Environment and Planning B: Planning and Design 2003, volume 30, pages 251 – 271

DOI:10.1068/b2983

Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore – Washington metropolitan area

Claire A Jantz¶
University of Maryland, Department of Geography, College Park, MD 20742, USA
Scott J Goetz
Woods Hole Research Center, PO Box 296, Woods Hole, MA 02543, USA;
e-mail: sgoetz@whrc.org
Mary K Shelley
The Fels Center of Government, 3814 Walnut Street, Philadelphia, PA 19104, USA;
e-mail: mshelley@sas.upenn.edu
Received 27 August 2002; in revised form 15 April 2003

Abstract. Declining water quality in the Chesapeake Bay estuary is in part the result of disruptions in the hydrological system caused by urban and suburban development throughout its 167 000 km^2 watershed. A modeling system that could provide regional assessments of future development and explore the potential impacts of different regional management scenarios would be useful for a wide range of applications relevant to the future health of the Bay and its tributaries. We describe and test a regional predictive modeling system that could be used to meet these needs. An existing cellular automaton model, SLEUTH, was applied to a 23 700 km^2 area centered on the Washington – Baltimore metropolitan region, which has experienced rapid land-use change in recent years. The model was calibrated using a historic time series of developed areas derived from remote sensing imagery, and future growth was projected out to 2030 assuming three different policy scenarios: (1) current trends, (2) managed growth, and (3) ecologically sustainable growth. The current trends scenario allowed areas on the urban fringe that are currently rural or forested to be developed, which would have implications for water quality in the Chesapeake Bay and its tributaries. The managed growth and ecologically sustainable scenarios produced growth patterns that were more constrained and which consumed less natural resource land. This application of the SLEUTH model demonstrates an ability to address a range of regional planning issues, but spatial accuracy and scale sensitivity are among the factors that must be further considered for practical application.

1 Introduction

The contemporary pattern of urban development in industrialized countries is increasingly taking the form of low-density, decentralized residential and commercial development. The term 'sprawl' is now commonly used to describe this form of development, the environmental and quality-of-life impacts of which are becoming central to debates over land use and land cover in urban and suburban areas. The Washington – Baltimore region constitutes a central portion of the Chesapeake Bay watershed, and is part of the 'Chesapeake metropolis' (Grumet, 2000). Because the water quality and aquatic habitats of the Chesapeake Bay have been compromised, in part because of urbanization and low-density development, the Washington – Baltimore metropolitan region has become exemplary of the sprawl debate, exhibiting many of the classic symptoms, such as loss and fragmentation of the natural resource base, declining water quality, and traffic congestion (Burchell et al, 1998), as well as policy development and implementation aimed at growth management and natural resource protection. 'Smart growth', a land-use policy orientation embodied by a suite of policies aimed at natural resource and agricultural preservation,

¶ Current address: Woods Hole Research Center, PO Box 296, Woods Hole, MA 02543, USA; e-mail: cjantz@whrc.org

transit-oriented development, and 'brownfield' redevelopment, is becoming a reality for some areas within the Washington–Baltimore region. The state of Maryland, for example, has implemented Priority Funding Areas (PFAs), within which state investments for infrastructure development are focused (Northrup and Duket, 1997).

Land cover is an essential element of ecological function, especially in terms of hydrological processes (Wickham et al, 2000). As urbanization has occurred, lands making up the natural resource base, such as forest, wetlands, and agriculture, have been replaced by surfaces that are impermeable to water, such as pavement and concrete. Increases in impervious surface cover significantly alter the hydrological regime and have a negative impact on water quality (Arnold and Gibbons, 1996; Ridd, 1995; US Environmental Protection Agency, 2000), but can have different effects depending on where and how land-use change has occurred. For example, the spatial pattern of agricultural and forest loss (Wickham et al, 2002) and the presence or absence of riparian buffers (Goetz et al, in press) influences potential exportation of nitrogen and phosphorus, which are principal contributors to eutrophication in aquatic systems. Likewise, increases in impervious surface areas have different impacts on water quality depending on where changes occur along urban–rural gradients (for example, Wear et al, 1998). Predicting future environmental outcomes, whether for water quality or quality of life, requires being able to predict the *spatial pattern* of land-use change.

In recent years, spatially explicit simulation models of urban growth patterns have emerged. The economic versions of these models estimate land-use transition probabilities using discrete choice methods based on the behavior of agents making land-use decisions (Bockstael, 1996). The spatially explicit model of Landis (1995) for the San Francisco Bay and Sacramento area is an example of a microlevel model that makes use of data from a geographic information system (GIS) to generate spatially disaggregated predictions of land-use change. Recent work in the Patuxent watershed of Maryland has sought to develop economic models of land-use change that are both spatially explicit and disaggregate, so that predicted outcomes may be linked with ecological models of landscape changes (Bockstael and Bell, 1997). These modeling efforts require detailed parcel-level and GIS data that are often not widely available, limiting the ability to apply the models to a broader region or transfer them to other areas altogether.

A relatively simple class of models, cellular automata (CA), has gained attention from researchers attempting to simulate and predict spatial patterns of urban development. CA models require that space be represented as a grid of cells that can change state as the model iterates. These changes are regulated by rules that specify a set of neighbourhood conditions to be met before a change in state can occur (O'Sullivan, 2001). Although CA models are conceptually elegant, they have the potential to simulate the complex behavior of systems, such as cities (Torrens and O'Sullivan, 2001). CA models have been used to simulate different types of urban forms (Yeh and Li, 2001) and development densities (Yeh and Li, 2002), and to investigate the evolution of urban spatial structure over time (White and Engelen, 2000). Although pure CA models have been quite successful at recreating *patterns* of urban development, they have been criticized for their seeming inability to account for *processes* driving urban change. Recently, advances have been made in developing hybrid CA that can incorporate process-based factors. Webster and Wu (2001), for example, incorporate microeconomic urban theory into a spatially explicit CA to investigate the effects of alternative planning regimes on land-use patterns. As planning tools, CA urban models have several benefits: they are interactive, potential outcomes can be visualized and quantified, they can be closely linked with GIS, and raster-based spatial data derived from remote sensing platforms are easily incorporated into the CA modeling environment (Couclelis, 1997).

In order to assess the potential effectiveness of smart growth policies in the Chesapeake Bay watershed, our objective was to develop a predictive modeling system capable of depicting the impacts of different land-use or land-management policies within a 23 700 km^2 area encompassing the metropolitan areas of Washington, DC and Baltimore, MD, about 15% of the Chesapeake Bay watershed (figure 1). The design and development of the model were specifically focused on a number of criteria to achieve the intent of the study: (1) the model should be policy driven to facilitate discussion and testing of the effects of different land-use management policies; (2) the model assumptions, implementation methodology, and results should be transparent to the average citizen; and (3) the model should be modular to facilitate the inclusion of additional scenarios and impact assessments.

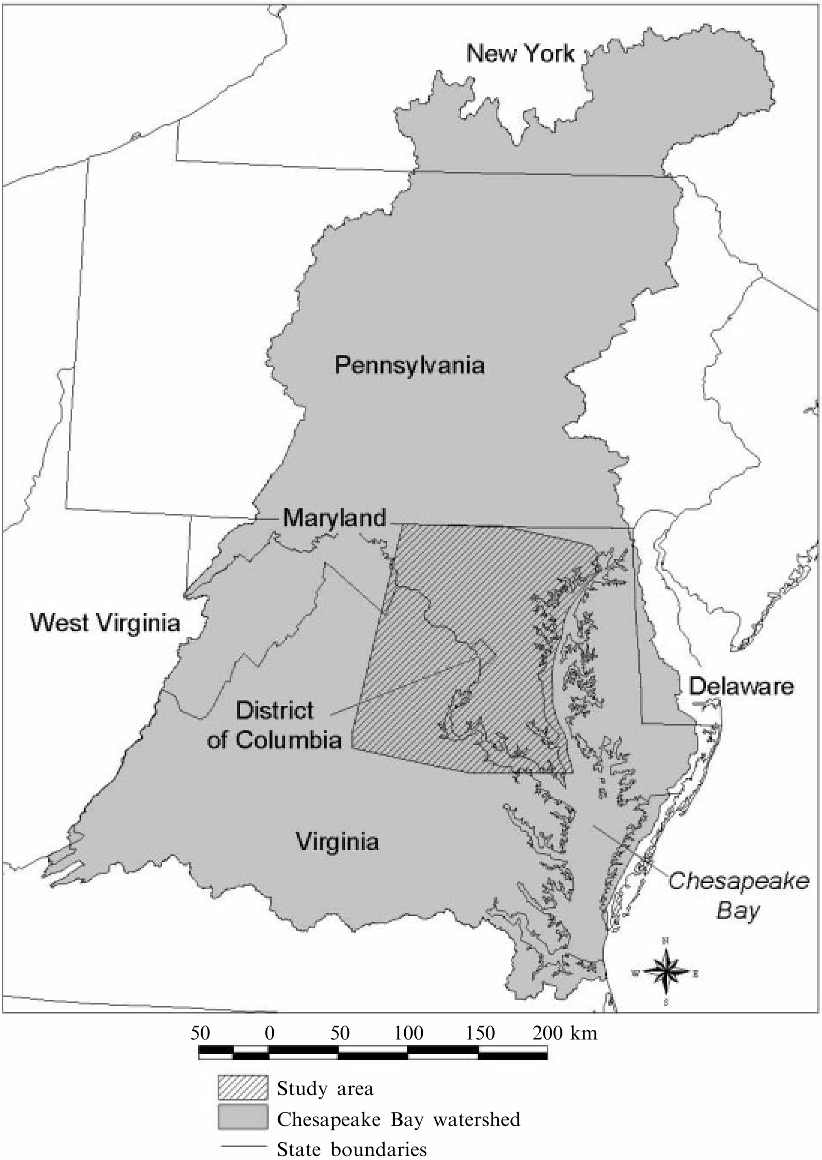


Figure 1. Study area within the Chesapeake Bay watershed.

2 Methods

2.1 Modeling approach

Given its success with regional scale modeling, its ability to incorporate different levels of protection for different areas, and the relative ease of computation and implementation, we adopted the SLEUTH model (slope, land use, exclusion, urban extent, transportation, hillshade) (USGS, 2003). SLEUTH belongs to the CA class of models, and the version used in this application, SLEUTH 3.0Beta, consists of an urban modeling module and a land-cover change transition model. For this application, only the urban module was utilized, so each cell in the study area had only two possible states: urbanized or nonurbanized. Whether or not a cell becomes urbanized is determined by four growth rules, discussed below, each of which attempts to simulate a particular aspect of the development process. In their seminal application of the Clarke urban growth model, a precursor to SLEUTH, in the San Francisco Bay area, Clarke et al (1997) stressed the utility of the model in simulating historic change, the description of which can aid in the explanation of growth processes at a regional scale, and in predicting future urban growth trends. The model was successful in simulating urban change between 1900 and 1990 for the San Francisco area, and was later applied to the Baltimore – Washington corridor (Clarke and Gaydos, 1998), where calibrations and long term predictions for both San Francisco and Baltimore – Washington were presented, allowing for an effective comparison to be made between the growth patterns and processes of the two urban systems.

SLEUTH simulates four types of urban land-use change: spontaneous growth, new spreading center growth, edge growth, and road-influenced growth. These four growth types are applied sequentially during each growth cycle, or year, and are controlled through the interactions of five growth coefficients: dispersion, breed, spread, road gravity, and slope (table 1). Each coefficient has a value that ranges from 0 to 100. The exact value assigned to each coefficient was, in our case, derived through a rigorous calibration procedure, described in detail in section 2.3. In conjunction with the excluded layer probabilities, the five growth coefficients determine the probability of any given location becoming urbanized. The user-defined excluded layer specifies areas that are wholly or partially unavailable for development. Water, for example, would have an exclusion value of 100, indicating that it is 100% excluded from development. If a cell that is chosen for potential urbanization has an exclusion value of 50, it has a 50% probability of being urbanized in any given simulation. Below we provide a summary of how SLEUTH simulates urban development, which is

Table 1. Summary of growth types simulated by the SLEUTH model.

Growth cycle order	Growth type	Controlling coefficients	Summary description
1	spontaneous	dispersion	Randomly selects potential new growth cells.
2	new spreading center	breed	Growing urban centers from spontaneous growth.
3	edge	spread	Old or new urban centers spawn additional growth.
4	road-influenced	road-gravity dispersion, breed	Newly urbanized cell spawns growth along transportation network.
Throughout	slope resistance	slope	Effect of slope on reducing probability of urbanization.
Throughout	excluded layer	user-defined	User specifies areas resistant or excluded to development.

described in detail in Clarke et al (1997), Clarke and Gaydos (1998) and US Geological Survey (USGS, 2003).

Spontaneous growth simulates the random urbanization of single pixels, which has the potential to capture low-density development patterns and is not dependant on proximity to existing urban areas or the transportation infrastructure. The overall probability that a single nonurbanized cell in the study area will become urbanized is determined by the dispersion coefficient.

New spreading center growth models the emergence of new urbanizing centers by generating up to two neighboring urban cells around areas that have been urbanized through spontaneous growth. The breed coefficient determines the overall probability that a pixel produced through spontaneous growth will also experience new spreading center growth.

A newly urbanized cluster can then experience *edge growth*, which simulates outward growth from the edge of new and existing urban centers. Edge growth is controlled by the spread coefficient, which influences the probability that a nonurban cell with at least three urban neighbors will also become urbanized.

The final growth step, *road-influenced growth*, simulates the influence of the transportation network on growth patterns by generating spreading centers adjacent to roads. When road-influenced growth occurs, newly urbanized cells are randomly selected at a probability level determined by the breed coefficient. For each selected cell, the existence of a road is sought within a search radius defined by the road-gravity coefficient. If roads are found near the selected cell, a temporary urban cell is placed at the closest location adjacent to a road. This temporary urban cell then searches along the road for a permanent location. The direction of the search along the road is random and the search distance is determined by the dispersion coefficient. The permanent location becomes a new spreading center, so up to three cells along a road can be urbanized at this point.

The slope coefficient accounts for the influence of topography on development patterns and is applied as a suitability test before any location is urbanized. A high slope coefficient value will decrease the likelihood that development will occur on steep slopes.

SLEUTH also has a functionality termed 'self-modification' (Clarke et al, 1997), which allows the growth coefficients to change throughout the course of a model run and which is intended to simulate more realistically the different rates of growth that occur in an urban system over time. When the rate of growth exceeds a specified critical threshold, the growth coefficients are multiplied by a factor greater than one, simulating a development 'boom' cycle. Likewise, when the rate of development falls below a specified critical threshold, the growth coefficients are multiplied by a factor less than one, simulating a development 'bust' cycle. Without self-modification, SLEUTH will simulate a linear growth rate.

Unlike the procedures for calibrating the growth coefficients, implementation of the self-modification functionality is not well documented. The manner in which users can determine the critical thresholds, for example, is not addressed in any of the current literature on SLEUTH; thus, we did not implement the self-modification functionality at any stage of the modeling application reported here. This did not pose a significant problem during the calibration phase because the growth rate in our historic data approached a linear trend. However, it necessitated a limiting assumption of linear growth when future predictions with SLEUTH were performed.

Implementation of the model occurs in two general phases: (1) calibration—where historic growth patterns are simulated; (2) prediction—where historic patterns of growth are projected into the future. For calibration, the model requires inputs of historic urban extent for at least four time periods, a historic transportation network for at least two time periods, slope, and an excluded layer.

2.2 Historic datasets

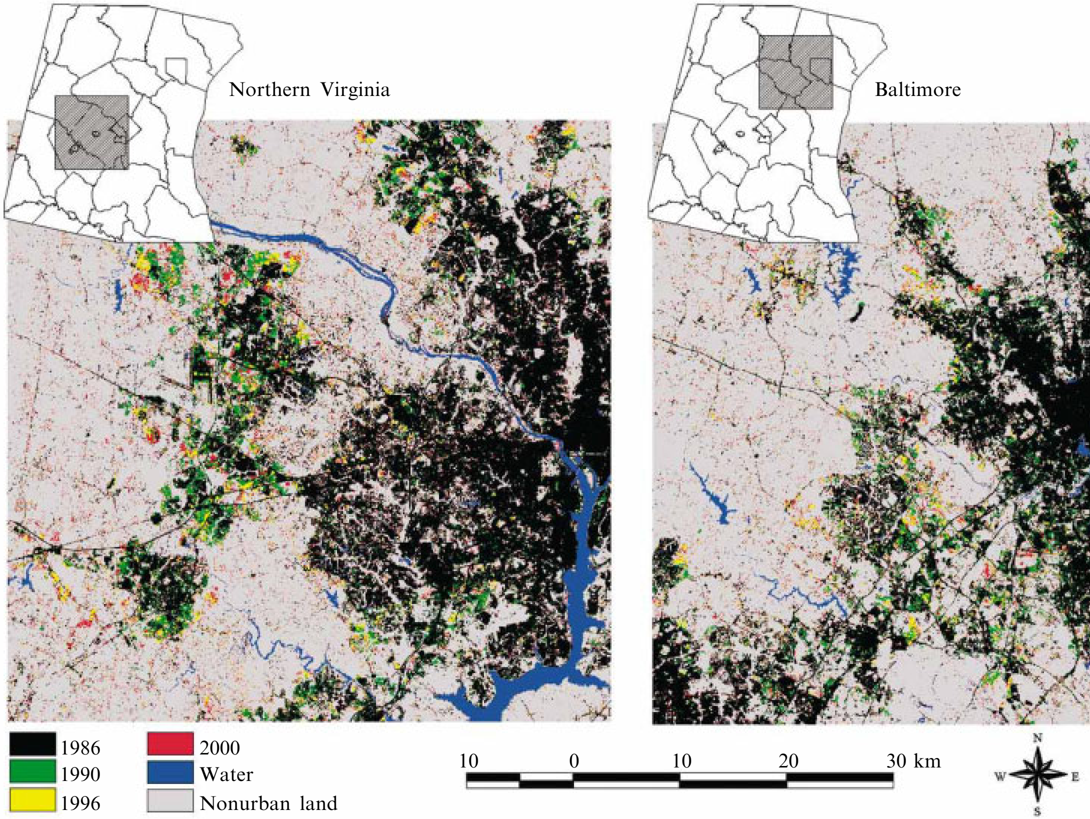
New techniques to map impervious surfaces from Landsat Thematic Mapper and Enhanced Thematic Mapper-Plus imagery (Smith et al, forthcoming), allowed us to map urban change for 1986, 1990, 1996, and 2000. The original data were at a resolution of 30 m, which produced an array that exceeded the available computational resources of a Beowulf PC cluster (described later). The data were therefore resampled to a resolution of 45 m to decrease the size of the array while maintaining the spatial extent of the study area. Because SLEUTH requires a binary representation of urban extent, these continuous data were transformed into binary maps of development extent using a threshold of 10% impervious area (color plate 1). We found the 10% threshold robustly captures development, including low-density residential areas. Optimal image pairs capturing leaf-on and leaf-off conditions in 1990 and 1996 were unavailable, so classification inconsistencies throughout the time series were minimized using a Boolean model For example, if a pixel that appeared as developed in 1986 and 2000 was not detected in 1990 or 1996, it was added to the dataset(s) from which it was missing. This temporal filling, which occurred in less than 1% of the study area, assured that all changes were unidirectional and assumed that developed areas did not revert to an undeveloped state.

Two time steps for transportation were also prepared. Roads layers for 1986 and 1996 were developed using the primary road network defined in the 1:100 000 scale USGS digital line graphs. A USGS 7.5 minute digital elevation model was used to create an input layer for slope, and an excluded layer was also produced. For the calibration phase, the excluded layer consisted of water, which was 100% excluded from development, as well as federal, state, and local parks, which were 80% excluded from development. This 80% level of exclusion was used because limited development within many of the parks had occurred in the historic time period. All input files were rasterized at a 45 m resolution to the spatial extent of the study area and checked for overlay accuracy.

2.3 Model calibration

The goal of calibration is to derive a set of values for the growth parameters that can effectively model growth during the historic time period, in this case 1986–2000. This was achieved in the SLEUTH modeling environment through a brute-force Monte Carlo method, where the user indicates a range of values and the model iterates using every possible combination of parameters. For each set of parameters, simulated growth is compared with actual growth using several least squares regression measures, such as the number of urban pixels, urban cluster edge pixels, the number and size of urban clusters, and other fit statistics, such as spatial match (Lee and Sallee metric).

The modeling software calculates these statistics internally and writes the results to a log file that can be manipulated by the user to evaluate the performance of different parameter sets. For each set of parameter values in a Monte Carlo iteration, the model calculates measurements of simulated urban patterns for each control year in the time series. These measurements are then averaged over the set of Monte Carlo iterations and compared to measurements calculated from the actual historic data to produce least squares regression measures (USGS, 2003). The Lee and Sallee metric (Lee and Sallee, 1970) is the only metric that specifically measures spatial fit. SLEUTH calculates a modified Lee and Sallee index by taking a ratio of the intersection and the union of the simulated and actual urban areas (Clarke and Gaydos, 1998). A perfect spatial match would result in a value of 1.0. As Clarke and Gaydos (1998)



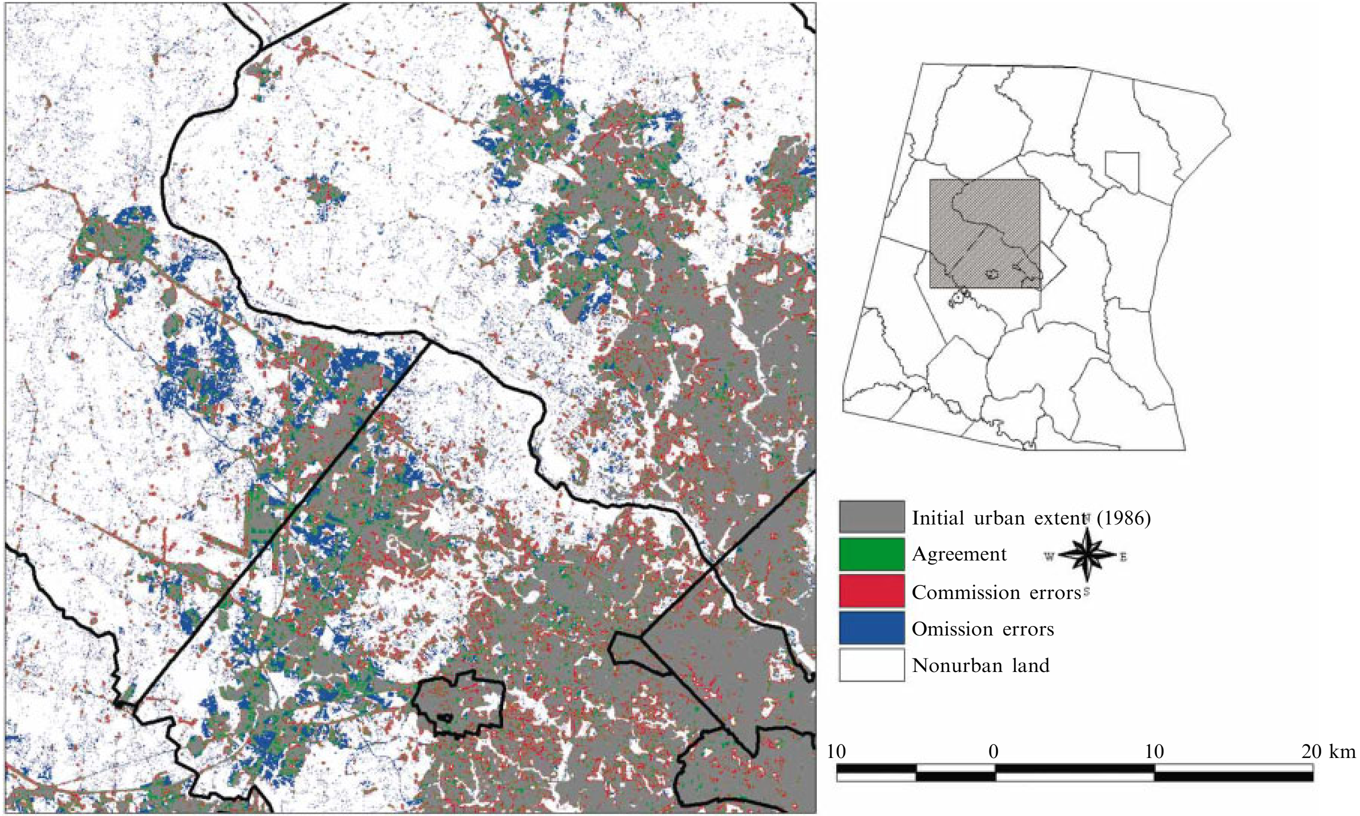
Color plate 1. Time series of urban development for northern Virginia and Baltimore, MD.

point out, however, achieving high values for this index is challenging: an otherwise good replication of urban *shape* would be penalized if the *location* of urban areas were not precise. With an earlier version of the model, Clarke and Gaydos (1998) did not report values of the Lee and Sallee statistic that exceeded 0.3, although recent applications of SLEUTH have achieved values that approach 0.6 (Silva and Clarke, 2002).

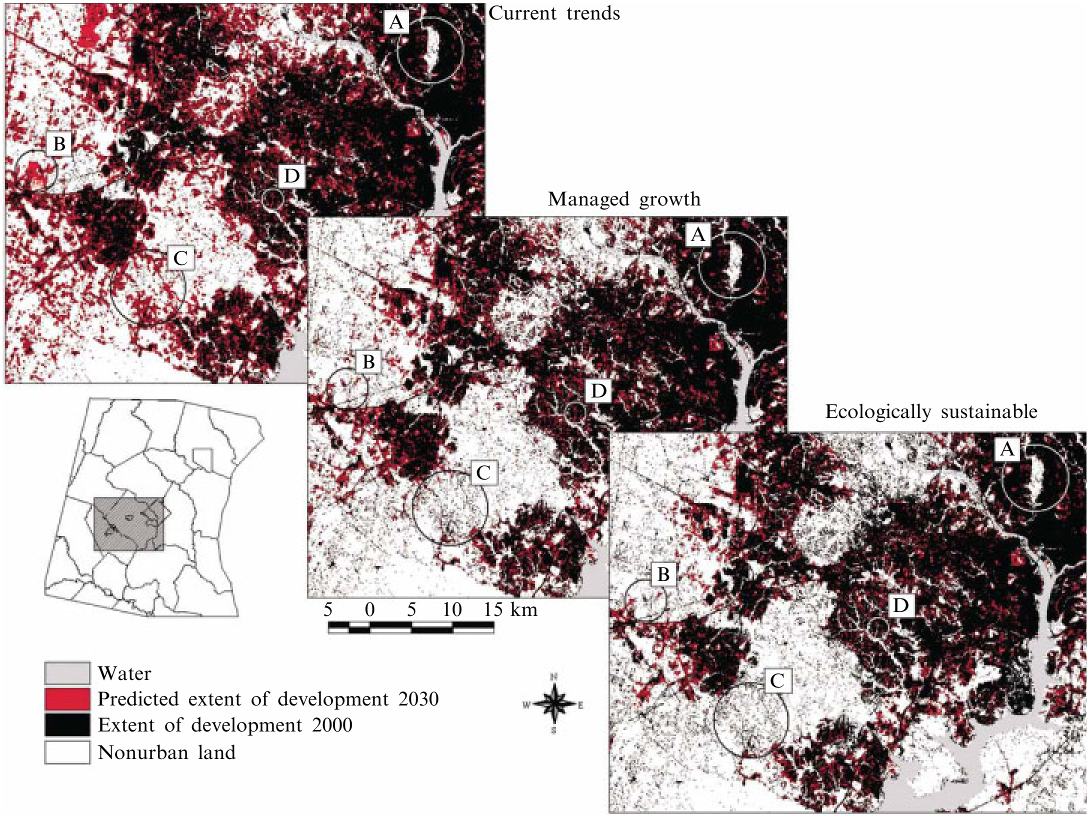
Because of the computational requirements of this approach, calibration was performed in three phases: coarse, medium, and fine. For the coarse calibration, the maximum parameter value range (1 – 100) was used, and the increment used by SLEUTH to step through the range was set to 25. Several of the output statistics were evaluated individually using the following method: a descending sort was performed on the dataset to isolate the parameter values that produced the maximum score for the statistic in question. SLEUTH was then run in test mode using this set of parameter values. The visual outputs were qualitatively compared with the corresponding control years, and output statistics, such as the population of urban pixels, were also used to evaluate the performance of several sets of parameters. Calibration was performed on a Beowulf PC Cluster at the USGS's Rocky Mountain Mapping Center in Denver, CO. The cluster is a 16-node system (1 master node and 15 computing nodes), with each node containing an AMD Athlon/Duron processor, an AMD 750-MHz Thunderbird CPU, and 1.5-GB RAM (Mark Feller, USGS, personal communication). Over a week of processing time was required to complete the calibration.

The primary metric we found most useful to evaluate the performance of the model was the compare statistic, a ratio of the modeled population of urban pixels in the final year to the actual number of urban pixels for the final year. The population statistic (pop), a least squares regression score (r^2) for modeled urbanization compared with actual urbanization for the time series, and the Lee and Sallee statistic were used as ancillary fit statistics. After each calibration phase, the top set of compare scores determined the range of values used in the subsequent phase of calibration. To identify the top scores, all were ranked and a break was identified where the value for the compare statistic dropped. Descriptive statistics, such as mean, median, mode, and standard deviation, were calculated for the group of top scores to aid in the identification of a suitable range that would be used in the next phase of calibration. A wider range was identified for parameters that were more variable, and a narrower range was used for more stable parameters. An increment size was chosen so that stepping through the selected range minimized the total number of simulations.

To perform a spatial accuracy assessment, the model was initialized with 1986 urban extent and growth was predicted out to the year 2000. One hundred Monte Carlo iterations were performed, and a map that showed the probability of any given cell becoming urbanized by 2000 was produced. In order to compare simulated patterns of growth with mapped patterns, the probability image was reclassified into a binary representation of urban extent using a probability threshold of 50%. The simulated map of urban extent in 2000 was compared with mapped 2000 extent at three scales: pixel, watershed, and county. The area comprising the extent of development in 1986 was not considered for this assessment, because this was used to initialize the model. For the pixel scale comparison, an error matrix, constructed from a sample of 200 000 points, was created from which errors of commission and omission and the κ coefficient of agreement were calculated (Lillesand and Kiefer, 1994). To compare accuracy at the watershed and county scales, the total developed areas that were predicted or observed to change between 1986 and 2000 were aggregated to the individual watershed or county spatial units and compared using least squares regression. Although aggregation of the data into irregularly shaped spatial units can introduce uncertainties



Color plate 2. Pixel scale accuracy of the SLEUTH model.



Color plate 3. Comparison of three scenarios for 2030. The effect of protection placed on parks, such as Rock Creek Park in downtown Washington, DC, is shown at A. An area that was seeded with new development in the current trends scenario is shown at B. The effect of the smart growth areas is shown at C, which experiences development only on the current trends scenario. The effect of increasing protection on streams in the ecologically sustainable scenario is shown at D.

into the analysis (Openshaw, 1983, pages 38–41), watersheds and counties are extremely meaningful units of analysis in terms of policy decisions. The watersheds used in this study are subdivisions of subbasins, and are defined by an eleven-digit hydrologic unit code (HUC11) in the USDA Natural Resources Conservation Service's (1995) hierarchical hydrologic unit coding scheme. As they range in size from 40 000 acres to 250 000 acres, several HUC11 watersheds can be contained in a single county.

2.4 Prediction

For prediction, SLEUTH requires the following inputs: urban extent for initialization, an initial transportation network (subsequent future networks can be incorporated on user-specified dates), an excluded layer, slope, and a hillshade, or background, image. Three future growth scenarios were simulated: current trends, managed growth, and ecologically sustainable. The excluded layer served as the primary instrument to differentiate between the three policy scenarios, but different future transportation networks were also created and incorporated into the model in 2010. In addition, the input image of urban extent was altered to include future planned developments in the current trends scenario. The Chesapeake Bay Foundation (a prominent regional environmental group) identified the approximate location size, and density of these developments and then random points were distributed within these areas at varying densities. These points were rasterized and incorporated into the 2000 image that initialized the prediction. Given the sensitivity of CA models to initial conditions, using a single random pattern to represent these new developments may have an impact on the predicted outcome. However, the areas seeded consist of less than 1% of the total study area so the overall effect is assumed to be minimal.

Simulations are produced through Monte Carlo averaging, which produces annual images of development probability. For these predictions 100 Monte Carlo runs were performed. A basic impact assessment on land-cover change for each future scenario was performed using the National Land Cover Database (NLCD) (USGS, 1999), which represents circa 1992 land cover, and our impervious surface map, which was used to represent developed lands for 2000. The probability images produced by SLEUTH were thresholded at 85% to create binary images of urban extent and areas and types of land-cover change noted.

3 Results

3.1 Trends in urban development 1986–2000

Observed growth rates were highest between 1986 and 1990 and between 1996 and 2000. Differences in the spatial pattern of the development occurred during these intervals. For example, the time series of new development (color plate 1) shows that new growth that appeared in 1990 was concentrated around existing urban and suburban centers. Although infill and edge development also occurred between 1996 and 2000, much new development during this time was low-density residential development. These patterns were evident in traditionally rural counties, such as Frederick County, MD and Loudoun County, VA, as well as in previously undeveloped areas within more urbanized counties, such as Fairfax County, VA and Montgomery County, MD.

3.2 Calibration

To avoid inaccuracies due to cell size sensitivity, which we noted in testing, the full resolution (45 m) dataset for the Washington–Baltimore study area was used. Although literature on SLEUTH encourages the use of the Lee and Sallee metric as the primary fit statistic, we found the parameter sets that produced higher values for the Lee and Sallee metric were associated with little or no growth. During the coarse calibration phase, for example, the maximum Lee and Sallee score was 0.73

Table 2. Calibration results summary.

	Growth parameter				
	dispersion	breed	spread	slope	road growth
Coarse calibration					
Range	1-100	1-100	1-100	1-100	1-100
Step	25	25	25	25	25
Monte Carlo iterations = 4					
Total number of simulations = 3 125					
Compare statistic = 1.00					
Population statistic (r^2) = 0.86					
Lee and Sallee statistic = 0.67					
Medium calibration					
Range	40-90	30-75	20-30	1-5	0-25
Step	10	15	2	1	5
Monte Carlo iterations = 7					
Total number of simulations = 3 600					
Compare statistic = 1.00					
Population statistic (r^2) = 0.86					
Lee and Sallee statistic = 0.68					
Fine calibration					
Range	50-60	45-55	23-28	3-8	15-20
Step	2	2	1	1	1
Monte Carlo iterations = 9					
Total number of simulations = 7 776					
Compare statistic = 1.00					
Population statistic (r^2) = 0.86					
Lee and Sallee statistic = 0.68					
Final coefficient values	52	45	26	4	19

and the associated parameter values were: dispersion = 1, breed = 25, spread = 1, slope = 100, road growth = 1. Among the top 100 scores, the breed and road-growth coefficients were quite variable, but dispersion and spread were consistently low while slope resistance was consistently high. After extensively testing various parameter sets based on different fit statistics, we found the parameters based on the compare metric were able to capture the *amount* of growth that occurred in the system, and were also able to simulate *urban form* successfully, as evidenced by the high value (0.67) for the Lee and Sallee metric (table 2). We therefore used the compare metric as the primary fit statistic throughout the calibration procedure. The dispersion and breed parameters were the most variable throughout the calibration process, and thus have higher ranges and coarser steps. After the fine calibration, the final parameter values that produced the highest score for compare were: dispersion = 52, breed = 45, spread = 26, slope = 4, road growth = 19. These parameter values determined the growth trends that were used to forecast future development patterns.

The results of the spatial accuracy assessment reveal some of the limitations of the model in simulating local patterns of urban development. Although the overall spatial accuracy at the pixel scale was quite high (93.1%), the overall κ statistic was low (0.19) (table 3). When we considered only areas where change was predicted or observed (roughly 22% of the study area), the overall accuracy dropped to 19%. Furthermore, the errors of omission (1−producer's accuracy) and commission (1−user's accuracy) for the urban class reveal that predicting the exact location of urbanized pixels was problematic. This is illustrated at the local scale in color plate 2, where areas of agreement (green), model commission (red), and model omission (blue) are indicated.

Table 3. Results of pixel scale accuracy assessment.

	Reference pixels	Modeled pixels	Number correct	Producer's accuracy (%)	User's accuracy (%)
Nonurban	193 391	188 789	184 176	95.2	97.6
Urban	6 609	11 211	1 996	30.2	17.8
Total	200 000	200 000	186 172		
Overall accuracy (%)	93.1				
κ	0.19				

Commission errors are primarily the result of the model overestimating the amount of edge growth, whereas we believe the omission errors largely result from the model's inability to capture local scale processes, such as spatially localized peaks in land demand that result in a sudden increase of development in an area.

The failure of the model to predict accurately the exact spatial location of development is not surprising, but accuracy at the pixel scale is not crucial for a regional assessment. The model performed quite well when estimates of developed land were aggregated to the 11-digit (HUC11) watershed scale ($r^2 = 0.72$, $P_{104} < 0.01$) and at the larger spatial units of counties ($r^2 = 0.86$, and $P_{44} < 0.01$).

We also observed that SLEUTH apparently underestimated the amount of low-density development that occurred over the time period. Despite a relatively high value for the dispersion coefficient (52) and a low value for spread (26) (table 2), we found that edge growth produced an average of 97% of the growth in the system between 1986 and 2000; spontaneous growth produced roughly 1%. From the maps of urban development used in calibration, however, we found that roughly 13% of new development occurred as single, isolated pixels. To some extent this finding is influenced by the parameters chosen during calibration, although we note that the dominance of the edge-growth parameter was not significantly impacted when the dispersion coefficient value was artificially raised. When the dispersion coefficient was set to its maximum value (100) and all other coefficients held constant, the average number of pixels produced by spontaneous growth consisted of only 2% of new growth.

3.3 Prediction

Data layers and probabilities of exclusion, or levels of protection, for each scenario are summarized in table 4 (over). Split probabilities (for example, 60/45) refer to situations where the probability of exclusion is different based on some spatial contingency. For example, the 45 m tidal water buffer in the current trends scenario has a 60% probability of exclusion in Maryland and a 45% probability of exclusion in Virginia. Likewise, contiguous forest in the managed growth scenario has a high probability of exclusion unless it is located within a smart growth area, in which case it has a lower probability of exclusion (50%) to reflect the higher growth pressures in those areas.

The *current trends* scenario reflects policies that are currently in place [figure 2(a), over]. All parks and easements are fully protected from development. Large, contiguous wetlands and riparian buffer strips along major streams have partial protection as does land adjacent to tidal waters. Keeping with current policies, a slightly higher protection applies to the tidal buffer in Maryland than in Virginia. In Maryland, land outside the state-designated PFAs has minimal protection. Major new planned roads and road widenings and planned or early-stage development in 2000 are also included in this scenario.

Table 4. Summary of data elements and levels of protection for each scenario.

Data element	Current trends[a]	P [a]	Managed growth[a]	P [b]	Ecologically sustainable[a]	P [b]
Protected areas						
State, federal, local parks, water, easements	Yes	100	Yes	100	Yes	100
Wetlands	2 or more acres	60	0.50 or more acres	80	0.50 or more acres	100
Bay preservation—tidal waters	45 m buffer in MD/VA; main stem and level-1 streams to fall line	60/45	135 m buffer; main stem and level-1 streams to fall line	80	135 m buffer; main stem and level-1 streams to fall line	100
Forests		0	Contiguous forest of 250+ acres outside/inside smart growth areas	70/50	Contiguous forest of 100+ acres and corridors outside/inside smart growth areas	90/50
Agriculture		0	Contiguous farmland of 5000+ acres outside/inside smart growth areas	70/50	Contiguous farmland of 5000+ acres outside/inside smart growth areas	90/50
Streams	45 m buffer around level-1 and level-2 streams	60	45 m buffer around level-1 – 4 streams	70	90 m buffer around level-1 and level-2 streams; 45 m buffer around level-3 – 7 streams	100
Growth management areas						
	Protection of land outside MD Priority Funding Areas	15	Protection of land outside UMD/CBF designated smart growth areas	35	Protection of land outside UMD/CBF designated smart growth areas	50
Transportation						
Metro stations		0	Protection on land outside 0.50 mile zone; CBF specified new stations	35	Protection on land outside 0.50 mile zone; CBF specified new stations	50
New roads	Major new roads as indicated by CBF, some secondaries promoted to reflect widening		No major new roads, some secondaries promoted to reflect widening		No major new roads, some secondaries promoted to reflect widening	
Seeds[c]	Yes		No		No	
Slope	Model limited over 21%		Model limited over 21%		Model limited over 21%	

[a] CBF refers to the Chesapeake Bay Foundation and UMD refers to the University of Maryland Department of Geography.
[b] P indicates the exclusion probability, or levels of protections. Split probabilities (for example, 60/45) refer to situations where the probability of exclusion is different based on some spatial contingency, which is indicated in the scenario description.
[c] *Seeds* indicates whether or not future development was seeded into the initialization image.

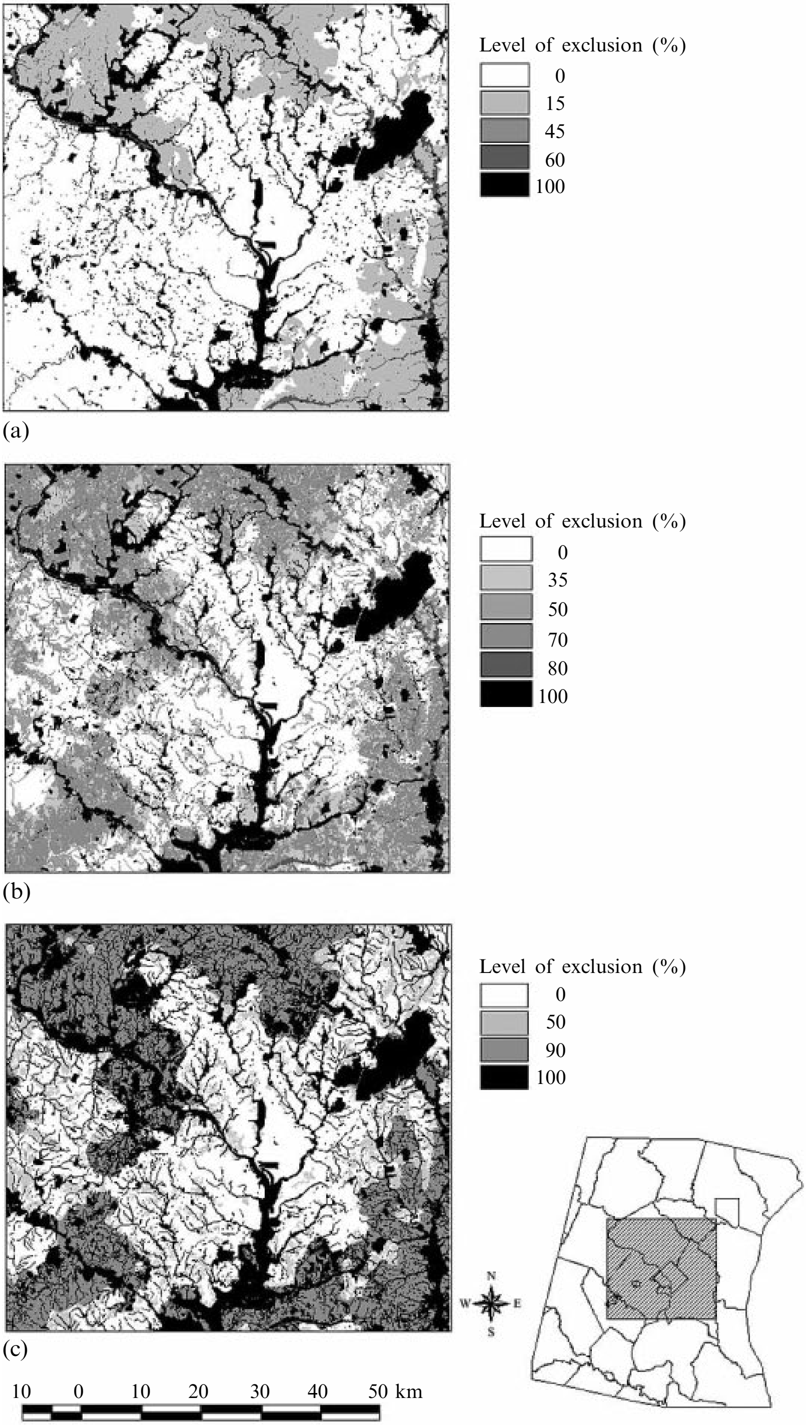


Figure 2. Excluded layers for (a) current trends, (b) managed growth, and (c) ecologically sustainable scenarios for the Washington, DC area. White indicates land that is theoretically open to development.

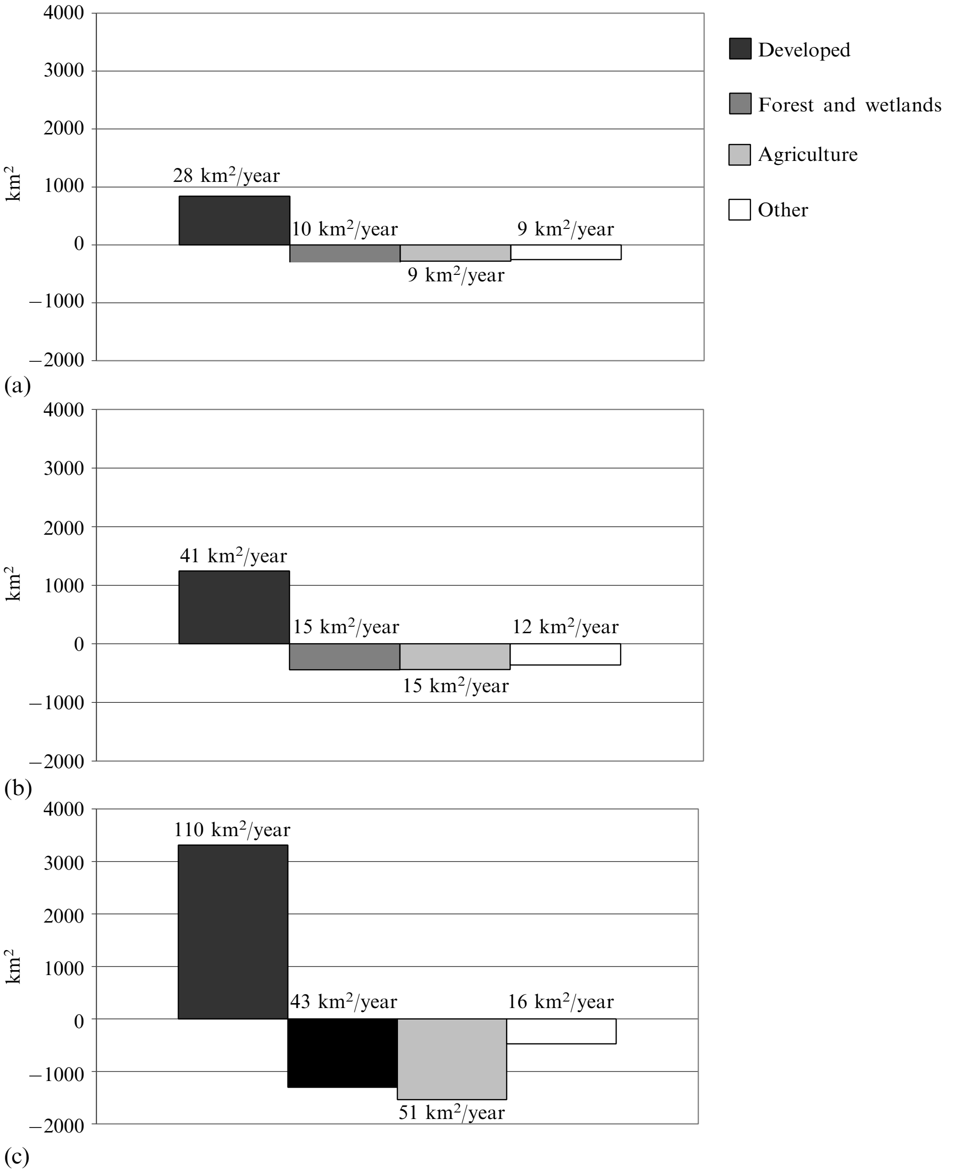


Figure 3. Results of impact assessment for (a) the ecologically sustainable scenario, (b) the managed growth scenario, and (c) the current trends scenario.

The *managed growth scenario* reflects a stronger commitment to spatially focused growth and resource protection [figure 2(b)]. In the excluded layer, wetlands, riparian buffer strips, and the tidal buffer have higher levels of protection. This includes all wetlands larger than 0.5 acres, a more extensive stream network, and a wider tidal buffer than the current trends exclusions. New 'smart growth areas' (SGAs) developed for both Maryland and Virginia increase exclusions outside of established urban centers. Forest and agriculture have greater protection under this scenario. The transportation network and the image of urban extent also reflect a commitment to focused growth; no new roads and no new major planned developments appear in this scenario.

The third scenario, *ecologically sustainable*, reflects a more stringent set of policies targeted toward limited growth and natural resource protection [figure 2(c)]. The data elements for the excluded layer are similar to those in the managed growth case, but protection levels are higher. In addition, riparian areas include a larger buffer and most headwater streams. Like the previous scenario, no new roads appear in the transportation network, and no new major planned developments exist.

The results of the scenario predictions (color plate 3) show higher dispersed development patterns for the current trends than the managed growth scenario, while the ecologically sustainable scenario shows highly constrained growth over the whole region, with most occurring in and around existing urban centers. The impact of development on resource loss for each scenario (figure 3) shows the current trends growth rate similar to that found between 1986 and 2000, and a continuation of low-density development patterns. This is predicted to lead to substantial land consumption throughout the study area with a simultaneous loss of resource lands. Because the higher levels of protection, the growth rates for the managed growth scenarios are reduced, producing a much lower predicted loss of resource lands.

4 Discussion

4.1 SLEUTH as a planning tool

Although some planning agencies at the state and local level within the Chesapeake Bay watershed have the technology and expertise to run simulations of future development, the results from this regional scale assessment have provided provocative insights into the future of the region. In terms of pinpointing areas at risk for future development, the performance of the model in terms of spatial accuracy must be carefully considered. As shown in section 3.2, SLEUTH was not successful at pinpointing the exact location of development at the pixel scale. We found the accuracy improved significantly when results were generalized to meaningful spatial units, such as HUC11 watersheds. Given these findings, SLEUTH could be an appropriate model for regional assessments of urban land-use change, the results of which could be used to guide more localized modeling efforts.

The visualization of potential land-use change has proven to be a powerful tool for raising public awareness and facilitating discussion. Reports about this research were published in several well-known media sources, such as the *Washington Post* newspaper (Huslin, 2002), and appeared on the website for the Chesapeake Bay Foundation. The results for the current trends scenario are especially salient to public discussion because they demonstrate the potential losses in resource lands that could occur if the observed rates of land-use change were to continue into the future. Furthermore, as efforts to improve the health of the Chesapeake Bay progress, the need for regional-scale land-use change assessments is becoming acute. That SLEUTH may be a tool that can meet these needs has been recognized by state and regional agencies, some of which we are working with to explore the use of SLEUTH as a potential tool for modeling environmental vulnerability.

The excluded layer proved to be an effective tool for exploring different policy scenarios, and illustrates the advantages of linking the modeling process to a GIS. All data integration and manipulation were performed within a GIS, allowing for the precise designation of target conservation areas, such as riparian buffer zones. For each scenario, all land within the study area was ranked in terms of conservation using a grid-based model. The resulting excluded layer was easily integrated into the model. Translating various policies into exclusion probabilities was not an intuitive process, however, and consisted of an informed qualitative ranking of the rigorousness of each conservation policy. These rankings of low, medium, or high were then translated into generalized exclusion probabilities.

Although the excluded layer is ideal for simulating the effects of conservation or regulatory policies, SLEUTH does not have an adequate mechanism to simulate the potential impacts of incentive policies. For example, Maryland's PFAs have been established to provide an incentive to develop within certain designated areas. By encouraging denser and more compact development in areas that have existing urban infrastructure, the State of Maryland hopes to decrease the amount of new development occurring in outlying areas (Northrup and Duket, 1997). We simulated this effect in the excluded layer by putting a resistance to development on land *outside* the PFAs, but were not able to simulate the potential attraction to development *within* PFAs that is the spirit of the policy. The inability to redirect growth pressure is a drawback to the SLEUTH model, which may not capture the real impact of implementing land-conservation measures. In their application of the California Urban Futures econometric model, for example, Landis (1995) found that strict growth control measures actually pushed development into outlying, rural areas.

4.2 Model sensitivity

Several questions regarding the model's sensitivity were raised as a result of this application. First, we found the model exhibited sensitivity to cell size. Because computational resources were not a strictly limiting factor, we therefore avoided using the hierarchical scale approach to calibration suggested by Clarke and Gaydos (1998). How the parameter values scale with resolution has been investigated and reported by Jantz and Goetz (forthcoming).

Another issue we noted was the temporal sensitivity of the model during calibration. Clarke and Gaydos (1998) found that the use of different data sources used in a historic analysis may have compromised the accuracy of the model, but they were able to produce a robust time series. By using a shorter time series, we were able to use a highly consistent and reliable dataset, which was derived solely from remote sensing imagery. More research is needed to understand the impact of using a shorter time series, although preliminary results indicate that shorter time series may actually produce better simulations (Candau, 2002). Because we were not producing long-term predictions, we found a shorter time series with consistent data produced reliable results.

The response of the fit statistics, particularly the Lee and Sallee metric, during calibration may also have been influenced by the short time series. We found the highest value of the Lee and Sallee statistic was produced when the parameters producing urban growth were low and when the slope coefficient was high—essentially resulting in a simulation where no growth would occur. This may not be the case when a longer time series is used, as evidenced in previous SLEUTH applications (Clarke and Gaydos, 1998; Clarke et al, 1997; Silva and Clarke, 2002).

Finally, we found some of the assumptions concerning growth processes that are operationalized in the model code and in the calibration procedure may limit the kinds of growth processes that can be represented by SLEUTH. One of the growth processes that was especially salient to this work was low-density development, which appeared in the urban extent data as single developed pixels or as small clusters of developed pixels. This growth type would arguably be captured by the dispersion and breed parameters, yet the SLEUTH code gives precedence to edge growth (Clarke et al, 1997), limiting the ability of the model to simulate other urban development processes. Furthermore, the pixels produced by the dispersion and breed parameters are spatially stochastic, and do not appear in the visualizations of future development unless they are consistently chosen throughout the set of Monte Carlo iterations. Although the average numbers of pixels produced by growth types that would capture low-density development patterns are recorded in the tabular output from SLEUTH, the use of thresholded probability maps may not be suitable for visualizing low-density growth.

In an exploration of the sensitivity of the growth parameters, we found results similar to those reported to Clarke and Gaydos (1998). The population fit statistic (the r^2 value for the actual versus predicted urban extent for each control year) was especially sensitive to changes in the dispersion parameter, but there was no apparent effect of this parameter on the compare statistic (the ratio of the actual versus predicted population of urban pixels for the final control year). None of the fit statistics was found to be sensitive to the road-growth parameter, and we found both the road-growth and dispersion parameter to be highly variable throughout our calibration procedure. We obtained significantly higher values for the Lee and Sallee measure than Clarke and Gaydos (1998), but this likely because we were working with a shorter time series—fifteen years compared with 200 years. We also worked with land-cover data that were obtained from a single source, satellite imagery, whereas Clarke and Gaydos (1998) had obtained data from a variety of cartographic sources. The raster format of the satellite data is more conducive to the SLEUTH modeling environment, and probably contributed to the higher values we obtained for the Lee and Sallee accuracy metric.

5 Conclusions

In the Chesapeake Bay watershed, where regional approaches to land-use management are being developed by the Chesapeake Bay Program and its partners, a realistic modeling system that can be used to explore different regional futures is critically needed. Because of an ability to simulate the complex behavior of urban systems, CA models represent a viable approach for regional scale modeling. Furthermore, consistent, regional datasets derived from satellite imagery and other sources can be readily integrated into the CA modeling environment. Our research explored the suitability of utilizing one CA, the SLEUTH model, for regional planning applications. SLEUTH was found to be useful for many of the demands for regional modeling, producing accurate estimations of growth at the HUC11 watershed level and coarser scales. Interactive scenario development and the ability to visualize and quantify outcomes spatially were key functionalities that SLEUTH provided. The availability and consistency of historic datasets, especially those that predate the satellite record, are potential issues for some applications. Empirical calibration of the model using Landsat Thematic Mapper image maps of past change provided what we believe is the first calibration of SLEUTH using fine-scale data, and aided the model predictions of future change. Calibration at this level of spatial detail remains a computationally intensive process, requiring ample use of a parallel computing environment, and may preclude the use of the model by local or nongovernmental agencies where computing resources may be a limiting factor. Other considerations include model sensitivity to cell size and to the historic datasets used for calibration. Some assumptions about growth processes prevent SLEUTH from being able to capture a wider range of growth patterns and processes, which limits its utility for infill development—one of several components of smart growth planning. Despite these considerations, we found SLEUTH to be a useful tool for assessing the impacts of alternative policy scenarios.

Acknowledgements. Andrew Smith developed the time series of impervious maps on which the model was calibrated. Steve Libbey and Lee Epstein at the Chesapeake Bay Foundation were instrumental in the development of the scenarios. Collaborators at the US Geological Survey, Janet Tilley, Jeannette Candau, Mark Feller, and Dave Hester, are acknowledged for their support. Preliminary calibration runs were performed using computing resources at the US Geological Survey offices in Reston, VA and the final calibration was run at the Rocky Mountain Mapping Center in Denver, CO. This work was supported by grants to S J Goetz from the Chesapeake Bay Foundation and NASA (NAG511149).

References

Arnold C L, Gibbons J C, 1996, "Impervious surface coverage: the emergence of a key environmental indicator" *Journal of the American Planning Association* **62** 243 – 259

Bockstael N E, 1996, "Modeling economics and ecology: the importance of a spatial perspective" *American Journal of Agriculture and Economics* **78** 1168 – 1180

Bockstael N, Bell K, 1997, "Land use patterns and water quality: the effect of differential land management controls", in *Conflict and Cooperation on Trans-Boundary Water Resources* Eds R Just, S Netanyahu (Kluwer, New York) pp 169 – 191

Burchell R W, Shad N A, Phillips H, Downs A, Seskin S, Davis J S, Moore T, Helton D, Gall M, 1998, "The costs of sprawl—revisited", report 39, Transit Cooperative Research Program, Washington, DC

Candau J, 2002, "Temporal calibration sensitivity of the SLEUTH urban growth model", master's thesis, Department of Geography, University of California, Santa Barbara, CA

Clarke K C, Gaydos L J, 1998, "Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore" *International Journal of Geographical Information Science* **12** 699 – 714

Clarke K C, Hoppen S, Gaydos L, 1997, "A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area" *Environment and Planning B: Planning and Design* **24** 247 – 261

Couclelis H, 1997, "From cellular automata to urban models: new principles for model development and implementation" *Environment and Planning B: Planning and Design* **24** 165 – 174

Goetz S J, Wright R, Smith A J, Zinecker E, Schaub E, in press, "Ikonos imagery for resource management: tree cover, impervious surfaces and riparian buffer analyses in the Mid-Atlantic Region" *Remote Sensing of the Environment*

Grumet R S, 2000, "Bay, Plain, and Peidmont: a landscape history of the Chesapeake Heartland from 1.3 billion years ago to 2000", report for the Chesapeake Bay Heritage Context Project, US Department of the Interior, National Park Service, Annapolis, MD

Huslin A, 2002, "Study forecasts huge loss of land by 2030" *The Washington Post* 1 May, page B1

Jantz C A, Goetz S J, forthcoming, "Sensitivity analysis of the SLEUTH urban growth model" *International Journal of Geographical Information Science*

Landis J, 1995, "Imagining land use futures: applying the California urban futures model" *Journal of the American Planning Association* **61** 438 – 457

Lee D R, Sallee G T, 1970, "A method of measuring shape" *The Geographical Review* **60** 555 – 563

Lillesand T M, Keifer R W, 1994 *Remote Sensing and Image Interpretation* (John Wiley, New York)

Northrup M, Duket L, 1997, "Smart growth: designating priority funding areas", report 97-08, Maryland Office of Planning, Annapolis, MD

Openshaw S, 1983 *The Modifiable Areal Unit Problem* Concepts and Techniques in Modern Geography, number 38 (GeoAbstracts, Norwich)

O'Sullivan D, 2001, "Exploring spatial process dynamics using irregular cellular automaton models" *Geographical Analysis* **33** 1 – 17

Ridd M K, 1995, "Exploring V-I-S (vegetation – impervious surface – soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities" *International Journal of Remote Sensing* **16** 2165 – 2185

Silva E A, Clarke K C, 2002, "Calibration of the SLEUTH urban growth model for Lisbon and Porto, Spain" *Computers, Environment and Urban Systems* **26** 525 – 552

Smith A J, Goetz S J, Prince S D, Wright R, forthcoming, "Estimation of sub-pixel impervious surface area using a decision tree approach, Ikonos and Landsat imagery" *Remote Sensing of the Environment*

Torrens P M, O'Sullivan D, 2001, "Cellular automata and urban simulation: where do we go from here?" *Environment and Planning B: Planning and Design* **28** 163 – 168

USDA Natural Resources Conservation Service, 1995, "Mapping and digitizing watershed and subwatershed hydrologic unit boundaries", National Instruction 170-304, National Cartography and Geospatial Center, Forth Worth, TX, http://www.ftw.nrcs.usda.gov/HUC/ni170304.html
US Environmental Protection Agency, 2000, "National water quality inventory: 1998 report to Congress", report EPA841-R-00-001, Assessment and Watershed Protection Division, Washington, DC
USGS, 1999, "National land cover data", US Geological Survey, http://landcover.usgs.gov/natllandcover.html
USGS, 2003, "Project gigalopolis: urban and land cover modeling", US Geological Survey, http://www.ncgia.ucsb.edu/projects/gig/
Wear D N, Turner M G, Naiman R J, 1998, "Land cover along an urban – rural gradient: implications for water quality" *Ecological Applications* **8** 619 – 630
Webster C, Wu F, 2001, "Coase, spatial pricing and self-organising cities" *Urban Studies* **38** 2037 – 2054
White R, Engelen G, 2000, "High resolution integrated modeling of the spatial dynamics of urban and regional systems" *Computers, Environment and Urban Systems* **24** 383 – 400
Wickham J D, Riiters K H, O'Neill R V, Rechhow K H, Wade T G, Jones K B, 2000, "Land cover as a framework for assessing the risk of water pollution" *Journal of the American Water Resources Association* **36** 1417 – 1422
Wickham J D, O'Neill R V, Riitters K H, Smith E R, Wade T G, Jones K B, 2002, "Geographic targeting of increases in nutrient export due to future urbanization" *Ecological Applications* **12** 93 – 106
Yeh A G, Li X, 2001, "A constrained CA model for the simulation and planning of sustainable urban forms by using GIS" *Environment and Planning B: Planning and Design* **28** 733 – 753
Yeh A G, Li X, 2002, "A cellular automata model to simulate development density for urban planning" *Environment and Planning B: Planning and Design* **29** 431 – 450