# A Hybrid Land Conversion Model Incorporating Multiple End Uses

**Nikhil Kaza, Charles Towe, and Xin Ye**

The need for models that forecast land use change spans many disciplines and encompasses many approaches. Pattern-based models were the first in which projections of change at specific locations in actual landscapes could be predicted. In contrast, recent economic models have modeled the underlying behavioral process that produces land use change. This paper combines attributes from each approach into a hybrid model using a multiple discrete continuous extreme value formulation that allows for multiple conversion types, while also estimating the intensity of each type of conversion, which is an important but often overlooked dimension. We demonstrate the simulation routine, which successfully predicts a majority of growth by type, time, and location at a disaggregated scale, for a three-county region in Maryland.

***Key Words:*** MDCEV, land conversion, regional planning, urban growth policy

Land use change has been forecasted using a number of techniques in various fields, including geography, planning, engineering, environmental science, and economics, for a variety of purposes, including evaluating policy outcomes. Each field, almost in isolation, has developed its own methods for modeling urban change and the attendant effects. Not surprisingly, these methods exploit the comparative advantage of each field and focus on outcomes conforming to their desired application.

Early economic land use models, while spatial, were stylized representations of abstract homogenous landscapes, and focused on distances to city centers. Geographers and natural scientists constructed models in which land use change could be modeled at specific locations in a heterogeneous environment. By gridding the landscape and applying algorithms based on past patterns of land use change, these researchers created a technique, commonly known as the pattern-based model, that is able to forecast land use change for any arbitrarily large geographic extent at any level of resolution, constrained only by computing power.

In contrast to the pattern-based models, which focused on replicated past patterns of development, models developed by applied economists focus on the behavioral decisions of landowners. This approach, known as a process-based model, considers the landowner to be a utility-maximizing agent and adopts the land parcel, rather than grid, as the logical unit of analysis. These models are highly data-intensive, and therefore tend to be limited in geographic scope (single county or metro area in the United States). By limiting the geographic scope of the model, social scientists can evaluate policy mechanisms designed to alter future development patterns, which cannot be done in the pattern-based model.

In the past few years the need to explore cross-disciplinary and hybrid approaches has gained traction. The biosciences, for example, have grown more interested in the underlying process of land use and land cover change, and have increasingly

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The authors gratefully acknowledge partial support for this work from the Maryland State Highway Administration. Conference participants at the 2010 American Agricultural Economic Association meeting in Milwaukee, Wisconsin, and the two anonymous referees provided detailed and excellent comments, for which we are grateful.

This paper was presented at the workshop "The Economics of Land Use Change: Advancing the Frontiers," organized by Lori Lynch (Center for Agricultural and Natural Resource Policy, University of Maryland) and Jacqueline Geoghegan (Clark University), in Washington, D.C., June 25–26, 2009. The workshop received financial support from the U.S. Environmental Protection Agency, the Lincoln Institute of Land Policy, and the Center for Agricultural and Natural Resource Policy at the University of Maryland. The views expressed in this paper are the authors' and do not necessarily represent the policies or views of the sponsoring agencies.

gravitated towards a perspective that integrates socioeconomic and demographic models of change with land cover/land use change (Irwin 2010). On a similar note, economists have begun to collaborate with geographers in pursuit of agent-based models that are data-driven but that "may be viewed as more process-based and deductive than the statistical or mathematical models common in land change science, in which emphasis is placed on fitting parameters to observations" (Robinson et al. 2007, p. 32).

Continuing this cross-disciplinary tradition, in this paper we combine attributes from multiple methods to create a hybrid model capable of projecting both type and intensity of urban development. Our model, which employs a multiple discrete continuous extreme value (MDCEV) framework following Bhat (2005) and Bhat and Sen (2006), allows us to forecast large-scale land conversion while still utilizing a data structure often seen only in economic models of land conversion. The model also allows us to estimate multiple land use end states, including single-family residential, multi-family residential, and other non-residential uses. By including a diversity of outcomes, our model can identify broader land change trends, including conversion of agricultural land into residential uses at the rural-suburban fringe, the development of agricultural land into commercial and residential land at the suburban-urban fringe, and infill development inside urban areas. While the latter two conversion types are often excluded from economists' models, our model can more accurately capture current trends in land use changes.

This paper is part of an ongoing land use modeling program and contributes to the literature in four primary ways:

- We model the decision to convert land into a multiplicity of developed states: *single-family residential* (SF), defined as any detached single-family structure; *multi-family residential* (MF), which includes attached dwellings such as townhouses, condominiums, and apartment buildings; and *non-residential* (NR), which includes office buildings, retail establishments, and industrial buildings.
- We simultaneously estimate determinants of the intensity of development in terms of square footage of new construction.
- We expand the traditional geographic scope of the land change model and demonstrate it in a multi-county region in Maryland, operating at a meso-geographic resolution.
- We demonstrate simulation outcomes and compare them to actual outcomes. Unlike the authors of much of the work in this area, we are not interested in a single outcome; rather, we provide a mechanism to evaluate the outcome from multiple simulations and compare them to observed land use change.

The land use change model is also designed to be integrated with existing economic and demographic projection models, transportation models, and environmental impact models for the multi-state Chesapeake Bay region.

We proceed as follows. First, we situate our model of land conversion in the economic literature. We then explain the econometric model in detail, justifying its inclusion by examining land use conversion data from Montgomery, Prince George's, and Howard Counties in Maryland. We then present the results of the estimation procedure and develop a simulation mechanism that illustrates the efficacy of this approach.

## Economic Model of Conversion

The economic model of land conversion draws from both traditional spatial economic models, where individuals choose their location based on distance to city centers (Muth 1969, Mills 1967), as well as from models where that attempt to explain urban spatial structure is theorized to be the result of a series of interactions among economic agents (Fujita and Ogawa 1982, Krugman 1991, Steen 1986). Recent versions of the land conversion model consider, among other things, congestion effects among residential land uses, apply a real options approach to landowners' decisions, and explain patterns of growth more complicated than the stylized monocentric city (Capozza and Helsley 1990, Capozza and Li 1994). The most recent land use change models meld these individual-based models with high-resolution heterogeneous spatial data and land use regulations.

The advantage of economic models is their focus on individual decision makers in the conversion process. Since economic models require large computational resources and data, we propose combining grid based models with economic analyses. Specifically, we explore whether the process of land use change can be analyzed by aggregating landowners into a grid, as is done in the natural sciences and geography, in order to provide more flexibility in both geographic extent and data resolution. Through a positive side effect of this scaling up, the model's output can be integrated with transportation and ecological models, and can be used to address a more diverse set of policy questions.

Most economic models of land use change implicitly assume that landowners base their conversion decision on some version of a net present value decision rule, where the benefits of the *status quo* land use are weighed against the expected returns to conversion (Carrion-Flores and Irwin 2004, Parks 1995, Brownstone and De Vany 1991, Stavins and Jaffe 1990). Other models have incorporated a real options approach (Cunningham 2007, Towe, Nickerson, and Bockstael 2008) into this conversion rule, adding the notion that uncertainty in the estimated returns may delay the development decision. This approach may be appropriate for localized policy evaluation, but quickly becomes intractable for large multi-country regions.

Therefore, we aggregate the underlying parcel and other environmental information into a grid. An observation, in our analysis, is a grid cell representing one-fourth of a square mile (~40 acres). Each of these grids have the option to convert land into one or more alternative uses. Using a grid for land use transformation analysis is not new (see, e.g., Kline 2003). Some grids have been constrained to include only single-family use, but many have the choice of commercial, single, or multi-family uses or some combination of the three.[1]

It is important to note that we aggregate from micro-level point data on parcels to attain the values used in each grid cell. Thus, this approach is only marginally less realistic than approaches that use circular buffers as parcel boundaries. However, aggregation of land conversion decisions into a grid is not without its caveats, as it requires the assumption of homogeneity of landowners within each grid. This assumption is not without merit, as demonstrated by many decades of neighborhood-sorting research (see, e.g., Schelling 1969, 1971), and more recently by policy research promoting inclusionary zoning to alleviate neighborhood socioeconomic homogeneity. Correlations between the different uses within our grids are very low, ranging from 0.005 for single-family and commercial to 0.068 for single-family and multi-family, suggesting a great deal of homogeneity by existing type.

## Econometric Model

One benefit of grid-level aggregation is the ability that many grids have the option to convert a grid cell into one or more uses. Of the 20,596 grids in the region, over 8,000 have potential to develop into more than one use and over 1,000 have potential to develop into all three uses. The Multiple Discrete Continuous Extreme Value (MDCEV) model is therefore appropriate in these circumstances. The MDCEV model not only allows for the simultaneous selection of multiple end states but also estimates the intensity of each potential change, as measured by the square footage of new construction. This approach allows us to consider conversion choices other than single-family residential, thus capturing much of the development activity in suburban landscapes. Models of this type have often been used by environmental economists, especially when modeling recreation demand (Phaneuf and Smith 2005, Phaneuf, Kling, and Herriges 2000, von Haefen, Phaneuf, and Parsons 2004, von Haefen and Phaneuf 2005). The MDCEV model formulated here represents an advanced version of the random utility model (RUM), which allocates a fixed and exogenous capacity of development among a nontrivial choice set. Other applications of this kind of model include activity models, where time is allocated, or purchase decision models, where income is the allocated constraint (Bhat 2005, Bhat and Sen 2006, Bhat 2008).

The first step in the process of estimation is to establish the capacity constraint for each grid. This constraint is obviously influenced but not completely determined by it. We calculate this capacity constraint using ordinary least squares regressions based on past conversion activity (elaborated on in the next section). These regressions are used to predict the allowable square footage

[1] There are many pockets of dense zoning and commercial use areas even in rural sections of Howard County.

of growth, $B$ from the square footage "budget," for the given time window and, as a function of zoning, existing structures, soils, slope, and excludable lands for each grid.

Each of the grids $i$ can then choose to allocate this allowable square footage $B_i$ among $K$ alternative land uses. In the current model, $K = 4$ with *single-family residential* (SF), *multi-family residential* (MF), *non-residential* (NR), and *no growth* (NG).[2] The presence of an NG alternative in the choice set ensures that at least one alternative is chosen. The allocation is performed by maximizing a utility function [equation (1)], which is both additive and non-linear, and modified based on a formulation proposed by Kim, Allenby, and Rossi (2002) to include a parameter measuring non-linear or diminishing marginal profitability in each alternative:

$$(1)\quad U \equiv \sum_{j=1}^{K} \frac{1}{\alpha_j}[(lu_j+1)^{\alpha_j}-1]\cdot \exp(\beta'_j x_j + \varepsilon_j),$$

where $lu_j$ is the land use in square footage in each type ($j$ = 1...$K$), and $\alpha_j$ are parameters that need to be estimated along with the vector β. The vector $x_j$ includes the variables that determine the baseline value for each type of land use $j$, and $\varepsilon_j$ is the random component of that baseline value. The $\alpha_j$ parameter incorporates the satiation effects (diminishing marginal return). The exponent $\exp(\beta_j x_j + \varepsilon_j)$ represents the baseline use value that controls whether a grid cell chooses a conversion or not (the extensive margin), and the exponential form ensures that the utility is positive. The satiation effects $\alpha_j$ are constrained to be positive but less than 1 (i.e., $0 < \alpha_j < 1$) to ensure that the function is increasing with respect to land use, since its first-order derivative is always positive. The negative second-order derivative captures the diminishing marginal effect.

Equation (1) is maximized subject to the constraint:

$$(2)\qquad \sum_{j=1}^{K} lu_j = B\,,$$

where $B$ is the allowable square footage for each grid, which differs across grid cells. From the Lagrangian, the following Kuhn-Tucker first-order conditions can be written out, as detailed by Bhat (2005):

(3)

$$\alpha_j (lu_j^*+1)^{\alpha_j-1}[\exp(\beta'_j x_j+\varepsilon_j)]-\lambda = 0,\ \text{if}\ lu_j^*>0$$

$$\alpha_j (lu_j^*+1)^{\alpha_j-1}[\exp(\beta'_j x_j+\varepsilon_j)]-\lambda < 0,\ \text{if}\ lu_j^*=0$$

$$\sum_{j=1}^{K} lu_j^* = B.$$

The econometric model specification assumes an extreme value distribution and assumes that the errors are independent of $x$, and independently distributed across the $K$ alternatives.[3] The probability that grid $i$ chooses $M$ of the $K$ alternatives and does not choose $K$–$M$ alternatives (or chooses with zero value) is:

(4)

$$P(lu_i^*>0 \text{ and } lu_s^*=0; i=1...M \text{ and } s=M+1...K)$$

$$=\left(\prod_{i=1}^{M} c_i\right)\cdot\left(\sum_{i=1}^{M}\frac{1}{c_i}\right)\cdot\left(\frac{\Pi_{i=1}^{M} e^{V_i}}{(\sum_{j=1}^{K} e^{V_j})^M}\right)\cdot (M-1)!\ ,$$

where

$$c_i = \frac{1-\alpha_i}{lu_i^*+1}$$

and $V_i = \beta' x_i + (\alpha_i - 1)\cdot \ln(lu_i^*+1)$. For the derivation of this equation, see Bhat (2005, 2008).

When $M = 1$, the model degenerates to a standard multinomial logit model because the entire development capacity is allocated to the one chosen alternative. The log-likelihood of this function is optimized using standard numerical optimization techniques and the optimization routine specified by Byrd et al. (1995).

This MDCEV characterization has several useful properties for this application. First, it allows heterogeneous conversion outcomes in a single grid within a single time period for discreteness

[2] This no-growth alternative represents the ability to allocate at least a portion of the budget to "no change," which is observed quite often in land use models and is the subject of a significant amount of literature (Titman 1985, Capozza and Helsley 1990, Towe, Nickerson, and Bockstael 2008, Cunningham 2007, and others).

3 This can be relaxed by estimating a mixed MCDEV model (MMCDEV), much like a mixed Logit model.

when multiple choices can be made at one decision point, affirming partial substitutability of the choices and allowing the outcome where more than one conversion type occurs in the same grid and the same time period. For example, some grids may experience multi-family and commercial or single-family and multi-family development in the same grid at the same time. Second, it allows for a non-linear relationship within the selected choices. In the utility framework, this represents diminishing marginal utility, while in this context it represents diminishing marginal returns to conversion intensity. In other words, if a large commercial development is profitable in a grid, three large commercial developments will not be three times as profitable.

## Data and Variables in the Models

Our application of the MDCEV model involves observations collected from two time intervals. The first interval, from 1995 to 2001, provides the data for estimating the capacity constraints; and the second interval, from 2002 to 2004, provides data for estimating the MDCEV allocation model. We estimate the capacity constraints as well as the observed intensive and extensive margin land conversion outcomes using grid-level aggregations of spatially explicit micro data for Montgomery, Prince George's, and Howard Counties in Maryland, which are suburbs of Washington, D.C., and Baltimore, Maryland. Data from the Maryland Department of Planning's "MDProperty View" (MPV)—a property planning tool—were combined with data on natural soils, land cover, easement, and travel time from the Maryland Statewide Transportation Model, which was developed by the National Center for Smart Growth Research and Education (Kaza, Knaap, and Meade 2008). MPV data were derived from assessment and taxation files from each county in the state, and include parcel-level attributes and each parcel's spatial coordinates. Table 1 describes the data used to estimate capacity constraints, and Table 2 describes the data in the MDCEV model.

Figure 1[4] illustrates the current land use patterns in the three-county region. While large portions of the region have some type of development, it is at a fairly low density. Very few grids are completely undeveloped, unless development is completely prohibited by the presence of federal lands and other undevelopable land uses. Grids closest to the Washington area have high single-family square footage; while predictably the nonresidential development follows the major highways. Multi-family development is sparse and is severely restricted by zoning in these suburban counties. Nevertheless, there are a substantial number of grids that show all three types of development.

It is important to note that we have taken great care to construct an estimation data set utilizing readily available data for all Maryland counties (and neighboring states) so the model can be expanded to a statewide (or regional) model of land change. However, we chose to focus on the selected counties because they are the suburban and exurban regions of two major cities, and as such are under development pressure for single and multi-family residential as well as non-residential development.

### *Capacity Estimation*

As mentioned previously, we need to define a budget or capacity constraint in terms of square feet of potential structures by grid cell in order to estimate the MDCEV. The simplest calculation would employ zoning regulations, but this calculation represents the build-out capacity of approximately twenty years of residential growth, not the three-year growth period that is utilized in the model. Furthermore, directly applying the zoning code has at least two other major deficiencies. First, the zoning code provides the number of homes per acre, not a direct estimate of new construction square footage; second, the code does not provide guidance for the size of nonresidential activity. Therefore, we estimate the capacity, or budget, of a grid, using ordinary least squares for each development type. This estimation is based on the observed new construction activity from our first time interval (1995 to 2001), as represented by equation (5):

$$LU^c = \gamma + \sigma Z + \rho D + \tau G + \varepsilon \,, \qquad (5)$$

where $LU$ is the development activity between 1995 and 2001 in square feet, and $c$ is SF, MF, and NR land uses. $Z$ are variables representing

[4] Color versions of Figures 1, 2, and 4–7 are available at AgEcon Search (http://ageconsearch.umn.edu/).

**Table 1. Capacity Estimation Summary Statistics**

| | SF model [a] | | MF model [a] | | NR model [a] | |
|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| OUTCOMES | | | | | | |
| Conversion sq ft (1995–2000) | 24,165 | 42,703 | 70,930 | 86,085 | 52,837 | 96,474 |
| VARIABLES | | | | | | |
| *% undevelopable* | 9.94 | 21.51 | 6.65 | 15.41 | 4.91 | 13.43 |
| *% under easements* | 0.07 | 0.32 | 0.00 | 0.00 | 0.01 | 0.12 |
| *Dwelling unit per acre* | 1.94 | 4.70 | 8.28 | 19.23 | 4.84 | 15.15 |
| *sq ft SF zoning* | 134,326.60 | 37,742.44 | 86,462.91 | 56,301.79 | 72,781.57 | 59,553.32 |
| *sq ft MF zoning* | 16,392.10 | 39,294.63 | 44,916.79 | 50,336.93 | 25,262.11 | 40,677.46 |
| *sq ft comm zoning* | 2,436.84 | 11,413.53 | 12,605.06 | 29,046.67 | 21,146.61 | 35,512.74 |
| *sq ft ind zoning* | 1,625.86 | 10,837.14 | 4,128.80 | 16,073.21 | 27,465.39 | 50,233.74 |
| *sq ft SF 1994* | 55,791.89 | 64,938.06 | 32,215.50 | 49,999.04 | 37,181.62 | 59,092.63 |
| *sq ft MF 1994* | 6,068.73 | 40,411.56 | 61,637.60 | 127,338.40 | 23,262.70 | 94,353.42 |
| *sq ft comm 1994* | 5,612.10 | 55,714.11 | 33,124.35 | 179,484.00 | 63,145.18 | 195,652.60 |
| *sq ft ind 1994* | 2,084.63 | 24,099.80 | 6,958.38 | 40,632.53 | 34,232.51 | 92,342.85 |
| *% highly erodible* | 0.03 | 0.15 | 0.06 | 0.21 | 0.05 | 0.18 |
| *% very highly erodible* | 0.13 | 0.29 | 0.15 | 0.30 | 0.19 | 0.33 |
| *% runoff high* | 0.27 | 0.37 | 0.29 | 0.36 | 0.31 | 0.39 |
| *% slope high* | 0.07 | 0.20 | 0.06 | 0.19 | 0.05 | 0.17 |
| *% floodplain* | 0.06 | 0.13 | 0.08 | 0.14 | 0.06 | 0.13 |
| *% land cover water 1970* | 0.00 | 0.03 | 0.00 | 0.02 | 0.00 | 0.04 |
| *% land cover ag 1970* | 0.13 | 0.23 | 0.04 | 0.11 | 0.06 | 0.15 |
| *% land cover forest 1970* | 0.22 | 0.25 | 0.22 | 0.22 | 0.16 | 0.21 |
| *% land cover road 1970* | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.03 |
| | N = 4,398 | | N = 311 | | N = 693 | |

[a] Conditional on non-zero square footage of conversion of this type from 1995 to 2000.

zoning (area of each grid zoned for residential, commercial, or industrial), $D$ are variables representing the existing constructed landscape as of 1994, and $G$ are other geographic grid-level attributes (such as soil attributes, slopes, and the proportion of land cover in forest, agriculture, or water). While capacity is determined through this equation, much of the capacity may not be realized in actual development.

Results from these regressions are presented in Table 3. Using these individual regressions, we predict the capacity of new construction for each grid cell by type of development. The total capacity used in the MDCEV model is the sum of the predicted square footage across all types of land uses, or

(6) $$\hat{B}_i \equiv \hat{SF}_i^c + \hat{MF}_i^c + \hat{NR}_i^c .$$

*MDCEV Model*

As mentioned before, the main outcomes of interest are the square footage of new single-family residential, multi-family residential, and non-residential development from 2002 to 2004. The data included in the allocation model provide insight into the attraction and repelling effects of different types of development, not unlike estimates by Irwin and Bockstael (2002). In this context, the amount of existing square footage in each land use type controls for density of development (and, thus, population), as well as a predeter-

**Table 2.** **MDCEV Summary Statistics**

| Variables | Mean | S.D. | Max |
|---|---|---|---|
| *Travel time to Baltimore* | 50.41 | 16.49 | 95.09 |
| *Travel time to D.C.* | 36.34 | 13.03 | 92.59 |
| *Travel time to Annapolis* | 54.59 | 16.64 | 107.76 |
| *Sq ft single family (neighborhood)* | 39,222 | 50,549 | 288,965 |
| *Sq ft multifamily (neighborhood)* | 8,001 | 32,609 | 818,651 |
| *Sq ft non-residential (neighborhood)* | 15,360 | 51,851 | 1,205,000 |
| *Sq ft single family* | 39,182 | 64,997 | 605,107 |
| *Sq ft multifamily* | 8,035 | 60,738 | 3,314,505 |
| *Sq ft non-residential* | 15,318 | 87,180 | 3,137,262 |
| *% agricultural land (neighborhood)* | 0.20 | 0.24 | 1.00 |
| *% forest land (neighborhood)* | 0.34 | 0.24 | 1.00 |
| *% agricultural land* | 0.20 | 0.30 | 1.00 |
| *% forest land* | 0.34 | 0.33 | 1.00 |
| *% in environmental preservation easements* | 0.03 | 0.13 | 1.00 |
| N = 20,596 | | | |

mined variable, which measures the application of existing zoning regulations and the general attractiveness of the area for development from the perspective of either supply or demand. The existing landscape configuration also assists in identifying the remaining prime areas for conversion based on available capacity. The MDCEV econometric model estimated in this paper is detailed in the following equations:

$$(7) \qquad U_{NG} \equiv \frac{1}{\alpha_{NG}}[(NG+1)^{\alpha_{NG}} - 1]$$

$$U_{SF} \equiv \frac{1}{\alpha_{SF}}[(SF+1)^{\alpha_{SF}} - 1].\exp\begin{pmatrix} \alpha_{sf} + \beta'_{1sf} X \\ +\beta'_{2sf} N_X \\ +\beta'_{3sf} TT \\ +\beta'_{4sf} P + \varepsilon_{SF} \end{pmatrix},$$

$$U_{MF} \equiv \frac{1}{\alpha_{MF}}[(MF+1)^{\alpha_{MF}} - 1].\exp\begin{pmatrix} \alpha_{mf} + \beta'_{1mf} X \\ +\beta'_{2mf} N_X \\ +\beta'_{3mf} TT \\ +\beta'_{4mf} P + \varepsilon_{MF} \end{pmatrix},$$

$$U_{NR} \equiv \frac{1}{\alpha_{NR}}[(NR+1)^{\alpha_{NR}} - 1].\exp\begin{pmatrix} \alpha_{nr} + \beta'_{1nr} X \\ +\beta'_{2nr} N_X \\ +\beta'_{3nr} TT \\ +\beta'_{4nr} P + \varepsilon_{NR} \end{pmatrix}$$

$$U \equiv U_{SF} + U_{MF} + U_{NR} + U_{NG}.$$

The utility of conversion into a particular land use type is dependent on *X*; grid-level attributes of existing single-family, multi-family, and non-residential square footage in 2001; $N_X$, the neighboring grid characteristics; *TT,* the travel time variables; and *P,* the land variables representing preservation programs and policies both within the grid and in its neighboring grids. Each attribute is allowed to impact each choice heterogeneously.

The specific variables included in the model are meant to be proxies for the following: the initial land use of the grid, demand pressure, distance and accessibility measures, costs of development, returns to alternative uses, zoning policies, and conservation or preservation easements (see Table 2 for detailed summary statistics). Variables included in all choice sets include vari-

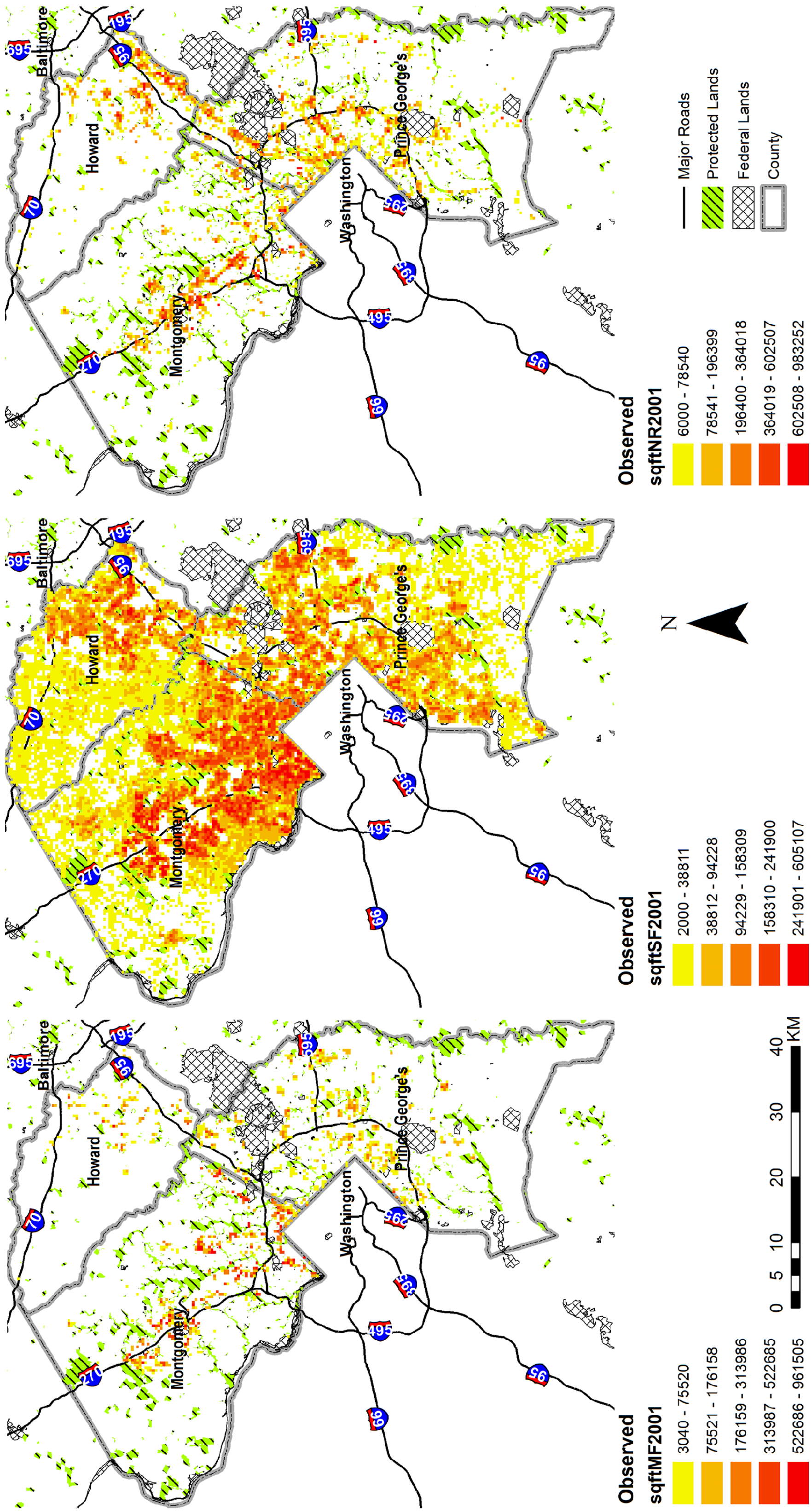


**Figure 1. 2001 Development Patterns: Multi-Family (left), Single Family (middle), and Non-Residential (right)**

**Table 3. Capacity Model Estimates**

| | SF model[a] | | MF model[a] | | NR model[a] | |
|---|---|---|---|---|---|---|
| Variables | Coeff. | SE | Coeff. | SE | Coeff. | SE |
| *% undevelopable* | -18.41 | 31.48 | -293.86 | 299.24 | 149.0259 | 287.3524 |
| *% under easements* | -554.76 | 2,092.55 | n/a | n/a | -34,649.53 | 30,140.94 |
| *Dwelling unit per acre* | -110.00 | 165.99 | 257.10 | 301.96 | -231.95 | 300.76 |
| *sq ft SF zoning* | -0.02 | 0.02 | 0.04 | 0.12 | -0.13 | 0.09 |
| *sq ft MF zoning* | 0.21** | 0.02 | 0.01 | 0.12 | 0.02 | 0.10 |
| *sq ft comm zoning* | -0.12** | 0.06 | 0.16 | 0.21 | -0.06 | 0.13 |
| *sq ft ind zoning* | -0.07 | 0.07 | 0.78** | 0.34 | 0.30** | 0.11 |
| *sq ft SF 1994* | -0.11** | 0.01 | -0.41** | 0.10 | -0.17 | 0.07 |
| *sq ft MF 1994* | -0.01 | 0.02 | 0.21** | 0.04 | 0.01** | 0.04 |
| *sq ft comm 1994* | 0.01 | 0.01 | -0.09** | 0.03 | 0.10 | 0.02 |
| *sq ft ind 1994* | -0.04 | 0.03 | -0.01 | 0.13 | -0.06 | 0.05 |
| *% highly erodible* | -17,388.11** | 4,985.38 | -20,388.85 | 48,822.26 | 40,818.33 | 32,399.46 |
| *% very highly erodible* | -9,717.06** | 3,456.38 | -12,415.01 | 46,968.14 | 11,918.50 | 27,360.47 |
| *% runoff high* | 5,762.12* | 2,901.99 | -14,208.58 | 45,148.03 | -33,130.52 | 26,015.70 |
| *% slope high* | 780.12 | 3,224.28 | -13,745.38 | 24,116.79 | -31,277.56 | 21,698.37 |
| *% floodplain* | -812.77 | 5,264.25 | -45,521.74 | 51,314.80 | 47,112.78 | 35,312.81 |
| *% land cover water 1970* | -33,963.75 | 21,322.71 | -150,671.30 | 204,512.70 | -64,578.57 | 100,365.30 |
| *% land cover ag 1970* | -39,342.11** | 3,319.01 | 13,591.35 | 40,697.31 | 37,441.60 | 24,694.32 |
| *% land cover forest 1970* | -27,106.84** | 3,010.26 | -61,013.89** | 23,529.16 | -8,118.66 | 18,361.14 |
| *% Land cover road 1970* | -24,479.03 | 76,367.75 | -166,338.70 | 418,742.50 | 49,885.90 | 125,725.10 |
| Constant | 41,652.28 | 3,435.71 | 90,738.27** | 19,536.88 | 61,074.28** | 13,615.79 |
| | N = 4,398 | | N = 311 | | N = 693 | |
| | R-Square 0.09 | | R-Square 0.25 | | R-Square 0.11 | |
| | Adj. R 0.08 | | Adj. R 0.24 | | Adj. R 0.09 | |

[a] Conditional on non-zero square footage of conversion of this type from 1995 to 2000.

Note: * represents significant at the < 0.10 level , ** represents significant at the < 0.05 level, and *** represents significant at the < 0.01 level.

ables measuring of the existing square footage of construction by type in each cell. Neighborhood is defined as all the grids with first-order Queen contiguity. All of the square footage measures are included in log form in the models, though Table 2 does not reflect this transformation.

Land preservation is an established priority of the state of Maryland, as demonstrated by the multitude of state and county preservation programs dating back to the mid-1970s. We've therefore included a measure of the amount of land in each grid cell in various permanent conservation and preservation easement programs. These variables represent an important policy variable (Lynch and Musser 2001, Towe, Nickerson, and Bockstael 2008, and many others). To proxy for construction costs as well as alternative land uses and amenities, we've included a measure of the proportions of agricultural and forest land in each grid. Forest includes all non-agricultural, non-open land, from brush cover to mature trees. These data were derived from laying grids over the 2001 land cover data. Following the insight of the basic urban bid-rent monocentric city models, travel times to Baltimore, Washington, and Annapolis are included in minutes. These travel times were derived from the Maryland Statewide Travel Demand Model, and reflect average travel times between the Statewide Modeling Zone (SMZ) and the SMZ that contains the centroid of the respective cities.

## Estimation Results

All the statistical analyses and simulations are performed in R (R Development Core Team 2010). We also use contributed R packages VGAM (Yee 2010), spdep (Bivand 2010), and spam (Furrer 2010) for the Gumbel distribution, spatial weighting matrices, and sparse matrices, respectively.

The model's coefficient estimates are presented in Table 4. We are pleased that the signs confirm much of previous research from simpler models, but also suggest interactions between uses that have not been previously estimated. With respect to current land uses and the single-family residential conversion decision, the model suggests that grids with a greater existing intensity of single-family homes prefer additional single-family land uses. Not surprisingly, the intensity of neighboring multi-family and commercial construction tends to repel new single-family construction. A similar result was found by Carrion-Flores and Irwin (2004) and Irwin and Bockstael (2002).

Existing land use patterns also impact multi-family and commercial activity in ways that are consistent with previous research. Multi-family construction is more likely in areas where similar use existed prior to 2001, and is repelled by single-family use in neighboring grids. Interestingly, the neighborhood impact of existing multi-family uses is positive for new commercial activity, while existing commercial uses repel new multi-family construction. This may be explained by the desire of commercial establishments to locate near densely developed areas.

Easements should impact single-family conversion, as they are potential amenities for nearby landowners (Towe 2008). This is borne out in the estimation results; the greater percentage of land under easement, the more likely a single-family development occurs. Finally, agricultural land cover, serving as a proxy for steepness and soil quality, is negative and significant for single-family construction, with no effect on commercial or multi-family construction. However, forest cover has a positive effect on single-family construction. Interpreting the sign of agriculture or forest cover is fraught with difficulty. In our area, forest cover constitutes a large percentage of the remaining open land, so the positive sign might simply reflect a recognition that development must occur in previously underdeveloped areas. Agricultural land has also become increasingly scarce in suburban areas, and is often the target of developers as well as preservationists.

The satiation parameters α for all the land use types (including *no-growth*) are less than 1 (between 0.56 and 0.97), which implies the existence of a dampened attraction effect of new development of similar types within each grid, as more of that type already exists in the grid. The diminishing marginal utility portion, i.e.,

$$\frac{1}{\alpha_j}[(lu_j+1)^{\alpha_j}-1]$$

as in equation (3), is plotted in Figure 2. As shown, the utility of single-family land use increases much faster than that of both multi-family and non-residential land use. This relationship indicates that there is a stronger tendency to convert the land use into single-family use than into multi-family or non-residential use purposes. While this confirms the results of a majority of the spatial interaction models, the coefficients of the neighborhood variables provide an interesting picture of the attraction and repulsion effects of various land uses. For example, while the coefficient estimates imply that single-family development is attracted to existing single-family development, the satiation parameter suggests that grids with more single-family development attract less new development due to both capacity and crowding. This suggests that less developed areas will tend to fill with new conversion before the last bits of capacity fill in existing developed grids. Both the signs and significance of the intercept terms also suggest that, in general, the grids have a strong status quo bias, and tend to allocate all their budgets to the no-growth alternative. This is to be expected, as we would not expect rampant development in only a three-year conversion period.

## Simulation Procedure

While estimation is useful to tease out the relative effects of variables and policies, we are primarily interested in simulating land use change. In this paper, we test if the model described here reasonably predicts the observed land use change between 2002 and 2004. It is important to keep in mind the two allocations that are necessary in the

**Table 4. Estimation Results MDCEV Model**

| | | | | | | |
|---|---|---|---|---|---|---|
| SATIATION PARAMETERS | | | | | | |
| No growth | 0.970*** | | | | | |
| Single family | 0.840*** | | | | | |
| Multi-family | 0.562** | | | | | |
| Non-residential | 0.606*** | | | | | |
| | Single Family Residential | | Multi-Family Residential | | Commercial | |
| VARIABLES | coeff. | s.e. | coeff. | s.e. | coeff. | s.e. |
| Constant | -1.615 | 0.266*** | 1.600 | 1.029 | -0.369 | 0.521 |
| *Sq ft of single family* | 0.176 | 0.009*** | -0.155 | 0.031*** | 0.079 | 0.019*** |
| *Sq ft of multi-family* | -0.019 | 0.010* | 0.693 | 0.093*** | -0.032 | 0.014** |
| *Sq ft of non-residential* | -0.077 | 0.007*** | 0.032 | 0.029 | -0.043 | 0.014*** |
| *Sq ft of single family in neighboring grids* | 0.051 | 0.021** | -0.756 | 0.104*** | -1.222 | 0.058*** |
| *Sq ft of multi-family in neighboring grids* | -0.145 | 0.007*** | 0.247 | 0.087*** | 0.740 | 0.048*** |
| *Sq ft of non-residential in neighboring grids* | 0.004 | 0.006** | -0.143 | 0.040*** | 0.309 | 0.027*** |
| *Travel time to Baltimore* | -0.023 | 0.002*** | -0.095 | 0.021*** | 0.003 | 0.009 |
| *Travel time to Washington, D.C.* | -0.011 | 0.002*** | -0.157 | 0.021*** | -0.080 | 0.010*** |
| *Travel time to Annapolis* | 0.011 | 0.002*** | 0.072 | 0.023*** | 0.038 | 0.009*** |
| *Forest land cover* | 0.106 | 0.103 | -0.045 | 0.849 | -0.197 | 0.373 |
| *Agriculture land cover* | -0.371 | 0.167** | 0.872 | 1.182 | 0.147 | 0.575 |
| *Forest land cover in neighboring grids* | -1.091 | 0.145*** | 0.512 | 1.901 | -2.396 | 0.700*** |
| *Agriculture land cover in neighboring grids* | -0.311 | 0.194 | 0.179 | 2.690 | -0.382 | 0.924 |
| *Area in environment preservation easements* | 0.414 | 0.204** | -0.074 | 10.500 | -0.024 | 6.787 |

Note: * represents significant at the < 0.10 level , ** represents significant at the < 0.05 level, and *** represents significant at the < 0.01 level.

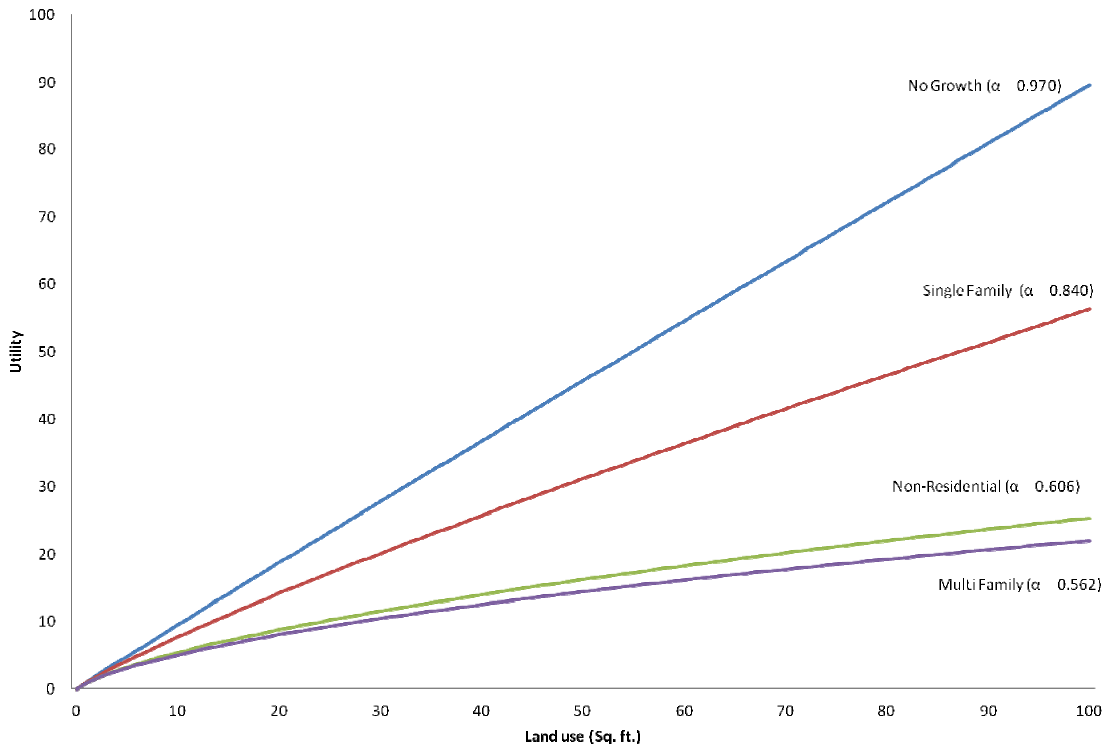


**Figure 2. Diminishing Marginal Utility When the Baseline Utility is Fixed at 1**

simulation. The first is the total capacity across the entire region, which represents job and population growth and is exogenously given. The second is the grid-level capacity estimation, which we discussed in the previous section.

The simulation procedure is a two-step process; the first is a logit regression that assigns the probability that a cell would get any development, and the second uses the constrained optimization of the MDCEV model (see Figure 3 for a conceptual view of the process). The prediction of the logit model orders the queue of the grids to be sampled for land use conversion. This probability is used as a weight in the sampling procedure to select a set of grids for the second stage, essentially structuring the queue of grids to absorb development activity for the Monte Carlo simulation. Others have simply selected the observational units, such as parcels or grids, in the descending order of probability (Irwin and Bockstael 2002). For computational convenience, we use a sample and allocate the budgeted square footage for fifteen grids at a time. We do not, for the sake of brevity, present the results of the logit model. More often than not, the queue of grids is exhausted before the required total square feet in the three land uses of the entire region is allocated; therefore, the queue has to be repopulated with an additional fifteen grids. These grids are selected using the same sampling procedure, but only after updating any capacity changes from the previous allocation round.

The MDCEV simulation model allocates each cell's available capacity of growth among the three conversion land uses and the no-growth alternative. The simulation procedure takes the form of a constrained optimization of the utility in each grid of the following equation:

$$\max_{lu_j, j=1\ldots K} \sum_{j=1}^{K} \frac{1}{\hat{\alpha}_j}[(lu_j+1)^{\hat{\alpha}_j} - 1].\exp(\hat{\beta}'_j x_j + \varepsilon_j),$$

$$\text{s.t. } \sum_{j=1}^{K} lu_j = B \text{ and } 0 \le lu_j \le z\_lu_j \forall j,$$

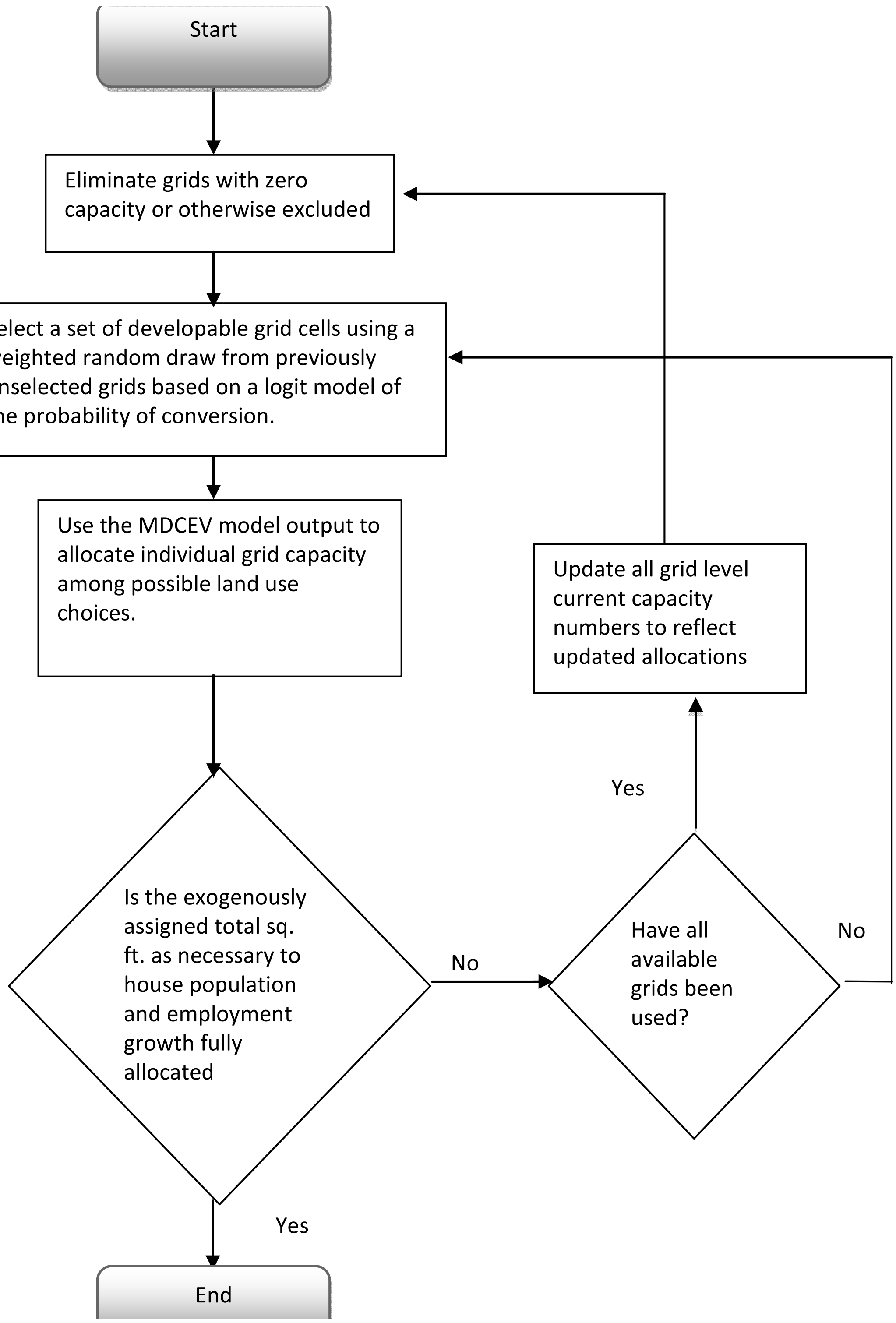


**Figure 3. Flowchart of a Single Simulation Procedure**

where $\varepsilon_j$ is drawn at random from a Gumbel distribution and $z\_lu_j$ is the upper limit imposed by the capacity constraint for each development category. This upper limit is updated in each iteration to reflect allocation into the development category until the next iteration.

We use the total of the observed change in the region as the stopping rule for the simulation. If the queue of grids is exhausted and development in the region is not fully allocated, the sequence is repopulated with all grids and with an updated grid-level budget constraint. The individual land uses are also updated to reflect the allocation into the various development categories. This multi-step process continues until all of the square footage in the tri-county area is allocated to the grids. The complete process constitutes one random realization of development in the region.

Figure 4 provides an example comparison of one random realization and the observed values in the same period. As can be gleaned from the map, the pattern of single-family development is reasonably well captured in the simulation outcome. The model has the advantage of illustrating both the spread among grids and the concentration within each grid cell. Of particular interest here is that each simulation produces its own path dependency; that is, each simulation produces a predicted output, which then becomes the baseline for the next prediction and allocation window. This continues until the desired prediction period of change is complete. While we used here only a three-year period, the model can be easily adapted to longer periods. Given the attraction and repelling effects of development activity within a grid, and the effect of neighboring grids, land conversion is path-dependent, which is one of the model's advantages. The difference in impact between early conversion and delayed conversion on long-term outcomes is readily apparent. For policy analysis, this is of utmost relevance because many land use policies seek to alter the timeframe of development, particularly policies like adequate facilities moratoria and development quotas.

However, a single realization is not necessarily a representative one. Therefore, the Monte Carlo simulations are repeated two hundred times; the outcomes are presented in Figures 5, 6, and 7. Figure 5 illustrates the type of output the model produces for single-family development. On the left is the amount of square footage of single-family development by grid cell in one three-year time period. On the right is the proportion of non-zero realizations from the Monte Carlo runs, which gives planners a probabilistic notion of where development is most likely to occur under a given policy regime.

These simulations are run on a Linux cluster of forty heterogeneous nodes, with each node running five simulations in a sequential fashion. Each simulation for the tri-county region took approximately one hour of computational time; therefore, the 200 simulations took five hours. The performance of the simulation is quite good compared to actual conversion activity. Of the 20,596 grids, the simulations suggest that between 3,297 and 3,437 (median 3,356) grids experience non-trivial development in the simulations, compared to 3,336 grids that actually developed.

The model consistently predicts the intensity of single-family conversions, while performing somewhat less precisely in the multi-family and non-residential sectors when comparing grid-level predictions to actual outcomes (Table 5). However, at a slightly higher level of aggregation—census tracts, for example—the model does a much better job of placing approximately 60, 30, and 50 percent of observed square footage of single-family, multi-family, and non residential in the correct tract and timeframe. While the grid-level correlations of simulated and observed development-type results are low, the census-tract level correlations are satisfactory and promising.

As seen in Figure 4, the model concentrates single-family land use within a single grid instead of distributing it more evenly throughout neighboring grids. It is also interesting to note that while the proportion of a grid being picked for single-family development can reach as high as 60 percent, only a few grids are picked more than 20 percent of the time for multi-family or non-residential development (Figures 5, 6, and 7). While the average development is reasonably well predicted by the model for both types of residential development, the model, expectedly, fails to capture outliers on the right (Table 4). Unlike other land conversion models, the simulation adequately projects both dispersed development of single-family residences in rural areas as well as infill development in mature suburbs.

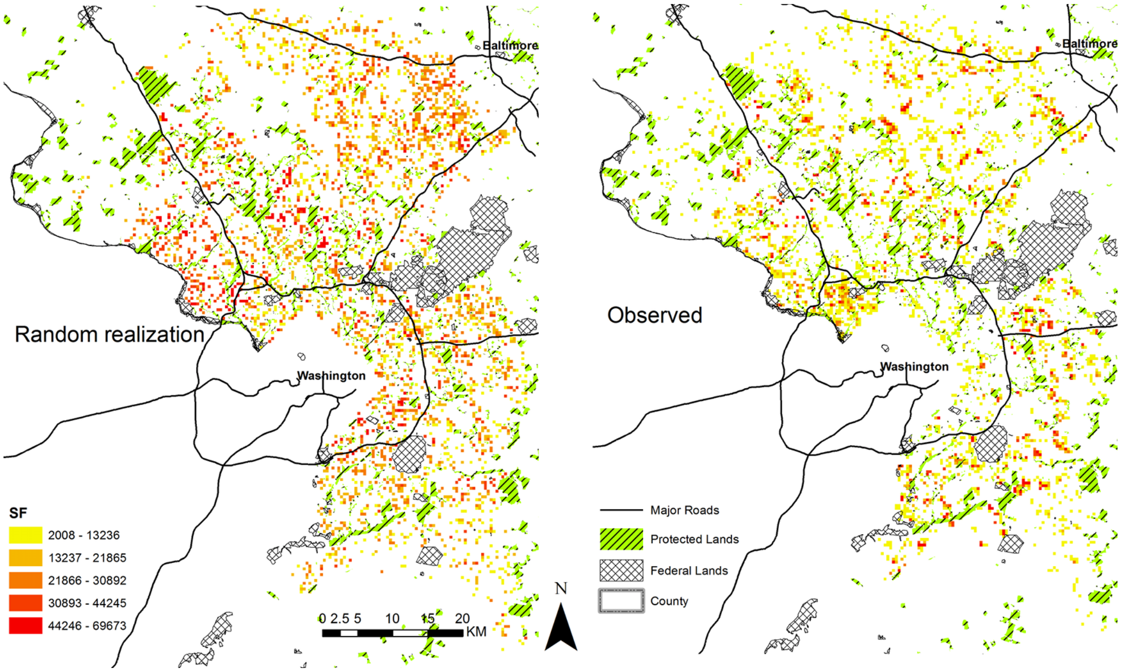


**Figure 4. Outcome of One Random Simulation Compared to the Observed Values for Single Family Type in 2001–2004**

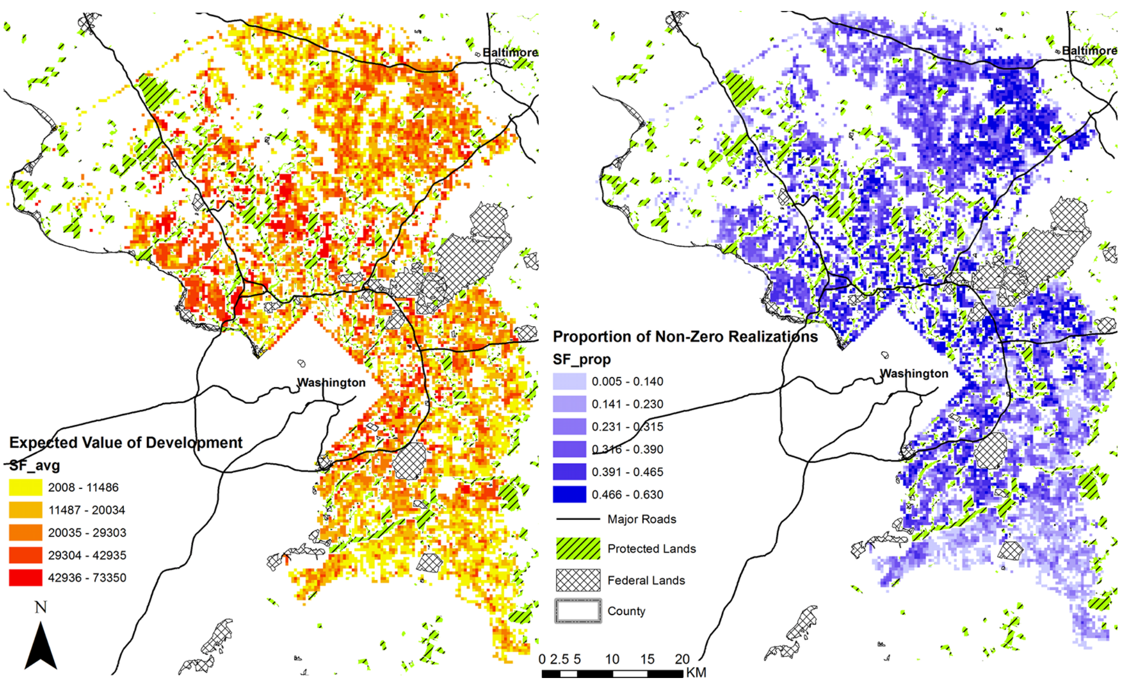


**Figure 5. Average Value of Single Family (SF) Square Feet Conditional on Non-Zero Realization (left) and Proportion of Non-Zero Realizations (right)**

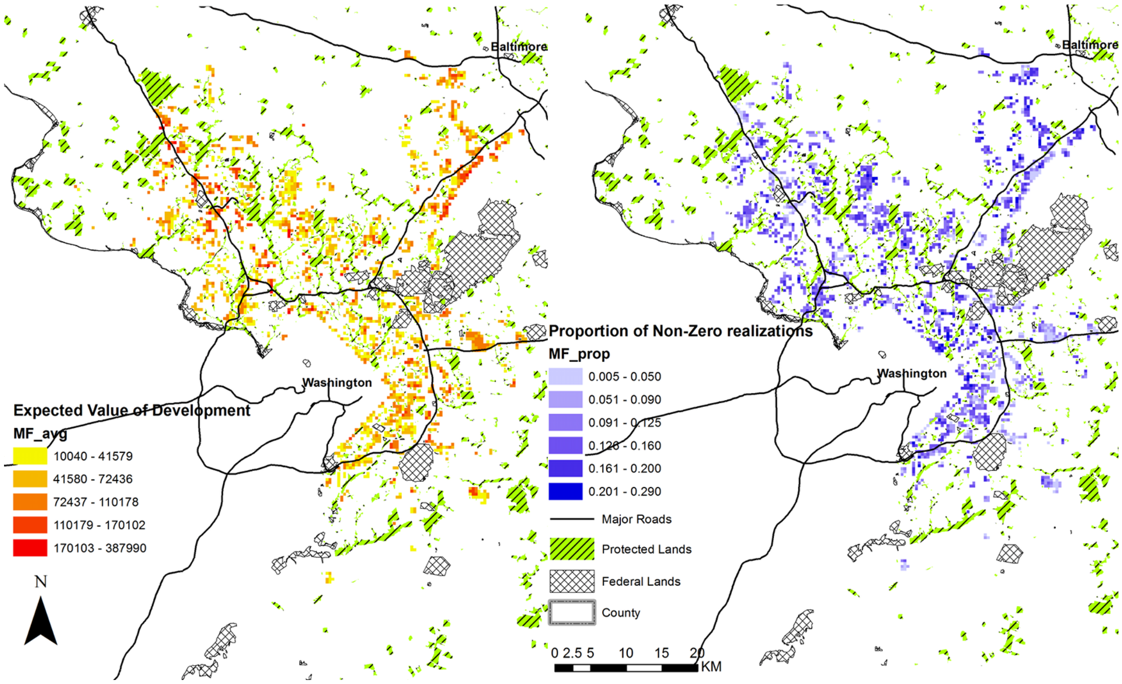


**Figure 6. Average Value of Multi-Family (MF) Square Feet Conditional on Non-Zero Realization (left) and Proportion of Non-Zero Realizations (right)**

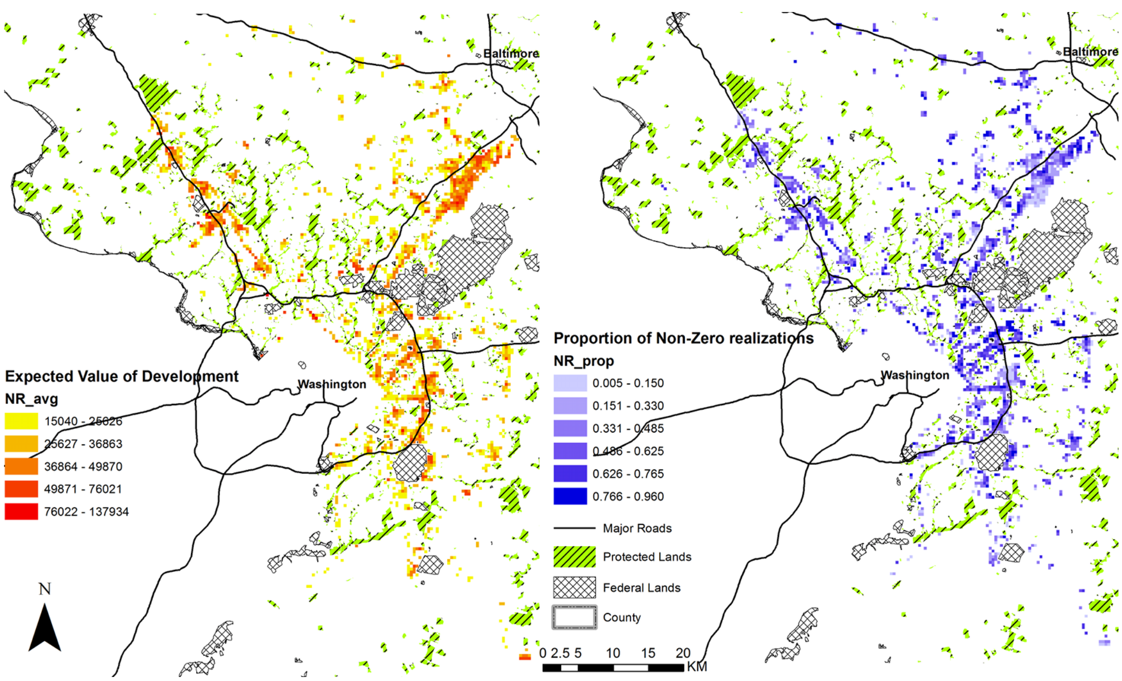


**Figure 7. Average Value of Non-Residential (NR) Square Feet Conditional on Non-Zero Realization (left) and Proportion of Non-Zero Realizations (right)**

**Table 5. Simulation Performance Statistics[a]**

| | Single Family | | | | Multi-Family | | | | Non-Residential | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Simulations[b] | | | | Simulations[b] | | | | Simulations[b] | | | |
| | Min | Max | Med | Actual | Min | Max | Med | Actual | Min | Max | Med | Actual |
| # of grids that experience non-zero development | 2,699 | 2,811 | 2,751 | 2,934 | 194 | 238 | 215 | 172 | 822 | 872 | 848 | 392 |
| Largest non-zero change | 65,973 | 73,350 | 73,172 | 623,400 | 138,603 | 556,317 | 236,675 | 658,661 | 111,979 | 175,123 | 141,435 | 1,244,733 |
| Average non-zero change | 21,919 | 22,828 | 22,397 | 21,000 | 53,581 | 65,694 | 59,313 | 74,141 | 32,512 | 34,500 | 33,433 | 72,344 |
| Grid-level correlation[a] | 0.08 | 0.11 | 0.09 | 1 | .0006 | 0.06 | 0.03 | 1 | 0.11 | 0.16 | 0.13 | 1 |
| Correlation[a] at Queen neighborhood 1st order (9 grids) | 0.30 | 0.34 | 0.32 | 1 | 0.06 | 0.17 | 0.11 | 1 | 0.35 | 0.39 | 0.37 | 1 |
| Correlation[a] at queen neighborhood 2nd order (25 grids) | 0.40 | 0.43 | 0.41 | 1 | 0.14 | 0.26 | 0.20 | 1 | 0.46 | 0.50 | 0.48 | 1 |
| Census tract-level correlation[a] | 0.51 | 0.61 | 0.56 | 1 | 0.03 | 0.28 | 0.16 | 1 | 0.41 | 0.51 | 0.46 | 1 |

[a] Correlations presented in this table are Spearman's rank correlation with the observed values.
[b] Of the 200 simulations.

## Conclusion

Researchers from a wide range of disciplines agree that modeling land use change is a necessary task, one that can act as an end result for local planning, as a prediction tool for proposed and existing land use policies, or as an intermediate result to evaluate environmental impacts of growth. This paper is an attempt to combine grid-based models with economic analyses leading to a hybrid approach. Additionally, the design of the simulation, which allows both short- and long-term predictions of land use change into multiple end states, is, to our knowledge, the first of its kind. In particular, this model uses a dataset that is widely available for the entire state of Maryland to make land use predictions at a large spatial extent and also a fairly fine spatial scale. We argue that the outcomes of these models are more amenable as inputs to environmental impact models because we model both the intensity and type of land use change, both of which are often overlooked in the literature.

This work focuses on a three-county region of Maryland sandwiched between Washington, D.C., and Baltimore; it simulates a short interval of growth across single-family, multi-family, and non-residential development, and then compares the results against the actual observed outcome. Each of these tasks requires a significant amount of effort, in terms of both data collection and computation, but the reward is a performance of the model that is surprisingly accurate at relatively small spatial scales. While these results are promising for the future of hybrid modeling efforts, more importantly they provide an initial foray for economists into the larger-scale policy discussion, while providing natural scientists with an approachable model with more realistic assumptions about future land use change.

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