Spatio-Temporal Analysis of Freight Patterns in Southern California

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16. Abstract

There has been a general trend to shift the location of warehouses and distribution facilities away from consumer markets (logistics sprawl) in Southern California. This shift has a negative impact on logistics cost (though with reduced facility costs) and the environment because freight vehicles have to travel longer to reach their destinations. However, during the last decade, this trend has not continued at a uniform pace, and it may have even reversed. Two main factors potentially explain this phenomenon: the 2008-2009 economic slow-down or recession, and an increase in e-commerce activity. E-commerce impacts are relevant for freight planning because of the many operational changes they require: changes in vehicle size to distribute smaller shipments at higher frequencies, consumer proximity requirements to improve delivery times, and the redistribution of freight activity and supply chain configurations. This research conducted spatio-temporal analyses of Caltrans Weigh-in-Motion data to validate some of these assumptions. There is evidence that during 2003-2015, short-haul volume has increased by 69%, whereas long-haul volume increased by 59%. The analyses identified changes in concentrations of trip flows by vehicle class, evidencing changes in long-haul versus last-mile distribution patterns. The results can help estimate changes in vehicle miles traveled, and more importantly, can identify the geographical areas of the most impacted communities.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; and Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education, and technology transfer aimed at *improving the mobility of people and goods throughout the region*. Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

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Abstract

There has been a general trend to shift the location of warehouses and distribution facilities away from consumer markets (logistics sprawl) in Southern California. This shift has a negative impact on logistics cost (though with reduced facility costs) and the environment because freight vehicles have to travel longer to reach their destinations. However, during the last decade, this trend has not continued at a uniform pace, and it may have even reversed. Two main factors potentially explain this phenomenon: the 2008-2009 economic slow-down or recession, and an increase in e-commerce activity. E-commerce impacts are relevant for freight planning because of the many operational changes they require: changes in vehicle size to distribute smaller shipments at higher frequencies, consumer proximity requirements to improve delivery times, and the redistribution of freight activity and supply chain configurations.

This research conducted spatio-temporal analyses of Caltrans Weigh-in-Motion data to validate some of these assumptions. There is evidence that during 2003-2015, short-haul volume has increased by 69%, whereas long-haul volume increased by 59%. The analyses identified changes in concentrations of trip flows by vehicle class, evidencing changes in long-haul versus last-mile distribution patterns. The results can help estimate changes in vehicle miles traveled, and more importantly, can identify the geographical areas of the most impacted communities.

Spatio-Temporal Analysis of Freight Patterns in Southern California

Executive Summary

This work addresses an important research topic of freight modeling by analyzing the freight patterns in Southern California. Specifically, this work analyzes the concentration of truck traffic in four Caltrans districts and six counties in Southern California between 2003 and 2015; and explores the spatial relationships between freight measurements for different vehicle types with time and distance by using centrographic and regression modeling techniques.

The work uses both aggregate and disaggregate approaches depending on the nature of the information available. For the aggregate approach, the analyses used aggregate vehicle counts (by vehicle class) for different Weigh-in-Motion (WIM) stations. The results confirm: 1) the existence of logistics sprawl, though the analyses indicate that this trend has not continued to increase after 2007; 2) that the locations of the weighted geometric center have shifted differently for some vehicle classes; and 3) that the concentration of small-medium duty truck flows tend to decrease with time, while the concentration increases for heavy duty trucks.

Using the WIM data, the team used simple and piecewise simple linear regression models to characterize the relationship between several statistical measurements of freight flows over time. Additionally, the team used centrographic analyses with geo-localized data, then estimated and compared the distance of the barycenter or the equilibrium center using the port of Los Angeles in Southern California as a reference; compared the results within vehicle classes; and considered the implications of such results.

These results are expected to have great planning and policy implications and to be of interest to practitioners, public and private entities and academia. Caltrans, Metropolitan Planning Organizations and the affiliated institutions of the Pacific Southwest Region University Transportation Center will directly benefit from the research, as the results will facilitate the development of policies and sustainable strategies for the freight transportation system.

This report provides a summary of data preparation and analysis techniques, as well as a description of the WIM data structure, data sampling and cleaning methods, and assumptions used in the analyses. This begins with a description of the data collection, and the limitation of the analysis to 9 vehicle classes. Then, the temporal patterns are described, with a focus on annual data. This analysis was necessary to separate the information by vehicle class and WIM station location to identify different patterns, and to establish the relationships between different statistical measurements over time. Overall, for the different locations and vehicle classes, the study evaluated the spatio-temporal changes in truck volumes, truck loading ratios, and gross vehicle weights.

I. Introduction

In the last several decades, several factors such as the economic recession, the rise of the on-demand economy, changes in the regulatory environment, and an increase in urbanization with its associated consumption have affected the distribution of goods. One example is a shift in the location of warehouses and distribution facilities away from consumer markets. This shift, or logistics sprawl, brings about unintended consequences, such as increased vehicle miles traveled and the concentration of freight activity in specific, usually disadvantaged, communities.

In California, especially Southern California, previous research has shown an increase in the concentration of these warehouse facilities at longer distances from their primary delivery locations ((Dablanc, 2014), (Jaller M. L., 2017c)). The research also provides evidence suggesting that while the trend exists in the region, it has not continued at a uniform pace in the last decade, and it may have even reversed. The 2008-2009 economic slowdown and the growth of e-commerce activity are two of the main factors that potentially explain this phenomenon. E-commerce impacts are relevant for freight planning because of multiple concurrent changes: in vehicle size to distribute smaller shipments at higher frequencies; in consumer proximity requirements to improve delivery times; and, in the redistribution of the freight activity and supply chain configurations ((Visser, 2004), (Weltevreden, 2007), (Gonzalez-Feliu, 2012), (Wang, 2015), (UPS, 2016), (Jaller M. L., 2017a) (Jaller M. L., 2017b), (Jaller & Pahwa, 2020) , (Jaller, Zhang, & Qian, 2020)).

Although previous analyses provided insights into these potential effects, they have not been explicitly quantified. Consequently, the objective of this research is to conduct spatio-temporal analyses of freight truck flows in Southern California to understand and quantify the changes in the types of vehicles doing freight operations during the last decade; the spatial distribution of the traffic; and, changes in freight loads throughout the region. Caltran's Weigh-in-Motion (WIM) database is used to evaluate shifts in the traffic distribution, temporal changes in those volumes, fleet compositions (i.e., vehicle classes), and the gross vehicle weights at the count stations. Such data allows the estimation of: truck volume per class, average annual/monthly truck traffic, load distribution for different vehicles, gross vehicle weight and load truck ratios for different vehicle classes (Lu, 2002), (Jiang, 2008), (Quinley, 2010).

Understanding changes in the way the freight system distributes goods is vital for healthy planning efforts, and for the development of effective policies and measures. Although there have been several advances in the last few years in our knowledge of the freight system, the topic is still in the early stages compared to passenger transport. However, freight transportation is receiving increased attention from academics. Changes in vehicles used and the spatial locations of facilities could affect future infrastructure requirements, maintenance and rehabilitation; or affect the routes used by these vehicles with direct impacts to specific communities. Different regulations affect different types of vehicles (size, technology) with implications for increased traffic of smaller and lighter vehicles resulting from increased e-commerce activity.

The remainder of this paper is structured as follows: Section 2 describes the project's data management. Section 3 offers the temporal analysis, including a discussion of temporal resolution and the required aggregation and disaggregation considering the variability of the data and the multiple dimensions of the data. Section 4 conducts a spatial analysis considering a centrographic assessment of the truck volume, and weight data (gross vehicle weight, truck load ratio) for aggregated Light-, Medium- and Heavy-heavy duty trucks. Finally, Section 5 presents our remarks and conclusions.

II. Data Collection, Gathering and Assembly

This study analyzes Caltrans Weigh-in-Motion (WIM) data collected from stations located in Southern California from January 2003 to December 2015. Those WIM devices capture and record axle weight, speed, axle type, vehicle classification and gross vehicle weight for vehicles traveling at reduced or normal speeds over a measurement site ((Caltrans, 2018), (Santero, 2005), (Zhang, 2014)). They help to identify vehicle compliance with weight limit regulations, and to collect data for monitoring, planning and management purposes. The California Department of Transportation (Caltrans) has installed WIM devices in about 150 sites. A number of stations are at PrePass locations, but the majority are spread throughout the transportation network as WIM data stations. The University of California Pavement Research Centers (UCPRC) at UC Davis manages an analysis of WIM data for Caltrans for pavement management and design. Considering the scope of the project, the team conducts a general assessment of the quality of the WIM data, but a detailed analysis of calibration factors, vehicle miss-classification, sensor degradation impacts, and other data accuracy issues are outside of the scope of this project.

District, Counties and Raw WIM

The Caltrans WIM database contains the information of the WIM data stations for a period of 13 years (2003-2015). Based on (Caltrans, 2019), California has twelve districts (see Figure 1). This analysis considers only the four districts in southern California, and their 39 stations, however two of these are not in the analysis because they do not have enough data to perform any analysis (828-Blackrock and 844 Calexico). Figure 2 shows the location of those WIM stations and Table 2 shows the city, district, county, the post mile location and the corresponding geo-localization coordinates (latitude, longitude) of each WIM Station. Figure 2 also includes each station's Euclidian distance from Port of Los Angeles and Long Beach (POLA/LB), and Figure 3 depicts the frequency distribution of WIM stations versus distance.

Figure 1. WIM Location taken from (Caltrans, 2019)

Figure 2. Location of WIM stations in Southern California

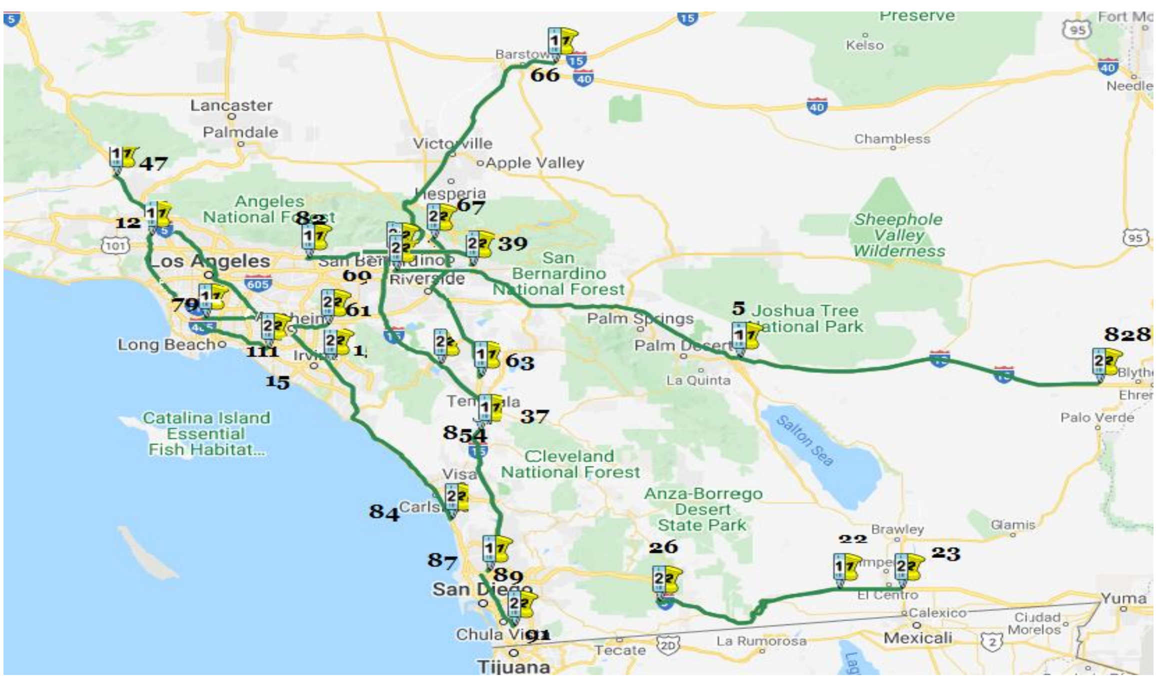

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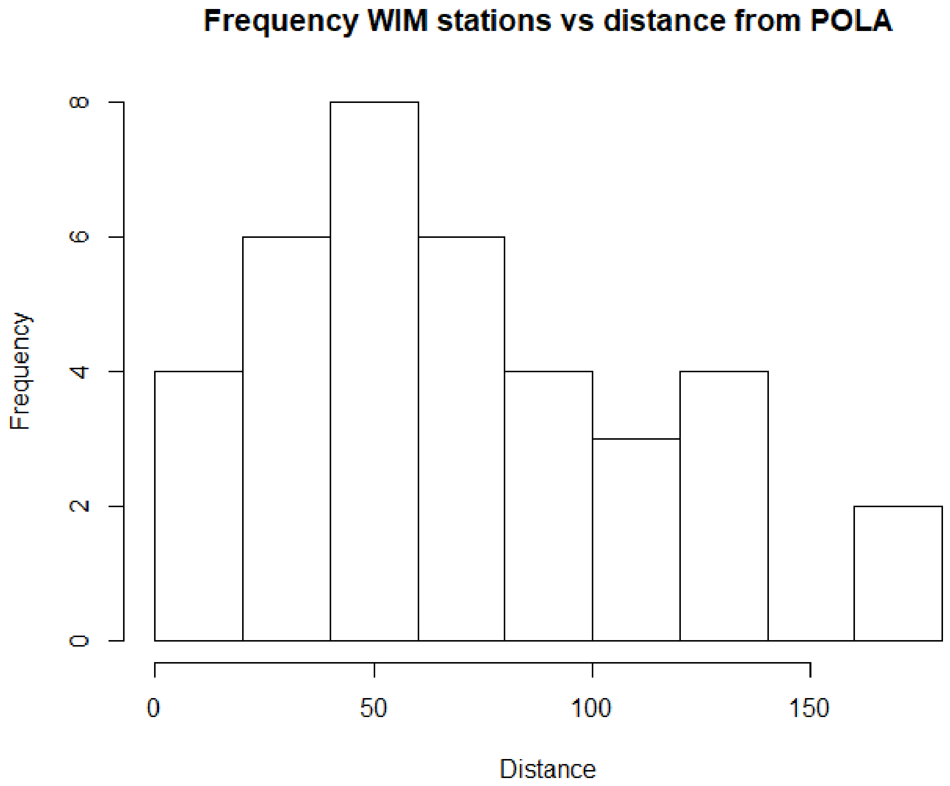
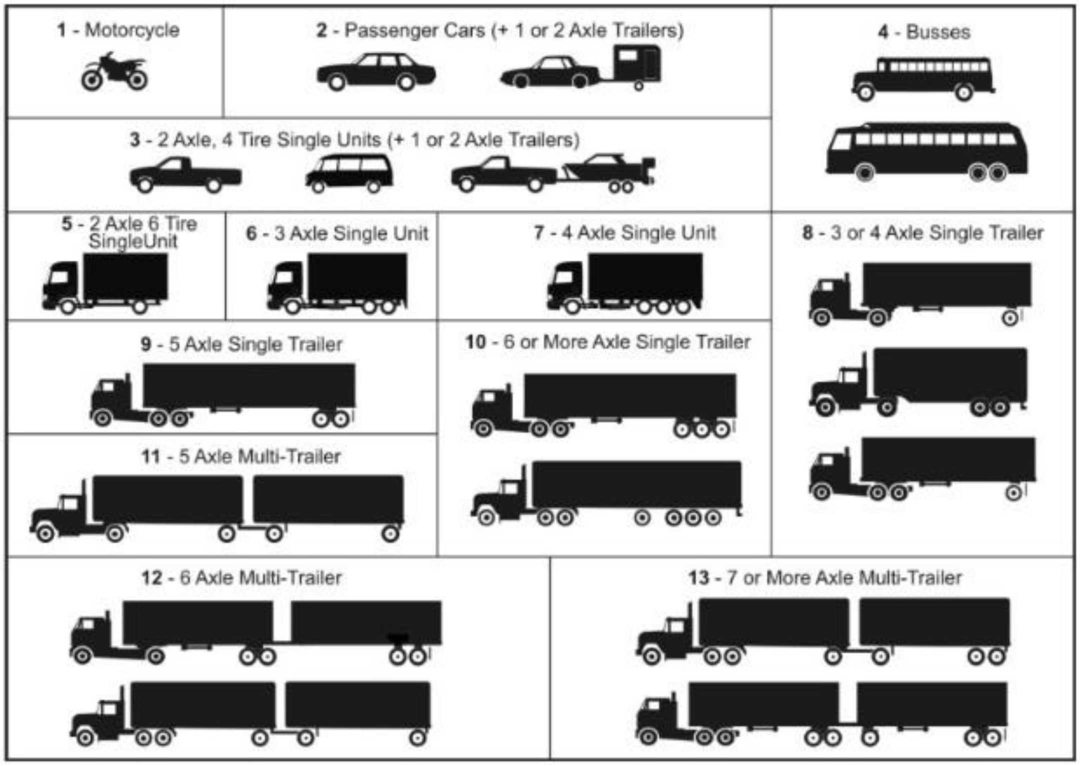
Figure 3. Frequency of WIM station vs. distance from POLA



Vehicle Classification (VC)

The WIM database contains eleven vehicle classes (VC), from VC 4 to VC 14. Figure 4 shows that vehicle class 4 is a bus service, and vehicle class 14 is unclassified. Additionally it shows the WIM classification (left) and the Federal Highway Administration (FHWA) (right) vehicle classifications; both classifications depend on the number of axles and type of trailer (Single Unit, Single trailer, or Multi-trailer). This study concentrates on WIM classes 5-13. For the purpose of analysis, the authors categorized the vehicles as light-heavy duty trucks representing single unit trucks (FHWA classes 5-7); medium-heavy-duty trucks or single-trailer trucks (FHWA classes 8-10); and heavy-heavy-duty trucks or multi-trailer trucks (FHWA classes 11-13). One important benefit of WIM station data is the ability to classify the vehicle type.

Figure 4. Vehicle classification



III. Temporal Analysis

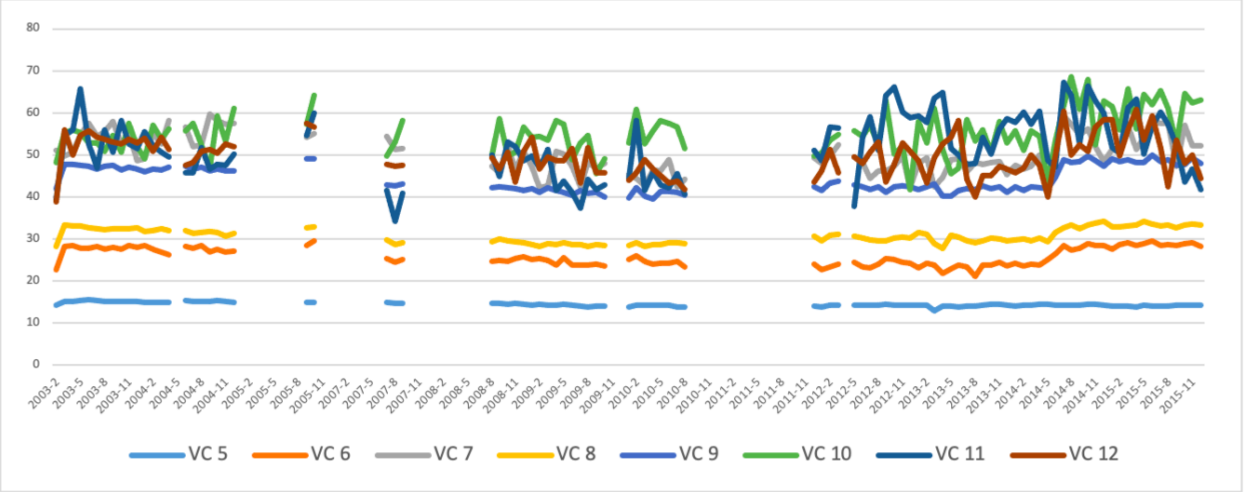
In this section, the authors perform a temporal analysis to provide insight into the hypothesis that e-commerce has been causing changes in traffic flows, weights and the payloads of trucks. For instance, with e-commerce, it is expected that the payload and weight has diminished for smaller vehicles, while the volume has increased with time. To analyze this behavior, the authors used the Gross Vehicle Weight (GVW) and estimated a Truck Load Ratio (TLR) as the measurements of weight and payload, respectively. The analyses focus on changes in three metrics: vehicle flows (volumes, V), gross vehicle weight (GVW), and truck load ratios (TLR) for each vehicle class or category. The data directly provides GVW, however, the authors had to estimate volumes for each vehicle class yearly, and the TLR for each observation. In doing so, the authors approximated the TLR, as noted in Equation 1.

Equation 1

$$TLR_k = \frac{GVW_k - \min(GVW_k)}{maxGVW_k - \min(GVW_k)}$$

Where the numerator estimates the load of the truck, by subtracting the unloaded weight (assumed to be the minimum of the GVW for vehicle type k at all times) of the truck from the loaded weight (Hernandez, 2017). The denominator expresses the maximum payload for each vehicle class. Similarly, because of the variability among classes and sub-classes, it was estimated by subtracting the empty vehicle weight (assumed as the minimum GVW) from the maximum GVW allowed by authorities. The TLR ranges from [0-1] if the vehicle meets the regulation, and “>1” otherwise. The temporal analysis is performed monthly and yearly. The monthly analysis does not show any particular pattern. In other words, the performance of GVW and LTR is almost constant within monthly time intervals (See Figure 15-Figure 18in Appendix 2). However, the performance of individual vehicle classes is different. Additionally, there is a lack of data, because there are several months without collected information. For instance, Figure 5 shows the behavior of the GVW average between February 2003 to December 2015. However, notice the lack of monthly information between February 2005 and April 2012; for this reason, the authors decided to continue the analysis inter-year.

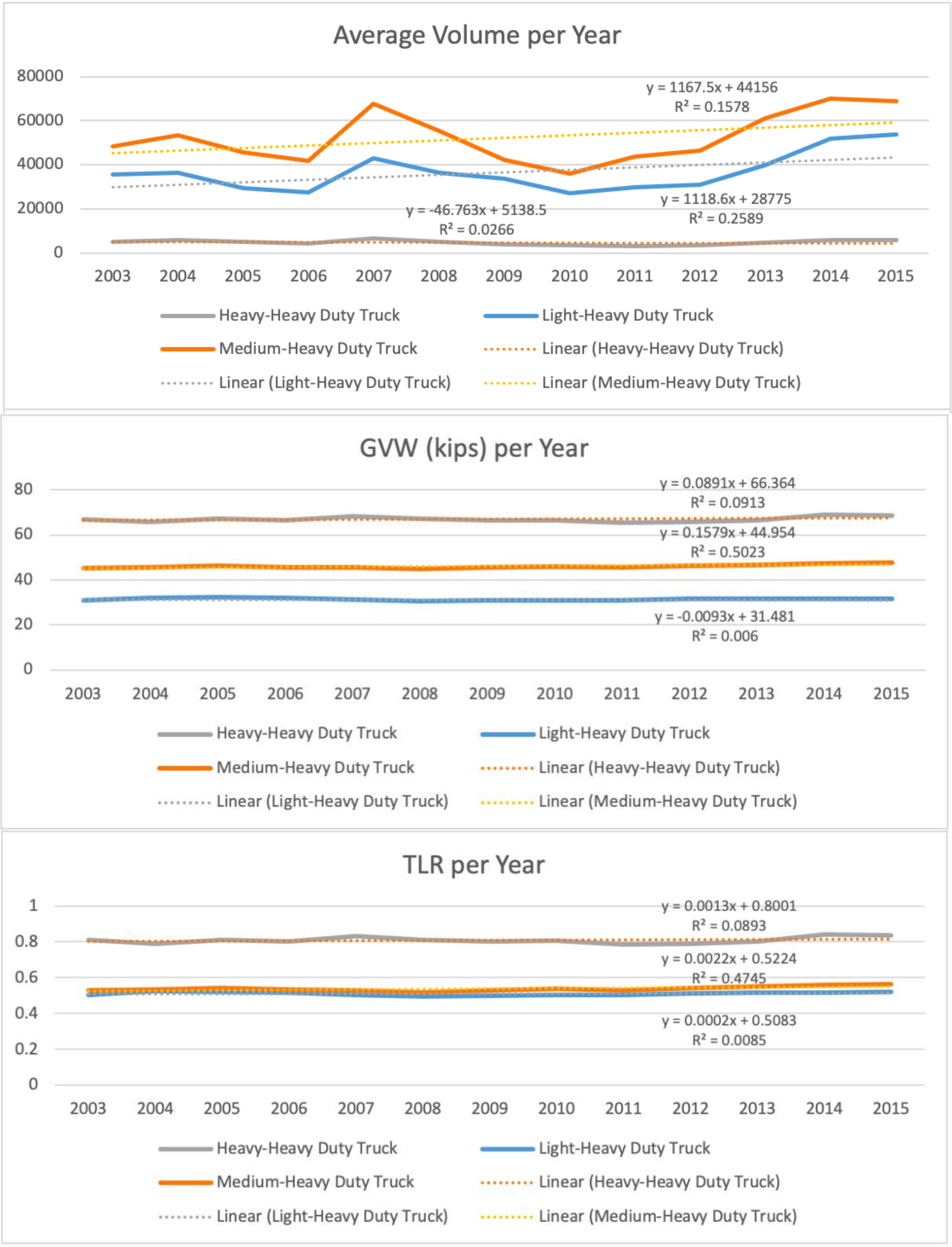
Figure 5. Monthly GVW average Feb-03 to Dec-15, WIM station 12



Additionally, Figure 19 and Figure 20 in Appendix 3 show the boxplot of the GVW and TLR for each vehicle class by including all of the WIM stations mentioned in Table 2 from 2003 to 2013. Notice that this allows us to determine whether trucks are carrying more or less freight over time. In this case, there are variations in some measurements (quartiles) over time in some vehicle classes, though they remain constant for other classes. Moreover, GVW and TLR exhibit similar behaviors. Figure 20 depicts that for all vehicle classes (except vehicle class 13), at least 75% of the volume of vehicles met the weight limit regulations or maximum gross vehicle weight, while about 25% were above the threshold.In the case of vehicle class 13, at least 50% of the vehicles had a GVW of over 80,000 pounds, which may be because class 13 includes overweight loads.

Aggregating the vehicle classes into the 3 vehicle categories reveals some interesting trends. Figure 4 shows average vehicle GVW, TLR and Volume per year.

Figure 6. Average Volume, GVW, and TLR per Year per vehicle category



The volume trend shows that after the 2008 financial crisis, the volumes across all vehicle categories for Light- and Medium-heavy duty decreased significantly (consistent with the economic slowdown), then slowly recovered between 2010 and 2012, and significantly increased thereafter. However, while the volumes of heavy-heavy-duty vehicles also experienced this trend, the changes were small, compared to those seen for Light- and Medium-heavy duty trucks. Between these two, the Light-heavy duty trucks is the one with the largest comparative increase during that period, which could be explained by the growth in e-commerce and last-mile deliveries. Moreover, Light- and Medium-heavy duty trucks represent, on average, more than 90% of the volume at the WIM stations.

The GVW shows that heavy-heavy-duty vehicles are, on average, around 65 kips (65000 pounds), while Medium- and Light-heavy duty trucks are around 45 (45000 pounds) and 30 kips (30000 pounds), respectively. The data do not show any significant change, and despite thepositive slope, indicative of an increase, its magnitude is very small, especially for light-heavy-duty vehicles. For others, the expected change in a 10-year period only represents about a 5% increase. The TLR analyses do show some increase in the loading factors, especially in the last few years after the recession, with Medium- and Heavy-heavy duty trucks achieving higher relative efficiencies compared to the smaller single-unit trucks. On average, multi-trailer or Heavy-heavy duty trucks have reached a loading factor of almost 85%, whereas single-unit or Light-heavy duty trucks, and single-trailer or Medium-heavy duty trucks have a general loading factor of around 50%. Interestingly, Class 5 trucks only have a mean TLR of around 25%. It is important to mention that the data were not filtered by the flow direction of the WIM station. The import and export trade deficit, and the clustering of warehousing facilities to the east of the study area, could affect the load factors. Nevertheless, the loading factors for last-mile delivery vocations tend to be lower than for larger vehicles, especially when considering the less-than-truck-load (LTL) and full-truck-load (FTL) vocations.

To uncover additional insights about these trends, the authors conducted disaggregate analyses for each vehicle class.

Disaggregate Temporal Analyses

In this section, the author analyzed the behavior of the GVW, TLRand volume between 2003 and 2015 for each vehicle class by disaggregating all of the WIM stations in all districts (7, 8, 11, and 12). First, the authors used simple linear regression (SLR), as follows in Equation 2:

Equation 2

$$Y_{stat-meas_{ijt}} = \beta_{0_{ij}} + \beta_{1_{ij}} * year_t$$

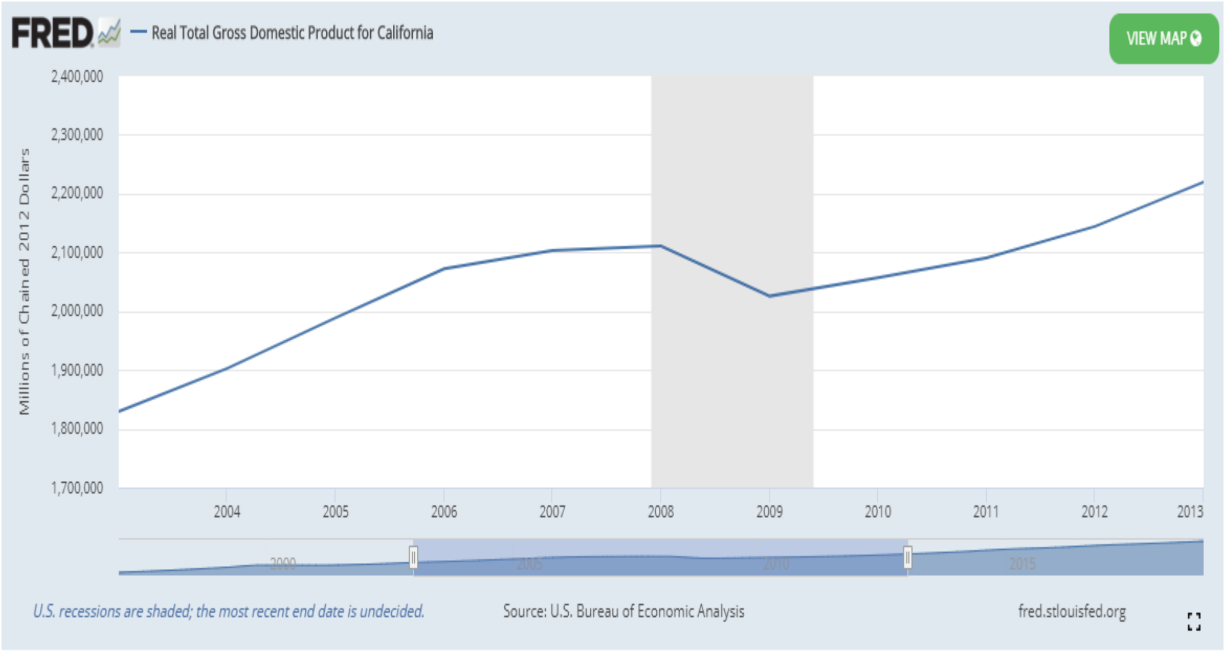
Where *i* refers to each of the 9 vehicle classes (5-13), *j* refers to each of the 37 WIM stations in southern California Stations, and *t* refers to each of the 12 years during the period analyzed (2003-2015). This SLR considered each combination of vehicle class–WIM station (vc-w) by using nine statistical measurements: mean of GVW ($\overline{GVW}$), mean of LTR ($\overline{LTR}$), the quartiles of

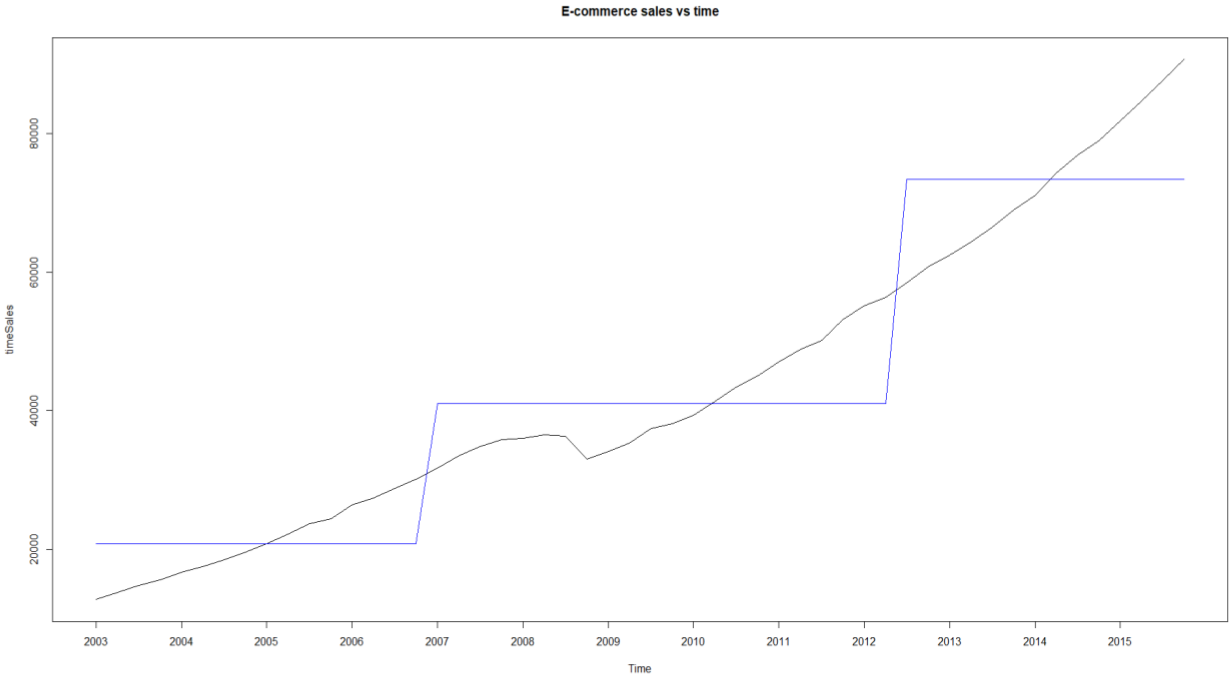
GVW and LTR (Q_1^{gvw}, Q_2^{gvw}, Q_3^{gvw}, Q_1^{ltr}, Q_2^{ltr}, Q_3^{ltr}), and the vehicle volumes (vol). This resulted in around 2979 SLR models. Quartile 3 gives us information about the most loaded vehicles, while quartile 1 gives information about the less loaded vehicles. Those quartiles are included because the team wants to identify if both groups have different behaviors in the analysis.

Considering the large amount of statistical data resulting from the modeling effort, the authors concentrated on the direction of the slope (for statistically significant slopes at the 90-95% confidence interval). A positive slope means that the measurements have been increasing over time (12 years); a negative slope would mean the opposite. Finally, no slope could mean a constant performance of the dependent variable in time, or a lack of linear relationship.

In the first approach, the authors found that most of the slopes for vehicle classes 5, 7, and 11 are negative, meaning that most of the statistics for those vehicle classes decreased linearly over time. Indeed, in at least 63% of the WIM stations the $\overline{GVW}$ diminished over time for the aforementioned vehicle classes. Additionally, several WIM stations have an inverse relationship between the slopes of $\overline{GVW}$ and vol. In some cases, when the $\overline{GVW}$ increases, the vol (number of vehicles) decreases, or vice-versa. However, it is important to note that GVW and TLR have almost the same behavior, and quartiles have similar behavior as their respective means. This means that the most loaded vehicles behave similarly to the less loaded vehicles. Therefore, from now on, the analysis and comparisons will focus on $\overline{GVW}$ and Volume. Another interesting situation is that in 55% of the 2979 simple linear regressions the slopes were statistically zero. One common reason for this result is a nonlinear relationship. This particular non-linearity is caused by a breaking point, which mainly occurred between 2008 and 2009. This is of great importance, as all of the measurements are similarly affected in terms of frequency by this phenomenon, with volume being the measurement most frequently affected among the regression models. Although the data does not provide any additional information regarding the potential cause of this change, the different studies conducted in this area show that this period coincides with how the financial crisis of 2008-09 affected freight operations. For instance, Figure 7 shows how the 2008-2009 economic recession affected the Gross Domestic Product in California, and how before 2007 e-commerce sales were lower than after 2012.

Figure 7. Real Total GDP for California obtained from (FRED, 2020), and e-commerce sales, obtained from (USCB, 2020)





The second approach corrects the coefficients equal to zero because of non-linearity, by performing a piecewise simple linear regression model with a breaking point in 2008-2009, as shown in Equation 3:

Equation 3

$$Y'_{stat-meas_{ijt}} = \beta'_{0_{ij}} + \beta'_{1_{ij}} * x_t + \beta'_{2_{ij}} z_t$$

$$x_t = year_t$$

$$dummyKnot = \begin{cases} 0, if\ year \leq 2008 \\ 1, if\ year > 2008 \end{cases}$$

$$z_t = (x_t - 2008) * dummyKnot$$

This second approach helps to analyze the effect of the 2008-2009 economic recession on the statistic measurement variables. The results show that this new model explains the zero slope in half of the models obtained in the first approach. Then the percentage of WIM stations and vehicle classes with constant behavior or an insignificant change over time was reduced to 30%. These results confirm that the breaking point in 2008-2009 explains the non-linear issue obtained in the first approach.

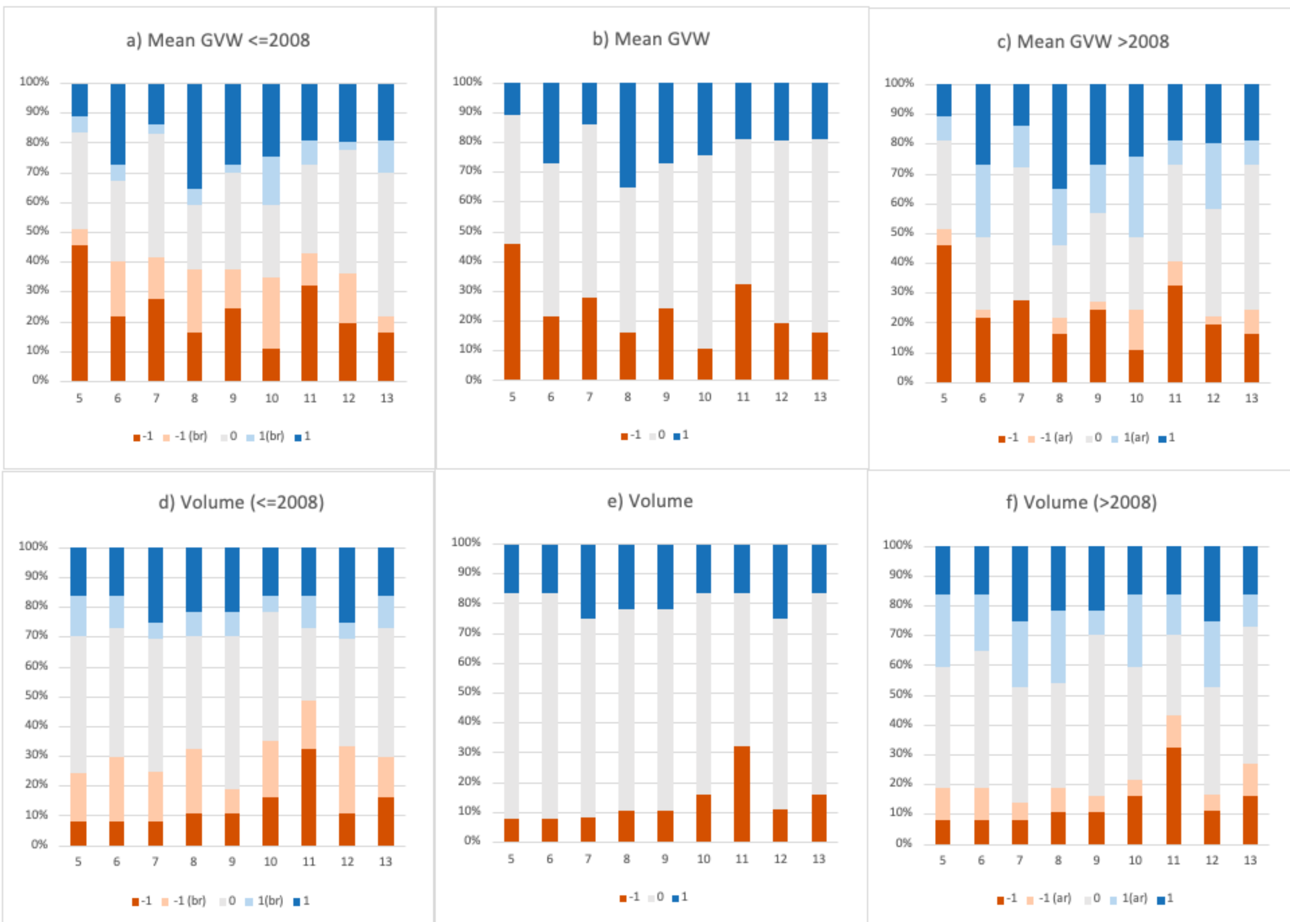
Figure 8 summarizes the results found in both described approaches. For instance, Figure 8 shows the distribution of the slopes of the mean of the GVW and volume for each vehicle class in three scenarios. The first scenario considers the first approach, while the second and third scenarios involve the first and second approaches. The first scenario considers data for the slopes of the SLR from 2003 to 2015 without the non-linearity correction (2nd column); the second scenario assumes the behavior before the economic recession for those with a zero slope (1st column); and the third scenario assumes the behavior after the economic recession for those with a zero slope (3rd column).

First, let us focus on the first scenario. Figure 8.b shows that the mean of the GVW in light-heavy duty trucks (5, 6, 7) has decreased in more WIM stations than for Medium- (8, 9, 10), and Heavy-heavy duty trucks (11, 12, 13). The vehicle class with the most percentage of decrease of the mean of the GVW with time is vehicle class 5, while the one with the greatest increase is vehicle class 8. Figure 8.e shows a larger percentage of WIM stations with constant behavior in volume compared with the mean of GVW. Notice, that on average, Heavy-heavy duty vehicles have the greatest percentage of WIM stations in which volume decreased in comparison with other heavy-duty trucks. The vehicle class with the highest percentage of WIM stations in which volume decreased is Vehicle class 11.

It is worth noting that Figure 8.a, and Figure 8.d include the slope direction that the piecewise model shows for 2003-2008, for those WIM stations with zero slope in Figure 8.a and Figure 8.b. Figure 8.c and Figure 8.f use the correction of the slopes of the piecewise model in 2009-2015.

In general, note that Light-heavy duty trucks have decreased GVW with time, while their volume has increased, especially vehicle class 5. This could be an unintended consequence of e-commerce implementation. On the other hand, Figure 8 shows that on average, the proportion of WIM stations that decreased the mean of GVW and volume over time is larger before the economic recession (br) than after the economic recession (ar), in almost all vehicle classes. The opposite occurs after the recession, where the proportion of WIM stations that increased GVW and volume, is, on average, larger than the proportion seen before the economic recession.

Figure 8. Proportion of WIM stations where mean GVW and Volume, decreased (-1), decreased before recession (-1(br)), decreased after recession (-1(ar)), (0) remained constant, increased (1), increased before recession (1 (br)), and increased after recession (1 (ar)) through time.



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IV. Spatio-Temporal Analysis

This analysis is performed to identify possible changes in the patterns of the flows and the weight of vehicle classes with distance and time, jointly. The authors merged the results of the SLR obtained in the temporal analysis with the distance of each WIM station to the Port of Los Angeles and Long Beach (POLA/LB) as the reference point (See Table 2). This spatio-temporal analysis has two parts. First, it analyzes the behavior of the measurements obtained in Section III, with respect to different buffers distance, and the second considers centrographic analysis.

For the first approach, WIM stations are classified by distance into eight groups: 20=(0-20], 40= (20-40], 60= (40-60], 80= (60-80], 100= (80-100], 120= (100-120], 140= (120-140], 160= (140-160], and 180= (160-180] miles from POLA. The results from Section III are the inputs to identify the trend for the various statistics for the three-vehicle classifications (Light-, Medium- and Heavy-Heavy duty trucks).

Figure 9 shows the share of WIM stations with positive, negative, or no temporal trends of volume over time, for each of the distance buffers. It includes information about Light-, Medium-, and Heavy-Heavy duty trucks, in the three scenarios: i) before the recession; ii) without a non-linearity correction; and iii) after the recession. The results show that the volume of heavy-heavy duty trucks has decreased over time in more WIM stations located less than 20 miles away from POLA/LB, and it has increased with distance. At this proximity, the volume of medium-heavy-duty trucks have remained constant, while light-heavy-duty trucks have increased. After 20 miles, the data shows an increase in volumes for all vehicle types. Additionally, after 100 miles there is an increment in volume, but such an increment may not be directly influenced by containerized traffic from the port, and might be affected a transition between different geographic areas.

On the other hand, Figure 10 shows the share of WIM stations that have increased, decreased or remained constant over time in Mean GVW, with time and vehicle category, in each scenario. Within 20 miles from POLA/LB, more WIM stations indicate increased GVW, across all vehicle categories. For light-heavy-duty trucks, after the 20-mile buffer, the data seems to indicate that the GVW have decreased more than for medium-, and heavy-heavy vehicles. For these vehicles, the analyses also show that their GVW not only decrease as the stations get further from POLA/LB, but also that the metrics increasingly decrease with distance, especially after 80 miles, which would be outside the urbanized area of the region. The behavior of TLR is almost similar to GVW; for this reason, it is not included in the graphical analysis.

Figure 9. Volume Changes (e.g., Increased, Decreased, remained constant) per Distance Buffer and vehicle Category (ar=after regression, br=before recession).

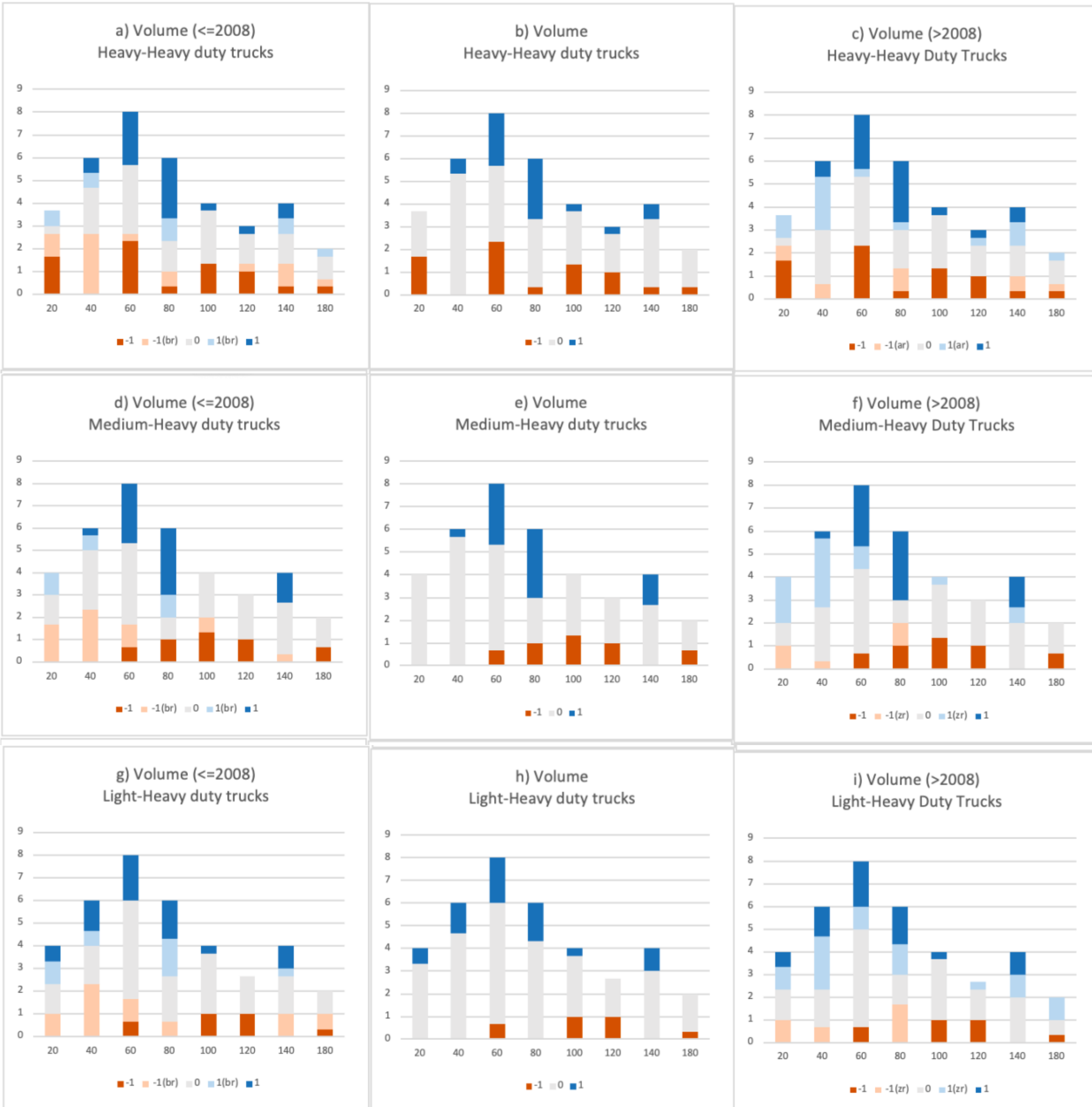
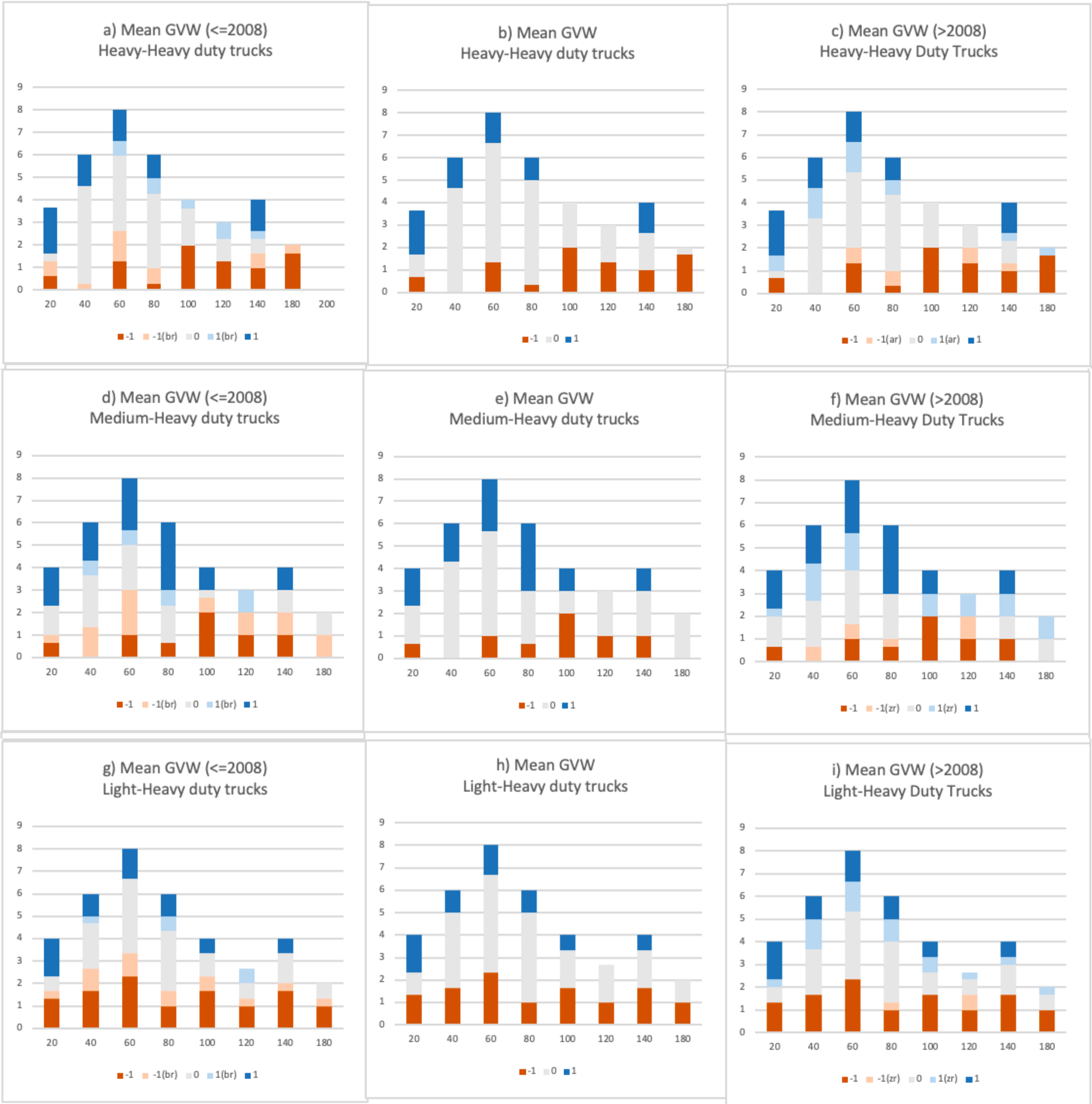


Figure 10. Changes of Mean of GVW (e.g., Increased, Decreased, remained constant) per Distance Buffer and vehicle Category (ar=after regression, br=before recession).



Consistent with the results previously discussed, Figure 11 compares the net sum of the slopes for GVW, TLR, and volume across the vehicle categories at the various distance buffers. As mentioned before, Figure 11 shows that the mean GVW has decreased over time for light-heavy-duty trucks in more WIM stations located over 20 miles away from POLA/LB. This trend does not occur with medium-heavy-duty trucks, however, for heavy-heavy-duty trucks it does occur when the distance from POLA is over 80 miles. This behavior shows that before the recession, the trend of the mean of GVW was decreased values, but after the recession GVW values increased. In terms of volume, Figure 11 shows that heavy-heavy duty trucks have tended to decrease their volume for distances below 20 miles, without being affected by the non-linearity before and after the recession. On the other hand, volume for Light-heavy duty vehicles has increased in more WIM stations near POLA, while in distances of 100 miles or more volume decreased.

Figure 11. Changes in GVW, TLR, and Volume per distance Buffer and Vehicle Category

Including the temporal dimension, Figure 12 clearly shows the changes in average daily volumes for the different vehicle categories at each of the distance buffer-aggregated WIM stations.

Figure 12 shows different behaviors between the light-, medium-, and the heavy-heavy duty trucks. In this case, the median of the volume of the heavy-heavy duty trucks tends to increase considerably after 20 miles, then it decreases after 60 miles. It has another peak after 140 miles, but this later peak is probably not influenced by POLA. On the other hand, for Light- and Medium-heavy duty trucks the percentage change with respect to the 20-mile buffer decreases with distance, but the changes are not as pronounced as those for Heavy-heavy duty trucks. These results show two distinct behaviors: i) because light-heavy-duty vehicles are mainly used for local distribution, their origins and destinations are concentrated in areas closer to the core of the consumer market; and ii) the large concentration of warehouses about 50-60 miles from POLA/LB tends to capture a larger share of the heavy-heavy-duty trucks. The case of the single-trailer (medium-heavy-duty) trucks is more diverse, in the sense that these are used in both LTL and FTL vocations, and short- and long-haul, exhibiting a mixed behavior. To provide additional insights, the authors estimated SLR models for the average daily volume and average GVW for each truck category and distance buffer. Confirming the previous analyses, Figure 13 shows that heavy-heavy-duty trucks have had a positive trend in GVW over time in the 0 to 40 mile buffers from POLA/LB, whereas volume has decreased. On the other hand, light-heavy-duty trucks have increased in volume near POLA/LB, and medium-heavy-duty trucks have increased in GVW over time, until they reach distances of 100 miles from POLA.

Figure 12. Percentage of change of the median of volume/year with distance with respect to the 20 miles buffer for Light-, Medium-, and Heavy-heavy duty trucks

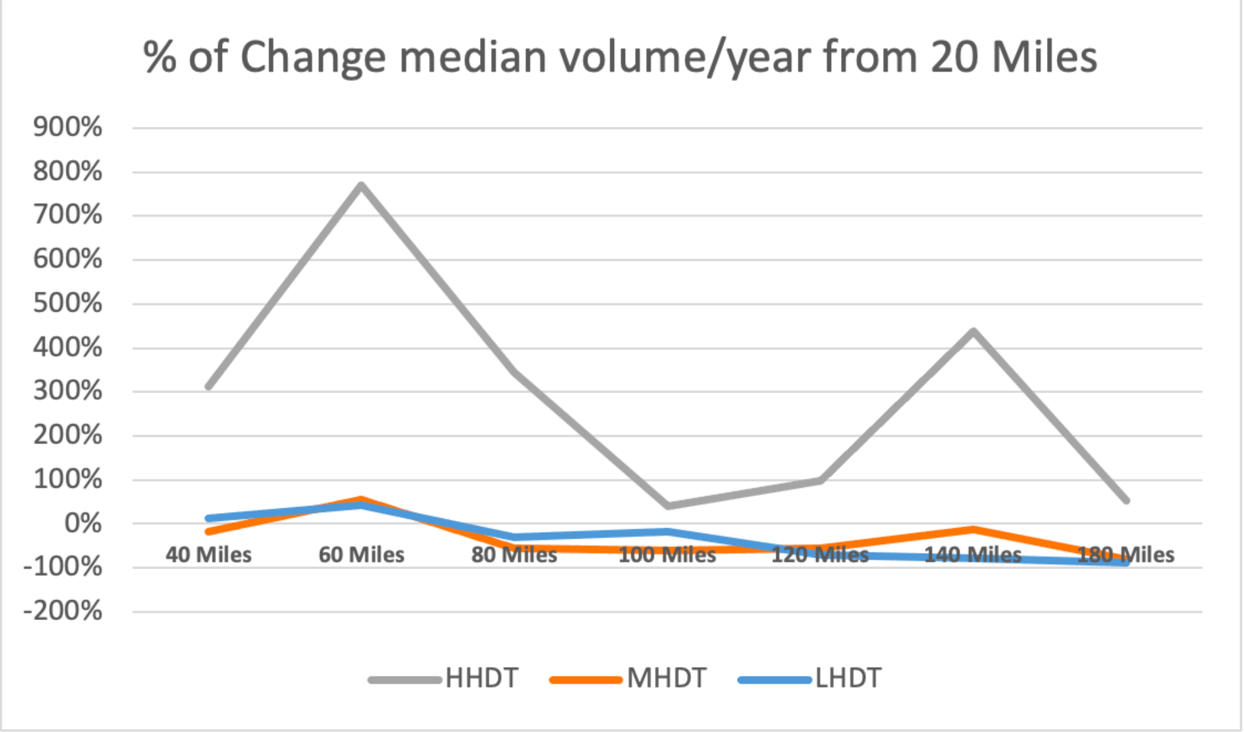
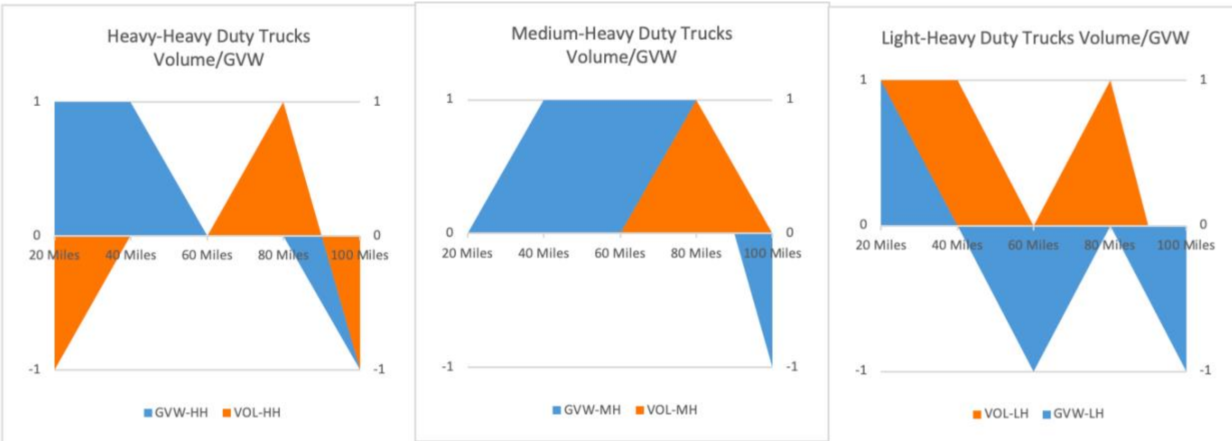


Figure 13. Slope average daily volume and GVW vs. year per Distance Buffer and Vehicle Category



Barycenter analysis

In this section, the authors estimated the geometric center or barycenter of the nine statistical measurements for Heavy-, Medium, and Light-heavy duty trucks, in a manner similar to previous work analyzing logistics sprawl in (Jaller M. L., 2017c), where the authors performed centrographic analyses. This is a methodology commonly used to measure the distance of the location of agents of interest (e.g., warehouse facilities, count stations) to their barycenter or geographic center, and their dispersion from that point (Dablanc, 2014).

Following Equation 1, the authors estimated the barycenter for each vehicle class for each year of analysis (Yeates, 1973). The authors used the different metrics as the weight (w) for each WIM station, independently.

Equation 4

$$\left(\bar{x}_w = \frac{\sum_{i=1}^{n} x_i w_i}{\sum_{i=1}^{n} w_i}, \bar{y}_w = \frac{\sum_{i=1}^{n} y_i w_i}{\sum_{i=1}^{n} w_i}\right)$$

Where,

$\bar{x}_w$ Latitude coordinate of the weighted barycenter for a particular year
$\bar{y}_w$ Longitude coordinate of the weighted barycenter for a particular year
x_i Latitude coordinate of WIM station i
y_i Longitude coordinate of WIM station i
w_i: $\overline{GVW}, \overline{TLR}, Q_1^{gvw}, Q_2^{gvw}, Q_3^{gvw}, Q_1^{tlr}, Q_2^{tlr}, Q_3^{tlr}, and\ \ V$ at station *i*

This section estimates the weighted geometric center using the information of truck flows, GVW and TLR at each of the stations for the different vehicle classes. Changes in the centroid location compared to a reference point (e.g., port facilities) provide insights about the potential shifts of freight traffic throughout the region during the study period. The reason for using

POLA/LB as the reference point is for consistency with previous spatial analyses (location of warehouse and distribution centers) in the study region. While POLA/LB do not necessarily represent major poles for e-commerce-related traffic, they still represent a single import traffic generator in the area.

In this analysis, the same nine measurements are used as weights (w) for the barycenter: mean, quartiles of GVW and LTR, and volume. This barycenter calculation is performed for each year in the period of interest (2003-2015). Then, the authors estimate the distance from the barycenter with respect to the POLA location. Finally, a simple regression analysis is performed for each vehicle class to identify the linear relationship between the average distances of the barycenter versus time in Equation 5.

Equation 5

$$distance_{vc_i meas_j} = \beta_0 + \beta_1 * year_t$$

When comparing the relationship between the distances of the barycenter, the authors did not find any linear trend for the mean of GVW in 2003 to 2015. However, three vehicle classes showed a trend in terms of volume: vehicle classes 5, 7 and 13. Among them, the class most related to e-commerce is vehicle class 5. In this case, the β_1 of vehicle 5 is negative, which means that traffic flow has been concentrating near POLA over time.

The authors performed a piecewise simple linear regression by using 2008 as the breaking point, to identify whether the significant change is because of a nonlinear relationship. Most of the vehicle classes do not show any linear statistical and significant relationship with the average distances of the barycenter over time in Equation 6.

Equation 6

$$distance'_{vc_i meas_j} = \beta'_{0_{ij}} + \beta'_{1_{ij}} * x_t + \beta'_{2_{ij}} z_t$$

$$x_t = year_t$$

$$dummyKnot = \begin{cases} 0, if\ year \leq 2008 \\ 1, if\ year > 2008 \end{cases}$$

$$z_t = (x_t - 2008) * dummyKnot$$

The results show that the mean of GVW remained constant between 2003 to 2008, however it decreased with time after 2009 for vehicle classes 6, 11, and 12. On the other hand, the distance of the barycenter for truck volumes (with respect to POLA) decreased after the recession for almost all vehicle classes, except vehicle classes 6 and 10, where it remained constant. Notice in Table 1 that vehicle class 8 increases before the recession, decreases after it, but after 2012 it increases again with distance from POLA. This means that during 2012, the last year studied, such vehicles may have been increasing their VMT, because most of the freight associated with port travel is class 8.

Table 1 summarizes the most relevant results of the volume analyses. The first column identifies the vehicle category; the second column notes vehicle class; the third column shows the slope of the volume between 2003 and 2015; the fourth column shows the slope before the recession (<=2008); and the fifth column shows the slope after the recession (>2008). The fourth column shows a scatterplot of the time series of the distance over time (2003-2015) for the barycenter of volume, and the fifth column shows the geographic location (latitude, longitude) of the barycenter each year in Southern California. Notice that the lightest heavy duty truck class (vc 5) has a negative slope. This means that the barycenter of the smallest vehicles has moved closer to POLA. The behavior of vehicle class 5 could be another possible consequence of e-commerce implementation.

V. Discussion

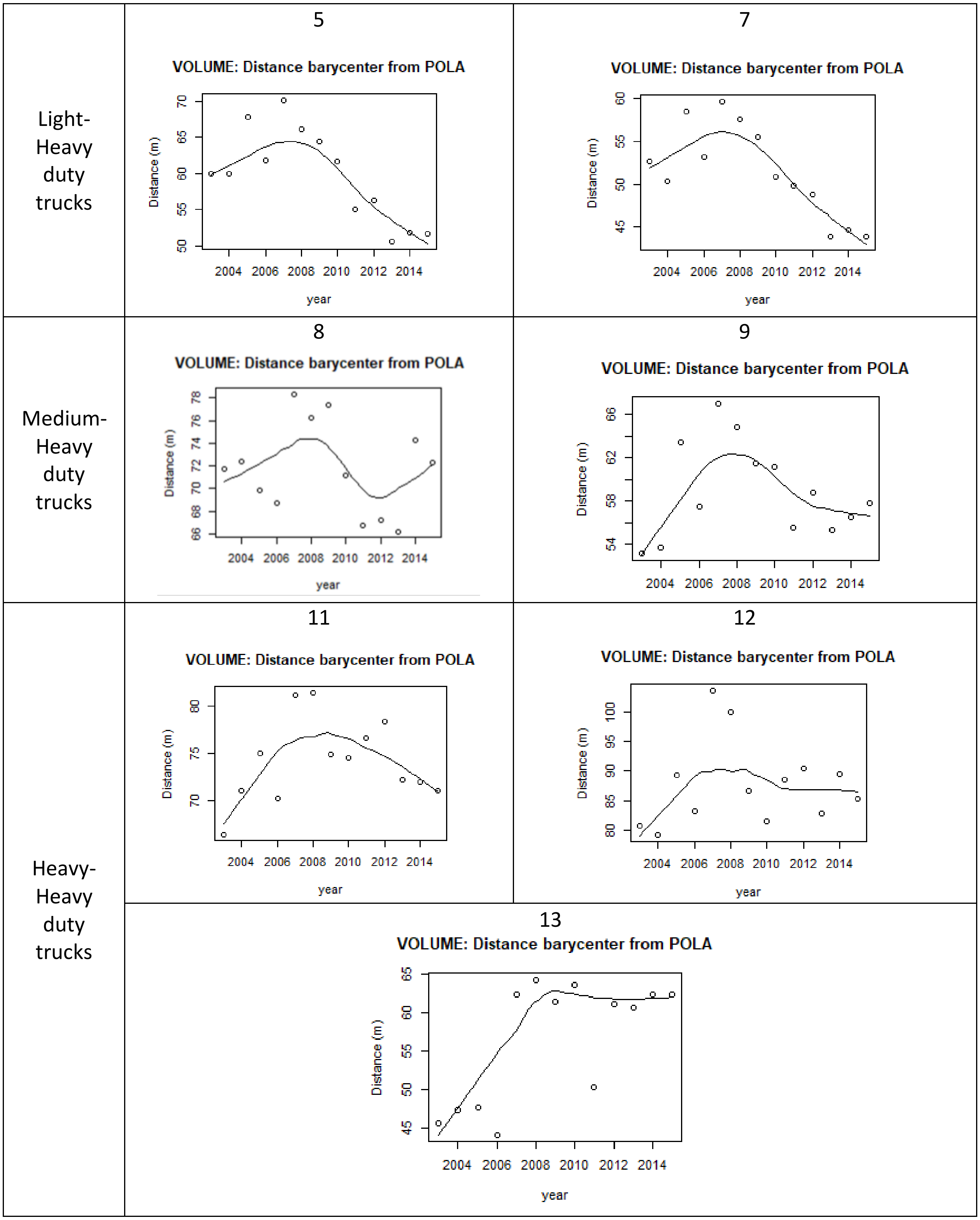
The empirical results from the analysis of WIM data between 2003 and 2015 are consistent with previous studies about the presence of logistics sprawl in Southern California such as (Jaller M. L., 2017c). Similarly, the analyses shows that there was a significant change in freight patterns before and after the 2008-2009 period, which again is consistent with changes in facility location after 2007-2008 noted by (Jaller M. L., 2017c). Moreover, estimates for the different vehicle classes exhibit distinct geographic concentrations and temporal patterns (when aggregated into Light-, Medium-, and Heavy-Heavy duty trucks), as illustrated by the movement of the weighted geometric center (Table 1 and Figure 14).

Table 1. Slopes from SLR and piecewise SLR, where Y is Average Distance Weighted by Volume vs. Time - Barycenter Coordinates per Year and Location

Vehicle category	Vehicle class	2003-2015	2003-2008	2009-2015
Light-Heavy duty trucks	5	-1	1	-1
	7	-1	1	-1
Medium-Heavy duty trucks	8	0	1	-1*
	9	0	1	-1
Heavy-Heavy duty trucks	11	0	1	-1
	12	0	1	-1
	13	1	1	-1

The observed trends could be the result of new logistics needs, for instance the reduction of delivery costs based on the economic recession during 2008-2009 (and reduced import flows); e-commerce; policy and environmental implications; and/or land value and availability. However, the nature of the WIM data does not allow for the identification of specific reasons for these trends, or their respective effects. Despite this, the results of this research show that the behavior (GWV, TLR, and Volume) of vehicle classes have significantly changed over time, and most of the statistical measurements for each vehicle class have a non-linear relationship, handled by the piecewise simple linear model analyzing the before and after 2008-2009 trends.

Figure 14. Changes in the Distance of the Volume's Barycenter to POLA per Vehicle Category



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Additionally, this study identified the relationship of nine statistical measurement patterns for each combination of vehicle class and WIM station (vc-w) over time. The results demonstrated that GVW and LTR have a direct relationship, i.e., when GVW increases, LTR increases. In at least 30% of the vc-w combinations, there was an inverse relationship between volume and the mean of GVW, which mostly signifies more vehicles carrying less cargo.

Two interesting result are: i) on average, the volume of vehicle class 5, the lightest heavy duty trucks, is getting closer to the reference point (Port of Los Angeles, or the LA core market); and, ii) vehicle class 5 has decreased weights, but its volume has increased with time. These two results could be caused by the implementation and growth of e-commerce as one unintended consequence in logistics and freight. Strictly speaking, the vc5 trends could be the result of: 1) more home deliveries, 2) population growth, 3) geographic shifting of distribution centers, because businesses have been purchasing or renting facilities closer to the core markets for warehousing and distribution (Jaller M. L., 2017a). These facilities tend to be an order of magnitude smaller than traditional facilities in the Inland Empire. Consequently, with less capacity, and shorter time delivery windows, the transport of goods out of these facilities uses smaller vehicles with smaller loads. Recalling from Figure 20, the median LTR for class 5 vehicles is about 20-25%.

Based on these results, agencies should develop plans and strategies to mitigate the potential impacts of this deconsolidation of cargo. The data do not provide information to assess the substitution rate between large and small vehicles, but it is possible that the system could be adding smaller vehicles at an increased rate, compared to reductions (or changes in geographical concentration) of larger vehicles. Furthermore, these analyses contribute to the understanding of freight requirements, and the identified changes in the last decade (since 2008) could help planning agencies manage the overall transportation system, and more importantly, take action on the dynamic infrastructure needs of freight flows and economic activity.

The results also show that the increased flows of small vehicles, with lower TLRs, concentrated in areas closer to the core markets, provide opportunities for efforts seeking to foster the use of zero and near-zero emission vehicles in the State. That is, without loss of generality, besides the financial and economic considerations, driving range and load capacity are among the critical factors affecting the use of electric vehicles. The results show that changes in the system may have already mitigated some of these potential technological limitations. However, the WIM data do not provide information about origins, destinations, commodities, or even industries, therefore they only represent a snapshot of the vehicle flows in the area. These analyses do confirm the merit of using these already and continuously collected data, to shed light into system dynamics, which could contribute to an improved management of the system.

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VII. Data Management

Products of Research

The project used the following private datasets:

- **Caltrans Weigh-in-Motion Data.** Collected by the California Department of Transportation (Caltrans). The team will use the data provided by Caltrans from the WIM stations discussed in the proposal. The team asks permission not to make public the raw data as this is not approved by Caltrans. Instead, the team will make public the aggregated analyses and aggregate data created during the project.

Data Format and Content

The team processed the raw data, and created one dataset:

- **Geo-located weight and volume data.** The team process the disaggregate data from Caltrans WIM Census Stations in Southern California and generate a number of dataset for aggregated temporal and geographical levels for volume, vehicle weight, vehicle classes. The data generated will be made available in Comma-delimited format. The data is useful for traffic management and spatial analyses.

Data Access and Sharing

The team made available to the general public the dataset used for the different modeling estimation processes through Dryad, an open access Publication from the University of California.

Data can be found at: https://doi.org/10.25338/B8X030

Reuse and Redistribution

There are no restrictions to sharing or distributing this research report. Any user should follow the copyright guidelines of the original datasets. For other sets produced by the research team, third party users should cite the work, and send an email to the PI, mjaller@ucdavis.edu to inform about the use of the data. The data may be cited as:

Rivera-Royero, Daniel et al. (2020), Dataset: Spatiotemporal analysis of freight patterns in Southern California, Dryad, Dataset, https://doi.org/10.25338/B8X030

VIII. Appendix

Appendix 1

Table 2. Raw WIM Location (Number, City, District, post mile, longitude, and latitude)

RAW WIM	CITY	DISTRICT	COUNTY	ROUTE	PFX	PM	X	Y	Distance POLA
12	VAN NUYS SB	7	LA	405		42.9	34.2	-118.5	34.2
47	CASTAIC SB	7	LA	5	R	56.1	34.4	-118.6	52.5
59	LA 710 SB	7	LA	710		11.5	33.9	-118.2	9.2
79	ARTESIA EB	7	LA	91	R	7.5	33.9	-118.3	9.2
82	GLENDORA EB	7	LA	210	R	42.6	34.1	-117.9	35.7
116	LONG BEACH PORT	7	LA	47		4.4	33.8	-118.2	3.1
8	CONEJO SB	7	VEN	101		12	34.2	-119.0	52.6
65	PIRU	7	VEN	126	R	30.8	34.4	-118.8	53.4
5	INDIO	8	RIV	10	R	59.4	33.7	-116.2	121.7
37	ELSINORE SB	8	RIV	15		21.6	33.7	-117.3	54.8
40	COACHELLA	8	RIV	86	R	16	33.6	-116.1	124.2
63	MURRIETA	8	RIV	215	R	15	33.6	-117.2	64.3
25	NEWBERRY	8	SBD	40	R	28.9	34.8	-116.5	124.7
39	REDLANDS	8	SBD	210	R	31.7	34.1	-117.2	66.5
66	CALICO	8	SBD	15	R	81.4	34.9	-116.9	112.7
67	DEVORE	8	SBD	215		14.8	34.2	-117.4	61.1
69	FONTANA SB	8	SBD	15		6.1	34.1	-117.5	50.6
71	HINKLEY	8	SBD	58	R	19.7	34.9	-117.3	98.9
77	COLTON EB	8	SBD	10		12.4	34.1	-117.5	50.0
95	ONTARIO EB	8	SBD	60	R	7.9	34.0	-117.6	44.3
97	CHINO	8	SBD	83		5.7	34.0	-117.7	40.7
98	PRADO	8	SBD	71	R	5.8	34.0	-117.7	37.6
22	JEFFREY	11	IMP	8	R	25.8	32.8	-115.8	160.3
23	EL CENTRO	11	IMP	8	R	40	32.8	-115.5	173.2
14	SAN MARCOS	11	SD	78		10.7	33.1	-117.2	74.7
26	CAMERON	11	SD	8	R	51.5	32.7	-116.5	125.8
84	LEUCADIA SB	11	SD	5	R	42.2	33.1	-117.3	74.2
87	BALBOA SB	11	SD	15	R	10.9	32.8	-117.1	91.3
89	DEKEMA SB	11	SD	805		24.5	32.9	-117.2	87.9
91	POGGI SB	11	SD	805		5.6	32.6	-117.0	105.5
100	MIRAMAR SB	11	SD	163		10.4	32.9	-117.1	90.8
848	OTAY MESA WB	11	SD	905	R	11.7	32.6	-116.9	113.2
854	RAINBOW SB	11	SD	15	R	53	33.4	-117.2	68.5
15	IRVINE SB	12	ORA	5	R	25.8	33.7	-117.8	29.3
61	PERALTA EB	12	ORA	91	R	11.9	33.9	-117.8	29.6
103	ORANGE SB	12	ORA	57		21	33.9	-117.9	26.4
111	SAIGON SB	12	ORA	405		18.6	33.8	-118.0	15.4

Appendix 2

Figure 15. WIM Station 082-Vehicle class 4-14 dispersion plot GVW, LTR vs. months in 2016 (vehicle classes: 4-14)

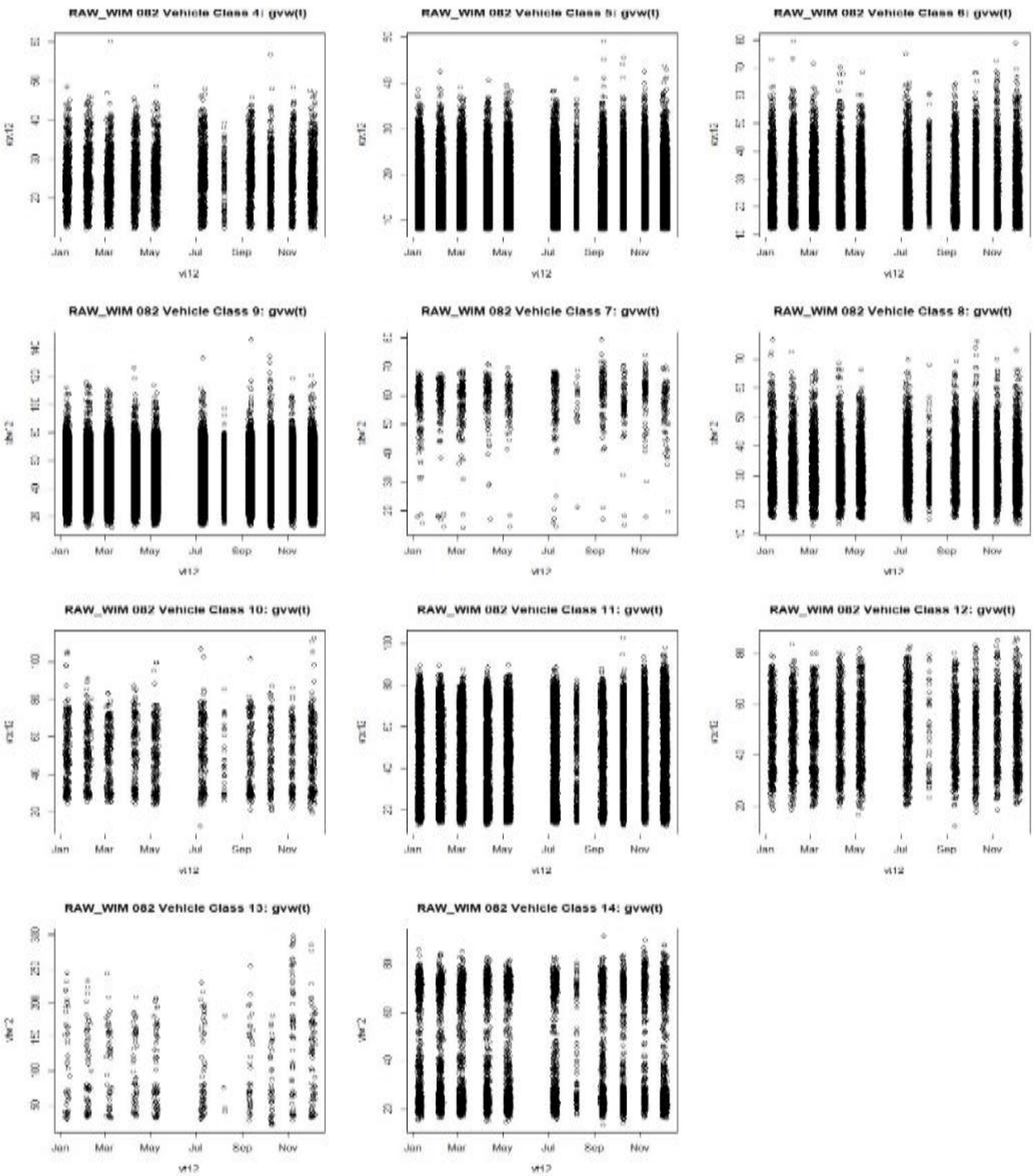


Figure 16. WIM Station 079-Vehicle class 4-14

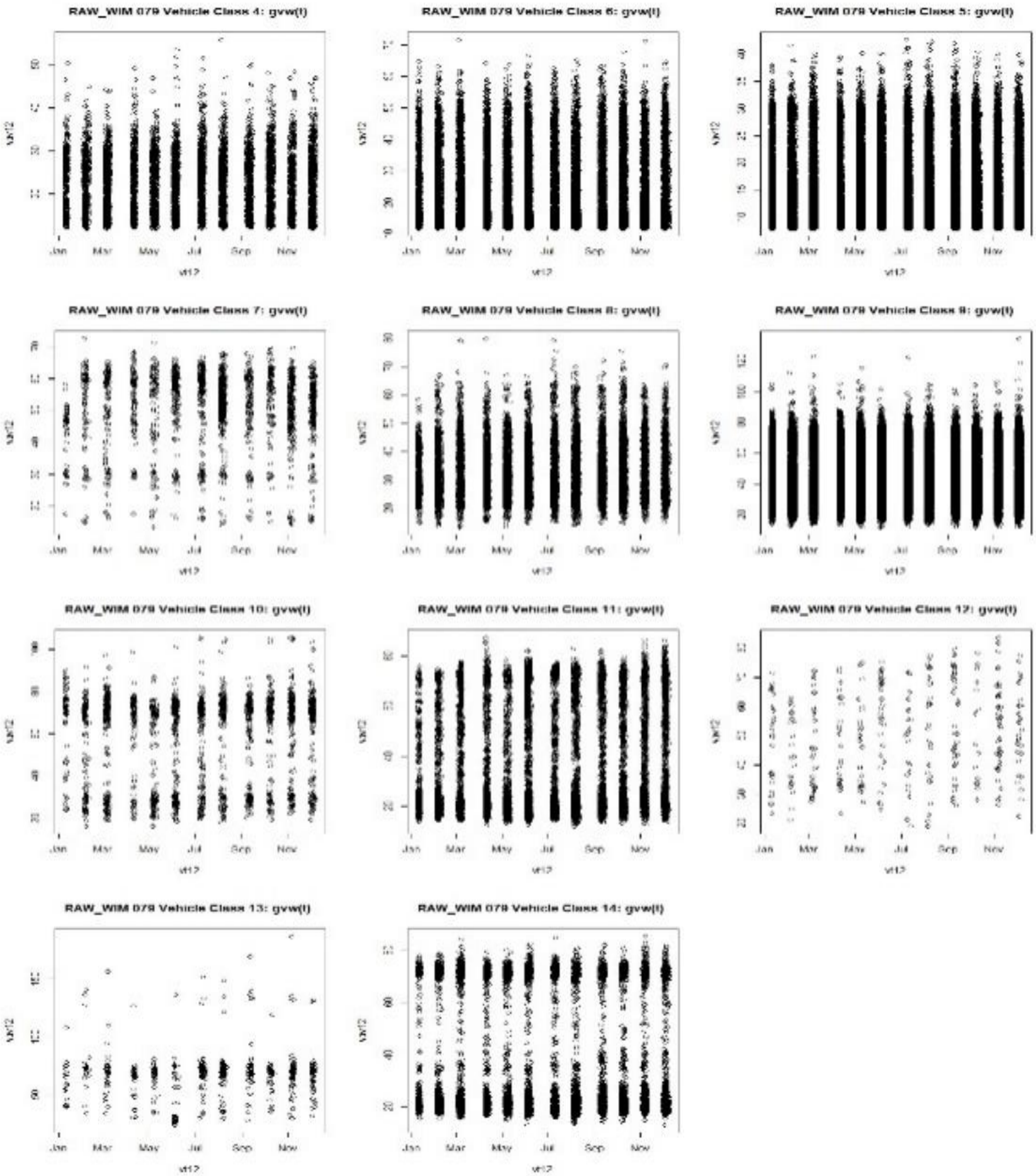


Figure 17. WIM Station 059-Vehicle class 4-14

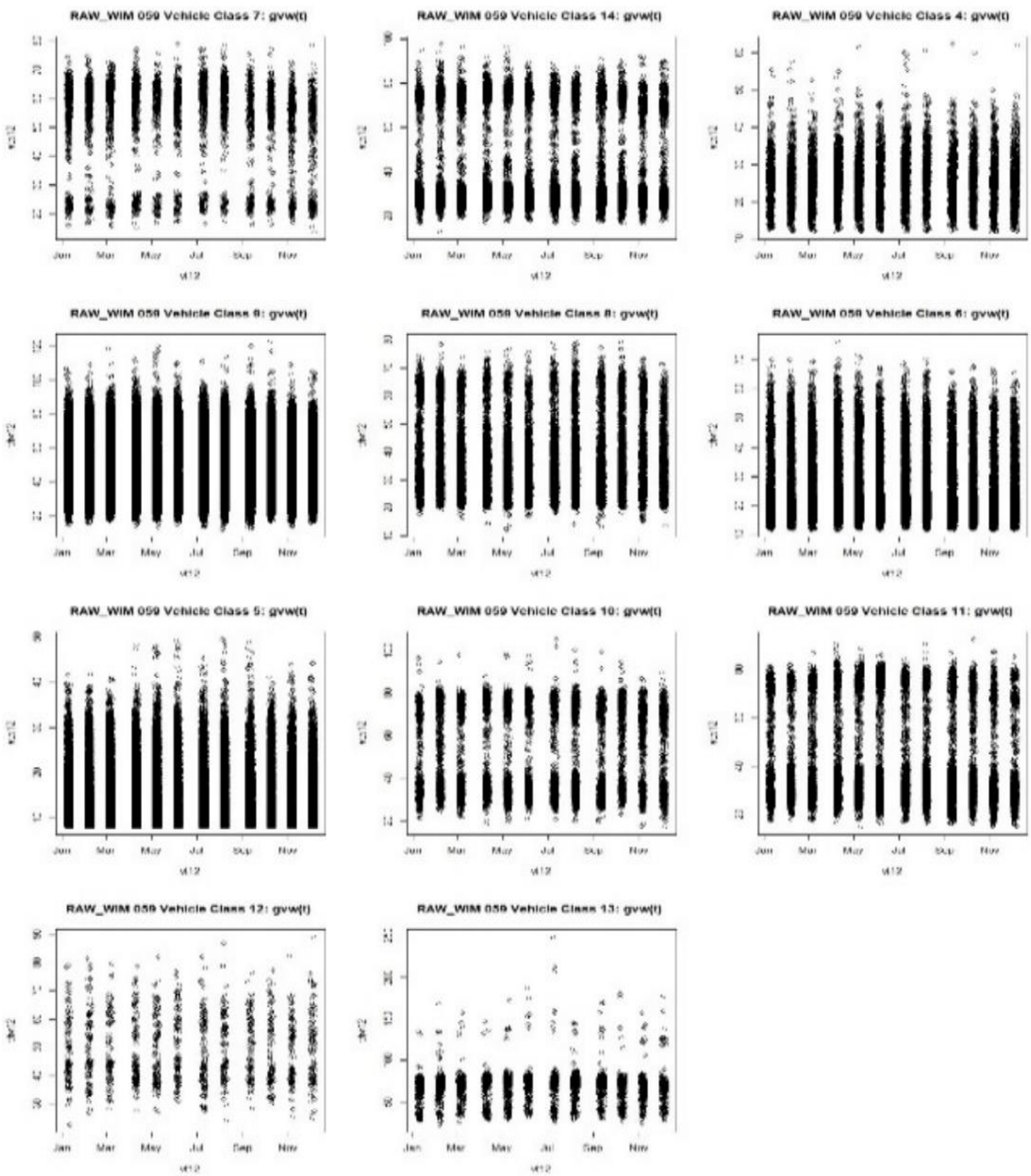
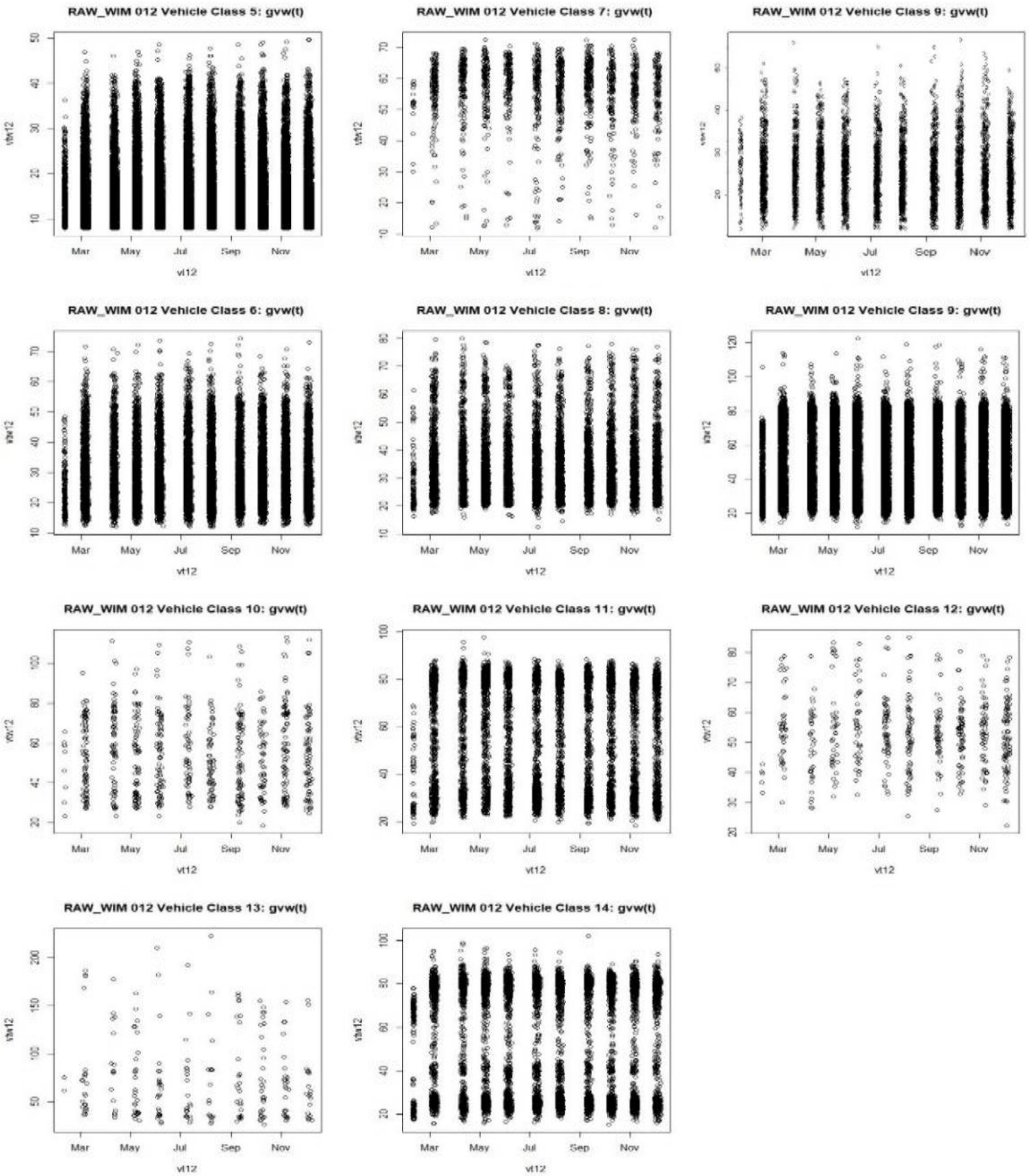


Figure 18. WIM Station 012-Vehicle class 4-14



Appendix 3

Figure 19. GVW vs. Year

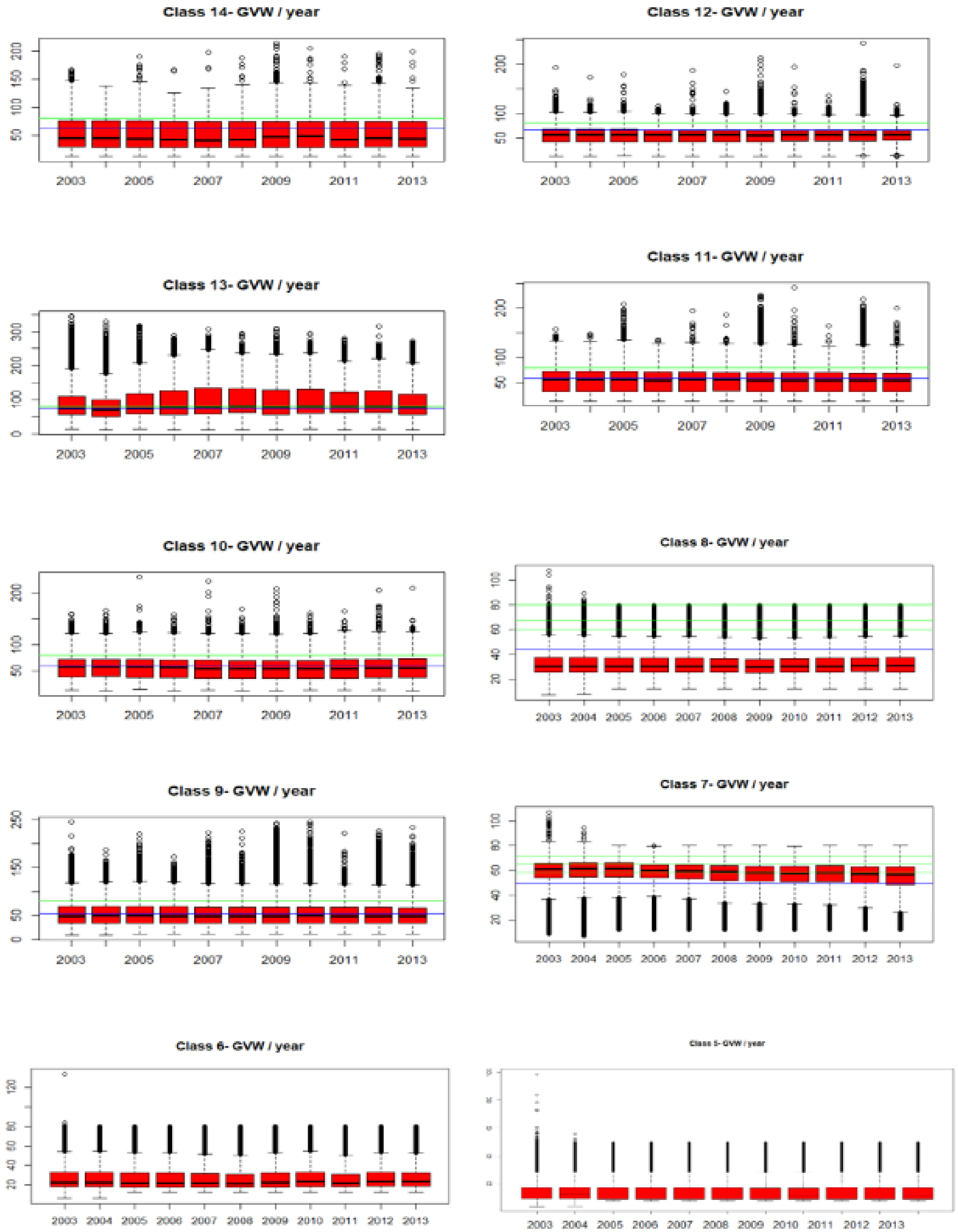


Figure 20. LTR vs. Year