TRANSPORTATION IMPACTS ON LAND USE CHANGE: AN ASSESSMENT CONSIDERING NEIGHBORHOOD EFFECTS

Antonio PAEZ
Lecturer
Center for Northeast Asian Studies
Tohoku University
Kawauchi, Aoba-ku, Sendai,
980-8576 Japan
Fax: +81-22-217-7477
E-mail: antonio@rs.civil.tohoku.ac.jp

Junya SUZUKI
City Planning Division
Public Works Department
Miyagi Prefecture
3-8-1 Honcho, Aoba-ku, Sendai,
980-8570 Japan
Fax: +81-22-211-3295
E-mail: tosikep9@pref.miyagi.jp

Abstract: Sustainability concerns have aroused renewed interest among many planners in the interrelated nature of transportation and land use systems. Considerable attention has been devoted to study the ways in which land use affects transport decisions. Less attention has been paid to the effects of transportation, in particular transit, on land uses. In this paper we draw from results in spatial statistics and apply a dynamic model of spatial discrete choice to explore the potential links between transportation infrastructure and land use change. Neighborhood effects are taken into consideration, to account for the influence of location and change. Using data from Sendai City, in the Japanese district of Tohoku, and California's BART system we study the process of land use change and its relationship to transit infrastructure.

Key Words: Logit model, neighborhood effects, transportation infrastructure, land use change

1. INTRODUCTION

Over the last decade, sustainability has been a keyword in the theory and practice of planning in general, and in transportation planning in particular. At the same time that transportation planners and officials show increased concern on sustainable development, a renewed interest on the interactions between the land use and transportation systems has also been observed. As a result of this interest, there have been increased efforts to study the effects of land use on transportation, as they are in fact an important element in many planning methodologies (for instance, in demand forecasting). However, the impacts of transportation on land use (in particular the effects of transit projects) have been less studied, despite the bi-directional links between the two systems and the importance that conventional wisdom assigns to such impacts when it comes to determining urban form (Landis *et al.*, 1995; Still *et al.*, 1999).

In this study we explore a simple method to assess the impacts of transportation projects on land use change. The method is based on a limited-dependent variable model (i.e. the logit model) that analyzes the probability of change in a given zone, based on variables such as distance to subway/train stations, availability of open land and other physical variables. In addition to physical factors such as distance to newly built stations, it has been argued that local dynamics may induce or discourage change, if neighboring zones tend to switch land uses or not. This is the so-called neighborhood effect. In order to include it within the modeling framework, we draw from results in spatial statistics and use a model that is spatial, in the sense that it explicitly considers the status of neighboring zones, and dynamic because the effect is modeled with a time lag (section 2). Although there is no dearth of applications of limited-dependent variable modeling in transportation planning, in particular in travel demand, we argue here that applications regarding land use have a spatial component that can and should be taken into consideration.

We take as a case study the city of Sendai in northeastern Japan and use data from 3 different years that span a period of 10 years, to describe, since operations began, the change of commercial land uses in the areas surrounding the subway line (section 3). A second case study uses data from California's Bay Area Rapid Transit (BART) Union City Station, to analyze land use change due to improved accessibility to transit services and neighborhood effects (section 4). To this data we apply the dynamic model described above, and study observed changes and their relationship to some variables of interest. Although in its current form the model in question is not fit for quantitatively forecasting changes, it could be a useful tool to assess the historical impacts of similar projects and to inform planners on the potential or likely impacts of new projects.

2. DISCRETE CHANGE AND NEIGHBORHOOD EFFECTS

Limited-dependent variable models, otherwise known as discrete choice models within a utility-maximization framework, have a long history of development and applications in transportation planning, in particular in the field of travel demand modeling (McFadden, 1974, 2000; Yai, 1989). The main characteristic of these models is that the objective variable assumes discrete, rather than continuous values. This is the case for instance in modal split assignment, where the values of the dependent variable are, say, 0 for automobile, 1 for bus and 3 for subway. The simplest case is when there are only two possible values of the dependent variable, say, 0 for car and 1 for bus. Other transportation-related applications include modeling locational choice (Anas, 1982; Miyamoto *et al*., 1997), a problem that is also clearly discrete in nature: either a location is taken or it is not. Seen from the locator's perspective, only one location may be chosen: the outcome of her decision is limited. Not all of these examples have a conspicuous spatial element. It has been argued, however, in the context of discrete choice models, that the process of making a decision might be influenced by the behavior and opinions of agents with whom there is contact (Case, 1992). For instance, to analyze technological change, Case derived a modified probit model that considers the possibility of interrelatedness in the decision making process. Adopters of a new technology influence others in the 'neighborhood' with the result that some may be encouraged to become adopters themselves. The concept of *neighborhood* (geographical in this case) is thus introduced in the model. Case's model, however, is cross-sectional, and thus limited since she notes that risk averse behavior, and delayed adjustment costs and learning times, among other factors, may lead to time lags in adoption. To overcome this perceived limitation, Dubin (1995) introduced a logit model that is at the same time spatial and dynamic, in the sense that it takes into consideration time lags between first stage and second stage adopters.

It is clear that land use change (or development), in addition to being a process with discrete outcomes, shares two important characteristics with the example of technology adoption. In addition to factors such as accessibility and availability of land, which can be and have been analyzed using standard limited-dependent variable models (McMillen, 1989; Landis *et al*., 1995), it is reasonable to expect that land developments of one kind will tend to encourage similar changes at adjacent locations. Landis *et al*. describe three reasons why we would expect this: reduced development costs (e.g. infrastructure and public services), the possible existence of agglomeration economies, and land-use regulations. The change is then likely to influence change in other, neighboring locations. Moreover, it is known that urban change processes, in particular construction, are among the slowest within an urban system with response periods of between 3 and 10 years (Wegener *et al.*, 1986). The influence of change is not immediate and most likely will take place, if it does, after a certain period of time has passed. These two characteristics (spatial interrelatedness and delayed effects) argue for a method of analysis that explicitly considers them. Therefore the interest in exploring the use of the spatial logit model (Dubin, 1995) to apply it to study the impacts of transportation infrastructure on land use change. The model is described in the following section.

3. THE SPATIAL LOGIT MODEL

Under the limited-dependent variable approach of the logit and probit models, we assume that there is an underlying response variable defined in regression form by:

$$y_i^* = X_i\boldsymbol{\beta} + u_i \tag{1}$$

In the above expression X_i is a 1 x k vector of characteristics or explanatory variables (size of zone, land use, distance to station, etc.) and $\boldsymbol{\beta}$ is a k x 1 vector of parameters. It is assumed that, in practice, the response variable is unobservable (hence the sometimes used term of latent variable models), and instead what we observe is a dummy variable defined by:

$$\begin{array}{ll} y_i = 1 & \text{if } y_i > 0 \\ y_i = 0 & \text{otherwise} \end{array} \tag{2}$$

From the above it follows that:

$$\begin{aligned} \Pr(y_i = 1) &= \Pr(y_i^* > 0) = \Pr(u_i > -X_i\boldsymbol{\beta}) \\ &= 1 - \mathrm{F}(-X_i\boldsymbol{\beta}) \end{aligned} \tag{3}$$

where F is the cumulative distribution function for error vector u. If the cumulative distribution of u is logistic, the logit model ensues:

$$\Pr(y_i = 1) = 1 - F(-X_i\boldsymbol{\beta}) = \frac{\exp(X_i\boldsymbol{\beta})}{1 + \exp(X_i\boldsymbol{\beta})} \tag{4}$$

In order to introduce neighborhood effects, it is considered that the probability of observing a change is a function of the vector of characteristics X_i plus the distance to locations where change has been previously observed ($y_{j,t-1}$):

$$y_{it}^* = X_{it}\boldsymbol{\beta} + \sum_{j=1}^{N} \rho_{ij} y_{j,t-1} + u_i = X_{it}\boldsymbol{\beta} + A_i + u_i \tag{5}$$

where y_{it} is the latent variable corresponding to location i at time t (i=1,…, N_t; N_t is the number of locations that did not change in the previous period and N is the total number of locations). The new element, ρ_{ij}, is a coefficient that represents the influence of change in location j on location i. This element is modeled as an exponential distance-decay function as follows:

$$\rho_{ij} = b_1 \exp(-D_{ij} / b_2) \tag{6}$$

In the above, D_{ij} is the distance between locations i and j, and b_1 and b_2 are spatial parameters to be estimated. The total influence of change in the previous period is then given by A_i. In this way, the closer a location is to others where change took place in the previous period ($y_{j,t-1}$) the larger the latent variable is, and the probability that change is also observed here:

$$\Pr(y_{it} = 1) = 1 - F\left(-\left(\boldsymbol{X}_i\boldsymbol{\beta} + A_i\right)\right) = \frac{\exp(\boldsymbol{X}_i\boldsymbol{\beta} + A_i)}{1 + \exp(\boldsymbol{X}_i\boldsymbol{\beta} + A_i)} \tag{7}$$

The log-likelihood of the above model is given by the following expression:

$$L = \sum \left[y_{it} \ln\left(\frac{\exp(\boldsymbol{X}_{it}\boldsymbol{\beta} + A_i)}{1 + \exp(\boldsymbol{X}_{it}\boldsymbol{\beta} + A_i)} \right) + (1 - y_{it}) \ln\left(\frac{1}{1 + \exp(\boldsymbol{X}_{it}\boldsymbol{\beta} + A_i)} \right) \right]$$

$$= \boldsymbol{\beta} \sum_{i=1}^{N_t} y_{it} \boldsymbol{X}_{it} + \sum_{i=1}^{N_t} y_{it} A_i - \sum_{i=1}^{N_t} \ln(1 + \exp(\boldsymbol{X}_{it}\boldsymbol{\beta} + A_i)) \tag{8}$$

The model has a total of k+2 parameters, in vector form $\boldsymbol{\theta} = [\boldsymbol{\beta}', b_1, b_2]'$. To obtain maximum likelihood estimates of these parameters, the log-likelihood function is maximized with respect to them. Dubin (1995) has derived the first and second order conditions needed to obtain the information matrix, the inverse of which, evaluated at the maximum likelihood estimates, gives the asymptotic variance matrix.

3.1 Estimation

The maximum likelihood function (equation 8) is non-linear in the parameters and a numeric optimization method has to be used to maximize it. A method commonly adopted when dealing with the standard logit model is the Newton-Raphson method, because of its implementation simplicity and efficiency. The information matrix is:

$$\mathbf{I}(\boldsymbol{\theta}) = E\left(-\frac{\partial^2 L}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}'} \right) \tag{9}$$

An initial value of parameter vector $\boldsymbol{\theta} = [\boldsymbol{\beta}_0', b_1, b_2]'$ (call it $\boldsymbol{\theta}_0$) is selected and used to compute the values of $S(\boldsymbol{\theta}_0)$ and $\mathbf{I}(\boldsymbol{\theta}_0)$, the score vector (the vector of first order conditions) and the information matrix respectively. When estimating a standard logit model, $\boldsymbol{\beta}_0 = \mathbf{0}$ is often a convenient guess, unless other values are available. In the case of the spatial logit $\boldsymbol{\beta}_0 = \boldsymbol{\beta}_S$ (the estimated parameters of a standard logit model), $b_1 = 0$ and $b_2 = 1$ appear to be sensible choices. These in turn are used to obtain a new estimate of $\boldsymbol{\theta}_1$ as:

$$\boldsymbol{\theta}_1 = \boldsymbol{\theta}_0 + [\mathbf{I}(\boldsymbol{\theta}_0)]^{-1} \cdot S(\boldsymbol{\theta}_0) \tag{10}$$

If a predetermined tolerance value is not achieved, then substitute $\boldsymbol{\theta}_0 = \boldsymbol{\theta}_1$ and repeat the operation. This procedure continues until convergence. We denote the final convergence estimates by $\hat{\boldsymbol{\theta}}$, and the asymptotic variance matrix is given by $[\mathbf{I}(\hat{\boldsymbol{\theta}})]^{-1}$. The following two sections are examples of application of the model to case studies. The interested reader is urged to consult Dubin's paper for GAUSS programs to estimate the spatial logit model. In addition, MATLAB routines are available from the authors upon request.

4. CASE STUDY: SENDAI CITY

4.1 Study Area and Data

Sendai City is the capital of Miyagi Prefecture in the northeastern Japanese region of Tohoku. With a population of about 1 million in 2000, Sendai is one of the 10 largest cities in Japan, and a major focus of regional growth in Tohoku. The city has a strong central business district, and most immigrants' locational choice lies around the CBD or in new development areas to the north of the city (Kitazume and Miyamoto, 1997). Rapid commercial development is observed around two locations, namely Nagamachi to the south, and Izumi to the north. The city has an efficient public transportation system meant to help shape the city, which includes radial railway lines in the south-north and east-west axes, and, since 1989, a subway line that runs in the south-north axis (see figure 1). It is the effect of this subway line on land use change that we try to assess in the present section.

Sendai City's subway service started operations in 1989 with a north-south line that communicates the central business district with the city's two most prominent sub-centers. However, a systematic study of the impacts of this transportation project on land uses has not been conducted. We use data from 3 different years that span a period of 10 years, to describe, since operations began, the change of commercial land uses in the areas surrounding the subway line. The main interest lies in analyzing, within a statistical modeling framework, the relative contribution of a number of accessibility and land use variables to determine land use change. More specifically, in this example land use change is defined as whether a given zone's share of commercial land uses increase or not. Clearly, this variable takes one of two possible values: 1 if growth is observed, and 0 else. The variables used to explore the relationship between transportation infrastructure and land use change are shown in table 1.

If accessibility to transit does indeed encourage land use change, the sign of the parameter DISTN (distance to nearest station) is expected to be negative. This means that all else being equal, locations closer to transit service will tend to develop commercial uses more frequently. Accessibility to the CBD and the city's sub-centers (Izumi and Nagamachi) is also expected to be an encouraging factor towards land change. Finally, we suggest that the neighborhood effects should be positive. This means that we expect the growth process to be transmitted by 'contagion': increased activity of one type (commercial in this case) would tend to spillover and encourage similar activities in neighboring zones, subject to land availability (Undeveloped).

Table 1. Sendai City: Variables and Definitions

Variable	Definition
COMM	Commercial land use increase (yes= 1; no= 0)
Undeveloped	Undeveloped land in the zone (%)
DIST_CBD	Distance to CBD (m)
DIST_IZUMI	Distance to Izumi Station (m)
DIST_NAGAMACHI	Distance to Nagamachi Station (m)
DISTN	Distance to Nearest Station (m)

Land use data was obtained from the Basic Planning Survey for Sendai Metropolitan Area for three years, 1988 one year before the subway line started operations, and 1992 and 1997. The zoning system for Sendai City Metropolitan Area is not consistent between years. To solve this situation we base our analysis on the most recent one corresponding to 1997, and apply overlay functions (using a Geographical Information System) to convert all the data to this system. We select all zones within 2 km of the subway line for the analysis to give a sample of 398 zones, and disregard more distant locations since it is not likely that the effects of accessibility to transit will extend beyond this range.

An increase of commercial land use intensity was observed in 220 zones between 1987 and 1992 (first stage adopters), and the same effect was observed between 1992 and 1997 in 66 zones (second stage adopters), as shown in figures 1a and 1b. Accessibility data (distance to stations) was obtained by means of GIS operations. In addition, a matrix of distances among zone centroids, necessary to calculate the neighborhood effect, was obtained from the GIS. In the following section we estimate two models for this study case: a standard logit model with no spatial effects, and a spatial logit model to take into account neighborhood effects.

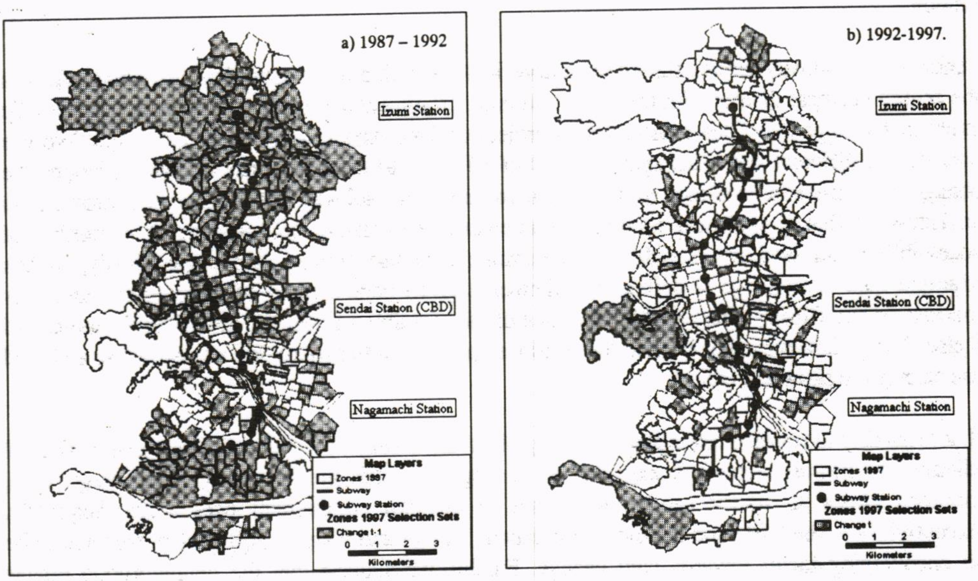

Figure 1. Sendai City – Subway Lane and Commercial Land Use Change

4.2 Results and Discussion

The results of estimating logit models for our case study appear in table 2. The two models use the same set of variables, but the spatial model, in order to consider in addition neighborhood effects (i.e. the influence of previous 'adopters'), also makes use of a matrix of distances among zone centroids of second stage adopters and first stage adopters (equation 6).

Regarding table 2, we notice that in general the two models produce very similar results, and there are no changes in the signs of the parameters. The signs mostly agree with our previous expectations: there appears to be a positive influence from land availability, and proximity to the city's CBD also appears to be a factor of change. The results are mixed regarding accessibility to the city's two sub-centers, since the sign of the parameters would lead us to conclude that proximity to these locations is a factor that does not weigh for change. Distance to the nearest station, on the other hand, is negative thus nominally meaning that the closer the zone is to a subway station the higher the probability of change. The high variance, however, indicates that this result is not significant, and therefore cannot be taken as evidence that infrastructure has had an impact in land use change at this stage in this case.

Table 2. Sendai City: Logit Model and Spatial Logit Model

	Standard Logit		Spatial Logit	
Independent Variables	Parameter	Variance	Parameter	Variance
CONST	-2.4179	4.13848	-3.3121	2.88607
Undeveloped	0.0249	0.00038	0.0246	0.00022
DIST_CBD	-0.0778	0.03187	-0.1100	0.02287
DIST_IZUMI	0.1612	0.04148	0.1884	0.02797
DIST_NAGAMACHI	0.2871	0.06901	0.3141	0.04893
DISTN	-0.2888	0.08908	-0.1441	0.06211
b_1			0.2434	0.21607
b_2			0.3688	0.11908
Log-Likelihood	-110.69		-109.91	
Log-Likelihood (0)	-118.52			

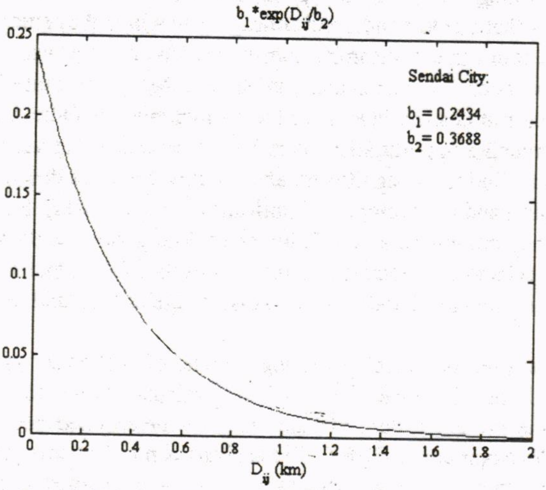

Figure 2. Distance-Decay Curve – Size and Extent of Neighborhood Effects in Sendai.

Regarding the effect of change in the neighborhood, the sign of parameter b_1 represents the direction of the effect. In this case, a positive sign implies that previous intensifications of commercial land use in neighboring zones tend to encourage similar developments. Regarding the size and extents of spatial effects, the spatial parameters (b_1 and b_2) result in a distance-decay curve such as seen in figure 2. Although the curve is not very steep (a characteristic controlled by parameter b_2) and the extents of the effect are rather wide, the size of the effect is not very large to start with (small b_1) and the net effect is that any (positive) contribution of previous adopters is rather small at distances beyond 400 m (less than 0.1; see figure 2). In addition, the large variance associated with these parameters suggests that neighborhood effects are not very important, at least at this scale of analysis. Although in general the variances are smaller in the spatial model, the Likelihood Ratio between the standard and the spatial model is not significant, and therefore no statistical advantage derives from estimating the spatial model in the present case. It is important at this point to note that the distance decay-curve is obtained for the period between 1992-1997, and that there is no manner at this stage to separate other socio-economic influences from neighborhood effects, an exercise that would necessitate longer periods of time with more cross-sections, and in all likelihood, additional explanatory variables. What can be done at this stage is to explore whether the scale of the analysis might be an important factor in determining the size and relative importance of neighborhood effects. To do this, we analyze a second example in the following section.

5. CASE STUDY: UNION CITY BART STATION

5.1 Study Area and Data

California's Bay Area Rapid Transit (BART) System is perhaps one of the most thoroughly studied transit systems in the world. BART is a modern, grade-separated system that offers fast and frequent service (Landis *et al.*, 1995). It began operations in 1972 and was fully operative in 1975 with transbay service. Although it was the object of several preliminary studies, including patronage demand forecasting using limited-dependent variable models (McFadden, 1974), one of the most recent reports is that due to Landis and colleagues in which they study the effects of transit investment (BART and four other Californian transit systems) on land uses and property values. Regarding the determinants of land use change, in general they found that distance to the station was not a significant factor of change, in *none* of the stations studied. Other variables of the model were a measure of intervening opportunities given by the percentage of vacant land closer to the station, which they didn't find to be significant, and dummy variables describing initial land use: residential (not significant) and undeveloped (significant in several cases). Finally, as a measure of neighborhood effects, they introduced a 'similarity index' to describe the dominant land use in the 8 immediately adjacent cells to each location. In most cases they found that high similarity indexes (i.e. similar land use in the neighborhood) tended to discourage further land use change.

In this section, we reanalyze, using the spatial logit model of section 2, one of the cases in the original study, namely Union City BART Station. This particular station constitutes an example of station area in which the present pattern of land uses was determined between 1965 and 1990, concurrently with the development of BART. The analysis is not the same, however, since Landis *et al.* studied land use change in general, whereas here we are concerned with residential land use in particular. More specifically, in this example land use change is defined as whether a given zone's dominant land use changed to residential or not. Again, this variable takes one of two possible values: 1 if it did, and 0 otherwise. We retake three variables from the original analysis: distance to station, percentage of undeveloped land use closer to the station, and a dummy variable of initial land use – undeveloped. The variables are shown in table 3.

The 'similarity index' is not used, because the neighborhood effects are an integral part of the spatial logit model. The object of the analysis is an area of 3.24 square kilometers around Union

City BART Station, in units of one hectare (see figure 3). The sample consists of 324 zones of which 12 changed to residential land use between 1965 and 1975, and 49 more between 1975 and 1990.

Table 3. Union City: Variables and Definitions

Variable	Definition
RES	Change to residential land use (yes= 1; no= 0)
DIST_ST	Distance to Station (km)
%UNDEVELOPED	Undeveloped land closer to station (%)
INIT_USE_U	Initial use (undeveloped=1; other=0)

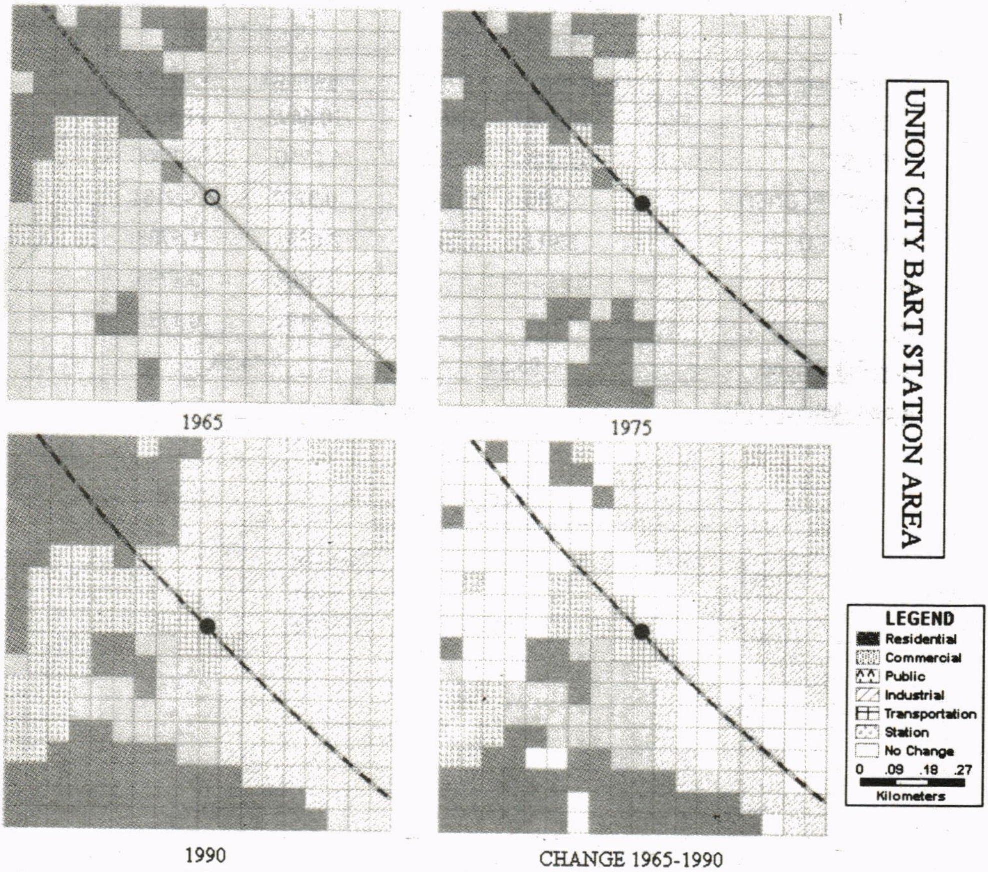

Figure 3. Union City – BART Station and Land Use Change

5.2 Results and Discussion

The results of estimating logit models for the second case study appear in table 4. As before, the two models use the same set of variables, but the spatial model considers in addition neighborhood effects. It can be seen in table 4 that there are now important differences between them. Although there are no sign reversals, the size of the parameters (of the effects) does change. The parameter corresponding to the variable Distance to Station is positive, which runs counter to what conventional wisdom would expect of the effects of transportation development and land use change. The high variance however, suggests that the parameter is not significant and can thus be ignored. The same is true for the second variable %UNDEVELOPED, which is negative but not significant. In fact, the only two factors that appear to be of some significance in the model are initial use, if the land was undeveloped, and the effect of change in the neighborhood. These results confirm previous findings by Landis *et al.* indicating that proximity to transit service has contributed little to determine land change in general. Our results show that the same is true of residential land development in particular.

Table 4. Union City: Logit Model and Spatial Logit Model

	Standard Logit		Spatial Logit	
Independent Variables	Parameter	Variance	Parameter	Variance
CONST	-10.1987	5.8601	-10.6693	11.5097
DIST_ST	11.6757	35.5304	5.2260	34.0000
%UNDEVELOPED	-6.9801	23.1352	-0.3772	19.9181
INIT_USE_U	3.9131	1.0442	3.6351	1.5708
b_1			0.6508	0.1796
b_2			0.5199	0.1724
Log-Likelihood	-95.33		-74.53	
Log-Likelihood (0)	-216.26			

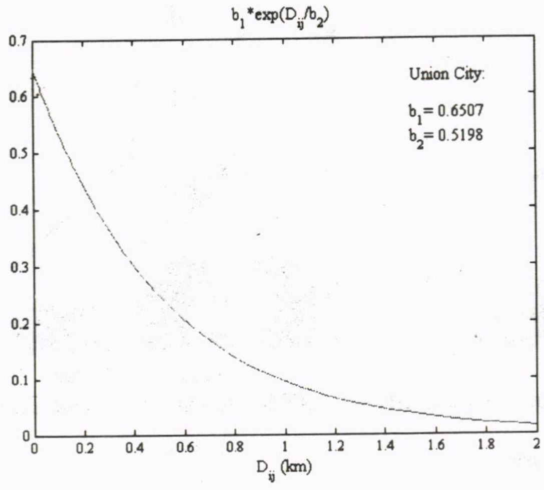

Figure 4. Distance-Decay Curve – Size and Extent of Neighborhood Effects in Union City.

Regarding neighborhood effects, the sign of parameter b_1 is positive again. Unlike the 'similarity index', which indicates resistance to change in zones where uses are already homogeneous, in this case parameter b_1 represents the positive influence towards change to similar uses. Now the size of the effect is considerably larger than in the previous case (section 4), with a value of almost 0.7 at the origin, and the rate of decay is even less pronounced (now the distance needed to discount the effect to 0.1 is 1 kilometer). Although we cannot directly compare the two case studies in this paper as they basically analyze similar but not identical problems, the results obtained seem to indicate that neighborhood effects tend to be more or less wide in range but considerably sharper at short distances, and most probably observable only at fine resolution. In any case, the likelihood ratio between the two models in this section is clearly significant, meaning that the spatial model is a better representation of the data than the standard model.

6. CONCLUSIONS

The impacts of transportation investment on land use are a current concern among transportation planners, given the potential usefulness of transportation infrastructure to shape urban growth, and thus to lead development towards more sustainable conditions. In this paper we have explored a method to assess the impacts of transportation infrastructure on land use change. Drawing from results in spatial statistics, we applied a spatial logit model to investigate the impacts of transportation infrastructure, and a number of land use variables, on land use change. The spatial logit model used is in addition dynamic in the sense that it takes into account time lags between periods of change. With this as a tool, we have tried to answer questions such as, what is the potential impact of transit infrastructure on land use change? Do neighborhood effects matter and to what extent?

Taking as case studies Sendai City's subway line, and Union City BART Station, we applied the model to find that:

1) Distance to a newly built station does not appear to be a determinant of land use change. In the case of Sendai City, proximity to a subway station did not seem to encourage increases in the share of commercial land use. The same is true in the case of Union City, where distance to the BART station did not influence change to residential land uses. In other words, in these examples, we found no evidence that rail transportation infrastructure was a factor of land use change.

2) Land use change is conditioned by land availability. In the case of Sendai City, although distance to the station was not significant, land availability in the zone had a positive effect and seemed to be a factor of more intensive commercial use. In the case of Union City, the change tended to be new development in previously undeveloped land.

3) Land use change of a given type is facilitated by similar change is adjacent areas. These neighborhood effects were dim in the case of Sendai City, but clearer in the case of Union City. This leads us to think that neighborhood effects in the context of land use change are likely to be moderately influential but highly localized, and observable only at high analysis resolutions.

Clearly, these are but two examples. However, our results confirm previous findings by Landis *et al.* in the sense that the process of land use change does not seem to be affected by proximity to transportation infrastructure (i.e. transit services), at least at the current scale of analysis. In addition, they help to refine the understanding of the size and extents of spatial (neighborhood) effects and how change spreads. Additional applications would help to confirm or refute the generality of these findings.

Regarding the method itself, it must be noted that during the course of our study, applying the spatial logit model to different sets of data sometimes resulted in negative values of the variance. Whether this was because of local optimum values, or because the model did not fit well the particular set of data was not clear. On the broader issue, this quirk indicates that more research regarding the properties of the model is required before it can be used with more reliability.

REFERENCES

Anas, A (1982) **Residential Location Markets and Urban Transportation**, Academic Press, New York.

Anselin, L. (1988) **Spatial Econometrics: Methods and Models**, Dordretch: Kluwer Academic Publishers.

Case, A. (1992) Neighborhood Influence and Technological Change, **Regional Science and Urban Economics 22**, 491-508.

Dubin, R. (1995) Estimating Logit Models with Spatial Dependence. In L. Anselin and R.J.G.M. Florax (eds.), **New Directions in Spatial Econometrics**. Springer-Verlag, Berlin, 229-242.

Kitazume, K. and Miyamoto, K. (1997) Effects of subway development on commuters' transportation mode choice in a city of Japan, **Journal of the Eastern Asia Society for Transportation Studies Vol. 2, No. 5**, pp. 1347-1355.

Landis, J., Guhathakurta, S., Huang, W. and Zhang, M. (1995) **Rail Transit Investments, Real Estate Values, and Land Use Change: A Comparative Study of Five California Rail Transit Systems**, IURD Monograph 48, Institute of Regional and Urban Development, Berkeley.

McFadden, D. (1974) The Measurement of Urban Travel Demand, **Journal of Public Economics 3**, 303-328.

McFadden, D. (2000) **Disaggregate Behavioral Travel Demand's RUM Side: A 30-Year Retrospective**, Department of Economics, University of California, Berkeley.

McMillen, D.P. (1989) An Empirical Model of Urban Fringe Land Use, **Land Economics Vol. 65, No. 2**, p.138.

Miyamoto, K., Sugiki, N., Uchida, T. and Páez A. (1997) A Detailed Land-Use Model Dealing with Building Types in a Metropolitan Area, **Journal of the Eastern Asia Society for Transportation Studies Vol. 2, No. 6**, pp. 1943-1960.

Still, B.G., May, A.D. and Bristow, A.L. (1999) The assessment of transport impacts on land use: practical uses in strategic planning, **Transport Policy 6**, 83-98.

Wegener, M., Gnad, F. and Vannahme, M. (1986) The Time Scale of Urban Change. In B. Hutchinson and M. Batty (eds.) **Advances in Urban Systems Modelling.** Elsevier Science Publishers, North-Holland, pp. 175-197.

Yai, T. (1989) Disaggregate Behavioural Models and Their Applications in Japan, **Transportation Research A Vol. 23, No. 1**, pp. 45-51.