Journal of Applied Sciences 7 (14): 1843-1853, 2007
ISSN 1812-5654

Calibration of the Sleuth Model Based on the Historic Growth of Houston

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Abstract: The SLEUTH cellular automaton urban growth model was calibrated against historical growth in the Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) from 1974-2002. The Houston CMSA presents an interesting case study of modeling urban growth using SLEUTH. Houston is perhaps the archetypal Sunbelt city and experienced rapid population growth over the calibration period. Compared to many other United States cities, Houston's local governments have a laissez-faire approach to development; in fact Houston is the only major US metropolitan area with no zoning regulations. Calibration of SLEUTH reveals that over the study period urban growth in the Houston CMSA was dominated organic growth, with urban expansion occurring at the urban edges of existing urban centers. Lack of zoning regulations is thought to play an important role on the outward growth of urbanization in Houston.

Key words: SLEUTH modeling, GIS, remote sensing, urban growth, houston CMSA

INTRODUCTION

The urbanization has been described as a massive unplanned global experiment affecting increasingly large areas of the Earth (Alig and Healy, 1987). Each year, the world's urban population is increasing by approximately 67 million people or 1.3 million every week. By 2030, approximately 5 billion people are expected to reside in urban areas and will account for 60% of the planet's 8.3 billion people (UN, 2002). The increasing global urbanization is mirrored within the United States. From 1990 to 2000, eight of the United States twenty-five largest metropolitan areas grew by at least 20% (USCB, 2001). The 11th fastest growing metropolitan area from 1990-2000 was Houston, Texas. Houston has been nicknamed the beltbuckle of the Sunbelt (Fisher, 2003) and is unique in that it is the only major metropolitan city that functions without zoning regulations or plans (Vojnovic, 2003).

Modeling, especially computer modeling is an essential tool for the analysis and particularly for the prediction of the urban growth (Silva and Clarke, 2002). In particular Cellular Automata (CA) models have been successfully used in modeling urban growth. Unfortunately, the successful application of a particular urban growth model in one particular geographical area does not necessarily mean that it will be successful in another area. This is because of the differences in the physical and social environments such as zoning regulations in Houston, TX. Therefore, before using urban growth models to imitate future growth of urban areas, it is necessary to test their ability in order to simulate past observed land transformations of specific areas (Batty and Xie, 1994; Clarke *et al*., 1996; Li and Yeh, 2000).

MATERIALS AND METHODS

Study area: The Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA) encompasses three Primary Metropolitan Statistical Areas (PMSAs) in eight counties on the Texas Gulf Coast (Fig. 1). In 2000, the total population of the Houston CMSA's was 4.67 million making it the 10th largest US metropolitan statistical area. Most of the region's population is concentrated in and around the city of Houston. The Houston PMSA occupies six counties: Chambers, Fort Bend, Harris, Liberty, Montgomery and Waller. The two other PMSAs, Galveston-Texas City and Brazoria, each occupy a single county, Galveston and Brazoria, respectively. The 2002 population of the statistical areas and counties is shown in Table 1.

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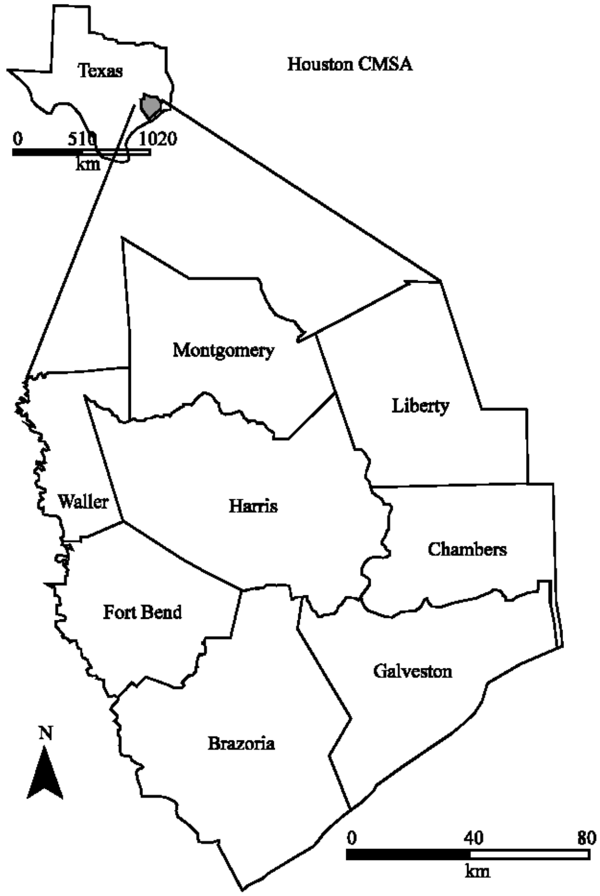

Fig. 1: The eight counties comprising the Houston Consolidated Metropolitan Statistical Area (CMSA)

Table 1: Area and population of geographic entities within the Houston CMSA study area

Regions	2000 population*	Area (km^2)
Houston CMSA	4,669,571	22,736
Houston PMSA	4,177,646	16,328
Brazoria PMSA	241,767	4,138
Galveston PMSA	250,158	2,270
Brazoria county	241,767	4,138
Chambers county	26,031	1,551
Fort Bend county	354,452	2,266
Galveston county	241,767	2,270
Harris county	3,400,578	4,605
Liberty county	70,154	3,004
Montgomery county	293,768	2,704
Waller county	32,663	1,335
City of Houston	1,953,631	1,539

*: US Census, 2001

Houston, Texas, is located on the low relief Gulf coastal plain approximately 50 miles from the Gulf of Mexico (Fig. 2). In 2000, Houston's population was 1.95 million making it the fourth most populous city in the nation, trailing only New York, Los Angeles and Chicago (US Census Bureu, 2001). The largest city in Texas, Houston is also the only United States city that functions without zoning regulations (Vojnovic, 2003).

During the 1970's the region experienced an economic boom fueled by high oil prices, but with declining oil prices during the 1980's the area had a severe economic downturn. However, despite Houston's 1980's economic downturn, its population doubled over the study period from approximately 2.2 million in 1970 to 4.5 million in 2000 (TSDC, 2003). Figure 3 shows past and projected population growth in the Houston CMSA from 1960 to 2030.

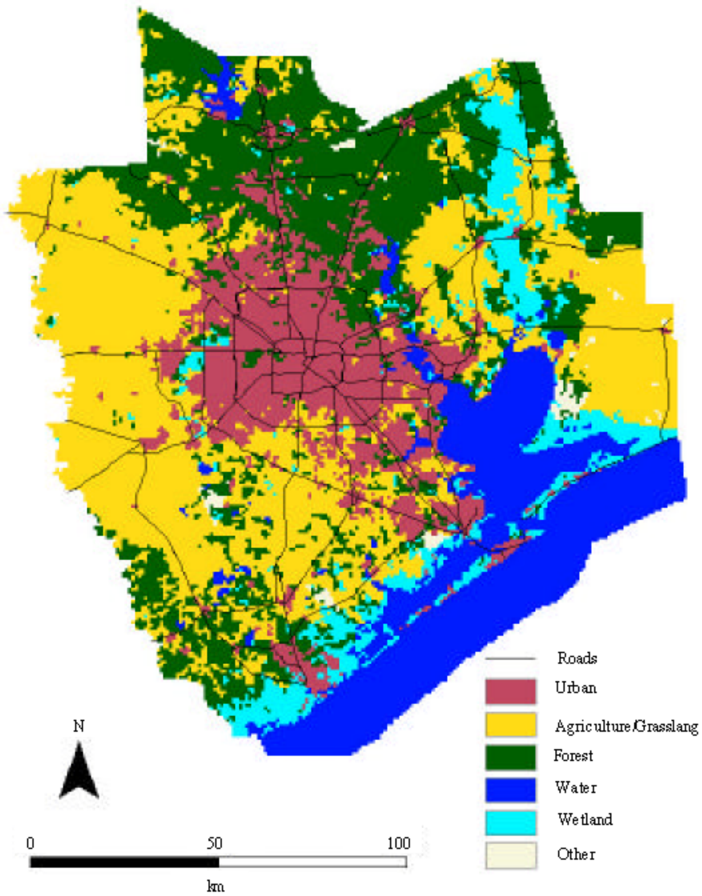

Fig. 2: 2002 Land use/land cover map of the Houston Consolidated Metropolitan Statistical Area (CMSA) derived from Landsat ETM+ images with roads and county lines overlaid

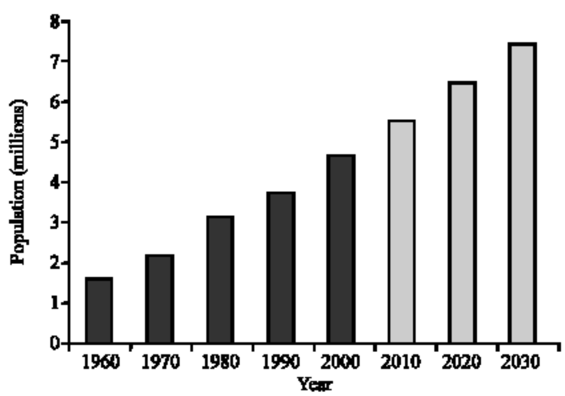

Fig. 3: Past (black bars) and projected (gray bars) population in the Houston Consolidated Metropolitan Statistical Area (CMSA). Population figures and estimates are from The Perryman Group (2002) and Texas State Data Center (2003), respectively

SLEUTH requires land use, urban extent, excluded areas, transportation network and slope themes (layers) to perform a simulation as well as hillshade image for visualization (Table 2). For statistical purposes, urban extent from at least four time periods and transportation layers from at least two years are required. If land use change analysis is of interest, land use/land cover from at least two time periods is also required.

The method of the study consisted of three main steps: 1 Pre-processing of digital images (geo-rectification), 2 Unsupervised ISODATA (Iterative self-organizing data algorithm) clustering and 3 Post-processing of digital images (resampling). All input images were reprojected into Albers Equal Area Conic Projection using first order polynomial transformation and nearest neighbor algorithm. After this procedure, subsets for the study area were extracted from original full-scene images. All images were resampled into 100 m after the classification of satellite images was finished. This selected spatial resolution represents a balance between adequate representation of the Houston's landscape and the processing (CPU) requirements of the SLEUTH model. This spatial resolution resulted in a model spatial domain of 184.3 by 210 km (1843 by 2100 pixels) encompassing approximately 22,736 km^2. All necessary resampling was accomplished using a nearest neighbor technique. Finally, all inputs were converted into the grayscale 8-bit GIF format which is required by SLEUTH.

Urban extent and land cover was obtained from the Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images listed in Table 3. For each time period, a mosaic of three MSS or TM scenes covered the 8-county metropolitan area. Four Landsat MSS Triplicate scenes were obtained from the USGS Land Processes Distributed Active Archive Center (DAAC). From the triplicates, only the 1974 MSS and 1984 TM scenes were used which were augmented by Landsat TM and ETM+ images from 1992 and 2002.

1992 and 2002 Land use/land cover information for the Houston metropolitan area were developed from two different sources. Land use for 1992 was obtained from the National Land Cover Dataset (NLCD) (MRLC, 2003). For the SLEUTH modeling, the NLCD's original land cover classes were reclassified to match the 2002 land use classification schema. 2002 Land cover map was obtained from three Landsat ETM+scenes (Table 3). Each scene was individually classified using the ISODATA unsupervised classification, the resulting land cover classes were then merged into six general land cover classes (Table 4).

Finally, the individual land cover maps were mosaiced into a single map (Fig. 1). The classification accuracy of the 2002 land cover map was assessed through comparison with a similar 2002 land cover map produced by the Houston-Galveston Area Council (H-GAC). A confusion matrix of the assessment is presented in Table 5 (Congalton, 1991; Congalton and Mead, 1983). Compared to the H-GAC map, the overall accuracy of the classification was 87.3% with a kappa (κ_{hat}) coefficient of 0.82.The water and agricultural classes had user's accuracies in excess of 90% while forest and urban areas were less accurately classified at 83.8 and 77.8%, respectively. This comparison provides at least a limited indication that the remote sensing derived urban extents and land cover, at least for 2002, are of adequate quality for SLEUTH inputs. Urban extent from 1974 and 1984 was derived using the using ISODATA unsupervised classification technique to segment the individual MSS and TM images (Table 3) into urban/non-urban classes which were then mosaiced. Urban extent for 1992 and 2002 were obtained from the Landsat TM-derived land cover maps. Urban extent for all years is shown in Fig. 4. Information concerning which areas

Table 2: Input data sources and years for SLEUTH model

Theme	Source	Format	Years
Urban	Landsat MSS, TM, ETM+	Raster	Approx** 1974, 1984, 1992, 2002
Lulc	Landsat TM, ETM+	Raster	Approx** 1992, 2002
Road*	Shapefiles	Vector	1974, 1984, 1990, 2002, 2025
Excluded	Landsat TM	Raster	N/A
Slope	National Elevation Dataset (NED)	Raster	N/A
Hillshade	National Elevation Dataset (NED)	Raster	N/A

*: Not used for calibration; **: Multiple satellite images were required to cover the study area shown in Table 3 for all image dates

Table 3: Landsat scenes used in the study

Sensor	Path/Row	Date
1970s Era		
MSS	025/039	1974-07-13; 1974-06-26
MSS	026/039	1974-06-26; 1974-06-27
MSS	025/040	1973-04-01; 1974-06-26
MSS	026/040	1975-10-17; 1976-09-22
1980s Era		
TM	025/039	1985-06-01
TM	026/039	1984-07-15
TM	025/040	1985-06-01
TM	026/040	1986-10-17
1990s Era		
TM	025/039	1992-07-06
TM	026/039	1990-07-08
TM	025/040	1992-07-06
TM	026/040	1992-10-01
2000 Era		
ETM+	025/039	2002-01-15
ETM+	026/039	2002-02-23
ETM+	025/040	2002-01-15
ETM+	026/040	Not used

Table 4: Land use/Land cover categories determined from the 2002 Landsat ETM+ and used in SLEUTH and their equivalents in the NLCD

SLEUTH	NLCD
Urban	Low intensity residential
	High intensity residential
	Commercial/Industrial/Transportation
Agriculture	Shrub land
	Orchards/Vineyards/Other
	Grasslands/Herbaceous
	Pasture/Hay
	Row crops
	Small grains
	Fallow
	Urban/Recreational grasses
Forest	Deciduous forest
	Evergreen forest
	Mixed forest
Water	Open water
Wetland	Woody wetlands
	Emergent herbaceous wetlands
Other	Bare rock/Sand/Clay
	Quarries/Strip mines/Gravel pits
	Transitional

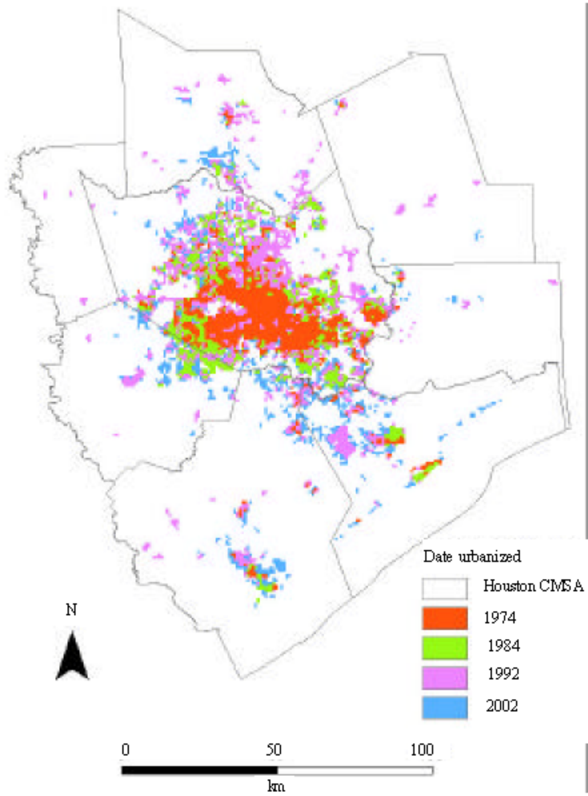

Fig. 4: Urban extent in the Houston Consolidated Metropolitan Statistical Area (CMSA) for 1974, 1984, 1992 and 2002

Table 5: Confusion matrix for the 2002 Land use/Land cover map

Land cover	Urban	Agric.	Forest	Water	Wetland	Other	Row total	Producers accuracy (%)	Users accuracy (%)
Urban	28	5	1	1	1	0	36	93.3	77.8
Agriculture	1	117	4	0	4	0	126	89.3	92.9
Forest	1	5	67	0	7	0	80	89.3	83.8
Water	0	0	1	35	0	0	36	97.2	97.2
Wetland	0	2	2	0	15	0	19	53.6	79.0
Other	0	2	0	0	1	0	3	---	---
Column total	30	131	75	36	28	0	300		

Overall classification accuracy: 87.3%; Kappa (κ_{hat}): 0.82

Table 6: Excluded layer with respective values to be used in calibration phase in SLEUTH model

Land cover	Area excluded from development (%)
Agriculture	40
Forest	40
Floodplain	40
Wetlands	60
Parks	90
Water	100
Unclassified	100

in the Houston CMSA should be excluded from development was obtained from a variety of sources. Because flooding is a major problem in Houston, floodplains were specifically excluded as were parks. For all counties except Harris, floodplain extent was derived from digital Federal Emergency Management (FEMA) floodplain maps. Harris County floodplain maps were obtained from the Texas Coastal Watershed Program. Park maps were obtained the Texas General Land Office. Forest, agriculture, wetland and water extents were determined from 2002 land cover classification. The percent of each land cover class that was determined to be excluded from development is shown in Table 6.

Transportation network maps for 1974, 1984, 1990 and 2002 were constructed as follows. First, vector GIS themes of the road infrastructure in the Houston CMSA in 1990 and 1999 were obtained from the Houston-Galveston Area Council (H-GAC). Then using printed Texas Department of Transportation (TxDOT) highway maps, major

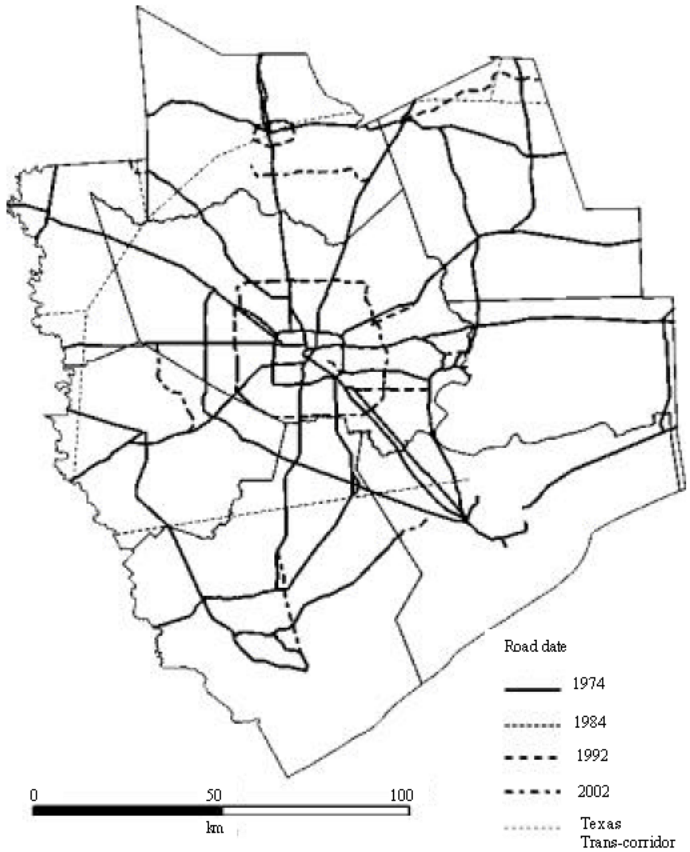

Fig. 5: Major roads in the Houston Consolidated Metropolitan Statistical Area (CMSA) in 1974, 1984, 1992 and 2002

highways existing during the four years of interest were identified and extracted from the original GIS themes. A vector-to-raster conversion was used to convert the selected roads into a raster grid. The route of the planned TxDOT's, Trans-Texas Corridor (TTC, 2006) road through the study area was also identified. This Corridor is planned to be constructed by 2025 and while not used in the calibration, forms an integral part of the transportation infrastructure that was used for predictive modeling of future urban extents. The road network for all years is shown in Fig. 5. Slopes and the hillshade image were derived using standard GIS techniques from the National Elevation Dataset (NED) Digital Elevation Model (DEM) (Gesch *et al*., 2002) which was obtained from the Texas Natural Resources Information System (TNRIS, 2006).

The number of recent publications (Batty and Xie, 1994; Birkin *et al*., 1996; Clarke *et al*., 1996; Landis and Zhang, 1998; Silva and Clarke, 2002) describing the calibration of SLEUTH for metropolitan areas worldwide attests to the importance of the calibration procedure. The model's ability to successfully reproduce observed growth and predict future growth of the Houston region depends on the success of the calibration phase.

SLEUTH utilizes a three phase (coarse, fine and final) calibration approach. During each phase, the calibration process identifies the values for the five growth coefficients that produce the model that best matches the observed pattern of urban growth over the calibration period. In this study the calibration period ran from 1974 to 2002 during which urban extent maps were available for 1974, 1984, 1992 and 2002.

The SLEUTH calibration process is an automated brute force method in which numerous permutations of the five control parameters are tested by performing multiple runs running over the 1974 to 2002 period. For each of the four comparisons, 13 different measures of the goodness-of-fit measures (Table 7) between the modeled and the mapped urban extent are used to assess the accuracy of the simulated urban growth.

While no single metric has been demonstrated to be the most effective at discriminating the best suite of coefficients, the Lee-Sallee metric has been used to

Table 7: Metrics that can be used to measure the goodness of fit in the SLEUTH model

Name	Description
Product	All other scores multiplied together
Compare	Modeled population for final year/actual population for final year, or IF $P_{modeled} > P_{actual}$ { 1 - (modeled population for final year/actual population for final year)}.
Pop	Least squares regression score for modeled urbanization compared to actual urbanization for the control years
Edges	Least squares regression score for modeled urban edge count compared to actual urban edge count for the control years
Clusters	Least squares regression score for modeled urban clustering compared to known urban clustering for the control years
Cluster Size	Least squares regression score for modeled average urban cluster size compared to known average urban cluster size for the control years
Lee-Sallee	A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years
Slope	Least squares regression of average slope for modeled urbanized cells compared to average slope of known urban cells for the control years
(%) Urban	Least squares regression of percent of available grid cells urbanized compared to the urbanized grid cells for the control years
X-Mean	Least squares regression of average x_values for modeled urbanized cells compared to average x_values of known urban cells for the control years
Y-Mean	Least squares regression of average y_values for modeled urbanized cells compared to average y_values of known urban cells for the control years
Rad	Least squares regression of average radius of the circle which encloses the urban grid cells
F-Match	A proportion of goodness of fit across land use classes. {#_modeled_LU correct/(#_modeled_LU correct + #_modeled_LU wrong)}

describe the replication of the historical datasets, in other words, as the primary goodness-of-fit measure.

At the end of the coarse and fine calibration stages, the calibration result metrics are sorted and parameters of the highest scoring model runs are used to begin the next, more refined sequences or permutations over the parameter space. This calibration approach relies on the availability of significant computing power and benefits significantly from parallel processing and high performance computing methods. Both coarse and fine calibrations were run on a 1.3 GHz Intel Linux workstation while the final calibration phase was run on a 16-node Beowulf PC Cluster in the Rocky Mountain Mapping Center of the U.S. Geological Survey.

During the coarse calibration phase, SLEUTH was tested values of 1, 25, 50, 75 and 100 for each of the five control parameters. This required testing of 3, 125 (5^5) different parameter sets, each of which required a separate model run. From all combinations, the three runs with the highest Lee-Sallee scores were selected to form the parameter range used in the fine calibration (Table 8).

For the fine calibration, same procedure was followed and resulted in the control parameter values shown in Table 9. A similar approach was taken during final calibration which produced the set of control parameters adapted for the Houston CMSA (Table 10). The second sections of Table 8-10 list the optimum values for the diffusion, breed, spread, slope and road gravity coefficients and shows the narrowing of the range of parameters for the best-fitting models produced at the end of each calibration stage.

The calibration process produces coefficient values that best simulate historical growth for a region. However, due to SLEUTH's self-modification qualities, the values of the five growth coefficients at the start of the calibration period may differ substantially from those at the end of the calibration period.

To achieve the best predictions of future growth in the Houston CMSA, it is desirable to use the best coefficients derived from calibrating and running SLEUTH for the entire historical calibration period that produces a single set of finishing date coefficients to initialize forecasting (Clarke *et al*., 1997). However, due to the random variability of the model, averaged coefficient values taken from multiple Monte Carlo-iterations will produce a more robust forecasting coefficient set than those taken from the single best simulation, therefore an average of the three best simulations was used.

It is possible to see that the coefficients that control urban growth over the calibration period change through time as it shown for the three comparison years in Table 11. The increase in the spread coefficient and decrease in slope resistance over the calibration period are the most obvious changes. The spread coefficient jumped from 77 to 100 after self-modification while slope resistance nearly halved from 40 to 22. One possible interpretation of these values is that these changes reflect the economic boom and bust cycles of Houston during the calibration period. The increase in the spread coefficient may indicate every increasing growth away from the study area's main nucleus-the city of Houston. Despite its relatively low slopes, as urban areas continue to expand, less space remains for urbanization. Thus, self-modification causes slope resistance to decrease.

An additional statistical validation of the models predictive performance was undertaken by running the model in prediction mode and using the 1974, 1984 and 1992 urban extents to predict urban extent in 2002. The modeled urban extent was then compared statistically to a 2002 urban extent map which was derived from Landsat EMT+images. This comparison is graphically shown in Fig. 6.

An error (confusion) matrix (Clarke and Gaydos, 1998; Congalton and Mead, 1983) and kappa coefficient were constructed to quantify the degree comparison accuracy (Table 12). The results are encouraging and support the fact that the calibration process resulted in a suite of control parameters suitable for predicting future urban

Table 8: Coarse calibration, 526 rows x 462 columns

Run	Product	Compare	Population	Edges	Cluster	Cluster size	Lee-Salee
70	0.00148	0.78558	0.99959	0.89401	0.61675	0.37173	0.54257
66	0.00448	0.78437	0.99950	0.92294	0.62635	0.38578	0.54219
60	0.00753	0.78066	0.99973	0.91913	0.97203	0.45256	0.54217
Diffusion	Breed	Spread	Slope resistance	Road gravity			
1	1	50	100	1			
1	1	50	75	25			
1	1	50	50	1			

Table 9: Fine calibration, 1051 rows x 923 columns

Run	Product	Compare	Population	Edges	Cluster	Cluster size	Lee-Salee
167	0.00032	0.64802	0.99942	0.76536	0.89472	0.47960	0.53129
153	0.00462	0.64451	0.99943	0.82819	0.62212	0.57374	0.53115
174	0.00514	0.64463	0.99927	0.82730	0.91520	0.52199	0.53115
175	0.00514	0.64463	0.99927	0.82730	0.91520	0.52199	0.53115
176	0.00514	0.64463	0.99927	0.82730	0.91520	0.52199	0.53115
154	0.00412	0.64626	0.99924	0.82067	0.74215	0.57311	0.53110
Diffusion	Breed	Spread	Slope resistance	Road gravity			
1	1	60	80	25			
1	1	60	60	15			
1	1	60	100	1			
1	1	60	100	5			
1	1	60	100	10			
1	1	60	60	20			

Table 10: Final calibration, 2100 rows x 1843 columns

Run	Product	Compare	Population	Edges	Cluster	Cluster size	Lee-Salee
485	0.00541	0.53550	0.99910	0.84385	0.99834	0.43084	0.51069
226	0.00501	0.53286	0.99927	0.86201	0.99666	0.38350	0.51061
215	0.00502	0.53284	0.99928	0.84966	0.99898	0.39583	0.51053
Diffusion	Breed	Spread	Slope resistance	Road gravity			
1	2	77	40	15			
1	1	77	35	12			
1	1	77	25	15			

Table 11: Derived forecasting coefficients results

Year	Diffusion	Breed	Spread	Slope resistance	Road gravity
1984	1	2	84	36	15
1992	1	2	91	31	16
2002	1	3	100	23	17

Table 12: Confusion matrix for predicted urban extent in 2002 in percent and (number of grid cells)

	Measured		
	Non Urban	Urban	Row totals
Modeled			
Non Urban	98.9 (3454104)	15.0 (56639)	90.7 (3510743)
Urban	1.1 (37368)	85.0 (322189)	9.3 (359557)
Column totals	90.2 (3491472)	9.8 (378828)	100.0 (3870300)

Overall accuracy: 97.57%; Kappa coefficient: 0.8593

growth in the Houston area. Overall agreement between the modeled and measured urban extents is 98% with a κ_{hat} value of 0.86, which according to Congalton (1996) represents a strong agreement between the two maps.

As is evident in Table 12, errors of omission, pixels for which the model failed to identify areas classified as urban in the Landsat images are larger (15%) than errors of commission where the model incorrectly predicted urbanized pixels to occur (1.1%). As can be shown in Fig. 6, the spatial distribution of omission errors is not uniform. The model under-predicts urban extent along the northwest to southeastern portions of the Houston metropolitan, along the coast as well as in the Freeport-Lake Jackson area.

RESULTS AND DISCUSSION

The calibration process has resulted in the determination of a set of diffusion, breed, spread, slope resistance and road gravity growth coefficients that enable SLEUTH to quite accurately simulate the observed growth in the Houston CMSA over the period 1974 to 2002. The successful calibration process also allows several conclusions concerning SLEUTH's ability to successfully model growth in the Houston Metropolitan area to be drawn.

First, it is important to recognize that compared with many other cities, urban growth in Houston is largely unimpeded by topography and zoning restrictions. Second, as is typical with many Sunbelt cities over the study period the population of Houston has soared, tripling from 1.5 million in 1960 to 4.5 million in 2000. This population growth is projected to continue with the Houston CMSA's population estimated at 7.5 million by 2030. The eight-county Houston metropolitan study

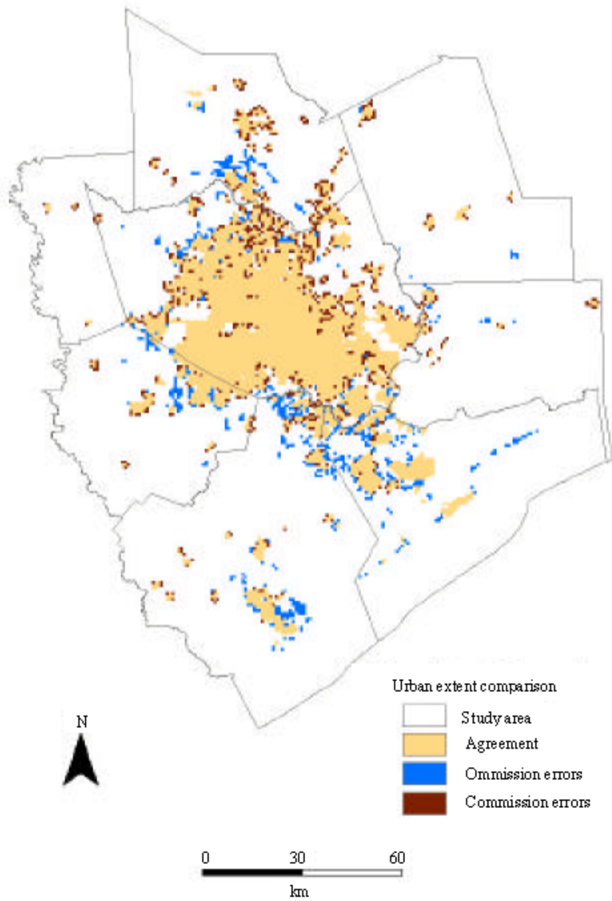

Fig. 6: Comparison of modeled and observed urban extents in 2002

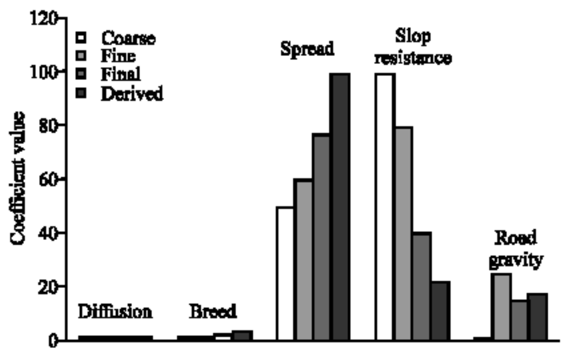

Fig. 7: SLEUTH growth coefficients obtained at the end of each calibration stage

contains a land area of 20,019 km^2. Only 5% was occupied by urban settlements in 1974, however, by 2002, the urbanized area accounted for 19% which represents nearly a quadrupling of urban area over the 28 year study period.

The Lee-Sallee metric was chosen our primary goodness of fit measure in selecting the appropriate model runs throughout the calibration procedure. If the model grows in different ways or in different directions the Lee-Sallee will reflect that. The Lee-Sallee metric computed by comparing the SLEUTH predicted urban extent in 2002 obtained after final calibration to an independently derived remotely-sensed land use/land cover map was 0.51. Few published SLEUTH results include output statistics that can provide a context for our results. Silva and Clarke (2002) modeled urban growth in Lisbon and Porto, Portugal using SLEUTH urban growth model. They achieved a Lee-Sallee value of 0.35 for Lisbon and 0.58 for Porto. Clarke and Gaydos (1998) achieved a Lee-Sallee value of 0.30 and they emphasized that even a 30% match was quite good for their study. Thus, it appears that the calibration process for Houston has been successful.

The Houston CMSA presents a very low value of diffusion and breed and very high spread coefficient and low slope coefficients (Fig. 7). The high values of the spread coefficient (100) relative to diffusion (1) and breed (3), indicates that the calibration process has successfully captured the organic nature of the Houston's growth. The spread coefficients found here are much higher than those found in previously published studies. Clarke and Gaydos (1998) have modeled urban growth in San Francisco and Washington/Baltimore, reported much lower spread coefficients of 19 and 21, respectively. Yang and Lo (2003) modeled urban growth in Atlanta, Georgia, using the SLEUTH and reported a spread coefficient of 41, respectively.

Compared to other areas, the slope resistance coefficients for this study (22) fall on the lower end of the range of previous studies. Clarke and Gaydos (1998) reported slope resistance coefficients of 31 for San Francisco and 10 for Washington/Baltimore. Yang and Lo (2003) reported a value of 95 for Atlanta. Houston's relatively low slope coefficient is probably due to lack of topographic constraints on growth in the Houston area. This gives extra strength to the model's own ability to automatically calibrate itself.

The determined road gravity coefficient for the Houston CMSA was 17. It may be low in part because highway expansion in the Houston metropolitan area during the study period present consisted primarily of upgrading existing roads rather than developing roads in areas where non existed before. However, a new major transportation construction, Texas Corridor, is planned to be finished in 2025 by Texas Department of Transportation (TXDOT) and will be included in predicting Houston's future growth.

CONCLUSIONS

As perhaps the city of Houston has grown rapidly since the 1970's, the Houston Consolidated Metropolitan Statistical Area presents a unique case study in modeling of urban growth using the SLEUTH cellular automata model. SLEUTH was found to be well suited in the historical growth of Houston for the period 1974-2002. This study is unique in several ways: first, it represents the first modeling of urban growth of a Consolidated Metropolitan Statistical Area using SLEUTH. Moreover, the city of Houston is the only major metropolitan area operating without a zoning plan and with very little topographic control on urban expansion. Therefore, this study represents calibration of the SLUETH model under the case where growth is virtually unrestricted by either natural barriers or governmental controls.

This study describes an exhaustive calibration of the SLEUTH model to data from the Houston-Galveston-Brazoria Consolidated Metropolitan Statistical Area (Houston CMSA). The derived coefficients are comparable with the limited published values from other SLUETH case studies. The coefficient values computed here during this demanding calibration phases will be used in predicting urban growth in Houston CMSA and also land use/land cover change will be simulated throughout 2030.

ACKNOWLEDGMENTS

Mr. Mark Feller from Rocky Mountain Mapping Center at USGS has run the calibration part for us on their AMD Athlon Beowulf PC Cluster. We appreciate all his help very much. Dr. John S. Jacob at Texas Coastal Watershed Program kindly provided Harris County Floodplain maps. Associate Professor and Extension Environmental Quality Specialist. Mr. Charles Dietzel, Ms. Jeannette Candau, Dr. Keith Clarke from University of California at Santa Barbara and Dr. Toby Carlson from Pennsylvania State University helped us during the model run. We also thank them very much for their unconditional support.

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