ABSTRACT

Title of Document: **EXURBAN DEVELOPMENT: QUANTIFICATION, FORECAST, AND EFFECTS ON BIRD COMMUNITIES**

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Rural landscapes in the United States have changed dramatically in recent decades due to the rapid development of private rural lands into low-density residential exurban development. This land conversion is a rising cause of concern due to its potential effects on biodiversity and ecosystem processes. Although exurbanized area is thought to have a significant increase in eastern deciduous forests, a rigorous assessment of exurban trends, drivers, and ecological consequences has yet to be undertaken. First, I develop a novel analytic approach to identify exurban areas and assess how much land has been converted to exurban development in the Mid-Atlantic region. The approach describes mixed pixels containing exurban development as a combination of land covers and uses decision-tree classification and morphological spatial pattern analysis to further separate exurban development from other forest disturbing events. The results indicate that exurban development is a pervasive and fast-growing form of land use in the region. Second, I evaluate the effectiveness of two contrasting modeling approaches in capturing exurban growth at a local and county scale. Exurban growth was effectively captured by the spatially-explicit econometric model at both scales and the pattern-based model only performed well at the county scale. Thus, pattern-based models like SLEUTH can forewarn potential coarse-scale losses of natural resources in exurban areas, but are less useful at finer scale or for assessing potential impacts of implementing land-use policies. Third, I assess whether exurban development degrades avian breeding territories over time and forest birds' response to those changes. I conclude that exurban development is degrading breeding habitats by reducing forest cover and increasing habitat fragmentation. Forest birds exhibited a threshold response to deteriorating breeding habitats in the vicinity of breeding territories and adjacent foraging areas being forest specialists the most sensitive group. To avoid the likelihood of sudden bird population declines amongst further habitat loss and fragmentation, a synergy among land managers, planners, and decision-makers will become increasingly important to mitigate the impacts of exurban development in the Mid-Atlantic region.

EXURBAN DEVELOPMENT: QUANTIFICATION, FORECAST, AND EFFECTS ON BIRD COMMUNITIES

By

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PREFACE

This dissertation contains an overall abstract and five chapters. Chapter II, III, and IV are presented in manuscript form; therefore, the study area may be repeated, pronouns reflect manuscript authorship, and tables and figures appear at the end. A single reference section occurs at the end for literature cited throughout the dissertation.

DEDICATION

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CHAPTER I

INTRODUCTION

The world's human population have been growing very rapidly over the 20th century resulting in the conversion of natural landscapes into pastures, agriculture, and urban development (Vitousek et al. 1997, Foley et al. 2005, Lepczyk et al. 2007, United Nations Population Fund 2007, Szlavecz et al. 2011). Residential housing development has outpaced population growth even in areas were human population has declined (Liu et al. 2003). For example, in countries with biodiversity hotspots between 1985 and 2000, annual growth in housing units was much higher (1.7 to 10.0%) than those of the population (0.5% to 7.0%). This rapid increase of housing units is often manifested as sprawl. Sprawl ensues higher per-capita resource consumption (Ewing et al. 2002) and thus, poses serious challenges to the provision of ecosystem services (Millennium Ecosystems Assessment 2005).

The rapid increase of housing development has not only occurred in urban fringes but also in rural areas (Riebsame et al. 1996, van den Berg and Wintjes 2000, Heimlich and Anderson2001, Hansen et al. 2005, McKenzie et al. 2011). Residential development beyond the urban fringe (i.e. exurban development) is characterized by low-density, scattered housing units further away from the suburbs but within commuting distance to an urban center (Lamb 1983, Nelson 1992, Daniels 1999, Theobald 2001, Berube et al. 2006). In the conterminous United States, development in rural landscapes has been prominent since the 1950s (Brown et al. 2005). Exurban development has been growing at a rate of about 10-15%, from 159 million acres in 1960 to 333 million in 1990 to 378 million acres in 2000 (Theobald 2001). By 2000, 25% of the nation was already considered exurbia (Brown et al. 2005).

The development of rural land has been driven by peoples' attraction to natural amenities (Hansen et al. 2002). Natural amenities such as scenery, environmental quality, outdoor recreation, and climate have been found to be important reasons for migrating to exurban areas (McGranahan 1999, Rasker and Hansen 2000). However, the ability of an amenity to attract exurban migrants changes both over time and by region (Nelson 2006, Larsen et al. 2011). For example, exurban residents of the state of Colorado are attracted by varied topography (McGranahan 1999, Gude et al. 2006) whereas residents in exurban Indiana and Illinois are seeking relatively affordable housing and privacy, compared to urban and suburban areas (Johnson 2008). This migration is driving large changes in the landscape.

Conversion of natural landscapes into exurban development is a rising cause of concern due to its potential effects on biodiversity and ecosystem processes (Sampson and DeCoster 2000, Hansen et al. 2005, Hansen and DeFries 2007, Wade and Theobald 2010). There have been a number of studies investigating the ecological repercussions of exurban development (Nilon et al. 1995, Miller et al. 2003, Fraterrigo and Wiens 2005, Phillips et al. 2005, Bock et al. 2008). However, the impacts of exurban development are not as well understood as effects from forestry and agriculture (Miller and Hobbs 2002). General findings suggest that as housing density increases, abundance of specialist species tend to decrease and human adapted species increase. In addition, species densities, richness, and community assemblages change (Odell and Knight 2001, Merenlender et al. 2009, Suarez-Rubio et al. 2011). Human activity also affects the behavior and habitat use of various species for example, by interrupting wildlife migration and movement (Gabrielson and Smith1995, Miller et al. 1998, Lepczyk et al. 2004). Moreover, exurban development may elevate wildfire risks, and propitiate invasive exotic species (USDA and USDI 2001, Hansen et al. 2005, Gavier-Pizarro et al. 2010). Besides affecting private lands, exurban development may also have an impact on adjacent protected areas (Hansen et al. 2002, Wade and Theobald 2010). The mechanisms behind these patterns are less understood but are generally associated with habitat loss and fragmentation, modification of disturbance regimes, and changes in biotic interactions (Hansen et al. 2005, Hansen and DeFries 2007; Table 1).

The Eastern Temperate Forest Ecoregion has experienced high population growth since 1970 (Brown et al. 2005) and is thought to have a significant increase in exurban areas since 1950 (Brown et al. 2005, Theobald 2005). However, a rigorous assessment of trends of exurban development has yet to be undertaken for this area of the country. Understanding historical trends of exurban development is critical to comprehend the causes and consequences of this type of development and make useful and reliable projections across temporal and spatial scales. In addition, considering that exurban development is relatively new, and that exurban areas are expanding and transforming the landscape (Johnson 2008), evaluation of avian response to habitat alteration is imperative to understand the effects of exurban development. Birds may be particularly sensitive to habitat loss and fragmentation (Rolstad 1991, Andrén 1994, Cornelius et al. 2000, Donovan and Flather 2002, Castelletta et al. 2005) and can react rapidly to changes in their environment (Reynaud and Thioulouse 2000). Birds are also attractive as ecological indicators because they are easy to identify and sample and their habitat affinities are well known (Canterbury et al. 2000, O'Connell et al. 2000). In addition, birds are conspicuous attracting interest by the public (Niemi and McDonald 2004). Therefore, birds provide a good model to study species response to exurban development.

The overall goal of this dissertation was to determine the historical magnitude and rate of exurban development in north and central Virginia and western Maryland, evaluate the appropriate modeling approach to project exurban development, and assess its effects on breeding forest birds. I focused on this study region because it has experienced high population growth since 2000 (Weldon Cooper Center 2010). In addition, its proximity to the Washington DC metropolitan area, the well-maintained transportation infrastructure, and natural amenities around this area (e.g., Shenandoah National Park) suggest that this region may attract exurban development. However, unlike other regions of North America where patterns of exurban development have been clearly documented (e.g., Gonzalez-Abraham et al. 2007a), it is uncertain whether this area of high population growth has also experienced an increase in exurban areas.

Research objectives and dissertation format

The main goals of my dissertation were to (1) develop a novel analytic approach to map exurban development and to assess its magnitude and rate in north and central Virginia and western Maryland, (2) evaluate a popular pattern-based model (SLEUTH) and a spatially explicit econometric model in predicting exurban development, and (3) assess whether exurban development significantly deteriorates suitability of avian breeding habitats (Figure 1).

Chapter II focuses on developing an analytic approach to map exurban development and assessing its magnitude and rate in north and central Virginia and western Maryland. The primary question was ***how much land has been converted from forest/agriculture to exurban development in north and central Virginia and western Maryland, and at what rate this conversion is occurring?*** I combined spectral mixture analysis, decision-tree classification, and morphological spatial pattern analysis to identify exurban areas. I used the consistent, long time series medium-resolution Landsat imagery that is broadly, and now, freely available. I described mixed pixels containing exurban development as a combination of land conversion and then used morphological spatial pattern analysis to further separate exurban development from other forest disturbing events. I also quantified the magnitude and rate of exurban development to determine whether this region, that has experienced high population growth since 2000 (U.S. Census Bureau 2010), has also been subject to the same rate of exurban development as other regions in the nation. Quantifying the extent of exurban development in eastern United States informed us about the pressure that eastern deciduous forests are facing.

Chapter III assesses two different approaches to project exurban development: a pattern-based model and a spatially-explicit econometric model. The question to address was ***what modeling approach effectively captures exurban growth?*** Pattern-based models are a common approach to model land-use change in urban environments. However, they do not account for individuals' decisions on the land conversion process and it is unclear whether these models would be useful to predict exurban spatial patterns. In contrast, spatially-explicit econometric models focus on land transactions based on individuals' decisions and profit maximization. However, econometric models are data hungry and do not easily incorporate accessible raster data because they often rely on parcel information. In the context of exurban development, individuals' living preferences play a major role in decisions regarding where to live (Fuguitt and Brown 1990). Therefore, the ability to effectively project exurban development requires an understanding of the role of both historical patterns and individuals' decisions.

Chapter IV focuses directly on the effects of exurban development on forest birds. The primary question was ***do forest birds respond, and if so in a nonlinear fashion, to changes in breeding habitat due to exurban growth?*** Forest birds are particularly susceptible to human settlement even at low housing densities typical of exurban areas and little is known about forest birds' response to changes in breeding habitat as exurban growth progresses. I evaluated breeding habitat composition (amount) and configuration (arrangement) for forest specialists, forest generalists, and forest edge species around North America Breeding Bird Survey stops between 1986 and 2009. In addition, I assessed whether selected bird species showed thresholds in both occurrence frequency and relative abundance and whether the response differed according to the spatial extent considered. Understanding how forest birds respond to breeding habitat alteration in exurban areas may guide planners and managers in mitigating effects of exurban development.

Chapter V summarizes the results, discusses general implications, and suggests future research directions.

Table 1. Summary of effects of exurban development found in previous studies

Study	Study area	Response variable(s)	Explanatory variable(s)	Effects
Friesen et al. 1995	Waterloo, southwestern Ontario	Neotropical migrant birds' diversity and abundance	Forest size and the number of houses surrounding a forest	- Neotropical migrants decreased in diversity and abundance as the level of adjacent development increased, regardless of forest size.
Nilon et al. 1995	Camden, Miller, and Morgan Counties, Missouri	Forest birds community composition and abundance	Wildland, dispersed and cluster development	- Forest interior migrant species were most abundant in wildland sites and least abundant in cluster development sites. - Cluster development sites were dominated by species generally found in urban areas. - Nest predators and brood parasites were more abundant in cluster sites than wildland sites.
Engle et al. 1999	Rural landscapes surrounding eastern edge of the Great Plains	Birds occurrence	Area with low-density urban sprawl and area with greater level of urban sprawl	- Birds associated with forests and forest edge decrease regardless sprawl level. - Dickcissel, a grassland bird, increases in the area of low sprawl. - Species associated with intense development (e.g., house sparrow) increase in the area with a greater level of urban sprawl.
Garrison and Wakeman 2000	Waukesha County, Wisconsin	Water quality and diatom communities	Exurban development around lakeshores	- Once-seasonal homes along lakeshores were converted to year-long use, the amount of impervious surface increased and consequently run-off and sediment load to the lakes also increased. - Increased levels of phosphorous, iron, and aluminum were tied to a shift from benthic to mainly planktonic diatoms and an increase in diatom taxa indicative of eutrophic conditions.

Kluza et al. 2000	Hampshire and Franklin Counties, Massachusetts	Forest interior, avian nest predators, and brood parasites abundance	Forests with different housing densities	- Abundances of ground/shrub nesting birds were greater in forest of low housing density. - Blue jays were more abundant in forest of moderate housing density. - As the amount of forest/rural development edge increased within a forested landscape, abundances of avian nest predators and brown-headed cowbirds increased.
Odell and Knight 2001	Pitkin County, Colorado	Songbirds and medium-sized mammals	Sites with different housing densities and along a distance gradient, and undeveloped sites	- For both groups, densities of individual species were different between the 30- and 180-m sites. - Six bird species were classified as human-adapted, and six were classified as human-sensitive for the house-distance effect. - Most avian densities did not differ significantly between high- and low-density developments, but were different from undeveloped sites. - Dogs and house cats were detected more frequently closer to homes than farther away, and in high-density developments. Red foxes and coyotes were detected more frequently farther away from houses and in undeveloped sites.
Hansen et al. 2002	Upper Gallatin, Madison, and Henry's Fork watersheds in the Greater Yellowstone Ecosystem	Bird species richness and abundance	Biophysical factors	- Distribution of rural homes overlaps significantly with hotspots for birds. - Bird species that either prey upon other birds or are brood parasites were more abundant near rural residential development. - Avian nest predators and brood parasites were significantly associated with density of homes within 6 km of bird hot spots.

Bosch et al. 2003	Back Creek watershed, Virginia	Watershed hydrology, land values, and local government costs and revenues.	Residential development forms	- Low density development has the greatest hydrological impact due to highest per capita impervious area. - Low-density development has the highest estimated land value and property tax receipts and largest increase in estimated net revenues. - Concentrated high-density development has higher increases in net revenues than evenly distributed high-density development because of lower water, and sewer costs.
Miller et al. 2003	Front Range of Colorado	Birds community composition	Lowland riparian sites with different levels of development on adjacent lands	- Migrant and low-nesting species were associated with lower-than-average levels of development. - Resident and cavity-nesting species tended to increase with urbanization. - Species that nested or foraged low for insects or seeds were the most sensitive to human trail use. - Bird communities and local habitats in riparian areas were both affected by development in the surrounding landscape.
Lepczyk et al. 2004	Southeastern Michigan	Landowner activities	Rural and urban landowners	- Landowners carried out at least one activity on their land and the average landowner carried out 4 activities. - Rural landowners have more bird houses and apply pesticides or herbicides in greater frequency. - Urban landowners had a greater density of bird feeders and houses, but planted or maintained vegetation in the lowest frequency.

Fraterrigo and Wiens 2005	Rocky Mountains of north-central Colorado	Birds species richness, occurrence, and abundance	Gradient of exurban development	- Abundance increased with building density. - The community was strongly associated with road and building density. - Incidence of some generalist species increased with building density, whereas the incidence of specialists decreased.
Phillips et al. 2005	Rural southern Ontario	Wood Thrush nesting success, rates of brood parasitism, and seasonal productivity	Woodlots with embedded or adjacent houses and undeveloped woodlots	- Individuals breeding in woodlots with embedded houses experienced higher rates of parasitism than individuals breeding in woodlots with adjacent houses, or undeveloped woodlots. - Individuals breeding in woodlots with embedded or adjacent houses experienced increased rates of nest predation compared to individuals breeding in undeveloped woodlots. - The increased nest predation resulted in significant reductions in seasonal productivity in developed woodlots.
Bock et al. 2008	Sonoita Valley, southeastern Arizona	Bird species richness, community composition, and abundance	Grasslands and savannas grazed by livestock, embedded in exurban developments	- Richness and abundance were higher in exurban neighborhoods than in undeveloped areas, independent of livestock grazing. - Richness on the exurban areas was negatively correlated with the number of homes nearby. - Positive influence of exurban development on abundance was greatest at the lowest housing densities.
Lepczyk et al. 2008	Midwestern US	Bird species richness and abundance	Anthropogenic land cover and housing units, as indices of human influence	- Native avian richness was highest where anthropogenic land cover was lowest and housing units were intermediate. - 40% were negatively associated with human influence measures, 6% were positively associated, and 7% showed an intermediate relationship.

Merenlender et al. 2009	Sonoma County, California	Bird community composition	Exurban development, suburban, and undeveloped natural areas.	- The proportion of tree-and-shrub feeders was similar between exurban and natural areas, whereas proportions of temperate migrants showed significant reductions at both suburban and exurban sites.
Gavier-Pizarro et al. 2010	Vermont, Connecticut, New Hampshire, Rhode Island, Maine, and Massachusetts	Invasive exotic plants distribution	Housing patterns	- Invasive exotic plant richness was equally or more strongly related to housing variables than to other human and environmental variables. - Richness was positively related to area of wildland–urban interface, low-density residential areas, change in number of housing units between 1940 and 2000; it was negatively related to forest area and connectivity
Wade and Theobald 2010	Conterminous United States	Structural context of protected conservation areas	Residential development	- Residential housing development has occurred preferentially near some cores. - If encroachment near cores continues at projected rates, the amount of buffer zone will have been reduced by a total of 12% by 2030.
Suarez-Rubio et al. 2011	Warren County, Virginia	Bird community composition and abundance	Forests and exurban development sites	- Species composition differed significantly between forest and exurban areas. - Relative abundance for forest specialist species changed significantly in exurban development versus forest. - Three species (e.g., Northern Cardinal) were indicators of exurban development and three species were indicators of forest (e.g., Wood Thrush).

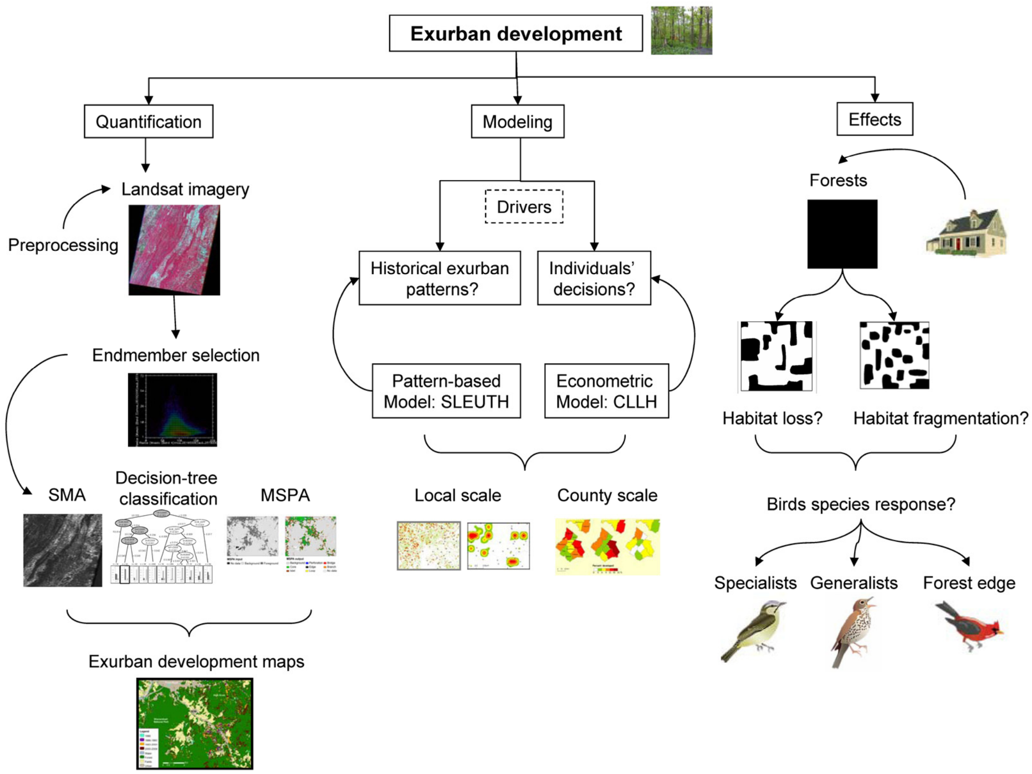

Figure 1. Dissertation flow diagram.

CHAPTER II

EXURBAN DEVELOPMENT FROM 1986 TO 2009 SURROUNDING THE DISTRICT OF COLUMBIA, USA

Abstract

People's preference for living in rural areas is converting rural landscapes into low-density residential development (i.e., exurban development). To assess the environmental impacts of exurban development (e.g., habitat fragmentation, threats to wildlife, and increased demand for natural resources) accurate maps of its spatial extent and change over time are needed. Mapping technologies that are based on spectral data alone have generally failed to separate exurban development from the surrounding landscape and from other mixed pixels with similar spectra. Although deciduous forests in the eastern United States are thought to have experienced a significant increase in exurbanized area, a rigorous assessment of exurban trends has yet to be undertaken. The purpose of this study was to develop a novel analytic approach to map exurban development and to assess its magnitude and rate in north and central Virginia and western Maryland. We applied spectral mixture analysis to Landsat TM images from 1986 to 2009 at 4 time steps to estimate the fractional cover of vegetation, shade, substrate, and non-photosynthetic vegetation endmembers within each image. Using training data based on aerial photos, we classified the resulting endmember fraction images using a decision tree. Finally, terminal nodes from the decision tree that did not differentiate between exurban and urban areas were analyzed using morphological spatial pattern analysis to assess the shape and form of landscape elements. Scattered, isolated

pixels were considered representative of exurban development. Overall classification accuracies ranged from 93 to 98%, an improvement of up to 34% over the decision tree alone. Our mapping approach effectively identified 7.3% of north and central Virginia and western Maryland as exurban development. Exurban development had a substantial expansion in the region, increasing on average 6.1% per year between 1986 and 2009. The information about land-cover changes beyond urban fringe provided by this classification procedure will inform policymakers, planners, and land managers in drafting policies to direct future growth, and to manage and mitigate potential adverse consequences.

Introduction

Rural landscapes in the United States have changed dramatically in recent decades due to the rapid development of private rural lands into low-density residential development (i.e., exurban development). Based on US Census data, it has been estimated that exurban areas grew more than twice as fast as metropolitan areas in the 1990s (Berube et al. 2006) and cover 25% of the contiguous US (Brown et al. 2005). The preference to live in rural areas is threatening wildlife and degrading ecosystem services (Liu et al. 2003, Hansen et al. 2005, Huston 2005). Evaluation of exurban development growth has been done for the United States (Brown et al. 2005, Theobald 2005), in the Midwest (Radeloff et al. 2005a, Gonzalez-Abraham et al. 2007b), and in the Mountain West (e.g., Theobald et al. 1996, Gude et al. 2006). Although the eastern deciduous forest region is thought to have had a significant increase in exurbanized area from 1950-2000 (Brown et al. 2005, Theobald 2005), a rigorous assessment of exurban trends has yet to be undertaken for this region of rapid population growth.

Exurban development occurs in relatively less altered landscapes, often adjacent to or nearby protected lands, and land-use activities tend to be less intensive than in urban areas (Theobald 2005). All these characteristics make exurban development difficult to detect and map with conventional land-use mapping technologies (Ward et al. 2000, McCauley and Goetz 2004). For example, National Land Cover Data (NLCD) is thought to underestimate the total amount of developed land use for the Mid-Atlantic region by around 5% and low-density development is not recorded at all (Irwin et al. 2007). One reason is that NLCD is based on medium-resolution sensors (i.e., Landsat 30-m data) that detect exurban areas as a mixture of different surfaces (i.e., mixed pixels). When traditional classification techniques are used, mixed pixels are misclassified (Small 2003, Xian and Crane 2005). Exurban areas, where the average cleared land area is a quarter of a pixel (Maryland Department of Planning 2008), are usually classified as forest. To avoid the mixed pixels problem when mapping exurban development, high spatial resolution satellite sensors (e.g., IKONOS 4-m data) offer an alternative. High resolution sensors can provide reliable land-cover classification and change detection results at a local level. However, high spatial resolution imagery generally lack long-term time series and the huge amount of data required to analyze large areas present challenges of processing loads, time, and cost (Ward et al. 2000, Lu et al. 2004). Therefore, medium-resolution imagery (e.g., Landsat 30-m data) remains the standard for regional to continental assessments of land-use change (including exurbanization) despite the analytical shortcomings of using these products.

Several methods used to quantify exurban development have used human population density (Theobald 2001, 2005) and housing density information (Radeloff et al. 2005a, b), both based on data from US Census Bureau. While these approaches have been important in estimating the extent of exurban development nationally (Theobald 2001, Brown et al. 2005, Theobald 2005), and regionally (e.g., Theobald et al. 1996, Radeloff et al. 2005b), there are some limitations. Due to privacy issues, data from the US Census Bureau are aggregated in census block groups. Block groups change with each census, vary in shape and size, and become larger and larger beyond the urban fringe (Clark et al. 2009). The variable-sized block groups cause possible inaccuracies, but there is no easy and practical solution to these difficulties (Longley et al. 2001). In addition, population data from the US Census Bureau are tied to the primary place of residence; therefore, measures based on population underestimate exurban development because housing units in the form of vacation and second homes are not represented (Theobald 2005). Housing density is a more complete and consistent measure of exurban development than population density (Theobald 2005), but issues about disaggregating block groups still persist (Radeloff et al. 2005b).

Another approach to quantify exurban development uses tax property data (McCauley and Goetz 2004) and maps of impervious surface (Xian and Crane 2005). Although tax property data provide digitized property-specific information, not all counties have this information available and each county has a different system to store these data. Impervious surface is quantified as a continuous field as opposed to discrete categories, is a well accepted indicator of urbanization (Goetz et al. 2003, Dougherty et al., 2004, Jantz et al. 2005), and has been used to estimate development in urban and suburban areas (Xian and Crane 2005). Whereas impervious surface indicates human alteration and the amount of impervious surface increases with density of development, there is a significant overlap in the amount of impervious surface among urban, suburban, and exurban areas, which makes threshold selection problematic when mapping exurban development. In addition, the estimate of impervious surface is greatly influenced by the type of imagery used, exurban development does not always include a large portion of impervious surface (Yang et al. 2003, Irwin et al. 2007), and mixed pixels spectra in exurban areas are likely to be very different from mixed pixels in suburban or urban areas (i.e., formed by a different mixture of spectra).

To enhance the understanding of exurban development in the eastern US, we developed a novel analytic approach (using spectral mixture analysis and morphological spatial pattern analysis) to map exurban development and assess its magnitude and rate in north and central Virginia and western Maryland. We used the consistent, long time series of medium-resolution Landsat imagery that is broadly, and now, freely available. This study is unique in that it describes mixed pixels containing exurban development as a combination of land covers and then uses morphological spatial pattern analysis to further separate exurban development from other forest disturbing events. Quantifying the pervasiveness of exurban development in eastern United States provides an important perspective on the land-use pressure facing eastern deciduous forests.

Methods

Study site

This study was conducted in 9 counties in north and central Virginia, US and 2 in western Maryland, US: Virginia – Clarke, Culpeper, Fauquier, Frederick, Madison, Page, Rappahannock, Shenandoah, and Warren Counties; Maryland - Washington and most of

Frederick (Figure 2). Virginia has the 12th largest population in the nation with an annual growth rate of 11% since 2000, and this growth is driven mostly by northern Virginia (Weldon Cooper Center 2010). For example, Loudoun County alone has experienced a population increase of 78% since 2000, and accounts for one-sixth of the total population increase for the entire state. Counties included in the study area had growth rates ranging from 40% (Culpeper County) to 4% (Page County) between 2000 and 2009 (U.S. Census Bureau 2010). In Maryland, Frederick County has also increased its population, with a growth rate of 17% between 2000 and 2009, whereas Washington County had an 11% increase (U.S. Census Bureau 2010). One reason for the growth is the easy access and connectivity to the metropolitan Washington, DC area, which provides employment opportunities even within the current economic climate (Weldon Cooper Center 2010).

Landsat data and preprocessing

Eight Landsat Thematic Mapper images (WRS path16 row 32 and path16 row 33) were acquired from 1986 to 2009 at 4 time steps (1986, 1993, 2000, and 2009; Table 1). Image dates were selected from relatively cloud-free scenes (<10%) acquired during late spring or early summer. Georeferencing was performed at the USGS prior to downloading the data (L1T level of systematic geometric accuracy) and no further refinement was deemed necessary. Two preprocessing steps were performed on Landsat TM data sets: atmospheric correction and topographic correction. The primary goal of atmospheric correction was to adjust the multitemporal dataset to a common radiometric scale (Song et al. 2001), therefore we employed a dark object subtraction to remove scene-by-scene variation in atmospheric scattering (Chavez 1989, Song et al. 2001). This technique assumes the existence of dark objects (i.e., zero or small surface reflectance) throughout a scene and a horizontally homogeneous atmosphere. The minimum DN value in the histogram from the entire scene is attributed to the effect of the atmosphere and is subtracted from all the pixels. This relatively simple correction method has been shown to improve classification and change detection accuracies at least as well as more complicated algorithms (Song et al. 2001). Topographic correction was performed to compensate for direction and illumination effects due to terrain and sun angle (Campbell 2002). Because topographic shading is not only due to slope but also to shadowing of one tree crown over another, we used sun-canopy-sensor correction (SCS; Gu and Gillespie 1998). The SCS method normalizes the sunlit area as a function of the geometry among the sun, sensor, and terrain slope. We did not apply exoatmospheric correction because all image data were from the same sensor (L5 TM) and the dark object subtraction put all the multitemporal dataset in the same radiometric scale (Song et al. 2001, Chander et al. 2009). We further tested whether the preprocessing steps effectively removed the atmospheric/illumination effects by selecting low and high albedo pseudoinvariant targets (PIV; Schott et al. 1988) in the corrected data. We quantified any residual temporal variability by regressing all PIVs ($n = 128$) for each band from each pair of years (e.g., 1986 vs. 1993).

Spectral mixture analysis

In areas of exurban development, individual pixels do not resemble the reflectance of a single land cover class (e.g., forest, impervious surface) but rather a mixture of reflectance of two or more classes (Small 2004, Xian and Crane 2005). The assignment of a mixed pixel to a single homogeneous class produces inaccuracies in the resulting thematic map (Small 2001). Spectral mixture analysis (SMA) quantifies spectral mixtures (Smith et al. 1990) by estimating the fractional cover of each 'endmember' material necessary to form (through linear addition) the pixel spectra (Adams et al. 1986). Endmembers are spectra that are representative of physical components of the surface and are not mixtures of other components. Because SMA describes mixed pixels as a combination of spectral endmembers, it has been successfully applied to detect selective logging and deforestation in tropical forests (Souza and Barreto 2000, Monteiro et al. 2003, Asner et al. 2004), to quantify regrowth rates and forest health in temperate forests (Sabol et al. 2002), to quantify vegetation change in semiarid environments (Elmore et al. 2000), and to estimate vegetation abundance in urban areas (Small 2001), and to map urban land cover (Rashed et al. 2003, Powell et al. 2007, Franke et al. 2009). To our knowledge this is the first application of this technique to recognize and discriminate exurban development.

A key step in SMA is the selection of appropriate endmembers. Endmembers were identified in and extracted from the 2009 image (i.e., image endmembers) using scatter plots, in which each point represented the position of the pixel in the space defined by the spectral response of different band pairs (Figure 3). The vertices of a simplex that enclosed all the points were assumed to represent the purest pixels in the images and were selected as our endmembers (Asner et al. 2003). The endmembers selected were vegetation (VEG), non-photosynthetic vegetation (NPV), substrate (SUB), and shade (SHD; Figure 4). We selected our endmembers from the image as opposed to reference endmembers (i.e., endmembers derived from reflectance spectra measured in the laboratory) because reference endmembers can suffer temporal variability in reflectance properties of cover types and can be troublesome in change detection analyses (Asner et al. 2003). The same endmember set (Figure 4) was used across the entire set of images to facilitate the comparison of endmember fractions between dates. In this way, areas that have not changed will have the same endmember fractions and areas of change are a direct function of changes in the relative coverage of materials represented by endmembers. It is important to note that SMA is a linear transformation of the data just like reflectance retrival, therefore as long as the data are spectrally aligned (Table 2) the same image endmembers can be used across multitemporal images (Elmore et al. 2000).

Selection of training data

We generated a training dataset based on aerial photos to supervise a classification of areas of no-change, change to exurban development (0.4-16.3ha/unit; Brown et al. 2005, Theobald 2005), and change to suburban or urban areas (<0.4ha/unit; Brown et al. 2005). We used true color photos from 1984, 2003, and 2008 (Table 2). These dates were selected based on the correspondence of photo availability and years of interest. Photos from 1984 and 2003 were georeferenced to the third year through a simple polynomial using 11 ground control points (RMSE = 2.1, 1.9, respectively). Because exurban areas in the eastern US occur in areas surrounded by forest, we were specifically interested in detecting the degradation of forested habitats due to exurban development. We visually examined aerial photos to identify areas that did not change or had undergone small or large change. No changes represented areas that were forest in the previous time step and remain forest in the next time step (hereafter forest). Spatially small changes represented areas that were forest in the previous time step but were exurban areas in the next time step (hereafter exurban development). Large changes represented areas that were forest or agricultural fields in the previous time step and change to suburban or urban areas in the next time step (hereafter urban). Exurban areas were distinguished in the aerial photos as isolated, scattered housing units outside cities and towns surrounded by forests (Daniels 1999) with housing densities between 0.4-16.3 ha/unit (Brown et al. 2005, Theobald 2005). The training data (i.e., polygons delineated in the aerial photos) were then overlaid on Landsat images to evaluate spectral differences between the classes. The spectral separability of the classes was evaluated using Jeffries Matusita (JM) distance (Richards 1993). JM distance ranges from zero to two, with values closer or equal to two indicating classes that are spectrally different. We plotted the training data on ternary diagrams to identify spectral characteristics of exurban development based on endmembers fractions. Twenty-five percent of the training data were reserved as an independent sample for validation purposes and subsequent accuracy assessment.

Decision-tree classification

We built a decision tree for each pair of image dates to rigorously classify change to exurban development using endmember fractions derived from SMA for the entire study area. An unbiased recursive partitioning algorithm using a conditional inference framework (Hothorn et al. 2006) was used to build the decision-tree classification. Conditional inference partitioning was used because it takes into account the distribution of dependent data in each split of the data. Thus, the method does not require bootstrapping from pooled data, results in smaller unbiased trees, and provides statistical significance of each split ($P < 0.05$). Training data (forest, change to exurban, and change to urban) were used as the dependent variable. Explanatory variables included endmember fractions for the latest time-period considered (e.g., 2009 VEG, NPV, SUB, and SHD fractions when the 2000-2009 time period was evaluated), difference in each of the endmembers (e.g., 2009-2000), change of all endmembers, and change statistics of all endmembers for 4 and 8 surrounding pixels (min, max, range, median, mean, sum, standard deviation). We included both 4 and 8 neighboring pixels to account for different definitions of exurban development (see below). Change of all endmembers was calculated using the equation (Parmenter et al. 2003):

$$\left[\sum_{i=1}^{4}[E_i(t_2) - E_i(t_1)]^2\right]^{1/2} \tag{1}$$

where, E_i are the endmember fractions, and t_1 and t_2 are the prior and posterior dates. This equation created gray scale images showing the Euclidean distance in endmember fractions space between the two dates compared. From this image we calculated change statistics of all endmembers for the 4 and 8 surrounding pixels. The decision trees were then applied to the entire study area.

Morphological spatial pattern analysis

Terminal nodes from the decision tree that were a mixture of exurban development and urban were disentangled using morphological spatial pattern analysis (MSPA; Soille 2003, Vogt et al. 2007a, b). MSPA is a technique for analyzing the shape and form of map elements using a binary or thresholded map (foreground and background). The method applies structural elements to define pixel connectivity and logical operators such as union, intersection, complementation, and translation to allocate each pixel to one of a mutually exclusive set of structural classes (Figure 5). For interpretability purposes, the structural classes can be named in any number of ways depending on the input data (Vogt et al. 2009). In the context of exurban development, we focused on 'islet' which indicated unclustered, scattered, and isolated pixels. In this way, we were able to discriminate exurban development from the urban class.

Given that there is no consensus on the definition of exurban development (see for example, Marzluff et al. 2001, Brown et al. 2005, Hansen et al. 2005, Theobald 2005), we produced two maps of exurban development to represent lower and upper bound estimates of exurban housing density (Small et al. 2005, 2011). The maps used different inputs and connectivity rules for creating the analytical structural element for MSPA. To create an upper bound estimate, we generated an input map with foreground corresponding to urban areas and mixed classes (exurban and urban) as classified by the decision tree. We used an 8-neighborhood rule as our structural element (i.e., both cardinal directions and diagonal neighbors are considered) to represent (Theobald 2005) definition of exurban development (1 unit/0.68ha ~ 8 pixels = 0.72 ha). The lower bound estimate was produced by also including the exurban development class of the decision tree into the input map for MSPA. In this case, our input map was composed of urban, mixed, and exurban classes from the decision tree. We used a 4-neighborhood rule (i.e., only cardinal directions are considered), which resulted in more isolated pixels to approximate housing density consistent with the definition of exurban development provided by Brown et al. (2005; 1 unit/0.4ha ~ 4 pixels = 0.36ha).

Final maps of exurban development

We refined the upper and lower bound estimates of exurban development by removing exurban development that was inside protected areas (GAP level 1 to 3; Conservation Biology Institute 2010). This resulted in reclassifying between 0.3% and 1.8% of exurban development pixels to forest. We also applied a non-reversal rule

(Powell et al. 2008) to make sure that once a pixel became exurban or urban, it could not revert to forest through the remainder of the time series. This resulted in increasing the number of exurban development pixels by up to 1.4%. Lastly, we estimated the magnitude and rate of exurban development in our time series. We created a 1986 map as an exurban development baseline. For this map, we focused on existent exurban and urban areas detected in the 1986 image instead of change. We followed the same procedure described above but the independent variables included in the decision tree were 1986 endmembers fractions and endember fractions for the 4 and 8 surrounding pixels.

Accuracy assessment

Accuracy assessment was performed to evaluate the quality of change detection results. We randomly selected 25% of the training data collected from aerial photographs for the assessments. Using an error matrix, we calculated overall accuracy, producer's accuracy (1 – omission error), user's accuracy (1 – commission error), and the kappa statistic (Congalton 1991).

Results

In applying spectral mixture analysis, four endmembers (VEG, NPV, SUB, and SHD) were selected to model the heterogeneous land cover of north and central Virginia and western Maryland. The selection of endmembers was appropriate as expressed by RMSE and the speckle of residual images. RMSE values were close to the measurement precision of the data (±1-2 DN; Elmore et al., 2000) and ranged from 1.07 to 1.77 (mean ± s.d.: 1986 - 1.77 ± 3.76, 1993 - 1.28 ± 1.14, 2000 - 1.18 ± 1.10, 2009 - 1.07 ± 1.28).

Although most of the images were cloud free, the 10% cloud cover of the 1986 image induced a higher RMSE than the other images.

The spectral separability of the training data (Table 3) illustrated that the three classes (forest, exurban development, and urban) are spectrally different in all pair of years. Forest and urban were highly distinct classes in all years (JM = 1.99). Urban and exurban development were generally more similar (mean JM = 1.56) than forest and exurban development (mean JM = 1.71). Separability of the same class (e.g., exurban was similar among pair of years as well as the separability of the no change class (i.e., forest, JM= 0.08).

Ternary diagrams (Figure 6) showed the spectral characteristics of forest, exurban development, and urban based on endmember fractions. Forest was characterized by 15-30% VEG, 25-60% SUB, and 70-85% NPV. Both 1986-1993 and 2000-2009 periods had similar spectral characteristics. Exurban development in 1986-1993 was characterized by 20-30% VEG, 25-60% SUB, and 70-80% NPV. In 2000-2009, the spectral signature of exurban development moved towards more SUB (20-75%) and less VEG (10-20%). Urban class in 1986-1993 had 10-20% VEG, 30-90% SUB, and 75-90% NPV. In 2000-2009, there was a large increase in SUB (30-95%) and NPV (75-95%), and a decrease in VEG (2-25%).

Decision trees were generated for each time period (see Figure 7 for decision tree example) and terminal node probabilities were interpreted as prediction accuracies (*sensu* Vayssiéres et al. 2000). Predictive accuracy is the ability to correctly classify new cases fitting the set of conditions described by the terminal node. For example, it is 90% accurate to state that any given pixel within the “90% exurban probability class” is exurban development (terminal node following the shaded area in (Figure 7). When decision trees for all the time periods were compared, vegetation endmember fraction of the latest year was consistently the strongest explanatory variable (i.e., first split variable). Substrate endmember fraction of the latest year and the difference in substrate endmember fractions also were common variables in all time periods. Decision trees varied in their use of shade fraction (important to 2000-2009 decision tree only) and change statistics for 8 surrounding pixels. The branching pattern to classify exurban development differed among the different time periods although some variables were common in all trees (i.e., vegetation fraction of the latest year and substrate fraction). For example in 2000-2009 (Figure 7), 90% prediction probability for exurban development was achieved for pixels with 2009 vegetation fraction of less than 0.333, 2009 substrate fraction of more than 0.014 but less than 0.048, and 2009 shade fraction of less than 0.236. In addition to vegetation and substrate fractions, in 1993-2000 and 1986-1993 exurban development was described by the sum and variability of endmember fraction changes in the surrounding 8 pixels, respectively.

Overall classification accuracy for exurban development using only the decision trees varied by years and ranged from 59 to 92% (kappa 0.31 to 0.86; Table 4). User's accuracy ranged from 0.46 to 1.00 and producer's accuracy ranged from 0.52 to 0.91. Using MSPA (Figure 5) to improve upon these accuracies, overall classification accuracies for upper bound estimates ranged from 93 to 98% (kappa 0.87 to 0.96), an improvement of up to 34% over the decision tree alone. Of the area labeled as exurban development, more than 69% actually corresponded to exurban development on the aerial photos (user's accuracy ranged from 0.69 to 1.00). However, more than 52% of exurban development pixels were correctly mapped (producer's accuracy range from 0.52 to 0.79). For example, 21% of exurban development in 1993-2000 was omitted and erroneously classified as forest. For lower bound estimates, the overall accuracy ranged from 92 to 96% (kappa 0.86-0.93). More than 89% of the area labeled as exurban development was designated as such in the aerial photos (user's accuracy ranged from 0.89 to 1.00). However, more than 38% of exurban development pixels were correctly mapped (producer's accuracy ranged from 0.38 to 0.57).

The extent of exurban development comprised 246.0 km^2 (2.3%) in 1986 and 782.5 km^2 (7.3%) of the region in 2009 (Figure 8). Our estimates of the extent of exurban development in western Maryland ranged from 14.0 km^2 (0.1%) to 35.7 km^2 (0.3%) in 1986 and from 69.2 km^2 (0.6%) to 142.9 km^2 (1.3%) in 2009 (Figure 9A). Frederick and Washington counties had similar magnitude of exurban development for the lower bound estimates, but Frederick County had more exurban development than Washington County for the upper bound estimates especially in earlier years. North and central Virginia had a greater extent of exurban development than western Maryland in all time periods for both the lower and upper bound estimates. Lower bound estimates of exurban development increased from 81.6 km^2 (0.8%) in 1986 to 366.1 km^2 (3.4%) in 2009, whereas upper bound estimates increased from 210.3 km^2 (2.0%) in 1986 to 639.6 km^2 (6.0%) in 2009. Fauquier County was the county with the highest amount of exurban development with upper bound estimates of 53.75 km^2 (25.6%) in 1986 and 143.0 km^2 (68.0%) in 2009. Clarke County had the lowest amount of exurban development throughout the study period.

Annual rates of exurban development varied among time periods and regions (Figure 9B). The overall mean annual rate for western Maryland and north and central Virginia was 6.1% between 1986 and 2009, and was higher for western Maryland (7.8%) than for northern Virginia (5.8%). However, regional patterns seem to be shifting in recent years. In 2000-2009, the annual rate slightly decreased in western Maryland (6.9%) compared to the previous time period (9.9%), and for the first time, was lower than the rate in north and central Virginia (9.3%). At the county level, both Maryland counties decreased their annual rate between 2000 and 2009 (Figure 10). Although Frederick County, Maryland had a greater extent of exurban development than Washington County, the latter had higher annual rates in all periods. In north and central Virginia, Fauquier County had the lowest mean annual rate (5.0%). Rappahannock County had the highest mean annual rate over the entire study period (8.2%); however, Frederick County, Virginia had the highest annual rate for the 2000-2009 time period (15.1%).

Discussion

Mapping approach

By combining spectral mixture analysis, decision-tree classification, and morphological spatial pattern analysis, our approach effectively identified exurban development, overcoming many of the obstacles previously associated with mapping this increasingly common land-use class. Spectral mixture analysis effectively characterized the mixed space of exurban areas, lead to an accurate classification of exurban development, and facilitated the understanding of the physical properties of exurban development and change over time (Figure 6). In the study area, the spectral characteristics of exurban development shifted towards more substrate and less vegetation between 1986-1993 and 2000-2009 time periods possibly because more vegetation removal, bright roofing, and ageing asphalt. This pattern suggests that exurban development is moving towards a more urban spectral signature in the region (Figure 6).

A separate decision tree was produced for each pair of years. Decision trees selected by the conditional partitioning algorithm varied regarding the number of variables, type of variables included, and split values. One pattern that emerged for all time periods was that substrate fraction greater than at least 0.014 was an important classifier. Vegetation fraction of the latest year also was consistently used as a criterion to classify exurban development. Higher vegetation fractions were required to discriminate exurban development from urban in 1986-1993 and 1993-2000, and low vegetation fractions were needed to discriminate exurban development from other classes in 2000-2009. This pattern may indicate that prior to 2000; exurban areas had greater proportion of vegetation while in recent years the proportion of vegetation has decreased. Taken together with the shifting spectral signature toward a more urban spectrum, these results suggest exurban areas may be transforming from isolated scattered settlements with high vegetation cover to more contiguous and concentrated settlements with low vegetation cover (though not yet reaching the density to be considered urban). This trajectory would be consistent with trends observed by (Clark et al. 2009) in their analysis of urban decentralization and spatial characteristics of exurban development.

Morphological spatial pattern analysis improved the accuracy of the decision tree classification by identifying isolated, scattered pixels from the mixed classes (mixture of exurban development and urban) generated by the decision-tree classification. Another advantage of MSPA is its ability to generate lower and upper bound estimates (Small et al., 2005, 2011) of the magnitude of exurban development in the region. We achieved this by modifying the input data and structural elements within the morphological analysis to consider alternative definitions rather than having to rely upon a sole estimate of housing density for defining exurban development. Although our final maps were overall highly reliable, our choice of input data for the morphological analysis did not allow us to separate mixed classes of exurban development and forests. In addition, some forested areas of the study region were defoliated by gypsy moths (*Lymantria dispar*) and are now regenerating. Given that these areas may have more non-photosynthetic vegetation and exposed substrate and less vegetation cover than other forest pixels, we could have misclassified these areas as exurban development. Including a range of upper and lower bound estimates as part of the morphology analysis is useful in addressing some of this uncertainty.

Extent of exurban development

Our results indicate substantial expansion of exurban development between 1986 and 2009. Exurban development occupied 7.3% of the study region in 2009, as urban boundaries of towns and small cities expanded and entirely new communities were built (Figure 8). We also found high levels of exurban development along protected areas, which supports the perception that this type of development is encroaching and threatening US protected areas (Wade and Theobald 2010). This trend may be at least partially responsible for the greater extent of exurban development observed for north and central Virginia than western Maryland. North and central Virginia has 7% more protected areas than western Maryland. The greater extent may also simply be a function of the high population growth experienced by north and central Virginia and domestic in-migration (i.e., county-to-county migration) in the last decade (Berube et al. 2006). Urban counties such as Arlington and Alexandria in Virginia experienced population loss due to net migration to suburbs (Berube et al. 2006). In turn, suburbs also experienced losses due to people moving to exurban areas like Fauquier County, which had the highest amount of exurban development in the study region.

Rate of expansion of exurban development

Exurban development increased on average 6.1% per year between 1986 and 2009 in the study region. Similar growth rates have been found in other forested regions of the US Midwest (Radeloff et al. 2005a, Gonzalez-Abraham et al. 2007b). Although growth rates of exurban development in our study region are not as high as rates in counties on the periphery of the Greater Yellowstone Ecosystem (7.6 to 12.1% per year; Hansen et al. 2002, Gude et al. 2006), the rate of expansion of exurban development observed in our study should be a cause of concern for the eastern deciduous forests of the region. Habitat loss and fragmentation, introduction of exotic species, increases in predation and parasitism, declines in water quality, and alteration of biotic interactions are some recognized effects of human settlements (Hansen et al. 2005), even at the lower housing densities that define exurban development.

Western Maryland experienced higher rates than north and central Virginia between 1986 and 2000. These higher rates may be related to population growth and in-migration (Berube et al. 2006). However, even with the higher rates in those years, western Maryland had six times lower extent of exurban development than north and central Virginia. In 1986, 0.3% of western Maryland was exurban development whereas

2.0% of north and central Virginia was already in this land-use class suggesting that north and central Virginia experienced higher rates of exurban development prior to 1986. In recent years (2000-2009), the rate of expansion of exurban development in western Maryland decreased, and north and central Virginia has once again overtaken western Maryland in the rate of exurban growth. The decline of the exurban growth rate in western Maryland may be related to differences in rule of government and land-use policies such as Smart Growth law, an initiative that started with the 1992 planning Act (Maryland Department of Planning 2010). In contrast, the exurban growth rate in north and central Virginia increased by 3.8% between 2000 and 2009. Such increase was driven by Frederick County which had a population increase of 26.6% during that period (U.S. Census Bureau 2010). In response to increasing development pressures in rural areas, the County created a Rural Areas Subcommittee to evaluate and formulate recommendations to manage rural areas growth (Frederick County Board of Supervisors' Rural Areas Subcommittee 2009).

Conclusion

Using traditional land-use mapping technologies to detect and map exurban development is problematic. Our approach of using spectral mixture analysis, decision-tree classification, and morphological spatial pattern analysis proved to be a powerful tool that decomposed mixed pixels into endmember fractions with physical meanings, characterized exurban development, refined the classification based on the shape and form of landscape elements, and developed lower and upper bound estimates of this problematic land-use class. Multitemporal Landsat images allowed us to measure land-use change to exurban development over time. Our findings suggest that exurban development is expanding into rural landscapes of the Mid-Atlantic at high rates and that eastern deciduous forests of the region are confronting high development pressures.

Table 2. Dates of satellite imagery and aerial photography acquisition

Type of imagery	Year	Day Month	Resolution (m)
Landsat TM	1986	21 June	30
	1993	24 June	30
	2000	26 May	30
	2009	29 May	30
Aerial photography	1984	11 April	2
	2003	6 June	1
	2008	13 October	0.5

Table 3. Separability of training data. Values under forest (no change class), exurban development (small change class −from forest to exurban), and urban (large change class −from forest/field to urban) represent the sample size (i.e., number of polygons) and in parenthesis the total number of pixels per class per year. JM_1 indicates Jeffries Matusita distance between forest and exurban development, JM_2 between exurban development and urban, and JM_3 between urban and forest.

Pair of years	Forest	JM_1	Exurban development	JM_2	Urban	JM_3
1986 - 1993	13 (1384)	1.57	61 (224)	1.64	13 (967)	1.99
1993 - 2000	13 (1384)	1.69	30 (245)	1.42	11 (879)	1.99
2000 - 2009	13 (1384)	1.71	44 (252)	1.47	10 (1134)	1.98

Table 4. Overall accuracy, kappa, user's, and producer's accuracy for decision tree classification and for upper and lower bound estimates of final maps of exurban development

	1986-1993			1993-2000			2000-2009		
	Decision tree	Upper bound	Lower bound	Decision tree	Upper bound	Lower bound	Decision tree	Upper bound	Lower bound
Overall accuracy	0.59	0.93	0.92	0.82	0.98	0.95	0.92	0.94	0.96
Kappa	0.31	0.87	0.86	0.64	0.96	0.90	0.86	0.91	0.93
User's	0.63	1.00	1.00	1.00	0.98	1.00	0.46	0.69	0.89
Producer's	0.91	0.52	0.38	0.72	0.79	0.38	0.52	0.52	0.57

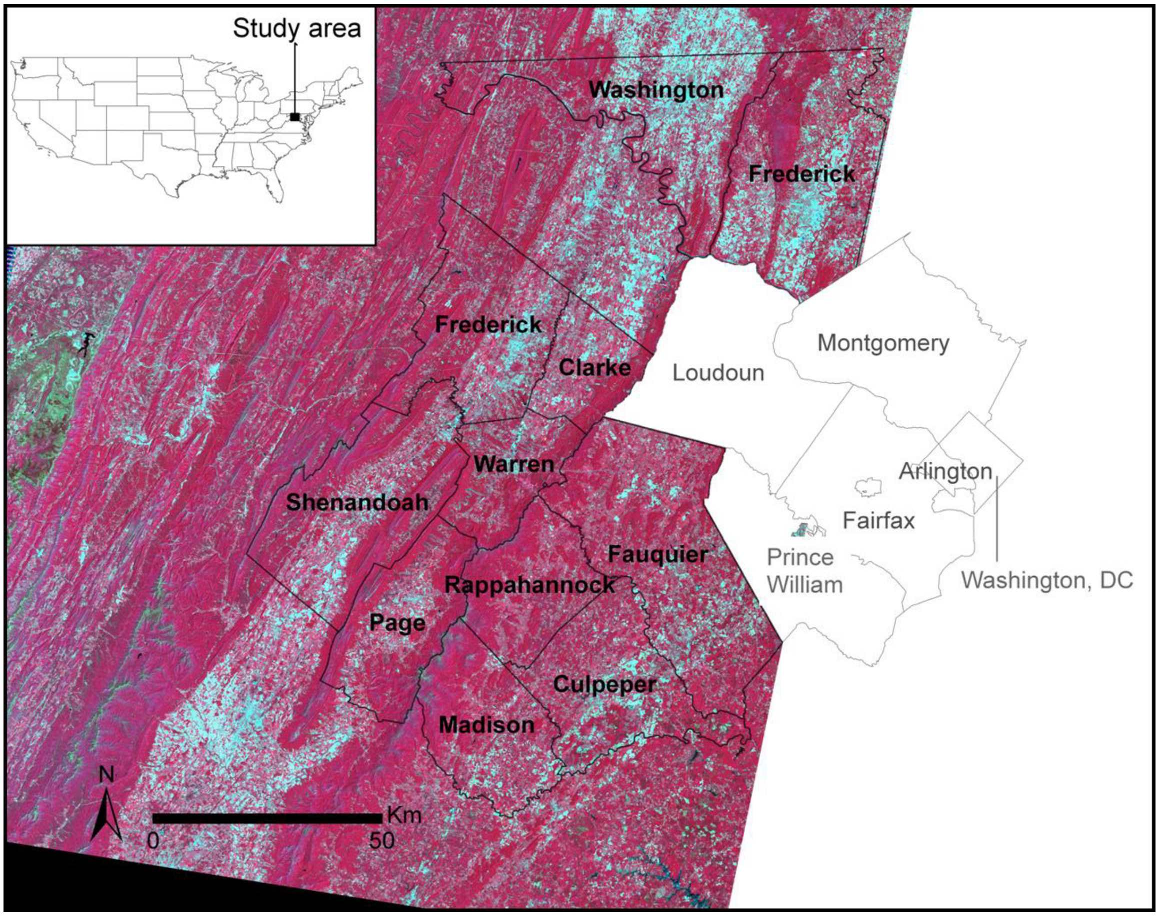

Figure 2. The delineated area over the Landsat TM image represents the study region which encompasses nine counties in north and central Virginia and two counties in western Maryland.

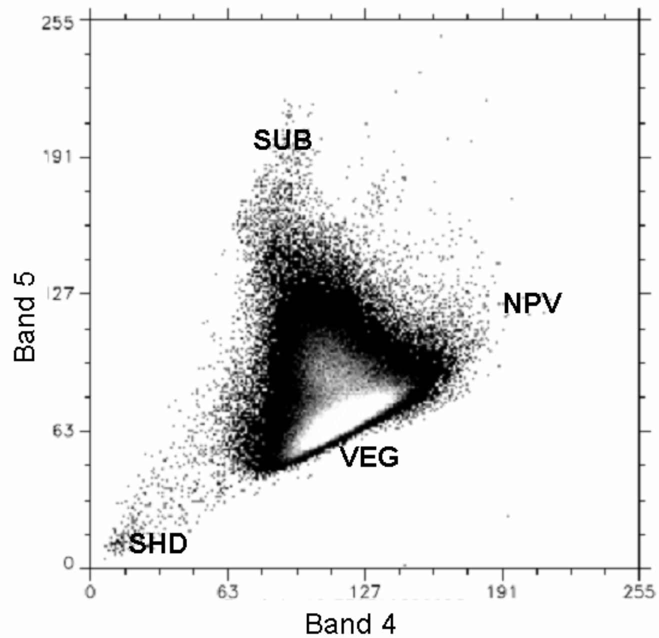

Figure 3. Density-shaded scatter plot show the mixing space of a spectrally diverse subscene. The mixing space is bounding by selected endmembers: substrate (SUB), vegetation (VEG), non-photosyntetic vegetation (NPV), and shade (SHD).

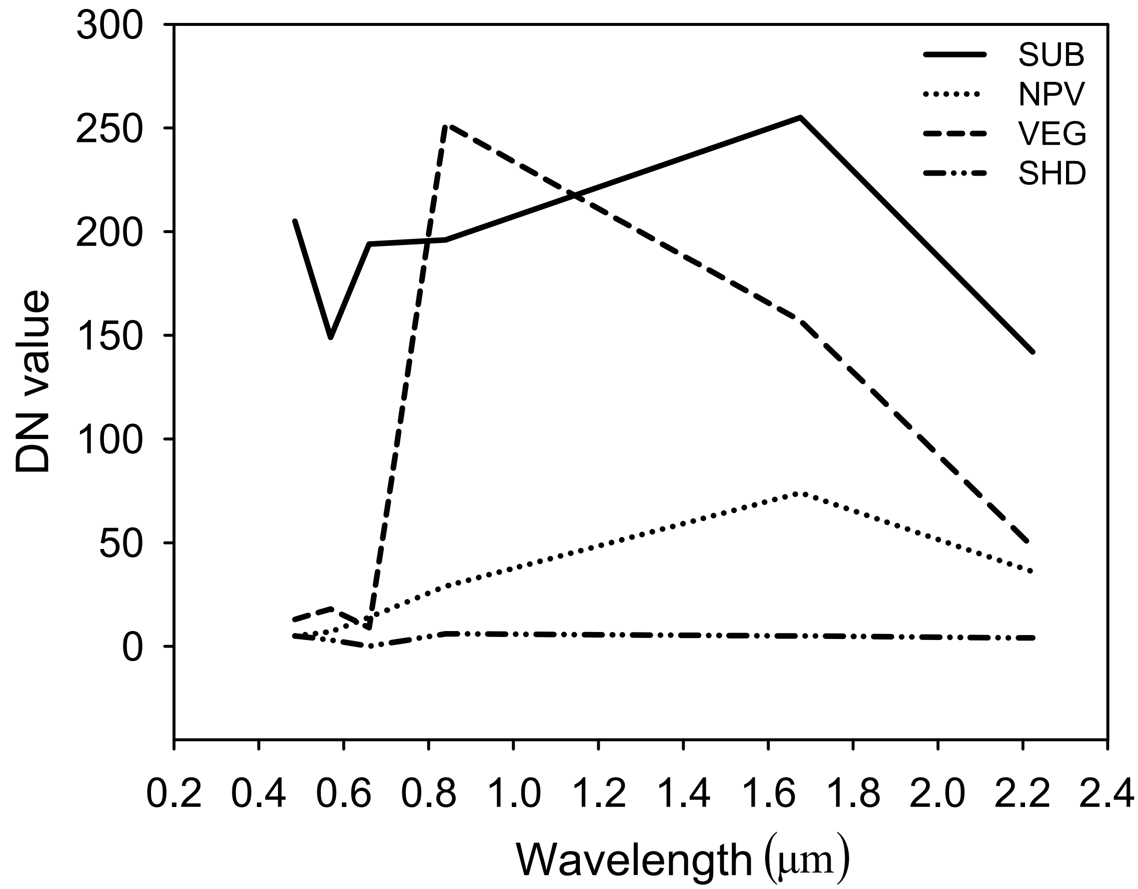

Figure 4. Image derived spectra of four selected endmembers used in the spectral mixture analysis.

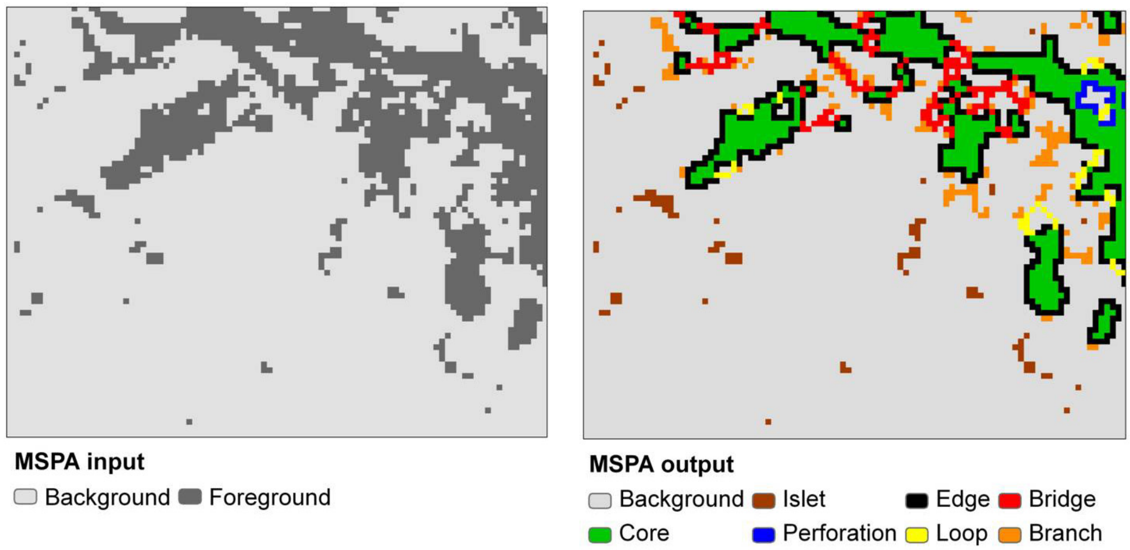

Figure 5. Representation of the morphological spatial pattern analysis (MSPA). Input consists of a binary raster map (background and foreground). Through logical operators such as union, intersection, complementation, and translation, the software package allocates each pixel to one of a mutually exclusive set of structural classes.

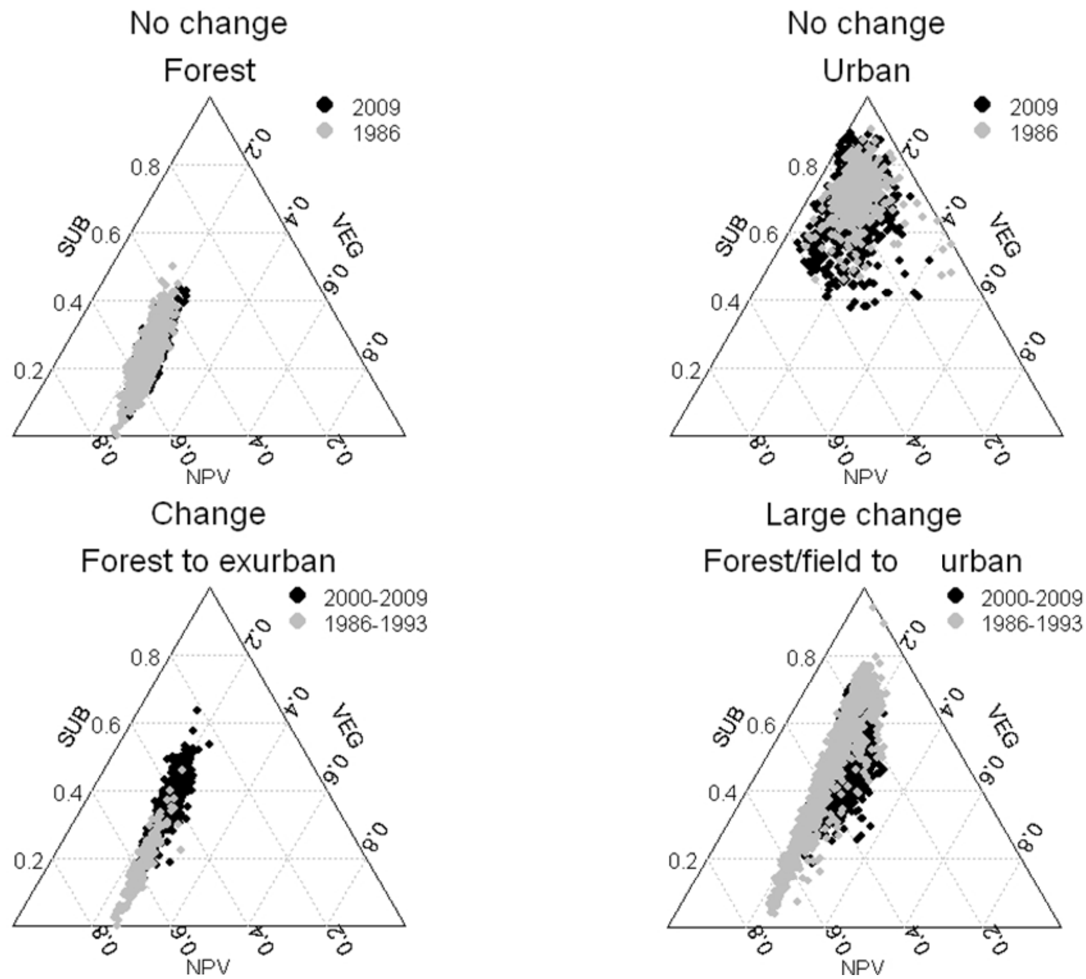

Figure 6. Ternary plots based on training data endmember fractions. Fractions were derived from spectral mixture analysis. The diagrams show the signature of pixels that have not changed (i.e., remain as forest or urban), had small changes (from forest to exurban development), and had large changes (from forest/fields to urban) between 1986-1993 (gray) and 2000-2009 (black). The shade endmember was omitted for representation purposes.

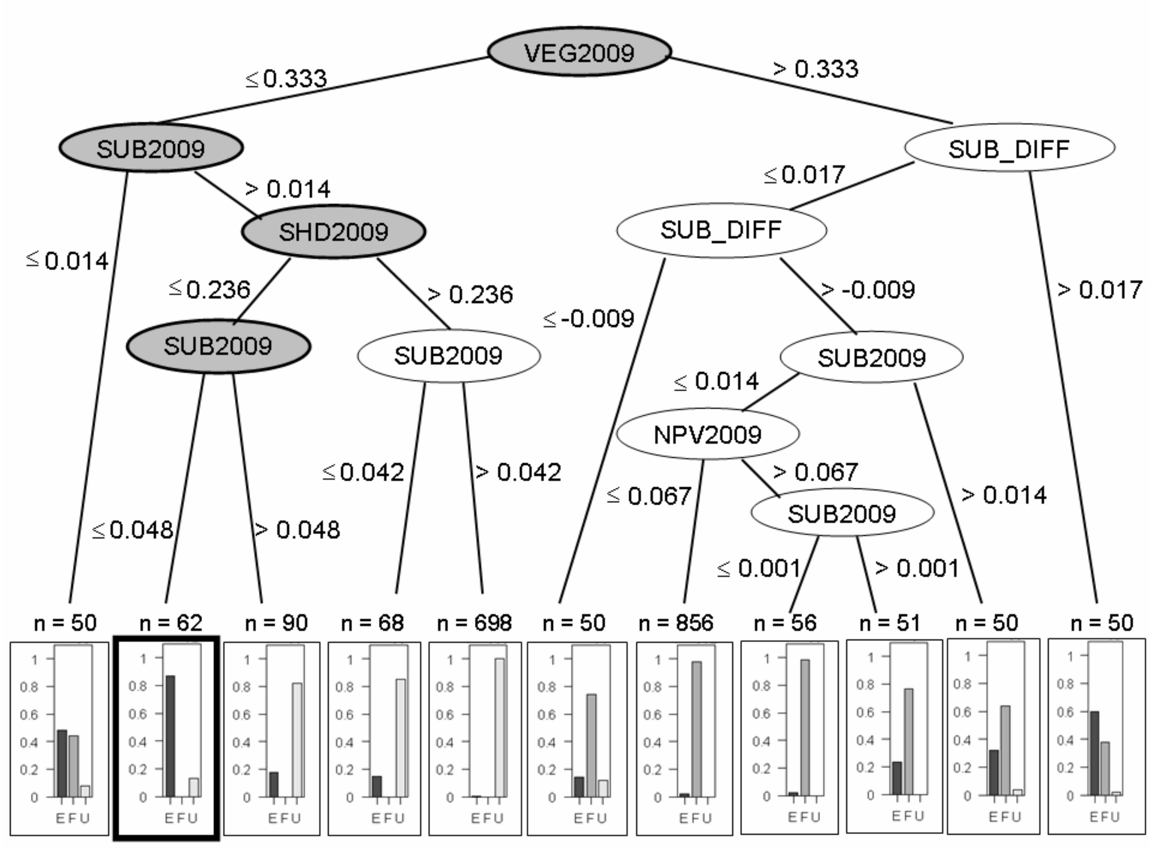

Figure 7. Structure of the decision tree used to classify 2000-2009 exurban development using substrate endmember difference between 2000 and 2009 (SUB_DIFF) and 2009 endmember fractions: vegetation (VEG), substrate (SUB), shade (SHD), and non-photosynthetic vegetation (NPV). Gray-shaded ovals illustrate the branching pattern toward exurban development terminal node. Any given pixel within the highlighted terminal node has a 90% probability of being exurban development. In the bar charts, proportion of exurban development (E), forest (F), and urban (U) classes are represented. All splits are significant at a 0.05 level.

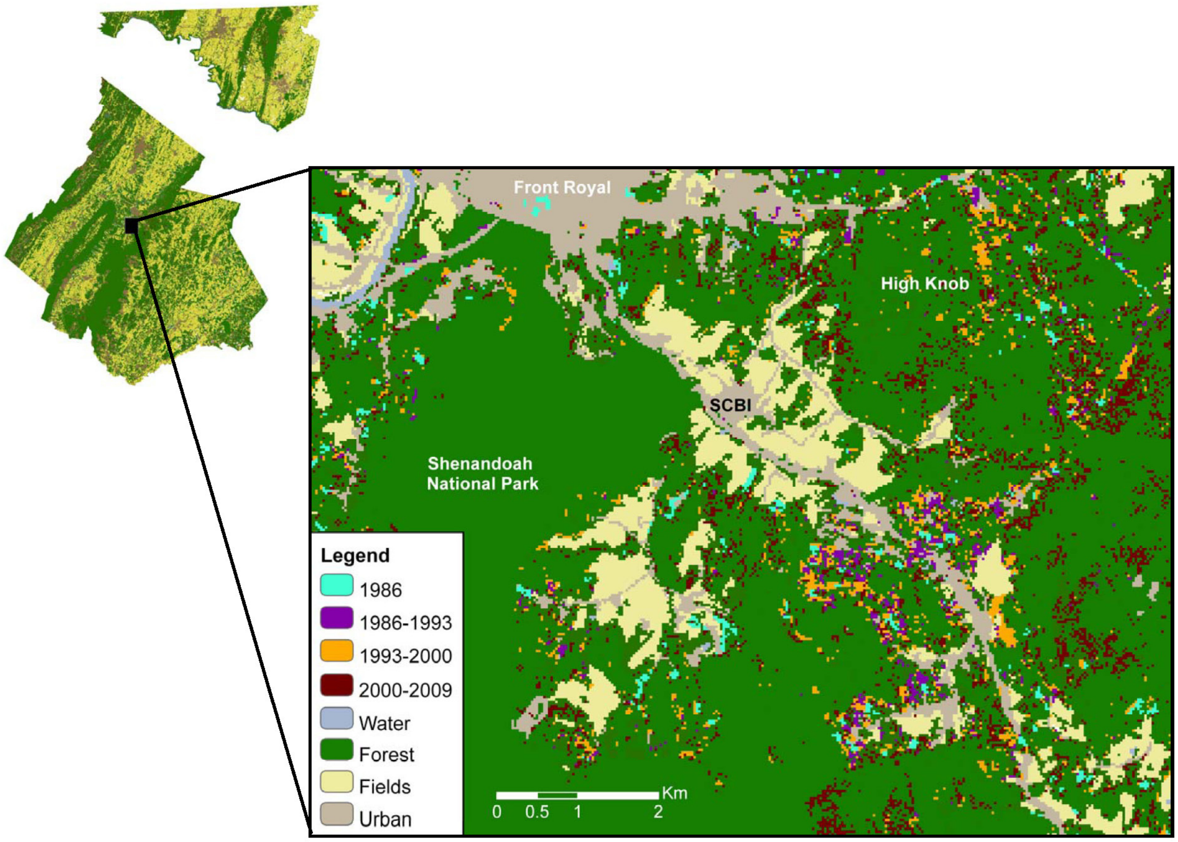

Figure 8. Map of the distribution of exurban development in north and central Virginia and western Maryland from 1986-2009. SCBI stands for Smithsonian Conservation Biology Institute.

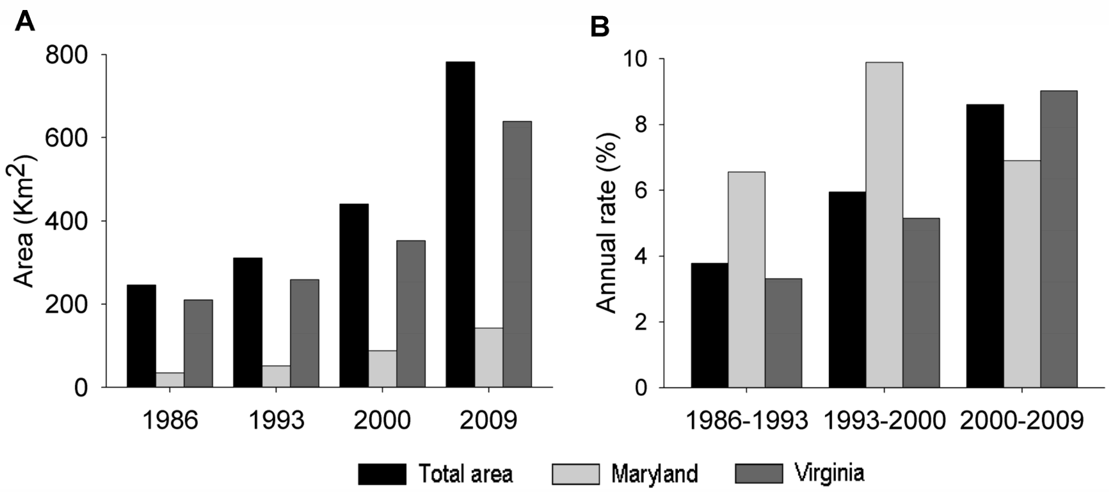

Figure 9. Extent of exurban development (A) and average annual rate (B) of total area, western Maryland, and northern Virginia between 1986 and 2009.

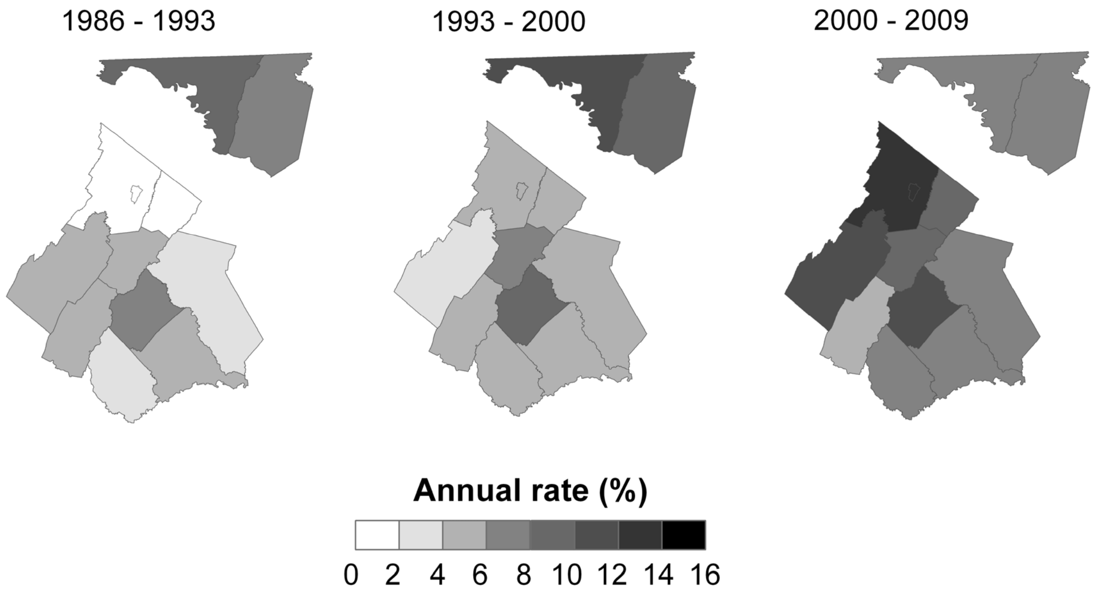

Figure 10. Mean annual rate in exurban development in different counties of western Maryland and northern Virginia for three time periods: 1986-1993, 1993-2000, and 2000-2009.

CHAPTER III

MODELING EXURBAN DEVELOPMENT: COMPARISON OF A PATTERN-BASED MODEL AND A SPATIALLY-EXPLICIT ECONOMETRIC MODEL

Abstract

The conversion of private rural lands into developed uses can significantly fragment landscapes, with potentially negative consequences on ecosystem services. Pattern-based models have been widely used to model urban growth but one criticism is that these models do not explicitly account for individual decision-making thereby making it difficult to model policies aimed at changing land use decisions. These models usually have been applied in urban environments and it is unclear whether they would be useful for predicting exurban growth. In contrast, spatially-explicit econometric models focus on land transactions and profit maximization. However, econometric models are data hungry and do not easily incorporate accessible raster data because they often rely on parcel information. The objective of this study was to compare a pattern-based model and a spatially-explicit econometric model for modeling exurban development in north and central Virginia and western Maryland. We used SLEUTH as our pattern-based model and forecasted exurban growth over a 24-year period. We parameterized a complementary log-log hazard model as our econometric model and used risk of conversion to create a map of development pressure. We compared model predictions to actual exurban conversion at two scales. The econometric model performed well at both local and county scales, whereas SLEUTH captured exurban growth only at a county scale. The results imply that pattern-based models like SLEUTH can forewarn potential

coarse-scale losses of natural resources in exurban areas, but are less useful at finer scale or for assessing potential consequences of how land use policy may change behavior.

Introduction

The rapid increase in exurban development (i.e., low-density residential development) in recent decades has been driven by people's preference for living in rural areas close to recreational and natural amenities, coupled with an extensive urban-to-rural transportation infrastructure (Hansen et al. 2002, Huston 2005, Gude et al. 2006). Exurban development has been growing more than twice as fast as development in metropolitan areas (Berube et al. 2006) and by 2000, this style of growth had increased to nearly 2% (93,538 km^2) of total land use and covered up to 25% of the contiguous United States (Brown et al. 2005). Rural land conversion to exurban development has resulted in loss of open space, habitat fragmentation, and deterioration in ecosystem services (Hansen et al. 2002, Bosch et al. 2003, Hansen et al. 2005, Gonzalez-Abraham et al. 2007b). Evaluating land conversion trends through modeling can be used to recognize spatial and temporal patterns, to understand the causes and consequences of exurban development, and to assist community leaders, planners, and natural resource managers to make informed decisions (Turner et al. 2001, Pocewicz et al. 2008).

The number of models and variety of approaches used to predict land-use change also have expanded greatly in recent years (Veldkamp and Lambin 2001, Agarwal et al. 2002, Berling-Wolff and Wu 2004). One popular approach is pattern-based models in which algorithms are developed to match patterns produced by the model to patterns found in time series of land use and then project those patterns into the future (e.g., White et al. 1997, Jenerette and Jianguo 2001, Herold et al. 2003, Fragkias and Seto 2007).

These models indirectly represent the outcome of socioeconomic processes by matching locations of new development to spatial data of drivers such as transportation networks (Wainger et al. 2007). Some advantages of pattern-based models include the ability to easily incorporate available spatially-explicit and remote sensing data (Jantz et al. 2003) and to easily visualize and quantify changes using GIS tools. However, such models do not directly model the behavior or decision-making of individuals, but rather assume that future decisions will follow historic patterns (Agarwal et al. 2002). Thus, pattern-based models do not explicitly account for the processes driving land-use change and have limited ability to represent changes in drivers other than those that can be mapped such as roads or septic development. The absence of a socioeconomic foundation limits the usefulness of these models for planning and policy-making purposes because they cannot respond directly to certain types of changes in incentive policies or drivers such as gas prices (Wainger et al. 2007). Nevertheless, these models have been widely used for predicting development trends in urban environments (Jenerette and Jianguo 2001, Fang et al. 2005, Geertman et al. 2007).

Econometric models of land-use change provide an alternative approach that focuses on land transactions and profit maximization by directly modeling multiple factors that affect land-use conversion such as expected value in new use and costs of conversion (Chomitz and Gray 1996, Pfaff 1999, Bell and Irwin 2002). The purpose of these models is to apply socioeconomic drivers to understand and project land-use change, often under alternative policy scenarios (Wear and Bolstad 1998, Seto and Kaufmann 2003, Bockstael and Irwin 2003). Spatially-explicit econometric models evaluate individuals' decisions at the parcel scale and aggregate many decisions to describe the resulting changes in regional pattern (Parks and Schorr 1997, Irwin and Geoghegan 2001, Wainger et al. 2007), however, data accessibility can constrain the ability to model large regions (Vance and Geoghegan 2002, Wainger et al. 2007). Econometric models have a greater ability than pattern-based models to include the effects of policies by evaluating their influence on the profitability of land use conversion, but still have limitations for modeling conditions that deviate from historic observations (Kline et al. 2001). Historically, econometric models have used parcel-based data which has the advantage of providing a direct link between the unit of observation (i.e., parcel) and management policies such as zoning. However, to ease data development for such models and to take advantage of time-series imagery of land use, econometric models have transitioned to the use of pixel-based approaches (e.g., Vance and Geoghegan 2002, Iovanna and Vance 2004).

Modeling exurban development requires an understanding of the role of historical exurban patterns and individuals' decisions in capturing exurban growth. Due to the sprawling aspect of exurban development, it is unclear whether pattern-based models would be as useful for modeling exurban growth as they are for urban environments. The aim of this study was to evaluate a popular pattern-based model (SLEUTH) and a spatially-explicit econometric model in predicting exurban development in north and central Virginia and western Maryland. We used the TM pixel as the unit of observation to allow comparison between both models and compared predictions from both models to actual land conversion at a local and county scale.

Methods

Study area

The study area comprised multiple counties of north and central Virginia (Clarke, Culpeper, Fauquier, Frederick, Madison, Page, Rappahannock, Shenandoah, and Warren Counties) and western Maryland (Washington and most of Frederick County; Figure 11). Virginia has had an annual population growth rate of 11% since 2000 and has the 12th largest population in the nation. Counties close to Washington, DC are experiencing the majority of this growth (Weldon Cooper Center 2010). For example, Loudoun County alone accounts for one-sixth of the total population increase for the entire state with a population increase of 78% since 2000. Counties included in the study area had growth rates ranging from 4% (Page County) to 40% (Culpeper County) between 2000 and 2009 (U.S. Census Bureau 2010). Much of this growth is in the form of exurban development in the region. For example, since 1986 north and central Virginia and western Maryland have increased in exurban areas by 6% (Chapter II). One reason for the expansion in exurban development is the transportation infrastructure and easy access to the metropolitan Washington, DC area, which provides employment opportunities even within the current economic climate (Weldon Cooper Center 2010).

Pattern based-model: SLEUTH

Overview of the SLEUTH model

SLEUTH is a cellular automaton model that has been widely used to represent and simulate the complexity of urban growth and land-use changes (Clarke et al. 1997, Herold et al. 2003, Mahiny and Gholamalifard 2007). SLEUTH is the acronym for the input layers required: Slope, Land use, Exclusion, Urban extent, Transportation, and Hillshade. An exclusion layer is used to constrain growth in areas where development is considered impossible or limited, such as in water bodies or along streams. At least two urban extent layers are needed in the most recent version of the model (Jantz et al. 2010), one to initialize the model and one or more "control years" to calibrate it. Transportation data are necessary to show the evolution of the transportation network through time and to illustrate the tendency of development to be attracted to locations of increased accessibility (Clarke et al. 1997, Dietzel and Clarke 2007). SLEUTH is implemented in two general phases: 1) a calibration phase, where the model is trained to replicate historic development trends and patterns, and 2) a prediction or forecasting phase, where historical trends are projected into the future.

The simulation of urban growth in SLEUTH is based on transition rules. The transition rules that are implemented involve taking a cell at random, assessing the spatial properties of that cell's neighborhood, and then deciding whether or not to develop the cell depending on local characteristics (Dietzel and Clarke 2007). Through the transition rules and five coefficients determined through the calibration procedure (diffusion, breed, spread, road gravity, and slope resistance), SLEUTH simulates four types of development during each growth cycle (e.g., year): spontaneous growth, new spreading center growth, edge growth, and road influenced growth (Figure 12; Clarke et al. 1997, Jantz et al. 2003). The model output consists of annual maps of development probability per pixel.

Database development

Data were developed from existing databases and through analysis of remote sensing imagery. Because we focused on exurban development, the urban extent layer comprised exurban areas only. Exurban development was identified from Landsat TM imagery for 1986, 1993, 2000, and 2009 by combining spectral mixture analysis, decision-tree classification, and morphological spatial pattern analysis (Chapter II). Three time steps for transportation were also prepared using TIGER roads layers for 1992, 2000, and 2008 from the Census Bureau. The exclusion layer consisted of water and protected areas derived from USGS/EPA National Hydrography Dataset and Conservation Biology Institute's Protected Areas Database, respectively. Slope and hillshade layers were derived from DEM data (U.S. Geological Survey 2010). All input files had 30m resolution.

Calibration and model execution

The four time-steps of exurban data (1986-2009) were used to calibrate the five growth coefficients (diffusion, breed, spread, road gravity, and slope resistance) which control the type of growth simulated. One of the components of the diffusion coefficient is the diffusion multiplier D_M, which controls the number of pixels that the model selects for potential new spontaneous growth in undeveloped areas that are not close to existing development, i.e., number of urbanization attempts (Dietzel and Clarke 2007). D_M was fixed in SLEUTH versions 1 and 2, which led to a deficiency of the model to capture dispersed settlement. The new SLEUTH-3r version allows the D_M value to be modified to increase or decrease the number of urbanization attempts for spontaneous growth (Jantz et al. 2010). To assign the D_M value for modeling exurban growth, growth coefficients were set to produce the maximum level of spontaneous growth allowed, i.e., all coefficients were set to zero except for the diffusion coefficient which was set to 100. Each simulation tested a different D_M value by running the model in calibration mode with seven Monte Carlo iterations until the amount of spontaneous growth produced by the model equaled the dispersed growth observed in the calibration time series. Seven Monte Carlo iterations were used because prior modeling found this number to be sufficient to capture historic dispersed patterns in the Chesapeake Bay area (Jantz et al. 2010).

Once the D_M value was determined, 'brute-force' calibration – in which every possible combination of potential values is compared – was initiated to identify the best values of growth coefficients (Jantz et al. 2003). Brute-force calibration may be performed at three levels. We conducted the calibration only to the coarse level because performance gains by doing fine and final calibration has been shown to be minimal (Jantz et al. 2005). To select the best coefficient values, we assessed population fractional difference (PFD) and cluster fractional difference (CFD) statistics. PFD and CFD are new metrics calculated by SLEUTH-3r that quantify the model's ability to simulate rates and patterns of observed development (Jantz et al. 2010). The best fit of the coefficients from the calibration were tested by running the model in calibration mode for 25 Monte Carlo iterations as suggested by previous work (Jantz et al. 2010). Using the output from the calibration, each candidate coefficient set was compared to the historical data and coefficients that matched PFD and CFD statistics within +/- 10% were selected.

To generate the SLEUTH forecast for 2009, the model was initialized with the 1986 urban extent map, the best fit coefficients, and an exclusion layer based on water and conservation protected areas. We ran the model in predict mode for 23 years with 25 Monte Carlo iterations to produce development probabilities for 2009.

Spatially-explicit econometric model: complementary log-log hazard model

Model overview

Spatially-explicit econometric models are used to estimate probability of land conversion as a function of site and location characteristics (e.g., accessibility) which may affect individuals' decisions to convert their land. These models describe the optimal timing of land conversion to residential use (Irwin and Bockstael 2002), i.e., when a parcel is likely to be developed. Individuals' optimal decisions depend on a complex multiplicity of site and location factors including market value of land in alternative uses (i.e., agriculture or forest), expectations about the future use of neighboring lands, and the surrounding composition of land ownership (Iovanna and Vance 2004).

The optimal timing for development was estimated here in the form of a survival or hazard model. Linear or logistic regression has also been used in these contexts, but they are poorly equipped to handle time-varying explanatory variables and censoring or truncation of the dependent variable (Iovanna and Vance 2007). A hazard model is based on the probability that in any given time period an event will occur, given it has not already occurred by the beginning of that time period. In the case of land conversion, it is the probability that a given parcel that is still undeveloped at time *T* will be converted by *T+1*, i.e. the parcel will fail to survive the period as an undeveloped parcel. To reconcile the temporal continuity of the conversion process with the discrete timing of measurement, a complementary log-log hazard (CLLH) model was used (Vance and Iovanna 2006, Iovanna and Vance 2007). The CLLH model is the discrete analogue of Cox's partial likelihood (Cox 1972) and assumes that the underlying process is continuous but that the data are grouped into discrete intervals (Allison 1999) to better match model predictions to data. The complementary log-log hazard model can be expressed as:

$$\log[-\log(1 - P_{i,t})] = a_t + \beta X_{i,T} + \varepsilon_i \quad (2)$$

where $P_{i,t}$ is the probability that development occurs in parcel i in interval t given that the parcel was not converted in any earlier periods, a_t is the complementary log-log transformation of the baseline hazard (i.e., the hazard for parcel i when all explanatory variables equal zero), $X_{i,T}$ are parcel attributes, and β is the vector of corresponding coefficients. The CLLH model allows time-varying variables to be accommodated and requires no assumptions on the functional form of the baseline hazard rate (a_t) or on the unobserved factors that may change this rate over time (ε_i; Iovanna and Vance 2007). This enables the focus to be specifically on the effect of explanatory variables (i.e., parcel characteristics) on the hazard of land conversion. Using this approach, we estimated which parcels are most likely to convert within a given time frame and which parcels will be subject to the most development pressure.

Database development

The CLLH model was estimated using Landsat TM satellite data for the dependent variable and static and time-varying covariates as explanatory variables. The dependent variable was generated by taking maps of exurban development for 1986, 1993, 2000, and 2009 (Chapter II) and creating binary maps where 1 represented conversion from forest to exurban development between two dates and 0 otherwise. For model estimation, we systematically drew a sample of 14,859 pixels 1.5 km apart that provided 566,665 observations (up to 4 observations per pixel depending on whether and in what year the pixel was converted). Systematic sampling is a commonly applied technique to address spatial autocorrelation of unobserved variables due to shared attributes of neighbor pixels (Kline et al. 2001, Iovanna and Vance 2007) which can cause biased estimates (Irwin and Bockstael 2001). Because exurban development is characterized by dispersed, isolated housing units and the average property size is 213 m^2 (Maryland Department of Planning 2008), 1.5 km pixel separation was considered an appropriate distance to minimize the likelihood of spatial autocorrelation.

Explanatory variables described site and location characteristics of the pixel that could influence the likelihood of land conversion and included accessibility, landscape configuration surrounding a pixel, environmental amenities, cost of conversion, and county-level socio-demographic indicators (Table 5). Accessibility represented travel cost and proximity to transportation infrastructure and cities. Travel cost increased with distance from the Washington, DC beltway and was weighted based on road types as a proxy for travel time. Travel cost was expected to have a negative effect on the conversion hazard because exurban residents commute to center of employment (Berube et al. 2006). Euclidean distance to the nearest highway and Euclidean distance to roads (primary, secondary, and neighborhood roads) was expected to have a negative effect given higher access costs. Euclidean distance to major cities (i.e., Washington, DC, Alexandria, Fairfax, Fall Church, Manassas, and Winchester in Virginia) was also expected to exert a negative effect on the exurban conversion hazard because these residents are looking for a semi-rural lifestyle (Berube et al. 2006).

Landscape configuration surrounding a pixel was derived for the four time periods (i.e., time-varying variable) and was calculated for a 0.15 km radius to depict immediate pixel surroundings and between 0.15 and 1 km radius to represent a larger region within easy walking distance from the house. For each distance class, we calculated the percent of exurban development and fragmentation index (perimeter to area ratio; Geoghegan et al. 1997) to capture individuals' perception of the extent and pattern of forests surrounding the focal pixel. Percent of exurban development within 0.15 km radius was expected to have a positive effect in the hazard of conversion given agglomeration effects associated with immediate housing units (Irwin and Bockstael 2002). On the contrary, percent of exurban development between 0.15 and 1 km radius was expected to have a negative effect given the repelling effects associated with the character of exurban development (i.e., low-density residential development; Irwin and Bockstael 2002). Fragmentation in immediate pixel surroundings was expected to have a positive effect because fragmented habitat reduces the cost of conversion by reducing cost associated with clearing the land for development, whereas fragmentation between 0.15 and 1 km radius was expected to have a negative effect due to repelling effects.

Six time-invariant variables were included to capture environmental amenities: percent of protected area, surface water, and forest; and proximity to the nearest protected areas, surface water, and forest. Percent protected areas (Gap 1-3; Conservation Biology Institute 2010) and percent surface water (USGS/EPA 1999) were measured in both within 0.15 km radius and between 0.15 and 1 km radius of the focal pixel. Percent protected areas in both buffers and percent water between 0.15 and 1 km were hypothesized to increase the amenity value of the pixel and have positive effects, whereas percent water within 0.15 km radius was expected to have negative effects due to the likelihood of flooding. Euclidean distance to nearest protected areas and surface water were expected to have negative effects because conversion to exurban development is more likely near natural and recreational amenities (Rasker and Hansen 2000, Radeloff et al. 2005a). Other time-varying variables included were percent forest within 0.15 km and distance to forest. These two variables were hypothesized to have positive and negative effects, respectively, through their effects on the scenic amenities of the pixel.

Seven time-invariant variables measured in the focal pixel were included in the model to capture the cost of conversion, including pixel characteristics of elevation, slope, wetland land use (USGS/EPA 1999), agriculture land use (Homer et al. 2004), and if the pixel was forested, forest economic ranking (Chesapeake Bay Program 2009). In addition, neighborhood characteristics thought to influence costs were distance to the nearest agricultural field and distance to nearest hazardous waste sites (U.S. Environmental Protection Agency 2010). Forest economic ranking identifies forested lands with the highest potential for future economic benefits associated with timber management activities. All these variables were expected to have negative effects due to higher conversion costs.

Four county-level and time-varying variables were also included in the model to capture socioeconomic drivers affecting profitability of land use conversion. Agriculture returns captured the opportunity costs of commodity uses and was calculated as county total farm receipts less costs, divided by farm acreage (USDA 2002). This metric was expected to have a negative effect on the conversion hazard. Population density, median household income (U.S. Census Bureau 2010), and gas prices (U.S. Energy Information Administration 2010) were included to represent demand for developed land. Population density and median household income were expected to have positive effects, whereas gas prices a negative effect. Socioeconomic indicators (except for gas prices which were calculated for the entire study area) were estimated at the county level and all pixels falling in a county were assigned that county's estimate. The county where the pixel was located was also included in the model to control for differences in quality of services (e.g., better public schools, lower crime rates).

Complementary log-log hazard model

The CLLH model estimated the likelihood that a pixel will be converted to exurban development within a given time frame based on the 27 explanatory variables (Table 5). From that model, we produced a map of development pressure to depict estimated conversion probabilities between 1986 and 2009. The development pressure map was created from the modeled pixels using a natural neighbor algorithm (Sibson 1981, Childs 2004) to avoid selecting an arbitrary distance to establish the influence of surrounding pixels.

Before using the output of the CLLH model, we transformed the estimated coefficients β (eq. 2) of the CLLH model to risk ratios for easier interpretation. Risk ratios represent the percent change in the hazard rate for a unit increase in a continuous explanatory variable. The risk ratio was calculated by subtracting one from e^{β} and multiplying by 100. For dummy variables, the risk ratio is equal to e^{β} and can be interpreted as the ratio between the estimated hazard for observations with a value of one over the estimated hazard for observations with a value of zero (Allison 1995).

Model assessment

We compared observed exurban development for 2009 against the SLEUTH forecast and the map of development pressure derived from the CLLH model. To evaluate the performance of the models at a local scale, we used Goodman and Kruskal's gamma (Goodman and Kruskal 1954, 1959, 1963) and receiver-operating characteristic (ROC) curves (Pontius and Schneider 2001). The Goodman and Kruskal's gamma is a non-parametric measure of correlation based on the difference between concordant and discordant pairs of predicted and observed conversion as percentage of all pairs ignoring ties. Gamma can be interpreted as the contribution of the independent variables in reducing the errors of predicting the rank of the dependent variable. ROC curves visually present the percentage of converted pixels correctly forecast (i.e., true-positive rate) against the percentage of non-converted pixels incorrectly forecast (i.e., false-positive rate). ROC aggregates into a single index of agreement the success of several models (Pontius and Schneider 2001). The area under the ROC curve can be interpreted as the proportion of correct forecasts for all possible prediction thresholds (Pontius and Schneider 2001). ROC was also used to determine the threshold that maximized the true positive rate of conversion and to aggregate both model predictions to the county level. We used t-tests and Spearman rank correlation coefficients to assess model performance at the county scale. ROC curves (Package ROCR; Sing et al. 2005), t-tests, and Spearman correlation were calculated in R.

Results

SLEUTH

The SLEUTH calibration procedure allowed us to determine the best fit for the diffusion multiplier (D_M) and growth coefficients. The D_M value determined for the study region was 0.035. This value was similar to values determined by Jantz et al. (2010) in sub-regions of central and south-central Virginia. The other calibrated coefficients were diffusion = 100, breed = 25, spread = 15, slope = 100, and road growth = 50. The road-growth coefficient was highly variable during the calibration procedure. We selected a value of 50 because it complied with the estimated value by Jantz et al. (2010) for the region.

When we compared the simulation with the observed data, we found that SLEUTH overestimated growth and suggested patterns that were not evident in the data. Simulated exurban development was spread throughout the study region (Figure 13A). SLEUTH overestimated the observed amount of exurbia by 5.8% (828 km^2 of exurban development were simulated compared to 783 km^2 observed amount for 2009). SLEUTH also overestimated the number of exurban clusters by 22.2% for the 24-year period (227,609 were forecast compared to 186,191 measured from data). The gamma value for SLEUTH was 0.47 and the area under the ROC curve was 0.67 (Figure 14). At the county level (Figure 15), observed and simulated percent of exurban development were similar ($t = -0.002$, $df = 10$, $p = 0.9$) and significantly correlated ($r_s = 0.77$, $p = 0.006$). Mean prediction error for all counties was 2.0%. Frederick was the worst underpredicted county (error = 4.1%), and Frederick in Maryland was the worst overpredicted county (error = 4.2%).

Complementary log-log hazard model

The estimated coefficients of the CLLH model were generally of the expected sign (Table 6) and the model fit was robust based on the fit statistics. The statistically significant variables that had the biggest positive influence on hazard of conversion (risk ratio > 5%) were fragmentation index (risk ratio = 1,689%), percent exurban (risk ratio = 13.3%), and percent of forest (risk ratio = 5.2%) all in immediate pixel surroundings (i.e., within 0.15 km radius). Statistically significant variables that had the foremost negative effect on the hazard of conversion were distance to forest (risk ratio = 100%), distance to water (risk ratio = 11.5%), and percent water between 0.15-1 km radius (risk ratio = 6.9%). Some variables had apparently a large influence on the hazard of conversion but were not statistically significant (e.g., distance to roads). Slope within the pixel and forest economic ranking had an unexpected significant positive effect on the hazard of conversion. Slope increased the hazard by 2.4%, whereas forest economic ranking increased the hazard by 0.7%. Finally, the county location of the pixel significantly affected the conversion hazard (Table 6), with Frederick in Virginia (risk ratio = 0.55%), Shenandoah County (risk ratio = 0.53%, and Fauquier County (risk ratio = 0.41%) having the top three highest hazards.

The model-predicted patterns of the highest hazards of development pressure were sparse and isolated (Figure 13B). We found a high correspondence between the CLLH high probability regions and observed exurban conversions. The gamma value for the CLLH model was 0.90 and the area under the ROC curve was 0.94 (Figure 14). At the county level (Figure 15), observed and estimated exurban development were similar ($t = -0.003$, $df = 10$, $p = 0.9$) and significantly correlated ($r_s = 0.91$, $p < 0.001$). The CLLH model estimated similar percentage of observed exurban land (error of < 1%) for half of the counties and mean prediction error for all counties was 1.4%. Fauquier County was the worst underestimated (error = 4.4%) and Washington County the worst overpredicted (error = 2.4%).

Discussion

Our results indicate that the spatially-explicit econometric (CLLH) model effectively estimated land conversion to exurban development at both local and county scales and that the pattern-based (SLEUTH) model only captured exurban growth adequately at a county scale (Figure 15). The better performance of the CLLH model at the local scale reflect the importance of capturing drivers of individual behavior at this scale rather than relying on historic land patterns to predict exurban growth. The adequate performance of SLEUTH at the county scale suggests that the need to capture local drivers may be less critical at the regional scale, although aggregating the CLLH model results to the county scale still performed somewhat better than SLEUTH.

The different accuracy of results at multiple scales highlights the challenge of capturing low-density land conversion using a pattern-based model. The SLEUTH calibration was able to successfully replicate the percentage of exurban development at the count level (Figure 15), but it was not able to accurately predict the conversion of land to exurban development at the local scale (Figure 14). Similar results were found by others who applied the SLEUTH model to the Chesapeake Bay watershed (Jantz et al. 2003, 2010). The model overestimated areas of dispersed development for rural landscapes at a pixel scale but its accuracy improved greatly when results were generalized to the watershed scale (Jantz et al. 2010).

There are strengths and limitations associated with both pattern-based and econometric modeling approaches. SLEUTH and other pattern-based models are highly dependent on the calibration procedure to generate reasonable projections, therefore having adequate control over calibration parameters is important. The new ability to calibrate the diffusion multiplier in the SLEUTH-3r version (Jantz et al. 2010) has made a significant improvement in the model's ability to simulate spontaneous growth, which is especially important for representing dispersed exurban settlement patterns. When we ran SLEUTH simulations using the previous default diffusion multiplier value (0.005), SLEUTH underestimated the number of exurban clusters by 62%, whereas with our calibrated value (0.035), the estimate deviated from the observed by only 22% for the study region.

The CLLH model did a better job capturing exurban conversion at both local and county scales but requires more effort to develop input data and model-results may be biased by variable selection. Caution should be exercised when identifying variables that may affect individuals' motivation to convert their land (Irwin and Geoghegan 2001) because of temporal dynamics in behavioral drivers. Selecting variables that change with time due to changes in land use can lead to inconsistent coefficient estimates. Another drawback to this approach is that input data should vary enough to serve as effective tests of their importance as drivers of land-use change. For example, the lack of a significant effect of distance to roads and to highways on the hazard of conversion may be because pixels were uniformly close to roads. Distance to roads has been documented to be a strong determinant on land development in agriculture and urban landscapes (Wear and Bolstad 1998). However, in exurban areas, where residents commute long distances to employment centers (Berube et al. 2006), travel cost (which was a significant factor in our model) might have a greater influence on the hazard of conversion than proximity to roads.

Similarly, other variables may not have had sufficient range to show effects or had an unexpected effect. Socioeconomic factors were generally not strong influences on exurban development predictions in the CLLH model, because these variables did not vary substantially among counties during the time period considered or they unexpectedly increased in the last period analyzed such as gas prices. Abrupt changes in gas prices may take time to induce behavioral changes (Lane 2010), thus it was difficult to capture the influence of gas prices on the hazard of conversion in the time frame considered. Two variables representing cost of conversion (e.g., forest economic ranking) had an unexpected positive effect on the hazard of conversion. The positive effect of future forest economic benefits on the conversion hazard suggests that economically attractive forest lands are also highly desirable for exurban development. A direct measure of opportunity costs from forest management would improve the model's ability to capture any tradeoffs.

Both modeling approaches provided insights into the land conversion process. SLEUTH growth coefficients derived during the calibration phase manifested the growth pattern of exurban development. The high value of the diffusion coefficient reflected a high likelihood of dispersive growth which was expected given the dispersiveness of exurban development. Low values of the breed and spread coefficients corresponded to the low probability of new detached settlements and already established exurban settlements to grow or expand like urban centers, which reinforced the typical characteristics of exurban areas. Slope had a high value which corresponds to the tendency of exurban development to occur in more hilly areas of the study region.

The spatially-explicit econometric model also informed about the drivers of land conversion. Landscape configuration (e.g., percent exurban) and environmental amenities (e.g., percent forest within 0.15 km) were important determinants of the land conversion process. Parcel-level analysis in central Maryland (Geoghegan et al. 1997, Irwin and Bockstael 2002) and pixel-level analysis in central North Carolina (Vance and Iovanna 2008) support the importance of amenity-driven decisions and spatial effects in the land conversion process. There are some commonalities between these two interpretations. Both models showed the positive association of exurban development with slope confirming the importance to include slope when modeling exurban growth in the study region.

Modeling exurban development may inform land-use change assessments at both local and coarse-scale. Even though SLEUTH did not perform as well as the CLLH model, SLEUTH can serve to highlight potential coarse-scale losses in natural resources (Jantz et al. 2005) and inform decisions about protection priorities in exurban areas. In contrast, an econometric model can be used to assess possible impacts of implementing land-use policies. The CLLH model is better able to capture individual choices and behavioral responses under alternative policy scenarios at a local and county scale, although it will be important to have appropriate variability in the input data to capture the influences of various drivers.

Table 5. Descriptive statistics for variables included in the complementary log-log hazard model.

Variable	Units	Mean	Standard deviation
Dependent variable (1 = conversion)	0, 1	0.019	0.136
Accessibility			
Travel cost	index	39.238	6.434
Distance to highways	km	8.511	6.344
Distance to all roads	km	0.170	0.212
Distance to major cities	km	44.574	21.289
Landscape configuration			
Percent exurban within 0.15 km radius	%	3.902	7.056
Percent exurban between 0.15-1 km radius	%	3.959	3.680
Fragmentation index within 0.15 km radius	index	0.063	0.102
Fragmentation index 0.15-1 km radius	index	1.992	1.453
Environmental amenities			
Percent forest within 0.15 km radius	%	41.857	40.043
Distance to forest	km	0.092	0.142
Percent protected areas within 0.15 km radius	%	15.160	33.636
Percent protected areas between 0.15-1 km radius	%	14.989	25.732
Distance to protected areas	km	1.356	1.421
Percent water within 0.15 km radius	%	0.614	4.459
Percent water between 0.15-1 km radius	%	0.630	1.905
Distance to water	km	1.509	1.130
Cost			
Elevation	m	248.732	160.742
Slope	%	8.064	7.918
Wetlands (dummy)	0, 1	0.018	0.134
Agriculture (dummy)	0, 1	0.412	0.492
Distance to agriculture	km	0.269	0.586
Distance to undesirable land use	km	6.849	4.300
Forest economic ranking	%	33.820	31.831
County-level socio-demographic variables			
Agricultural returns	$1/acre	68.29	105.85
County population density	people/km^2	24.820	17.772
County median household income	$	51597.04	16263.68
Gas price	$/barrel	36.42	33.24

Table 6. Complementary log-log hazard model of conversion. Bold indicates significant variables at a 0.05 level.

Explanatory variables	Estimated coefficient	Likelihood-ratio chi-square	Risk ratio
Travel cost	0.044	**8.08**	4.467
Distance to highways	0.013	3.10	1.319
Distance to all roads	-0.277	0.90	-24.187
Distance to major cities	-0.027	**25.28**	-2.664
Percent exurban within 0.15 km radius	0.125	**1269.09**	13.326
Percent exurban between 0.15-1 km radius	-0.041	**14.26**	-3.979
Fragmentation index within 0.15 km radius	2.884	**15.23**	1688.925
Fragmentation index between 0.15-1 km radius	-0.186	1.66	-16.956
Percent forest within 0.15 km radius	0.050	**478.29**	5.148
Distance to forest	-13.673	**66.75**	-100.000
Percent protected areas within 0.15 km radius	0.001	0.39	0.140
Percent protected areas between 0.15-1 km radius	0.008	**5.44**	0.833
Distance to protected areas	-0.001	0.00	-0.130
Percent water within 0.15 km radius	-0.015	1.81	-1.528
Percent water between 0.15-1 km radius	-0.072	**8.61**	-6.900
Distance to water	-0.123	**7.03**	-11.547
Elevation	0.000	0.05	-0.010
Slope	0.024	**10.47**	2.439
Wetlands (dummy)	-0.435	2.80	0.647
Agriculture (dummy)	-0.725	**48.13**	0.484
Distance to undesirable land use	-0.036	**10.19**	-3.546
Distance to agriculture	-0.258	1.46	-22.702
Forest economic ranking	0.007	**17.79**	0.682
Agricultural returns	-0.001	0.37	-0.050
County population density	-0.035	0.00	-3.439
County median household income	0.000	**5.40**	0.001
Gas price	0.004	0.00	0.361
Constant	-6.268		
Chi^2 county dummies		**58.08**	
Chi^2 year dummies		0.00	
Deviance	3848.465		
Log likelihood	-1924.2326		
Number of observations	56665		

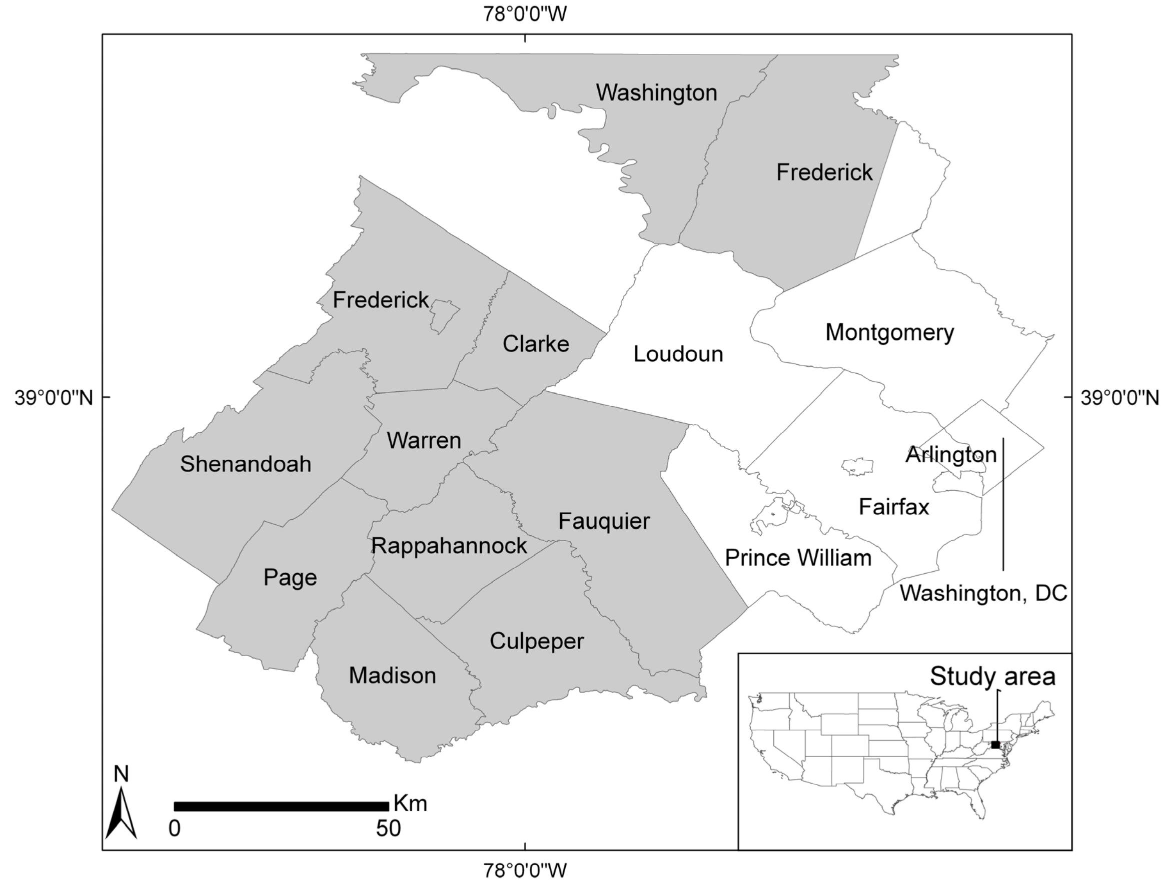

Figure 11. The study region encompasses nine counties in north and central Virginia and two counties in western Maryland (shaded area).

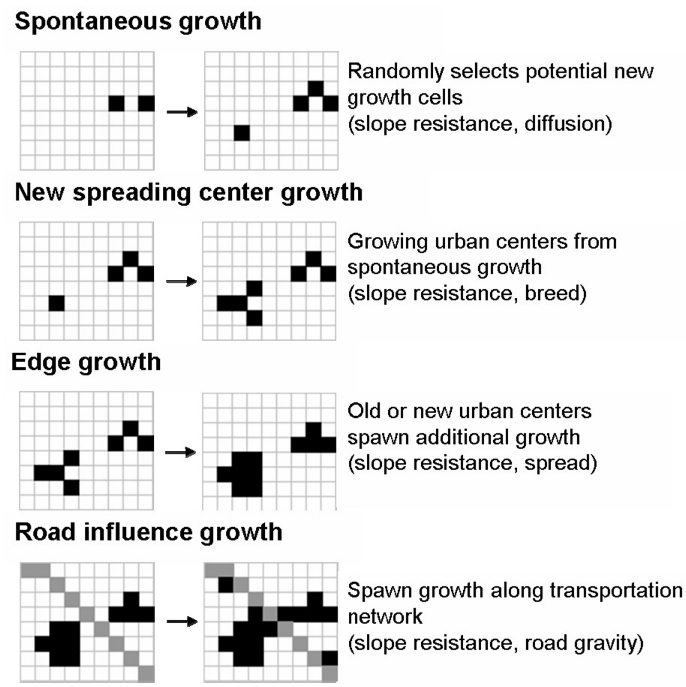

Figure 12. Schematic representation of growth types and controlling coefficients in parenthesis simulated by SLEUTH (Adapted from Clarke et al. 1997).

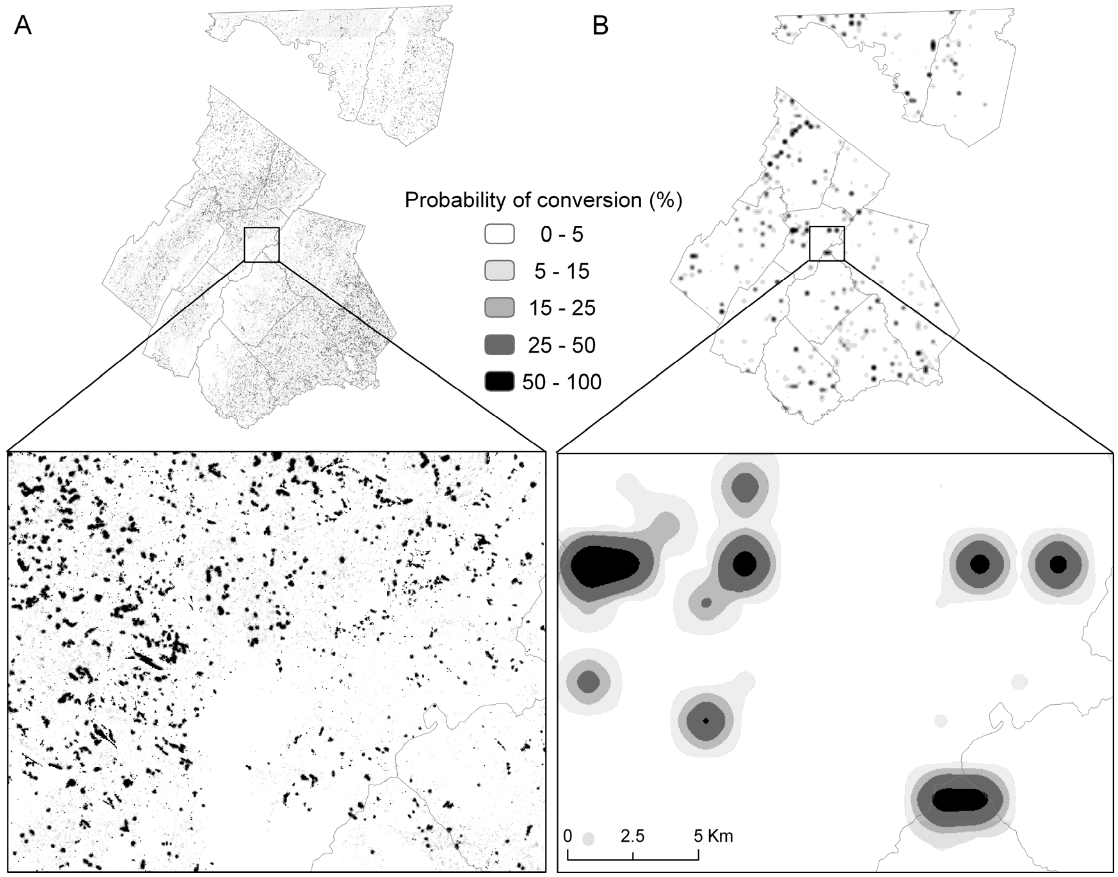

Figure 13. Probability of conversion to exurban development simulated using (A) SLEUTH and (B) complementary log-log hazard model for for north and central Virginia and western Maryland. Zoom in windows illustrate the difference in the spatial pattern between models.

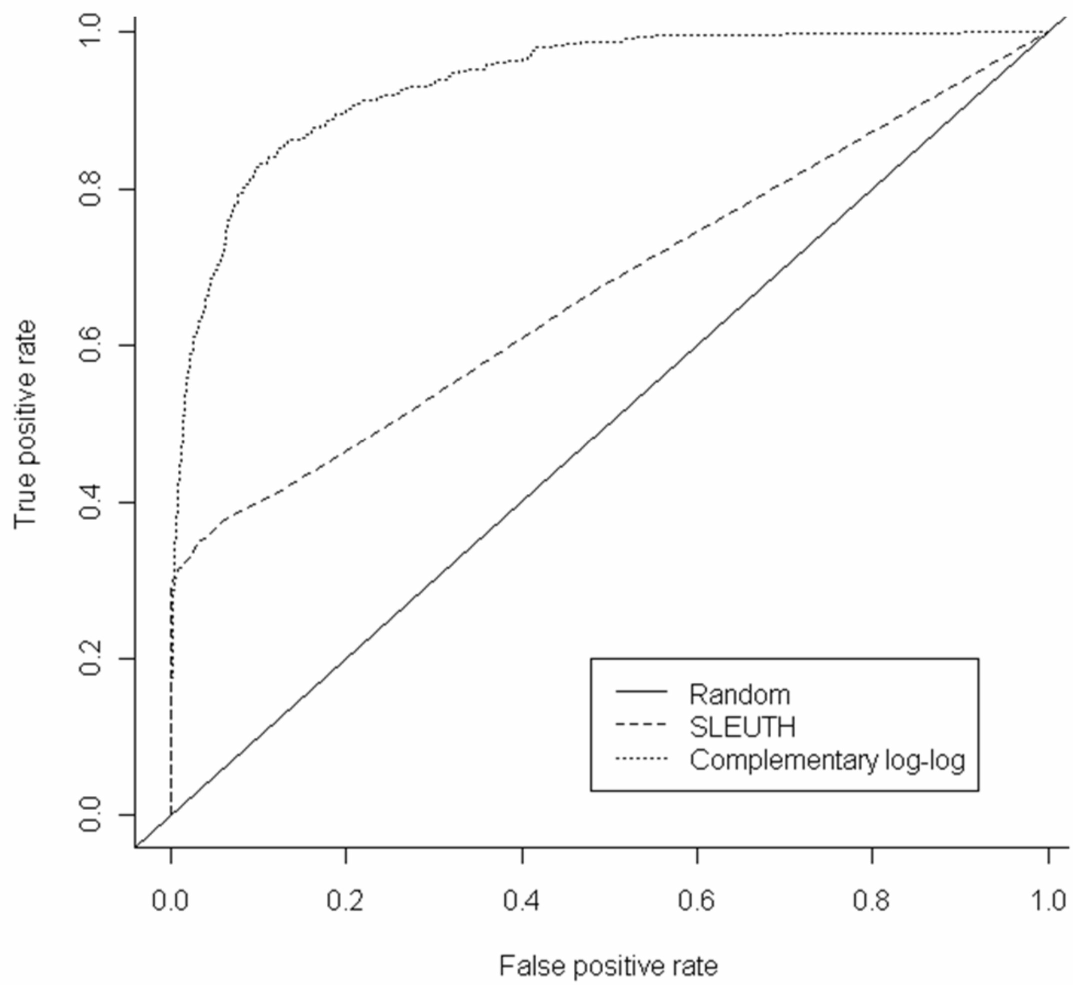

Figure 14. Receiver-operating characteristic (ROC) curves to evaluate SLEUTH and the complementary log-log hazard model performance. ROC close to the diagonal indicates the performance of the model is no better than random.

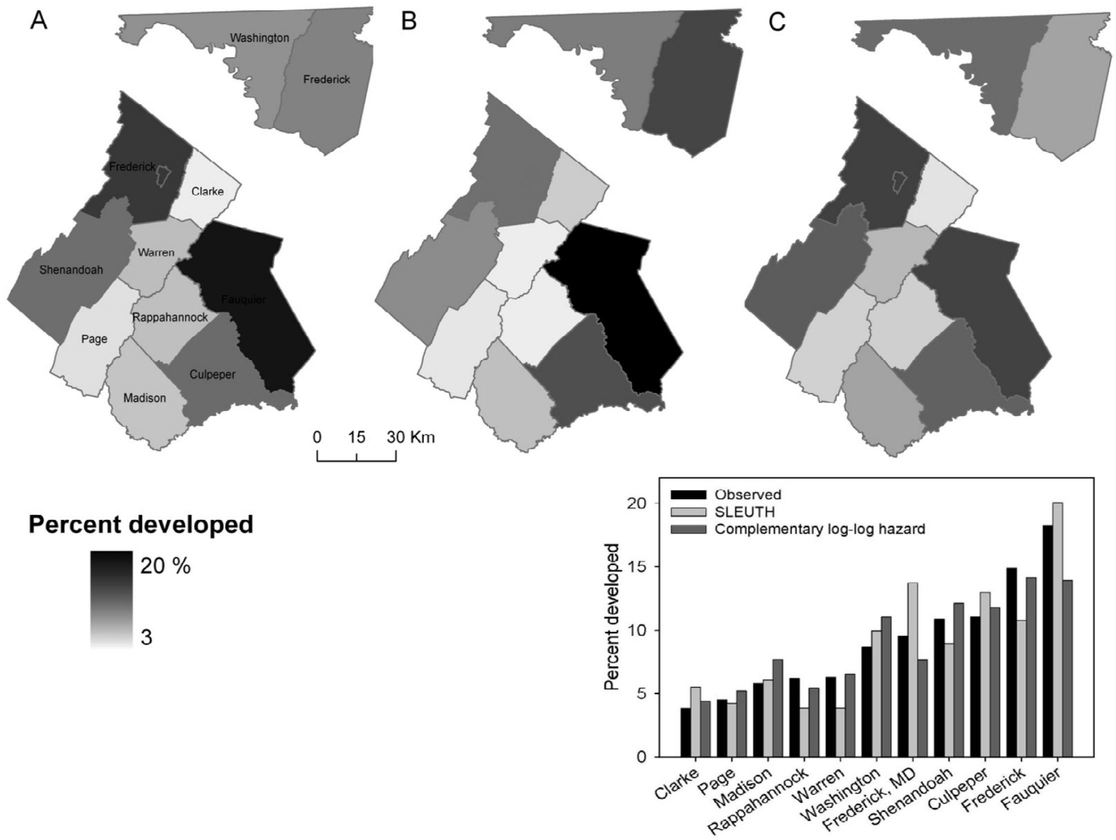

Figure 15. Percent of each county's exurban developed area: (A) observed in 2009, (B) simulated by SLEUTH, and (C) estimated by the complementary log-log hazard model for north and central Virginia and western Maryland.

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CHAPTER IV

FOREST BIRDS RESPOND TO DETERIORATED BREEDING HABITAT AROUND EXURBAN AREAS

Abstract

Exurban development is often embedded within a matrix of protected areas and natural amenities, which has raised concern about its ecological consequences. Forest birds are particularly susceptible to human settlement even at low housing densities typical of exurban areas. However, few studies have examined the response of forest birds to this increasingly common form of land conversion. The aim of this study was to assess whether forest birds respond, and if so in a nonlinear fashion, to changes in breeding habitat due to exurban growth. We evaluated changes in breeding habitat composition (amount) and configuration (arrangement) for forest specialists, forest generalists, and forest edge species around North America Breeding Bird Survey (BBS) stops in north and central Virginia and western Maryland between 1986 and 2009. We used a new method (Threshold Indicator Taxa Analysis) to detect change points in species occurrence. We also evaluated whether species responded differently to changes of breeding habitats at two spatial extents (400 m- and 1 km-radius buffer). Our results show that exurban development is degrading breeding habitats around BBS stops by reducing forest cover and increasing habitat fragmentation. Forest birds responded nonlinearly to most measures of breeding habitat deterioration at both extents. However, for number of forest patches and proportion of forest edge, the direction of the response changed with the extent. Forest specialists were most sensitive to habitat deterioration followed by forest generalists. The positive responses of forest edge species to changes in

the landscape generally agreed with their perceived habitat preferences. These differences in habitat preferences together with the range at which forest birds exhibited strong threshold response to habitat loss and fragmentation in exurban areas may guide planners and managers in mitigating effects of exurban development to these declining forest resources.

Introduction

The expansion of human settlement in the urban-rural fringe has received considerable global attention in recent decades (Burnley and Murphy 1995, Struyk and Angelici 1996, van den Berg and Wintjes 2000, Liu et al. 2003, Theobald 2005). In the United States, conversion of privately owned rural lands into low-density residential development (i.e., exurban development) has expanded dramatically in recent decades (Hansen et al. 2002, Theobald 2005). Nationally, exurban development increased five- to sevenfold between 1950 and 2000 (Brown et al. 2005). In the Mid-Atlantic region of the United States, the dispersed, isolated housing units typical of exurban areas are embedded within a forest matrix, often close to protected areas (Wade and Theobald 2010) and natural amenities (McGranahan 1999, Kwang-Koo et al. 2005). Understanding the impacts of exurban development on wildlife is crucial to successful conservation planning within this region (Miller and Hobbs 2002, Hansen et al. 2005).

Human settlements generally remove, fragment, and degrade natural habitats (Donnelly and Marzluff 2006, McKinney 2008, Evans et al. 2009). Both habitat loss and fragmentation modify the spatial pattern of remnant habitats, creating smaller and isolated fragments, thus compromising habitat quality and quantity. Bird species respond in a variety of ways depending on species traits and life histories (Marzluff 2001, McDonnell and Hahs 2008). Some species thrive in these environments whereas others, such as forest birds, decline rapidly (e.g., Blair 2001, Chace and Walsh 2006). Possible reasons for long-term reductions of forest-bird species in these environments include predation (Newhouse et al. 2008), brood parasitism (Chace et al. 2003), and competition with human-adapted species (Engels and Sexton 1994). Forest birds have been shown to be particularly susceptible to human settlement even at housing densities as low as 0.095 house/ha (Friesen et al. 1995, Engle et al. 1999, Odell and Knight 2001, Fraterrigo and Wiens 2005, Merenlender et al. 2009, Suarez-Rubio et al. 2011).

Exurban development (as a specific case of land cover conversion) is fragmenting eastern temperate forests of the Mid-Atlantic at unprecedented rates (Brown et al. 2005, Chapter II). Understanding how exurban development degrades forest bird breeding habitat over time is a conservation priority. Forest birds are generally positively related to proportion of forest cover (e.g., Pidgeon et al. 2007,Valiela and Martinetto 2007) but the spatial distribution of suitable habitat also affects their occurrence and fecundity (Jones et al. 2000, Donovan and Flather 2002). Declines of forest birds have been well documented in eastern North America, and these declines have been highly associated with habitat loss and fragmentation due to roads, power lines, and residential development (Askins 1995, Mancke and Gavin 2000, Hansen et al. 2005). However, few studies have examined the response of species through time as residential development progresses (Chace and Walsh 2006).

In addition, species may respond nonlinearly to habitat loss and fragmentation (reviewed by Swift and Hannon 2010). Theoretical models predict the existence of a change point or threshold in which an abrupt reduction in occupancy occurs despite the presence of sufficient suitable habitat (Gardner et al. 1987, Andrén 1994, With and Crist 1995, Fahrig 2001). Some studies show empirical evidence for threshold existence (Radford et al. 2005, Betts et al. 2007, Poulin et al. 2008, Zuckerberg and Porter 2010) although others have not found any evidence to support threshold responses (Lindenmayer et al. 2005). It is uncertain whether threshold declines in forest birds apply to exurban development. If these relationships are appropriately characterized by threshold models, determining the range at which exurban development induces population crashes may provide guidance for landscape planning, management, and conservation.

The aim of this study was to assess how exurban development deteriorates the suitability of breeding habitats in north and central Virginia and western Maryland. We evaluated breeding habitat composition (amount) and configuration (arrangement) for selected bird species (forest specialists, forest generalists, and forest edge) around North America Breeding Bird Survey stops between 1986 and 2009. The approach accounted for year-to-year variability in species abundances and investigated species responses to both breeding habitat loss and fragmentation as exurban development increased since 1986 in the study region. In addition, we assessed whether selected bird species showed thresholds in both occurrence frequency and relative abundance. We used a new method (Threshold Indicator Taxa Analysis; Baker and King 2010) to detect change points in species occurrence. We evaluated two spatial extents (400 m- and 1 km-radius buffer) to determine if species responded differently to changes at the local and landscape scales. We expected that forest specialists and forest generalists would exhibit a strong negative response to breeding habitat degradation due to exurban development at both extents, whereas forest edge species would, if anything, respond positively to high levels of exurban land cover.

Methods

Study area

The study area encompassed 11 counties in north and central Virginia (Clarke, Culpeper, Fauquier, Frederick, Madison, Page, Rappahannock, Shenandoah, and Warren) and two counties in western Maryland (Washington and most of Frederick; Figure 16). The region has experienced a remarkable population growth. Virginia has the 12th largest population in the nation with an annual population growth rate of 11% since 2000. For example, Loudoun County alone accounts for one-sixth of the total population increase for the entire state with a population increase of 78% since 2000 (Weldon Cooper Center 2010). Counties included in the study area had growth rates ranging from 4% (Page County) to 40% (Culpeper County) between 2000 and 2009 (U.S. Census Bureau 2010). In Maryland, Frederick County has increased its population by 17% between 2000 and 2009, and Washington County had an 11% increase (U.S. Census Bureau 2010). Beside the population growth, the region has also experienced an increase in exurban areas since 1986 (6.1% per year; Chapter II) and by 2009, north and central Virginia and western Maryland had 7.3% of its territory occupied by exurban development (Chapter II). One reason for the increased exurban development is the easy access and well-maintain transportation infrastructure to the metropolitan Washington, DC area which provides employment opportunities even within the current economic climate (Weldon Cooper Center 2010).

Breeding Bird Survey

We used the North America Breeding Bird Survey (BBS; Peterjohn and Sauer 1994, Sauer et al. 2003) to gather bird species relative abundance data. The BBS is a large-scale annual roadside survey to monitor the status and trend of breeding bird populations in the United States and southern Canada since 1966. The survey is performed along secondary roads by experienced volunteer observers in late May to early July, the peak of the breeding season. Routes are 39.4 km long and consist of 50 survey stops located at 0.8 km intervals. During the survey, observers record all birds heard or seen within 0.4 km in a 3-min period. We focus our analysis on survey stops instead of the entire route because our interest was on local characteristics of breeding territories and routes might vary in local environmental conditions (Sauer et al. 1995, Veech and Crist 2007). From the 16 routes located in the study area, we uniformly selected at most 10 survey stops per route (every fifth stop along the route). We only considered survey stops that had detailed direction descriptions and fell within the study region (125 survey points in total; Figure 16). This information was important for geocoding and characterizing site-specific features of selected survey stops. A maximum of 10 stops per route was chosen to reduce overlap between circular areas around survey stops and decrease the likelihood of spatial autocorrelation.

We focused on 11 forest-nesting passerine species whose habitat preferences included forest specialists ─Ovenbird (*Seiurus aurocapilla*), Red-eyed Vireo (*Vireo olivaceus*), American Redstart (*Setophaga ruticilla*); forest generalists ─Wood Thrush (*Hylocichla mustelina*), Scarlet Tanager (*Piranga olivacea*), Eastern Wood-Pewee (*Contopus virens*), Eastern Phoebe (*Sayornis phoebe*); and forest edge species ─Eastern

Towhee (*Pipilo erythrophthalmus*), Gray Catbird (*Dumetella carolinensis*), Northern Cardinal (*Cardinalis cardinalis*), and Indigo Bunting (*Passerina cyanea*; Poole 2005). We defined forest specialists as species that favor interior forested habitats. Forest generalists are birds that utilized a wide variety of deciduous and mixed deciduous-coniferous forest types. Forest edge species are those species that are strongly associated with forest edges and open habitats (Mikusiñski et al. 2001). These species were selected to represent a range of habitat preferences and because they were detected on at least 5% of surveys during the 1986-2009 interval. In addition, many of these species have experienced population declines or reduced fecundity in their distribution range due to habitat loss or fragmentation (Hagan 1993, Sherry and Holmes1997, Donovan and Flather 2002, U.S. NABCI Committee 2009). Our study was designed to determine if the specific land conversion process of exurban development resulted in population changes for these species.

Landscape structure around Breeding Bird Survey stops

We established circular areas of 400 m and 1 km radius around selected BBS stops. These areas were chosen to characterize both breeding bird territories (Bowman 2003, Mazerolle and Hobson 2004) which were assumed to be in the immediate surroundings of survey stops and areas feasibly visited during bird daily movements (Krementz and Powell 2000, Lang et al. 2002). To quantify landscape structure around selected survey stops over time at these two extents, we used Landsat TM imagery for 1986, 1993, 2000, and 2009 and combined spectral mixture analysis, decision-tree classification, and morphological spatial pattern analysis to identify exurban development in the study region (Chapter II). This procedure allowed us to distinguish exurban areas from forest and urban areas and create a land-cover map that was used to characterize areas around survey stops.

We used FRAGSTATS 3.3 (2002) and GUIDOS 1.3 (Soille 2003, Vogt et al. 2007a) to estimate both landscape composition and configuration within the two circular areas around selected survey stops for 1986, 1993, 2000, and 2009. Landscape composition variables described the amount of habitat and included proportion of area occupied by forest and exurban development. Landscape configuration variables described the arrangement of forest habitat and included area-weighted average patch size, number of forest patches greater than 0.45ha, and proximity index (Gustafson and Parker 1992). Proximity index is a measure of isolation that considers both patch size and proximity of a focal patch to all forest patches around. We only considered forest patches ≥ 100ha within 2500m of the focal patch. A 2500m range was selected to reflect dispersal patterns of most songbirds (dispersal median distance range: 0.3 - 7.3 km; Sutherland et al. 2000). The proximity index increases as the neighborhood is increasingly occupied by forest patches and as those patches become closer and more contiguous or less isolated. GUIDOS was used because it identifies and graphically depicts the different aspects of the fragmentation process (Vogt et al. 2007a). The software package analyzes the geometry of map elements by applying mathematical morphological operators to allocate each pixel to one of a mutually exclusive set of classes. We used the proportion of forest interior (core class), forest fragments (islet class), and forest edge (edge and perforation classes).

We also estimated change in the amount of forest and exurban development between years to assess whether bird species responded to the change in landscape composition or to the proportion of habitat. Although some of these variables are not necessarily independent, many have been shown to affect abundance of birds (Ambuel and Temple 1983, Blake and Karr 1987, van Dorp and Opdam 1987, Robinson et al. 1995, Donovan and Flather 2002) and represent different aspects of potential breeding habitat degradation.

Analysis

BBS data have unknown precision due to observers' differences (Sauer et al. 1994), first-year observers' skills (Erskine 1978, Kendall et al. 1996), environmental conditions (Robbins et al. 1986), and habitat features (Sauer et al. 1995). We used a hierarchical Bayesian model to adjust BBS counts and account for these limitations. We modeled count data as hierarchical over-dispersed Poisson variables and fit models using Markov Chain Monte Carlo (MCMC) methods in WinBUGS 1.4.3 (Lunn et al. 2000). Hierarchical Bayesian models are frequently applied to BBS data (LaDeau et al. 2007, Link and Sauer 2002, Sauer and Link 2011) and are better able to account for variability in complex time series than previous, largely frequentists, methods (Clark 2005). We specified C_{it} as the count for each species on stop i and time t where i =1,..., N; t = 1,…, T; and N and T were the number of stops and the number of years species was observed, respectively. Conditioned on the model, counts (C_{it}) were independent across years and stops, and these conditional distributions for C_{it} were assumed to be Poisson with mean μ_{it}:

$$C_{it} \sim Pois(\mu_{it}) \quad (3)$$

The full model was then:

$$\log(\mu_{it}) = \beta_{0stop} + \beta_{1stop} * Year_t + \beta_2 * Firstyear_{it} + Route_{it} + Observer_{it} + Noise_{it} \quad (4)$$

where each stop was assumed to have a separate intercept (β_0) and time trend (β_1). The model also included several sources of variability including unknown route level effects ($Route_{i,t}$), observer effects ($Observer_{i,t}$), and an additional noise component ($Noise_{i,t}$) to help account for over-dispersion in the data. BBS observers tend to over or under-record certain species in their first year relative to subsequent years (Link and Sauer 2002, Link and Sauer 2007) and to incorporate this effect we treated an individual's first year ($First\ year_{it}$) as a binary indicator variable (β_2). The precision parameters (τ^2) for $\beta_{0\text{-}2}$, observer, route, and noise effects were assigned vague inverse gamma prior distributions (Berger 1985) with parameters (0.001, 0.001).

We used two Markov chains for each model and examined model convergence and performance through Gelman-Rubin diagnostics and the individual parameter histories (Gelman 2004, Link and Barker 2010). Time to convergence varied among species depending on the amount of data for that species (30,000 – 200,000 iterations required). Once convergence was reached we obtained derived estimates of the count at each stop and in each year, and these adjusted counts were then used for the threshold analysis. In addition, we estimated for each selected species the linear trend coefficient (i.e., the slope of abundance over time on a log scale) and percent annual change (the expected count in the last year divided by the expected count in the first year raised to 1/number of years). For trend coefficients (slope and percent annual change), we interpreted significance based on values with 95% credible intervals not overlapping zero.

We estimated potential species thresholds to landscape variables in space and time using Threshold Indicator Taxa ANalysis (TITAN; Baker and King 2010). TITAN identifies abrupt changes in both occurrence frequency and relative abundance of individual taxa along an environmental gradient. It is able to distinguish responses of individual taxa with low occurrence frequencies or highly variable abundances and does not assume linear response along all or part of an environmental gradient. TITAN uses normalized indicator species taxa scores (z) to establish a change-point location that separates the data into two groups and maximizes association of each taxon with one side of the partition. Z scores measure the association of taxon abundance weighted by their occurrence and is normalized to facilitate cross-taxa comparison. Thus, TITAN distinguishes negative (z-) and positive (z+) indicator response taxa.

To measure the quality of the indicator response and assess uncertainty around change-point locations, TITAN bootstraps the original dataset and recalculates change points with each simulation. The uncertainty is expressed as quantiles of the change-point distribution. Narrow intervals between upper and lower change-point quantiles (i.e., 5 and 95%) indicate nonlinear response in taxon abundance whereas broad quantile intervals are characteristic of taxa with linear or more gradual response. Diagnostic indices of the quality of the indicator response are purity and reliability. Purity is the proportion of bootstrap replicates that agree with the direction of the change-point for the observed response. Pure indicators (purity ≥ 0.95) are those that consistently assign the same response direction during the resampling procedure. Reliability is the proportion of change-point individual value scores (IndVal) among the bootstrap replicates that consistently have p-values below defined probability levels (0.05). Reliable indicators (reliability ≥ 0.95) are those with consistently large IndVal. Because purity and reliable indices did not differ for most metrics, we only reported the reliable index. We ran

TITAN for the 11 selected bird species and each of the landscape variables in R 2.11.1 (R Development Core Team 2011). We used five as the minimum number of samples on each side of a threshold split and 250 permutations to compute z scores and diagnostic indices. Five is the minimum number of observations required by TITAN to compute IndVal, z scores, and associated statistics and more than 250 permutations seem to be unnecessary to obtain precise individual taxa z scores in large dataset such as ours (Baker and King 2010).

Results

Breeding Bird Survey

There were 2481 counts on selected survey stops where at least one individual of the selected species was observed between 1986 and 2009. The Indigo Bunting was the most detected species (44.7% of surveys) and the Eastern Phoebe was the least detected (7.7%; Table 7). Forest edge species were the most abundant group (4374 individuals, adjusted mean 1.83) followed by forest generalists (2143, 0.90), and forest specialists (1535, 0.64). Annual mean adjusted abundances (i.e., posterior means) showed population trends of selected species between 1986 and 2009 accounting for differences in route, observer, and detection year (Figure 17). The Gray Catbird, Northern Cardinal, American Redstart, Ovenbird, and Red-eyed Vireo showed a significant increase in estimated abundance between 1986 and 2009 (Table 7). American Redstart had the highest percent change per year (3.1%). For the other six species, the estimated abundance did not significantly change through the 24-year period.

Landscape structure around Breeding Bird Survey stops

Landscape composition and configuration varied among years (Table 8). For the 400 m-radius buffer, amount of forest decreased from 49.2% in 1986 to 41.1% in 2009 whereas, the amount of exurban development increased from 1.7% in 1986 to 6.0% in 2009. The greatest change in the amount of forest and exurban development was between 2000 and 2009 (forest decreased by 5.0% and exurban development increased by 2.8%). Configuration of forest patches also differed among years. Although the number of forest patches greater than 0.45ha remained nearly constant, area-weighted average patch size decreased by an average of 2.1ha in the last time period. This decrease in patch size was accompanied by a 3.8% decrease in forest edge. As the amount of forest decreased from 1986 to 2009, forest interior declined from 39.8% to 29.3%, proportion of forest fragments rose by 8.5%, and proximity index decreased from 25,156.8 to 9884.6. In general, all metrics changed much more in later time periods than early years reflecting the increasing rate of exurban development in the study region.

Similar patterns were observed for the 1-km radius buffer except for the magnitude of some of the configuration variables. More forest patches greater than 0.45ha were found in the larger 1 km-radius buffer (1 km: 5.2 vs. 400 m: 1.6 mean number of patches), and these patches were generally bigger (125.3 vs. 20.7ha mean area-weighted patch size). The larger buffer also contained fewer forest fragments (19.9 vs. 31.9% in 2009), but underwent a greater loss in forest interior from 1986 to 2009 (6.5% for 1-km buffer vs. 4.4% for 400-m buffer).

Threshold response of bird species to landscape structure

In general, forest specialists exhibited threshold responses to both landscape composition and configuration as expected (Figure 18). For the 400 m-radius buffer for example, forest specialists (American Redstart, Ovenbird, and Red-eyed Vireo) were positive indicator taxa for the amount of forest (mean change point: 30.6%), forest interior (21.2%), area-weighted average patch size (7.1ha), and proximity index (9078.9). In contrast, they were negative indicator taxa for the amount of exurban development (0.3%), proportion of forest fragments (9.0%), and number of forest patches (1.5 patches). American Redstart was the only forest specialist that responded negatively to forest edge (change point: 29.1%), whereas Red-eyed vireo and Ovenbird responded positively (16.1%). Red-eyed Vireo also responded positively to increased exurban development (11.9%) and to the number of forest patches and was the only forest specialist species that responded negatively to the rate of change in the amount of forest between 1986 and 2009 (1.26%; Table 9).

Forest generalists had relatively consistent threshold responses. For the 400 m-radius buffer for example, three of the forest generalist species (Wood Thrush, Scarlet Tanager, and Eastern Wood-Pewee) were positive indicator taxa for the amount of forest (mean change point: 18.0%), forest interior (9.2%), area-weighted average patch size (4.3ha), proximity index (9817.6), and forest edge (10.3%). In contrast, they were negative indicator taxa for the amount of exurban development (0.1%), proportion of forest fragments (30.4%), and number of forest patches greater than 0.45ha (0.8 patches). Scarlet Tanager and Eastern Phoebe were the only forest generalists that were negatively impacted by the magnitude of forest reduction (1.2%). In addition, Eastern Phoebe was the only forest generalist that declined with 100% amount of forest, proportion of forest interior (76.7%), and area-weighted average patch size (49.3ha). This species unexpectedly responded positively to the amount of exurban development (1.4%), proportion of forest fragments (0.2%), and number of forest patches (Table 9).

Forest edge species varied in their threshold response to landscape composition and most of the configuration metrics at both extents (Figure 18). For the 400 m-radius buffer for example, all forest edge species responded positively to the number of forest patches (mean change point: 0.6 patches). Gray Catbird and Northern Cardinal increased sharply with amount of exurban development and proportion of forest fragments (Table 9). These two species responded negatively to the amount of forest (97.3%), forest interior (47.3%), area-weighted average patch size (46.7ha), and proximity index (23725.3). Eastern Towhee and Indigo Bunting were positive indicator taxa for the amount of forest (13.5%), forest interior (25.2%), area-weighted average patch size (3.7ha), proximity index (6621.0), and forest edge (2.4%), and were negative indicator taxa for the proportion of forest fragments (23.0%). Eastern Towhee was the only forest edge species that responded negatively to the amount of exurban development (0.2%) and had similar change points to those exhibited by forest specialists.

Although selected bird species exhibited threshold responses, the quality of the indicator and certainty around change-point locations varied for some landscape structure variables. For example, the forest specialist Red-eyed Vireo responded positively to the amount of exurban development. However, the indicator was moderately reliable for the 400 m-radius buffer (reliability = 0.70; Table 9). Reliability also changed with extent of analysis for some species and indicators. For example, the forest generalist Eastern

Phoebe was moderately reliable indicator for the proximity index within 400 m-radius buffer (reliability = 0.74) but was unreliable for 1 km-radius buffer (reliability = 0.38). Gray Catbird, an edge species, had a positive response for the number of forest patches greater than 0.45ha within the 400-m radius buffer and a negative response within the 1-km radius buffer. However, the reliability for the 1 km-radius buffer was poor (reliability = 0.32). In general, where there were differences in reliability at different extents, the 400-m relationships were more reliable.

Regarding certainty around change-point locations, forest specialists had relatively narrow bootstrapped change-point distributions for most landscape structure characteristics indicating confidence about the existence of a threshold. For some landscape structure characteristics, forest generalists exhibited variable bootstrapped change-point distribution width. For example, some species (e.g., Eastern Wood-Pewee) had a sharp response to the amount of forest whereas others (e.g., Eastern Phoebe) had a more gradual response. In general, forest edge species (except for Eastern Towhee) had broad bootstrapped change-point distribution suggesting a more gradual response for most landscape structure characteristics.

Similar patterns in threshold response were observed for the two buffer widths except for number of forest patches greater than 0.45ha and proportion of forest edge. In the case of these two variables, the direction of the response for roughly half of the species changed with the extent. In most cases, the direction of the response was positive for the 400 m-radius buffer but negative for the 1 km-radius buffer. However, the quality of indicators for the proportion of forest edge was moderately reliable for the 1 km-radius buffer. None of the selected species had a reliable threshold response to change in the amount of exurban development in any of the extents.

Discussion

Our results demonstrate that exurban development deteriorated breeding territories by reducing forest cover and increasing habitat fragmentation. In addition, selected forest bird species exhibited threshold responses to breeding habitat deterioration in both the immediate surroundings and adjacent foraging areas. Responses to changes in landscape structure varied according to species' habitat preferences. For example, species that positively responded to the amount of exurban development (e.g., Northern Cardinal) are often found throughout a range of habitats from shrubby sites in logged and second-growth forests to plantings around buildings (Halkin and Linville1999). Sensitive species who responded negatively to amount of exurban development (e.g., Wood Thrush) are more frequently found in well-developed deciduous and mixed forests (Evans et al. 2011). However, none of the selected species responded to the change in amount of exurban development. This suggests that for the time period considered the magnitude of change was marginal when compared to the changes induced to the landscape structure. Our results support the existence of nonlinear responses to habitat loss and fragmentation (Andrén 1994, Betts et al. 2007, Zuckerberg and Porter 2010) and that the variation in sensitivity to alteration of landscape structure depends on species habitat specificity (Andrén et al. 1997, Betts et al. 2007).

Despite breeding habitat deterioration (e.g., loss of forest and increase of exurban development), populations significantly increased during the 24-year period for five of the 11 species analyzed. Two of the forest edge species (Northern Cardinal and Gray

Catbird) increased their population between 1986 and 2009. These species are known to be found in forest edges and clearings, fencerows, abandoned farmland, or residential areas. Thus, larger population in exurban areas may indicate that these species have been taking advantage of the increased availability of suitable breeding habitats and supplemental feeding provided by landowners (Lepczyk et al. 2004). Although we did not expect to find a threshold response, the direction of the response showed by these species corresponded with their habitat preferences. In other words, these species were indicators of habitat fragmentation due to exurban development (e.g., increased in abundance with increase in forest fragments and decrease in forest interior). The species also had broad change-point distributions indicating gradual responses to the land cover change.

The other three species that experienced population increases were forest specialists (American Redstart, Red-eyed Vireo, and Ovenbird). This was surprising given documented population declines for the Red-eyed Vireo and the Ovenbird due to habitat loss and fragmentation (e.g., Donovan and Flather 2002, U.S. NABCI Committee 2009). The population increase of American Redstart and Red-eyed Vireo is likely related to the forest opening created by exurban development. American Redstart and Red-eyed Vireo are forest birds but seem to occur more frequently in early and mid-successional forest habitats and even start to decline as forests mature (Graber et al. 1985, Hunt 1998, Holmes and Sherry 2001). Thus, the type of forest disturbance associated with exurban development may benefit these species. The regrowth of eastern forests due to farmland abandonment since the early twentieth century (Matlack 1997, Smith et al. 2004, Bowen et al. 2007) may explain the slight increase of Ovenbird populations.

However, this species showed a strong threshold response to amount of forest, suggesting that the species is sensitive to reduced forest cover. It seems that population increase in the region is occurring disproportionately in relatively old-growth forests adjacent to exurban areas and dispersal among these areas can confound the negative effects that forest degradation (Donovan and Flather 2002) in exurban areas may have.

Although species showed similar response patterns at both extents, for two of the landscape configuration variables (number of patches and forest edge), the direction of the response changed with the extent. Similar results were found by Smith et al. (2011) who demonstrate that fragmentation effects depend on the landscape extent considered. Thus, the extent should be explicitly accounted for when evaluating the effects of these two metrics on forest birds.

Some notable differences in group sensitivity to landscape composition and configuration occurred. In general, forest specialists were most sensitive to habitat loss and fragmentation followed by forest generalists. Although the majority of species responses were consistent with our classification regarding habitat preferences, there were two species (Eastern Phoebe and Eastern Towhee) whose response did not correspond to the assigned group. Eastern Phoebe is generally a woodland species (Hill and Gates 1988) and was classified as a forest generalist. However, this species had threshold responses similar to those exhibited by forest edge species for most of the landscape structure variables. This may be explained by nest placement preferences. Eastern Phoebe is mostly constrained by availability of suitable nest sites (Hill and Gates 1988) and nests are often located on bridges, culverts, buildings, and rock outcrops in the vicinity of water (Weeks 2011). Thus, change in landscape structure due to exurban development may benefit this species but further monitoring of its population is recommended. In contrast, Eastern Towhee exhibited a response similar to those showed by forest specialists. This species is thought of as an edge-associated generalist and places its nests on or above ground, usually at 1.5 m in shrubby areas (Greenlaw 1996). However, these results suggest that Eastern Towhees may be more sensitive to breeding habitat degradation due to exurban development than previously expected.

The threshold responses that we detected for selected forest bird species indicate that species were affected in a nonlinear fashion by breeding habitat deterioration. However, the thresholds observed may not necessarily be similar for forest bird communities as a whole. In addition, threshold responses detected should not be used as a point below which a population will not persist (Betts et al. 2010) but rather as guidelines for management practices in areas prone to exurban development.

Conclusion

Rural private lands in the Mid-Atlantic region are being converted to exurban development at high rates and present a potentially serious threat to eastern deciduous forest ecosystems (Chapter II). Moreover, this trend is likely to continue into the future (Theobald 2005). Our results show that exurban development is degrading breeding habitats and that forest birds exhibited a threshold response to landscape structure alteration in both the immediate vicinity of breeding territories and adjacent foraging areas. The majority of forest birds' responses could be predicted by their habitat preferences indicating that management practices in exurban areas need to consider species requirements. In addition, the range at which forest birds exhibited strong threshold response to habitat loss and fragmentation in exurban areas may guide planners and managers in mitigating effects of exurban development.

Table 7. Hierarchical-model estimates based on Breeding Bird Survey stops for forest specialist, forest generalists, and forest edge species. American Ornithologist´s Union alpha codes for English common names are in parenthesis. For each species, the number of total detections (percentages), adjusted abundance (mean ± sd), trend coefficient (slope on a log scale of abundance over time), and percent change per year are shown. Values in bold font indicate 95% credible intervals not over-lapping zero.

Species	Number of total detections	Mean adjusted abundance	Trend coefficient	Percent change/year
Forest specialists				
American Redstart (AMRE)	225 (9.1)	0.132 ± 0.015	**0.042**	**3.10**
Ovenbird (OVEN)	248 (10.0)	0.137 ± 0.016	**0.029**	2.70
Red-eyed Vireo (REVI)	632 (25.5)	0.373 ± 0.027	**0.024**	**2.70**
Forest generalists				
Eastern Phoebe (EAPH)	190 (7.7)	0.090 ± 0.014	0.005	1.80
Eastern Wood-Pewee (EAWP)	490 (19.8)	0.237 ± 0.018	-0.001	-0.20
Scarlet Tanager (SCTA)	364 (14.7)	0.180 ± 0.018	-0.004	0.30
Wood Thrush (WOTH)	618 (24.9)	0.396 ± 0.027	0.008	1.10
Forest edge species				
Eastern Towhee (EATO)	526 (21.2)	0.313 ± 0.025	0.007	1.00
Gray Catbird (GRCA)	509 (20.5)	0.401 ± 0.048	**0.025**	**2.80**
Indigo Bunting (INBU)	1108 (44.7)	0.657 ± 0.031	-0.006	0.50
Northern Cardinal (NOCA)	808 (32.6)	0.461 ± 0.027	**0.022**	**1.50**

Table 8. Descriptive statistics of landscape structure variables surrounding selected Breading Bird Survey stops (n = 125) at 400m- and 1 km-radius buffer (mean ± sd) for 1986, 1993, 2000, and 2009.

Variables	1986	1993	2000	2009
400 m-radius buffer				
Forest (%)	49.2 ± 39.3	48.3 ± 39.3	46.2 ± 39.4	41.2 ± 39.2
Exurban development (%)	1.7 ± 2.5	2.1 ± 2.6	3.1 ± 3.4	6.0 ± 6.8
Change in forest (%)	-	-0.9 ± 1.7	-2.1 ± 2.8	-5.0 ± 6.1
Change in exurban development (%)	-	0.4 ± 0.9	1.0 ± 1.4	2.8 ± 4.1
Forest interior (%)	39.8 ± 32.2	38.1 ± 31.9	35.8 ± 31.8	29.3 ± 32.4
Area- weighted average patch size (ha)	22.2 ± 20.8	21.7 ± 20.7	20.6 ± 20.6	18.5 ± 20.5
Forest fragments (%)	23.4 ± 35.7	23.5 ± 35.6	25.1 ± 37.9	31.9 ± 40.9
Number of forest patches (> 0.45 ha)	1.7 ± 1.1	1.7 ± 1.2	1.6 ± 1.2	1.6 ± 1.4
Forest edge (%)	24.1 ± 14.7	24.3 ± 14.8	24.5 ± 16.4	20.7 ± 16.2
Proximity index	25156.8 ± 071.5	23165.1 ± 749.6	14763.0 ± 2712.3	9884.6 ± 4949.1
1 km-radius buffer				
Forest (%)	51.0 ± 35.7	50.0 ± 35.6	47.9 ± 35.7	42.7 ± 35.8
Exurban development (%)	1.8 ± 1.6	2.2 ± 1.9	3.2 ± 2.6	6.2 ± 5.6
Change in amount of forest (%)	-	-1.0 ± 1.3	-2.7 ± 2.4	-5.2 ± 5.0
Change in exurban development (%)	-	0.5 ± 0.7	1.0 ± 1.2	3.0 ± 3.4
Forest interior (%)	55.6 ± 28.9	53.1 ± 28.9	49.4 ± 30.2	40.1 ± 32.4

Area- weighted average patch size (ha)	134.4 ± 123.5	131.8 ± 123.1	123.2 ± 121.7	111.6 ± 121.3
Forest fragments (%)	10.2 ± 17.8	11.2 ± 19.6	14.4 ± 24.5	19.9 ± 28.8
Number of forest patches (> 0.45 ha)	5.0 ± 4.2	5.0 ± 4.2	5.3 ± 4.3	5.4 ± 4.4
Forest edge (%)	23.6 ± 11.3	24.5 ± 11.8	24.4 ± 12.6	22.5 ± 12.8
Proximity index	25957.0 ± 205.7	23906.8 ± 060.7	15272.4 ± 1243.6	10533.3 ± 4917.0

Table 9. Threshold Indicator Taxa ANalysis (TITAN) results for forest specialist, forest generalists, and forest edge species for 400 m- and 1 km-radius buffer. Only significant species at a 0.05 significant level are shown.

	400m-radius buffer						1km-radius buffer					
			Change point						Change point			
	Indicator	z	Obs.	5%	95%	Reliability	Indicator	z	Obs.	5%	95%	Reliability
Forest (%)												
AMRE	z+	14.91	33.15	28.23	69.35	1.00	z+	15.98	37.45	24.79	57.14	1.00
OVEN	z+	18.46	24.69	16.97	49.69	1.00	z+	18.18	29.41	25.12	54.55	1.00
REVI	z+	22.08	33.93	15.16	49.69	1.00	z+	22.85	36.79	19.27	43.45	1.00
EAPH	z-	10.52	100.00	11.14	100.00	0.94	z-	9.75	99.95	12.59	100.00	0.71
EAWP	z+	19.50	9.64	8.11	17.67	1.00	z+	15.26	16.22	12.10	38.36	1.00
SCTA	z+	26.69	24.64	14.75	39.52	1.00	z+	26.40	28.36	22.85	41.30	1.00
WOTH	z+	19.93	19.61	4.57	28.17	1.00	z+	18.20	21.97	16.67	37.91	1.00
EATO	z+	19.68	24.64	14.97	68.77	1.00	z+	18.80	55.04	29.21	69.74	1.00
GRCA	z-	5.65	95.57	12.32	94.27	0.99	z-	5.42	16.22	14.98	84.17	1.00
INBU	z+	14.72	2.32	1.16	6.08	1.00	z+	11.70	9.98	2.99	12.94	1.00
NOCA	z-	26.62	98.93	89.88	100.00	1.00	z-	25.56	98.68	88.77	100.00	1.00
Exurban development (%)												
AMRE	z-	12.35	0.36	0.18	1.43	1.00	z-	12.97	1.40	1.21	1.89	1.00
OVEN	z-	14.21	0.18	0.00	0.85	1.00	z-	13.85	1.35	0.28	1.71	1.00
REVI	z+	5.46	11.94	0.00	12.31	0.70	z+	6.59	4.50	0.19	7.97	0.87
EAPH	z+	11.72	1.44	0.18	3.28	1.00	z+	12.52	0.71	0.57	3.08	1.00
EAWP	z-	5.86	0.00	0.00	8.63	0.86	z-	5.82	0.31	0.00	4.40	0.92
SCTA	z-	9.68	0.18	0.00	0.18	0.99	z-	9.83	0.29	0.00	1.03	0.98
WOTH	z-	7.62	0.18	0.00	4.11	0.94	z-	8.70	0.83	0.22	1.28	1.00
EATO	z-	13.50	0.18	0.00	0.36	1.00	z-	14.14	0.22	0.02	1.17	1.00
GRCA	z+	3.02	0.00	0.00	9.01	0.84	z+	4.01	0.11	0.00	3.76	0.98
INBU	z+	4.61	2.14	0.71	9.09	0.94	z+	2.73	4.41	0.11	7.81	0.62

NOCA	z+	17.07	0.00	0.00	0.18	1.00	z+	27.10	0.00	0.00	0.29	1.00
Change in amount of forest (%)												
REVI	z-	4.61	-1.26	-4.10	-1.07	0.98	z-	6.05	-2.24	-3.87	-1.40	1.00
EAPH	z-	7.90	-5.48	-6.42	-0.36	1.00	z-	7.87	-3.32	-5.42	-0.37	1.00
SCTA	z-	5.65	0.00	-2.39	0.00	0.83	z-	5.54	-1.38	-2.51	0.00	0.88
Forest interior (%)												
AMRE	z+	14.90	29.35	17.28	51.58	1.00	z+	15.44	51.57	33.32	62.69	1.00
OVEN	z+	16.61	29.51	8.31	50.86	1.00	z+	16.34	46.55	38.31	66.01	1.00
REVI	z+	17.78	5.88	3.29	28.07	1.00	z+	17.58	32.01	29.28	47.99	1.00
EAPH	z-	9.73	76.69	66.39	81.55	0.99	z-	10.13	83.51	80.60	92.37	1.00
EAWP	z+	19.64	10.53	1.98	16.30	1.00	z+	12.53	31.48	10.86	63.11	1.00
SCTA	z+	23.17	6.85	4.96	25.12	1.00	z+	21.29	40.08	31.06	57.38	1.00
WOTH	z+	20.72	10.20	1.48	20.36	1.00	z+	14.84	33.81	11.19	62.51	1.00
EATO	z+	18.10	50.49	2.00	56.02	1.00	z+	16.97	62.58	54.54	70.31	1.00
GRCA	z-	5.95	15.67	12.28	81.49	1.00	z-	5.07	27.88	23.42	81.74	1.00
INBU	z+	11.68	0.00	0.00	10.50	1.00	z+	10.39	11.91	7.12	23.46	1.00
NOCA	z-	27.08	78.87	67.28	81.61	1.00	z-	26.64	83.02	79.14	92.44	1.00
Area-weighted average patch size (ha)												
AMRE	z+	15.24	6.55	7.26	29.42	1.00	z+	15.43	28.30	36.48	125.34	1.00
OVEN	z+	18.16	9.13	4.77	26.44	1.00	z+	16.87	27.85	33.63	150.75	1.00
REVI	z+	21.27	5.69	3.46	20.04	1.00	z+	21.24	71.36	21.01	98.24	1.00
EAPH	z-	9.70	49.28	19.57	50.11	0.95	z-	9.89	295.16	11.54	313.66	0.87
EAWP	z+	17.78	2.40	1.94	7.46	1.00	z+	14.40	25.49	9.33	99.18	1.00
SCTA	z+	24.75	5.69	3.59	13.37	1.00	z+	23.51	52.89	17.56	109.40	1.00
WOTH	z+	22.31	4.89	2.02	7.49	1.00	z+	17.28	89.31	19.02	113.37	1.00
EATO	z+	19.47	7.12	2.74	31.99	1.00	z+	17.47	129.26	69.60	165.96	1.00
GRCA	z-	5.77	43.79	3.01	48.96	0.99	z-	6.20	177.78	8.62	234.90	1.00
INBU	z+	12.54	0.33	0.19	1.69	1.00	z+	9.31	6.18	1.17	7.95	1.00

NOCA	z-	26.81	49.55	44.66	49.86	1.00	z-	25.91	309.60	264.68	312.12	1.00
Forest fragments (%)												
AMRE	z-	14.77	3.22	0.60	7.67	1.00	z-	15.74	7.09	1.79	8.64	1.00
OVEN	z-	16.26	2.33	0.65	15.53	1.00	z-	17.11	2.67	1.16	6.72	1.00
REVI	z-	19.09	21.51	3.79	35.60	1.00	z-	21.57	2.98	2.71	10.98	1.00
EAPH	z+	6.97	0.20	0.00	0.61	0.98	z+	9.78	0.02	0.00	19.40	0.83
EAWP	z-	16.01	38.00	4.22	55.40	1.00	z-	14.31	2.98	2.03	19.36	1.00
SCTA	z-	21.71	27.63	4.99	42.86	1.00	z-	21.97	14.01	3.36	18.08	1.00
WOTH	z-	18.53	25.68	15.96	53.97	1.00	z-	17.97	14.76	2.94	18.21	1.00
EATO	z-	16.44	1.30	0.59	39.88	1.00	z-	16.78	1.32	0.91	9.79	1.00
GRCA	z+	6.65	3.97	0.00	26.11	1.00	z+	5.45	2.52	0.16	19.40	1.00
INBU	z-	7.98	44.77	15.40	100.00	0.99	z-	12.97	26.75	17.50	31.77	1.00
NOCA	z+	17.03	0.21	0.00	0.58	1.00	z+	25.06	0.02	0.00	0.12	1.00
Number of forest patches												
AMRE	z-	12.47	2.00	1.00	2.00	0.99	z-	14.48	6.00	3.45	7.00	1.00
OVEN	z-	14.32	1.00	1.00	2.00	1.00	z-	16.29	2.00	2.00	6.00	1.00
REVI	z+	14.27	0.00	0.00	1.00	1.00	z-	16.05	5.00	4.00	6.28	1.00
EAPH	z+	8.79	2.00	1.00	2.00	1.00	z+	6.26	2.00	1.00	3.00	1.00
EAWP	z+	11.96	1.00	0.00	1.00	0.98	z-	9.00	3.00	1.00	6.00	1.00
SCTA	z+	14.62	0.00	0.00	1.00	1.00	z-	17.05	5.00	3.00	6.00	1.00
WOTH	z+	16.24	0.00	0.00	1.00	1.00	z-	9.56	3.00	1.00	6.00	0.99
EATO	z+	11.23	0.50	0.00	2.00	0.85	z-	14.78	5.00	2.00	5.00	1.00
GRCA	z+	4.27	1.00	1.00	4.00	0.78	z-	5.44	13.00	1.00	13.00	0.32
INBU	z+	13.93	0.00	0.00	1.00	1.00	z+	3.28	0.00	0.00	14.00	0.92
NOCA	z+	9.11	1.00	1.00	2.00	1.00	z+	17.72	1.00	1.00	2.00	1.00
Forest edge (%)												
AMRE	z-	12.16	29.12	24.18	35.78	0.98	z-	14.97	28.02	23.19	29.16	1.00
OVEN	z+	13.72	16.08	0.00	25.58	0.84	z-	15.51	23.94	16.01	30.38	1.00
REVI	z+	16.36	16.08	0.00	16.87	1.00	z-	9.43	28.27	6.81	32.85	0.87

EAPH	z+	9.75	23.53	18.31	25.72	1.00	z+	11.49	12.03	9.68	16.06	1.00
EAWP	z+	16.84	16.73	0.00	16.88	1.00	z-	6.83	27.73	0.00	36.53	0.82
SCTA	z+	19.79	15.42	0.00	16.76	1.00	z-	13.53	24.16	22.91	30.61	0.97
WOTH	z+	18.41	11.60	0.00	16.75	1.00	z+	8.80	5.96	0.00	28.55	0.46
EATO	z+	16.11	0.00	0.00	16.70	1.00	z-	14.06	13.02	9.42	26.19	1.00
INBU	z+	10.33	4.73	0.00	17.46	0.98	z+	5.33	2.93	0.00	34.48	0.98
NOCA	z+	11.41	19.83	18.35	25.94	0.98	z+	18.68	13.02	7.56	16.01	1.00
Proximity index												
AMRE	z+	8.45	9075.3	9008.0	23749.3	0.92	z+	8.08	8910.6	8688.6	9108.2	0.97
OVEN	z+	9.03	9075.3	8993.5	9108.2	1.00	z+	7.65	9108.2	8711.5	23749.3	0.96
REVI	z+	7.71	9086.1	8829.7	12855.1	0.94	z+	6.14	9023.7	8737.5	19193.7	0.46
SCTA	z+	10.46	9075.3	8993.5	9108.2	1.00	z+	8.65	9023.7	8610.9	9108.2	1.00
WOTH	z+	7.45	0.0	0.0	9076.1	0.97	z+	2.74	23739.6	8409.9	36803.3	0.53
EATO	z+	6.66	8865.9	0.0	9108.2	0.97	z+	5.38	8688.6	8637.5	27322.3	0.84
GRCA	z-	5.72	23749.3	9108.2	25507.3	0.98	z-	6.01	24914.9	9108.2	27801.1	1.00
INBU	z+	7.21	4376.1	0.0	25811.3	0.78	z-	3.10	8449.8	8394.4	32095.0	0.98
NOCA	z-	6.36	23701.4	9048.2	25674.9	0.99	z-	7.12	23747.8	8820.7	25780.0	1.00

Note: TITAN observed change points (obs.) and bootstrap confidence intervals (among 250 simulation iterations) correspond to the value of independent variables resulting in the largest z scores for each taxon. Purity is the mean proportion of correct response direction (z- or z+) assignments and reliability is the mean proportion of p-values ≤ 0.05 among 250 simulation iterations.

Taxa IDs correspond to the American Ornithologist´s Union alpha codes for English common names.

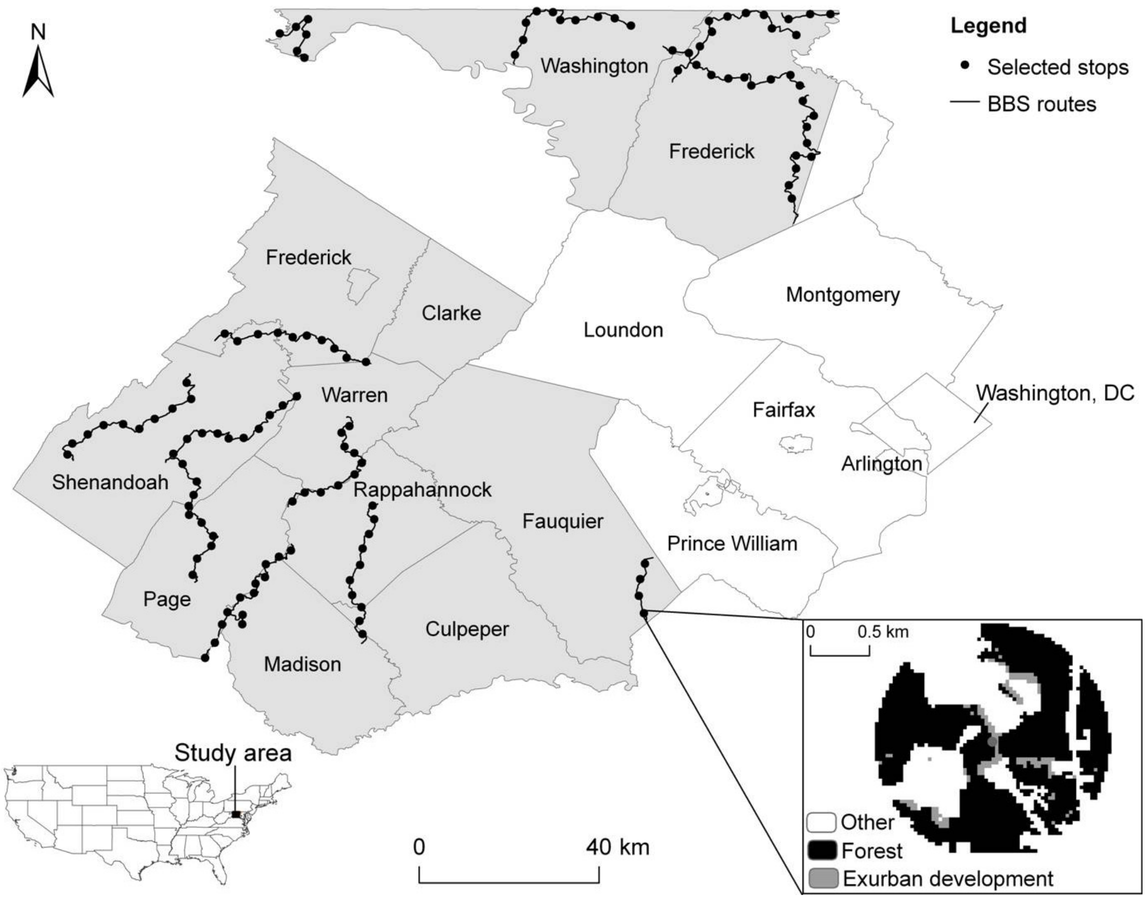

Figure 16. The study region (shaded area) includes nine counties in north and central Virginia and two counties in western Maryland. From the North American Breeding Bird Survey (BBS) routes located in the study area, 125 survey stops (circles) were uniformly selected. Zoom-in window shows an example of a landscape within a 1 km radius circular area around one of the selected survey stops.

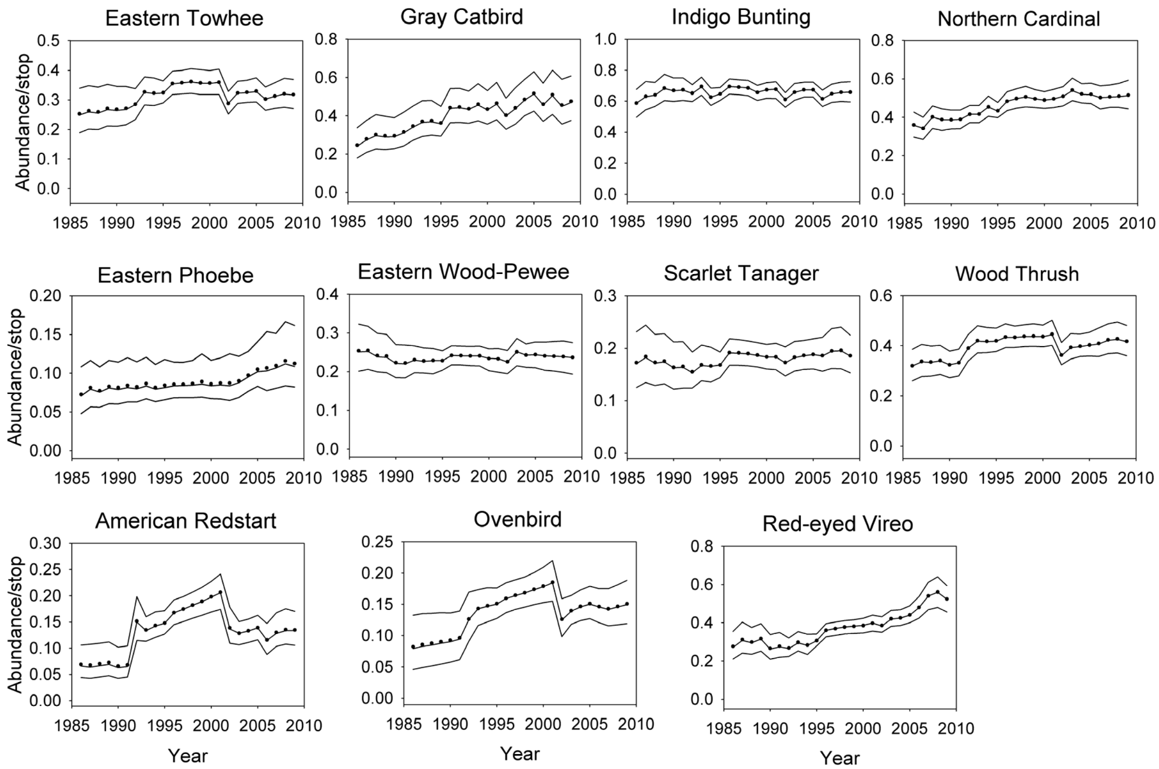

Figure 17. Time series of mean abundance adjusted for missing observations and observer differences. The lines indicate the posterior median (line nearly coincident with the circles) with 95% confidence intervals.

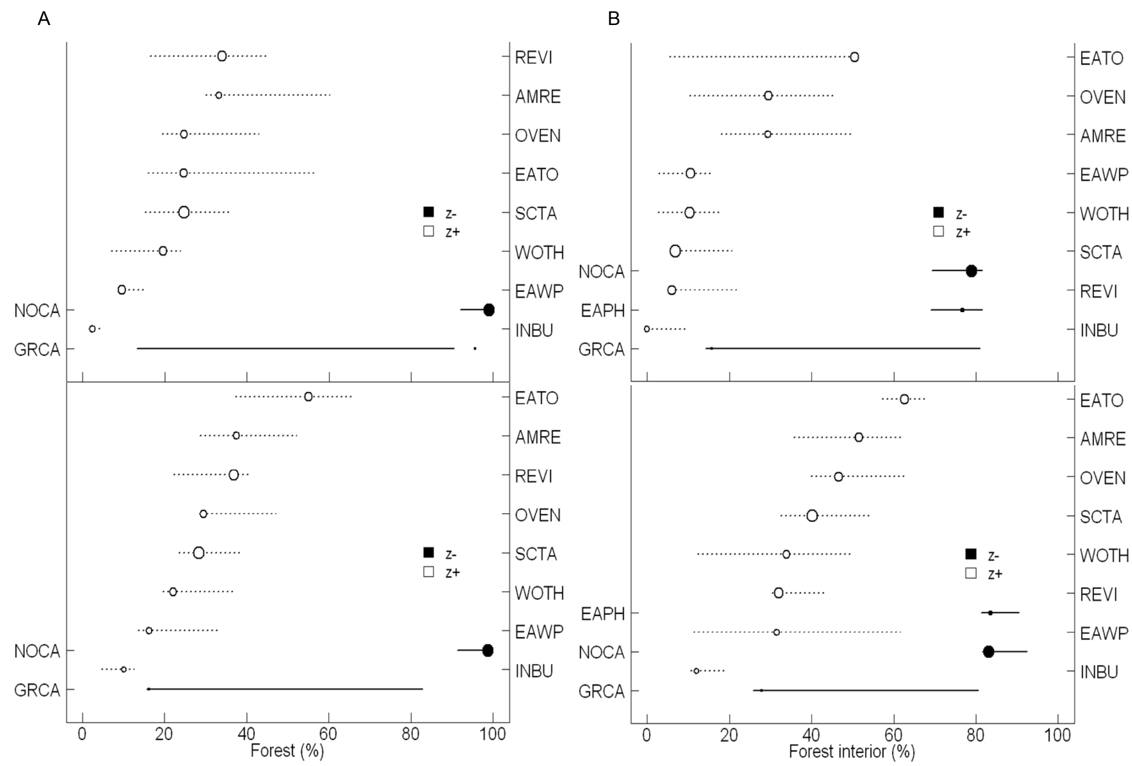

Figure 18. Threshold Indicator Taxa ANalysis (TITAN) using landscape variables as a predictor of threshold changes in individual bird species in 400 m (top panel) and 1 km circular area (bottom panel) between 1986 and 2009 in north and central Virginia and western Maryland. Only indicator taxa (purity ≥ 0.95 and reliability ≥ 0.95) are plotted in increasing order with respect to their observed change point. Solid circles correspond to negative (z-) indicator taxa and open circles correspond to positive (z+) indicator taxa. Circles are size in proportion to z scores. Lines overlapping each circle represent 5th and 95% percentiles among 250 bootstrap replicates. Landscape variables evaluated were (A) forest, (B) forest interior, (C) area-weighted averaged patch size, (D) exurban development, (E) forest fragments, (F) number of forest patches, (G) proximity index, and (H) forest edge. Taxa IDs correspond to the American Ornithologist´s Union alpha codes for English common names.

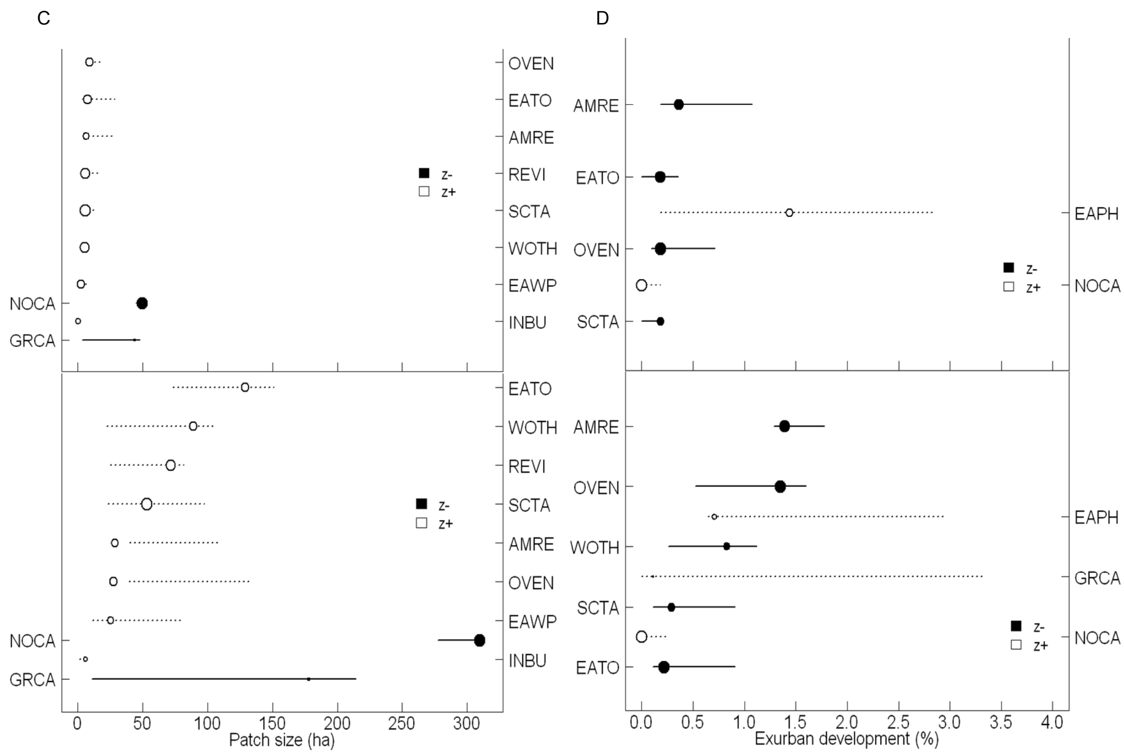

Figure 18 continued

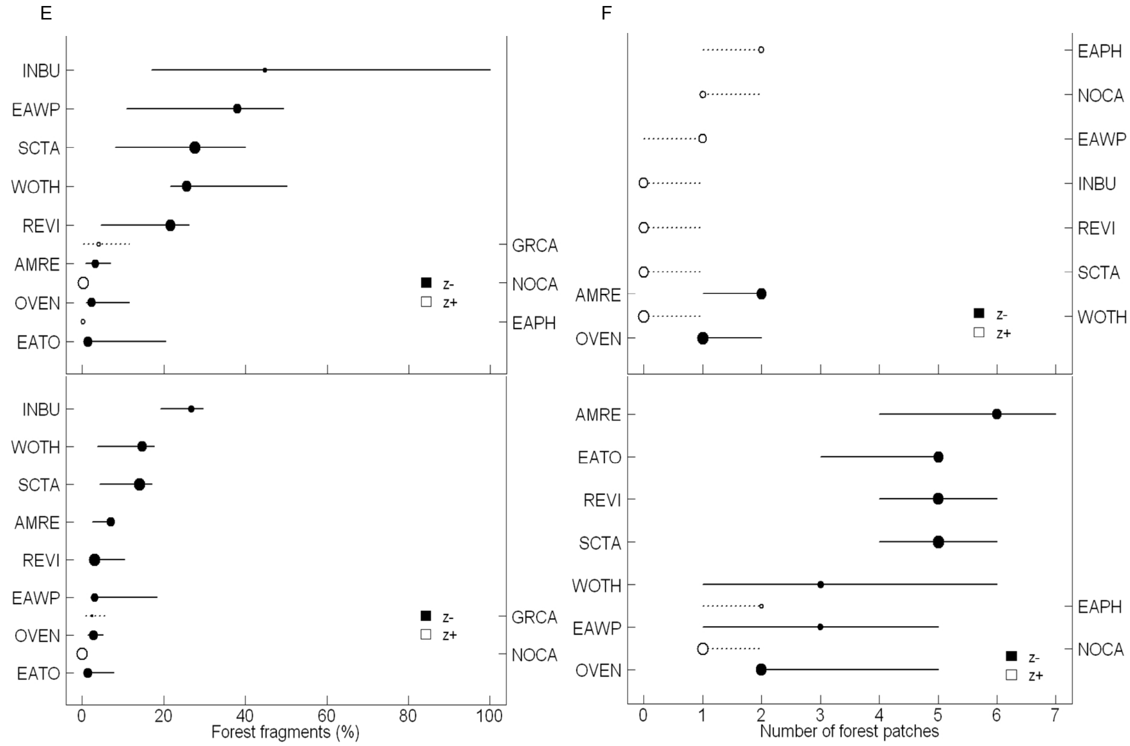

Figure 18 continued

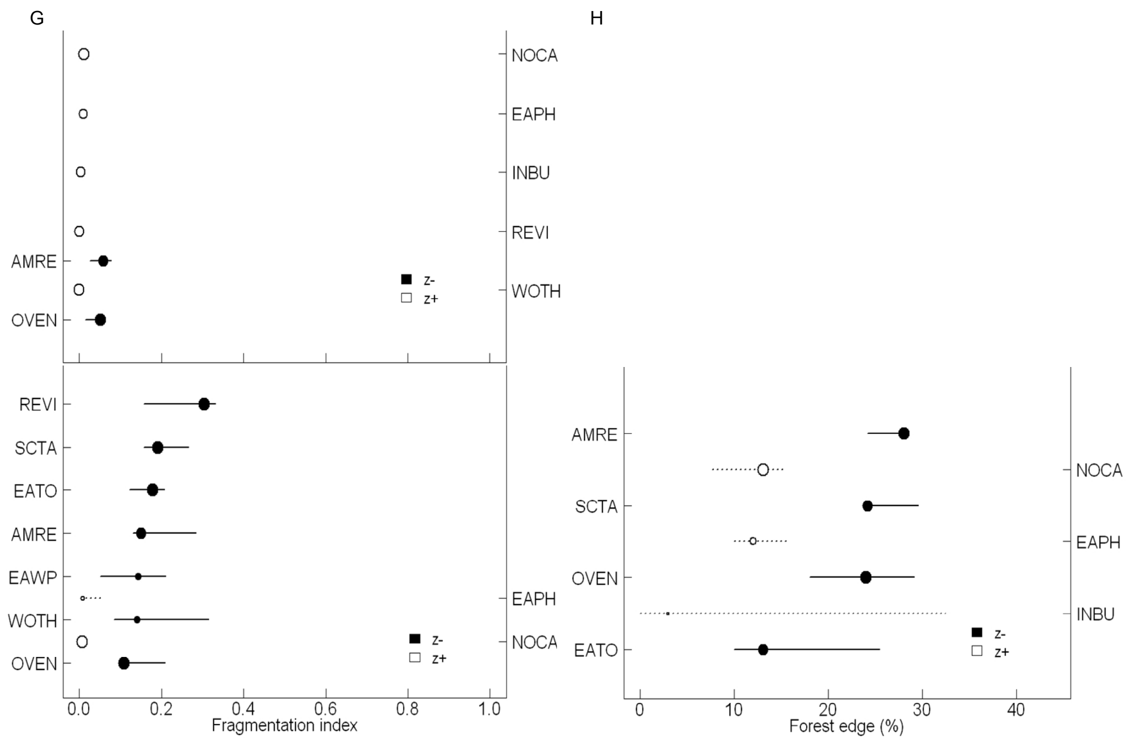

Figure 18 continued

CHAPTER V

CONCLUSION

Exurban development is a prevalent form of land-use change in the contiguous United States and is increasing faster than metropolitan areas (Brown et al. 2005, Hansen et al. 2005). The location of exurban development is correlated with natural and recreational amenities that humans desire, raising concerns about its effects on biodiversity and ecosystem processes. However, exurban development characteristics of scattered, isolated housing units within a landscape dominated by native vegetation have hindered the assessment of its effects. In an effort to enhance our understanding of land conversion to exurban development in the Mid-Atlantic region, I have developed a new approach to map exurban development (Chapter II), evaluated exurban historical trends to comprehend drivers of this type of development (Chapter III), and assessed whether forest birds respond, and if so in a nonlinear fashion, to changes in breeding habitats due to exurban growth (Chapter IV).

The identification and quantification of exurban development was estimated here by the development of a novel analytical approach which identified mixed pixels containing exurban development (Chapter II). This approach then used decision-tree classification and morphological spatial pattern analysis to separate exurban development from other forest disturbing events, overcoming many of the obstacles previously associated with mapping this increasingly common land-use class. The methodology was found to be robust and can be used in other regions depending on the availability of reference data sources (e.g., aerial photos) for the development of the training data required to interpret changes. However, as for any application using remote sensing data, the pre-processing step is critical to ensure that the change recorded is not due to changes in spectral properties of pixels throughout the imagery (Kennedy et al. 2009).

Exurban development has become a pervasive and fast-growing form of land-use change in the Mid-Atlantic region. As in other regions of the country, exurban development is expanding into rural landscapes and along protected areas at high rates. By 2009, total exurban land cover was 7% in north and central Virginia and western Maryland. The rate of exurban expansion (6% per year) was much higher than the national average (2% per year; Theobald 2005) but similar to other areas of the US experiencing high population growth (e.g. Mountain West: 8% per year; Hansen et al. 2002). This suggests that eastern deciduous forests of the Mid-Atlantic are facing high pressure from exurban development and there is a danger of losing these diverse and valuable habitats. The improved understanding of the spatial and temporal patterns of exurban development I have provided offer the potential for land managers and conservation practitioners to better manage growth in rural residential development areas.

Understanding the drivers of this land conversion and establishing which analytical tools make reliable projections across temporal and spatial scales can help anticipate future exurban development and its effects (Chapter III). Once the spatial and temporal patterns of exurban development were identified, I could determine factors that have been driving exurban growth since 1986 and analyze the role of historical spatial patterns and individuals' decisions in shaping exurban patterns. Human preference for certain attributes on the landscape (i.e., environmental amenities and landscape configuration surrounding landowners' land) played a major role in the hazard of conversion. Land conversion to exurban development was effectively captured by the spatially-explicit econometric model at both local and county scales and the pattern-based model only performed well at the county scale. Thus, pattern-based models like SLEUTH can forewarn potential coarse-scale losses of natural resources in exurban areas, but are less useful at finer scale or for assessing potential consequences of land-use policy on people's behavior. This knowledge can be used by local and regional governments to guide land-use planning schemes and evaluate the effects of land-use policies prior to their implementation in an effort to foresee indirect policy results.

Most insights about the effects of exurban development on wildlife have been transferred from research in urban and suburban areas. Some studies have addressed explicitly the effects of exurban development on bird communities (Friesen et al. 1995, Engle et al. 1999, Odell and Knight 2001, Fraterrigo and Wiens 2005, Merenlender et al. 2009, Suarez-Rubio et al. 2011) but few studies have examined the response of species through time as residential development progresses (Chace and Walsh 2006). I assessed whether exurban development degrades avian breeding territories over time and estimated forest birds' response to those changes (Chapter IV). I learned that exurban development is indeed degrading breeding habitats by reducing forest cover and increasing habitat fragmentation around Breeding Bird Survey stops. Selected forest birds exhibited a response to deteriorating breeding habitats in the vicinity of breeding territories (400 m-radius buffer) and adjacent foraging areas (1 km-radius buffer). Forest specialists were most sensitive to habitat deterioration followed by forest generalists. Forest edge species also responded to breeding habitat deterioration but the magnitude of the response varied according to their habitat preferences. The results suggest that species were affected by deteriorating breeding habitats in a nonlinear fashion.

Taken together, these results indicate that exurban development has increased in recent decades and has occurred disproportionately in areas with high natural amenities and around the boundaries of protected areas. Therefore, exurban development not only affects private lands, but also erodes habitat quality close to and inside protected areas.

The knowledge gained from this study regarding drivers of exurban development and the modeling approach that best captures exurban growth at local and county scales is highly relevant for land-use planning. Reliable projections can support the planning process. By simulating future growth, planners can visualize different growth scenarios and estimate the impacts that are likely to emerge from new or changed policy. In addition, the spatially explicit econometric model can inform the extent to which relevant parameters influence exurban growth. This information could guide the drafting of policies and assist the design of programs to redirect growth.

My findings show that exurban development has been degrading the quality of avian breeding habitats and that forest birds are responding to this habitat degradation. Alarmingly low levels of exurban development around breeding territories (400m- and 1km-radius buffer) corresponded to sharp declines of forest specialists (except Red-eyed Vireo) and forest generalists (except Eastern Phoebe), whereas some forest edge species increased with exurban development.

The prevalence of thresholds (Chapter IV) to this relative novel and fast-growing form of land use (i.e., exurban development; Chapter II) suggests that ecological effects of exurban development will be seen in the study area. Of the125 BBS stops located in the study area, 74.4% of BBS stops (for the 400 m-radius buffer) have already passed levels of exurban development associated with reduced frequency and abundance of the

Ovenbird, Scarlet Tanager, Wood Thrush, and Eastern Towhee (Table 10). Sixty percent of BBS stops have levels of exurban development associated with the frequency and abundance of the forest edge species, Indigo Bunting. Overall, exurban development is favoring forest edge species over forest specialists and generalists.

The counties driving this trend are those with more than 0.5% of exurban land cover (i.e., Fauquier, Frederick, and Shenandoah in Virginia; Frederick and Washington in Maryland; Table 11). Based on the thresholds identified for the 1 km-radius buffer surrounding BBS stops, the amount of exurban development in Fauquier County (1.3%) has already reached the level at which forest specialists and generalists would be expected to have negative responses. Forest specialists, Ovenbird and American Redstart, exhibited threshold declines in frequency and abundance in response to 1.4% exurban development surrounding breeding habitats. In contrast, the proportion of exurban development in Page and Clarke Counties (0.31%) is below the threshold exhibited for the Ovenbird and American Redstart but close to the threshold exhibit by forest generalists, Eastern Wood-Pewee and Scarlet Tanager (0.30%).

Exurban development is differentially affecting forest bird species. Species that require large and continuous tracts of forests may not be able to persist in exurban areas (e.g., Ovenbird). In contrast, species taking advantage of more open and disturbed habitats would thrive in these environments (e.g., Northern Cardinal). These results emphasize the importance of protecting forest interior from exurban development in an effort to conserve forest specialist species. In addition, the range at which forest birds exhibited strong negative threshold response to habitat loss and fragmentation in exurban areas may be used to guide land management plans and design effective mitigation strategies to minimize the likelihood of sudden bird population declines.

Table 10. Percent of Breeding Bird Survey (BBS) stops (n = 125) that were above exurban development threshold values. Positive response (z+) indicates high frequency and abundance for sites above threshold. Negative response (z-) indicates low frequency and abundance for sites above threshold.

Species	Response	Threshold value (% exurban)	Percent of BBS above threshold
400 m-radius buffer			
OVEN, SCTA, WOTH, EATO	z-	0.18	74.4
AMRE	z-	0.36	72.0
EAPH	z+	1.44	63.2
INBU	z+	2.1	60.0
REVI	z+	11.94	19.2
1 km-radius buffer			
GRCA	z +	0.11	84.8
EATO	z -	0.22	84.8
SCTA	z -	0.29	84.0
EAWP	z -	0.31	84.0
EAPH	z +	0.71	82.4
WOTH	z -	0.83	82.4
OVEN	z -	1.35	78.4
AMRE	z -	1.40	78.4
INBU	z +	4.41	59.2
REVI	z +	4.50	59.2

Note: Species IDs correspond to Ovenbird (OVEN), Scarlet Tanager (SCTA), Wood Thrush (WOTH), Eastern Towhee (EATO), American Redstart (AMRE), Eastern Phoebe (EAPH), Indigo Bunting (INBU), Red-eyed Vireo (REVI), Gray Catbird (GRCA), and Eastern Wood-Pewee (EAWP).

Table 11. Percent of exurban development per county and exurban development threshold values for the 1 km-radius buffer surrounding Breeding Bird Survey stops. Bird species responded positive (z+) or negative (z-) to exurban development threshold values.

County	Percent of exurban per county	Species	Response	Threshold value (% exurban)
Clarke	0.28	NOCA	z +	0.00
Page	0.33	GRCA	z +	0.11
Madison	0.43	EAPH	z +	0.71
Rappahannock	0.45	INBU	z +	4.41
Warren	0.46	REVI	z +	4.50
Washington	0.64	EAWP	z -	0.31
Frederick, MD	0.70	EATO	z -	0.22
Shenandoah	0.79	SCTA	z -	0.29
Culpeper	0.81	WOTH	z -	0.83
Frederick	1.09	OVEN	z -	1.35
Fauquier	1.34	AMRE	z -	1.40

Note: Species IDs correspond to Northern Cardinal (NOCA), Gray Catbird (GRCA), Eastern Phoebe (EAPH), Indigo Bunting (INBU), Red-eyed Vireo (REVI), and Eastern Wood-Pewee (EAWP), Eastern Towhee (EATO), Scarlet Tanager (SCTA), Wood Thrush (WOTH), Ovenbird (OVEN), and American Redstart (AMRE).

Future directions and recommendations

Although this study examines multiple perspectives of exurban development, it is by no means comprehensive. There are several topics that could be expanded and many gaps in our knowledge about the effects of exurban development that require further investigation, including:

- Improve information about sensitivity of SLEUTH growth coefficients. Evaluating the relative importance of growth coefficients would guide the selection of best-fitting coefficients.
- Simulate alternative policy scenarios and forecast exurban growth. Assessing possible outcomes of policy implementation could provide input about their effectiveness and highlight conservation priority areas.
- Assess the relative effects of habitat loss and fragmentation beyond the 1km-radius buffer. Understanding the footprint of habitat degradation due to exurban development will inform conservation and planning decisions.
- Increase knowledge about the ecological mechanisms that underlie the response of forest birds to exurban development. Understanding ecological mechanisms will enhance our ability to manage and mitigate negative impacts of exurban development on forest birds.

In order to maintain a balance between future exurban growth, environmental quality, and avian ecological requirements, local policy decisions will become increasingly important. Incentives to encourage growth near existing towns could minimize the continued subdivision of large, privately owned woodland parcels. Identifying large areas of forests and purchasing development rights before they become fragmented by rural residential development can be an effective way to conserve forest specialist species. Synergy among local governments, counties, and agencies in developing a comprehensive regional plan (Daniels 1999) can move forward biodiversity conservation and reduce ecological impacts of exurban development. Individual landowners also have a role to play in how they manage their lands; for example, by landscaping with native plant species, to mitigate impacts of exurban development. I have shown exurban development to be an increasingly pervasive form of land use in the Mid-Atlantic with tangible ecological consequences. Coordination among all relevant stakeholders will become increasingly important to conserve and mitigate the future impacts of this landscape change.

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