Understanding oversize/overweight industry freight flow and safety in Kansas using the Kansas Truck Routing and Intelligent Permitting System (K-TRIPS)

by

Blake N. Moris

B.S., Kansas State University, 2017

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Civil Engineering
College of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2019

Approved by:

Major Professor
Dr. Eric Fitzsimmons

Copyright

Abstract

Oversize and overweight (OSOW) trucks are an integral part of traffic movement throughout the state of Kansas and the United States as a whole, along with the freight they haul. The unique dimensions (length, width, height, and weight) of these loads makes the movement of them more challenging, and less safe for all on the road. With key east-west and north-south interstate access, Kansas is many times a required pass through point for these OSOW trucks. The Kansas Department of Transportation (KDOT) developed an automated permitting system called the Kansas Truck Routing and Intelligent Permitting System (K-TRIPS) to award permits for all large trucks in the state, including OSOW trucks. Using four years of data from K-TRIPS (2014-2017), the research team developed a series of heat maps using ArcGIS to help visualize the routes OSOW trucks were using to travel through the state of Kansas. It was found that around 87 percent of the approximately 72,000 annual OSOW trips in Kansas were taken by five industries (general construction equipment, general freight, agriculture equipment/implements, wind energy, and oil and gas equipment), and that the majority of fluctuation in the consistency of routes travelled came from two industries (wind energy and oil and gas equipment).

The four years of K-TRIPS data, along with three years of crash data (2014-2016, provided by KDOT), were used to develop a logistic regression to determine factors that increased the odds of a fatal/injury (F/I) crash occurring among OSOW crashes. This was warranted due to the fact that the mass action areas aligned with the routes with the highest travel density, along with the discovery of two separate locations in the state with multiple crashes with the same sequence of events. It was found that three separate first harmful event (FHE) categories (Other non-collision, Motor vehicle in-transport, and Fixed object) were significant and all increased the odds of an F/I crash occurring, if they were the FHE. The odds of an F/I

crash were higher for an asphalt road than a concrete road. Lastly, the later into the day it was, the lower the odds are to be in an F/I crash.

The research team found a unique and important connection between yearly heat maps of OSOW truck routing and OSOW crashes. The mass action areas were found to have similar locations the highest-travelled routes during the three years of the dataset. These findings were similar to previous research that indicated through statistical analyses that when the percentage of trucks increased on a roadway, the amount of predicted crashes increased. This finding could be a primer for the state of Kansas to upgrade safety measures on known truck corridors that experience a high number of OSOW trucks. The ability to reduce fatal or serious injury crashes involving OSOW would have a positive net benefit for the state of Kansas, however considerable investment will be needed by the state to address all OSOW crash concerns.

Table of Contents

List of Figures

List of Tables

List of Equations

Acknowledgements

I would like to thank all of the people at KDOT who have been a part of this project: John Culbertson, Eddie Dawson, John Maddox, and Dominique Shannon. Without their support, this project would not have existed. Without their expertise, this project would not have been able to be completed.

I want to thank Jia Lang for his help in getting me versed in the language of logistic regressions. Without him, the odds of me understanding the model were much lower than the odds of it happening without him.

Thank you to my office mates: Mirza, Peng, and Jack. It is always nice to have friends around to bounce ideas off and to make sure what I am trying to say actually makes sense to other people.

Thank you to Dr. Fitzsimmons, not only for the opportunity to work on this project, but for all of your help throughout the process. From the countless meetings to the trips to KDOT, I am very grateful for the lessons I have learned and all of the opportunities he has given me.

Lastly, I want to thank my smart, beautiful, caring, understanding, and all-around amazing fiancée; Carly. Without her support, I know this whole journey would have been much more difficult. But on the other hand, she told me that I only had to start helping with the wedding planning once my thesis was done, so that is why I added an extra semester.

Chapter 1 - Background

Oversize and overweight (OSOW) freight movement across the United States are becoming more common as the need increases to move large infrastructure components across the highway system for such industries as large construction projects, wind-generation components, and fracking for oil. OSOW trucks often require special tractors, trailers, and pilot cars to ensure damage to the roadway network infrastructure are limited, including access areas and local roadways. These large, sometimes multi-axle vehicles, can encounter challenging roadway geometry such as horizontal curves with steep superelevation, roundabouts, and intersections with limited curb radii. Additionally, bridge structures not capable of handling such trailer configurations, including weight or dimensions, small communities with limited routes or roadways in poor conditions, or interaction with other passenger cars also present safety concerns.

The Federal Highway Administration (FHWA) defines mandated parameters for maximum weights on interstate systems. These include 80,000 lbs. gross vehicle weight (GVW) for a truck, 20,000 lbs. GVW for a single axle, and 34,000 lbs. for a tandem axle. The FHWA also states the federal width of a vehicle is to be 102 inches (FHWA, 2003). In addition to federal heavy-vehicle dimensions and weights, the state of Kansas defines large-vehicle dimensions and weight standards. These include a maximum of 80,000 lbs. GVW on interstates, and 85,500 lbs. GVW for all other roads. Tandem axle maximum weights are the same as the FHWA. Additionally, the maximum height of a vehicle [other than those carrying hay bales at 14.5 feet] is defined as 14 feet and 8.5 feet wide (KHP, 2018). In Kansas, a pilot car system is currently not required to accompany OSOW trucks; however, many haulers use pilot cars either due to extreme dimensions of the load that may influence a passenger car driver's behavior (e.g. wind turbine blades), or company policy.

OSOW trucks operate similarly to large semi-tractor trailers in which drivers receive the same training and must obtain the same credentials. Overall, the number of truck-related fatalities, for OSOW loads and all other large trucks, have been increasing in recent years. For example, 2009 had the lowest number of nation-wide fatalities involving large trucks since 1975 when the Insurance Institute for Highway Safety (IIHS) began keeping records of fatal crashes. The IIHS defines large trucks as any truck weighing more than 10,000 pounds. Since 2009, however, the number of fatalities rose from 2,223 to 3,986 in 2016, an increase of 79 percent. The number of truck-occupant fatalities in the same time span increased by 47 percent (from 449 to 660). In 2016, 92 percent of all fatalities in large-truck crashes occurred on interstates, freeways, and other major roads (IIHS, 2018). The state of Kansas has also seen a similar trend as the rest of the country in respect to large-truck crashes. The total amount of crashes in 2016 was 3,714, an 11 percent increase from the low of 3,195 in 2009. The amount of fatalities from those crashes increased by 22 percent in the same time period. In 2016, large trucks were involved in 5.3 percent of all crashes, but accounted for 18.9 percent of the number of fatal crashes in the state (KDOT, 2016).

A study by the Center for Transportation Research and Education (Hallmark et al. 2009) analyzed how roadway factors effected truck crashes. The research team found that location was one of the most significant variables in the crash rates of trucks. Urban roadways had higher crash rates than rural roadways did. The authors stated that this was because urban roads generally have a higher traffic volume than rural roads, but also because they are different road types as well. The study goes on to state that interstates are more likely to have truck crashes than other road types (Agent and Pigman, 2002) and that 16 percent of truck crashes happen at interchanges (Vallette et al. 1981), while another 40-50 percent occur on straight and level roads (Garber and Joshua, 1989).

Spainhour et al. (2005) noted in a study that evaluated track crashes in the state of Florida that urban locations experienced a higher crash rate than rural locations. It was found that rural crashes accounted for 55 percent of the total crashes, while urban and suburban crashes made up the remaining 45 percent. It was also noted that trucks are less likely to have fixed object crashes or crashes on an interstate ramp (Agent and Pigman, 2002).

A study conducted by Dissanayake and Amarashingha (2012) investigated the relationships between large truck crash probabilities, geometric characteristics, and traffic characteristics. The study used 6 years of data from KDOT, including the Kansas Accident Reporting System (KARS) and Control Section Analysis System (CANSYS) databases. Using a Poisson regression model and a negative binomial regression model, significant variables were found to have an effect on the occurrence of large truck crashes. Among the list of many significant variables that increased the amount of predicted crashes was the truck percentage. This means that as the truck percentage on a road increased, so did the predicted amount of crashes on that road.

A study conducted by Bittner et al. (2010) identified the industries that had the highest OSOW vehicle demands for the state of Wisconsin. The Wind Energy industry was seen substantial growth in the state, with up to a 39 percent average annual growth during a five-year period. While this improved the state's economy with bringing in thousands of jobs, the infrastructure damage took its toll. As the number of loads increased, local roads became damaged, bridges were subjected to loads in a higher quantity than ever before, and the traffic flows in the towns and communities needed to be changed to accommodate the large loads. The already low local budgets were struggling to keep up with the added reconstruction projects that large amounts of OSOW vehicles brought to a community. Another high demand industry was the Road and Bridge Construction industry. This industry was constantly and will continue to be one of the main drivers of OSOW movements through a state (Adams, 2013).

Russell and Landman (2012) conducted a study to optimize the analysis of routing OSOW through Kansas, in the hopes of providing efficient freight corridors. With OSOW load movement through the state having a positive economic impact on the state, the authors felt that developing a route system for OSOW loads to travel was worth the economic burden of providing the geometry needed for these vehicles to travel on. The study also noted that may fixed objects on routes can be difficult to navigate when driving an OSOW load, like bridges, wires, signs, signals, utilities, etc. (Russell and Landman, 2012).

In another OSOW study conducted in Kansas, Russell et al. (2013) looked at accommodating OSOW loads at roundabouts. They found that roundabouts should have a maximum truck apron, splitter island, and curb height of three inches in order to OSOW to safely use them without damage of the roundabout. The main cause of this finding was a special trailer type called a “low boy”. These trailers have a very low vertical clearance, and can catch on a truck apron larger than three inches (Russell et al. 2013).

Electronic permitting for OSOW trucks is becoming a more common tool for state highway agencies to implement. Electronic permitting allows for efficient permitting, safer routing, and also a catalog of the types of vehicles and goods that are being used on the roadway network. The Texas Department of Transportation (TxDOT) Motor Carrier Division has created a permitting system call the Texas Permit Routing Optimization System (TxPROS) (Middleton, 2012). TxPROS is a system that automates the OSOW permitting process. The major features of TxPROS include the following:

(1) Mapping: TxPROS uses a TeleAtlas transportation network along with the TxDOT roadway inventory data to illustrate the best route selected by the system for any given permit, given the current restrictions and impedances at the time of the application. (2) Restriction Management: This system has the ability to find and generate the best route to take, along with alternate routes for OSOW loads. At any given time, there are over 1,500 physical and temporal restrictions in place in the state of Texas, so a system that can take those ever-changing restrictions and give the optimum route is a necessity. (3) Routing: TxPROS incorporates a routing algorithm that uses the restrictions mentioned above and creates the optimum route, along with alternate routes, for the size and weight of load given in the permit application. (4) Reporting: TxPROS can generate reports on parameters including permit types and vehicle dimensions. These reports can help in identifying freight corridors, the impact of a certain restriction in a location, or even with researching the impacts of OSOW loads on congestion in a system.

OSOW truck permitting data have also allowed state highway agencies to adopt proposed policies. A study by Bilal et al. (2010) investigated OSOW truck permit and regulations from two neighboring states of Indiana, Ohio and Illinois. The research team collected data including fee amounts, fee structures, ease of permit acquisition and what dimension policies were in place. They found that the three states have not adopted set dimensional and weight values for OSOW trucks. It was also found that OSOW permit fees are significantly influenced by such input variables as trip circumstance, permitting criteria, trip frequency and distance. The researchers also noted that the states investigated had a revenue stream of over $12 million from trucking permits and that more information is needed to determine roadway deterioration from OSOW trucks and the optimal number of axles for a specified dimension or weight.

In summary, the research team found very limited research that specifically investigated OSOW trucks including crash experience, permitting, and routing. Most previous literature focused on large trucks in general and assumed OSOW trucks were part of this class of vehicles. However, as stated previously OSOW trucks have sometimes very different dimensions, types of freight, pilot cars, and turning radii which complicates the driving process for not only the truck driver but other vehicles on the roadway.

Chapter 2 - Research Objectives

Oversized and overweight truck movement continues to be a necessary part of the movement of freight across the country and within the state of Kansas. These multi-axle tractor trailers trucks spanning sometimes hundreds of feet and weighing more than a traditional semi-truck provide challenges for not only the state highway agency but local communities and other drivers. Although a significant breadth of research exist that has investigated large truck operations, safety, and crash experience, very limited research has been conducted to specifically look at OSOW vehicles. The research team noted that much of the previous literature combines OSOW trucks with traditional heavy trucks when considering crash experience. The primary objective of this research study is to fill the identified research gap and determine where OSOW trucks are traveling within and through the state of Kansas using KDOT's K-TRIPS database, which has not previously been evaluated.

Secondary objectives include evaluating which industries have applied for OSOW permits, where are they traveling, and whether there are yearly trends among the data. Finally, the research team will perform a safety analysis of OSOW truck crashes in the state of Kansas and develop a statistical model to determine commonality of these crashes to predict crash severity using significant variables.

This thesis is comprised of four chapters. Chapter 1 includes the study background and literature review; Chapter 2 covers the research objectives; Chapter 3 details the research methodology, gives analysis and discusses the results of the K-TRIPS study, and covers the OSOW crash study; and Chapter 4 discusses the significant finding of the thesis. In addition to the four chapters there are: a list of references; Appendix A, which gives the full K-TRIPS permit cost list; and Appendix B, which shows the code used to develop the logistic regression used in this study.

Chapter 3 - Research Methodology

To haul an OSOW load across or within the state of Kansas, a truck operator, trucking company, or forwarder must register its load with the Kansas Department of Transportation (KDOT), who will issue a one-time or indefinite permit. A relevant permit price list for this project can be found in Table 3.1, while a full K-TRIPS permit price list can be found in Appendix A.

OSOW permit distributions are administered by a software package called the Kansas Truck Routing and Intelligent Permitting System (K-TRIPS), which is a simple secure interface to input vehicle data for all large trucks that travel through Kansas. K-TRIPS has been in operation since December 2013 and catalogs data collected for each permit, which can be extracted at a later time for analytics. It should be noted that K-TRIPS can only give information on permits that were awarded to companies who apply for one, as many OSOW vehicles travel across or within the state of Kansas without a permit. Any OSOW load without a permit is subject to being stopped by a law enforcement officer and could potentially have to redistribute or unload the cargo (Uniform Act, 2016). For the purpose of this study, a permit awarded was the same as a trip taken.

The research team requested OSOW permit data from a private consultant who manages the K-TRIPS system for KDOT. Four years of data were extracted (2014 – 2017) as shapefiles (.shp). A total of 288,642 permits were issued by KDOT during the four-year period. Over these four years, it was found a drop in the number of OSOW permits, as shown in Table 3.2, which was approximately 633 fewer OSOW permits per month in 2017 than in 2014.

Table 3.1: K-TRIPS permit price list (K-TRIPS, 2018)

Permit Type	Price
Standard Annuals	$150.00
Overdimension Oversize and/or Overweight	$20.00
Overdimension Poles, Beams, and Girders	$20.00
Overdimension Large Structure	$30.00
Overdimension Superload	$50.00
Harvest Overdimension	$10.00

Table 3.2: OSOW permits by year in the State of Kansas

Year	OSOW Permits	Change from Prev. Year
2014	75,571	-
2015	74,735	836
2016	72,966	1,769
2017	65,370	7,596

The private consultant provided monthly permit data and every row entry of the database was a permit issued. Variables for each permit included: permit ID, permit type, GVW (lb), length of vehicle (inches), width of vehicle (inches), height of vehicle (inches), industry code, load description, origin, destination, number of axles, axle span, axle weight, axle width, and proposed trip length. Table 3.3 summarizes this data including the corresponding minimum, maximum, and average values for each variable. A unique feature K-TRIPS offers permit applicants is a recommended route based on the variables inputted by the applicant. Although drivers of OSOW vehicles have the sole discretion of the final route to take, K-TRIPS does provide critical information of routes in Kansas, especially when an OSOW vehicle has to cross over or under a bridge structure. Unique trucks and OSOW superloads, in many instances, may need KDOT to conduct an engineering study on bridge structures if K-TRIPS flags the vehicle description and proposed destination.

Table 3.3: Permit variables: minimum, maximum, and average values

Variable	Minimum	Maximum	Average
Permit ID	-	-	-
Permit Type	-	-	-
GVW (lb)	14	1,307,000	133,606.4
Length (in)	36	5,134	1,141.3
Width (in)	2	1,608	137.1
Height (in)	1	480	169.0
Index Code	-	-	-
Load Description	-	-	-
Origin	-	-	-
Destination	-	-	-
Number of Axles/veh.	7.49	7.79	7.6
Axle Span (in)	0	2,136	139.9
Axle Weight (lb)	1	61,400	18,038.3
Axle Width (in)	0	282	112.0
Trip Length (mi)	0.1	1,323	198.3

3.1: ArcMAP Model – No Special Characters

The geographical information system (GIS) ArcMAP was used to analyze these data. The suggested routes the K-TRIPS system generated were placed over a map of roadways in Kansas. This was done to get a better visual representation of where the OSOW loads were traveling. ArcMAP has tools that can organize datasets to whatever combination is desired. In this case, the data were received in 48 separate .shp files, but the research team wanted to see how trip routes change from year to year or how different industry's routes changed on a yearly basis. Using the organizational tools available, ArcMAP had the ability to create models to get data into the desired order and grouping.

Two different models were used to extract data from the monthly files. Some industries could be run as an iteration, as they didn't have any character restrictions such as hyphens or dashes while some had to be run individually using a different model due to the before mentioned character restrictions. For example, the model shown in Figure 3.1 was created to make files for each individual industry that did not have a special character in the name of the industry code. Figure 3.1 shows the coding blocks and features used for the iteration process.

First, the desired industry names were entered into the 'Multiple Value' parameter control. The list of names was then inputted into the 'Iterate Multivalue' iterator. This function reads each industry name, one at a time, and outputs them into the 'Value' variable. For example, when this model is executed, the 'Iterate Multivalue' iterator takes the first value shown in the 'Multiple Value' parameter control (which in this case would be "General Construction Equipment") and puts it into 'Value'. This value is what the variable will remain until the model has completely finished one cycle, then the model will move to the next name on the list until every name within the 'Multiple Value' parameter control has been used. After the 'Value' variable is set, the model then moves on to the 'Select Layer by Attribute' tool. The dialogue box is shown in Figure 3.2.

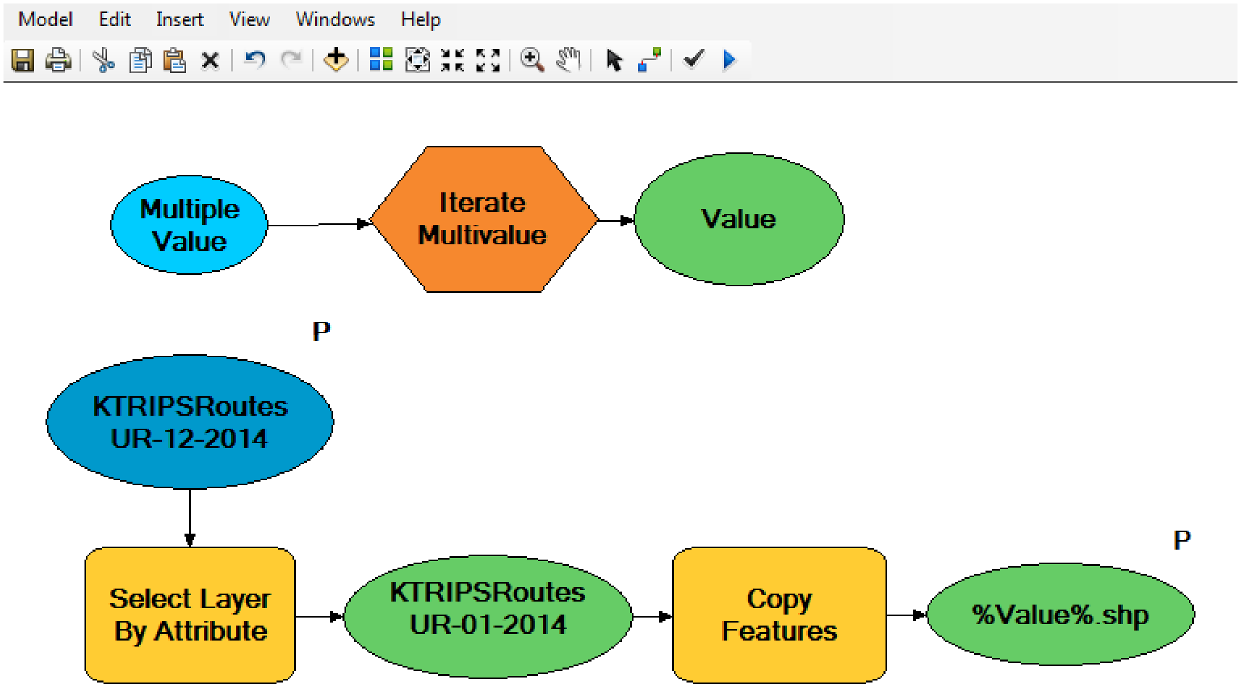


Figure 3.1: Model used to create industry files - no special characters

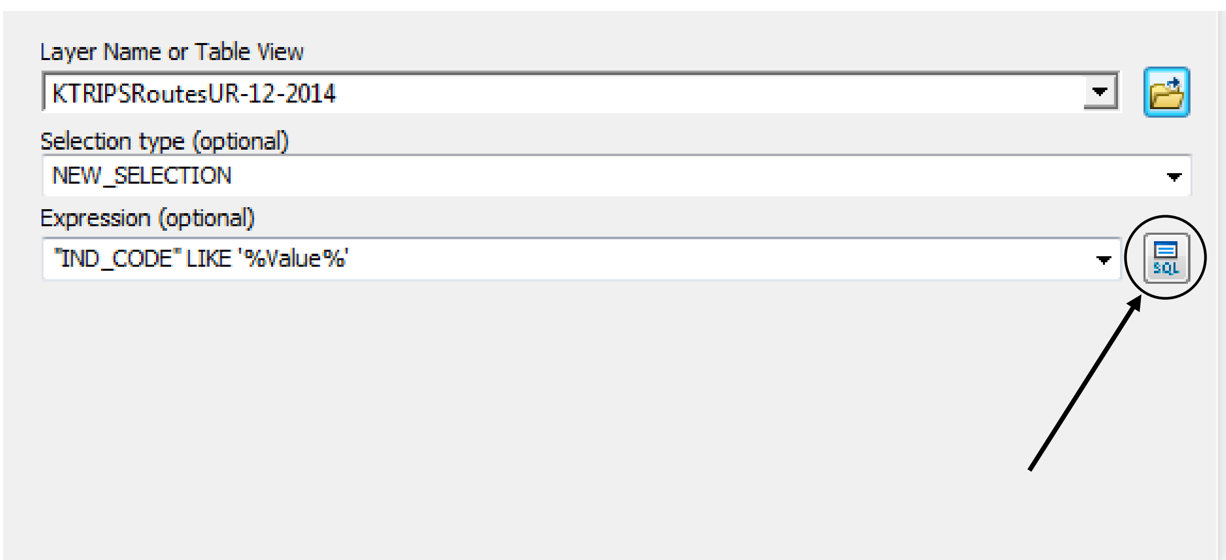


Figure 3.2: 'Select Layer by Attribute' tool dialogue box

The first input line shown in Figure 3.2 is for the file that will be run, which were the individual monthly shape files for this study. The selection type was set as 'NEW_SELECTION' so that when the model was iterated through, it only selected the trips for that industry, and not any other industry. The expression input was what tied this part of the model to the iterative tool. The SQL button, which is circled in Figure 3.2, opened up a dialogue box called a query builder that helped build the desired expression. This query builder is shown in Figure 3.3.

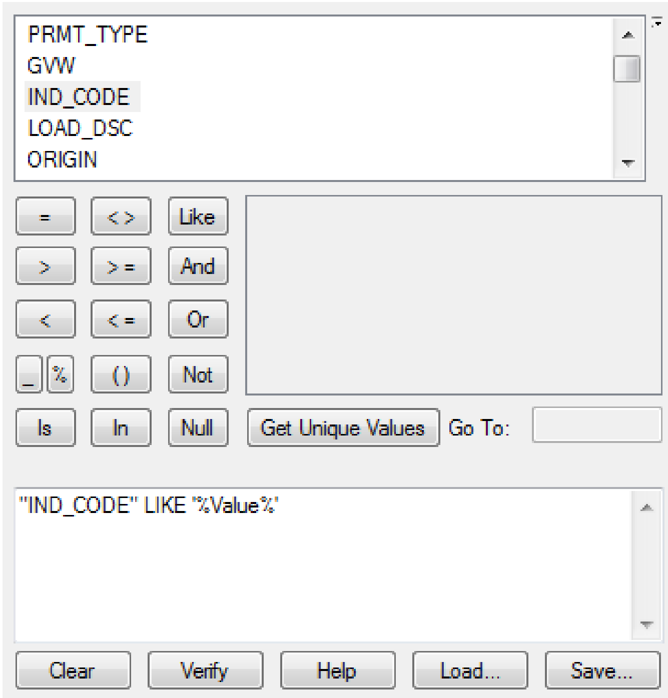


Figure 3.3: 'Query Builder' dialogue box

The query builder had a list of all of the fields within the file being used in the 'Select Layer by Attribute' tool. IND_CODE was selected so the model would search through the types of industries, 'LIKE' was selected so the model would know to search for names similar to the value in whichever variable is to be listed next in the query, and %Value% was used so the model knew to search for the Industry code that was like the name that was currently in the 'Value' variable. With all three of these fields identified, the 'Select Layer by Attributes' tool created a temporary file with just the trips that had the Industry code that was being held in the 'Value' variable. This temporary file was then the input file of the 'Copy Features' tool. This tool copied all of the features in the input file and created a separate file with just the information that had been selected in the 'Select Layer by Attributes' tool. The location of the file was given as '%Value%.shp' to create a shapefile with the name of the industry it belonged to. The file was then inputted to the 'Select Layer by Attribute' tool, and the model could then run its course. The file input name and the file location output were both made into model parameters, so they could be changed with each month of data and each different industry.

In summary, this model used an inputted file and selected all of the data points that have the value that is next in the 'Iterate Multivalue' tool. It then copied all of those trips and made a separate shape file for each industry that was identified. Finally, it saved the files under the name of the industry. This process was done for each of the 48 months in the data set. This model worked extremely well except for the fact that ArcMAP will not save files with special characters, such as – or /, so none of the industries with these characters could be run using this model.

3.2: ArcMAP Model – Special Characters Included

A similar model as to the one shown in Figure 3.1, was created for the industries with special characters in their name; this model is shown in Figure 3.4. The main difference is this model was unable to iterate through each industry file, they had to be run individually.

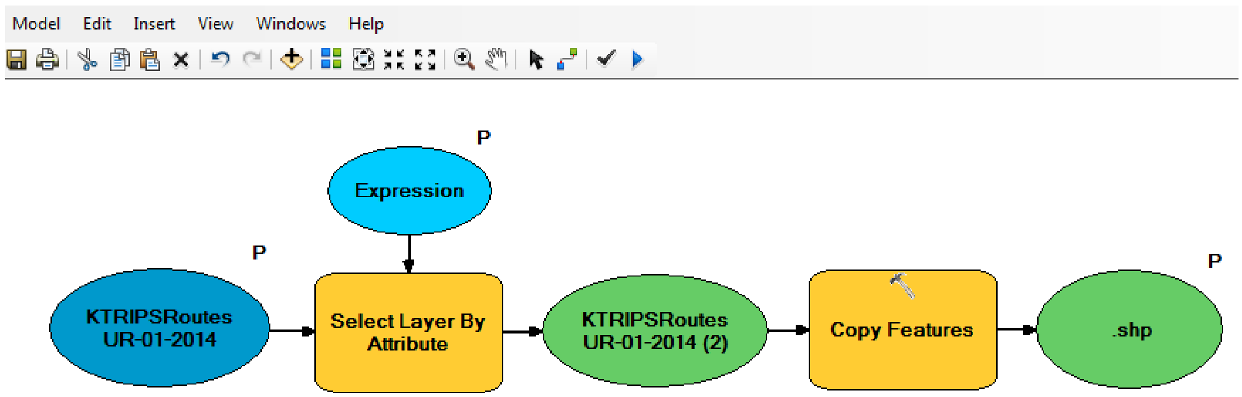


Figure 3.4: Model used to create industry files - special characters included

As shown in Figure 3.4, the second model developed had the ability to change what was selected from the files; it does not just have to be the industry code. The 'Expression' parameter had the same dialogue box as Figure 3.3, and could select whatever parameter was needed. For example, a specific permit type, weight of vehicle, or destination of the truck. The only drawback found with this model was that each industry needed to be inputted individually so ArcMAP could save the files. For example, if the industry code was "Wind Energy – Tower Section", the file would need to be saved as "Wind Energy Tower Section" for the program to save to a folder. This had to be done manually in the '.shp' model parameter for each run of the model. After creating separate files for each industry and specific permit types, each file for each month was combined, using the 'Merge' tool, for each year. This resulted in four different files (one for each year) for each industry, as well as all of the different permit types. The same merging process was performed for each month of each year, to make four separate files representing every trip from each year. In total, 92 different files were created; 22 different industries/permit types for four total years, as well as four full year files.

Each of the 92 developed files then had the 'Kernel Density' tool run on them. The Kernel Density tool "calculates a magnitude-per-unit area from point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline (Kernel, 2017)”. This function outputted a “heat map” that illustrated, in the case of this study, the density of trips along certain roads throughout the state of Kansas. The higher the density, the more trips there were within that area. The scales of each industry were set to be the same for all four years of data in order to show how the flow of the loads might have changed over the time period. A heat map was needed because, as Figure 3.5a shows, the number of trips on any given section of roadway could not be identified visually looking at the raw shape file. Figure 3.5a and Figure 3.5b illustrates what a file looked like prior to, and after running the Kernel Density tool.

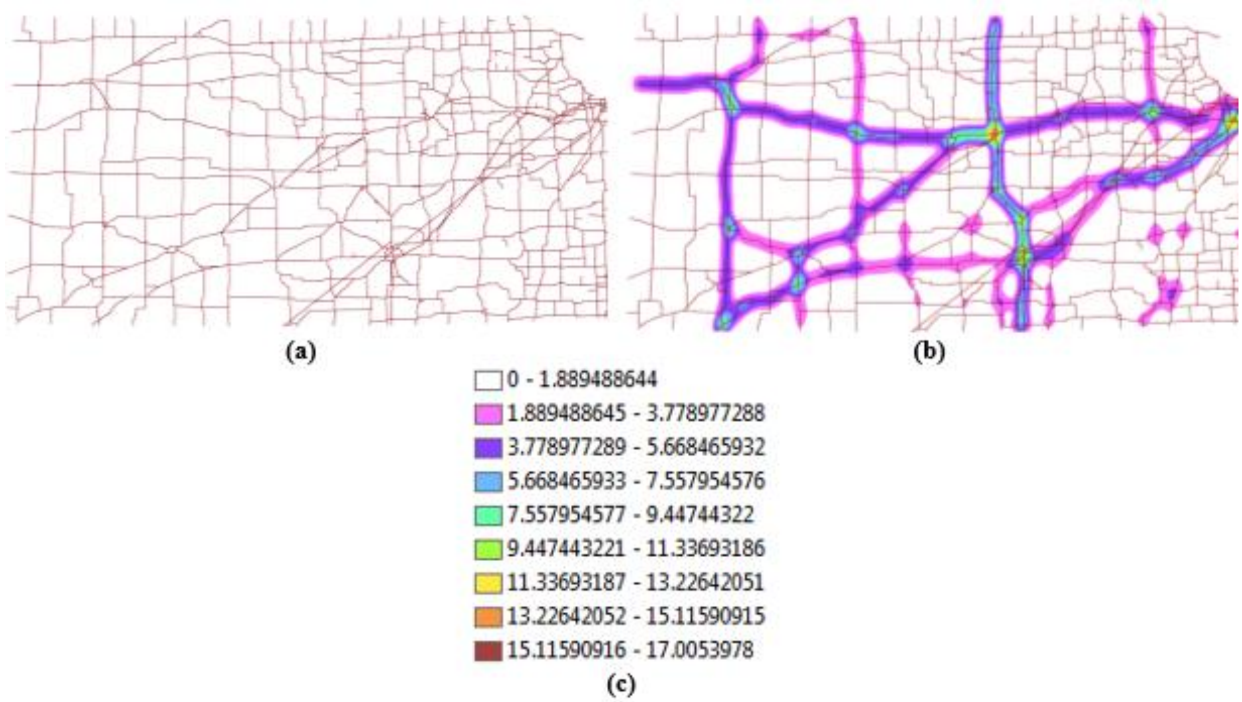


Figure 3.5: Kernel Density results

Shown in Figure 3.5, the legend that Kernel Density creates, is the actual density, or the total length of trips within a search area. The map area was set in decimal degrees, in order to input latitudes and longitudes of crash data later in the study. However, this did not create density magnitudes that are commonly used. The units that were created by the Kernel Density were $\frac{\text{Decimal Degrees}}{\text{Decimal Degrees}^2}$. The main take away from these maps is to see how the flow of OSOW vehicles throughout the state, for certain industries, changed from year to year. Each file had an attribute table that gave each vehicle's dimensions, weight, load type, etc., but the length of each trip was not recorded. The trip length was then calculated by ArcMAP and added to the table for each industry. The tables from each file were then exported to Microsoft Excel, graphs and charts were then produced to better visualize how the data changed throughout the four years, as well as how much they stayed constant.

3.3: Data Introduction

As stated previously, K-TRIPS provides a wealth of information through user inputted variables to understand freight movement through the state of Kansas through an electronic permitting system. Similar to regular large trucks, the variables coded into K-TRIPS are similar for OSOW trucks (e.g., GVW, dimensions, number of axles, etc.). The research team was particularly interested in the industry code and where significant industries are hauling OSOW freight within or passing through the state of Kansas. Using ArcMAP, the research team joined the monthly OSOW permit .shp files to create yearly .shp files to investigate possible changes (if any) in routing from year to year. Each month was also separated into the individual industries, and then merged together to have complete year files for each industry. Shown in Figure 3.6 are the number of permits for each industry type per year for four consecutive years.

Industries were arranged by total number of permits over the entire study period, with each year being represented separately. It was found that five different industries filed the most permits with KTRIPS which included: general construction equipment, general freight, wind energy, oil and gas equipment, and agricultural equipment/implements. These industries were responsible for 252,115 of the 288,642 of the total number of OSOW permits, or approximately

87 percent. Additionally, these five industries were evaluated in two different ways; steady or fluctuating industries.

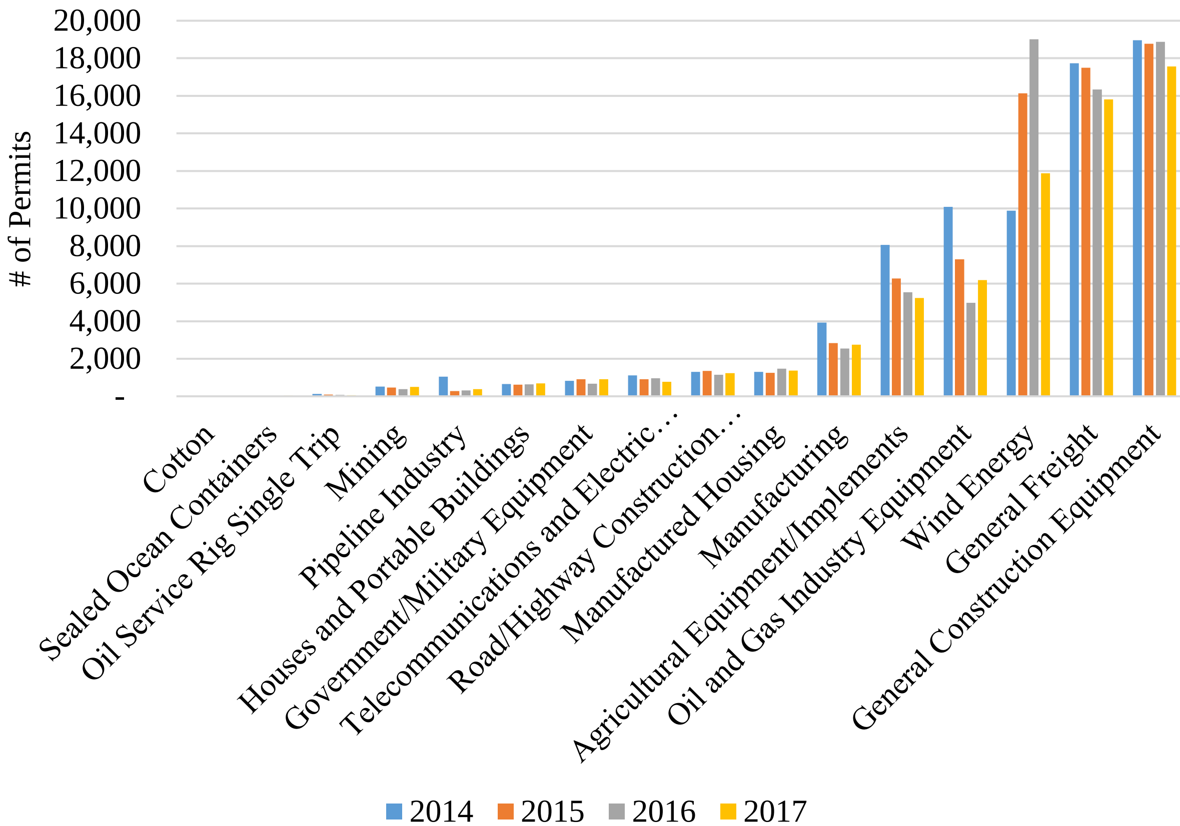
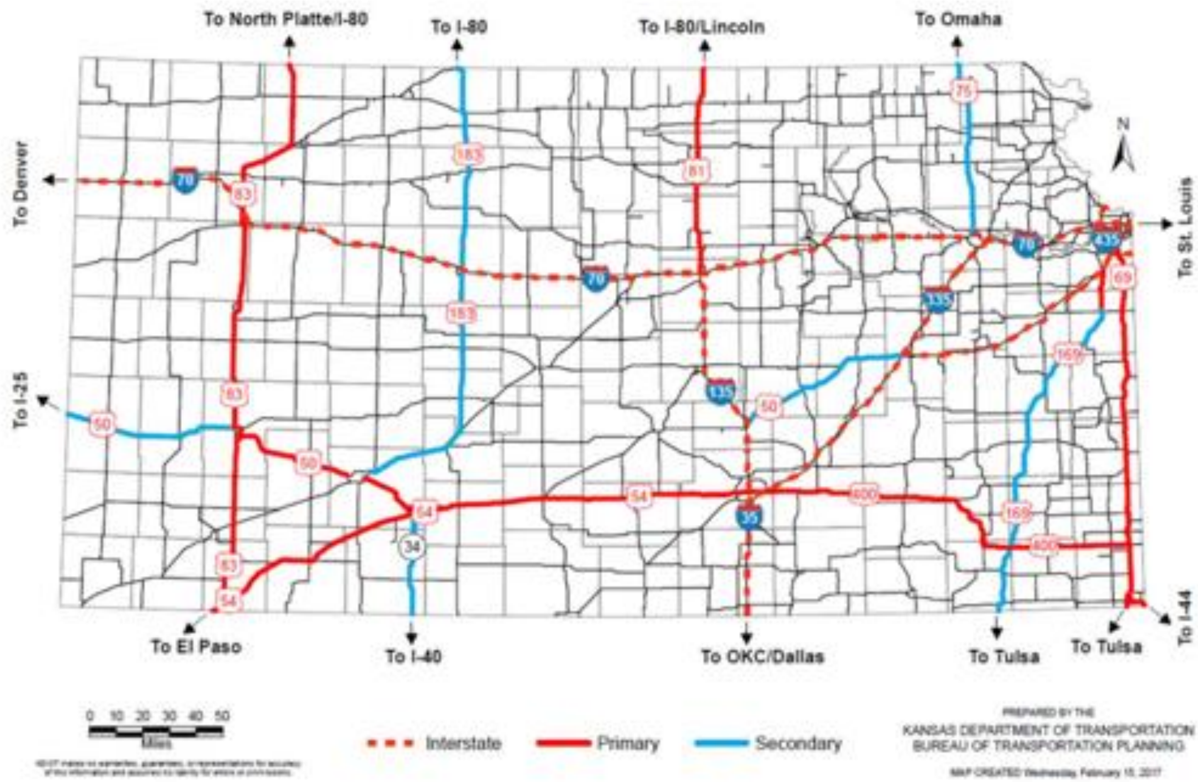


Figure 3.6: OSOW permits for type of industry (2014-2017)

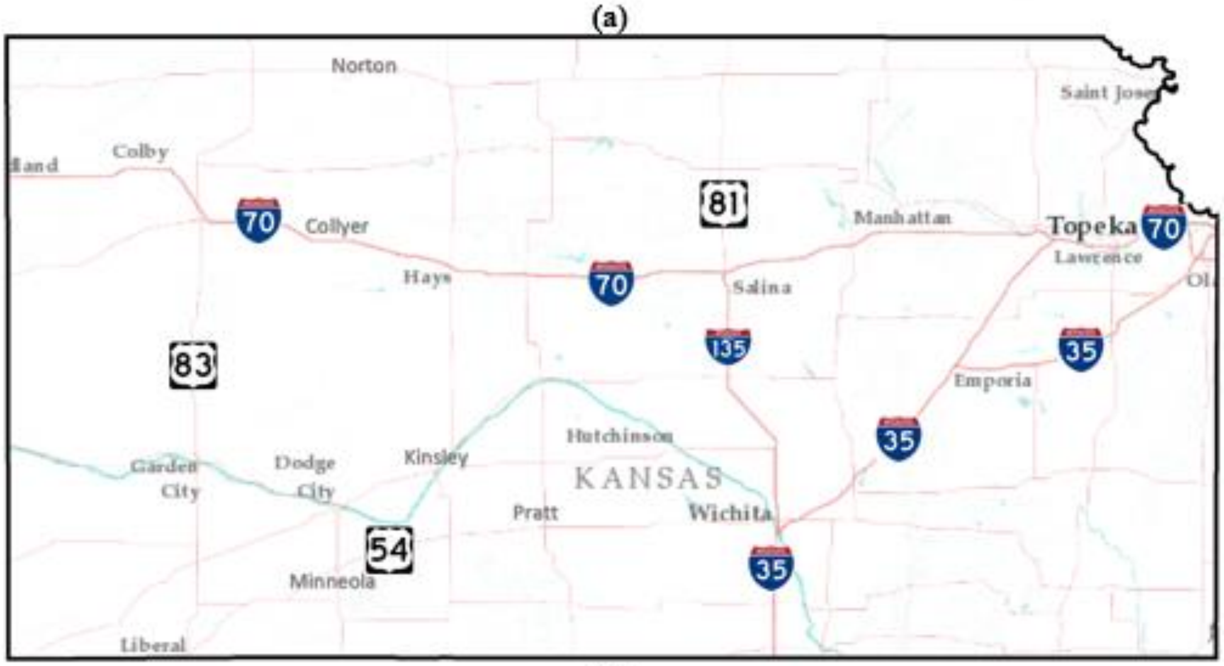
As shown in Figure 3.6, the general construction equipment, general freight, and agriculture equipment/implements industries were considered steady industries, based on the consistency of routes travelled and the limited changes in the number of trips taken each year. General construction equipment was found to have the highest number of trips taken over the four-year study period with a total of 74,169 trips, an average of 18,542 per year. This industry was also the most consistent of the top five in the number of trips made per year, with only a 7.3 percent fluctuation between the highest and lowest permit counts within the study period (18,953 in 2014 to 17,564 in 2017). General freight and agricultural equipment/implements had similar trends, with 10.8 percent and 35.1 percent fluctuations, respectively.

The other two industries found to have a high number of OSOW permits were wind energy and oil and gas equipment. These two industries were considered fluctuating industries, because of the variation in the number of trips taken, as well as the routes travelled during the trips. The wind energy industry was the best example of a fluctuating industry. The number of permits needed were based on how many wind turbines components needed to be shipped out of the lay-down yards around the state with the largest lay-down yard located in Garden City, Kansas. KDOT corroborated, as Figure 3.6 illustrates, that 2016 was a very busy year for the wind energy industry which resulted in a higher number of permits. The data also indicated the industry as a whole saw a 17.8 percent increase in trips from 2015, and a 92.5 percent increase from 2014. A total of 19,016 trips by the wind energy industry in 2016, the highest amount of any industry during the study period. A shown in Table 3.6, in 2017 the demand lowered, and the number of permits fell by 37.5 percent to only 11,877. While the wind energy industry experienced an increase in the number of trip numbers, the oil and gas equipment industry was also experiencing a decrease in the number of trips. The oil and gas equipment industry saw a 50.6 percent decrease in trips from 2014 to 2016 (10,082 to 4,978 permits), followed by a 24.2 percent rebound in 2017 (6,185 permits).

Besides understanding which industries apply for OSOW permits most often through the K-TRIPS system, the research team was also interested in where these OSOW trucks were traveling. As stated previously, K-TRIPS provides recommended routes for OSOW trucks to travel based on their load-inputted data. Additionally, in 2016, KDOT designated specific Interstate and U.S. Highways within Kansas as freight corridors. Figure 3.7a shows freight corridors, and Figure 3.7b provides interstate and highway locations compared to communities in Kansas as a reference (KDOT, 2017).



(a)



(b)

Figure 3.7: (a) Freight corridors of significance (KDOT, 2017); (b) Significant interstates, highways, and communities in Kansas

As shown in Figure 3.7a, three types of roadways were identified which included Interstates, U.S. Highways, and Kansas secondary states highways. These corridors were identified by the Kansas Freight Advisory Committee based on the National Highway Freight Network (NHFN), which were defined under the previous federal transportation authorization, referred to as MAP-21 (KDOT, 2017).

To determine OSOW freight routes taken by specific industries and specified by K-TRIPS, the research team used the yearly .shp files and created heat maps using ArcMAP's kernel density tool. In other words, K-TRIPS provided routing for each permit as a line file and the research team wanted to understand how many lines were on top of one another indicating the more than one trip was made over a certain roadway section. The easiest way to quantify the line density to indicate the number of trips being made over a certain line section was a head map which changed color based on the number of trips detected. This was accomplished by converting coordinate system produced by K-TRIPS (in decimal degrees) into a unit coordinate in which ArcMAP could easily display the data. Line decimal degrees (length of the line) were then divided by decimal degrees squared (arc of the line). Although this conversation does not make physical sense because decimal degrees are not a common unit of measurement, the results of the conversion provided a unique way to display line data on a traditional GIS map that are commonly used by KDOT.

3.3: OSOW Permit Routes

A critical aspect to this research project was exploring where OSOW freight moved through the state of Kansas. As stated previously, dedicated freight corridors have been defined in Kansas. These roadways (including Interstates, U.S. Highways and Kansas secondary highways) are routes that have been found to have a greater presence of large trucks. Additionally, the state of Kansas has increased safety and operational efficiency on some of these routes including the addition of guardrail, leveling slopes, installing wider shoulders, and constructed passing lanes. Using the routing data from K-TRIPS and establishing the top five OSOW industries as described previously, (general construction freight, general freight, wind energy, oil and gas equipment, and agricultural equipment/implements) route densities were developed. The kernel density function as described previous was used to develop heat maps of the most traveled routes for each of the top five industries. The kernel density function in ArcGIS cannot distinguish between trips traveled on roadways that intersect each other. This means that when two heavily trafficked routes intersected, the density was found to be higher than the individual routes before the intersection of routes. Figure 3.8 through Figure 3.13 show results of the routing analysis using heat maps. In order to explain the maps presented herein, communities and U.S. highways within the state of Kansas will be used as references as to what the research team believed was occurring. Additionally, Figure 3.7b presented previously can be used as a reference. As a higher-level evaluation of the K-TRIPS routing data, Figure 3.8 shows a summary of all OSOW permits and roadways having the highest number of trips by year.

As shown in Figure 3.8, the highest density of OSOW truck travel was in the year 2015 at the intersection of I-135 and I-70, which is significant intersection of north-south, east-west interstates near the middle of the state. Since 2015, this location was found to have the highest density of the four years. Because of this, all further map densities (including Figure 3.9 through Figure 3.13) were set to the 2015 color heat-map scale as a reference.

Many OSOW routes consistently were among the higher travelled from 2014 to 2016 which included: I-70 from Kansas City, Kansas to the Colorado border in Western Kansas; I-35 from the Oklahoma border north to Wichita, Kansas; I-35 from Emporia, Kansas to Kansas City, Kansas; I-135 from Wichita, Kansas to Salina, Kansas; US-81 from Salina, Kansas north to the Nebraska border; US-83 from Oklahoma border north to the Nebraska border; and US-54 from Liberal, Kansas to Minneola, Kansas. These routes where found to carry a majority of the OSOW trips taken on interstates and Kansas highways in the four-year study period. However, as stated previously, some identified industry routing remained constant and some routing fluctuated within the study period. Industries with OSOW routes that remained constant were found to be the reason the previously mentioned routes show up boldly on the full-year heat maps. Industries that were found to have high variability in trips every year were the reason why new routes stood out, or other routes became more travelled. The research team then isolated each industry for evaluation, Figure 3.9 shows the heat map for general construction equipment.

As shown in Figure 3.9, for general construction equipment industry, as stated before, was found to be a consistent industry from year to year. The heat map supports this claim by illustrating how similar the routes were for the four years study period. The primary routes taken by the OSOW (with slight deviation each year) included: I-70 and I-35 across the state of Kansas, and I-135 North and South within the state of Kansas were found to be the main routes taken by OSOW trucks. Additionally, it was found that lesser-traveled routes were consistent among the study period was well as indicated by the heat maps. This indicated that not only were similar amounts of trips being travelled by this industry, but they seem to be taking very similar routes each year.

The research team also evaluated the general freight industry routes similar to the general construction equipment industry. While the number of trips was found to be not as consistent and dense as the general construction equipment industry (10.8 percent difference from the largest to smallest yearly total), the routes were nearly as consistent throughout the four-year study period as general construction equipment, as shown in Figure 3.10. The main routes that were found to be taken by the OSOW trucks remained constant throughout the study period, with only slight variations in trip density, although slightly more variant than what was found for general construction equipment OSOW trips. Similar to general construction equipment the following routes were found to have the highest number of trips: I-70, I-35, and I-135 across the state of Kansas were found to be the main routes taken by these trucks. Additionally, it was found that even the lesser-traveled routes were found to be almost consistent with similar densities during the study period. It was also found that US-54 and US-81 were less traveled by OSOW trucks than the interstates routes but were found to be very consistent year to year. Additionally, it was found that the routes on US-83 started out being a common route for OSOW trucks 2014 but became less traveled as the years progressed through the study period. This indicated not only that similar amounts of trips were being travelled by OSOW trucks for this industry, but they were consistent each year from 2014 to 2016. The research team also evaluated OSOW truck trips for agriculture equipment/implements industry follows using the same methodology as described for the previous two industries. It was found that that this industry followed the same routing trends as general construction equipment and general freight industries. However, it was noted that the agriculture equipment/implements industry had a far greater difference in the number of trips taken. It was found that there was approximately a 35.1 percent difference in the number of trips taken from the largest to smallest yearly total during the study period. It was noted that this difference in trips taken resulted in the heat map showing the highest yearly trip totals were more involved than the beginning years of the study period and this can be clearly seen in Figure 3.11. Knowing that the number of trips taken by this industry were higher for the year 2014 than remaining years of the study period, it can be expected that more routes would have registered on the 2014 map. However, it was found the routes mainly taken from 2014 also appeared in the other three years of data; however, at a lower density. The analysis of agriculture equipment/implements industry found that many of the OSOW traveled on the following routes: I-35 and I-135 across the state of Kansas were the highest traveled routes, US-81, US-50, and US-54 were found to the other predominant routes.

The research team also investigated what was believed to be two industries that were highly influenced by changes in demand, federal and state policy, and also where to haul the OSOW freight within the state. These industries included wind, oil, and gas industries which have a significant presence in the state of Kansas.

To investigate these trip fluctuating industries, the research team first evaluated the trips taken by OSOW trucks for the wind energy. The yearly analysis is shown in Figure 3.12. As shown, the wind energy industry was found to predominately take different routes each of the study years. Looking at the year 2014, the OSOW trucks mainly traveled on US-83 from Liberal, Kansas to Norton, Kansas (using US-383, which is not illustrated in Figure 3.7b) and from Liberal, Kansas to Minneola, Kansas along US-54. However, it was found in 2016 the routes shifted and US-83 (as described previously) became a low-density traveled route by OSOW trucks. However, highways between Garden City, Kansas; Dodge City, Kansas; and Kinsley, Kansas became the dominant routes. It should be noted that a wind turbine lay-down yard is located just outside of Garden City, Kansas. Overall, the maps presented in Figure 3.12 indicate a fluctuating change in route demand and fluctuating route chosen by the industry in changes in overall demand of wind turbine components year to year. As stated previously, wind energy trips were found to have increased by 92.5 percent in a two-year period during the four-year study period. The breakdown of trips for wind energy were as follows: 14 percent in 2014; 22 percent in 2015; 26 percent in 2016; and 18 percent in 2017.

The research team also investigated another OSOW trip fluctuating industry - the oil and gas equipment industry. This industry, similar to wind energy is the result of demands and changing energy policy both in Kansas and at the federal level of government. The analysis of data showed that unlike the wind energy which changed predominant routes around the state of Kansas yearly, the oil and gas equipment industry had one main route. This route was US-83 and the number of trips taken on this route varied year to year. It was found that from 2014 to 2016, this gas and oil equipment industry was found to have a 50.6 percent decrease in trips taken. This decrease in trips (or density of lines) can be clearly viewed in the heat maps for those respective years in Figure 3.13. One noted difference by the research team was that the oil and gas equipment industry had from the other four major industries that utilized OSOW routing in this study was the fact that the number of trips in 2017 was found to have increased from the number of trips in 2016; and all other major industries had fewer trips in 2017 than 2016.

Overall, the research team believes the industries that utilize OSOW for construction, general freight, and agriculture equipment /implements shows consistent routing for the four-year study period in similar and different corridors within the state of Kansas. The research team also believes these industries had established routing within and through the state of Kansas prior to the study period and are currently not influenced heavily by changes in national and regional demand and technology changes. It is recommended that KDOT and metropolitan planning organizations (MPOs) in the state of Kansas look to these industries for safety improvement and long-term planning considerations when it comes to OSOW vehicle traffic on Interstates and highways.

The research team did confirm that KDOT was alerted in 2016 to the changes in the number of OSOW trips for the wind energy, and again in 2017 for a decrease in the number of OSOW truck trips. Additionally, the wind energy expected to increase the number of OSOW trips in 2019 as the demand for wind energy continued to increase. These alerts by the industry has allowed KDOT to refine K-TRIPS and also target engineering studies for bridge structures and the research team believes advanced notification for more industries would increase safety operations for OSOW trucks.

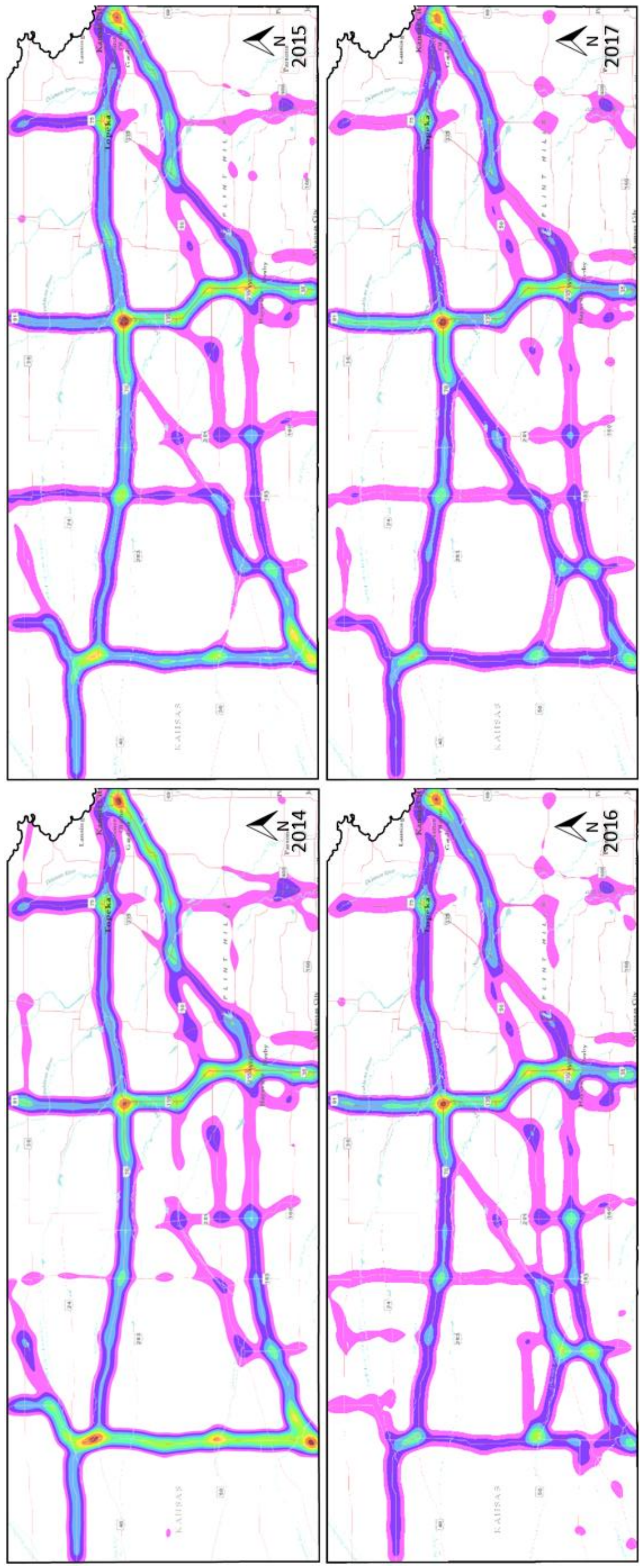


Figure 3.8: Heat maps for all OSOW trips in Kansas (2014-2017)

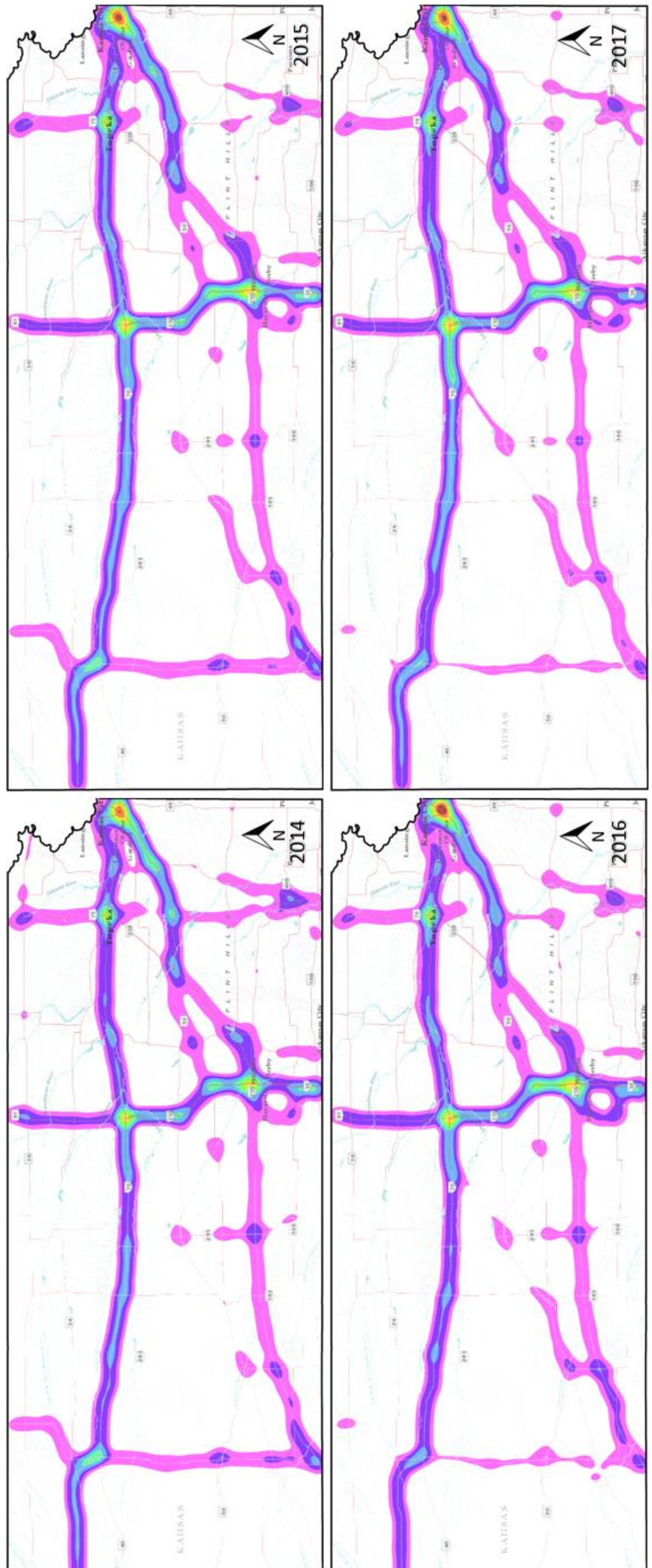


Figure 3.9: Heat map for all general construction equipment OSOW trips in Kansas (2014-2017)

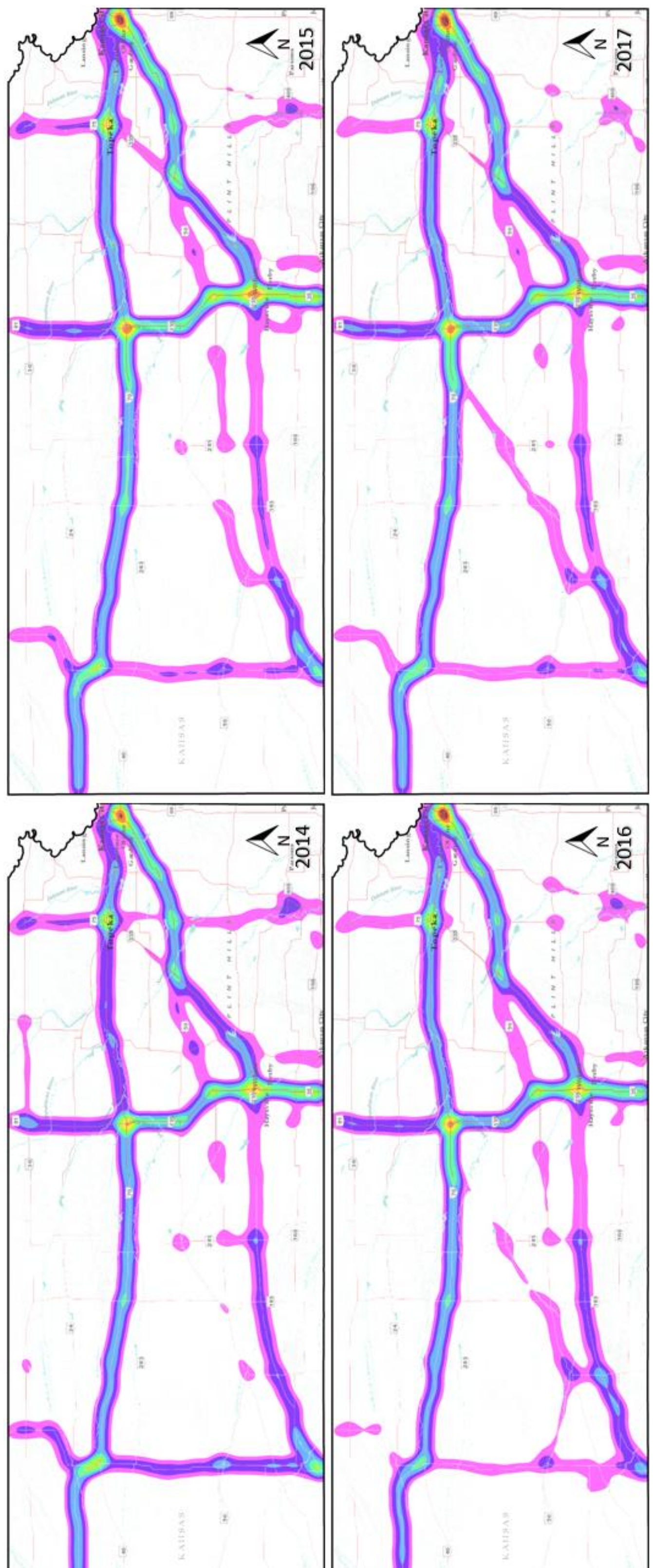


Figure 3.10: Heat map for all general freight OSOW trips in Kansas (2014-2017)

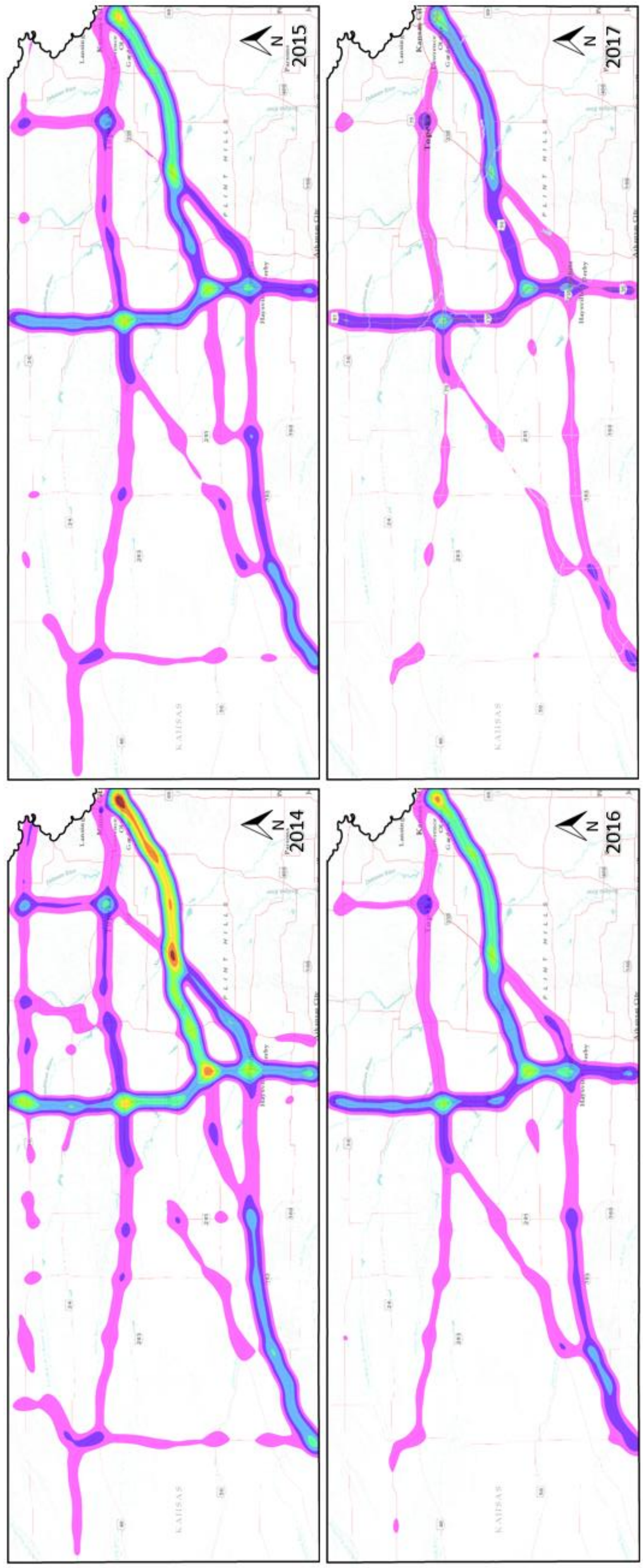


Figure 3.11: Heat maps for all agriculture equipment/implements OSOW trips in Kansas (2014-2017)

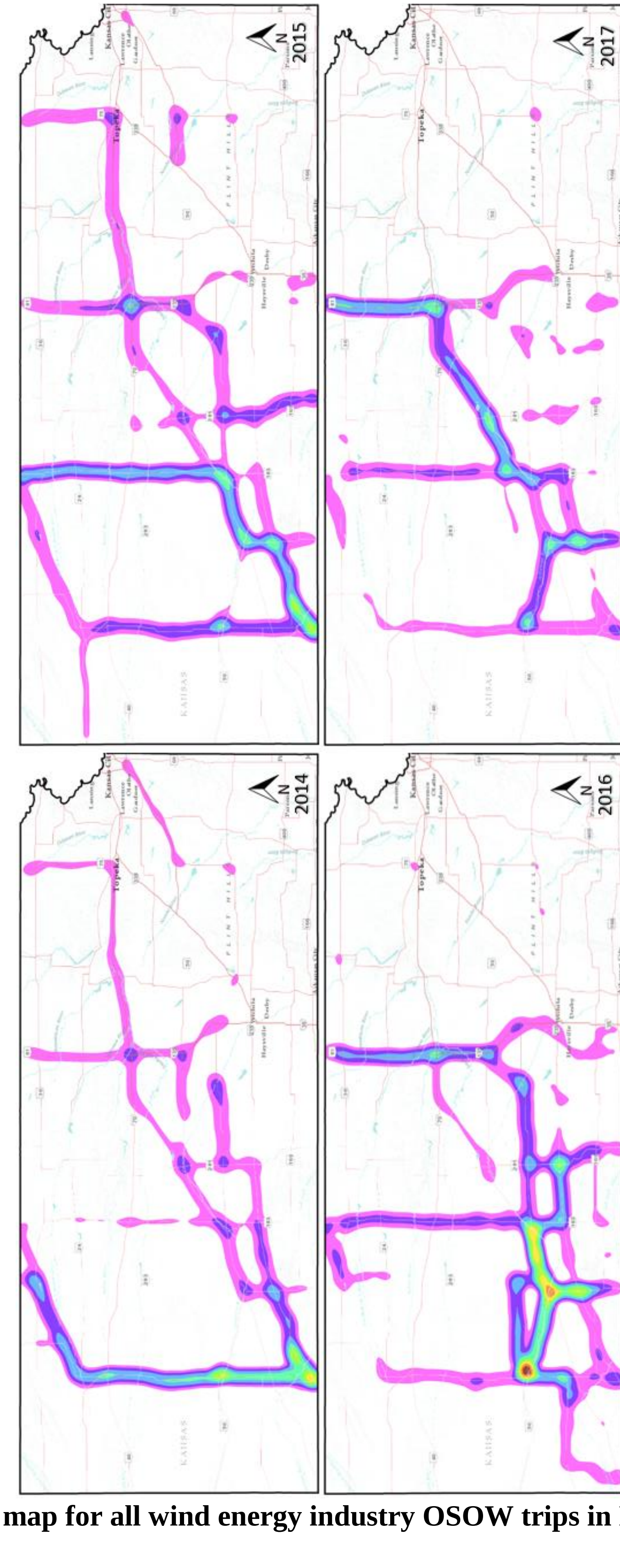


Figure 3.12: Heat map for all wind energy industry OSOW trips in Kansas (2014-2017)

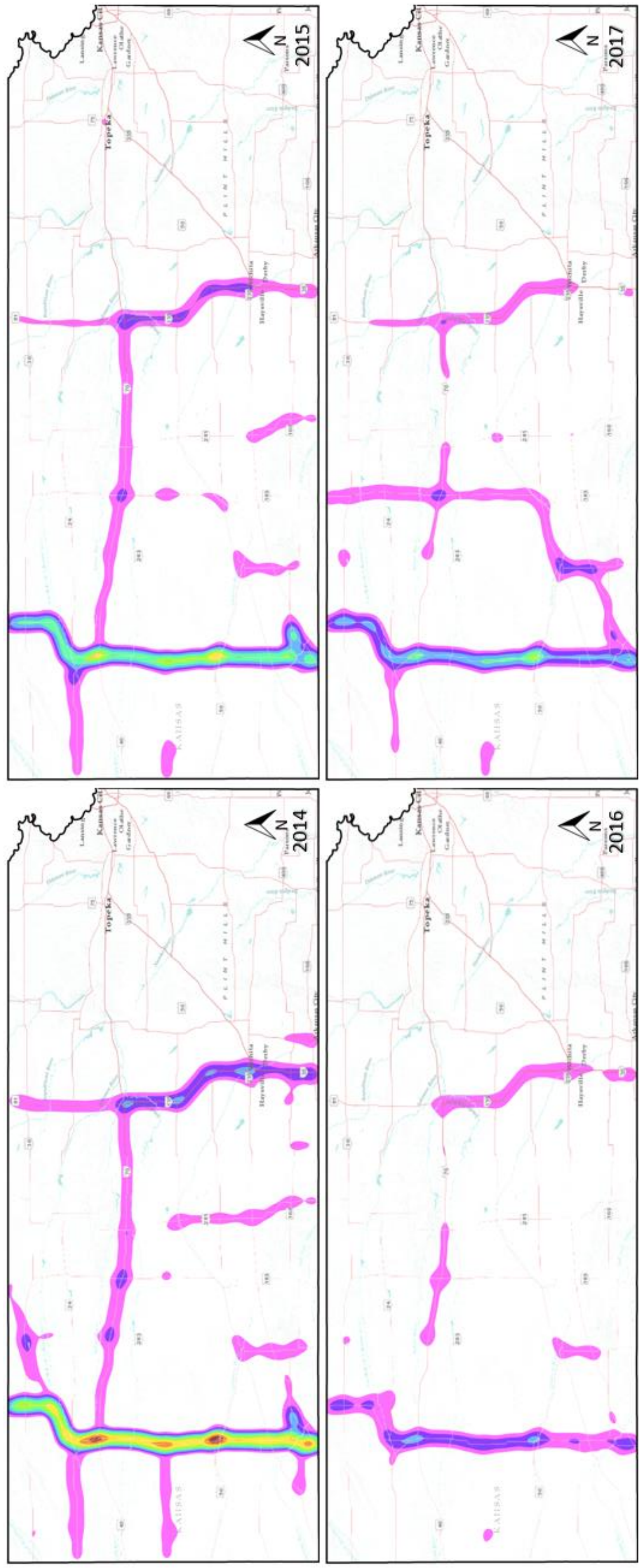


Figure 3.13: Heat maps for all oil and gas equipment OSOW trips in Kansas (2014-2017)

3.4: OSOW Crashes

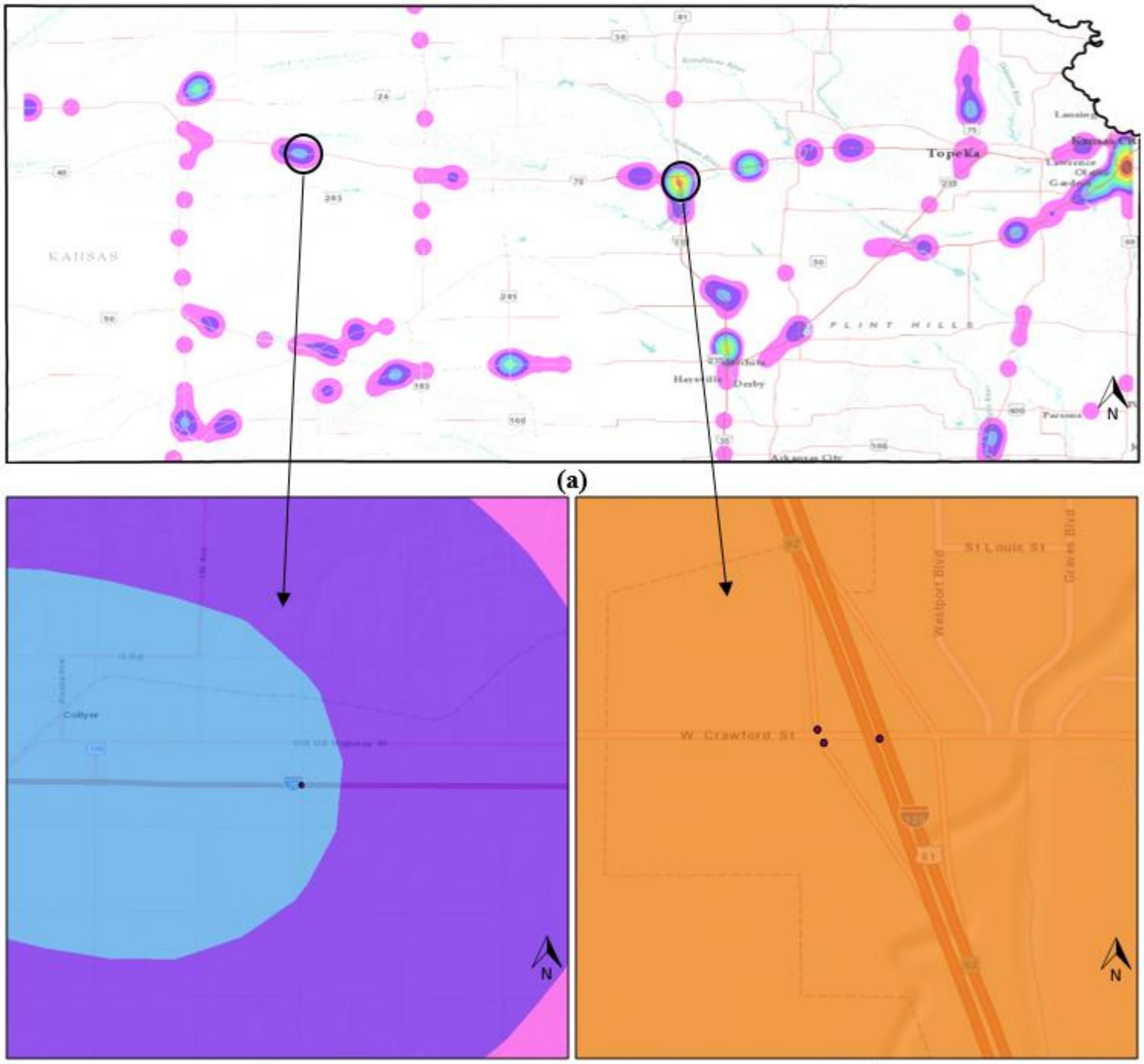
3.4.1: Data description

Confirming that a significant percentage of the OSOW truck loads were following the Kansas freight corridors with other trucks shown in Figure 3.7a, the research team investigated OSOW truck crashes, which were constrained to the Kansas freight corridors. Using crash data extracted by KDOT from the Kansas Crash Analysis and Reporting System (KCARS), this included truck crash data in which at least one truck was involved, this dataset also included OSOW truck crash data. The research team merged the extracted crashes with the Kansas freight corridor roadway layer (Figure 3.7a) using ArcMAP. Isolating OSOW truck crashes, a total of 148 crashes were recorded from 2014 to 2016 in which the crash involved at least one OSOW truck, or an OSOW truck involved with at least one other vehicle (either another truck or passenger car).

The research team was also interested in the location of the OSOW crashes, and wanted to determine if roadway geometric features, traditional roadway safety devices (e.g. guardrail) or roadside hazards were significant variables in these crashes, especially in rural areas. Similar to investigating the routes of OSOW trucks, a heat map was generated to determine where clusters of OSOW crashes occurred (2014 to 2016) on the Kansas freight corridors and are shown in Figure 3.7a where areas of red indicate more than one crash in a particular area occurred.

As shown in Figure 3.14a, purple areas were generally found to be a single OSOW crash while blue and purple areas were found to represent more than one OSOW crash. It should be noted that the heat-map areas could be extended for multiple miles because of the scale of the heat map used. Two mass-action areas were selected for further investigation, which are shown in Figures 3.14b and 3.14c. Figure 3.14b shows that two crashes occurred on I-70, east of

Collyer, Kansas. As shown, there was only one data point visible in this image because both of the crashes occurred at the same location over a period of two years. Both of these crashes were caused by the OSOW truck striking the bridge-structure on the 150 Avenue overpass of I-70.



(b) (c)

Figure 3.14: (a) Heat map for all OSOW crashes from 2014-2016; (b) Western Kansas crash cluster; (c) Central Kansas crash cluster

The research team believes this analysis could save considerable damage to the infrastructure in Kansas and recommends that KDOT deploy appropriate low-cost countermeasures at this location which may include enhanced bridge height signs and/or targeted delineation. Figure

3.14c shows a second identified location where multiple OSOW crashes occurred during the study period. This location was the Crawford Street and I-135 interchange in Salina, Kansas. Three OSOW crashes were identified during the study period in which all of the crashes involved roadway guardrail strikes. One of the identified crash occurred at the off-ramp on I-135 South, the second crash occurred at on the on-ramp to 1-135 South, and the third occurred on Crawford Street itself. Further investigating the interchange area, it is recommended that KDOT enlarge the clear zone distance, increase the guardrail lateral distance from the roadway, as well as enlarge the intersection turning radius to accommodate OSOW trucks.

3.4.2: Descriptive statistics

As stated previously, a total of 148 crashes involving OSOW vehicles were extracted for a study period from January 1, 2014 to December 31, 2016. To investigate what geometric, environmental, and driver variable might have influenced the result of the crash, descriptive statistics were performed on the crash data variables. Crash severity during the study period ranged from fatal crashes to property damage only crashes. It was found that most of the recorded crashes were property damage only (PDO) crashes, with 117. Additionally, there were 29 injury crashes and 2 fatal crashes as shown in Figure 3.15.

Additionally, time of day when the crash occurred was analyzed and it was found that the largest number of OSOW trucks crashes occurred between 2:00 pm and 3:59 pm. The full data set is shown in Figure 3.16. It was found that between 2:00 am and 3:59 pm the number of crashes show a natural increase in frequency, and then decreases between 4:00 pm and 1:59 am. It is worth noting that both recorded fatal crashes occurred during the 2:00 pm to 3:59 pm time period.

Day of the week was also investigated in the the crash analysis and is shown in Figure 3.17. It was found that the two most common days for an OSOW crash were on Thursday and then Friday. Additionally, the two days that were found to have the lowest number of OSOW truck crashes were Saturday and Sunday.

Crash data also indicated that OSOW crashes occurred on two different pavement types during the study period, concrete and asphalt. There were 57 crashes that occurred on concrete and 91 that occurred on asphalt. Additionally, the pavement condition was evaluated and shown in Figure 3.18, 117 crashes occurred under dry road conditions and 20 more occurred while the road was wet. The other 11 crashes occurred with pavement having ice, snow, or slush present.

Roadway geometry was also considered and shown in Figure 3.19 it was found that 106 crashes occurred on straight and level roadways, while 25 crashes occurred on straight and graded/sloped roadways. The remaining 17 crashes occurred on roadways that were curved (both level and sloped) or straight at a hillcrest.

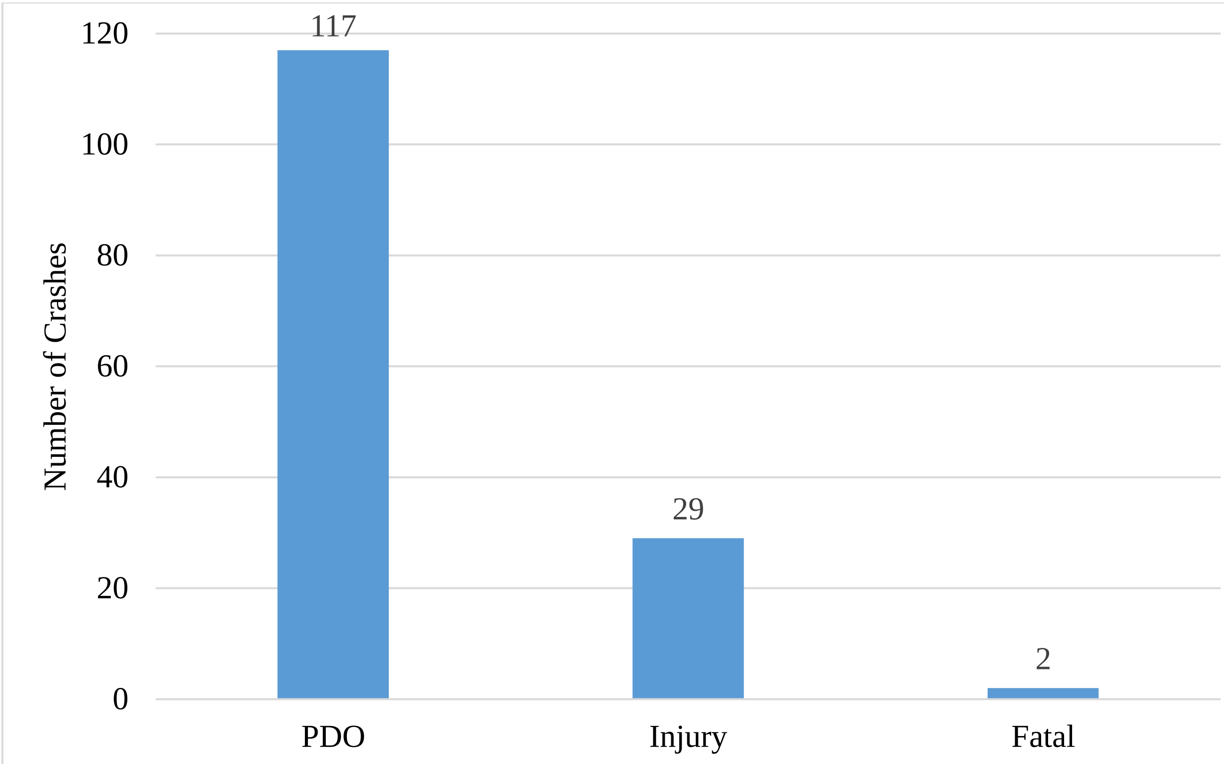


Figure 3.15: Crash Severity (2014-2016)

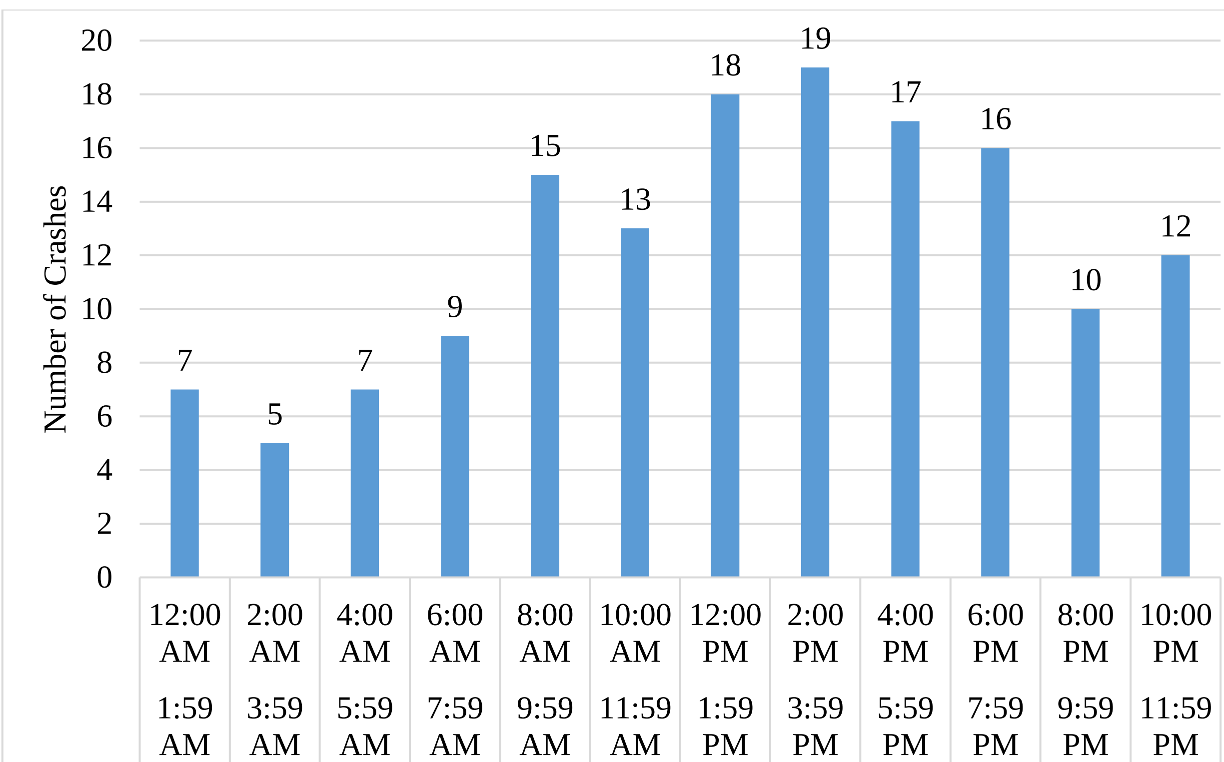


Figure 3.16: Time of Crash (2014-2016)

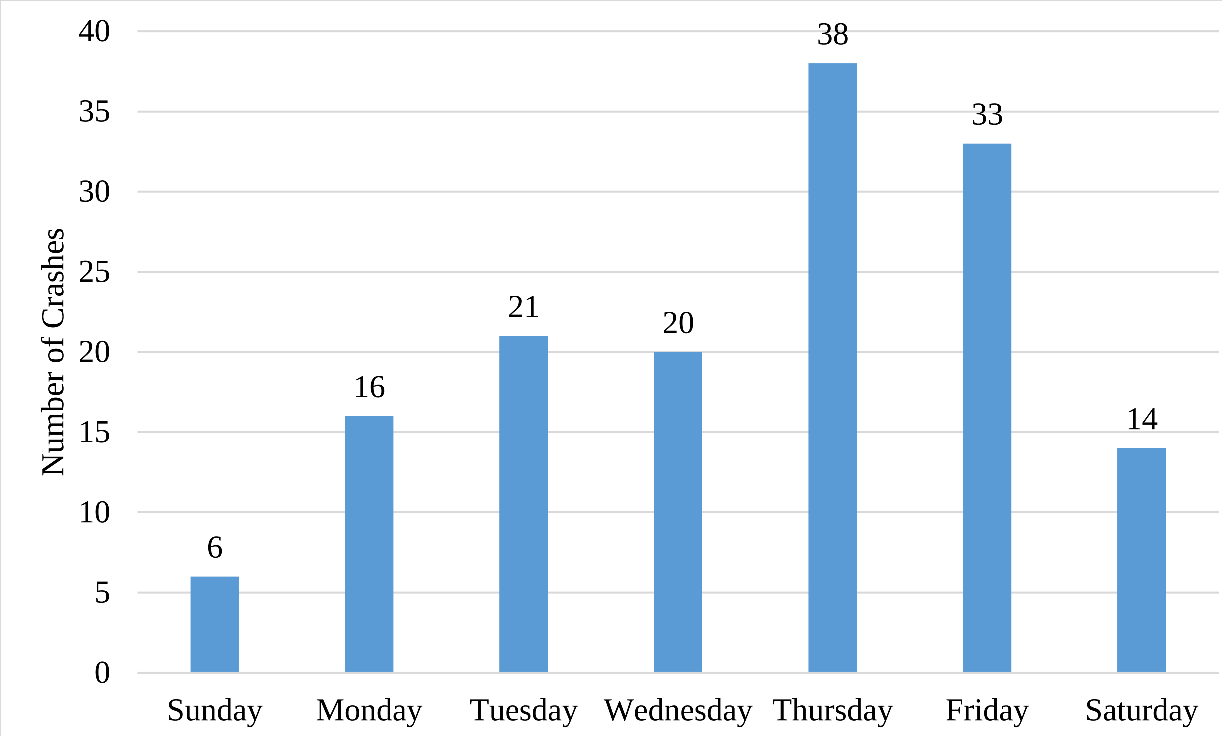


Figure 3.17: Day of week at time of crash (2014-2016)

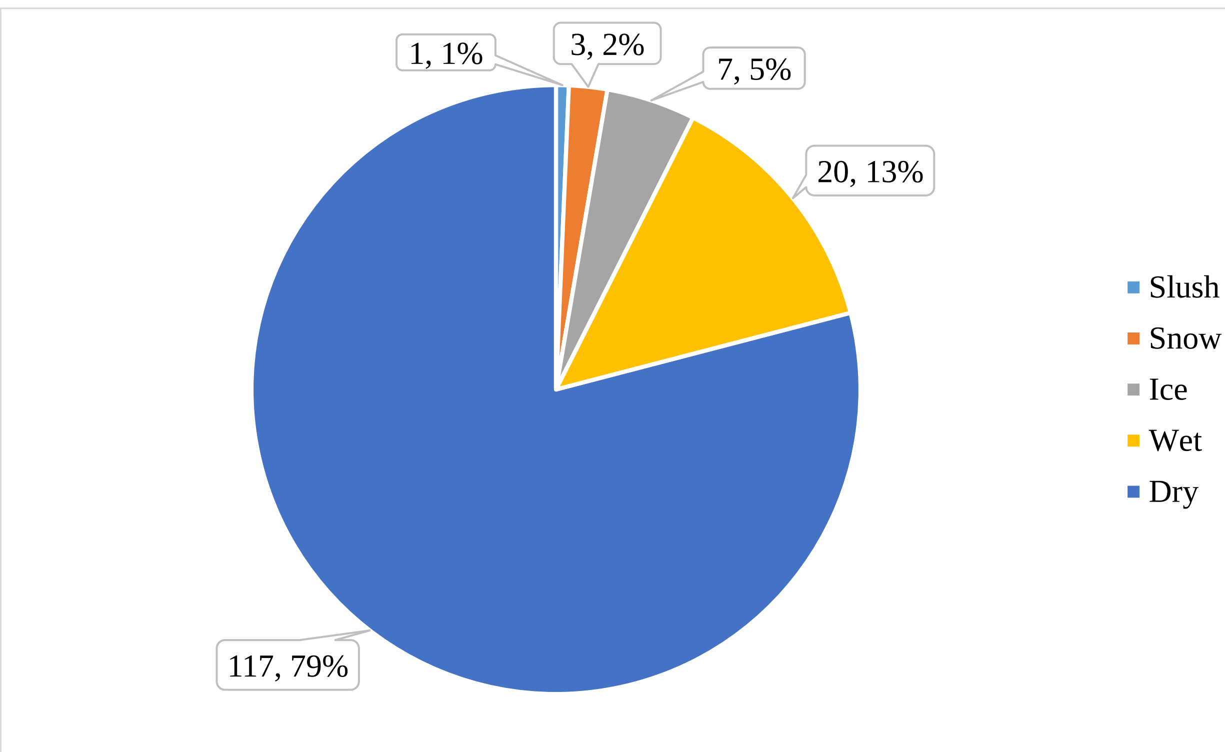


Figure 3.18: Pavement surface conditions at time of crash (2014-2016)

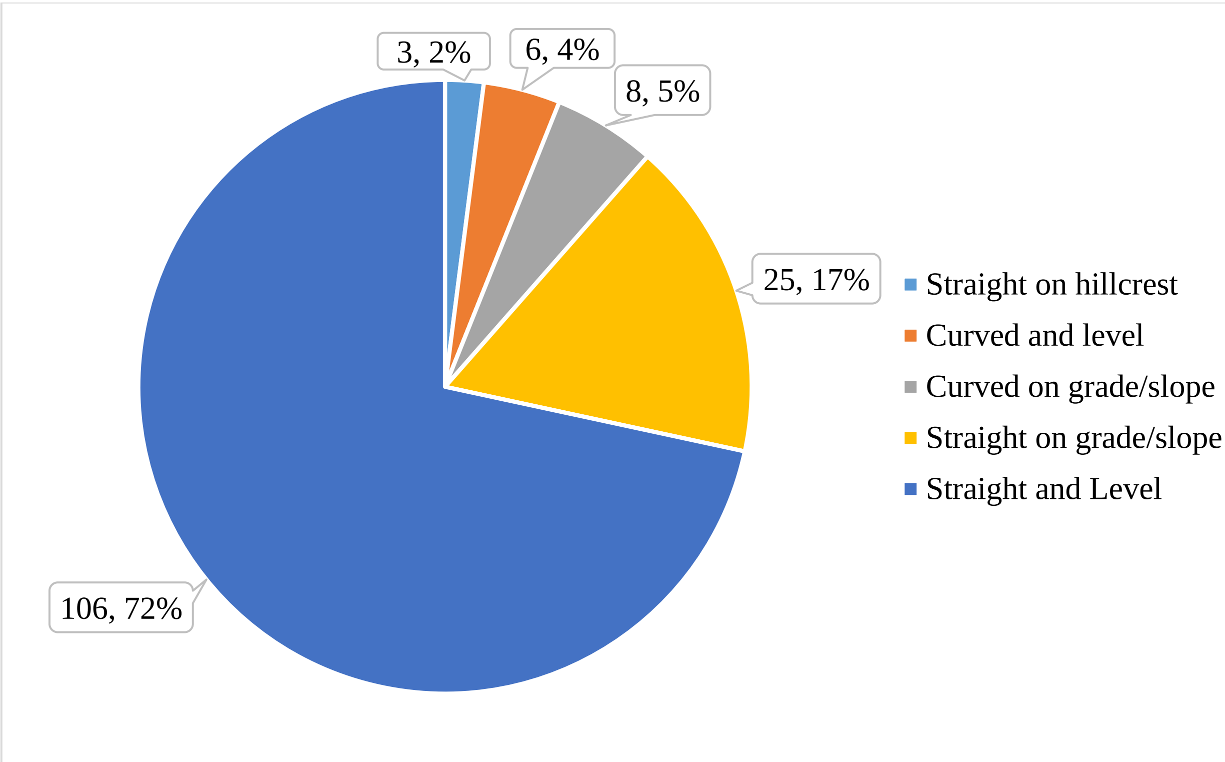


Figure 3.19: Roadway characteristics at time of crash (2014-2016)

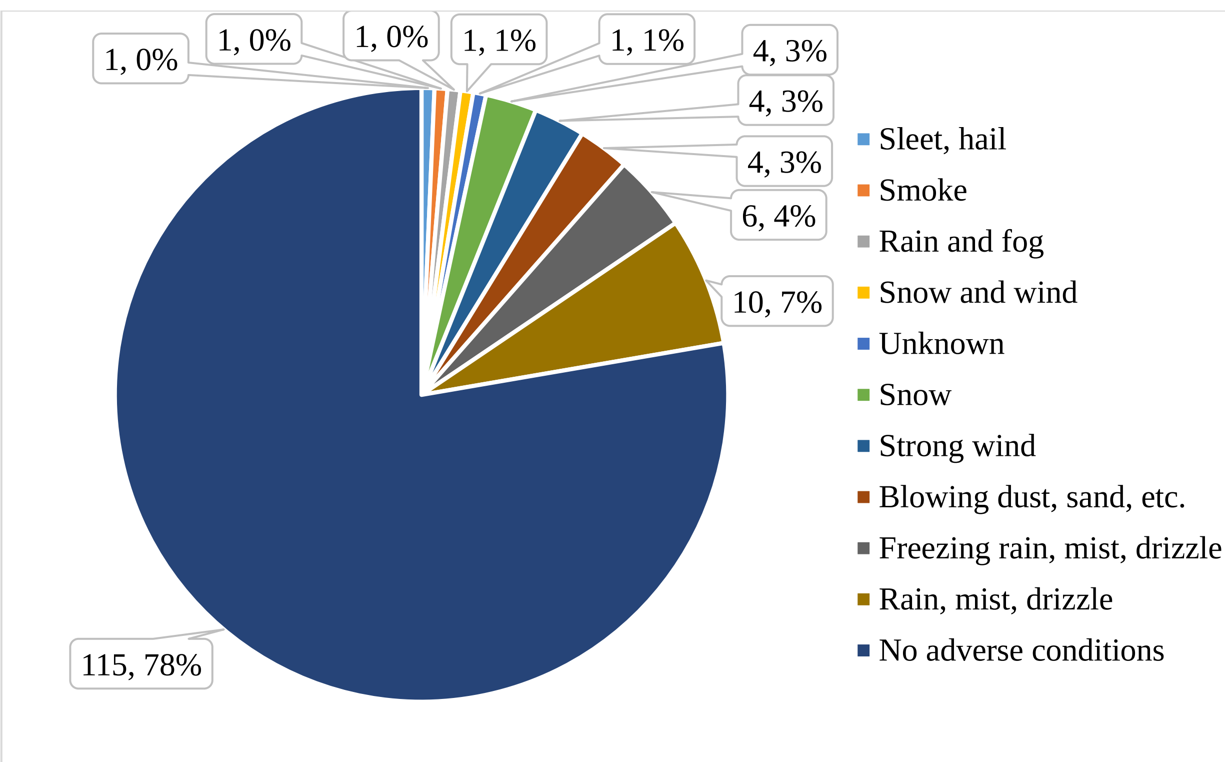


Figure 3.20: Weather conditions at time of crash (2014-2016)

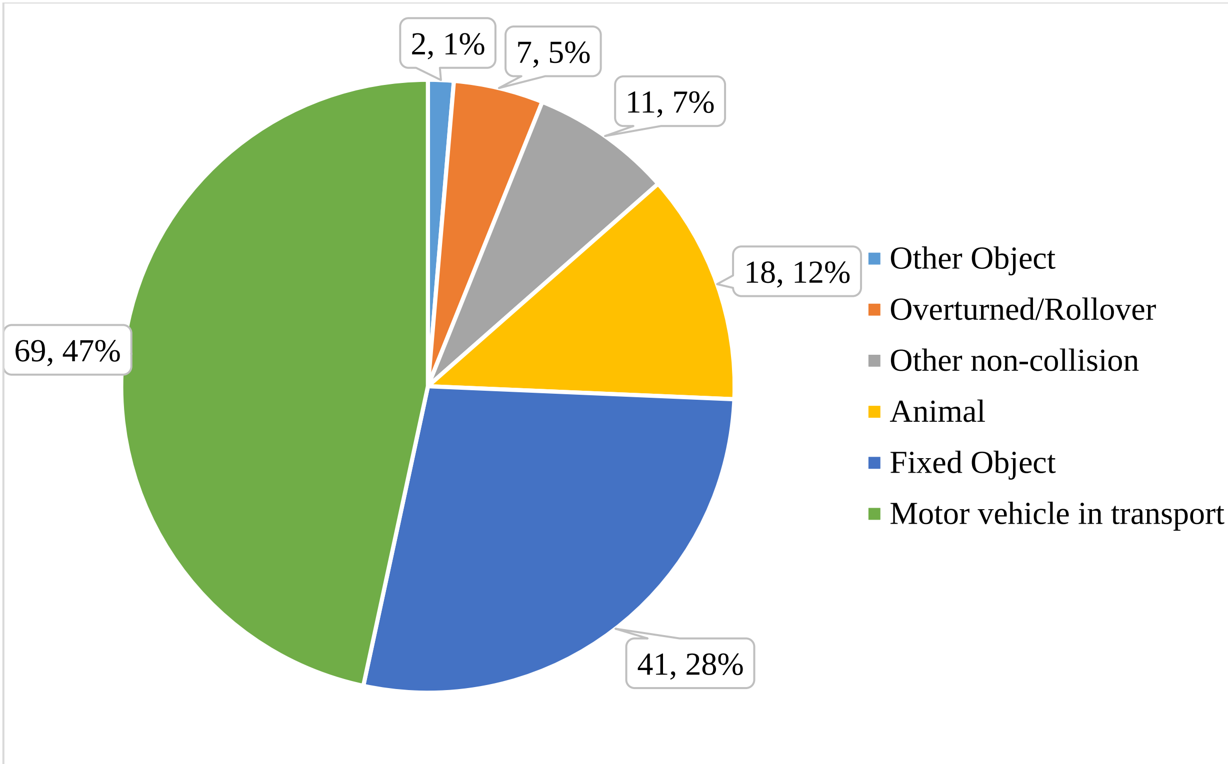


Figure 3.21: First harmful event of crash (2014-2016)

Weather conditions at the time of the crashes were also analyzed and are shown in Figure 3.20. It was found that approximately 115 crashes occurred under no adverse conditions. Additionally, 10 occurred while it was raining, misting, or drizzling. Finally, six occurred while freezing rain, mist, or drizzle existed. Eight crashes occurred during strong winds / blowing dust, sand, etc. The remaining nine occurred with weather conditions of; snow, snow and wind, rain and fog, smoke, sleet / hail, unknown.

One of the most important variables when investigate crashes is the first harmful event (FHW), or the event the crash sequence is based on. Shown in Figure 3.21, approximately 69 of the crashes were found to have an FHE of a motor vehicle in transport. This means that 47 percent of crashes involved an OSOW load making contact with another vehicle while moving on the roadway. Another 41 crashes had an FHE of hitting a fixed object, or an object in or near the clear zone that cannot be physically moved easily. Additionally, 18 crashes involved striking an animal, 11 were classified as other / non-collision, seven were overturns / rollovers, and the remaining two were with other objects.

Overall, it was found that a majority of crashes occurred with ideal driving conditions which included: 79 percent occurred on dry pavement, 78 percent occurred with no adverse weather conditions, 72 percent occurred on a straight and level road. 56 percent occurred between 10:00 am and 7:59 pm, and 47 percent had a motor vehicle in transport as the FHE.

3.4.3: Regression Analysis

Data from the 148 identified OSOW crashes were analyzed for statistically significant variables at a 90 percent confidence level. Each OSOW crash had an associated crash report in which the police officer at the scene of the crash recorded what was observed. The response variable for the statistical model was crash severity or the seriousness of the crash. A logistic regression was selected as the appropriate statistical model framework with the available variables from the crash reports. A logistic regression was selected in place of a traditional linear regression where the response variable was categorical instead of quantitative. Since the OSOW crash data showed that injury or fatal crash categories not exceeding 30 observations individually, these two severities were combined in order to have a significant regression. Backwards selection of significant variables was used to determine which variables would be included in the model. The general form of a logistic regression is given below in Equation 3.1. The full R-coding used for the final model development can be found in Appendix B.

$$\boldsymbol{log\left(\frac{p}{1-p}\right) = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k} \qquad \textbf{(eq. 3.1)}$$

Where: $p =$ *proportion of fatal/injury crashes compared to total crashes*

β_k = *estimates*

X = *parameters*

k = *number of parameters*

For the OSOW crash dataset, the $\boldsymbol{\beta_0}$ was found to be not significant at the 90 percent confidence level, so it was removed from the model. A summary of the variables tested as well as the p-value are shown in Table 3.4.

Table 3.4: Variables included in the final logistic regression

Parameter	Estimate	Standard Error	z value	Pr(>|z|)
FHE: Other non-collision	**2.165**	**1.082**	**2.001**	**0.0454**
FHE: Overturned/Rollover	-1.434	1.181	-1.215	0.2244
FHE: Motor vehicle in-transport	**1.628**	**0.7940**	**2.050**	**0.0403**
FHE: Animal	19.61	1448	0.014	0.9892
FHE: Fixed object	**3.561**	**0.9259**	**3.846**	**0.0001**
FHE: Other object	18.79	4599	0.004	0.9967
Surface Type: Asphalt	**0.8458**	**0.5060**	**1.671**	**0.0946**
Time of Crash	**-9.365 x $\mathbf{10^{-4}}$**	**4.761 x $\mathbf{10^{-4}}$**	**-1.967**	**0.0492**

As shown in Table 3.4, significant variables found are shown in bold that had a p-value less than 0.1 (90 percent confidence level). These variables include FHE: other non-collision, motor vehicle in-transport, fixed object, surface type: asphalt, and time of crash

The FHW indicates what the "First Harmful Event" of the crash was, according to the police report filed for each crash. 'FHE: Motor vehicle in transport' means the first harmful event of the crash was the OSOW load hitting another motor vehicle while it and the other vehicle were both driving. All other FHE variables can be explained in a similar way, with the 'other' categories were what the officer's labeled certain crashes that did not fall into any of the other variables.

It was found that there were only two different pavement types in the dataset which included concrete and asphalt. 'Surface Type: Asphalt' showed that for this model, asphalt pavement was the predictor of crash severity. All of the FHE variables and the Surface Type variable were binary variables ("yes" or "no"). This means, for example, that a crash can either have an FHE be a fixed object hit, or not. The only exception in this dataset was the 'Time of Crash' which was considered a continuous variable having a range between zero and 2400 hours. It should also be noted that even though backwards selection was used to select significant variables, there were still insignificant variables in the model with a p-value greater than 0.10. The reason for this was that the insignificant variables were all categorical predictors as part of the FHE variable. This means that as long as any of the FHE causes were significant, all of them needed to stay as predictors in the model.

In order to determine how much more likely a fatal or injury (F/I) crash was based on the developed logistic regression, the estimates were taken out of natural log form. This is performed by taking the value "e" and raising it to the β_k power. This provided the odds ratio for a selected variable in the model. For a specific binary variable that was significant in this model, if the odds ratio was larger than one, the odds of an F/I crash occurring if the predictor did happen were e^{β_k} higher than the odds of an F/I crash occurring if the predictor did not happen. For example, when an OSOW crash occurred with an FHE categorized as an 'other non-collision' the estimate was found to be 2.165. Since the estimate was larger than zero, the variable will increase the odds of an F/I crash occurring. To find out how much the odds increase, the value 'e' is raised to the power of the estimate for that variable. For an FHE: Other non-collision, the odds of that crash being an F/I crash was $e^{2.165} = 8.7$ times larger than the odds of it being an F/I crash without the FHE being categorized as 'Other non-collision'. The odds ratios for each of the significant variables are shown in Table 3.5.

Table 3.5: Odds ratios of significant variables

Parameter	Estimate	Odds Ratio
FHE: Other non-collision	2.165	8.71
FHE: Motor vehicle in-transport	1.628	5.09
FHE: Fixed object	3.561	35.2
Surface Type: Asphalt	.8458	2.33
Time of Crash	-9.365×10^{-4}	.999

For all of the FHE significant variables to have odds ratios greater than 1 seemed logical. It was expected that if the odds of a F/I crash occurring were higher when an OSOW vehicle struck another moving vehicle or a fixed object, compared to that of an OSOW vehicle not striking one of those variables. The positive odds ratio for the asphalt surface type also seemed logical as well. With a high number of centerline miles in Kansas being consisting of two-lane rural highways - many of which are paved with asphalt and have little to no shoulder, it was understandable that this surface type had a higher odds ratio for a crash to be F/I.

When the continuous variable had an odds ratio less than one, it meant that for every one unit increase in the variable, the odds would be e^{β_k} times less than before the increase. Also, if an odds ratio was less than one, then the odds of the response happening decrease by (1-odds ratio)x100 percent. For example, the odds ratio for the 'Time of Crash' predictor was 0.999. This indicated that for every one unit increase in the time of the crash, the odds of an F/I crash occurring decrease by (1-.999)x100 percent, or 0.1 percent. This same method can also be applied to hourly changes. The odds of an F/I crash occurring at 1:00 am (100 in the model), were 10 percent lower than an F/I crash occurring at 12:00 am (000 in the model). This was found to have a minimal decrease in odds from hour to hour. However, it was found that a crash being later in the day does decrease the odds of a crash being an F/I crash. While this variable is statistically significant, it is inconclusive based on the extracted crash data. It was found that with all the F/I crashes extracted for four years, approximately 29 percent (9 out of 31 crashes) occur prior to 12:00 pm, while 39 percent (56 out of 148 crashes) of the overall crashes occurred prior to 12:00 pm. At this time, it inconclusive why the model is producing counterintuitive results, with the significant number of crashes occurring in the second half of the day (afternoon and evenings) for both F/I and all other crashes but the model showing that it is less likely to be in an F/I crash later in the day. The best hypothesis is that the sample size and other variable may be influencing the time or data variable estimate.

The AIC value for the final model was 130.14. By itself, that number is fairly insignificant, so it was compared to the original model's AIC of 165.12. A lower AIC value indicates a model with better fit, or a more accurate description of the data being used. The code found under R-code used for Backwards Selection in Appendix B was used to find the model that had the lowest possible AIC value. That code selected the final model, with the results presented in Table 3.4. The final model having the lowest AIC of any of the models proposed in the backwards selection means that it was the best possible model to help predict OSOW crash severity, given the data provided.

Although the developed logistic regression analysis provided insight into OSOW crashes in Kansas, it is recommended a further analysis be undertaken. As described previously, exposure due to changing travel patterns by each industry, changes in roadway features, and other characteristics may influence the over model development. More crash data and associated K-TRIPS data are needed to verify the current statistical model.

Chapter 4 - Significant Findings

4.1: Discussion of Results

Oversize and overweight trucks and the freight they haul are an integral part of the movement of freight across the United States. As a subset of large truck traffic, OSOW trucks are unique in that many times their dimensions (length, width, height, and weight) makes the movement of their corresponding freight a challenge to move down the roadway. The state of Kansas is an integral, and many times required, pass through point across the country by both large trucks and OSOW trucks due to its east-west and north-south interstate access (I-70, I-35, and the Kansas Toll Authority Roadways) as well as key U.S. Highway and state routes. With an average of more than 72,000 OSOW permits granted by KDOT per year through its K-TRIPS electronic permitting system, the primary objective of this study was to evaluate historical data collected by K-TRIPS and perform analyses to determine trends in the data including evaluating the industries that typically apply for OSOW permits, the routes these trucks take, and also the safety experience. The results of the analysis are expected to assist KDOT with future policy and engineering decisions regarding permitting and routing of OSOW vehicles moving throughout the state.

Four years of K-TRIPS data were evaluated (2014-2017) and OSOW permits were isolated for the entire truck permitting database. When considering OSOW permits, approximately 87 percent of the permits were distributed to five industries which included: general construction equipment, general freight, agriculture equipment/implements, wind energy, and oil and gas equipment. The general construction equipment industry showed a prominent set of fixed annual routes that do not vary greatly during the study period. The routing for two other industries followed this trend as well including the general freight industry and the agriculture equipment/implements industry with minimal deviation from routes recorded between 2014 and 2017. However, the wind energy and oil and gas equipment industries, were found to not have a consistent set of routes during the study period. It was found that both of these industries routes changed every year of the study period. The research team believes and there was also evidence as stated by KDOT that deviation was mainly due to the changing economic conditions as well and the need to transportation energy equipment to certain parts of the state each year.

The wind energy industry was also found to be highly variable each year during the study period. This was found by evaluating the taken, but also the number of permits awarded. The number of permits awarded saw an approximately 93 percent increase from 2014 to 2016. By comparison, the general construction equipment industry only saw a 7.3 percent difference in permits awarded between its highest and lowest years within the study period.

Along with evaluating which industries made up the significant number of the trips in the state of Kansas, the research team also analyzed the safety effects of OSOW trucks by performing a crashes analysis and model development during the same time period. Mapping the crash data provided by KDOT, it was found that two locations had multiple OSOW truck crashes with the same recorded sequence of events. At one of the locations, two separate bridge strikes on the same overpass located at I-70 outside of Collyer, Kansas. The other location had three OSOW trucks strike a guardrail at the same interchange located on I-135 in Salina, Kansas. The descriptive statistics showed that of the 148 OSOW truck crashes during the study period, 31 crashes were either a fatal or injury crash. Approximately 79 percent of the crashes occurred with dry pavement conditions, 72 percent occurred on a straight and level road, and 78 percent occurred under no adverse weather conditions. Additionally, 56 percent of crashes occurred between 10:00 am and 7:59 pm. The analysis of crash variables indicated that OSOW truck crashes in Kansas occurred under normal driving conditions. To determine what crash variables were significant when predicting OSOW crash severity, a logistic regression was developed using a 90 percent confidence level since the primary output was binary (fatal/injury crash, or PDO crash). A backwards selection was used in order to find the model with the lowest AIC value, making it the best predictor of crash severity possible with the data available for this study. It was found that three separate first harmful event categories (Other non-collision, Motor vehicle in-transport, and Fixed object) were significant and all increase the odds of a fatal/injury crash occurring, if they were the FHE. If the pavement surface was asphalt, the odds of a fatal or injury crash are higher than if the pavement is concrete. Lastly, the later into the day it gets, the lower the odds are to be in a fatal or injury crash for OSOW loads.

This study provided KDOT with critical information on multiple fronts based on both K-TRIPS data as well as corresponding crash data. The research team recommends to KDOT distribution of industry information to companies and provide this report as a part of the K-TRIPS system. Additionally, the research team recommends KDOT investigate mass-action areas identified by the crash analysis and make safety improvements to the two identified locations.

4.2: Limitations and Future Research

Although this study was conducted with the best available data provided by KDOT, limitations were identified throughout the research process. First, K-TRIPS has only been in operation with KDOT since December 2013 and crash data was only available (and verified) through 2016. With only four years of OSOW permit data and only three years of crash data to analyze, this particular study can only reveal so much as to how the amount of OSOW vehicles on the road correlates to the number and severity of crashes. Furthermore, the research team recommends evaluating additional crash and K-TRIPS data to verify initial findings in this report.

Another limitation identified by the research team was the accuracy of the data inputted by truck companies and owner/operators into the K-TRIPS web portal. There were numerous permits with values that, presumably, did not match up with the units asked for in the software. When speaking with KDOT representatives familiar with K-TRIPS, they speculated that these errors were caused by any of three different reasons:

- The user only entered the weight/dimensions of the load, not the entire vehicle;
- The user entered weight values in kips, not pounds; and
- User error / mistyping.

Finally, it was found that there is not a viable way to incorporate exposure on routes travelled into this study. The permits awarded did not have dates on them as many of the permit types are able to be used for extended periods of time, not just a single day. With that being the case, there is no way to accurately estimate when and where an individual truck is traveling, or how many trucks are traveling past a particular section of road on any given day.

It is recommended that KDOT work with their private consultant to minimize these errors to enhance future studies evaluating the K-TRIPS OSOW truck permits. Since the information provided in K-TRIPS was relatively new, there are many different additional research projects that could stem from this study. To start, this study could be replicated as often as KDOT would like in order to keep track of the major industries that apply for OSOW permits in the state of Kansas. Of particular interest further analyses of the two fluctuating route industries (wind energy and oil and gas equipment), it would be advantageous to see where those loads are traveling, at what time of the year, and how the routes are changing. Along those same lines, a pavement study is recommended along the highly travelled routes. This could give KDOT a better estimate on pavement life of these routes in Kansas. Knowing how much these loads weigh, along with the axle information, an analysis on the amount of ESALs on a particular stretch of road can be done and can be compared to the anticipated usage of that road. This study could serve as a guide to what parts of the highway network need to be analyzed for safety, taxed heavier, or reconstructed sooner.

4.3: Contribution to Highway Safety

The research team found a unique and important connection between yearly heat maps of OSOW truck routing and OSOW crashes. The mass action areas were found to have similar locations the highest-travelled routes during the three years of the dataset. These findings were similar to previous research that indicated through statistical analyses that when the percentage of trucks increased on a roadway, the amount of predicted crashes increased. This finding could be a primer for the state of Kansas to upgrade safety measures on known truck corridors that experience a high number of OSOW trucks. The ability to reduce fatal or serious injury crashes involving OSOW would have a positive net benefit for the state of Kansas, however considerable investment will be needed by the state to address all OSOW crash concerns.

References

Adams, T., Perry, E., Schwartz, A., Gollnik, B., Kang, M., Bittner, J., Wagner, S. *Aligning Oversize/Overweight Fees with Agency Costs: Critical Issues.* Report No. CFIRE 03-17, University of Wisconsin, Madison, 2013.

Agent, K.R. and Pigman, J.G. *Investigation of the Impact of Large Trucks on Interstate Highway Safety*. Kentucky Transportation Cabinet, University of Kentucky, Lexington, Kentucky, 2002.

Bilal, M.K., Irfan, M., Ahmed, A., Labi, S., Kumares, C. *A Synthesis of Overweight Truck Permitting*. Report FHWA/IN/JTRP-2010/12, Indiana Department of Transportation, Indianapolis, Indiana, 2010.

Bittner, J., Kleinmaier, D., Levine, J. *Transportation of Wind Energy Industry Components: Planning for Growth in the Heartland*. 12th National Conference on Transportation Planning for Small and Medium-Sized Communities, Williamsburg, VA, 2010.

Dissanayake, S., Amarashingha, N. *Effects of Geometric Design Features on Truck Crashes on Limited-Access Highways*. Report: MATC-KSU: 454, Mid-America Transportation Center, Lincoln, Nebraska, 2012.

Federal Highway Administration (FHWA). *Freight Management and Operations*. Report FHWA-OP-03-099, Federal Highway Administration, United States Department of Transportation, Washington, D.C., 2013.

Garber, N.J., Sarath, J. *Characteristics of Large truck Crashes in Virginia*. In *Transportation Quarterly*, Vol. 43, pp. 123–128, 1989.

Hallmark, S., Hsu, Y., Maze, T., McDonald, T., Fitzsimmons, E. *Investigating Factors Contributing to Large Truck Lane Departure Crashes Using the Federal Motor Carrier Safety Administration's Large Truck Crash Causation Study (LTCCS) Database*. Center for Transportation Research and Education, Iowa State University, Ames, 2009.

Insurance Institute for Highway Safety (IIHS). *Fatality Facts – Large Trucks*, Insurance Institute for Highway Safety, 2018. Accessed from http://www.iihs.org/iihs/topics/t/large-trucks/fatalityfacts/large-trucks/2016

K-TRIPS. *Permit Price List*. Kansas Department of Transportation, 2018. Accessed from https://www.k-trips.com/Kansas%20Permit%20Price%20List.pdf

Kansas Department of Transportation (KDOT). *2016 Kansas Traffic Crash Facts: Crashes Involving Heavy/Large Trucks*. Kansas Department of Transportation, Topeka, Kansas, 2016a.

Kansas Department of Transportation (KDOT). *Kansas Statewide Freight Plan.* Kansas Department of Transportation, Topeka, Kansas, 2017. Access from from https://www.ksdot.org/Assets/wwwksdotorg/bureaus/burRail/Rail/Documents/KDOTFreightPlan.pdf

Kansas Highway Patrol (KHP). *Weight Enforcement in Kansas*, Kansas Highway Patrol, Topeka, Kansas, 2018. Accessed from https://www.kansashighwaypatrol.org/DocumentCenter/View/178/Weight-Enforcement-Facts-PDF

Middleton, D., Li, Y., Le, J., Koncz, N. *Accommodating Oversize and Overweight Loads: Technical Report.* Report No. 0-6404-1, Texas A&M Transportation Institute, College Station, Texas, 2012.

Russell, Eugene R., and E. Dean Landman. 2012. *Optimizing the analysis of routing Oversize/Overweight loads to provide efficient freight corridors.* Kansas Department of Transportation, KTRAN: KSU-11-4.

Russell, Eugene R., E. Dean Landman, and Ranjit Godavarthy. 2013. *Accommodating Oversize/Overweight vehicles at roundabouts.* Kansas Department of Transportation, KTRAN: KSU-10-1.

Spainhour, L.K., Brill, D., Sobanjo, J.O., Wekezer, J., Mtenga, P.V. *Evaluation of Traffic Crash Fatality Causes and Effects: A Study of Fatal Traffic Crashes in Florida from 1998-2000 Focusing on Heavy Truck Crashes*. Florida State University and Florida A&M University, Tallahassee, FL, 2005.

Vallette, G.R., McGee, H.W., Sanders, J.H, Enger, D.J. *The Effect of Truck Size and Weight on Accident Experience on Traffic Operations*. Report FHWA-RD-80-135, Federal Highway Administration, United States Department of Transportation, Washington, D.C., 1981.

Uniform Act Regulating Traffic; Size, Weight and Load of Vehicles, (2016).

Appendix A

K-TRIPS Permit Price List (Current as of 7/05/2018)

Permit Type	Price
Standard Annuals	$150.00
Annual Special Vehicle Combination	$50.00
Annual SVC Company Fee	$2000.00
KTA Access Annual	$10.00
Hay – Five Year Hay	$25.00
Overdimension Oversize and/or Overweight	$20.00
Overdimension Poles, Beams, and Girders	$20.00
Oil Service Rig Single Trip	$20.00
Overdimension Large Structure	$30.00
Overdimension Superload	$50.00
Fuel & Registration 3 Day Permit	Fuel - $25.00 Registration - $46.00
Fuel 10 Day Permit	$88.00
Fuel 24 Hour	$13.00
Fuel 7 Day Permit	$63.00
Fuel 72 Hour	$25.00
Harvest 30 Day Permit Foreign Based	20,001-24,000: $46.00 24,001-26,000: $51.50 26,001-30,000: $51.50 30,001-36,000: $59.38 36,001-42,000: $71.88 42,001-48,000: $88.13 48,001-54,000: $113.13 54,001-60,000: $143.13 60,001-66,000: $168.13 66,001-74,000: $208.75 74,001-80,000: $233.75 80,001 or Greater: $258.75
Harvest 30 Day Permit Kansas Based	$46.00
Harvest 60 Day Permit Foreign Based	20,001-24,000: $49.50 24,001-26,000: $68.67 26,001-30,000: $68.67 30,001-36,000: $79.17 36,001-42,000: $95.83 42,001-48,000: $117.50 48,001-54,000: $150.83 54,001-60,000: $190.83 60,001-66,000: $224.17 66,001-74,000: $278.33 74,001-80,000: $311.67 80,001 or Greater: $345.00

Harvest Overdimension	$10.00
KTA Access 6 Month	$5.00
Liquid Fuel Temporary	$5.00
Registration 30 Day	20,001-24,000: $46.00 24,001-26,000: $51.50 26,001-30,000: $51.50 30,001-36,000: $59.38 36,001-42,000: $71.88 42,001-48,000: $88.13 48,001-54,000: $113.13 54,001-60,000: $143.13 60,001-66,000: $168.13 66,001-74,000: $208.75 74,001-80,000: $233.75 80,001 or Greater: $258.75
Registration 6 Day	$92.00
Registration 72 Hour	$46.00
Registration 9 Day	$138.00
Registration Beyond Local	$46.00
Registration Dealer Demo	$46.00
Registration Dealer Demo 15 Day	$120.00
Unladen Vehicle Registration	$46.00
Weight 6 Day	$92.00
Weight 72 Hour	$46.00
Weight 9 Day	$138.00

Appendix B

R-code used for the Final Logistic Regression Model

```
m1<-
glm(ACCIDENT_SEVERITY~as.factor(ACCIDENT_CLASS_FHE)+as.factor(ON_ROAD_SU
RFACE_TYPE)+(TIME_OF_ACCIDENT)-1
        , family= binomial, data = data)

summary(m1)

Deviance Residuals:
        Min         1Q          Median      3Q          Max
        -2.89831    0.00009     0.39785     0.68975     1.45133

Coefficients:

                                      Estimate     Std. Error    z value Pr(>|z|)
as.factor(ACCIDENT_CLASS_FHE)0        2.165e+00    1.082e+00     2.001   0.04544 *
as.factor(ACCIDENT_CLASS_FHE)1        -1.434e+00   1.181e+00     -1.215  0.22447
as.factor(ACCIDENT_CLASS_FHE)3        1.628e+00    7.940e-01     2.050   0.04038 *
as.factor(ACCIDENT_CLASS_FHE)7        1.961e+01    1.448e+03     0.014   0.98919
as.factor(ACCIDENT_CLASS_FHE)8        3.561e+00    9.259e-01     3.846   0.00012 ***
as.factor(ACCIDENT_CLASS_FHE)9        1.879e+01    4.599e+03     0.004   0.99674
as.factor(ON_ROAD_SURFACE_TYPE)2      8.458e-01    5.060e-01     1.671   0.09464 .
TIME_OF_ACCIDENT                      -9.365e-04   4.761e-04     -1.967  0.04920 *
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 205.17 on 148 degrees of freedom
Residual deviance: 114.14 on 140 degrees of freedom
AIC: 130.14
```

R-code used for Backwards Selection

```
m<-
glm(as.factor(ACCIDENT_SEVERITY)~as.factor(ACCIDENT_CLASS_FHE)+as.factor(ON_R
OAD_SURFACE_TYPE)+(TIME_OF_ACCIDENT)+as.factor(ACCIDENT_CLASS_MHE)+

as.factor(DAY_OF_ACCIDENT)+as.factor(ON_ROAD_SURFACE_TYPE)+as.factor(ON_RO
AD_SURFACE_COND)+as.factor(ON_ROAD_SURFACE_CHAR)+as.factor(ACCIDENT_L
OCATION)+as.factor(ALCOHOL_INVOLVEMENT)+as.factor(WEATHER_CONDITIONS)-
1, family= binomial, data = data)
```

```
> back<- step(m)
Start:  AIC=165.12
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
   as.factor(ON_ROAD_SURFACE_TYPE) + (TIME_OF_ACCIDENT) + as.factor(ACCIDEN
T_CLASS_MHE) +
   as.factor(DAY_OF_ACCIDENT) + as.factor(ON_ROAD_SURFACE_TYPE) +
   as.factor(ON_ROAD_SURFACE_COND) + as.factor(ON_ROAD_SURFACE_CHAR) +
   as.factor(ACCIDENT_LOCATION) + as.factor(ALCOHOL_INVOLVEMENT) +
   as.factor(WEATHER_CONDITIONS) - 1
```

	Df	Deviance	AIC
- as.factor(ACCIDENT_LOCATION)	8	79.688	153.69
- as.factor(WEATHER_CONDITIONS)	10	85.954	155.95
- as.factor(DAY_OF_ACCIDENT)	6	79.291	157.29
- as.factor(ON_ROAD_SURFACE_COND)	4	75.665	157.66
- as.factor(ACCIDENT_CLASS_MHE)	4	78.368	160.37
- TIME_OF_ACCIDENT	1	75.495	163.50
- as.factor(ON_ROAD_SURFACE_CHAR)	4	82.790	164.79
<none>		75.122	165.12
- as.factor(ON_ROAD_SURFACE_TYPE)	1	77.526	165.53
- as.factor(ALCOHOL_INVOLVEMENT)	1	77.907	165.91
- as.factor(ACCIDENT_CLASS_FHE)	5	93.696	173.70

```
Step:  AIC=153.69
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
   as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT + as.factor(ACCIDENT
_CLASS_MHE) +
   as.factor(DAY_OF_ACCIDENT) + as.factor(ON_ROAD_SURFACE_COND) +
   as.factor(ON_ROAD_SURFACE_CHAR) + as.factor(ALCOHOL_INVOLVEMENT) +
   as.factor(WEATHER_CONDITIONS) - 1
```

	Df	Deviance	AIC
- as.factor(WEATHER_CONDITIONS)	10	91.874	145.87
- as.factor(ON_ROAD_SURFACE_COND)	4	80.800	146.80

- as.factor(DAY_OF_ACCIDENT)	6	84.939	146.94
- as.factor(ACCIDENT_CLASS_MHE)	4	84.574	150.57
- TIME_OF_ACCIDENT	1	80.532	152.53
<none>		79.688	153.69
- as.factor(ON_ROAD_SURFACE_CHAR)	4	88.497	154.50
- as.factor(ALCOHOL_INVOLVEMENT)	1	82.848	154.85
- as.factor(ON_ROAD_SURFACE_TYPE)	1	82.959	154.96
- as.factor(ACCIDENT_CLASS_FHE)	5	103.496	167.50

Step: AIC=145.87
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT + as.factor(ACCIDENT
_CLASS_MHE) +
as.factor(DAY_OF_ACCIDENT) + as.factor(ON_ROAD_SURFACE_COND) +
as.factor(ON_ROAD_SURFACE_CHAR) + as.factor(ALCOHOL_INVOLVEMENT) -
1

	Df	Deviance	AIC
- as.factor(DAY_OF_ACCIDENT)	6	97.964	139.96
- as.factor(ACCIDENT_CLASS_MHE)	4	94.731	140.73
- as.factor(ON_ROAD_SURFACE_COND)	4	95.898	141.90
<none>		91.874	145.87
- as.factor(ON_ROAD_SURFACE_CHAR)	4	100.210	146.21
- TIME_OF_ACCIDENT	1	95.357	147.36
- as.factor(ALCOHOL_INVOLVEMENT)	1	95.971	147.97
- as.factor(ON_ROAD_SURFACE_TYPE)	1	96.292	148.29
- as.factor(ACCIDENT_CLASS_FHE)	5	113.302	157.30

Step: AIC=139.96
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT + as.factor(ACCIDENT
_CLASS_MHE) +
as.factor(ON_ROAD_SURFACE_COND) + as.factor(ON_ROAD_SURFACE_CHAR) +
as.factor(ALCOHOL_INVOLVEMENT) - 1

	Df	Deviance	AIC
- as.factor(ACCIDENT_CLASS_MHE)	4	101.947	135.95
- as.factor(ON_ROAD_SURFACE_COND)	4	101.960	135.96
- as.factor(ON_ROAD_SURFACE_CHAR)	4	104.173	138.17
<none>		97.964	139.96
- as.factor(ALCOHOL_INVOLVEMENT)	1	100.290	140.29
- TIME_OF_ACCIDENT	1	101.584	141.58
- as.factor(ON_ROAD_SURFACE_TYPE)	1	102.004	142.00
- as.factor(ACCIDENT_CLASS_FHE)	5	120.658	152.66

Step: AIC=135.95
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT + as.factor(ON_ROAD_SURFACE_COND) +
as.factor(ON_ROAD_SURFACE_CHAR) + as.factor(ALCOHOL_INVOLVEMENT) -
1

	Df	Deviance	AIC
- as.factor(ON_ROAD_SURFACE_COND)	4	106.54	132.54
- as.factor(ON_ROAD_SURFACE_CHAR)	4	108.86	134.86
<none>		101.95	135.95
- as.factor(ALCOHOL_INVOLVEMENT)	1	104.38	136.38
- TIME_OF_ACCIDENT	1	105.85	137.85
- as.factor(ON_ROAD_SURFACE_TYPE)	1	106.59	138.59
- as.factor(ACCIDENT_CLASS_FHE)	6	143.49	165.49

Step: AIC=132.54
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT + as.factor(ON_ROAD_SURFACE_CHAR) +
as.factor(ALCOHOL_INVOLVEMENT) - 1

	Df	Deviance	AIC
- as.factor(ON_ROAD_SURFACE_CHAR)	4	113.30	131.30
<none>		106.54	132.54
- as.factor(ALCOHOL_INVOLVEMENT)	1	108.87	132.87
- TIME_OF_ACCIDENT	1	109.95	133.95
- as.factor(ON_ROAD_SURFACE_TYPE)	1	110.08	134.08
- as.factor(ACCIDENT_CLASS_FHE)	6	147.70	161.70

Step: AIC=131.3
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT + as.factor(ALCOHOL_INVOLVEMENT) -
1

	Df	Deviance	AIC
- as.factor(ALCOHOL_INVOLVEMENT)	1	114.14	130.14
<none>		113.30	131.30
- as.factor(ON_ROAD_SURFACE_TYPE)	1	115.95	131.95
- TIME_OF_ACCIDENT	1	117.74	133.74
- as.factor(ACCIDENT_CLASS_FHE)	6	159.53	165.53

Step: AIC=130.14
as.factor(ACCIDENT_SEVERITY) ~ as.factor(ACCIDENT_CLASS_FHE) +
    as.factor(ON_ROAD_SURFACE_TYPE) + TIME_OF_ACCIDENT - 1

	Df	Deviance	AIC
<none>		114.14	130.14
- as.factor(ON_ROAD_SURFACE_TYPE)	1	116.94	130.94
- TIME_OF_ACCIDENT	1	118.31	132.31
- as.factor(ACCIDENT_CLASS_FHE)	6	159.85	163.85