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Modeling the Urbanization Process across Maryland in the Context of Chesapeake Bay Restoration

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Abstract

Smart Growth policies have been formulated in Maryland to address the exurbanization process, and to mitigate its impacts. Measuring and understanding land use change is key to predicting the impacts of these policies. In this paper we use data based on satellite imagery to map and monitor the expansion of residential and commercial land cover to estimate the amount of different types of land that were replaced by development. We then calibrate a cellular automaton model that measures the rates and patterns of change, and predicts future development under a suite of policy scenarios. We also use a very different type of approach which models economic decisions in the context of the regulatory environment and does so using data at the land parcel level. The parameters of this spatially explicit economic model are estimated and out of sample predictions are made to demonstrate the usefulness of the approach. The approaches are then compared, highlighting strengths and shortcomings of both. Regional analysis of broad policies such as those supported through the Chesapeake Bay Program can be most successful if hybrid models that incorporate strengths of both can be developed.

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Introduction

The contemporary pattern of urbanization is increasingly taking the form of low density, decentralized residential and commercial development (Irwin and Bockstael 2006, 2007). These dispersed development patterns have been linked to loss of agricultural and forest lands and resulted in degraded water quality. A number of studies have shown, for example, that when impervious surface coverage within a watershed exceeds 10%, degradation of stream quality occurs (Schueler 1994, Snyder et al. 2005). Smart growth techniques have been proposed as a means to mitigate these impacts through the preservation of open space (natural areas and farmland), using compact development patterns, creating communities that include a mix of land uses, and developing residential areas where they can take advantage of existing amenities (e.g. public transit) (Cohen 2002, EPA 2006).

In the Chesapeake Bay region, there is an emphasis on aspects of smart growth policies that decrease the amount of impervious surface area, in order to reduce ecosystem impacts, including inputs of lawn fertilizers and pesticides (Milesi et al. 2005). The rate of conversion of forests and wetlands is likewise diminished, allowing these landscapes to maintain their ecosystem functions. In Maryland, often viewed as a leader in smart growth, initiatives have included the 1997 Smart Growth Areas Act, the 1997 Rural Legacy Act (a land preservation program), Brownfields cleanup and revitalization incentive programs, and a Live Near Your Workplace program, among others (Cohen 2002). Most recently (2007) Maryland has initiated a "Green Fund" which functions as an impervious surface "tax" via local stormwater utility fees designated to mitigate the influence of increased stormwater runoff in more impervious areas.

Our objectives here were to measure, using satellite imagery, changes in land cover and associated impervious cover over the period during which Smart Growth policies were initiated, and to explore two quite different modeling approaches that have potential for forecasting future change.

Expansion of the Built Environment and Resource Land Consumption

In previous work satellite imagery was used to illustrate how lands comprising the natural resource base have been replaced by a matrix of the built environment (Jantz et al. 2005), and how these changes impact stream biota in Maryland (Goetz et al. in press). In work using a variety of data sources Irwin and Bockstael (2004) review urban land use trends in the U.S. and find evidence that substantial proportions of recent development activity is of the low density, discontinuous form and in regions outside established urban areas. Of particular importance, these patterns appear to be pervasive when studied at a fine scale in many outer suburban and exurban areas, but often disappear at coarser scales of analysis. Irwin and Bockstael (2006) attempt measures of changes in this low density development using tax map (parcel boundary) data and overflight land use data for parts of Maryland. Due to the growth in low density development, small population increases can have rather large impacts on land conversion. This is important because the placement and spatial configuration of land development is often thought to be as important as the total amount of developed area (Forman 1995). It is also important because it highlights the difference between land cover and land use which will play a major part in the comparison of modeling approaches in this paper. Where development is dense, land cover and land use are almost synonymous. But in areas of low density, fragmented development, large parcels can be developed at their full potential even though only a small percentage of the land is covered with impervious surface.

For the analysis presented here the amount and location of change in the built environment were estimated by simply differencing maps of impervious surface cover in the years 1990 and 2000 (Figure 1). The maps were derived from analysis of Landsat satellite imagery (see Goetz et al. 2004). Areal estimates of developed land in the two time periods were calculated by summing the area of each 900 m^2 image "pixel" with 10% or greater impervious cover. Analysis of growth patterns in the region indicates that, for the 1990-2000 time period, urbanization was primarily associated with existing urban and suburban centers, such as areas surrounding Washington, DC and Baltimore, MD (Table 1, Figure 1). Although Montgomery County has been at the forefront of Smart Growth implementation policies, particularly the Rural Legacy program, it is estimated to have experienced the largest absolute increase in impervious cover over the 10 year time period. This is partly because the policies were only fully implemented late in the time period we analyzed (post 1997), but also because of the proximity of Montgomery County to Washington DC and the amount of development already present in 1990. Rates of change in outlying counties, however, exceeded those in urban areas (Table 1). In addition, urbanization patterns in urban and suburban counties tend to be characterized by more clustered and high-density development. In outlying counties, development patterns tend to be more dispersed, particularly in rural counties just adjacent to metropolitan regions characterized by larger residential lots, shopping complexes and business parks. These results are quite consistent with recent findings of Shen and Zhang (2007), which was also focused on Maryland but using a very different methodological approach.

There are many examples of smart growth ordinances in municipalities across the region, but Maryland remains the only state in the region to have adopted a state-wide smart growth policy. Even within Maryland, however, the effectiveness of smart growth planning varies widely across counties. We were not able to adequately document the impact of Smart Growth policy implementation, because we only had state-wide maps for two time periods (1990 and 2000) that span the initiation of implementation. However, we also developed maps of impervious cover from Landsat imagery for four years (1986, 1990, 1996 and 2000) for a smaller region encompassing just those jurisdictions that are part of the Metropolitan Washington DC Council of Governments (COG). It is difficult to draw conclusions based solely on these four time intervals (again because of the initiation of Smart Growth programs late in the observation period), but it does appear that, when analyzed by watersheds, growth rates declined in the period 1996-2000 for more developed watersheds relative to rates observed in earlier time periods (Figure 2a). It is difficult to know whether this was due to land use policies, slowing of economic growth in the region, or simply the reduced amount of land in these watersheds available for additional development. Conversely, watersheds in more outlying areas and with lower total amounts of impervious cover grew faster post-1995 than before. This result is depicted in Figure 2b as a ratio of change in impervious cover for the period 1996 to 2000 over that for the period 1986 to 1996. These same recently changing watersheds, with greater growth rates post-1995, appear in the top half of figure 2a. Using these data sets to assess the rate of change in impervious cover requires augmentation with more recent Landsat observations and associated analyses, which have not yet been done, but the initial results support those of Shen and Zhang (2007) who noted the variable effectiveness of smart growth policies across the different counties of Maryland.

We also used our maps of impervious cover to calculate the types of lands displaced by the observed changes in the built environment as measured by Landsat. This was done by simply overlaying the impervious surface change map on a 1990 map of land cover. Loss of resource lands (farms, forests, wetland) were then summarized, identifying the land cover classification of areas that experienced change between 1990 and 2000 and creating maps of lands converted to impervious cover (see Jantz et al. 2005). Across both Maryland and the Chesapeake Bay watershed, most of the resource land loss occurred on agricultural lands (64%). Not surprisingly, counties with a significant amount of agricultural lands near fast growing urban areas experienced the highest rates of agricultural land conversion. Development of agricultural lands in more outlying areas may reflect home buyers willingness to live further away from places of employment in exchange for more open space and potentially lower housing costs. While overall loss of agricultural lands across the entire Chesapeake watershed was about 2%, the amount of loss was quite variable by county, with some experiencing conversion rates exceeding 30%. The likelihood of future losses in resource lands is explored further below in the context of forecasts of impervious surface change conducted under different land use policy scenarios.

One of the needs for implementing smart growth policies at any scale is the ability to evaluate alternative land use scenarios, both in terms of their spatial form and their potential environmental impacts. Forecasting future land use change is a daunting task, however. Different approaches depend on different types of data, focus on different dimensions of change, and produce different types of output. In the next two sections we present two very different approaches to illustrate how varied the methods are that can potentially be applied to this problem, even though both are essentially spatial models. One approach is a cellular automata model, where the land surface is represented as a regular grid of cells that can change state based on the application of transition rules over a series of time steps. We report on this approach and show some projections of future losses in resource lands. The second approach is based on economic reasoning and relies on data about economic decisions. We explain this model and provide some validation by estimating the parameters of the model using data from 1990 through 1996 and then comparing predictions for 1997 through 2000 against actual development activity.

Cellular Automata Urban Change Model

In conjunction with the Chesapeake Bay Program, we have developed spatial modeling approach for the 168,000 km^2 Chesapeake Bay watershed that allows regional planners to envision alternative growth scenarios and to evaluate their environmental impacts. Using the 1990-2000 impervious surface maps discussed above, we calibrated the SLEUTH urban growth model (Clarke et al. 1997), and simulated historic development patterns. We then used SLEUTH to predict into the future under different scenarios, including a baseline scenario of what the future built environment would look like if rates of change in impervious cover remained unchanged. We also simulated alternative futures where rates of change increase or decrease under different scenarios of smart growth implementation, applying different levels of protection to natural resource lands (see Jantz et al. 2004 for a description of this process).

We note here that SLEUTH is essentially a pattern-extrapolation model, which simulates urban dynamics through the application of different types of growth rules that are parameterized as part of the calibration process. The calibration includes a multi-phase, brute force process, where different combinations of parameter sets are systematically tested across a series of Monte Carlo simulations. Various fit statistics are then used to converge on a set of parameters that best represent observed patterns of urbanization (the latter derived, in our case, from the time series of impervious surface cover described above). The result of a model calibration is compared to observations from analysis satellite imagery (Figure 3).

As part of this activity we have documented the calibration process and described the sensitivity of the model to scale (grain size) and calibration methodology (Jantz and Goetz 2005). Further, we conducted a series of code modifications that reduce the model's memory requirements by 75% and processing speed by about 500%. Also, until recently, the model had no ability to attract (rather than simply resist) development, so we recently added this capability (Jantz et al. *in press*). This last point is useful for attempting to simulate the influence of, for example, priority funding areas where growth is encouraged through tax incentives (i.e. infill or brownfield development).

The outputs of SLEUTH are probabilistic, meaning that the value of each output grid cell is the probability of that cell being converted to impervious cover over the period of interest (in our case the years 2000 to 2030). The grain of our predictive analysis was the same as the 30m Landsat imagery used for model calibration. The probabilities are generated, as in the calibration phase, from many individual simulations.

We developed several different scenarios simulating the effects of alternative land use policies by manipulating a cost surface (or "exclusion layer") input to SLEUTH. The cost surface was developed from overlaying a series of geographic map layers that included protected areas, land cover types, riparian zones, rural legacy areas, and so on. These were developed in collaboration with a group of stakeholders via a process facilitated by the Chesapeake Bay Program (see Jantz et al. *in press* for additional information). The various model scenarios based on these cost surfaces included, first, a current trends or "business as usual" (BAU), which assumed growth would continue as it had over the calibration period (1990 to 2000, see Figure 3). Second was a "managed growth" scenario where additional protections were placed on different components of the landscape. Third we developed a "smart growth" scenario which incorporated existing protected lands to designate areas that are completely off-limits for new development, and assumed stronger protection on lands valued for cultural or natural resources. Maps of model forecasts for Maryland under a BAU and Smart Growth scenario are shown in Figure 4. We then used these maps to conduct a vulnerability assessment of future resource land conversion to impervious cover.

Vulnerability Assessment of Future Land Conversion

The Maryland Department of Natural Resources (DNR) has developed several data products designed to facilitate forested lands management and preservation. The strategic forest lands assessment (SFLA) (Maryland Department of Natural Resources, 2003) scores all forested land cover in the state from 0-100 to indicate its ecologic or economic value. The DNR green infrastructure (GI) assessment (Weber, 2003) identifies "hubs," or large unfragmented natural areas that provide critical ecosystem functions, and "corridors," which are linear remnants of natural lands that connect the hubs. Patterns of economic and ecologic value ascribed to forest lands are similar across the state, with many of the high value forests concentrated in the western and eastern counties (Figure 5). Lower value forests are found in the central part of the state. For ease of exposition , the following discussion will refer to the probability of a cell being converted to impervious cover as the 'development probability'.

We conducted a vulnerability assessment of the strategic forest lands by combining the maps of development probability with the maps showing the economic or ecologic value. We first applied an equal interval classification to the economic and ecologic value maps to create three categories (low, medium, and high value). These classified maps (Figure 5) were then combined with the maps of development probability from SLEUTH (Figure 4), allowing for a visualization and quantification of development risk across value classes.

We performed a similar assessment with the GI hubs, although in this case we considered two kinds of risk associated with development: (1) the wholesale loss of hub area; (2) the risk of hub fragmentation. These types of risk are related, but the risk associated with fragmentation becomes important in areas where development pressure is relatively low, yet development patterns are highly dispersed (such as the outlying watersheds in Figure 3). To calculate the risk associated with the loss of hub area, we calculated the average number of pixels that were forecast to be developed within a GI hub. To estimate the risk of fragmentation, we also considered the potential area over which the forecasted development could occur (i.e. clustered or dispersed throughout the patch).

In terms of vulnerability, forests with low economic and ecologic value are projected to experience the highest risk for development in all three scenarios (Table 2). The low value category for the ecologic strategic forests is at a particularly high risk, with more than 25% of its total area being forecasted for development. Moderately and highly valued ecologic strategic forest lands tend to be more protected in all three scenarios when compared to the economic strategic forest lands. The vulnerability analysis of green infrastructure hubs showed that fragmentation is a more serious problem than wholesale loss. In the current trends scenario, for example, many of the hubs in western Maryland are projected to lose less than 1% of their total area to development, and most hubs in the state are projected to less than 25% of their area (Figure 6a). The potential area affected by development within each hub, however, shows higher risks for fragmentation (Figure 6b). While the managed growth and smart growth scenarios both show a decrease in the loss of hub area, only complete protection of the existing hubs under the smart growth scenario would significantly lower the risk associated with fragmentation.

The results of this analysis show the effect of dispersed settlement patterns and high rates of land consumption. Only under a smart growth scenario was new development spatially clustered and loss of forest lands minimized. These scenario simulations and associated maps of future development show that the spatial pattern of development is important in a landscape context, and that the potential of land use decisions to influence spatial development patterns can indeed minimize environmental impacts.

The Economic Model of Land Use Change

The application of cellular automata models, such as that described above, is greatly facilitated by the use of satellite image-derived products, like impervious cover. Land cover information derived from satellite imagery is invaluable as it is available somewhat uniformly over space (i.e. throughout the U.S.) and to a lesser extent over time. However, neither cellular automata models, nor the satellite imagery they are based on, can provide the basis for an economic analysis of land use change. Modeling approaches such as SLEUTH can only simulate rates and patterns of land *cover*, not the mechanisms that underlie the changes in land *use*. Land conversion is fundamentally an economic decision. Because pattern-based models are not driven by an understanding of this decision, it is valuable to explore alternative approaches that have the potential to explain historical conversion and predict future change.

The economic model we report on here attempts to capture the decision process and the regulatory/policy environment in which that process takes place (Bockstael 1996, Towe et al. 2007). A spatial perspective enters into such models, as location is important for a number of reasons, but space and spatial pattern are not the only dimensions that matter. The economic model differs from the cellular-automata type models such as SLEUTH in several important ways. Perhaps most important, the unit of observation is the parcel – an irregular unit of land privately or publicly owned. As such, the dimension of the landscape of interest is land *use* and not land *cover*. Because it focuses on land use *decisions* directly and because the unit of observation is the owned parcel and not a cell in the landscape, the economic model cannot rely on satellite data as the basis of the analysis. Instead our economic model is based on GIS data of actual parcel boundaries linked with historical data from tax assessment records.

To illustrate the importance of these points, consider Figure 7 which represents a small portion of western Howard County. Parcel boundaries and structures are delineated and parcels are 'typed' according to their broad land use for this illustration. Pink parcels are previously developed housing lots, blue parcels are developable but not yet developed at their full capacity given zoning, and yellow denotes parcels that are for some reason protected or preserved and cannot be developed. In contrast, 30 meter cells are delineated somewhat randomly on the map illustrating the size of satellite imagery cells relative to housing lots in low density development.

Figure 7 illustrates how difficult it is to make a translation between impervious surface and development activity. If one is interested in impervious surface cover, then the satellite image products are appealing, although they miss some portion of low density housing (omission errors) and require careful screening to avoid false positives (commission errors such as rocky outcrops, which are impervious but not man made).[1] In contrast, the economic development decision is related to the *parcel* and occurs at densities governed by regulations which in turn affect that decision. Thus explaining and predicting where development will happen under differing regulations may be better suited to a model that uses parcel level rather than cell-based observations.

Since the form of the economic model relies on theories about how landowners make decisions as to the land use of their parcels, the data for our analysis include all parcels that as of 1990 could have been developed, given land use regulations. The decision modeled is whether to convert a parcel. Landowners' decisions are expected to be

[1] This occurs because a house in low density developments makes up only a portion of any 30 meter cell and may be surrounded by cells with no impervious surface. If impervious surface is the only consideration, then missing this type of development may or may not be troubling.

affected by a) the expected value of housing lots if the parcel were subdivided and the variability in those expectations, b) the costs of developing the infrastructure necessary for subdivision, and c) the foregone future returns from the parcel's current use (e.g. agriculture or forestry) if the parcel were developed. These expected returns from development, net of conversion and opportunity costs, will be functions of attributes of the parcel and the owner, the land market, and the regulatory environment.

Drawing on a carefully constructed data set that pieces together historical information, we have been able to reconstruct the history of Howard County development since 1990 in explicit spatial terms. We combine these observations with measures that affect returns to development, infrastructure costs and opportunity costs. These include such parcel-varying data as commuting distances to major employment centers and surrounding land uses that are expected to affect how much individuals would pay for housing lots, as well as time varying variables such as the interest rate and measures of overall demand pressure for housing. Parcel-varying infrastructure costs are captured by such measures as road and septic suitability, parcel slopes, and existing land cover, while opportunity costs are reflected in quality of soils for agriculture, farm parcel size and category of land use land use activity prevailing at the time of the decision.

Regulations enter into the model in a number of ways. For example zoning specifies minimum lot sizes and open space requirements that will affect the size and number of housing lots, and therefore the expected returns from subdividing. Utility service boundaries affect infrastructure costs as publicly supplied water and sewer substitutes for well and septic costs. The analysis also incorporates specific growth control regulations such as adequate public facilities moratoria, and eligibility for voluntary open space preservation programs. This is important because many growth controls operate by providing incentives or disincentives rather than outright prohibitions on development (which are typically unconstitutional). The analysis tests for significant effects of these factors and produces quantitative estimates of these effects on the probabilities of development. By understanding how regulations affect profitability of development and how this profitability alters likelihood of development, the mechanistic approach provides a means of evaluating the effects of at least some proposed (and as yet unimplemented) changes in regulations.

The parameters of the economic model are estimated in the context of a statistical model of 'failure' over time – often called a hazard or duration model. Developable parcels (depicted in Figure 8) are tracked over the study period. The analysis uses historical data to attempt to explain the relationship between our explanatory data (measures of factors expected to affect decisions) and the timing of development decisions.

Model Validation

In order to test how well the model simulates future land use change, we estimated the parameters of the model using historical activity between 1990 and 1996. This weakens the model predictions, as these few years of data give us little to base our estimates on. Elsewhere, a more complex model is estimated using data from 1990 through 2001 (Towe et al. 2007, Towe 2007) We then apply the estimated parameters to the remaining parcels at risk of development and predict the probabilities of development in the years 1997 through 2000.

There are a variety of ways of presenting the outcomes of this simulation. The predicted probabilities are often not intuitive, so one way to use them is to generate specific realizations of outcomes. To do this the parcels remaining at risk for development as of 1997 are weighted by their probabilities of development. A random draw from that weighted probability distribution produces a realization of the probabilistic process for each year from 1997 through 2000. The process takes into account the changing landscape and changing risk set that results from each year's predicted development as input into the subsequent year's prediction.

Figure 9 presents one such realization as a comparison to what really happened during the 1997 through 2000 period. We depict the both the actual and predicted development in terms of the *parcels* that were affected. Different parcels would translate into different amounts of impervious surface per acre because zoning regulations dictate the maximum density allowed in different parts of the county. A translation between predicted developments and predicted impervious surface is possible, relying on these allowable densities together with open space requirements, but are not natural outcomes of the economic model. The background of Figure 9 looks more like the satellite imagery, as they are designed to reflect impervious surface as of 1996. However, these maps are based on Howard County planimetrics of rooftops, roads driveways and parking lots. A comparable realization from the SLEUTH model (Figure 10) shows how differently these two modeling approaches predict change.

In the economic model simulation we predict several of the exact parcels that were actually developed during the study period. For the county as a whole, 44% of the parcels we predict to develop do actually develop during these 4 years. A more complete comparison of this realization is presented in Figure 11. Total number of acres developed and total number predicted to be developed during the 1997-2000 period are aggregated to the subwatersheds found in Howard County. From these plots one can see that our simulation (in blue) over-predicts the actual amount of development (in red) expected in those years but the distribution of predicted development over subwatersheds is reasonably good.

Comparisons and Conclusions

The fundamental differences between the two types of modeling approaches (microeconomic modeling at the parcel level versus a cellular automata model based on pixels) are important both for understanding and simulating the land use change process. The distinctions between the two approaches are summarized in Table 3.

Using data on actual parcel boundaries and subdivision activity has the potential of greater realism and accuracy relative to map products derived from satellite imagery because they allow modeling of the underlying process of development, as presented in this chapter, as well as the modeling of land preservation decisions and the time-varying demand pressure for new development.[2] However, data sets such as those used in the economic model are impossible to construct unless localities have digitized their tax maps and, even where they have, these data sets are costly to assemble. In comparison satellite data is uniformly and universally available and so cellular automata models can be more easily applied and are more 'transportable'.

The nature of the output produced by the two models is quite different. The cellular automata models mimic the patterns and changes of impervious surface cover to which they were calibrated. The economic approach attempts to explain the decision process, but the development decision process only indirectly affects impervious surface outcomes. We model the act of subdividing, as this is the point in time when the intent to change land use takes place. From that point until the time at which impervious surface manifests itself is, on average, about 1-2 years depending on the size of the subdivision. Downturns in the economy can slow the process of subdividing, but can also slow the construction of housing on subdivided parcels. Thus, the general economic climate enters the process in important ways that are not captured in the SLEUTH model, but also can affect the translation between the output of the economic model (the subdivision decision) and the actual appearance of impervious surface.

Models of land use change are perhaps most useful if they can be used to test the effects of policies and forecast the outcomes of policy change. The cellular automata model can attempt to capture policy when that policy is of the 'command and control' form. That is, assumptions about the extent and nature of the outcomes of the policy are necessary before policy scenarios can be obtained. When policies provide incentives and disincentives rather than direct prohibitions, it is necessary to incorporate the nature of the policy into a model of decision making. Typically we cannot know the actual outcomes of policies because they can often have unintended consequences. In the context of the economic model, regulations are linked to consequences that affect the net returns of development for specific parcels. As a result changes in regulations can more easily and realistically be simulated.

[2] The model reported on here does not include a model of the preservation decision per se, as no new preservation activity was funded during the validation period of 1997-2000. However, a complex competing risk model has been developed (see Towe 2007).

Evaluating the effects of policy is a difficult task even for one locality. Evaluating something as far reaching as the Chesapeake Bay Program is an even greater challenge. Most land use policy is made at the level of the local government and these differ widely across both Maryland and the Chesapeake Bay watershed. Using economic modeling at the regional becomes impractical as the necessary data for each locality simply don't exist. Modeling land use change at the parcel level across a large spatial domain like the Chesapeake watershed requires a combination of approaches that address both local realities and broad regional patterns and trends. Successful policy evaluation is likely to require hybrid models that exhibit some of the strengths of both types of modeling approaches.

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Tables

Table 1. Population and impervious surface area statistics for the counties of Maryland.

County	*Population 2000*	*Population Change (%) 1990-2000*	*Impervious Cover (ha) 2000*	*Impervious Change (ha) 1990-2000*	*Impervious change (%) 1990-2000*
Allegany	74,930	0	3,795	1,186	45
Anne Arundel	489,656	15	24,840	6,658	37
Baltimore	754,292	9	30,708	5,765	23
Baltimore city	651,154	-12	16,173	708	5
Calvert	74,563	46	3,095	1,220	65
Caroline	29,772	10	3,669	1,763	93
Carroll	150,897	22	9,353	4,383	88
Cecil	85,951	20	5,242	1,468	39
Charles	120,546	19	5,943	2,445	70
Dorchester	30,674	1	5,570	1,988	56
Frederick	195,277	30	15,326	5,661	59
Garrett	29,846	6	2,472	1,287	109
Harford	218,590	20	10,072	2,904	41
Howard	247,842	32	11,850	4,534	62
Kent	19,197	8	2,634	1,127	75
Montgomery	873,341	15	29,688	7,288	33
Prince George's	801,515	11	31,908	7,053	28
Queen Anne's	40,563	19	4,263	1,783	72
Somerset	24,747	6	3,240	2,255	229
St. Mary's	86,211	13	4,894	1,398	40
Talbot	33,812	11	4,129	1,435	53
Washington	131,923	9	9,919	3,445	53
Wicomico	84,644	14	8,662	5,548	178
Worcester	46,543	33	7,112	4,150	140

Table 2. Total projected forest loss (km^2), and proportion lost (%), of Maryland's strategic forest lands through 2030 under different growth scenarios. These data represent the totals for each category and do not account for the overlap between them.

SFLA Type	*Current trends*	*Managed growth*	*Best case*
Ecologically strategic	1,427 (12%)	1,170 (10%)	804 (7%)
Economically strategic	1,456 (12%)	1,197 (10%)	829 (7%)

Table 3: Comparison of the land use modeling approaches employed.

	Cellular automaton modeling	**Economic modeling of the development decision**
Unit of observation	Cell in landscape	Privately owned parcel of land
Nature of approach	Pattern-based	Process-based
Nature of land use change processes	Stochastic process regulated by conceptually simple transition rules. SLEUTH employs rules that model edge, dispersed, new spreading center, and road-influenced growth.	Stochastic model of behavior of land owners, who choose the optimal timing (in an economic sense) of development and optimaltiming of preservation where that option is available.
"Driving forces"	State of current land cover, physical features of the landscape, user-defined areas that are protected from development	Value of land in undeveloped and developed uses, and conversion costs. All are functions of: current land cover, physical and locational features of parcel, public goods provision, nature of land market (including variability in returns) and relevant regulations.
Analytical methods	Cellular automaton model that simulates cell changes using growth coefficients derived from an iterative calibration process based on observed cell changes.	Hazard model analysis of the timing of development and competing hazard models where preservation is also modeled. Parameters of models are estimated statistically using historical data.
Data requirements	Urban extent and road network data for at least two points in time; slope; GIS data for calibration and predictive scenarios.	Parcel level data, including locations of parcels, data on attributes of parcels and how the regulatory and market environments affect those parcels.
Source of growth pressure information	Historic rates and patterns of development.	County allocations and economic pressures for new housing.

Figures

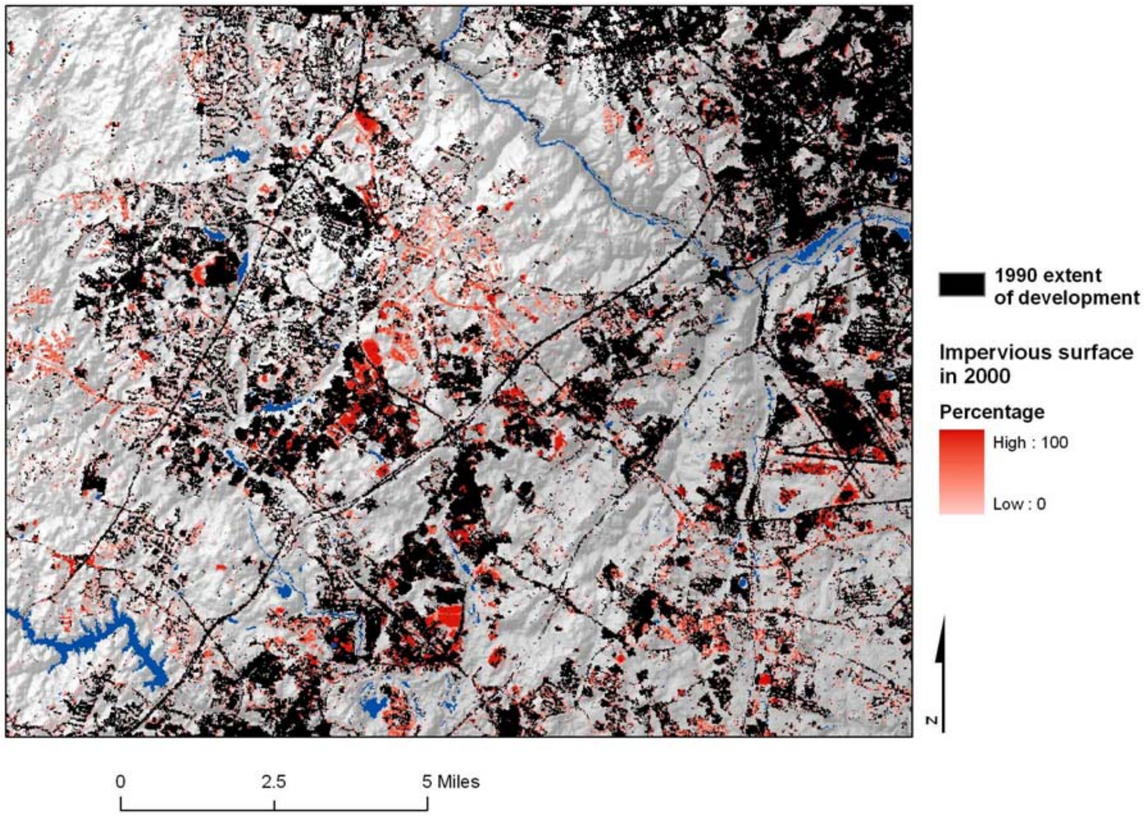

Figure 1. Map of impervious cover derived from Landsat satellite imagery acquired in the year 2000. This area, selected as an example, is just south of Baltimore Maryland (BWI airport is visible on right side of the image, as are Interstate 95 and the Baltimore-Washington Parkway). Also shown, in black, are areas that were already developed as of 1990. Gradients of orange show the intensity of development between 1990 and 2000, with clear differences between commercial developments (large blocks) and residential areas (finer dispersed development).

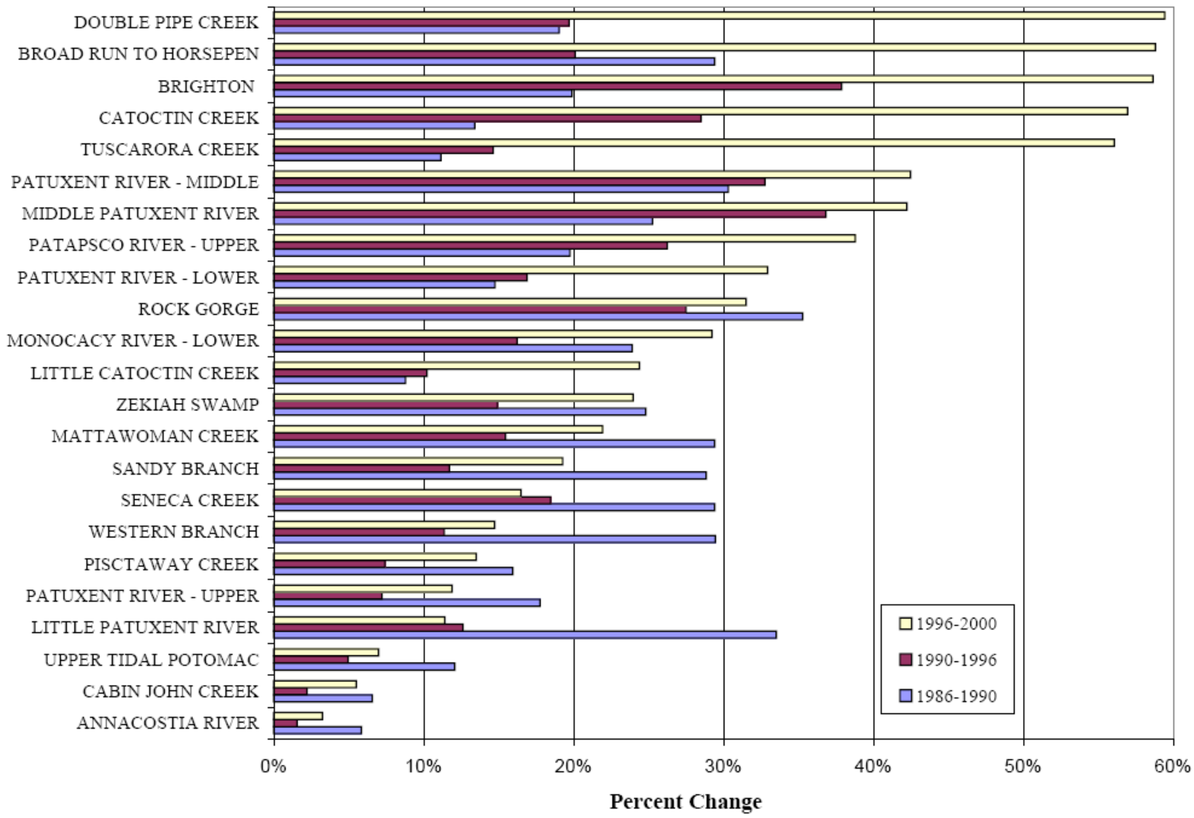

Figure 2a. Change in impervious cover (percent) for watersheds at least 90% within the state of Maryland for three different time intervals (1986-1990, 1990-1996, 1996-2000).

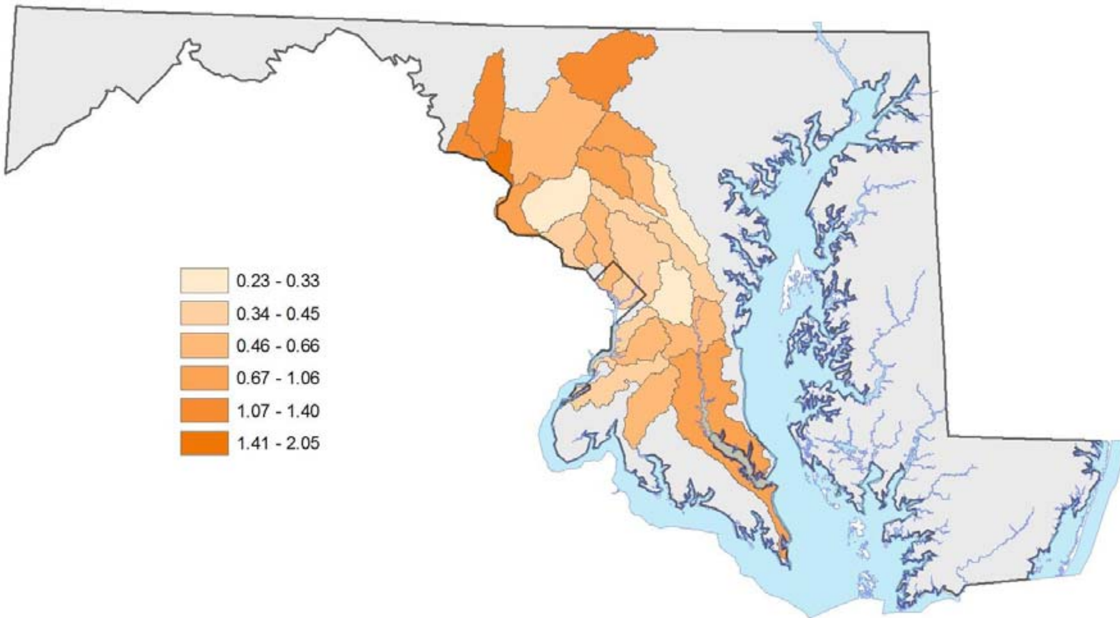

Figure 2b. Ratio of the rates of change in impervious cover for the period 1996 to 2000 over that for the period 1986 to 1996, for the watersheds listed in Figure 2a. Darker colors represent watersheds where change post-1996 is greater than before the initiation of Smart Growth policies, and lighter colors the inverse.

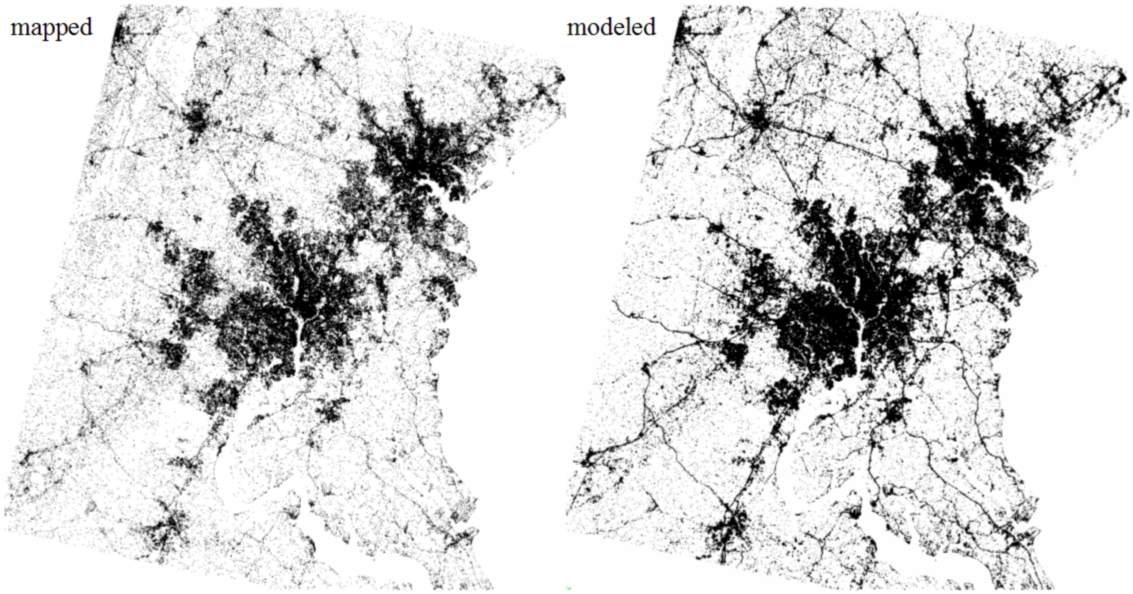

Figure 3. Calibration of the SLEUTH model to replicate the patterns of urban development in the Baltimore – Washington DC region for the period 1990 to 2000 (right) relative to those mapped from Landsat satellite imagery (left).

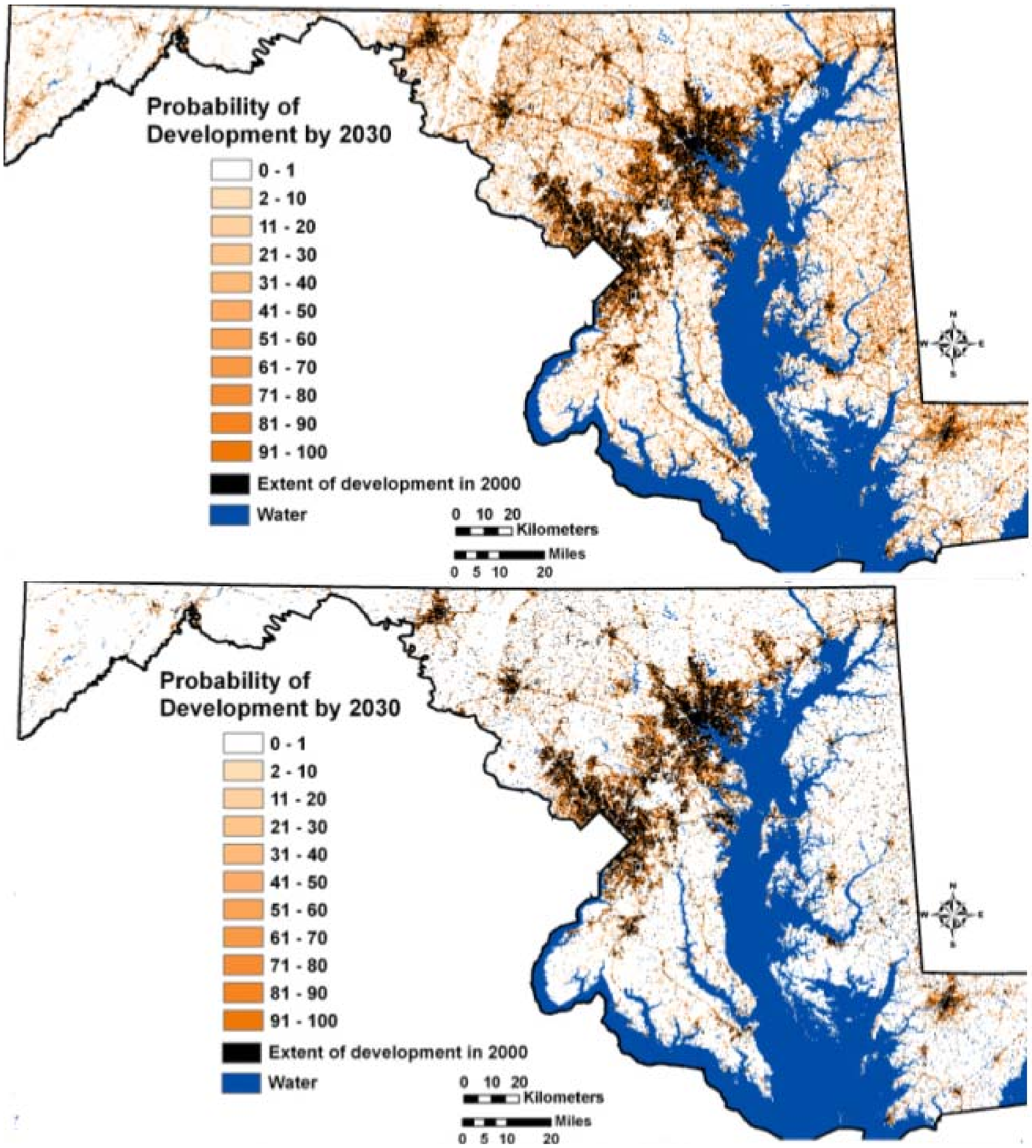

Figure 4. Forecasts of future development in Maryland (to 2030) from the SLEUTH model under (a) a current trends scenario (b) a Smart Growth scenario.

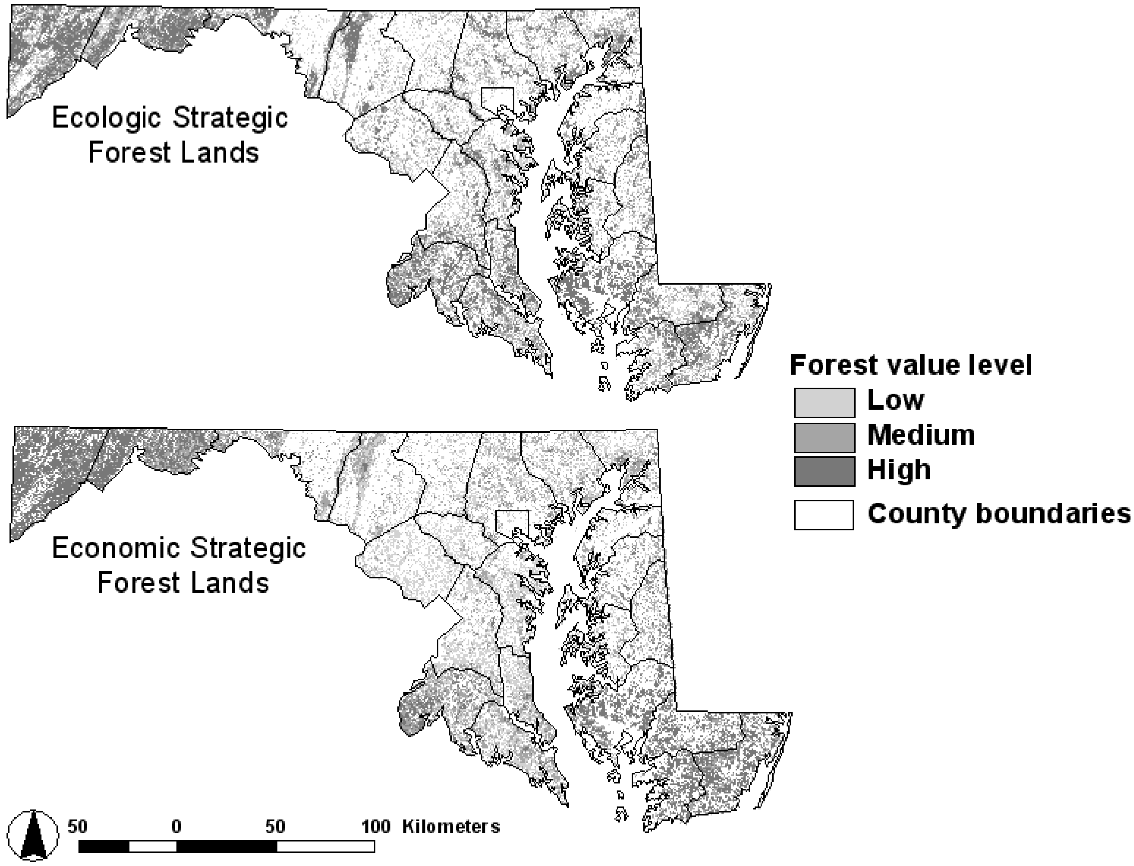

Figure 5. Economic and ecologic strategic forest lands for Maryland. Source: Maryland Department of Natural Resources (2003).

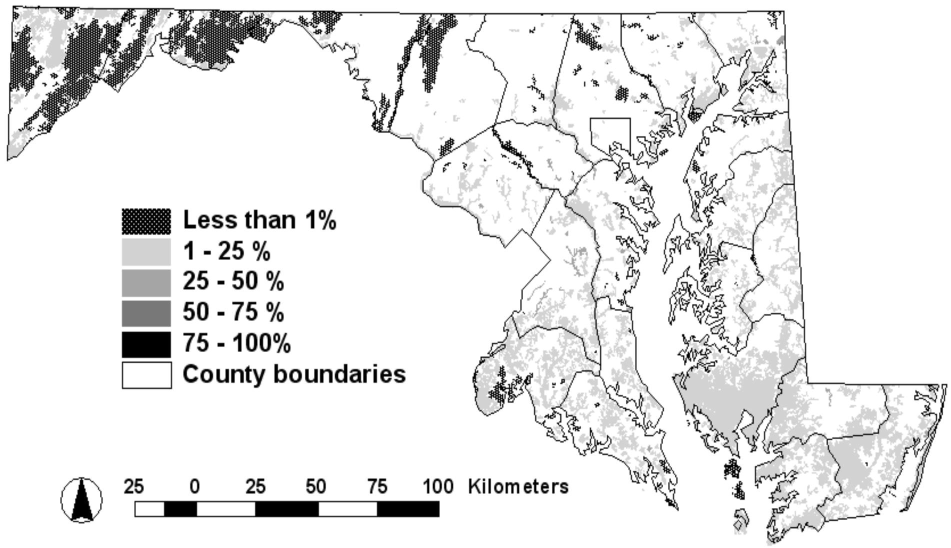

Figure 6a. The potential loss of area within each Green Infrastructure hub by 2030 for the current trends scenario, expressed as a percent of the total hub area.

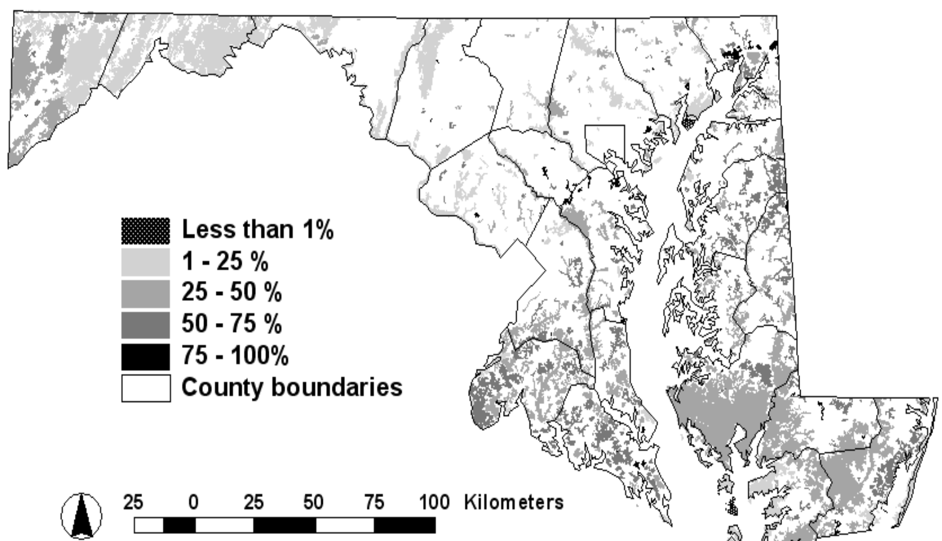

Figure 6b. The same as figure 6a but for the smart growth scenario.

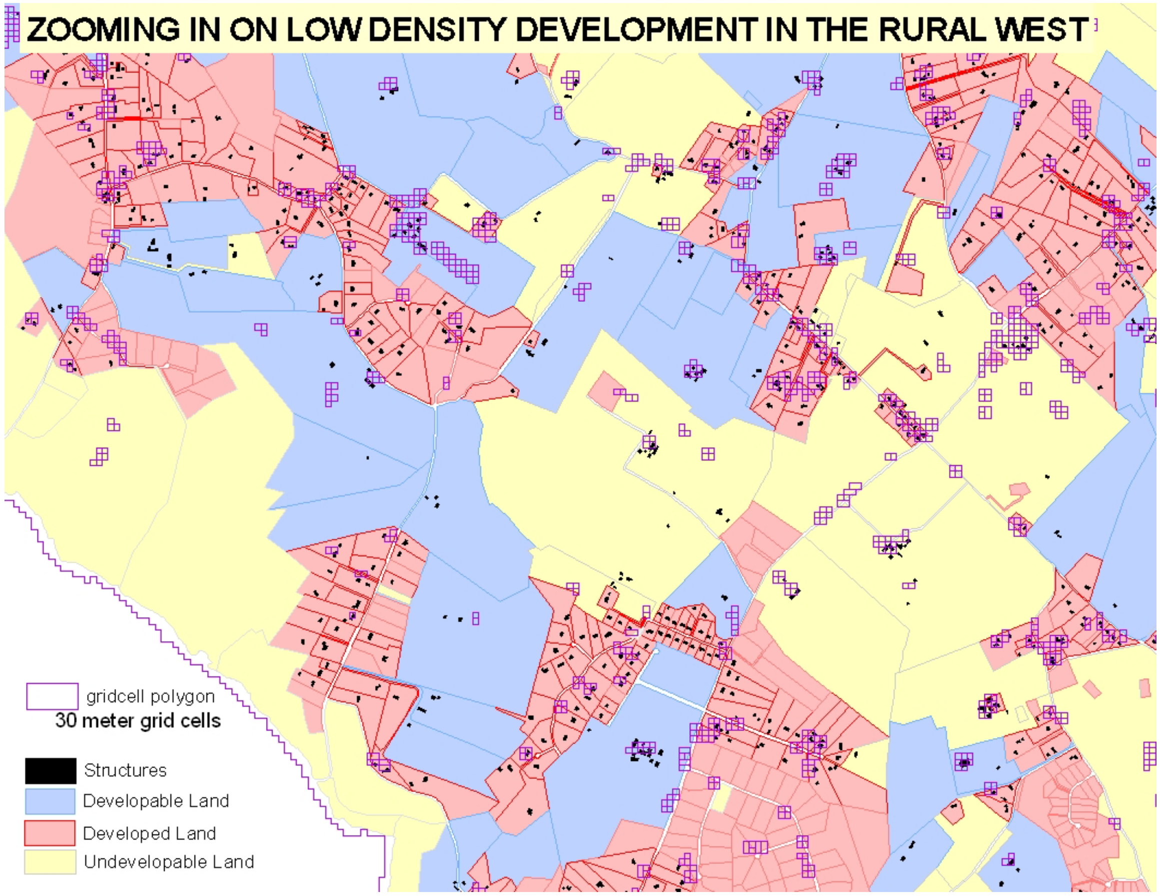

Figure 7. A contrast in data - the scale of parcel level data and rooftops compared with 30 meter cells available through satellite imagery.

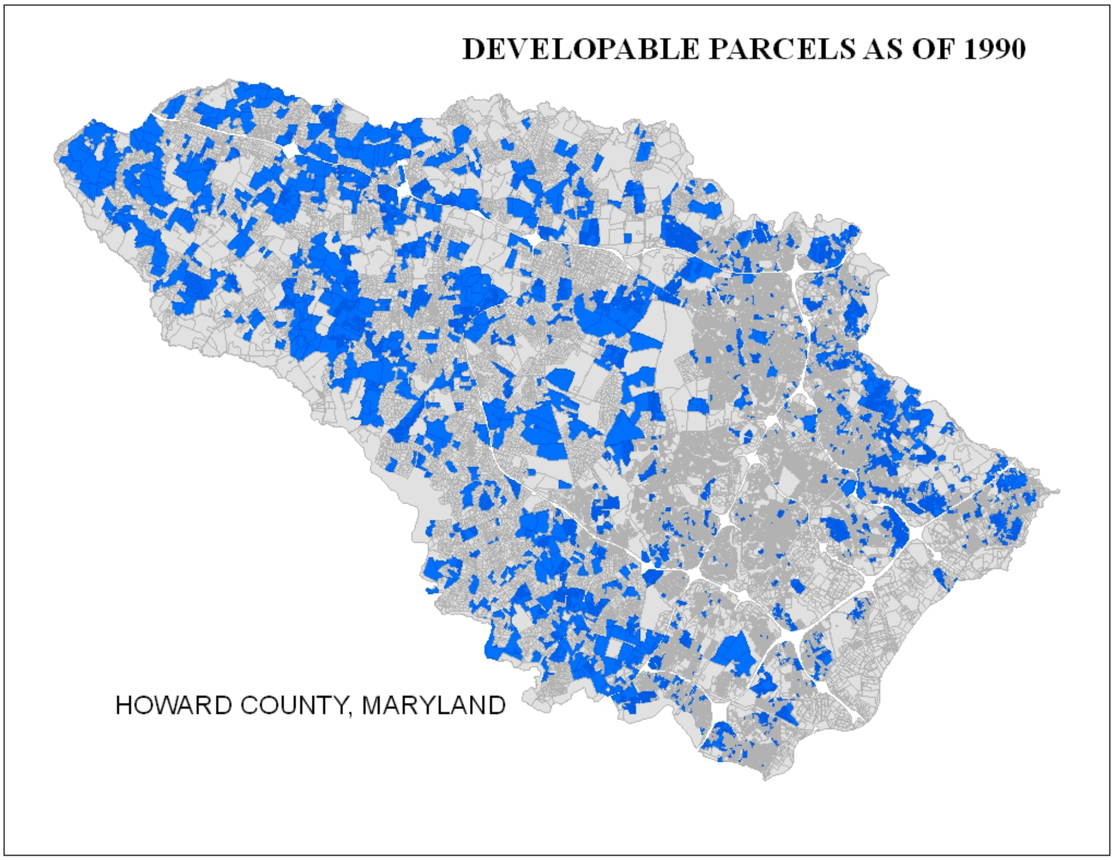

Figure 8. The set of observations in the economic model.

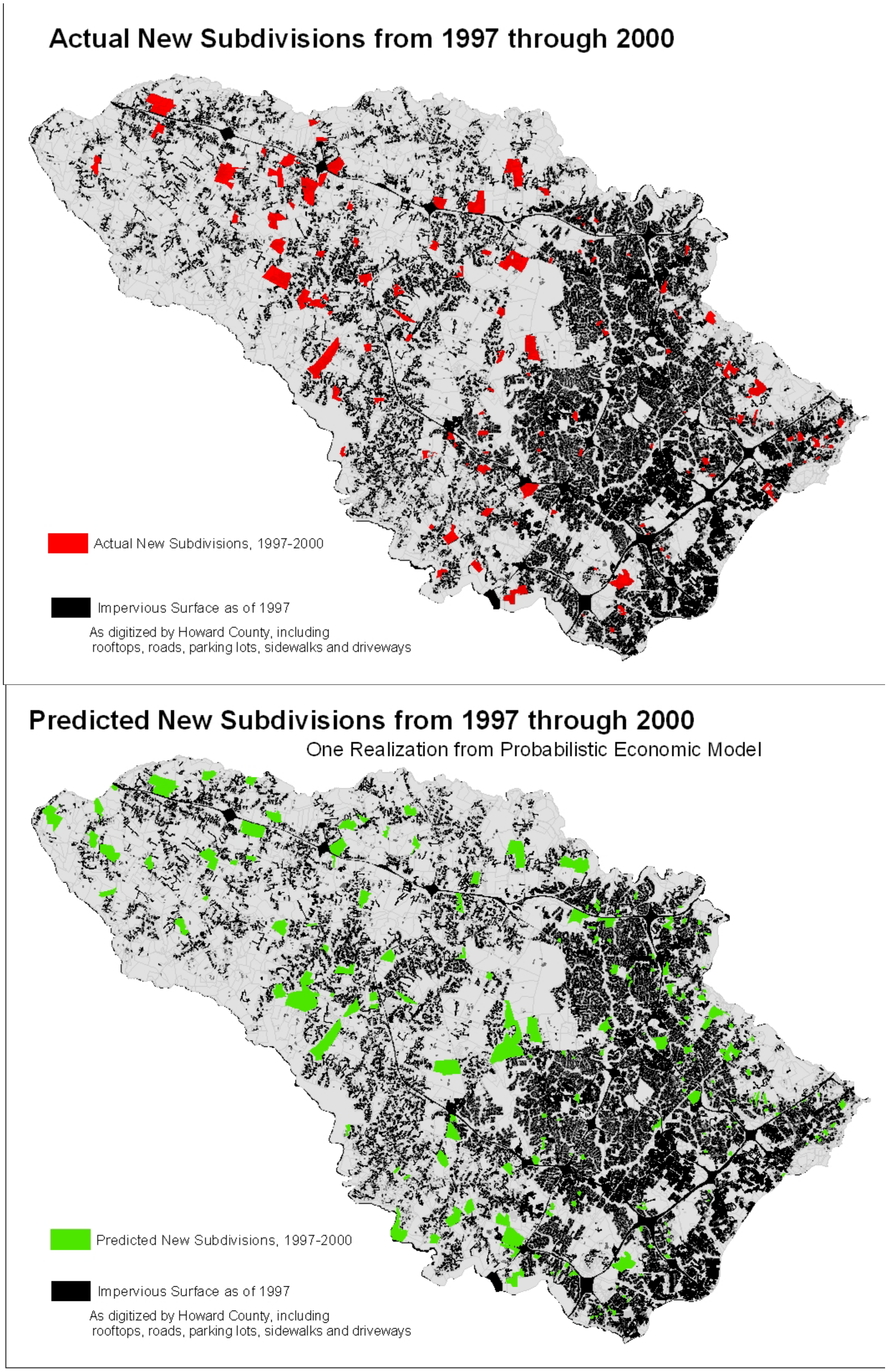

Figure 9. Actual and economic model predicted new subdivisions, 1997-2000.

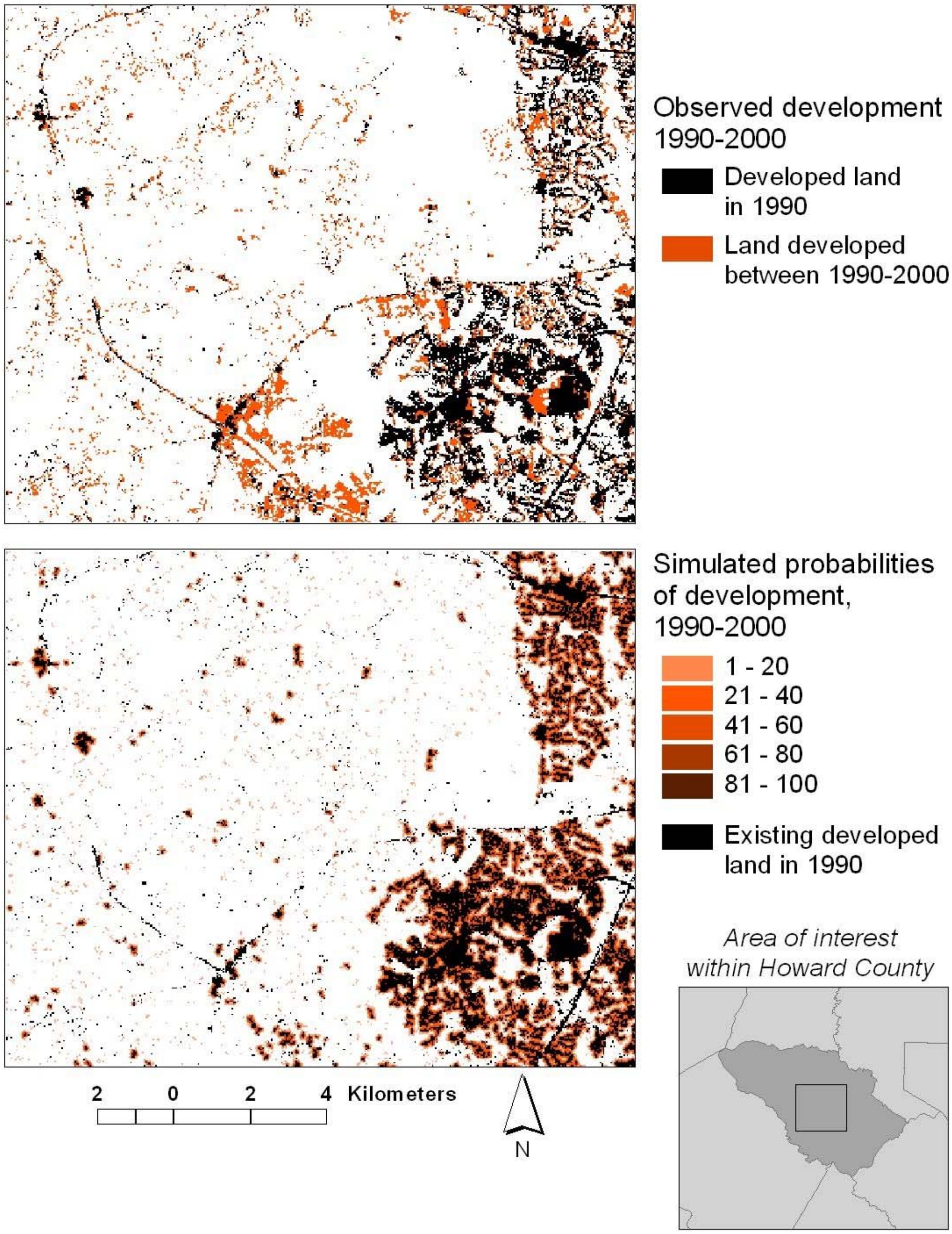

Figure 10. SLEUTH model predictions from 1990 to 2000 for a portion of Howard County, showing the very different type of model output to that depicted in Figure 9.

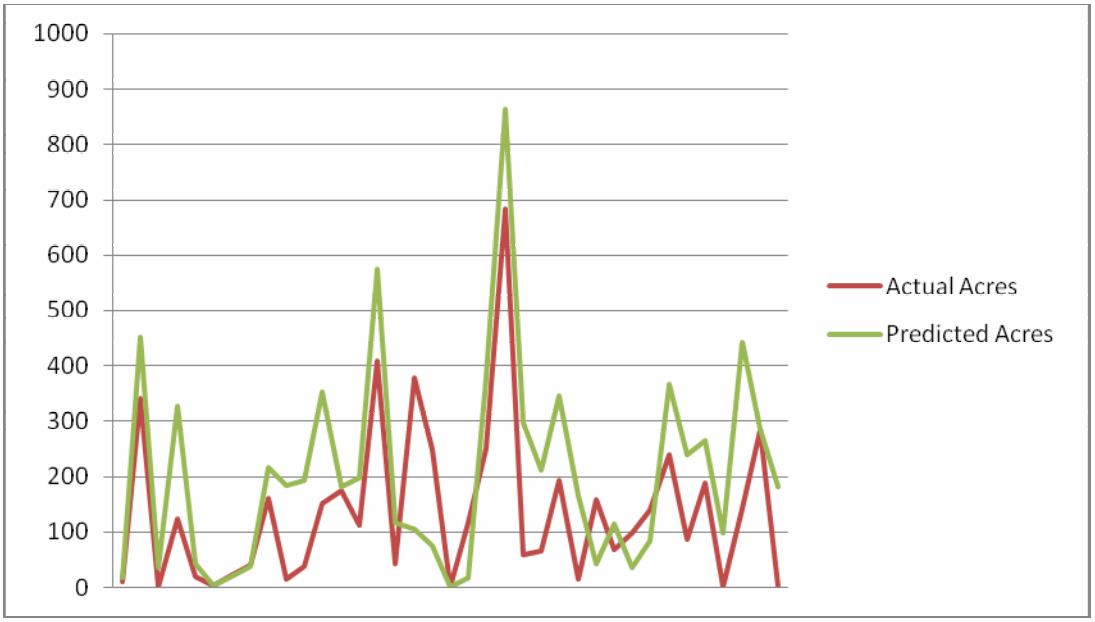

Figure 11a. Economic model predicted acres developed, 1997-2000, for 37 subwatersheds in Howard County compared to actual acres developed.

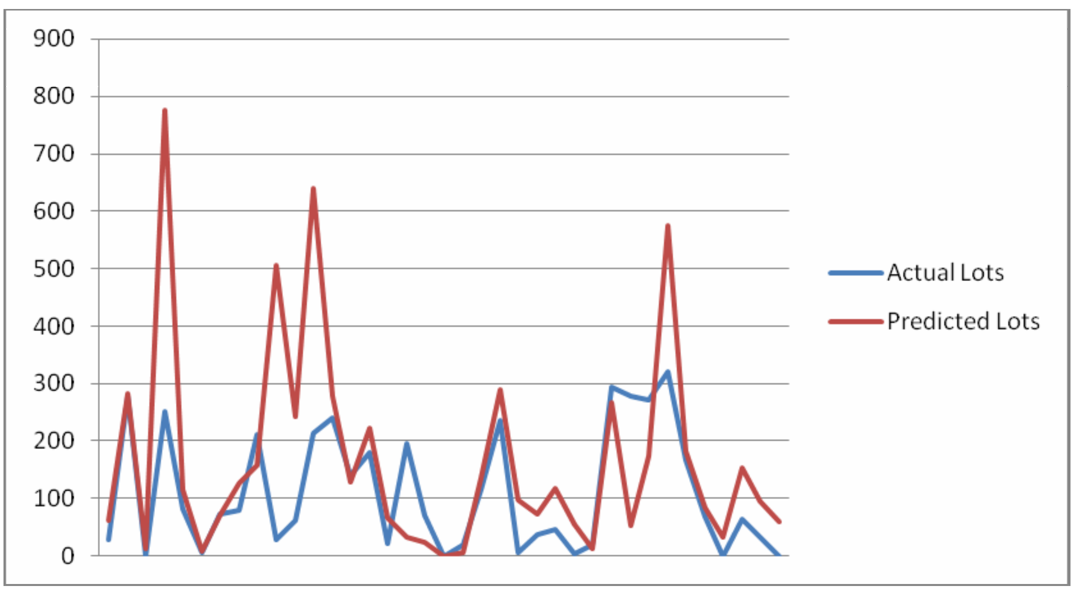

Figure 11b. Economic model predicted lots developed, 1997-2000, for 37 subwatersheds in Howard County compared to actual lots developed.