

Spatial Investigation of Mineral Transportation Characteristics in the State of Washington

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This study investigates the spatial relationships between construction aggregate shipments and the per axle payload weights of trucks as they pertain to highway deterioration in the state of Washington. A previous study investigated the transportation characteristics of mined aggregates using a spatial autoregressive model, where a significant positive relationship between payload weights and shipment distances was established. This paper expands the previous study by assessing the contribution of aggregate hauling trucks to pavement deterioration using per-axle loads by truck configuration.

Results showed a positive relationship between weights per axle load and several shipment distance categories. According to the well-established per axle weight and pavement damage relationship, incremental changes in per axle payload weights resulting from longer shipment distances clearly suggest that longer haulage increases the magnitude of pavement deterioration. This direct relationship between road impact and the distance hauled emphasizes the importance of the proximity of mine sites to different end users.

INTRODUCTION

The primary objective of this study is to investigate the spatial relationships between construction aggregate¹ shipments and the per axle payload weights of trucks as they pertain to highway deterioration in the state of Washington. Because the productive life of the pavement is directly affected by frequent, heavy aggregate shipments traveling long distances, this study focuses on the relationship between hauling distances and per-axle payload weights. Many studies have examined the relationship between transportation costs and haul unit productivity,² but there is minimal information available pertaining to the direct relationship between per-axle payload weights and shipment distances, which may contribute to highway deterioration. Furthermore, this analysis will provide state transportation planners and policy makers with a more detailed understanding of the operational characteristics of mined aggregates and factors influencing shipment distances.

This study utilizes data from a survey investigating the transportation and operational characteristics of Washington's mined products conducted under the Strategic Freight Transportation Analysis (SFTA) at Washington State University, a six-year comprehensive research and implementation project. A previous study investigated the transportation characteristics of mined aggregates using a spatial autoregressive model, where a significant positive relationship between payload weights³ and shipment distances was established (Khachatryan and Jessup 2007). This paper expands the previous study by assessing the potential contribution of aggregate hauling trucks to pavement deterioration using per-axle loads by truck configuration.

Results showed a positive relationship between weights per axle load and the first two haul distance categories (0-5 miles and 6-10 miles representing 56% of the total aggregates mined in the state of Washington). The next distance category (11-20 miles, representing 24% of the total production volume) revealed a reduction in per-axle payload weights by 1.4 tons, possibly indicating a change in truck configurations (more axles) to accommodate longer distances. The estimate for the 21-40 mile distance category (13% of the total production) recovers the direct relationship by increasing per-axle payload weights by nearly one ton. Slight reduction of per axle payload weights from the 21-40 mile category to the 41-100 mile category does not significantly disrupt the trend of

increasing per axle payload weights, since the 41-100 mile category represents only a small portion (4%) of the total mined aggregate.⁴

This relationship justifies the Department of Transportation and private aggregate mining firms in utilizing gravel sources close to the job site, even if they lack economies of scale. Clearly, one tradeoff (for the DOT) is the choice between hauling the aggregate from DOT owned mines farther away from the construction project versus buying it locally from privately owned mines. The first may lower overall construction costs, but it will also lead to increased impact on highway infrastructure.

LITERATURE REVIEW

While there are numerous studies investigating highway damage, the review of literature for this paper was limited to those studies involving transportation of aggregates. Prior studies of mine operations have focused on issues related to route selection, as with Berck (2005). Berck presents a least-cost route selection model for aggregate hauling as a part of constructors' cost minimization strategy, suggesting that the opening of the new quarry would change the aggregate transportation pattern. As a result of the new quarry opening, the study found no significant increase in the demand for construction aggregate as well as a decrease in some environmental externalities (emissions reduction). Another public cost consideration may be the deterioration of road networks used for aggregate hauling, which involves investigation of data on per-axle payload weights and/or the distance of the mined shipments. Road deterioration may also be due to the desire of construction contractors to increase productivity by maximizing the payload weights of the truck shipments (Schexnayder et al. 1999).

Additionally, because the shipments represent a major component of construction costs payload weights may even exceed legal limits, creating a strong relationship between the distance and the payload weights (Chronis 1987). Chronis (1991) also suggests that overloading trucks by 20% may lead to a decrease in per ton transport cost of aggregate because labor costs will not change and the fuel price is relatively unaffected. This assumption may not hold with recent fuel cost increases, and it does not consider externalities like highway damage or environmental impact.

Prior research efforts have mentioned the relationship between aggregate hauling and construction unit productivity, but there is minimal information available to understand the relationship with hauling distances as they pertain to highway deterioration (Day 1991). Therefore, this paper focuses on investigating the relationship between increasing shipment distances and axle load weights in an effort to understand the impact of the aggregate industry on the highway system.

TRUCK – PAVEMENT RELATIONSHIP

Highway infrastructure protection has always been a major consideration for changes in truck size and axle weight policies. The productive life cycle of highway pavement depends on several different factors, including pavement structure, quality of the construction materials, weather conditions and truck-related factors (number of axles, the distance between axles, the speed of a vehicle, and tire pressure). However, vehicle-specific factors such as spacing between axles, vehicle suspension, and tire pressure are not examined in this study because they are relatively insignificant for investigating the impact of the per-axle payload weights on highway system durability (U.S. Department of Transportation 2000). Nevertheless, measuring the actual damage to the pavement is not the purpose of this paper. Accordingly, this section only highlights the relationship between axle load and highway deterioration.

The distribution of the payload weight over axles or axle groups influences the magnitude of pavement deterioration because more axle groups result in less force imposed on the pavement (Casavant and Lenzi 1989). The relationship between truck axle load and deterioration level can be investigated with the following damage function (Tolliver 1994):

$g = (N/\tau)^\beta$ where, $g \in [0,1]$ denotes an index of damage or deterioration ($g = 1$ indicates maximum damage), where N is the number of passes per axle group at a specified weight and configuration (18,000 pound/single axle), τ is the number of axle passes at which the section of pavement reaches failure, and β is the rate of deterioration.

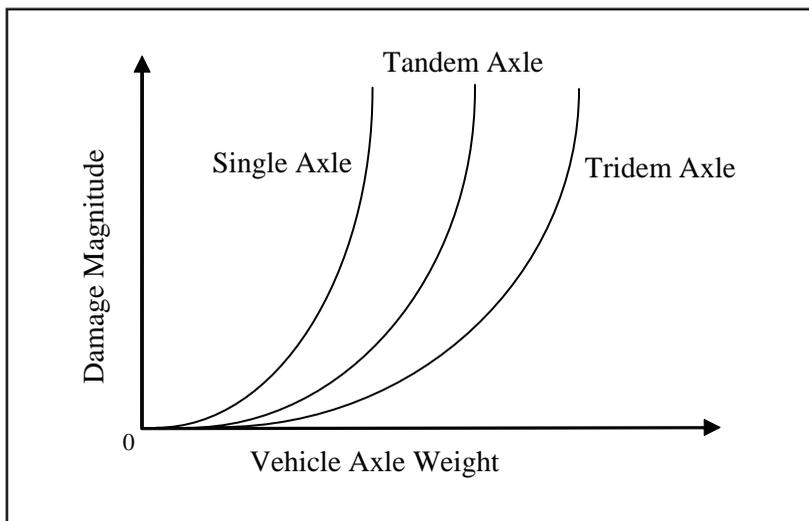
Further, the influence of transportation efficiency on the aggregate industry is also discussed. This relationship leads to an increasing number of overloaded aggregate hauling trucks on highways. According to the well-established relationship between heavy weights and pavement deterioration, this directly affects the durability of the highway system.

Figure 1 depicts the general relationship between the trucks' per axle weight and the damage function described above, where the damage increases at a much higher rate than does the per-axle load.

To ascertain the relationship between increased haulage distances and highway deterioration, consideration of the following scenarios is useful: (1) truck configurations are changed, allowing more axle groups for heavier loads, thus preserving the same weight per axle load, (2) truck configurations are changed, but not proportionally to the increase in the payload weights, thus increasing per-axle weights.

Under the second scenario, the incremental effect on pavement deterioration will sharply increase with an increasing weight per-axle load. Generally, a fourth power relationship is found for pavement damage resulting from increased per-axle loads. For example, as a result of a 100% increase in per-axle weight, the impact on the pavement will increase by a factor of 16.

Figure 1: Damage Functions (Pavement Damage Magnitude and Vehicle Axle Weight)



Source: Casavant and Lenzi (1989).

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 Geographic Information System (GIS) files were downloaded from the WSDOT GeoData Distribution Catalog. Annual production levels, payload weights, volume of aggregates shipped within different distances, and proportions of production levels by shipment distances were obtained from Khachatryan et al. (2007).

According to the same source, 35% of the aggregate production was shipped within five miles of the production origin; 21% was transported to distances within six to 10 miles; 24% - within 11 to 20 miles; 13% - within 21 to 40 miles; about 4% - within 41 to 100 miles; and only a small

proportion of the production was hauled beyond 100 miles. The number of axles varies depending on the truck type. The same source also indicates that the number of axles for trucks leaving mining facilities ranges from two to six, with an average of 3.4 and mode of three axles. Trailer (if used) axles ranged from two up to seven, with an average and mode of three. The total number of axles for truck or tractor ranges from two to nine, with an average of 3.6 axles. With the average of three, the total number of axles on the first trailer varies from two to five.

METHODOLOGY

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.

An evaluation of the mining industry data received from the Transportation of Mining/Mineral Survey showed substantial variation across Washington’s regions. Naturally, spatial non-stationarity is involved in any process that takes place over geographical locations (Unwin and Unwin 1998). In other words, the process under investigation might not be constant over the entire study area. Therefore, because the transportation characteristics of the mining/mineral industry involve data containing geographic location information, in most cases the data were expected to have spatial dependence, or spatial autocorrelation, which is the weaker form of spatial dependence.

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 locations, creating positive autocorrelation. Whereas high and low value patterns between neighboring areas represent negative autocorrelation (Upton and Fingleton 1985).

For example, a larger percentage of mines can be found in operation (with large volume of production), in the western regions of the state, due to the availability of many construction projects (demand) or favorable weather conditions. This may result in relatively heavier payload shipments than in the eastern part of the state (Khachatryan et al. 2007).

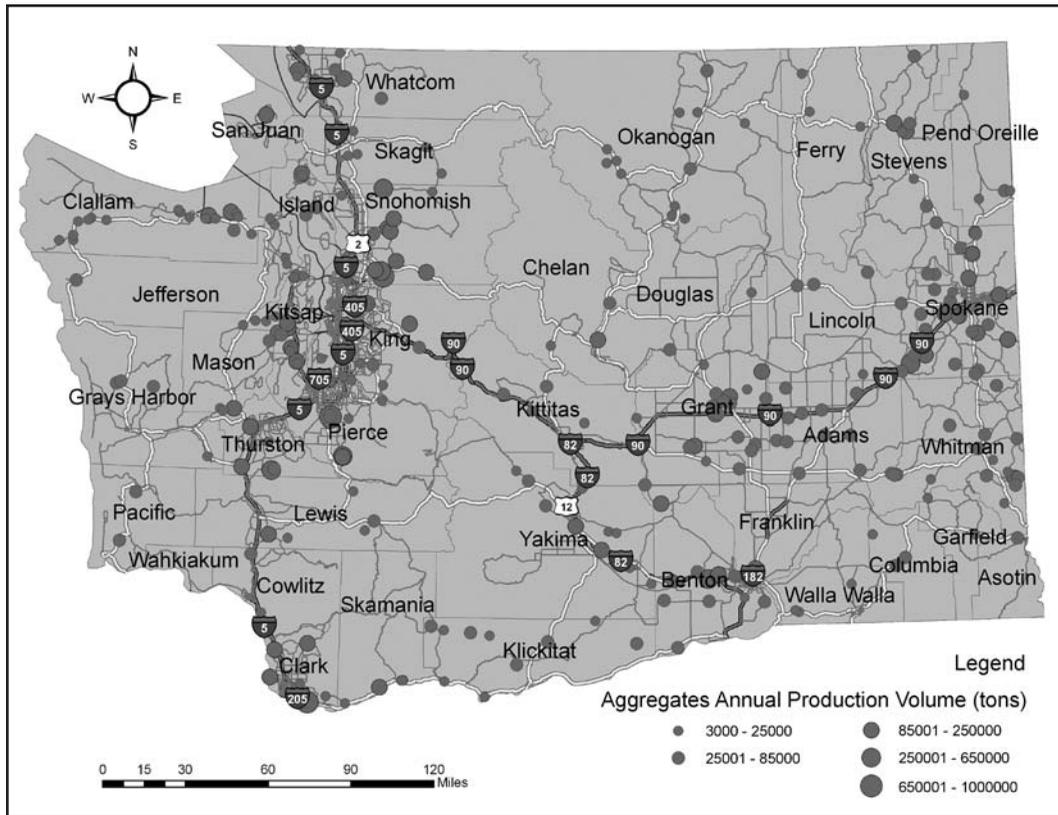
Consequently, spatial dependence in the data would mean that most of the classical estimation procedures and methods are inappropriate for this analysis. Generally, spatial dependence is the existence of a functional relationship between one location and the rest of the locations in the study area, which then translates into the lack of independence (independence that is assumed by classical estimation procedures) among observations in cross-sectional data sets.⁵ Therefore, specifications such as spatial lag or spatial error model are necessary to address the problem.

The geographic distribution of aggregate mines throughout the state is relatively even. However, upon closer investigation of these mine locations in relation to the road network and highly urbanized areas, one may find local clustering (Figure 2). This is partially explained by a high concentration of highway, home and office construction in highly urbanized areas (Finnie and Peet 2003).

In addition to visual inspection of the location pattern, exploratory data analysis using GIS and statistical software GeoDa showed systematic patterns in the spatial distribution of variables such as payload weights and annual production volumes.

The wide array of studies in the field of spatial econometrics represents diverse approaches for addressing spatial autocorrelation in the data. A search of the literature did not reveal any studies of spatial autocorrelation of aggregate mining industry data. However, a number of local and global spatial statistics are available to test for 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), which, when applied to polygon or point data, compares the value of a specific variable at any one location with that of all other locations and emphasizes similarities over space (Fotheringham et al. 2002).

Figure 2: Aggregates Mines in Relation to Washington State Highways by Annual Production Volume



The equation for calculating Moran’s I statistic is given as:

$$(1) I = \frac{N \sum_i \sum_j W_{i,j} (X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j W_{i,j}) \sum_i (X_i - \bar{X})^2}$$

where N is the number of point observations (locations), X_i is the value of the variable at location i , X_j is the value of the variable at location j , \bar{X} is the mean of the variable, and $W_{i,j}$ is a spatial weight matrix applied to the comparison between locations i and j . Calculations throughout the study area resulted in a value of Moran’s $I = 0.1115$ for payload weights, and Moran’s $I = 0.16$ for per axle loads.

Global Moran’s⁶ I values indicate statistically significant spatial autocorrelation in the regression residuals, which then requires addressing the issue of spatial autocorrelation. This violates the assumption that the values of the observations in each sample are independent. Positive spatial autocorrelation can occur if samples are taken from geographically close locations.

In the case of the mining industry, the global forms of spatial 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 (Fotheringham et al. 2002). In this aspect, the global statistics will fail to properly represent relationships between processes, especially when translated into a local investigation of those processes. The localized version of Moran’s I statistic (LISA), which exhibits tendencies in the data in the vicinity of each point in study area, has the following form:

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

where N is the number of observations, X_i is the observed value of the variable X at location i , X_j is the value of the variable at location j , \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 1995).

Spatial Weights 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 polygon data, i.e. 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 of weight matrix, in turn, can be different according to specified order of contiguity or distance band. For the contiguity-type weight matrices, “neighbors” can be classified as spatial units that share a border. Anselin (2005) and Anselin and Bera (1998) provide details on higher order contiguity weight matrices – queen-based and/or rook-based.⁷

Distance-based matrices can be based on either the distance between i and j locations of observations or number of neighbor observations. For the distance-based 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, the number of points/neighbors should be specified in order to be considered as neighbors. For example, if for some specific purposes the four nearest neighbors approach is adopted, the weights matrix will consider only the four nearest points for each point in the study area. The weights with number of nearest neighbors (KNN) approach standardizes the number of neighbors, which assumes that an equal number of neighbors is more important than the distance between neighbors.

Each type of spatial weights can be formed based on specific situations or nature of the spatial data; however, there is no agreement about the type of weight matrix to be employed for spatial analysis (Anselin 1988). In the spatial N by N (positive and symmetric) weight matrix, each element $w_{ij} = 1$ when i and j are neighbors⁸ and $w_{ij} = 0$ otherwise. By convention, the diagonal elements of the matrix are set to zero. Rows of the N by N weight matrix are standardized such that:

$$(3) \quad w_{ij}^s = \frac{w_{ij}}{\sum_j w_{ij}}$$

where w_{ij}^s is the element of the standardized weight matrix. The resulting weights matrix is no longer symmetric, which ensures averaging neighboring values (Anselin and Bera 1998). Also, it guarantees comparability of spatial parameters (in many spatial stochastic processes) across models.

In line with the imprecision about the type of weights matrices to utilize, the distance band above the threshold distance for the formation of the weights matrices is another issue that is unresolved in spatial econometrics. Generally, the threshold distance method ensures that every location has at least one neighbor. GIS calculations of local average⁹ distances (between mine locations), and shipment distances (that most of the aggregate production is hauled) provided strong foundations for the threshold distance method adoption. Therefore, this study employed the threshold distance-based weighting matrix.

SPATIAL ERROR MODEL

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 farther away. One reason for spatial dependence in an estimated model could arise as a result of mine site location being near highly urbanized regions of the study area. Urbanization is usually positively related with aggregate consumption. Thus, mine sites located near 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 shipments' payload weights, as well as shipment distances.

Different methods for estimating the spatial autocorrelation model are widely covered in the existing spatial econometrics literature. The spatial regression model selection decision was made according to Anselin et al. (1996) and Anselin (2005), one of the most accepted approaches of choosing between spatial lag or spatial error options. Following the suggested approach, analysis started with Ordinary Least Squares (OLS) regression. Next, the Lagrange Multiplier Error (LM-Error) and Lagrange Multiplier Lag (LM-Lag) diagnostics provided the basis for the type of spatial autoregressive model selected. If neither of the test statistics is significant, the OLS method is suggested. If one of the test statistics is significant, while the other is not, then according to Anselin (2005) the model (spatial error or spatial lag) with the significant test statistic should be utilized. In this case, both LM-Error and LM-Lag tests showed statistically significant results, which led to examination of Robust LM-Error and Robust LM-Lag test statistics. While the Robust LM-Lag was not significant, the Robust LM-Error statistic showed statistically significant results. Accordingly, the spatial error model was chosen for the regression analysis (a widely used spatial autoregressive process in the error terms).

The spatial error model assumes the following linear regression:

$$(4) \quad y = X\beta + \varepsilon \quad \text{with} \quad \varepsilon = \lambda W\varepsilon + v$$

where y is a vector of observations on the dependent variable (weights per axle load), X is a matrix of observations on continuous variables (volume of mined aggregates shipped within different distance categories, such as from zero to five miles, from six to ten miles, 11-20 miles, 21-40 miles and 41-100 miles), β is a vector of parameters to be estimated, ε is a vector of spatially autocorrelated error terms, W is the spatial weights matrix, λ is a spatial autoregressive coefficient for the error lag $W\varepsilon$, and v is a vector of homoskedastic error terms.

RESULTS

The regression results reveal a significant positive relationship between per-axle payload weights (dependent variable) and several distance categories. The OLS regression output and diagnostics for spatial dependence for the distance-based weight matrix are summarized in Tables 1 and 2, respectively.

Regression diagnostics (Moran's I, LM-Error tests) disclose considerable non-normality and a high degree of spatial autocorrelation, which could be spillovers from mining operations from adjacent districts being transmitted through economic activities.

Next, in Table 3, output for the spatial error model is presented. The estimates for the autoregressive parameter of the error process are represented by lambda.

Table 1: OLS Regression Output

Shipment Distances*	Coefficient	Standard Error	t-Statistic	P-Value
Constant	-0.462	0.266	-1.734	0.084
0-5 miles	4.560	0.405	11.244	0.000
6-10 miles	6.524	0.438	14.873	0.000
11-20 miles	4.611	0.456	10.095	0.000
21-40 miles	5.030	0.648	7.759	0.000
41-100 miles	5.009	1.083	4.621	0.000
Adjusted R ²	.55			
Log Likelihood	-540.689			
AIC ¹⁰	1093.3			
SIC ¹¹	1115.36			

Number of observations = 288.

*Shipment distances are observations on continuous variables that represent the volume of mined aggregates shipped within different distance categories.

Table 2: Diagnostics for Spatial Dependencies

Test	MI/DF*	Z-Value	P-Value
Moran's I (error)	0.16	N/A	N/A
Lagrange Multiplier (error)	1	22.169	0.000

*Moran's I/Degrees of Freedom.

Table 3: Spatial Error Regression Output

Shipment Distances*	Coefficient	Standard Error	t-Statistic	P-Value
Constant	-0.421	0.278	-1.511	0.131
0-5 miles	4.429	0.380	11.638	0.000
6-10 miles	6.129	0.421	14.536	0.000
11-20 miles	4.714	0.441	10.670	0.000
21-40 miles	5.598	0.626	8.934	0.000
41-100 miles	5.422	1.018	5.323	0.000
Lambda	0.373	0.078	4.719	0.000
Pseudo R ²	0.59			
Log Likelihood	-531.317			
AIC	1074.64			
SIC	1096.61			

Number of observations = 288.

*Shipment distances are observations on continuous variables that represent the volume of mined aggregates shipped within different distance categories.

In spatial autoregressive specifications, R^2 is not the appropriate measure of fit to make comparisons (Anselin 1988). Instead, the maximized log likelihood should be utilized (the larger the value, the better the fit). Notice the fact that the log likelihood is affected by the number of variables, as well as by sample size. To adjust it, two information criteria (IC) are introduced - Akaike and Schwartz criterion (the smaller the value, the better the fit). To understand the conclusion suggested by both criteria, the following discussion is useful.

Following Anselin (1988), the ICs can be calculated as follows:

$$(5) \quad IC = -2L + f(K, N)$$

where L and $f(K, N)$ = function of number of variables (K) and number of observations (N).

Using equation (5):

$$(6) \quad f(K, N) = 2K$$

$$(7) \quad f(K, N) = K \ln(N)$$

Equations for both ICs can then be formed as the following:

Akaike Information Criterion:

$$(8) \quad AIC = -2L + 2K$$

Schwartz Information Criterion:

$$(9) \quad SIC = -2L + K \ln(N)$$

To compare the spatial error model's fit to that of the OLS model, the Akaike and Schwartz criterion can also be manually recomputed using equations 8 and 9.

Generally, the number of variables (K) does not include the spatially lagged variable W , since its coefficient ϵ is treated as a nuisance parameter. However, for comparison purposes the calculation must include W . Then the number of variables (K) including W is six, and the number of observations (N) is 288.

For the OLS Model (using maximized log likelihood value and number of variables):

$$(10) \quad AIC = -2 \times (-540.689) + 2 \times 6 = 1093.3$$

$$(11) \quad SIC = -2 \times (-540.689) + 6 \times \ln(288) = 1115.36$$

For the Spatial Error Model (following similar procedure):

$$(12) \quad AIC = -2 \times (-531.317) + 2 \times 6 = 1074.65$$

$$(13) \quad SIC = -2 \times (-531.317) + 6 \times \ln(288) = 1096.61$$

Maximum likelihood estimates the parameter values β and λ are the most likely fit given observed data. Therefore, the interpretation of a goodness of fit measure, such as the maximized log likelihood, is the extent to which the estimated parameter(s) makes the observed data most likely. In other words, higher log likelihood values represent better measures of fit than lower log likelihood values.

To interpret ICs, an additional step is required because in these cases the log likelihood (goodness of fit) is adjusted by the degrees of freedom. Equations 8 and 9 show that the difference between the two criteria is that AIC adjusts for the number of variables while SIC adjusts for the number of variables and the sample size (with natural logarithm). The idea here is to include a "penalty"

for lost degrees of freedom. Consequently, that “penalty” translates into a larger IC value – the $K \ln(N)$ part of the equation 9. Therefore, the smaller the IC value, the better the fit of the model.

Tables 1 and 2 show that log-likelihood is increased from -540.689 (for OLS) to -531.317 (for spatial error model), AIC is decreased from 1093.3 (for OLS) to 1074.64 (for spatial error model), and SIC is decreased from 1115.36 (for OLS) to 1096.61 (for spatial error model). The spatial autoregressive coefficient (λ) is estimated as 0.37 and is highly statistically significant. Compared to the OLS regression results, all three goodness of fit measures are improved in the spatial error specification.

As mentioned earlier, results disclose a positive relationship between weights per axle load and the first two haul distance categories. Particularly, as shown in Table 3, a change from the zero to five mile category to the six to 10 mile category resulted in a considerable increase (1.7 tons) in per-axle payload weights. That is to say, trucks hauling aggregates within six to 10 miles carry 1.7 tons more per axle than those hauling within five mile distances. To emphasize the significance of this observation, note that more than half (56%) of total aggregate production was hauled within those two distance categories. At the same time, the third distance category (11-20 miles) revealed a reduction in axle load weights by 1.4 tons, possibly indicating a change in truck configurations (more axles) to accommodate longer distances. This category represents 24% of total aggregate production. In fact, the reduction may be partially explained by more restrictive local (county level) regulations on truck size and weight (in addition to the state level regulation), which eventually leads to an increase in transportation per ton-mile cost. On the contrary, the estimate for the 21-40 mile category representing 13% of total aggregates mined, recovers the increasing relationship by increasing per-axle payload weights by nearly one ton. Furthermore, the slight reduction from the 21-40 mile category to the 41-100 mile category doesn't disrupt the trend of increasing per-axle payload weights, because the 41-100 mile category represents only a small portion (4%) of the total mined aggregates. The mining firms participating in the survey indicated that shipments within this distance category were not frequent, thus, the result is less useful for interpretation.

CONCLUSION

The aggregate industry is highly influenced by transportation efficiency in terms of the high cost of shipments. Therefore, the proximity of mine site location to the construction site or any other end-use location is crucial. The cost of transportation may explain the high correlation between mine and construction site locations. Despite the low value per ton characteristic, aggregate is heavy, which makes truck transportation very costly, but necessary.

The primary objective of this study was to investigate the spatial relationships between construction aggregate shipments and the per axle payload weights, in an effort to determine if there is any systematic pattern between the two. Autoregressive model results showed that the positive relationship exists for several distance categories. Namely, an increase from the first distance category to the second, and from the third category to the fourth category resulted in a considerable increase in per-axle load weights.

Due to the high cost of aggregate transportation, many mining firms fully or over utilize payload weight capacities for truck shipments, thus ignoring public external costs of highway system deterioration. The link between per-axle weights and pavement damage is a well established relationship. With this in mind, incremental changes in per-axle payload weights resulting from several shipment distance categories clearly suggest that aggregate haulage contributes to the magnitude of pavement deterioration (for segments within identified distances). This direct relationship between road impact and the distance hauled emphasizes the importance of the proximity of mine sites to different end-users. Therefore, state agencies such as the Department of Natural Resources, which have exclusive authority to endorse reclamation plans and mining permits, should consider facilitating the existing complicated process of issuing mining permits. This will partially ensure that aggregate is provided in a timely manner to newly opened highway or other construction sites.

State agencies such as the DOT own mines in different regions of the state that make aggregate available at relatively low cost for road construction projects. This paper reveals the tradeoff between using low cost aggregate hauled from longer distances versus buying aggregate locally (at a relatively higher cost) from privately owned mines. Thus, the positive relationship between per-axle payload weight and hauling distances may partially impact the durability and longevity of the highway system as it pertains to the transportation of mined aggregate production. Furthermore, the spatial analysis technique adopted in this paper can be used to analyze issues regarding shipments of heavy, low value freight such as agricultural commodities.

Endnotes

1. Aggregate refers to the mixture (or aggregation) of sand and gravel where gravel accounted for 25% or more of the mixture (McLaughlin et al. 1960).
2. Haul unit productivity refers to vehicle (truck in this case) efficiency.
3. Payload is the load a vehicle can carry, excluding the vehicle weight.
4. According to Khachatryan et al. (2007), most of the mining firms participating in the survey mentioned that shipments of more than 40 miles were rare.
5. Usually, all spatial data reveal some form (negative or positive) of autocorrelation (Anselin 1988).
6. Often, Moran's I statistic is called Global Moran's I to emphasize its difference from the localized version - LISA.
7. A rook-based contiguity weights matrix defines a location's neighbors as those areas with shared borders, in contrast to a queen-based weights matrix, which defines a location's neighbors as those with either a shared border or vertices. The vertex is the node that defines the boundary corner of a polygon (for example corner points of county or state area).
8. In other words, $w_{ij} = 1$ when $d_{ij} \leq \delta$ and $w_{ij} = 0$ otherwise, where d_{ij} is the distance between locations i and j , and δ is the distance band for distance-based spatial weight matrix.
9. Local averaging helps to preserve important spatial characteristics and variations of point pattern.
10. AIC – Akaike Information Criterion.
11. SIC – Schwarz Information Criterion.

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