Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal

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Abstract

The SLEUTH model (slope, landuse, exclusion, urban extent, transportation and hill-shade), formerly called the Clarke Cellular Automaton Urban Growth Model, was developed for and tested on various cities in North America, including Washington, DC, and San Francisco. In contrast, this research calibrated the SLEUTH model for two European cities, the Portuguese metropolitan areas of Lisbon and Porto. The SLEUTH model is a cellular automaton model, developed with predefined growth rules applied spatially to gridded maps of the cities in a set of nested loops, and was designed to be both scaleable and universally applicable. Urban expansion is modeled in a modified two-dimensional regular grid. Maps of topographic slope, land use, exclusions, urban extents, road transportation, and a graphic hillshade layer form the model input. This paper examines differences in the model's behavior when the obviously different environment of a European city is captured in the data and modeled. Calibration results are included and interpreted in the context of the two cities, and an evaluation of the model's portability and universality of application is made. Questions such as scalability, sequential multistage optimization by automated exploration of model parameter space, the problem of equifinality, and parameter sensitivity to local conditions are explored. The metropolitan areas present very different spatial and developmental characteristics. The Lisbon Metropolitan Area (the capital of Portugal) has a mix of north Atlantic and south Mediterranean influences. Property is organized in large patches of extensive farmland comprised of olive and cork orchards. The urban pattern of Lisbon and its environs is characterized by rapid urban sprawl, focused in the urban centers of Lisbon, Oeiras, Cascais Setúbal, and Almada, and by intense urbanization along the main road and train lines

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radiating from the major urban centers. The Porto Metropolitan Area is characterized by a coastal Atlantic landscape. The urban pattern is concentrated among the main nuclei (Porto and Vila Nova de Gaia) and scattered among many small rural towns and villages. There are very small isolated patches of intensive agriculture and pine forests in a topography of steep slopes. These endogenous territorial characteristics go back in time to the formation of Portugal — with a ''Roman-Visigod North'' and an ''Arabic South'' [Firmino, 1999 (Firmino, A., 1999. Agriculture and landscape in portugal. *Landscape and Urban planning, 46*, 83–91); Ribeiro, Lautensach, & Daveau, 1991 (Ribeiro, O., Lautensach, H., & Daveau, S., 1991. *Geografia de portugal* (4 Vols., published between 1986 and 1991). Lisbon, Portugal: João Sá de Costa)]. The SLEUTH model calibration captured these city characteristics, and using the standard documented calibration procedures, seems to have adapted itself well to the European context. Useful predictions of growth to 2025, and investigation of the impact of planning and transportation construction can be investigated as a consequence of the successful calibration. Further application and testing of the SLEUTH model in non-Western environments may prove it to be the elusive universal model of urban growth, the antithesis of the special case urban models of the 1960s and 1970s.

1. Introduction

Modeling is essential for the analysis, and especially for the prediction, of the dynamics of urban growth. Yet the successful application of a model in one particular geographical area does not necessarily imply its successful use in another setting where local characteristics, territorial constraints and the classic site and situation properties of economic geography ensure that different development paths have been followed. Urban and environmental models need to be adapted to or able to ''learn'' the endogenous characteristics of the particular milieu that they explain and predict. Models are often judged by their predictive power. Yet, to model urbanization across locales, it is just as important to test the efficacy of the model's algorithms at capturing and simulating the land transformations that are specific to a place (Batty & Xie, 1994b; Clarke, Hoppen, & Gaydos, 1996; Li & Yeh, 2000).

This paper focuses on calibrating the SLEUTH model, formerly the Clarke Cellular Automaton Urban Growth Model (Clarke & Gaydos, 1998; Clarke, Hoppen, & Gaydos, 1997) for two Portuguese metropolitan areas. SLEUTH is an acronym for the input layers that the model uses in gridded map form: Slope, Land Use, Exclusion, Urban Extent, Transportation and Hillshade. The basic growth procedure in SLEUTH is a cellular automaton, in which urban expansion is modeled in a spatial two-dimensional grid. Diffusion, breed, spread, slope and road coefficients control the behavior of the cellular automaton, and four types of growth behavior can take place: spontaneous, diffusive, organic and road-influenced. Self-modification of the rules changes the control parameters when modeled growth rates are exceeded, so that the model's behavior includes feedback (Clarke et al., 1997). In cellular automata simulating artificial life, self-modification is equivalent to adaptation or evolution, and the calibration method used allows the model to ''learn'' its

local setting over time (Clarke et al., 1996). This learning is quantified by the variation during calibration of the five control parameters. Calibration of the model has taken place for many cities within North America, but not elsewhere. Application of the model to Lisbon and Porto in Portugal is the first application to European cities, and indeed the first major application outside of the United States.

The SLEUTH model was applied to the metropolitan areas of Lisbon and Porto. These Portuguese cities present very different environmental and geographic characteristics that test the model's flexibility to adapt to different urban realities. Lisbon is the capital of Portugal, and the administratively defined metropolitan area includes large patches of farmland comprised of olive, cork, and fruit orchards surrounding the mouth of the Tagus River. The urban pattern of Lisbon and its environs is characterized by recent rapid urban sprawl, focused in the urban centers of Lisbon, Oeiras, Cascais Setúbal, and Almada, and by intensive urbanization along the main roads and train lines radiating from those major urban centers. By contrast, the Porto Metropolitan Area is characterized by a coastal Atlantic landscape at the west-facing mouth of the smaller River Douro and is surrounded by mountains. The urban pattern is concentrated at main nuclei (Porto and Vila Nova de Gaia) and settlements are scattered among many small rural towns and villages with small patches of intensive agriculture and pine forests.

2. Urban modeling and SLEUTH

One of the major criticisms of the first generation of computer-based urban models was their specificity to the cities to which they were applied (Lee, 1973). It has taken a new generation of computational models, using very different methods, to escape this legacy. How global models reflect local characteristics is a central challenge if modeling is ever to move beyond the comparison of case studies. Therefore, an effort should be directed to an understanding of how increased spatial resolution improves sensitivity to local factors. SLEUTH's calibration involves such a multistage optimization of the model to a specific parameter space. Thus, we can learn about global properties from local behavior of SLEUTH's parameters. It is commonly accepted that growth dynamics have measurable dimensions, both built and natural environmental to their global nature. Urban sprawl is associated with suburbanization, automobile dependency, and highway investments. In urbanized natural systems, hydrologic impacts include increased run-off, stream channelization, and increased contamination of surface water with urban by-products. Urban and regional models are usually supported by a set of variables and parameters that feed system dynamics and process interactions built into the models. Depending on which variables are required by the model and for policy manipulation, common elements can be defined and assigned behavior and significance, such as the importance of roadways, urban extent, topographic slope, parks and reserves. Most urban and regional models incorporate these general characteristics of urban settlement and change.

Urban models usually internalize general and known characteristics that include local variation for a specific area such as employment, population growth and

highway construction. Alternatively, a model can include these general characteristics, but give the user the freedom to incorporate local variation and adaptations into the model structure in a way that allows model reuse from city to city and from application to application. A statement of the central problem would be: how can one apply a model developed for a specific urban context in another? The most accepted process to answer this question is to build a general-purpose model and to use a technique in modeling called *calibration*.

This paper documents the process of adapting and calibrating the SLEUTH model to the local characteristics of two different Portuguese Metropolitan Areas. The purposes were: (1) to demonstrate that the same model could apply not only to North American but also to European cities; (2) to demonstrate how important structural and geographical differences between applications could be revealed by the calibrations that may be of use in comparative urban study; (3) to reveal how spatial resolution improves model performance by making the model more sensitive to local conditions; and (4) how a sequential multistage optimization throughout different phases of calibration is the key to model application comparison.

A model is a simplified representation of part of the real world or its systems, that retains enough aspects of the original system to make it useful to the modeler (Ford, 1999). In modeling, observations of system behavior are generally transposed into a structure of model elements and their relations, that are then converted into equations and usually coded as a computer program that can be run as a simulation. Understanding the complexity of urban landscapes and their behavior helps to assure that planned human interventions in the processes benefit society and the environment. Modeling and simulation are contributing to the rapid spread of geographic information into planning (Birkin, Clarke, Clarke, & Wilson, 1996; Scholten & Stillwell, 1990; Stillwell Geertman, & Openshaw, 1999). The power that geographic information systems (GIS) have brought to urban spatial analysis has considerably broadened the scope of urban and regional planning (Clarke, 1999; Fischer, 1999; Goodchild, 2000; Goodchild & Steyaert, 1996).

Modeling geographic systems with cellular automata is a relatively recent process. The potential of the approach was first related to planning during the 1980s (Batty & Longley, 1994a; Batty, Xie, & Sun, 1999; Couclelis, 1985, 1997), and has seen heightened interest in the last decade. Cellular automata (CA) are particularly well suited to model complex dynamical systems composed of large numbers of individual elements linked by nonlinear couplings (Openshaw & Openshaw, 1997; p. 247). This versatility is responsible for the growth in the application of CA to the diverse fields of urban and regional growth analysis (Clarke & Gaydos, 1998; Clarke et al., 1997; Landis & Zhang, 1998), regional economics, demographics and land use (White & Engelen, 1997), and location choices (Roy & Snickars, 1998). The utility of GIS in providing real-world environments for CA is clear, yet the full integration of CA tools directly into GIS has not yet been achieved (Park & Wagner, 1999). Research on geographic modeling with CA is still exploring and building upon modeling capabilities (Clarke & Gaydos, 1998; Li & Yeh, 2000).

Calibration is one of the most important elements of successful model application, since it allows us to narrow down the resulting values of the model to reflect the

characteristics of the local: Birkin et al. (1996; p. 93) contends that "the key component of the modeling process [. . .] is calibration: the process by which numerical values are assigned to the model parameters in such a way that the model accurately reproduces the real patterns". The importance of calibration is reflected by the publication of calibration results that document this phase of model development (Batty & Xie, 1994c; Birkin et al., 1996; Clarke et al., 1996; Landis & Zhang, 1998). The absence of a calibration phase in model development and application reflects poorly on a model's applicability, verifiability, portability and robustness.

3. Calibration of SLEUTH

The calibration of the SLEUTH model for Lisbon and Porto followed the techniques developed for the model as applied to the San Francisco and Washington/ Baltimore areas (Clarke & Gaydos, 1998, Clarke et al., 1996, 1997) and documented on the Internet at url: www.ncgia.ucsb.edu/projects/gig. Version 2.1 of the model was downloaded from the web site. The program code is written in the C programming language, and supports three different modes: test, calibration, and prediction modes.

The SLEUTH urban model is a CA model developed with sets of predefined growth rules applied in a set of nested loops. An outer loop executes each growth history and retains statistical data, while an inner loop executes the growth rules for a single year. The "seed year" that the model takes is generally the earliest year, against which the model runs and compares the modeled data with the available real urban data (Clarke et al., 1997).

Besides the urban layers (that for statistical purposes need to number at least four), the model requires at least two transportation layers of different years (in each road layer it is also possible to define a road hierarchy), a single layer contains percent topographic slope, one layer with areas excluded from urbanization (the model allows classification in the layer by probability of exclusion), and a hillshade layer for use only as a background with the graphical version of the model.

The growth of urbanized areas is the result of four growth rules applied to the input layers: (1) spontaneous neighborhood growth, which simulates growth in areas with suitable slope to develop under the control of the diffusion coefficient; (2) diffusive growth and creation of new growth centers; (3) organic growth which replicates the expansion of cities into their surroundings and infill; and (4) road influenced growth, which expresses the importance of road gravity and road density by allowing growth to happen on and along roads.

Besides these initial growth rules, a second level of behavior rules is defined in this model. Each time the model records rapid growth, or little or no growth, the model adapts itself to this new set of conditions. In the case of rapid growth, the model multiplies the growth control parameters by a multiplier greater than one. Little or no growth causes the control parameters to be multiplied by values less than one. These "self-modification" rules are fundamental in order for the model to reflect more accurately the typical S-curve growth rate of urban expansion. The

parameter values increase most rapidly at the beginning of the growth cycle when there are many cells available to urbanization, and then, with time, the parameters are decreased as expansion levels off and the growth rate falls below the critical low. Without self-modification the model would produce only linear or exponential growth.

Both growth rules and self-modification rules are the core of the model, they reflect the universal understanding of the process of urbanization, but, to be successfully used they need to be refined to the locale. Without calibration it will be impossible to correctly describe the behavior of the system and predict its possible futures; this is done through the process of calibration. This phase is of such importance that the authors considered it separately from the predictions, which will be reported in future papers.

The model calibration is described in detail in Clarke et al. (1996). This process has been automated, so that the model code tries many of the combinations and permutations of the control parameters and performs multiple runs from the seed year to the present (last) data set, each time computing 13 different measures of the goodness of fit between the modeled and the real distributions (see Appendix for a detailed description of these scores and coefficients). The calibration process, known as ''brute force calibration'', relies on the availability of significant computing power, and benefits significantly from parallel processing and high performance computing methods. Results are sorted, and parameters of the highest scoring model runs are used to begin the next, more refined sequences or permutations over the parameter space. Initial exploration of the parameter space uses a condensed, resampled and smaller version of the data sets, and as the calibration closes in on the ''best'' run, the data are increased in spatial resolution.

By running the model, a set of control parameters is refined in the sequential calibration phase (coarse, fine and final calibrations). Between phases in the calibration, the user tries to extract the values that best match the five factors that control the behavior of the system: diffusion (overall scatter of the growth), breed (likelihood of new settlements being generated), spread (growth outward and inward from existing spreading centers), slope resistance (flat ground is preferred) and road gravity (attraction of urbanization to roads and diffusion of urbanization along roads). Coefficient combinations result in combinations of the 13 metrics: each either the coefficient of determination of fit between actual and predicted values for the pattern (such as number of pixels, number of edges, number of clusters), for spatial metrics such as shape measures, or for specific targets, such as the correspondence of land use and closeness to the final urban pixel count (Clarke & Gaydos, 1998). The highest scoring numeric results from each factor that control the behavior of the system from each phase of calibration feed the subsequent phase, with user-determined weights assigned to the different metrics. Calibration relies on maximizing spatial and other statistics between the model behavior and the known data at specific calibration data years. Monte Carlo simulation is used, and averages are computed across multiple runs to ensure robustness of the solutions.

Therefore, it is possible to carefully adapt the model to local characteristics throughout calibration, by using different spatial resolutions and a sequential

multistage optimization of the coefficients that control the system. For instance, the user assumes that he does not know the importance of roadways in a specific area, and therefore, the maximum range of possible values (100) is proposed. Next, several attempts are made to adjust that range to local characteristics. Then, each calibration phase corresponds to a multistage selection that depends both on the increased spatial resolution and the control values that the previous calibration phase identified. A new output file (control.stats) contains the new refined control values that once again will feed the next calibration phase and a more detailed spatial resolution. Besides the behavior of the growth rules, the self modification rules included in the model increase the score values, or decrease the values, each time the system records a modification in the parameter values, and forces the four growth rules to improve their spatial behavior, speeding up or down the growth rates.

The calibration mode of SLEUTH is the most important phase for the success of predictions. It determines "given a starting image of urban extent, which set of initial control parameters leads to a model run which best fits the observed historic data" (Clarke & Gaydos, 1998; p. 706). By narrowing both the spatial scale and the range of parameters in three calibration sequences, the model user can close in on the parameter set that best simulates the application data. These parameters are then used to determine the parameter values that best allow the model to run into the future, i.e. to predict.

To complete the explanation of the model before describing the case studies, it is also important to briefly mention the test mode phase before the calibration mode. Prior to calibration, the first step in the application of the SLEUTH model is the verification of the data sets and their initial reaction to the input data (test mode), including assuring that they conform to data input specifications. A minimum of four urban years, two road years and at least one excluded layer, one hillshade image and one slope layer are required, and the code verifies the correct input of each of these data sets. The test mode also allows simulation of the growth for known data years up to the present and visual verification that the model is reacting as expected. This step revealed itself to be very important, for example in the Lisbon Metropolitan Area (AMP), water bodies and land outside the AMP were initially not defined correctly in the excluded layer, and consequently the model was seen expanding urbanization to these areas. It was also observed during this test phase that the slope layer was not contributing to the model calibration, for the test mode statistics did not seem to be sensitive to changes in slope. It was found that the percent slope image had been altered during its conversion from TIF to GIF format. Without this initial test, the model could run for days during calibration, and the time would be unnecessarily lost. It is prudent to first run the model in test mode at all the different resolutions and to verify the statistical files as well as the different GIF images produced.

Once the test mode is complete, the next phase is the calibration mode, as previously described, the most important step for the success of model prediction. When the calibration mode is complete, the results are used for forecasting studies, and no validation is possible without repeating the calibration.

4. Case studies

The results of the calibration applied to the Lisbon Metropolitan Area and to the Porto Metropolitan Area (Fig. 1), are presented and then compared. In order to better understand the resulting metrics within the calibration results, the two metropolitan areas are first described. The metrics that best describe each system are explained in terms of their behavior according to the landscape characteristics and history. Finally, we compare the scores and coefficients of both metropolitan areas to understand to what extent the model reflects different realities, and which metrics were more sensitive.

Several events crisscrossed both metropolitan areas and the country resulting from different political, social-economic and cultural changes during recent times. The first event marks the period before the revolution of 1974. The second time period comprises the years between 1974 and the end of the 1980s. The third period corresponds to Portuguese membership in the European Community from 1986 until the present. After the end of the dictatorship in 1974, a period of political instability, worldwide economic crisis followed, including a massive return of population from Portugal's former overseas colonies, characterized by a period of unorganized and irregular growth (including the development of slums). In the years after 1974, Portugal had to house 650 000 citizens from the colonies, around half of whom settled in the Lisbon Metropolitan Area (Lisbon, Amadora, and Almada were some of the municipalities that received those citizens). The decade of the 1980s, especially after
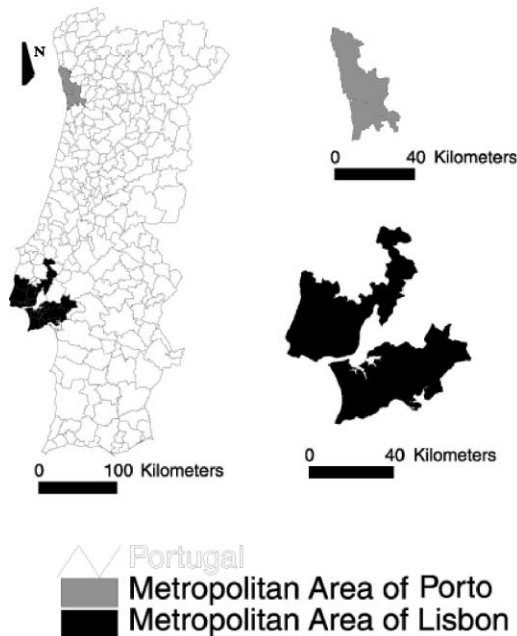

Fig. 1. Lisbon and Porto Metropolitan Areas in Portugal.

the European Community's massive investments, and a growing European and world economy invigorated a Portuguese "urban renaissance". During this period the importance of planning was also significantly reinforced.

Two other factors are important to describe the two metropolitan areas. First, the housing market and the rental laws protected property renters. During the dictatorship, rents in the area of both Lisbon and Porto Metropolitan Areas were frozen, and were restrained in the rest of the country. After the revolution, Portugal implemented urban rent control countrywide. The major consequence was a decline in the rental markets, degradation of the urban old areas, and mainly, the acceleration of construction in the peripheries. In the majority of the cases in the north of Portugal, new houses were built by the land owners, in their small parcels, for their own use, promoting a more scattered urban pattern, and compromising the viability of planning new developments because of their irregular spatial growth. In the south of Portugal, small developers tended to market and sell to a local clientele, creating new urbanization in the immediate periphery of Lisbon.

The second important factor was the law of municipal economic autonomy, yielding to each municipality the right to income from licenses it gave to build new homes. These factors, and low mortgage rates, led to very rapid urbanization all over the country.

5. Case study A — Lisbon Metropolitan Area (AML)

The Lisbon Metropolitan Area contains 2 554 240 inhabitants in an area of 312 km^2 for a population density of 817 people/km^2. Population is concentrated mainly around the city of Lisbon, the central urban nucleus and then extends out along main roadways and railways (along the municipalities of Cascais, Oeiras, Amadora, and Vila Franca de Xira). Since early times it was clear that the capital of the country and its environs needed integrated planning. Therefore, a metropolitan plan was developed and proposed to guide the future activities and urbanization. In 1964, the regional plan "Plano Director da Região de Lisboa" was established to organize housing, industry, harbors, airports and tourism in the metropolitan area. This regional plan was the definition of a clear structure for transportation in the entire area. A second phase in the planning of the metropolitan area was the regional plan "Plano Regional de Ordenamento do Território" in 1992, once again the different activities were organized throughout the entire metropolitan areas with special emphases given to the transportation infrastructure and its hierarchy. Neither of these plans were ever approved, but nevertheless they were important elements in structuring the transportation infrastructure and therefore constraining the intensity, direction and shape of urban growth (Silva, 1999).

Two main bridges were built during these two decades that have had a major impact in the organization of the space. The "Ponte 25 de Abril" in 1966, and the "Ponte Vasco da Gama" in 1998. The first is considered to be one of the main factors contributing to the intense urban pressures on the west side of the south margin of the Tagus River (municipalities of Almada, Seixal, Barreiro), and it seems to be

clear that a similar process will happen in the east side of the south bank because of the 1998 bridge (mainly in the municipalities of Alcochete and Palmela). Main trends related with the location of economic activity and residential development as identified for the Lisbon Metropolitan Area by Gaspar (1997; p. 165) are: (1) the strengthening of the city of Lisbon, as the principal nucleus of tertiary economic activity; (2) the emergence of tertiary centers related to the use of the private car and oriented towards expressways, having an important land speculation component; (3) a growing concentration of population on the axis served by railways; and (4) The spread of residential areas of low density, based upon transport by private car.

The collection of data for the Lisbon Metropolitan Area database involved a variety of sources, including Landsat imagery, published maps and reports, and transportation plans. Maps with cells of 100×100 m for urbanization, roads, excluded areas, topographic slope, and a hillshaded backdrop were created in the ArcInfo GIS and converted into the 8-bit GIF format used by the SLEUTH Model (Fig. 2). By observing the urban extent over time (urbanization maps for the control years: 1984, 1995, 1997, and the seed year of 1975) it is clear that intense and rapid growth is affecting the entire Metropolitan Area, and that once new urban centers start to grow, growth increases substantially in each year. The analyses of the results strengthened this conclusion and explore the nature of the growth.
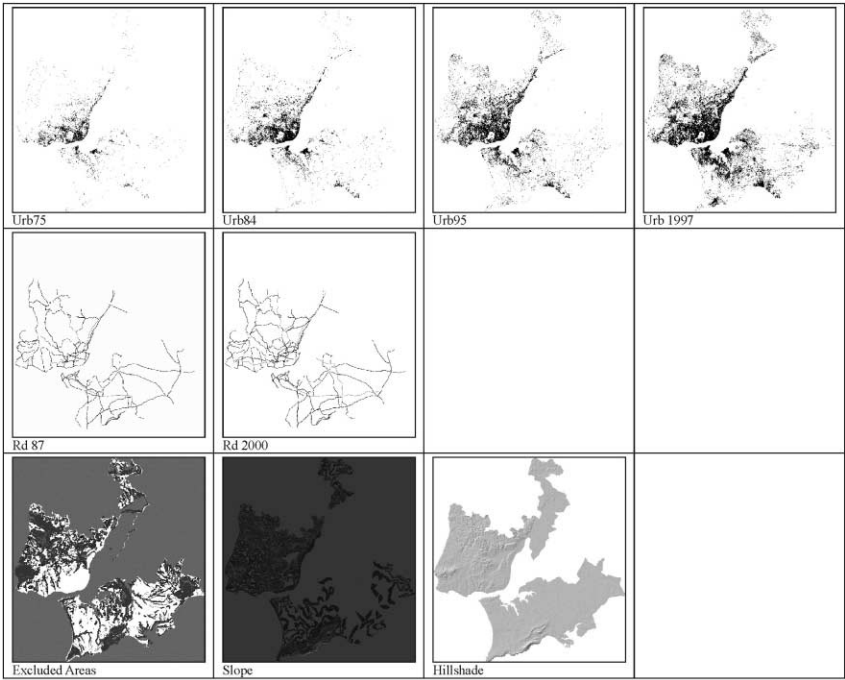

Fig. 2. The Lisbon Metropolitan Area input data sets to SLEUTH.

6. Calibration results for the Lisbon Metropolitan Area

Results from the three phases of the calibration mode (Coarse, Fine, and Final calibrations) are presented in Tables 1–3. Each table presents the sorted top five highest scoring results from thousands of model runs.

The values marked in bold define the composite results of the optimum values for the diffusion, spread, slope and road gravity parameters. The tables show successive improvement in the parameters that control the behavior of the system. From a set of initial control parameter values ranging from 1 in the case of the diffusion coefficient (the minimum value possible at which diffusion would occur) and 100 as the maximum values for each of breed, spread, slope resistance and road gravity. In the coarse calibration, the resulting values were narrowed to 1, 100, 50, 25, 20 and became even more sensitive to the locale with the final calibration results presenting, respectively, values of: 16, 57, 50, 25, and 30. The importance of this sequential multistage optimization is shown by extensive automated exploration of the parameter space throughout the selection of the different scores, which allowed narrowing to actual values that better reflect the characteristics of the metropolitan area. The sensitivity to local conditions will be explored later.

The comparison of the model final "population" (number of urban pixels) and the urbanization for the control years gives a high summary correlation of 0.90 (compare_score), making it possible to state that the prediction of the model based on the initial seed year of the present urban pattern using those refined values is very similar to what happened in reality. The shape and form of urbanization seems also to confirm that calibration adjusts the values to reflect local characteristics. The final calibration correlations were 0.78 in the case of the score r^2_edges (modeled urban edges against the urban edges of control years), and 0.87 in the case of the cluster_r^2 score (modeled urban clustering against known urban clustering).

How sensitive is the model to the characteristics of the locale, now that besides having the values of the model we also know the history of this region? Why is the road coefficient higher than the diffusion coefficient? Why are the breed and spread coefficients higher then the other coefficients? The lower value of 16 of the diffusion coefficient controls the overall dispersiveness of the growth. As previously characterized, the urbanization of the metropolitan area tended to occur from the main nucleus (that is why the spread_coefficient is high at 50) and clearly along the main transportation infrastructures. The breed coefficient at (57) reflects the intense investment that was made in transportation infrastructure (mainly highways) spread urbanization in space, allowing for the creation of new nuclei on bare land, yet close to the main nodes of such highways.

7. Case study B — the Porto Metropolitan Area (AMP)

The Porto Metropolitan Area has a population of 1 196 850, an area of 817 km^2, and a population density of 1464.1 people/km^2 (AMP-INE, 1998). Porto is characterized by dispersed urban settlements with the highest densities in the

Table 1
AML — coarse calibration, 196×209 run time 06.01.2000:11:42–06.02.2000:5:14

Composite score	Compare r^2	Population[a] r^2	Edge r^2	Clusters	Mean cluster size r^2	Leesalee	Average slope r^2	pct Urban r^2	xmu r^2	ymu r^2	sdist r^2	lu Value	Diffusion coefficient	Breed coefficient	Spread coefficient	Slope resistance	Road gravity
0.23	0.97	0.92	0.98	0.93	0.97	0.32	0.99	0.92	0.98	0.97	0.99	1	1	100	50	25	20
0.22	0.99	0.91	0.96	0.90	0.98	0.33	0.99	0.91	0.98	0.97	0.98	1	1	75	50	25	30
0.22	0.97	0.91	0.95	0.98	1	0.32	0.99	0.91	0.97	0.97	0.98	1	1	1	50	25	1
0.22	0.97	0.91	0.96	0.91	0.97	0.33	0.97	0.91	0.99	0.99	0.9	1	25	25	50	25	40
0.22	0.93	0.91	0.96	0.99	0.97	0.33	0.99	0.91	0.96	0.94	0.98	1	1	25	50	1	40

[a] Population indicates no. of urban oixels.

Table 2
AML — fine Calibration, 392×418 run time: 06.02.2000:14:14–06.02:2000:20:02

Composite score	Compare r^2	Population[a] r^2	Edge r^2	Clusters	Mean cluster size r^2	Leesalee	Average slope r^2	pct Uurban r^2	xmu r^2	ymu r^2	sdist r^2	lu Value	Diffusion coefficient	Breed coefficient	Spread coefficient	Slope resistance	Road gravity
0.19	0.88	0.91	0.99	0.85	0.98	0.34	0.99	0.91	0.97	0.95	0.98	1	20	51	50	25	30
0.19	0.88	0.91	0.99	0.85	0.98	0.33	1	0.91	0.96	0.95	0.98	1	15	76	50	25	1
0.19	0.88	0.91	0.99	0.87	0.98	0.34	0.98	0.91	0.96	0.94	0.98	1	20	51	50	25	15
0.19	0.87	0.91	1	0.92	0.97	0.34	0.92	0.91	0.96	0.94	0.98	1	25	51	50	25	5
0.19	0.87	0.91	0.99	0.83	0.903	0.34	0.99	0.91	0.96	0.96	0.98	1	20	51	50	25	20

[a] Population indicates no. of urban oixels.

Table 3
AML — final calibration, 784×836 run time: 06.03.2000:16:35–06.15.2000:13:45

Composite score	Compare r^2	Population[a] r^2	Edge r^2	Clusters r^2	Mean cluster size r^2	Leesalee	Average slope r^2	pct Urban r^2	mu r^2	mu r^2	sdist r^2	lu Value	Diffusion coefficient	Breed coefficient	Spread coefficient	Slope resistance	Road gravity
0.15	*0.90*	*0.91*	*0.78*	*0.85*	*0.89*	*0.35*	*0.99*	*0.91*	*0.97*	*0.97*	*0.98*	*1*	*16*	*57*	*50*	*25*	*30*
0.15	0.91	0.90	0.77	0.85	0.89	0.35	0.99	0.90	0.97	0.96	0.98	1	**16**	**55**	**50**	**25**	**5**
0.15	0.90	0.91	0.78	0.84	0.89	0.35	0.99	0.91	0.97	0.97	0.98	1	**16**	**76**	**50**	**25**	**25**
0.14	0.90	0.91	0.78	0.83	0.90	0.35	0.99	0.91	0.97	0.97	0.98	1	**17**	**58**	**50**	**25**	**5**
0.14	0.90	0.91	0.77	0.85	0.89	0.36	0.98	0.91	0.97	0.96	0.98	1	**15**	**57**	**50**	**25**	**25**

[a] Population indicates no. of urban oixels.

municipalities of Porto, Vila Nova de Gaia, and Matosinhos. Just as in the Lisbon Metropolitan Area, the last 25 years have also seen intense urbanization.

Two main time periods define the evolution of the Porto Metropolitan Area: the decades of the 1950s and the 1980s. During the 1950s, new roadways linked the north and the Lisbon Area (e.g. Vias Norte and Via Rápida). This period also saw construction of the "Ponte da Arrábida", finished in 1963. This bridge was one of the major elements to shape the future of urbanization on both banks of the Douro River.

The 1950s also saw a major political action that moved urbanization outward to Porto's urban fringe, the Porto plan "Plano de Melhoramentos" (1956). This plan, though confined to the city of Porto, was a very important force in the renewal of the industrial population from the city center that lived in slums called "ilhas". This kind of "urban renewal" period had a major influence on the relocation of population to the urban periphery. This plan also favored providing low cost housing, making the Municipality of Porto the biggest landlord in the country (Cardoso, 1996; p. 24). Development of the north–south transportation infrastructure along the Littoral, as well as the development of the new port "Porto de Leixões" also took place. The consequence was a west urbanization axis, which included the Municipalities of Matosinhos and Vila Nova de Gaia. Industries, facilities for tourism, and housing built densely in the seashore areas.

The 1980s saw construction of the "Ponte do Freixo" that began a second phase of urban/transportation change. This time another axis developed, first intensifying the east–west connection reinforcing the municipalities of the metropolitan areas, and in a second phase, regionally within the east and northeast of northern Portugal. At the same time, the roadway system of the western municipalities of the Porto Metropolitan Area was consolidated. This encouraged reinforcement of the connectivity with the center of Portugal (mainly the littoral), and with the capital of the country (Lisbon).

Two other main characteristics should be highlighted in order to understand the Porto Metropolitan Area urban pattern. The first is related to the defense by the state authorities of a polycentric model of dispersion (Cardoso, 1996; p. 90), both by trying to extract advantages from historical patterns (populations and activities scattered throughout the area) and, at the same time, reinforcing even more that tendency. The second characteristic was a total absence of regional planning in the area that now comprises the Porto Metropolitan Area, reinforcing once again the scattered populations and activities.

Similar to the Lisbon Metropolitan Area, the same data themes were compiled in the database and were used as input to the model for Porto, comprising four urban layers, two road layers, one excluded layer, one slope layer and one hillshade layer (Fig. 3). Due to data availability, the years do not match those of the Lisbon Metropolitan Area. Nevertheless, their time period covers approximately the same 25 years. The same methods of data collection were used, to allow comparison of the case studies.

7.1. Calibration results for the Porto Metropolitan Area

Once again, calibration narrowed the total universe of parameter values to a very small set that best represent the historical growth pattern of the Porto Metropolitan
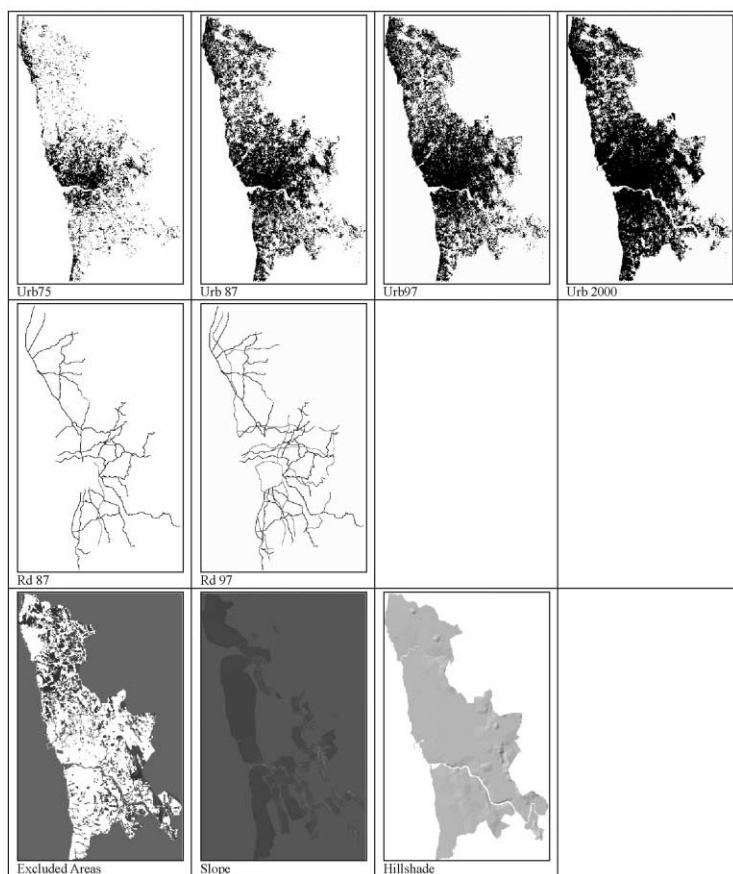
Fig. 3. The Porto Metropolitan Area input data sets to SLEUTH.

Area. The comparison of the modeled urbanization to the urbanization of the four control years presents a high correlation of 0.97, and very high correlation values of form and shape of urban areas. A r^2_cluster of 0.99, and a 0.98 in the case of the r^2_edges result from the final calibration (Tables 4–6).

It is possible to demonstrate the advantages of a sequential optimization of the parameters throughout the refinement of the values that best describe the spatial characteristics. From initial coefficient ranges of 100 given to breed, spread, slope, roads, and diffusion, it is possible to isolate the output values of the coarse calibration that should feed the next calibration phase (fine calibration; diffusion = 1, breed = 100, spread = 50, slope = 50, roads = 75). The sensitivity to local characteristics was greatly improved in the next two calibrations by narrowing the, scores and naturally, also as a result of the improvement in spatial resolution. From coarse to final calibration the spatial resolution is improved by two fold from coarse to fine, and by four fold from fine to final resolution.

Table 4
AMP — coarse calibration 86×140 run time: 06.09.2000:10:18–06.09.2000:13:22

Composite score	Compare r^2	Population[a] r^2	Edge r^2	Clusters	Mean cluster size r^2	Leesalee	Average slope r^2	pct Urban r^2	xmu r^2	ymu r^2	sdist r^2	lu Value	Diffusion coefficient	Breed coefficient	Spread coefficient	Slope resistance	Road gravity
0.41	*0.94*	*0.99*	*0.98*	*0.97*	*0.99*	*0.53*	0.99	0.99	0.90	0.96	0.98	1	*1*	**100**	**50**	**50**	**75**
0.39	0.89	0.99	1	0.91	0.95	0.53	0.99	0.99	0.99	0.99	0.98	1	**1**	**1**	**25**	**25**	**50**
0.39	0.93	0.99	0.97	0.94	0.98	0.53	0.99	0.99	0.95	0.94	0.98	1	**1**	**75**	**50**	**25**	**1**
0.39	0.98	0.99	0.96	0.95	0.99	0.51	0.93	0.99	0.98	0.94	0.97	1	**50**	**1**	**25**	**25**	**25**
0.39	0.96	0.99	0.99	0.95	0.98	0.53	0.99	0.99	0.87	0.96	0.98	1	**1**	**75**	**50**	**50**	**100**

[a] Population indicates no. of urban oixels.

Table 5
AMP — fine calibration 173×281 run time: 06.16.2000–06:18.2000:23:41

Composite score	Compare r^2	Population[a] r^2	Edge r^2	Clusters	Mean cluster size r^2	Leesalee	Average slope r^2	pct Urban r^2	xmu r^2	ymu r^2	sdist r^2	lu Value	Diffusion coefficient	Breed coefficient	Spread coefficient	Slope resistance	Road gravity
0.47	*0.99*	*0.99*	*0.99*	*0.95*	*0.99*	*0.57*	0.98	0.99	0.98	0.91	0.98	*1*	*40*	*1*	*35*	*40*	*25*
0.47	0.99	0.99	0.99	0.99	0.99	0.57	0.99	0.99	0.99	0.88	0.98	1	1	50	35	30	25
0.47	0.92	0.99	0.99	0.97	0.99	0.58	0.99	0.99	0.99	0.91	0.98	1	1	75	45	45	25
0.47	0.99	0.99	0.99	0.95	0.99	0.56	0.98	0.99	0.96	0.95	0.98	1	30	100	30	45	25
0.46	0.99	0.99	1	0.96	0.99	0.56	0.99	0.99	0.97	0.90	0.98	1	20	25	35	50	25

[a] Population indicates no. of urban oixels.

Table 6
AMP — final calibration 347×563 run time: 06.16.2000:17:02–06.22.2000:05:22

Composite score	Compare r^2	Population[a] r^2	Edge r^2	Clusters	Mean cluster size r^2	Leesalee	Average slope r^2	pct Urban r^2	xmu r^2	ymu r^2	sdist r^2	lu Value	Diffusion coefficient	Breed coefficient	Spread coefficient	Slope resistance	Road gravity
0.48	0.97	0.99	0.98	0.99	0.97	0.58	1	0.99	0.98	0.92	0.98	1	20	20	40	45	20
0.47	0.97	0.99	0.98	0.99	0.97	0.58	0.99	0.99	0.99	0.82	0.98	1	1	40	40	35	20
0.47	0.97	0.99	0.98	0.98	0.96	0.58	0.99	0.99	0.98	0.93	0.98	1	1	20	40	40	20
0.47	0.97	0.99	0.98	0.98	0.96	0.58	1	0.99	0.98	0.93	0.98	1	1	1	40	40	30
0.47	0.98	0.99	0.97	0.99	0.97	0.57	0.99	0.99	0.97	0.93	0.98	1	20	40	35	30	25

[a] Population indicates no. of urban oixels.

In the case of the Porto Metropolitan Area the scores and coefficients resulting from each model run seem to present an adjustment to the local characteristics between the coarse–fine and then fine–final calibration. It seems that the model needs to adapt itself to a kind of chaotic system, tending to push the values further down than needed and then adjusting those values to the "real" upper value in the final calibration. The most extreme adjustment happens with the breed coefficient, the values pass from 100 to one, from coarse to fine calibration, and then the calibration makes an adjustment of the system, bringing the value to 20. Smaller adjustments to the high values of the fine calibration happen also in all the other composite scores (e.g. in the coarse–fine calibrations from values of spread of 50 to 35, and then from 35–40 from fine to final calibration).

The same question posed of the Lisbon Metropolitan Area can also be posed of the Porto Metropolitan Area. The resulting values from the model seem to reflect local characteristics, and therefore, validate the importance of the different calibration phases, even for the short historic evolution that characterizes this region. The proof seems to be the initial erratic behavior of the model trying to adjust to a chaotic system, with dispersed populations and activities, and where no integrated urban system in the region existed. Could the model's sensitivity to local condition be improved if spatial resolution was increased, or if more scores and coefficients were calculated, or if the model were run more times? With a cell size of 100×100 m it is hard to extract details from layers such as the slope. The fact that the Porto Metropolitan Area is a very small area mapped at a relatively coarse resolution makes it difficult to detail elements with a spatial resolution closer to Lisbon. Nevertheless, the model seems to reflect the same scattered character of populations and activities throughout the Metropolitan Area of Porto, which our analysis of history and landscape characteristics seems to present.

8. Self-Modification Rules

Finally, regarding the boom and bust phases that the mechanism of self-modification rules allows, how were they included in the calibration results when simulating urbanization to the present, or predicting the future (prediction mode)? To answer this question we ran parameter averaging on the best results from the final calibration. The self-modification qualities of the model alter coefficient values during a run. The finishing values of all the coefficients (located in a file called param.log) were used to find the final best values that describe the boom and boost periods in the system. After this parameter run was completed, the param.log file from the finish year can be used as input for a utility included with the model that sorts and averages the output values. This utility averages the finishing coefficient values stored in the param.log file, and returns a set of five integers that represent the best coefficient values resulting from the entire process of calibration, reflecting both the growth rules, and the self modification rules.

The result of this sorting and averaging was reflected in a change to higher values in the final coefficients that control the model. The start values for Lisbon in the

final calibration phase of: 16, 57, 50, 25, 30, changed with the self-modification rules to values of: 19, 70, 62, 38, 43. In the case of the Porto Metropolitan Area to the final calibration phase start values of: 20, 20, 40, 45, 50, were refined throughout self-modification rules to values of: 25, 25, 51, 100, 75 in diffusion, spread, slope, and road gravity, respectively. It seems that the Lisbon Metropolitan Area is more susceptible to intense boom phases, seen in the high amplitude of the change in the Breed coefficient: from 57 to 70 after the self-modification rules. In the Porto Metropolitan Area, the change that immediately catches one's attention is the 100 value of slope_resistance after self-modification. The conclusion could be that urbanization grows all over in the Porto Metropolitan Area with exception of high slopes that seem to be the only constraint to urbanization. Careful attention should be paid when making this conclusion due to several reasons. First since the area of the Porto Metropolitan Area is substantially smaller than the Lisbon Metropolitan Area, urbanization spread over greater distance than in the Porto Metropolitan Area. Therefore, it may be better to increase the spatial resolution in the Porto Metropolitan Area, to increase substantially the sensitivity of the model to the local characteristics (e.g. increase slope variability would probably narrow down the slope scores).

9. Findings and discussion

Table 7 presents the selected calibration results for both metropolitan areas (the underlined values extracted from Tables 1–6). The two first lines give the composite scores one and two (all the scores multiplied together and a ratio comparison of model final urban areas to the actual urban area) the r^2 values are the regression scores for urbanization, urban edges and urban clusters. And the final lines correspond to the five factors that control the behavior of the system.

Table 7
Best overall calibrations by resolution (extracted from italic values in Tables 1–6)

	AML			AMP		
Score/resolution	784×836	392×4181	196×209	347×563	173×281	86×140
Composite score	0.15	0.19	0.23	0.48	0.47	0.41
Compare	0.90	0.88	0.97	0.97	0.99	0.94
r^2 Population[a]	0.91	0.91	0.92	0.99	0.99	0.99
Edges r^2	0.78	0.99	0.98	0.98	0.99	0.98
Cluster r^2	0.85	0.85	0.93	0.99	0.95	0.97
Leesalle	0.35	0.34	0.32	0.58	0.57	0.53
Diffusion	16	20	1	20	40	1
Breed	57	51	100	20	1	100
Spread	50	50	50	40	35	50
Slope	25	25	25	45	40	50
Roads	30	30	20	20	25	75

[a] Population indicates no. of urban oixels.

From the overall analysis of both results we conclude:

1. Model performance in both metropolitan areas was improved with increased spatial and parameter resolution. As we can see from initial values of 100 or one (in the case of diffusion) the five coefficients (diffusion, breed, spread, slope resistance, and road gravity) were narrowed down to more accurately reflect each metropolitan area. From an initial breed coefficient of 100 in the metropolitan area of Lisbon and Porto it was possible to narrow down to a breed coefficient of 57 in the case of Lisbon and a breed coefficient of 20 in the case of Porto.

2. A first improvement in model performance took place initially in the coarse calibration phase. Before coarse calibration, the maximum extreme values were given, from that maximum of 100, in all the coefficient values except diffusion that was given one (the objective was to see how much diffusion could increase). From that initial value, the resulting set of values output from coarse calibration were 1, 100, 50, 50, 75 in the case of the Porto Metropolitan Area, and 1, 100, 50, 25, 25 in the Lisbon Metropolitan Area. As already explained before, these values fed the next calibration phase (fine calibration).

3. The most substantial improvement in model performance was reached between the coarse and the fine calibration phases. For instance, during coarse calibration, and for both metropolitan areas, the maximum value of breed coefficients was 100. In the case of the Lisbon Metropolitan Area, that value was narrowed to 51, and in the Porto Metropolitan Area it assumed the opposite extreme value of one (reflecting the previously mentioned erratic behavior of the model trying to adjust itself to an ''unknown reality''). In the case of diffusion, because this is a coefficient that measures organic growth, we wanted to see how far it could increase, so we began assuming that it spread outward one cell per year in the coarse calibration in both metropolitan areas. In the Lisbon Metropolitan Area it was possible to see that calibration extended approximately 20 pixels of urban extent from the initial urban nucleus. In the Porto Metropolitan Area the model gave the result of 40 urban pixels of spread. Therefore, other self-adjustments had to be made in order to tune the values to the spatial characteristics of the Porto Metropolitan Area.

4. An adjustment of the values, less intense than in the previous calibration phases, happened between the fine and final calibration phases. Using the same examples, it was possible to see that from fine to final calibration a, slight adjustment was made to the values of the Lisbon Metropolitan Area (they passed from 51 to 57 in the case of breed, and 20 to 16 in the case of Diffusion). In the case of the Porto Metropolitan Area this adjustment was higher, the values of breed passed from one in fine calibration to 20 in final calibration, and from diffusion values of 40–20, respectively from final-to-fine calibration.

5. Initial values for the coefficients of diffusion, breed, spread, slope, and road gravity improved from coarse to fine and then to final calibration in both metropolitan areas. The intensity and values of this improvement varied with the local environmental and urban characteristics of both metropolitan areas. Consequently:

○ The Lisbon Metropolitan Area presented a more regular transition from coarse, fine and final calibration (Fig. 4); the values tend to adjust to local characteristics gradually.

○ The Porto Metropolitan Area, due to its landscape characteristics, shows a decrease of model performance after the coarse phase, with a later increase in model performance from coarse to fine calibration. During the second phase, from fine to final calibration the model needed to adjust itself to higher values in order to reflect the detailed nature of the diffuse urban settlements. In other words, the model became more sensitive to the actual pattern of urbanization only at the finest spatial scale and therefore near the very end of the calibration process.

Comparing the different scores of both models in detail, other differences between these metropolitan areas are evident. Comparison of the simulated urbanization against the urbanization of the control years reflected in the compare_score, shows that in both case studies the model accurately reflects through calibration the evolution of urbanization in both metropolitan areas (a score of 0.90 for Lisbon and 0.97 for Porto). Through calibration, it was not only possible to simulate accurately the evolution of both metropolitan areas, it also allows us to interpret the different character of the urban evolution in each case, as seen in the leesallee score. This score measures the degree of shape match between the modeled growth and the known urban extent for the control years, if the model grows in different ways or with different intensities and directions this index will reflect that. The shape index presented a value of 0.35 for the Lisbon Metropolitan Area in the final calibration, against a value of 0.58 in the Porto Metropolitan Area. Knowing that it is very hard to obtain high values of shape match in this index (Clarke & Gaydos, 1998, p. 708) a value of 0.35 is very good for the Lisbon Metropolitan Area. In contrast, the very
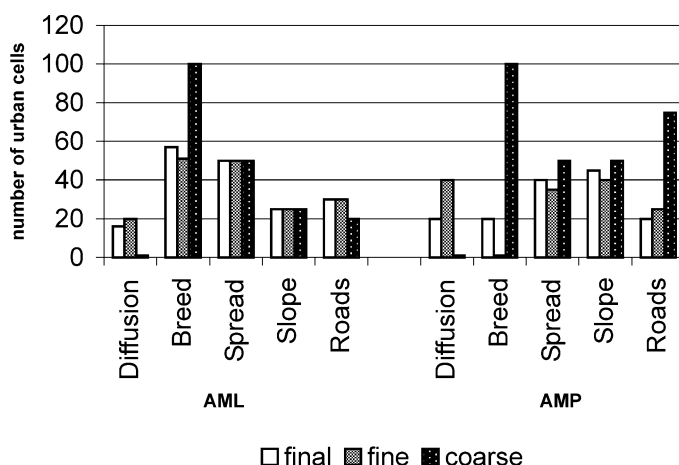

Fig. 4. The behavior of each Metropolitan Area to the different coefficients (represented in bold at Tables 1–6, and described in detail in the Appendix).

defined shape of road influenced urbanization in Lisbon that makes it hard for the model to fit the actual shape exactly. Porto also has scattered urbanization throughout its area, making it harder to define many particular shapes or forms at this scale except by scattering pixels of urbanization all over. In such a case, a high shape value could only be achieved through a highly unlikely exact match.

The same can be stated when comparing the five coefficients that control the system and that the user passes on to each new calibration phase (diffusion_coefficient, breed_coefficient, spread_coefficient, slope_resistance, and road_gravity). Variation in these coefficients seems to reflect the experience we have from these case studies, and also the human and environmental history of the cities. Porto presents a higher value of diffusion compared with Lisbon; because Porto has more scattered urbanization. It is also understandable why Lisbon presents a much higher breed value compared with Porto, because the amount of vacant land suitable for development is more abundant in Lisbon than in Porto. This observation is reinforced when looking at the slope and road values. Lisbon has fewer constraints to urbanization due to slope and has as a result high values of road influence. The slope factor allows us to predict that the south margin of the Tagus River will suffer intense urban pressures because of flatter land, and because of a transportation infrastructure that is recently built with a high capacity to spread urbanization. This is another reason why the spread coefficient is higher in Lisbon. In contrast, Porto presents much higher slope values and a transportation network that is still restructuring itself, and therefore, has less impact on the urban growth, compared with the capital of the country.

It is also important to report that the self-modification rules were internalized very well by the model and played a crucial role in capturing the character of both metropolitan areas. It is known that, historically, population tended to grow more constantly in Porto. Lisbon, by contrast tended to have periods of *boost*, followed by periods of less intense growth. This fact certainty influenced the Lisbon Metropolitan Area breed score. New nuclei were formed during these intense periods of migration of population, investments in new highways, and development of new urban areas. Porto retains an older structure, with a more stable population, growing constantly, and so giving higher values of diffusion.

A final question could be posed: why did the overall behavior of the scores present a final better fit for Porto than for Lisbon, a composite score of 0.15 in the case of Lisbon, and a composite score of 0.48 in the case of Porto? The first conclusion would be that the model performed better for Porto than Lisbon. But, the question should be: by increasing the spatial resolution of the data in the case of Porto, could it be easier to capture detail and therefore better narrow down the values to the local characteristics? If so, it would be harder to exactly simulate the patterns and processes, and consequently it would be harder to reach the optimum correlation and model performance. This seems important in the discussion of spatial resolution and sufficiency of local conditions. Finally, could we improve detail and refine even more sensitivity to the local conditions, and therefore narrow down, for instance, the high value of slope_resistance in the case of the Porto Metropolitan Area? Questions such as this one seem to be very hard to answer, but more studies in this

metropolitan areas (and other areas) using different scales, more variables, and more model runs can clarify this discussion.

10. Conclusions

The most important finding from our calibration experiments is the fact that detailed and exhaustive calibration improves the performance of the SLEUTH model in a significant way. The most interesting finding is the observation of how these two different urban settings constrained the evolution of the three calibration phases in order to adjust the model more closely to the reality of each area.

Looking at the results (Fig. 4) one might deduce that in the Lisbon Metropolitan Area, where growth is concentrated along main axes and radials, the calibration of the model was facilitated, reaching the best values sooner. However, the more rapid closure on results also reflects an urban reality that easily corresponds both to the history of human settlement and to the roots of the computational models of urbanization and land use change that have been applied (Oppenheim, 1980; Wegener, 1998). On the other hand, accurately modeling the Porto Metropolitan Area's diffusive growth well gives extra strength to the model's own ability to automatically calibrate itself.

Since the model is a cellular automaton, each pixel in space assimilates past evolution, but reacts independently to allow the model to adjust to a pattern of growth that depends more on local characteristics than on regional models and laws. This sense of individuality present in each cell seems more suited to market dynamics, and consequently, to the genesis of modern urban settlements. An independent individual basis for modeling substantiates the fact that from the final calibration a set of numerical values are estimated for each metropolitan area (through averaging). These numbers can be used to predict future growth in the SLEUTH model prediction mode. However, they also both reflect the adaptation of the CA to the urban environment in the model, and allow comparative analysis of different cities using the same model (Clarke & Gaydos, 1998). Thus, cities may show a higher degree of influence of infill from a relatively modest number of existing centers (as in Porto) or stronger impact of transportation on growth (Lisbon). Throughout calibration these different characteristics can be captured in the set of final coefficients that best describe the specific system/reality under study at the same time, and so can predict future developments. For Lisbon, the calibration yielded a set of starting parameter values in 1975 of: diffusion = 19, breed = 70, spread = 62, slope = 38, roads = 43. For Porto, the equivalent values were: diffusion = 25, breed = 25, spread = 51, slope = 100, roads = 75.

11. Recommendations for future research

We present the results of an exhaustive and rigorous calibration of the SLEUTH model to data from two Portuguese metropolitan areas. During the calibration

process, several impediments to CA modeling were detected and, as a result of the experience, some recommendations for future research and improvements can be made.

First, data quality is one of the most important elements for a successful model calibration. This was observed in the slope layer and the 2000 urban extent layers for Porto, which posed a problem during the calibration process. The need to improve these two data layers in order to improve the calibration and allow a successful run of the model in prediction mode was revealed only by carefully following a data pre-testing procedure as described in the model documentation.

Second, we seek to assess to what extent improving the spatial resolution of the Porto Metropolitan Area could narrow down the scores and make the model more sensitive to the local conditions. Naturally, improved resolution could pose problems if a direct comparison was to be made between the Porto and Lisbon Metropolitan Areas. Another solution could be, to run more Monte Carlo iterations, and try to see if in that case more particularities of the landscape could be seen without having to change spatial resolution. For instance, would a 1000 Monte Carlo iterations improve the model sensitivity? The third question is related to the sequential multistage optimization by extensive automated exploration of the parameter space. This step-by-step action is very important in adapting the model to local conditions. The question could be: what is the best value resulting from each calibration if other procedures were applied instead of the averaging of best parameter values; or if other input layers were added, or if different scores were calculated? These questions could be tested in further studies in order to better understand the model behavior and performance, and to reinforce that interpretation of the output values of the model should rely on a solid basis of experience.

Fourth, remotely sensed images were one of the most important data sources to extract urban land use. Accurate extraction of urban features is hard, even more so when trying to apply the same methodologies to different areas and at different dates. Bahr (1999); Canters, Erens, and Veroustraete (1999), and Cihlar (2000), Morain and Baros (1996) discuss in more detail some of the current methods in remote sensing suitable for urban analysis.

Finally, the computation time needed in each of the phases of calibration is significant. High performance computing and parallel processing techniques offer real promise here and the advantage of using these techniques have been examined (Mineter & Dowers, 1999; Niccanna & Bean, 1997; Openshaw & Openshaw, 1999). Version 3 of the SLEUTH model, now in beta release, will allow the model to be run on parallel processor machines. Finally, urban modeling with CA is ongoing research. Forecasting (using prediction mode) presents another challenge, by allowing us to simulate how the two cities will evolve, what will be the possible shapes, sizes, and problems of the future cities that will form gigalopolis.

In summary, we assembled data for two metropolitan areas of Portugal, and applied the SLEUTH model. While modeling involved many individual steps and there are many pitfalls for the modeler, overall, the SLEUTH model was relatively simple to use, requiring only large amounts of computer time once data were assembled. We conclude that the basic CA model is highly versatile, and does indeed

apply equally as well to European cities as to the North American cities for which it was designed, representing in detail local characteristics of each metropolitan area. Without rigorous calibration, this suitability of the model to local characteristics would be compromised. Individual-based complex systems modeling with automated adaptive calibration may indeed offer a first vision of a single, universal model of urban growth with important planning applications.

Acknowledgements

Appendix

Scores and coefficients defined in the Tables 1–6

Scores
   For all scores: 1 = exact match of modeled to control data.

   Composite score: all other scores multiplied together.
   Compare: comparison of modeled final population[1] to real data final population[1].
   r^2 Population[2]: least squares regression score for modeled urbanization compared with actual urbanization for the control years.
   Edge_r^2: least squares regression score for modeled urban edge count compared with actual urban edge count for the control years.
   r^2 Clusters: least squares regression score for modeled urban clustering compared with known urban clustering for the control years.
   Mean_cluster_size_r^2: least squares regression score for modeled average urban cluster size compared with known mean urban cluster size for the control years.
   Leesalee: a shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years.

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[1] Units measure in numbers of urban pixels.
[2] Population indicates No. of urban pixels.

Average_slope_r^2: least squares regression of average slope for modeled urbanized cells compared with average slope of known urban cells for the control years.

pct_Urban_r^2: least squares regression of percent of available pixels urbanized compared with the urbanized pixels for the control years.

xmu_r^2: (center of gravity [x]) least squares regression of average x_values for modeled urbanized cells compared with average x_values of known urban cells for the control years.

ymu_r^2: (center of gravity [y]) least squares regression of average y_values for modeled urbanized cells compared with average y_values of known urban cells for the control years.

sdist_r^2: standard deviation averaged over (XY).

lu_Value: a proportion of goodness of fit across landuse classes.

Coefficients

Diffusion_coefficient[1]: determines the overhaul dispersiveness of growth, for both single grid cells and of the movement of new settlements outward through the road systems.

Breed_coefficient[1]: determines how likely a newly generated detached settlement is to begin its own growth cycle.

Spread_coefficient[1]: controls the amount of outward ''organic'' expansion.

Slope_resistance[1] >: influences the likelihood of settlement extending up steeper slopes.

Road_gravity[1]: encourages new settlements to develop near or along the transportation network.

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