Spatial Dependence among County-Level Land Use Changes

by

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Abstract

Spatial econometric methods are used to investigate whether land use changes in one county are affected by changes in surrounding counties. Spatial dependence is hypothesized to arise from land substitution effects among neighboring counties. The estimation uses data on land use change for 1,055 counties of 12 Midwest states.

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Introduction

Many areas of the U.S. have witnessed an increase in urbanization rates within the last couple of decades. Nationally, the estimated amount of land developed annually during 1992-1997(3,193,200 acres) was more than twice as high as that during 1982-1992(1,388,410 acres).[1] This phenomenon is noteworthy from the viewpoint of public policy because this conversion may threaten the space and resources needed for agriculture and wildlife. Moreover, urbanization is likely to be irreversible[2] and is expected to keep rising as growth pressures increase. Since urbanization can have significant impacts on local communities in terms of public finance, quality of life, and environmental costs, it is important to identify the factors driving land use conversion decisions.

Factors affecting the rate and pattern of urbanization can be broadly categorized as: site characteristics, locational conditions and legal constraints. Site characteristics refer to surface and near surface qualities of the land, which include land characteristics,[3] such as soils, slope, vegetative cover, and other criteria that are derived mainly from the physical qualities of land at each site. Locational conditions describe the location of a site relative to its surrounding area, such as accessibility to urban centers,[4] transportation routes, public infrastructure, proximity to water or roads, etc. Land use controls, such as

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[1] Source: USDA Natural Resources Conservation Service, 1997 National Resources Inventory.
[2] Everything could be reversible over a long time horizon, the notion "irreversible" here emphasizes on the fact that the conversion from urban land to other land uses is much more costly compared to other conversions.
[3] Research includes Plantinga *et al*.
[4] Related research includes the monocentric model developed by Alonso, Muth, Mills, and the polycentric model by Richardson.

zoning regulations[5] and subdivision ordinances, are examples of typical legal restrictions. At present, the empirical research on land use change has focused predominantly on how these factors have influenced the rate and pattern of urbanization in one *specific* area rather considered how the spatial *process* of land use change may lead to interdependencies across neighboring areas.

This paper investigates the possibility that land use changes in one area may be influenced by land use changes in surrounding areas. If local land markets are interdependent, due to imperfect substitution of land among neighboring areas, then this suggests the possibility of a spatial interaction among the urbanization rates of neighboring areas, in which the amount of land conversion in one area influences the amount of conversion in another area. Accounting for this type of interaction is important, both for empirical and policy reasons. Empirically, if the demand for urban land in an area is estimated without recognizing these potential interaction effects, the resulting estimates will be biased and hypothesis testing invalid. From a policy viewpoint, the presence of interactions among local land markets suggests that uncoordinated land use policies at the local level may result in suboptimal land use patterns at a region level due to land use spillovers.

In this study, a model of land use conversion is developed, in which the hypothesized interaction among neighboring counties is represented as a spatial lag. This article is organized as follows. First, the concept of spatial dependence is elaborated. The next

[5] Research includes Siegan, McMillen and McDonald, and Bogart.

section presents the economic and econometric model used to model spatial dependence among land use changes. This is followed by data description and empirical results, in which the interaction hypothesis is tested using data between 1987 and 1992 on land use changes and other socio-economic variables for 1055 counties of 12 Midwest[6] states. Conclusions are then drawn in the final section.

Spatial Dependence[7]

Spatial dependency can be considered to be a functional relationship between what happens at one point in space and what happens elsewhere (Anselin, 1988). Tobler's *first law of geography*- " everything is related to everything else, but near things are more related than distant things" -shows the importance of distance and space. It also implies why we should care about the possibility of spatial dependence when we analyze land use decisions.

In order to envisage the possible spatial dependence in this study, the exploratory spatial data analysis in Map 1[8] shows the change from other lands to urban land between 1987 and 1992 in the Midwest. From this, we can approximately visualize how land use change varies within this region. In order to picture a more general phenomenon, Map 1 can be represented with contour lines. Map 2 shows the resulting contour of the surface.

In Map 2, each isoline is delineated by connecting the potential equal value points. It can be inferred that the isolines located together indicate steep land use change gradients

[6] Midwest states in this study include IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD and WI
[7] This is also called spatial autocorrelation in some studies.

in short distance, whereas isoline located farther apart suggest more gradual changes in land use change relative to distance of spatial relationships (Vandeveer *et al*.). Evidence of positive autocorrelation would be expected when a contour map produces areas where isolines are far apart, indicating similar change gradients over a large area. Such a pattern would indicate that nearby or neighboring tracts of land are similar in land use patterns. This provides some visual evidence of positive autocorrelation in terms of land use changes. Knowledge of spatial autocorrelation is of concern because its presence among observations indicates interdependence in the data; this preliminary evidence is helpful for model specification and later data analysis.

Two broad classes of conditions can lead to spatial dependence: spatial lag dependence[9] and spatial error dependence.[10] Spatial error dependence is a byproduct of measurement errors for observations of contiguous spatial units. These errors may result from model misspecification or incomplete variable specification (i.e. omitted variables). Thus, similar patterns of land use changes may occur because of unobserved common exogenous factors. For example, a cluster of similar land use changes may be driven by the cluster's relative proximity to employment opportunities. Spatial error dependence is a residual effect, which is more related to estimation and methodological issues than to an underlying spatial process. Examples of land use models that account for this dependence include hedonic models of land values (Bell and Bockstael; Leggett and Bockstael).

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[8] Maps are produced using ArcView 3.2.
[9] This is also called spatial interaction or spatial autoregressive in some studies.
[10] This is also called spatial autoregressive disturbance or spatial residual autocorrelation in some studies (Anselin *et al.*, 1996).

Spatial lag dependence arises from the interaction of the dependent variable across observations. Unlike the spatial error dependence, spatial lag dependence is more fundamental to social science since it acknowledges the existence of spatial interaction phenomena, which is more important in analyzing human behavior. Examples of spatial lag models include studies that have focused on policy interdependence at different governmental levels. Case, Rosen and Hines used states expenditures as decision variables to analyze fiscal policy interdependence among states. Brueckner studied the strategic interaction of growth control measures among cities in California. Lenon, Chattopadhyay and Heffley studied the interdependence of local zoning decision among competing counties. These studies find evidence of policy interdependence among neighboring local governments.

Economic Structural Model of Spatial Dependence

In order to show the interdependency of land use changes across jurisdictions in a theoretical framework, we start from demand-supply equilibrium conditions. In the literature, it has been suggested single-equation estimations should be avoided because of the ambiguity between demand and supply it will cause. Additional concerns arise because single-equation estimation implies only a one-way relationship (Shilling, Sirmans and Guidry). Therefore, simultaneous-equation models should be used. By doing so, these models can simultaneously incorporate the separate and distinct effects from both demand and supply sides. The following discussion shows how land use changes across neighboring jurisdictions may be dependent on each other, given the market price is decided by demand and supply.

Without loss of generality, consider the case for only two jurisdictions: A and B. We can express supply-demand relationships in two jurisdictions as follows,

$$(1) \qquad Q_i^s = f(P_i; X_i^s) \quad i = A \ or \ B$$

$$(2) \qquad Q_i^d = f(P_A, P_B; X_i^d)$$

Equation (1) is the supply for newly developed urban land in jurisdiction i, which is a function of land price in i, P_i and X_i^s, a vector of variables influencing the supply of urban land, including the opportunity cost of developing land, land characteristics and expected returns from developing land in i.

Equation (2) is the demand for newly developed urban land in jurisdiction i. Because of the substitution relationship for land between jurisdictions, the quantity demand in A is not only decided by land price in its own jurisdiction, P_A, but also the land price in the neighboring jurisdiction, P_B. X_i^d is a vector of variables thought to influence the demand for urban land, including income, and population growth in i.

Based on the above demand-supply relationship, the equilibrium condition in each jurisdiction is as follows,

$$(\textit{equilibrium condition in } B)$$

$$(3) \qquad Q_B^{s*} = Q_B^{d*} = Q_B^* = f(P_A^*, P_B^*; X_B)$$

$$(\textit{equilibrium condition in } A)$$

$$(4) \qquad Q_A^{s*} = Q_A^{d*} = Q_A^* = f(P_A^*, P_B^*; X_A)$$

Equation (4) can be rearranged as the inverse function. After the rearrangement, we can obtain (5) as follows,

$$(5) \qquad P_A^* = g(Q_A^*, P_B^*)$$

Substitute (5) into (3), we can derive (6) as follows,

$$(6) \qquad Q_B^* = h(Q_A^*, P_B^*; X_B)$$

Although land has the characteristics of immobility, equation (6) shows the equilibrium quantity of newly developed urban land in jurisdiction B is dependent on equilibrium quantity of newly developed urban land in jurisdiction A. Therefore, the equilibrium land use in different jurisdictions is interdependent. This kind of relationship basically results from the substitutability of land across different jurisdictions. The direction of the interdependence can be either positive or negative; however, depending on whether the forces causing land use changes are mainly demand-driven or supply-driven.

Figure 1 shows the graphic representation of the demand-driven interdependence. Suppose the initial equilibrium in A jurisdiction is the intersection of demand, $D_{A,}$ and supply, S_A. Demand could shift from D_A to $D_A{}'$ because of an increase in either income or population growth. At the same time, because of the substitution of land between A and B, the higher price driven by demand in A will motivate developers to seek cheaper land for conversions. That is, the demand in A will be shifted to B. Finally, the demand in A shifts to D_A', and that in B shifts from D_B to D_B'; the equilibrium prices are P_A^* and P_B^*, respectively. The equilibrium quantities increase from Q_A to Q_A^* in A, and from Q_B to Q_B^* in B. The increases of quantities of land used for development in both jurisdictions imply positive interaction between the land use changes in two jurisdictions.

Figure 2 shows the graphic representation of the supply-driven interdependence. The initial equilibrium in A jurisdiction is still the intersection of demand, $D_{A,}$ and supply, S_A. But now the supply could shift from S_A to S_A' because the supply of land in A is restricted,[11] this will also cause an increase in the land price in A. Likewise, because of the substitution of land use between A and B, the higher price driven by the shift in the supply in A will encourage developers to seek cheaper land for conversions. Ultimately, the equilibrium quantities decrease from Q_A to Q_A^{**} in A, but increase from Q_B to Q_B^* in B. The decrease of quantity of land in A and the increase of quantity of land in B imply negative interaction relationship between the land use changes in two jurisdictions.

Econometric Model

As mentioned before, there are two conditions resulting in spatial dependence: spatial lag and spatial error. In county-level land markets, the land use changes in neighboring counties is hypothesized to affect land use changes within a county through the adjustment of markets. This kind of dependency, spatial lag, can be described as the following mathematical relationship (Anselin,1988);

[11] This might be caused by stricter land use controls, higher development fees, etc.

$$(7) \quad y_i = f(y_1,...,y_{i-1,}y_{i+1},...,y_n)$$

Where y_i is the land use decision of i county and y_1,y_{i-1},y_{i+1}...,y_n are the decisions made by the neighboring units, which are spatial lags of the dependent variable. Like y_i, these spatial lagged dependent variables are jointly determined, that is, they are also endogenous. The consequences of ignoring a spatial lag effect will cause biased and inconsistent estimates.

Although spatial lag is the main concern in terms of both economic and econometric considerations, spatial error dependence is likely to be a problem due to common unobserved factors directly affecting the land use decision in each county at the same time. An example is the proximity of land to a major employment center. If this center is sufficiently large to influence surrounding land conversion to residential and other urban uses, then similar patterns of land use changes could occur across counties. That is, to some extent, the land use changes in different counties will be affected similarly and positive correlation of land use conversion rates may arise across neighboring counties. In spatial econometrics, the spatial error dependence can be expressed as follows,

$$(8) \quad \varepsilon_i = f(\varepsilon_{1,...,}\varepsilon_{i-1},\varepsilon_{i+1},...,\varepsilon_n)$$

Where ε_i is the spatial residual in county i , ε_1,...,$\varepsilon_{i-1,}$ ε_{i+1},...,ε_n are spatial residuals in the neighboring counties.

Based on equations (7) and (8), we can write the complete model for this study as follows (Anselin, 1988; Kelejian and Prucha),

$$(9) \qquad y_n = \rho W_n y_n + x_n \beta + \varepsilon_n$$

$$(10) \qquad \varepsilon_n = \lambda M_n \varepsilon_n + \mu_n$$

Formula (9) is a more complete form of (7); and formula (10) is a more complete form of (8). y_n is a $(n\times1)$ vector of observations on a dependent variable. x_n is a $(n\times k)$ matrix of explanatory variables, and β is a $(k\times1)$ vector of parameters. W_n and M_n are $(n\times n)$ spatial weight matrices which will be discuss in more detail later. $W_n y_n$ is the spatial lag of y_n; ρ and λ are scalar spatial parameters. The disturbance ε_n is the $(n\times1)$ vector of regression disturbances, and μ_n is $(n\times1)$ vector of innovations, which is distributed independently and identically with mean zero, variance σ_μ^2.

Data

The spatial dependence model developed for 12 Midwest states consists of Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. A total of 1,055 counties were examined. We consider the acreage changes in land use from all other land to urban land between 1987 and 1992 (TURB8792) as the dependent variable. This variable was aggregated to the county level from the USDA's detailed plot-level survey, *National Resource Inventory (NRI).*

The following variables comprise the vector of explanatory variables which can either influence the demand or supply for the newly developed urban land. These inclued: the acreage changes in land use from all other land to urban land between 1982 and 1987 (TURB8287), acreage of land for urban use in 1982 (URBAN82), population in 1987 (POP87), percentage of population change between 1982 and 1987 (DP8287), per capita income in 1987 (PCINC87), average estimated market values of land and building in farms per acre in 1987 (P2FVA87), area of each county (AREA), distance from each county to the closest major cities[12] (SQMIND), dummy for whether the county is within a Metropolitan Statistical Area (MSA), acreage of land in Land Capability Class (LCC) I or II[13] in 1987 (LCC87), average LCC in 1987(PAVLCC87), and finally the percentage change of LCC I or II between 1987 and 1992(DLC8792).[14] Among these variables, P2FVA87 serves as the opportunity cost of converting land from agricultural to urban uses. SQMIND represents the locational conditions. PAVLCC87 measures the average land characteristics for each county; it captures the possible heterogeneities of site characteristics among counties. The higher the value of PAVLCC87, the lower is average land quality. Adopting the idea of Plantinga *et al.*, LCC87 is used to control for

[12] These include the cities with population more than 100,000, which include (Michigan) Flint, Grand Rapid, Lansing, Ann Arbor, Detroit; (Indiana) South Bend, Gary, Fort Wayne, Evansville, Indianapolis; (Wisconsin) Madison, Milwaukee; (Illinois) Rockford, Peoria, Springfield, Chicago; (Missouri) Kansas City, St. Louis, Springfield; (Iowa) Cedar Rapids, Des Moines; (Minnesota) St. Paul, Minneapolis; (South Dakota) Sioux Falls; (Nebraska) Omaha, Lincoln; (Kansas) Kansas City, Topeka, Wichita; (Ohio) Cleveland, Columbus, Cincinnati, Dayton, Toledo, Akron; (Pennsylvania) Erie, Pittsburgh, and (Kentucky) Louisville.

[13] Land capability classes I and II represent land with physical characteristics best suited to crop production (USDA Soil Conservation Service).

[14] According to the endogeneity test, this variable is actually an endogenous variable which is simultaneously decided with the dependent variable. Instrumental variable estimation method is used to estimate and control for the simultaneity.

some degree of within-county variation in land quality. Table 1 presents the descriptive statistics for these data.

Empirical Results for 12 Midwest States

Without considering the possible spatial dependence, the ordinary least regression (OLS) results are reported in the first column of Table 2. Most of the coefficients estimates by OLS are significant at 5%. However, without recognizing the potential spatial dependence, the resulting estimates may be biased and inefficient; these will affect the statistical validity of results. In order to account for the possible spatial dependence, it is necessary to incorporate the spatial variable by specifying the spatial weight matrix.

Specification of the Spatial Weight Matrix

The spatial dependence is represented by the weight matrix W_n and $M_{n.}$ Empirically, we assume that the impact of other counties' land use changes on county i depends on a weighted average of all other counties' changes. The nonzero elements of the weights matrix reflect the potential spatial dependence between two observations. The specification of spatial weight matrix plays an important role in spatial models since it represents degree of potential dependence between neighboring locations (for discussions of the importance of spatial weight matrix, see Ord; Cliff and Ord; Upton and Fingleton; Anselin, 1988). The misspecification of the weight matrix can substantially lower the power of the tests (Anselin and Rey). Spatial weight matrix can be derived from information on degree of contiguity, distance contiguity (having centroids within a critical distance band), or in function of inverse distance or squared inverse distance (Anselin, 1998).

There is no definite rule regarding how to choose spatial weight matrices to date. In order to judge the robustness of the results to the assumption of a spatial weight matrix, several specifications of the spatial weight matrix are compared based on different distance-contiguity weighting schemes. These weights are defined as

$$\begin{aligned} w_{ij} &= 1 \quad if \quad d_{ij} < c \\ w_{ij} &= 0 \quad if \quad i = j \;\; or \;\; d_{ij} > c \end{aligned}$$

d_{ij} is the distance between observation i and j, c is the cut-off distance. It can be expected that the larger the value of c, the less sparse the weight matrix. Table 3 lists the name, descriptions and spatial dependence tests[15] of four different matrices.

As shown in Table 3, **DISARC1** has largest average link while **DISARC4** has the least. However, no matter how the average links change across different specifications, Moran's I tests are all highly significant at 5%, indicating both or either one of the spatial dependence (error or lag) might cause the results. While Moran's I cannot be used to discriminated between the two forms of dependence, from the test statistics of Robust LM (error) and Robust LM (lag), we found spatial lag should be responsible for the underlying spatial dependence process since the test statistics in Robust LM (lag) are all

[15] These tests are calculated from the residuals of OLS and the correspondent spatial weight matrix. Moran's I has power against both forms of spatial dependence, yet it cannot be used to discriminated between these two forms (Anselin and Rey). Robust LM (error) is robust to the presence of spatial lag. Robust LM (lag) is robust to the presence of spatial error dependence.

significant at 5% across different specification while Robust LM (error) are not.[16] Based on these test statistics results, the following estimation will base on spatial lag specification as shown in equation (9), in which ε_n is assumed to follow an iid error structure.

When OLS is used to estimate the spatial lag model, the presence of spatial lag of the dependent variable will lead to inconsistent estimator because of the correlation between the error term and the spatial lagged dependent variable. An alternative approach[17] is the instrumental variables (IV) estimation method.[18] IV has similar asymptotic properties as the MLE,[19] and is much easier to implement when sample size is large. The major implementation problem of IV method is the selection of instruments. It has been suggested by Kelejian and Robinson that a series of spatially lagged exogenous variables are the proper set. In this study, we used the spatial lags of all exogenous variables as the instruments -- that is, the spatial lagged dependent variable (W_TURB8792) is instrumented by the spatial lags of exogenous (WX). The estimation results under different weighting schemes are presented in the columns 2-5 of Table 2.

The most important results in Table 2 are the estimates of spatial lagged dependent variables (W_TURB8792), all of the weighting specifications suggest that spatial

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[16] Even if the test statistics in Robust LM (error) in **DISARC1** is significant in a loose sense (5% p-value criterion), according to Anselin and Rey, if both tests are significant, the test with the higher value indicates the correct form of dependence.
[17] Other approaches include maximum likelihood estimation (MLE) approach and Bayesian approach. Please refer to Anselin (1988) for the comparison.
[18] This is also called two-stage-least-square (2SLS) estimation.
[19] Since the assumption of normally distributed error terms is not needed in IV method, it is a robust alternative to MLE (Anselin, 1998).

relationship really matters, and the magnitude ranges from 0.1252 to 0.2197. Since the signs are all positive, indicating there is positive interaction of land use changes among counties. This complies with the demand-driven interdependence suggested earlier in the economic structural model.

The coefficients of TURB8287, URBAN82 and DP8287 are all positive and significantly different from zero across different spatial weight matrices. The positive coefficient on TURB8287 indicates that the more land conversion to urban use between 1982 and 1987, the same situation will last in the following years; unless the saturation point is reached, this phenomenon is expected to continue since the conversion cost is lower in the area which is partly converted. The positive coefficient of URBAN82 can be explained in the same context as TURB8287. The positive DP8287 coefficient suggests that the land use tends to get converted more in the area with higher population growth. In contrast, the negative and significant coefficient of POP87 reflects the conversion less happens in the areas with higher population. It is likely that the demand for urban land in those areas is higher, which directly causes higher land price. Because of the price spillover effect and the substitution of land use among neighboring counties, the higher price will motivate developers to seek cheaper land for conversion in neighboring less populated counties.

Although not persistently significant across different weighting schemes, both of the coefficients on PCINC87 and AREA are positive. The positive coefficient of PCINC87 simply confirms the intuition that more development usually occurs in the high-income area. Since the main purpose of AREA is to scale the dependent variable, positive coefficient of AREA reflects it positively scales TURB8792.

Since P2FVA87 serves as the opportunity cost of converting land from agricultural to urban uses, the negative coefficient of P2FVA87 indicates that if the average estimated market values of land and building in farm are higher, it will encourage land to be kept in agricultural use. The negative and significant[20] coefficients of SQMIND imply the closer to the nearest major city; the county will have more conversion. As expected, the coefficients of MSA are all positive, not significant, however. This might result from the little variation in MSA in the data set; there are only 177 MSAs in the 1055 observations. The ambiguous signs of LCC87 show the inconstancy of the estimates; however, they are not significantly different from zero. Since intuition suggests the poor quality of land would be converted first, this result is unexpected, though the similar results can be found in the literature (Plantinga *et al*.). The possible explanation is that urban land uses might not be as selective as agricultural land; especially we only include two best quality of land as the distinction. Conversely, the coefficients of PAVLCC87 are constantly positive across different specifications, indicating the lower the average land quality (correspondent to higher value of PAVLCC87), the more land tends to be converted. The coefficient of the last variable, DLC8792, is negative and significant across specifications. Since this variable is endogenous, it reflects the decreases in land quality and the increases in urban land are simultaneously decided.

[20] Except in the DISARC4 specification, it is significant at 10%, however.

Concluding Remarks

The data show spatial dependence to be an important determinant of land use changes among 1,055 counties of 12 Midwest states. For the different weighting schemes, the coefficients of spatial lagged dependent variable (W_TURB8792) are all positive and significant at 5%, indicating the importance of spatial interaction due to the land substitution among neighboring counties. In other words, the result suggests that land use models without recognizing spatial effect will suffer from specification errors.

The study also suggests that the conversion to urban uses is more related to socioeconomic variables than to the quality of land. The results indicate the following explanatory variables are all significant at 5% under different specification of spatial weight matrices: the land conversion to urban between 1982 and 1987(TURB8287), land in urban use in 1982 (URBAN82), population in 1987 (POP87), percentage of population change between 1982 and 1987 (DP8287). While not significant in all specifications, the square root of distance from each county to the closest major cities (SQMIND) are significant for 3 out of 4 spatial models - DISARC1, DISARC2 and DISARC3; per capita income in 1987 (PCINC87) are significant for 2 spatial models - DISARC1 and DISARC4. On the contrary, for the land characteristic variables, such as LCC I or II in 1987 (LCC87) and the square of the average LCC in 1987(PAVLCC87) are not significant at all across different weighting schemes.

For both empirical and policy reasons, models of land use conversion should not only consider the factors affecting land use changes in the *specific* area, but also the spatial *process* of land use change and more specifically, the spatial dependence across neighboring areas. This is important empirically since otherwise biased and inconsistent estimates will result if the spatial lag process is ignored. From a policy perspective, the presence of these spatial spillover effects suggests that uncoordinated policies enacted by individual localities may result in suboptimal land use conversion patterns at a regional scale. Individual counties acting in their own self-interest will fail to consider the potential external effects of their policies on the demand for newly converted urban land in neighboring counties. As a result, a suboptimal pattern of urbanization may result at the regional level. Regional coordination of local policies affecting land use can better account for the otherwise external costs and benefits that individual counties may inflict upon each other and therefore offers a more efficient approach to managing regional growth.

Table 1. Variables used in analysis of spatial dependence

Variable	Mean	Standard deviation	Description
TURB8792 (Acres in 100)	12.277	25.521	The acreage changes in land use from all other land to urban land between 1987 and 1992
TURB8287 (Acres in 100)	10.838	20.926	The acreage changes in land use from all other land to urban land between 1982 and 1987
URBAN82 (Acres in 100)	133.10	279.66	Acreage of land for urban use in 1982
POP87 (Number of persons)	56009	204757	Population in 1987
DP8287 (%)	-2.067	5.606	Percentage of population change between 1982 and 1987
PCINC87 ($)	13114	2187	Per capita income in 1987
P2FVA87 ($$1000^2$)	942929	2313402	The square of average estimated market values of land and building in farms per acre in 1987
AREA (Acres in 100)	4649	3110.8	Area of each county
SQMIND (miles$^{1/2}$)	8.924	4.017	The square root of distance from each county to the closet major cities
MSA	0.1678	0.3738	Dummy=1 if county is within a MSA
LCC87 (Acres in 100)	1687.2	1264	Average of land in LCC I or II in 1987
PAVLCC87 (rating^2)	11.863	6.882	The square of the average LCC in 1987
DLC8792 (%)	- 0.6633	2.1905	The percentage change of LCC I or II between 1987 and 1992

Sources: TURB8792, TURB8287, URBAN82, DLC8792, LCC87, PAVLCC87 are calculated from NRI, 1982 and 1992. POP87, DP8287, PCINC87 are from Bureau of Economics Analysis. P2FVA87 is from the Census of Agriculture. SQMIND is calculated from ZIPFIP developed by USDA. MSA is extracted from the software program - Community 2020.

Table 2. Estimation of TURB8792

Explanatory Variables	Model				
	OLS	DISARC1	DISARC2	DISARC3	DISARC4
W_TURB8792	-	0.2197	0.1687	0.1252	0.1748
		(0.0005)*	(0.0044)*	(0.0250)*	(0.0022)*
CONSTANT	-12.4913	-14.0557	-6.7633	-7.6157	-13.235
	(0.0012)	(0.0089)	(0.2137)	(0.2774)	(0.0236)
TURB8287	0.3442	0.2968	0.3380	0.3857	0.3779
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*
URBAN82	0.0592	0.0358	0.0261	0.0306	0.0313
	(0.0000)*	(0.0068)*	(0.0193)*	(0.0052)*	(0.0019)*
POP87	-5.3786×10^{-5}	-3.4299×10^{-5}	-3.5355×10^{-5}	-3.8981×10^{-5}	-4.0419×10^{-5}
	(0.0000)*	(0.0030)*	(0.0005)*	(0.0001)*	(0.0000)*
DP8287	0.5130	0.3087	0.3822	0.3069	0.3047
	(0.0000)*	(0.0057)*	(0.0005)*	(0.0036)*	(0.0038)*
PCINC87	0.0013	0.0011	0.0005	0.0006	0.0010
	(0.0000)*	(0.0063)*	(0.1699)	(0.2439)	(0.0258)*
P2FVA87	-1.0891×10^{-6}	-1.7236×10^{-6}	-1.9939×10^{-7}	-8.6941×10^{-8}	-4.7832×10^{-8}
	(0.0000)*	(0.0431)*	(0.8492)	(0.9316)	(0.9634)
AREA	0.0009	0.0008	0.0011	0.0004	0.0004
	(0.0000)*	(0.0251)*	(0.0103)*	(0.2978)	(0.1811)
SQMIND	- 0.3837	-0.3881	-0.5419	-0.4669	-0.3103
	(0.0164)*	(0.0211)*	(0.0057)*	(0.0262)*	(0.0933)
MSA	4.3718	2.1904	1.1576	2.1190	0.8789
	(0.0024)*	(0.1811)	(0.4994)	(0.1973)	(0.5847)
LCC87	- 0.0012	-0.0003	-0.0003	0.0005	0.0002
	(0.0347)*	(0.6688)	(0.6756)	(0.4679)	(0.7582)
PAVLCC87	0.0116	0.0813	0.0798	0.1987	0.1735
	(0.9137)	(0.5280)	(0.5963)	(0.1386)	(0.2230)
DLC8792	- 2.8620	-6.6213	-72347	-5.8360	-5.7010
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0004)*	(0.0000)*
(Pseudo) R^2	0.7044	0.8315	0.9272	0.8144	0.8429
Adjusted R^2	0.701	-	-	-	-
Squared Correlation	-	0.6497	0.6303	0.6583	0.6712

Notes: 1. Estimations and test are carried out by SpaceStat version 1.90(Anselin, 1998).
2. Probability values (*p*-value) are given in parenthesis. * denotes significant at 5%.

Table 3. Description and spatial dependence test for different weight matrices

	DISARC1[1]	DISARC2[2]	DISARC3[3]	DISARC4[4]
Average links	42.97	15.69	10.77	6.53
Moran's I (lag or error)	4.21[5] (0.000025)	5.17 (0.0000)	5.30 (0.0000)	6.54 (0.0000)
Robust LM (error)	3.97 (0.0446)	1.86 (0.172)	0.46 (0.498)	0.041 (0.84)
Robust LM (lag)	8.66 (0.0032)	24.28 (0.0000)	32.42 (0.0000)	57.28 (0.0000)

Notes: 1. Weight equals 1 if cut-off point is 100 arc distance, 0 otherwise; row standardized.
2. Weight equals 1 if cut-off point is 60 arc distance, 0 otherwise; row standardized.
3. Weight equals 1 if cut-off point is 50 arc distance, 0 otherwise; row standardized.
4. Weight equals 1 if cut-off point is 40 arc distance, 0 otherwise; row standardized.
5. Values shown in Moran's I, Robust LM (error), and Robust LM (lag) are test statistics and their corresponding probability (*p*- value, in parenthesis).

Figure 1

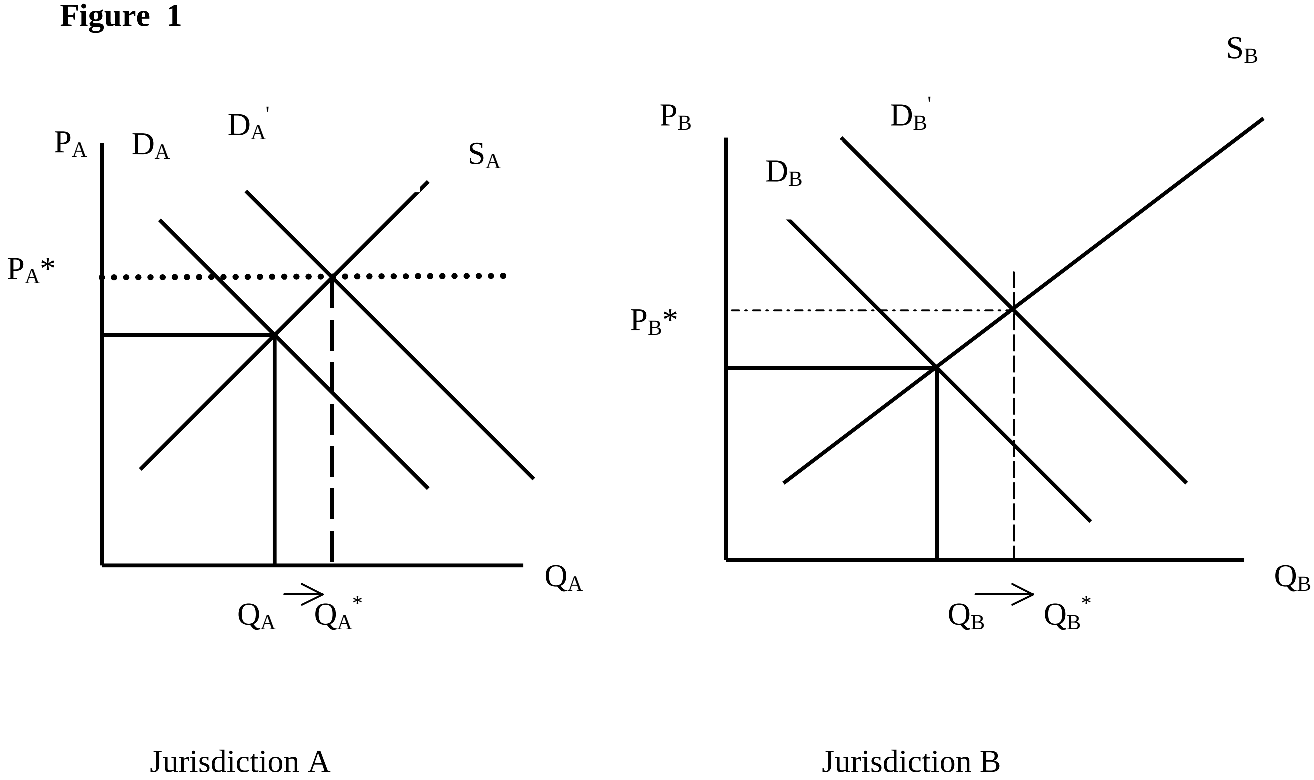
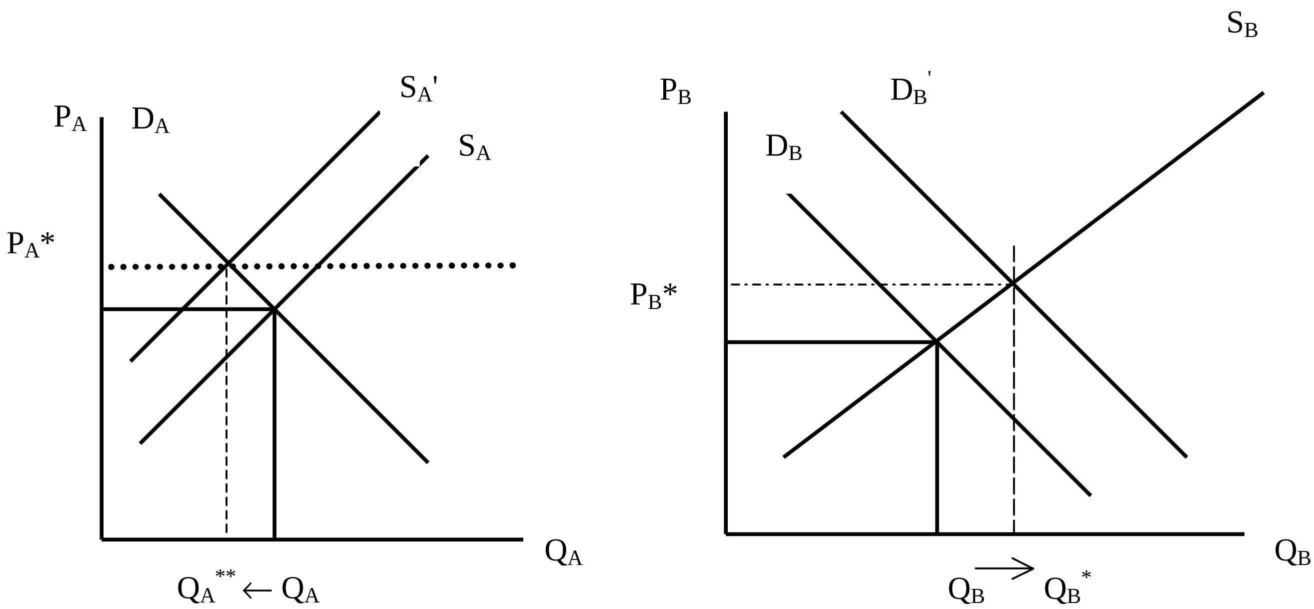


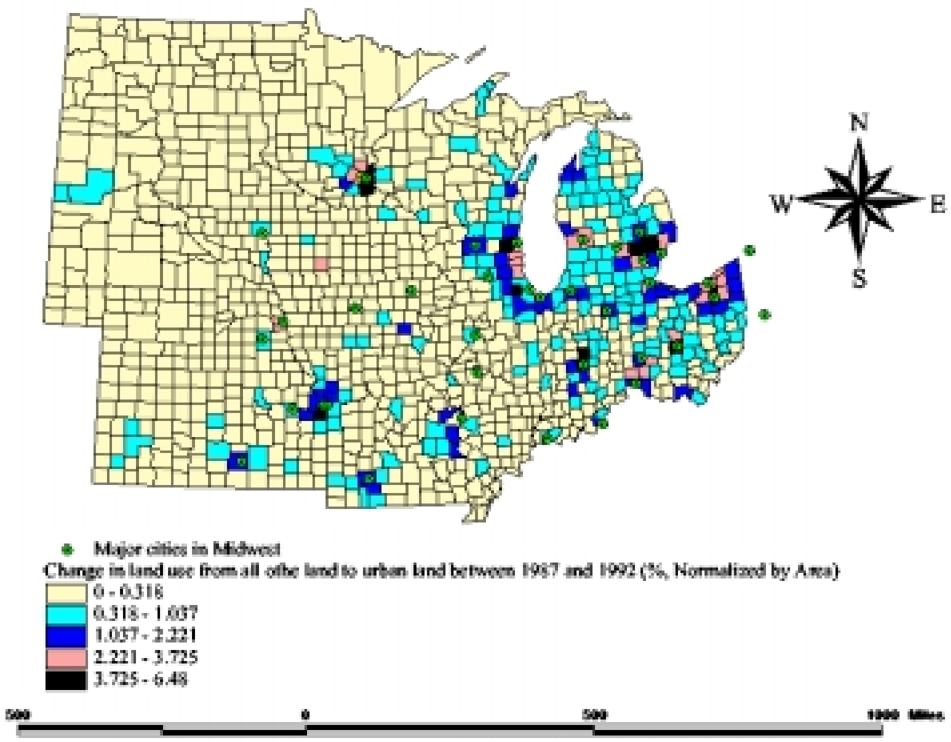
Figure 2



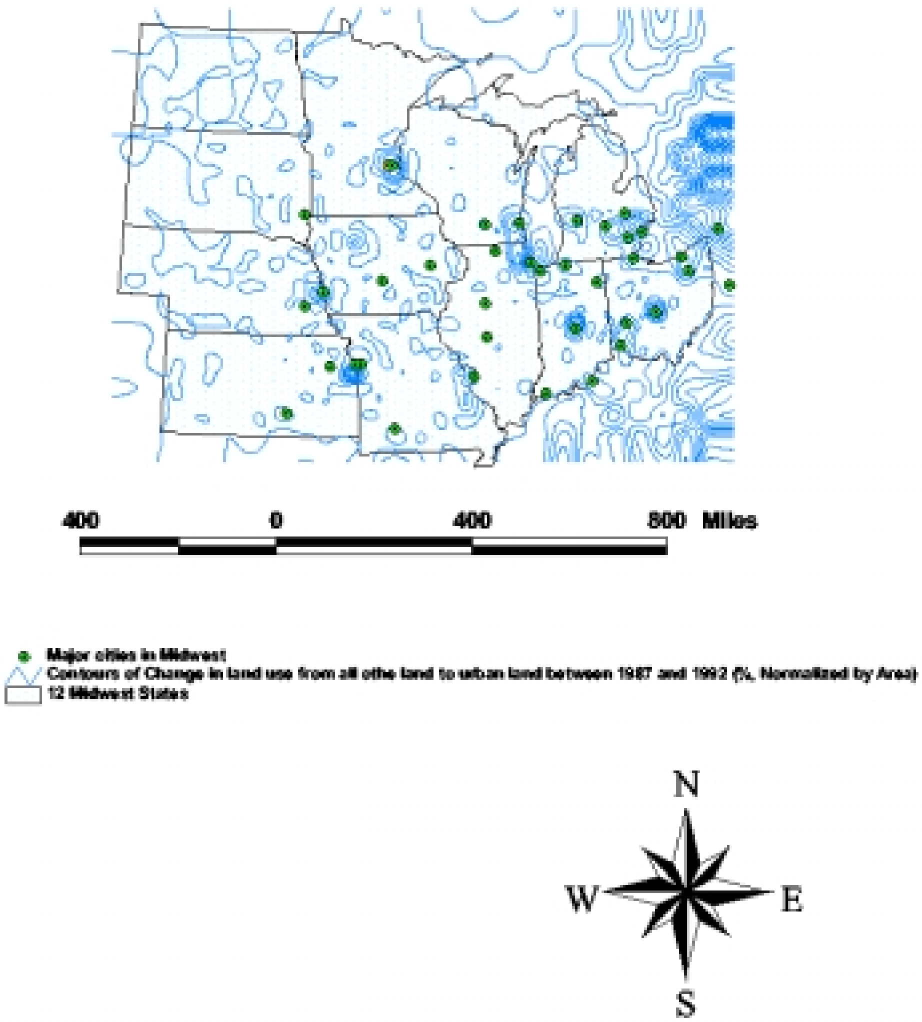
Jurisdiction A

Jurisdiction B

Map 1: Changes from Other Lands to Urban Uses between 1987 and 1992 in Midwest



Map 2: Contour Map of Changes from Other Lands to Urban Uses between 1987 and 1992 in Midwest



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