Spatial Models of Open Space Loss in the Mid-Atlantic Region of the U.S

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Abstract

The recently released National Land Cover Data set is used to analyze the loss of open space in the Mid-Atlantic area of the US. The emphasis here is on rural areas. The main objective of the study is to identify the drivers which influence the loss of open space. The study is then extended to incorporate spatial dependence proving to be important in explaining the dynamics of this loss. Different econometric models are presented. Results reveal that while population growth is an important driver of open space loss, initial population density is more important. It is also found that Pennsylvania loses open space at a consistently faster rate than all other states. Spatial models showed the presence of spill-over effects between regions both in the drivers and in the regression errors. The findings have significance for land use policy making at the local and regional levels.

Section 1: Introduction

The study of land use and land cover change is a fertile area of research. A survey of literature reveals that there are many studies documenting the patterns of land use change and analyzing the different factors which drive it. However there is a considerable dearth of research when it comes to analysis from a socioeconomic perspective. In the light of this, the present study deals with the pattern of land use change and its driving factors in the Mid-Atlantic United States. One of the unique aspects of the present analysis is the data that it uses. The land cover data are part of a very recently released data set which has not been used by many studies to explicitly model the loss of open space as a particular land use type. The area of study includes parts of Pennsylvania, New Jersey, Delaware, Virginia, Maryland, North Carolina and New York. These states have a high population pressure which translates into a negative consequence on the total area of open space available. Open space refers to undeveloped *land which retains most of its original characteristics and is prone to future development* (Fausold and Lilieholm, 1999). Undeveloped land includes wetlands, forests, grazing, recreational lands and agricultural lands, all of which generate substantial market and non-market benefits for the surrounding population. However rapidly increasing population and economic activity in this region has put a pressure on the open space.

There are three objectives in this paper. The first is the identification of the important drivers of open space loss with a special emphasis on the socio-economic drivers. The second is the analysis of the loss of open space in a spatial framework. Land as an immobile resource has an important spatial dependence extending in multiple directions. This would be true for the loss of land in open space uses in any region as well. As Bell

(2005) appropriately mentions every land parcel generates "private" and "public" flows and an analysis of land dynamics should incorporate these flows. An investigation into the possible causes of open space loss will contribute towards the greater understanding of the land cover change dynamics and help in the prediction of future rates of land use change as well as inform land cover conservation policies. Moreover spatial dependence if present needs to be incorporated into the analysis to avoid the problematic issues of biased and inconsistent estimates with erroneous signs (Irwin and Geoghegan, 2001). From the perspective of land use policy, different states have different forms of the land use, and this is expected to have a bearing on the nature of loss of open space. And in this respect tests are conducted to obtain a flavour of which of the models might be the best in explaining the loss of open space. Once this is established, policy prescriptions are expected to have greater confidence. The third objective of this paper is to analyze if there are actual differences in the pattern of the loss across the rural areas of the Mid-Atlantic states. Differences in the dynamics of the loss might be indicative of the efficacy or inefficacy in different kinds of land use policies adopted by different states to conserve their quanta of open space.

The paper is arranged into the following sections. Section 2 provides a review of the existing literature looking at the issue of land use change as well as providing a background on various spatial models. Section 3 presents a brief overview of the different factors influencing changes in land use patterns. In Section 4 a description of the models included in this analysis is presented. Section 5 describes the data and the empirical model. This is followed by detailed analysis of the important drivers of land use change and the relationships that they have with open space loss, in Section 6. Section 7 focuses on the results of models which incorporate spatial dependencies. Section 8 briefly introduces the issue of model selection and which of them might be the best representation of the data. The final section 9 is devoted to a discussion on policy implications stemming from the results. Future directions in this research are mentioned here as well.

Section 2: Existing Body of Work

Issues related to changes in land use and land cover is a fertile area of research with contributions from fields of economics, geography, and landscape ecology. The important point to note is that there are always multiple facets of the problem related to land. For example with respect to urban sprawl different views exist with some viewing it as an indication of regional economic development and others as intrusive and environmentally harmful. On the one hand presence of open space enhances the amenity value of an area which increases property values (Kim et al 2003). Using data on parks from Greenville, South Carolina, Espey and Owusu-Edusei (2001) find that the presence of these open space areas positively influences the neighboring residential property values. On the other hand, land in open space uses is vulnerable to development as it affords greater housing and varied economic opportunities for existing and new residents moving into the area. A review of the literature also reveals that amenity values associated with open space are lower in low income neighbourhoods. Netusil, et al. (2000) using sales data from the Portland metropolitan area, find no statistically significant amenity effects for open space in a neighbourhood with low to medium value homes, which is directly correlated with the economic status of the residents of that area. This is an important finding as low value of open space in these areas makes it more prone to development. It is hence expected that income levels of the residents are an important determinant of the total quantity of open space in a region.

The research site in this study is one of the most densely populated areas of the United States and in this respect, the total area of undeveloped unprotected land here is highly vulnerable to development. Many studies have looked at this issue of vulnerability. In these studies a germane issues is to analyze the spatial externalities and spillovers of neighbouring areas on a region's open space. A wide variety of models have been developed mostly by geographers utilizing different types of data to predict future vulnerability of open space to development. An important aspect of these models is the inclusion of spatial dependence while analyzing the vulnerabilities and the impact levels. Important models in this respect are the Cellular Automata based models like SLEUTH (Claggett et al. 2004), dynamic simulation models with statistical components like Markov Random Field specifications which are used to operationalize the neighbourhood structure (Banerjee et al. 2004) and predict the changes in land use patterns. Other models use remote sensing data to estimate changes in land cover or land use (see Seto and Kaufmann, 2003 for an analysis of drivers of land use change integrating remote sensing and socio-economic data). However, as mentioned by Irwin and Geoghegan, (2001) more research on the spatial issues related to land use dynamics incorporating human behaviour i.e.socio-economic behaviour is needed. This is an important extension as in most cases changes in land use and/or land cover is manifested as a direct response of the population to appearance of various economic opportunities (Lambin et al., 2000).

In terms of the spatial treatments in this paper, it is in light of the important position that spatial econometrics has come to occupy in applied economic research. Starting with Anselin (1988), many researchers have devised different kinds of models and estimation techniques to analyze issues related to spatial dependence and heterogeneity (Kelejian and Prucha 1998). There is a rich body of literature which has looked at the analysis of property values in a spatial framework and how open space contributes to them in studies associated with the vulnerability of parcels to development and transformation (West and Anderson, 2006 and Irwin and Bockstael, 2002). Spatial econometrics is used to deal with spatial dependence issues in this paper. Moreover, we include spatial spillovers which is expected to have significance for co-operative policy making across state, county and other administrative jurisdictions.

Section 3: Drivers of Open Space Loss

Many studies have documented various factors which fuel growth in regions. In studies by Zhang (2001), Alig and Ahearn (2006) and others, factors like initial population, income, population growth, presence of white individuals were found to be important determinants of growth and development of cities. A positive relation between highway development and urban expansion is described in Hylton (1995) and Parker (1995). The present study alludes to two classes of development - residential and commercial. In this respect a study by Hite et al. (2001) reveals that most of the residential development takes place in rural areas and away from city centers. With respect to commercial development, the same locates near other commercial enterprise besides, other areas. In terms of looking at the age of inhabitants of an area Erickek and McKinney (2004) found that the presence of an aging population has a negative effect on development of a small city. These studies however focus on urban areas only. The present study aims to test whether the above variables would be meaningful in explaining open space loss (synonymous with development) in rural areas as well.

Section 4: Econometric Models

This section provides a brief exposition of the different forms of spatial models considered in this study. The models used are of two broad classes, those which capture the spatial dependence in the observable components of the model and the other which considers the existence of the same in the unobserved error structure.

Section 4.1: Spatially Lagged Independent Variables Model

Spatial lag models capture spatial dependence between locations through the effects of the independent variables of the each location's neighbours. The error term has no spatial component. All spatial effects are assumed to be modelled through the lagged covariates (subset of the covariates of neighbours).

Thus the mathematical representation of the model is as followed:

$$Y = X\beta + (WS)\gamma + \varepsilon$$

where W is the row standardized adjacency matrix with every element in a row obtained by dividing each element by the number of neighbours for each location. Thus for a row with n neighbours, each element in the W matrix is 1/n if the corresponding element in the neighbour list is 1, and is 0 otherwise. Matrix multiplication of W and S which is a subset of the X matrix, gives the average values of the neighbours' covariates for each location affecting the dependent variable. The number of covariates to include is largely dependent on the nature of the problem. ε is the i.i.d error and is of order nx1.

Section 4.2: Spatially Lagged Dependent Variable Model

In this model spatial dependence is modelled with the help of the lagged value of the dependent variable. There is still no spatial component in the error terms. Following is the first order autoregressive model where only first order neighbours are considered:

$$Y = X\beta + \rho(WY) + \epsilon$$

where ρ is the spatial autoregressive coefficient and W has similar interpretation. Inclusion of the lagged value of the dependent variable introduces endogeneity into the model which will yields biased and inconsistent estimates. Thus recourse is taken to maximum likelihood estimation to obtain values of the same.

Section 4.3: Spatial Autoregressive Error Model

This is the final model in this analysis which represents the spatial dependence in the unobservable components, the error term. The spatial component refers to the unobserved effects of an area's neighbours on its open space loss. The error term here has two components - spatial and non-spatial. Thus the model is

$$Y = X\beta + \epsilon$$
$$\epsilon = \lambda W\epsilon + u$$

ϵ is the spatial error term and λ is the coefficient in a spatial autoregressive structure for the disturbance. u is the i.i.d error term.

Depending upon the model structure, different kinds of adjacency matrices W can be considered in the same problem. However for the present study, for tractability of analyses and ease of interpretation of results, spatial structure has been imposed on the basis of first order contiguity with the same W matrix utilized for all the models.

Section 5: Data and Empirical Model

Both physical and socio-economic variables are included in this study. Land cover variables have been compiled from the National Land Cover Dataset (NLCD) produced by the United States Geological Survey (USGS). More information about the NLCD is available at \textbf{\textcolor{blue}{http://www.mrlc.gov}}. This exercise was first done using satellite images taken during or around 1992. It is currently being done again using satellite images taken during or around 2001. Maps showing 2001 land cover are currently available only for some regions of the U.S. The NLCD land cover determinations were aggregated into two broad categories: land in open space undeveloped state and the same in developed uses. Land in agricultural uses, forests, and wetlands were considered open space. Barren land, which includes quarries and land that has been cleared for development, was considered a developed use. Areas like national and state forests, game lands and wilderness areas which are protected from future development were not considered in the calculation of the total open space (undeveloped unprotected land) for an area. Other topographical variables included in the analysis are the mean distance to an interstate highway and slope values for land at 5% and greater and 10% and greater slope in the area. Slope data were obtained from the National Elevation Dataset from the USGS. Distance from highway was found by overlaying a map of each state where interstate highways are present, in Arc Map with a 300 meter by 300 meter grid.

An important issue in empirical spatial research is the misalignment between the spatial scale of the process under consideration and the scale at which is measured. In terms of socio-economic research this is important as physical variables may be measured at one scale (eg. as a continuous process) while all economic variables are available at some other scale (eg. at the level of the county). Thus the administrative unit might be larger than the unit at which the physical process operates and this in turn requires aggregation of physical data at the level of the administrative unit. This leads to a substantial loss in intra-spatial unit variability (Anselin 2001). In order to mitigate any potential problems which might arise from the above issues, the unit of observation for the present study has been chosen to be a Minor Civil Division (MCD). This decision was made based on the fact that in many states like Pennsylvania, the land use policy decisions take place at this level. Data on demographic variables for each MCD are obtained from the US Census for the years 1990 and 2000. The data include information on the Total Population, Percentage of African American and Latino Individuals, Mean Household size, Percentage of population 65 and older, Population Density, Median Household Income, and Family Size.

The dependent variable in the sample is the percentage loss of open space in the MCD between 1992 and 2001. This value is then used to calculate the percentage of open space for the given period. To convert this to a rate of open space loss per decade, this variable was multiplied by 10/9. Overall a total of 1265 observations are obtained. For some MCDs that experienced very little land cover change, the calculated loss in open space was negative due to differences in interpretation of the satellite images in the two years. Values greater than 1 have been restricted to 1. Negative values of open space loss were replaced by a value of 0. The histogram of the truncated OSLOSS variable is presented in Figure 1.

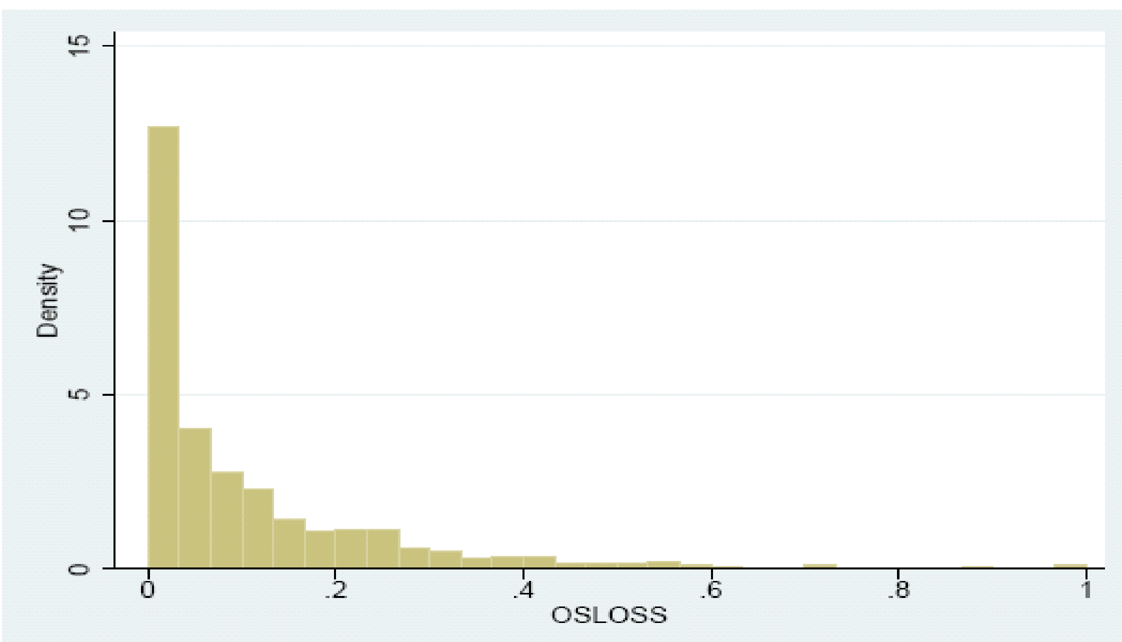

Figure I: Histogram of Open Space Loss

Some observations have been eliminated due to measurement error. The final dataset used, therefore, contains 1214 observations. The average rate of open space loss during the study period was 3.8%. In the study, heavily urbanized MCDs are differentiated from rural ones, as the main objective is to analyze the open space loss dynamics in rural areas. The choice of urban MCDs was made on the basis of the total percentage of developed land in 1992. MCDs with more that 75% of their land in developed uses are designated as urban. It is expected that land cover change dynamics in urban MCDs will follow different rules than in rural ones. The claim is supported by a LM test which rejected the null hypothesis of identical estimates across urban and rural MCDs. However for completeness of the study, all 1214 observations have been included in the analysis. The differentiation between urban and rural MCDs has been done by dummies interaction with all independent variables in the analysis to obtain two sets of estimates. However, only results for rural model are reported.

The set of explanatory variables included in the analysis are the Median Household Income, the Population Density, the Percentage of African Americans, the Percentage of people 65 years and Older for the year 1990 and the Population Growth between 1990 and 2000. The population growth variable was calculated as a change in the population density of the MCD over the period of 9 years. The set of topographical and physical variables included are the Slope of Land in excess of 10%, the Mean Distance from an Interstate Highway, the Initial Percentage of Open Space in the MCD in 1992 and its square term. The inclusion of density and distance to highway variables is similar to the way Serneels and Lambin(2001) look at the causes of land use change in rural areas. Spatial spillovers due to neighbours' attributes are represented by the lag variables of initial population density and population growth. Spill-over effects arising from neighbours' rate of open space loss are captured by the lag variable on open space loss.

Dummy variables have been utilized to distinguish the patterns in open space loss in the different states across rural and urban areas. This is represented by D. The preliminary results reveal that the patterns of loss in rural Pennsylvania are quite different from those in the other states who have similar patterns. Since one of the chief interests of the present research is to focus on rural Pennsylvania, the state effects have been incorporated in the models with the help of a single dummy which differentiates Pennsylvania from all the other states. Dummy variables have been interacted with the population variables as well to capture the effects of not only an intercept shift but also a slope shift. There is a second layer of dummy interaction for the slope and the intercept accounting for the rural-urban differences. In Table 1, the summary statistics of all the variables included in the analysis are presented.

OSLOSS : Open Space Loss (Dependent Variable);
PUDEVUP9 : Percentage of Undeveloped Unprotected Land (1992);
PUDEVUP2 : Percentage of Undeveloped Unprotected Land (1992)- Squared;
PERAFAR90 : Percentage of African American Population;
MEDINC90 : Median Household Income (USD per year);
PER6590 : Percentage of Population age 65 and older (1990);
DISTHWY : Distance from highway (metres);

POPGROWTH : Population growth rate (annual);
SLOPE10 : Slope 10 percent or greater (metres);
PDEN90KM : Initial Population Density (per sq. metre)

Variable	Obs	Mean	Std. Dev.	Min	Max
OSLOSS	1214	0.109418	0.150365	0	1
pudevup92	1214	0.706456	0.31202	0.013561	1
pudevup2	1214	0.596357	0.36767	0.000184	1
perafr90	1214	12.44211	17.28612	0	97.75
pden90km	1214	620.8697	877.1395	0.76	5274.7
medinc90	1214	39024.57	13015.77	6980	114301
disthwy	1214	22036.63	27842.86	100	138585
slope10	1214	14.45818	16.50456	0	81.56
per6590	1214	12.88343	5.35578	0	57.97
popgrow	1214	35.47004	120.8691	-674.1	2180.38

Table 1: Summary Statistics of Variables included in the Analysis

Section 6: Results from Ordinary Least Squares

In line with the objectives of the paper, the present section is devoted to the analysis of the different drivers of open space loss. No spatial effects have been considered and the error terms are i.i.d. A perusal of the results in Table 2 reveals expected signs and significance levels. A majority of the results discussed below are for Pennsylvania. However, dummy interactions for the intercept and the two population variables allow an explanation for driving forces of open space in others states.

A positive sign on PUDEVUP9 implies that MCDs starting off with a higher percentage of open space are more likely to lose faster than those with lower percentage of open space. The quadratic term, PUDEVUP2 has been included to test for the presence of a non-linear relationship between the loss of open space and the initial percentage of open space. This negative and significant coefficient indicates that MCDs lose open space over time at a decreasing rate.

Moving on to DISTHWY, the estimate is negative and significant. An area's proximity to a highway implies a higher risk of being developed as it is closer to higher levels of economic activity. Higher development fuels an increase in the loss. In terms of the final topographical variable in the analysis, it is seen that the greater is the slope of the terrain; the lower is the chance of loss of open space. Steeper slope of land induces higher costs of development. Since loss of open space is positively correlated with higher development of land, the negative (significant) sign coincides with expectations.

Variable	Coefficient	t-statistic	t-probability
const	-4.792619	-5.649926	0
PUDEVUP9	40.591672	8.406391	0
PUDEVUP2	-28.572793	-6.728231	0

PDEN90KM	20.945679	16.803991	0
PERAFR90	-0.040124	-3.628271	0.000297
MEDINC90	-0.046326	-0.26979	0.787369
PER6590	0.075607	2.225723	0.02622
POPGROW	42.305455	10.214236	0
DISTHWY	-0.023776	-3.613728	0.000314
SLOPE10	-0.123201	-10.333805	0
DOT	-3.980315	-7.798501	0
DPDEN90KM	-5.417796	-4.30724	0.000018
DPOPGROW	0.461	0.085737	0.93169

Table 2: Results of the OLS Model

The estimates on the demographic variables indicate interesting results. The variables of importance here are POPGROWTH and PDEN90KM in 1990. The estimates related to both the variables are positive with the effect of an increasing population greater than that of the initial population as is to be expected. A higher initial population pressure in the MCD in 1990 implies a greater demand for housing and other economic services like shopping malls and other retail outlets for the existing population. Growth in population further exacerbates the loss - with more people moving into an area, the pressures on undeveloped unprotected land are further intensified.

Median household income has a negative impact and is not statistically significant in explaining the loss in open space. Looking at the variables PERAFAR90, the estimate is negative and significant. This result is expected given that we are looking at rural MCDs where a high percentage of African American population is not found. A 2002 Census report shows that 52 percent of all African Americans live within the central city of metropolitan areas and only 13 percent of them live in non-metropolitan areas. Since the majority of African American population locates in heavily populated and developed areas where there is very little open space to begin with, an increase in the percentage of African Americans might not lead to an increase in open space loss in the rural areas.

The final explanatory variable in the analysis is PER6590 which has a positive sign and a low magnitude implying a weak relationship. Rural areas tend to be characterized with a higher percentage of the elderly whose demands for housing space maybe high. One reason is that they might want larger quarters to live in. This demand for large housing area and other assorted services contributes to the higher rate of open space loss. This effect does not match up with the study of Erickek and McKinney (2004) who found that presence of an aging population in an urban area slows down growth.

In the present analysis, the estimates capturing the state effects are of special significance. The CONSTANT term contains information on the amount of loss independent of other variables for MCDs in rural Pennsylvania while DOT is the dummy for rural MCDs in all other states. Comparing the signs and magnitudes for these two estimates reveals that MCDs in rural Pennsylvania lose open space at a much faster rate than rural MCDs in all other states.

The interaction terms DPDEN90KM and DPOPGROWTH provide insight for the extant impacts of initial population density and population growth in the other states. Quite surprisingly, results reveal that population growth does not play a very significant role in explaining the loss of open space in rural areas of other states. This is true for all the spatial models as is revealed by the results to follow. However the effect of population growth is quite significant and high for Pennsylvania. This might be attributed to the high developmental pressures in rural Pennsylvania with more people and economic enterprises moving in to the rural areas to service increasing local demand of a greater population. In terms of the effects of initial population in Pennsylvania and the other states, the estimates PDEN90KM and DOTPDEN90KM both reveal that the effects of initial population are much higher for Pennsylvania than for the other states. Thus, in terms of the effects of population rural Pennsylvania is much more vulnerable to losing open space than other states. The relationship between initial population density and open space loss for Pennsylvania and other states is depicted in Figure 2. It can be seen that regardless of the levels of initial population density, being in Pennsylvania means a higher rate of open space loss than being in other states.

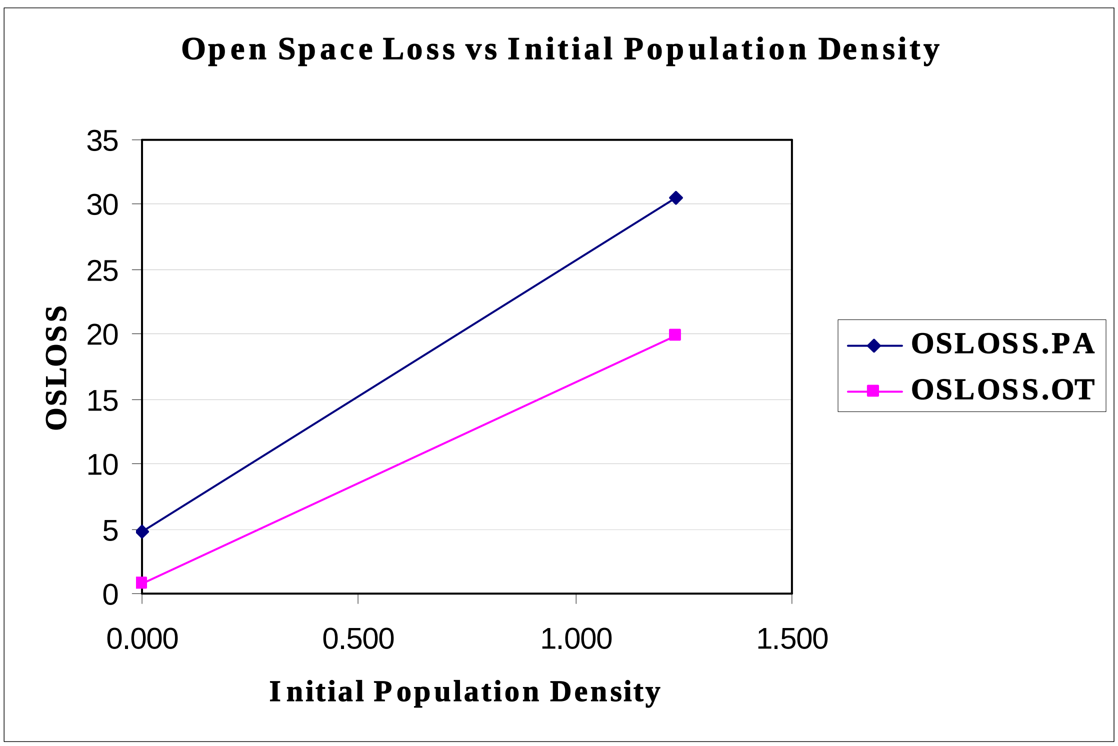

Figure 2: OSLOSS vs Initial Population Density

Section 7: Spatial Models: An Analysis of the Results

Modeling spatial dependence is an important part of this research. In moving from the non-spatial to the spatial models, useful insights are obtained about the dynamics of open space loss across the region. It is interesting to note that in two of the three models presented, median household income (MEDINC90) is a significant driver explaining the loss of open space. With respect to the other variables, the relationships are invariant to the introduction of spatial effects. For the sake of brevity and to avoid repetition, the discussion in this section focuses only on the income variable and the variables capturing the spatial structure.

Section 7.1: Results from Spatially Lagged Independent Model

The results for the spatially lagged independent model is presented in Table 3. According to expectations, income should manifest as a significant driver of open space loss and the direction of impact should be positive. With higher incomes, there would be a higher demand for housing and other services which occupy a large amount of space. The result obtained here is, however, negative. This is slightly hard to argue for. The fact that the data do not support this might be attributed to the rural nature of the MCDs, where higher incomes are associated with larger residences located mostly on farms. Farms in the present study are considered as developed land and not included in the calculation of open space area.

The coefficient estimates for population density variables and spatially lagged variables, LAGPDEN90KM and LAGPOPGROWTH are positive and statistically significant. Higher population pressures stimulate greater development to service not only home grown demand but neighbouring demand. The growing population and higher densities, therefore, increase open space loss. Similarly, people living in MCDs surrounded by highly densely populated MCDs have higher chances of losing open space because the population in the neighbouring MCDs put an upward pressure on the areas' remaining open space. Estimates for PDEN90KM and POPGROWTH are higher than the corresponding lagged estimates, which indicate that the local population impacts are higher than those of the neighbours.

Variable	Coefficient	t-statistic	t-probability
const	-5.251459	-6.275558	0
PUDEVUP9	38.674578	8.140735	0
PUDEVUP2	-25.83561	-6.146839	0
PDEN90KM	21.389274	17.49957	0
PERAFR90	-0.044962	-4.145194	0.000036
MEDINC90	-0.510226	-2.823732	0.004826
PER6590	0.060605	1.809999	0.070549
POPGROW	40.923411	10.002859	0
DISTHWY	-0.020887	-3.229715	0.001273
SLOPE10	-0.112365	-9.540782	0
LagPDEN90KM	3.379792	4.538556	0.000006
LagPOPGROW	21.773108	5.139642	0
DOT	-3.020315	-5.792476	0
DPDEN90KM	-7.280777	-5.733114	0
DPOPGROW	-4.811815	-0.904983	0.365659

Table 3: Results of the Spatially Lagged Independent Variable Model

Section 7.2: Results from Spatially Lagged Dependent Variable Model

With the objective of investigating different spatial structures the spatially lagged dependent variable model specification is considered. In this model, the spatial dependence is presented by the lagged values of the dependent variable. Estimates are based on Maximum Likelihood rather than OLS as the latter gives biased and inconsistent results. Table 4 represents the results of the spatially lagged dependent variable model model. ρ is the autoregressive coefficient with its sign and magnitude representing the manner in which neighbours' rate of open space loss affects an MCD's rate of loss in open space.

The analysis reveals that the autoregressive coefficient is positive and significant. This implies the presence of a significant level of spatial dependence in the rate of open space loss among neighbouring MCDs. An increase in the rate of open space loss in neighbouring areas leads to a higher rate of loss in the local MCD. In other words, developmental pressures which influence losses in adjoining areas spill over to cause losses in the focal areas. This result is important as it indicates the inter-dependence in the loss patterns which in turn has significance for policy efforts to curb the loss of open space. The effect of the income variable is similar to that obtained for the SLM.

Variable	Coefficient	Asymptot t-stat	z-probability
const	-7.222184	-13.459867	0
rho	0.3789	8.109	0
PUDEVUP9	43.409937	13.563999	0
PUDEVUP2	-31.481294	-13.903276	0
PDEN90KM	18.951957	17.544969	0
PERAFR90	-0.030902	-3.206975	0.001341
MEDINC90	-0.307727	-2.95088	0.003169
PER6590	0.067071	2.441407	0.01463
POPGROW	36.914504	10.518319	0
DISTHWY	-0.017951	-3.102045	0.001922
SLOPE10	-0.094675	-9.383625	0
DOT	-2.178206	-5.461313	0
DOTPDEN90KM	-4.735049	-4.272893	0.000019
DOTPOPGROW	0.697593	0.145106	0.884627

Table 4: Results of the Spatially Lagged Dependent Variable Model

Section 7.3: Results from Spatial Autoregressive Error Model

In this section, the results of the spatial autoregressive error model are presented in Table 5. The spatial autoregressive coefficient λ is again positive and significant. We can then infer that there is a strong spatial effect of the unobservable characteristics of a region's neighbours on its loss of open space. The impact of the unobservables is stronger than that of the observables modeled through the lag values of the dependent variable. Quite interestingly, MEDINC90 again becomes insignificant in this model. In all, comparison of results across states for all the spatial models, the results are found to be in accordance with the same obtained for the non-spatial model. The fact that Pennsylvania is losing space much faster than the other Mid-Atlantic states is true across all models.

Variable	Coefficient	Asymptot t-stat	z-probability
const	-4.491418	-6.126601	0
lambda	0.489988	21.615	0
PUDEVUP9	46.605511	12.560689	0
PUDEVUP2	-33.674204	-14.005419	0
PDEN90KM	18.815688	16.706627	0
PERAFR90	-0.034405	-2.769326	0.005617
MEDINC90	-0.161265	-1.349229	0.177263
PER6590	0.03387	1.216281	0.223878
POPGROW	36.92842	10.183585	0
DISTHWY	-0.031036	-3.296682	0.000978
SLOPE10	-0.129079	-9.634687	0
DOT	-3.718136	-5.949419	0
DPDEN90KM	-5.161145	-4.255844	0.000021
DPOPGROW	2.964878	0.592616	0.553438

Table 5: Results of the Spatial Autoregressive Error Model

Section 8: A note on model selection

In the presence of significant estimates indicating spatial dependence, the next objective is to make some conclusions about which of the models are most appropriate in explaining the nature of the dependence. Two statistics- the R Square and LM statistics are computed to provide insight to the effect.

In terms of the R-Squared values for the models, it is seen that the values of the same increase with the imposition of spatial structure indicating that incorporating the spatial dependence in the analysis helps to explain the pattern of the loss better than the absence. At the same time, it is found through comparisons of the SEM and the SEM with the lagged independent variables that the latter has a value of R Squared equal to 0.61 as opposed to 0.59 for the SEM. Thus in terms of predictive accuracy, the latter model is better in explaining spatial dependence.

To obtain further information regarding the nature of spatial dependence, LM statistics were calculated to test the hypothesis regarding whether the spatial dependence is explained by the dependent variable or through spatial autocorrelation in the errors. In both the cases the Null hypothesis is rejected implying that other more robust tests needs to be employed to obtain conclusive evidence about the nature of the spatial dependence.

At this point, it is useful to add a few comments on which of the models make most sense in terms of theoretical foundations. As far as the SAR model is considered, it is too narrow in terms of the restrictions that it puts on how the spatial effects of the drivers is felt in a focal region. In this sense the SLIVM is more flexible as it allows delimitation of specific drivers as determinants of the spatial dependence. However in terms of the statistics which have been computed, the hybrid model combining the SLIVM with spatial autocorrelation in the error structure might be the best of all models.

Section 9: Conclusion

The present analysis provides important insights into the different economic and geographical variables which influence the loss of open space in a region. This is useful evidence which can form the backbone of effective land use policies which will help in the conservation of open space and all the attendant benefits (better amenity values and favourable property values) that come with it. The presence of appreciable spatial effects is a reiteration of results of past studies advocating the importance of space in explaining the loss of open space. The fact that all estimates are significant implies that non-consideration of spatial effects will provide a less than complete picture. Also the presence of significant spatial spillover effects of population variables has great significance for local land use policy planning. In this respect the importance of the SLIVM is established as it gives information about specific drivers which influence the loss of open space. In terms of policy formulation, across MCDs and states greater effectiveness in protecting precious open space in a region can be achieved through cooperation at the level of the MCD rather than isolated efforts confined to a single administrative devision only. In other merits the present study is one of the very first to look at an explicit representation of the issue of open space loss using a relatively new data set, the NLCD and is an addition to the increasing database of studies looking at spatial interactions as a chief component in explaining the dynamics of a system.

In the present analysis computed LM statistics reveal that both hypotheses about rejecting the null hypothesis of no spatial dependence in favour of spatially autocorrelated errors and dependence through the dependent variable are rejected. Future work on this study involves analyzing through other robust tests, which of the above models is the best representation of the spatial dependence which exists in the data.

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