Spatial Investigation of Mineral Transportation Characteristics in the State of Washington

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ABSTRACT

Highway construction and maintenance relies heavily upon mined aggregates as a core ingredient. The proximity of aggregate mine sites to highway or other construction locations is an important issue since the total project costs are highly affected by transportation cost/efficiency and also deterioration of the existing highway infrastructure as influenced by frequent, heavy shipments traveling long distances. Likewise, the transportation costs for hauling mined aggregates are minimized when shipments are loaded to capacity payload weights.

This is the first attempt in a series of forthcoming studies to explore mineral shipment characteristics with a spatial regression model. A comprehensive survey was conducted to determine both the location and type of need for road improvements. This study investigates the spatial relationships between construction aggregate shipments and the hauling trucks' payload weights as it pertains to highway deterioration in the State of Washington. Many studies have examined the relationship between transportation cost and construction unit productivity but there's minimal information available pertaining to the relationship between payload weights, shipment distances and highway deterioration.

To identify impacted highway segments resulting from aggregates shipments, mine locations and shipment distances in cooperation with payload weights are examined. Naturally, spatial non-stationarity of the data is possible whenever any process takes place over many different geographical locations. As such, it's appropriate and necessary to test the mining industry data for spatial dependences. As a result, the paper employs a spatial error regression model with distance based weights matrix to address spatial autocorrelation, to capture the interaction between spatial units and to predict the incremental change in payload weights resulting from increasing hauling distance. Results show a highly significant positive relationship between payload weights and increasing shipment distances.

INTRODUCTION

The aggregates industry is highly influenced by transportation efficiency in terms of high cost of shipments. Therefore, the proximity of mine site location to the construction site or any other end use location is crucial. That actual cost of transportation may explain the high correlation between mine and construction site locations (Transportation of Mining/Mineral Survey: Summary Report, Khachatryan, Jessup (unpublished data)). Despite the low value per ton characteristic, an aggregate is heavy, which makes truck transportation very costly but necessary. According to the Transportation of Mining/Mineral Survey the majority of aggregate is hauled within close distances from its production origin. Particularly, about 80% of total production (78% of mine sites) was hauled within 20 miles or less from the mine location. For the determination of most deteriorated highway segments by heavily loaded trucks and for construction investments to be efficient, the distance of aggregate shipments in cooperation with payload weights are examined.

This study utilizes data from the survey investigating the transportation and operational characteristics of Washington's mined products conducted by the Strategic Freight Transportation Analysis (SFTA) at Washington State University. This data is utilized to investigate the spatial relationship between mine locations, payload weights and shipment distances. While the survey included 12 separate types of mined minerals, only construction aggregates (sand and gravel, rock/stone) related information was used in this study. To analyze and evaluate that purpose, a Geographic Information Systems (GIS) and GeoDa (Anselin, 2003) *(1)* are used as analytical tools to create desired maps and to conduct spatial analysis.
The geographic distribution of aggregates mines throughout the state is relatively evenly dispersed. However, upon closer investigation of these mine locations in relation to the road network and highly urbanized areas one may find local clustering. This is partially explained by a high concentration of highways, homes and office construction in highly urbanized areas (B. Finnie, J. Peet 2003) (2).

In addition to the general visual inspection of the point pattern, exploratory data analysis using GIS and GeoDa showed systematic pattern in the spatial distribution of the data variables such as payload weights and annual production volumes. Global Moran's I (an indicator for spatial autocorrelation) value showed statistically significant spatial autocorrelation in the regression residuals, which then requires addressing the issue of spatial autocorrelation. The importance of this assumption in most of the statistics that the values of observations in each sample are independent can be violated by positive spatial autocorrelation if samples are taken from geographically close locations. Consequently, utilizing data on aggregate mine locations, production volumes, shipment payload weights, configurations of trucks, as well as information on number of axles and transportation characteristics in general, this paper employs a spatial error regression model to address spatial autocorrelation of the data and to predict the incremental change in payload weights resulting from an increase in hauling distance.

The regression results show a statistically significant, positive relationship between shipment distance (aggregates haulage) and payload weights. Additionally aggregate costs significantly increase with the increasing distance, causing longer hauls to potentially result in higher deterioration to state highways. In order to investigate the relationship between payload weights and shipment distance by axle load, forthcoming study will include data on truck configuration and number of axles per truck.

LITERATURE REVIEW

Prior studies focusing on mine operations have focused on issues related to route selection, as with Peter Berck 2005 *(3)*. Berck presents a least cost route selection model for aggregates hauling as a part of constructors' cost minimization strategy, suggesting that the opening of the new quarry would change the aggregates transportation pattern. As a result of the new quarry opening the study found no significant increase in the demand for construction aggregates as well as a decrease in some environmental externalities (emissions reduction). Another public cost consideration may be the deterioration of road networks used for aggregates hauling, which involves investigation of data on payload weights and/or number of axles per truck. This also follows with the desire of construction contractors attempting to increase productivity by maximizing the payload weights of the truck shipments (Schexnayder, et. all. 1999) *(4)*.

Additionally, because the shipments represent a major component of construction costs payload weights may even exceed allowable measures, thus creating a strong relationship between the distance and the payload weights (Chronis, 1987) *(5)*. Chronis 1991 *(6)*, also suggests that overloading trucks by 20% may lead to a decrease in per ton cost of aggregate, since labor costs will not change and the fuel price is relatively unaffected. This assumption might not hold with recent fuel price advances, as well as it does not consider corresponding public cost, externalities like highway damage or environmental impacts. In this aspect, many prior research efforts mention the relationship between aggregate hauling and construction unit productivity, and there is only minimal information available to understand the relationship with hauling distances as they pertain to highways deterioration (Day 1991) *(7)*.

This study explores the relationship between incremental changes in payload weights as shipment distances increase, while simultaneously detecting and accounting for spatial autocorrelation in the data. The identified positive relationship between the aforementioned variables suggests that not only longer distances cause higher cost to construction contractors, but may also result in higher deterioration level to the roads.

Descriptive evaluation of the mining industry data received from the Transportation of Mining/Mineral Survey results showed substantial variation across Washington's regions. Naturally, spatial non-stationarity is involved in any process which takes place over real geographical locations (A. Unwin, D. Unwin, 1998) *(8)*. In other words, the process under investigation might not be constant over the entire study area. In this aspect, the global statistics will fail to properly represent relationships between processes, especially when translated into local investigation of those processes. Therefore, because the transportation characteristics of the mining/mineral industry involves data containing geographic location information, in most cases the data was expected to have spatial dependence or in other words spatial autocorrelation (the weaker form of spatial dependence). Consequently, spatial dependence in the data would mean that most of the classical estimation procedures and methods are inappropriate for this analysis.

The wide array of studies in the field of spatial econometrics represents diverse approaches for addressing spatial autocorrelation in the data. However, a search of the economic literature did not bring favorable results on investigation of spatial autocorrelation of the data representing aggregates mining industry.

DATA

The precise geographic site information for each mine was obtained from the Washington Department of Natural Resources, Division of Geology and Earth Resources. The county and state highway system GIS files were downloaded from the WSDOT GeoData Distribution Catalog. Annual production (tons) was obtained from Transportation of Mining/Mineral Survey results.

Information related to mining operations and characteristics was obtained from the Transportation of Mining/Mineral Survey results conducted by the research and implementation project Strategic Freight Transportation Analysis (SFTA). The main objective of this survey was to examine the transportation characteristics of Washington's mining industry and to analyze spatial relationship between mine locations and the road network. To collect relevant data, the first phase began with a survey to mining firms/companies in late December of 2005. The second phase of the survey, designed for non-responder companies, followed after about two weeks. The first phase of the survey resulted in a response rate of 20.4% (mining sites), which increased to 47.2% at the end of the second phase.

The survey results show that aggregates represent about 96 % of Washington's mined minerals volume (Transportation of Mining/Mineral Survey: Summary Report, Khachatryan, Jessup (unpublished data)). More than 90% of transported mined commodities were hauled using trucks as a mode of transportation from mine pit to points of sale or processing plants (Wallace P. Bolen, 2004) *(9)*. With the average payload weight of 23.2 tons, about 37% of aggregates are moved by straight truck, 44% by straight truck & trailer, and 14% by tractor & trailer; the remaining portion is shipped using other truck configurations.

According to the survey results 35% of the aggregates production was shipped within 5 miles of the production origin, 21% were transported to distances within 6 to 10 miles, 24% - within 11 to 20 miles, 13% - from 21 to 40 miles, 4% - from 41 to 100 miles, and only a small proportion of the production was hauled to longer distances. The number of axles typically on the ground varies depending on the truck type. According to the survey results, the number of axles (typically on the ground) for trucks leaving mining facilities ranges from 2 to 6, with the average of 3.4 and mode of 3 axles. Trailer (if used) axles on the ground ranged from 2 up to 7, with an average and mode of 3. Total number of axles for truck or tractor ranges from 2 to 9, with average of 3.6 axles. With the average of 3, the total number of axles on 1st trailer varies from 2 to 5.

Spatial Autocorrelation

The first law of geography states "everything is related to everything else, but near things are more related than distant things"—Waldo Tobler. The simplest definition of spatial autocorrelation is a correlation of one variable with itself throughout space. Many authors state that spatial autocorrelation exists as a systematic spatial variation in values across space, where high values at one location are associated with high values at neighboring location creating positive autocorrelation. Whereas high and low value patterns between neighboring areas represent negative autocorrelation (Upton and Fingleton, 1985) *(10).*

As such, spatial autocorrelation is a problem for regression models when the error terms introduce some spatial pattern in which areas or points close together display similar values than areas or points further away (in this study points are represented by x y coordinates of mine site locations). Because the mining industry data involves geographic location information of mine sites, it is appropriate and necessary to test the data for spatial dependences. The number of local and global spatial statistics is available for the test for the complete spatial randomness of the data depending on its form. One of the oldest indicators of global spatial autocorrelation is Moran's I (Moran, 1950) *(11)*, which (applied to polygon or point data) compares the value of specific variable at any one location with that of all other locations and emphasizes similarities over space (Fotheringham et. al. 2002) *(12).*

$$I = \frac{N\sum_i \sum_j W_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j W_{i,j})\sum_i (X_i - \bar{X})^2}$$

where N is the number of point observations (locations), X_i is the value of variable at location *i*, X_j is the value of variable at location *j*, $\bar{X}$ is the mean of the variable and W_{ij} is a spatial weight matrix applied to the comparison between locations *i* and *j*.

In contrast, local statistics emphasize differences over space and can be used to check for the spatial stationarity of the data. While global statistics assumed invariant, local statistics vary over space and are spatial, thus can be mapped *(12*). In other words, global Moran I's major limitation is that it tends to average local variations in the strength of spatial autocorrelation.

In the case of the mining industry the global forms of statistics might not be representative of the situation in any particular region of the state and may hide some interesting and important local variations of the characteristics that the study investigates *(12)*. For example in the Western regions of the state, due to availability of many construction projects (demand) or favorable weather conditions, larger percentage of mines can be found in operation, or more aggregate shipments than it would be in the Eastern part of the state (Transportation of Mining/Mineral Survey: Summary Report, Khachatryan, Jessup (unpublished data)). This is where the important local variation in relationships would be partially or completely unnoticeable. Preliminary manipulation of the data showed some dissimilarity in the data across study area regions, which builds a strong foundation for the idea of investigating the data using local forms of spatial analysis.
The localized version of Moran's I statistic (LISA) has the following form:

$$I_i = \frac{(X_i - \bar{X})\sum_j W_{ij}(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2 / N}$$

where N is the number of observation, X_i is the observed value of the variable X at location i, $\bar{X}$ is the mean of the variable, and W_{ij} is a spatial weight matrix, which represents the strength of the linkage between i and j locations (Anselin L. 1995) *(13)*.

Spatial Weight Matrices

The potential interaction between two spatial units can be expressed by the spatial weight matrix *W*. Contiguity based spatial matrices can be used for the data involving areas such as counties, regions, states or even countries. Distance based weights can be appropriate for point data, as well as for polygon data if centroids are calculated. Each type in turn can be different according to specified order of contiguity, distance band or number of neighbors. Although, each type of spatial weights can be formed based on specific situations or nature of the spatial data, however, there is no precise agreement about the type of weight matrix to be employed for spatial analysis (Anselin, 1988) *(14)*. In the spatial N by N weight matrix, each element $w_{ij} = 1$ when i and j are neighbors and $w_{ij} = 0$ otherwise, the diagonal elements of which are set to zero. Rows of the N by N weight matrix are standardized such that $w_{ij}^s = \frac{w_{ij}}{\sum_j w_{ij}}$. Resulting weights matrix is no longer symmetric, which ensures averaging neighboring values (Anselin and Bera 1998) *(15)*.

For the contiguity type weight matrices "neighbors" can be classified spatial units that share a border. Anselin, 2005, (16), *(15)* provide details on higher order contiguity weight matrices – queen, rook. Distance based matrices can be based on either the distance between *i* and *j* locations of observations or number of neighbor observations. Where, in the first case "neighbors" for one location can be considered all points/locations that are within the specified distance from that point. While for the "number of nearest neighbor" approach, number of points/neighbors should be specified in order to be considered as neighbors. For example, if for some specific purposes 4 nearest neighbors approach is adopted, the weights matrix will consider only 4 nearest points for each of the point in the study area. Weights with number of nearest neighbors (KNN) approach standardize the number of neighbors, which assumes that an equal number of neighbors are more important than the distance between neighbors.

THE MODEL

Spatial Error Dependence

One reason for spatial dependence in an estimated model could arise as a result of mine site location near to highly urbanized regions of the study area. Urbanization is usually positively related with aggregates consumption. Thus, mine sites located near to densely populated areas might operate with higher annual production levels, than those located in less populated regions. Similar local demand characteristics could partially explain production levels or shipment's payload weights, as well as shipment distances.

As mentioned earlier, spatial autocorrelation is a problem for regression models when the error terms introduce some spatial pattern in which areas or points close together display similar values than areas or points further away. Widely used specification is a spatial autoregressive process in the error terms. The spatial error model assumes the following linear regression:
$y = X\beta + \varepsilon$, with $\varepsilon = \lambda W\varepsilon + \upsilon$,
Where λ is the spatial autoregressive coefficient for the error lag $W\varepsilon$, and υ is homoskedastic error term.

Spatial Regression Model Selection

Spatial regression model selection decision was made according to Luc Anselin's comprehensive guide to GeoDa statistical software – "Exploring Spatial Data with GeoDa™: A Workbook" *(15)*. Regression analysis started with Ordinary Least Squares regression; further, Lagrange Multiplier (LM) diagnostics provided basis for the spatial autoregressive model selection. Both LM-Error and LM-Lag tests showed statistically significant results, which led to examination of their Robust form statistics. At this step Robust LM-Error statistic showed statistically significant results, accordingly the spatial error model was chosen for next stage of the regression analysis.

RESULTS

To investigate the relationship between payload weights and shipment distances, payload weights of aggregates shipments by trucks was selected as a dependent variable; proportion of shipments within 5 – 10, 11 – 20, 21 – 40 and 41 – 100 mile distances were analyzed as explanatory variables.

The regression results indicate that payload weights and all distance categories are positively related, with an adjusted R^2 of 0.28. In addition to the less favorable fit, there are quite a few specification problems. Particularly, regression diagnostics disclose considerable non-normality and high level of spatial autocorrelation. Moran's I, LM-Error, LM-Lag and LM-Sarma tests are all significant. Moran's I scatter plot (Figure 2) visualizes the statistic indicated in the Table 1, under the "Diagnostics For Spatial Dependence" section. As it was described in the "Spatial

Error Dependence" section, the decision for the model selection was based on LM-Error and LM-Lag test statistics. Because both tests showed statistically significant results, the Robust forms for both tests were examined. Consequently, as a result of significant Robust LM-Error statistic, spatial error regression was employed.

TABLE 1 Regression Summary of Output: Ordinary Least Squares Estimation

Dependent Variable	Payload weights	Number of Observations	288
Mean dependent var.	19.9097	Number of Variables	6
S.D. dependent var.	12.6885	Degrees of Freedom	282
R-squared	0.290294	F-statistic	23.0695
Adjusted R-squared	0.277711	Prob(F-statistic)	2.06E-19
Sum squared residual	32907.2	Log likelihood	-1091
Sigma-square	116.692	Akaike info criterion	2193.99
S.E. of regression	10.8024	Schwarz criterion	2215.97
S.E of regression ML	10.6893		

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	2.381654	1.79817	1.324488	0.1864126
0_5_MILE	17.24359	2.74068	6.29172	0.0000000
6_10_MILE	23.31129	2.956789	7.883989	0.0000000
11_20_MILE	16.8195	3.084599	5.452736	0.0000001
21_40_MILE	23.32615	4.375268	5.331365	0.0000002
41_100_MILE	31.64233	7.334185	4.314362	0.0000222

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 5.926111

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	27.7393	0.0000009

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB

Breusch-Pagan test	5	8.05721	0.1531107
Koenker-Bassett test	5	7.023928	0.2188668
SPECIFICATION ROBUST TEST			
TEST	DF	VALUE	PROB
White	20	39.02313	0.0066234
DIAGNOSTICS FOR SPATIAL DEPENDENCE			
FOR WEIGHT MATRIX : treshold distance based (row-standardized weights)			
TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.111457	3.503859	0.0004587
Lagrange Multiplier (lag)	1	7.213300	0.0072365
Robust LM (lag)	1	0.357543	0.5498742
Lagrange Multiplier (error)	1	10.86660	0.0009791
Robust LM (error)	1	4.01084	0.0452086
Lagrange Multiplier (SARMA)	2	11.22414	0.0036535

Next, the residual standard deviational map (high-high and low-low values suggesting positive autocorrelation, high-low and low-high values – negative autocorrelation) is examined, which suggests the presence of spatial autocorrelation from "visual inspection", but only the proper specification tests can permit for an assessment of the significance of this autocorrelation and for an indication of the use of alternative spatial model. Figures 3 and 4 represent locations (hot spots) with significant local Moran statistics of the study area. The legend for the significance map provides p-values in different shades of green.

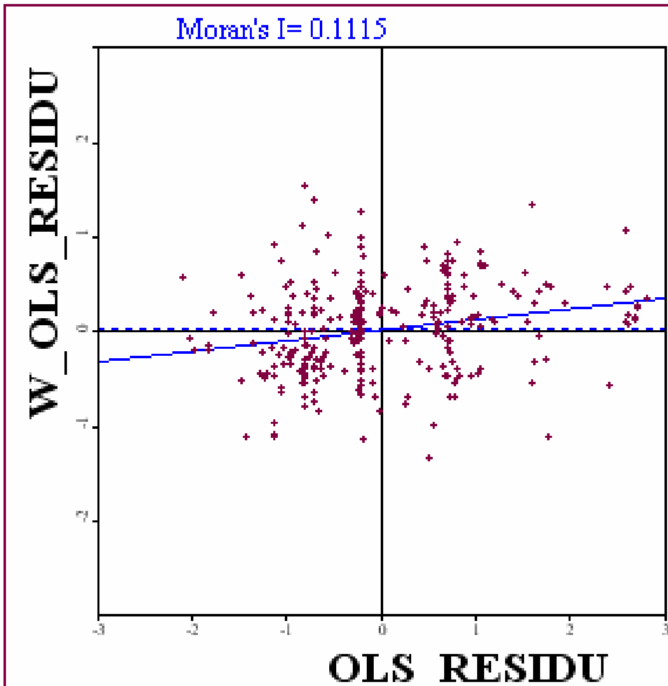

FIGURE 2 Moran scatter plot for OLS residuals.

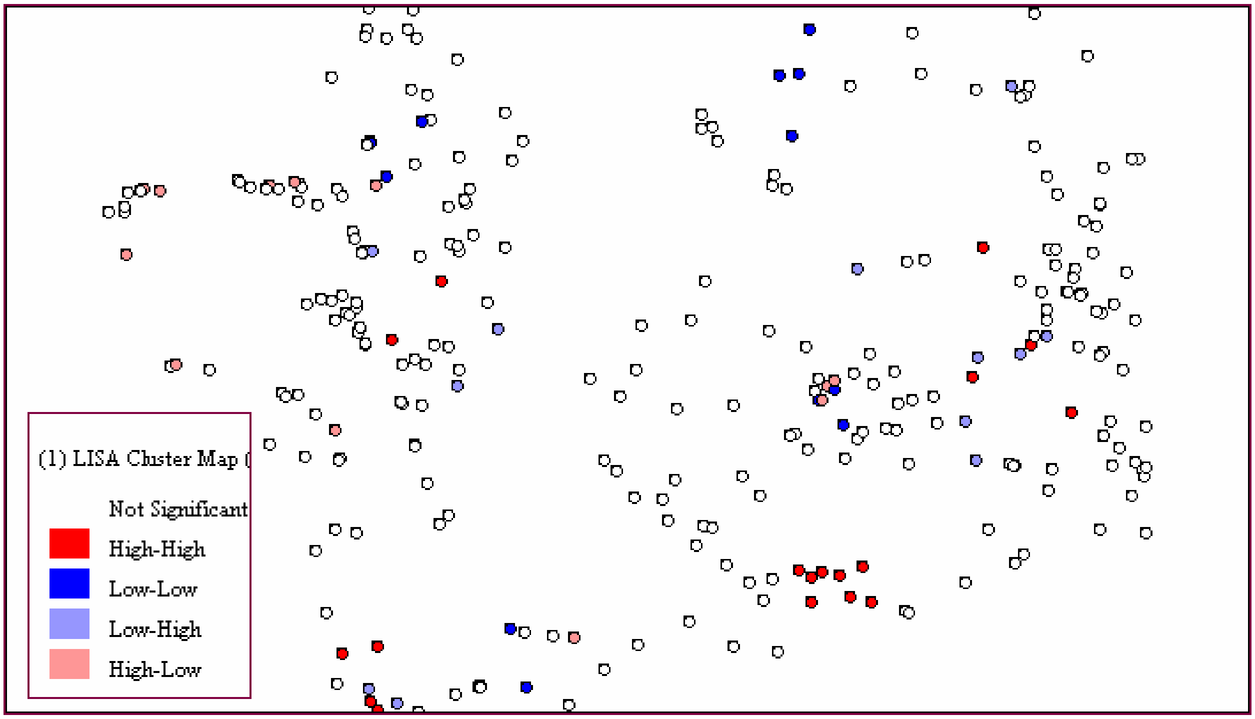

FIGURE 3 LISA cluster map for OLS residuals.
Note: significance filter is set to 0.05

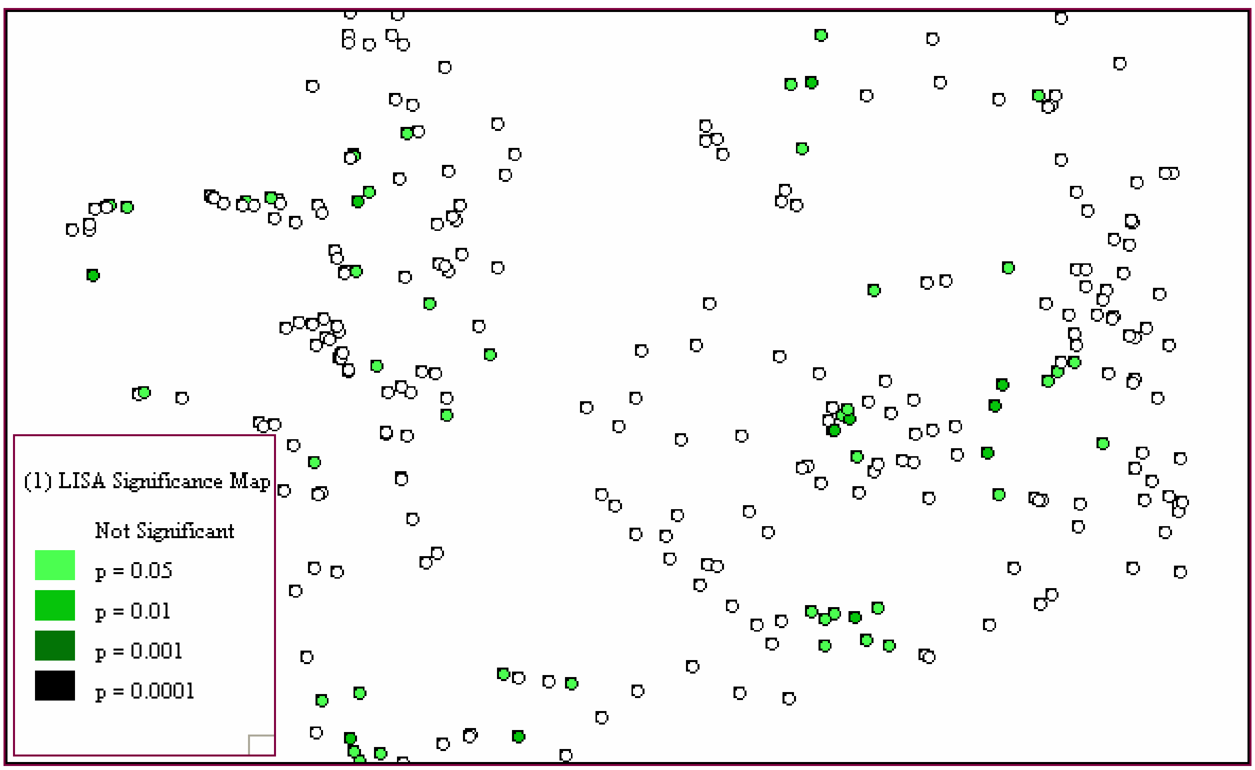

FIGURE 4 LISA significance map for OLS residuals.
*Note: significance filter is set to 0.05

The results of spatial error regression are represented in the Table 2, where the estimates for the autoregressive parameter of the error process are represented next to Lambda. The result is positive and significant, which more time ensures the suggestion from the OLS estimation diagnostics (based on LM-Error, LM-Lag, and Robust form test statistics).

TABLE 2 Regression Summary of Output: Spatial Error Model – Maximum Likelihood Estimation

Spatial Weight:	Threshold distance based		
Dependent Variable	Payload weights	Number of Observations	288
Mean dependent var.	19.9097	Number of Variables	6
S.D. dependent var.	12.6885	Degrees of Freedom	282
Lag coeff. (Lambda)	0.301007		
R-squared	0.325897	R-squared (BUSE)	
Sum squared residual		Log likelihood	-1085.85
Sq. Correlation		Akaike info criterion	2183.71
Sigma-square	108.529023	Schwarz criterion	2205.69
S.E of regression	10.4177		

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	1.68742	1.867309	0.9036638	0.3661736
0_5_MILE	18.26757	2.630924	6.943402	0.0000000
6_10_MILE	22.13488	2.895299	7.645112	0.0000000
11_20_MILE	18.7434	3.039997	6.165599	0.0000000
21_40_MILE	26.32215	4.305979	6.112932	0.0000000
41_100_MILE	31.56302	7.050658	4.476606	0.0000076
LAMBDA	0.3010072	0.084690	3.554222	0.0003792

REGRESSION DIAGNOSTICS

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	5	8.024456	0.154893

DIAGNOSTICS FOR SPATIAL DEPENDENCE

SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX weights_treshhold.GWT

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	10.28267	0.0013429

In this estimation the R^2 is listed as a pseudo-R^2, and it cannot be compared with that of OLS results. Instead, for this model the Log-likelihood, Akaike information criterion (AIC) and Schwarz criterion (SC) are appropriate measures of the fit. Compared to the OLS diagnostics all three are improved in this specification. Particularly, Log-likelihood is increased from -1091 (for OLS) to -1085.85, AIC is slightly decreased from 2193.99 (for OLS) to 2183.71, and SC - from 2215.97 to 2205.7. The spatial autoregressive coefficient (λ) is estimated as 0.30 and is statistically highly significant.

While the relationship between the dependent and explanatory variable is also positive and highly significant, the coefficients are slightly changed compared to the OLS results. In the process of spatial error regression predicted values ($\hat{y}$), prediction errors (the difference between the observed and predicted values, $y - \hat{y}$), and model residuals ($\hat{\upsilon}$) are saved in the attributable table as vectors, which will be used to map or to recalculate Moran's I index for comparison with previous results. In Figure 5 a new scatter plot indicates Moran's I statistic of -0.00042, which is essentially the same as zero. As expected, this is the indication of proper use of the spatial error specification, which led to elimination of spatial autocorrelation. Note that residuals here are estimates for spatially filtered (uncorrelated) model error term, $\hat{\upsilon} = (I - \hat{\lambda}W)\hat{\varepsilon}$ where $\hat{\varepsilon} = \hat{\lambda}W\hat{\varepsilon} + \hat{\upsilon}$.

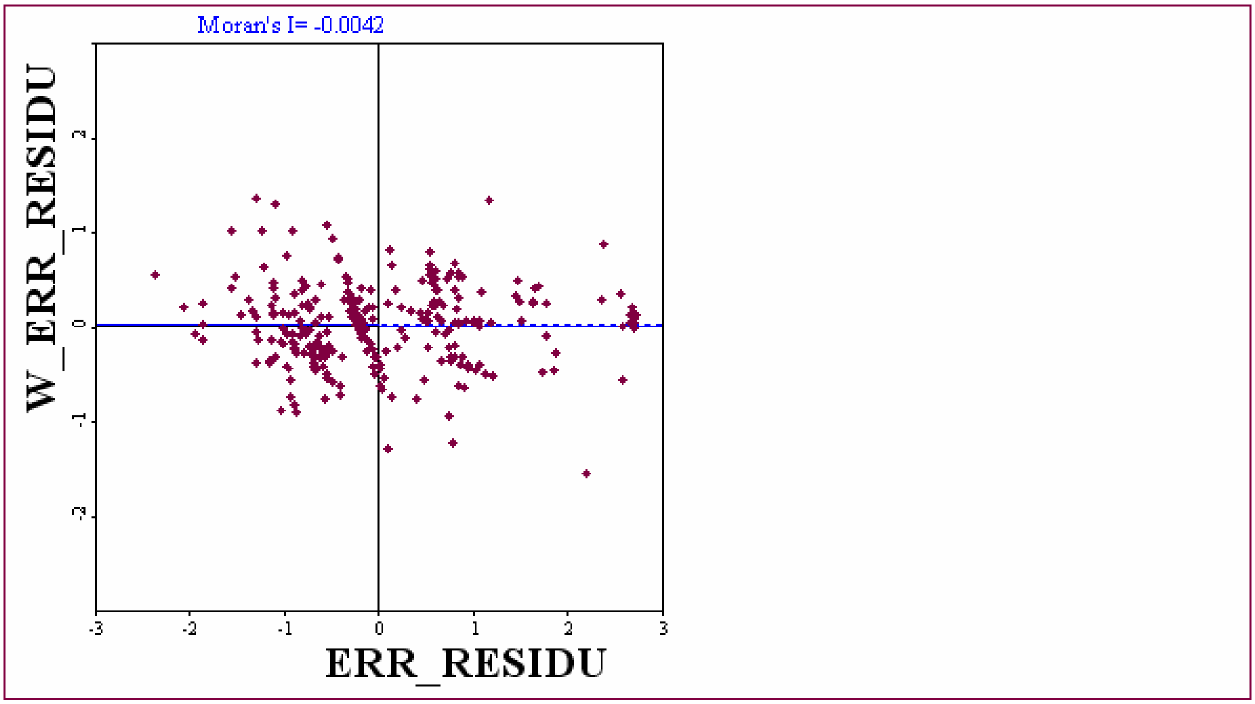

FIGURE 5 Moran scatter plot for spatial error residuals.

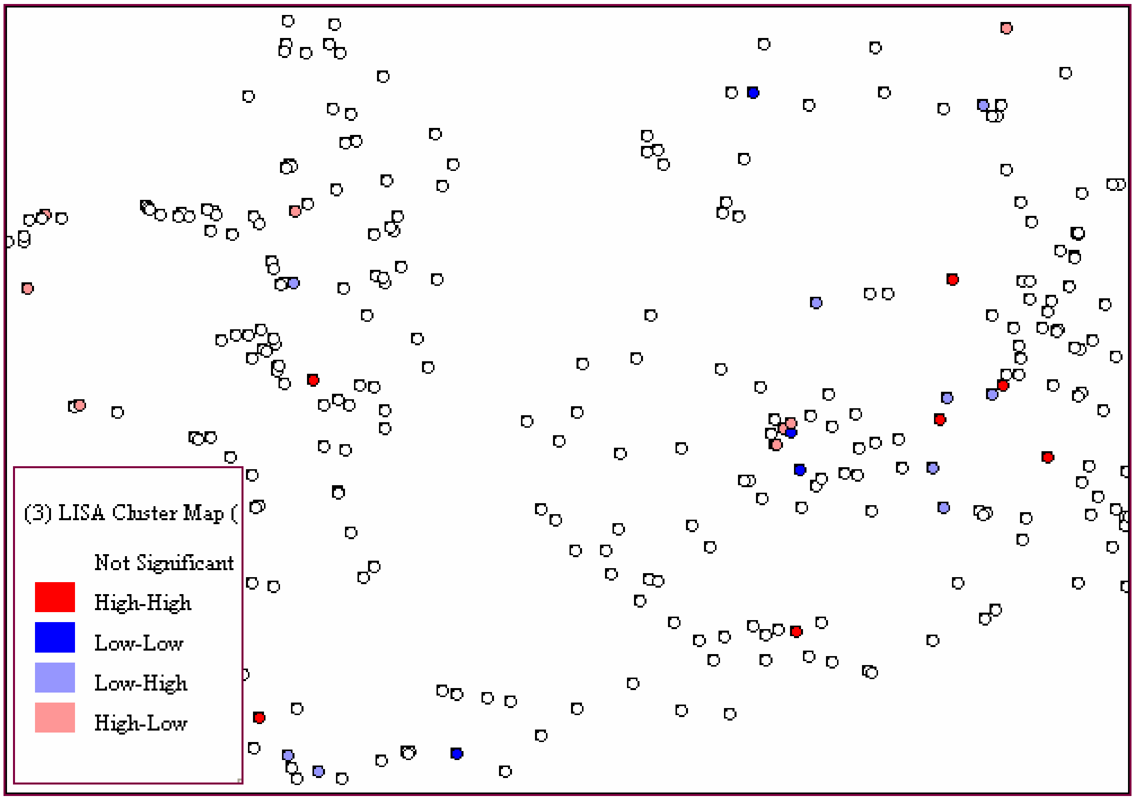

FIGURE 6 LISA cluster map for error residuals.

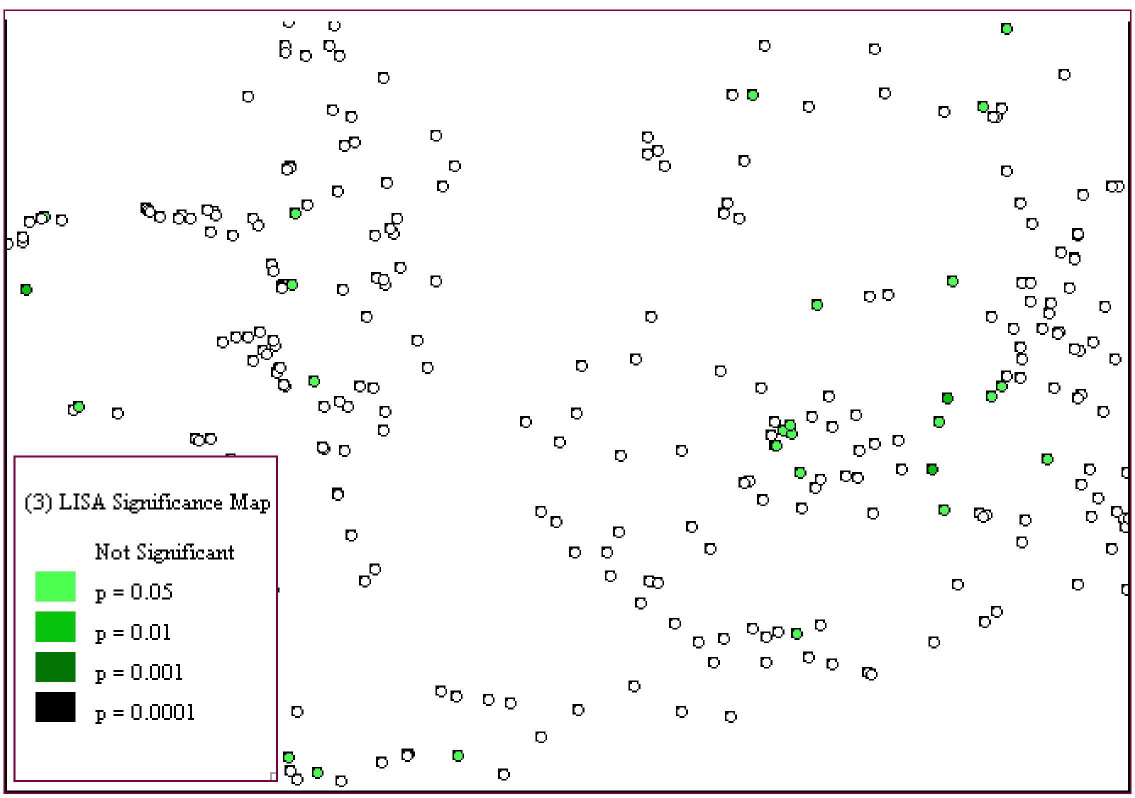

FIGURE 7 LISA significance map for error residuals.

Figures 6 and 7 represent the cluster activity and significance map using error residuals received from the spatial regression model. The results of the cluster map show the elimination of spatial autocorrelation in the data, which is supported by the probability significance map. In comparison with the mapped OLS regression residuals, considerable reduction of hotspots can be observed.

The spatial error regression results (Table 2) show a sizeable increase (about 4 tons) in payload weight from 0 – 5 to 6 – 10 mile distance shipments. For the next distance change, the payload weights are reduced by 3.4 tons (to 18.3 tons). This can partially be explained by local, more restrictive regulations on truck size and weight (in addition to the state level regulation), which eventually leads to transportation cost per-ton-mile increases. Shipment distances from 21 – 40 and from 41 – 100 miles were estimated with an increase by 7.5 and 5.2 tons accordingly.

In addition to the shipment distances and payload weight data, the GIS database designed and used in this study will allow querying and easy manipulation of aggregates transportation related data, such as annual production tons, configurations of aggregate hauling trucks, number of trucks operating for particular mine site, number of axles on trucks and/or trailers, highway routes used for shipments, mine operational hours, production shipment and operational months, as well as information on factors that influence monthly shipments, proportions of shipments to different end uses (construction or road site, warehouse, factory, etc.).

CONCLUSIONS AND RECOMMENDATIONS

The main objective of this study was to investigate the relationship between payload weights and shipment distances, using aggregates as the first subject. Visual examination of the point data (shapefile) followed by exploratory data analysis detected a systematic pattern in the spatial distribution of the variables of main interest. The data involved geographic locations of mine sites, which led to the investigation of spatial dependences or spatial autocorrelation over the study area. Accordingly, the appropriate statistical tests for the assessment of the level of the spatial autocorrelation were performed. Significant results confirmed and ensured the use of spatial autoregressive model to address that issue of the autocorrelation.

The second objective of this study was to create a supportive basis for continuing research activities where axle load and truck configurations are being investigated. Results help to assess the relationship between shipment distances and per axle weights in order to estimate the "contribution" of the mining industry to pavement deterioration. For cost minimization purposes many mining operations fully utilize payload weight capacities for truck shipments, thus eliminating public costs of highway system deterioration. The adopted spatial error regression model suggested highly significant positive relationship between payload weights and increasing shipment distances. With the exception for shipments within 11 – 20 mile distances, all other distances showed an increase in payload weights by approximately 4 to 7 tons. This directly relates to the above-mentioned payload weight maximization goal and emphasizes the importance of the mines proximity to the construction sites due to the high cost of aggregates transportation. Meanwhile, the relationship suggests accurately monitoring of truck configuration selection in accordance to the payload weights and shipment distances, which will partially ensure the durability of the highway system as it pertains to the transportation of mining industry production.

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