Payload Weights and Hauling Distances: The Potential Effects on Highway Deterioration

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Introduction

The primary objective of this study is to investigate the spatial relationships between construction aggregate shipments and the per axle payload weights of trucks as it pertains to highway deterioration, applied in this case to the State of Washington. Because the productive life of the pavement is directly affected by frequent, heavy aggregates shipments traveling long distances, this study focuses on the relationship between pavement damage and per axle payload weights. Many studies have examined the relationship between transportation cost and construction unit productivity but there's minimal information available pertaining to the relationship between per axle payload weights, shipment distances and highway deterioration.

This study utilizes data from a survey investigating the transportation and operational characteristics of Washington's mined products conducted under the six-year comprehensive research and implementation project Strategic Freight Transportation Analysis (SFTA) at Washington State University. 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 by assessing the "contribution" of aggregates hauling trucks to pavement deterioration using per axle loads by truck configurations. Results showed again a positive relationship between road impact and distance hauled, supporting the

Department of Transportation and private aggregate mining firms in utilizing gravel sources close to job site, even if they lack economies of scale.

Transportation of Mining/Mineral Survey

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. 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 *(1)* 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. 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.

Truck – Pavement Relationships

Highway infrastructure protection has always been a major consideration for changes in truck size and axle weight policy decisions. The productive life cycle of highway pavement depends on different factors including pavement structure, quality of the construction materials, weather conditions, 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 since they represent relatively less importance for estimating pavement damage magnitude than per axle loads (Comprehensive Truck Size and Weight Study) *(2).*

The distribution of the payload weight over axles or axle groups influences the magnitude of pavement deterioration since more axle groups result in less force imposed on the pavement

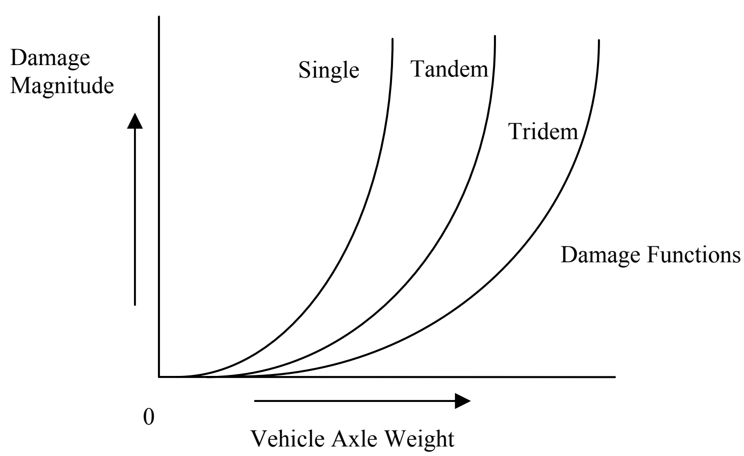
(Casavant, K., and J. C. Lenzi) *(3)*. The relationship between truck axle load and deterioration level can be investigated with the following damage function (Tolliver) *(4)*:

$g = \left(\frac{N}{\tau}\right)^{\beta}$ where, $g \in [0,1]$ denotes an index of damage or deterioration (g = 1 indicates maximum damage), 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, in the literature review section, the influence of the transportation efficiency on the aggregates industry is discussed. This dual relationship leads to an increasing number of overloaded 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 the per axle load.

Figure 1. Pavement Damage and Vehicle Axle Weight



Source: Casavant, K., and J. C. Lenzi.

To ascertain the relationship between increasing haulage distances and highway deterioration, the consideration of the following scenarios is useful: (1) truck configurations are changed, allowing more axle groups for heavier loads, thus preserving the same 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 per axle load. Generally, a fourth power relationship is considered as a measure for pavement damage resulting from increasing per axle loads *(1)*. 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.

Literature Review

Prior studies focusing on mine operations have focused on issues related to route selection, as with Peter Berck 2005 *(5)*. 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 per axle payload weights and/or the distance of the mined commodities shipments. 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) *(6).*

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) *(7).* Chronis 1991 *(8)*, 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) *(9)*.

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. 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.

Methodology

Spatial Autocorrelation

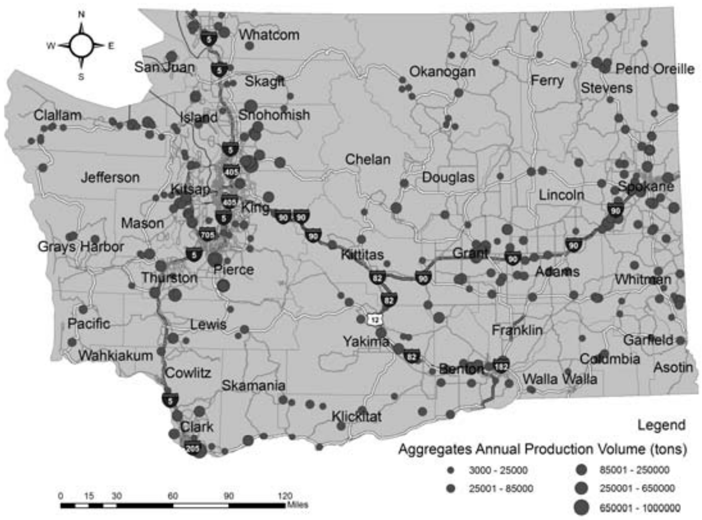
An evaluation of the mining industry data received from the Transportation of Mining/Mineral Survey showed substantial variation across Washington's regions. Naturally, spatial non-stationarity is involved in any process which takes place over real geographical locations (A. Unwin, D. Unwin, 1998) *(10)*. 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 a local investigation of those processes. Therefore, because the transportation characteristics of the mining/mineral industry involve data containing geographic location information, in most cases the data was expected to have spatial dependence, or spatial autocorrelation, which is the weaker form of spatial dependence.

For example, in the western regions of the state, due to the availability of many construction projects (demand) or favorable weather conditions, a larger percentage of mines can be found in operation. This results in relatively heavier payload shipments than in the eastern part of the state *(1)*.

Consequently, spatial dependence in the data would mean that most of the classical estimation procedures and methods are inappropriate for this 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 (Figure 2).
This is partially explained by a high concentration of highways, homes and office construction in highly urbanized areas (B. Finnie, J. Peet 2003) *(11)*.

Figure 2. Aggregates mines in relation to Washington State highways by annual production volume



In addition to the visual inspection of the point pattern, exploratory data analysis using GIS and GeoDa showed systematic patterns in the spatial distribution of the 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. However, a search of the economic literature did not bring favorable results on investigating spatial autocorrelation representing aggregates mining industry data.

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) *(12)*.

The number of local and global spatial statistics is 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) *(13)*, 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) *(14)*.

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

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

where N is the number of point observations (locations), *Xi* is the value of the variable at location *i, Xj* is the value of the variable at location *j*, $\bar{X}$ is the mean of the variable, and *Wij* 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's 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 *(14)*.

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 observations, *Xi* is the observed value of the variable *X* at location *i*, *Xj* is the value of the variable at location *j*, $\bar{X}$ is the mean of the variable, and *Wij* is a spatial weight matrix, which represents the strength of the linkage between *i* and *j* locations (Anselin L. 1995) *(15)*.

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 the 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 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) *(16)*. In the spatial N by N weight matrix, each element *wij* = 1 when *i* and *j* are neighbors and *wij* = 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) *(17)*.

For the contiguity type weight matrices "neighbors" can be classified spatial units that share a border. Anselin, 2005 *(18)* & *(17)* 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. This study employed threshold distance based weighting matrix.

Spatial Error Model

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:

$$y = X\beta + \varepsilon \text{ with } \varepsilon = \lambda W\varepsilon + \upsilon,$$

where λ is the spatial autoregressive coefficient for the error lag $W\varepsilon$, and υ is homoskedastic error term.

Spatial regression model selection decision was made according to Luc Anselin's comprehensive guide to GeoDa statistical software – "Exploring Spatial Data with GeoDaTM: A Workbook" *(18)*. 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 & Conclusions

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

Table 1. OLS Regression Output

Shipment Distances (in miles)	Coefficient	Standard Error	t-Statistic	Probability
Constant	-0.4619785	0.2663406	-1.73454	0.0839149
0-5 mile	4.560459	0.4055854	11.24414	0.0000000
6-10 mile	6.523676	0.4386133	14.87341	0.0000000
11-20 mile	4.611568	0.4568085	10.09519	0.0000000
21-40 mile	5.030289	0.6482578	7.759705	0.0000000
41-100 mile	5.009317	1.083914	4.621509	0.0000058
Adjusted R^2	.55			
Log Likelihood	-540.689			
AIC[1]	1093.3			
SC[2]	1115.36			

*Number of observations = 288

Table 2. Diagnostics for Spatial Dependencies

Test	MI/DF	Value	Probability
Moran's I (error)	0.16	N/A	N/A
Lagrange Multiplier (error)	1	22.169176	0.0000025

[1] AIC – Akaike Info Criterion
[2] SC – Schwarz Criterion

Regression diagnostics (Moran's I, LM-Error tests) disclose considerable non-normality and a high level 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 represented. The estimates for the autoregressive parameter of the error process are represented by lambda.

Table 3. Spatial Error Regression Output

Shipment Distances (in miles)	Coefficient	Standard Error	t-Statistic	Probability
Constant	-0.421304	0.2787575	-1.511364	0.1306959
0-5 mile	4.428516	0.3805101	11.63837	0.0000000
6-10 mile	6.129497	0.4216894	14.53557	0.0000000
11-20 mile	4.714083	0.4418261	10.66954	0.0000000
21-40 mile	5.597888	0.6265768	8.934082	0.0000000
41-100 mile	5.421976	1.018583	5.323058	0.0000000
Lambda	0.3726214	0.078964	4.718877	0.0000024
Pseudo R^2	0.59			
Log Likelihood	-531.317			
AIC	1074.64			
SC	1096.61			

*Number of observations 288.

In the spatial autoregressive specifications, appropriate measures of the goodness of fit are log-likelihood, AIC and SC tests. Compared to the OLS diagnostics, all three are improved in this specification. Particularly, log-likelihood is increased from -540.689 (for OLS) to -531.317, AIC is decreased from 1093.3 (for OLS) to 1074.64, and SC is decreased from 1115.36 (for OLS) to 1096.61. The spatial autoregressive coefficient (λ) is estimated as 0. 37 and is highly statistically significant.

The spatial error regression results (Table 3) represent a considerable increase (1.7 tons) in per axle payload weight from the 0-5 category to the 6-10 category for the shipment distances. For the next distance category, per axle payload weights are reduced by 1.4 tons, possibly indicating a change in truck configurations (more axles) to accommodate longer distances.[3] The change from the mile category 10-20 to a longer distance category, 21-40 miles, resulted in a nearly 1 ton increase in per axle payload weight[4]. Due to the high cost of aggregates transportation, many mining firms fully or over utilize payload weight capacities for truck shipments, thus eliminating public costs of highway system deterioration. 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. Because of this, state agencies such as the Department of Natural Resources, which have exclusive authority to endorse reclamation plans and mining permits, should consider facilitating the process of issuing permits. This will ensure that the aggregates are provided in timely manner to newly opened construction sites. Consequently, this will also prevent the haulage of gravel from longer distances, therefore reducing the level of road deterioration.

Furthermore, the relationship also suggests the importance of closely monitoring the selection of the specific truck configuration in accordance to the payload weights and shipment distances. This will partially ensure the durability of the highway system as it pertains to the transportation of mining industry production.

[3] Also, 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 an increase in transportation cost per-ton-mile.

[4] The 41-100 mile category represents only 4% of mining firms' annual production shipments and, therefore, is less useful for interpretation.

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