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The Effect of Weather Events on Truck Traffic Patterns Using Fixed and Mobile Traffic Sensors

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16. Abstract

Severe weather conditions, i.e. snowfall, floods, ice storms, etc. can have major effects on traffic volumes along the highway network. Unlike passenger vehicles, which may choose not to travel during inclement weather, freight trucks need to adhere to delivery schedules requiring them to alter their route rather than cancel a trip. While previous studies have modeled the effects of weather on total traffic volumes, very few studies have examined the effect of weather on truck volumes. Due to differences in travel behaviors between passenger and freight trucks, the study of weather effects on truck volumes requires advanced modeling techniques that are able to capture effects over space. This study applies spatial regression techniques to develop a predictive model that relates variations in truck traffic patterns to weather conditions, with a focus on extreme weather events. The study uses traffic classification data from six Weigh-in-Motion (WIM) stations and weather data from six weather stations in Arkansas. The study shows that, as expected, reduction in truck volume occurs due to extreme weather events such as snowfall, fog, hail, winter storms, flash flood, etc. Notably, through the spatial model, the negative spatial autocorrelation parameter explains that reductions in truck volume at one site are countered by higher truck volumes at neighboring sites- thus explaining rerouting behaviors of trucks. The study finds extreme cold events (i.e. snow) reduces daily truck volumes by approximately 22% while heavy rainfall, flood, flash flood reduces daily truck volumes by 13%, compared to average daily truck traffic. The study can assist state and regional transportation agencies in developing freight-oriented programs and policies for road and winter maintenance, structural and geometric pavement design, highway life cycle analysis, and long-range transportation planning.

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
in	inches	25.4	millimeters	mm
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5*(F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candle	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	pound-force	4.45	newtons	N
lbf/in^2	pound-force per square inch	6.89	kilopascals	kPa

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS FROM SI UNITS				
SYMBOL	**WHEN YOU KNOW**	**MULTIPLY BY**	**TO FIND**	**SYMBOL**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yard	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candle	fc
cd/m^2	$candela/m^2$	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	pound-force	lbf
kPa	kilopascals	0.145	pound-force per square inch	lbf/in^2

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THE EFFECT OF WEATHER EVENTS ON TRUCK TRAFFIC PATTERNS USING FIXED AND MOBILE TRAFFIC SENSORS

Final Report

December 2017

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EXECUTIVE SUMMARY

Severe weather conditions, i.e. snowfall, floods, ice storms, etc. can have major effects on traffic volumes along the highway network. Unlike passenger vehicles, which may choose not to travel during inclement weather, freight trucks need to adhere to delivery schedules requiring them to alter their route rather than cancel a trip. While previous studies have modeled the effects of weather on total traffic volumes, very few studies have examined the effect of weather on truck volumes. Due to differences in travel behaviors between passenger and freight trucks, the study of weather effects on truck volumes requires advanced modeling techniques that are able to capture effects over space.

This study applies spatial regression techniques to develop a predictive model that relates variations in truck traffic patterns to weather conditions, with a focus on extreme weather events. The study uses traffic classification data from six Weigh-in-Motion (WIM) stations and weather data from six weather stations in Arkansas. As expected, reduction in truck volume occurs due to extreme weather events such as snowfall, fog, hail, winter storms, flash flood, etc. The study finds extreme cold events (i.e. snow) reduces daily truck volumes by approximately 22% while heavy rainfall, flood, and flash flood reduces daily truck volumes by 13%, compared to the average daily truck traffic. Non-weather variables including road type, day of week, season, and presence of construction all had statistically significant impacts on daily truck volume relative to Annual Average Daily Truck Traffic (AADTT). Comparison of the Ordinary Least Squares (OLS) approach used in previous studies to the spatial regression model used in this work shows that the spatial model is able to explain 7% more variability in the data than the OLS model. The adjusted R^2 goodness-of-fit statistic of the spatial model was 53% compared to 46% for the OLS model. In addition to better fit, the spatial model estimates the degree of spatial autocorrelation in the data. In this study, the spatial autocorrelation parameter was negative (-1.73). This parameter captures truck re-routing behavior, e.g. reductions in truck volume at one site are countered by higher truck volumes at neighboring sites.

The study can assist state and regional transportation agencies in developing scenario-based, freight-oriented programs and policies for road and winter maintenance, structural and geometric pavement design, highway life cycle analysis, and long-range transportation planning. For instance, the results of this study can quantify the shifts in truck volumes that may occur as extreme winter storms increase in frequency or duration. Future work will examine (i) the applicability of spatio-temporal models intended to capture both spatial and temporal autocorrelation and (ii) the use of mobile sensor data from truck GPS units to expand the spatial coverage of truck volume data beyond the limited number of WIM sites. Mobile sensor data from truck GPS would also allow for estimation of truck vehicle miles travelled (VMT) and truck vehicle hours traveled (VHT) which would further enhance winter maintenance and freight operations, programming, and planning decision.

INTRODUCTION

PROBLEM STATEMENT

Trucking is a critical component of freight transportation system. Although freight shipments traverse a multimodal system comprised of air, rail, water, and truck modes, trucking is and is forecast to be the dominant mode for freight. In 2007, trucks accounted for 68% and 65% of the market by both weight and value, respectively [1]. Further, the Freight Analysis Framework Version 3 (*FAF3*), FHWA's national freight forecasting model, estimates that the weight of freight shipments moved by truck will grow 43% between 2012 and 2040 [2]. A reliable estimation of freight travel demand by truck is important for effective planning, design, and management of the freight transportation system.

Severe weather conditions such as cold temperatures, high wind speed, ice, and snowfall, affect traffic volumes along the highway network especially in regions subject to extreme weather patterns [3]. Extreme weather events such as tornadoes and flooding can cause significant disruptions to the freight transportation network resulting in economic impacts to the trucking industry and industries served by the trucking industry. Impacts include displaced congestion effects as well as shipment delays and related costs. Impacts to or in the vicinity of Primary Freight Network (PFN) segments, in particular, will have far reaching effects on freight movements across the nation. Understanding the impacts of weather events on freight movements can help state agencies assess the economic impacts of such events in order to provide monetized benefit estimates for highway infrastructure maintenance or upgrades. To assess impacts such as route changes and time delays, more accurate models are needed to predict the number of affected vehicles and geographic extent of the impacts.

The impact of a weather event, such as a winter storm, can be measured in part by the difference in traffic volumes along the highway network. Faced with adverse weather, drivers may postpone a trip (i.e. temporal shift), change routes (i.e. spatial shift), or cancel a trip all together (i.e. volume reduction). Unlike passenger traffic, freight traffic is subject to more rigid pickup/delivery windows and assigned schedules. Thus, freight truck traffic exhibits less flexibility in the decision to travel than passenger traffic. Consequently, while reductions in total traffic volumes may occur due to severe weather, truck traffic may actually increase along certain routes as a result of spatial shifts.

BACKGROUND

Previous research has found that in the presence of adverse weather such as snowstorms, total traffic volumes can reduce as much as 56% [4] since many travelers cancel their trips. However, prior studies, although limited, show differing effects for freight trucks [5,6]. For instance, due to re-routing, traffic volumes at the weather-impacted site may decrease while the neighboring sites may experience volume increases. Using truck GPS data, Pierce and Short [7] showed spatial volume shifts in truck traffic caused by flooding along Arkansas Interstate 40 in May 2011. The study showed that many trucks choose regional detours to re-route around the flooding closure [7].

Ordinary least square (OLS) regression is a commonly used method to measure the effect of weather events on total traffic volume [8,9,10,11,12,13,14,15,16]. The body of work related to the effects of weather on truck traffic volumes is considerably more limited. First, there are very few studies that model the effects of weather on truck traffic separately from that of total traffic due in part to limited truck count data. Previous studies on traffic volume variations due to weather events have used traffic data from fixed sensors such as Automatic Traffic Recorders (ATR) to obtain total traffic volumes and Weigh-in-Motion (WIM) sensors to obtain truck traffic volumes. Of all traffic sensors types, WIM provide the highest level of detail about the vehicle population. WIM sensors measure axle configuration, axle weight, vehicle length, and speed to predict vehicle type. Information on truck type allows analysis of weather related impacts to be determined solely for the truck population. Restricting analysis to semi-tractor trailer trucks allows for an even finer level of impact assessment on freight trucks since these types of trucks are responsible for the majority of freight commodity movements (single unit trucks, for instance, tend to be service or local delivery trucks).

Second, considering that trucks may choose to re-route rather than cancel a trip in the presence of adverse weather, it is necessary to incorporate spatial effects into explanatory models. Though OLS models can explain a normally distributed linear relationship, they are not suitable when dependent or independent variables show spatial autocorrelation. When spatial autocorrelation is suspected, spatial regression techniques are more appropriate than OLS. There are several reasons to consider spatial autocorrelation in truck traffic volumes as they related to weather conditions. First, as indicated by previous studies, trucks are more likely to re-route rather than opt out of traveling. This means negative spatial auto-correlation may exist in traffic volumes such that low volumes along the main route due to adverse weather correspond to higher volumes along alternate routes. Second, due to the inherent form of the highway network, spatial patterns of dependent and independent variables may exhibit spatially non-stationarity. For instance, the density of the road network differs across each region. In regions with high network density, detours around adverse weather may be more feasible compared to regions of low network density. Thus, there may be spatial correlation in traffic volumes if network density is not explicitly captured as an independent variable. Lastly, willingness to delay a trip due to a weather event may be contingent on the commodity transported, e.g. refrigerated and perishable goods would be more sensitive to delays than would manufactured products. As freight trip generation is tied to land use, it is possible that spatial autocorrelation exists due to commodity types.

OBJECTIVES

The goal of this study is to develop a predictive model that relates the spatial variations in long-haul, freight truck traffic volumes to weather conditions, with a focus on extreme weather events (i.e. snowfall, winter storms, flash flood, heavy rain, tornado, high wind, etc.). The main objectives of the study include:

i. Fusing fixed truck traffic sensor measurements (e.g. WIM data) with weather sensor data.

ii. Developing ordinary least squares (OLS) and spatial regression models to explain and predict the impact of weather events on truck traffic volumes and travel patterns.

iii. Investigating the feasibility of fusing static (e.g. WIM) and mobile (e.g. Global Positioning System, GPS) data to predict Vehicle Miles Traveled (VMT) and Vehicle Hours Traveled (VHT) impacts based on forecasts of extreme weather events

The study employs a spatial regression model to predict the percentage change in daily freight truck volume due to weather conditions including extreme heat and cold temperatures, wind speed, and precipitation. The spatial regression model incorporates (i) temporal data including historical truck volume trends, seasonality, and daily variations in traffic volumes, and (ii) environmental factors such as road type (i.e. interstate, highways, etc.).

A better understanding of the effect of weather events on truck traffic can help state and regional transportation agencies to develop freight-oriented programs and policies for winter road maintenance programs, extreme event maintenance, structural and geometric pavement design, highway life cycle analysis, and long-range transportation planning. Likewise, freight carriers need to understand how severe weather events impact the spatial and temporal traffic patterns of their trucks to better plan routes.

REPORT ORGANIZATION

The body of this report is organized as follows. The methodology section details the traffic and weather data sources and model specification. The results section compares the OLS and spatial regression models and interprets the significant coefficients of the spatial regression model. The report concludes by highlighting significant findings, noting limitations, and suggesting future improvements.

LITERATURE REVIEW

Multiple studies have examined the effect of extreme weather on total traffic volumes [4,9,6,11]. Studies show statistically significant reductions in total traffic volumes that result from winter storm events. Hanbali and Kuemmel [4] applied multiple linear regression (MLR) models to conduct a regional analysis covering 11 sites across New York, Wisconsin, Minnesota, and Illinois. They found reductions in total traffic volume between 8% and 56%, depending on the depth of the snowfall. In Iowa, Knapp and Smithson [9] reported reduction in total traffic volume between 16% and 47% during winter storm events characterized by more than four-hour durations of snowfall at 0.51 cm (0.2 inch) per hour. Similar to Hanabali and Kuemmel [4], Knapp and Smithson (*2010*) used MLR including independent variables representing snowfall intensity and total snowfall to predict the percent reduction in total traffic volume. Maze [6] found that strong wind and reduced visibility due to snow lead to traffic volume reductions as great as 80%. Dalta and Sharma [11] reported reductions of around 30% during periods with air temperatures below -25°C and reductions of 51% during periods of snowfall of 30 cm (12 inches) or more in Alberta, Canada. Dalta and Sharma [11] found that reduction in traffic volume due to snow and cold varies with day of week, hour of day, type of highway, and adversity of cold with traffic volume reductions of 80% during snowy days when the visibility is less than a quarter mile and wind speed is more than 40 mph.

Modeling efforts also revealed that roads carrying non-discretionary trips experience less volume reduction (0.5% - 1.7%) than the roads that carry recreational trips (0.5% - 3.15%) [11]. In their MLR model, the authors use historical traffic data, snowfall depth, temperature, and an interaction term on snow depth and temperature as independent variables. Keay and Simmonds [10] use OLS to predict the percentage change in traffic volume relative to the mean traffic volume. The authors developed two models, one for daytime and another for nighttime conditions, using historical traffic volumes, day of week, and rainfall as independent variables. Roh [12] used MLR to develop models predicting passenger cars and freight truck volume based on snowfall, temperature, snowfall-temperature interaction term, and four-year average of daily truck volume factors, i.e. expected volume for a given day of the week and day of the year.

Studies also find that in addition to extreme weather events other meteorological parameters, i.e. maximum temperature, minimum temperature, rainfall, wind speed, etc. can have an effect on traffic volumes [11]. Shang et al. [15] found that traffic volume decreased by 6% to 14% depending on the intensity of rainfall. Keay and Simmonds [10] found that 2mm to 5mm rainfall in the Spring reduced traffic volume by 3.43%.

Compared to the body of work related to total traffic, limited research exists on the effect of weather events on the spatial and temporal variations in truck traffic volumes. Roh [14] found that truck traffic increased during extreme winter storms, possibly due to trucks shifting away from secondary highways to primary highways that had higher priority in winter maintenance programs. In addition, the impact of weather on truck traffic was generally found to be similar for weekdays and weekends [12]. Similarly, Maze [6] found that, compared to passenger vehicles, trucks were less likely to divert trips due to inclement weather conditions.

Beyond developing a model specifically for truck traffic volume prediction, several novel expansions of the studies described above are presented in this paper: (1) improvements in the spatial and temporal scope and resolution of the traffic data and (2) expansion of existing modeling techniques to include spatial regression techniques. Eleven years (2005-2015) of daily truck volume data from six Weigh-in-Motion (WIM) stations and six corresponding weather stations in Arkansas are used to develop the spatial regression model. None of the studies mentioned above consider the spatial autocorrelation of weather and/or truck traffic volume. Therefore, in this study spatial diagnostic statistics are applied to an OLS model to determine then estimate an appropriate spatial model. Spatial Error (SE) and Spatial Lag (SL) models are considered in this study to predict the percentage change in truck volume due to extreme weather events (i.e. snow, flood, etc.), precipitation, humidity, wind gust speed, and extreme hot and cold temperatures with respect to day of week, season, highway functional classification, and historical trends in daily truck volumes.

METHODOLOGY

The study develops a predictive model that explains the spatial relationships between percentage change in truck traffic volume and weather conditions. The model incorporates traffic variables (Annual Average Daily Truck Traffic, AADTT and Expected Daily Volume Factor, EDVF), daily weather variables (i.e. humidity, precipitation, wind speed etc.), extreme weather events, seasonality, and network variables (e.g. highway functional classification). After detailing the data sources and pre-processing steps, a discussion of the model specification is provided.

DATA PRE-PROCESSING AND ANALYSIS

The study requires two types of data: (i) weather data to track the occurrence of extreme events and (ii) Weigh-in-Motion (WIM) data to measure truck volumes. The following section provides a brief description of the two datasets and the pre-processing tasks required to comply with later modeling efforts.

Weather Data

Since the WIM stations do not collect weather data, it was necessary to gather weather data from an alternate source. Daily and hourly weather data were obtained from the National Oceanic and Atmospheric Administration (NOAA). In addition, '5-minute' weather data from 40 weather stations were obtained from the Arkansas Department of Agriculture. The study used daily weather data for 11 years (2005-2015) to develop the regression model as it was more temporally complete and provided more weather parameters. Weather data includes:

1. temperature (°F)
2. dew point (°F)
3. wind speed (knots)
4. maximum speed (knots)
5. maximum temperature (°F)
6. minimum temperature (°F)
7. precipitation (inches)
8. snow depth (inches)

Since the main objective of this project is to know how weather affects trucks patterns, a deeper analysis of the weather parameter in the state of Arkansas was necessary to determine the distance to consider the weather as homogenous, this distance is called the 'cut-off distance'. The cut-off distance was used to pair each weather station with a WIM station. Next, extreme weather events were incorporated into the weather data set. Finally, a correlation analysis was performed to reduce set of weather variables to a statistically valid sub-set for regression modeling. The methodology developed for each task is described in this section.

Selection of Cut-off Distance for WIM-Weather Station Pairing

Roh [12] argues in his paper that homogenous distance for weather parameters varies from 15km to 24 km in Canada during winter. Tessier [16] states that weather is considered homogenous at a certain range depending on the area under study. As

Arkansas has different weather characteristics and topography than Canada, it was necessary to determine a new cut-off distance for this study.

A *cut-off* distance defining homogeneous weather patterns was defined to determine how to best pair of each WIM station with the nearest weather station when more than one weather station was located near the WIM site. First, the monthly average of each weather parameter was calculated. Next, a correlation matrix representing the Pearson correlation [18] between each pair of weather stations for each weather variable was calculated according to Equation 1:

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\overline{\frac{A_\iota - \mu_A}{\sigma_A}}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right) \qquad \text{Equation 1}$$

Where,

N = Number of observations
μ_A = Mean of A
σ_A = Standard deviation of A
μ_B = Mean of B
σ_B = Standard deviation of B

Next, the Euclidean distance between each pair of weather stations was calculated as per Equation 2. The resulting distances between each pair of weather stations was referred to as the distance matrix.

$$d_{st}^2 = (x_s - y_t)(x_s - y_t)' \qquad \text{Equation 2}$$

Where,

d_{st}^2 = Squared distance between two stations
x_s = Latitude coordinates of the station
y_t = Longitude coordinate of the station

Figure 1 shows the correlation (R^2) vs the distance (miles) for each pair of weather stations. To get the maximum possible homogenous weather pattern, the study fit a quadratic curve to the data and defines the *cut-off* distance. In the example shown in Figure 1, if the distance between two weather stations is 65 miles, the weather pattern is 94% homogenous. Thus, if the distance between a WIM and weather station exceeds 65 miles, then that WIM site cannot be included in the study.

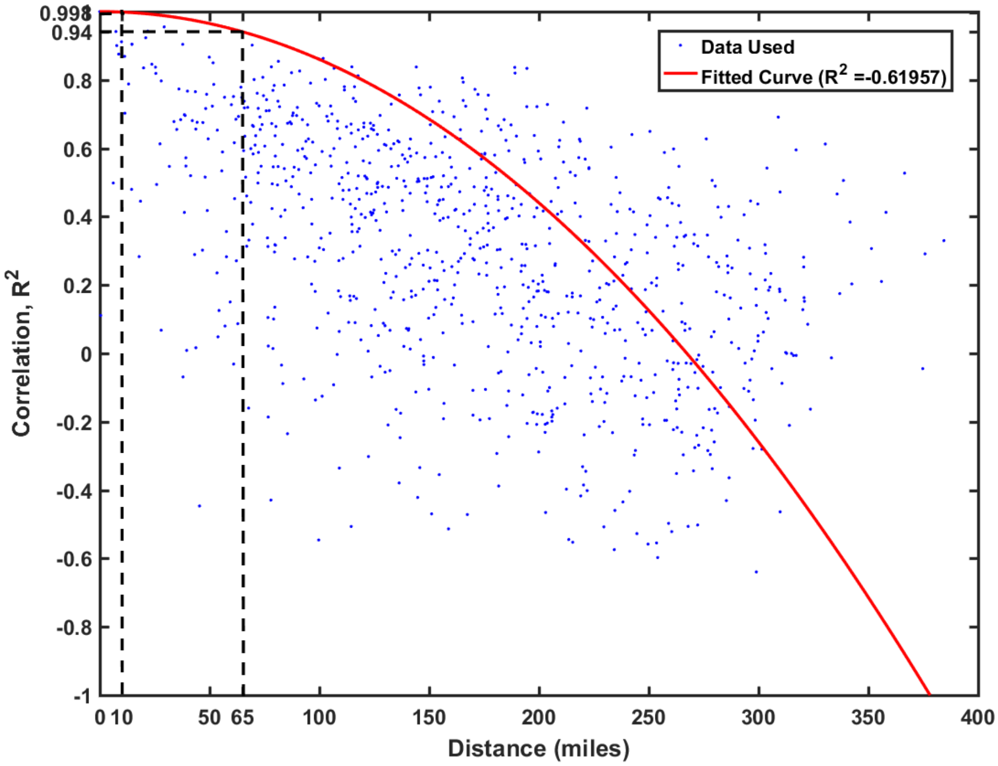

Figure 1: Correlation vs Distance for Precipitation in 2015

Extreme Weather Events

Extreme event data includes the time and date of the extreme weather event with a beginning and ending latitude-longitude, which represents the spatial extent of the event. The research team identified the nearest weather station for each event. Table 1 shows the number of extreme events in Arkansas during the study period of 2005-2015.

Table 1: Number of Extreme Events in Arkansas

Year	Number of Cold Events	Number of Precipitation Events	Number of Wind Events	Number of Heat Events
2005	4	335	71	28
2006	44	559	51	37
2007	125	402	24	39
2008	161	912	153	3
2009	103	996	61	4
2010	120	444	59	249
2011	156	981	105	490
2012	51	371	23	474
2013	120	358	41	148
2014	167	318	35	0
2015	157	628	29	61
Total	**1208**	**6304**	**652**	**1533**

Correlation Analysis

Correlation analysis was applied to the weather variables to identify possible multicollinearity among variables. The study used Equation 3 to calculate correlation coefficients:

$$r = \frac{\Sigma(x-\bar{x})(y-\bar{y})}{\sqrt{\Sigma(x-\bar{x})^2\,\Sigma(y-\bar{y})^2}} \qquad \text{Equation 3}$$

Where,

r = Correlation coefficient
x = First weather variable
y = Second weather variable
$\bar{x}$ = Mean of variable *x*
$\bar{y}$ = Mean of variable *y*

Temperature was found to be highly correlated to maximum and minimum temperature. Wind speed was directly correlated to maximum wind speed. Therefore, the study used temperature and wind speed in the regression analysis and omitted maximum temperature, minimum temperature, and maximum wind speed. Since dew point was correlated to temperature, the study removed dew point from the regression analysis. Moreover, the existence of snow, i.e. a binary variable, was used instead of snow depth variable to avoid multicollinearity. Lastly, humidity (%) was calculated using average temperature and dew point temperature (Equation 4) and serves as a proxy for the probability of precipitation. The use of humidity, extreme cold and extreme heat variables reduces the presence of multicollinearity among model variables.

$$H_d = 100 - \frac{25}{9} \times (t_d - d_d) \qquad \text{Equation 4}$$

Where,

H_d = Humidity of a particular date *d*
t_d = Average temperature of a particular date *d*
d_d = Dew point temperature of a particular date *d*

<u>Weigh-in-Motion (WIM) Data</u>

There are 69 WIM stations in Arkansas that collect temporally continuous traffic data. Data from six of the 69 stations was used in this study after applying the homogenous weather distance cut-off described in the previous section. Figure 2 shows the locations of WIM sites and corresponding weather stations. Five of the six WIM sites are located along the interstate and one is located along a non-interstate route. The location and site characteristic details for each of the WIM sites are found in Appendix A.

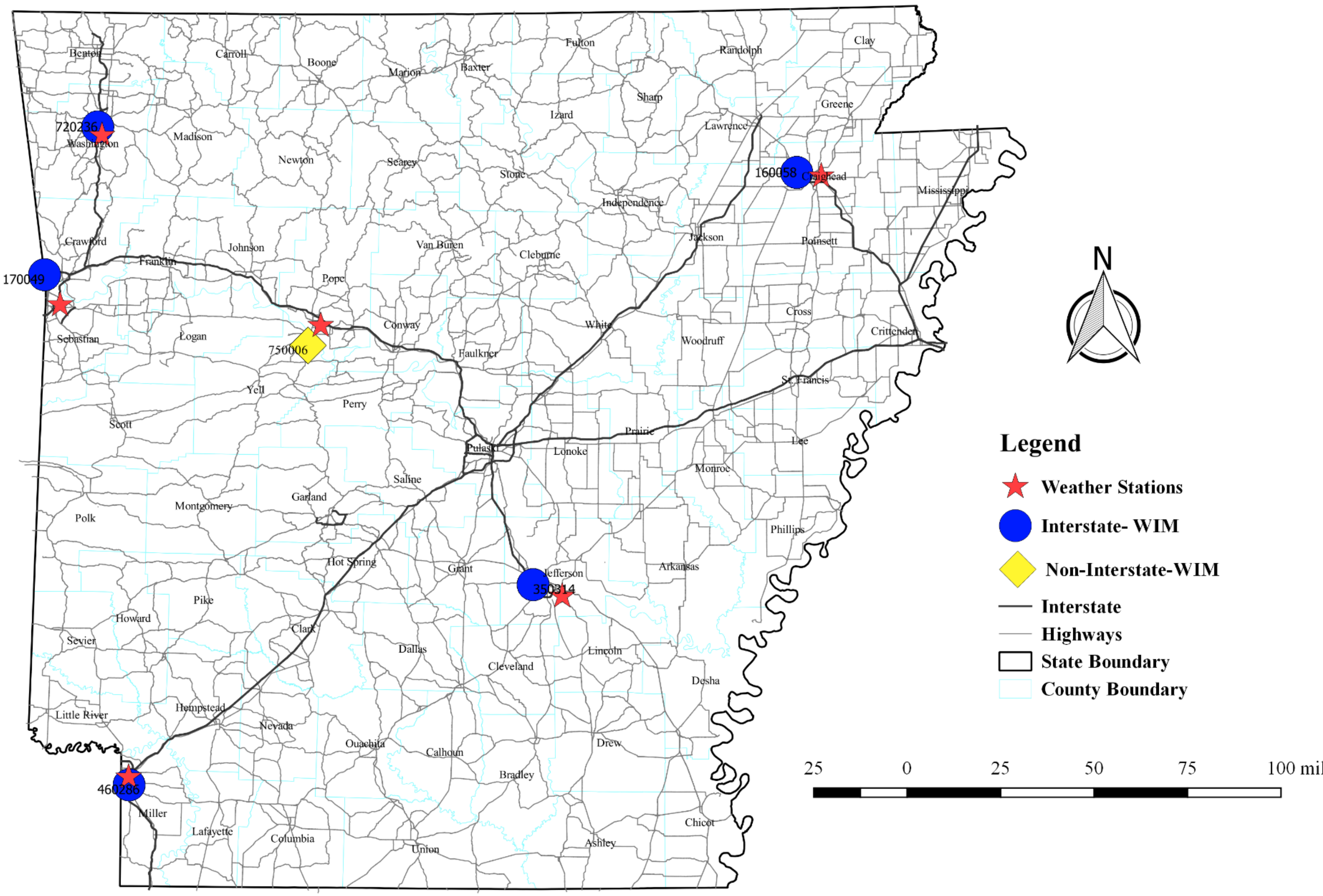

Figure 2: WIM Station Locations and Selection of Study Sites

WIM data includes timestamps, vehicle configuration (i.e. axle counts, axle spacing, and axle-based classification), and truck weight. The research team obtained 11 years of data (2005-2015) from the Arkansas Department of Transportation (ARDOT). The data was provided as “Per Vehicle Record” (PVR) data. PVR files contain the individual truck records. For this study, the PVR data was aggregated to hourly volumes by vehicle class from which Annual Average Daily Truck Traffic (AADTT) was calculated. All holidays were removed from the data before calculating model parameters. Highway Functional class (e.g. interstate, other freeways and expressways, rural principal arterial, another principal arterial, etc.) was gathered for each WIM site location. Road construction zone information was gathered from ARDOT for the dates corresponding to the study period [19].

In this study, we consider only the volumes of five-axle tractor-trailers, e.g. ‘3-S2’ configuration or FHWA Class 3 according to Scheme F, as these are most likely to be long-haul freight trucks. The volume of long-haul tractor-trailers, e.g. FHWA Class 9 or ‘3S2’ configured trucks, varies from year to year as shown in Figure 3 for 2010 to 2015. Figure 4 shows the average across all years (2010-2015). The highest truck volume was recorded in February 2012 while the lowest truck volume was recorded in September 2011. On average, 2013 has a lower truck volume throughout the year compared to other years.

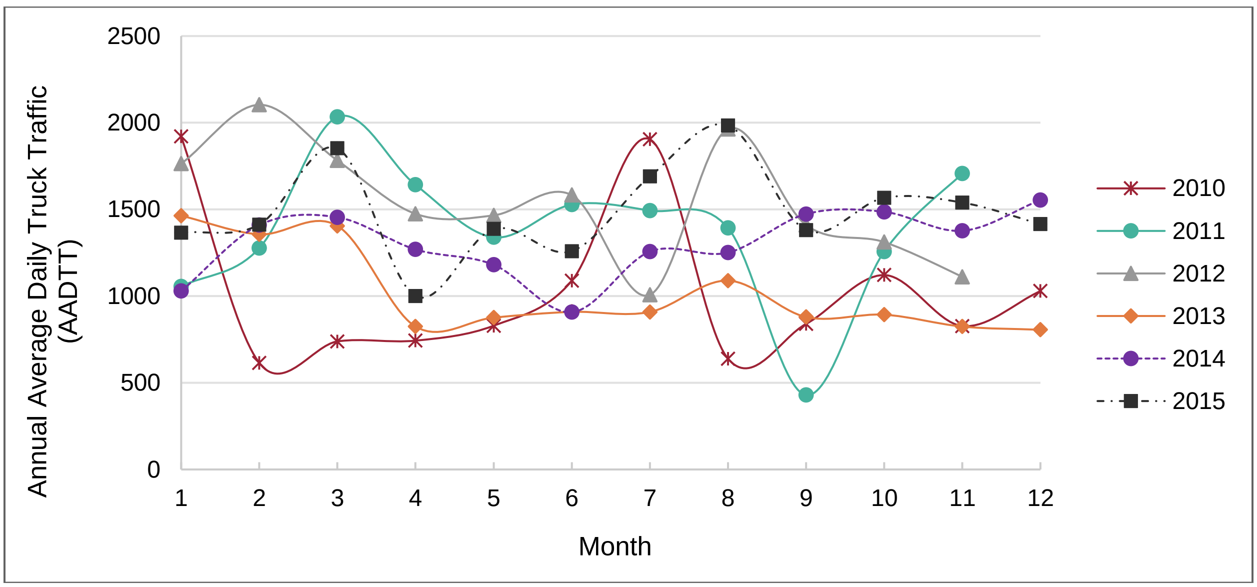

Figure 3: Average Daily Truck Volume by Month in Arkansas by Year from 2010-2015

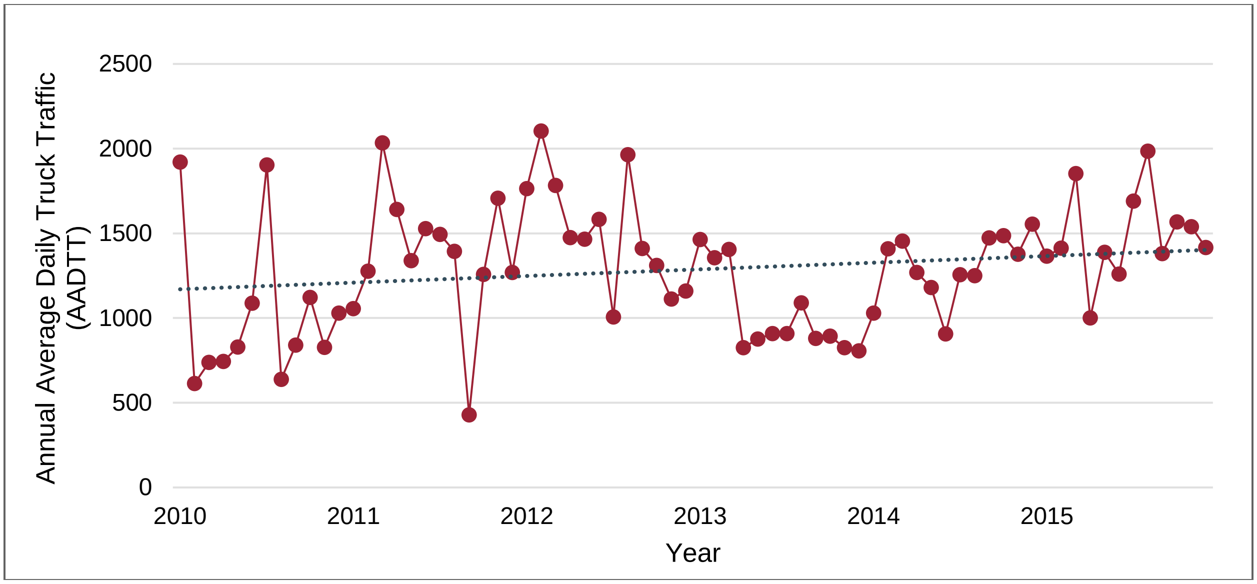

Figure 4: Average Daily Truck Volume by Month Across All Years from 2010-2015 in Arkansas

Figure 5 shows the average hourly truck volume of weekdays for 2010 to 2015. It indicates that all weekdays follow the same general pattern with a peak during the mid-day hours between 10AM and 4PM. Tuesday, Wednesday, and Thursday have the highest truck volume. Figure-5 also shows that truck volume varies with time of the day. 10AM to 4PM are the peak hours for truck movement having more than 40% of truck volume. After 4PM truck volume starts decreasing till 11PM.

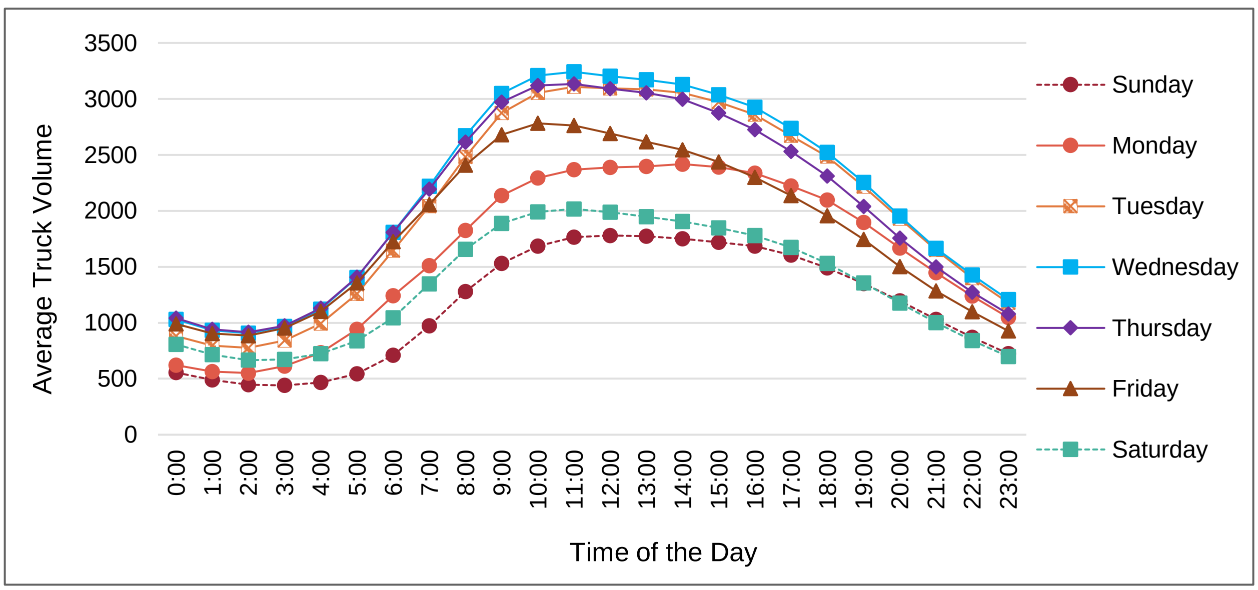

Figure 5: Average hourly truck volume of weekdays (solid) and weekends (dashed) (2010-2015)

This study uses historical truck volumes as an independent variable in the regression analysis. Specifically, the Expected Daily Volume Factor, EVDF. EDVF captures the historical trend of truck volume and is calculated according to Equation 5 [12]. It represents the average daily truck volume factor over a six-year period (2005 to 2010). This period was chosen based on available data.

$$EDVF_{i,j,k,s} = \frac{\sum_{r=2005}^{r=2010}\left(DVF_{i,j,k,yr,s}\right)}{6} \qquad \text{Equation 5}$$

Where,

$EDVF_{i,j,k,s}$ = Expected daily volume factor for a particular day *i* of the week (i.e. Monday, Tuesday), a particular week *j* of the month (i.e. Week 1 – Week 5), a particular month *k* of the year (i.e. January – December) of station *s*

$DVF_{i,j,k,yr,s}$ = Daily Volume Factor for a particular day *i* of the week (i.e. Monday, Tuesday), a particular week *j* of the month (i.e. Week 1 – Week 5), a particular month *k* of the year (i.e. January – December) of station *s* in year *yr* (i.e. 2005-2014) calculated as

$$DVF_{i,j,k,yr,s} = \frac{\bar{v}_{i,j,k,yr,s}}{AADTT_{s,yr}}$$

$AADTT_{s,\,yr}$ = Annual Average Daily Truck Traffic of WIM station *s* in year y*r*

$\bar{v}_{i,j,k,yr,s}$ = Average truck volume for a particular day *i* of the week (i.e. Monday, Tuesday), a particular week *j* of the month (i.e. Week 1 – Week 5), a particular month *k* of the year (i.e. January – December) of station *s* in year *yr* (i.e. 2005-2014)

The study uses the percentage change in daily truck volume ($y_{d,s,yr}$) relative to the AADTT ($AADTT_{s,yr}$) of each WIM station (s) as the dependent variable in the regression analysis. Equation 6, and Equation 7 show the formula to obtain the estimated $AADTT_{s,yr}$ and $y_{d,s,yr}$.

$$AADTT_{s,yr} = \frac{\sum_{d=0}^{N} v_{d,s,yr}}{N} \qquad \text{Equation 6}$$

Where,

$AADTT_{s,\,yr}$ = Annual Average Daily Truck Traffic of WIM station *s* in year *r*

$v_{d,s,yr}$ = Truck volume for a particular date *d* of station *s* in year *r*

N = Number of days in year *r* for which data was recorded

$$y_{d,s,yr} = \frac{v_{d,s,yr} - AADTT_{s,yr}}{AADTT_{s,yr}} \times 100 \qquad \text{Equation 7}$$

Where,

$y_{d,s,yr}$ = Percentage change in daily truck volume to the AADTT for a particular date *d* of station *s* in year *r*
All other variables as previously defined.

REGRESSION ANALYSIS

The study includes the independent variables listed in Table 2 to predict the percentage change in truck volume relative to the AADTT ($y_{d,s,yr}$). An ordinary least squares (OLS) regression model was estimated to determine the type of spatial model appropriate for the data.

Table 2. Model Parameters included in Regression Analysis

Parameter Group	Parameters
Historical traffic volumes	▪ Expected Daily Volume Factor (EVDF)
Weather variables	▪ Extreme heat[1] (e.g. temperature > 100 degrees F) ▪ Extreme cold[1] (e.g. temperature < 32 degrees F) ▪ Gust Speed (knots) ▪ Precipitation (inches) ▪ Humidity (%) ▪ Cold Event[1] (i.e. snow, winter storm, hail, fog, etc.) ▪ Heat Event[1] (i.e. drought) ▪ Precipitation Event[1] (i.e. flash flood, flood, heavy rainfall, etc.) ▪ Wind Event[1] (i.e. tornado, high wind storm, etc.)
Highway environment	▪ Functional Classification[1] (e.g. Interstate or Other) ▪ Presence of construction zone[1]
Temporal variables	▪ Day of week dummy variables (e.g. Tuesday, Wednesday, etc.) ▪ Seasonal dummy variables: fall (September, October, and November), winter (December, January, and February), and spring (March, April, and May)
[1]: Binary variables with ‘1’ representing the existence of an event/characteristic and ‘0’ the absence of the event/characteristic.	

Ordinary Least Squares Regression

OLS regression analysis is commonly used to explain relationships among weather variables and traffic volumes. OLS is the most common method for estimating multiple linear regression (MLR) models [20]. OLS provides a global model of the effect of the explanatory variables on the dependent variable and takes the form shown in Equation 8 [21]:

$$y = a_o + \sum_{k=1}^{n} a_k\, x_k \; + e \qquad \text{Equation 8}$$

Where,

y = dependent variable (Estimated daily truck volume)

x_k = Independent variables (i.e. EDVF, temperature, etc.)

a_k = coefficient of explanatory variable x_k

a_o = coefficient of intercept

e = disturbance term

Spatial Regression

An OLS model cannot explain the effect of the independent variables when there is spatial dependence. Instead, a spatial regression model is required. Spatial regression models explain the effect of the independent variables after removing the effect of spatial dependence. There are two common types of spatial regression models: Spatial Error (SE) and Spatial Lag (SL) models.

Spatial Error Model

SE models are appropriate when errors are spatially correlated due to random features associated with location and when both the dependent and the independent variables have spatial autocorrelation. SE captures the effect of the independent variables on the dependent variable after removing the effect of spatial dependencies from dependent and independent variables. Equation 9 shows the specification for an SE model.

$$(1 - \lambda W)y = (1 - \lambda W)x_k\beta_k + \mu \qquad \text{Equation 9}$$

Where,

y = dependent variable (e.g. $y_{d,s,yr}$)

W = Weight matrix of spatial model

x_k = explanatory variables (i.e. EDVF, temperature, etc.)

β_k = coefficient of explanatory variables, x_k

λ = Spatial autoregressive parameter

μ = a vector of homoskedastic and uncorrelated errors

Spatial Lag Model

SL models are appropriate when the dependent variable is spatially correlated. It means that spatial dependencies exist directly among the levels of the dependent variable. SL captures the effect of the independent variables on the dependent variable after removing the effect of spatial dependencies from the dependent variable. SL residuals show a random pattern while the OLS residuals have a non-random pattern and/or clustering. Equation 10 shows the formation of SL model.

$$(1 - \rho W)y = x\beta + \; e \qquad \text{Equation 10}$$

Where,

Wy = spatially lagged dependent variable

ρ = Spatial autoregressive parameter
e = a vector of error terms
Other terms as previously defined

Model Selection

A Lagrange Multipliers (LM) test was used to determine the specific spatial dependence of the data [22]. A LM test statistic is identical to Moran's *I* according to [22]. In this study, Moran's *I* value was -0.09 and significant at the 99% level of confidence, indicating a dispersed spatial relation in the data.

Next, a Robust Lagrange Multipliers test was used to determine the best spatial model for the study. The result of Robust Lagrange Multipliers test showed that a SL model is more representative of the type of spatial dependency in the data than the SE model. Therefore, a SL model was applied to predict the effect of weather events on daily truck volumes.

RESULTS

Based on the spatial diagnostic statistics, a Spatial Lag (SL) Model was applied to determine the effect of weather events on truck traffic volume. WIM and weather data from 2005-2015 was collected from six WIM and six corresponding weather stations. Data from 2005-2010 was used to compute EVDF while the data from 2011-2015 was used to estimate the model. Comparative results of the OLS model and SL model are shown in Table 3.

Table 3: Estimated Coefficients of OLS Model and Spatial Lag Model

Independent Variables	**OLS Model**		**SL Model**	
Constant	-31.18	* * *	23.61	* * *
EDVF	25.79	* * *	14.67	* * *
Interstate[1]	12.79	* * *	6.78	* * *
Construction	-4.52	*	-11.41	* * *
Tuesday[2]	10.74	* * *	12.12	* * *
Wednesday[2]	12.32	* * *	14.13	* * *
Thursday[2]	11.02	* * *	12.44	* * *
Fall[3]	4.93	* * *	4.90	* * *
Winter[3]	4.42	* *	5.93	* * *
Extreme Heat Day	2.63	* *	3.87	* * *
Extreme Cold Day	-7.82	* * *	-8.34	* * *
Gust Speed (knots)			-0.25	* * *
Humidity			-0.08	* * *
Precipitation (in)	-4.26	* * *		
Cold Event	-22.68	* *	-21.82	* * *
Precipitation Event	-8.97	* *	-12.73	* * *
Spatial Autoregressive Parameter, rho (ρ)			-1.73	* * *
Wald test of rho (ρ)			0.00	* * *
Likelihood ratio test of rho (ρ)			0.00	* * *
Lagrange multiplier test of rho (ρ)			0.00	* * *
No. of Observations	822		822	
Log-Likelihood	-3211.92		-3166.12	
R-Squared / Variance Ratio	0.47		0.52	
Adjusted R-squared/ Squared Correlation	0.46		0.53	
RMSE/ Sigma	12.15		11.35	

* * *significant at 99% confidence level; * * 95% confidence level; * 90% confidence level
1. Reference variable is Non-Interstate
2. Reference variable is Monday
3. Reference variable is Summer

The spatial autoregressive parameter rho (ρ) was negative (-1.73) for the SL model. Statistical evaluation including the Wald test, Likelihood ratio test, and LM test of rho (ρ) show that rho is significant at the 99% level of confidence. Rho (ρ) reflects the spatial dependence inherent in the data. Recall that the SL model explains spatial autocorrelation in the dependent variable, percentage change in daily truck volume ($y_{d,s,yr}$). It is measured as the average influence of observations by neighboring observations. The negative value of rho indicates that dissimilar values are in close spatial proximity, e.g. high values at one site correspond to low values at a neighboring site. Negative spatial autocorrelation captures the re-routing behavior of trucks in this study. Consider, for example, a constant total daily truck volume traveling along a primary and alternate route between an origin and a destination. If a weather event closes the primary route reducing its volume to zero, and all trucks must still make the journey from origin to destination, the alternate route will see an increase in truck volume. This is captured by the negative spatial autoregressive parameter.

The squared correlation represents the pseudo-adjusted-R^2 value of the spatial regression model. It signifies that the spatial regression model can explain 53% of the data while OLS regression model can explain 46% of the variance in the data. The SL model also has a lower log-likelihood value than the OLS model indicating a better fit.

Each of the significant variables not related to weather included in the estimation of the SL model are summarized as follows:

- The estimated parameter values of the SL model show that EDVF has a positive effect on the percent change in daily truck volume ($y_{d,s,yr}$). If higher volumes are expected for that particular station on that particular day based on historical data, then an increase is expected in the percent change in volume relative to AADTT, all else held constant.
- Daily truck volumes increase by 6.78% on interstate compared to non-interstate according to the SL model. This potentially captures trucks shifting to interstate routes from local routes since interstate routes provide straighter alignments and higher speeds and are more suitable for heavy-trucks.
- Presence of a construction zone on the route of the WIM site decreases truck volume by 11.41%.
- Tuesday, Wednesday, and Thursday have higher daily truck volumes relative to AADTT compared to Monday. The parameters for Tuesday, Wednesday, and Thursday were 12%, 14%, and 12%, respectively. This is similar to findings in previous studies. Hallenbeck [23] show in their paper that Monday truck volumes tend to be the lowest while Wednesday has the highest truck volume of a week (excluding weekends).
- Higher truck volumes are expected in fall and winter seasons compared to summer. The estimated parameters are approximately 5% and 6% for fall and winter, respectively. This is potentially due to fall and winter experiencing higher volumes due to the movement of agricultural goods during harvest (fall) and planting (winter). Considering the dominance of agricultural industries in Arkansas this is a feasible outcome. Hallenbeck [23] found that lower truck volume is seen in the winter months while higher truck volume is observed in the late spring through early fall. However, land use in the two study areas differ leading to these conflicting results.

Overall, controlling for day of week, season, facility type, and historical truck volumes, weather related variables in the SL model have varied impacts on daily truck volumes relative to AADTT. Results are summarized as follows:

- Extreme heat and cold have opposing effects on truck volumes with estimated parameter coefficients of approximately 4% and -8%, respectively. The occurrence of an extreme heat day indicates a higher truck volume, i.e.

positive coefficient, while the occurrence of an extreme cold day indicates a lower truck volume, i.e. negative coefficient, compared to AADTT. Extreme cold days correlate with the occurrence of snow, fog, hail, black ice, etc. Due to the inclusion of separate independent variables for extreme cold/heat, season, and extreme weather events, compounding effects are present in the model. For example, an extreme cold day (coefficient of -8.34% in SL model) occurs in tandem with a cold event (-21.82%) and would tend to occur during the winter (5.93%). Thus, the overall effect of a cold event is a decrease of 24.23% in volume relative to AADTT (-24.23 = -8.34-21.82+5.93).

- Truck volume is higher on days when maximum temperature exceeds 100˚F, e.g. extreme heat day, which would tend to occur in the summer months when volumes tend to be higher. However, summer is the reference variable for seasons and thus the extreme heat day variable can be interpreted independently. Heat events (e.g. drought) do not significantly affect daily truck volumes.
- Cold events (i.e. snowfall, winter storm etc.) and precipitation events (i.e. flood, heavy rainfall etc.) decrease truck volumes relative to AADTT. Both cold events and precipitation events may physically hinder truck movements depending on the severity of the event and the response time for special road maintenance, i.e. snowplowing, salt spreading, etc. In terms of the magnitude of the impact on truck volume, cold events like snow and ice are more dangerous for trucks than rain or heat. Therefore, cold events have the highest negative impact on the percent change in daily volume relative to AADTT in the SL model with an estimated coefficient of -21.82%.
- Gust speed and humidity are significant in the SL model but not in OLS model. These variables have negative effects on truck volumes after removing the effect of spatial autocorrelation. If gust speed increases by 1 knot, daily truck volumes compared to AADTT will decrease by 0.25% at that WIM site. Similarly, if humidity (the probability of rainfall) increases by 1%, daily truck volumes will decrease by 0.08% relative to AADTT.

CONCLUSIONS AND RECOMMENDATIONS

This study investigated the effect of weather on truck traffic volume. It considered the spatial variation of weather effects on truck volume through the application of a Spatial Lag (SL) model. The SL model has higher explanatory power than an ordinary least squares (OLS) approach. The SL model is able to explain 7% more variability in the data compared to the OLS model (the adjusted-R^2 of the SL model was 53% compared to 46% with the OLS model). The estimated model explains how one unit change in weather parameters (i.e. precipitation, humidity, gust speed, etc.) can affect the daily truck traffic volume relative to the Annual Average Daily Truck Traffic (AADTT), controlling for day of week, season, facility type, and presence of construction activities.

A historical truck volume factor, e.g. EDVF, was computed over a six-year period (2005-2010) to predict future truck volumes (2011-2015). Other weather variables i.e. humidity, gust speed, precipitation, extreme hot and cold days, and cold, heat, and precipitation events were used as independent variables in the model and found to be significant.

The study finds that the percentage change in daily truck volume depends on the type of road, i.e. interstates, day of week, season, and presence of construction. Monday has comparatively lower truck volume relative to AADTT than other days (i.e. Tuesday, Wednesday, etc.). Truck volume is higher during the harvesting season (Fall) and planting season (Winter) compared to summer season. The greatest reduction in truck volume is attributed to cold events (22% reduction in daily volume relative to AADTT), including snowfall, fog, hailstorm, etc. Precipitation events including flood, flash flood, and heavy rainfall decrease daily truck volume but to a lesser percent (13%). The difference in magnitude between the effects of cold events and precipitation events can be attributed to the severity of the event on drivability and safety.

While passenger vehicles may cancel a trip due to bad weather, truck drivers must stick to rigid schedules and thus choose to re-route rather than cancel a trip. The estimated model captures this effect through the spatial autoregressive parameter. In this study, truck volume presented statistically significant spatial dependency, specifically negative spatial autocorrelation. To capture spatial dependency, it was appropriate to estimate a spatial regression model, rather than adopt an ordinary least squares approach. Analysis using spatial modeling explains the re-routing behaviors of trucks in the face of inclement weather. A negative spatial autoregressive parameter indicates that neighboring values tend to be dissimilar, i.e. volume increases along a route are countered by volume decreases on neighboring routes for a fixed volume of trucks.

Results of this work can improve highway planning and maintenance operations. For example, the results of the model can support planning for winter weather maintenance. Specifically, scenarios of winter weather event frequency and severity can be evaluated using the SL model estimated in this study to determine truck volumes along various interstate and non-interstate routes. The results allow decision makers to prioritize winter maintenance scheduling based on freight impacts.

Improvements to the methodology described in this paper include expansion of the methodology to investigate spatial-temporal models and expansion of the dataset by using mobile sensor data. First, there is likely to be temporal correlation among traffic volume and weather variables. Not only may trucks re-route (e.g. spatial shift), they may also delay a trip (i.e. temporal shift), or there may be a temporal offset between the occurrence of a weather event and a volume shift. While the spatial lag model addressed spatial correlation, higher explanatory power is possible by explicitly considering temporal correlation among independent and dependent variables. Future studies will consider such temporal effects together with spatial effects with spatio-temporal models.

Additionally, this study used data from only six of 69 available WIM stations. Sixty-three WIM stations with quality truck volume data could not be used for the study because no weather stations were in close enough proximity to the WIM station. Instead of relying on static sensor data, e.g. WIM sites, as the dominate means of collecting truck volumes it is possible to measure approximate truck volume and activity using mobile sensors such as GPS. Using GIS tools, the number of trucks can be measured via GPS traces at each weather station. In this way, the study would not be limited to the WIM site locations, but could be expanded to a much more spatially diverse study area. The research team has already collected mobile sensor data from the American Transportation Research Institute (ATRI), a non-profit organization that collects and distributes GPS data from trucking fleets across the country. The raw data was processed as part of an ongoing ARDOT project (ARDOT TRC 1702, 2016). Raw pings were converted to truck trips which were then extracted for each WIM site. Trip length, number of stops, route used, origin/destination, and other freight characteristics were extracted from the processed GPS data. In future studies, the research team will collect truck volumes by time of day at each weather station using truck GPS data and use this to estimate OLS and spatial regression models to more fully capture the re-routing behaviors of trucks due to weather events.

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APPENDIX A
WIM STATION DESCRIPTION

Table A-1: Description of WIM and Weather Stations

WIM Site ID	Weather Station ID	Distance from WIM to Weather Station (in miles)	Latitude of WIM Site	Longitude of WIM Site	Latitude of Weather Station	Longitude of Weather Station	City of WIM Site	County of WIM Site	Interstate Number/ County Road Number of WIM Site
160058	723407-03953	13.40	35.85	-90.77	35.83	-90.65	Jonesboro	Craighead	63
350314	723417-93988	16.35	34.22	-92.07	34.18	-91.94	Pine Bluff	Jefferson	530
460286	723418-13977	3.45	33.42	-94.00	33.45	-94.01	Texarkana	Miller	49
750006	723429-53920	11.17	35.18	-93.16	35.26	-93.10	Dardanelle	Yell	7
170049	723440-13964	15.79	35.45	-94.44	35.33	-94.36	Dora	Crawford	40
720236	723445-93993	4.47	36.04	-94.19	36.01	-94.17	Fayetteville	Washington	49