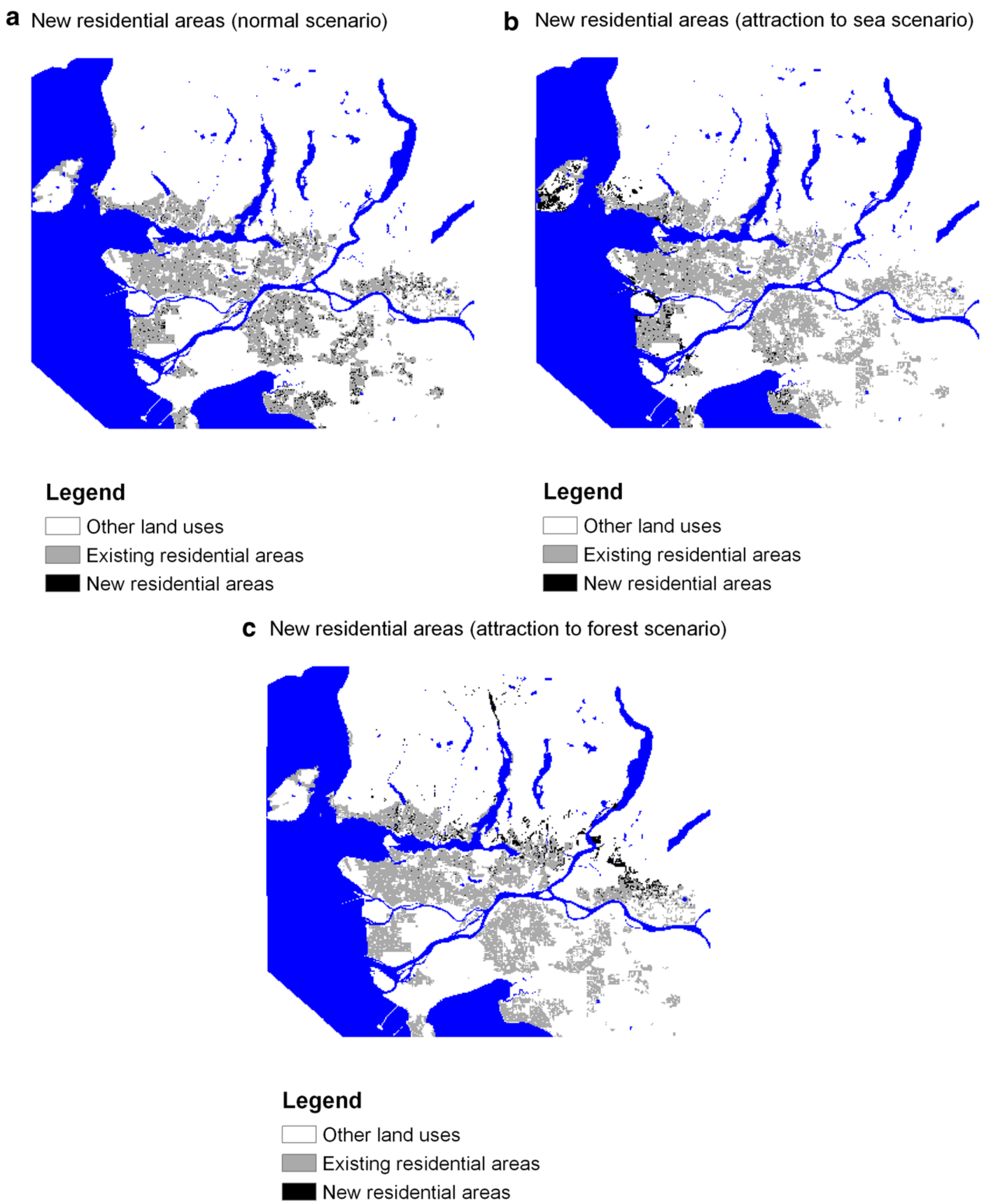

Fig. 6. Location of new urban land use for (a) the standard scenario, (b) the attraction to forest and protected nature scenario and (c) the attraction to water scenario (c). Black represents newly allocated *residential* land use and grey represents already existing *residential* land use. Water surfaces are depicted for spatial reference.

ably when they were used in the neighborhood effect. This indicates a subdivision in the allocation procedure. Long distance interactions determine in which part of the area new developments take place, while the effects at short range determine the exact allocation of pixels on the land use maps. However, errors are not distributed evenly over the municipalities. Because of strict zoning maps and a lack of transportation networks in specific areas, the model underestimates urban growth in those areas. Still these long range interactions can be interpreted as an additional effect in land use allocation. First, land uses for the GVRD are determined, exogenously. Then the long range effects determine in which part of the city people will live, while the short range interactions determine the exact allocation within that part.

Land use data limited the simulation period for this application to the 5 years between 1996 and 2001. This allows for a calibration, but not for independent validation. Since more recent land use data for the GVRD was unavailable, extrapolation of the simulation could not be tested against real world data. Moreover, simulations over longer periods, with more land cover to change, might give a stronger confirmation of the variable grid concept and therefore a stronger argument for using more remote land use information in dynamic spatial models.

Acknowledgements

This research is supported by the Social Sciences and Humanities Research Council of Canada (SSHRC). Data was provided by Metro Vancouver (former Greater Vancouver Regional District – GVRD) and Greater Vancouver Transportation Authority (TransLink) of British Columbia, Canada. Geonamica software was made available by the Research Institute for Knowledge Systems (RIKS). The variable grid CA is developed within the DeSurvey project, funded by the European Commission 6th Framework Program, Global Change & Ecosystems, Integrated Project Contract No. 003950. Moreover, the authors would like to thank the anonymous reviewers for their helpful comments.

References

Andersson, C., Lindgren, K., Rasmussen, S., & White, R. (2002a). Urban growth from "first principles". *Physical Review E, 66*, 026204-1–026204-9.

Andersson, C., Rasmussen, S., & White, R. (2002b). Urban settlement transitions. *Environment and Planning B, 29*, 841–865.

Barredo, J., Kasanko, M., McCormick, N., & Lavalle, C. (2003a). Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. *Landscape and Urban Planning, 64*, 145–160.

Barredo, J., Lavalle, C., Demichelli, L., Kasanko, M., & McCormick, N. (2003b). *Sustainable urban and regional planning: The MOLAND activities on urban scenario modelling and forecast*. Luxembourg: Office for Official Publications of the European Communities.

Barredo, J., Demichelli, L., Lavalle, C., Kasanko, M., & McCormick, N. (2004). Modelling future urban scenarios in developing countries: An application case study in Lagos, Nigeria. *Environment and Planning B, 32*, 65–84.

Batty, M., & Longley, P. (1994). *Fractal cities: A geometry of form and function*. London: Academic.

Batty, M., & Xie, Y. (1994). From cells to cities. *Environment and Planning B, 21*, 31–48.

Batty, M. (2005). *Cities and complexity*. The MIT press.

BC STATS (2006). Population projections 2006–2031. URL: <http://www.gvrd.bc.ca/growth/keyfacts/popproj.htm> last Accessed 23.03.2007.

Bishop, Y., Fienberg, S., & Holland, P. (1975). *Discrete multivariate analysis: Theory and practice*. Cambridge: MIT Press. pp. 393–400.

Brown, D., Page, S., Riolo, R., Zellner, M., & Rand, W. (2005). Path dependency and the validation of agent-based spatial models of land use. *International Journal of Geographic Information Science, 19*(2), 153–174.

Clarke, K., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B, 24*, 247–261.

Couclelis, H. (1997). From cellular automata to urban models: New principles for model development and implementation. *Environment and Planning B, 24*, 165–174.

van Delden, H., Luja, P., & Engelen, G. (2007). Integration of multi-scale dynamic spatial models of socio-economic and physical processes for river basin management. *Environmental Modeling and Software, 22*, 223–238.

Engelen, G., White, R., & Nijs, T. de (2003). Environment Explorer: spatial support system for the integrated assessment of socio-economic and environmental policies in the Netherlands. *Integrated Assessment, 4*(2), 97–105.

Frankhauser, P. (1994). *La fractilite des structures urbaines*. Paris: Economica.

Frankhauser, P. (2004). Comparing the morphology of urban patterns in Europe – a fractal approach. *European Cities – Insights on Outskirts, 2*, 79–105.

Geertman, S., & Stillwell, J. (2004). Planning support systems: an inventory of current practice. *Computers, Environment and Urban Systems, 28*, 291–310.

GVRD (1999). Livable region strategic plan. URL: <http://www.gvrd.bc.ca/growth/lrsp/LRSP.pdf> last Accessed 23.03.2007.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80*, 185–201.

Hagen, A. (2003). Fuzzy set approach to assessing similarity of categorical maps. *International Journal of Geographical Information Systems, 17*(3), 235–249.

Hagen-Zanker, A., Straatman, B., & Uljee, I. (2005). Further developments of a fuzzy set map comparison approach. *International Journal of Geographical Information Systems, 19*(7), 769–785.

Hagen-Zanker, A., & Lajoie, G. (2008). Neutral models of laandscaape change as benchmarks in the assessment of model performance. *Landscape and Urban Planning, 86*, 284–296.

Hägerstrand, T. (1967). *Innovation diffusion as a spatial process*. Chicago: University of Chicago Press.

Kocabas, V., & Dragisevic, S. (2006). Assessing cellular automata model behaviour using a sensitivity analysis approach. *Computers, Environment and Urban Systems, 30*(6), 921–953.

Nijs, T. de, Niet, R. De, & Crommentuijn, L. (2004). Constructing land-use maps of the Netherlands in 2030. *Journal of Environmental Management, 72*, 35–42.

Parker, D., & Meretsky, V. (2004). Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. *Agriculture, Ecosystems and Environment, 101*, 233–250.

Pontius, R. (2002). Statistical methods to partition effects of quantity and location during comparison of categorical maps at multiple resolutions. *Photogrammetric Engineering and Remote Sensing, 68*(10), 1041–1049.

Power, C., Simms, A., & White, R. (2000). Hierarchical fuzzy pattern matching for the regional comparison of land use maps. *International Journal of Geographical Information Science, 15*(1), 77–100.

Remmel, T., & Csillag, F. (2003). When are two landscape pattern indices significantly different? *Journal of Geographical Systems, 5*, 331–351.

Riitters, K., O'Neill, R., Hunsaker, C., Wickham, J., Yankee, D., Timmins, S., et al. (1995). A factor analysis of landscape pattern and structure metrics. *Landscape Ecology, 10*(1), 23–39.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography, 46*(2), 234–240.

Verburg, P., Nijs, T. de, Ritsema van Eck, J., Visser, H., & Jong, K. (2004a). A method to analyse neighbourhood characteristics of land use patterns. *Computers, Environment and Urban Systems, 28*, 667–690.

Verburg, P., Ritsema van Eck, J., Nijs, T. de, Dijst, M., & Schot, P. (2004b). Determinants of land use patterns in the Netherlands. *Environment and Planning B, 31*, 125–150.

White, R., & Engelen, G. (1993). Cellular automata and fractal urban form: a cellular modelling approach to the evolution of land use patterns. *Environment and Planning A, 25*, 1175–1199.

White, R., Engelen, G., & Uljee, I. (1997). The use of constrained cellular automata for high-resolution modeling of urban land use dynamics. *Environment and Planning B, 24*, 323–343.

White, R., & Engelen, G. (2000). High resolution integrated modeling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems, 24*, 383–400.

White, R. (2005). Modelling multi-scale processes in a cellular automata framework. In J. Portugali. Complex artificial environments (pp. 165–178).

White, R. (2006). Pattern based map comparisons. *Journal of Geographical Systems, 8*, 145–164.

Wolfram, S. (1984). Universality and complexity in cellular automata. *Physica D, 10*, 1–35.

Wu, F. (1998). SimLand: A prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. *International Journal of Geographical Information Systems, 12*(1), 63–82.