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Research Article

Spatial Differences in Multi-Resolution Urban Automata Modeling

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Abstract
The last decade has seen a renaissance in spatial modeling. Increased computational power and the greater availability of spatial data have aided in the creation of new modeling techniques for studying and predicting the growth of cities and urban areas. Cellular automata is one modeling technique that has become widely used and cited in the literature; yet there are still some very basic questions that need to be answered with regards to the use of these models, specifically relating to the spatial resolution during calibration and how it can impact model forecasts. Using the SLEUTH urban growth model (Clarke et al. 1997), urban growth for San Joaquin County (CA) is projected using three different spatial grains, based on four calibration routines, and the spatial differences between the model outputs are examined. Model outputs show that calibration at finer scaled data results in different parameter sets, and forecasting of urban growth in areas that was not captured through the use of more coarse data.

1 Introduction

Despite past failures in urban modeling (Lee 1973, 1994), there has been a renaissance of spatial modeling in the last two decades due to increased computing power, improved availability of spatial data, and the need for innovative planning tools for decision support (Brail and Klosterman 2001, Geertman and Stillwell 2002). The power of these tools has become important for city planners, economists, ecologists and resource managers oriented towards sustainable development of regions (Clarke et al. 2002), and studies have attempted inventories and comparisons of these models (Wegener 1994, Klostermann 1999, Agarwal et al. 2000, US EPA 2000). Many of these models are new,

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or are extensions of those applied in previous urban growth studies (White and Engelen 1993, Clarke and Gaydos 1998). These models include the development of new computational methods, including micro-simulation, agent-based and cellular automata (CA), which show potential in representing and simulating the complexity of the dynamic processes involved in urban growth and land use change, and can provide an additional level of knowledge and understanding of spatial and temporal change. Furthermore, the models have been used to anticipate and forecast future changes or trends of development, to describe and assess impacts of future development, and to explore the potential impacts of different policies (Pettit et al. 2002, Verburg et al. 2002). Because many of these models are being used to provide information from which policy and management decisions are made, it is important that modelers have a clear understanding of how the spatial resolution at which that they are calibrating and modeling influences the forecasts their models produce.

The concept of spatial resolution and how changing it through aggregation affects data has been examined in the context of many ecological and physical models (Costanza and Maxwell 1994, Dungan et al. 2002). Generally speaking, when resolution changes, there is some expected statistical difference that occurs (Dungan et al. 2002). In the case of urban models, the effects of spatial resolution on model outputs may be overlooked or brushed aside due to two constraints that inhibit this type of modeling in general: (1) many times researchers struggle to get the necessary data to run the models, at any spatial resolution; and (2) as the spatial resolution of data gets finer, the computational time increases, sometimes in more of an exponential manner than a linear one. These two issues have prohibited urban modelers from sufficiently addressing the issue of resolution and how it relates to urban model output, but even more importantly, how calibration at different resolutions can impact model forecasting and final outputs.

Model calibration has become an increasingly important consideration in the development phase of modeling (Batty and Xie 1994, Landis and Zhang 1998), and has been addressed for some time (Batty 1977), yet there is still a need for development of stronger calibration techniques for cellular automata models (Torrens and O'Sullivan 2001). For any model, the parameter space is defined as the area or volume of parameters that is searched to find the parameter set. The parameter space is defined as an area or volume depending on the number of individual parameters. If there are only two parameters, then the parameter space is an area; any more than two then it is an *n*-dimensional volume. The parameter set is then the 'best-fit' set of parameters that describe the behavior of the system within the framework of the model. Yet the high flexibility in rule definition used in cellular automata modeling, and application of these rules to manipulate cell states in a gridded world, makes parameter estimation a difficult process (Wu 2002). In the case of CA models where the transition rules consist of heuristics for determining future state variables, they generally consist of several linked conditions for each land use, and these are complexly interrelated, so that calibrating a model may require the fitting of tens, if not hundreds of parameters (Straatman et al. 2004). The general difficulty in finding the 'golden set' of parameter values of cellular automata is due to the complexity of urban development (Batty et al. 1999). Failure to calibrate a model to the input data results in an application that is not robust or justifiable. While several efforts have focused on better calibration and definition of the parameters for CA models (Silva and Clarke 2002, Wu 2002, Straatman et al. 2004), none of them have focused on how calibration at different spatial resolutions changes the parameter set and the model outputs. A better understanding of how spatial resolution changes a model's parameter set, and hence its model outputs, is an important area of research, especially when many of these models are used in the decision making process.

The SLEUTH urban model is a cellular automaton model that has been widely applied (Esnard and Yang 2002, Yang and Lo 2003, Jantz et al. 2004) and has shown its robust capabilities for simulation and forecasting of landscape changes (Clarke et al. 1997, Clarke and Gaydos 1998). The model makes use of several different data layers for parameterisation, e.g. multi-temporal land use and urban extent data, transportation network routes and digital elevation model data. Application of the model necessitates a complex calibration process to train the model for the spatial and temporal urban growth (Silva and Clarke 2002). This paper documents work conducted on the calibration of SLEUTH using four different routines, from which the resulting parameter sets were used to forecast urban growth. The four calibration routines were the traditional multi-resolution method described in Silva and Clarke (2002), along with a quarter, half, and full resolution routine. The traditional method of sequentially using quarter, half, and then full resolution data in narrowing the parameter space was originally developed due to computational time required to run the model with large scale data sets, and is described later in more detail. Computational constraints required by the SLEUTH calibration process have now been lifted with the development of faster computers and the advent of cluster computing. The results from the model forecasts were then compared and statistically analyzed to determine if and what differences there are between different calibrations forecasts. This analysis is then used to provide some general considerations about the spatial resolution that modelers should think about when working with urban and land use models.

2 Methods

2.1 Modeling urban growth using SLEUTH

Modeling geographic systems using cellular automata models is a recent advance relative to the history of the geographic sciences (Silva and Clarke 2002). Tobler (1979) was the first to describe these models in geography, briefly describing five land use models that were based on an array of regular sized cells, where the land use at location i, j was dependent on the land use at other locations. Applying this method of modeling to urban systems for planning applications was recognized early (Couclelis 1985), and application of these models has proliferated in the last decade (Ward et al. 2000, Li and Yeh 2001, de Almeida et al. 2003), including the development of SLEUTH.

SLEUTH is a moniker for the input data required to use the model: Slope, Land Use, Exclusion, Urban, Transportation, and Hillshade. The slope layer helps to implement topographic constraints on the model, focusing growth on flatter, more suitable areas that are less costly to develop. Inclusion of land use in modeling with SLEUTH is optional; the model does not require land use data, but does have a separate model, termed the 'deltatron model,' to model land use change. Two layers of land use, with any number of classes, but the same classification are required if the modeling of land use is desired. Implementation of scenarios within the framework of this model is largely done through the manipulation of the exclusion layer. This layer allows the user to implement constraints on the model, prohibiting growth in some areas, providing resistances or attractions in others. The simulation of urban growth is the main focus of the model. Recognizing that urban growth is not a linear process, four input data layers of urban extent are required so that a more dynamic model of growth can be presented. If both urban growth and land use change are simulated, then it is necessary for the urban land use class in both of these data to be redundant of one another. The influence of transportation on urbanization is a well-known relationship, so a transportation layer is included in the model. Roads are classified into three classes based on their accessibility; so major interstates and highways would be one class, state routes and major arterial routes would be another, and local collector streets would be a third class. But the user has complete control over the classification of these routes. The final layer is a hillshade, or topographic relief layer. The only purpose of this layer is to add some positional reference to the output maps so that users have a geographic sense of where urbanization is forecast to take place. Upon assembly of these data, a user can calibrate, and then forecast urbanization and land use change.

Calibration of SLEUTH produces a set of five parameters (coefficients), which describe an individual growth characteristic and that when combined with other characteristics, can describe several different growth processes. For this model, the transition rules between time periods are uniform across space, and are applied in a nested set of loops. The outermost of the loops executes each growth period, while an inner loop executes growth rules for a single year. Transition rules and initial conditions of urban areas and land use at the start time are integral to the model because of how the calibration process adapts the model to the local environment. Clarke and Gaydos (1998) describe the initial condition set as the 'seed' layer, from which growth and change occur one cell at a time, each cell acting independently of the others, until patterns emerge during growth and the 'organism' learns more about its environment. The transition rules that are implemented involve taking a cell at random and investigating the spatial properties of that cell's neighborhood, and then urbanizing the cell, depending on probabilities influenced by other local characteristics (Clarke et al. 1997). Five coefficients (with values 0 to 100) control the behavior of the system, and are predetermined by the user at the onset of every model run (Clarke et al. 1997, Clarke and Gaydos 1998, Candau 2000). These parameters are:

1. *Diffusion* – Determines the overall dispersiveness of the outward distribution.
2. *Breed Coefficient* – The likelihood that a newly generated detached settlement will start on its own growth cycle.
3. *Spread Coefficient* – Controls how much contagion diffusion radiates from existing settlements.
4. *Slope Resistance Factor* – Influences the likelihood of development on steep slopes.
5. *Road Gravity Factor* – An attraction factor that draws new settlements towards and along roads.

These parameters drive the four transition rules that simulate spontaneous (of suitable slope and distance from existing centers), diffusive (new growth centers), organic (infill and edge growth), and road influenced (a function of road gravity and density) growth.

By running the model in calibration mode, a set of control parameters is refined in the sequential 'brute-force' calibration phases: coarse, fine and final calibrations (Silva and Clarke 2002), although other methods of calibration, including the use of genetic algorithms have been suggested and tested (Goldstein 2004). During the calibration, numerous parameter sets are tested for their ability to reproduce the historical growth patterns that take place between the input data years. The input data then serve as control points in evaluating the performance of each parameter set in recreating the historical urban growth trends through time. Typically the calibration of SLEUTH is a three-step process:

1. *Coarse*. Input data are resampled to one quarter of their initial resolution (100 m resolution data is resampled to 400 m) and the model attempts to simulate the historical growth patterns for a wide range of parameter values across the entire parameter space, using the first layer of input data as a seed-layer, and the remainder as control points. The ability of the parameter to recreate the time series of input data is evaluated using a variety of spatial metrics, but most commonly the Lee-Salle metric, although others have been used (Yang and Lo 2003, Jantz et al. 2004). This metric describes the degree of spatial matching between the simulated data and the input historical data. The results of the calibration are sorted based on their fit, and the parameter values are narrowed around the parameter set that produced the best fit between the historical and simulated data.
2. *Fine*. The input data are resampled to half of their original resolution (100 m resolution data is now resampled to 200 m). Using this half resolution data, the narrowed range of parameters from the previous step are used to simulate the historical growth patterns. Results of these simulations are evaluated using spatial metrics of fit, and the range of parameters is narrowed.
3. *Final*. The input data are used at their full resolution. The first year provides a seed for the set of parameters tested, which then simulate urban growth and then evaluate it compared to the actual control data. The set of parameters that best recreates the urban growth is then used in model forecasting.

One advantage of this method is that by beginning the calibration with data of a coarser resolution, the computational time is reduced from what it would be if calibration were done using the full resolution for each step. But it is unknown how varying the resolution during the calibration phases impacts the final parameter set. Additionally, it should be noted that the method does have the possibility of arriving at a local optimum of fit instead of a global optimum.

2.2 Input Data

Using San Joaquin County (CA) as a study area (Figure 1), input data for modeling urban growth using SLEUTH were compiled (Table 1). Data sources for historical urban extent are listed in Table 1. Urban extent data for San Joaquin County for the years 1940, 1954, and 1962 were digitized from historical USGS 1:250,000 maps and based on air photo interpretation and supplemental ground survey information. Data from 1974 and later were captured directly from space-based remotely sensed imagery. The urban extent data for 1974 and 1996 were based on LANDSAT MSS and LANDSAT TM mosaics compiled by the USGS Moffet Field, California office (http://ceres.ca.gov/calsip/cv/). Additional data for 1984, 1992, 1996, and 2000 were obtained from the California Farmland Mapping and Monitoring Program (CA-FMMP 2003) that utilized aerial photography as a base-mapping source (http://www.consrv.ca.gov/DLRP/fmmp/). The 1996 CA-FMMP data were merged with the 1996 USGS data to create a composite image of growth for that year. Urban extent through time was treated as a cumulative phenomenon so that each time period built on the previous one,

Table 1 Sources, description, and resolution of data used in SLEUTH modeling of San Joaquin County (CA). All data were resampled to 100 m resolution

Data Layer	Source	Description	Resolution
Slope	CASIL	Derived from 30 m DEM	30 m
Land Use	CA-DWR	Not used in this modeling	
Exclusion	CASIL	Vector coverage of Federal and State owned land	N/A
Urban Extent	USGS	Urban extent for 1940, 1954, 1962, 1974, 1996	100 m
	CA-FMMP	Vector coverage of developed land from 1984 to present in 2 year intervals	N/A
Transportation	CalTrans	Vector coverage of functionally classified roads from 1940 in 5 year increments	N/A
Hillshade	CASIL	Derived from 30 m DEM	

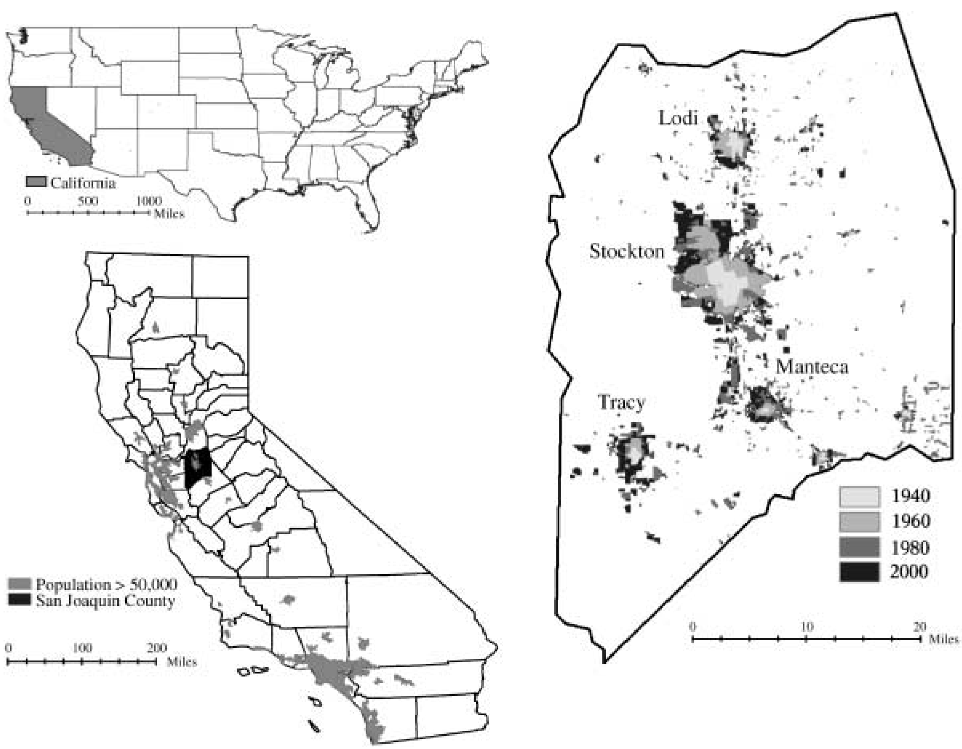

Figure 1 Location of San Joaquin County in relation to places with a population greater than 50,000 in California, along with the urban extent in 1940, 1960, 1980, and 2000

and urban extent was not allowed to disappear once it was established. All data processing was accomplished within a GIS environment, and the data used had a resolution of 100 m after processing.

Slope and hillshade were derived from 30-meter digital elevation models for the State of California, downloaded form the California Spatial Information Library (CASIL) (http://www.gis.ca.gov). Transportation networks were developed using the roads layer available from the CalTrans Data Library (http://www.dot.ca.gov), and historical coverages were generated using these data in conjunction with historical roadmaps. For the exclusion layer, it was decided that all land under public ownership would be excluded from future development in the forecasting of land use change and urbanization. The modeling of land use change was not considered in this research.

Using these data, four calibration methods were tested to determine how differences in spatial resolution change a model's parameter set, and hence its outputs. The first calibration method used was the traditional or *regular* method described above as well as in Silva and Clarke (2002). To examine the role of spatial resolution on model calibration and outputs, the other three calibrations tested were performed at fixed resolutions. One calibration, referred to as the *quarter* calibration, was performed using only the quarter resolution data (the data used in the first step of the *regular* calibration, 400 m resolution). The other two calibrations were the *half* and *full* calibrations. These calibrations used the data from the second (200 m resolution) and third steps (100 m resolution) of the *regular* calibration. The parameters derived from these calibrations were used to forecast urban growth through 100 Monte Carlo simulations from 2000 to 2040, producing both graphical and tabular outputs. Graphical outputs from the years 2010, 2020, 2030, and 2040 were converted from GIF format into grids for analysis of the urban extents within a GIS. The differences between the model forecasts using the parameters from the *regular*, *quarter*, *half*, and *full* calibrations were detected for the 2040 forecasts. Tabular data of total urban area (hectares) were output from the model and the quarter, half, and fine scale calibrations were independently tested for differences (95% confidence interval) between themselves and results from the traditional calibration routine for the time periods of 2000–2010, 2000–2020, 2000–2030, and 2000–2040.

3 Calibration and Forecasting Results

The four different calibration routines resulted in four different parameter sets for use in model forecasting (Table 2). These parameters were used to forecast with the model from 2000 to 2040, using 100 Monte Carlo simulations for each year (Figure 2). Total urban area (hectares) was plotted against time from tabular data outputs (Figure 3).

T-tests (95% confidence interval) between the means of the total urban area for forecasting based on the traditional calibration routine and the alternatives, for the periods 2000–2010, 2000–2020, 2000–2030, and 2000–2040, showed that there was a significant difference between the total urban area forecast from the *regular* and *quarter*, *half*, and *full* calibration routines for each time period.

Spatial differencing between model outputs from the regular calibration routine and the *quarter*, *half*, and *full* calibrations showed where there were spatial differences in model output (Figure 4). A numerical count of the pixels that were different allowed for the calculation of the total area that the *regular* calibration routine's forecast had in

Table 2 Resultant coefficients from the four tested calibration routines

	Coefficients				
Calibration	Diffusion	Breed	Spread	Slope	Road
Regular	2	2	54	1	3
Quarter	2	2	36	1	5
Half	2	4	38	1	4
Full	2	2	79	41	8

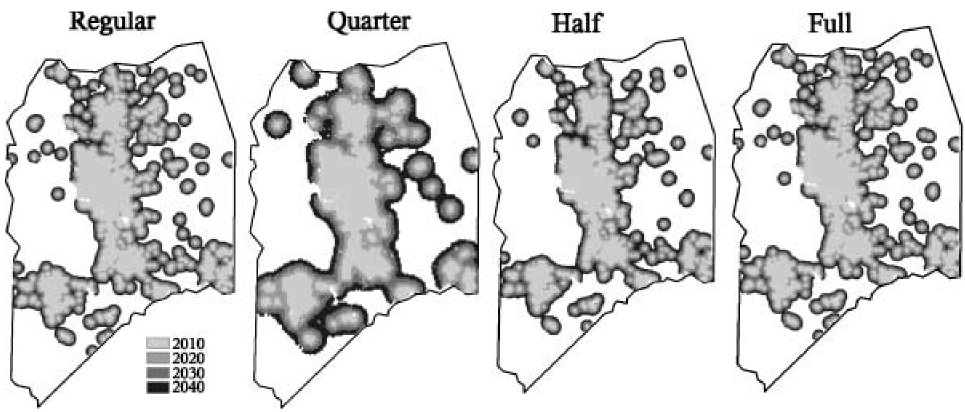

Figure 2 Model forecast for the *regular*, *quarter*, *half*, and *full* calibrations. Urban extents for 2010, 2020, 2030, and 2040 are shown

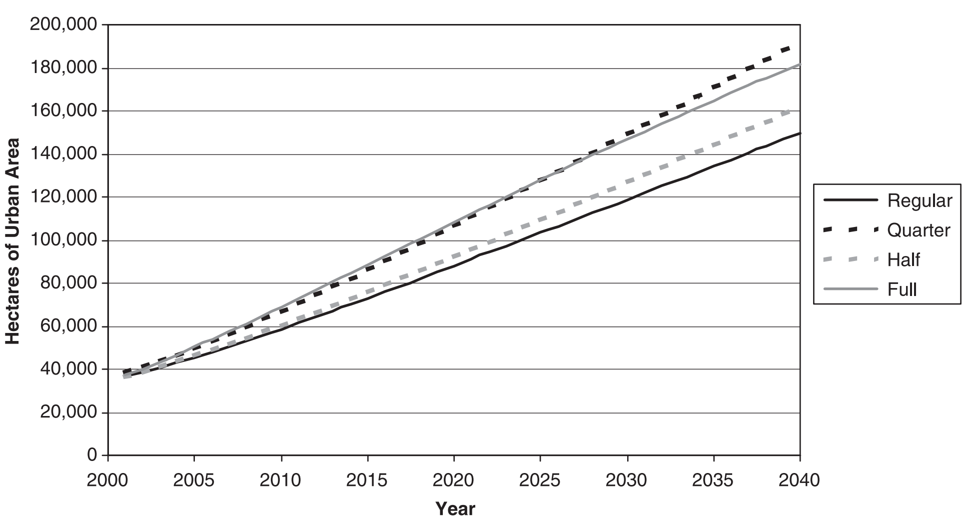

Figure 3 Total hectares of urban area forecast, based on each calibration routine

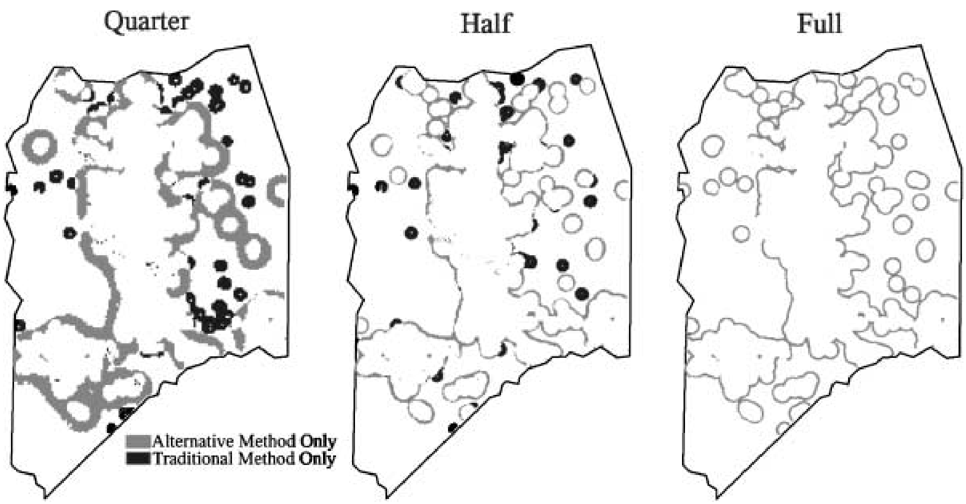

Figure 4 Areas of difference between the forecasting based on the traditional (*regular*) calibration routine and the alternatives. Gray areas are where only forecasting using the traditional routine predicted growth; black areas are where only the forecasting using the alternative routine predicted growth

Table 3 Percent of total urban area produced in forecast based on alternative calibration routines compared to forecasts from the traditional calibration routine

	Calibration Routine		
% of total urban landscape	Quarter	Half	Full
Found only in alternative	16.5	6.6	8.7
No Difference	78.3	90.1	91.3
Found only in traditional	5.2	3.3	0

common with the three alternatives (*quarter*, *half*, and *full*), as well as the percent of the total area that only the *regular* and alternative routines forecast (Table 3).

One of the prominent problems of increasing spatial resolution in modeling is the increased computational time required for model calibration. SLEUTH allowed for the logging of the average computational time required to complete one Monte Carlo simulation of the tested parameter space. If there were a linear relationship between resolution and computational time, then doubling the resolution from 400 m to 200 m would in fact create a four-fold increase in computational time. Results from the model showed that as resolution was increased from 400 m to 200 m, that the increase in computational time more than doubled, but was less than quadruple the initial time as might be expected from transforming one 400 m cell into four 200 m cells (Figure 5). Similar results were found to be true for the *full* resolution data when compared to the *half*. Although the computational time increased, the increase was not the degree that might be expected.

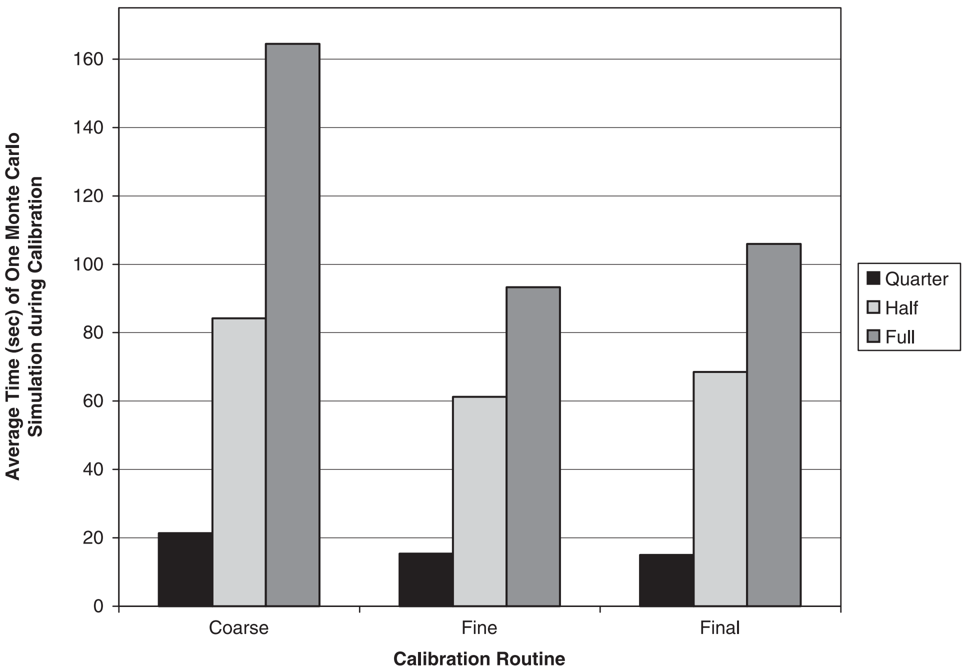

Figure 5 Average time in milliseconds for one Monte Carlo simulation during the coarse, fine, and final calibration routines for the quarter, half, and full resolution data

4 Discussion and Conclusions

Calibration and forecasting with the SLEUTH model using four different calibration routines produced statistically different pictures of the total urban area in the future for the same geographic area based on the same input data, by varying spatial resolution. Parameters derived for use in forecasting growth were different for each of the calibration routines (Table 2). While the actual parameter values and sets do not have an explicit meaning, comparison between the different parameter sets can provide some insightful information on system dynamics, and can be considered to be the 'digital DNA' of the system. Despite using a different resolution in each calibration routine, they all had very similar diffusion, breed, and road gravity parameters, indicating that, at least for this system, these parameters may not be sensitive to spatial resolution. The value of the spread parameter was lowest for the *quarter* and *half* resolution calibrations, and highest for the *full* calibration, with the *regular* calibration having a value in roughly the middle. This suggest that the spread parameter is sensitive to scale, and in increasing the spatial resolution during the *regular* calibration, that the parameter value was able to drift towards the value obtained by calibrating solely at the finest resolution. Yet the parameter that was most sensitive to scale seems to be the slope parameter, where the value differed between the *full* calibration and all others. It seems that this parameter may be the most scale-sensitive. This may be largely due to the fact that increasing the resolution in the slope input layer also increases the detail in the topography, which can strongly alter the value of this parameter, since the slope parameter is driven by topography and proximity to urban growth.

T-tests on tabular data for total urban area indicated that the model outputs were statistically different across the four decades modeled. Spatial differencing between the final (2040) model outputs from the *regular* parameter set and those from the *quarter*, *half*, and *full* showed the urban area that was common and different between the methods. The greatest differences in model outputs were found between the *regular* calibration routine and using the *quarter* calibration routine. Model forecasts had only a 78.3% percent spatial similarity between these two calibrations methods as opposed to the *half* and *full* scale routines, which showed approximately the same spatial agreement with the *regular* routine (90.1 and 91.3%). The spatial differencing between the outputs also showed that the *full* routine did not fail to predict any areas that the *regular* routine did, but that it did predict more growth around the fringe of all areas. This was most likely determined by the higher value in the spread parameter. Both the *quarter* and *half* routines failed to predict new individual centers of growth that were forecast by the *regular* (and *full*) routine. This is an especially important result because, while planners and decision makers can easily plan for organic growth (the emergence of new urban areas along an existing urban fringe), it may be the new seeded areas that arise outside existing urban centers that have the largest impact on the system. This is in part due to the fiscal impact associated with new development, including but not limited to utilities and transportation, and to the impact brought on by creating new spreading centers that may diffuse and coalesce unexpectedly with other urban areas.

Two additional points should be noted. First, this research suggests that there need to be changes to the calibration of the SLEUTH model. While the *regular* method presented in Clarke and Gaydos (1998) and Silva and Clarke (2002) is a operational method that produces credible looking results, it may not produce a set of parameters that accurately depict the historical growth process as well as a set derived from calibration at full spatial resolution. The development of the *regular* method was largely driven by computational limitations of computers at the time; but today's computers can readily handle calibration of SLEUTH at full resolution, so this needs to be considered. Second, the calibration time did not increase the expected amount with an increase in spatial resolution, indicating that it may be possible to model finer scale data without the increased degree of computational time than might previously have been anticipated or predicted.

Determining the proper resolution to calibrate and forecast with for urban models is a very tricky art; and our knowledge on this subject has not yet made it a science. For San Joaquin County, calibrating and modeling using *quarter* scale data (400 m resolution) prevented the forecasting of several areas that appeared while calibrating and forecasting based on using the *half*, *full*, and the *regular* method.

For a study area of this size, something on the order of 10 m resolution would have been too fine to calibrate and forecast at full scale, primarily because the resolution of the data would have been finer than the spatial scale that urban and land use decisions are made at. The results presented above would suggest that when using urban models for county level data, data with a resolution of 100 m and a calibration routine at this scale might be the optimal method for modeling because it captured the entire area forecast using the *regular* calibration routine, as well as additional areas. This is not to say that 100 m at full scale would be the best for some other area, although it might be correct to assume that the smaller the area being modeled, the finer the resolution that would be optimal. And the converse is probably true as well.

With the widespread availability of remotely sensed data from both public and commercial sources, providing wide ranging spatial and temporal data, modelers should

Table 4 Proposed guidelines for appropriate spatial resolutions and partial set of sources for gathering data that could be used in calibrating and forecasting urban models

Spatial Footprint	Geographic Extent	Resolution for Urban Modeling	Potential Sources of Data
>100,000 km^2	State/Nation	1 km^2–250 m^2	AVHRR, MODIS
100,000 km^2–30,000 km^2	State	250 m^2	MODIS
30,000 km^2–1000 km^2	Metropolitan City/Region	100 m^2–30 m^2	Landsat 5/7, ASTER
<1,000 km^2	Small City	30 m^2–10 m^2	Landsat 5/7, ASTER, SPOT

seek to find the appropriate resolution data corresponding to the geographic size of their study areas. While remote sensing now has the capability to monitor and analyze the spectral properties at resolutions less than 1 m, this fine a resolution does not make sense for use in urban and regional modeling efforts, but it may provide highly accurate data for modeling. Because of the variability in spectral resolutions and data sources, a proposed set of guidelines for appropriate spatial resolutions and possible sources for data to be used in calibrating and forecasting urban models is presented (Table 4). The finest resolution suggested is 10 m data, because anything finer would be looking at changes happening at levels smaller than the parcel, which is the minimum area for which planning and policy decisions are generally made.

Modelers should continue to work to determine how the scale and resolution that they calibrate and model at affects their outputs. While the role of scale and resolution issues within the calibration and forecasting routine might appear to be a too finely detailed area to warrant extensive research efforts, this paper has demonstrated that changes in either of these two factors can result in significantly different model outputs, and in some cases, even the exclusion of large areas during forecasting. Future efforts should continue research on current working models, using the knowledge gained to improve them, or to build new ones to better forecast the future. It is only after the models and their behavior are fully understood that they should they be used in the planning and decision making process.

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