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# Approaches to simulating the “March of Bricks and Mortar”

Noah Charles Goldstein\*, J.T. Candau, K.C. Clarke

*Department of Geography, University of California, Ellison 3610, Santa Barbara, CA 93106, USA*

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## Abstract

Re-creation of the extent of urban land use at different periods in time is valuable for examining how cities grow and how policy changes influence urban dynamics. To date, there has been little focus on the modeling of historical urban extent (other than for ancient cities). Instead, current modeling research has emphasized simulating the cities of the future. Predictive models can provide insights into urban growth processes and are valuable for land-use and urban planners, yet historical trends are largely ignored. This is unfortunate since historical data exist for urban areas and can be used to quantitatively test dynamic models and theory. We maintain that understanding the growth dynamics of a region's past allows more intelligent forecasts of its future. We compare using a spatio-temporal interpolation method with an agent-based simulation approach to recreate the urban extent of Santa Barbara, California, annually from 1929 to 2001. The first method uses current yet incomplete data on the construction of homes in the region. The latter uses a Cellular Automata based model, SLEUTH, to back- or hind-cast the urban extent. The success at historical urban growth reproduction of the two approaches used in this work was quantified for comparison. The performance of each method is described, as well as the utility of each model in re-creating the history of Santa Barbara. Additionally, the models' assumptions about space are contrasted. As a consequence, we propose that both approaches are useful in historical urban simulations, yet the cellular approach is more flexible as it can be extended for spatio-temporal extrapolation.

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## 1. Introduction

The 1829 etching by George Cruikshank, “London Going Out of Town—The March of Bricks & Mortar,” depicted the impending spread of London, England,

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\* Corresponding author. Tel.: +1-805-893-4519; fax: +1-805-893-3146.

*E-mail address:* [noah@geog.ucsb.edu](mailto:noah@geog.ucsb.edu) (N.C. Goldstein).

into the surrounding countryside owing to the developing of Camden Town (Fig. 1). An army of chimney pots, with mortar as heads, advancing on the battlefield of industrialization, is illustrated. Factories loom in the background, some shooting bricks as ammunition at the scared and fleeing haystacks, cattle and trees. While a poignant critique of urbanization, this artwork aptly relates the fact that urban growth can get out of control—and that this is not a recent phenomenon. London has a long and varied past and has grown in fits and spurts over its rich history. It would be an invaluable resource to possess a picture of, as Cruikshank put it, the “march of bricks and mortar”—to observe how London grew, building-by-building, year-by-year. What could be realized is insight into the true nature of urbanization and, with that, the real consequences of war, economic booms and busts, technological change, environmental disasters, and the affects they had on city growth.

Of course this history, the temporal profile of a city or region, needs to be abbreviated to some degree, as no person has the ability to observe the entire history of London in “real time.” Should a complete temporal history of the city of London exist, one would need to generalize it in order to understand the complex drivers and processes that defined its evolution. However, what we are left with is a legacy of what has been recorded, and most of the detail of urban growth has been lost to history. Today we possess not only the tools to re-create the dynamic history of a city and its growth over time but also the ability to employ such information for other studies. The following research assesses the performance of two methods of re-creating urban spatial extent and explores the potential uses of temporally interpolated urban data.



Fig. 1. “London going out of Town—The March of Bricks and Mortar” by George Cruikshank, 1829.

### 1.1. Urban modeling

Both global and local forces shape urbanization. These forces, such as the environment, politics, culture, geography, and many others, affect the city and its growth at many spatial and temporal scales. Describing the drivers associated with urban change, and understanding their interrelatedness, is a massive and necessarily imperfect undertaking. Temporal and spatial realities of urbanization can be simplified through modeling. The task of urban modeling is to bring urban dynamics into view in a spatial and temporal context. However, there are many kinds of models embedded in urban simulations. First is the data model (Clarke, 1995) that describes how the urban fabric will be represented in a computer. The most common forms of representation are the table (or flat file), the vector coverage, and the raster or grid coverage. Many Geographic Information Systems (GIS) applications employ these three data models as standard input. Second is the metaphor model. Modeling one's interpretation of the real world is a difficult task, yet many conventions have been used. For example, roads and rivers are frequently represented as lines, and altitude is commonly represented in a grid, the digital elevation model (DEM) or digital terrain model (DTM). Third is the computational model, used to perform calculations on urban data. This can vary greatly in complexity and scope. Using a GIS to create a "green buffer" for a river in a city is a relatively simple example. More difficult is calculating all of the potential locations suitable for urban growth. Fourth and last is the dynamic model. Dynamic modeling allows components of an urban landscape to react and interact in a spatially explicit manner. This approach is valuable in that quantitative and qualitative measurements of urban growth can be made and visualized for historical, present and potential contexts.

A current focus in urban modeling is in using dynamic models to "grow" a city. In this process, the model is initialized with data from the city's current state, and growth is simulated over time so that the urban region's potential spatial extent is forecast into the future. Some of these models take the approach of representing land use or land cover change, while others attempt to simulate the city's structure itself, the "bricks and mortar," as it marches on the landscape. These models are parameterized by a variety of data, depending on their theoretical origin or use. Statistical modeling approaches are dependent on sources such as economic and population data (Landis & Zhang, 2000). These produce top-down projections of future urbanization. Other urban modeling approaches facilitate the emergence of patterns from local interactions. The generation of complex structures resembling urban systems purely from the use of simple transition rules (Clarke, Hoppen, & Gaydos, 1997), as well as from population or economic controls in addition to the simple transition rules (Batty, Couclelis, & Eichen, 1997; Semboloni, 1997; Wu, 1998), have been quite successful.

Surprisingly, these models seldom incorporate the spatial modeling of the past or the historical geographic extent of a city. There appear to be several reasons for this. First, some growth models are created as a theoretical exercise in urban dynamics, and the analysis of their results is not dependent upon real data (White & Engelen, 1993). Second, the objectives of many modeling projects are to "forecast" the

potential future, because the past is already known. Third, the paucity of historical spatial data at the local scale limits consistent spatio-temporal modeling. Fourth, current spatial statistics are not entirely sufficient for the dynamic spatio-temporal measurement of simulated growth as compared with actual data, thus making accuracy difficult to assess and models difficult to calibrate. However, methodologies to incorporate spatial and non-spatial metrics to produce a successful measurement of spatial growth over time have been developed (Clarke et al., 1997), and their efficacy is being tested (Candau, 2002).

There are many potential benefits in modeling the past of an urban area. Every region has its own history, with its own unique attributes that have influenced urban growth. A large part of a city's historical configuration is a result of the technology available at the time. For instance, the high-density, pedestrian-scale city cores of older Eastern US and European cities, such as those in New York and Paris, do not exist in the more recently established sprawling Southwestern cities built in the time of automobile transportation, like Los Angeles and Phoenix. However, many of these unique attributes have as the result of singular events. For example, one cannot fully understand San Francisco's structure and organization without acknowledging the earthquake and related fires of 1906. The same is true for Chicago's fire of 1871 and the 11 September 2001, terrorist attacks on New York City. Similarly, other singular events may have a less disastrous impact on a region but still greatly affect the trajectory of a city's growth, such as Portland's establishing a "green boundary" in 1979. By examining the influence of such singular events, it is possible to see how cities could have grown, or their policies changed, if such events had not occurred, or had occurred at a different time. From this approach stems the realization that we can change the nature of a city's spatial growth trajectory, based on decisions and policies made today, and model the effect those changes will have on the future.

The lack of sufficient long-term spatio-temporal data for urban modeling is a very real problem. Although historical data for urban areas exist, it is not always possible or easy to incorporate such information into a temporal geographic database. Most often, sources contain statistics that are very useful but aspatial, such as US Census data before 1980. At other times, the information may give geographic context, but it is badly distorted, as in Panoramic maps used before photography. Since the concept of multi-regional studies for urban systems did not exist many years ago, good sources of data that do occur may be limited in extent by political boundaries and often be spatially incomplete, such as aerial photos of parts of cities, or they may be temporally sporadic, such as the Sanborn fire insurance maps (Sanborn Map Company, 1907). Some methods of acquiring data have been more forthcoming, such as using historic records of property boundaries for a small town (Jackson, 1990) or interpreting point locations, such as sewage permits of a rural Montana County (Aspinall & Hill, 2000). These methods are valuable, but can be used only if the data exist and if the region is small enough for the labor-intensive endeavor. In general, no standard GIS techniques that exist for incorporating temporally and spatially inconsistent data about human settlements.

### 1.2. Uncertainty in temporal models

One major consequence of the lack of historical urban data is that there is little certainty that the model will have any credence in any projections based on hind-casting of urban growth into the future. If one possesses data for only one point in time, then the uncertainty increases when modeling the future and the past (Fig. 2a). The further away from the present a given state is simulated, the greater the uncertainty regarding that simulated rendering, simply because time has passed, allowing for state changes to occur.

Alternatively, Fig. 2b represents the benefit of additional data in the modeling process. This example contains not only current data, but data from the recent past. When more data are present, the uncertainty in historical re-creations diminishes and is very low for data years. However, as one models back in time, uncertainty again rises.

The presence of historical data affects the uncertainty of projections as well. Since there was data for the recent past (Fig. 2b), modeling the near future will have less overall uncertainty. Note how in Fig. 2b, the maximum uncertainty is lower than the maximum uncertainty in Fig. 2a. This illustrates the benefit of additional data, however temporally inconsistent, and implies that: when dynamically modeling a city, having more data is better.

### 1.3. Temporal interpolation

Issues in historical data availability and quality are compounded by the lack of GIS techniques for incorporating temporal data. Traditionally, a GIS is created for data that are spatial, and in essence, exist in the present (Peuquet, 1999). Time is not

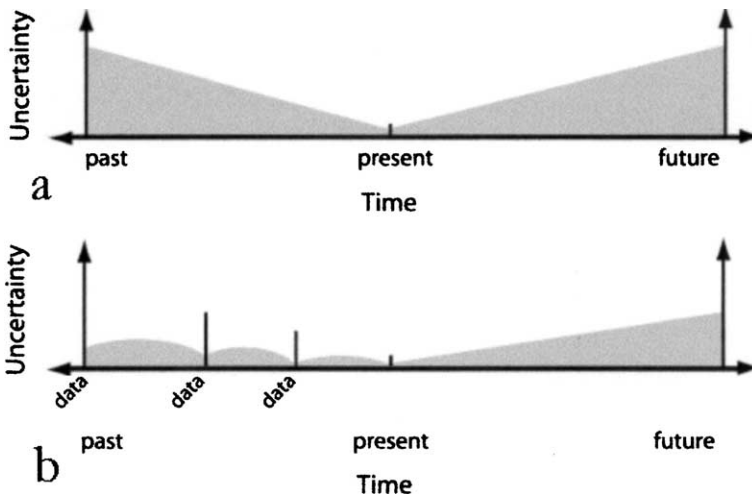


Fig. 2. Uncertainty in urban models over time. In (a), only data for the present are included. For (b), three historical data sets are included in the modeling.

incorporated into geographic data in any other manner than as an attribute, no different from elevation or ownership. Data are frequently compiled in static “snapshots,” where dynamics and fluid temporal processes are frozen in time. This perspective of discrete time is the simplest method, as most geographic data are fixed in space and time. An alternative form of temporal modeling employs “continuous” time, where data are constantly changing and are captured in a specific spatial and temporal context.

Fig. 3 illustrates how discrete temporal data are inconsistently distributed in time and generally are more highly populated in the recent than in the distant past. Conversely, historical urban data represented as “continuous” over time occur at or below the temporal resolution of dynamic modeling. Although the units that make up such data are in fact discrete themselves, if looked upon through the lens of an annual scale, the data are, in effect, continuous. Or to illustrate the point in a commonly used instance: continuous data are to discrete, as motion pictures are to photographs. For a more complete discussion of discrete versus continuous time, see Liu and Andersson (this issue).

#### 1.4. From discrete temporal data to continuous temporal data

This paper introduces two techniques for transferring between discrete and continuous temporal urban data. The first method, spatio-temporal interpolation, employs computational models, and the alternative, using an urban growth model, is dependent on dynamic modeling.

One method of re-creating missing time steps in urban data is through spatio-temporal interpolation. There are a variety of methods for spatial interpolation

### Comparison of Discrete and "Continuous" Temporal Data

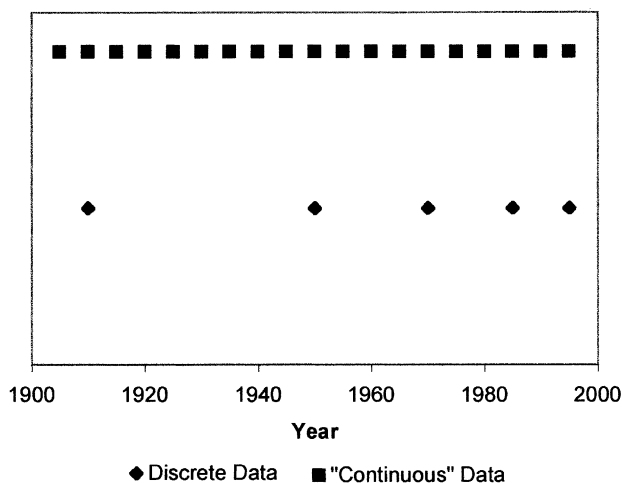


Fig. 3. Discrete time vs. continuous time.

(Lam, 1983) that are dependent upon the type of data being modeled, whether point interpolation or areal interpolation. The method of tessellation by Thiessen (or Voronoi or Dirichlet) proximal mapping creates non-smooth surfaces by determining neighborhood relationships between points in an area (Halls, Bulling, White, Garland, & Harris, 2001). The result of this process is a triangular network of polygons containing points of proximal values. There is no inherent grain of resolution in Thiessen Tessellation, per se; rather the points and their attributes composing the area determine the shape and size of the resulting polygons.

An alternative method of recreating missing historical areal extent, dynamic spatial modeling, does not use an interpolation method at all but instead allows form to evolve from a set of initial conditions. Dynamic urban models can take as a starting point the applications of theoretical models (Batty & Longley, 1994; White & Engelen, 1993, 1997). Others, such as spatial allocation (Steinitz, 1993) and economics-driven models (Landis & Zhang, 2000), take on the assumption of external values (often derived from other models) as controls. However, evidence to support such universal constraints over the evolution of spatial structure has not been empirically demonstrated. Rather, most convincing interpretations of the real world see macro-scale pattern as the result of the micro-scale interactions of the components that make up the system.

Such an idea stems from complex systems approaches that suggest the multitude of interactions on a large-scale, or individual level, form the basis of systemwide, or aggregate, behavior. To this end, cellular automata (CA) have several traits that make them seem natural tools for simulating urban dynamics. Cells can represent many of the elements that make up an urban system: built structures, parcels, census units, automobiles, traffic analysis zones, etc. Similarly, cell states may be assigned for the attributes of an urban area. A simple example is the binary attributes of urban/non-urban. The inherently spatial qualities of CA models also make them uniquely qualified for applications to geographic phenomena. Neighborhoods provide spatial context to influence transitions at discrete locations. Change at each cell has a spatial and temporal autocorrelation that imitates the interactive properties of urban spatial settlement decisions. By placing urban elements as attributed cells within a dynamic CA, urban processes can be studied as a synthetic system. Additionally, the physical form of the city exhibits several of the signature characteristics of complex systems, including fractal dimensionality and self-similarity across scales, emergence, and self-organization (Batty, 1997; Batty, Couclelis, & Eichen, 1997; Longley, Batty, & Shepherd, 1990; Torrens, 2000).

As a way of simulating the dynamics of urban processes Clarke et al. (Clarke, Hoppen, & Gaydos, 1996, 1997) developed a modified cellular automaton model of urban growth. The model derives its name from the input themes used to initialize the model, *Slope*, *Land-use*, *Exclusion*, *Urban*, *Transportation*, and *Hillshade*: SLEUTH. To provide portability, the SLEUTH growth rules are general and can be tailored to a specific geographic region by the calibration of parameters. Further, the data inputs for SLEUTH are simple image files (GIFs). These growth rules simulate the response to slope, the attraction to roads, the creation of new urban nuclei, and the spread of urbanization from the city edge. SLEUTH is a scale independent model

that has been applied in the San Francisco Bay Area (Clarke & Gaydos, 1998; Clarke et al., 1997), in the Middle Rio Grande Basin in New Mexico (Hester & Mark, 2002), and in other areas. Current research on SLEUTH is focusing on calibration methods (Candau, 2002; Goldstein, Candau, & Moritz, 2000), runoff and local climate (Arthur, 2001), and integration with an aspatial model of urban dynamics for Santa Barbara, based on the Forrester system's model of urban dynamic processes (Onsted, 2002).

This research used one method of continuous temporal data from discrete data by means of spatio-temporal interpolation to assess the re-creation of historical urban extent using SLEUTH. These two methods were applied to the same geographical region as a case study. The southern coast of Santa Barbara County, California (Fig. 4), was used because of the availability of excellent spatio-temporal data sets and as a continuation of previous work in historical and future urban growth modeling.

## 2. Methods and data

### 2.1. Description of region

The region of Santa Barbara County's South Coast used in this study stretches from 119°25' to 120° W longitude and 34°25' to 34°30' N latitude and extends approximately 50 km east-west at its widest, comprising approximately 45,000 ha (Fig. 4). Relative to earlier research using SLEUTH in Santa Barbara (Candau, 2000; Goldstein et al., 2000), this research includes a larger spatial extent, owing to the recent availability of newly acquired high-resolution aerial photographs. The South Coast is sandwiched between the Pacific Ocean to the south, and the Santa Ynez Mountains to the north, with elevations above 1200 m. Large tracts in the low elevations have long been used for agriculture and human settlement. The foothills and mid-to-high elevations are the home to Los Padres National Forest, composed

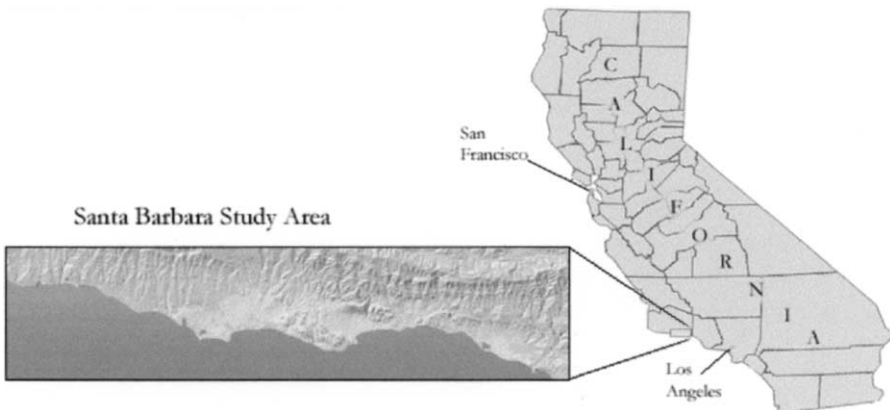


Fig. 4. Location of study area.

of fire-adapted chaparral. There have been many wildfires since the 1900s (Ford & Cullom, 1991; Goldstein et al., 2000) that have burned parts of the city of Santa Barbara. One significant fire was the Painted Cave fire of 1990, notorious for “jumping” the freeway, US 101, and spreading to the lowlands, causing hundreds of millions of dollars of damage in the process (Clarke & Gaydos, 1998).

## 2.2. Description of data

There are two major data sources for the study area’s urban history. First is the County of Santa Barbara’s Assessor Office’s Parcel Map (referred to as the Parcel Map). This data set is an Arc/Info polygon coverage that consists of polygons of ownership parcels in the Santa Barbara region, obtained for research purposes from the Santa Barbara County Regional GIS and maintained by the Santa Barbara County Assessor’s office. The data also contain a field in the Polygon Attribute Table (PAT) of the construction date of the parcel. The temporal data are at an annual temporal resolution, starting before 1900 and ending in 1993 (Fig. 5). However, data exist only for about 36% of the residential parcels, and there is very little temporal data for the non-residential parcels. Although an imperfect data set, the Parcel Map still portrays the general trend in urban growth for Santa Barbara (Fig. 6). The rapid urbanization in the late 1920s, the post WWII years, and the early 1960s is clearly evident, as is the recent slowing of urbanization since the 1980s. The Parcel Map is a spatially incomplete, temporally continuous data set for Santa Barbara.

The second data source for the study area is the SLEUTH calibration data set. Data are organized for SLEUTH in two components: urban extent and related geographic layers. The urban extent maps are visual interpretations of aerial photographs taken

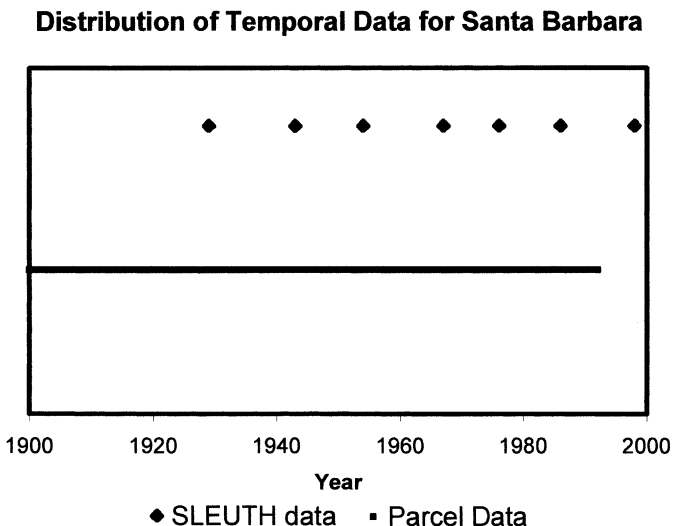


Fig. 5. Temporal distribution of data.

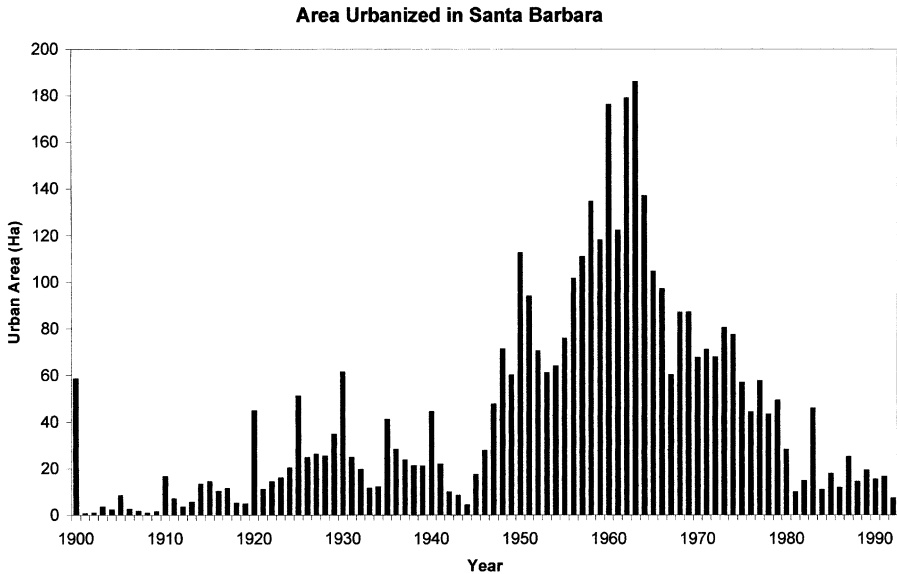


Fig. 6. Area urbanized in the Santa Barbara study area, according to the incomplete Parcel data.

of the region in 1929, 1943, 1954, 1967, 1976, 1986, and 1998 (Fig. 5). Other geographical layers included in this data set include slope, road networks, land use maps (not used in this research), and an excluded layer that indicates where urban growth cannot occur (Gigalopolis, 2001). The SLEUTH data form a spatially complete, temporally discrete data set for the Santa Barbara study area.

### 2.3. Description of methods of creating continuous spatio-temporal data

There are various tasks required to create spatially and temporally continuous urban historical data for a study region. For the Parcel data (spatially incomplete, temporally continuous), an interpolation model was used to create spatially continuous data for this set. To create a temporally continuous array for the SLEUTH data set for the study area data, a dynamic model (SLEUTH itself) was used.

#### 2.3.1. Using the parcel data

The Parcel map contained information on annual building dates for 51% of the parcels, making up 11.2% of the study area available for urbanization. A method was needed to interpolate in time and both extrapolate and interpolate in space to obtain spatially and temporally continuous data. While many methods of interpolation are readily available in GIS packages (Burrough & McDonnell, 1998), most of these assume that the desired surface is smooth and continuous. We used Delaunay triangulation as a way of recreating the “terrain” of built structures over time (Berg, 2000). This method is useful when we do not know the underlying pattern necessary for interpolation, yet we have high confidence in the known areas and the points that compose them.

### 2.3.2. Spatio-temporal interpolation

The Santa Barbara Assessor's parcel map is a polygon coverage containing "builddate" information for 51% of the polygons in the coverage. The Parcel map was converted from a polygon to a point coverage, with points spaced 30 m apart, to match the resolution of the SLEUTH data set and the regional DEM. If available, each point was given the value of "builddate." The THIESSEN command in Arc/Info was then used to create Thiessen polygons. This method temporally interpolates to data points inside the convex polygon and spatially extrapolates to areas outside the convex polygon. These polygons were then converted to a 30 m grid so that comparisons of metrics with the SLEUTH temporal modeling could be performed.

### 2.3.3. Using SLEUTH data

The historical urban layers for Santa Barbara were obtained as described in (Goldstein et al., 2000) but are summarized here as well. Aerial photographs of the Santa Barbara study area for the years 1929, 1943, 1954, 1967, 1976, 1986, and 1998 were scanned at a resolution of 300 dpi and georeferenced using ESRI's ArcView. Using on-screen digitization, the extent of built structures was interpreted. This polygon data were then converted to raster format at a resolution of 30 m, forming binary grids of urban/non-urban classes.

Because SLEUTH is a portable CA model of urban growth, its parameter values must be calibrated to the growth dynamics of a specific region. Clarke et al. (1997) and Candau (2002) described a method of brute force calibration that defined model parameter values by initializing the model with data from some point in the past and then using the model to "predict" the present. Using SLEUTH, locations were altered from non-urban to urban through the application of four transition rules. The first rule selects locations for new urban settlements to occur without respect to existing urban infrastructure, simulating urban development "going out of town." The second rule allows a portion of these newly urban locations to become growth centers instead of remaining non-attracting, isolated settlements. The third rule models urban edge growth and in-fill by propagating growth adjacent to existing urban lands. The fourth rule generates new, growth-attracting urban centers next to transportation routes as an effect of road-influenced growth. What effect these rules produce on the data is dependent upon (a) the configuration of the urban and other input values, (b) the values of five parameters, and (c) random chance. In order to stabilize the effect of randomness and increase the robustness of model results, SLEUTH is run in a Monte Carlo approach, and probability maps of predicted urban growth are generated (Candau, 2000).

Because of the "self-modification" properties of SLEUTH (Clarke et al., 1997) coefficient values at the end of a simulation are not necessarily the same as their initial values. After each "year" of growth, an analysis of the growth rate is made. If the model detects the system is entering a period of accelerated or depressed growth, the parameters are adjusted slightly to amplify such trends. For more on SLEUTH calibration, see Clarke et al. (1997), Giralopolis (2001), Candau (2002), and Silva and Clarke (2002).

Once the initializing parameters for the period 1929–1998 were obtained, the model was applied to each intermediary time interval. In order to use the historical data to its full advantage, we initialized each interval with the appropriate urban layer for the start year and the best parameter set for that interval that was recorded during calibration. One hundred Monte Carlo iterations were run for each time interval, producing a probabilistic map of historical urban extent at each year. Locations selected 90 or more times out of the 100 Monte Carlo simulations (i.e. with a probability of 90% or greater) provided the greatest amount of certainty in predicted urban growth and were used for comparison.

Spatial metrics for each time layer were calculated using Fragstats (McGarigal, Marks, & Pacific Northwest Research Station, 1995), a software package that analyzes landscape metrics of a region, including fractal dimension and cluster statistics. We examined the trends of various spatial metrics in graphic form. Intersection of the historical urban layers from each modeling approach was completed using Arc/Info GIS, version 8.0.

### 3. Results

#### 3.1. General trends

The general trend in Santa Barbara's modeled urban growth can be seen in Fig. 7. As the areal extent of the study area is the same for both models, the metrics of

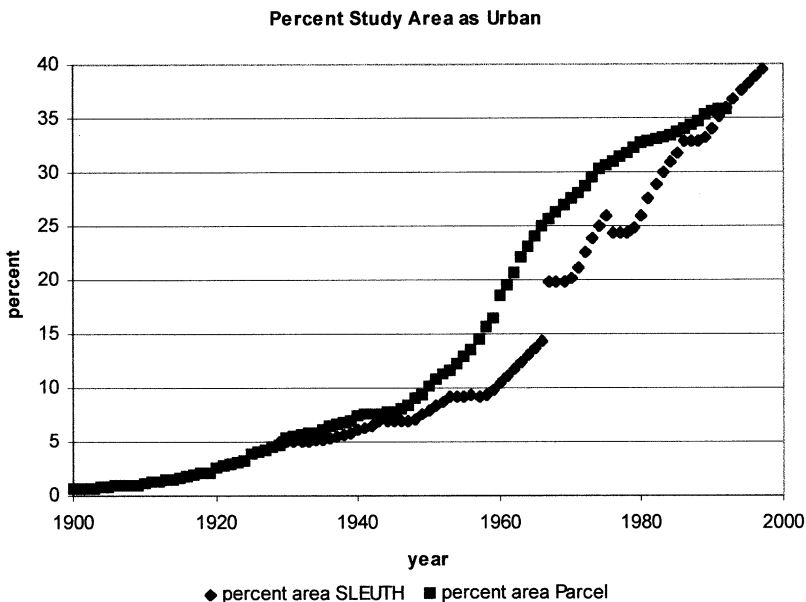


Fig. 7. Percent of study area urban.

urban extent are plotted on a percentage scale, rather than an areal scale. Growth for the Parcel interpolation approach began in 1900, and SLEUTH's backcasting was initialized with 1929 data. Both simulations exhibited an initial slow rate of growth that increased over time, forming a J-shaped curve. As the simulation progressed, the rate of growth for the Parcel interpolation slowed forming an S-shaped curve, seen in many urban areas (Clarke & Gaydos, 1998). However, the growth patterns generated by SLEUTH exhibited a series of interstitial J-curves. This behavior is primarily due to the seeding of the known urban data for the years 1929, 1945, 1954, 1967, 1976, and 1986. For each interval, a different set of optimal calibration coefficients was used, and the urban seed of the backcast layer was reset. This resulted in discontinuities in the amount of urban area through time, the most notable being due to the seeding of the 1967 data (from 14.3% of the study area urban in 1966 to 20% of the study area urban in 1967). Additionally, in all cases except for one (the 1976 seed year), SLEUTH underestimated the historic urban growth extent shown in the data.

The behavior of the two modeling approaches was described by a variety of metrics derived from Fragstats. While these metrics are sensitive to the spatial scale of the data used, this work assumes that the resolution of the real-world phenomena of urban growth was captured at 30 m. The first metric, Perimeter-Area Fractal Dimension (PAFRAC), reflects the complexity of the landscape across different spatial scales. The metric is derived from the slope of the regression obtained by regressing the log of patch area vs. the log of patch perimeter. A "patch" is a contiguous region of consistent topology; in this case, an urban "blob". The idea of using a patch for representing regions for the use of fractal and metric analysis is comes from Landscape Ecology (Milne, 1991). PAFRAC can range between 1 and 2, 1 indicating a simple linear feature, existing in only one dimension (such as a line). A PAFRAC value of 2 represents a completely space-filling feature, existing wholly in two dimensions (such as a filled-in square). Correspondingly, a city, which at some scales is not completely filled in and usually has a contorted perimeter, would have a fractal dimension between 1 and 2. Batty and Longley (1994) report the fractal dimension for a variety of cities, ranging from 1.312 (Tokyo 1960) to 1.494 (Albany 1990) to 1.93 (Los Angeles 1990).

As evident in Fig. 8, the two methods of historical rendering of urban Santa Barbara have very different behaviors. The SLEUTH interpolation method decreases in complexity over time and is continuously "reset" higher by the seeding of the known years of data. Thus, because of the assumption of 90% certainty in the modeling as illustrated in Section 1.2, SLEUTH tends to generalize over time. Alternatively, the Parcel Map interpolation reveals a complicated oscillation and gradual decrease of PAFRAC toward a simpler landscape with the coalescence of urban "blobs." This illustrates that the Parcel interpolation matches the fractal dimensions of the control years from remote sensing. The SLEUTH backcasted results deviate from the control years considerably.

### 3.2. Patch behavior

Fragstats generated two metrics of patch behavior of growing urban Santa Barbara. These are the Number of Patches (NOP) and the Largest Patch Index (LPI).

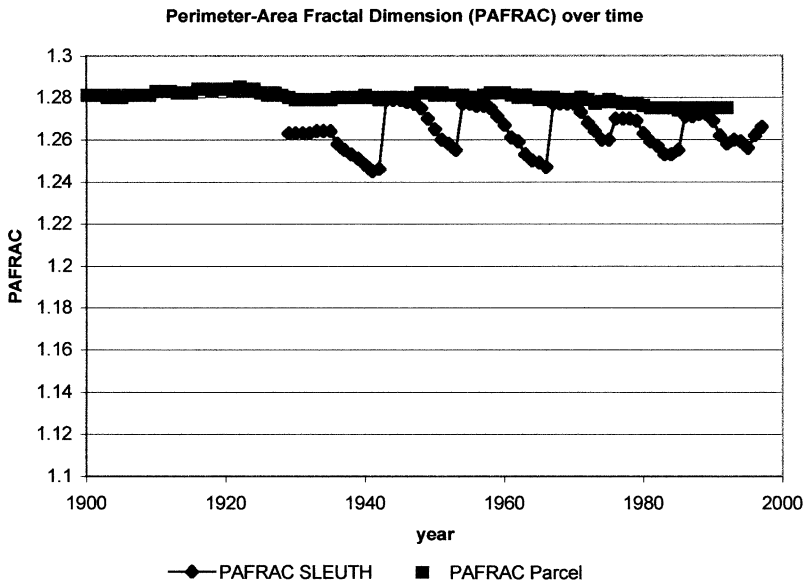


Fig. 8. Perimeter–area fractal dimension.

The LPI is defined as the percentage of the study area composed of the largest urban patch. For instance, a city with one urban blob of size 20 units and another of size 7 units, in a landscape of 100 units large, would have an LPI of 20%. It is immediately evident that the LPI changes with the size of the study area. However, in this study, the study area was held constant. The NOP reflects the spatial fragmentation of the landscape and allows a different perspective on the growth rate of a city. The NOP for a city with six patches would have an NOP of 6. Again, the spatial scale of the measurements can be an issue. In this study, the smallest patch will be a 30 m grid cell (900 m<sup>2</sup>). In theory, if we were to use a finer resolution data set, with a resolution of 5 m, for example, the NOP index would be in the same range, but different.

As visible in the figure of the NOP index, Fig. 9, there is a notable difference between the two approaches to urban backcasting. The parcel map interpolation began with more patches and increased in number of patches over time, reaching a maximum in 1948 with 598 patches. The patches coalesced into larger contiguous urban areas over time, leveling off in the 1990s with 393 patches. The SLEUTH backcasting method once again was heavily influenced by the seeding of the control years. However, the number of patches steadily decreased over time after the seeding. This is similar to the pattern of PAFRAC decreasing (and decreased complexity) for the SLEUTH backcasting methods. Again, the 90% threshold of the SLEUTH modeling results in fewer patches, as many small and infrequent patches occur in different places in each individual SLEUTH run.

The LPI index indicates the percentage of the total area making up the largest patch. Fig. 10 shows that a larger patch increasingly made up Santa Barbara over time and that there was a greater rate of coalescing of the urban area after the late

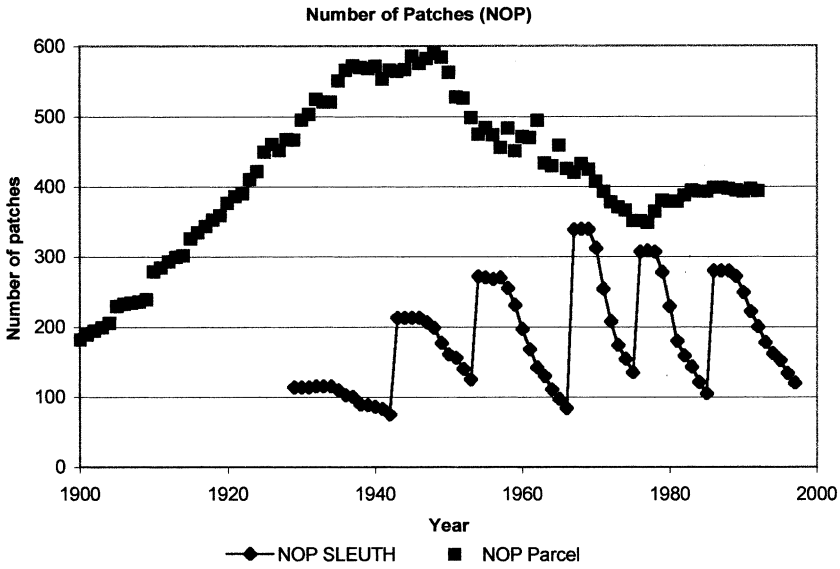


Fig. 9. Number of patches over time.

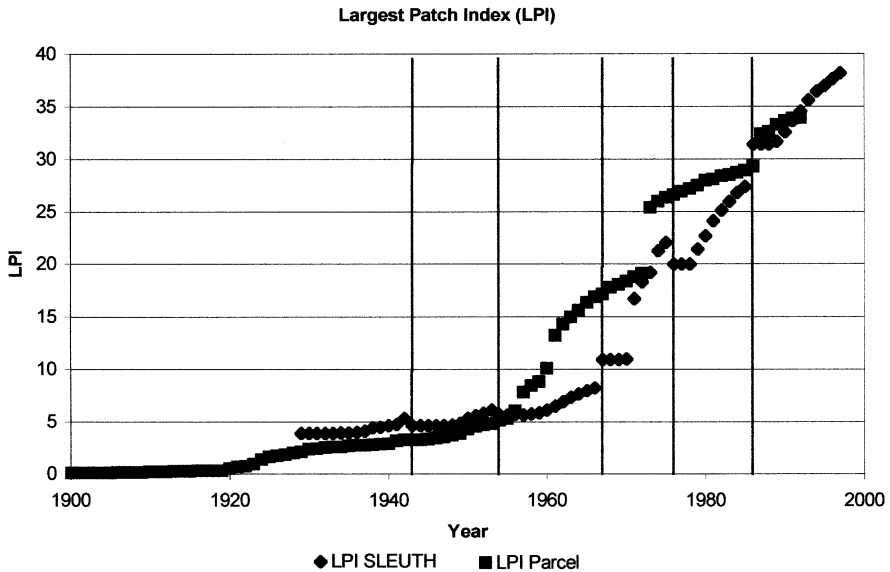


Fig. 10. Largest Patch Index over time. The red lines indicate SLEUTH control years.

1950s to early 1960s. What are also notable are the discontinuities in the Parcel interpolation method in 1960, 1973, and 1987. This may be an indication of times of rapid urban development, or of periods of cessation of granting construction permits.

In order to assess the amount of spatial coincidence in the two methods of re-creating Santa Barbara’s urban history, the spatial overlap of the two methods was

determined. The Lee–Sallee statistic is a measure of the intersection of two polygons divided by the union of the polygons (Lee & Sallee, 1970). A Lee–Sallee of 1 indicates that the two polygons are completely spatially congruent, and anything less than 1 is a deviation from complete congruence. Fig. 11 illustrates both the Lee–Sallee statistic for the union of two backcasting methods as well as the residual proportion of the union areas composed by each individual method. It is not surprising to see Lee–Sallee rise over time as both methods converge on one spatial solution—a map of the present. In general, the Parcel interpolation was more different from the spatial intersection relative to the SLEUTH backcasting method. This is illustrated in Fig. 12. Over time, the Parcel model (in white) is more “independent” than the SLEUTH model, as it spreads urbanization in areas not occupied by the union of the two models or the SLEUTH model.

#### 4. Discussion

This work demonstrates that there is more than one way to quantify the dynamics of a growing city. Both approaches presented here are viable methods to create temporally and spatially continuous historical urban data from temporally discrete and spatially discontinuous data. Each method presented, that of spatio-temporal interpolation (used on the Parcel data) and dynamic modeling (used on the SLEUTH dataset), differed in applicability to the different data types used and the specific mechanisms underlying each method.

The method of interpolation, performed on the Parcel data, was shown to render a “smoother” recreation of the urban Santa Barbara, relative to the SLEUTH dynamic modeling (Fig. 7). The fact that the Parcel data were temporally continuous

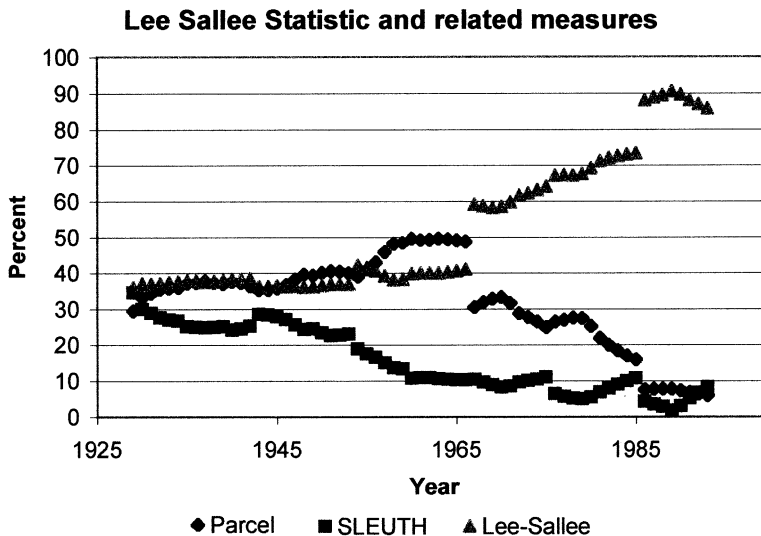


Fig. 11. The Lee–Sallee statistic over time.

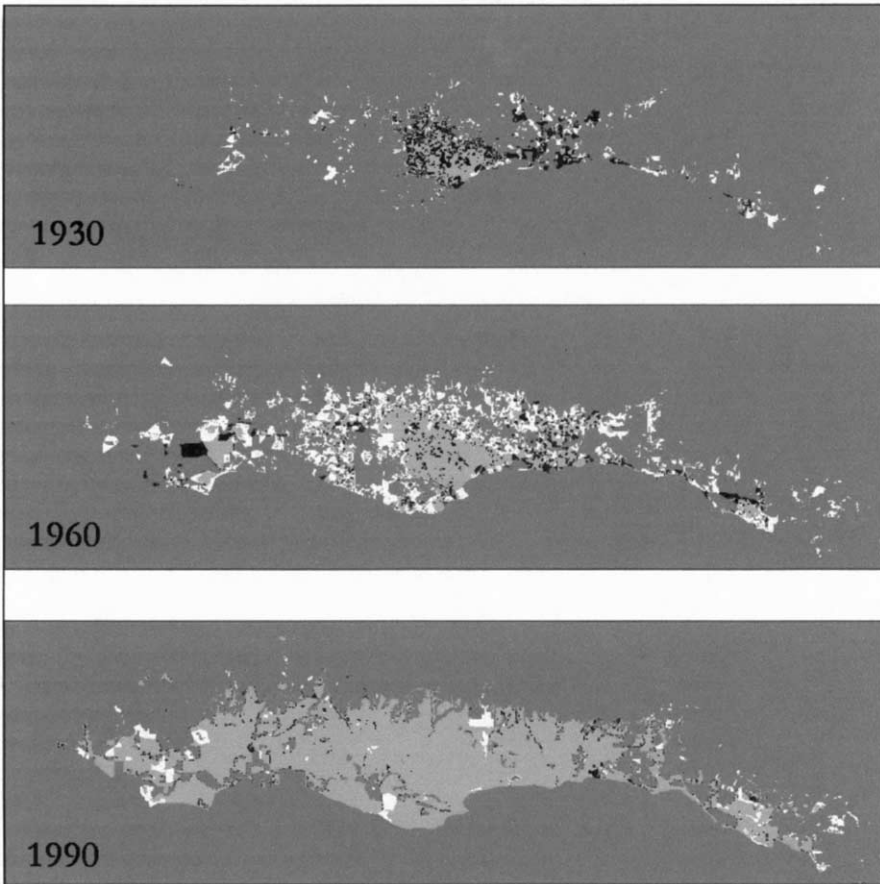


Fig. 12. Intersection of both interpolation methods over time. White is the Parcel interpolation, black is the SLEUTH backcasting and gray is the intersection of the two. Dark gray is the background.

largely contributes to this, as does the extent of the temporal dispersal of the SLEUTH data. While the Parcel data had no gap from 1900 to 1993, the SLEUTH data were full of temporal gaps (1929 to 1943, 1943 to 1956, etc...). One way to improve these results is to constrain urban growth in SLEUTH by allowing Santa Barbara to only spread into regions that it will occupy in the “past” future. In essence, this means using 1943 to constrain growth of Santa Barbara from 1929 to 1942, or using 1998 to limit urban growth from 1986 to 1997. Alternatively, the dependencies to the input data could be lessened. In an attempt to take advantage of the rich historical data available, SLEUTH was reseeded for each interstitial period. This methodology differs from our calibration approach and greatly affected simulation performance, as the reseeding dates repeatedly appear as artifacts in the results. Instead, SLEUTH could have been seeded with the earliest urban year (1929) and run, uninterrupted, to 1998.

This most likely would have produced growth forecasts without the discontinuities found in this exercise.

The indices describing the behavior of historical urban patches (Figs. 9 and 10) lend insight into differences between dynamic modeling of the past (via SLEUTH) and computationally interpolating the past (using the Parcel data). The number of patches in the landscape represents how the urban areas are growing, be it by small kernels of growth or large tracts of development. While there is no “correct” manner that Santa Barbara has developed, the two models illustrate two different possibilities. The Parcel interpolation clearly shows a Santa Barbara growing by small parcels (Fig. 9) until 1960, then coalescing until 1980, and plateauing in the 1990s. Such growth captures the post WWII urbanization boom that affected Santa Barbara most strongly in the late 1950s through the 1960s. This pattern suggests a linear process of urban growth that progresses in three stages. In the first stage, a large percentage of land within an urban system is available for new development. Urban settlements are small and widely spaced from one another, with the exception of a larger urban core. In the second stage, the small settlements grow and begin to spread into one another, forming fewer, larger urban communities. In the third phase, almost all open land has been developed, and growth slows and/or levels off, frequently in the form of infill. Alternatively, the SLEUTH modeling of Santa Barbara shows a reiterative process of condensation and fast seeding of urban patches. Although this pattern might be an artifact of the reseeding methodology, it points toward a possible urban settlement cycle of highly dispersed new settlement, followed by a period of focused edge growth and infilling, which is again followed by another wave of dispersed small settlements (Candau, 2002).

The metric of the largest patch (LPI, Fig. 10) allows comparisons of the “dominance” of the urban centers in the region (Fig. 12). Both modeling approaches resulted in different behaviors of the LPI, yet there were some similarities. The Parcel interpolation exhibited sharp discontinuities in concert with gradual decreases in LPI over time. The SLEUTH backcasting also demonstrated discontinuities in the LPI, resulting from time periods of conglomeration and increased dominance of the downtown Santa Barbara urban cluster. In recent simulation years, the SLEUTH backcasting was more influenced by a single urban cluster than was the Parcel interpolation technique. This represents the nature of Santa Barbara’s urban growth, because the cultural and political center of the region is the city of Santa Barbara itself.

The metric of fractal dimension indicates trends in global processes of urbanization. The fractal dimension of the entire study area changed very little over time, in contrast to the findings of Batty and Longley (1994), who reported that as cities aged, they sprawled and increased in fractal dimension. The lack of significant changes in fractal dimension of Santa Barbara is therefore surprising, especially since the NOP and LPI metrics did show change. The constant fractal dimension implies that the global processes of urbanization did not change significantly from 1900 to the present and that the contemporary extent of Santa Barbara is essentially a larger version of the older Santa Barbara. In essence, urban Santa Barbara grew in a self-similar manner over time. We take this to mean that the NOP and LPI indices illustrate the dynamic nature of local urban processes while the fractal dimension

index illustrates that the local processes of urbanization were consistent with the global character of Santa Barbara's urban growth. This is perhaps due to the limited land availability in the region and the fact that the major transportation route, connecting it to the North and the South, has not changed in function.

It must be noted that the methodological decision to select only locations with a probability of 90% or greater from the SLEUTH results had a direct effect on both the NOP and the LPI findings. The Monte Carlo probability images smooth the forecasted urbanization, causing instances of settlement that occur infrequently to be excluded or hidden. Urban transitions that occur without a strong spatial dependency, such as new spreading centers without reference to urban areas or roads, are very difficult to predict with high statistical accuracy. However, growth that is spatially referenced to the existing infrastructure, such as edge and road-influenced growth, can be predicted with a much greater certainty. Since we selected only locations with the highest probability of urban transition for comparison, many of the dispersed settlements produced by SLEUTH (which would have increased the NOP and altered the LPI metrics) were not included in our analysis. As an alternative, measurement of each single Monte Carlo simulation could be made. This approach would include a greater number of unique urban patches and an average of the metrics could be calculated for comparative analysis.

The Modified Lee–Sallee statistic (Fig. 11) shows not only the amount of spatial agreement in the two methods but also the amount of “independence” of each model relative to the other. For the first 35 years of contemporary simulation (1929–1964), the Lee–Sallee statistic remained constant. It increased suddenly in 1967 and continued increasing until 1985, when it again rapidly increased. The increase of the Lee–Sallee statistic toward the present indicates that both models converge on the common certain solution: modern Santa Barbara. While this is partially due to the use of modern Santa Barbara to spatially constrain both models, the degree to which the two modeling techniques coincide is significant, as seen from the Lee Sallee, NOP and SPI indices. The agreement between the two methods shows consistency and increases the confidence in the dynamically modeled findings of SLEUTH. The SLEUTH back-casting model's “independence” decreased over the entire simulation (Fig. 12), indicating that the union of the two models was increasingly similar to the spatial extent of the SLEUTH model itself. The Parcel interpolation model showed more independence than the SLEUTH model. In the 1960s the Parcel model dominated the landscape, relative to the union of the two models, and the SLEUTH model independently. This may have been due to the fine resolution of the original Parcel data, accounting for the developing of unique parcels, “islands” of urban growth, in undeveloped regions. The Modified Lee–Sallee statistic shows only spatial co-occurrence. It would be interesting to extend the metric to account for urban pixels “nearby” in time as well as space.

## 5. Conclusion

Through historical reconstruction a simplification of the “march of bricks and mortar” can be generated. This modeled history describes the dynamics and pattern

of urbanization for a particular region. Understanding the settlement patterns of the past, and the relation of those patterns on the future will guide urban planning in an informative way. With respect to the work presented here, the two methodologies produce different flavors of that historical growth with related issues in the validity of those approaches. The interpolation method generated a smooth progression of urban development and favored growth patterns of dispersed urbanization with many small patches. The dynamic modeling approach exercised by SLEUTH back-casting generated cyclic phases of dispersion and coalescence and favored a system with a spatially dominant urban center being of increasing importance. By and large, both of these approaches tended toward agreement, which in turn lends confidence to the simulated histories. These approaches are generalizable and can be repeated in any urban setting, if the appropriate data are available.

Data availability determines the appropriate method to use in the reconstruction of historical urban extent. The SLEUTH data set is relatively easy to obtain, as the historical images of many cities are in the public domain. A challenge in creating the SLEUTH data set lies in the interpretation from the aerial photographs (or digital imagery): determining what is “urban” and what is not (Forster, 1985). This process can introduce error into the model, from many sources, including photo interpretation error or problems in the imagery caused by atmospheric conditions. However, novel data sources can be used for supplemental historical data layers, such as the Defense Meteorological Satellite Program’s Operational Linescan System, which provides snapshots of urban areas at night and can be extrapolated to determine regional urban boundaries (Sutton, Roberts, Elvidge, & Baugh, 2001). In addition, as more remote sensing products become freely available, this approach will be more viable, at least for recreating *recent* historical urban extents. To date, there has been no empirical research on the effect of using multiple data sources in SLEUTH modeling. This being said, SLEUTH performed well in modeling the historical interstitial periods of Santa Barbara’s urban history. SLEUTH captured the general trend of the city’s growth, but failed to capture the small, new settlements that arose to the east and west of downtown. We estimate that SLEUTH can be run for forecasts of urban extent for a time period as long as the historical data; essentially 70 years. Beyond 70 years, the future predictions are more uncertain. The temporal limits to urban growth modeling are an underrepresented area of research and worthy of more focus.

Obtaining temporally continuous data like the Parcel data can be difficult, as much of this type of information is collected by local and regional governments but is not freely available. Some data on building construction are available from local governments, but from private businesses only on a per-parcel basis. These types of challenges hinder the widespread usage of continuous temporal data in urban historical modeling. However, in the near future, the promise of frequently released remote sensing products will allow for utilizing continuous data in modeling urban areas.

These approaches also highlight issues common to urban modeling. One of these is the interpretation of spatial and temporal scales. For the purposes of this study, the finest temporal unit was a year, and the finest spatial unit was a 30 m pixel. Many processes that occur below those temporal and spatial resolutions will be

unrepresented in these applications. Processes that occur at much larger temporal scales might be excluded as well, such as major earthquakes, floods, global sea level rise, and reconstruction, because the maximum time interval of this study was only 100 years. A second issue is the type of data used for modeling. This research used an explicitly spatial, urban/non-urban classifier as the basic unit of analysis. This prevents us from making inferences regarding intra-urban dynamics or socio-economic drivers. The scale of metric analysis also limited the findings of this exercise. If relationships such as the percentage of road to urban area or percentage of urban area on steepening slopes were captured, additional detail could be added to the area's growth profile.

The products of this work can have a multitude of potential applications. Santa Barbara, like most parts of California, is expecting an increase in population over at least the next 30 years. Area leadership has recognized that increased pressure to develop limited available lands could jeopardize the high quality of life enjoyed by Santa Barbara residents. Because of this, over the last several years an aggressive approach has been taken to involve a diverse cross section of the community in discussing the future urban growth of the region and initiating planning efforts to protect the many amenities found in Santa Barbara, while maintaining a strong and growing economy. The products of this work will greatly contribute to this effort by providing data for its regional models (Onsted, 2002) and will allow the visualization of the growth over time to gain insight into the nature and geography of Santa Barbara's growth (Acevedo & Masuoka, 1997). The annual temporal layers can also be used to examine relationships with other systems, such as in historical hydrologic or wildfire regimes (Goldstein et al., 2000). Future work with the historical reconstruction of urban Santa Barbara will be to re-create the population distribution in the city, in a "pseudo census." The pseudo census will use auxiliary data, in addition to the spatial census data, to re-create an annual distribution of people over time.

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## References

- Acevedo, W., & Masuoka, P. (1997). Time-series animation techniques for visualizing urban growth. *Computers & Geosciences*, 23(4), 423–435.

- Arthur, S. T. (2001). *A satellite based scheme for predicting the effects of land cover change on local microclimate and surface hydrology*. Doctoral Thesis, Pennsylvania State University, Department of Meteorology.
- Aspinall, R., & Hill, M. (2000). Urban growth-analysis, modelling and prediction of past, present and future land use changes in Gallatin Valley, Montana (1860–2010). In *4th International Conference on Integrating Geographic Information Systems (GIS) and Environmental Modeling*, Banff, Canada, University of Colorado.
- Batty, M. (1997). Cellular automata and urban form: a primer. *Journal of the American Planning Association*, 63(2), 266–274.
- Batty, M., Couclelis, H., & Eichen, M. (1997). Urban systems as cellular automata. *Environment and Planning B-Planning & Design*, 24(2), 159–164.
- Batty, M., & Longley, P. (1994). *Fractal cities: a geometry of form and function*. London, San Diego: Academic Press.
- Berg, M. D. (2000). *Computational geometry: algorithms and applications*. Berlin, New York: Springer.
- Burrough, P. A., & McDonnell, R. (1998). *Principles of geographical information systems*. Oxford, New York: Oxford University Press.
- Candau, J. (2000). Calibrating a cellular automaton model of urban growth in a timely manner. In *4th International Conference on Integrating Geographic Information Systems (GIS) and Environmental Modeling*, Banff, Canada, University of Colorado.
- Candau, J. T. (2002). *Temporal calibration sensitivity of the SLEUTH urban growth model*. Masters Thesis, Department of Geography, University of California, Santa Barbara.
- Clarke, K. C. (1995). *Analytical and computer cartography*. Englewood Cliffs NJ: Prentice Hall.
- Clarke, K. C., & Gaydos, L. J. (1998). Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, 12(7), 699–714.
- Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B-Planning & Design*, 24(2), 247–261.
- Clarke, K. C., Hoppen, S., & Gaydos, L. J. (1996). Methods and techniques for rigorous calibration of a cellular automaton model of urban growth. In *Third International Conference/Workshop on Integrating GIS and Environmental Modeling*, Santa Fe, New Mexico, National Center for Geographic Information and Analysis.
- Ford, R., & Cullom, K. (1991). *Santa Barbara wildfires: fire on the hills*. Santa Barbara CA: McNally & Loftin.
- Forster, B. C. (1985). An examination of some problems and solutions in monitoring urban areas from satellite platforms. *International Journal of Remote Sensing*, 6(1), 139–151.
- Gigalopolis, P. (2001). Project Gigalopolis, NCGIA. Available: <http://www.ncgia.ucsb.edu/projects/gig/>.
- Goldstein, N. C., Candau, J. T., & Moritz, M. A. (2000). Historical Santa Barbara up in flames: a study of fire history and historical urban growth modeling. In *4th International Conference on Integrating Geographic Information Systems (GIS) and Environmental Modeling*, Banff, Canada, University of Colorado.
- Halls, P., Bulling, M., White, P., Garland, L., & Harris (2001). Dirichlet neighbours: revisiting Dirichlet tessellation for neighborhood analysis. *Computers, Environment & Urban Systems*, 25, 105–117.
- Hester, D. J. a. F., & Mark, R. (2002). Landscape change modeling. *Ground-water resources of the Middle Rio Grande Basin, New Mexico: US Geological Survey Circular 1222*. J. R. Bartolino, & J. C. Cole.
- Jackson, J. M. (1990). Building an historic settlement database in GIS. In K. M. S. Allen, S. W. Green, & E. B. W. Zubrow (Eds.), *Interpreting space: GIS and archaeology* (pp. 274–283). London, New York: Taylor & Francis.
- Lam, N. (1983). Spatial interpolation methods: a review. *The American Cartographer*, 10(2), 129–149.
- Landis, J. D., & Zhang, M. (2000). Using GIS to improve urban activity and forecasting models: three examples. In A. S. Fotheringham, & M. Wegener (Eds.), *Spatial models and GIS: new potential and new models* (pp. 63–81). London, Philadelphia: Taylor & Francis.
- Lee, D., & Sallee, G. (1970). A method of measuring shape. *Geographical Review*, 60, 555–563.

- Liu, X., & Andersson, C. Assessing the impact of time representation on dynamic land use change modeling. *Computers, Environment and Urban Systems* (this issue).
- Longley, P. A., Batty, M., & Shepherd, J. (1990). Shape size and dimension of urban settlements. *Transactions, Institute of British Geographers*, 16(1), 75–94.
- McGarigal, K., & Marks, B. J., Pacific Northwest Research Station (Portland OR). FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. Portland OR: US Department of Agriculture Forest Service Pacific Northwest Research Station.
- Milne, B. T. (1991). The utility of fractal geometry in landscape design. *Landscape and Urban Planning*, 21(N1–2), 81–90.
- Onsted, J. (2002). *SCOPE: an application and modification of the Forrester model to the South Coast of Santa Barbara County*. Masters thesis, Department of Geography, University of California, Santa Barbara.
- Peuquet, D. (1999). Time and GIS and geographical databases. In P. Longley, M. Goodchild, D. Maguire, & D. Rhind (Eds.), *Geographical information systems: principles, techniques, management and applications* (pp. 91–103). New York: John Wiley & Sons.
- Sanborn Map Company. (1907). *Insurance maps of Santa Barbara, California: including Miramar and Summerland*. New York: Sanborn Map Company.
- Semboloni, F. (1997). An urban and regional model based on cellular automata. *Environment and Planning B-Planning & Design*, 24(4), 589–612.
- Silva, E. A., & Clarke, K. C. (2002). Calibration of the SLEUTH Urban Growth Model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems* 26, 525–552.
- Steinitz, C. (1993). A framework for theory and practice in landscape planning. *GIS Europe*, 42–45.
- Sutton, P., Roberts, D., Elvidge, C., & Baugh, K. (2001). Census from Heaven: An estimate of the global human population using night-time satellite imagery. *International Journal of Remote Sensing*, 22(16), 3061–3076.
- Torrens, P. M. (2000). How cellular models of urban systems work, Centre for Advanced Spatial Analysis: [http://www.casa.ucl.ac.uk/how\\_ca\\_work.pdf](http://www.casa.ucl.ac.uk/how_ca_work.pdf) (08/2002).
- White, R., & Engelen, G. (1993). Cellular automata and fractal urban form- a cellular modelling approach to the evolution of urban land-use patterns. *Environment & Planning a*, 25(8), 1175–1199.
- White, R., & Engelen, G. (1997). Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning B-Planning & Design*, 24(2), 235–246.
- Wu, F. (1998). Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a geographical information system. *Journal of Environmental Management*, 53(4), 293–308.