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Research Article

Analysis of scale dependencies in an urban land-use-change model

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Different processes shaping land-use patterns are observed at different scales. In land-use modelling, scale can influence the measurement and quantitative description of land-use patterns and can therefore significantly impact the behaviour of model parameters that describe land-use change processes. We present results of a rigorous sensitivity analysis of a cellular urban land-use-change model, SLEUTH, testing its performance in response to varying cell resolutions. Specifically, we examine the behaviour of each type of urban growth rule across different cell sizes, and explore the model's ability to capture growth rates and patterns across scales. Our findings suggest that SLEUTH's sensitivity to scale extend beyond issues of calibration. While the model was able to capture the rate of growth reliably across all cell sizes, differences in its ability to simulate growth patterns across scales were substantial. We also observed significant differences in the sensitivity of the growth rules across cell sizes, indicating that SLEUTH may perform better at certain cell sizes than at others. These findings emphasize the importance of scale considerations in land-use-change modelling research, particularly in terms of determining the relevant and appropriate scales of enquiry for the processes being simulated.

1. Introduction

The relationship between land-use patterns and the processes that form them changes over time and space (Carlile *et al.* 1989, Gibson *et al.* 2000, Goetz *et al.* 2004). Process-based relationships may be easier to discern at fine scales, where land-use changes can be explicitly linked to the activity of agents in the landscape. These relationships are less apparent when the emergent land-use-change patterns are observed over coarser scales where other processes, such as environmental or macro-economic factors, become dominant (Kok and Veldkamp 2001). In the context of land-use modelling, the scale of observation can influence the model's ability to capture the underlying processes that drive land-use changes, and relationships established at one spatial scale may not translate to another spatial scale in a linear fashion (Gardner *et al.* 1989, Jenerette and Wu 2001, Kok and Veldkamp 2001).

Urban models operating at a particular scale tend to focus on land-use-change processes that are relevant at the scale of analysis. Micro-scale models of urban land-use change, for example, often attempt to simulate the decision-making processes of individual landowners, modelling local change at the parcel scale (e.g. Bockstael 1996). Traditional large-scale urban models focusing on whole cities or regions may simulate interaction patterns between broad-scale factors, such as

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transportation networks, land use, demographic patterns, and regional economics (Johnston and Barra 2000). Ecologists have frequently considered the scale issue for landscape models (Carlile *et al.* 1989, Gardner *et al.* 1989, Obeysekera and Rutchey 1997), and there are recent examples of land-use modelling frameworks that integrate multiple scales (Verburg and Chen 2000, Walsh *et al.* 2001, Soares-Filho *et al.* 2002). By linking ecosystems theory with land-use-change modelling, scale interactions become a central component in the modelling framework (Grimm *et al.* 2000, Wu and David 2002).

Many of these recent modelling efforts incorporate cellular automata (CA) to accomplish spatially explicit land-use-change modelling. In contrast to top-down large-scale urban models, models based on cellular automata simulate land-use-change processes using local neighbourhood interactions, from which complex urban patterns emerge (Batty 1998). While CA-based models have been applied to biological or ecological systems, the approach is relatively new in urban modelling and has evolved into an active area of research focused on both the techniques and the theory of using CA to model urban processes (Sui 1998, Wu and David 2002). Because they are cell-based, CA behaviour and the quantification of urban patterns can be influenced by both the resolution of the data and the extent of the study area. However, few studies have explicitly addressed scale sensitivity issues for urban CA.

Here, we present results from a series of sensitivity tests of a widely used CA-based urban model, SLEUTH (slope, land use, exclusion, urban extent, transportation, hillshade), to investigate how the model responds to changes in cell resolution. Specifically, we examine the ability of the model to capture urban growth patterns across varying cell resolutions and how the behaviour of the growth rules changes in response to different cell sizes.

2. Background

2.1 *CA-based urban models*

Cellular automaton models have been widely used to explore urban dynamics. For example, CA modelling techniques have been employed to study different types of urban forms (Yeh and Li 2001) and development densities (Yeh and Li 2002), as well as the evolution of urban spatial structure over time (White and Engelen 2000). The CA approach has also been used to model patterns of pedestrian movement (Batty 2003), and to explore urban growth and sprawl (Clarke *et al.* 1997, Batty *et al.* 1999). In formal CA theory, a homogenous lattice of cells, each of which can change state through time, represents space. Cell changes are regulated by universal transition rules that specify a set of neighbourhood conditions that, when met, will initiate a change in state. Within a CA modelling environment, complex global structures emerge through these local neighbourhood interactions. The CA framework is appropriate for urban simulation because of this link to complexity theory and the representation of local-global interactions, but cellular models of urban systems frequently depart from the formal CA framework, particularly when links to real systems are desired (O'Sullivan and Torrens 2000). The traditional CA framework may not, therefore, be well suited to model land-use dynamics, which can depend on the characteristics of the land itself, overall demand for each particular land use, and the effects of neighbouring land uses.

Stochastic CA models, where transitions are constrained by local land-use suitability factors and non-local demographic and economic dynamics, have been developed to address these constraints (White and Engelen 1997). Constrained cellular models (e.g. Clarke *et al.* 1997, White and Engelen 1997, Yeh and Li 2001) are examples of what Couclelis (1997) calls 'the new generation of more realistic CA-based urban and regional models'. These models incorporate real data through geographical information systems (GIS) and relax many of the assumptions of classic CA theory, such as homogeneity of space, uniformity of neighbourhood interactions, and universal transition functions. Because they are interactive, constrained CA models are attractive in applied settings as planning tools. Potential outcomes can be visualized and quantified, the models can be closely linked with GIS, and raster-based spatial data derived from remote-sensing platforms can be easily incorporated into the modelling environment.

2.2 *SLEUTH*

The SLEUTH cellular automaton model is a CA-based urban growth model (UGM) coupled with a land-cover-change model (US Geological Survey 2003). The UGM can be run independently of the land-cover-change model, and has been the primary focus of the model's developers and users. In their seminal application of the Clarke urban growth model, a precursor to SLEUTH, in the San Francisco Bay area, Clarke *et al.* (1997) stressed the utility of the model in simulating historic change, the description of which can aid in the explanation of growth processes at a regional scale, and in predicting future urban growth trends.

SLEUTH is essentially a pattern-extrapolation model (Clarke *et al.* 1997, Clarke and Gaydos 1998, Candau 2002, US Geological Survey 2003). It is calibrated to simulate urban development patterns over a historic time period, and then can forecast these patterns into the future. Within the UGM, urban dynamics are simulated using four growth rules, which are applied sequentially during a growth cycle, or year. The growth rules are defined through five growth coefficients, each of which can take on a value ranging from 1 to 100. The values for the growth coefficients are derived during the calibration process, discussed later, where different parameter sets are tested for their ability to replicate historic growth patterns.

Despite the many examples of recent and ongoing SLEUTH applications (Silva and Clarke 2002, Land Use Change Assessment Group 2003, Yang and Lo 2003, Jantz *et al.* 2003), there has been little sensitivity testing of the model since the initial work of Clarke *et al.* (1997). To date, many of the improvements in the model involve efforts to refine the computationally intensive brute force calibration process, such as the development of parallel processing capability (US Geological Survey 2003) or exploring the use of more efficient genetic algorithms (e.g. Land Use Change Assessment Group 2003). A notable exception to this is recent work focused on the temporal sensitivity of SLEUTH (Candau 2002), which suggests that the density of observation points in the historic time series, as well as the length of time represented in the series, affects the performance of the UGM. Previous work with the UGM (Clarke *et al.* 1997, Clarke and Gaydos 1998) suggested that the control data set should be resampled to a coarser resolution in order to conserve computing resources, but Candau (2002) found the optimum coefficient set for the full resolution sample data set could be excluded if resampled data were used for calibration.

The growth types simulated by SLEUTH are spontaneous new growth, new spreading centre growth, edge growth and road-influenced growth. Spontaneous new growth simulates the random urbanization of land. The overall probability that a single non-urbanized cell in the study area will become urbanized is determined by the dispersion coefficient. New spreading centre growth simulates the development of new urban centres around cells that have urbanized through spontaneous growth. The breed coefficient determines the overall probability that a pixel produced through spontaneous growth will also experience new spreading centre growth. Edge growth causes cells adjacent to new or existing urban centres to urbanize and is controlled by the spread coefficient, which influences the probability that a non-urban cell with at least three urban neighbours will also become urbanized. Road-influenced growth simulates the influence of the transportation network by generating new spreading centres in the vicinity of roads and is controlled by the road gravity coefficient, which defines the distance from roads that can be influenced by road growth.

Constraints to urban development are introduced through the use of a slope suitability test. The model requires a raster layer containing the percentage slope at all cell locations, and slope resistance is calibrated empirically through the slope coefficient. The user introduces another set of constraints through an 'excluded layer', which designates areas that are partially (e.g. zoning) or wholly (e.g. water, parks) excluded from development.

Because it is stochastic, SLEUTH utilizes Monte Carlo routines to generate multiple simulations of growth. As noted earlier, calibration is typically achieved using a brute-force method, where the user indicates a range of parameter values, and the model iterates using every possible combination of parameter sets. Each simulation is compared with the control years within the time series, and averaged fit statistics are produced to measure the performance of a given set of coefficient values in reproducing the observed urban development patterns. Because of the computational requirements of this approach, calibration of SLEUTH typically occurs in three iterative phases: coarse, medium, and fine. For the coarse calibration, the maximum parameter value range (1–100) is used, but the model steps through the range at a coarse increment of 25 to minimize the total number of simulations. The results of the coarse calibration are evaluated using the fit statistics generated during the model run, and narrower ranges for each parameter are selected for the subsequent calibration phase. Several recent publications discuss this calibration procedure (Candau 2002, Silva and Clarke 2002, US Geological Survey 2003, Jantz *et al.* 2003). When predictions are produced, multiple simulations are run to create images showing the probability of any cell becoming urbanized over a series of annual time steps and to create averaged tabular output (Clarke *et al.* 1997, Clarke and Gaydos 1998).

SLEUTH also has a 'self-modification' function (Clarke *et al.* 1997), which changes the values for the growth coefficients as the model iterates through time, and which is intended to more realistically simulate the different rates of growth that occur in an urban system. When the rate of growth exceeds a specified critical threshold, the growth coefficients are multiplied by a factor greater than one, simulating a development 'boom' cycle. Likewise, when the rate of development falls below a specified critical threshold, the growth coefficients are multiplied by a factor less than one, simulating a development 'bust' cycle. Without self-modification, SLEUTH will simulate a linear growth rate, producing the same number of new urban pixels, on average, each year until the availability of developable land diminishes.

3. Methods

3.1 *Base data sets*

For calibration, SLEUTH requires inputs of historic urban extent for at least four time periods, a historic transportation network for at least two time periods, slope, and an excluded layer. In our previous application of SLEUTH to the Washington, DC–Baltimore, MD area (Jantz *et al.* 2003), we created a data set to map urban change for 1986, 1990, 1996, and 2000. Derived solely from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper-Plus (ETM+) satellite imagery, this data set robustly captured developed land cover, including low-density settlement patterns (Goetz *et al.* 2004). Originally at a resolution of 30 m, the data were resampled to 45 m resolution so that available computer resources could accommodate the array. For this research, we use a subset of the 45 m Washington, DC–Baltimore, MD data set that is focused on the suburbs west of Washington, DC in northern Virginia and central southern Maryland (figure 1).

A USGS 7.5-minute digital elevation model was used to create an input layer for slope. An excluded layer was also produced that consisted of water, which was 100% excluded from development, as well as federal, state, and local parks, which were 80% excluded from development. This 80% level of exclusion was used since limited development within many of the parks had occurred in the historic time period.

Two time steps for transportation were derived from Environmental Systems Research Institute's (ESRI) (2003) US Streets data set, which represents interstate highways, major roads and local streets for the circa 2000 transportation network. We created a 1986 transportation network by overlaying the 2000 roads with a 1986 Landsat TM satellite image and removing roads that did not appear at that time. The road network used in this study is based on limited access and other major highways. In the SLEUTH modelling environment, roads can be weighted to extend the search radius of the road gravity coefficient. In this study, we assigned a uniform, constant weight of one to all roads, assuming that all roads have the same influence on growth patterns through time. While we acknowledge that this is not likely to be the case, this assumption is made less problematic by the fact that we utilize only a primary road network. Furthermore, the uniform road weighting allowed for a more straightforward interpretation of the response of the road growth parameter to changes in cell size.

All input files were rasterized at a 45-m resolution to the spatial extent of the study area and checked for overlay accuracy. This 45-m base data set represented the finest cell size that we utilized in these analyses. To create coarser resolution data sets, all input files were resampled to 90 m, 180 m, and 360 m cell sizes using a nearest-neighbour resampling algorithm (figure 2), resulting in four input data sets to test SLEUTH's performance across four different cell sizes.

3.2 *Cell-size sensitivity analyses*

3.2.1 Parameter behaviour. We performed four separate coarse calibration procedures, using seven Monte Carlo iterations for each cell size, and evaluated the resulting fit statistics and parameter behaviour across scales. Model fit scores are improved only minimally in the medium and fine calibration phases, so any sensitivities would be revealed in the coarse calibration phase, precluding the need to perform additional calibration runs and incur substantially higher computational costs (Candau 2002, Land Use Change Assessment Group 2003, Jantz *et al.* 2003).

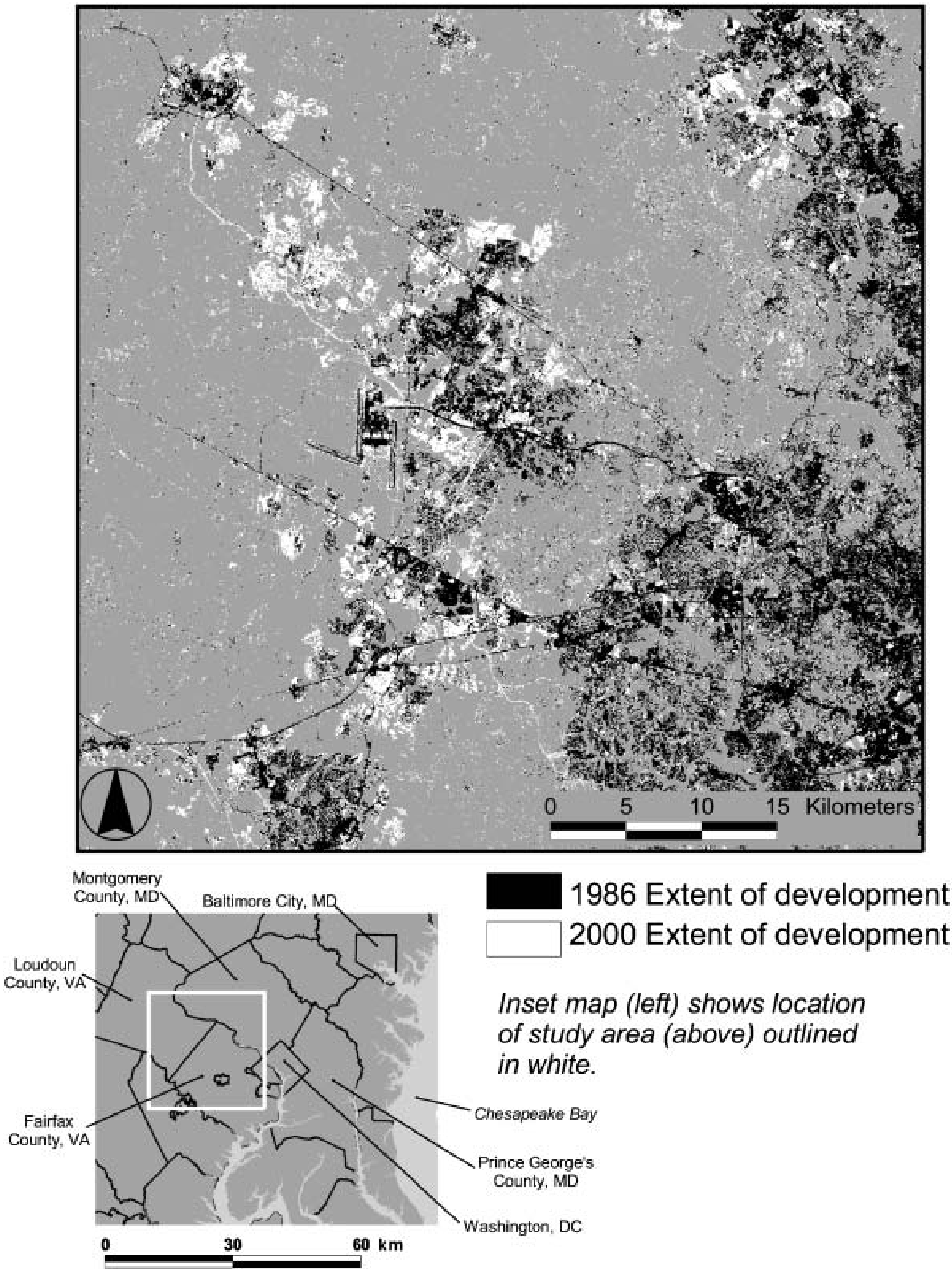

Figure 1. Location of study area showing urban change between 1986 and 2000. The cell resolution of these data sets is 45 m.

Because the implementation of the self-modification function is not well defined, the model was run with this function disabled. This did not pose a problem since the growth rate in the historic data was nearly linear (Jantz *et al.* 2003).

The results of a calibration run can be evaluated based on one or more of the dozen fit statistics (table 1), each of which captures some aspect of SLEUTH's

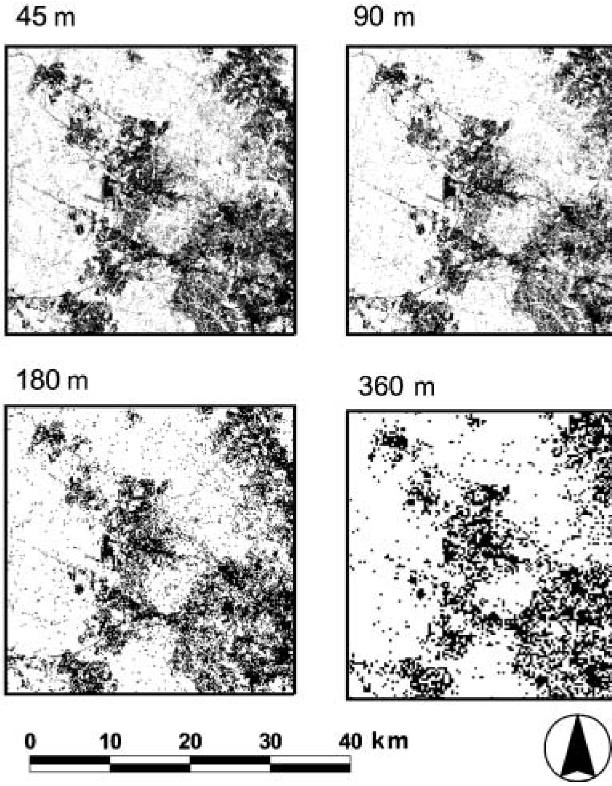

Figure 2. Examples of resampled data sets showing the 45, 90, 180, 360 m cell sizes for 2000 urban extent.

performance in simulating growth rates, patterns or shape. There is no consensus regarding which performance measure or set of performance measures to use. Clarke *et al.* (1997) relied primarily on four metrics: population, edges, clusters, and Lee and Sallee. Recent examples show that others have relied on a weighted sum of all the statistical measures (Yang and Lo 2003), or an unweighted product score of several metrics (Candau 2002).

The inclusion of multiple metrics complicates interpretation of the model's behaviour (Candau 2002). We therefore assessed the response of the model by individually optimizing four fit statistics related to how SLEUTH captures growth rates and patterns (table 1). The *compare* metric, a ratio of the number of modelled urban pixels to actual urban pixels for the final control year, indicates how well the model captures the overall rate of development. The growth rate is defined as the percentage of new urban pixels produced in one year divided by the total number of urban pixels. On an annual basis, the total amount of new growth is the sum of the growth produced by each growth rule. In the SLEUTH modelling framework, the amount of expected development is not provided exogenously in the form of, for example, expected population growth or new housing starts. Rather, the amount of annual growth produced in the system is determined by the behaviour of, and interaction between, the growth rules and can be constrained by the amount of developable land. Growth rate, therefore, is one aspect of urban form for which SLEUTH can be calibrated to optimize.

Table 1. Fit statistics calculated by SLEUTH[a].

Fit statistic	Definition
Compare	Ratio of modelled population (P_M) of urban pixels to the observed population of urban pixels (P_O) for the final control year: Compare$=P_{M(\text{final year})}/P_{O(\text{final year})}$ If $P_M>P_O$, then Compare$=1-(P_{M(\text{final year})}/P_{O(\text{final year})})$
Lee and Sallee	Ratio of the intersection to the union of the simulated (S_{Mi}) and the actual urban areas (S_{Oi}) for each control year (i) averaged over all control years (N_i): Lee and Sallee$=\frac{\sum (S_{Mi} \cap S_{Oi}/S_{Mi} \cup S_{Oi})}{N_i}$
Population	OLS regression score for modelled urban pixels compared with actual urban pixels for each control year
Edges	OLS regression score for modelled urban edge pixels compared with actual urban edge pixels for each control year
Clusters	OLS regression score for modelled number of urban clusters compared with actual urban clusters for each control year; urban clusters are areas of contiguous urban land; in cell space, clusters can consist of a single pixel or multiple, contiguous urban pixels; contiguity is determined using the eight-neighbour rule
Cluster size	OLS regression score for modelled average cluster size compared with actual average urban cluster size for each control year
Slope	OLS regression score of the average slope for modelled urban pixels compared with actual urban pixels for each control year
% Urban	OLS regression score for the percentage of available pixels urbanized during simulation compared with the actual urbanized pixels for each control year
X-mean	OLS regression score of average x-axis values for modelled urban pixels compared with actual average x-axis values for each control year
Y-mean	OLS regression score of average y-axis values for modelled urban pixels compared with actual average y-axis values for each control year
Radius	OLS regression score of the average radius of the circle that encloses the simulated urban pixels compared with the actual urban pixels for each control year
Product	All scores multiplied together; unweighted composite score

[a]Measurements derived from the modelled data are averaged over the set of Monte Carlo iterations. Ordinary least-squares (OLS) regression scores are calculated by fitting a linear model, $y=mx+b$, where modelled values for each control year are represented by the dependent variable y, observed values for each control year are represented by the independent variable x, slope (m) describes the increase in y as x increases over each time step, and b is the y-intercept.

The *clusters* and *edges* metrics are non-spatial pattern metrics. The *edges* metric is a least-squares regression score for the modelled urban edge pixel count compared with the actual urban edge pixel count for the control years. *Clusters* is a least-squares regression score for the modelled number of urban clusters compared with the actual number of urban clusters for the control years. Urban clusters are areas of contiguous urban land. In cell space, clusters can consist of a single pixel or multiple, contiguous urban pixels. Contiguity is determined using the eight-neighbour rule. Finally, the Lee and Sallee shape index (Lee and Sallee 1970, Clarke *et al.* 1997) is an explicit measure of spatial fit, and is calculated by taking the ratio of the intersection and the union of the simulated and actual urban areas, averaged over all control years.

Qualitatively, these goodness-of-fit measures range from completely non-spatial (compare focuses entirely on matching the amount of growth in the final control year) to non-spatial pattern metrics (edges and clusters), to explicitly spatial (Lee and Sallee). By evaluating how the model behaves when optimizing a single fit score, we sought to characterize how the growth parameters influence the simulation of these different aspects of urban form.

Parameter behaviour was observed separately for each optimized metric by plotting parameter values against the goodness-of-fit score under consideration. In previous SLEUTH applications, researchers have focused only on a few top scores to narrow the parameter range during calibration. We calculated the average, minimum and maximum fit score produced by each parameter value for all 3125 simulations, giving a complete picture of 'parameter space' (Candau 2002). This allowed us to observe what, if any, parameter values or ranges of values were associated with high or low fit scores. A narrow range of values consistently associated with high fit scores indicates that the parameter has an influence on the model's performance. High variability in parameter values across fit scores indicates that the parameter has little or no influence. We also compared the maximum score for each goodness-of-fit measure across cell sizes.

3.2.2 Range of growth rule functionality. To identify the potential range of influence that each growth rule could exert on an urban system, and how this may vary with scale, we used the output from the calibration procedures described in the previous section. Instead of examining the fit of the model, however, we identified the parameter sets that produced the maximum and minimum levels of growth for each growth rule at each scale, and noted the corresponding maximum and minimum levels of growth.

In addition to these tabular data, we utilized visual outputs. We initialized SLEUTH with the 1986 urban extent and predicted growth to 2000 using the parameter sets that would maximize each type of growth. We note that the goal of these predictive scenarios was to illustrate the behaviour of the growth rules, not to simulate historic growth patterns. SLEUTH can produce images from a single Monte Carlo iteration where each pixel is classified according to the type of growth from which it resulted. The patterns produced by each growth type can therefore be visualized and evaluated independently. Although these visualizations represent only one possible realization of growth patterns, the images produced by a single Monte Carlo iteration more effectively communicate the general spatial behaviour of each growth type than cumulative probability images. There can be variability in the amount of growth produced by each growth rule in each Monte Carlo simulation, although in all cases, we noted very low standard deviations relative to the average amount of growth, indicating minimal variability. While the cumulative probability images contain information about the certainty associated with the spatial location of predicted changes, images produced from a single iteration contain no indication of certainty. We therefore emphasize the illustrative purposes of the images presented here, and focus on the general spatial patterns produced by each growth rule.

3.2.3 Goodness of fit. The goodness-of-fit measures calculated by SLEUTH during calibration evaluate the performance of the model in capturing some aspect of urban form, whether it is the absolute rate of growth (compare metric), the number of urban agglomerations (clusters metric), the total amount of urban edge (edges metric), or the exact shape and location of urban areas (Lee and Sallee metric). While others have noted that SLEUTH seems unable to capture dispersed settlement patterns at fine resolutions (Yang and Lo 2003, Jantz *et al.* 2003), the influence of scale on SLEUTH's ability to capture different aspects of urban form has not previously been explicitly addressed. We visually and quantitatively evaluated the urban patterns produced by parameter sets that maximized the four fit statistics discussed previously: compare, edges, clusters, and Lee and Sallee.

SLEUTH was initialized with the 1986 urban extent data using the parameter set that produced the maximum score for each fit statistic for each cell size, and 2000 urban extent was predicted. Using the averaged tabular results from 100 Monte Carlo iterations, we examined how urban form was simulated by each set of optimized parameters by comparing the simulated area developed, number of edge pixels, and number of urban clusters to the control data set for 2000. This enabled us to evaluate (1) how well the model captured the different aspects of urban form across scales, (2) aspects of urban form sacrificed when another aspect is optimized, (3) the utility of the fit statistics in describing the model's fit.

4. Results

4.1 *Parameter behaviour*

We found that plotting parameter values against the full range of fit scores was useful for revealing parameter behaviour and sensitivity, resulting in 16 sets of plots that compared parameter behaviour across four cell sizes for four different fit statistics. Each parameter was considered separately and, due to the coarse calibration procedure, parameters could only take on the values 1, 25, 50, 75 and 100. The mean fit score was calculated for each parameter value, and the maximum and minimum fit values indicate the total range of fit scores.

An example of a set of plots for the 360 m data set presents parameter behaviour when the model fit was evaluated by optimizing the compare metric (figure 3). In this example, the spread coefficient has a strong influence on model performance, where low spread parameter values are consistently associated with high fit scores. There is also a clear trend in the mean fit score, which decreases noticeably as the spread parameter increases. Spread also exhibits low variability across all parameter values, i.e. each parameter value is associated with a tight range of fit scores. In contrast, there is not a clear trend in the mean fit score across parameter values for the dispersion and breed parameters. In both cases, however, the lowest parameter values never produce the highest fit score. While fit scores for the values between 25 and 100 are highly variable, these parameter ranges produce somewhat higher fit scores. The road gravity and slope coefficients are also highly variable across the range of fit statistics and seem to have no clear influence on the model's ability to optimize the compare metric at this scale.

To summarize these results across cell sizes, we noted the stable range of parameter values associated with high fit scores for each set of plots (table 2). No range is indicated if the parameter's behaviour was highly variable.

Differences in the behaviour of the growth parameters were observed in response to different cell sizes. There were also differences in parameter behaviour corresponding to the fit statistic being used. For example, when the model results were considered for optimization of the compare metric, which is a measure of how well the model captures the rate of urbanization, the spread coefficient appeared to influence the fit of this metric across all cell sizes (table 2A). High fit scores were consistently associated with a specific range of values for this coefficient, although it

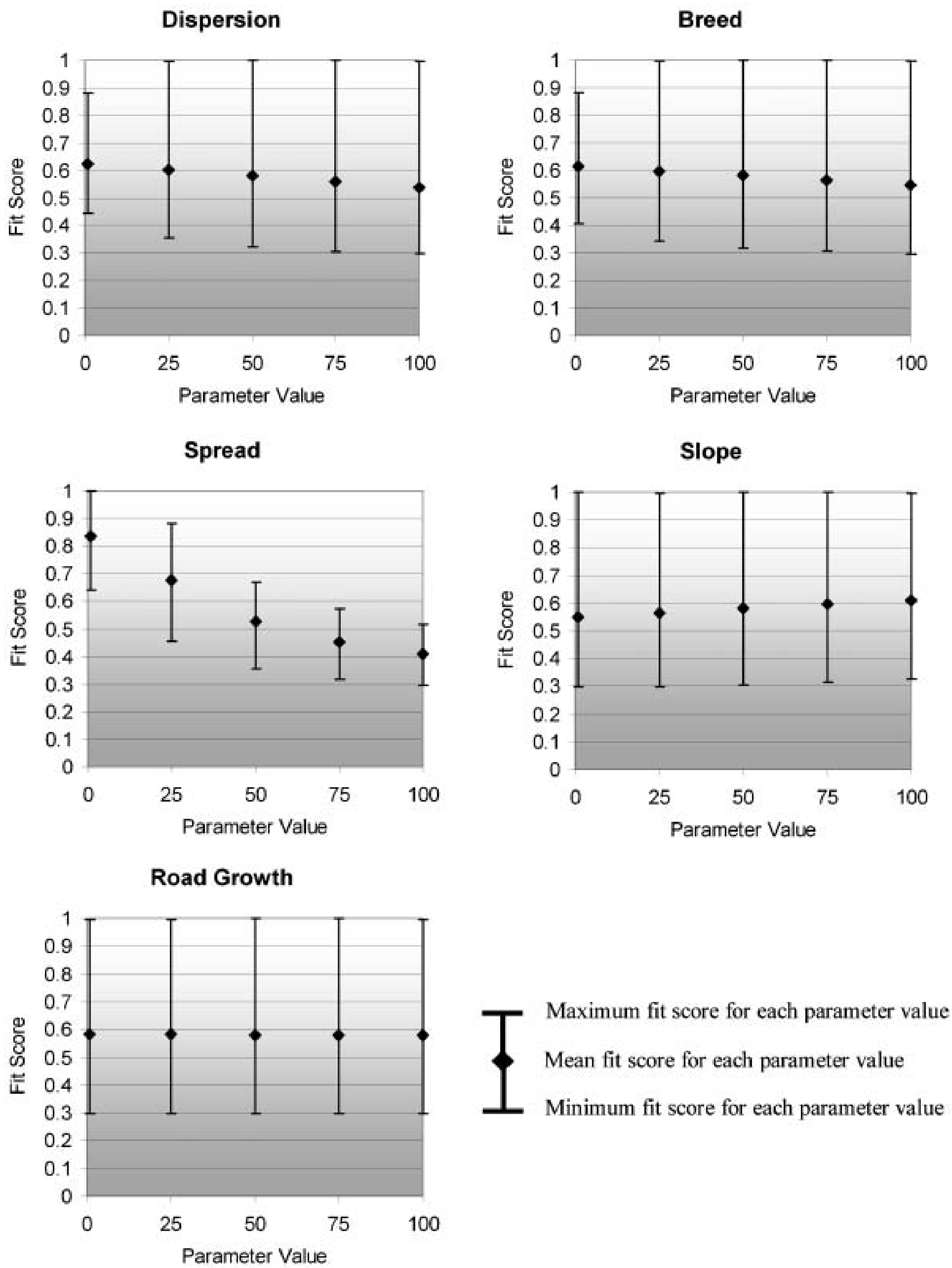

Figure 3. Example of plots used to evaluate parameter sensitivity for the 360 m data set when the compare metric is optimized.

should be noted that the value *range* was not consistent. In general, the value for the spread parameter tended to be higher (25–50) for the finer-resolution data sets (45 and 90 m) and lower (1–25) for the coarser-resolution data sets (180 and 360 m). Few of the other parameters exhibited an influence on model performance when optimizing the compare metric, although slope showed some influence at the finer

Table 2. Summarized results from cell size sensitivity tests[a].

Cell size	Compare	Edges	Clusters	Lee and Sallee	Dispersion	Breed	Spread	Slope	Road gravity
A: Fit scores (maximizing COMPARE metric)					*Best-fit parameter range*				
45 m	1.0	0.93	0.65	0.64	–	–	25–50	1–25	–
90 m	1.0	0.83	0.75	0.64	–	–	25	75–100	–
180 m	1.0	0.89	0.65	0.59	–	–	1–25	–	–
360 m	0.99	0.85	0.45	0.60	25–100	25–100	1–25	–	–
B: Fit scores (maximizing EDGES metric)					*Best-fit parameter range*				
45 m	0.76	1.0	0.69	0.66	25–100	–	25	–	–
90 m	0.63	1.0	0.78	0.54	–	–	25–50	1–50	–
180 m	0.56	1.0	0.66	0.50	–	–	25–75	–	–
360 m	0.30	1.0	0.47	0.33	–	–	25–100	–	–
C: Fit scores (maximizing CLUSTERS metric)					Best-fit parameter range				
45 m	0.57	0.38	0.86	0.49	–	–	1	–	–
90 m	0.38	0.75	0.94	0.41	25–100	–	–	–	–
180 m	0.57	0.81	0.92	0.50	75–100	25–100	25–100	1–50	–
360 m	0.65	0.82	1.0	0.48	75–100	–	25–100	–	–
D: Fit scores (maximizing Lee and Sallee metric)					*Best-fit parameter range*				
45 m	0.58	0.84	0.77	0.69	1–25	–	1	25–75	–
90 m	0.62	0.88	0.85	0.71	1–25	–	1	–	–
180 m	0.62	0.86	0.80	0.71	1–25	1–25	1	–	–
360 m	0.64	0.90	0.70	0.72	1–25	1–25	1	–	–

[a]In cases where the parameter values were highly variable, '–' indicates that a best-fit range was not identifiable.

cell sizes. Dispersion and breed showed a minor influence on fit at the coarsest cell size, but the parameter value range was large (25–100).

When maximizing the edges pattern metric, the spread parameter was again the most influential coefficient, particularly for the 45 and 90 m data sets (table 2B). The dispersion coefficient showed some effect but a wide range (25–100) at high fit scores for the 45 m data set. The slope coefficient had some influence on fit for the 90 m data set, ranging between 1 and 50 at high fit scores. Breed and road gravity did not have any influence on this metric at any scale.

When the clusters metric was maximized, the spread coefficient was less influential on the fit score across all cell sizes (table 2C). Spread was variable for the 180 m and 360 m data sets, and showed no effect on fit at the 90 m resolution. The effect of the dispersion parameter is magnified as resolution decreases, and the parameter value range associated with high fit scores becomes narrower.

For the Lee and Sallee metric, patterns in parameter behaviour across scales were strikingly similar. Both slope and road gravity were highly variable, with slope only exhibiting an influence on model performance between 25 and 75 at high fit scores for the 45 m data set (table 2D). Low values for the spread and dispersion parameters were associated with high fit scores across all cell sizes, and breed exhibited similar behaviour for the coarser cell sizes. It should be noted that the road gravity parameter never showed any influence on model performance using any of the fit statistics considered in this study at any scale. Because of the high variability displayed by this parameter, we were unable to identify a stable range of parameter values associated with high fit scores.

In terms of the model's performance as measured by the fit statistics, it was apparent that SLEUTH was able to capture the overall rate of development at all cell sizes used in this analysis, producing a perfect or near-perfect fit score for the compare metric (table 2A). The edges pattern metric was also easily replicated, achieving a perfect fit for all cell sizes (table 2B). There were, however, some differences in the model's ability to capture the number of urban clusters across scales (table 2C). The maximum score achieved for this metric for the 45 m data set was 0.86, while a perfect fit was achieved for the 360 m data set. Fit for the Lee and Sallee metric was similar across scales (table 2D), although it was slightly lower at finer scales.

4.2 *Range of growth rule functionality*

The ability of the growth rules to replicate a range of urban growth patterns varied across scales (figure 4). In general, the maximum amount of growth produced by each growth type was highest at the 360 m cell size and lowest at the 45 m cell size. Edge growth was the least sensitive to cell size, with maximum growth levels between the 180 m and 360 m cell sizes being nearly identical. We note the dominance of the edge growth type, where the maximum growth potential was an order of magnitude greater than the maximum growth levels for the other growth types. Edge growth was also the only growth type where the minimum level of growth did not approach zero.

The parameter sets that produced the maximum and minimum growth levels for each growth type were identical across cell sizes, except that the maximum level of road growth depended on the value for the dispersion parameter, which was lowest at the coarsest cell size and highest at the finest cell size (table 3).

The parameter sets producing the minimum level of growth were less stable, and road growth did not show the same scaling effects (table 3). The minimum level of growth produced by spontaneous new growth occurred when dispersion was at its lowest value, and the values for spread and slope resistance were relatively high

Table 3. Parameter sets that produce the maximum and minimum levels of growth for each growth type[a].

	Dispersion	Spread	Breed	Slope resistance	Road gravity
Maximum growth levels					
Spontaneous	100	1	1	1	–
New spreading centre	100	1	100	1	–
Edge	100	100	100	1	–
Road (360 m)	25	1	100	1	–
Road (90, 180 m)	50	1	100	1	–
Road (45 m)	100	1	100	1	–
Minimum growth levels					
Spontaneous	1	50–100	–	50–100	–
New spreading centre	1	–	1	–	–
Edge	–	1	–	100	–
Road	–	100	1	–	–

[a]–: variable parameter range.

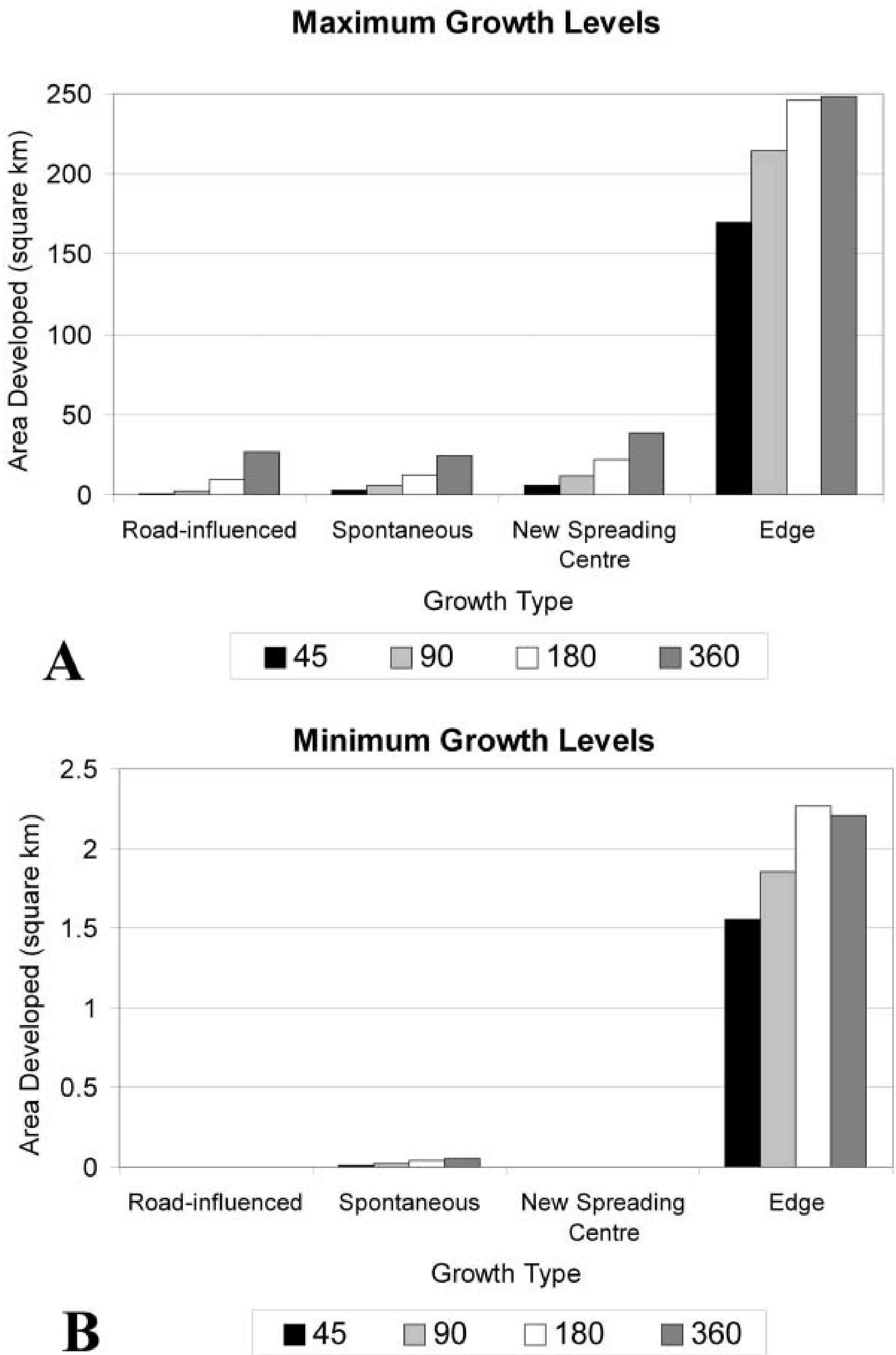

Figure 4. (A) Maximum and (B) minimum growth levels for each growth type across scales.

(50–100). The least amount of new spreading centre growth occurred when dispersion and breed were low. When edge growth was minimized, spread was low, and slope resistance was at its maximum value. To minimize road growth, spread was at its maximum value, and breed was at its lowest value.

The visual results (figure 5) represent the maximum influence that any of the growth rules can have on the system, and each image shows only the pixels produced by each type of growth, not the total growth in the system. Both spontaneous new growth and new spreading centre growth show relatively disaggregated and sparse development patterns. Edge growth dominates the study area at its maximum level, while road growth forms linear patterns along the road network. The degree of development produced by each growth rule is noticeably different across scales, with all growth types reaching their greatest extent at the coarsest cell size. While the dominance of edge growth at the finest scale is observed, spontaneous new growth and new spreading centre growth are less dominant, and the development produced by road growth is minimal.

4.3 *Goodness of fit*

The choice of appropriate goodness-of-fit measures is crucial, since it determines how SLEUTH will simulate urban patterns and how forecasts of urban growth will be created. We evaluated SLEUTH's performance using four goodness-of-fit measures—compare, clusters, edges and the Lee and Sallee index—each of which measures an aspect of how well the model captures rate, spatial pattern, or exact spatial fit (table 1). The parameter values used to produce each of the highest fit scores varied across cell sizes and according to the fit statistic in question (table 4). Frequently, the values producing a high score for one fit statistic were in opposition to the values producing a high score for another statistic. For example, for the 45 m and 90 m data sets, the dispersion, breed and spread parameters were at their

Table 4. Parameter values based on optimum fit scores for all cell sizes.

	Dispersion	Breed	Spread	Slope	Road growth
Compare metric					
45 m	1	25	25	1	25
90 m	25	1	25	100	100
180 m	100	100	1	1	50
360 m	50	75	1	50	50
Edges metric					
45 m	100	25	25	50	75
90 m	1	100	25	50	75
180 m	75	100	75	25	100
360 m	25	100	100	1	75
Clusters metric					
45 m	100	100	100	1	100
90 m	100	100	100	1	100
180 m	100	100	25	25	1
360 m	100	25	25	1	1
Lee and Sallee					
45 m	1	1	1	100	1
90 m	1	1	1	100	1
180 m	1	1	1	75	1
360 m	1	1	1	100	1

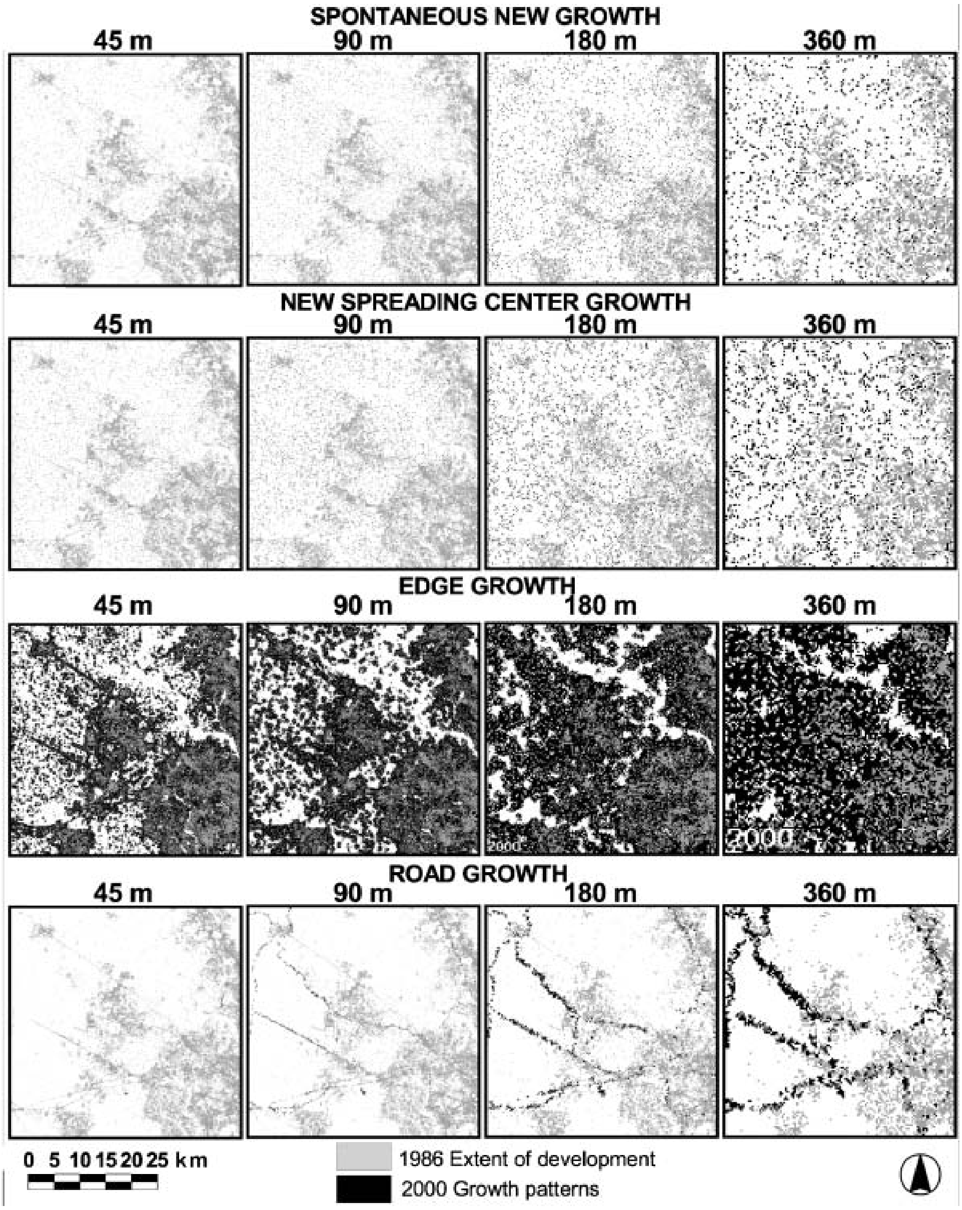

Figure 5. Visual results from a single Monte Carlo simulation for growth patterns produced by spontaneous new growth, new spreading centre growth, edge growth and road growth across all cell sizes with a road network based on limited access and primary roads.

maximum setting to optimize the cluster fit score, while they were much lower (1–25) when the compare statistic was maximized.

The model's ability to replicate urban form was considered by comparing simulated development patterns to actual development patterns for the year 2000. The measures of urban form we considered were: area of development, number of urban edge pixels, and number of urban clusters. These measures were compared across all cell sizes for simulations that maximized the compare, edges, cluster, and Lee and Sallee fit statistics (figure 6).

The parameter sets that optimized the compare metric succeeded in replicating developed area successfully across all cell sizes. The parameter sets that optimized the cluster metric overestimated developed area in all cases, although the discrepancies between the 45 m and 90 m data sets were larger than those between the 180 m and 360 m data sets. The Lee and Sallee parameter sets underestimated area across all cell sizes. Optimizing the edges metric reproduced the amount of area

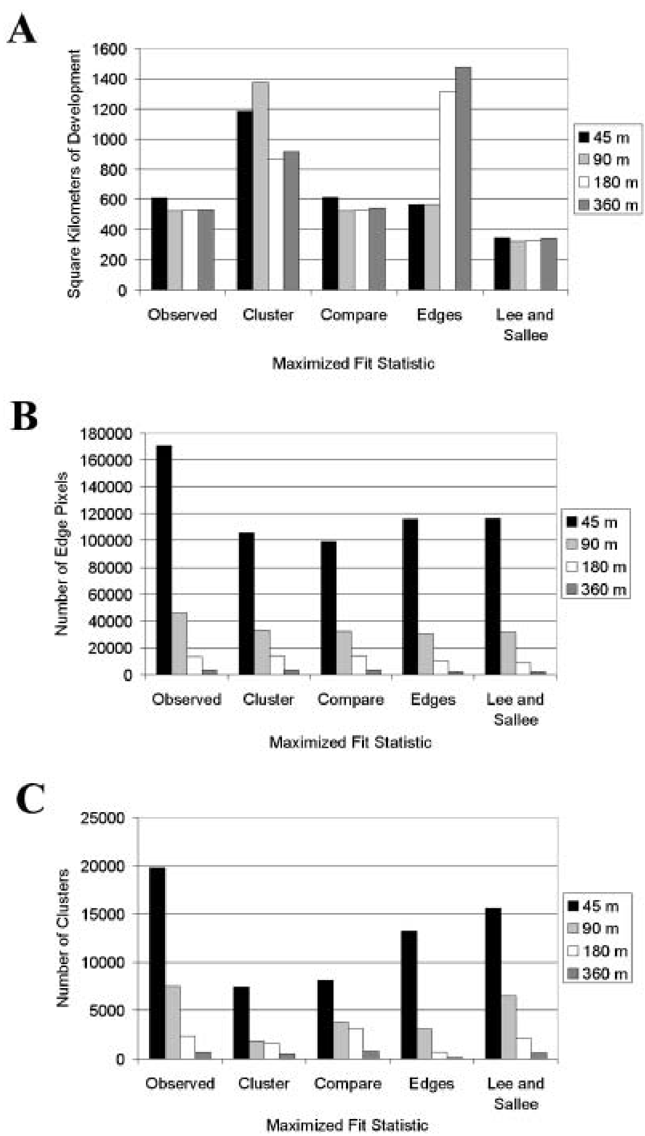

Figure 6. Simulations based on optimized parameter sets for the cluster, compare, edges, and Lee and Sallee metrics compared with the observed development patterns in 2000 in terms of (A) area of development, (B) number of urban edges and (C) number of urban clusters.

developed reasonably well at the 45 m and 90 m resolutions, but overestimated development at the 180 m and 360 m cell sizes.

The number of urban edge pixels was scale-dependent. For the control data set, the number of urban edge pixels was highest in the 45 m data set and lowest in the 360 m data set. Despite a high fit score (table 2B), the number of urban edge pixels was consistently underestimated by all parameter sets for the 45 m and 90 m data sets. This underestimation was most extreme for the 45 m data set. For the 180 m and 360 m data sets, the number of urban edges was matched quite well by the parameter sets that maximized the cluster and compare metrics, but were slightly underestimated using parameter sets based on the edges and Lee and Sallee metrics. It is interesting to note that widely different parameter sets could produce similar numbers of edge pixels. For example, the two parameter sets that maximized the edges and Lee and Sallee metrics for the 45 m data set were quite different, yet produced similar numbers of edge pixels.

As expected, the number of urban clusters also decreased as resolution increased. Nearly all parameter sets across all scales underestimated the number of urban clusters that exist in the system in 2000, and it was notable that the parameter set that optimized the cluster score produced the fewest clusters for all cell sizes except the 360 m data set. In terms of matching the number of urban clusters for the 2000 control year, the parameter values derived from maximizing the Lee and Sallee statistic performed the best, although the compare and cluster parameter sets also provided good estimates for the 180 and 360 m data sets.

To visually assess urban growth patterns, we present images from single Monte Carlo simulations for each optimized parameter set at each cell size (figure 7). For the compare metric, the 45 and 90 m data sets relied primarily on the edge parameter to match the amount of growth in the control data set, while the diffusion and breed parameters generated most of the growth in the 180 and 360 m data sets (table 4). The influences of the respective parameter sets were apparent: for the compare metric, growth occurred in a clustered pattern in the two finer-resolution data sets, but was more dispersed in the coarser-resolution data sets.

The patterns across scales also varied widely for the edges metric. While most growth was generated by the spread parameter, the 45 m data set also had a high value for the dispersion parameter (table 4) and the resulting diffuse growth patterns were evident. Growth patterns for the 90, 180 and 360 m data sets were more clustered, although the influence of the high values for dispersion and breed was also evident in the 180 m data set. High values for the spread parameter in the two coarser-resolution data sets resulted in an overestimation of developed area.

High values for dispersion, breed, and spread tended to produce high fit scores for the clusters metric, and the interaction of these parameters was apparent in the third set of images in figure 7, all of which showed high levels of growth. The optimized parameter sets based on the Lee and Sallee statistic had uniformly low values, producing little simulated growth in the system.

5. Discussion and conclusions

5.1 *Parameter behaviour*

SLEUTH clearly exhibits sensitivity to cell size in terms of the influence that growth rules have on replicating urban form across cell sizes. The association between high fit scores and a specific value or range of values for a given parameter indicates that

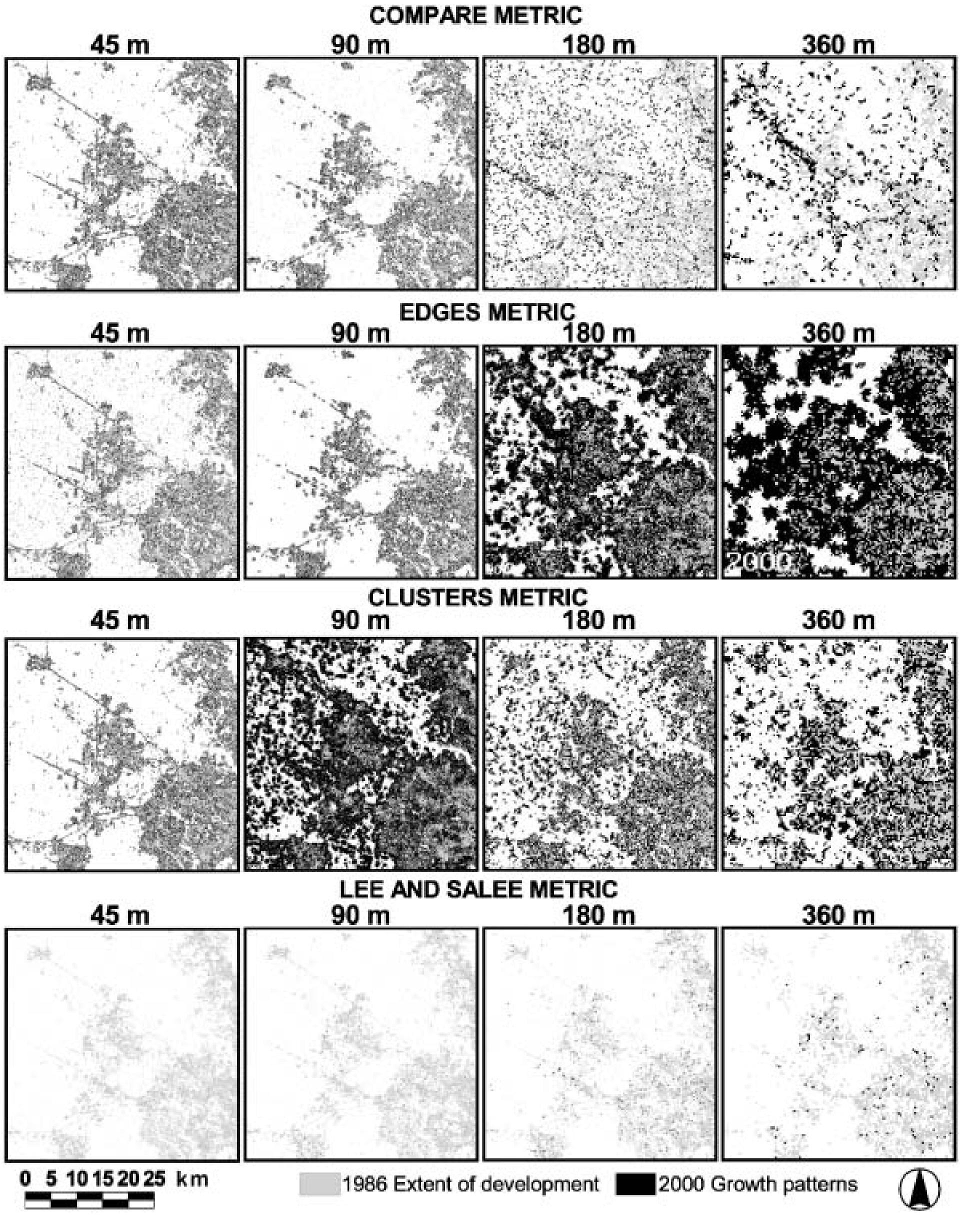

Figure 7. Simulated urban patterns from a single Monte Carlo simulation for all cell sizes using parameter sets derived from different optimized fit statistics.

the parameter plays a key role in replicating that aspect of urban form being measured. The spread parameter, for example, is instrumental at all scales in replicating rates of urban development and in matching the number of urban edge pixels (table 2). The fact that some parameters exhibit stability at certain cell sizes and not at others indicates that scale influences the parameters differently. That dispersion and breed are instrumental in maximizing the clusters metric only at coarser cell sizes exemplifies this point. Parameter instability poses an issue for calibration, since it makes the choice of appropriate parameter value ranges difficult. It also points to deeper issues with the ability of the parameters to function at certain scales.

Related to this issue, SLEUTH was not able to achieve high fit scores for the clusters metric across scales. The highest fit was achieved at the coarsest cell size, while lower fit scores occurred as the resolution of the input data increased. The clusters metric is one that could potentially be used to capture dispersed settlement patterns, such as low-density residential 'sprawl,' yet it is clear that SLEUTH was unable to optimize this metric at fine scales in this study area.

The results for the Lee and Sallee metric reveal the limitations of evaluating a CA-based model in terms of its ability to match the exact spatial location of change, particularly over a short time period. Stable parameter values were low at all cell sizes, resulting in simulations where little change was predicted to occur. This indicates that the exact location of actual development in 1986 was more similar to development in 2000 than in any simulated version of urban form. The likelihood that SLEUTH, or any other CA-based model of land-use change, could achieve an exact spatial match is very low, and not necessary or perhaps even desirable for some applications.

The failure of the road growth parameter to show a relationship to any fit statistic at any scale is an important finding, yet difficult to interpret, since this parameter shows potential to influence growth patterns. Relating growth patterns to the transportation network is not straightforward, since the transportation network is both an exogenous force driving growth and an endogenous aspect of the development process. Whether these results point to a failure of the model to capture these relationships, or whether the relationship between growth patterns and the transportation network is not well defined in this particular study area, requires additional consideration and testing.

The fact that the individual parameters respond to changes in scale differently can be linked to the operational scales of the land-use-change processes that each parameter is attempting to capture. Highly dispersed settlement patterns apparent at fine resolutions, for example, may be the result of local scale factors that SLEUTH fails to capture. Behavioural CA-based models such as SLEUTH, which use development rules to mimic the spatial behaviour of certain types of development (Wu 2002), must be dynamic across scales so that the rules defining development events can capture the phenomenon of interest at the scale of interest.

5.2 *Range of growth rule functionality*

The parameter sets producing the maximum growth levels for spontaneous, new spreading centre, and edge growth followed an expected trend based on the order in which each was applied in the growth cycle: (1) to produce the maximum amount of spontaneous new growth, dispersion was at its maximum value, and spread was equal to one; (2) to maximize new spreading centre growth, dispersion and breed were at their maximum values with spread equal to one; (3) dispersion, spread, and breed were at their maximum values to produce high levels of edge growth. Likewise, slope resistance in these cases was consistently at its lowest value.

For the maximum level of road-influenced growth, it was interesting to note that the spread parameter was at its lowest value. Road growth is always applied last in the growth cycle and the number of successful urbanization attempts that occur in previous steps determines the number of potential road growth cells. More successful urbanization attempts would increase this number, so a higher value for the spread parameter would be expected. Because of the dominance of edge growth, however, it can significantly limit the number of cells available for development. This may explain why high levels of road growth require that the spread parameter be low. The value for the road growth parameter itself did not have a significant impact on producing high levels of road-influenced growth. Rather, the values for dispersion and breed influenced this growth type.

In terms of the visual results (figure 5), the strongest influence of any parameter occurred at the coarsest scale (360 m). The dependencies of the growth rules on the order in which they occur in the growth cycle also became apparent. For example, new spreading centre growth is applied only to cells that were previously urbanized by the application of the spontaneous growth rule. The spatial patterns produced by each of these growth rules are therefore similar. Road-influenced growth created linear patterns of development along the road network, although the influence of road growth was not readily apparent at the 45 m resolution.

The resolution of the data used to represent the urban system played a dominant role in determining each parameter's functional range, i.e. the range of resolutions within which each parameter is able to accurately capture urban development patterns. In all cases, the minimum level of growth potential was similar across scales, often approaching zero. The maximum level of growth potential varied, however, so that the growth rules were constrained at fine cell resolutions. The amount of growth that could be produced through spontaneous growth at a resolution of 360 m, for example, was more than five times the amount at the 45 m resolution. This discrepancy was even greater for road-influenced and new spreading centre growth, while edge growth was least impacted by scale and had the most influence on the model's ability to capture certain growth patterns at certain scales.

These findings emphasize the importance of defining the functional range of land-use-change models, the land-use-change characteristics of the study area, and relating these factors to the scale of observation. The scale issues encountered in this study area may not appear in areas where urban patterns are more clustered, when fine-scale urban features are not mapped, or when local-scale urban change processes are not important to capture. The functional range of a land-use-change model may not, therefore, be absolute, but depends on the data used to represent land-use patterns and the specific objectives of the application.

5.3 *Goodness of fit*

The conclusion that SLEUTH can be functionally limited to certain scales is reinforced when the performance of the model at capturing various aspects of urban form is examined. While the model can accurately capture the rate of growth across scales, SLEUTH consistently underestimates the number of urban edge pixels and the number of urban clusters at fine resolutions. In this study area, SLEUTH's ability to match these pattern metrics to the control data set was maximized at coarse scales.

In addition to the scale dependencies discussed above, the results from our analyses indicate the potential difficulty in evaluating the fit of the model using multiple fit statistics simultaneously (e.g. with a weighted or unweighted composite score). In many cases, the parameter sets that produced a high fit score for one statistic were opposed to those producing a high fit for another, increasing the difficulty in interpreting the parameter sets when multiple fit scores are combined. Identifying the aspect of urban form most relevant for a particular application and using a single fit statistic that captures that phenomenon of interest may produce more straightforward and interpretable results.

The utility of the fit statistics must also be considered. In most cases, the fit statistics consist of least-squared regression scores that describe the strength of the relationship between modelled and actual urban patterns. The only tabular information produced by the model, however, is the value for the r^2 statistic; no additional information is generated to describe the linear relationship, such as the slope or y-intercept, which may indicate a systematic bias of the model to over- or underestimate growth patterns, or statistical significance. When quantitative results for the number of simulated urban edge pixels and number of clusters were compared with the control data (figure 6), for example, the model showed significant bias, even though the r^2 values were high (table 2). Since the compare metric is a ratio, a high fit score was easier to interpret, but this metric focuses only on the final control year, while the other fit scores describe how well the model captures trends through time.

Calibration and validation remain fundamental issues for land-use-change models (Kok *et al.* 2001). Our results emphasize the importance of developing fit metrics that accurately capture the aspects of pattern and process that are central to the modelling effort. In this case, the use of Pearson correlation coefficients alone did not provide enough information to measure the true performance of the model, calling into question the validity of the calibration results. While pattern metrics are valuable descriptors of urban spatial structure, other measures, such as spatial autocorrelation, can be useful for calibration (Wu 2002). The scale-dependent performance of the model reinforces recent findings regarding the importance of multi-scale validation in land-use-change models (Kok and Veldkamp 2001).

5.4 *Summary*

Any effort at land-use-change modelling requires that many decisions be made, such as the resolution of the input data or choice of fit statistic(s) used during the calibration process. Our results demonstrate how these decisions can impact the overall performance of an urban land-use-change model, the influence of the growth rules, and interpretation of results.

To date, research based on the widely available SLEUTH model has focused on refining the applications-oriented technical issues, such as the development of parallel processing capability for calibration, scenario development, and the integration of results into geographical information systems. Whereas the relative ease of use and ability to visualize results have made SLEUTH one of the better known spatial predictive urban land-use-change models, our results suggest that users must consider their specific objectives in the context of the potential scale dependencies of the model, and the variability in output products that result from the choice and utilization of fit statistics. Scale dependencies are often not addressed in land-use-change modelling, despite a growing interest in multi-scale approaches (Kok *et al.* 2001). For generalized land-use-change models, such as SLEUTH, which can theoretically be applied to any landscape, the criteria that emphasize pattern and process, are crucial considerations.

We suggest that sensitivity analyses be conducted on each application such that the variability in map output can be assessed and incorporated into the interpretation of results with an acceptable level of confidence. Key urban processes or patterns specific to the application should be identified a priori, appropriate fit statistics identified, and model performance evaluated across multiple scales to identify the scales at which a model can capture the phenomena in question.

The scale at which the land-use data are represented can impact the quantification of land-use patterns and the ability of a model to replicate spatial patterns. Because there is currently no elegant theory to address scale dependencies in land-use-change modelling (Obeysekera and Rutchey 1997), we emphasize the importance of considering scale as an integral issue during each phase of a modelling effort.

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