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Li An[a]; Daniel G. Brown[b]; Joan I. Nassauer[b]; Bobbi Low[b]
[a] Department of Geography, San Diego State University, San Diego, CA, USA [b] School of Natural Resources and Environment, University of Michigan, Ann Arbor, MI, USA

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Variations in development of exurban residential landscapes: timing, location, and driving forces

Li An[a]*, Daniel G. Brown[b], Joan I. Nassauer[b] and Bobbi Low[b]

[a]*Department of Geography, San Diego State University, San Diego, CA, USA;* [b]*School of Natural Resources and Environment, University of Michigan, Ann Arbor, MI, USA*

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Residential land-use expansion, an important component of urban sprawl, has a variety of drivers and environmental implications. The goal of this article is to address the timing, location, and mechanisms of different types of residential development. Using land-parcel data and aerial imagery taken between 1950 and 2000 for eight townships in southeastern Michigan, we sampled and classified polygons (854 in total) of four residential types. Socioeconomic characteristics were collected from US census data at the township level and assigned to sample polygons based on the township in which they fell. We then applied survival analysis to achieve the above goal. We found that (1) the development rates varied between residential types over time and (2) the evolution of these types can be explained by different factors. Differentiating such residential types and their associated time-variant patterns usefully sheds light on environmental effects of residential land-use expansions in exurban areas.

Keywords: land-use changes; residential typology; survival analysis; temporal patterns; southeastern Michigan

1. Introduction

As more and more people choose to live in exurban subdivisions (Robinson, Newell, and Marzluff 2005), the United States in the past five decades has witnessed a fivefold increase in exurban[1] residential areas. As a result, approximately 25% of the area of the 48 contiguous states was in census blocks that were settled at exurban densities in 2000 (Brown, Johnson, Loveland, and Theobald 2005). Rates of conversion to residential land use in exurban areas have usually outpaced human population growth, resulting in low-density, discontinuous, and land-intensive land-use patterns (Irwin and Bockstael 2002). This situation brings forward a growing need to study the mechanisms and environmental consequences of residential developments in exurban areas at appropriate scales (e.g., Mieszkowski and Mills 1993; Brown *et al.* 2005).

Existing research shows that different types of exurban residential developments may give rise to varying ecological and/or environmental effects. For instance, a study on exurban land developments in Colorado has shown that, compared to dispersed housing, clustered housing developments caused substantially different habitat-use patterns for some bird species such as the Common Grackle and American Robin. Such differences may play an important role in conservation biology (Lenth, Knight, and Gilgert 2006). Variables like

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*Corresponding author. Email: lan@mail.sdsu.edu

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housing density and distances between habitat and houses show considerable effect on human-adapted and human-sensitive species (Odell and Knight 2001). In general, variability in exurban residential development regimes, through effects on settlement density, land-cover patterns, and ecological processes on the landscape, may affect the survival and reproduction of some wildlife species, the richness and composition of native and exotic species, and related ecosystem services (Taylor, Brown, and Larsen 2007). In addition, this variability may cause spatial variation in biogeochemical processes, greenhouse gas emissions, and vegetation structure (Dale, Archer, Chang, and Ojima 2005).

Despite such ecologically and environmentally significant effects, ecologists have traditionally focused their research on wild or semi-wild lands, leaving the effects, drivers, and spatial configurations of residential developments in exurban areas relatively unexplored (Hawbaker, Radeloff, Hammer, and Clayton 2005). In particular, little is known about the factors and processes that determine the timing and location of developments that may have different ecological effects. Given available data, much effort has been devoted to analysis of settlement patterns and potential drivers at relatively coarse scales (e.g., counties; Hammer *et al.* 2004; Brown *et al.* 2005; Theobald 2005). What is needed to support ecological assessments and planning is additional information at finer scales (Gustafson, Hammer, Radeloff, and Potts 2005). Whatever the macro-sociological phenomena that create a market for exurban settlements (e.g., enhanced preference for esthetic quality), these settlements are frequently provided by developers. Such developers usually make their decisions about where to develop by considering, among other factors, spatial variation in such factors as accessibility of cities and environmental land characteristics (Vigmostad 2003). Additionally, they make choices about the types of landscapes to construct based on their understanding of the preferences of home buyers and site factors like terrain, water features, soils, and existing vegetation.

Much empirical work has aimed at understanding the factors that drive residential location decisions at the household level (e.g., Irwin and Bockstael 2001; Bell and Irwin 2002; Geoghegan 2002). Comparably little work, however, has been devoted to understanding actions and decisions by developers or at the level of whole developments. Because many aspects of landscape pattern are determined by developers, who provide the options available to homebuyers, understanding the mechanisms and effects of developers' decisions is important for understanding exurban landscape pattern evolution. Furthermore, differentiating among types of development is critical to understanding the ecological implications of development. Although the decisions of developers are both constrained by local land-use law (e.g., zoning; Rolleston 1987) and affected by the nature of the residential marketplace, we believe that analysis of exurban dynamics requires an explicit focus on these meso-scale actors as important determinants of landscape pattern.

Our research characterizes the supply side of the exurban development phenomenon in the context of a large amount of previous work on the demand side, that is, the residential preferences of buyers (Fernandez, Brown, Marans, and Nassauer 2005). Under a framework that integrates geographic information science and survival analysis, we assembled a panel data set based on aerial photographs, plat maps, and governmental archives. This article aims to further our understanding of the mechanisms and dynamics of different residential development types at the scale of subdivisions and neighborhoods. Our specific goals are, therefore, to

(1) differentiate residential development types, describe their spatial and temporal patterns in southeastern Michigan, and

(2) model the location and timing of these residential development types on the basis of geographical, biophysical, and socioeconomic variables.

2. Methods

2.1. Residential development typology

Based on variations in environmental and socioeconomic characteristics of subdivisions and their land-cover effects, a new residential typology has been proposed and tested for the purpose of describing variations in exurban landscapes (Table 1; Brown *et al.* 2008). The typology recognizes four types of exurban residential developments: (1) rural lots, (2) country subdivisions, (3) horticultural subdivisions, and (4) remnant subdivisions (Table 1). Detailed descriptions of each type were developed for use in consistently identifying the types using available spatial data, including aerial photographs, roads, and parcel boundaries. As a small field or a portion of a larger field that a farmer decides to sell to an individual homebuyer, a *rural lot* requires direct access to county roads and can vary in size from less than one to greater than 15 acres (e.g., Figure 1a). A *country subdivision* is a denser collection of housing units where each lot is about an acre or less in size, and the inner roads that connect such units are often perpendicular to each other (Figure 1b). A *horticultural subdivision* is a collection of housing units on larger lots (>1 acre) and with curved inner roads to connect all the units (Figure 1c). A *remnant subdivision* is similar to a horticultural subdivision, but incorporates a remnant forest (i.e., a contiguous tree area >10 acre or 10% of total area if the total subdivision is less than 100 acres) or other natural features (e.g., adjacent to lakes or streams; Figure 1d). Except for rural lots, each of these subdivision types is typically developed by a single real estate developer and then sold to many individual homebuyers. These definitions were used to identify instances of these types within southeastern Michigan (Section 2.3).

2.2. Analytical framework

Our research aims to elicit developers' preferences for timing and location of developments using empirical data related to their past developments. To achieve this aim, we adopt an analytical framework assuming that developers pursue maximum economic returns in

Table 1. Typology of exurban residential development.

	Owner(s)	Lot size (acres)	Adjacent to county road	Inner roads	Tree cover or nearness to water	Cost[a]
Rural lots	One	1–15	Yes	N/A	N/A	Variable
Country subdivisions	Many	Around One	N/A	Yes (perpendicular)	Low	Less expensive
Horticultural subdivisions	Many	>1	N/A	Yes (curved)	Low-moderate cover, long distance	Expensive
Remnant subdivisions	Many	>1	N/A	Yes (curved or perpendicular)	High cover, short distance	Expensive

Note: [a]Cost is not one of the criteria used in type identification.

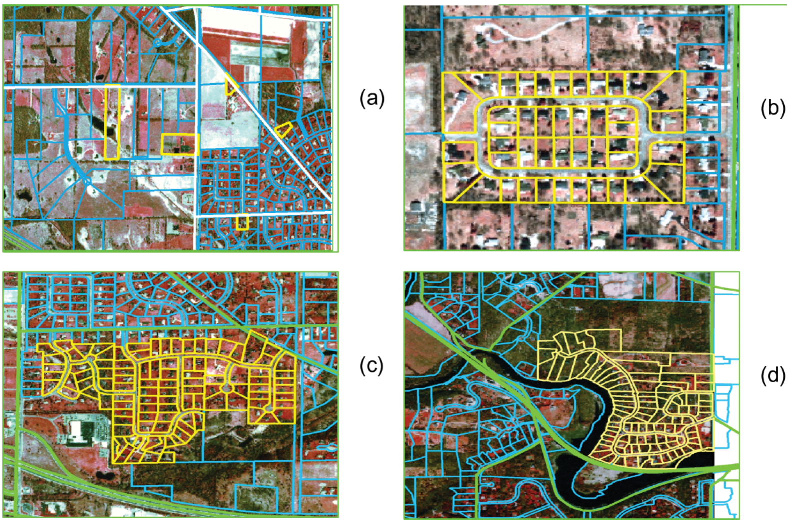

Figure 1. The four development types: (a) rural lots; (b) country subdivisions, (c) horticultural subdivisions, and (d) remnant subdivisions. Shown in each case are polygon boundary lines, delineating the parcel or subdivision, overlain on an aerial photograph.

consideration of several related factors, similar to previous work on spatially explicit land-use change modeling (Pfaff 1999; Verburg, Koning, Kok, Veldkamp, and Bouma 1999; Mertens and Lambin 2000; Irwin and Geoghegan 2001; Schneider and Pontius 2001; Bell and Irwin 2002; Hansen *et al.* 2002; Walsh, Soranno, and Rutledge 2003). Within this framework, we give special attention to the timing of such decisions and temporal effects of related factors[2] using survival analysis models. Although not explicitly expressed in economic terms, our model includes three types of variables that may affect the development costs and sale prices of developments (Table 2): geographic factors, biophysical factors, and socioeconomic factors. At the same time, to account for reductions in the total number of available parcels over time, and the fact that development hazards themselves may vary over time as a result of other unknown variables that are highly correlated with time, we use time (decade in our case) as an independent variable.

Geographic factors describe proximity and access to employment opportunities, shopping centers, schools, and recreation sites (e.g., Mertens and Lambin 2000; Geoghegan *et al.* 2001; Irwin, Bell, and Geoghegan 2003). As in classic von Thünen models (von Thünen 1966), distance from city center is considered as a key factor that affects both developers' and homebuyers' decisions. We consider cities at three size categories: Detroit (big city), five mid-level cities (Lansing, Jackson, Flint, South Lyon-Howell-Brighton, and Ann Arbor), and towns and villages; and roads of two different sizes: highways and county roads. The geographic factors include distances (in kilometers) to the nearest city (represented as the centroid of the urbanized area polygon) of the three different sizes (Figure 2), to the nearest lakes or streams, and to the nearest roads of the two different types. These distance variables represent an area's proximity and access to work and urban facilities (such as shopping centers), water features, and the transportation network, respectively, which may affect the demand and prices of such developments. For instance, longer distance to Detroit is expected to negatively influence a remnant subdivision's value because its purchasers, who are relatively rich and capable of affording remnant subdivisions (see Section 2.3), may prefer

Table 2. Variables used in the models.

Variable type	Variables	Description	Mean	SD	Minimum and maximum	Source	Spatial resolution	Temporal resolution
Dependent variable	s_time	The time that a particular parcel survives (not developed), represented as intervals (lower, upper) in some cases	2.73	1.63	0.5, 5.50	Visually interpreted from areal photos	Parcel[a]	Decade
	type	The land-use type that a parcel was/is at a time – used with s_time insurvival models; singly used in logistic models	N/A	N/A	N/A		Parcel	N/A
	decade	Decade that a record is associated with	N/A	N/A	N/A			
Geographic factors	dist_dtw	Distance from the parcel/subdivision centroid to Detroit (km)	67.68	22.01	28.57, 109.32	GIS analysis	Parcel (change over parcels)	Decade (constant over decades)
	dist_5ct	Distance from the parcel/subdivision centroid to the nearest city among five mid-level cities (km)[b]	26.44	18.00	3.90, 73.56			
	dist_all	Distance from the parcel/subdivision centroid to the nearest urbanized area (km)[c]	12.89	4.50	3.10, 23.68			
	dist_wtr	Distance from the parcel/subdivision centroid to the nearest lake, >1 acre pond, or stream (m)	310.71	235.07	1.55, 1317.00			
	dist_hwy	Distance from the parcel/subdivision centroid to the nearest highway (km)[d]	3.37	2.41	0.03, 9.76			
	dist_ctyrd	Distance from the parcel/ subdivision centroid to the nearest county road (m)	184.59	163.32	5.80, 1163.47			
Biophysical factors	pt_cover	Percent of tree cover	20.34	22.24	0, 100			
	primesoil	Soil quality, represented as 2 (prime soil) and 1 (non)	1.21	0.41	1, 2			
	slope	Parcel slope (the ratio between the rise and the run)	1.45	1.66	0, 14.44			
Socioeconomic factors	pop_d	Number of people per square kilometer	10.17	10.41	1.28,51.59	US census year-books, Michigan	Township (change over townships)	Decade (change over decades)
	pop_r	Population growth rate compared to past decade	33.64	34.15	–0.63, 160.84			
	edu	Percent of college degree or above among 25+ years	0.13	0.11	0.02,0.43			
	med_age	Median ages at the township level over five decades	28.23	3.10	24.40, 35.10			
	income	Median household income at the township level ($1000)	18.76	16.29	2.76, 56.86			

Note: [a] It means that variable s_time has a spatial resolution at the parcel level. Similar to other resolution measures in the same column and the column for temporal resolution.

[b] Lansing, Jackson, Flint, South Lyon-Howell-Brighton, and Ann Arbor.

[c] Defined by US census.

[d] The straight (Euclidean) distance between the centroid and the nearest highway in kilometers using the Arc/Info command ‘near’.

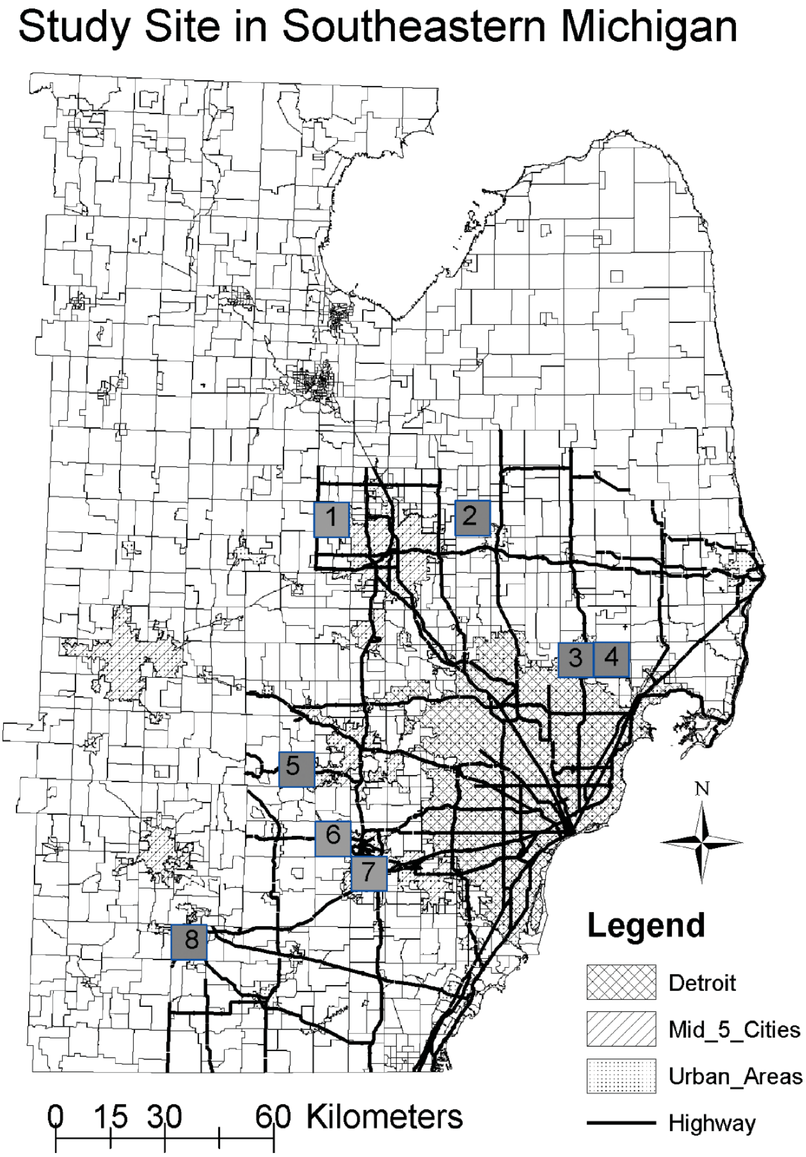

Figure 2. The location of the study sites. The numbers in the squares represent the sampled townships in southeastern Michigan: Flushing (1), Oregon (2), Washington (3), Ray (4), Putnam (5), Scio (6), Pittsfield (7), and Woodstock (8).

convenience and fast access to their jobs in Detroit and its suburbs, all other things being equal. We did not include the effects of changes in the road network in the model because empirical work shows that the spatial distribution of highways and county roads in southeastern Michigan has remained largely unchanged in the past four to five decades, though there surely have been changes in road capacity and quality (Brown *et al.* 2008).

Biophysical factors may affect esthetic quality (e.g., landscape view), agricultural productivity, and the farmer's willingness to sell or the bid for sale (e.g., Mertens and

Lambin 2000; Geoghegan *et al.* 2001; Serneels and Lambin 2001), which may affect both the sales price and costs to developers. These variables include soil quality, initial amount of tree cover, and topographic slope (in percent). Soil quality is represented as a binary variable indicating whether or not the land was classified as prime farmland based on data from the Natural Resources Conservation Service (http://soils.usda.gov). Soil quality may affect land supply to developers because farmers, trying to stay in farming, may sell less-productive parcels as a means of raising capital for farming (Daniels 1999). On the other hand, parcels with good soils sometimes have lower costs for development, lowering the costs of converting from undeveloped to developed (Irwin *et al.* 2003). More tree cover and higher slope, on the other hand, may also increase the esthetic value of parcels. We treat the geographical and biophysical variables as unchanging through time, the implications of which will be discussed later.

Socioeconomic factors relate to the population characteristics of an area and the structure of residential demand in the regional metropolitan land market, and as a result, to the value of parcels. These factors may affect the preferences of homebuyers, their ability to pay, the nature of the housing market within which the developer is operating (e.g., Mertens, Sunderlin, Ndoye, and Lambin 2000; Serneels and Lambin 2001; Geoghegan 2002; Vance and Geoghegan 2002), and ultimately, the decisions of developers that seek maximum economic returns. We included population density, population growth rate, median household income, education level, and median age at township level, because they may affect the demand (e.g., population density and growth rate) and ability-to-pay (e.g., median household income) of homebuyers. We discuss the implications of the coarse resolution of such data later in Section 4.2. We collected the data for these variables from the decennial US Census from 1950 to 2000. Because land-related policies are implemented at the level of municipalities, we used a township dummy variable to capture the effects of policy differences among townships.

2.3. Sampling and data

Using a time series of land-use maps derived from aerial photos, we collected longitudinal and cross-sectional data for residential land-use change using a stratified random sampling strategy. Specifically, eight townships in southeastern Michigan, including Flushing (in Genesee County), Oregon (Lapeer), Pittsfield (Washtenaw), Putnam (Livingston), Ray (Macomb), Scio (Washtenaw), Washington (Ray), and Woodstock (Lenawee; Figure 2), were selected to "represent a range of conditions with respect to the amount and timing of population growth and development" (Brown *et al.* 2008). For all the eight townships, we acquired such aerial photos at increments of approximately 10 years from 1960 (±2) to 2000 (±2).[3] These photos were all scanned at 2 m resolution and georeferenced to the UTM coordinate system using the road network as reference. They varied in source scale and emulsion type (i.e., black and white, color, and color infrared). Plat maps of the most recent time (around 2000) delineating individual land-ownership parcels were acquired from the corresponding township or county governments. Because recombination after subdivision of parcels is rare, we used the most recent parcels as our units for temporal analysis.

Based on the township plat maps, we randomly sampled 4% of all parcels (regardless of their developed status and possible land-use regulations) within each township. The data thus obtained met our need for a relatively large sample for statistical analysis, whereas the parcels thus sampled are adequately distant from each other to minimize spatial autocorrelation (the mean and median nearest distances are 563.09 and 482.93 m, respectively). In accordance with our development typology, each polygon was visually classified as one of the four types or as a *farm* based on its environmental and geographic characteristics interpreted from aerial photos and GIS-based data. The term farm indicates undeveloped land and includes some small forested areas. We merged neighboring parcels that belonged to the same subdivision to create a subdivision polygon because such parcels were very likely to have been subdivided by a developer at the same time. Rural lots, developed by individual homebuyers, were not merged with neighbors. After merging parcels with neighbors in the same subdivision, we had 854 polygons for analysis.

For each polygon, we identified its development time from aerial photographs at 10-year intervals, for example, a polygon was developed between 1970 and 1980. The observed land-use transformations were unidirectional – from farms to any of the residential types – that is, once a parcel was developed, it remained in that type without further transition. To examine the accuracy of these development dates based on aerial photo interpretation, we used data at a yearly resolution available in the townships of Pittsfield and Scio. We visited the Online Tax, Assessing and Utility Information for each township (http://www.twp.scio.mi.us/ and http://www.pittsfieldtwp.org/links – last accessed on 23 March 2009) and recorded the years in which all the houses on each sampled subdivision were built. We labeled each subdivision with the earliest date of development among all housing units in the subdivision. This simplified the usually small variations in development time within a subdivision. Because of the unavailability of data in some parcels, we were able to obtain development dates for only 79 parcels (67%) in these two townships. We found that approximately 90% were accurate for the three subdivision types and approximately 65% for rural lots. Therefore, we exercised caution when interpreting results for rural lots because of the relatively low classification accuracy.

A previous analysis of the classified polygons in Scio and Pittsfield townships (near Ann Arbor, MI) showed that country subdivisions had the lowest median state equalized valuation (SEV; representing one-half the value of a house as assessed by the municipality) in 2003 ($94.97 K; 1 K = $1000), followed by rural lots ($154.39 K) and horticultural subdivisions ($170.46 K). Remnant subdivisions had the highest SEV ($197. 28 K). In terms of average lot sizes, country subdivisions were smallest (0.48 acre), followed by horticultural subdivisions (2.02 acres), remnant subdivisions (3.12 acres), and rural lots (5.27 acres). In addition, our previous empirical analysis on the changes of tree cover (in percent) shows that remnant subdivisions can substantially increase tree cover after the developments ($p < 0.05$ for testing the null hypothesis that there is no change before and after the developments), whereas the other two subdivision types tended to have decreased or maintained constant ($p > 0.10$) tree cover after the development. These results were consistent with the definitions in Table 1.

2.4. Data analysis and modeling

We used survival analysis (SAS vs. 9.1) to analyze the occurrence and timing of development events. Survival analysis has found extensive application in the study of mortality in medicine, public health, and epidemiology (hence the name survival analysis; Klein and Moeschberger 1997; An and Brown 2008). One of the key strengths of survival analysis is the ability to handle time-dependent variables (i.e., variables that take values that change over time) and censored data. When the precise timing of events is unknown, but they are known to occur earlier or later than a certain time, or within a certain time interval, the survival times are referred to be left-, right-, and interval-censored, respectively (An and Brown 2008). Several researchers (e.g., Vance and Geoghegan 2002; Irwin *et al.* 2003; Irwin and Bockstael 2004; Plantinga and Irwin 2006) have successfully used this type of model in land-change analysis.

Two critical concepts in survival analysis, the survival function, $S(t)$, and hazard function, $h(t)$, are defined as

$$S(t) = \Pr(T > t) = \exp\{-\int_0^t h(x)dx\} \tag{1}$$

and

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\{t \leq T \leq t + \Delta t | T \geq t\}}{\Delta t} = -\frac{d}{dt}\log S(t) \tag{2}$$

where T is the time at which development occurred. The survival probability is the probability that an individual survived beyond time t (i.e., the survival time (T) is greater than t or the event does not occur until after t). This term, if calculated in a frequentist manner, offers a general indicator of what proportions of land parcels under investigation may remain undeveloped over time. The hazard is the instantaneous ($\Delta t \rightarrow 0$) risk that an event will occur at time t given that the individual survives to time t. The hazard can be understood as an intrinsic property of any individual and is conceptually different from probability. For instance, hazards may go up and down, whereas survival probabilities are always non-increasing over time. In practice, we can assume parametric forms for the hazards, for example, $h(t) = \lambda t^{\alpha}$, where λ and α are constants of the Weibull distribution (which reduces to the exponential distribution when $\alpha = 0$). We can also calculate overall hazards based on the aggregate data of all individuals over several periods (Machin *et al.* 2006, pp. 23–49).

To identify temporal patterns of development in the past five decades and identify the possibility of different mechanisms underlying the development of the different types, we computed the pooled survival probabilities and hazard rates for rural lots versus subdivisions. Observed differences provide some validation for the use of the residential typology in describing exurban development and suggest directions for future analysis. To understand relationships between development hazards of different types and the explanatory variables, we built several models of the following general form

$$\log h_i(t) = \alpha_i(t) + \beta_1 X_{i1}(t) + \beta_2 X_{i2}(t) + \ldots + \beta_k X_{ik}(t) \tag{3}$$

where $h_i(t)$ is the time-varying hazard rate for parcel i, $X_{ik}(t)$ is the value of explanatory variable X_k for parcel i at time t (time-dependent variables), and β_k are the coefficients for the kth variable ($k = 1, 2, \ldots, K$). For the time-dependent socioeconomic variables, we used their values one decade prior to the development in the regression, for example, $h_i(t)$ was regressed against population density at t–1 rather than at t. This choice arose from the fact that earlier socioeconomic conditions (such as population density) will attract or repulse later developments.

We employed the piecewise exponential approach to survival analysis because it performed better in tests of several alternative modeling approaches (including the commonly used Cox model; see An and Brown 2008). To implement this approach, we broke the entire time frame into n ($1 \leq n \leq 5$) periods, where one period is one decade. Then we created one record for each period during which the parcel was either at risk of development or was under the process of development. For periods at risk, we assigned the survival time to be one decade but right-censored (see Section 2.4 for definition; also see Allison 1995, pp. 208–209). For periods within which development occurred, we treated survival times as interval-censored data because of the 10-year time interval of our data. For instance, a parcel developed to a remnant subdivision between 1980 and 1990 had three parcel periods. The first two parcel periods (for 1960–1970 and 1970–1980) had right-censored survival times equal to 10 years, whereas the third one for 1980–1990 was labeled as developed to remnant subdivision at (0,10). For parcels developed before 1960 (our starting time), we labeled it as left-censored. For parcels remaining undeveloped until 2000 (the end of our time frame), we assigned survival times to be a decade with a right-censored label for all the five parcel periods. We treated all such parcel-period data as independent observations. In survival analysis this is acceptable because the likelihood function factors into a distinct term for each parcel period (c.f., Allison 1995, pp. 108 and 200–206) and, because once a parcel is developed, it is not subject to other developments within our study time frame.

We used the *lifereg*[4] procedure in SAS to model the relationships between the hazards of a parcel being developed to each type under investigation and the explanatory variables based on Equation 1 (Allison 1995, pp. 104–109). Our approach allows for time-dependent variables, all types of censored data, competing risks (a land parcel may be developed into one of multiple types), and various explanatory variables for models of different residential types under investigation (An and Brown 2008).

Because of fundamental differences in the units of analysis and actors involved between rural lots and the other three development types (see Section 2.1 for what they are), we analyzed differences among development types in two different ways. We first treated all three subdivision types as a single type and compared them with rural lots. Next, we considered differentiations among subdivision types by treating rural lots as right-censored data.

As this analysis has an emphasis on temporal aspects of land-use change drivers, we created two types of models for each development type: the base model and the comprehensive model. The major difference is that the latter incorporates interaction terms between time (decade in Table 4) and each potentially time-dependent variable as candidate explanatory variables.[5] This choice will allow us to test whether some variables may have temporally variant effects. Specifically, the base model included all explanatory variables listed in Table 2, including a variable called 'decade' for reasons explained in Section 2.2. The comprehensive models also included the dummy variables for each of the eight townships to capture the effects caused by township characteristics or policies (e.g., zoning).

To compare models, we examined differences in deviance, which conform to a χ^2-distribution with degrees of freedom equal to the number of dropped or added variables (Hosmer and Lemeshow 1989, pp. 30–34). We also used common goodness-of-fit metrics such as generalized R^2, Akaike information criterion (AIC), and Schwarz's Bayesian criterion (SBC) to evaluate nested models (SAS online documentation).

The base and comprehensive models for each type (e.g., Models 1 and 2 for rural lots) were complementary to each other and we refer to both base and comprehensive models when presenting the results. Because these different model specifications represent different conceptual models about developers' decision-making processes (e.g., the comprehensive model includes interaction effects and differences in townships), the one with a slightly better statistical fit is not necessarily superior to the other. Also, given the multiple measures of fit, a model may be a better fit on one measure but worse on another.

3. Results

3.1. Temporal patterns

The hazards and survival probabilities of these four residential types vary over time, showing that these types may have different temporal patterns. As expected, the overall survival probability declined over time (Figure 3a), indicating that it became increasingly unlikely for

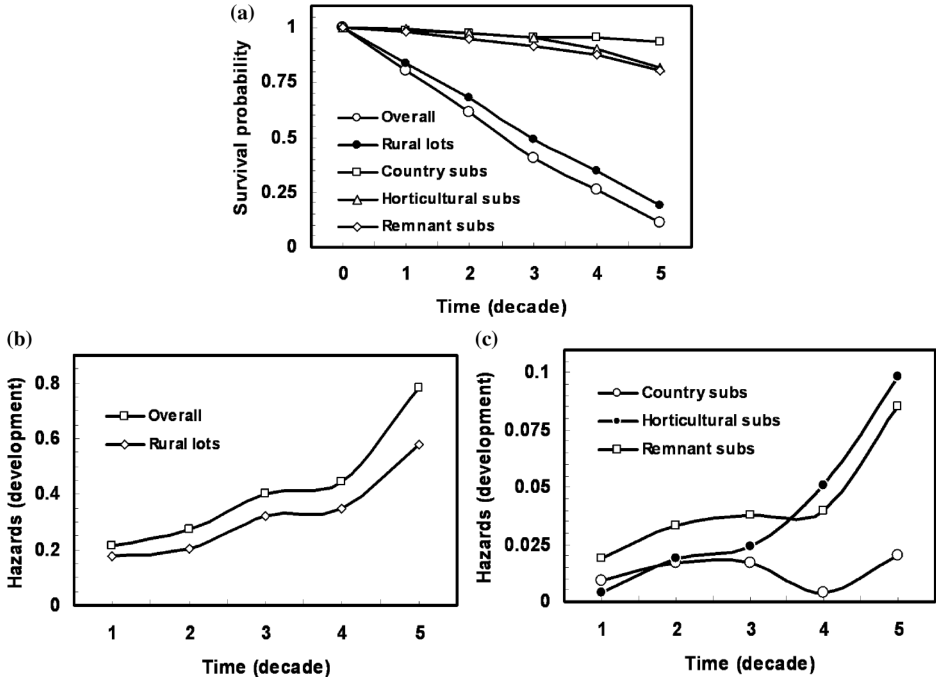

Figure 3. The survival probabilities and hazard rates over a span of 50 years: (a) the survival probabilities that farm parcels were developed (regardless of what type was developed into) and developed into one of these four types; (b) the hazards of farm parcels being developed (regardless of what type was developed into) and being developed into rural lots; (c) the hazards of farm parcels being developed into the three subdivision types.

any farm parcel to remain undeveloped with time. Large differences in survival probabilities were observed among the development types. The survival probability curve for rural lots was very similar to that of overall development, because of the abundance of rural lots (562 in 2000; Table 3). Country subdivisions had relatively flat curves, indicating that not many parcels were developed into this type over time (27 in 2000) and that there was very little change in the likelihood of their being developed. Horticultural subdivisions and remnant subdivisions had relatively steep curves among the three subdivision types, especially after decade 4, indicating that subdivisions of these two types became increasingly popular (53 and 73 in total, respectively).

The four development types evolved over time in different manners. Rural lots had the largest number of parcels over time (a consequence of our data-collection approach which counted individual rural lots as single parcels, but also counted entire subdivisions as parcels). The shape of the rural lot hazard curve resembled that of the overall development, though its magnitude was smaller because overall development had contributions from the other three subdivision types as well (Figure 3b). The rate of horticultural subdivision development outpaced the other types with its total number of subdivisions increasing from 3 to 53 and total area from 0.17 to 9.15 km^2 between 1960 and 2000 (Table 3). Following a slow increase in hazards between decades 1 and 3, the hazards for country subdivisions declined between decades 3 and 4, and started to rise after decade 4 (Figure 3c). Although horticultural and remnant subdivisions had increasing hazards over time, their

Table 3. Descriptive statistics of the four development types over time.

Types	Variables[a]	1960	1970	1980	1990	2000
Rural lots	Counts	129	245	379	474	562
	Area (km^2)	1.89	3.16	5.32	7.16	8.93
	Pt_cover (%)	16.51	13.20	17.89	24.87	26.11
	dist_dtw	65.62	65.99	66.28	65.48	65.37
	dist_5ct	28.78	27.97	27.39	26.42	27.18
	dist_all	12.54	13.76	13.60	13.62	13.35
	primesoil	1.19	1.19	1.20	1.20	1.20
	slope	1.37	1.36	1.37	1.39	1.34
Country subdivisions	Counts	7	17	23	24	27
	Area (km^2)	0.38	1.70	2.29	2.39	2.95
	Pt_cover (%)	41.43	17.35	17.61	23.33	15.93
	dist_dtw	80.98	65.17	68.51	69.08	68.38
	dist_5ct	28.48	36.99	32.26	31.58	29.35
	dist_all	9.26	13.70	13.06	13.18	12.96
	primesoil	1.57	1.41	1.36	1.39	1.38
	slope	1.39	1.00	0.96	1.00	0.94
Horticultural subdivisions	Counts	3	14	24	38	53
	Area (km^2)	0.17	2.18	4.07	7.60	9.15
	Pt_cover (%)	5.00	5.00	8.96	16.84	18.30
	dist_dtw	70.93	66.28	63.72	61.42	58.09
	dist_5ct	16.25	18.03	17.58	15.83	19.74
	dist_all	9.53	11.97	11.75	11.79	12.28
	primesoil	1.00	1.11	1.17	1.21	1.26
	slope	0.84	0.98	1.06	1.32	1.28
Remnant subdivisions	Counts	9	25	41	51	63
	Area (km^2)	1.21	5.51	9.72	12.34	15.34
	Pt_cover (%)	21.11	15.00	29.02	37.94	36.83
	dist_dtw	61.51	66.89	66.16	63.87	65.13
	dist_5ct	23.22	20.13	20.78	20.29	22.11
	dist_all	14.99	13.30	12.69	12.89	12.86
	primesoil	1.00	1.05	1.09	1.11	1.26
	slope	2.49	2.34	2.44	2.45	2.33
Total	Counts	148	301	467	587	705
	Area (km^2)	3.66	12.56	21.39	29.49	36.37
	Pt_cover (%)	84.05	50.55	73.48	102.98	97.17
	dist_dtw	279.04	264.33	264.67	259.85	256.97
	dist_5ct	96.73	103.12	98.01	94.12	98.38
	dist_all	46.32	52.73	51.10	51.48	51.45
	primesoil	4.76	4.76	4.82	4.91	5.10
	slope	6.09	5.68	5.83	6.16	5.89

Note: [a]See Table 2 for definitions and units.

rates differed. Horticultural subdivisions showed a monotonic increase after decade 3, whereas remnant subdivisions increased more rapidly after decade 4, reaching the largest total area (15.34 km^2) in 2000. Among all three subdivision types, the hazard rates for horticultural subdivisions dominated after the midpoint between decades 3 and 4 – remnant subdivisions dominated before that time. The increasing hazard rates of these two subdivision types do not necessarily imply increasing numbers of new occurrences for these two types, because the supply of land fell with time (Allison 1995, p. 46).

3.2. Models of rural lots and subdivisions

The models for the dichotomous classification (i.e., rural lots and subdivisions) and the models for the three subdivision types have varying degrees of fit and different predictor variables. The models for rural lots (Models 1–2) had better fits (generalized $R^2 \geq 0.150$) than those for the combined subdivisions (Models 3–4 with generalized $R^2 < 0.046$; Table 4), but neither model was strong. This should be interpreted with caution because of the low accuracy of the rural lot dates (see Section 2.3). The low generalized R^2 for subdivisions could be evidence that the determinants of the different subdivisions were sufficiently different and a single model was insufficient. Rural lots were near county roads, whereas subdivisions were farther away from county roads (Models 2 and 4). Rural lots and subdivisions were both likely to be in places with lower population densities (but tended to be less so over time, indicated by the positive interaction terms between decade and population density), and rural lots alone tended to be in places with higher rates of increase in population. Rural lots were not significantly related to distances to the three types of cities, but subdivisions were near the mid-level cities and far away from small cities and highways. Rural lots had increasing hazards over time and were negatively associated with Oregon Township. Subdivisions occurred increasingly closer to Detroit over time (Model 3) and had higher hazards in Woodstock Township (Model 4). Soil and slope were insignificant for both rural lots and subdivisions in the comprehensive models (Table 4).

3.3. Models of three subdivision types

When the individual subdivision types were considered separately, the fits improved substantially for horticultural and remnant subdivisions, especially in the case of remnant subdivisions: the generalized R^2 of the comprehensive model increased from approximately 0.046 to 0.067 (Table 4).

Country subdivisions were near county roads (only marginally significant) and far from highways (Model 6), and in places with higher population density. It is likely that country subdivisions were in places close to Detroit, suggested by the marginally significant coefficient for distance to Detroit (dist_dtw) −0.063 (Model 5). Parcels in Washington Township had higher hazards of being developed into country subdivisions. Horticultural subdivisions were more likely to be located in areas far away from Detroit (marginally significant; Model 7), but this trend was minimized (even reversed) in later decades according to a negative interaction between decade and distance to Detroit (Model 8). Had this interaction term not been considered, we might have concluded that horticultural subdivisions were closer to Detroit based on the significant negative coefficient (Model 7). Hazards of being developed into horticultural subdivisions were higher for the parcels near highways and for later decades (Model 8). Horticultural subdivisions were found in places with higher population densities (marginally significant; Model 7). Remnant subdivisions tended to be close to Detroit and five mid-level cities (both Models 9 and 10), but far from small cities and highways (Model 10). Remnant subdivisions, occupying poorer soil at earlier times, tended to be developed in places with increasingly better soil over time (Model 10). Places with low population densities (marginally significant), in Woodstock Township (Model 10), or with higher tree covers (marginally significant; Model 9) had a higher risk of being developed into remnant subdivisions.

Table 4. Regression results.

	Rural lots		Subdivisions		Country subdivisions		Horticulture subdivisions		Remnant subdivisions	
Model numbers	1(Base)	2 (Comp)	3 (Base)	4 (Comp)	5 (Base)	6 (Comp)	7 (Base)	8 (Comp)	9 (Base)	10 (Comp)
Intercept	**–1.741**	**–0.581**	**–2.706**	–1.963	0.062	–6.880	–0.0187	**–10.879**	–1.1413	4.171
dist_ctyrd	**–0.007**	**–0.007**	**0.003**	**0.002**	–0.003	–0.008*	–0.001	–0.001	0.001	0.001
dist_wtr	0.189	0.101	0.125	–0.009	0.633	0.277	1.437	1.368	1.266	1.369
ptcover					0.008	–0.001	–0.010	–0.021	0.012*	0.005
soil	–0.137	–0.119	0.171	–0.675	–0.467	–1.125	–0.011	0.495	–0.001	**–4.226**
slope	**0.050**	0.044	0.085	0.071	–0.323	0.086	0.105	0.054	0.052	0.011
pop_d	0.018	**–0.100**	0.010	**–0.124**	0.084	**0.861**	0.109*	0.055	0.010	–0.113*
pop_r	0.001	**0.003**	**–0.010**	–0.003	0.003	–0.013	–0.013	–0.005	0.001	0.001
dist_dtw	0.0002	–0.004	**–0.020**	–0.015	–0.063*	0.016	**–0.041**	0.094*	**–0.035**	**–0.090**
dist_5ct	0.002	–0.004	**–0.029**	**–0.051**	–0.056	0.002	–0.001	–0.061	**–0.048**	**–0.119**
dist_all	0.016	0.001	0.011	**0.055**	0.040	–0.005	–0.035	0.068	0.067	**0.278**
dist_hwy	0.002	0.008	0.071	**0.144**	0.329	**0.609**	–0.342*	–0.401*	0.016	0.282*
decade	**0.437**	**0.306**	**0.388**	0.482		–0.101		**3.698**		–0.773
pop_d × income						–0.028*				
decade × pop_d		**0.028**		**0.032**						
decade × soil				0.282						**1.107**
decade × dist_dtw				**–0.009**				**–0.052**		
Washington[a]						**4.358**				
Oregon		**–0.407**						1.982		
Ray										–23.926
Woodstock				**1.789**						**4.311**
Sample size	2012	2012	1926	1926	593	593	593	593	593	593
Censoring status[b]	1558,100, 354	1558,100, 354	1828, 14,84	1828,14,84	584,1,8	584,1,8	582,1,10	568,1,24	568,1,24	568,1,24
–Log likelihood	867.92	862.46	326.73	315.90	38.30	32.71	40.19	33.99	89.42	78.67
AIC	1759.84	1753.88	677.46	669.26	98.60	93.42	102.38	95.98	200.84	187.34
SBC	1827.12	1832.38	744.74	758.97	146.84	154.81	150.62	157.37	249.08	253.12
Generalized R^2	0.150	0.154	0.036	0.046	0.021	0.040	0.041	0.061	0.032	0.067

Note: Bold figures stand for significance at 5% level.

*Marginally significant ($0.05 < p < 0.15$).

[a] Dummy variable for being in township Washington (same for others).

[b] The number of right-, left-, and interval-censored values, respectively.

4. Discussion

4.1. Implications for development patterns and policy

Although none of our models was strong in predicting conversion to any of our residential development types, they do indicate that the different development types appear to have varying temporal dynamics (Figure 3), which may reflect macroeconomic or social changes. For instance, the rapidly increasing hazards for horticultural and remnant subdivisions since decades 3 or 4 (Figure 3) may be caused by continued out-migration from the city of Detroit and into the exurbs because of both push (related to the continued decline of the city's manufacturing base) and pull (related to desire for larger lots and more natural surroundings) factors. Such development types also have different locations on the landscape and different driving forces. For instance, our differentiation of the three subdivision types gave rise to different effects of soil: soil was insignificant in the pooled models (Models 1–4; Table 4), but became more important with time for remnant subdivisions (Model 10 in Table 4). This is corroborated by the increasing value for the soil variable (Table 3). An increasing demand for residential land, especially for remnant subdivisions – the type that had the biggest lot size and monetary value, may trigger farmers to abandon farming or sell some land parcels with good soil at later times to maximize their economic returns.

Among the three subdivision types, country subdivisions and horticultural subdivisions were less well predicted by the selected variables than the remnant subdivisions were. Country subdivisions had a tendency to occur in places with higher population densities, farther away from highways, and in Washington Township. Land regulations such as tax rates and zoning in this township could be driving forces behind this township dummy variable (similar for other significant township dummy variables). Their small lot size may contribute to higher density in a township, and higher density may reduce the overall aesthetic quality of a township, perhaps reducing the attractiveness of the township to developers and residents of more expensive subdivisions. The marginally significant negative interaction between income and population density (Model 6 in Table 4) may indicate that, at a given population density, these subdivisions tend to locate in townships with relatively lower income levels, which is consistent with the above characteristics such as small lot size, low monetary value, and nearness to county roads.

Horticultural subdivisions were relatively far away from Detroit at earlier times, but were closer in later decades (Model 8 in Table 4), which is corroborated by the decreasing average distances over time (Table 3). This may arise from land scarcity and the increasing preference for easier access to jobs and all the facilities that Detroit can provide. The significant positive coefficient for decade may indicate that this type was becoming more popular with time, relative to the others, but does not necessarily indicate a rise in the absolute numbers of newly developed horticultural subdivisions because the land supply was declining.

Remnant subdivisions were associated with areas having higher tree cover, which is consistent with our typology and other characteristics of this type, for example, bigger lot size, higher price, and better aesthetic quality (Table 1). Remnant subdivisions were more likely developed in places with lower population densities, which is consistent with their larger lot sizes and the possibility that they are located for aesthetic, rather than accessibility, reasons. At earlier times with more available land, remnant subdivision developers used areas with poor soils, which might save development costs. As time went on, remnant subdivisions were developed in areas of better soils because of many reasons such as decreasing land supply, certain biophysical and aesthetic features correlated with such good soils, or some land-use and zoning policies that steer development of remnant subdivisions in such areas. In terms of location relative to existing cities, remnant subdivisions were closer to Detroit and the five mid-level cites, but farther away from all urban areas (small towns plus mid-level to big cities) compared with other residential types. This may reflect a preference for job access and good services provided by mid-sized to large cites, but aversion to all the “urban disamenities” at a more local level (e.g., noise and pollution). Remnant subdivisions were also distant from highways, which may be because of the higher aesthetic values of such remote areas.

The above findings may help landscape ecologists, land planners, and landowners better understand the causes, mechanisms, and consequences of exurban land changes, achieving ‘. . . the oldest task in human history: to live on a piece of land without spoiling it’ (Leopold 1991). First, each residential type was found to be related to various factors, with varying dynamical effects, suggesting that policy makers or land-use managers should consider different drivers for different development types. Second, the effects of some variables (e.g., distance to Detroit; see Model 8) may change over time, and land-use managers or policy makers should recognize the dynamic nature of development processes and trends. Third, because the development types have very different effects on the physical landscape their differential placement can help explain the regionalization of landscape patterns observed within exurban areas. For example, areas that attract remnant subdivisions will tend to have higher ecological and aesthetic quality because of both the original characteristics of that landscape (e.g., more tree cover) and the design and planning effects of remnant subdivisions on it (e.g., the preservation or even restoration of the natural habitats through large lots or community open space). Managing for ecological quality, then, may require an explicit recognition of the variations in factors driving the placement of various residential development types. Because of the link between SEV and the different residential types as mentioned earlier (see Section 2.3), whatever conditions predict a certain residential type (e.g., remnant subdivisions) may be predictive of the corresponding land values. For instance, a place with higher tree cover, low population density, and away from highways may have higher economic value because it is suitable for a remnant subdivision.

4.2. Data reliability and sample size

The spatial and temporal resolution of our study was limited by available data. Our socioeconomic data were collected at the township level, which (somewhat coarsely) conforms to the scale of local land-use planning jurisdictions in Michigan. These data serve as the context under which the developers make decisions, which by nature operate at coarser scales. The socioeconomic factors were not significant predictors in most cases, which could arise from the fact that such factors are not important or that the resolution was not fine enough. Similarly, our geographic and environmental data had a relatively fine spatial resolution (i.e., at the level of individual parcels), but some of them may suffer from the lack of characterization over time. For example, a parcel’s access to employment and its distance to all urban areas (dist_all) would become shorter if new urban areas were added nearby. Such variations were not accounted for in our model.

Our sample consists of 854 polygons or parcels (4% of total, see Section 2.3), which is dominated by rural lots (66%). To some extent this is an artifact of our typology that keeps rural lots and subdivisions, two very different residential types (see Sections 2.1 and 2.3), in one analysis. When breaking into three subdivision types, there are only 27, 53, and 63 country, horticultural, and remnant subdivisions in 2000, respectively (Table 3). These numbers should not be interpreted as the effective sample sizes for estimating the corresponding models. The reason is that, for instance, when considering development of remnant subdivisions, the parcels developed into other subdivisions or that remained undeveloped also contribute to estimating the hazards and the related coefficients. Also our survival analysis method does not estimate separate models at EACH discrete time point, but monitors and uses the whole development trajectories over time. For this reason, the effective sample sizes are larger than what those low numbers at early times (e.g., nine remnant subdivisions in 1960; Table 3) might suggest.

4.3. Land regulations, scarcity, and choice of survival analysis

We were unable to directly characterize the effects of land regulations such as zoning and taxation on the observed developments. Such data may affect developers' decisions on what set of land parcels could be developed at how much cost and with what return (Hite, Sohngen, Templeton 2003). For example, the minimum allowable lot size was found to be positively related to hazard rate (Irwin *et al*. 2003). It is possible that some variables, like the average income and township dummy variables, serve as partial surrogates for zoning. For example, wealthy areas may be more likely to restrict small-lot development. More importantly, our use of township dummy variables provides a reasonable surrogate for zoning because zoning decisions are made at the township level in Michigan. If a township has a zoning different from other townships, its corresponding township dummy variable should be significant given that all other conditions are equal. Our results did show that several township dummy variables affected different types of developments (Table 4). Future analyses should include zoning as an explicit variable as such regulations may direct (even determine) developers' decisions regarding whether and how they would choose their development projects (Vigmostad 2003). In such models, attention needs to be paid to possible endogeneity of zoning with the development process. In addition, the model fit could be improved if we include an open space variable because of its spillover effects on nearby development (Irwin and Bockstael 2001).

In studying land-use/cover changes, there is an inherent problem that is associated with land immobility and scarcity. The status (developed or undeveloped) of one land parcel affects the development potentiality of surrounding parcels over both space and time. Higher population density may repulse (or attract in rare situations) further development. To account for this problem, we included both time and population density as explanatory variables. If the hazard change is solely caused by past development in surrounding areas (i.e., decreasing land supply), the variable population density should capture this effect and become a significant positive explanatory variable. In addition, the land supply was assumed constant within each period (here decade) in our piecewise exponential model, which may be defensible as long as a period is not too long, or the developments are in urban–rural fringe or solely rural areas that have vast available land. On the other hand, the hazard rate (a conditional probability density) can be interpreted as the instantaneous risk that a parcel is developed at a given time *in the context of all the previous developments* (An and Brown 2008). The concept of hazard thus encapsulates the history of all the past events. So hazards of land-use/cover change can be interpreted as the attraction and attrition of a place: high hazards mean high attraction and low attrition, and vice versa.

5. Conclusions

Our research shows that in studying exurban land changes, an overall category of 'residential' development type may mask many important features associated with different subdivision types. These subdivision types (Table 1) are usually located on the landscape differently, driven by different factors, characterized by time-variant relationships, and associated with different ecological effects. Such differentiation of subdivision types in timing, location, and driving mechanisms could help landscape planners and managers make ecologically sound and economically appropriate decisions. Aiming to understand residential development from developers' perspectives, this article provides information about how various residential types interact with different sociodemographic, geographic, and biophysical drivers over time in exurban areas. Additional work is needed to examine the ecological and environmental effects that may emerge from, and feedback to affect, future residential development.

Notes

1. Our operational definition of exurban areas, in the context of several other definitions (e.g., Hammer, Stewart, Winkler, Radeloff, and Voss 2004; Theobald 2005; Berube, Singer, Wilson, and Frey 2006) is low-density settlements that are contiguous with metropolitan urbanized areas but disconnected from city services of sewer and water.
2. Vigmostad's (2003) in-depth interviews with 15 successful real estate developers in Michigan revealed that such factors include predictions of 'where the growth is going,' financial situations, physical features of the site (e.g., slope), 'where there is water and sewer,' 'school district,' 'where the customer seems to want to be going,' differences among municipalities, 'soil conditions,' and 'tax laws and zoning.' One developer mentioned his concern about preservation of watershed and waterfront by looking at Michigan Natural Features Inventory, and others mentioned some ethical and religious concerns such as 'walk our talk' and 'reputation is extremely important' (Vigmostad 2003).
3. For easier description, we refer to 1960, 1970, . . ., and 2000 without pointing out ±2 years or the fact that these are approximate years.
4. Survival times are used as the response variable in the SAS lifereg procedure, and the coefficients thus obtained should be reversed in signs if interpreting them as coefficients of hazards (Allison 1995, pp. 68–70).
5. Such interactions include (1) terms between each potential independent variable (Table 2) and decade to capture any dynamic effect associated with these variables and (2) terms between population density and each of the three socioeconomic variables to control the effects simply caused by a changed land demand (population density as a proxy).

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