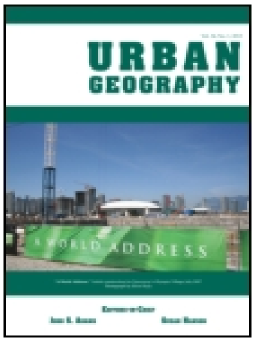

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Modeling Spatial Processes of Urban Growth in African Cities: A Case Study of Nairobi City

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MODELING SPATIAL PROCESSES OF URBAN GROWTH IN AFRICAN CITIES: A CASE STUDY OF NAIROBI CITY[1]

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Abstract: Africa's urban population growth has been especially rapid, averaging about 5% per year over the past two decades. As a result, many urban areas have experienced dramatic growth that is seriously outstripping the capacity of most cities to provide adequate services for their residents. Although population growth and urbanization rates in Africa have slowed recently due to a number of factors including HIV/AIDS, urban growth is still expected to double by 2030, leading to dramatic sprawl with serious environmental and social consequences. Using Nairobi as an example of a rapidly urbanizing African city, we studied the dynamics of land use and land cover change using satellite data and addressed the need for models and urban management tools that can guide sustainable urban planning policies. Cellular Automata, which integrate biophysical factors with dynamic spatial modeling, are used in this study. The model was calibrated and tested using time series of urbanized areas derived from land use/cover maps, produced from remotely sensed imagery, with future urban growth projected to 2030. Model assessment results showed high levels of accuracy, indicating that simulation findings were realistic, thereby confirming the effectiveness of the model. Results further showed that the model is a useful and effective tool to foresee the spatial consequences of planning policies in the context of many African cities. The forecast for Nairobi showed unsustainable sprawl. [Key words: urban growth, Cellular Automata, African cities, Nairobi.]

Urbanization in Africa has sharply accelerated, with an increasing proportion of the population in many countries concentrating in large urban centers. By 2020, Africa will have 11 mega-cities of more than 10 million, and nearly 3,000 cities with populations of more than 20,000—an increase of almost 300% since 1990 (World Bank, 1999; Fay and Opal, 2000; Rakodi, 2004). Understanding urban growth in these rapidly changing environments is critical for city planners and resource managers. The estimation of future outcomes of current spatial plans and policies on land use development, and the consideration of alternative planning and policy scenarios for impact minimization, are of particular interest.

The environmental and social consequences of a growing population in a loosely planned urban system could be dramatic, especially when urban areas experience accelerated growth in a short period of time. This is the case for most cities in Africa. In

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Nairobi, Kenya, for example, the population has grown exponentially: it is 3.5 million today, and is expected to reach 7 million within 20 years (Obudho, 1997). This is mainly because Nairobi is a magnet for those seeking work from across the country (Ngigi, 2007). According to the 1999 population census, nearly 70% of Nairobi's residents were born outside the metropolitan area. Nairobi is now faced with serious urban management problems, exacerbated by the fact that hundreds of thousands of its residents live in slums and other informal settlements (Ikiara et al., 2004; Mundia and Aniya, 2007) afflicted by decaying infrastructure, lack of proper sanitation facilities, and inadequate drainage systems.

To anticipate the consequences of urban growth in Africa and other developing countries is a difficult task. There are complex rules at work that make it difficult to forecast the operation of urban dynamics. Modeling of urban growth in African cities can help in the analysis of past and present spatial patterns of phenomena. Such an approach can also provide projections of the desired future conditions and requisite policies.

DATA AND COMPLEXITY CONCERNS

To begin to deal with these urban challenges in Africa requires accurate projections of future urban growth, which in turn must be based on both a solid foundation of quality analysis and a good understanding of the likely patterns and trends of urban change (Abiodun, 1997; Rakodi, 1997; Hope and Lekorwe, 1999). Understanding the unique urban growth and urban land use change in African cities is also critical for city planning and resource management in these rapidly changing environments. For an integrated urban planning strategy, it is necessary to recognize, anticipate, measure, and understand urban dynamics and their consequences (Li and Yeh, 2000; Baredo and Demicheli, 2003). The complexity of the urban system is usually an impediment, which is enhanced even more in African cities, where many factors increase the unpredictability of the urban system.

There are enormous difficulties in obtaining reliable data on urban growth, and significant errors have been made in the past with projections in developing-country cities such as Mexico City and Lagos (Cohen, 2004). Because of these complex factors, predictions about the future development of cities encounter a high degree of uncertainty, and therefore require the use of innovative tools.

In recent years, dynamic spatial models have gained popularity as a modeling tool for the simulation of spatially distributed processes. Several approaches have been proposed for modifying standard Cellular Automata (CA) in order to make them suitable for urban simulation (e.g., Batty and Longley, 1986, 1987; White and Engelen, 1993; Clarke and Gaydos, 1998; Li and Yeh, 2000, 2002; Sui and Zeng, 2001).

Cellular Automata are a joint product of the science of complexity and the computational revolution (Couclelis, 1986). Despite their simplicity, CA models deal with processes that involve complex systems. Cellular Automata have been defined as simple dynamic spatial systems in which the state of each cell in an array depends on the previous state of cells within a neighborhood and operate according to a set of transition rules (White et al., 1999). What is surprising in CA is their potential for modeling complex spatiotemporal processes despite their very simple structure.

Cities studied as dynamic systems show complexity and characteristics that can be modeled using CA in an integrated approach (White and Engelen, 2000). Cellular Automata have also been considered idealizations of partial differential equations and demonstrate behaviors analogous to nonlinear ordinary differential equations (Wolfram, 1984). From this point of view, it is not surprising that CA can produce and simulate complex spatial processes that show nonlinear dynamics, including such sociospatial processes as the segregation of socioeconomic groups. Moreover, CA can produce spatial patterns that show chaotic behavior in the sense of irregular dynamics in a deterministic system. In this kind of system, behavior depends on the system's internal logic (Clarke et al., 1997; Couclelis, 1997).

The aim of this study is to analyze land use/land cover change and to predict urban growth in Nairobi using a dynamic spatial model. We adopted an approach that integrates land use/land cover factors with cellular automata for modeling future urban growth scenarios for this urban area. The model was calibrated by using a multistage Monte Carlo method that involved the use of a set of spatial metrics and coefficients. A 30-year simulation was then run through the year 2030, when Kenya hopes to join the ranks of world's medium-growth economies.

METHODOLOGY

Nairobi is one of the fastest-growing urban areas in Sub-Saharan Africa. Problems with data availability and accuracy in such cities make their analysis difficult, and require the use of models that can be applied in data-sparse environments. Recognizing this problem, our model utilizes satellite data that are widely available and routinely collected. The Clarke Cellular Automata urban growth model (Clarke and Gaydos, 1998) was modified and calibrated accordingly in order to produce urban growth simulations for Nairobi. The framework adopted for the land use/cover change analysis and urban expansion modeling encompassed GIS and CA modules. The GIS module allowed GIS analyses to determine suitability factors, model constraints, and land use/cover change while the CA module was useful for model calibration and for applying transitional change rules.

The urban growth simulation used CA, terrain mapping, and land use/cover modeling to address urban growth. A number of input data layers were employed: *slope*, *land use/cover*, *areas excluded from development*, *urban areas*, *road network*, and *hillshade*. Table 1 summarizes the characteristics of the satellite data and Table 2 outlines the sources, descriptions, and resolutions of the data used in modeling. Various types of urban growth categories were simulated. These included spontaneous growth, new spreading-centers growth, edge growth, and road-influenced growth. These growth categories were applied sequentially during each growth year and were controlled through the interactions of growth parameters that describe individual growth characteristics and when combined with other characteristics describe several different growth processes.

Landsat images for 1976, 1988, and 2000 were used in a post-classification analysis with GIS to map land use/cover changes. Original data sets were at 30 m resolution for TM and ETM, and 60 m for the MSS imagery. These were resampled at a common resolution of 100 m while maintaining the spatial extent of the study area. The land use/cover classification results for 1976, 1988, and 2000 are shown in Figure 1, and statistics on land use/cover changes are summarized in Table 3 (Mundia and Aniya, 2006). The

TABLE 1. CHARACTERISTICS OF LANDSAT SATELLITE DATA USED FOR MODELING URBAN GROWTH IN NAIROBI CITY

Data type	Satellite	Resolution (m)	Acquisition date
Landsat MSS	Landsat 2	79/120	February 11, 1976
Landsat TM	Landsat 4	30/120	October 17, 1988
Landsat ETM+	Landsat 7	15/30/60	January 30, 1995
Landsat ETM+	Landsat 7	15/30/60	February 21, 2000

TABLE 2. SOURCES, DESCRIPTION, AND RESOLUTION OF DATA USED FOR MODELING URBAN GROWTH OF NAIROBI

Data layer	Source	Description	Resolution
Urban extent	Land use/cover map	Land use/cover map for 1976, 1988, 1995, and 2000	30 m
Road network	Road map	Classified roads for 1976 and 1988	n.a.
Slope	1:50,000 topographic map	Derived from TIN	30 m
Exclusion	1:50,000 topographic map	Vector coverage of protected lands	n.a.
Hillshade	1:50,000 topographic map	Derived from contours	30 m
Population	Population census	Population census for 1979, 1989, and 1999	n.a.
GDP	Economic survey	Household surveys for 1979, 1989, and 1999	n.a.

extents of urban areas for the various years were extracted from the land use/cover maps. Two time periods for transportation were prepared from 1976 and 1988 topographical maps. Slope layers and the layer of all "areas excluded from development" were also generated from topographical maps. All input files were rasterized at 100 m resolution within the study area. Additional dataset preparations including geo-registration, data-type standardization, and resolution check, were necessary to ensure that all datasets had the same areal extent, the same data standards, and the same number of rows and columns. Using these data, calibration was carried out to derive parameters for simulating urban growth.

Model Calibration

The growth model was calibrated by predicting the present extent of the urban area from the past, and using longitudinal data layers as a test of how well a given set of coefficient values represent the data. This was achieved through a brute-force Monte Carlo calibration method. This method (Mundia and Aniya, 2007), given an initial image of urban areal extent, determines a set of initial control parameters that lead to a model run that best fits the observed data.

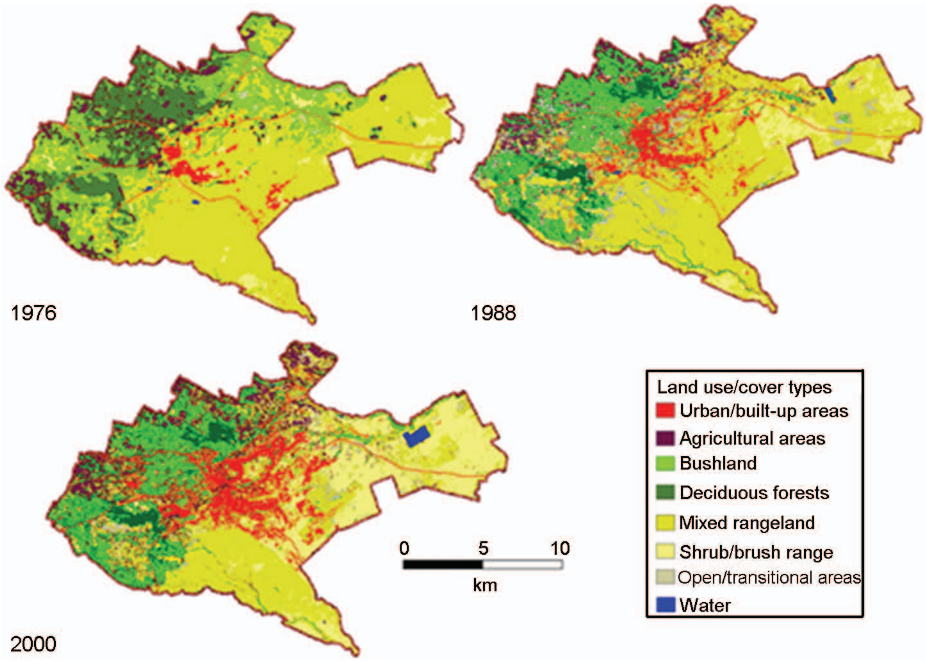

Fig. 1. Land use/cover maps of Nairobi for 1976, 1988, and 2000 (modified from Mundia and Aniya, 2006).

TABLE 3. LAND USE/COVER CHANGE STATISTICS

Land use/cover	Year					
	1976		1988		2000	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Urban/built up areas	13.99	1.9	41.18	5.8	61.25	8.6
Agricultural areas	49.83	6.9	57.83	8.1	87.78	12.3
Deciduous forests	100.15	14.0	29.09	4.1	23.56	3.3
Bushland	154.48	22.3	101.49	14.2	95.98	13.5
Mixed rangeland	357.32	50.1	340.62	47.7	237.63	33.3
Shrub/brush range	25.22	3.5	64.19	8.9	170.78	23.9
Open transitional areas	6.92	0.9	77.96	10.9	32.72	4.6
Water	0.50	0.1	1.09	0.2	3.77	0.5
Total	713.41	100.0	713.44	100.0	713.45	100.0

By running the model, a set of control parameters were refined in sequential calibration phases (coarse, fine, and final calibrations). Between calibration phases, attempts were made to extract the value that best matched the five coefficient factors that controlled Nairobi's expansion: diffusion (overall scatter of growth); breed (likelihood of new settlements being generated); spread (growth outward and inward from existing spreading centers); slope resistance (flat more preferred); and road gravity (attraction of urbanization to roads).

Coefficient combinations resulted in a number of measures. One of the measures (*compare*) is a final-year comparison of the total number of urban pixels. For checks against all historical data, the Pearson product–moment correlation coefficient (r^2) was used as a measure of fit between modeled and observed outcomes. These included a score of the modeled number of urban pixels compared to the actual count (*population_*r^2), a score of the modeled urban edge count compared to actual the urban edge (*edge_*r^2), a score of modeled urban clustering compared to observed urban clustering (*cluster_*r^2), a score of modeled average urban cluster sizes compared to observed mean urban cluster sizes (*mean_cluster_size_*r^2), and a shape index measurement of spatial fit between the modeled urban growth and the known urban extent (*leesallee*). The initial parameters for the final calibration and the 10 best coefficient sets from the final calibration and related statistics are summarized in Table 4.

The calibration using Monte Carlo simulations computed the averages across multiple runs to ensure robustness of the solutions. This made it possible to adapt the model to existing characteristics of Nairobi throughout the various stages of calibration by using different spatial resolutions and the sequential multistage optimization of the coefficient that controlled the system. To examine the role of spatial resolution on model calibration and outputs, calibrations were performed at different fixed resolutions. The quarter calibration was performed using only the quarter resolution data (216 × 186). The other two calibrations were the half (432 × 372) and the full (864 × 743) calibrations. By narrowing both the spatial scale and the range of parameters in the three calibration sequences, it was possible to close in on the parameter set that best simulated the urban growth of Nairobi. These parameters were then used to determine the coefficient values that best allow the model to predict the future urban growth of the urban area.

Results from the three phases of calibration (coarse, fine, and final calibrations) indicated successive improvement in the parameters that control the behavior of urban expansion. After the coarse calibration, the resulting calibration values narrowed and became more sensitive to local conditions within the metropolis. The comparison of the modeled final "population" (number of urban pixels) and the urbanization of the control years yielded a high summary correlation of 0.97 and a comparative statistic of 0.11, making it reasonable to say that the prediction of the model based on the initial year of the current urban pattern was accurate. These correlation values also suggest that the calibration phases adopted for Nairobi allowed the model to simulate urban growth with a high degree of fit. The shape and form of urbanization seem also to confirm that calibration-adjusted values reflect the actual characteristics of urban expansion. Figure 2 summarizes the resulting final calibration coefficients.

Calibration results for Nairobi indicated that the Spread coefficient is the highest, followed by the Road Gravity coefficient. The Slope coefficient was ranked fourth, suggesting that slope has minimal influence on the urbanization pattern. The resulting coefficients suggest that urban expansion tended to occur from the main nucleus (Spread coefficient at 98) and along the highway network (Road Gravity coefficient at 75) with little regard for the local terrain (Slope coefficient at 4).

TABLE 4. INITIAL PARAMETERS FOR THE FINAL CALIBRATION AND THE BEST 10 COEFFICIENT SETS FROM FINAL CALIBRATION AND THE RELATED STATISTICS

(A) Initial parameters for the final calibration

	Diffusion	Breed	Spread	Slope	Road Gravity
Start	1	1	90	1	35
Step	1	5	2	1	5
Stop	5	20	100	5	75
Number of Monte Carlo iterations	10				
Total number of runs	100,000				
Input data resolution	Full (864 × 744)				

(B) Coefficients sets from final calibration

Model runs	LeeSallee	Compare	Clusters	Pop	Edges	Diffusion	Breed	Spread	Slope	Road Gravity
6525	.09026	.1101	.3246	.9740	.5680	5	20	92	4	40
6527	.09026	.1101	.3246	.9740	.5680	5	20	92	4	45
6535	.09026	.1101	.3246	.9740	.5680	5	20	92	4	40
6544	.09026	.1101	.3246	.9740	.5680	5	20	92	3	40
6553	.09026	.1101	.3246	.9740	.5680	5	20	92	4	40
6536	.09026	.1101	.3246	.9740	.5680	5	20	92	1	45
6562	.09026	.1101	.3246	.9740	.5680	5	20	92	5	40
6545	.09026	.1101	.3246	.9740	.5680	5	20	92	4	45
226	.09026	.1101	.3246	.9740	.5680	5	20	92	4	35
235	.09026	.1101	.3246	.9740	.5680	5	20	92	5	40

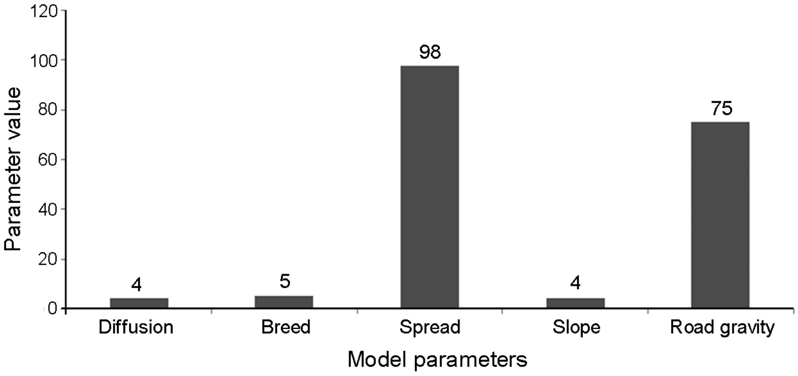

Fig. 2. Final model coefficients for Nairobi.

TABLE 5. MODEL ACCURACY ASSESSMENT RESULTS

Class name	Producer's accuracy, pct.		User's accuracy, pct.
1995			
Urban	47.2		69.6
Non-urban	95.4		79.9
Overall accuracy, pct.		80.0	
2000			
Urban	45.2		67.6
Non-urban	97.4		80.9
Overall accuracy, pct.		86.2	

Accuracy Assessment and Model Prediction

The goal of calibration was to derive a set of values for the growth patterns that could effectively simulate growth during the time period studied (1976–2000). To ascertain that the calibration coefficients obtained were accurate, the simulated growth patterns for 1995 and 2000 were compared to the actual growth shown in satellite images, using several least squares regression statistics. Figure 3 and Table 5 summarize the spatial accuracy assessment for 1995 and 2000. Overall accuracy was high at 80% for 1995 and 86% for 2000. Errors of omission (producer's accuracy) and commission (user's accuracy) for the urban class for both years suggest that the prediction of the location of urbanized pixels was reasonably accurate.

After confirming the accuracy of our calibration, the set of coefficients derived during calibration were used to predict future urbanization patterns. Our model used the following inputs: urban extent for initialization, an initial transportation network with provision

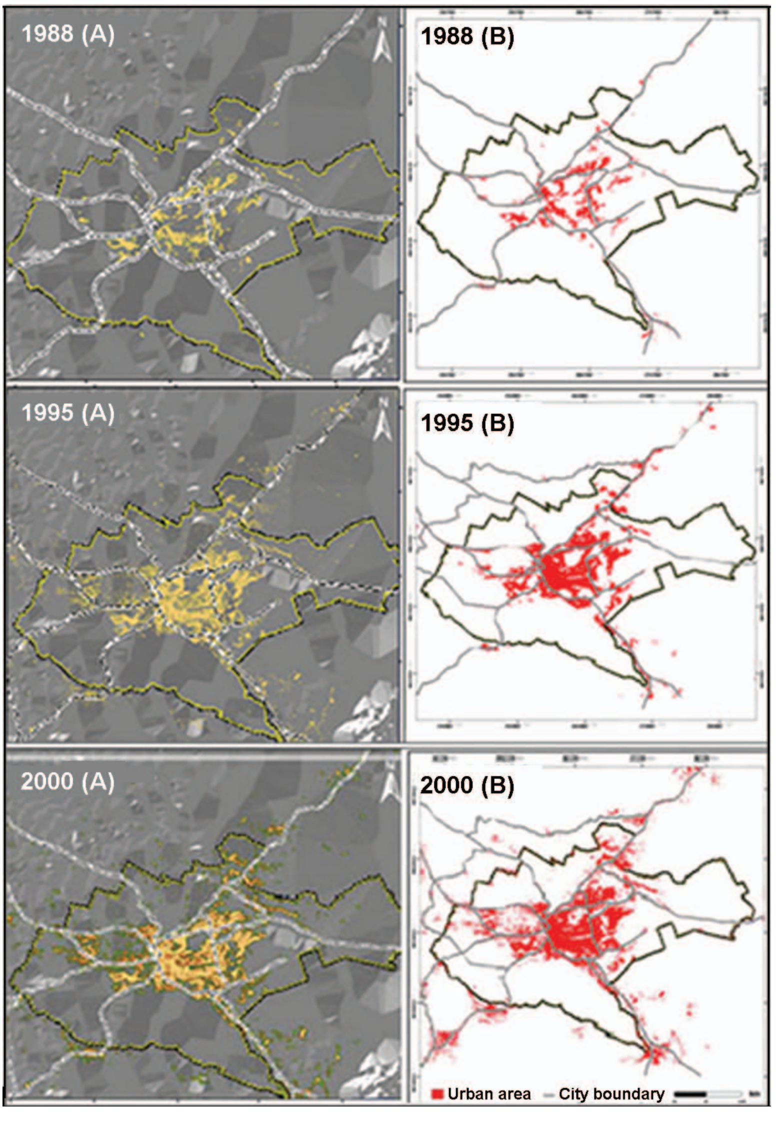

Fig. 3. Spatial accuracy assessment: (A) simulated results and (B) results from satellite data.

for incorporation of future networks, an excluded layer, and a slope and hillshade layer. This allowed us to model current trends that reflect policies currently in place. Our model made the following assumptions: (1) that there would be continuation of economic development at the current annual rate of 4.3%; (2) that population increase would continue at the current rate of 4.2% per annum; (3) topographical slope beyond 21% would inhibit urban growth; (4) existing urbanization would encourage peripheral growth; and (5) the road network would be a primary correlate of urban growth.

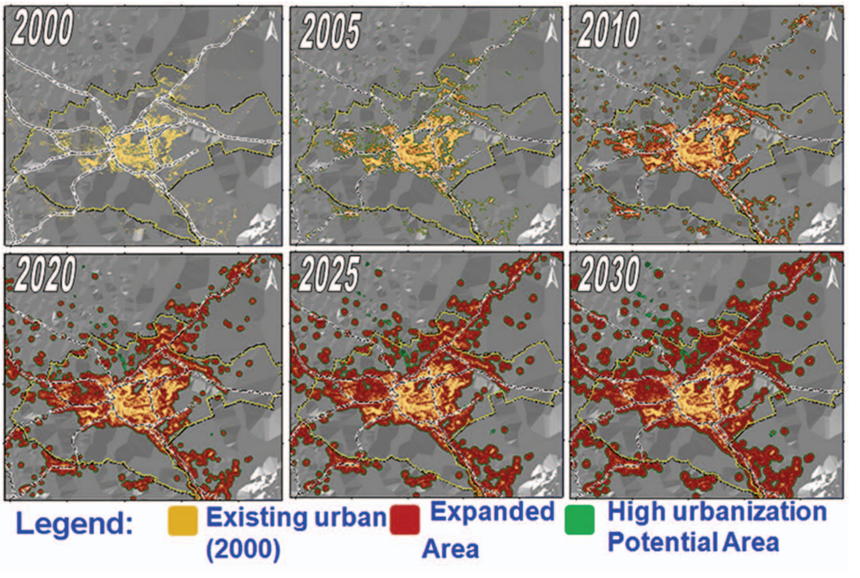

Fig. 4. Simulated urbanized areas for Nairobi through 2030. *Source:* Mundia and Aniya (2007).

RESULTS

The land use/cover changes and the projected growth patterns of Nairobi city through 2030 are shown in Figures 1 and 4, respectively. The results show that substantial land use/cover changes have taken place throughout the study area. There is notable urban expansion accompanied by the loss of forests and urban sprawl. The results from the model prediction output indicate a significant amount of growth from 2000 to 2030, including the settlement of large tracts of nonurbanized land (Fig. 4). Such massive growth is expected to cause substantial change to the landscape and loss of vital land resources.

From a visual point of view, the simulated results maintain a spatial pattern similar to the current metropolitan layout. The results suggest that the urban area will continue expanding mainly to the northeast, southeast, and northwest, following the major road network. Results also show that such factors as terrain and slope have not been important for urban development in Nairobi. The simulations, unconstrained by these factors, have produced an extensive sprawl development. In general, the results of the simulated development of the city are not surprising given the absence of adequate planning by Nairobi's city council. The last strategic planning for the city was implemented in 1973 and has not been revised since. Most of the built-up areas have grown continuously outward from the original city core.

Economically, there will be increased pressure on urban infrastructure. Rapidly expanding residential, commercial, industrial, and service centers require more roads, bridges, water, and sewer lines as well as other municipal services such as fire stations, schools, and hospitals. Balancing this need for urban growth with the efficient use of

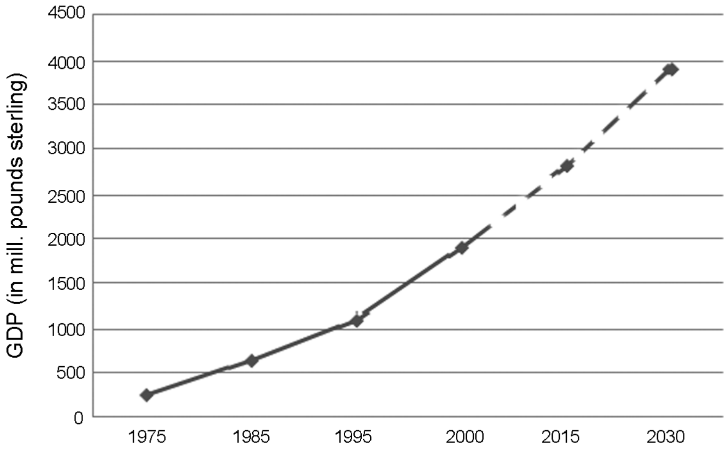

Fig. 5. Nairobi's gross domestic product projected to 2030. *Source:* Republic of Kenya (1975, 2000).

resources is a formidable challenge for policymakers and planners, especially given the limited resources of African cities.

Ecologically, this process inevitably involves altering or destroying natural environments, building barriers to natural processes, and altering geochemical cycles through pollutant disposal. Preliminary analyses of the simulated urban area suggest the continued loss of forest land, cropland, and further landscape fragmentation. Even if policies and regulations are implemented to protect some areas from development, they could not guarantee that these protected areas will not become polluted and degraded.

DISCUSSION

The land use/cover changes revealed for Nairobi city have occurred as a result of the interactions of a number of environmental as well as demographic, social, and economic forces. Economic development has been one of the dominant driving forces. Nairobi's gross domestic product (GDP) was about £254 million in 1975, £645 million in 1985, and £1.5 billion in 1995. The national economic survey (Republic of Kenya, 2002) put Nairobi's GDP at £1.9 billion, and is projected to more than double by 2030 (Fig. 5). This economic development led to the establishment of additional industries, a real estate boom, and the subsequent expansion of the urban area.

Population change in Nairobi is presented in Figure 6. The 1969 population census put Nairobi's population at slightly over half a million people, and the population rose to 1.35 million in 1989. The current population is estimated to be 3.5 million, a fivefold increase since 1969.

The transportation network is another major factor influencing urban expansion in Nairobi. Nairobi is at the center of a series of radial roads that link it to other parts of the country. Although Nairobi started as the headquarters of the Kenya–Uganda railway,

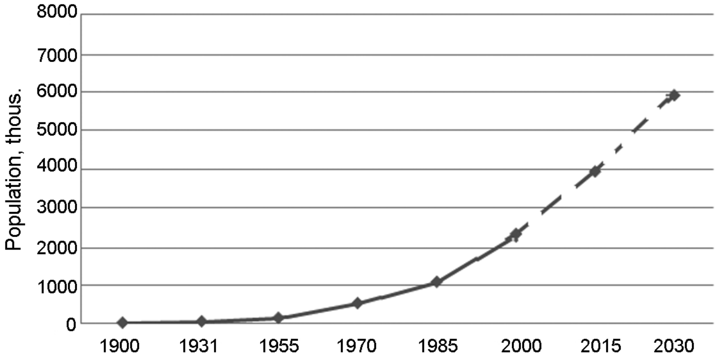

Fig. 6. Nairobi's population growth projected to 2030. *Source:* Republic of Kenya (1989, 1999).

commuting by rail within Nairobi seems to have been abandoned and the network has not been upgraded to serve local transport needs.

CONCLUSION

Understanding dynamics of complex urban systems and evaluating the impact of urban growth on the environment require robust modeling and simulation techniques. In recent years, dynamic modeling has rapidly gained popularity among geographers and planners as a tool for urban landscape simulation. Cellular Automata (CA) models in particular have evolved into a promising tool for the exploration of complex urban systems.

At the theoretical level, this study examined the spatial consequences of urban growth in metropolitan Nairobi. The land use/cover changes observed and the results obtained in the simulation for 2030 raised some interesting questions about urban growth in Africa. There is an urgent need to rethink urban planning tools to manage Nairobi, taking into consideration the existing demographic, economic, political, and social constraints. The CA modeling was found to be suitable for simulating growth in cities characterized by urban sprawl. Like other major African cities, Nairobi has experienced a rapidly changing spatial structure over the last three decades. The model's longitudinal simulation shows both accretion and a linear growth trend in the evolution of urban spatial form, which is compatible with studies from social and economic perspectives. These simulations also indicate that new developments have occurred around the periphery as well as in linear growth corridors along major transportation routes.

This study has also attempted to address the question of modeling urban growth in data-sparse environments. Most urban growth models focus primarily on cities in the industrialized world, where data are readily and widely available. In many African countries, data are in most cases incomplete, inaccurate, unreliable, or nonexistent, making it especially difficult to analyze and model urban growth. To get around this, our urban growth model utilized remote sensing data that are widely available and routinely collected, and hence appropriate for African cities.

Our findings should be useful to those who study urban dynamics and those who need to manage resources and provide public services in rapidly changing environments. GIS-based dynamic modeling can facilitate a sound approach to regional planning and sustainable development. Our model would only be useful in addressing planning challenges in Africa if certain issues that characterize the uniqueness of many cities are also addressed. These challenges include political instability, urban politics, delegitimized city councils, and highly dependent African economies.

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