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Spatio-temporal dynamics in California's Central Valley: Empirical links to urban theory

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This paper explores an addition to theory in urban geography pertaining to spatio-temporal dynamics. Remotely sensed data on the historical extent of urban areas were used in a spatial metrics analysis of geographical form of towns and cities in the Central Valley of California (USA). Regularities in the spatio-temporal pattern of urban growth were detected and characterized over a hundred year period. To test hypotheses about variation over geographical scale, multiple spatial extents were used in examining a set of spatial metric values including an index of contagion, the mean nearest neighbor distance, urban patch density and edge density. Through changes in these values a general temporal oscillation between phases of diffusion and coalescence in urban growth was revealed. Analysis of historical datasets revealed preliminary evidence supporting an addition to the theory of urban growth dynamics, one alluded to in some previous research, but not well developed. The empirical results and findings provide a lead for future research into the dynamics of urban growth and further development of existing urban theory.

1. Introduction

Dynamic urban processes, from local sprawl to global urbanization, affect both natural and human systems at all spatial scales. Interest in abstracting urban change across cities and scales has a long tradition in the field of Geography (Burgess 1925, Hoyt 1939, Harris and Ullman 1945). Although the concepts and ideas used to model urban systems have been widely recognized, they have for the most part remained hypothetical and only marginally representative of the spatial and temporal complexity of urban change (Batty 2002, Franck and Wegener 2002). It is only recently through the exploration of new approaches such as cellular automata, complex systems theory and agent-based simulations that the focus has shifted towards addressing the spatio-temporal characteristics of urban dynamics both theoretically and empirically (Portugali 2000). Some of this work stems from the evolving field of Geographic Information Science (GIScience). GIScience provides a framework for spatial analysis and modeling that is based on geographic principles and seeks to integrate the analytical capabilities of remote sensing, geographic information systems, and spatial statistics to broaden the understanding of real world systems (Goodchild 1992).

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Early research (1950s–1970s) was largely based on demographic or socio-economic research because the ability to efficiently conduct detailed spatio-temporal pattern analysis at anything other than aggregate levels did not exist. This era generated significant research contributions and raised compelling questions regarding urban theory. One such question that persists is: how do cities form over time? Among the early contributions to this discussion was Blumenfeld's (1954) theory of spatio-temporal urban dynamics that proposed the use of a wave analog for describing urban growth. Based on oscillations in urban population density over a one hundred year cycle, Blumenfeld stated that the "zone of maximum growth" would move outwards from the city core with a particular periodicity. This concept was spatialized by Boyce (1966), who incorporated changes in density over time and distance from the city center. Newling (1969) extended the exponential population density model introduced by Clark (1951) by formulating a "density-profile classification of urban growth" similar to the wave approach of Blumenfeld (1954) and Boyce (1966). Newling's (1969) wave-like profiles were used as a theoretical diagnostic to identify population density characteristics of cities in different stages of development. Socio-economic research proposed both a sequence of transitions between different phases, based on changing economic and technological conditions, and a mosaic of patterns caused by social stratification (Johnson 1972; Schnore 1965). This work was paralleled by Korcelli's (1976) review of urban phase concepts, many of which are analogous with the ecological notions of successional stages of colonization, succession, invasion, and competition. Similarly, the concept of distinct urban expansion phases and cycles was developed by Hoover and Vernon (1959), Cressy (1939), Duncan *et al.* (1962), and Winsborough (1962). While the theoretical foundations of many of these early formulations vary in strength, the basic notion of urban cycles or phases is apparent in all of them. This idea has more recently been posed in a similar form by White *et al.* (2001) through their investigation of form as it relates to European land use processes, yet they do not fully expand on the concepts of phases, but do suggest some temporal component as being explanatory of form. White *et al.* (2001) were still left with many questions at the conclusion of their research, including: how spatial patterns of land use evolve through time; do they vary from city to city; and what do they tell about the system and underlying processes? Consequently this research is along similar lines, drawing on older geographic concepts as a basis, and again raising the question: do urban systems exhibit oscillatory behavior over time? Specifically, if such harmonics can be shown to exist, how can they be quantified and modeled?

More recent studies have typically described urbanization in the context of demographic and economic dynamics. Research has become more focused on isolating the drivers of growth rather than the emerging geographic pattern of developing urban landscapes. The processes of diffusion limited aggregation (Fotheringham *et al.* 1989, Batty 1991) and fractal growth (Batty and Longley 1994) have been used to explore the spatial dynamics of cities. These developments have resulted in a variety of new spatial urban models, for example the use of cellular automata (CA) to describe and model urban systems. Modeling geographic systems using CA models is a recent advance relative to the history of urban studies and geographic science. Tobler (1979) first described these models in geography, briefly reporting 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 by Couclelis (1985), and application of these models has proliferated in the last decade (Li and Yeh 2001), including the development of the SLEUTH urban growth CA model (Clarke *et al*. 1997). While new urban models have provided insights into urban dynamics, a deeper understanding of the physical and socioeconomic patterns and processes associated with urbanization is still limited by the available data and related empirical studies (Longley and Mesev 2000, Franck and Wegener 2002).

Remote sensing is a significant, yet under-used, data source for the study of urban phenomena (Longley 2002). Aerial photographs and satellite imagery provide a means of compiling comprehensive historical time series of land surface features and urban areas (Haack *et al.* 1997, Jensen and Cowen 1999). These data provide a freeze-frame view of the spatio-temporal patterns associated with urban change, and are an invaluable source for studying urban dynamics and improving the modeling of urban systems (Batty and Howes 2001, Longley 2002, Herold *et al.* 2003). In particular, the sequential snap-shots allow quantitative descriptors of the geometry of urban form to be computed and compared over time. Geometric indices for quantifying the structure and pattern of thematic maps (including those of urban areas) are commonly used in landscape ecology where they are referred to as landscape metrics (O'Neill *et al.* 1988, Gustafson 1998). Spatial metrics are defined as quantitative and aggregate measurements derived from digital analysis of thematic-categorical maps showing spatial heterogeneity at a specific scale and resolution. Calculation of spatial metrics is based on a categorical, patch-based representation of the landscape as developed for landscape ecology (Gustafson, 1998). Patches are defined as homogenous regions comprising a specific landscape property of interest such as "urban" or "rural". The landscape perspective assumes abrupt transitions between individual patches that result in distinct edges. These measures provide a link between the detailed spatial structures derived from remote sensing and urban change processes, and spatial analysis and modeling in GIScience (Luck and Wu 2002, Herold *et al*. 2003, in press). Pioneering research in the use of urban metrics was done some time ago (Fotheringham *et al.* 1989, Batty 1991, Batty and Longley 1994), but recently there has been increasing interest in applying spatial metric techniques to the analysis of urban environments, where they have been used to examine unique spatial components of intra- and inter-city urban structure as well as the dynamics of change and growth (Alberti and Waddell 2000, Herold *et al.* 2002). These more recent works have built on the fractal measures previously used to measure form, and have used a wider variety of metrics to describe urban form (Herold *et al.* in press).

The strength of combining remotely sensed data and spatial metrics is its process-from-form perspective. Most dynamic models and theories that relate to urban structure and growth adopt a form-from-process perspective, deriving urban structures as the spatial outcomes of pre-specified processes of urban change. Combining remotely sensed data and spatial metrics allows the quantification of actual spatial structures over time, and permits the relation of changes to specific processes, albeit spatial rather than socioeconomic ones. The patterns obtained from remote sensing data, however, usually represent the complex overlapping outcomes from the interaction between multiple individual and interacting processes, making it difficult to disentangle and isolate specific variables and trends of interest. This being the case, a potential advantage could come from using both of these approaches in combination; the process-first perspective would help to narrow down the possibilities suggested by the detailed analysis of changing urban structure, while the form-first approach could help identify and compare significant spatial patterns. Applying metrics to datasets that are scaled appropriately in terms of their spatio-temporal resolution, extent and thematic representation, can focus the investigation on specific process-related structures. This opens an avenue for taking the empirical observations a step further towards an exploration of more general theoretical concepts that relate to the spatio-temporal nature of urban growth and the evaluation of existing dynamic spatial frameworks. In the same way, Zipf's rank-size "law" begins with an empirical regularity in urban systems and uses the parameters of a mathematical relationship to compare structures between systems and over time.

This study observes and evaluates urban growth dynamics in one of the fastest urbanizing regions in the western United States: California's Central Valley. We start our investigation by developing a hypothetical framework of spatio-temporal urban expansion in terms of alternating processes of diffusion and coalescence. This framework is based on the idea of urban growth phases (Cressy 1939, Hoover and Vernon 1959, Duncan *et al.* 1962, Winsborough 1962) and the concept of urban growth having wave-like properties (Blumenfeld 1954, Boyce 1966, Newling 1969). The framework hypothesizes that urban growth can be characterized as having two distinct processes, diffusion and coalescence, with each process following a harmonic pattern. To test this hypothesis, spatial metrics were computed as a way to show spatial-temporal urban growth dynamics for three centers of urbanization in the Central Valley of California. The time span of the study ranged from 1940 to 2040 and is based on historical maps, remotely sensed data and results from the SLEUTH urban growth model (Clarke *et al.* 1997). The purpose of using both historical data and urban growth forecasts was to investigate whether the model produced forecasts that were spatially quantitatively similar to the historical data that was used to calibrate the model, and to see whether trends based in the past might be continued into the future by the model.

2. Spatio-temporal urban growth hypotheses

A conceptual framework will represent our hypotheses regarding spatio-temporal urban evolution based on collective observations, and our understandings of urban dynamics. Later these hypotheses will be addressed in the context of the empirical results from this study. In general, the patterns of urbanization are a consequence of socioeconomic, natural, and technological factors that drive and influence the evolving spatial structure of cities. We hypothesize that the spatial evolution of cities can be described as a two-step process of diffusion and coalescence, as represented in Figure 1. The process starts with the expansion of an urban seed or core area. As the seed grows, it disperses growth to new development centers or cores. While urban diffusion continues, it is accompanied by organic growth which leads to the outward expansion of existing urban areas and the infilling of gaps within them. This is different from a classical diffusion process in particle physics, for example, because once settled, no single zone "moves" or deurbanizes. It is more similar to spilling a viscous liquid onto a surface without evaporation; it both splashes outward and spreads simultaneously.

As the process continues, the diffusion of urban areas reaches a point where they begin to coalesce towards a saturated urban landscape. This fully built-out urban agglomeration can also be seen as an initial urban core for this process to continue

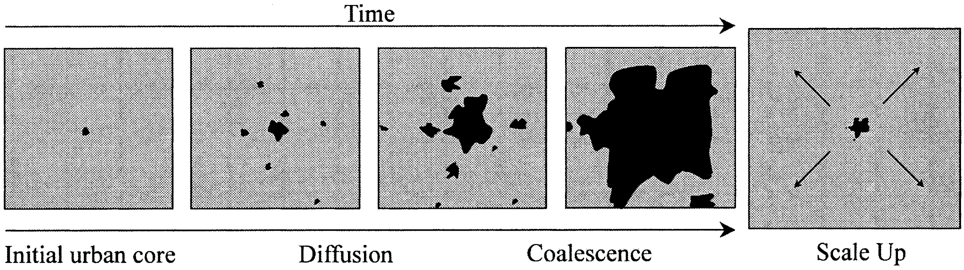

Figure 1. Hypothetical sequence of the spatial evolution of an urban area.

at a coarser spatial scale. In some traditional urbanization studies this "scaling up" is analogous to changing the spatial extent of concentric rings, or distances, around a central urban core or between urban centers (Blumenfeld 1954, Luck and Wu 2002). Self-similarity is assumed in the fractal cities analyzed by Batty and Longley (1994).

The hypothesized process of urban growth (Figure 1) can be detected using spatial metrics. The spatio-temporal characteristics for a hypothetical full cycle of urbanization and uniform isotropic growth at a fixed scale are shown in Figure 2. The graph on top reflects the dominance of diffusion in the early stages of urbanization. The heterogeneity of the landscape, described by the contagion, is expected to be highest in the intermediate period of development and with the beginning of coalescence. With progressing coalescence the heterogeneity of the landscape decreases until complete build-out. More specific spatial urbanization patterns are presented in the bottom graph of Figure 2. In the early stages of diffusion the nearest neighbor distances between individual urban areas are the highest and drop until more individual urban developments are allocated and a peak in urban patch density occurs. With the onset of coalescence of the urban areas, the decrease in the nearest neighbor distances is less significant as nearby patches are the first to spatially aggregate. High urban patch density reflects the dominance of the diffusion process and decreases once the coalescence begins. During this time, the difference of total urban area and the amount of urban land in the central urban core is the highest since the urbanized area is spatially most dispersed. The edge density peaks when the process of coalescence results in larger, heterogeneous urban areas, and then decreases as the process moves towards the urbanization of the landscape.

This hypothesized process of spatio-temporal urban dynamics emphasizes that the spatial evolution of urban areas oscillates between the diffusion and coalescence of individual urban areas in relation to the central (historical) urban core. There is currently no one specific theory to support this idea of oscillatory behavior between diffusion and coalescence, but if both processes exhibit wave-like properties through time (Blumenfeld 1954, Boyce 1966, Newling 1969), then they (waves of diffusion and coalescence) must be out of phase to exist mutually. The patterns represent the dynamics at a defined spatial extent. However, it can be hypothesized that similar growth characteristics are observed for varying spatial extents. For example, if a city progressively expands from its central core, the spatial processes will also occur within concentric rings with increasing distance from the center. Based on the work of Alonso (1964) and White *et al.* (2001), we expect the growth periodicity to be longer as a function of distance from the central core. Given this hypothesis, we

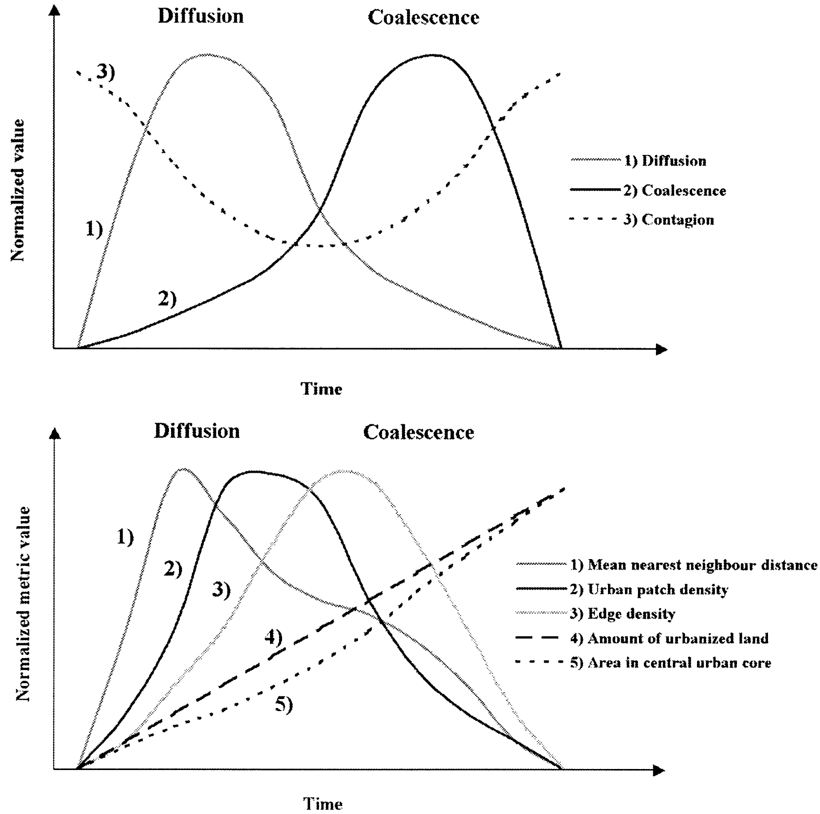

Figure 2. Theoretical temporal signatures of spatial metrics for a full cycle of urbanization for uniform isotropic growth at a fixed spatial extent.

measured actual spatio-temporal growth patterns for three rapidly urbanizing regions of California's Central Valley using data from historical remote sensing to represent the spatial configuration of urban and rural land. Results generated by the SLEUTH urban growth model were used to project urban growth of three urban regions into the future. These model results were not used as empirical evidence in testing the hypothetical framework. However, the urban growth model is calibrated to fit historical growth patterns and the results provide some measure of evaluating if the framework would hold true for the future. We applied spatial metrics, using the Fragstats program (McGarigal *et al.* 2002), to derive spatio-temporal patterns of urban growth at multiple spatial extents, defined using concentric rings around the central urban cores. The empirical observations were then placed into the context of the hypothetical framework to determine to what degree the observed patterns reflect regularities and variations among different urban regions at varying spatial extents.

3. Data and methods

3.1 *Study area*

We focus on three important urban centers in the Central Valley of California: Stockton-Modesto, Fresno, and Bakersfield (Figure 3). These areas were chosen

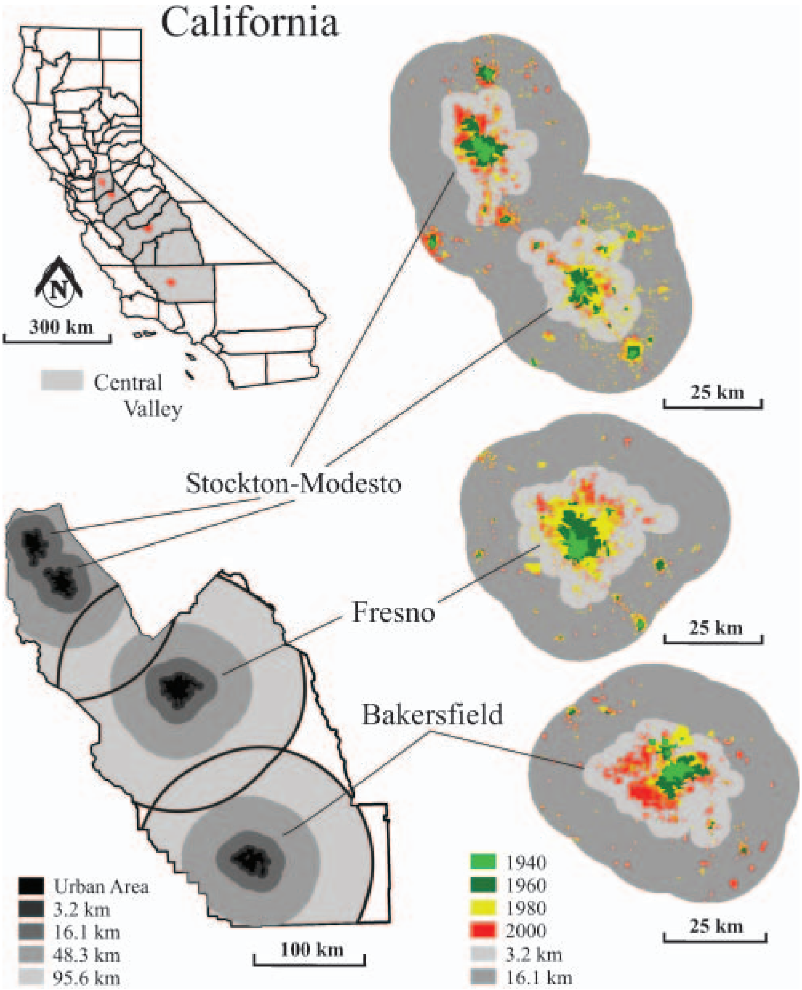

Figure 3. Geographic location and historical urbanization of Stockton-Modesto, Fresno, and Bakersfield.

because they are fast-growing economic centers in a region of the state where the current population of three million is predicted to double to six million by the year 2040 (State of California Department of Finance 1998). The area is situated between three of the major metropolitan areas of the state: the San Francisco Bay Area, Sacramento, and Los Angeles. The Stockton-Modesto area is situated in proximity to the San Francisco Bay Area and Sacramento. These metropolitan areas influence the local job market, economic development, commuting patterns, and play a role in defining Stockton-Modesto's 'Northern California' character. Fresno is located at the heart of the Central Valley, surrounded by mainly agricultural land uses, and is thought of as the somewhat independent 'Capital of the Valley'. Bakersfield is located less than one hour north of metropolitan Los Angeles, and at the intersection of two major transit routes. Bakersfield's permissive policy attitude towards growth and development is similar to that of Los Angeles and other major metropolitan areas in Southern California.

Table 1. Sources, description, and resolution of data used in the SLEUTH modeling and metric analysis.

Data Layer	Source	Description	Resolution
Topography/Slope	USGS	Digital elevation model, Slope	100 m
Exclusion	CaSIL	Vector coverage of Federal and State owned land	N/A
Urban Extent	USGS	Urban extent for 1940, 1954, 1962, 1974, 1996, 2000	100 m
	CA-FMMP	Developed land from 1984 to 2000 in 2 year intervals (used 1984, 1992)	100 m
Transportation	CalTrans	Vector coverage of functionally classified roads from 1940 in 5 year increments	N/A

3.2 *Data*

Data sources for historical urban extent are listed in Table 1. Data that capture urban extent for the years 1940, 1954, and 1962 were digitized from historical USGS 1:250,000 maps that were based on air photo interpretation and supplemental ground survey information. Data from 1974 and later were compiled using satellite-based remotely sensed imagery. The urban extents for 1974 and 1996 were based on Landsat MSS and Landsat TM mosaics compiled by the USGS's Moffet Field, California office (http://ceres.ca.gov/calsip/cv/). Additional data for 1984, 1992, and 2000 were obtained from the California Farmland Mapping and Monitoring Program (CA-FMMP), which utilized aerial photography as a base mapping source (http://www.consrv.ca.gov/DLRP/fmmp/). The CA-FMMP data for the year 1984 were only available for the areas of Stockton/Modesto and Fresno: no information for this specific year was available for Bakersfield. The 1996 CA-FMMP data were merged with the USGS data to create a composite dataset of urban extent. Urban extent through time was treated as a cumulative phenomenon so that each time period built on the previous one, and urban extent was not allowed to disappear once it was established. These instances can be attributed to registration errors or map generalization. All data-processing tasks were accomplished within a GIS environment.

3.3 *SLEUTH urban growth modeling*

To capture the full temporal scale of the urban dynamics proposed in the hypothetical framework, data on urban extent for one hundred years are believed to be necessary (Blumenfeld 1954). Data of this temporal length are not readily available, and the accuracy of any historical data from cartographic sources has a large degree of uncertainty that cannot easily be validated. This has led us to use modeled data to fill in the remainder of the one hundred years not covered by our existing data, giving a period of urbanization from 1940 to 2040. Model outputs from 2000 to 2040 were used to test the forecasting assumptions of the model; the main analysis was based on the historical datasets.

CA models can be used to advance understanding of general complex adaptive systems, which include urban systems, and to advance urban theoretic or urban geographical research by exploring ideas in urban economics, urban geography, and urban sociology (Torrens and O'Sullivan 2001). The use of urban CA models in the literature is prolific, but few are portable. SLEUTH (Clarke *et al.* 1997) is a model that has been widely cited in the literature, uses a well-documented calibration routine, and has been applied in numerous geographic locations (Silva and Clarke 2002, Esnard and Yang 2003, Yang and Lo 2003, Leão *et al.* 2004). Admittedly, the spatial analysis of model forecasts has a large degree of uncertainty associated with it since the future cannot be validated (Goldstein *et al.* 2004). Nevertheless, SLEUTH is a model that is exhaustively calibrated based on the historical patterns and dynamics of an urban system. The ability to capture these dynamics and forecast them into the future provides some degree of comfort that any historical dynamics, similar to those suggested by the hypothetical framework, will be evident in model forecasts.

The SLEUTH urban growth model was applied to generate forecasted future urban extents for 2010, 2020, 2030, and 2040. The model makes use of several different data layers for parameterization, e.g. multi-temporal urban extent, transportation network and digital elevation model data. Some areas are prevented from becoming urbanized in the model by an exclusion layer that consisted of federal and state-owned managed land, and protected areas. Application of the model necessitates a complex calibration process to train the model for the spatial and temporal urban growth using brute-force methods. Using data encompassing the Stockton-Modesto, Fresno, and Bakersfield urban areas (see Table 1), SLEUTH was calibrated using the calibration routine described in Clarke and Silva (2002) and Dietzel (in press).

Calibration of SLEUTH produces a set of five parameters (coefficients) that describe an individual growth characteristic that, when combined with other characteristics, can describe several different growth processes. Transition rules and initial conditions of urban areas at the start time are integral to the model because of how the calibration process adapts the model to the local 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). The 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). These parameter values drive the four transition rules, which simulate 1) spontaneous (of suitable slope and distance from existing centers), 2) diffusive (new growth centers), 3) organic (infill and edge growth), and 4) road-influenced growth (a function of road gravity and density). By running the model in calibration mode, a set of control parameters is refined through a sequential brute-force method; the derived parameters are then used in model forecasting.

The model outputs for 2010, 2020, 2030, and 2040 followed a general "business as usual" scenario that assumes that spatio-temporal growth behavior and restrictions depicted in the historical calibration data will continue into the future. The forecasted urban development allowed for an extension of the temporal frame of the study to the full century of urbanization that has been identified as appropriate for regional scale growth studies (Blumenfeld 1954, Boyce 1966). It should be reemphasized at this point that the model results contain a significant level of uncertainty because we have no means of validating future growth projections (Goldstein *et al.* 2004). Therefore, they were only used as general trend indicators and all quantitative analysis and the derivation of general assumptions were based on the actual historical remote-sensing-based measurements.

With modeled urban growth patterns, regardless of their source, it is possible to perform an analysis that is both scientific and hypothetical in nature (Torrens and O'Sullivan 2001). Furthermore, the extension of the time span of analysis can be generated using different models or different sets of constraints, and the resulting patterns analyzed in terms of phases of growth, or changes in general spatio-temporal patterns; thus the method applied in this research is valid regardless of the particular model used.

3.4 *Definition of multiple concentric rings showing spatial extent*

Buffers around the central urban cores were used to conduct the multi-scale analysis. Scaling in this context is changing the spatial extent encompassed by the buffers, not changing the spatial resolution. The spatial resolution was held constant (100 m $\times$ 100 m grid cell size) for all extents, since it has been shown that many of the metrics used are resolution sensitive (Saura and Martinez-Millan 2001). The boundaries of the three core urban centers (Stockton-Modesto, Fresno, and Bakersfield) were based on the 2000 US Census Urbanized Areas dataset. Buffers of 3.25, 16, 48, and 96 kilometers (2, 10, 30 and 60 miles) around the 2000 urban area boundary were generated and intersected with the historical urban extents from 1940, 1954, 1962, 1974, 1984, 1992, 1996, and 2000, as well as with the forecasted future urban development (Figure 3). The results of this procedure were binary grids (urban/rural) for each of the three study areas, for 12 dates and five spatial extents. The finest scale, the urban extent according to the 2000 Census with no buffer, describes the urban development within the 2000 Census urbanized land and represents the historical urbanization of the central urban core to date. The buffers at 3.25 and 16 kilometers (2 and 10 miles) captured the smaller and larger local pattern of growth in direct relation to the central core, while the 48 and 96-kilometer (30 and 60 miles) buffers captured the large-scale regional growth pattern surrounding the three urban centers. With a distance between the three urban centers of about 160 kilometers (100 miles), these large-scale buffers partly overlap and capture the connection between spatial urban networks within California's Central Valley Region (Figure 3).

3.5 *Spatial metrics*

Binary grids representing the multi-scale spatio-temporal urban development for the three areas were analyzed using differences in the values of computed spatial metrics. Spatial metrics provide a means of quantifying the spatial heterogeneity of individual patches, all patches in a class, and over the whole landscape as a collection of patches. Some metrics are spatially non-explicit scalar values, but still capture important spatial properties. Spatially explicit metrics can be computed as patch-based indices (e.g. size, shape, edge length, patch density, fractal dimension) or as pixel-based indices (e.g. contagion) computed for all pixels in a patch (Gustafson 1998, McGarigal *et al.* 2002). The metric calculations were performed for the "urban" class, using the public-domain software FRAGSTATS version 3.3 (McGarigal *et al.* 2002). Table 2 describes the spatial metrics used in this research. The selection of the metrics was based on their ability to quantify unique spatial urban characteristics identified in previous research on urban areas (Alberti and

Table 2. Spatial metrics used in this study, after McGarigal *et al*. (2002).

Metric	Description/Calculation scheme	Units	Range
PLAND – Percentage of landscape	PLAND equals the sum of the areas (m^2) of a specific land cover class divided by total landscape area, multiplied by 100.	Percent	$0 < \text{PLAND} \leqslant 100$
PD – Patch density	PD equals the number of patches of a specific land cover class divided by total landscape area.	Numbers per 100 ha	$\text{PD} \geqslant 1$, no limit.
ED – Edge density	ED equals the sum of the lengths (m) of all edge segments involving a specific class, divided by the total landscape area (m^2) multiplied by 10000 (to convert to hectares).	Meters per hectare	$\text{ED} \geqslant 0$, no limit.
LPI – Largest patch index	LPI equals the area (m^2) of the largest patch of the corresponding class divided by total area covered by that class (m^2), multiplied by 100 (to convert to a percentage)	Percent	$0 < \text{LPI} \leqslant 100$
ENN_MN – Euclidian mean nearest neighbor distance	ENN_MN equals the distance (m) mean value over all patches of a class to the nearest neighboring patch based on shortest edge-to-edge distance from cell center to cell center.	Meters	$\text{ENN\_MN} > 0$, no limit.
ENN_SD – Euclidian nearest neighbor distance standard deviation	ENN_SD equals the standard deviation in Euclidian mean nearest neighbor distance of land cover class.	Meters	$\text{ENN\_SD} > 0$, no limit.
FRAC_AM – Area weighted mean patch fractal dimension	Area weighted mean value of the fractal dimension values of all patches of a land cover class, the fractal dimension of a patch equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter.	None	$1 \leqslant \text{FRAC\_AM} \leqslant 2$
CONTAG –Contagion	CONTAG measures the overall probability that a cell of a patch type is adjacent to cells of the same type.	Percent	$0 < \text{CONTAG} \leqslant 100$

Waddell 2000, Luck and Wu 2002, Herold *et al.* 2003, in press). A more detailed description, including the mathematical equations, for all of the metrics can be found in McGarigal *et al.* (2002).

Most metrics have fairly simple and intuitive values, such as the percentage of the landscape covered by urban land (PLAND), the urban patch (PD) and edge density (ED), and the measures of mean Euclidean distance (ENN_MN) and standard deviation (ENN_SD). The largest patch index (LPI) metric describes the percentage of the total urban area concentrated in the largest patch, hence the central urban core. The contagion index (CONTAG) is a general measure of landscape heterogeneity and describes the extent to which landscapes are aggregated or clumped (O'Neill *et al.* 1988). Landscapes consisting of relatively large, contiguous patches are described by a high contagion index. If a landscape is dominated by a relatively large number of small or highly fragmented patches, the contagion index is low. The fractal dimension describes the complexity and fragmentation of a patch by a perimeter–area ratio. Low values indicate that a patch has a compact form with a relatively small perimeter relative to its area. If the patches are more complex and fragmented, the perimeter increases, resulting in a higher fractal dimension. The fractal dimension was calculated as the area weighted mean patch fractal dimension (FRAC_AM). FRAC_AM averages the fractal dimensions of all patches by a higher weighting of larger land cover patches. The shape of smaller patches is more a function of image pixel size than actual spatial characteristics (Saura and Martinez-Millan 2001).

4. Empirical observations of the urban growth pattern

The results of spatial metric analysis will be described in terms of temporal metric signatures. The growth signatures for all eight of the investigated metrics at the Fresno test site are presented in Figure 4. The individual lines represent the metric signatures derived for the different spatial extents. The metric shown in the upper left diagram in Figure 4 describes the percent of urbanized land for each of the buffered zones. It is the highest for the central area (no buffer) and shows the largest increase during the 1960s and 1970s. The larger spatial extents follow this general pattern with increasing distance from the urban core. The contagion metric is a general measure of landscape heterogeneity and is lowest when the urban/rural configuration is most dispersed and fragmented. For the central area the lowest contagion is found for the year 1974, when the landscape was most heterogeneous. With further expansion of the urban core the contagion increases, and so the landscape homogenizes towards its final stage. The spatio-temporal signature of the contagion metric follows a pattern similar to a sine wave. The general wave shape is evident for all concentric rings, but with varying wavelengths. The wavelength represents the stage of urbanization for each scale, and generally increases with distance from the central core.

For the central urban area the number of patches significantly increased between 1962 and 1974. This increase coincided with the highest rate of urban sprawl and diffusion, and generally supports the theoretical pattern introduced earlier. Urban expansion is characterized by the diffuse allocation of new development units around the central core. This trend is confirmed by the spatial metric describing the amount of urban land in the largest patch. The values decrease by 1974, meaning that the urban growth is focused on the spread of new cells outside of the core area rather than the expansion of the urban core itself. For the central

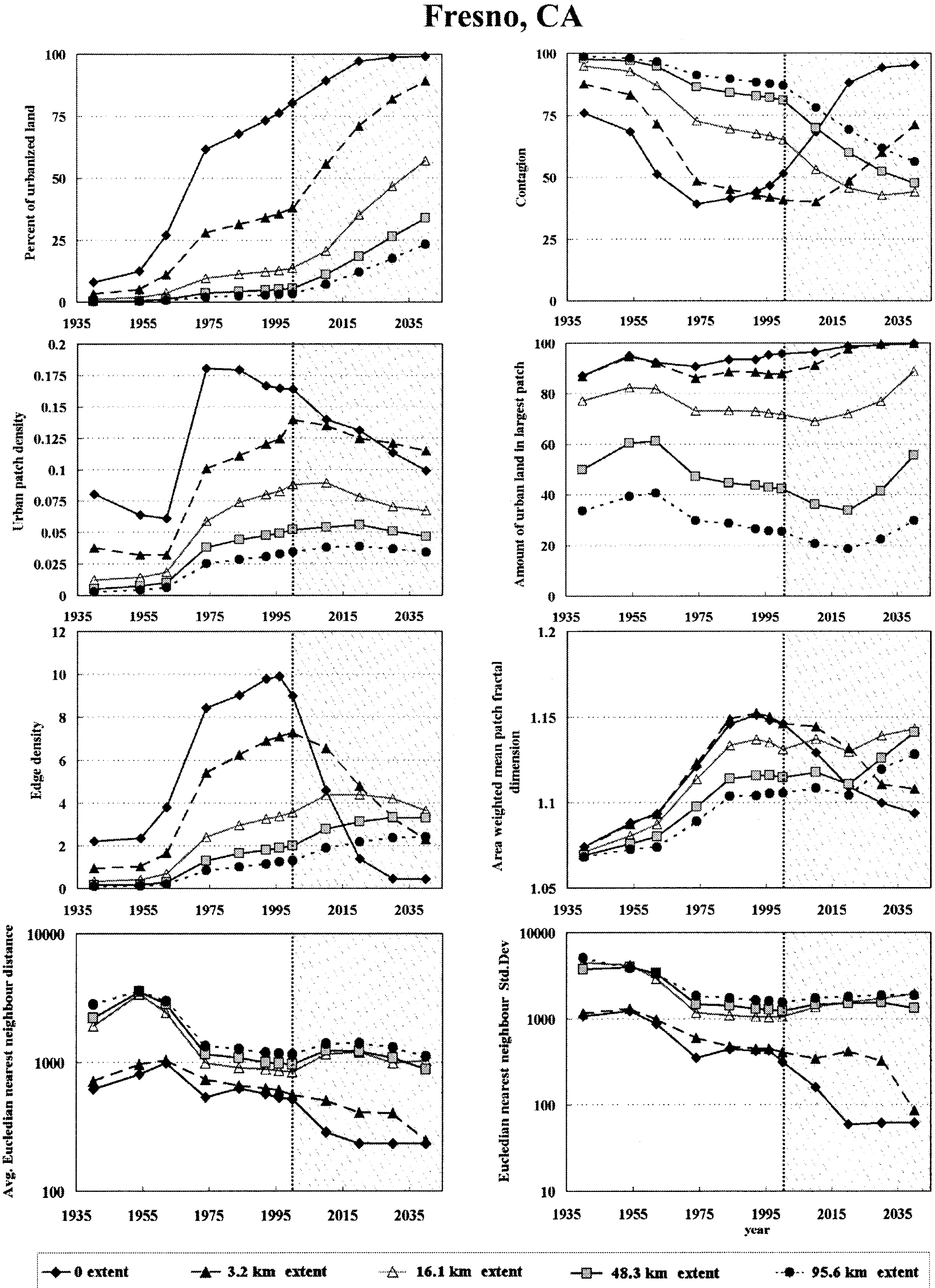

Figure 4. Spatial metric growth signatures for the Fresno urban area for multiple concentric ring buffers (Note: Metric values until 2000 are actual measurements, 2010–2040 are from modeling results. The vertical dashed line in each graph emphasizes this.)

core, the patch density decreases after 1974 as the new individual units grow together and become connected to the urban center. This development results in larger, more heterogeneous and fragmented urban patches. The spatial process that generates this general fragmentation pattern is reflected by the edge density and fractal dimension metrics, both of which have a peak in the mid-1990s. The process of coalescence of the individual urban patches and expansion into open spaces continues towards the later stage of urbanization of the landscape. This is reflected by the decreasing patch density and edge density in later dates. Also observed in the contagion metric, the patch density metric, and edge density metric, is that they all appear to have similar wave-like shapes for all spatial extents. The metric's value peaks first in the smallest scale and in chronological order the larger scales respond as the urbanization pattern moves outwards from the central core.

The diagrams at the bottom of Figure 4 show the changes in the Euclidean nearest neighbor distances. The average nearest neighbor distance shows a peak in the 1950s and 1960s for all scales. This time period represents the initial phase of diffuse allocation of new development units separated by large distances. With the major spread of new distinct urban development units in the late 1960s and 1970s the Euclidian nearest neighbor distances drop. The system of urban areas gets increasingly denser until the year 2000. A similar trend is shown for the nearest neighbor standard deviation metric that describes the regularity in the spatial arrangement of the individual urban patches. All scales show the highest values for the average Euclidian nearest neighbor distance metric in the early years; this is indicative of a diffuse and irregular urban patch configuration. As the diffusion of urban land continues, the pattern gets more regular, and the decreasing standard deviation in the nearest neighbor distances reflects this. This behavior in the spatial metrics is most pronounced in the period from the 1960s to the 1980s. The trends in both nearest neighbor metrics are similar for all observed scales until the year 2000 with the smallest scale having the lowest nearest neighbor distances and standard deviation.

With regard to the modeled future urban extents (2010, 2020, 2030 and 2040) the increase in the average Euclidean nearest neighbor distances can be directly attributed to the way the model emulates the growth behavior. CA-based urban growth models rely on the growth rules derived from the historical time series calibration data. The growth rules are focused on the local pixel neighborhood and as a result the urban patches with close proximity have a higher probability of coalescing. This is reflected by the increases in the mean nearest neighbor distances and the fractal dimension of the urban patches for those scales that still have a heterogeneous spatial structure, the 16 and 48 kilometers (10 and 30 mile) buffers. While these forecasts provide some indication of future trends in spatial patterns and a measure of evaluating if the framework holds true for the future, they cannot be considered when making conclusions. The only conclusive evidence is provided by the quantitative analysis derived from the historical datasets.

The metric signatures of the Bakersfield and Stockton/Modesto areas shown in Figure 5 appear to corroborate the hypothesized dynamic patterns in the multi-scale spatio-temporal urban growth. The graphs show four selected metrics for both of these areas. The contagion metric shows the wave-like shape for the landscape heterogeneity among the different scales. Urbanization, based on the historical data, provides the circumstantial evidence of a transformation from a homogenous non-urban, to a heterogeneous mix of urban and non-urban, and then a transition to a homogenous urban landscape. The other three spatial metrics, average Euclidian nearest neighbor distance, urban patch density and edge density, capture the

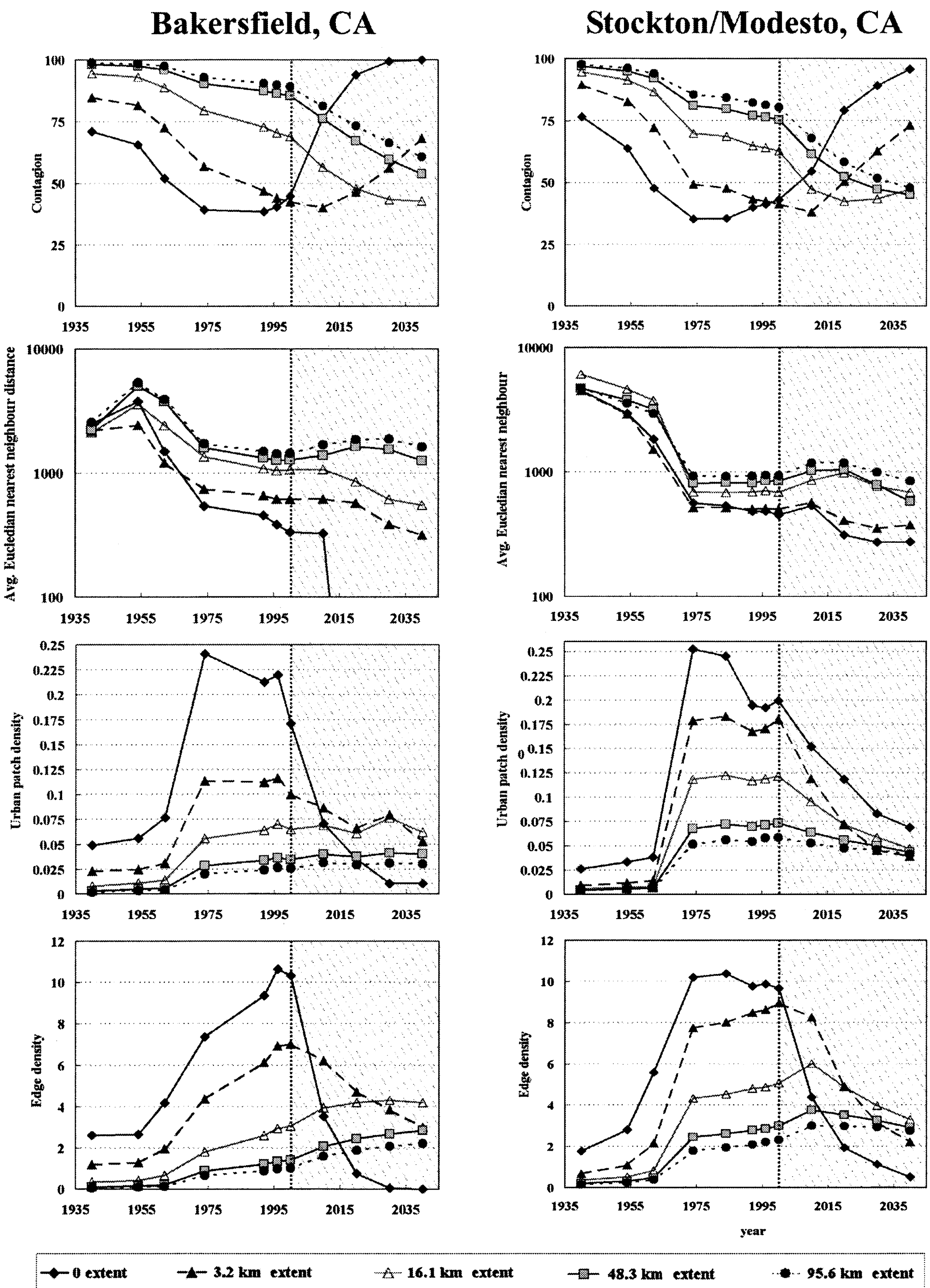

Figure 5. Spatial metric growth signatures for the Bakersfield and Stockton/Modesto urban area for multiple concentric ring buffers. (Note: Metric values until 2000 are actual measurements; 2010–2040 are from modeling results. The vertical dashed line in each graph emphasizes this.)

theoretical spatio-temporal phases of diffusion and coalescence. This is best shown by the central urban core that has completed a full "cycle" of urbanization at this scale. This cycle is characterized by an early diffusion of urban areas with the distances between them being relatively large and variable. As diffusion continues, patch density peaks and nearest neighbor distances decline. The agglomeration of urban patches gets denser and spatially more regular. During this time the process of coalescence begins to appear in the metrics; the patch density declines and the individual urban patches spatially aggregate. This process results in a lower number of larger patches that are more spatially heterogeneous and fragmented. This is reflected by a peak in the edge density metric. After the peak in edge density, the coalescence of the urban areas continues with a corresponding decrease in the patch density, edge density and the nearest neighbor distance metrics towards an increasingly homogenous urbanized landscape.

5. Discussion

The results from the empirical observations emphasize the general regularities in spatio-temporal urban growth dynamics. The regularities are apparent among different urban regions and for the different spatial extents. In terms of the hypotheses presented in section 2, the observed growth dynamics confirm the general assumptions. The processes of diffusion and coalescence are clearly identified in the spatio-temporal development of the investigated urban areas. Specific spatial metrics reflect these processes and can be used to describe and quantify them. Consequently, the results of this study have provided an advance on the theoretical aspects of urban growth dynamics and help to establish a link between the empirical, remote sensing based observations and urban theory represented by the theoretical framework presented in the beginning.

The study has also shown that the link between empirical measurements and the theoretical concept is, for now, only of a qualitative nature. There is no direct link to process. However, quantitative comparison reveals obvious differences among the metric signatures, in amplitude, duration, location and extent. Discrepancies appear between "real world" and theoretical patterns, among the investigated urban areas, and for the multiple concentric extents as they do with respect to most urban theories (von Thünen 1826, Burgess 1925, Hoyt 1939, Harris and Ullman 1945, Alonso 1964). These differences were anticipated in light of the fact that urban growth is not constant over time and among the different regions, and the spatial configuration of these areas is not uniform. Local urban growth factors and drivers such as topography, transportation network, growth barriers or planning efforts affect the spatial growth pattern. Exogenous factors (both spatial and thematic) must also be present. However, the local variations yield important information about the ongoing processes. The general processes of urbanization (diffusion and coalescence) are anticipated, but the local growth characteristics affect the evolving spatial pattern, and so they can be interpreted as "distortions": amplifications, lagging, or damping in the metric signatures. As in other models, the distortions can be thought of as the residual between the growth pattern under uniform, isotropic spatial and temporal conditions and the observed real-world urbanization dynamics. Again, examples of factors that determine the spatial and temporal variations are the rate of urban growth, topographic constraints, road attraction, growth barriers, exogenous factors such as the business cycle, and planning efforts. Although these factors are quite diverse, there is usually sufficient information and appropriate datasets available to describe them, so it may be possible to account for these distortions and relate them to the observed and theoretical patterns as well as to account for residuals. Given a sufficient representation of local growth characteristics it should be possible to replicate the theoretical harmonic growth patterns under "ideal" conditions, based on the idea of urban growth phases (Cressy 1939, Hoover and Vernon 1959, Duncan *et al.* 1962, Winsborough 1962) and the concept of urban growth having wave-like properties (Blumenfeld 1954, Boyce 1966, Newling 1969). This concept has great potential to further establish and ultimately provide a quantitative link between empirical observation and urban theory.

An important issue in this context relates to the initial and final conditions of the urbanization process. The initial conditions are determined by the first date for which information about the urban extent is available. This first date of mapped urban extent may or may not indicate the stage of urbanization a particular city is in. Ideally, the first available dataset represents the urban area in its initial core or urban seed. This is usually not the case, since most settlements were established a century ago or more. In any case, the initial spatial urban landscape configuration is of special importance if the urbanization process is to be analyzed in the light of the framework and methods applied in this study. Under unconstrained conditions, an area can achieve a state of 100% urbanization characterized by a completely built-out landscape. However, if constraints or barriers are introduced, or are already present, the final spatial configuration of the urban landscape will show some degree of heterogeneity and may not follow a hypothetical "ideal" cycle of urbanization.

Another major objective is to explore the relationship of the metrics among the different concentric ring buffers. Analogies between the behavior of waves and the concentric spatial expansion of urban areas have been previously discussed (Blumenfeld 1954, Boyce 1966). The theoretical framework may be adaptable to the scaling of relationships concerned with changes in the spatial extent as investigated in this study, i.e. the spatio-temporal characteristics of the diffusion and coalescence processes (wavelength and amplitude of cycles) as a function of distance from the central urban core. The empirical observations have revealed some trends in the spatial metrics. Most metrics appear to follow the hypothesized pattern with longer cycles of urbanization with increasing distance from the central core, e.g. for contagion and edge density. The nearest-neighbor standard distance measures and the urban patch density on the other hand seemingly indicate a parallel behavior among the multiple scales. This suggests that the diffusion process similarly influences the overall growth pattern of all spatial extents whereas coalescence changes consistently outwards from the central core with an increasing wave-like form for larger distances.

This research regarding theoretical phases of urban growth bears some resemblance to prior research. Work on theoretical urban wave patterns described by Blumenfeld (1954) and Newling (1969) also included projections of future trends and alluded to the fact that a wave theory was not in itself an explanation for the observed patterns. Different in the approach applied here is that the detailed multi-temporal spatial dataset and the analysis of structure using spatial metrics was quantitative not qualitative. Also different is the timeframe; including model outputs to increase the temporal scale has generated an interesting picture of the spatio-temporal dynamics of urban growth, providing the groundwork for future research in this area.

Ultimately, the theoretical considerations should directly support the analysis and modeling of urban growth dynamics. The knowledge gained from this approach about the spatio-temporal patterns of development of urban areas might contribute to known problems in spatial urban modeling. As indicated in Figure 4, and in other related studies (O'Sullivan and Torrens 2001, Wu 2002), CA-based urban models tend to result in compact and overly aggregated urban growth due to the dependence on local growth rules (Luck and Wu 2002). This behavior is undoubtedly reflected in particular spatial metrics; the patch density drops significantly, and the average nearest neighbor distance rises as proximate urban patches become increasingly connected. In terms of the spatial processes, the CA model overemphasizes the coalescence of urban areas, or does not allow for sufficient diffusion. Given sufficient information that describes the process of diffusion and coalescence for a particular area, the model outputs might be able to serve as a guide or reference for potentially more accurate representations of dynamic spatial processes (Torrens and O'Sullivan 2001). Similarly, a measure of model success is the inability to detect the transition from real to forecast data in the metric signatures.

6. Conclusion

Analysis, modeling, and management of urban growth require a fundamental understanding of the spatial process itself. As a contribution to improving common knowledge of urban dynamics, we approached this problem by developing a theoretical framework that represents our general hypotheses of spatial urban evolution, and evaluating and comparing those assumptions with measured observations of urbanization patterns in California's Central Valley. The empirical investigations combined the use of remotely sensed data sources, spatial modeling and spatial metric analysis techniques to provide a time frame of 100 years of historical and forecasted urban growth.

The approach has proven to be useful for investigating spatio-temporal urban dynamics from an empirical perspective. In this study it was possible to begin isolating some structural components of urban growth, to link them to spatial processes, and to characterize these processes within the proposed theoretical framework. More specifically, the interpretations of the empirical results confirm the dynamic spatio-temporal cycles of diffusion and coalescence by which an urban area evolves at a given spatial extent. Metrics such as edge density, patch density and nearest neighbor Euclidian distance have shown their utility for identifying both phases of urban expansion (diffusion and coalescence). The link between empirical observation and urban theory is only of a qualitative nature since the comparison of both patterns did show substantial differences. However, it is argued that they can be understood as distortions, e.g. the residuals that result from, among other things, the initial conditions prior to the onset of rapid urbanization, particular spatial factors such as barriers to growth, urban development management efforts or differential growth rates. Considering available information about these factors, it should be possible to account for the distortions and extend the link to urban theory.

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7. References

ALBERTI, M. and WADDELL, P., 2000, An integrated urban development and ecological simulation model. *Integrated Assessment*, **1**, pp. 215–227.

ALONSO, W., 1964, *Location and Land Use* (Cambridge: Harvard University Press).

BATTY, M., 1991, Generating urban forms from diffusive growth. *Environment and Planning A*, **23**, pp. 511–544.

BATTY, M., 2002, Thinking about cities as spatial events. *Environmental and Planning B*, **29**, pp. 1–2.

BATTY, M. and HOWES, D., 2001, Predicting temporal patterns in urban development from remote imagery. In *Remote Sensing and Urban Analysis*, by J.P. Donnay, M.J. Barnsley and P.A. Longley editors (London: Taylor and Francis), pp. 185–204.

BATTY, M. and LONGLEY, P.A., 1994, *Fractal cities: A Geometry of Form and Function* (London: Academic Press).

BLUMENFELD, H., 1954, The tidal wave of metropolitan expansion. *Journal of the American Institute of Planners*, **20**, pp. 3–14.

BOYCE, R.R., 1966, The edge of the Metropolis: The wave theory analog Approach. *British Columbia Geographical Series*, **7**, pp. 31–40.

BURGESS, E.W., 1925, The Growth of the City: an Introduction to a Research Project. In *The City*, by R.E. Park, E.W. Burgess and R.D. McKenzie, editors (Chicago: The Chicago University Press), pp. 47–62.

California Farmland Mapping and Monitoring Program, 2003. http://www.consrv.ca.gov/DLRP/fmmp/.

CLARK, C., 1951, Urban population densities. *Journal of the Royal Statistical Society*, **64**, pp. 490–496.

CLARKE, K.C. and GAYDOS, L., 1998, Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographic Information Science*, **12**, pp. 699–714.

CLARKE, K.C., HOPPEN, S. and GAYDOS, L., 1997, A self-modifying cellular automata model of historical urbanization in the San Francisco Bay area. *Environment and Planning B*, **24**, pp. 247–261.

COUCLELIS, H., 1985, Cellular worlds: a framework for modeling micro-macro dynamics. *International Journal of Urban and Regional Research*, **17**, pp. 585–596.

CRESSY, P.F., 1939, Population succession in Chicago, 1898–1930. *American Journal of Sociology*, **44**, pp. 59–69.

DIETZEL, C., In Press, Spatio-temporal differences in model outputs and parameter space as determined by calibration extent. In *Geodynamics*, by P. Atkinson, G. Foody, S. Darby and F. Wu, editors (London: Taylor and Francis).

DUNCAN, B., SABAGH, G. and VAN ARSDOL, M.D., 1962, Patterns of city growth. *American Journal of Sociology*, **67**, pp. 418–429.

ESNARD, A.M. and YANG, Y., 2002, Descriptive and comparative studies of the 1990 urban extent data for the New York Metropolitan Region. *URISA Journal*, **14**, pp. 57–62.

FOTHERINGHAM, A.S., BATTY, M. and LONGLEY, P., 1989, Diffusion-limited aggregation and the fractal nature of urban growth. *Papers of the Regional Science Association*, **67**, pp. 55–69.

FRANCK, G. and WEGENER, M., 2002, Die Dynamik räumlicher Prozesse. In *Raumzeitpolitik*, by D. Henckel and M. Eberling, editors (Opladen: Leske & Budrich), pp. 145–62.

GOLDSTEIN, N.C., CANDAU, J.T. and CLARKE, K.C., 2004, Approaches to simulating the "March of Bricks and Mortar." *Computers, Environment and Urban Systems*, **28**, pp. 125–147.

GOODCHILD, M.F., 1992, Geographical information science. *International Journal of Geographical Information Systems*, **6**, pp. 31–45.

GUSTAFSON, E.J., 1998, Quantifying landscape spatial pattern: What is the state of the art? *Ecosystems*, **1**, pp. 143–156.

Haack, B.N., Guptill, S.C., Holz, R.K., Jampoler, S.M., Jensen, J.R. and Welch, R.A., 1997, Urban analysis and planning. In *Manual of Photographic Interpretation*, by W.R. Philipson, editors (Falls Church: American Society of Photogrammetry), pp. 517–554.

Harris, C. and Ullman, E., 1945, The nature of cities. *Annals of the American Academy of Political and Social Science*, **242**, pp. 7–17.

Herold, M., Clarke, K.C. and Scepan, J., 2002, Remote sensing and landscape metrics to describe structures and changes in urban landuse. *Environment and Planning A*, **34**, pp. 1443–1458.

Herold, M., Goldstein, N.C. and Clarke, K.C., 2003, The spatiotemporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment*, **86**, pp. 286–302.

Herold, M., Couclelis, H. and Clarke, K.C., in press, The role of spatial metrics in the analysis and modeling of land use change. *Computers, Environment and Urban Systems*.

Hoover, E.M. and Vernon, R., 1959, *Anatomy of a metropolis. The changing distribution of people and jobs within the New York Metropolitan Region* (Cambridge: Harvard University Press).

Hoyt, H., 1939, The structure of Growth of residential neighborhoods in American Cities (Washington DC: Federal Housing Authority).

Jensen, J.R. and Cowen, D.C., 1999, Remote sensing of urban/suburban infrastructure and socio-economic attributes. *Photogrammetric Engineering and Remote Sensing*, **65**, pp. 611–622.

Johnson, R.J., 1972, Towards a general model of intra-urban residential patterns: some cross-cultural observations. In *Progress in Geography, Volume 4* (London: Edward Arnold).

Korcelli, P., 1976, Theory of intra-urban structure: Review and synthesis. A cross-cultural perspective. *Geographica Polonica*, **31**, pp. 99–131.

Leão, S., Bishop, I. and Evans, D., 2004, Spatial-temporal model for demand allocation of waste landfills in growing urban regions. *Computers, Environment and Urban Systems*, **28**, pp. 353–385.

Li, X. and Yeh, A., 2001, Zoning land for agricultural protection by the integration of remote sensing, GIS, and cellular automata. *Photogrammetric Engineering and Remote Sensing*, **67**, pp. 471–477.

Longley, P.A., 2002, Geographical information systems: Will developments in urban remote sensing and GIS lead to 'better' urban geography? *Progress in Human Geography*, **26**, pp. 231–239.

Longley, P.A. and Mesev, V., 2000, On the measurement of urban form. *Environment and Planning A*, **32**, pp. 473–488.

Luck, M. and Wu, J., 2002, A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan region, Arizona, USA. *Landscape Ecology*, **17**, pp. 327–339.

McGarigal, K., Cushman, S.A., Neel, M.C. and Ene, E., 2002, FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps, www.umass.edu/landeco/research/fragstats/fragstats.html.

Newling, B.E., 1969, The spatial variation of urban population densities. *Geographical Review*, **59**, pp. 242–252.

O'Neill R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H. and Graham, R.L., 1988, Indices of landscape pattern. *Landscape Ecology*, **1**, pp. 153–162.

O'Sullivan D. and Torrens, P., 2001, Cellular models of urban systems. In *Proceedings of the Fourth International Conference on Cellular Automata for Research and Industry* (London: Springer), pp. 108–116.

Portugali, J., 2000, *Self-organization and the City* (New York: Springer-Verlag).

SAURA, S. and MARTINEZ-MILLAN, J., 2001, Sensitivity of landscape pattern metrics to map spatial extent. *Photogrammetric Engineering and Remote Sensing*, **67**, pp. 1027–1036.

SCHNORE, L.F., 1965, On the spatial structure of the cities in the two Americas. In *The Study of Urbanization*, by P.H. Hauser and L.F. Schnore, editors (New York: Wiley and Sons), pp. 347–398.

SILVA, E.A. and CLARKE, K.C., 2002, Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems*, **26**, pp. 525–552.

State of California, Department of Finance, 1998, County population projections with age, sex, race/ethnic detail, http://www.dof.ca.gov/HTML/DEMOGRAP/Proj_age.htm.

TOBLER, W., 1979, Cellular geography. In *Philosophy in Geography*, by S. Gale and G. Olsson, editors (Dordrecht: D. Reidel Publishing Group), pp. 379–386.

TORRENS, P. and O'SULLIVAN D., 2001, Cellular automata and urban simulation: where do we go from here? *Environment and Planning B*, **28**, pp. 163–168.

United States Geological Survey, 2003, Preliminary Assessment of Urban Growth in California's Central Valley, http://ceres.ca.gov/calsip/cv/.

VON THÜNEN, J.H., 1826, "The Isolated State".

WEGENER, M., FEIDRICH, G. and VANNAHME, M., 1986, The time scale of urban change. In *Advances in Urban Systems Modelling*, edited by B. Hutchinson and M. Batty, editors (Amsterdam: Elsevier Science), pp. 145–197.

WHITE, R. and ENGELEN, G., 1993, Cellular automata and the fractal evolution of form: a cellular modelling approach to the evolution of urban-land use patterns. *Environment and Planning A*, **25**, pp. 1175–1199.

WHITE, R., LUO, W. and HATNA, E., 2001, Fractal Structures in Land Use Patterns of European Cities: Form and Process, 12th European Colloquium on Quantitative and Theoretical Geography, September 7–11, 2001. St-Valery-en-Caux, France.

WINSBOROUGH, H.H., 1962, City growth and city structure. *Journal of Regional Science*, **4**, pp. 35–50.

WU, F., 2002, Calibration of stochastic cellular automata: the application to rural–urban land conversions. *International Journal of Geographic Information Science*, **16**, pp. 795–818.

YANG, X. and LO, C.P., 2003, Modelling urban growth and landscape change in the Atlanta metropolitan area. *International Journal of Geographical Information Science*, **17**, pp. 463–488.