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Land-use changes in a pro-smart-growth state: Maryland, USA

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Abstract. In this paper we present a study of the effectiveness of the smart-growth initiatives in Maryland, USA, for shaping the spatial pattern of urban growth in the state by channeling development into designated areas. By estimating binary logit models of land conversion for selected counties in Maryland for both pre-smart-growth and post-smart-growth time periods, we find that the governmental policy has generally been successful in achieving its objective. However, there are significant variations across local counties in terms of policy effectiveness. Planners must pay much closer attention to these interjurisdictional differences in the effectiveness of smart-growth programs, examine the likely causes and consequences, and formulate strategies for making improvement.

Introduction

How cities grow spatially has profound implications for economic efficiency, social equity, and environmental sustainabiilty. In the United States, for more than half a century the dominant form of urban growth has been low-density and auto-oriented suburban expansion (Downs, 1998). This urban-development pattern has raised many issues, including higher costs of infrastructure provision (Burchell et al, 2002), auto dependence (Newman and Kenworthy, 1999), central-city decline (Downs, 1999), poor transportation accessibility and longer trips (Ewing, 1997; Handy, 1996), spatial barriers for people relying on public transport to seek economic opportunities (Shen, 1998; 2000), and general deterioration of environmental conditions (Daniels and Daniels, 2003).

The growing concern that the prevailing development pattern is not in the long-term interest of cities has become a powerful driving force behind the smart-growth movement, which emerged in the late 1990s and has since gained great momentum. Although there is no universally accepted concise definition of 'smart growth', this term is generally used by its proponents to portray some vision of urban development that promises to help cities achieve certain goals deemed desirable for the community, the economy, and the environment.[1] The most frequently stated goals are to facilitate economic growth while protecting the environment, to reduce development costs, to revitalize central cities, and to improve community liveability. Smart growth is described as development that helps to achieve these goals by following certain principles, such as mixing land uses, creating housing and transportation choices, preserving open space and farmland, fostering distinctive communities with a strong sense of place, directing new growth toward existing urban areas, and encouraging community and stakeholder collaboration in development decisions.

[1] See, for example, online documents by the US Environmental Protection Agency, (http://www.epa.gov/smartgrowth/about_sg.htm), Smart Growth America (http://www.smartgrowthamerica.com/whatissg.html), and Smart Growth Network (http://www.smartgrowth.org/about/default.asp).

The State of Maryland, consisting of twenty-three counties and Baltimore City (see figure 1), has been a leader in the smart-growth movement.[2] In 1997 the state government implemented a number of policy programs collectively known as the Maryland Smart Growth legislation. A primary objective of the Maryland Smart Growth legislation is to support existing communities by targeting state resources to support development in areas where the infrastructure is already in place. To achieve this objective, the legislation includes a core initiative, the 'Smart Growth Area Act', which channels state funding for transportation, infrastructure, housing, and economic development into areas designated as 'Priority Funding Areas' (PFAs). The intent is to use incentives to promote development and revitalization in central cities and inner suburbs, while discouraging urban growth in the peripheral areas by denying the state government's subsidies for it (Cohen, 2002). Meanwhile the legislation includes another key initiative, the 'Rural Legacy Act', which is essentially a grant program that aims to protect valuable agricultural, forestry, and natural and cultural resources by providing funds to local government and land trusts to purchase land, easements, and transferable development rights from willing sellers in designated 'Rural Legacy Areas' (RLAs) (Cohen, 2002).

Although Maryland's smart-growth programs encourage and support sensible growth in designated areas, they do not carry the regulatory power to prevent development either inside or outside the designated areas. For planners and policymakers in Maryland, it is crucial to find out whether or not the smart-growth initiatives have facilitated positive changes in urban-development patterns, and to identify possible ways to improve their effectiveness. Additionally, planners and policymakers at the state level will benefit from research that examines internal variations in urban development patterns in this pro-smart-growth state. It will allow them to gain a fundamental understanding of factors other than state policies that influence the pace and form of urban growth.

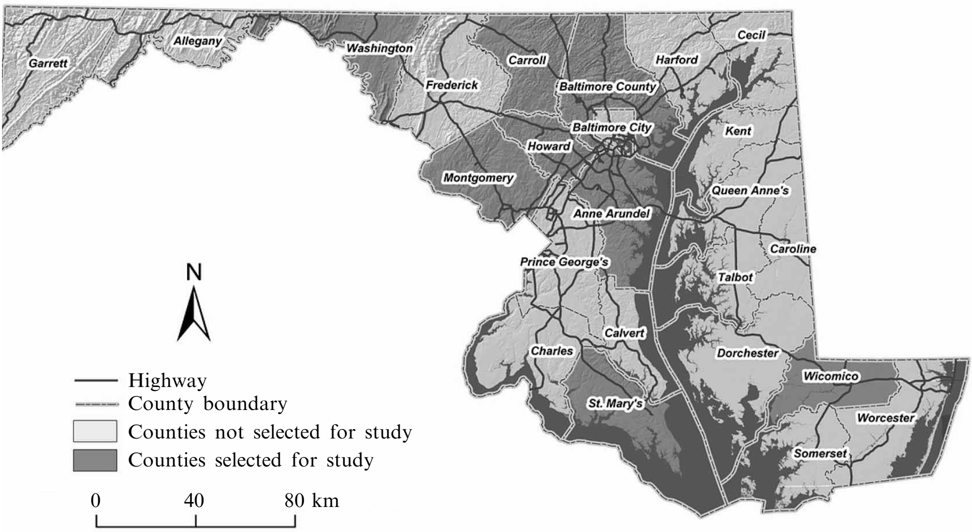

Figure 1. State of Maryland and the eight counties selected for empirical analysis. A color version of this and subsequent figures is shown on the *E&P* website at http://www.envplan.com/misc/a3886/.

[2] The State of Maryland is situated on the Atlantic Coast and bordered by Washington, DC and Virginia in the south and Pennsylvania in the north. It has a total area of approximately 32 000 km^2, including almost 7000 km^2 of water area (Maryland Office of Planning, 1991). Its population in 2000, according to the decennial census conducted by the US Census Bureau, was nearly 5.3 million.

More importantly, for planners and policymakers elsewhere who are interested in learning from the experience of Maryland, a basic understanding of the impact of smart growth programs on its urban development patterns is essential.

This research is an attempt to examine the effectiveness, or the lack thereof, of Maryland's smart-growth initiatives in reshaping urban-growth patterns in the state. It is focused on the influence of the 'Smart Growth Area Act' and 'Rural Legacy Act' on the location of new development. Three research questions are addressed. First, does the PFA designation of an area increase the likelihood for it to be developed? Second, does the RLA designation decrease the land's development probability? Finally, does the effectiveness of these two programs vary significantly across local jurisdictions?

Literature review

In this paper we build upon, and extend, literature on urban growth and land-use change. The existing literature includes a large collection of theories of land-use change that stem from different epistemological and disciplinary traditions [see Briassoulis (2000) for a good overview of theories of land-use change]. However, as Briassoulis (2000) points out, only some theories, especially ones based on a positivist epistemology, can effectively filter down to operational models for analyzing the causes and effects of land-use change. To address the research questions raised above, in our literature review we focus on two strands of the literature: one in which the effects of growth-management policies on land use and urban development are examined, and the other in which approaches to modeling land-use change are explored.

Effects of growth management on land use and urban development

There is a large volume of literature on the spatial, economic, and social impacts of governmental regulations on land use and urban development. In an influential early study in this field, Dowall (1984) found that growth controls enacted by local jurisdictions in California placed a major constraint on residential land supply and development and caused substantial housing-price increases. Shen (1996) examined the cumulative regional impact of locally enacted growth regulations in the case of the San Francisco Bay Area. He found that there were substantial spillovers of urban growth from jurisdictions that enacted such restrictions to the rest of the region. Pendall (1999) studied the relationship between land-use regulations and urban sprawl, which he defined as low-density urbanization. He found that land-use controls that shift the cost of development onto builders reduce sprawl, whereas regulations that mandate low densities increase sprawl. Carruthers and Ulfarsson (2002) analyzed effects of government policies on urban development by focusing on the relationship between political fragmentation and low-density urban growth. Their empirical result indicated that political fragmentation results in lower densities.

The aforementioned studies all showed that governmental land-use regulations enacted by local jurisdictions significantly affect the spatial pattern of urban growth, but the effects may not be what are considered desirable for the metropolitan area or region as a whole. One important implication, therefore, is that the regional or state government should play the key role in designing and implementing policies and programs for managing urban growth.

Studies of effects of state-level growth-management policies on patterns of land use have presented contrary findings. Nelson (1999) researched the impacts of growth management on population density and farmland preservation. He found that two states, Florida and Oregon, which had growth-management policies, witnessed only modest decreases in population densities during the 1980s, whereas a comparison state, Georgia, witnessed a substantial drop in density. He also found that, during the same time period, Florida lost 0.27 hectares of farmland for each new resident, Oregon lost only 0.13 hectares per new resident, but Georgia lost 0.85 hectares for each additional resident. Nelson's findings, however, were challenged by Kline (2000), who showed that ten states in the United States performed better than Oregon in preventing urban sprawl, whereas twelve states performed worse than Georgia, and that eleven states performed better than Florida in preserving farmland, whereas twenty states, including Georgia, performed better than Oregon.

A recent study by Anthony (2004) also suggests that the existing knowledge of the relationship between state growth-management efforts and urban land-use patterns has major gaps. Anthony measured the change in urban densities in forty-nine states over a fifteen-year period from 1982 to 1997, and found that growth-management states generally experienced a lower population-density decrease than states without growth management. However, his regression analysis indicates that state growth management did not have a statistically significant effect on population-density change.

Is Maryland's Smart Growth legislation, which is a state effort, effective in achieving its objectives? The answer provided in a recent study by Howland and Sohn (forthcoming) is mixed. Howland and Sohn looked at the spatial distribution of water and sewer investments in Maryland after the implementation of the 'Smart Growth Area Act'. They found that there were variations across counties in their compliance with the Smart Growth initiative. Although projects built between 1997 and 2002 were located primarily inside PFAs, a significant percentage of both state-funded and locally funded projects went outside PFAs. Their empirical analysis suggests that high population-growth rates and stronger local tax bases increase the likelihood for infrastructure investments to take place outside PFAs, whereas greater state subsidies in a project and higher county per capita income generate the opposite effect.

In another recent study, Jantz et al (2003) assessed the potential impacts of regional policies on future urban growth in the Washington–Baltimore metropolitan region, and found Maryland's smart-growth initiatives ineffective in conserving natural-resource land. Applying a cellular automaton model, they projected future urban growth in the region based on three policy scenarios. The 'current trends' scenario, which reflects the existing governmental policies including the PFA designations in Maryland, provides minimal protection for land located outside the designated growth areas. Meanwhile the other two scenarios, 'managed growth' and 'ecologically sustainable growth', execute higher levels of protection of natural-resource land located outside the PFA. The simulation result for the 'current trends' scenario shows that, despite Maryland's smart-growth policies, low-density development patterns will continue and areas on the urban fringe that are currently rural or forested will be urbanized. However, as the authors acknowledge, as a result of the design of the adopted model the effect of the PFA was simulated indirectly by putting a resistance to development on land *outside* the PFA, which raises the question of whether it adequately captured the essence of the 'Smart Growth Area Act', that is, creating incentives for development *inside* the PFA.

Models of land-use change

Since the early 1980s there has been some significant progress in developing formal models of urban growth and change. Wegener (1994) identified several important advances in urban modeling. One fundamental advance in this field was the incorporation of random-utility theory into models of land use and travel demand. Another major development was the maturing of geographical information systems (GIS) as a powerful tool for processing, managing, and analyzing microscale data on land use and activity patterns. These developments resulted in a variety of new or improved models for urban planning and management.

For the purpose of developing a methodology to address the research questions for this paper, we carefully reviewed a considerable number of recent publications on modeling land-use change. There are several thorough overviews of models of land-use change (Agarwal et al, 2002; Briassoulis, 2000; EPA, 2000), which provide a rich set of operational approaches for us to compare in terms of their suitability for our paper. We decided that the most useful approaches for our paper are the ones developed by Kitamura et al (1997), Landis (2001), Landis and Zhang (1998a; 1998b), and Morita et al (1997).

Landis and Zhang (1998a; 1998b) adopted the multinomial logit modeling framework to study land-use change in California. Their starting point for conceptualizing the model was the observation that the process of land-use change is fundamentally discrete. They noticed that land-use change in a metropolitan area occurs as the sum of individual, parcel-level, land-use changes, and that the traditional techniques of regression analysis are poorly suited to modeling discrete processes. The alternative they adopted was the discrete choice framework (Ben-Akiva and Lerman, 1985; Domencich and McFadden, 1975). Specifically, Landis and Zhang employed the multinomial logit framework based on several assumptions:

(1) the decision to change land use on a site will be based on a rational evaluation of the prospective profit or rent associated with different development forms;

(2) the potential profit or rent associated with each land-use change is determined by a set of attributes;

(3) the land-use-change function is probabilistic because some attributes are unobservable.

In their model, the probability of land-use change is a function of initial site use, site characteristics, site accessibility, community characteristics, policy factors, and relationship to neighboring sites. A total of nine different types of land-use change were considered, and more than two dozen independent variables were employed to determine the probability of land-use change. Similar approaches were taken by Kitamura et al (1997) and Morita et al (1997) to examine land-use change in a Japanese case study.

In his more recent work, Landis (2001) simplified the multinomial framework to make it a binary logit model of land conversion from nonurban to urban. This model, with the dependent variable measuring the binary choices of whether a unit of land stays nonurban or becomes urbanized, services an especially useful example for our research. The key methodological components of our research, explained in the next section, require a model of land conversion from nonurban to urban.

Research methodology

The research methodology consists of two major components. The first is a longitudinal analysis of land conversion for the state of Maryland. Adopting the idea of using models as a quasiexperimental mechanism for urban policy research (Shen, 1996), two binary logit models are estimated to characterize land-use change from nonurban to urban: one model for the pre-smart-growth period (1992–97) and the other for the post-smart-growth period (1997–2002). These models will show us whether the implementation of smart-growth initiatives, especially the establishment of PFAs and RLAs, has had a significant overall effect on urban development patterns in the state.

The second methodological component is a cross-sectional comparison of land conversion among individual counties. Again, two binary logit models are estimated for the two time periods, but here the models are estimated for individual counties. By comparing the model estimates across counties we can identify variations in the effectiveness of the smart-growth programs across local jurisdictions.

Model specification

Following Landis (2001), Landis and Zhang (1998a), and Morita et al (1997), the specification of the logit models of land conversion assumes that the probability for a given land area to change from nonurban to urban use is a function of site characteristics, proximity to transportation infrastructure and existing urban areas, and regulatory constraints. Ideally the geographical unit of analysis for studying land-use change should be the parcel. The MdProperty View, a GIS database created and updated annually by the Maryland Department of Planing, includes parcel data.(3) However, these parcel data contain parcel centroids and size attributes only (that is, parcel boundaries are unavailable) and have rather incomplete information about when the land was first developed, which make the data unsuitable for modeling land conversion. We therefore used the 1 ha (100×100 m) grid cell as the unit of analysis.

Using grid cells as units of analysis has both advantages and disadvantages. The fundamental disadvantage is that grid cells are not the natural unit for making a land-use decision. A 1 ha grid cell is much larger than a typical residential parcel, which is roughly 0.1 hectares, but much smaller than a typical zoning district. Therefore, using this artificially created unit of analysis may not lead to a satisfactory understanding of dynamics in land use. Moreover, it is vulnerable to the modifiable areal unit problem. On the other hand, the most important advantage of working with grid cells is that it allows us to make use of land-use and land-cover (LULC) data derived from satellite imagery to map land-use changes. Further, grid cells have stable boundaries over time, which simplifies the task of identifying land conversion.

For each time period, the sample for estimating the logit model consists of all grid cells that were nonurban at the beginning of the period.(4) During the time period, each grid cell can either retain its original nonurban status or it can change from nonurban to urban. The converse land-use change, from urban to nonurban, is assumed never to occur. If the land is nonurban by the end of the time period, the dependent variable takes on a value of '0'. Alternatively, if the land is urbanized by the end of the time period, the dependent variable takes on a value of '1'. The general expression of the binary logit model is as follows:

$$P_i = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k)]}, \qquad (1)$$

where P_i is the dependent variable measuring the probability for a grid cell to become urbanized, and $X_1, X_2, ..., X_k$ are independent variables influencing the probability of land conversion from nonurban to urban.

Six types of independent variables were included in each model: (1) smart growth policies, which include two dummy variables indicating whether a grid cell is within a PFA or RLA, respectively, for the post-smart-growth period; (2) location characteristics, which measure the proximity of each grid cell to other features of interest, such as urbanized lands, highways, and municipalities; (3) site characteristics, which measure the physical characteristics of each grid cell; (4) characteristics of neighboring sites, which are used to address the potential problems of neighborhood effects or spatial autocorrelation; (5) demographic characteristics; and (6) infrastructure characteristics. All these variables are listed in table 1. The expected direction of

(3) The MdProperty View database includes property-tax maps and assessment data, monthly property sales records, highway and road maps, LULC data, satellite imagery, and maps of PFAs for jurisdictions in Maryland.

(4) As we will explain later in this paper, we added some constraints on the selection of grid cells for logit modeling. Consequently, the actual sample is smaller.

Table 1. Independent variables and their expected effects on the probability of land development.

Independent variables	Expected effect	Source
Smart-growth policies		
Priority Funding Area	+	Maryland Department of Planning, MdProperty View
Rural Legacy Area	–	Maryland Department of Natural Resources
Local characteristics		
Distance to urban area	–	Maryland Department of Planning, MdProperty View
Distance to highway	–	Maryland Department of Planning, MdProperty View
Distance to municipality	–	Maryland Department of Planning, MdProperty View
Site characteristics		
Floodplain	–	Federal Emergency Management Agency
Slope	–	US Geological Survey
Characteristics of neighboring sites		
Difference between average adjacent slope and site slope	–	US Geological Survey
% of adjacent grid cells urbanized	+	Maryland Department of Planning, MdProperty View
Demographic characteristics		
Population density in 1990	+/–	US Census of Population and Housing
% of population white in 1990, 2000	+/–	US Census of Population and Housing
% of population foreign-born in 1990, 2000	+	US Census of Population and Housing
Infrastructural characteristics		
Sewerage service area	+	Maryland Department of Planning

influence of each variable on the probability of land conversion from nonurban to urban is indicated by the plus or minus sign shown in the table.

For some of the independent variables the expected effects on the dependent variable are well established theoretically and/or empirically. The first smart-growth-policy variable, PFA, is expected to have a positive effect because the state funding should provide added incentive for development to take place in these target areas. The second one, RLA, is expected to have the opposite effect, because the state policy should protect the target areas from urban development.

The three variables that measure the location characteristics are all expected to be negatively related to the probability of urban development. The farther a site is located from any existing urbanized land, the less likely it is to be developed. Similarly, the farther a site is located from highways, or from a municipality, the lower the possibility for it to change from a nonurban to an urban use.

The two site characteristics variables are both expected to reduce the probability of development. If land is inside a 100-year or 500-year floodplain it is less likely to be developed because of the risk of flood. Higher slope of the site will increase the infrastructure and construction costs and hence lower the development probability.

One of the two variables characterizing the neighboring sites of a given piece of land is expected to increase the development probability of the land. Specifically, a given grid cell is more likely to be urbanized if more of its neighboring grid cells are urbanized. The other neighboring site characteristic variable is likely to generate the opposite effect. As the difference between the slope of a given cell and the average slope of adjacent cells becomes larger, the infrastructure and construction costs increase, which subsequently lower the development probability.

For two of the demographic characteristic variables, the expected influence on nonurban-to-urban land conversion is ambiguous. Preexisting population density, measured as the gross density for the block group in which a given grid cell is located, can either be an indication of high demand for urban land in the area or an indication of having little open space left in the area. In the former case higher population density will increase development possibility, whereas in the latter case higher density will be negatively related to the probability of development. Similarly unclear is the influence of the percentage of residents in the block group who are white. The conventional notion of 'white flight' being the primary source of suburban growth would suggest that a higher percentage of white population will have a positive effect on the development probability. However, if suburban growth is fueled by the city-to-suburb migration and international immigration of people with diverse ethnic backgrounds, this variable may show a negative relationship with the dependent variable. The third demographic variable, the percentage of residents in the block group who are foreign-born, is expected to have a positive effect on land-development probability because international immigration is a major source of population growth, especially in large metropolitan areas, and because immigrants show the tendency to form ethnic residential and commercial clusters.

Finally, the infrastructure characteristic variable is expected to facilitate urban development. If land is inside an existing sewerage service area, it is more likely to be developed because the sewerage infrastructure will increase the land value and subsequently the development probability. Water infrastructure generates the same positive effect, but it was not included in our models as an independent variable because we found it to be highly correlated with sewage infrastructure and provided no additional explanatory power.

It is important to note that the above list of independent variables is not exhaustive. Many other factors, ranging from macroeconomic conditions (for example, employment growth and interest rate change) to microenvironmental and social conditions (for example, presence of hazardous materials and availability of public-transportation service and quality public schools), may also play significant roles in influencing land-use decisions. Despite the omission of these variables, we believe that our model specification is adequate because it includes all the key determinants (microlevel factors) of land-use change discussed in the literature on modeling land-use change. Further, the model estimation is not expected to be significantly affected by the omission of the omitted macrofactors because they influence all land areas.

Data and analytical procedure

Due to the extraordinarily large amount of data processing and analysis required for this work, we decided to select only eight of the twenty-three local jurisdictions in Maryland for the empirical study. These eight counties are Anne Arundel County, Baltimore County, Carroll County, Howard County, Montgomery County, St Mary's County, Washington County, and Wicomico County, which are shown in figure 1.

These eight counties were chosen for the empirical analysis because, to some extent, they are representative of counties with different histories of growth management and different patterns of urban growth.[5] Anne Arundel County, the home

[5] Facts about these eight counties come from three sources: (1) the United States Census Bureau's 1990 and 2000 censuses of population and housing; (2) a report on models and guidelines for managing Maryland's growth published by Maryland Office of Planning (1995); and (3) county codes for counties in the state of Maryland.

county of the state capital, Annapolis, has a long coastline along the Chesapeake Bay, a primary focus of environmental conservation in Maryland. This county experienced substantial growth during the 1990s, with a 14.6% increase in the number of residents. Its population in 2000 was close to 490 000.

Baltimore County has a long tradition of growth management. It is nationally known for implementing urban-growth boundaries to influence land-use patterns. Surrounding Baltimore City, which lost over 84 000 residents between 1990 and 2000, Baltimore County has probably absorbed a large portion of out-migration from the central city. The county experienced a fairly high pace of population growth (9.0%) during the 1990s. Its population in 2000 reached 750 000.

Carroll County, another county within the Baltimore Primary Metropolitan Statistical Area, experienced rapid population growth (22.3%) during the 1990s. Its population in 2000 was approximately 123 000. The county had few growth management measures in place prior to 1997. However, since 1997 the county's strong desire to preserve its rich tradition of agriculture has resulted in tremendous rates of participation in one of the most successful agricultural-land-preservation programs in the country.

With its location between Washington, DC, and Baltimore City, Howard County has been viewed as a desirable place for residential development. In fact, during the 1990s the county witnessed very fast growth of the population (32.3%) and housing units (27.9%). Its population reached almost 250 000 in 2000. Another notable characteristic of Howard County is that, among all counties in Maryland, it has the highest average household income and its adult residents are on average the most highly educated.

Located immediately northwest of Washington, DC, Montgomery County has long been a sought after suburban location in the District of Columbia metropolitan area. Between 1990 and 2000 the county continued to experience fast growth with a 14.5% increase in the number of residents. With a population of over 870 000 it is the most populous and one of the most affluent among counties in Maryland. Montgomery County has a long tradition (starting in the 1960s) of implementing policies and programs—which include a growth boundary—to shape urban-growth patterns, preserve open space, and protect agricultural lands.

St Mary's County is located in southern Maryland on the western shore of the Chesapeake Bay, with only slightly more than 86 000 residents in 2000. Its population has been steadily increasing for several decades, including a 13.5% increase during the 1990s. The county ranked first in Maryland in job growth and personal-income growth from 1996 to 2001. This rapid growth has not been managed with strong growth-control measures.

Washington County, a county with a rich agricultural tradition, is located in the Great Valley of western Maryland. With a modest 8.7% of growth during the 1990s, its population in 2000 was close to 132 000. Starting from its 1983 Comprehensive Plan, the county has deliberately introduced growth management through the adoption of designated 'growth areas'.

Located in the center of the Delmarva Peninsula, Wicomico County is one of nine counties constituting Maryland's Eastern Shore. With slightly fewer than 85 000 residents in 2000, the county experienced moderate population growth during the last three decades, including a 13.9% increase of residents during the 1990s. It witnessed substantial loss of its prime agricultural lands to low-density urban development.

The dependent variable for logit models, which indicates whether the land use in a grid cell is urban, is measured on the basis of LULC data. The data for 1992, known as the 1992 National Land-Cover Data (NLCD), were obtained from the US Geological

Survey (USGS). The LULC data for both 1997 and 2002 were provided by the Maryland Department of Planning as part of the MdProperty View database.

It is important to note some significant differences between the NLCD data from the USGS and the LULC data from the Maryland Department of Planning. The 1992 NLCD data were obtained using a modified version of the level II Anderson LULC classification system, and were derived from maximum likelihood classification of two-date thematic-mapper imagery at 30 m resolution with the focus on land-cover classification (Vogelmann et al, 1998). The accuracy of this dataset was reported as being relatively low, especially for low-density developed areas (McCauley and Goetz, 2004; Stehman et al, 2003). The 1997 and 2002 LULC data, on the other hand, were obtained using the Level II Anderson classification system, and were derived from manually interpreted image analysis focused on land-use classification. These data products provide relatively high accuracy. Notwithstanding the differences, we matched these datasets for the different years because there was no better option. To reduce discrepancies between the two data sources, we used the parcel 'year-built' information provided by the MdProperty View database to make adjustments to the 1992 NLCD. Although there are remaining data discrepancies, they are unlikely to significantly and systematically affect the results of our analysis.

We designated a grid cell 'urban' for a given year if its centroid is located inside a land area in the corresponding NLCD or LULC map that is shown to be developed. It can be residential, industrial, commercial, or another class of urbanized land. For the 1992 NLCD, the 'urban' designation is an aggregation of three classes of 'developed areas' plus the 'urban/recreational grasses' land. For the 1997 and 2002 LULC data, the 'urban' designation is an aggregation of eight more detailed classes of 'urban built-up' areas plus the 'transportation' land.

To identify land-use conversion taking place among the original nonurban grid cells during each time period, we used GIS to overlay the LULC layers for the three years. The resulting maps of land-use change are shown in figure 2.

On the basis of the data on land-use change, we obtained the samples for modeling. We excluded those grid cells that are extremely unlikely to be developed. These include grid cells known to be wetlands or protected lands.[6] Grid cells located more than 10 miles (approximately 16 km) from the nearest highway or with a slope exceeding 15° were excluded as well. Realizing that conversion of land from nonurban to urban use occasionally occurs in locations beyond 10 miles from any highway, we later also ran models without applying this criterion for excluding cases. The resulting regression coefficients and levels of statistical significance were quite similar, but the goodness of fit of estimated models dropped when the samples included huge numbers of remotely located grid cells that remained nonurban throughout the time periods. In this paper we report results that were obtained using only observations located within 10 miles from the nearest highway.

The data sources for the explanatory variables are indicated in table 1. The smart-growth policy variables were obtained by overlaying the GIS layers of PFA and RLA with the layers of land-use change. The PFAs and RLAs for the eight counties are shown in figure 3. Note that these counties display several distinctive patterns of land conversion. In Baltimore, Montgomery, and Washington—counties which have a strong tradition of growth management—development tended to take place near the existing urban areas during 1992–97 as well as 1997–2002. In Carroll, Howard, and St Mary's,

[6] According to the Maryland Department of Natural Resources (DNR), the protected lands include Agricultural Land Preservation Foundation Easements/Districts, County Parks, DNR land, Environmental Trust Easements, Federal Land, Forest Legacy Easements, and Private Conservation Properties.

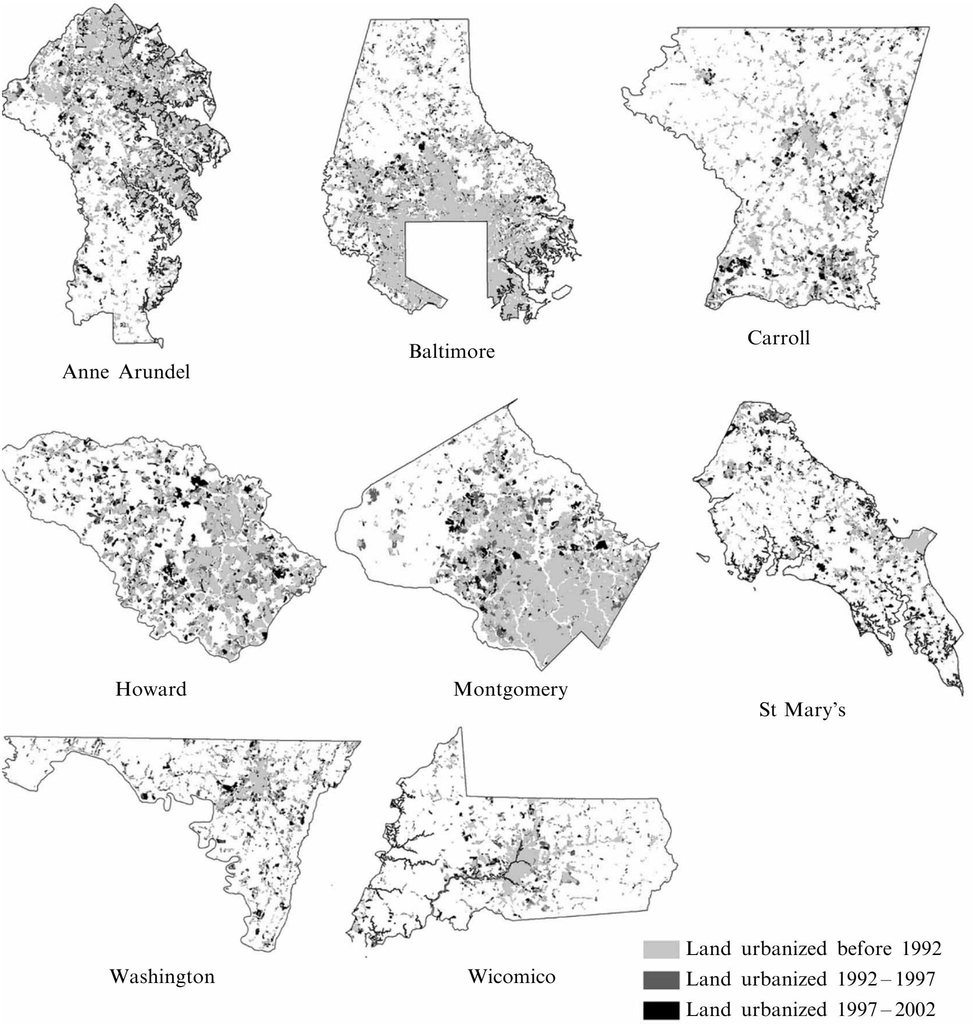

Figure 2. Land-use changes in eight Maryland counties, 1992 – 2002.

on the other hand, development appeared to be more scattered. The most interesting development patterns are seen in Anne Arundel County, where land conversion was scattered all over the county during the first period, but became much more concentrated near the existing urban areas during the second period.

Location characteristics were measured on the basis of GIS layers of highways, urbanized areas, and municipalities, which are elements of the MdProperty View database. The site characteristics data originated from two governmental agencies. The floodplain data were from the Federal Emergency Management Agency, and the slope data were derived from the digital elevation model (DEM) data provided by USGS. The MdProperty View database was also the data source for determining the percentage of adjacent grid cells that are urban. Difference between average adjacent slope and site slope was derived from the USGS DEM data.

The demographic characteristics are block group data obtained from either the 1990 or 2000 US Census of Population and Housing. Finally, the infrastructural characteristics were measured by whether the land is located inside sewage service areas, based on GIS data obtained from the Maryland Department of Planning.

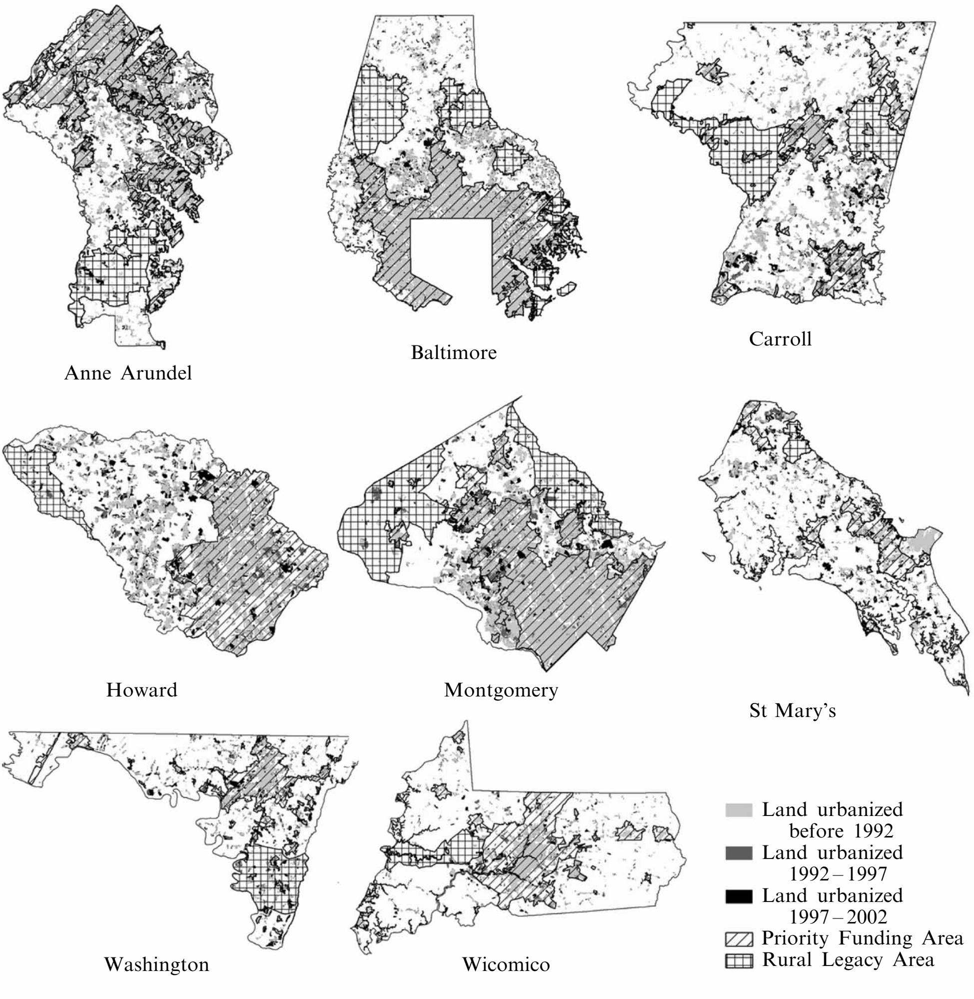

Figure 3. Priority Funding Areas and Rural Legacy Areas in eight Maryland counties.

To examine the overall effects of the smart growth programs on patterns of land conversion in the state, we used the pooled data for the eight counties to estimate two logit models for 1992 – 97 and 1997 – 2002, respectively. Table 2 displays the descriptive statistics of the variables included in the first model, and table 3 displays the parallel information for the second model.

To make comparisons among the eight counties of the effectiveness of the smart-growth program we also used data for individual counties to estimate the logit models.

Primary findings

We will first look at the estimated models for the pooled data for the eight counties to examine the effectiveness of the 'Smart Growth Area Act' and 'Rural Legacy Act' in the state as a whole (as indicated by the eight counties jointly as a group). We will then discuss the results for individual counties to understand variations in the policy effectiveness across the counties.

Table 2. Descriptive statistics of the pooled data, 1992–97.

	N	Minimum	Maximum	Mean	SD
Urbanized	484 455	0.00	1.00	0.08	0.27
Distance to urban area (km)	484 455	0.00	4.81	0.45	0.40
Distance to highway (km)	484 455	0.02	16.10	4.62	3.88
Distance to municipality (km)	484 455	0.00	39.22	8.56	7.63
Floodplain	484 455	0.00	1.00	0.05	0.22
Slope	484 455	0.00	15.00	2.62	2.13
Difference between average adjacent slope and site slope	484 455	0.00	7.91	0.48	0.52
Percentage of adjacent grid cells urbanized	484 455	0.00	100.00	9.11	18.47
Population density, 1990	484 455	0.02	71.43	1.41	2.94
Percentage of population white, 1990	484 455	0.00	100.00	91.20	12.63
Percentage of population foreign-born, 1990	484 455	0.00	59.03	2.16	3.33
Sewerage service area	484 455	0.00	1.00	0.08	0.27
Valid *N* (listwise)	484 455				

Note: SD, standard deviation.

Table 3. Descriptive statistics of the pooled data, 1997–2002.

	N	Minimum	Maximum	Mean	SD
Urbanized	453 159	0.00	1.00	0.11	0.32
Priority Funding Area	453 159	0.00	1.00	0.17	0.38
Rural Legacy Area	453 159	0.00	1.00	0.15	0.35
Distance to urban area (km)	453 159	0.00	4.81	0.42	0.35
Distance to highway (km)	453 159	0.02	16.10	4.68	3.88
Distance to municipality (km)	453 159	0.00	39.22	8.63	7.66
Floodplain	453 159	0.00	1.00	0.05	0.22
Slope	453 159	0.00	15.00	2.65	2.17
Difference between average adjacent slope and site slope	453 159	0.00	7.92	0.48	0.53
Percentage of adjacent grid cells urbanized	453 159	0.00	100.00	8.84	17.11
Population density, 1990	453 159	0.00	75.41	1.29	2.75
Percentage of population white, 2000	453 159	2.28	100.00	89.50	12.56
Percentage of population foreign-born, 2000	453 159	0.00	88.05	3.53	4.62
Sewerage service area	453 159	0.00	1.00	0.06	0.24
Valid *N* (listwise)	453 159				

Note: SD, standard deviation.

General patterns of land conversion in the state

The results of model estimations for the state, as represented by the eight counties, are shown in table 4. Notice, first, that the two models, for the time periods 1992–97 and 1997–2002, respectively, are generally consistent in terms of the signs and statistical significance of most regression coefficients. In both models, being located farther from an existing urbanized area, in a floodplain, or in a block group that has a higher percentage of residents who are white reduces the probability for the site to be urbanized. On the other hand, having a higher percentage of adjacent grid cells

Table 4. Models of land conversion in Maryland, estimated using the pooled data from eight counties for 1992 – 1997 and 1997 – 2002.

1992 – 1997 model		1997 – 2002 model	
Independent variables	Coefficient	Independent variables	Coefficient
		Priority Funding Area	0.828***
		Rural Legacy Area	−0.528***
Distance to urban	−2.103***	Distance to urban	−2.726***
Distance to highway	0.003	Distance to highway	−0.025***
Distance to municipality	−0.012***	Distance to municipality	0.015***
Floodplain	−0.259***	Floodplain	−0.227***
Slope	−0.026***	Slope	0.082***
Difference of slopes	−0.074***	Difference of slopes	0.029*
Percentage of adjacent grid cells urban	0.041***	Percentage of adjacent grid cells urban	0.008***
Population density	−0.066***	Population density	0.023***
Percentage of population white	−0.004***	Percentage of population white	−0.005***
Percentage of population foreign-born	0.047***	Percentage of population foreign-born	0.017***
Sewerage service area	0.872	Sewerage service area	0.369***
Constant	−2.244***	Constant	−1.474***
Sample size = 484 455		Sample size = 453 159	
Nagelkerke R^2 = 0.317		Negelkerke R^2 = 0.215	
Percentage correctly predicted = 92.9%		Percentage correctly predicted = 88.4%	

* Significant at the 0.05 level; *** significant at the 0.001 level.

urbanized, being located in a block group where a higher percentage of residents are foreign-born, or being located inside a designated sewerage service area increases the likelihood for the land to be developed. These results are consistent with the expectations indicated earlier in table 1.

Second, several variables show inconsistent effects on the dependent variable. The two variables measuring the distances to the nearest highway and municipality have different signs in the two models. This inconsistency is probably attributable to the dominance of the variable 'distance to urban area' in explaining the influence of site location on land conversion, which leaves relatively little to be captured by the distances to the nearest highway and municipality. Also showing inconsistent results are the variables measuring site slope, the difference between site slope and average slope of adjacent cells, and gross population density in the census block group. It is especially unexpected to see the positive coefficients for both slope variables in the model for the post-smart-growth period. These positive coefficients suggest that development was more likely to occur on lands with steeper slopes. It is possible that these unexpected signs actually capture the reality that, in some of the counties located near the Chesapeake Bay or the Atlantic Ocean, much of the undeveloped flat land is at very low altitude and subject to flooding, which causes new developments to increasingly locate in areas with higher elevations and slopes. Indeed, upon closer examination of data for individual counties, we found that slope is positively and significantly related to land conversion in Wicomico and St Mary's counties. The association is negative for five counties and, in several cases, statistically insignificant.

Finally, and most importantly, in the model for 1997 – 2002, the smart-growth policy variables, PFA and RLA, both show statistically significant effects on the dependent variable with the expected signs. This means that, during the post-smart-growth period, land areas designated as PFA were more likely to be developed, whereas land areas designated as RLA were less likely to be developed, than otherwise comparable land outside PFAs and RLAs. If the coefficient of 0.828 for PFA is converted to odds ratio, it will indicate that the odds of land-use change from nonurban to urban are almost 2.3 times higher for land located within PFAs than for otherwise comparable land located outside PFAs, everything else being constant. Likewise, if the coefficient of -0.528 for RLA is measured in terms of odds ratio, it will show that the odds of nonurban to urban conversion for land inside RLAs are only 0.6 times as high as those for otherwise comparable land outside RLAs. These results indicate that the smart-growth programs have been at least partly effective in achieving their intended objectives.

As indicated by the modest goodness-of-fit measures for these two logit models, there is a large amount of unexplained variation in the patterns of land conversion in Maryland. Nonetheless, the estimated models present a general picture of the fundamental forces shaping the spatial patterns of urban development in this state during the pre-smart-growth as well as post-smart-growth periods.

Variations in policy effectiveness among counties

To examine variations in the effectiveness of smart-growth policies among local jurisdictions, eight pairs of logit models—one pair for each of the eight counties—were estimated. Tables of the regression outcomes for individual counties are omitted from this paper to save space. The results are summarized and compared below. Part of the model interpretation is based on discussions with several planners who are highly knowledgeable of urban-growth issues in these counties.

First, the variable PFA is positive and statistically significant for the 1997–2002 models for six of the eight counties (Anne Arundel, Baltimore, Carroll, Montgomery, Washington, and Wicomico). This suggests that in most counties land located in priority funding areas has a higher likelihood of development than otherwise comparable land outside PFAs. The magnitude of the policy effect of PFA varies among these counties, as indicated by the different values of the coefficients. The greatest policy effect was observed in Baltimore County, and the second greatest effect was observed in Anne Arundel County. These results are consistent with what we saw previously in the patterns of land-use change shown in figure 3.

Surprisingly, the smart-growth policy variable PFA is not statistically significant for Howard and St Mary's counties. For Howard County, this result was probably due to the fact that some of the county's zonings districts were inconsistent with PFA designations. Indeed, the zoning map of Howard County shows that a large portion of the middle county area is designated for low-density residential development even though it is located outside PFAs. For St Mary's County, the result probably caused by the combination of a lack of effective local policies to restrict development in rural areas and the inclusion of land areas that are unattractive for urban development in the PFAs. These outcomes indicate that there were significant variations among counties in their compliance with the smart-growth initiative.

Second, the variable RLA shows the expected negative and statistically significant coefficients for most counties, with Anne Arundel, Washington, and Wicomico as the exceptions. The regression outcomes indicate that, for Baltimore, Carroll, Howard, Montgomery, and St Mary's, the RLA is effective in protecting valuable agricultural resources. For Wicomico, the statistically insignificant coefficient is probably due to the fact that there is only a relatively small rural legacy area in this county and/or the demand for urban development is rather low in its rural legacy area. The coefficients for RLA in the cases of Anne Arundel and Washington are positive, which is surprising.

Based on our conversations with several urban planners, a plausible explanation for the positive associations is that when the RLAs in these two counties were designated, some of the land located inside the RLAs was already under enormous market pressure for development.

Third, distance to nearest highway, floodplain, and sewerage are the variables with relatively stable relationships with the dependent variables across different counties and time periods. However, the empirical results also show considerable inconsistencies in terms of the signs and levels of statistical significance of regression coefficients for several independent variables. These variables change signs across models for the different time periods and/or counties, suggesting that the effects of some demographic, location, and site factors on land conversion vary across local jurisdictions.

Continuity and discontinuity in the patterns of land conversion

Does the implementation of the Smart Growth Area Act and the Rural Legacy Act cause fundamental and drastic changes in the patterns of urban land conversion? On the one hand, it is conceivable that the designations of the PFA and RLA largely reflected the preexisting development patterns shaped by market forces and/or local growth-management policies.(7) If that was the case, the smart-growth initiatives would have largely reinforced the preexisting patterns. On the other hand, it is also possible that the designations of PFA and RLA represented a fundamental departure from the preexisting development patterns and caused discontinuities in the preexisting patterns of land-use conversion.

To address this question, we added the PFA and RLA dummy variables to the 1992–97 models. To conceptually distinguish the same geographic areas for the pre-smart-growth period from those for the post-smart-growth period, we renamed the two dummy variables for the 1992–97 models as 'area later became PFA' and 'area later became RLA'. Again, we first estimated the model for the eight counties as a group, and then estimated the models for individual counties. The regression outcome based on the pooled data for eight counties is shown in table 5. Several important insights can be obtained from this estimated model.

First, the variable 'area later became PFA' shows a positive and statistically significant relationship with the dependent variable measuring the probability of land conversion from nonurban use to urban use in the period 1992–97. In other words, areas that were later designated as PFAs had already tended to be desirable locations for urban growth before the Smart Growth legislation was in place. However, the regression coefficient is only 0.402, which translates into an odds ratio of approximately 1.6. This coefficient is smaller than the 0.828 for the PFA variable for the post-smart-growth period, which translates into an odds ratio of almost 2.3. Thus, the data analysis demonstrates that the PFA has a relatively greater positive effect on development probability than 'area later became PFA'. The PFA designation makes urban development more concentrated in the target areas than before.

Second, the variable 'area later became RLA' shows a negative and statistically significant effect on the probability of nonurban to urban land conversion in the period 1992–97. This means that, even in the pre-smart growth period, land located in areas that later became RLAs was less likely to be urbanized. The result is, again, unsurprising because the 'Rural Legacy Act' was not the first policy attempt to protect Maryland's

(7) For example, the Maryland Economic Growth, Resource Protection, and Planning Act of 1992 played an important role in that it required several visions to be incorporated into county and municipal comprehensive plans. One of the visions required development to be concentrated in suitable areas. Some counties, notably Baltimore, Montgomery, and Washington, embraced these visions and designated their own 'suitable areas' which turned out to be highly consistent with the state-designated PFA.

Table 5. Models of land conversion in Maryland [with 'area later became Priority Funding Area (PFA)' and 'area later became Rural Legacy Area (RLA)' dummy variables].

1992–1997 model		1997–2002 model	
Independent variables	Coefficient	Independent variables	Coefficient
Area later became PFA	0.402***	PFA	0.828***
Area later became RLA	−0.258***	RLA	−0.528***
Distance to urban	−2.006***	Distance to urban	−2.726***
Distance to highway	0.018***	Distance to highway	−0.025***
Distance to municipality	−0.009***	Distance to municipality	0.015***
Floodplain	−0.271***	Floodplain	−0.227***
Slope	−0.017***	Slope	0.082***
Difference of slopes	−0.056***	Difference of slopes	0.029*
Percentage of adjacent grid cells urban	0.041***	Percentage of adjacent grid cells urban	0.008***
Population density	−0.073***	Population density	0.023***
Percentage of population white	−0.003***	Percentage of population white	−0.005***
Percentage of population foreign-born	0.046***	Percentage of population foreign-born	0.017***
Sewerage service area	0.666***	Sewerage service area	0.369***
Constant	−2.498***	Constant	−1.474***
Sample size = 484 455		Sample size = 453 159	
Nagelkerke R^2 = 0.320		Negelkerke R^2 = 0.215	
Percentage correctly predicted = 92.9%		Percentage correctly predicted = 88.4%	

* Significant at the 0.05 level; ** significant at the 0.01 level; *** significant at the 0.001 level.

valuable farmland, forestry, and natural and historic resources. To find out whether or not the smart-growth program has strengthened the protection of rural-legacy areas we can compare the regression coefficient for 'area later became RLA' with the regression coefficient for RLA: −0.258 and −0.528, respectively. The corresponding odds ratios are 0.77 and 0.59, respectively, for pre-smart-growth and post-smart-growth periods. Clearly, the 'Rural Legacy Act' was effective in adding protection to designated areas.

To show that the coefficients for PFA and RLA are statistically different from the coefficients for 'area later became PFA' and 'area later became RLA', we adopted the method proposed by Gujarati (1970) to test the equality between two sets of coefficients. We pooled the two datasets for pre-smart-growth and post-smart-growth periods and added a dummy variable, S, to indicate if a grid cell is from the post-smart-growth period. We generated a set of new independent variables by multiplying each independent variable with the dummy variable. The expression of the modified logit model is as follows:

$$P_i = \frac{1}{1+\exp[-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k+\gamma_0 S+\gamma_1 X_{\mathrm{S1}}+\gamma_2 X_{\mathrm{A2}}+\ldots+\gamma_k X_{\mathrm{S}k})]}, \quad (2)$$

where γ_0 is the differential intercept, and $\gamma_1, \gamma_2, \ldots, \gamma_k$ are differential coefficients indicating the differences between the slopes of the variables for post-smart and pre-smart periods.

The test result is shown in table 6. The coefficients for PFA_S and RLA_S are 0.425 and −0.269, respectively. Both are statistically highly significant. This means that land located inside PFAs is more likely to be developed during the post-smart-growth period than it was during the pre-smart-growth period. Land located inside RLAs, on the other hand, is less likely to be developed during the post-smart-growth period than it was during the pre-smart-growth period.

Table 6. Differences between pre-smart-growth and post-smart-growth land conversions.

Independent variables	Coefficient
Area later became Priority Funding Area (PFA)	0.402***
Area later became Rural Legacy Area (RLA)	−0.258***
Distance to urban	−2.006***
Distance to highway	0.018***
Distance to municipality	−0.009***
Floodplain	−0.271***
Slope	−0.017***
Difference of slopes	−0.056***
Percentage of adjacent grid cells urban	0.041***
Population density	−0.073***
Percentage of population white	−0.003***
Percentage of population foreign-born	0.046***
Sewerage service area	0.666***
Differential intercept	1.024***
PFA_S	0.425***
RLA_S	−0.269***
Distance to urban_S	−0.719***
Distance to highway_S	−0.043***
Distance to municipality_S	0.025***
Floodplain_S	−0.044
Slope_S	0.099***
Difference of slopes_S	0.084***
Percentage of adjacent grid cells urban_S	−0.033***
Population density_S	0.096***
Percentage of population white_S	−0.002**
Percentage of population foreign-born_S	−0.029***
Sewerage service area_S	−0.297***
Constant	−2.498***
Sample size = 937 614	
Nagelkerke R^2 = 0.269	
Percentage correctly predicted = 90.7%	

** Significant at the 0.01 level; *** significant at the 0.001 level.

To save space, we do not report the details of the estimated models with the 'area later became PFA' and 'area later became RLA' variables for individual counties. However, we would like to make several observations about the results for 'area later became PFA', which are helpful for understanding continuity and change in patterns of land conversion in individual counties. For the majority of the counties, including Baltimore, Carroll, Montgomery, Washington, and Wicomico, 'area later became PFA' has positive and statistically significant coefficients. Given that in the models for 1997–2002 the variable PFA also has positive (and in most cases larger) and statistically significant coefficients for these counties, one can conclude that establishing the PFAs has reinforced, or at least sustained, the pattern of relatively concentrated urban growth in these counties. Note that, as described earlier, Baltimore, Montgomery, and Washington had local growth-management policies in place before the state passed the smart-growth initiatives in 1997.

Both the 'area later became PFA' and PFA variables are statistically insignificant for Howard and St Mary's, indicating that the 'Smart Growth Area Act has not been effective for shaping growth in these two counties.

Anne Arundel County is a special case because, although in the 1992–97 model the 'area later became PFA' has a statistically significant negative relationship with the dependent variable, in the 1997 – 2002 model the PFA has a statistically significant positive relationship with the dependent variable. This discontinuity in the pattern of land conversion suggests that the 'Smart Growth Area Act' has generated highly effective outcomes in Anne Arundel, where the previously dispersed pattern of development has become concentrated in the PFAs for the post-smart-growth years, as shown previously in figure 3.

Conclusion

Our logit models of land conversion in Maryland have shown that the State's Smart Growth Area Act and Rural Legacy Act have generally been successful in achieving their policy objectives. Although areas now designated as PFA had been the locations for much of the urban growth during the pre-smart-growth years, the 1997 legislation and its programs reinforced the pattern of relatively concentrated development. Likewise, the 1997 Rural Legacy Act reinforced the preexisting tradition of protecting the state's valuable farmland, forestry, and natural and historic resources.

The effectiveness of the Smart Growth Area Act and the Rural Legacy Act varies across the counties, however. Although the empirical evidence we have gathered is somewhat limited, our models of land conversion show that smart-growth policies have reinforced the relatively compact patterns of urban growth in counties that have a strong tradition of managing growth, and have drastically changed spatial distribution of land conversion in some of the counties where the preexisting patterns of urban development were spatially highly scattered. But the policies may not have a significant effect on other counties. These results provide important insights about the significance of local physical, socioeconomic, and political environments in influencing the pace and patterns of urban development.

Planners and policymakers must pay close attention to these interjurisdictional differences in the effectiveness of smart-growth programs, examine the likely causes and consequences, and formulate strategies for improvement. Our findings imply that it is important to establish collaboration between state and local governments in designing and implementing smart-growth policies.

We have so far focused on examining the effectiveness of two important smart-growth programs in achieving their stated objectives. Future research should investigate the economic efficiency, social equity, and environmental sustainability implications of alternative patterns of urban growth, issues which remain the primary focus of debate over smart growth.

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