Predicting Land Use Change

How Much Does Transportation Matter?

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This paper proposes to measure the extent of the influence of transportation systems on land use change. With a set of high-resolution land use data for the Twin Cities, Minnesota, metropolitan region, logistic regression models of land use change are estimated for a 10-year period from 1990 to 2000. The models account for existing land use types, neighboring land uses, and transportation network variables that measure the physical proximity of highway networks, as well as the level of accessibility associated with a specific location. The models are estimated with and without the transportation variables and compared to assess the extent of their influence. Transportation-related variables exert some influence on changes to land use patterns, though not as much as variables representing existing and neighboring land uses.

The mutual relationship between transportation network growth and changes to patterns of urban land use is by now a well-accepted concept in urban planning, engineering, geography, urban economics, and related fields. The physical location of road, rail, and other types of networks, along with the levels of accessibility that they provide, can exert a strong influence on patterns of urban settlement and activity. In turn, the location of activity, particularly new activities such as new housing and commercial developments, can influence the location of additions to or expansion of transportation networks.

This paper proposes to measure the extent of the influence of transportation systems on land use change. With a set of high-resolution land use data for the Twin Cities, Minnesota, metropolitan region, logistic regression models of land use change are estimated for a 10-year period from 1990 to 2000. The models account for existing land use types, neighboring land uses, and transportation network variables that measure the physical proximity of highway networks, as well as the level of accessibility associated with a specific location. The models are estimated with and without the transportation variables and compared to assess the extent of their influence. Transportation-related variables exert some influence on changes to land use patterns, though not as much as variables representing existing and neighboring land uses.

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LITERATURE REVIEW

Several methods have been developed for forecasting land use change, with varying degrees of sensitivity to the influence of transportation networks. The simplest types of models for forecasting land use change are Markovian models (1–3) such as Markov chain models, which tend to treat land use change as a stochastic process. Assuming that rates of change between land use types are more or less constant from one period to the next, Markovian models project land use transitions forward to any given future date, eventually reaching an equilibrium distribution of land uses. These models tend to have a limited ability to incorporate transportation networks and other spatial features, except as states (e.g., land use types) in the model. More often, they are applied to analyses of land cover change.

Cellular and agent-based models have recently gained greater acceptance as tools for simulating land use change in urban areas. Advances in computational power and data storage have facilitated the development of models that disaggregate urban space to a greater degree and can operate with individuals or land parcels as the units of analysis, rather than zones. These include microsimulation models of urban development (4), as well as models based on a cellular automata framework (5, 6). Cellular automata models emphasize neighbor effects and dynamic interactions between agents (with land use cells as agents), while microsimulation models treat individual households and firms as agents and attempt to simulate their behavior in terms of location and travel choices. Microsimulation models of land use are often coupled with transportation models and are integrated into larger urban simulation models (4, 7).

Despite these methodological advances, regression models continue to be a popular method for modeling and simulating land use change. Indeed, many simulation models with a land use component use regression methods, either in the form of discrete models of land use change (8, 9) or within hedonic or bid-rent frameworks for land prices (4, 10). Regression models allow the identification of exogenous variables, which are thought to influence patterns of development. The variables can represent physical and social influences on development (11, 12), neighborhood effects (12, 13), or the effects of transportation and accessibility (14, 15). It is these latter effects that are of the greatest interest in the current context. While regression techniques have been used previously to identify the correlates of highway network growth in terms of land use and population characteristics (16), here we will focus our attention on relationships running in the opposite direction, that is, changes in land use types as a function of transportation and other attributes.

METHODOLOGY

To identify and formally model the relationship between transportation and land use change, land use type is treated as a discrete variable, and a logistic regression framework is adopted. The objective,

then, is to find a set of covariates that serve as reliable predictors of land use change, using 75-m by 75-m land use cells as units of analysis. Various factors relating to neighboring land uses, existing or previous land uses in a given cell, and location relative to transportation networks are incorporated into the specification of the model.

The model predicts the probability of a given outcome, conditional upon the presence of a set of attributes. The various land uses constitute J separate outcomes. The outcomes can then be related to the attributes (x_i) by a linear predictor of the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} \quad (1)$$

The linear predictor is analogous to the utility function commonly employed in econometric choice modeling. If the individual land use cells are each denoted with the subscript i , then for a specific land use type j , the probability that the observed outcome (y_i) will be equal to j is given by the expression

$$P(y_i = j) = \frac{\exp(\mathbf{X}_i\boldsymbol{\beta}_j)}{1 + \sum_j \exp(\mathbf{X}_i\boldsymbol{\beta}_j)} \quad (2)$$

where

- $\mathbf{X}_i$ = vector of explanatory variables (attributes) for land use cell i ;
- $\boldsymbol{\beta}_j$ = vector of unknown parameters to be estimated, typically by the method of maximum likelihood; and
- J = set of all outcomes and land use types.

In estimating models of land use change, attention is focused on five land use types: residential, commercial, industrial, vacant, and an “other” category that will account for the remaining land use classes. These land uses include parks, public land uses, airports, railways, and cells covered by water. These land uses are considered to be either fixed in nature or relatively unresponsive to land market forces that drive much of the change observed in the remaining land uses. This narrows the set of possible outcomes from 10 land uses to five. Furthermore, in each model, one category of the dependent variable must be designated as a reference category. This category is then omitted from the analysis. The parameter estimates are interpreted as relative risk ratios, which are the exponentiated beta coefficients. These ratios represent the change in the odds of being in the dependent variable category versus the reference category associated with a one-unit change in the independent variable.

Because of interest in predicting the change in land use states over time, the models to be estimated employ a dynamic specification, that is, predicting land use in cell i at time t (L_{it}) using observations on several variables at a previous time period ($t - 1$). The set of variables that is defined as a covariate relates to a cell's previous land use and that of its neighboring land uses, the presence of a highway network link in the cell and its neighbors, and the accessibility of the cell at time $t - 1$. The variables are formally defined as follows:

- L_{it} represents land use in cell i at time t .
- $L_{i,t-1}$ represents land use in cell i at time $t - 1$.
- $L_{j,t-1}$ represents the number of neighboring cells in the adjacent Moore neighborhood in land use j at time $t - 1$. This variable is defined for residential, commercial, industrial, and vacant land uses and is denoted, respectively, as L_R , L_C , L_I , and L_V .
- $A_{i,t-1}$ represents the regional accessibility to employment in cell i at time $t - 1$. The measure is extracted from the larger transportation analysis zone within which cell i is located.

- $N_{i,t-1}$ is a dummy variable representing the presence or absence of land classified as “highway” in cell i at time $t - 1$, and serves as a measure of proximity to transportation networks that might be expected to influence the land use in i at time t . The “highway” classification is applied to roads and adjacent highway-related land along state trunk highways and federal primary and secondary highways (Interstate and U.S. highway system) in the National Highway System.

- $N_{j,t-1}$ represents the number of neighboring cells containing land classified as “highway” at time $t - 1$.

The resulting model is then written in general form, relating land use at time t to the above variables:

$$L_{i,t} = f(L_{i,t-1}, L_{j,t-1}, A_{i,t-1}, N_{i,t-1}, N_{j,t-1}) \quad (3)$$

The expression represents the probability of observing a particular land use in cell i at time t , given the set of covariates. The covariates represent the inputs to the linear predictor in Equation 1, which are in turn used to predict the probabilities from Equation 2.

DATA

The land use data employed in this study build from a previous set of land use data used by Levinson and Chen (2) in an earlier study of the Twin Cities. The expanded data set comprises a time series with observations for the years 1958, 1968, 1978, 1984, 1990, 1997, 2000, and 2005. Land use data for years prior to 1984 were manually digitized from paper copies of land use maps stored at the John R. Borchert Map Library at the University of Minnesota. Data for selected years from 1984 to 2005 were obtained from the Metropolitan Council, the Twin Cities' regional planning agency and designated metropolitan planning organization, which maintains a parcel-level land use inventory for the region that is updated every few years.

The parcel-level land use data were converted to a raster format and rectified to reduce geometric distortion. Some error remains due to the manual digitization process and the lower level of accuracy associated with earlier mapmaking processes. Differences in classification schemes for land use across years were addressed by adopting a common set of 10 generalized land use classes. These land use classes include

- Airports,
- Commercial,
- Highway,
- Industrial,
- Parks,
- Public,
- Railroads,
- Residential,
- Vacant, and
- Water.

The data set covers a large portion of the core seven counties of the Twin Cities region. Some portions of the region could not be covered due to a need to limit the analysis to the part of the region for which common land use data sets could be acquired for each year. The portions left out of the study area are comprised mostly of low-density residential and nonurban uses, which would likely be classified as vacant under the present scheme. The resulting study

FIGURE 1 Trends in Twin Cities land use, 1958–2005.

area covers approximately 3,426 km² (1,322 mi²). The study area is partitioned into a grid of 75-m by 75-m cells, a spatial resolution much finer than the 188-m square cells used in Levinson and Chen's study (2), leading to a roughly tenfold increase in the number of land use cells in the study area. This produces a data set containing over 610,000 cells. Each cell is assigned a land use class according to its predominant land use. Figure 1 presents a summary of long-term trends among the land use classes from 1958 to 2005.

Virtually all land use classes have increased in coverage over this period, with the greatest increase in land use registered by the residential category. This growth has largely come at the expense of vacant (including agricultural) land, as the region has been able to accommodate growth over the years via outward expansion. Attention focuses specifically on the years 1990 and 2000 (and on the set of five land use classes identified in the previous section), as these are years for which more reliable measures of regional accessibility are available. Figures 2 and 3 depict regional land use in the Twin Cities for the years 1990 and 2000.

RESULTS

To evaluate the influence of transportation networks on land use change, the logistic regression model is fitted twice, once with the full set of covariates and again with a limited set of variables that excludes transportation network and accessibility variables. In each case, land use in 2000 is modeled as a function of 1990 land use and network attributes. The independent variables are not assumed to be generic, and so are given separate coefficients for each of the four outcome classes. The "other" land use category is treated as a reference category in the model.

Table 1 summarizes the fit of the model with the full specification. Given the extremely large sample size (each cell is a separate observation), nearly all independent variables are statistically significant at the

$p < .01$ level. The first four variables in each outcome class are the dummy variables representing a cell's land use type in 1990, and their coefficients are estimated relative to the reference category. For each land use class, having the same land use in 1990 greatly increases the likelihood of remaining within the same land use class. This represents the "inertial" or dampening effect that the existing stock of housing and buildings has on land use change. The set of neighbor variables also increases the likelihood of transition to each of the four land uses considered, relative to the reference category. In this case, the coefficients are associated with the number of neighboring cells of each land use type. For example, in the case of predicting residential land use, each neighboring residential cell increases the linear predictor by 0.59 unit, up to a maximum of eight neighboring residential cells. The neighbor cells appear to be slightly less important than the previous (1990) land use in predicting change to each of the given land uses.

Having highway networks in neighboring cells appears to increase the likelihood of transition to commercial and industrial land uses while having no real effect on transition to vacant land and having a negative influence on the likelihood of transition to residential use. The magnitude of the road neighbor coefficients is smaller than those for the neighboring land use and previous land use variables. The accessibility variable represents a measure of gravity-based accessibility to employment, measured in terms of jobs weighted by access travel time, and is scaled so that the coefficients reflect the effect of access to 10,000 additional jobs. High levels of accessibility in 1990 are associated with a higher likelihood of transition to commercial land use and, to a lesser extent, industrial land use. The effect of employment accessibility on transition to residential land use is slight, and negative in the case of the likelihood of transition to vacant land. These two findings are to be expected. Urban economic theory predicts that commercial and industrial land uses tend to outbid residential uses for scarce land in highly accessible locations. In turn, residential land in relatively accessible locations is more valuable than vacant land, much of which remains agricultural in the current study area.

FIGURE 2 Twin Cities regional land use, 1990. (Source: Metropolitan Council, Nexus Research Group.)

FIGURE 3 Twin Cities regional land use, 2000. (Source: Metropolitan Council, Nexus Research Group.)

TABLE 1 Estimated Regression Model of Land Use Change, 1990–2000

Variable	Coefficient	SE	t-Statistic
Residential			
Land use ($t - 1$)			
Residential	4.64	0.03	169.55
Commercial	2.57	0.06	42.70
Industrial	2.53	0.07	35.20
Vacant	2.47	0.03	84.49
Neighbor land use ($t - 1$)			
Residential	0.59	— ^a	118.40
Commercial	0.18	0.01	14.95
Industrial	0.11	0.01	8.64
Vacant	0.30	— ^a	64.28
Road dummy ($t - 1$)	-0.98	0.05	-20.61
Road neighbor ($t - 1$)	-0.11	0.01	-11.32
Accessibility ($t - 1$)	0.00	0.00	2.80
Constant	-4.66	0.03	-173.57
Commercial			
Land use ($t - 1$)			
Residential	2.88	0.06	48.04
Commercial	4.55	0.06	74.27
Industrial	3.64	0.08	47.95
Vacant	2.46	0.06	43.63
Neighbor land use ($t - 1$)			
Residential	0.22	0.01	23.33
Commercial	0.75	0.01	63.19
Industrial	0.44	0.01	34.73
Vacant	0.21	0.01	24.70
Road dummy ($t - 1$)	-1.14	0.06	-18.51
Road neighbor ($t - 1$)	0.22	0.01	18.32
Accessibility ($t - 1$)	0	0	32.82
Constant	-6.43	0.05	-128.04
Industrial			
Land use ($t - 1$)			
Residential	1.95	0.08	25.69
Commercial	3.28	0.07	44.81
Industrial	4.12	0.06	65.11
Vacant	2.21	0.05	40.88
Neighbor land use ($t - 1$)			
Residential	0.01	0.01	0.98
Commercial	0.47	0.01	34.23
Industrial	0.65	0.01	61.55
Vacant	0.22	0.01	27.02
Road dummy ($t - 1$)	-1.14	0.07	-17.11
Road neighbor ($t - 1$)	0.10	0.01	8.11
Accessibility ($t - 1$)	0.00	0.00	14.36
Constant	-5.51	0.04	-130.81
Vacant			
Land use ($t - 1$)			
Residential	2.11	0.03	65.17
Commercial	1.65	0.07	24.00
Industrial	2.20	0.06	38.72
Vacant	2.80	0.02	112.15
Neighbor land use ($t - 1$)			
Residential	0.20	0.01	40.53
Commercial	0.19	0.01	15.28
Industrial	0.49	0.01	52.57
Vacant	0.35	— ^a	87.96

(continued)

TABLE 1 (continued) Estimated Regression Model of Land Use Change, 1990–2000

Variable	Coefficient	SE	t-Statistic
Road dummy ($t - 1$)	-0.92	0.04	-23.85
Road neighbor ($t - 1$)	0.01	0.01	1.20
Accessibility ($t - 1$)	0.00	0.00	-103.04
Constant	-2.36	0.02	-129.51

NOTE: Dependent variable: land use at time t (2000); $N = 606,936$; likelihood ratio = 944,398.68; log likelihood = -326,876.65; $\rho^2 = 0.59$.

^a— indicates $SE < 0.005$.

Table 2 shows the results of the model fitted without the transportation-related variables. For the most part, the land use-related variables are not greatly affected by the absence of the transportation-related variables, indicating a robustness in the original specification. One measure of the overall fit of the model is the ρ^2 statistic, which is reported for each of the fitted models. This statistic calculates a ratio of the maximized log likelihood values for the fitted model and a constant term-only model for each specification. This ratio is subtracted from 1, implying that a smaller ratio will yield a higher ρ^2 value and will indicate a better model fit. We can see from Table 2 that the value of ρ^2 declines only slightly when the transportation-related variables are removed, from 0.59 to 0.58. The likelihood ratio value for the second model declines slightly as well.

A more formal way to test the influence of the transportation-related variables is to compare the two fitted models using a partial joint test. This is essentially a test of the null hypothesis that the coefficients of the transportation-related variables are jointly equal to zero. The test statistic is calculated by comparing the maximized log likelihood values of the two models, namely, the fully specified model and the model that omits the transportation-related variables. Formally, the test statistic is calculated as

$$-2[\log_e \lambda(\hat{\mathbf{a}}_A) - \log_e \Lambda(\hat{\mathbf{a}})]$$

where $\log_e \Lambda(\hat{\mathbf{B}}_A)$ is the maximized log likelihood of the model excluding the transportation-related variables (that is, constraining their parameters to zero), and $\log_e \Lambda(\hat{\mathbf{B}})$ is the log likelihood of the fully specified model. The test statistic is distributed χ^2 with three degrees of freedom, equal to the number of parameters constrained to be zero under the restricted model. The test statistic for the partial joint test takes a value of 21,671.64, much larger than the critical value for the χ^2 with three degrees of freedom at the $p = 0.001$ level, which is about 16.27. Thus, there is fairly strong evidence that the transportation-related variables add explanatory power to the land use change model and should not be ignored in the specification of the model.

CONCLUSION

The question of how much influence transportation networks have on processes of land use change is still largely an open one. This study has provided an empirical framework using established statistical methods to offer some tentative evidence on this question. The

TABLE 2 Estimated Regression Model of Land Use Change Without Road Network Attributes, 1990–2000

Variable	Coefficient	SE	t-Statistic
Residential			
Land use ($t - 1$)			
Residential	4.68	0.03	172.69
Commercial	2.60	0.06	43.84
Industrial	2.61	0.07	36.16
Vacant	2.51	0.03	87.61
Neighbor land use ($t - 1$)			
Residential	0.58	— ^a	119.67
Commercial	0.16	0.01	13.71
Industrial	0.10	0.01	8.25
Vacant	0.30	— ^a	65.21
Constant	−4.68	0.02	−204.10
Commercial			
Land use ($t - 1$)			
Residential	3.10	0.06	51.59
Commercial	4.70	0.06	76.71
Industrial	3.90	0.08	49.88
Vacant	2.71	0.06	47.93
Neighbor land use ($t - 1$)			
Residential	0.18	0.01	19.21
Commercial	0.74	0.01	64.15
Industrial	0.39	0.01	31.68
Vacant	0.11	0.01	13.62
Constant	−5.58	0.04	−137.70
Industrial			
Land use ($t - 1$)			
Residential	2.10	0.08	27.74
Commercial	3.40	0.07	46.82
Industrial	4.39	0.06	67.90
Vacant	2.41	0.05	44.70
Neighbor land use ($t - 1$)			
Residential	−0.01	0.01	−0.87
Commercial	0.46	0.01	34.31
Industrial	0.61	0.01	57.97
Vacant	0.17	0.01	21.84
Constant	−5.18	0.04	−145.96
Vacant			
Land use ($t - 1$)			
Residential	2.10	0.03	67.84
Commercial	1.75	0.07	26.33
Industrial	2.48	0.05	45.72
Vacant	2.72	0.02	115.76
Neighbor land use ($t - 1$)			
Residential	0.16	— ^a	33.33
Commercial	0.00	0.01	−0.42
Industrial	0.33	0.01	37.69
Vacant	0.42	— ^a	110.79
Constant	−3.58	0.02	−224.26

NOTE: Dependent variable: land use at time t (2000); $N = 606,936$; likelihood ratio = 922,727.05; log likelihood = −337,712.47; $\rho^2 = 0.58$.

^a— indicates $SE < 0.005$.

results from the estimated logistic regression models suggest that proximity to transportation networks and levels of regional accessibility both exert an influence on the likelihood of transition to various land uses. Commercial and industrial uses in particular appear to be associated with locations near highway networks and with high levels of accessibility.

The comparison of the two models, fit with and without the transportation variables, suggests that the specification of the land use change model is incomplete when transportation influences are omitted. However, the question of magnitude, suggested in the paper's title, requires consideration of statistical versus practical significance. While tests showed that, both individually and jointly, the transportation-related variables were statistically significant, the magnitude of their influence was still comparatively modest. The land use change model estimated without these variables exhibited only a slightly poorer fit. Furthermore, the magnitude of the coefficients on the various land use variables indicated that they were significantly more important predictors of land use change.

This question is worthy of greater academic interest and is worth pursuing further. Extensions of the present work would help to lend greater credibility to the findings presented here. Foremost, the land use and transportation systems of interest should be represented in greater detail. In the current study, they were treated as one-dimensional variables. Important transportation characteristics, such as network flows and travel times, could provide greater definition for the transportation network variables. Land use classes could be modified to reflect intensity of use, rather than just type. Different measures of accessibility might also be employed, for example, a measure of access to labor markets in the case of commercial (and perhaps industrial) land use. A more ambitious extension would be to include other policy-relevant variables, such as data on local zoning or other land use regulations, or access to other critical infrastructure networks (e.g., water, sewer). Accounting for these influences would give us a better sense of how much power we should really be attributing to transportation as a force for shaping urban land use.

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