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A Decade of Cellular Urban Modeling with SLEUTH: Unresolved Issues and Problems

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Abstract

SLEUTH is a mature cellular automaton urban model, now applied to over 100 different cities and regions. In this paper, the model's context and history is introduced, the applications reviewed and some model improvements and sensitivity tests summarized. A section discusses how the model works and then the model's limitations and assumptions are critically examined with the intent of revealing where further work could inform and improve SLEUTH and other urban models. A final example of a validation of a 1996 application is given. A conclusion urges future researchers to build upon lessons learned in the model's refinement and testing.

Introduction

SLEUTH is a model for the computational simulation of urban growth and the land use changes that are caused by urbanization. The model uses the cellular automaton (CA) approach, a direct result of prior work on modeling the spread and behavior of wildfire (Clarke et al. 1993; Clarke et al., 1995). The model grew from discussions on land use change with USGS Geographer Len Gaydos at the NASA Ames research center in 1991, and the development of the first operational version of SLEUTH (then called the Urban Growth Model) was a component of the Urban Dynamics research program at USGS (Kirtland et al. 1994). Further USGS support allowed the extension of the model to simulate land use change in addition to urbanization (Clarke 1997). The reformulated model was released on the World-wide Web under project Gigalopolis (Clarke et al. 1997), first at New York's Hunter College and then at the University of California, Santa Barbara. After 1996, the project web site was extended to include documentation and a discussion forum, and the model was extended to version 2, with dynamic memory allocation. With further funding from USGS and the EPA, the team rewrote the model code and included calls to the Message Passing Interface, making SLEUTH suitable for EPA's Cray supercomputers. Key programming work was by Tommy Cathey and Mark Feller, resulting in the release of version 3 of the computer code (Clarke et al., 2007), nominally still a beta release since maintenance is only occasional. With federal support, the model has been open source since its outset, and a complete set of source code and test data can be downloaded from the website. Recent notable contributions have allowed the model to run under Linux and cygwin, a Windows-based UNIX emulator.

The initial application of SLEUTH was to the San Francisco Bay area (Clarke and Gaydos, 1998), and the animations created by the model had some immediate public acceptance. The San Francisco application completed the simulations for a broad area from San Jose to Sacramento in 1996, but at a coarse resolution of 600 meters and with urban extent data up to 1990. Later work in Washington, D.C. and Maryland repeated this experience. SLEUTH is calibrated with historical data, and while the incompatibility of paper maps and remotely sensed imagery was a challenge, eventually many and varied sources were employed, including historical road maps (for highways) and the CORONA declassified spy satellite imagery. The USGS still uses SLEUTH in its Urban Dynamics program, and has experience in modeling at least 8 urban regions with the model.

Release of the code and documentation to the World Wide Web was key to the model's success. Through the web site a UCSB discussion forum open to all users (at http://bbs.geog.ucsb.edu) was created and remains active, since then supplemented by another public forum (sleuth-users@yahoogroups.com). SLEUTH has been included in two major inventories of land use change models (Agarwal et al. 2002; Gaunt and Jackson 2003), comparing and classifying the model and its functionality. At last count, the number of applications of the model to cities and regions was over one hundred. By any measure, this makes SLEUTH a highly successful urban and land use change model.

Nevertheless, in spite of extensive attention to the model's calibration process and exhaustive sensitivity testing, there has been as yet no assessment of the unsolved issues and problems that have arisen in the many applications and computational experiments. In this paper, the model will be examined from first principles as regards its unexplored assumptions and inherent limitations. This is followed by a practical examination of application and calibration problems, and of the inherent assumptions that constrain the models forecasts. As with all models, SLEUTH makes the world abstract and urban behavior is simplified. Better understanding of these inherent limitations of models in general, and SLEUTH in particular, can enhance the use and application of this and many other models of land use change. Lastly, the 1996 San Francisco application was recovered, and the forecast to 2007 compared with actual urban extents using the GoogleEarth viewer, with the intent of conducting a forensic examination of a past forecast as a way of evaluating SLEUTH.

How Sleuth Works

A cellular automaton (CA) is a theoretical framework that permits computational experiments in spatial arrangements over time. Components of a CA model are: (1) a reference set of cells, usually a raster grid of pixels covering an urban area; (2) a set of states associated with the cells, which can be in the set {urban, not urban} or more detailed land uses such as {urban, forest, agricultural, wildland, wetlands, water}, and such that all cells have a state at any given time; (3) a set of rules that govern state changes over time; (4) an update mechanism, in which rules are applied to the state at one time period to yield the states of the same cells in the next time period; and (5) a initial condition of the framework. In SLEUTH, a gridded raster of the study area is digitized or created from imagery, and the framework has a given and fixed spatial resolution or ground size of the cells, and also a fixed spatial extent, usually a bounding rectangle for the study area. Successive application of the rules to the states yields states beyond the initial conditions, and one rule application with syncronous update of all cells is considered a “year” in time.

SLEUTH’s rules are fixed, but vary from complete to zero influence at each time step based on behavioral parameters. Five parameters control SLEUTH’s behavior entirely, each with a possible integer value between 0 and 100. It is assumed that one set of five parameters is the best set to mimic the behavior of an actual urban growth sequence. To select the best parameter set, model sequences are empirically compared against a series of control dates, that is images for the urban or land use sequence as it actually occurred. So, for example, a CA may have initial conditions reflecting actual land uses in 1950, with a modeling goal of forecasting the urban pattern on 2050. However, the performance of a parameter set creating feasible system behavior may be controlled by having actual data on urban areas for 1965, 1980, 1990 and 2006. A discussion of the uncertainty that this “hindcasting” method introduces is included in Goldstein et al. (2004). Successive search using brute force methods (Silva and Clarke, 2002) or genetic algorithms (Goldstein, 2005) then reveals the “best” parameter set, and these values are used to run the model with the present day as the starting data set, any desired distance into the future.

The five parameters are obviously critical to SLEUTH’s application. The calibration process is automated, so SLEUTH “learns” the best set for any given application from the data. The parameters were chosen after extensive testing by trial and error. They include parameters that control the random likelihood of any pixel turning urban (dispersion), the likelihood of cells starting their own independent growth trajectory (breed), the regular outward expansion of existing urban areas and infill (spread), the degree of resistance of urbanization to growing up steep slopes (slope) and the attraction of new development toward roads (road gravity). Furthermore, these parameters are interrelated. So, for example, when development is attracted to a road by the road gravity factor, it can relocate via a random walk along the road network a distance in proportion to the dispersion factor. Lastly, the system as a whole allows self-modification. That is, as the entire system grows faster or slower, control parameter values are changed as a consequence. The net effect is to amplify rapid growth and retard stagnation, in what are termed “boom” and “bust” stages.

Calibration of SLEUTH begins by first creating historical data for the hind-casting. Data sets should be carefully registered with each other, and should include raster maps for topographic slope, land use, excluded areas, urban extent, transportation and hill-shading for the visualizations. Two land use layers are used, so that transition probabilities can be computed from the change matrix. Any set of land use or cover classes is suitable, but only one urban class is permitted. Exclusions include a layer with non-developable land (e.g. lakes and parks), and can include probabilities for other land, perhaps based on land value or zoning. Urban extent is a binary map showing urban and non-urban, and at least four are necessary for calibration. The transportation layer is normally roads, and multi-level systems (e.g. interstate, state road, local road and unsurfaced road) are supported. The user then decides how the five parameters are to be explored. One “run” is a single set of five parameters from the earliest or start date, to the latest (present) date. The code matches model behavior with the actual data when it reaches the data years, and computes a total of 13 measures of the goodness of fit between a model run and reality. A composite of these measures, averaged over several Monte Carlo iterations, then “scores” the parameter set. Three phases are used in calibration, with user choices between them. At first, large increments of the parameters are used to cover the whole space. When the outcomes are scored and ranked, the highest scoring parameter sets are used to “bracket” the next round of values, and smaller increments used. Again, runs are scored and ranked, and a last round with unit increments is used to select the “best” parameter set. This set is then used to start the model, and the finishing parameter set saved to start a forecast run into the future. Explanations for the procedure to follow are included in the documentation, and have been improved upon in the reported literature.

The Land Use change component of SLEUTH, called the Delatron model, is a second CA that operates in change space. Two land use layers are differenced, to yield a matrix of change probabilities that are first normalized to a one year time step. Land use change is controlled by the amount of urban growth in the UGM at each year, and pixels selected for change based on random, on topographic slope, on feasible class transitions, and on the prior changes reflected in the deltatron space. Changes are spread to simulate expansion, and after a short cycle, deltatrons are killed off so that subsequent change can take place at the same location (Candau et al., 2000).

Sleuth Applications

SLEUTH's applications were evaluated by contacting all discussion forum users and by conducting a literature search, which identified 32 major studies with published results (Clarke et al., 2007). The result was an addition to the web site of an inventory of applications, and for about 20 of them, results of the city calibrations and data. Many more applications have been conducted since, including most recently for multiple California counties (Tietz et al., 2005; Onsted, 2007), Honolulu, Hawaii (James, 2004), Gdansk, Poland (Rozwasowski, 2006), Chiang Mai, Thailand and Taipei, Taiwan (Sangawongse et al., 2005), Tijuana, Mexico (Le Page, 2000), Alexandria, Egypt (Azaz, 2004), Yaounde, Cameroon (Sietchiping, 2004) and Sydney, Australia (Liu and Phinn, 2004).

The first application of SLEUTH's precursor, the Urban Growth Model (UGM) was to the San Francisco Bay area at a coarse resolution of 600m Clarke et al. (1997). The urban extent was digitized from maps and remotely sensed images from 1850 to 1990. Linked with transportation and topographic data, forecasts and animations of the spatial growth patterns were created, statistics describing the spatial growth were calculated, and UGM was used to predict future urbanization to the year 2100. The 1997 paper provided the details of the mechanics of the UGM, describing the necessary data layers, the five coefficients, and the four types of urban growth behavior, and self-modification. A second application to Washington-Baltimore, and a comparison of the two applications followed (Clarke and Gaydos, 1998). This paper examined the role that geographic information systems played in modeling, and advocated using GIS to loosely-couple models and their results together using systems of models.

The first applications of the UGM focused solely on the modeling of urban growth, but there was a need to include other landscape changes in the model. In spite of the advocacy for loose coupling, the solution was a code-level tight coupling of a second CA to simulate land use change. The Deltatron model (Candau and Clarke, 2000) was first used for modeling land use change in the EPA's Mid-Atlantic Integrated Assessment region. In modeling the eight state region, land use data were classified using the Anderson Level I categories for 1975 and 1992. This produced a map of predicted land use in the year 2050, and introduced the land use uncertainty map, which SLEUTH calculates and plots.

The principal drawback of using SLEUTH is its time consuming calibration process. Though discussed in Clarke et al. (1997) and in Clarke and Gaydos (1998), the definitive description is that documenting the application of the model to Lisbon and Porto, Portugal (Silva and Clarke, 2002). This paper presents four key findings: that SLEUTH is applicable to both North American and European cities; that increasing the spatial resolution and detail of the input datasets makes the model more sensitive to local conditions; that using a multistage calibration method can better refine the model parameters to find those that best replicate the historical growth patterns of an urban system; and that the model parameters can be compared across different systems. Following on from the last finding, Silva (2004) developed the concept of urban DNA, further explored in a theoretical context (Silva and Clarke, 2005; Gazulis and Clarke, 2006). Further large scale applications of SLEUTH added knowledge of how best to work with the calibration process to yield the best forecasts (Jantz et al. 2003; Yang and Lo 2003; Dietzel and Clarke 2004a).

Some applications have involved the coupling of SLEUTH outputs with social modeling efforts, while others have linked with physical models. Claggett et al. (2004) coupled SLEUTH with the Western Futures Model (Theobald 2001), demonstrating the ability of the SLEUTH to categorize the growth into different classes of ‘development pressure’ based on forecasts of population growth. Leão et al. (2001; 2004), coupled SLEUTH outputs into a multi-criteria evaluation of landfill suitability (Siddiqui et al. 1996) to determine where around Porto Alegre City (Brazil) land was unlikely to be urbanized, and so was suitable for landfills. Arthur (2001) coupled SLEUTH to an urban runoff model in Chester County, Pennsylvania. Syphard et al. (2007) examined the consequences of urban development on wildfire regime and vegetation succession in Southern California’s Santa Monica Mountains, and coupled the LANDIS land use model to SLEUTH, testing the coupling strategy. Cogan et al. (2001) compared using SLEUTH and the California Urban Futures model (Landis, 1994) to assess stresses on biodiversity. Solecki and Oliveri (2004) used SLEUTH in simulating climate change scenarios in New York.

Through the “Urban Change Integrated Modeling Environment” project, the value of using scenarios as a presentation of SLEUTH results became evident. SLEUTH’s application to Santa Barbara reported by Herold et al. (2002) was part of a study that sought to increase local residents’ awareness of smart growth principles through modeling. Both SLEUTH and SCOPE were used to create a set of scenarios that could be used to experiment with alternative futures. SCOPE is a systems dynamics model in the Forrester tradition, coded in the STELLA modeling language and including various social, economic, and demographic variables (Onsted 2002). SLEUTH allows policy and plans to be incorporated through new transportation layers, and through variations in the excluded layer. Choosing scenarios and using models, including SLEUTH, led to work on the nature of scenario planning (Xiang and Clarke, 2003) and on simplicity in modeling (Clarke, 2005). An aspect in the modeling for scenarios that was addressed was that of visualization, important because of the long series of public meetings that were part of the Regional Impacts of Growth Study (RIGS) by the Santa Barbara Economic Community Project (Figures 1 and 2). Two important visuals were perspective views in which satellite views were simulated by repeating an urban “pattern” across areas forecast to be urbanized under the scenarios (Figures 3 and 4), and items called “Postcards from the Future”, vehicles to encourage thinking about the future scenarios and their implications (Figure 5). More recently, the link between parameters, model behavior, and scenario generation has been the subject of further investigation (Dietzel et al., 2005). Onsted (2007) has conducted extensive amounts of SLEUTH modeling for California counties, using information at the parcel level about land conservation status to prove that a carefully constructed exclusion layer can vastly improve forecasts.

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Acevedo and Masuoka (1997) presented the general methodologies used to create 2-D and 3-D animations of the Baltimore-Washington DC region by using SLEUTH to create video frames for animations. Candau (2000) explored ways of visualizing the spatial uncertainty of urban growth in a simulated landscape. Aerts et al. (2003) continued this idea by experimenting with human test subjects about their understanding of the uncertainty in urban growth forecasts for a section of Santa Barbara using different display methods.

SLEUTH has been used as a tool in theoretical investigations of urban processes. Bierwagen's (2003) dissertation focused on simulating generic urban forms and their connectedness in the landscape to asses the viability of different urban growth forms on butterfly habitat. Goldstein et al. (2004) compared using SLEUTH for the "backcasting" of urban extent with spatiotemporal interpolation. To explore urban development, SLEUTH has been used to trace urban form using landscape metrics (Herold et al. 2003), in new descriptions of urban evolution (Dietzel et al., 2005a; 2005b) and by Goldstein et al. (2000), where historical urban-wildfire conflicts were investigated. Judging by contacts through the discussion forum, SLEUTH applications continue, with many results appearing in dissertations, theses and in gray literature such as planning reports.

Unsolved Issues and Problems

Over time, the literature on SLEUTH has examined and conducted sensitivity tests for a large number of the SLEUTH assumptions and control parameters. For example, temporal sensitivity was examined by Candau (2002), land use class aggregation by Dietzel and Clarke (2004), and the Monte Carlo stochastic sensitivity by Goldstein et al. (2005).

An unexamined element of the work to date is the distinction between variables and constants in the model. While the five variable parameters that are maximized through the calibration process control SLEUTH's growth and change behavior, another ten constants were arrived at through experiments and other means. First of these is the number of Monte Carlo iterations necessary for the calibration, a value initially believed to be best set high, put later shown to perform just as well set low, considerably improving model performance (Goldstein et al., 2005). This research showed that almost all variance captured and measured in Monte Carlo simulation is contained in the first few iterations, and that increasing the number of iterations quickly has diminishing returns in terms of model fit.

Secondly, the SLEUTH scenario file which initializes the model requires the user to submit a random number seed code. The random number generator used is ran1 (Press et al., 1996). There is a surprising lack of attention in spatial modeling to the idiosyncrasies of pseudo-random number generators (Van Niel and Laffan, 2003). Use of this algorithm and independent specification of the seed allow a high degree of certainty in both the lack of repetitive cycling in the random numbers, and the ability to replicate sequences across computational platforms.

A third constant is a set of assumptions in the land use change model about deltatron aging. A deltatron is the means by which land use persistence or “memory” is simulated. The aging process is on CAs that exist only in change space, and the persistence is both of type (i.e. which land use transition changed to which) and time, since changes are spatially autocorrelated in time and space. How long deltatrons survive before being “killed off” by the aging process was coded by trial and error. Further research could determine the actual amount of persistence by measurement, or could allow calibration of this parameter for a given landscape.

A fourth assumed constant relates to how the transportation network impacts growth. The fourth behavior type simulated is “road gravity”, in which new growth is attracted to and allowed to travel along the road network. In an effort to remove scale sensitivity from the model, a constant was established which is used to adjust the current road gravity value (0-100) to the size of the image in use. The constant is computed as the starting road gravity value as a proportion of the maximum (100), times the average of the map width and height divided by 8. This value is also a maximum search radius for a road when new growth takes place. Again, this value was chosen to best suit the model, and is not well tested across applications. A best value could be found through calibration, or by analysis of developing transportation networks. It would be of interest to determine is the value changes over time, over space, or with transportation technology.

The slope sensitivity has a significant impact on SLEUTH growth simulations, and involves three constants. The slope coefficient is used to calculate slope weights by first calculating an exponent. This exponent is then used in a look-up table to find an actual slope resistance factor as a function from zero to the constant “critical slope”. Above the critical slope value, which is left for the user to decide upon locally (often in the range of 20-30 percent slope), growth is excluded. At slopes below the value, the slope factor creates different shape functions based on the form in figure 6.

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At a slope coefficient of 50, there is a linear relation between topographic slope and urbanization probability, i.e. the value used in the random number calls. Below 50, flatter slopes are favored, while above 50, mid-range slopes are more favored. The calibration process determines which pattern best fits the actual slopes for an application, but the shape of the curve itself, and the complete exclusion above the critical slope are assumptions. While actual cities are usually on flatter slopes, and the cost of building and risk increase with slope, the exact form of the relation could be empirically tested.

Furthermore, there is clearly a scale effect with slope. Slope computed from 1m resolution cells is very different from that at 1km. Computing slope from the digital elevation model directly also gives different results than averaging slope over cell areas.

The remaining four constants all determine how the model implements self-modification. Self-modification is macro-scale behavior. At each time step, the model tabulates aggregate system behavior by monitoring the overall rate of growth of the urban system. Two rates (critical high and critical low) form upper and lower bounds on behavior. Above critical high, during periods of rapid growth, several of the control parameters are multiplied by a factor greater than one (“boom”). Correspondingly, during periods of decline, control parameters are multiplied by a value less than one (“bust”). The result of this feedback is acceleration of rapid growth and damping of decline. Self-modification was implemented to duplicate the “lazy-S” shape of system growth over time. Many cities grow little for long periods, then have short bursts of very rapid growth followed by stability. Settings for these four constants were arrived at by examining growth rates of cities over time, but are otherwise the result of trial and error. Few researchers have changed their default values, although some have chosen to disable self-modification by using artificially high/low critical values. It is possible that the study of growth rates of cities will yield considerable insight into urban process and form, as is suggested by the theoretical modeling with SLEUTH (Gazulis and Clarke, 2006; Dietzel et al., 2005b).

Much work on SLEUTH has focused on improving the calibration process, and a recent publication (Dietzel and Clarke, 2007) to a great extent “solves” the problems and provides an optimal metric. This value was arrived at by conducting an exhaustive calibration, then using data reduction methods (Self-Organizing Maps) to regionalize the multidimensional behavior space. Curiously, the research also showed that SLEUTH can suffer from overfit. The most powerful model of the future state of a system is simply the current state, and so the calibration can lead to a solution which simulates least or no change, a trivial outcome when growth is prevented by low values of the behavioral parameters. Conveniently, the phased exploration approach used in SLEUTH’s calibration avoids this pitfall. Nevertheless, the currently high level interest in sensitivity testing of SLEUTH’s outcomes is desirable, and will hopefully continue.

Early on in SLEUTH’s history, attention was paid to temporal sensitivity. Candau (2002) proved that SLEUTH gives superior results when used with short histories and shorter forecast horizons than longer. A long history produces a less convincing short term forecast than a short one. Other issues, such as the timing of a single time step, and the relation between time and study area size, and the sequence of implementation of the four behavior types, remain untested. Candau et al. (2000) also examined and detailed precisely the full set of inter-parameter interactions in SLEUTH. These were essentially fixed after version 1 of the model, yet were arrived at through software testing and visualization, not derived from theory. A complete derivation of the consequences for the assumed behavior interactions should be explored theoretically rather than empirically (Gazulis and Clarke, 2006).

Some issues related to data and data preparation remain to be explored. Goldstein et al. (2004) presented a theoretical model of uncertainty in data within SLEUTH. Just what role error in data preparation plays could be tested empirically, perhaps by using hypothetical data with controlled random perturbation. There is also scope for further testing the scalability of the model (Jantz and Goetz, 2005). An early goal for SLEUTH was modeling of the whole United States urban system, something still beyond the computational power available. But is this different from aggregating models regionally? Does an application to a state produce different results than aggregating results by county? Some work has looked at land use class aggregation effects, but much work remains to be done in this regard.

Any complex software system must deal with versioning. By the author's count, the model has been rewritten from first principles five times, and has been duplicable from first principles in different modeling environments. While the increments from version one to two, and two to three were tested for bitwise compatibility, and the results posted in the release, nevertheless there are improvements and changes over time. Given the great number of improvements in calibration, an application today has superior knowledge and should produce better results than one ten years ago. There have also been slightly different interpretations and uses of parts of the model. Nevertheless, the essential capture of a city's growth behavior in the five parameters does allow cross-city and even cross-time comparison. Little has been done yet to compare cities in different environments—US, Europe versus developing world—against each other with directly similar data. The same dates, scales, resolutions, land use schema, etc. could be used so that results can be definitively compared. Such work would allow a new scientific urban geography with fully replicable outcomes.

While SLEUTH has been applied many times and become intertwined with Planning Support Systems in the wider sense, an important purpose for modeling is to relate to policy and the decision-making process. The key issues influencing planning and local decision-making today relate to sustainability of communities, and to public participation. Central to the New Urbanism movement is the concept of density planning, trading development and redevelopment at the city core for more sprawl, encouraging transit-oriented neighborhoods accessible to public transportation nodes, and mixed-use zoning. SLEUTH is not really suited to these issues, although modifications or coupling with other models could make it more feasible. While an entropy measure for failed urbanization attempts has already been explored (Dietzel and Clarke, 2007), a means of counting repeated urbanization attempts at a single location could be devised and allowed to accumulate as increased density. Thus SLEUTH could, with only minor change, output a density layer with its forecasts. Similarly, if pixels were tracked for age, as deltatrons currently are, they could become available for redevelopment as the model iterates forward.

Lastly remains the issue of exactly how SLEUTH and its forecasts fit into the broader Planning Support Systems framework. While model results can be used effectively in scenario planning (Xiang and Clarke, 2003), and indeed SLEUTH has frequently been used for scenario generation, the degree of interactivity is limited by the time needed to run the model, although in one case, SLEUTH forecasts were run overnight during a two-day planning charrette (Silva 2006).

Conclusion

All models have lifetimes, defined by the period in which they provide abstractions of the known world that have value for planning or study. Urban modeling too, has had eras of models based on paradigms that have fallen into and out of favor. Cellular Automata models have been used extensively over the last decade, including SLEUTH. They have shown satisfactory performance, generated useful forecasts and integrated well with scenario-based planning. SLEUTH can be used to generate scenarios by one or more of five methods. First, known urban plans and patterns can be placed into the future and their consequences explored (Kramer, 1996). Secondly, the future transportation network can be modified, and the consequences determined. Thirdly, and most usually, different zoning or planning codes are turned into weighted exclusion layers, and their consequences tested. Fourthly, parameters can be deliberately adjusted, to change the impact of transportation into the future for example. This we have termed “genetic engineering” (Gazulis and Clarke, 2006; Silva and Clarke, 2005). Lastly, SLEUTH can be one component of a system of integrated models. The latter approach gets around the common criticism of SLEUTH that it does not include social or economic variables, and research has shown that coupled modeling is both effective and powerful.

SLEUTH has enjoyed a longer than typical lifetime as an urban model. With close to 100 applications over a decade, the ultimate validation test is becoming possible. At the 2000 GIS-EM4 conference, a workshop received a challenge for modelers to openly post and share common data for a test city, to model the city ten years hence, and to seal results for a decade to permit an eventual true test against reality. In this spirit, the 1996 UGM results for San Francisco were recovered from the author’s dusty collection of data CDs, and brought into the GoogleEarth viewer. The KML file that allows anyone to see the results can be downloaded at:
http://www.geog.ucsb.edu/~kclarke/GoogleEarth/GrowthSimulation.kml. This is the original UGM application at 600m resolution, with probability levels for urbanization assigned red at 90-100%, and progressively darker green down to 50%. While browsing the area shows many forecast errors, some related obviously to the coarseness of the slope values at 600m, nevertheless there are many partially correct and some perfect forecasts of urban development.

Little can be done to test the validity given these data, but in future work tests of the decade old forecasts against the same forecasts repeated with superior data and methods will be conducted, and real measures of SLEUTH’s accuracy as a forecasting tool reported. With attention to the limitations and assumptions of SLEUTH and the other CA models, hopefully a new generation of superior urban models can arise that gain from the cumulative experience with SLEUTH, and that model urbanization with completely accountable accuracy.

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Figure Captions

Figure 1. SLEUTH Forecast for Santa Barbara urbanization to 2050. Red is growth under assumption of enforced urban growth boundary. (Image by Martin Herold and Jeffrey Hemphill)

Figure 2: SLEUTH Forecast for Santa Barbara urbanization to 2050. Red is growth under assumption of removal of restrictions on growth. (Image by Martin Herold and Jeffrey Hemphill)

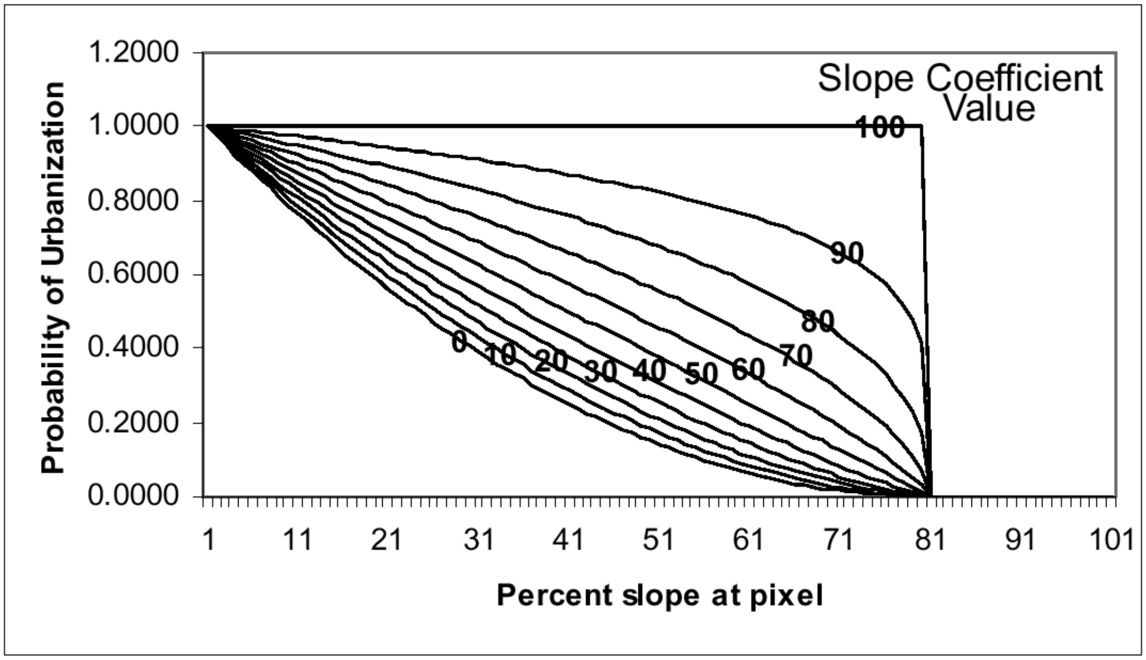
Figure 3: Visualization of Santa Barbara urban status in 1997. Higher resolution (SPOT satellite data) is urban land in 1997, lower resolution (Landsat 7) is non-urban. (Image by Martin Herold and Jeffrey Hemphill)

Figure 4: Equivalent of Figure 3, but as forecast for 2050 assuming scenario of no growth restrictions. Image texture over newly urbanized area is simulated to give impression of urban spread. (Image by Martin Herold and Jeffrey Hemphill)

Figure 5: Postcards from the Future. Visual stimulus concept used to encourage scenario-based thinking in various planning meetings. (Photos and graphics by Susanna Baumgart).

Figure 6. Slope factors in SLEUTH


Santa Barbara
Santa Barbara
Santa Barbara
Santa Barbara


Slope Coefficient Value
Probability of Urbanization
Percent slope at pixel
1.2000
1.0000
0.8000
0.6000
0.4000
0.2000
0.0000
1
11
21
31
41
51
61
71
81
91
101
100
90
80
70
60
50
40
30
20
10
0