DEVELOP NEW METHODS TO USE ODOT WEIGH-IN-MOTION DATA FOR PREDICTING FREIGHT FLOW AND/OR COMMODITY PATTERNS

Final Report

SPR-821

RESEARCH

Oregon Department of Transportation

DEVELOP NEW METHODS TO USE ODOT WEIGH-IN-MOTION DATA FOR PREDICTING FREIGHT FLOW AND/OR COMMODITY PATTERNS

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by

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16. Abstract

This study presents the results of a detailed analysis of Oregon WIM data. First, a quality control analysis was conducted considering ODOT Class 11 (FHWA Class 09 trucks). Next, a set of descriptive analyses were conducted, one focusing on all WIM stations and one focusing on select WIM stations. In both analyses, the primary focus was on truck volume and average monthly observed combined (truck and cargo) weight. For the select WIM stations, average monthly percentages, day-of-week trends, annual growth rates, and summaries of truck volume, cargo weight, and empties were provided. Following the descriptive analysis, data comparisons were made to Freight Analysis Framework (FAF) and ODOT traffic counts. Finally, using EROAD data, industry types, distance traveled, and origin-destination locations were analyzed relative to select WIM stations. This report concludes by providing a comprehensive conclusion and specific recommendations as it pertains to WIM data and corresponding analyses in Oregon.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS					APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	When You Know	Multiply By	To Find	Symbol	Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH					**LENGTH**		
in	inches	25.4	millimeters	mm	mm	millimeters	0.039	inches	in
ft	feet	0.305	meters	m	m	meters	3.28	feet	ft
yd	yards	0.914	meters	m	m	meters	1.09	yards	yd
mi	miles	1.61	kilometers	km	km	kilometers	0.621	miles	mi
		AREA					**AREA**		
in^2	square inches	645.2	millimeters squared	mm^2	mm^2	millimeters squared	0.0016	square inches	in^2
ft^2	square feet	0.093	meters squared	m^2	m^2	meters squared	10.764	square feet	ft^2
yd^2	square yards	0.836	meters squared	m^2	m^2	meters squared	1.196	square yards	yd^2
ac	acres	0.405	hectares	ha	ha	hectares	2.47	acres	ac
mi^2	square miles	2.59	kilometers squared	km^2	km^2	kilometers squared	0.386	square miles	mi^2
		VOLUME					**VOLUME**		
fl oz	fluid ounces	29.57	milliliters	ml	ml	milliliters	0.034	fluid ounces	fl oz
gal	gallons	3.785	liters	L	L	liters	0.264	gallons	gal
ft^3	cubic feet	0.028	meters cubed	m^3	m^3	meters cubed	35.315	cubic feet	ft^3
yd^3	cubic yards	0.765	meters cubed	m^3	m^3	meters cubed	1.308	cubic yards	yd^3
~NOTE: Volumes greater than 1000 L shall be shown in m^3.									
		MASS					**MASS**		
oz	ounces	28.35	grams	g	g	grams	0.035	ounces	oz
lb	pounds	0.454	kilograms	kg	kg	kilograms	2.205	pounds	lb
T	short tons (2000 lb)	0.907	megagrams	Mg	Mg	megagrams	1.102	short tons (2000 lb)	T
		TEMPERATURE (exact)					**TEMPERATURE (exact)**		
°F	Fahrenheit	(F-32)/1.8	Celsius	°C	°C	Celsius	1.8C+32	Fahrenheit	°F

*SI is the symbol for the International System of Measurement

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DISCLAIMER

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1.0 INTRODUCTION

Accurate and affordable data is necessary to model and predict truck freight moving on Oregon highways. Oregon Department of Transportation (ODOT) weigh-in-motion (WIM) truck data is currently an untapped source of information that, when combined with supplemental data, enables analysts to improve truck freight volume estimation, long-range freight forecasts, and the allocation of strategic investments to relieve congestion and freight bottlenecks.

1.1 PROJECT OBJECTIVES

Accurate truck-freight forecasting is key to strategic highway investment, especially for an export-dependent economy such as Oregon's with increasing challenges related to freight bottlenecks and truck parking. Improved current information and forecasts support better investment decisions. This research project partially addresses the freight data gap that currently exists regarding available statewide freight and commodity flow information by developing and implementing a statewide freight data capture methodology that incorporates new freight data collection techniques with existing data (e.g., weigh-in-motion). Up-to-date data is key to understanding the current movement of freight as well as developing useful analysis tools for strategic investment and long-range planning.

At any given time, trucks are carrying full loads of cargo, partial loads, and some that are empty. An accurate source of the distribution of truck weights is needed to understand truck freight movement on Oregon highways. This information is required in order to model truck patterns of travel, including seasonal, daily, and hourly variation; estimate stress imposed on highway pavement (Oregon Highway Cost Allocation Study), and accurately determine cargo loads transported via truck for commodity flow analysis. About 75% of commodities in Oregon move by commercial motor vehicles.

One data source used in Oregon and across the U.S. is the U.S. Census Bureau Vehicle Inventory and Use Survey (VIUS), which was discontinued in 2002 and is outdated. Even if we had current VIUS data, the sample is small for Oregon and of limited value. ODOT weigh-in-motion (WIM) scales provide a rich set of data over many years. This data can provide affordable real-world information to improve our understanding of truck freight attributes regarding truck configuration, operating weight, volumes, etc.

The objective of this research is to evaluate WIM data for use by ODOT for short-term and long-term highway investment prioritization and the tools and methods used to conduct freight analysis. This research recommends methods of using the data to produce information, i.e., related to heavy truck patterns, ultimately leading to improved analytical tools and methods based on current and emerging patterns of truck movement. The research also identifies and evaluates other data sources (both public data such as FAF and private data such as EROAD) with the potential to enhance the information generated using WIM data, such as truck speed data, automatic traffic recorders, and commodity flow data. This study produces an inventory of potential data sources available to ODOT, identifying the pros and cons associated with each and gaging the usefulness to meet the needs of freight mobility.

1.2 ORGANIZATION OF REPORT

This report first presents an overview of WIM systems and identifies the WIM sensor type used most in Oregon. The WIM data collection system overview is followed by an extensive literature review of domestic WIM-related research and international WIM-related research. This is followed by an explicit focus on WIM in Oregon; specifically, the type of WIM stations (enforcement vs. virtual), WIM station locations, and a summary of Oregon-specific WIM research. The report then presents a data inventory, including ODOT-specific data sources, public freight data sources (e.g., Freight Analysis Framework (FAF), Commodity Flow Survey (CFS)), and private freight data sources (e.g., EROAD, FleetSeek).

After the data inventory, the results from a WIM data quality control analysis are presented; this analysis and corresponding results are for ODOT Class 11 trucks only. Next, a descriptive analysis of all WIM stations in Oregon is conducted based on truck volume, average monthly observed combined (truck and cargo) weight, and data availability for four classification groups: (1) ODOT Class 03 to ODOT Class 10, (2) ODOT Class 11, (3) ODOT Class 12 to ODOT Class 19, and (4) all trucks (ODOT Class 03 to ODOT Class 19. Classes 04 and Class 07 are always excluded from the analysis as they correspond to bus types. Based on results from the descriptive analysis of all WIM stations, a descriptive analysis of select WIM stations is conducted, where the select WIM stations are: Ashland (NB)/Ashland(SB), Woodburn(NB)/Woodburn(SB), Cascade Locks (EB)/Wyeth (WB), Olds Ferry (EB)/Farewell Bend (WB), and Klamath Falls (NB)/Klamath Falls (SB). The focus on the select WIM stations includes directional and seasonal trends in terms of volume and average monthly observed combined (truck and cargo) weight, monthly percentages of volume and combined weight, day-of-week trends, the calculation of annual growth rates (both by WIM station and overall), and a summary of truck counts, average cargo weight, and proportion of empties by WIM station.

The final sets of analyses first include a data comparison. The first comparison is made to FAF data using WIM stations on the Oregon-California border (Ashland and Klamath Falls). The following comparison is to that of ODOT traffic counts at two locations where directional counts were available, the I-84 WIM stations of Cascade Locks, Wyeth, Olds Ferry, and Farewell Bend. The final analysis was the assessment of EROAD data, a private data source. This included providing information on industry type by WIM station, distance traveled by WIM station, and information on origins and destinations. The report closes with conclusions and recommendations.

2.0 OVERVIEW OF WIM SYSTEMS

WIM is described as the process of measuring dynamic tire forces of a vehicle in-motion and using these dynamic forces to estimate corresponding tire loads of the vehicle as though it were static (Al-Qadi, Wang, Ouyang, Grimmelsman, & Purdy, 2016; ASTM E1318-09, 2017).[1] To accomplish this process, sensors are used to measure axle loads by utilizing signals recorded by said sensors (i.e., voltage, strain, and resistance). In nearly all cases, WIM sensors for data collection are embedded in the roadway surface at specific locations throughout a state (most often on primary freight corridors). By embedding such systems in the roadway surface, WIM systems can collect data related to weight, vehicle speed, axle weight, axle spacing, and (in most states) vehicle classification based on the 13 vehicle classifications defined by the Federal Highway Administration (FHWA) (see Figure 2.1).[2] However, the accuracy and validity of this collected data remain a primary concern for state agencies, as discussed in the coming chapters of this report.

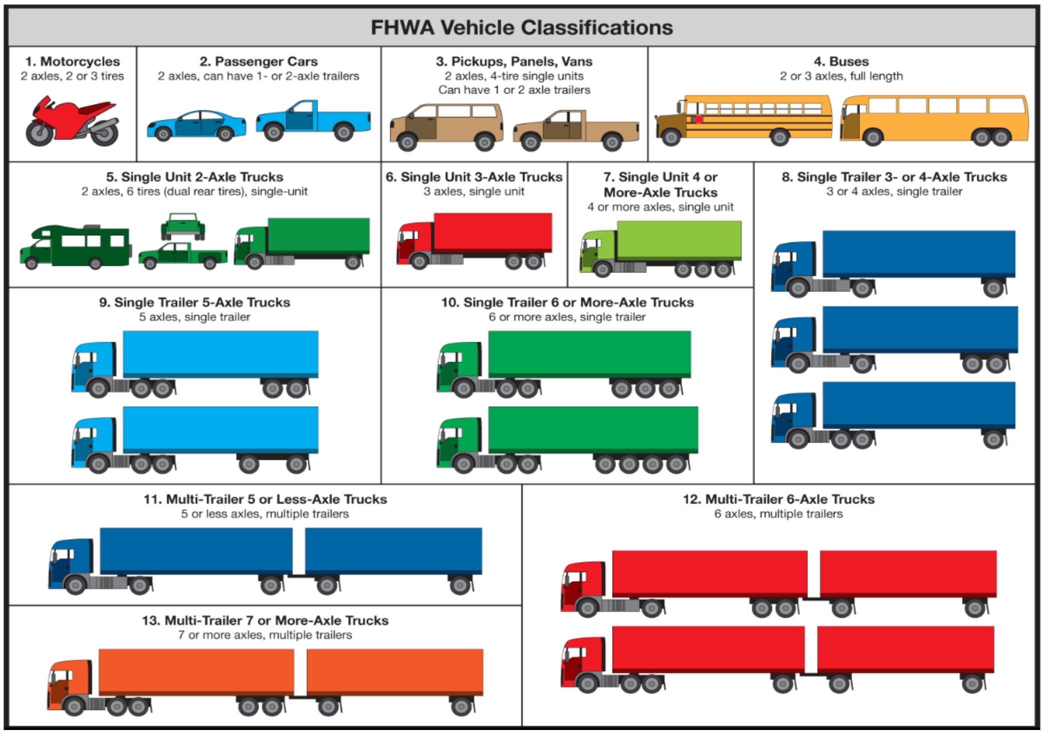

Figure 2.1: FHWA 13 vehicle classification (Source: Federal Highway Administration, 2016)

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[1] ASTM E1318-09 was originally approved in 2009, but the most recent version was reapproved in 2017.

[2] Although most states use the 13 vehicle classification system, Oregon uses a 19 vehicle classification system. An example of Oregon's classification system is shown in Chapter 4.1.

The weight data collected at these locations has most often been used for roadway surface design and bridge design, but in recent years the diversity in applications of WIM data has been increasing (most notably for freight traffic analysis and forecasting) (Cetin, Sahin, & Ustun, 2015; Eluru et al., 2018; Florida Transportation Data and Analytics Office, 2018; Lu et al., 2003). Common sensors used to collect data at WIM sites are presented in Chapter 2.1.

2.1 WIM SENSOR TYPES

Although there are several types of in-road WIM sensors available, five sensors remain the most frequently used in the United States (Federal Highway Administration, 2018). The different WIM sensors can vary in the accuracy of collected data, as well as cost. Therefore, inherently, each WIM sensor has its assets and liabilities. Still, all WIM systems must meet the functional performance requirements, as stated by ASTM E1318-09 (2017). Table 2.1 displays these functional performance requirements for WIM systems. The five most frequently used sensors are discussed in the succeeding sub-chapters.

Table 2.1: Functional Performance Requirements for WIM Systems

Function	Tolerance for 95% Compliance[A]				
	Type I	Type II	Type III	Type IV	
				Value ≥ lb (kg)[B]	±lb (kg)
Wheel Load	±25%		±20%	5,000 (2,300)	300 (100)
Axle Load	±20%	±30%	±15%	12,000 (5,400)	500 (200)
Axle-Group Load	±15%	±20%	±10%	25,000 (11,300)	1,200 (500)
Gross-Vehicle Weight	±10%	±15%	±6%	60,000 (27,200)	2,500 (1,100)
Speed			±1 mi/hr (2 km/hr)		
Axle-Spacing and Wheelbase			±0.5 ft (0.15 m))		

A 95% of the respective data items produced by the WIM system must be within the tolerance.
B Lower values are not usually a concern in enforcement.
Source: ASTM E1318-09 (2017)

2.1.1 Bending Plate Sensor

The first of the five most common WIM sensor technologies is the bending plate. To collect data, the bending plate uses strain gauges that are bonded to the bottom of the plate. In general, these sensors weigh about 250 pounds each and have dimensions of 72"x20"x1". This sensor-type is often configured in a staggered layout, in which data is collected by measuring the strain on the plate as axles pass over. The bending plate does this measurement roughly 2,000 times per second at highway speeds, then determines the load needed to produce the measured strain. For an example of a bending plate, refer Figure 2.2.

(a)

(b)

Figure 2.2: (a) Bending plate sensor and (b) bending plate installed in roadway surface (Source: Federal Highway Administration, 2018)

As is the case with each type of sensor, the bending plate has its advantages and disadvantages. The bending plate is considered one of the more accurate WIM sensors available (Federal Highway Administration, 2018). The bending plate is long-lasting and can have a lifespan of up to 12 years. Contingent on speeds or climate, the bending plate is nearly speed independent, and there is little to no temperature dependency. Lastly, the sensors in the bending plate can achieve a calibration accuracy in the range of $\pm$ 3.0%.

With that in mind, the bending plate does have its disadvantages. The first of these is the surface type that bending plates can be used with; that is, the bending plate has been recommended to be used only on Portland cement concrete pavements. If being installed in different types of materials, the frame around the bending plate can begin to break after time. In regards to care, maintenance of bending plates should happen, at the very least, on an annual basis.

2.1.2 Load Cell Sensor

The next most frequently used WIM sensor is load cell sensors. This sensor works through two platforms, each with a weighing mechanism (Federal Highway Administration, 2018). The 70"x36"x2" plates are laid adjacent to one another to cover a 12-foot traffic lane. Unlike the bending plate sensor, the load cell sensors measure the force applied to each scale through hydraulic or mechanical transducers (Federal Highway Administration, 2018). The measurements recorded by the transducers are recorded and analyzed by the system to compute tire and axle loads of the passing traffic. Similar to the bending plate, the applied force is measured roughly 2,000 times per second at highway speeds (this is done per axle passage). Figure 2.3 shows a load cell sensor and a load cell sensor that has been installed.

As is the bending plate sensor, the load cell sensor is one of the more accurate sensors on the market (Federal Highway Administration, 2018). According to the Federal Highway Administration (2018), state agencies have reported that weight is measured consistently with an accuracy of $\pm$6% error. Like bending plates, the load cell sensor (if installed correctly and maintained regularly/adequately) can have a lifespan of up to 12 years.

As for disadvantages, the load cell sensor is the most expensive and time-consuming to install. A crane is required to lift the load cell and place it into a concrete vault. Further, because the load cell needs to be in a concrete vault, it is challenging to install in asphalt surfaces.

(a) (b)

Figure 2.3: (a) Load cell sensor and (b) installation of load cell sensor (Source: Federal Highway Administration, 2018)

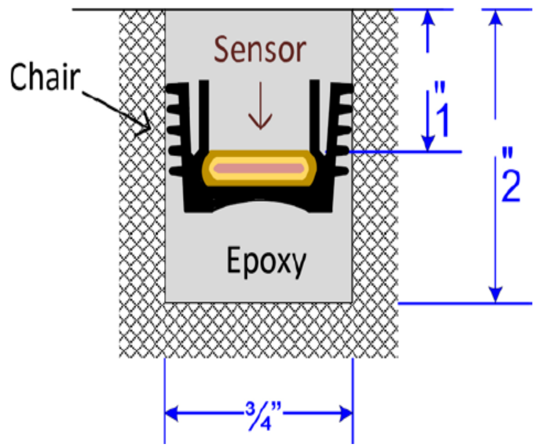
2.1.3 BacPolymer Piezo Sensor

The third sensor used most often for WIM systems is the polymer piezo sensor. The polymer piezo sensor is a copper strand wire that is covered by a piezoelectric polymer material, then covered by brass (Federal Highway Administration, 2018). To record data, the piezo sensors identify a change in voltage as a result of pressure applied to the sensor by the tires. This pressure generates an electric charge, in which the larger the charge, the higher the weight of the passing vehicle. These systems, however, cannot be implemented on their own, as a WIM system using polymer piezo sensors must also have at least one inductive loop as part of the system. An example of a polymer piezo sensor is shown in Figure 2.4.

The most advantageous aspect of polymer piezo sensors is their cost, as they are the least expensive among all WIM system sensors. Also, the sensors are easily installed or replaced. Another strength is the ability for polymer piezo sensors to record vehicle classification, as opposed to only recording vehicle weight. Unlike the previous two sensors discussed, polymer piezo sensors seldom need to be replaced or physically maintained.

Although the polymer piezo sensors may be tempting due to their price, they are the least accurate of the five common sensors. This is mostly attributed to the polymer piezo sensors being significantly sensitive to temperature and changes in pavement stiffness (Federal Highway Administration, 2018). Moreover, these sensors are not ideal for measuring overloads or a limited range of heavy loads. Polymer piezo sensors are best suited for measuring average truckloads, installation in moderate climates, and installation on high truck volume roadways.

(a)



(b)

Figure 2.4: (a) Polymer piezo sensor and (b) installation schematic of polymer piezo sensor (Source: Federal Highway Administration, 2018)

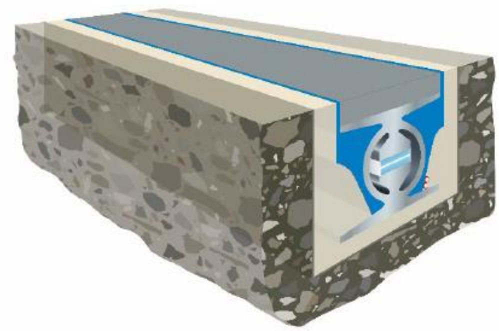
2.1.4 Quartz Piezo Sensor

The fourth sensor is a quartz piezo sensor. The quartz piezo sensor is made in 1.5 meters or 2 meters (length) but can be connected in various lengths to meet the required length (i.e., half-lane, full-lane, etc.). These sensors are relatively small compared to the previous sensors, as the quartz piezo sensor is often 2" wide, 2" thick, and can weigh up to 20 pounds (Federal Highway Administration, 2018). The quartz piezo sensor measures weight based on force, in which a wheel in-motion applies forces that are then distributed through the quartz in the sensor. Upon distribution of the forces, the quartz generates an electrical charge proportional to the forces applied by the dynamic wheels. An example of a quartz piezo sensor is shown in Figure 2.5.

In contrast to the previous sensors, quartz piezo sensors can be installed in either asphalt concrete or Portland cement concrete surfaces. However, they are said to be more durable if installed in a Portland cement concrete surface (Federal Highway Administration, 2018). Analogous to the polymer piezo sensor, the quartz piezo sensor is maintenance free. However, different from the polymer sensor, the quartz sensor is less sensitive to temperature changes.

Quartz piezo sensors being overly dependent on structural support from the roadway surface is a key disadvantage. Due to their narrow width, these sensors may also be prone to larger errors in measurements.

(a)



(b)

Figure 2.5: Quartz piezo sensor and (b) installation schematic of quartz piezo sensor (Source: Federal Highway Administration, 2018)

2.1.5 Strain Gauge Strip Sensor

The fifth, and final, most used WIM system sensor is the strain gauge strip sensor. These sensors come in three different lengths and can be installed in sets of one to four pairs (i.e., two to eight sensors) (Federal Highway Administration, 2018). Strain gauge sensors compute weight through a system that measures vertical strain placed on the sensor. The resultant change in the strain gauge properties is then converted into the dynamic load, the wheel, axle, and weight.

One of the key advantages of the strain gauge strip sensor is its ability to be installed on all roadway surfaces. Further, the strain gauge strip is essentially maintenance free and less sensitive to temperature changes. However, the lifespan of these sensors has not been tested beyond five years.

2.2 SUMMARY OF WIM SENSORS

As stated previously, each WIM sensor technology has its own advantages and disadvantages, cost, and recommended usage. Table 2.2 summarizes the WIM sensor technologies discussed in this Chapter.

Table 2.2: Summary of WIM Sensor Technologies

WIM Sensor Type	Advantages	Disadvantages	ASTM Type	Suggested Usage
Load Cell	• High Accuracy	• Used in Concrete Only • High Cost • High Maintenance	I, II, III	• Highway Monitoring • Highway Design • Planning • Pre-Screening
Bending Plate	• High Accuracy	• Used in Concrete Only • High Cost	I, II, III	• Highway Monitoring • Highway Design • Planning • Pre-Screening
Quartz Piezo	• High Accuracy • Low Maintenance	• Moderate Cost	I, II, III	• Highway Monitoring • Highway Design • Planning • Pre-Screening
Strain Gauge Strip Sensor	• High Accuracy • Low Maintenance	• Limited Long-Term Performance Record • Implemented With a Limited Number of Controllers	I, II, III	• Highway Monitoring • Highway Design • Planning • Pre-Screening
Permanent Polymer Piezo	• Low Cost • Low Maintenance	• Sensitive to Temperature • Requires Frequency Calibration	II	• Highway Monitoring • Planning
Portable Polymer Piezo	• Low Initial Cost • Easy Setup • Portable	• Low Accuracy • Sensitive to Temperature • Requires Local Calibration	II	• Planning

Source: Federal Highway Administration (2018)

3.0 LITERATURE REVIEW

With emerging technologies and the need for reliable, affordable freight data, WIM-related research has increased in recent years. Many of the recent works do offer innovative ideas for using WIM data to model or predict freight traffic characteristics, as well as methodologies for installation, calibration, and/or quality assurance of the data. In addition, although not in the context of the current study, several recent works utilize WIM data for bridge and/or pavement design.

For ease of discussion and organization of Chapter 3.0, WIM data research is presented in alphabetical order by domestic and international studies.

3.1 DOMESTIC WIM RESEARCH

To begin, Al-Qadi et al. (2016) summarize current weight regulations. According to Al-Qadi et al. (2016) and the U.S. Department of Transportation (2000), existing national regulations limit single axles to 20,000 pounds and tandem axles to 34,000 pounds. In addition, gross vehicle weight (GVW) is limited to 80,000 pounds, and states cannot levy "stricter" weight limits than the federal regulations. However, states can have a state-specific version of weight limit regulations. For Oregon-specific weight regulations, see (Unnikrishnan et al. 2019).[3]

Federal legislation regarding GVW or axle weight limits has offered states exceptions to have state-specific versions (Al-Qadi et al., 2016; Poirot et al., 2002). To briefly summarize regulations by states, National Academies of Sciences, Engineering, and Medicine (2014) has provided the following:

- 36 of 50 states set limits for axle loads at 20,000 pounds.
- 14 states set higher limits on axle loads, where the highest limit is 24,000 pounds.
- 33 of 50 states set tandem axle load limits to 34,000 pounds.
- 17 states set higher limits on tandem axle loads, where the highest limit is 48,000 pounds.
- 32 states set GVW limits to 80,000 pounds.[4]
- 9 states set GVW limits of greater than 100,000 pounds, where the highest limit is 164,000 pounds.

[3] Oregon's weight regulations can be viewed here.
[4] This is the regulation as defined by the Vehicle Weight Limitations - Interstate System, Title 23. U.S. Code §127, 2012.

- Some states have season exceptions in regard to legal load limits.

To conclude, Al-Qadi et al. (2016) provide a comprehensive review of WIM installation and accuracy. In regards to accuracy, several factors can impact WIM accuracy. However, there are three specific factors that have accuracy-related impacts. The first of these is temperature, as the temperature can alter the performance of many WIM technologies and roadway surface properties. The second factor that impacts accuracy is roughness. This refers, in general, to roadway characteristics (e.g., geometry, slopes, surface condition, etc.). The most impactful factor in this category is roadway surface roughness, as it can cause variations in the dynamic axle force being measured by the WIM sensor. The final factor is associated with vehicles. That is, vehicle characteristics (e.g., speed, tire type, tire pressure, suspension, etc.) can affect WIM sensors and their corresponding measurements.

As for the installation of WIM sensors, Al-Qadi et al. (2016) and AMEC Earth and Environmental (2012) recommend the following:

- Install WIM sensors in good weather (i.e., not freezing, wet, or extremely hot conditions).

- WIM sensors should be even with the roadway surface, within 0.04 inches.

- The top of the WIM sensor should be separate from the roadway surface.

- WIM sensor system electronics should be protected from extreme temperatures, dirt, humidity, and insect or rodent invasion.

- WIM sensor equipment should be protected from power surges.

- WIM equipment should be installed to ensure regular maintenance can take place without data disruption.

In another study conducted at a federal level, Quinley (2010) developed a WIM data analyst’s manual. Through the development of this manual, Quinley (2010) aimed to recommend procedures to perform validation and quality control checks of WIM data. Quinley (2010) determined that WIM systems typically store both summary (binned) data and vehicle record data for each day, where binned data and vehicle record data are as follows:

- Binned Data: All of a day’s vehicles are binned by count for hour-of-day, lane, classification, and speed range. In addition, binned data does not contain individual vehicle data characteristics.

- Vehicle Record Data: This data includes characteristics for individual vehicles. In this system, the user can define parameters (e.g., classification, front axle weight threshold, etc.) to determine if a record is to be stored for a vehicle or if a vehicle is to be counted in the binned data.

Quinley (2010) also identified factors affecting the quality of WIM data that are tantamount to the findings of Al-Qadi et al. (2016). Other findings include that some agencies utilize their own systems to automate the raw data and perform validation checks, while the remaining agencies use third-party software for such processes. Quinley (2010) concluded by developing steps to validate WIM data, assess individual vehicle records, and a recommendation for automated validation programs.

The final relevant study pertaining to the federal level is a study by Southgate (2015). The purpose of this work was to develop a methodology to determine the quality of WIM data, as well as to identify firm guidelines for making judgment calls on whether to keep or exclude WIM data observations. To accomplish this, Southgate (2015) developed a methodology consisting of linear and log-log regressions to assess the quality of WIM data and to calibrate WIM systems. In doing this, Southgate (2015) provides a step-by-step procedure to replicate the quality checks and/or system calibration. However, due to this process being labor intensive, Southgate (2015) strongly recommends that a program be written to conduct these analyses more efficiently.

3.1.1 Alabama

Due to the Mechanistic-Empirical Pavement Design Guide being able to simulate every truck axle, as well as the corresponding stresses and strains imposed on the roadway surface, Mai et al. (2013) investigate quality control of WIM data by incorporating threshold values and rational procedures. To accomplish this, Mai et al. (2013) utilize three years of data (2006 to 2008) from 12 bending plates WIM sensor locations. Pertaining to the threshold values, this refers to detecting improbable values in truck weight measurements. For rational procedures, Mai et al. (2013) propose examining patterns in axle load distributions and relationships among the variables collected in WIM data. Specifically, Mai et al. (2013) use a peak-range check, peak-shift check, and correlation analysis to quantify the comparison of axle load spectra during rational checks. Results suggest that the proposed rational checks be implemented in future WIM data quality checks. In addition, Mai et al. (2013) recommend that the rational check be integrated with the data collection process.

3.1.2 Arizona

In a project conducted for the Arizona Department of Transportation, Selezneva and Wolf (2017) surveyed other state DOTs and developed a WIM Guidebook for successful WIM installation, calibration, maintenance, and data quality. Through their survey, Selezneva and Wolf (2017) identified WIM equipment for the surveyed agencies, as shown in Table 3.1. In addition, it was discovered that some agencies collect, or do not collect, specific data-types:

- Louisiana WIM systems do not report GVW but do report axle weight.
- Florida WIM systems collect temperature data.
- New Mexico WIM systems do not collect speed, axle weight, or per-vehicle data.

Table 3.1: Summary of WIM Equipment of Surveyed Agencies

Agency	Number of WIM Systems	WIM Controller	WIM Sensor	ASTM Type	Road Surface Type
Connecticut DOT	10	Telemetrics	Piezo-Polymer	II	Asphalt
	100	Raktel	Piezo-Polymer	I	Asphalt
Florida DOT	25	IRD-iSINC	Piezo-Quartz	I, III	Asphalt
	4	IRD-iSINC	Bending Plate	I, III	PCC
	3	PAT Traffic	Piezo-Quartz	I, III	Asphalt
	1	PAT Traffic	Bending Plate	I	Asphalt
Georgia DOT	6	Peek ADR	Piezo-Polymer	I, II	Asphalt
	9	Peek ADR	Piezo-Quartz	I	PCC
	1	IRD-iSINC	Piezo-Quartz, Piezo-Polymer	I	PCC
Louisiana DOT	5	IRD TC540	Bending Plate	Unknown	PCC
New Mexico DOT	11	Peek ADR	Piezo-Quartz	Unknown	Asphalt
	2	IRD	Piezo-Quartz	Unknown	Asphalt
	3	IRD	Bending Plate	Unknown	PCC
Pennsylvania DOT	11	IRD-iSINC	Piezo-Quartz	I	Asphalt
	1	PAT Traffic	Piezo-Polymer	I	Asphalt
	1	PAT Traffic	Piezo-Quartz	I	Asphalt
Texas DOT	17	PAT Traffic	Peizo-Quartz	II	Asphalt
	15	PAT Traffic	Bending Plate	II	PCC
Virginia DOT	7	Peek ADR	Piezo-Quartz	I	Asphalt (3), PCC (4)
	1	IRD-iSINC	Bending Plate	I	PCC
West Virginia DOT	50	ECM	Piezo-Polymer	Unknown	Asphalt
FHWA LTPP	1	Mettler-Toledo	Load Cell	I	PCC
	11	IRD-iSINC	Bending Plate	I	PCC
	13	IRD-iSINC	Piezo-Quartz	I	PCC (2), Asphalt (11)

Source: Selezneva and Wolf (2017)

3.1.3 California

In an attempt to develop detailed truck flow pattern data, Hyun et al. (2017) developed a truck tracking algorithm and model to estimate flow paths. By implementing a linear data fusion methodology with WIM data and data from inductive loop point sensors, the authors are able to accomplish this. To develop the model, data was obtained from two WIM sites spanning 26 miles on I-5 in California: (1) San Onofre (upstream) and (2) Leucadia (downstream). Over this 26 miles, there are two major highway intersections and 17 on/off ramps. In addition, included in the collected data were still images of license plates of vehicles, where these were manually linked to the WIM data and inductive loop signatures. Over two days, Hyun et al. (2017) collected 5.5 hours of data and split the collected data into test and training datasets. Then, using the collected data, Hyun et al. (2017) matched vehicles to detail truck flow. To match individual vehicles with better performance, key feature variables were chosen and weighted through a Bayesian model. Results showed that the proposed methodology correctly matched 81% of the through trucks.

To derive average payloads, critical inputs for commodity-based forecasting models, Hernandez (2017) presents a methodology using WIM data. For this work, Hernandez (2017) collected data at four WIM sites in California, each of which was collected during "*several 2- to 3-day periods*." These data collection periods included days in the fall, winter, and spring seasons, various time periods, and collected over one year (2012 to 2013). For a summary of collected data by Hernandez (2017) by date and time, refer to Table 3.2.

Table 3.2: Data Collection Sites, Dates, and Time-Periods

WIM Site	Site Description	Date of Collected Data	Time Period of Collected Data
Irvine, CA	• I-5 • Southbound • Urban • 45 Miles From Nearest Port • 5% Truck Traffic	• September 21, 2012 • October 2, 2012 • October 3, 2012 • March 20, 2013 • March 25, 2013	• 10:45 a.m. to 6:00 p.m. • 1:00 a.m. to 6:45 p.m. • 6:30 a.m. to 9:15 a.m. • 6:30 a.m. to 7:45 p.m. • 7:30 a.m. to 4:15 p.m.
Fresno, CA	• CA-99 • Southbound • Semi-Urban • Agriculture • 22% Truck Traffic	• November 7, 2012 • November 8, 2012	• 10:15 a.m. to 5:15 p.m. • 6:15 a.m. to 4:45 p.m.
Willows, CA	• I-5 • Northbound • Rural • 25% Truck Traffic	• December 10, 2012 • December 11, 2012 • December 12, 2012	• 10:30 a.m. to 4:45 p.m. • 7:15 a.m. to 4:45 p.m. • 7:00 a.m. to 3:00 p.m.
Redding, CA	• I-5 • Southbound • Rural • 120 Miles From Oregon Border • 25% Truck Traffic	• December 10, 2012 • December 11, 2012 • December 12, 2012	• 1:30 a.m. to 5:00 p.m. • 7:00 a.m. to 4:45 p.m. • 7:00 a.m. to 1:00 p.m.

To first find average payloads by truck type, Hernandez (2017) subtracts an estimated average empty weight from an estimated average loaded weight - these weights are a result from a Gaussian mixture model to fit a GVW distribution. In doing so, enhancements are made to the truck equivalency factor (TEF) estimation method.[5] Hernandez (2017) then determines the total

[5] A summary of the TEF method is discussed in Fekpe (2011).

number of trucks needed to move specific tons of commodities. To do this, body type of truck is used in relation to VIUS data (2002 VIUS data was used for this comparison). Through the analysis, it was found that VIUS data may be overestimating payloads and underestimating empty weights.

By developing a modified decision tree model and Gaussian mixture model, Hyun et al. (2015) use WIM data to estimate truck volumes and GVW distributions by body configuration for five-axle semi-tractor trailers, respectively. Data used for this work consisted of WIM data collected at three locations in California: (1) Fresno, (2) Redding, and (3) Willows. A fourth location was also selected to test for spatial and temporal transferability. From these locations, Hyun et al. (2015) collected 10,904 truck records across "*multiple days*."

To account for potential errors in the WIM data, Hyun et al. (2015) also conducted a sensitivity analysis by increasing each measure by a constant 10%. Results show that the proposed methods are spatially and temporally transferrable, as the errors are acceptable. In addition, the model is capable of capturing daily variations (i.e., time-of-day) of truck travel movements. Ultimately, the proposed methodologies provided more accurate predictions than the baseline models.

3.1.4 Florida

Eluru et al. (2018) conducted a study for Florida, in which the authors developed a methodology to fuse several data sources into an accessible database. This was done by developing algorithms to disaggregate FAF data, using TRANSEARCH data, at a traffic analysis zone scale. In regards to details of all datasets used for their analysis, they are as follows:

- FAF[4] dataset. The baseline year is 2012.
- TRANSEARCH dataset. Eluru et al. (2018) purchased this data for the year 2011.
- American Transportation Research Institute (ATRI) dataset. Eluru et al. (2018) used ATRI data from a previous project in Florida. Data included GPS records of trucks for March, April, May, and June of 2010.
- WIM dataset. Data from WIM stations were collected from 2010 to 2015. WIM sites, in which data were collected, are located across 26 counties in Florida for a total of 40 sites.
- Land use dataset.

After this was completed, the authors used optimization methods and econometric methods to estimate county-level commodity flow behavior. WIM data was used to generate origin-destination flows by various weight categories. The authors found that the integration of these data sources can serve as a viable tool for state planning agencies.

In another study performed for Florida, Florida Transportation Data and Analytics Office (2018) aimed to quantify truck empty backhaul using WIM data obtained from WIM sites on interstates only. Using two years of WIM data (2015 to 2017) and considering only Class 09 trucks, any observation that did not meet a certain threshold was excluded. The authors further validated the WIM data using a range and constraint validation, which consisted of the following:

- Dimensional integrity.
- Weight integrity.
- Classification integrity.

Also as part of their analysis, the authors estimated variables, as shown in Table 3.3. Using the derived variables, the authors were able to better understand the commodity movement, the direction of travel with the greatest flow, and a general idea of the pattern of imports and exports. Lastly, using TRANSEARCH and FAF data, the authors conducted reasonableness checks.

Table 3.3: Definition of Derived Variables Using WIM Data

Name and Definition of Derived Variable	Formula for Derived Variable
Linear ${}^{\text{GVW}}/_{\text{Unit Length}}$ ratio. This is defined as the ratio of GVW and length of wheelbase.	$\text{Ratio} = \frac{\text{Gross Vehicle Weight}}{\text{Length of Wheelbase}}$
Axle weight distribution. This is used to determine the skewness of the weight distribution across axles. This was computed for each axle of every truck as the ratio of every axle weight to its GVW.	$\frac{\text{Axle Weight}_i}{\text{Gross Vehicle Weight}} \ \forall \ \text{axle weight } i$
Conversion of GVW from a continuous variable to a categorical variable. Categories were considered in increments of 5,000 pound of GVW.	$0 < \text{GVW} < 20{,}000$ $20{,}000 < \text{GVW} < 25{,}000$ $25{,}000 < \text{GVW} < 30{,}000$ $30{,}000 < \text{GVW} < 35{,}000$ $35{,}000 < \text{GVW} < 40{,}000$ $40{,}000 < \text{GVW} < 45{,}000$ $45{,}000 < \text{GVW} < 50{,}000$ $50{,}000 < \text{GVW} < 55{,}000$ $55{,}000 < \text{GVW} < 60{,}000$ $60{,}000 < \text{GVW} < 65{,}000$ $65{,}000 < \text{GVW} < 70{,}000$ $70{,}000 < \text{GVW} < 75{,}000$ $75{,}000 < \text{GVW} < 80{,}000$ $80{,}000 < \text{GVW} < 85{,}000$ $85{,}000 < \text{GVW} < 90{,}000$ $90{,}000 \leq \text{GVW}$

Source: Florida Transportation Data and Analytics Office (2018)

Using probabilistic models and WIM data, Watson, Jr. et al. (2017) determined the probability of observing a single or concurrent truckload that exceeds weight limits. Although this particular study was applied to bridge locations, the methodology can be applied to any location in which a

WIM site is present. Of the 37 WIM sites considered, three were selected based on criteria defined by the authors. For the three selected WIM sites, data were collected between January 2008 and May 2014. In addition, contingent on WIM station, the exact time period of data collection differed.

As it pertains to the analysis, the authors first calculate truck entry and exit times using specific formulae utilizing information provided by the WIM data. After calculating these times, Watson, Jr. et al. (2017) assessed the frequency and likelihood of observing various truckloads through a probabilistic modeling approach. To accomplish this, the authors fit a distribution to each month of data, in which an exponential distribution was determined to be adequate for each month of their data. Then, to account for uncertainty, the authors introduce a Monte Carlo simulation to be conducted with the derived exponential distribution PDF. At last, Watson, Jr. et al. (2017) use the PDF for each WIM station and combine with the binomial distribution to generate plots of predicted overweight trucks.

3.1.5 Indiana

Utilizing WIM data obtained in Indiana, Cetin and Nichols (2009) use the assignment problem to improve the accuracy of vehicle re-identification algorithms. Data used by Cetin and Nichols (2009) include data collected at a weigh station on I-70 (near Terre Haute, Indiana) for two days in July 2004. This particular weigh station is comprised of a mainline WIM sensor (i.e., located on the interstate) and a ramp WIM system. These two WIM systems are separated by just 0.8 miles, in which the mainline sensor is for trucks with transponders, and the ramp sensor is for trucks without a transponder.

To improve the accuracy of vehicle re-identification algorithms, Cetin and Nichols (2009) decompose this process into two stages. The first stage is completed by matching vehicles from the downstream station to the most similar upstream vehicle (this is the typical method in re-identification). This is accomplished through an Euclidean distance method, Bayesian method, and finite mixture models. In the second stage, Cetin and Nichols (2009) take all upstream vehicles that are matched more than once, and those that have not been matched, are selected corresponding to the set of downstream vehicles that are assigned to the same upstream vehicles. Using a cost matrix and the Hungarian algorithm, the assignment problem is solved. After the assignment problem is solved, each vehicle is matched to only one other vehicle. The analysis was conducted based on two scenarios, where the accuracy of re-identification was considerably improved through the two-stage approach.

3.1.6 Kentucky

In a study for the Kentucky Transportation Cabinet, Pigman et al. (2015) updated the processing of traffic characteristics through various quality control and analytical programs. Using WIM data, the goal is to estimate the following parameters:

1. Average daily traffic.
2. Percent of trucks.

3. Percent of trucks that are classified as heavy/coal.

4. Axles per truck.

5. Axles per heavy/coal truck.

6. Equivalent single axle loads (ESALs) per truck axle.

7. ESALs per heavy/coal truck axle.

8. Total ESALs.

Several years of data (2007, 2011, and 2012 to 2013), collected at 41 stations, were used to produce average values of vehicle classifications and weights. Data collection was then followed by a regression analysis to generate "smoothed" values for each parameter of interest (the parameters listed previously). Specifically, linear regression was used to determine the growth rate of truck volumes based on existing WIM data. This was conducted on specific roadway classifications. Pigman et al. (2015) determined this was an adequate methodology to estimate the parameters of interest; therefore, the authors provided a step-by-step procedure and computer code to replicate the estimation of the parameters.

Martin et al. (2014) conducted a study to determine if a comprehensive statewide plan to procure, manage, and share WIM stations in Kentucky is needed. The authors surveyed fellow DOTs to assess their use of WIM data. It was determined that information provided by WIM stations across states is consistent, yet there is no pattern on data-sharing. Martin et al. (2014) state that some states are more willing to share WIM data than others. In addition, Martin et al. (2014) identified specific WIM data format, storage, and analysis software for select surveyed DOTs. For WIM data format, storage, and analysis software for the surveyed states, refer to Table 3.4. Based on their findings, the authors suggested several recommendations for WIM data collection and usage:

1. Motor Carrier Divisions and Planning Agencies should have a discussion on potential partnerships and methods to share WIM equipment, data, and costs.

2. Agencies requiring WIM data can contact WIM product vendors to improve the performance and accuracy of WIM systems.

3. Local DOTs can consider making WIM data readily available for researchers and planning departments, such as a web-based portal.

4. Data dictionaries regarding WIM data should be updated frequency, as well as making them more user friendly.

Table 3.4: Summary of WIM Data Format, Analysis Software, and Storage by Surveyed States

State	Available Data Formats	Analysis Software(s)	Data Storage
Connecticut	• Adobe • Excel • Word • Access • Outlook • PowerPoint • Digital Highway • Google Earth • DOS • .txt to Document	• Diamond: IRD-PEEK • TraffMan: TELMIKROS-Prosoft	Stored Locally
Kentucky	• FHWA's TMG W-Card Format	• PEEK's Viper program for data retrieval via IP addressable modems • Chaparral's TRADAS program for data entry manipulation, QC, storage, etc.	Stored Locally
Mississippi	• TMG	• Mikros' TEL	Stored Locally
New Jersey	• ASCII • Excel • Word • PDF	• WIM Manufacturer • VTRIS • TMAS • TRADAS	Stored Locally
Ohio	• Weight Data (.pvr) • Classification Data (.bin)	• Peek ADR 2000+ • Peek TOPS	Stored Locally
Washington	• Text • PDF • Excel	• iAnalyze-Vendor Supplied • SAS Statistical Software	Stored Locally

Source: Martin et al. (2014)

3.1.7 Montana

In Montana, Stephens et al. (2017) attempted to develop a strategy for WIM and automatic traffic recorder data collection, with a specific focus on the former. The authors begin by stating freight and fleet management benefits as a result of traffic monitoring through WIM data, in which notable benefits are as follows (Miller & Sharafsaleh, 2010; Stephens et al., 2017):

- Reliability of scheduling highway-based freight deliveries.
- Increased productivity.
- Monitoring of driver performance and compliance.
- Fleet tracking and goods tracking capabilities.

To achieve the benefits noted above, the Montana Department of Transportation (MDT) requires reliable data received from the WIM systems. As such, MDT performs quality control analyses to screen the collected data. The quality control checks are performed automatically through the system's software, where specific items (related to WIM systems) checked are shown in Table 3.5. Upon assuring the quality of data, MDT then creates trends based on the collected data (e.g., temporal trends, spatial trends, trends by classification, trends by weight, etc.).

Table 3.5: Summary of Montana Department of Transportation Data Quality Control Checks

Data Quality Error	Description	Warning	Error
Axle Count is Too High	Maximum number of axles for a credible vehicle.	14	20
Axle Count is Too Low	Minimum number of axles for a credible vehicle.	-	1
Axle Spacing is Too High	Maximum credible spacing between consecutive axles.	50	99
Axle Spacing is Too Low	Minimum credible spacing between consecutive axles.	3	2
Sum of Axle Weight and GVW	Sum of reported axle weights and GVW are within 90% of each other.	-	90
Axle Weight is Too High	Maximum credible single axle weight.	-	500
Axle Weight is Too Low	Minimum credible single axle weight.	-	5
Axles vs. Spaces	Axles minus one must equal number of spaces.	-	On As Error
Axles vs. Total Axles	Axles counted do not equal the total number of axles	-	On As Error
Length Less Than Wheelbase	Vehicle length is less than the length of the wheelbase	-	On As Error
Length Equal to Wheelbase	Vehicle length is equal to the length of the wheelbase.	On As Warning.	-
Low 9/11 First Axle Weight	Minimum credible steer axle weights for Class 09 and Class 11 vehicles.	70	5
Missing Data	Data entry check.	-	On As Error
No Class Code	The vehicle is not classified.	-	On As Error
Speed 0	Speed is equal to zero.	-	On As Error
Speed is Too High	Speed exceeds a specific value.	90	155
Speed is Too Low	Speed is lower than a specific value.	39.9	9.9

Source: Stephens et al. (2017)

3.1.8 North Carolina

As part of a Master's Thesis, Ramachandran (2009) performed a WIM data analysis. For the study, 12 consecutive months of WIM data (at a time between 1997 and 2007) collected from 45 WIM sites were used. The analysis began with an approach to obtain WIM-related statistics. In doing so, trends in axle weight, axle spacing, vehicle classification, etc., are readily attained. The data analysis consisted primarily of manual data quality checks. Namely, if quality checks are not performed before obtaining the data, the data is checked manually via graphical displays that show distributions, summary statistics, etc.

3.1.9 Texas

Faruk et al. (2016), using Texas as a case study, implement a portable WIM system to collect data and analyze aforesaid data. The portable WIM system was placed in Hidalgo County, near the U.S.-Mexico border, on Highway FM 1016 (in both directions of travel). For this case study, data was collected at this location for a total of 21 days.

The analysis consisted of generating traffic parameters, such as traffic volume, load spectra, and overloading information (both GVW and axle weight). After sensor calibration, the authors collected data on the following:

- Traffic volume, speed, and vehicle classification.
- GVW distribution and axle weight distribution.
- Overweight vehicle distribution.

The authors, though their analysis, performed a week-by-week comparison of the characteristics mentioned above. The authors identified a possible loss of sensitivity to detect light-weight vehicles over time; this was observed through a decrease in ADT and a decreasing trend in Class 02 and Class 03 vehicles. However, the large truck volumes did remain consistent from week-to-week (Class 04 vehicles to Class 13 vehicles). In terms of temporal trends in traffic flow, Faruk et al. (2016) determined that traffic volume was least on weekends, with Sunday having the lowest traffic volumes. In addition, an on-average peak hour was identified to be between 2:00 p.m. and 6:00 p.m. The trends for traffic flow and vehicle classification followed trends from historical traffic data. The authors conclude by stating that such systems can be used to obtain information for design, analysis, and traffic monitoring.

Figliozzi et al. (2000) used WIM data to calibrate trade-derived estimates of Mexican trade truck volumes (i.e., North American Free Trade Agreement equivalent trade truck data). The WIM data was collected from nine sites across Texas, where these nine sites were further complemented by three specific WIM sites at Laredo and El Paso.

Using the nine WIM sites, Figliozzi et al. (2000) first classified vehicles by bus or trucks, then associated the vehicles with the number of axles on the unit. This process continued to identify the number of axles on the first trailer, the number of axles on the second trailer, and the number of axles on the third trailer. After this classification, four truck types were found to be represented most on the highways considered for analysis. The authors then plot histograms of total truck weight and observed three possible scenarios, based on peaks and distributions in the histogram, as it pertains to the weight of the truck: (1) Net weight of tractor and semi-trailer, (2) Truck weight limit, and (3) Partially loaded or lighter commodity trucks.

Figliozzi et al. (2000) continue by investigating specific truck characteristics based on WIM data. Specifically, trends and characteristics related to overloaded trucks, empty trucks, cube out and weight out, effects due to direction of travel, seasonal effects, and time-of-day are observed. The authors conclude by analyzing overweight axle loads, in which axle loads measured at WIM sites and axle loads measured on NAFTA highway corridors were found to have substantial differences.

In a similar study conducted in Texas, Figliozzi et al. (2001) use two methods of estimation using two specific datasets to derive truck flows. Of the datasets used for analysis, the first included truck numbers from border bridge systems and U.S. Customs (this data could also be collected through WIM systems). The second dataset used is U.S. international trade data and commodity densities, truck weights, and truck volumes. Other utilized datasets in their work include the Transborder Surface Freight Database, commodity densities from Memmott (1983), trailer data provided by the Laredo base of Schneider, Inc., and Standard International Trade Code data (this was obtained via special order from the U.S. Department of Commerce).

Results from the first method and dataset (truck counts) show that Laredo and El Paso have the largest truck volumes. Regarding the second method (method using the U.S. international trade data) used by Figliozzi et al. (2001), truck weight per commodity is calculated based on commodity densities. This is done by using representative commodity group densities, which can then be multiplied by the truck capacity to give the commodity group. Two fundamental assumptions are used to conduct this portion of the analysis: (1) truckloads are weighing out or cubing out, and (2) a single commodity per truck is assumed. Using this method, it was determined that truckload values vary by commodity group. Figliozzi et al. (2001) further state that the first method can better estimate truck volumes if there were more data on density and volumes by commodity group.

3.1.10 Washington State

One of the earlier WIM-related research studies in Washington was conducted by Hallenbeck and Hooks (1987). In their work, Hallenbeck and Hooks (1987) document the testing and research performed by the Washington State Transportation Center using the FHWA bridge WIM system. In doing so, the authors provided additional information on using bridge WIM systems to collect truck weight information to be used for planning and enforcement purposes. Using five selected sites, four located on I-5 and one on I-90, it was determined that for planning purposes, weight collection is the most important, as are the weight distributions. For enforcement purposes, it was found that a one-to-one comparison of dynamic and static weight measurements is most important.

In the same year, Hallenbeck et al. (1987) conducted a study to document the testing of a piezo-electric cable WIM truck scale. Tests were directed towards the accuracy of the system's static weight estimates, vehicle speed estimates, and classification of vehicles. It was determined that speed and vehicle classification estimates performed well. However, the weight estimates did not perform well, as the standard deviation between WIM and static weight measurements was roughly 20%.

Also in the 1980s, Hallenbeck (1989) detailed the needs of the Washington State Department of Transportation in regards to truck weight data, as well as potential plans to meet those needs. Hallenbeck (1989) determined that the bending plate system gave the most accurate and reliable weight estimates, while also ranking alternatives based on measures of accuracy, reliability, and cost.

In the early 1990s, Hallenbeck and Kim (1993) conducted an analysis using WIM data from ten permanent sites in Washington. Their objective was to provide an overview of weight patterns at these ten locations. Hallenbeck and Kim (1993) found that weights, roadway classifications, and traffic volumes varied significantly due to the WIM stations being geographically dispersed across the state.

In yet another study, Hallenbeck et al. (2003) used WIM truck transponders to assess the viability of converting transponder reads into meaningful data to detail facility performance. Specifically, this was aimed at determining travel times. It was determined that due to long lengths between WIM stations, and that trucks may stop to rest, a large number of transponder tags are required to calculate reliable travel times.

3.2 INTERNATIONAL WIM RESEARCH

The following sub-chapter summarizes WIM research conducted in countries outside the United States.

3.2.1 Australia

Of particular interest is a study by Mitchell (2010), in which WIM data obtained from 1997 to 2009 is used to determine trends in freight movements. In Australia, the majority of WIM sites are located on the National Land Transportation Network and were the WIM sites used by Mitchell (2010). Utilizing this WIM data, Mitchell (2010) developed a series of three mixed-effects models (i.e., panel data methods)[6], estimated separately for each corridor, to estimate trends in non-urban road freight. As described by Mitchell (2010), the series of three mixed-effects models consisted of the following:

1. Estimate a mixed-effects model of average annual daily truck traffic (AADTT) volumes, regressed against a time trend term, across all WIM locations on the corridor.

2. Estimate a mixed-effects model of truck traffic shares, regressed on a spline time trend term, across all WIM locations on the corridor.

3. Estimate a mixed-effects model of average truckloads, by truck type, regressed against a spline time trend term, across all WIM locations on the corridor.

Using the mixed-effects models, the author provides estimates for both directions of traffic. In addition, this specific model specification uses fixed-effects for the intercepts and random effects for the time trend term. Through this methodology, Mitchell (2010) determined that the mixed-

[6] Mixed effects models are models that estimate parameters using both fixed- and random-effects. This is accomplished by adding one or more random-effects to the estimated fixed-effects.

effects model specification predicts growth in AADTT well. For truck traffic shares, the author introduced period-specific indicator variables. This, in addition to the time trend term, captured the growth trend well. Lastly, for the average truckloads model, indicators were included to account for variations in average loads. Then, using these estimates, class-specific truck volumes are derived by multiplying the model estimates by the class-specific truck traffic shares.

3.2.2 France

Using a statistical software developed by the National Science Foundation[7], Schmidt et al. (2016) analyzed loading and behavior patterns, and axle load distributions by axle rank and truck category. Data used for analysis contained millions of truck records recorded at three WIM stations on high traffic volume highways and motorways during one year in France (September 2013 to August 2014).

The authors begin by classifying the large trucks for analysis, in which classification criteria were based on the number of axles, axle spacing, and the number and location of drive axles. According to the authors, all statistical analyses for load distributions took place in the statistical software R. The authors were able to analyze load distributions using finite mixture models. As for axle load distributions, the authors used mathematical optimization techniques and assumed all axle distributions were Gaussian.

3.2.3 Poland

In an attempt to manage freight traffic management, Oskarbski and Kaszubowski (2016) use one year (2012) of truck traffic data to assess the effectiveness of freight management due to WIM sites. Data is collected, and the study is conducted in Gdynia, Poland. Specifically, Oskarbski and Kaszubowski (2016) develop a model, through a simulation-based approach, to show how WIM systems can be used to control large trucks' access to specific areas of the city. This was accomplished by comparing theoretical control scenarios and their impact on traffic parameters and emissions. For their analysis, the authors excluded any WIM location based on the roadway surface causing increasing errors, significant vertical alignment, and locations prone to hard braking and acceleration, and bridges. After eliminating these WIM locations, the authors collected data and investigated the following:

- Change in travel time.
- Less traffic in central areas.
- New traffic conditions (time lost, queue length, and number of stops).
- Changes in vehicle-miles-traveled.

[7] The software being referred to is Mixtools. Mixtools, now a package in R, is a tool for analyzing finite mixture models. The package is a result of work supported through the National Science Foundation, Grant No. SES-0518772.

- Estimated changes in the effects on the environment.

Using a transport modeling package SATURN, the authors considered three specific WIM scenarios: (1) Baseline condition - Existing situation with no system to control large truck access using WIM, (2) Reduced large truck volume as a result of WIM, and (3) Reduced large truck volume in the city center as a result of WIM. Results showed that Scenario 1 had a substantial reduction in the number of large trucks entering the city and the city center. In contrast, Scenario 3 showed a significant decrease in the number of large trucks on access roads to the city and no large trucks on entries to the city center. Ultimately, the proposed scenarios showed that WIM sensor locations could mitigate large truck traffic volume in specific areas of urban cities; that is, WIM systems can be used to control truck access.

3.2.4 Malaysia

An article, conducted by Abdullah (2011) as a dissertation, uses WIM data to determine the interaction effects of GVW and vehicle classification on speed. Abdullah (2011) also uses WIM data for an 85th percentile speed distribution analysis to find the appropriate speed limit when GVW is accounted for. This study utilized WIM data collected at a single site on Federal Road 54 over four months (October 2009 to January 2010).

In regards to the analysis of interactions effects, Abdullah (2011) applied a two-way ANOVA analysis and found that vehicle classification and GVW both have statistically significant effects on speed. Further analysis determined that the majority of large truck drivers were driving below the posted speed limit.

3.3 WIM SITES AND DATA IN OREGON

Being that the current study is based on WIM data in Oregon, Chapter 3.3 focuses on WIM characteristics in Oregon. This includes a summary of WIM systems in Oregon, their usage, and WIM research in Oregon. For information on Oregon's weight regulations and weight-mile tax, see Unnikrishnan et al. (2019).[8,9]

3.3.1 Enforcement WIM Locations in Oregon

Currently, Oregon has 21 WIM systems used for enforcement, three virtual WIM systems used only for data collection,[10] two locations with license plate readers, and one WIM site with license plate readers (the location of this WIM site was not disclosed). Of the 21 WIM systems used for enforcement, more than half are present on two corridors: I-5 and I-84. On I-5, there are six WIM systems: (1) Two near Woodburn, OR, (2) Two near Booth Ranch, OR, and (3) Two near Ashland, OR. Figure 3.1 shows the WIM system locations along I-5. As for I-84, there are also

[8] Oregon weight regulations can be viewed here.

[9] A summary of weight-mile tax by state can be viewed here.

[10] In Oregon, weight from a virtual WIM site is not enforceable. However, data is collected and is used for audit purposes. In addition, virtual WIM sites are not associated with a weigh station, while a WIM site is associated with a weigh station. The virtual WIM stations in Oregon are for data collection purposes only.

six WIM sites: (1) Near the Farewell Bend Port of Entry, (2) Near Olds Ferry Weigh Station, (3) Near La Grande Weigh Station, (4) Near Emigrant Hill Weigh Station, (5) Near Cascade Locks Port of Entry, and (6) Near Wyeth Weigh Station. Figure 3.3 shows the WIM system locations along I-84.

Also with a large proportion of Oregon WIM systems is US-97, in which there are five WIM sites: (1) two near Juniper Butte, (2) two Near Klamath Falls, OR, and (3) one near Bend, OR. For WIM system locations along US-97, see Figure 3.2. Of the remaining five WIM system locations, one is located on US-30 near Rocky Point, one is situated on OR-58 near the Lowell Weigh Station, one is located on I-82 near the Umatilla Port of Entry, and two are located on OR-730 near the Cold Springs Weigh Station. These WIM sites are shown in Figure 3.4.

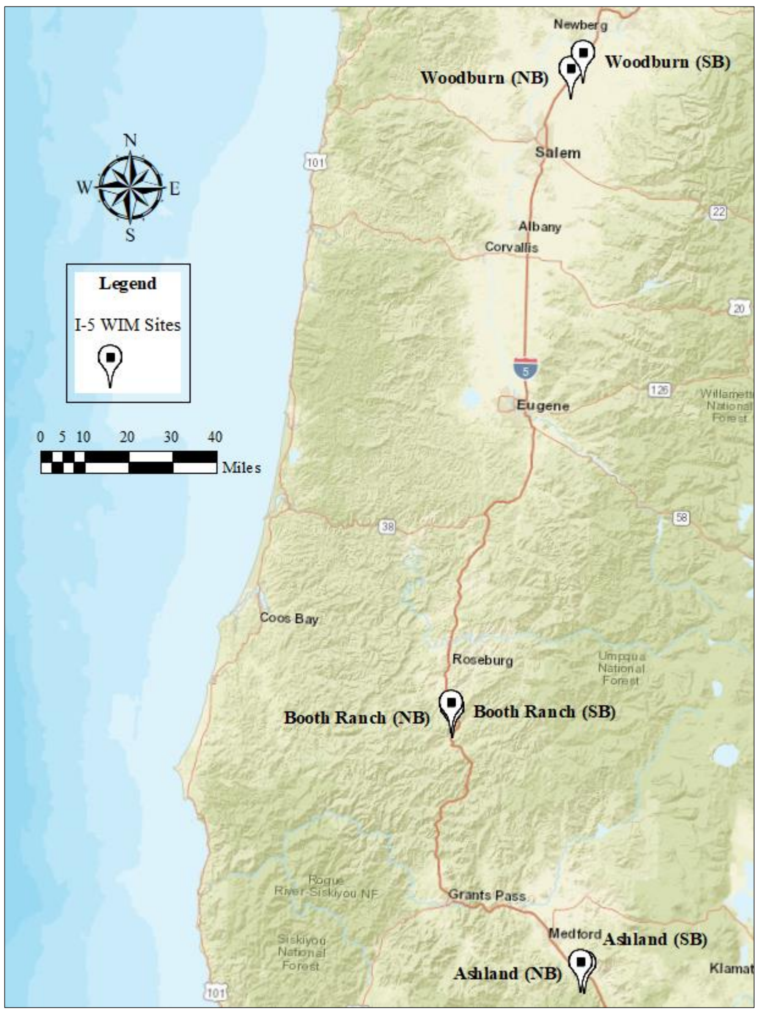


Figure 3.1: WIM sites on I-5

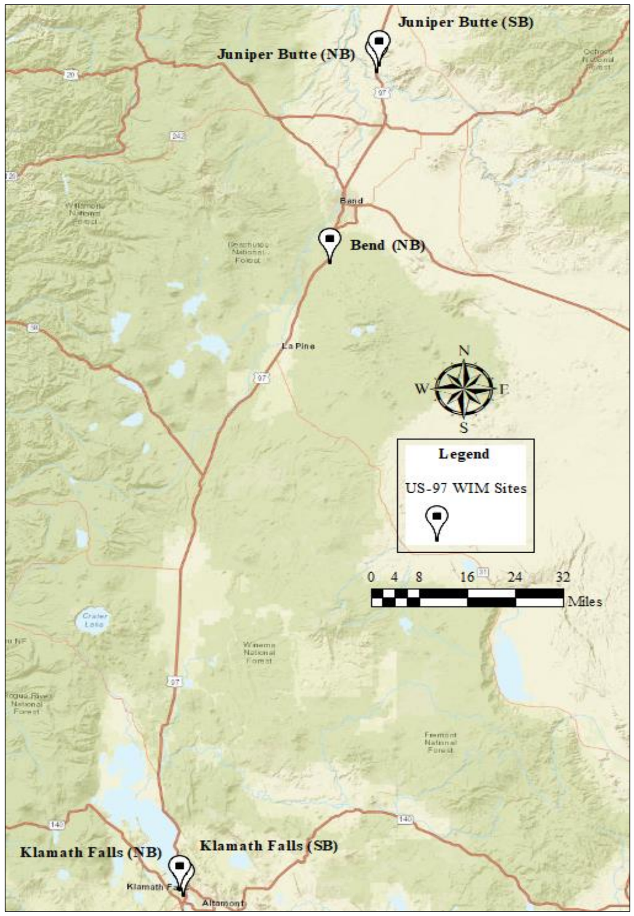


Figure 3.2: WIM sites on US-97

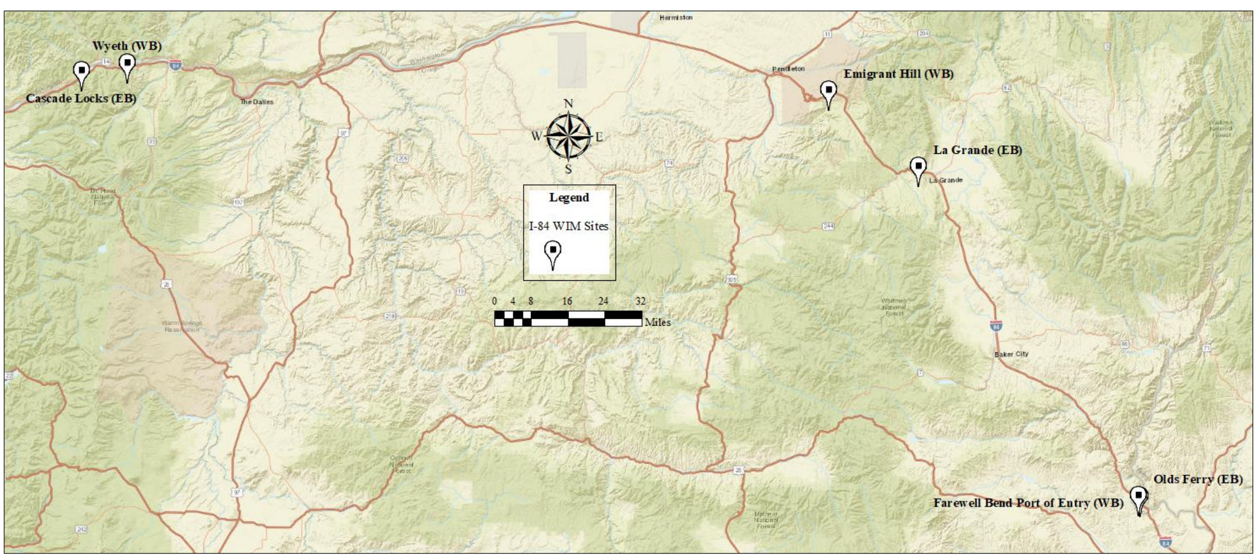
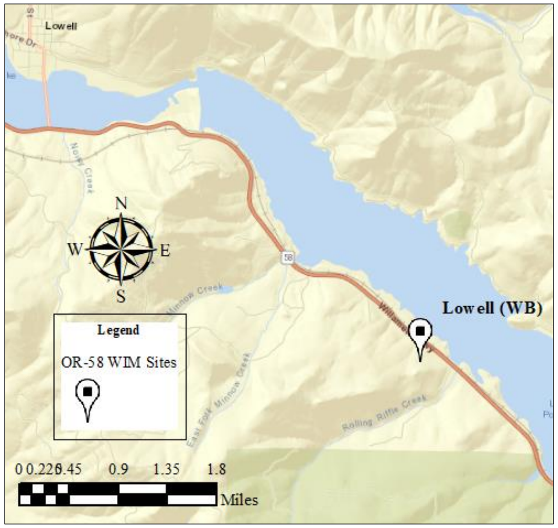
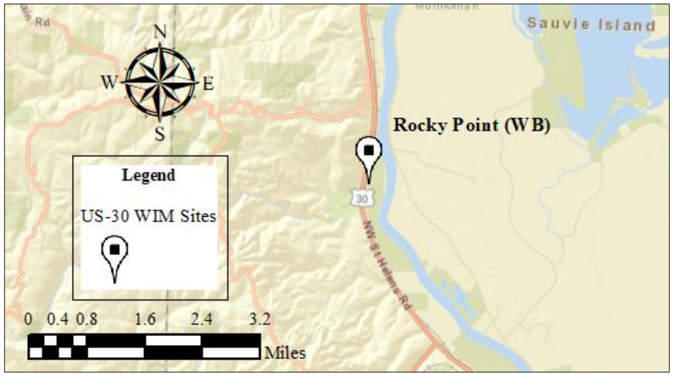


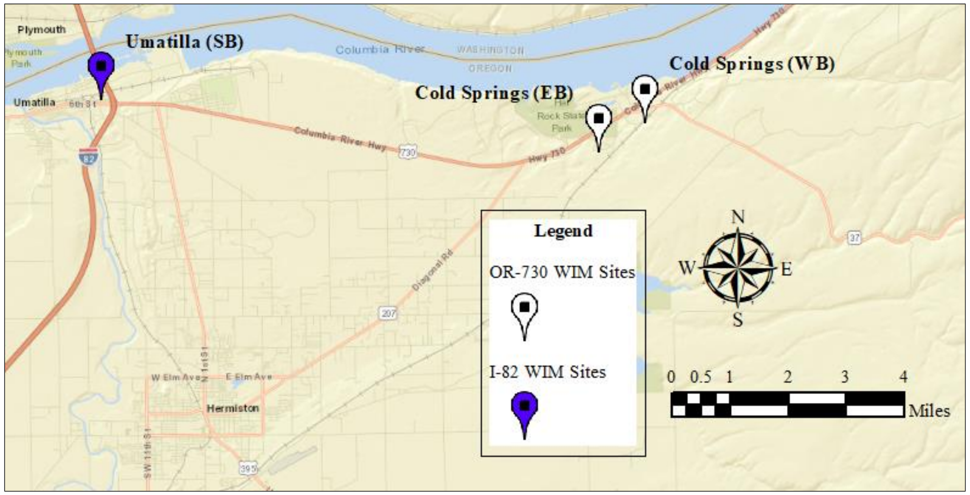
Figure 3.3: WIM sites on I-84



(a)



(b)



(c)

Figure 3.4: WIM sites on (a) OR-58, (b) US-30, and (c) OR-730

3.3.2 Virtual WIM and License Plate Readers in Oregon

In addition to the 21 WIM locations used for enforcement, there are three virtual WIM locations used only to collect data and two sites with license plate readers. Regarding the license plate readers, these are located at the Woodburn WIM stations on the northbound and southbound interstate ramps of I-5 at Exit 271. Exit 271 is located just north of "Woodburn (NB)" and just south of "Woodburn (SB)" in Figure 3.1.

As for virtual WIM locations, there is one located on US-97 at Modoc Point and two located on OR-99W near Junction City. Once more, these locations are used only to collect data. Virtual WIM locations in Oregon are shown in Figure 3.5.

(a) (b)

Figure 3.5: Virtual WIM locations on (a) OR-99W and (b) US-97

3.3.3 Summary of WIM Sites in Oregon

For a holistic view of WIM systems in Oregon, see Figure 3.6. In addition, for a summary of WIM locations, refer to Table 3.6. Of the identified WIM systems on Oregon highways, the majority are strain gauge strip sensors. With these systems, Oregon has experienced easier installations, less expensive systems to implement, and systems that require less maintenance. These systems also allow Oregon to double threshold parameters to ensure accuracy of recorded data, can be installed same-day where traffic does not need to be disturbed (i.e., lane closures), can be driven over immediately after installation, and are adaptable to most system electronics. Lastly, any WIM location that has not been updated to a strain gauge strip sensor is being updated as highway renovation projects take place at WIM locations in Oregon.

Table 3.6: Summary of WIM Sites in Oregon

WIM Type	WIM Name	Traffic Direction	Highway	Milepost
WIM Sites (Enforcement)	Woodburn Port of Entry	Southbound	I-5	276.00
	Woodburn	Northbound	I-5	271.42
	Ashland Port of Entry	Northbound	I-5	17.50
	Ashland Weigh Station	Southbound	I-5	18.62
	Booth Ranch Weigh Station	Northbound	I-5	110.69
	Booth Ranch Weigh Station	Southbound	I-5	112.06
	Farewell Bend Port of Entry	Westbound	I-84	353.96
	Olds Ferry Weigh Station	Eastbound	I-84	353.57
	La Grande Weigh Station	Eastbound	I-84	257.97
	Emigrant Hill Weigh Station	Westbound	I-84	227.56
	Cascade Locks Port of Entry	Eastbound	I-84	44.01
	Wyeth Weigh Station	Westbound	I-84	55.10
	Juniper Butte Weigh Station	Northbound	US-97	107.97
	Juniper Butte Weigh Station	Southbound	US-97	106.72
	Bend Weigh Station	Northbound	US-97	146.55
	Klamath Falls Port of Entry	Northbound	US-97	272.26
	Klamath Falls Weigh Station	Southbound	US-97	270.90
	Cold Springs Weigh Station	Westbound	OR-730	193.69
	Cold Springs Weigh Station	Eastbound	OR-730	192.76
	Umatilla Port of Entry	Southbound	I-82	0.49
	Lowell Weigh Station	Westbound	OR-58	17.60
	Rocky Point Weigh Station	Westbound	US-30	16.03
Virtual WIM Sites (Data Collection)	Junction City	Northbound	OR-99W	112
	Junction City	Southbound	OR-99W	112
	Modoc Point	Southbound	US-97	258

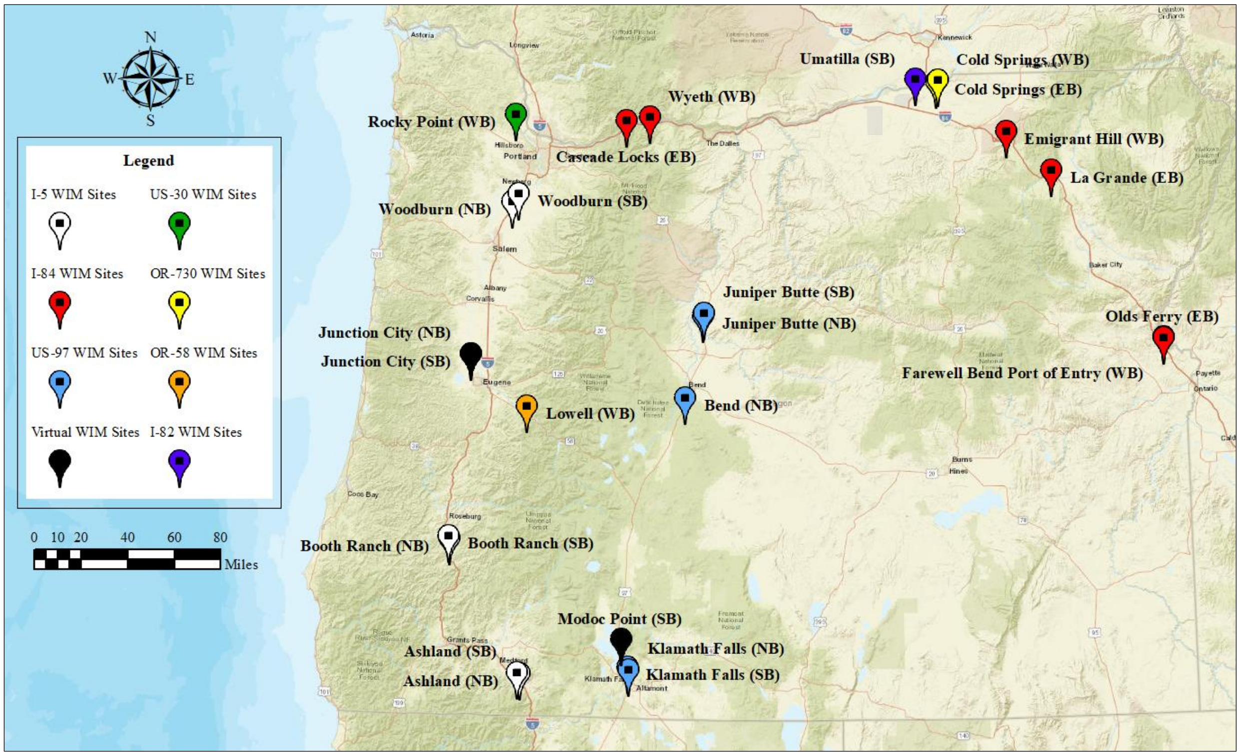


Figure 3.6: WIM and virtual WIM stations in Oregon

3.4 WIM RESEARCH IN OREGON

One of the earlier WIM-related research studies in Oregon was conducted by Strathman (1998). At the time, WIM systems appeared to be capable of estimating static GVW within ±10% at a high level of confidence. Strathman (1998) performed a one-year field test of a slow-speed WIM system on I-84, in which data was recovered in August of 1994. After the data was collected, a regression analysis was used to increase the accuracy and precision of WIM measurements by accounting for temporal, weather, and vehicle speed effects. Using the regression model, correction improved accuracy to one-half of 1% at axle and vehicle levels. The proposed regression model also resulted in 95% of observations falling within 6.8% of the static scale weight (this was at the axle level). In regards to vehicle level, accuracy increased to within 4.4%. This methodology corrected for vehicle and tandem axles bringing the levels to Type IV in the ASTM standard specifications (in the most recent revision of theses specifications, there is only Type I to Type III).

Strathman and Theisen (2002) used WIM data to explore the incidence of overweight trucks and their relation to enforcement. Specifically, Strathman and Theisen (2002) aimed to assess scale operations as it pertains to weight violations and potential effectiveness of enforcement levels, preclearance systems, and WIM systems. To achieve this, Strathman and Theisen (2002) used a segment of I-5 and collected WIM data before, during, and after an extended closure of the nearby weigh station. The WIM data was collected from three WIM sites over four months in 2001. Findings showed that traffic volume did not suggest evasion behavior on alternate routes or evasion behavior to I-5 during the weigh station closure. I-5, however, did experience an increase in mean GVW from before closure to during closure, then a decrease once the weigh station reopened. Further, the percentage of overweight trucks increased from before closure to during closure, then a drop upon the reopening of the weigh station. Strathman and Theisen (2002) concluded that "relatively" aggressive enforcement in Oregon may create a climate in which closure of a weigh station (i.e., temporary suspension of weighing activity) has less effects on operations.

In a different application, Pelphrey and Higgins (2006) utilized WIM data to calibrate the Load and Resistance Factor Rating (LRFR) code for load rating bridges. The LRFR code allows for jurisdiction-specific recalibration if there is sufficient WIM data, both in quantity and in quality. Using Oregon WIM data obtained from four sites in 2005 (one on I-5, one on US-97, one on OR-58, and one on I-84), Pelphrey and Higgins (2006) discovered that Oregon-specific LRFR factors are lower than the factors found in the LRFR (i.e., values based on national averages). The authors also concluded that the lower LRFR factors are a result of fewer overloaded trucks in Oregon. Possible explanations for this, provided by Pelphrey and Higgins (2006), include low cost of overweight permits, high number of overweight permits, ease of obtaining overweight permits, weight-mile tax, and cost of penalties for overweight trucks.

The following WIM-related study in Oregon, conducted by Elkins and Higgins (2008), developed axle weight and spacing spectra using WIM data. Using four WIM sites, highway segments with low, moderate, and high average daily truck traffic (ADTT) were used for the analysis. In addition, the authors considered seasonal variations by exploring data over the four seasons. The final data used for analysis consisted of one month of data that had a continuous record for each day in the month, in which the representative seasonal month was selected for each WIM site considered. The representative months chosen were based on WIM data collected from September, 2005 to August, 2006. Through analysis, the programs used predicted similar ADTT values to that of the actual counts. More, the authors found evidence of seasonal variation in traffic volume. In the end, the resulting data-characterization was integrated with the Mechanistic-Empirical Pavement Design Guide software program to allow state and ADTT volume-specific axle weight spectra, average axle group spacing, and hourly volume data to be used for pavement design and/or analysis.

Another WIM-related study in Oregon explored the viability of using truck transponder data to generate freight corridor travel times and real-time travel information. In particular, Monsere et al. (2009) used WIM to support their analysis. WIM data used consisted of data collected from 22 WIM sites in 2007 and 2008. In addition, a station in Washington was used, in which data was collected during March 2008. Lastly, Monsere et al. (2009) utilized probe data. For this, Oregon state employees drove eight specific routes while logging data.

To complete their study, Monsere et al. (2009) utilized two specific algorithms. The first, an algorithm to match truck transponders of all vehicles in a specified time window between upstream and downstream stations. The second algorithm, an algorithm used to filter matches for through trucks. To validate the filter, Monsere et al. (2009) compared estimated travel times during a winter delay (as a result of weather). Preliminary findings showed that freight travel times, at the corridor-level, could be generated. The next step was to determine the viability of using the same data to generate real-time travel information. This step was accomplished through ground truth probe vehicle data. After the real-time information analysis, travel time estimates from WIM data and the probe data were used to fit a linear regression model. The regression took place on probe travel time, where the covariates were truck travel time, length of the segment, average weighted uphill grade, percentage of the total uphill grade length with respect to the total length of the link, uphill length in miles of a grade more than 2% on the probe travel time, and total link length. This resulted in a relationship between passenger vehicle travel time and truck travel time. To conclude, Monsere et al. (2009) found that long distances between stations were a challenge in regards to directly adapting WIM data to real-time use.

In a more recent study, Cetin et al. (2011) developed re-identification methods to match trucks between two WIM sites in Oregon. The two WIM sites considered are located 145 miles from one another, and the data used was collected during October 2007. Utilizing this WIM data, vehicle length and axle data are used to classify and characterize vehicles. Upon characterization, Cetin et al. (2011) developed a Bayesian model. The Bayesian model developed is based on a probability density function generated by fitting a Gaussian mixture model to a sample (or training) dataset of matched trucks. Using this method, and a test dataset, Cetin et al. (2011) matched vehicles at an accuracy of 91%. However, not all vehicles cross the upstream and downstream locations; therefore, Cetin et al. (2011) propose a second procedure to account for mismatched vehicles. In their methodology, several approaches are developed to allow the analyst to trade-off the total number of matched vehicles and acceptable error. Through two scenarios, the authors found that the mismatch error can be reduced to as low as 1% with an associated mismatching of 25%.

In a more recent Oregon study utilizing WIM data, Bell and Figliozzi (2013) evaluate the accuracy of Oregon's Truck Road Use Electronics (TRUE) data. With the freight inputs of Oregon's Statewide Integrated Model, Version 2, (SWIM2) being economic commodity flows, transport model time and distance skims, and economic activity by type in each transport zone, Bell and Figliozzi (2013) seek to show the ability of TRUE data for addressing freight modeling, performance measures, and planning needs. The TRUE data consisted of 172,385 records collected during the entire year of 2011. This data was collected for a total of 17 vehicles from three different freight carriers. As for the WIM data, it consisted of the collected WIM data for the 17 pilot vehicles.

The authors compared metrics from the TRUE data to the WIM data (i.e., axle counts and GVW). For axle counts, 39% did not match between the two datasets (TRUE axle count was higher than the WIM axle count). For GVW, there was a much smaller difference (3%); but, due to the large difference in axle counts, there may be an accuracy issue with the weight recorded in the TRUE data. Lastly, in terms of emissions, Bell and Figliozzi (2013) determined that TRUE data, integrated with WIM data, can greatly improve the estimates of freight emissions.

To conclude, Bell et al. (2013) use TRUE data in association with ODOT WIM data to estimate emissions through a sensitivity analysis. The authors state that when combined with WIM data, weight class, truck type, and commodity codes can be obtained. To determine the correct weight ranges to model, Bell et al. (2013) investigated weight distributions using ODOT WIM data. Bell et al. (2013) found that emission rates from combination trucks were often higher compared to single-unit trucks at the same weight. When considering speed, the percent change for single-unit trucks was more pronounced. Grade was also found to have a substantial impact on emissions.

3.5 SUMMARY

Through the extensive literature review, it was found that several states have conducted recent works regarding WIM (a full summary of reviewed literature by study objective is provided in Appendix A). Of the WIM-related research, the major focus is on freight flow characteristics, installation, calibration, and quality checks of the collected data. Of the work that focuses on freight flow characteristics, the most common is related to distribution fitting and re-identification approaches. In these works, the distribution fitting and re-identification approaches are significantly similar, which leaves room for new methods to be applied. The variation in the amount of WIM data varies considerably, as some studies use as few as 5.5 hours of data while others use up to 10 years of WIM data. Further, these works often integrate WIM data with similar data sources to predict freight flow. In light of this, there is an opportunity for different approaches to be applied and various data sources to integrate (i.e., data sources listed in Chapter 4.0). Some studies merge datasets such as cross-border data to estimate truck and commodity flows.

Of the identified WIM systems on Oregon highways, the majority are strain gauge strip sensors. With these systems, Oregon has experienced easier installations, less expensive systems to implement, and systems that require less maintenance. These systems also allow Oregon to double threshold parameters to ensure accuracy of recorded data, can be installed same-day where traffic does not need to be disturbed (i.e., lane closures), can be driven over immediately after installation, and are adaptable to most system electronics. Lastly, any WIM location that has not been updated to a strain gauge strip sensor is being updated as highway renovation projects take place at WIM locations in Oregon.

Lastly, WIM research in Oregon was reviewed. Previous Oregon WIM-related research has consisted of estimating static weight and assessing overweight trucks. Additionally, Oregon WIM research has used WIM data for structural-based research; specifically, the calibration of load and resistance factor ratings, and the development of axle weight and spacing spectra for bridge design. Freight corridor travel times and real-time travel information has also been a focus, as well as truck re-identification. Finally, Oregon WIM research has seen a specific data comparison: WIM data compared to TRUE data.

4.0 DATA INVENTORY

Being that the current study is a data-driven analysis, it is imperative to inventory the available data. For the present work, both public and private (for-purchase) data sources are considered. This chapter evaluates the following data in the following sub-chapters:

- Oregon WIM data.
- Available Oregon data (e.g., data available through TransGIS).
- Public freight data (e.g., FAF, Commodity Flow Survey, etc.).
- Private freight data (e.g., TRANSEARCH, EROAD, etc.).

4.1 OREGON WIM DATA

Through its WIM sites discussed in Chapter 3.3, Oregon collects the characteristics shown in Table 4.1.

Table 4.1: Recorded Variables in Oregon WIM Data

Variable	Description
Time stamp	Time the record was taken.
WIM Site	Location of WIM site by scale number.
Site Description	Includes highway number, milepost marker, and direction of travel.
Vehicle Classification	Motor Carrier's vehicle classification scheme, where vehicles are classified from 01 to 19 (see Figure 4.1).
Number of Axles	Total number of axles of passing vehicle.
Gross Vehicle Weight	Total weight of passing vehicle (lbs.).
Vehicle Length	Length of passing vehicle (ft.).
Direction	Travel direction of passing vehicle.
Speed	Measured speed of passing vehicle.
Lane Number	Lane identifier for recorded measurements.
1st Axle Spacing	Spacing of 1st axle (ft.).
1st Axle Weight (Left)	Weight of 1st axle on the left-side of the vehicle (lbs.).
1st Axle Weight (Right)	Weight of 1st axle on the right-side of the vehicle (lbs.).
1st Axle Weight	Total weight of 1st axle (lbs.).
12th Axle Spacing	Spacing of 12th axle (ft.).
12th Axle Weight (Left)	Weight of 12th axle on the left-side of the vehicle (lbs.).
12th Axle Weight (Right)	Weight of 12th axle on the right-side of the vehicle (lbs.).
12th Axle Weight	Total weight of 12th axle (lbs.).

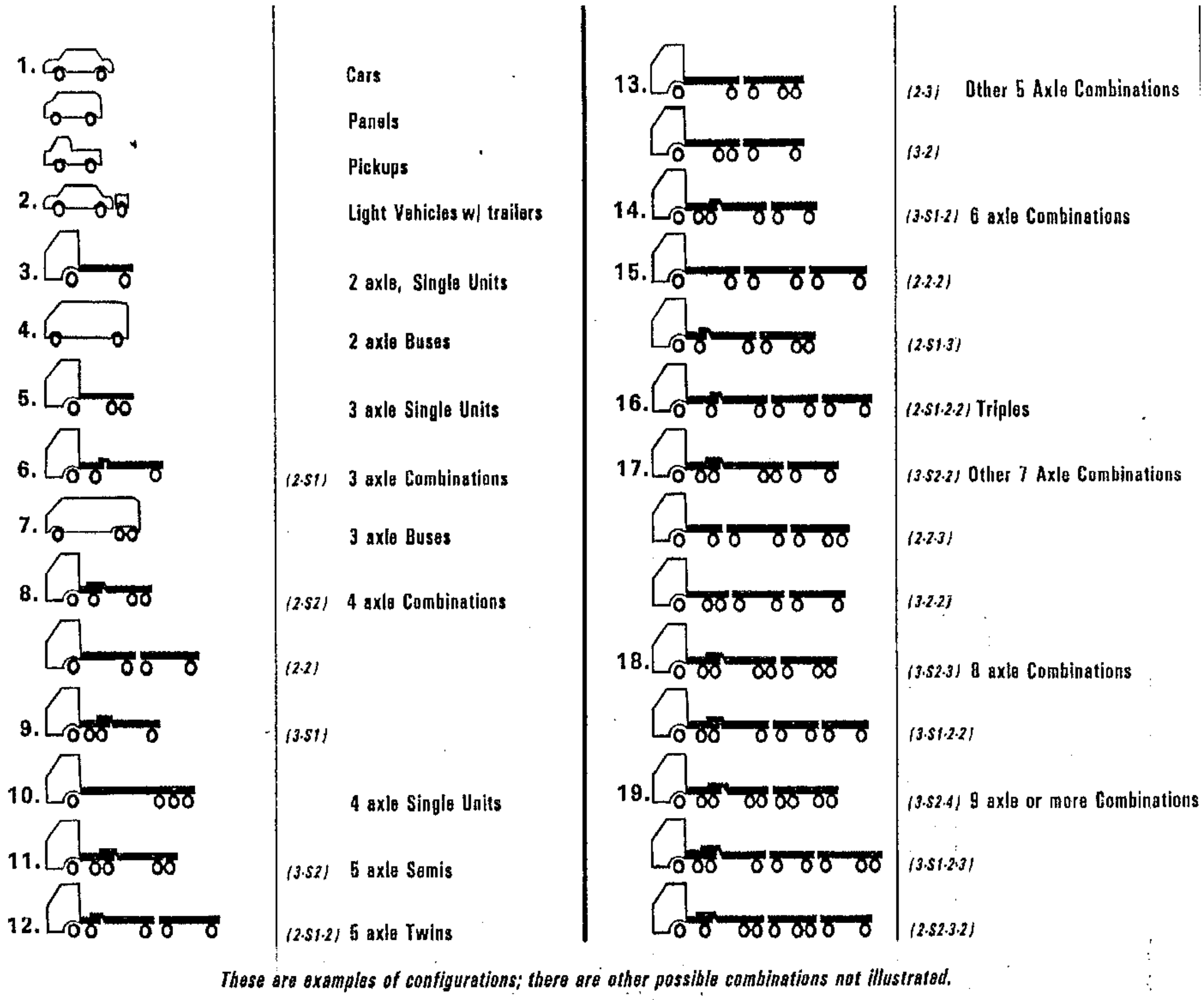


Figure 4.1: 19 Vehicle classifications used by ODOT Motor Carrier (Source: Elkins & Higgins, 2008)

4.2 OREGON TRANSGIS DATA

As part of Oregon's TransGIS website,[11] several data are collected. Data potentially relevant to the current study include:

- Oregon Highway Plan (OHP) Freight Routes
- Reduction review freight routes.
- Highway equipment locations.
    - Signs, signals, ITS locations, and automatic traffic recorder (ATR) stations.

[11] The Oregon TransGIS website can be viewed here.

- Traffic volume data.

The following sub-chapters provide further detail each of the aforementioned datasets.

4.2.1 OHP Freight Routes

OHP is the Oregon Highway Plan, which classifies Oregon's state highway system into four categories: (1) Interstate highways, (2) Statewide highways, (3) Regional highways, and (4) District highways.

The OHP dataset includes information on whether the route is an interstate, U.S. highway, or Oregon highway. For an example of the OHP data in relation to WIM sites, refer to Figure 4.2.

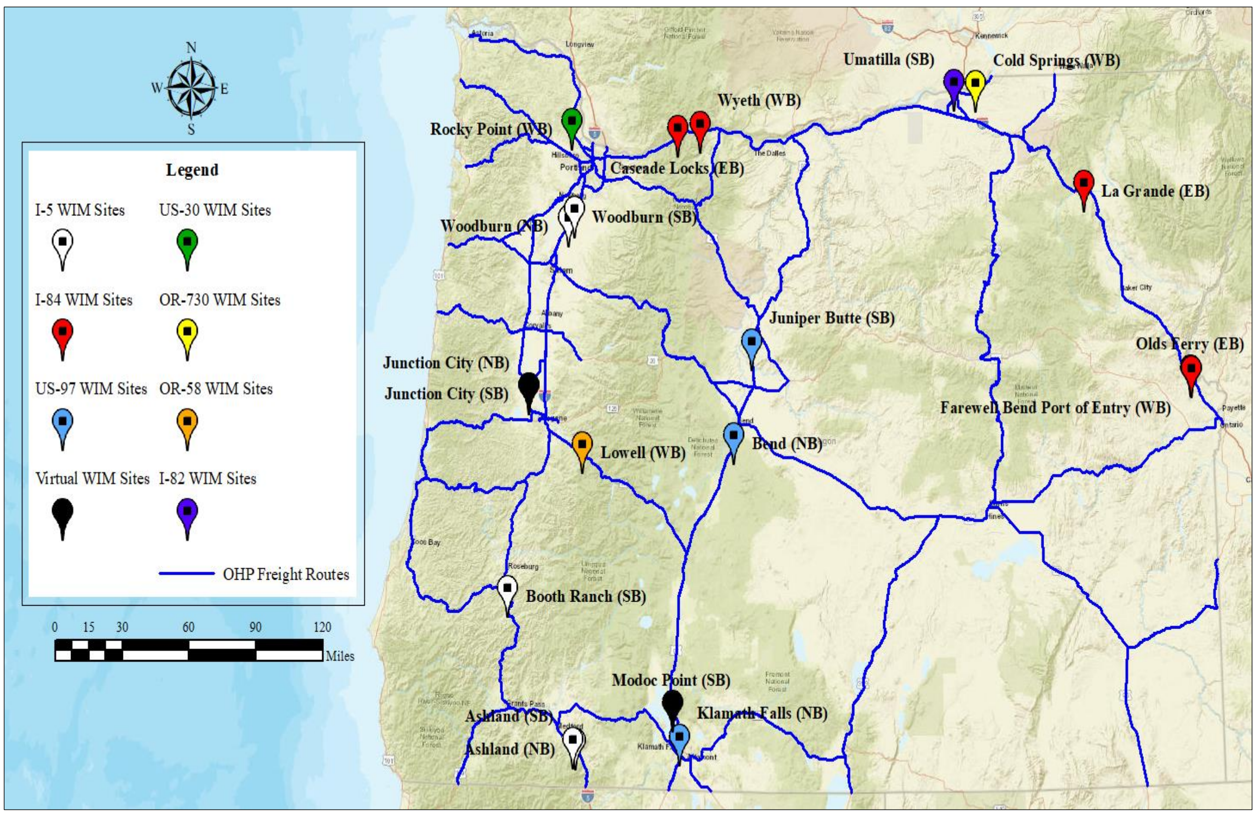


Figure 4.2: WIM sites and OHP freight routes

4.2.2 Reduction Review Freight Routes

Reduction review freight routes include all parts of highways that must be traveled to complete the prescribed route and/or connect with another highway (Oregon Revised Statutes 366.215). This also includes any couplets, as well as on/off ramps. For an example of reduction review freight routes in association with WIM sites, see Figure 4.3.

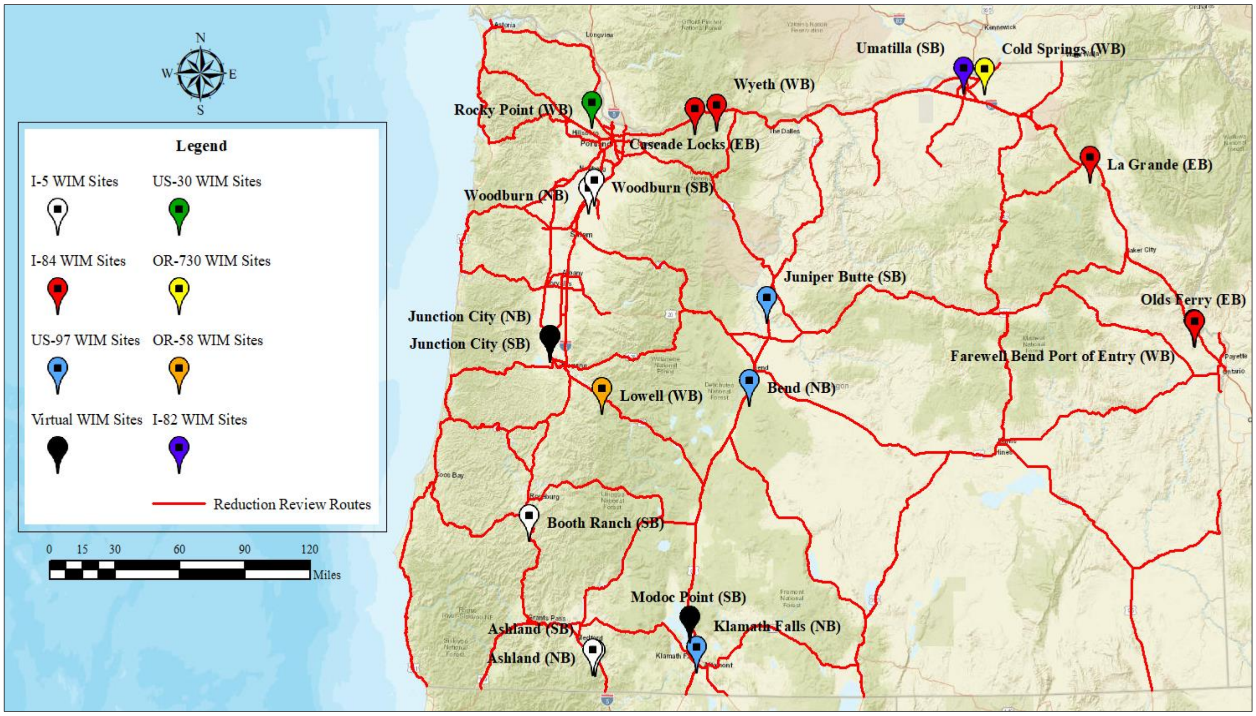


Figure 4.3: WIM sites and reduction review routes

4.2.3 Highway Equipment Locations

The highway equipment data includes information on signals, signs, intelligent transportation system (ITS) locations, and the locations of automatic traffic recorder (ATR) stations. Of this information, potentially relevant data may include signs, ITS locations, and ATR station locations.

4.2.3.1 Signs

In regards to signs (see Figure 4.4), data included consist of the following:

- Location.
- Sign Type (i.e., standard, custom, support).
- Standard Sign ID (e.g., standard sign ID for 45 mi/hr speed limit: W13-1-24-45).
- Description of Sign.
- Installation date.
- Reflective material.

4.2.3.2 ITS

In the ITS data, there is information regarding ITS systems across Oregon. For select ITS locations in relation to WIM sites, refer to Figure 4.5. Information within the ITS data includes:

- Asset description (route, the direction of travel, and milepost).
- Description (e.g., camera, detector station, ramp gate, ramp meter, etc.).
- ODOT region.
- Group asset (e.g., weather warning system, curve warning signs, variable advisory speed signs, etc.).

4.2.3.3 ATR Locations

The last potentially relevant highway equipment data pertains to ATR locations (see Figure 4.6 for ATR locations in relation to WIM sites). Included information in the ATR data consists of the following:

- Site ID and location description.
- Average annual daily traffic (AADT), truck AADT, and truck percentage.
- ATR setup (e.g., class, speed and length, volume).
- Device type, ATR ID, and ATR name.
- Percentage of vehicles at each ATR location by vehicle classification.

Figure 4.4: WIM sites and signage along corridors with WIM systems

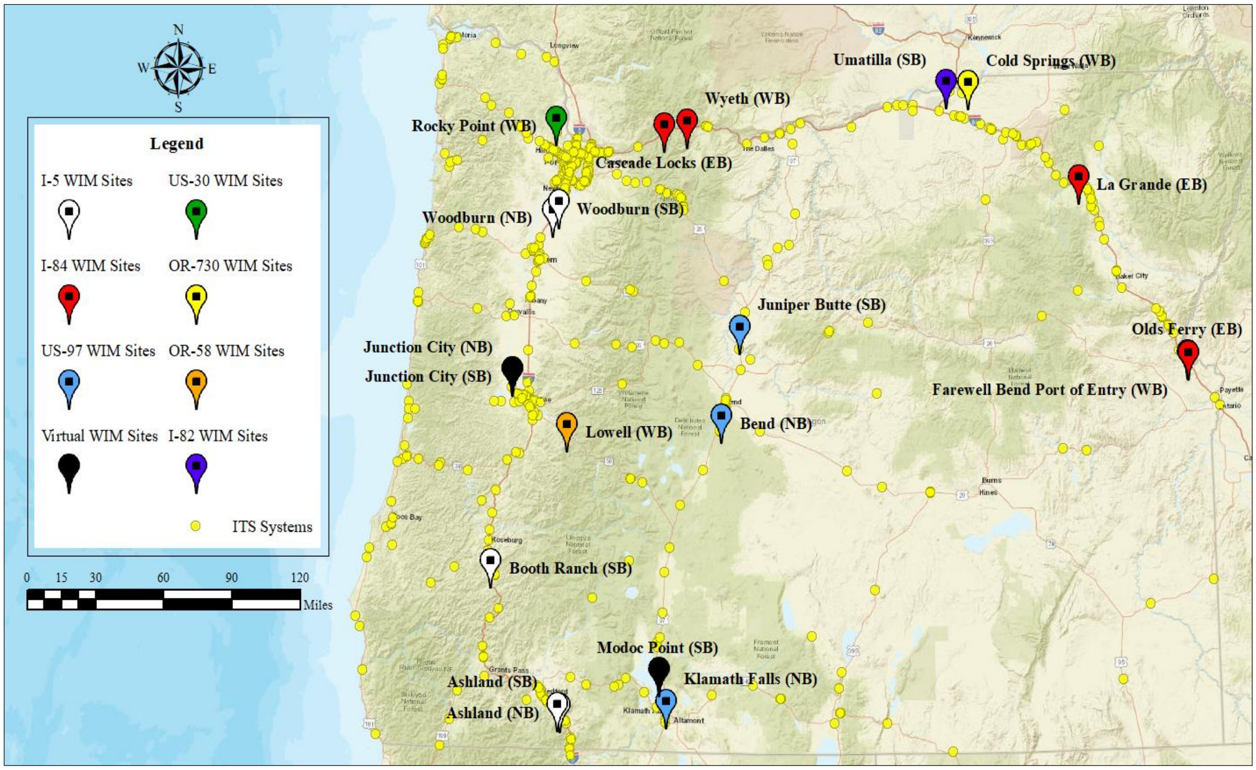


Figure 4.5: WIM sites and ITS Systems

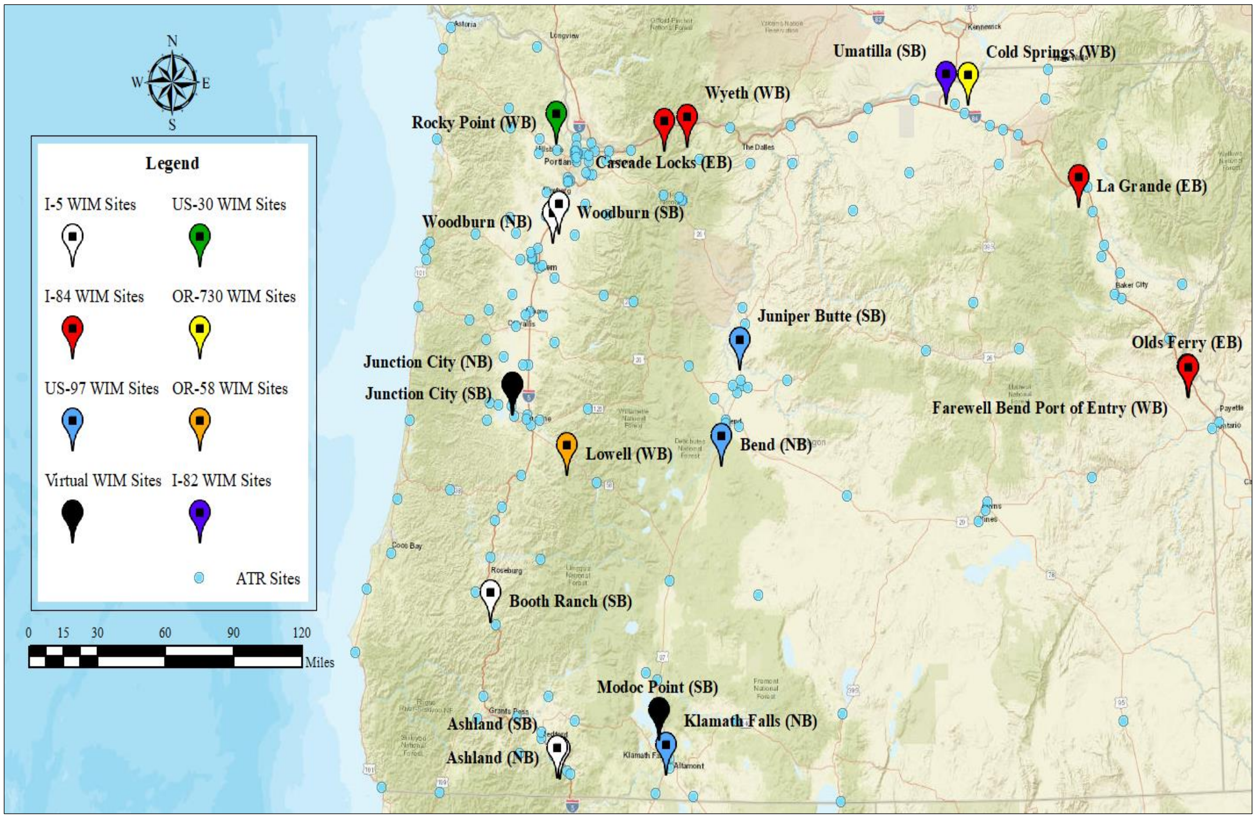


Figure 4.6: WIM sites and ATR locations

4.2.4 Traffic Data

The final dataset from Oregon's TransGIS website is traffic volume collected and maintained by ODOT's Transportation Systems Monitoring Unit.[12] WIM sites and locations of available traffic volumes are shown in Figure 4.7. Included information in the traffic volume data are:

- Length of segment (can calculate VMT).
- AADT, truck AADT, and vehicle classification.

[12] More information on ODOT's Transportation Systems Monitoring Unit can be viewed here.

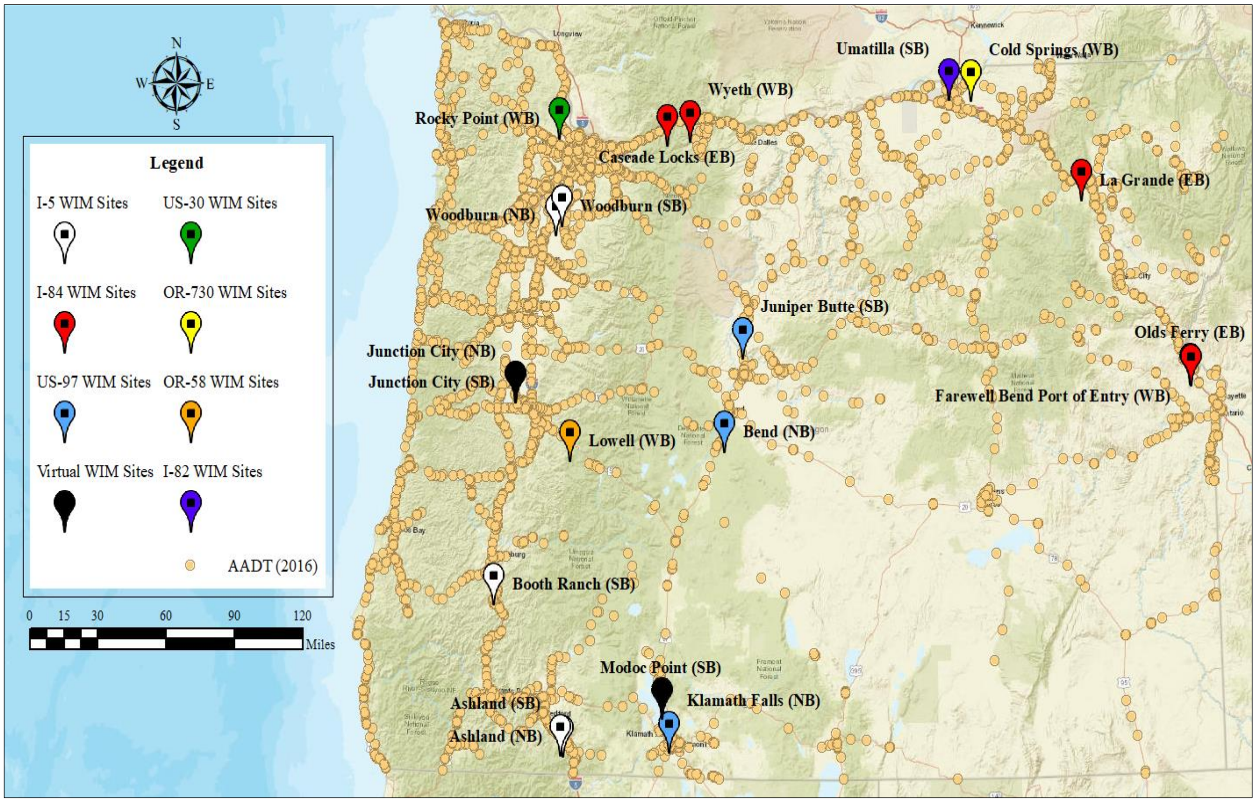


Figure 4.7: WIM sites and traffic volume

4.3 PUBLIC FREIGHT DATA

Also of interest to the current study may be publicly available freight data sources. Some of these data sources include:

- Freight Analysis Framework.
- Commodity Flow Survey.
- Transborder Freight Database.
- Vehicle Inventory and Use Survey.
- County Business Patterns Data.
- Industry Economic Accounts.
- Regional Economic Accounts.

The following sub-chapters add further detail each of the aforementioned public freight datasets.

4.3.1 Freight Analysis Framework (FAF)

FAF data is produced through a joint effort by the Bureau of Transportation Statistics and the Federal Highway Administration. This data source is generated by integrating data from various sources to provide comprehensive freight movement between FAF regions. Sources used to generate the FAF data include economic census data and data from the Commodity Flow Survey. As such, new FAF is created after each 5-year economic census and Commodity Flow Survey. Included in this data are estimates for tonnage, value, and ton-miles of commodities shipped by mode and origin-destination regions. The data also contains freight forecasts. However, this source provides an aggregate picture of freight movement, where freight movements within FAF regions are not available. For WIM sites and Oregon FAF regions, see Figure 4.8.

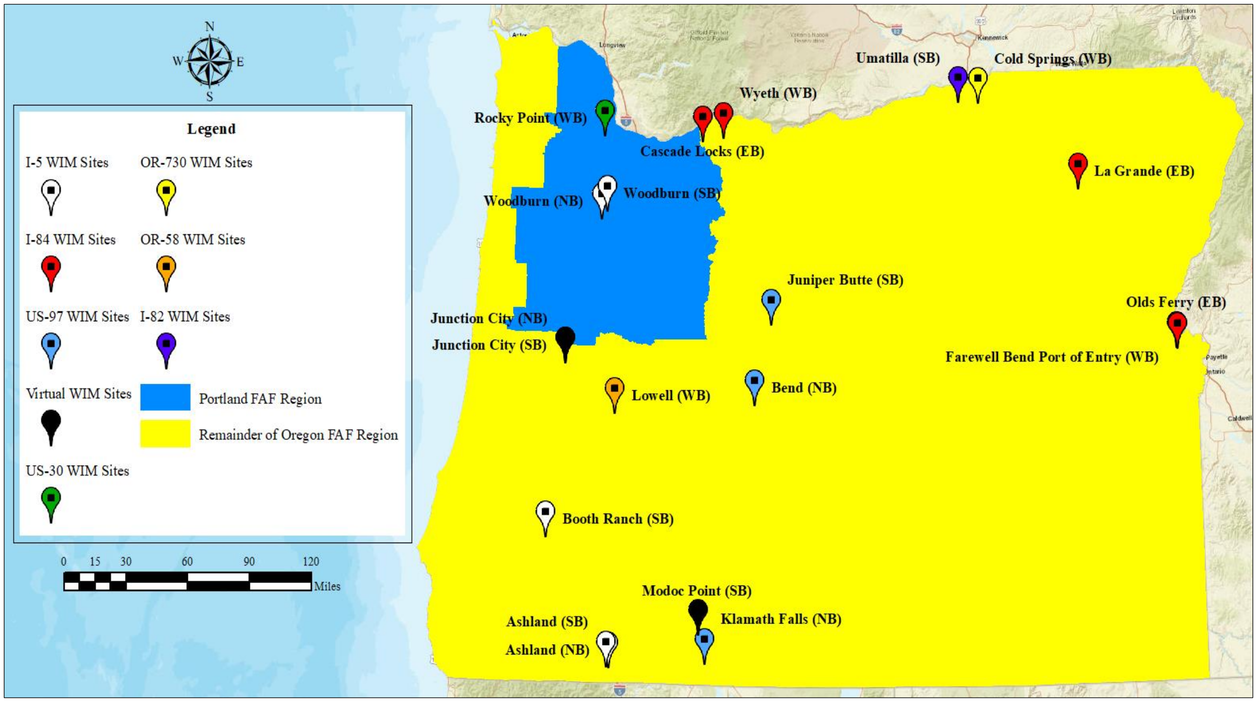


Figure 4.8: WIM sites and Oregon FAF/CFS regions

4.3.2 Commodity Flow Survey

Similar to FAF data, the Commodity Flow Survey (CFS) is a joint effort. Involved in the CFS are the Bureau of Transportation Statistics, the U.S. Census Bureau, and the U.S. Department of Commerce. According to the U.S. Census Bureau (2018), the CFS is the primary source of data on domestic freight shipments. Included in the data are estimates on the type of shipment, origin-destination, value, weight, mode of transport, distance shipped, and ton-miles of commodities shipped. This data is updated every five years as part of an economic census, in which the most recent year it was conducted is 2012. The resolution of this data is tantamount to the FAF data discussed in Chapter 4.3.1, as the CFS regions are the same regions shown in Figure 4.8. However, different than the FAF data, the CFS includes instruction on estimating totals, average miles per shipment, and coefficients of variation.

4.3.3 Transborder Freight Database

The Transborder Freight Database provides freight flow information by commodity type and mode of transport for U.S. exports and imports, to and from Mexico and Canada. Commodity-based data and geographic details are also included to help with monitoring North American freight flow. This data, like previously discussed data, can have its limitations. Key limitations with this data include non-sampling errors, filing procedure errors, and it does not offer a domestic representation of freight movements. Of relevance to the current study are ports of entry along the U.S.-Canadian border (refer to Figure 4.9).

Figure 4.9: U.S. ports in the Pacific Northwest (Source: Bureau of Transportation Statistics, 2018)

4.3.4 Vehicle Inventory and Use Survey (VIUS)

The purpose of the VIUS data is to measure physical and operational characteristics of the truck population in the United States. Vehicles included in the survey are both private and commercial trucks that are registered or licensed in the United States. The survey is mailed to a group of selected trucks, in which a stratified random sample is selected in each of the 50 states. In addition, the data is collected every five years. The most recent version, however, is from 2002. Specific physical characteristics information included in the VIUS dataset are as follows:

- Date of purchase.
- Weight.
- Number of axles.

- Overall length.
- Type of engine.
- Body Type.

Also included in the VIUS data are operational characteristics:

- Type of use.
- Lease characteristics.
- Operator classification.
- Base of operation.
- Gas mileage.
- Annual and lifetime miles driven.
- Weeks operated.
- Commodities hauled by type.
- Hazardous materials carried.

4.3.5 County Business Patterns (CBP)

The CBP data is collected annually and provides sub-national economic data by industry type (U.S. Census Bureau, 2018b). This data is often used to study the economic activity of small areas, analyze economic changes over time, and used as a benchmark for other surveys and databases. Government agencies, specifically, often use CBP data for administration and planning purposes. Information included in the CBP data are:

- Industry type and code.
- Total number of establishments, both by employer and non-employer.
- Employment numbers.
- First quarter payroll in thousands of dollars.
- Annual payroll in thousands of dollars.
- Non-employer receipts in thousands of dollars.

4.3.6 Industry Economic Accounts

The industry economic accounts data provides a detailed picture of the relationships between producers and users, as well as the contribution to production across industries (Bureau of Economic Analysis, 2018a). This data is often used by policymakers and businesses to understand interactions within industries, trends in productivity, and changes in the U.S. economy. Included in the Industry Economic Accounts data are:

- Gross Domestic Product (GDP) by Industry.
    - This measures an industry's contribution to the U.S. GDP. Specifically, this includes all GDP by industry, compensation of employees, gross operating surplus, and taxes.
- Gross Output by Industry.
    - Through the inclusion of business-to-business spending that is required to produce goods and services, as well as deliver them to consumers, the gross output by industry in the industry economic accounts data reflects the full value of the supply chain.
- Input-Output Accounts.
    - This provides detailed information showing how industries interact with one another and how they interact with the economy. For supply tables, the total value of goods and services available in the domestic economy are shown. This includes production, imports, and services from foreign producers. The use tables show how the supply of goods and services is used.
- Employment by Industry.
    - Provides statistics on national employment and compensation by industry.
- Integrated Industry-Level Production Account.
- Contains estimates of sources of economic growth.
    - This data allows analysts to trace GDP growth from its origins to changes in several factors. This data is often used for studying structural change, globalization, the impact of communication and information technology, and industry origins.

4.3.7 Regional Economic Accounts

Regional economic accounts data is similar to that discussed in the preceding section. However, the purpose of this data is to be used at a more disaggregated level. Where the Industry Economic Accounts discussed in Section 4.3.6 is at the national level, the Regional Economic

Accounts data provides information at the county, metro, and “other” level areas (Bureau of Economic Analysis, 2018b). The following are part of the Regional Economic Accounts data:

- Consumer Spending by State.
- Employment by State.
- Employment by County, Metro, and Other Areas.
- GDP by Metro Area.
- GDP by County
- GDP by State.
- Personal Income by State.
- Personal Income by County, Metro, and Other Areas.
- Real Personal Income by State and Metro Area.
- Regional Price Parities by State and Metro Area.

4.4 PRIVATE FREIGHT DATA SOURCES

In addition to the readily available public freight data, there are also private freight data sources. Potentially useful private freight data sources are as follows:

- EROAD
- IMPLAN
- FleetSeek
- INRIX
- HERE
- Transearch (HIS)
- American Transportation Research Institute (ATRI)

The following sub-chapter add further detail each of the aforementioned private freight datasets.

4.4.1 EROAD

EROAD is a freight telematics data company that collects data through their electronic logging devices (ELDs). Although headquartered in New Zealand, a large number of trucks in Oregon are equipped with their devices. EROAD collects data for fleet management, such as:

- Historical daily fleet activity.
- Fuel consumption.
    - Miles per gallon, speeding events, idle minutes, total gallons, and total distance traveled.
- Fleet tracking.
- Trip investigator.
    - Shows exactly where trucks have traveled in the previous days or weeks.

EROAD also collects data related to transportation planning, such as:

- Origin-destination.
- Real-time freight movements.
- Driver behavior data.
    - Speeding event, hard braking events, hard acceleration events, and cornering.

Specifically, as it pertains to Oregon, EROAD offers electronic weight-mile-tax management. This device generates required trip information to support distance records requirements. For an example of EROAD data, see Figure 4.10.

Figure 4.10: Origin-destination data in New Zealand collected by EROAD devices

4.4.2 IMPLAN

IMPLAN is a data source that has region economic research data within the United States. IMPLAN data is available at each regional level in the country, the data covers several years, and the data is available for up to 536 sectors for analysis. In addition, the data is available in multiple forms, such as export industry details, commodity demands, and demographics by state, county, zip code, or custom region. Of particular interest, IMPLAN's flow information that provides information on how goods and services move between economies. In Oregon, IMPLAN data is available at the following levels:

- County.
- MSAs.
- Congressional Districts.
- Zip codes.

4.4.3 FleetSeek

FleetSeek is a sales and business intelligence research tool for the trucking industry (FleetSeek, 2018). Over 100 data points per fleet are available for the characteristics shown in Table 4.2. This data is updated monthly to ensure quality and can be filtered by fleet attributes for specificity. However, this data provides aggregate details and is intended primarily for fleet characteristics. In addition, FleetSeek does not sell state-specific data. Rather, the data must be purchased by region or at a national level. In terms of payment, FleetSeek data is based on subscriptions billed on an annual basis; although, custom packages can be made by contacting a sales representative. An example of the FleetSeek data interface is shown in Figure 4.11.

Table 4.2: FleetSeek Data

Category	Type of Data
Equipment	• Total Vehicles. • Vehicles Owned. • Vehicles Leased. • Total Trucks. • Make and Model. • Engine Type. • Trucks Owned. • Trucks Leased. • Total Tractors. • Tractors Owned. • Tractors Leased. • Trailers Leased. • Total Trailers. • Trailers Owned. • Total Hazmat Trucks. • Hazmat Trucks Owned. • Hazmat Trucks Leased. • Total Hazmat Trailers. • Hazmat Trailers Owned. • Hazmat Trailers Leased. • Trailer Types.
Fleet Details	• Fleet Type. • Operating Type. • Motor Carrier Number. • USDOT Number. • Commodities Carried. • SIC. • SCAC Number. • GVW Classes. • Total Drivers. • Total CDLs.
Safety	• CSA Safety Indicators. • Insurance Types. • Insurance Expiration. • Dates. • Insured Amounts. • Insurance Carrier. • Crash and Inspection Data.
Fleet Contacts	• Contact Names. • Email Addresses. • Website. • Telephone Numbers. • Fax Numbers. • Mailing Addresses. • Physical Addresses.

Figure 4.11: Example of FleetSeek data interface

4.4.4 INRIX

INRIX, a relatively new company (founded in 2005), manages traffic by analyzing data for both road sensors and vehicles. INRIX data can be provided at a high resolution and consists of the characteristics in Table 4.3. An example of analysis results of drive time data is shown in Figure 4.12, and an example of results from performance measures data is shown in Figure 4.13. INRIX also has parking information, but this data is geared towards passenger vehicles. As it pertains to purchasing INRIX data, no pricing or subscription information is readily available through the INRIX website.

Table 4.3: Summary of INRIX Data

Data	Description
Drive Time	• Measures distance traveled in minutes. • Based on typical traffic conditions rather than actual traffic volumes. • Can be used to analyze the extent of a drive by day of the week, time-of-day, or length of trip.
Roadway Analytics	• On-demand, cloud-based analytics suite. • Uses INRIX global traffic data to help public agencies monitor, measure, and manage road network performance. • Can be used to benchmark and improve roadway performance. • Collected from historical GPS data from over 300 million sources. • Data available for three years up to the previous day.

Performance Measures	• On-demand, cloud-based analytics suite.
	• Uses INRIX global traffic data to help public agencies monitor, measure, and manage road network performance.
	• Data is only available in the United States.
	• Designed to be easily extracted.
	• Features Include:
	    • Region Explorer.
	    • Performance Charts.
	    • Congestion Scan.
	    • Trends.
	    • Bottleneck Rankings.
	    • User Delay Costs

Population Analytics	• Provides information in regards to how people within large populations move.
	• Features Include:
	    • Real-Time Population Density.
	    • Origin-Destination Matrices.
	    • Real-Time Population Flow.

Trips	• Provides insights regarding the trips people take.
	• Alternative to traditional survey-based methods.
	• Derived from geospatial data processing.
	• Features Include:
	    • Trip Reports.
	    • Trip Matrices.

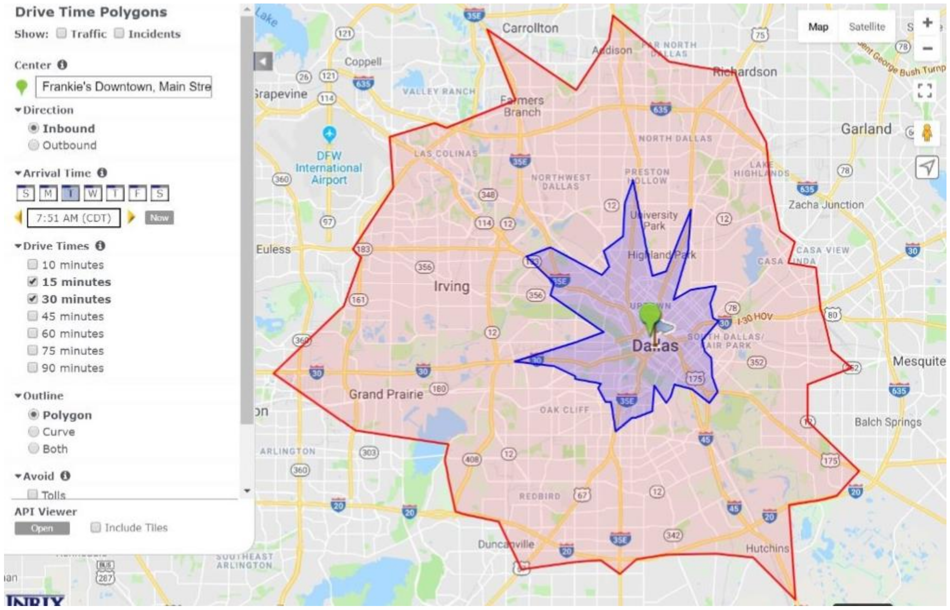


Figure 4.12: Example of INRIX output from drive time data

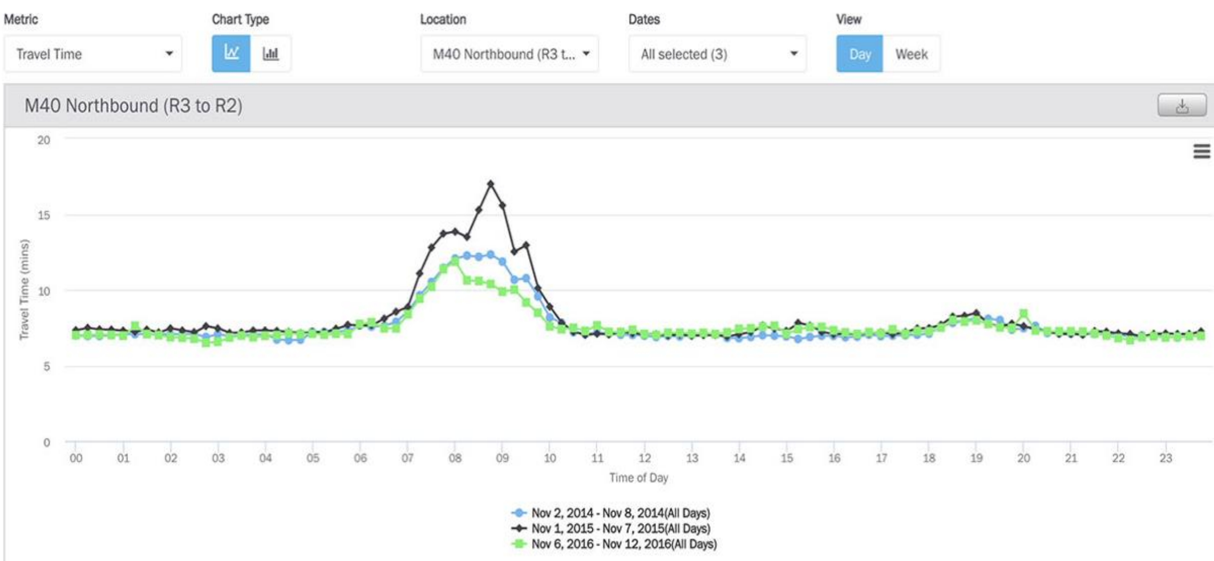


Figure 4.13: Example of results from INRIX performance measures data

4.4.5 TRANSEARCH (IHS)

Transearch data, provided by IHS Markit, provides freight data with the goal of predicting freight flows and planning for future transportation needs. Their data can be used to predict freight flow, for as far out as 30 years, by origin, destination, commodity type, and mode of transport. Transearch data can be obtained at the national level, business economic area, or the county-level. Other features include the ability to track modal competition and commodity groups, benchmark performance, and estimate market potential. Specific data provided by Transearch includes:

- Outbound, inbound, intra, and through shipments by geography.
    - Geography includes 172 business economic areas, more than 3,000 counties, state-level detail for Mexico, and province/municipal data for Canada.
- Volumes on routes along individual trade lanes or corridors.
- Tonnage, volume, and units of shipments.
- Truck, rail, marine, and air freight data.
    - Sub-mode details available for rail and truck.
- Over 340 commodity types.
- Canada and Mexico cross-border flows.

Unfortunately, no immediate purchase information is readily available on the Transearch website. Potential buyers are encouraged to contact a sales representative.

4.4.6 ATRI

ATRI, headquartered in Virginia, has collected freight data and conducted research since 1954. Data collected by ATRI has been used to conduct research covering several freight issues, including:

- Operational costs.
- Bottlenecks, congestion, and infrastructure funding.
- Truck parking.
- Hours-of-service.
- Autonomous vehicle technology.
- Driver health and wellness.
- CSA.
- Safety.
- Trucking economics.

- Environmental impacts.
- Traffic incident management.

In regards to types of data, it is know that ATRI has truck GPS data; however, their website provides little to no information on the type of data available. In addition, no cost information is readily available. To obtain this information, one would need to contact a sales representative of ATRI.

4.5 DATA SUMMARY

As illustrated in Chapter 4.0, several potential sources of data are available for analysis. The first data discussed, WIM data, is a key component of the analysis. Characteristics, such as observed combined (truck and cargo) weight and vehicle classification, can be used to explore the viability of predicting freight flow and/or commodity patterns. In addition to Oregon WIM data, several potential datasets maintained for Oregon's TransGIS website have been discussed. These datasets are readily available and may supplement the WIM data to address freight flow and/or commodity flow predictions.

Also of interest are publicly available freight datasets. As discussed, this may consist of FAF data, CFS data, or economic data. However, some of these datasets are provided at an aggregated level, which may prove problematic during analysis; specifically, FAF and CFS data. The economic data, at the regional level, may offer information at a higher resolution that can be integrated with the Oregon data that has been presented.

Lastly, potential private freight data sources have been presented. Unfortunately, due to the proprietary nature of the data, some companies do not provide much information (e.g., ATRI). In general, these datasets consist of freight movement information, while others include additional attributes such as hard braking or acceleration (EROAD) and fleet characteristics (FleetSeek). In addition, pricing is not readily available for any of the data sources discussed; hence, the viability of purchasing the data is unknown at this time.

From the inventoried ODOT data sources, this study uses ODOT traffic counts for volume comparison to WIM data (see Chapter 8.2). From the public data sources that were inventoried, this study uses FAF data to compare observed cargo weight in the WIM data to reported cargo weight in the FAF data (see Chapter 8.1) Lastly, from the private data sources that were inventoried, this study selected EROAD data. For analysis of the obtained EROAD data, see Chapter 9.0

5.0 QUALITY CONTROL OF WIM DATA

As is the case with any data analysis, quality is of utmost importance. Therefore, to ensure the quality of the WIM data being analyzed in the current study, a series of quality control procedures were conducted for each year of WIM data (2015 to 2018). As stated previously, this has become common practice when conducting WIM-related research (Fei, 2014; Mai et al., 2013; Quinley, 2010; Ramachandran, 2009; Southgate, 2015).

As a first step, the distribution of vehicle classifications at each WIM station was assessed. For an example of vehicle distribution plots, refer to Figure 5.1. For all vehicle classification plots by WIM station, year, and month, see Unnikrishnan et al. (2019).13 The distribution shown in Figure 5.1 was observed at all WIM stations found in Oregon; that is, other than passenger vehicles, ODOT Class 11 trucks accounted for the largest proportion of recorded vehicles (see Unnikrishnan et al. 2019). With all WIM stations exhibiting similar distributions in vehicle classifications, a quality control analysis of ODOT Class 11 trucks at each WIM station for each year was conducted. Based on previous work and the WIM Data Analyst's Manual, the quality control analysis checks are summarized in Table 5.1 (Fei, 2014; Quinley, 2010; Ramachandran, 2009). The quality control analysis was conducted only for ODOT Class 11 trucks, as these checks are well-known and documented.

[13] All vehicle classification plots can be viewed here.

Table 5.1: Summary of WIM Quality Control Checks for ODOT Class 11 Trucks

Check	Description
Number of Axles consistent with the Number of Axle Spacings	If Number of Axles ≠ Number of Axles Spaces + 1 Then Error
Number of Axles consistent with the Number of Axle Weights	If Number of Axles ≠ Number of Axle Weights Then Error
GVW consistent with the sum of axle Weights	If Sum of Axle Weights ≠ Total Weight Then Error
Number of Axles consistent with the Vehicle Class	If Number of Axles ≠ range of axles for that vehicle class Then Error
Sum of Axle Spacings consistent with maximum wheelbase	If Sum of Axle Spaces > 98.2 ft Then Error
Axle Weights within acceptable range	If 441 lbs. < Axle Weight < 44,100 lbs. Then Ok
Axle Spacings within acceptable range	If 1.97 ft. < Axle Spacing < 49.2 ft. Then Ok
Sum of axle spaces is greater than or equal to recorded vehicle length	Any vehicle where the sum of the axle spaces is greater than the recorded vehicle length is flagged
Visual Checks	
Speed Distribution	
Number of Noon-Hour Trucks is Greater Than Number of Midnight-Hour Trucks	
Number of Trucks by Hour	
Visual interpretation of the Front Steering Axle Weight Frequency Distribution for each class to check whether the majority of axles fall within the proper range (8,000 lbs. to 12,000 lbs.)	
Visual review of the Observed Weight Frequency Distribution for each class to check consistency with the peaks for loaded and unloaded vehicles (28,000 lbs. to 36,000 lbs. for unloaded and 70,000 lbs. to 80,000 lbs. for loaded)	

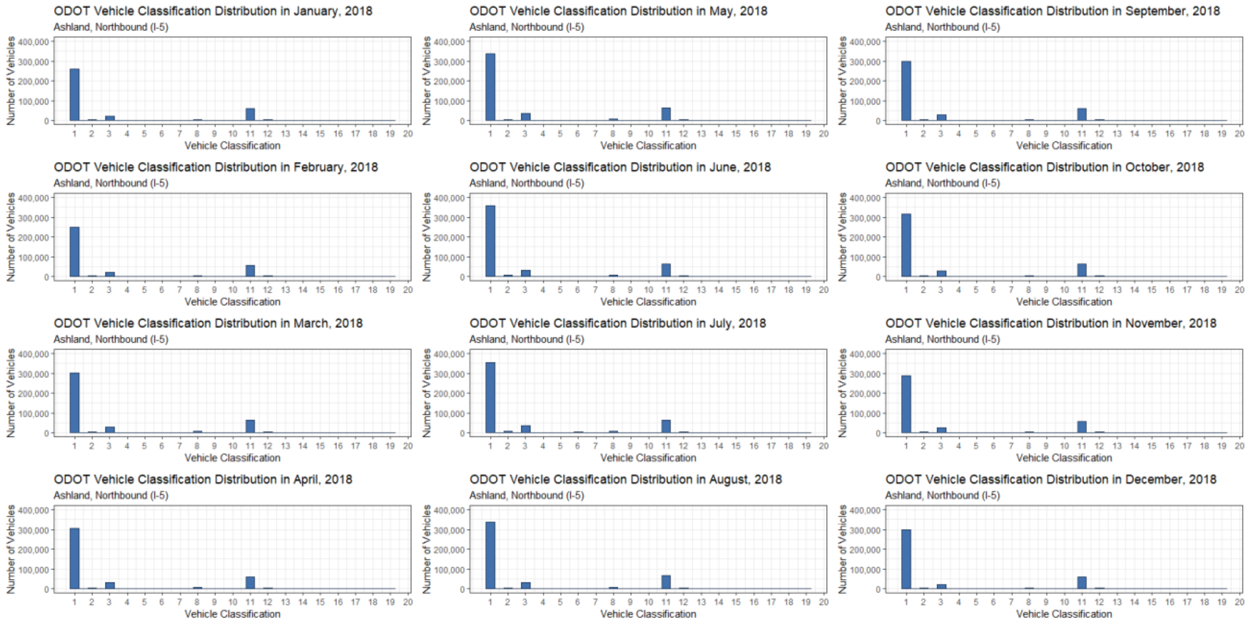


Figure 5.1: Vehicle classification plots at Ashland (NB) WIM station

For quality control analysis, a series of R scripts were written. Any observation that did not meet the logical tests in Table 5.1 was removed, and then a visual review was conducted to ensure the data met quality requirements. For speed distribution, an example of the generated plots for Ashland (SB) in 2018 is shown in Figure 5.2. For speed distribution plots at all WIM stations by year and month, see Unnikrishnan et al. (2019).[14] The plot shows that average observed speed remains relatively consistent throughout the year, with the lowest average observed speed being in January (58 mi/hr) and the highest observed average speed being in July (61 mi/hr). As for the 95th percentile observed speed, July, August, and September have the highest at just over 67 mi/hr. Figure 5.3 shows an example of the comparison of noon-hour to midnight-hour truck counts at Ashland (SB) in 2018. For noon-hour and midnight-hour truck count comparisons at all WIM stations by year and month, see Unnikrishnan et al. (2019).[15] Figure 5.3 shows that for each month, the noon-hour experiences higher truck volumes than the midnight-hour. For the noon hour, the maximum number of trucks is observed in June (3,413), and the minimum number of trucks is observed in April (2,969). For the midnight-hour, the maximum number of trucks is observed in June (1,202), and the minimum number of trucks is observed in February (839). To illustrate the plots for the number of trucks by the hour, refer to Figure 5.4. For plots of truck counts by the hour for all WIM stations, years, and months, see Unnikrishnan et al. (2019).[16] These plots identify periods in which the WIM sensors recorded no truck counts. Figure 5.4 shows that January had a significant length of "zero-hours" (consecutive hours in which no trucks were observed). Specifically, this is observed for the entire day on January 9, 2018. Also with consecutive zero hours is February 19, 2019 (4:00 a.m. to 6:00 a.m.), August 2, 2018 to August 3, 2018 (11:00 p.m. to 3:00 a.m.), and December 2, 2018 to December 3, 2018

[14] All speed distribution plots can be viewed here.
[15] All noon-hour to midnight-hour plots can be viewed here.
[16] All number of trucks by hour plots can be viewed here.

(11:00 p.m. to 4:00 a.m.). Potential reasons for these consecutive zero hours may be attributed to lane closures (e.g., weather, crashes, work zone, etc.) or WIM maintenance. For the observed weight of the steering axle, an example plot is shown in Figure 5.5. For steering axle weight distribution plots at all WIM stations by year and month, refer to Unnikrishnan et al. (2019).[17] Based on Figure 5.5, the highest average observed steering axle weight is in August (10,435 lbs.) and the lowest in December (9,566 lbs.). In terms of 95th percentile steering axle weight, the highest average observed weight is in August (11,331 lbs.) and the lowest in December (10,317 lbs.). Lastly, an example of observed combined (truck and cargo) weight distribution plots is shown in Figure 5.6 (summary statistics associated with this plot are shown in Table 5.2). The dashed red lines in the observed combined weight distribution plots indicate where the peaks in the distribution should be observed. These values are based on previous WIM research and the widely known and accepted values for unloaded and fully loaded trucks: 32,000 pounds and 80,000 pounds. For loaded conditions, based on previous research, the distribution peak should fall within 70,000 pounds and 80,000 pounds (as indicated in by the red dashed lines). For unloaded conditions, based on previous research, the distribution peak should fall within 28,000 pounds and 36,000 pounds (as indicated by the red dashed lines). As with the previous plots, observed weight distribution plots for all WIM stations by year and month can be found in Unnikrishnan et al. (2019).[18]

After the quality control analysis, a before-after comparison was conducted for each WIM station. An example is shown in Table 5.2. The percent decrease in the number of trucks after the quality control analysis varied by WIM station, but in each case, a decrease was observed. In the case of the Ashland (NB) WIM station, shown in Table 5.2, about 2.28% of the WIM records (or about 17,000 observations) in 2018 did not pass the quality control checks detailed in Table 5.1. Being that WIM stations measure weights dynamically, dynamic forces on the truck can influence weight measurements (Federal Highway Administration, 2016). Therefore, measurements that do not meet the quality control checks can be a result of site-specific characteristics (e.g., pavement roughness), vehicle characteristics (e.g., suspension, tire pressure, etc.), or atmospheric conditions (e.g., wind) (Federal Highway Administration, 2016). As such, and as illustrated in Table 5.2, the process of quality control is essential to remove any incorrect WIM records that may result from the aforementioned characteristics. Additionally, a complete summary of the quality control analysis by WIM station and year is provided in Table 5.3. As observed in Table 5.3, the reduction in data is consistent across WIM stations, with the exception of Ashland (NB), Ashland (SB), Booth Ranch (SB), Bend (NB), and Rocky Point (WB). For Ashland (NB), data reduction ranges from 1.32% (observed in 2015) to 2.28% (observed in 2018). For Ashland (SB), data reduction ranges from 2.23% (observed in 2015) to 2.46% (observed in 2017). For Booth Ranch (SB), data reduction ranges from 1.89% (observed in 2015) to 2.39% (observed in 2017). For Bend (NB), large data reductions were observed only in 2017 (5.30%, also the largest reduction observed across all WIM stations) and 2018 (2.29%). Also with large data reductions in 2017 and 2018 only was Rocky Point (WB), where there was a 1.83% reduction in 2017 and a 3.10% reduction in 2018.

[17] All steering axle weight distribution plots can be viewed here.
[18] All observed combined weight distribution plots can be viewed here.

Table 5.2: Before and After Quality Control Analysis at Ashland (NB) WIM Station

*

Month	Before[a]	After[b]	Percent Change	Mean Observed Combined Weight[c]	Median Observed Combined Weight[c]	95th Percentile Observed Combined Weight[c]
January	60,203	59,178	-1.70%	58,948	60,629	69,651
February	58,112	57,190	-1.59%	58,939	60,704	69,858
March	65,506	63,900	-2.45%	60,240	62,048	71,593
April	60,177	59,335	-1.40%	62,320	64,032	73,644
May	65,497	64,589	-1.39%	63,087	64,807	74,356
June	65,093	60,667	-6.80%	62,903	64,777	73,803
July	62,812	61,569	-1.98%	62,352	64,218	73,185
August	65,795	64,463	-2.02%	61,452	63,251	72,278
September	60,120	58,929	-1.98%	60,373	61,888	71,245
October	64,908	63,768	-1.76%	59,388	60,662	70,207
November	55,976	54,829	-2.05%	58,290	59,357	69,374
December	61,106	59,902	-1.97%	57,636	58,739	68,656
Total	**745,305**	**728,319**	**-2.28%**			

* Statistics are for the year 2018

[a] Number of ODOT Class 11 Trucks Before Quality Control Analysis

[b] Number of ODOT Class 11 Trucks After Quality Control Analysis

[c] All Weight Statistics are Based on the Number of ODOT Class 11 Trucks After the Quality Control Analysis

Table 5.3: Summary of Before and After Quality Control Analysis by WIM Station and Year

	2015			2016			2017			2018		
WIM Station	**Before[a]**	**After[b]**	**% Difference**	**Before[a]**	**After[b]**	**% Difference**	**Before[a]**	**After[b]**	**% Difference**	**Before[a]**	**After[b]**	**% Difference**
Ashland (NB)	702,581	693,321	-1.32%	721,791	711,400	-1.44%	743,216	730,383	-1.73%	745,305	728,319	-2.28%
Ashland (SB)	635,030	620,838	-2.23%	669,938	654,820	-2.26%	677,950	661,275	-2.46%	684,227	668,234	-2.34%
Booth Ranch (NB)	673,127	673,045	-0.01%	656,845	656,675	-0.03%	698,532	698,455	-0.01%	619,758	619,647	-0.02%
Booth Ranch (SB)	660,641	648,149	-1.89%	689,415	674,747	-2.13%	716,389	699,236	-2.39%	713,176	698,266	-2.09%
Woodburn (NB)	1,261,511	1,261,192	-0.03%	1,273,026	1,272,732	-0.02%	1,034,311	1,034,184	-0.01%	1,072,030	1,071,975	-0.01%
Woodburn (SB)	886,002	885,969	0.00%	947,629	947,598	0.00%	948,932	948,897	0.00%	919,466	919,433	0.00%
Cascade Locks (EB)	394,709	394,662	-0.01%	409,051	409,002	-0.01%	374,724	374,680	-0.01%	417,906	417,860	-0.01%
Wyeth (WB)	401,774	401,669	-0.03%	414,692	414,574	-0.03%	342,432	342,171	-0.08%	426,650	426,485	-0.04%
La Grande (EB)	370,349	370,231	-0.03%	384,034	383,408	-0.16%	462,092	461,969	-0.03%	490,750	490,665	-0.02%
Emigrant Hill (WB)	332,585	332,480	-0.03%	364,452	364,258	-0.05%	217,521	217,143	-0.17%	297,686	297,321	-0.12%
Olds Ferry (EB)	442,106	441,974	-0.03%	444,125	444,003	-0.03%	354,921	354,743	-0.05%	490,081	490,025	-0.01%
Farewell Bend (WB)	389,221	389,034	-0.05%	455,241	454,997	-0.05%	461,920	461,704	-0.05%	477,623	477,385	-0.05%
Klamath Falls (NB)	118,083	118,057	-0.02%	117,437	117,413	-0.02%	121,044	120,987	-0.05%	112,518	112,504	-0.01%
Klamath Falls (SB)	200,634	200,624	0.00%	198,265	198,241	-0.01%	206,140	206,121	-0.01%	196,289	196,257	-0.02%
Bend (NB)	111,551	110,614	-0.84%	116,226	115,488	-0.63%	94,583	89,574	-5.30%	112,398	109,826	-2.29%
Juniper Butte (NB)	118,738	118,720	-0.02%	121,807	121,798	-0.01%	67,289	67,268	-0.03%	NA	NA	NA
Juniper Butte (SB)	169,307	169,282	-0.01%	168,916	168,882	-0.02%	170,940	170,929	-0.01%	64,823	64,821	0.00%
Cold Springs (EB)	59,083	59,058	-0.04%	68,625	68,612	-0.02%	59,282	59,265	-0.03%	69,812	69,757	-0.08%
Cold Springs (WB)	54,698	54,453	-0.45%	71,649	71,625	-0.03%	69,116	69,106	-0.01%	80,385	80,373	-0.01%
Lowell (WB)	68,775	68,761	-0.02%	64,638	64,607	-0.05%	10,139	10,136	-0.03%	NA	NA	NA
Rocky Point (WB)	47,288	47,286	0.00%	47,762	47,674	-0.18%	45,334	44,504	-1.83%	44,112	42,744	-3.10%
Umatilla (SB)	353,783	353,753	-0.01%	377,948	377,880	-0.02%	253,159	253,144	-0.01%	NA	NA	NA

[a] Number of ODOT Class 11 Trucks Before Quality Control Analysis
[b] Number of ODOT Class 11 Trucks After Quality Control Analysis

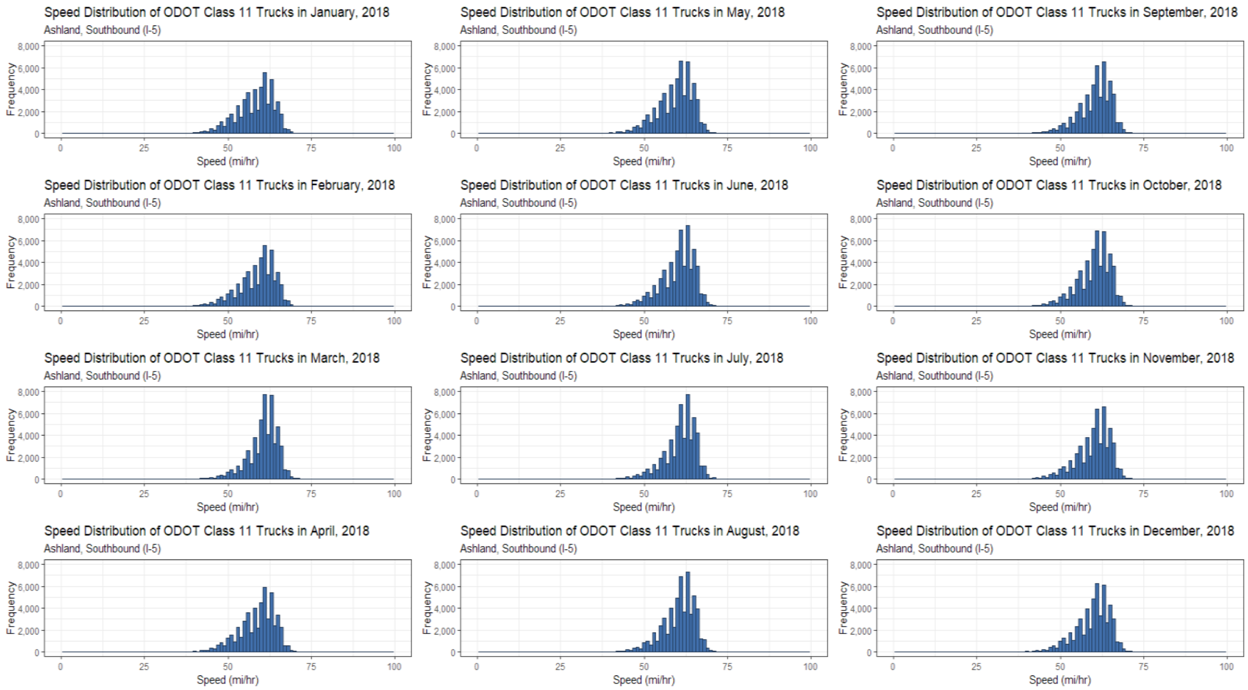


Figure 5.2: Speed distribution plots for ODOT Class 11 trucks at Ashland (SB) WIM station

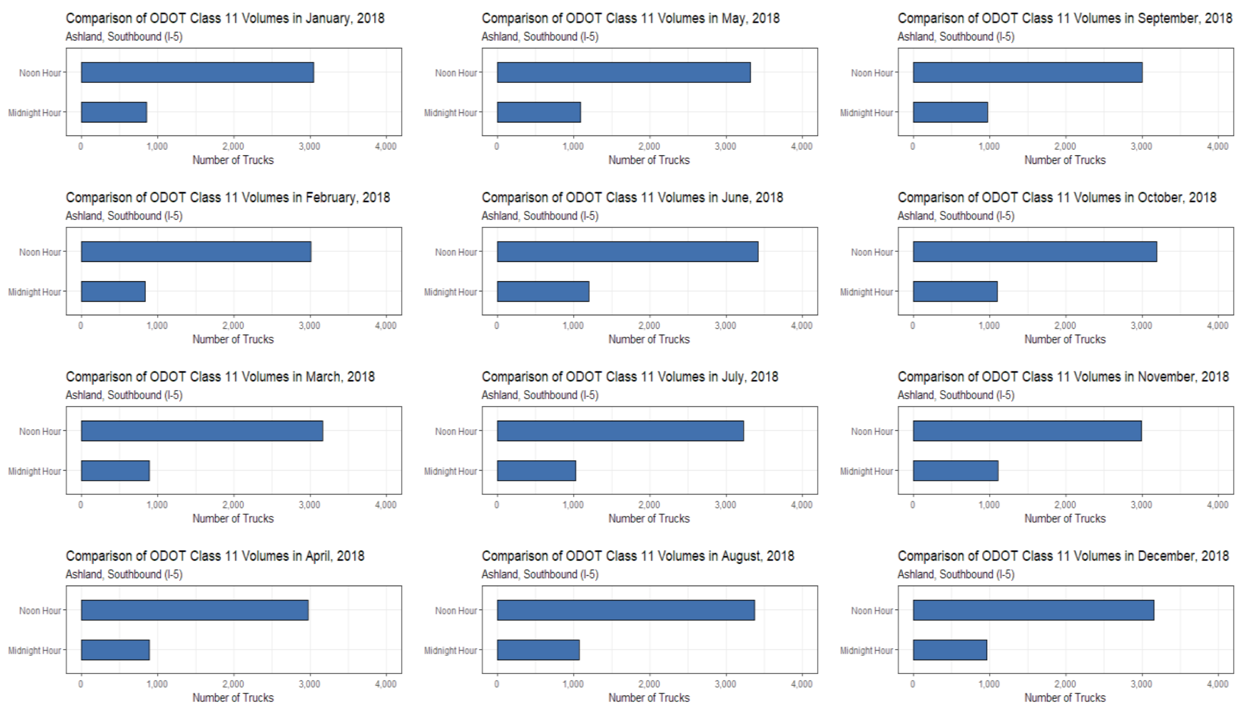


Figure 5.3: Comparison of noon and midnight hour ODOT Class 11 truck counts at Ashland (SB) WIM station

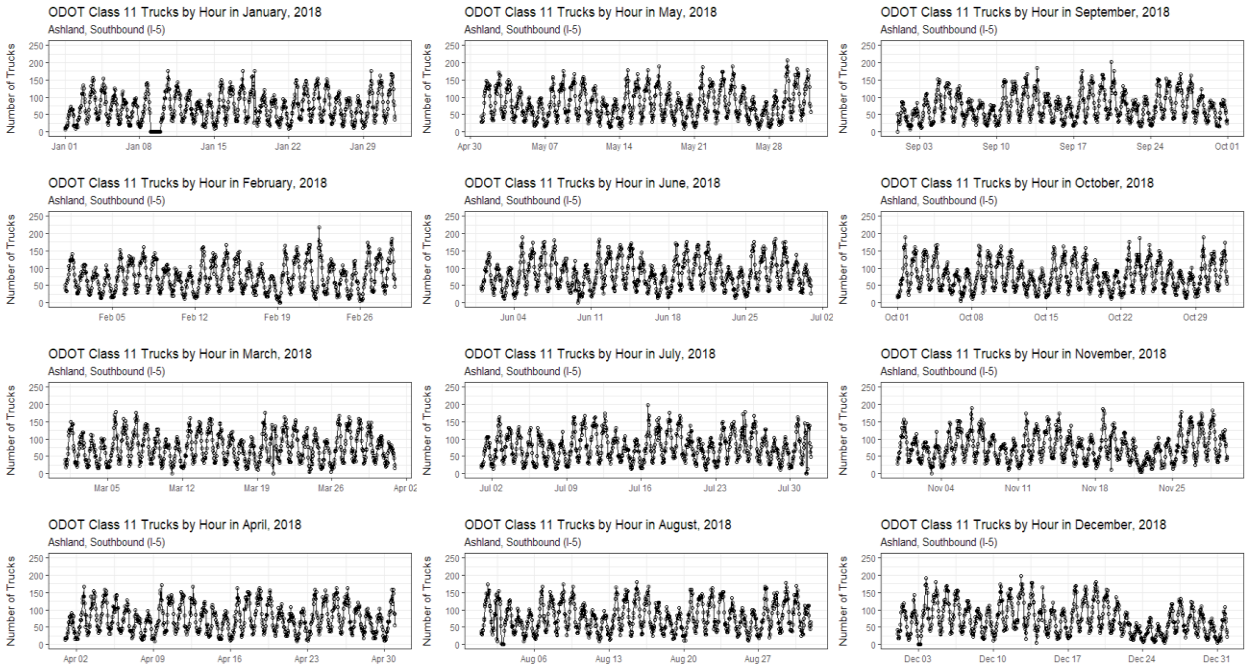


Figure 5.4: Number of ODOT Class 11 trucks by hour at Ashland (SB) WIM station

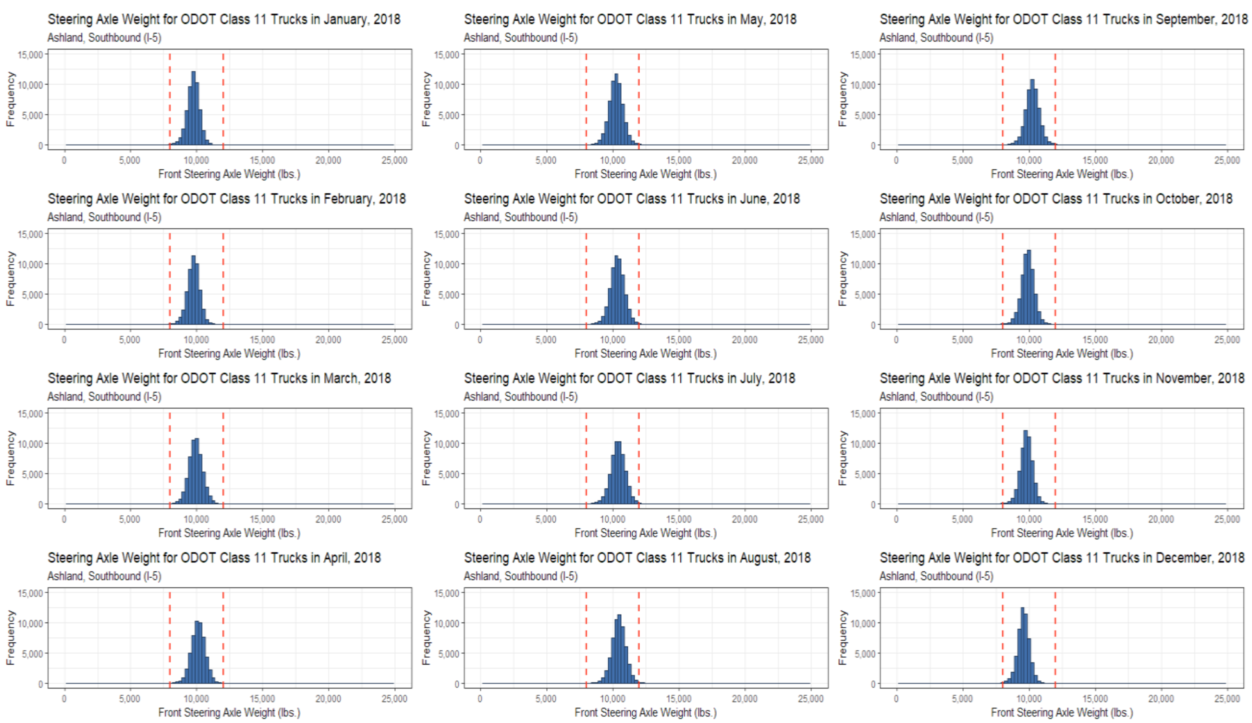


Figure 5.5: Observed steering axle weight for ODOT Class 11 trucks at Ashland (SB) WIM station

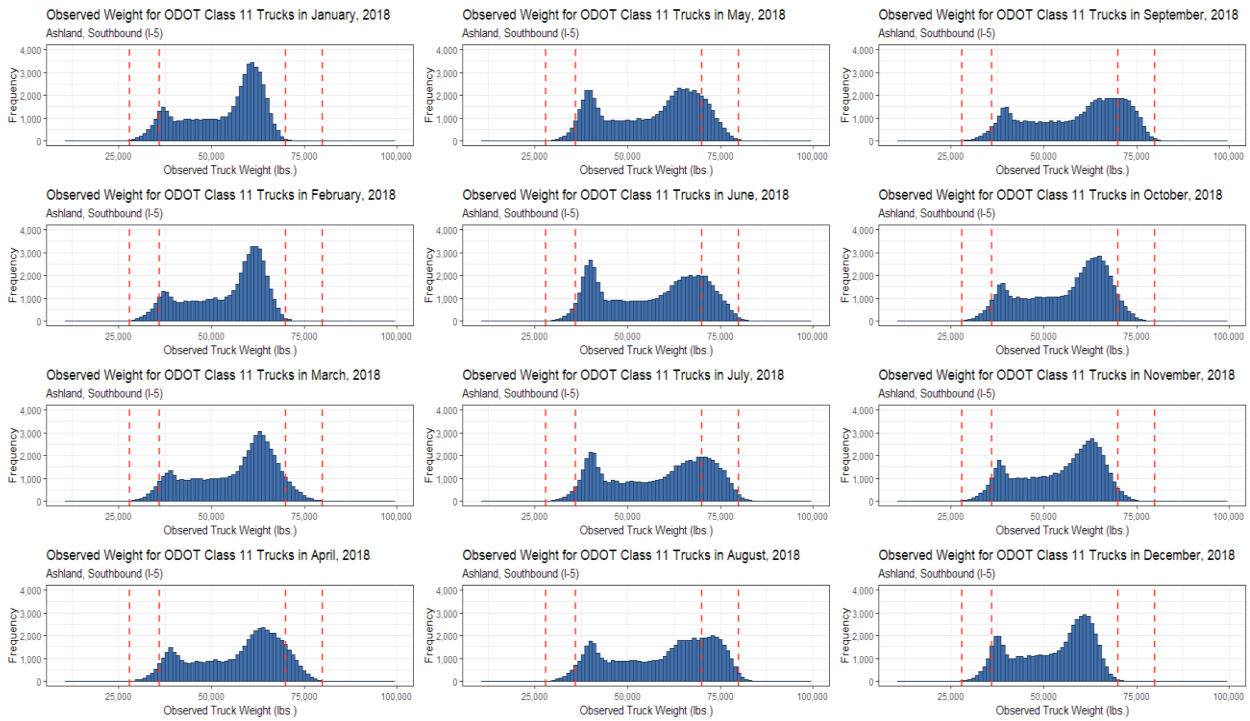


Figure 5.6: Observed combined (truck and cargo) weight for ODOT Class 11 trucks at Ashland (SB) WIM station

5.1 QUALITY CONTROL SUMMARY

Based on previous WIM-related research and widely established values for ODOT Class 11 trucks, a quality control analysis was conducted for ODOT Class 11 trucks only. In addition to the characteristics of these trucks being widely known, they also account for the greatest proportion of freight-related vehicles. Relative to all trucks (ODOT Class 03 to ODOT Class 19, excluding Class 04 and Class 07), ODOT Class 11 trucks account for approximately 40% of all WIM records across all WIM stations. It should be noted, however, that the proportion of freight-related vehicles in Classes 03 to 10 are difficult to definitively differentiate without further investigation. However, relative to ODOT Class 11 to ODOT Class 19 trucks (all of which are freight-related vehicles), ODOT Class 11 trucks account for roughly 70% of all WIM records across all WIM stations. Through a series of quality control procedures, erroneous WIM records were removed before analysis of this classification. Unfortunately, being that characteristics of other classification are less established, a quality control analysis on other truck classifications could not be conducted. Without an explicit focus on developing quality control checks for these classifications, the percent data reductions are unknown. It is also unknown if they would follow patterns observed for the presented analysis of ODOT Class 11 trucks. In general, the data reduction was consistent across WIM stations, with most reductions being less than 1.0%. However, the Ashland WIM stations, Booth Ranch (SB), Bend (NB) in 2017 and 2018, and Rocky Point (WB) in 2017 and 2018 all experienced higher data reduction after completion of the quality control analysis. Specifically, data reduction at the Ashland WIM stations ranged from 1.32% to 2.28% in the northbound direction and 2.23% to 2.46% in the southbound direction. At Booth Ranch (SB), data reduction ranged from 1.89% to 2.39%. Lastly, at Bend

(NB) and Rocky Point (WB), data reduction ranged from 2.29% to 5.30% and 1.83% to 3.10%, respectively. In concluding, all reductions fall within the WIM system requirements presented in Table 2.1

6.0 DESCRIPTIVE ANALYSIS

This descriptive analysis consisted of summarizing all 21 WIM stations in Oregon. Since the data comparisons discussed in Chapter 0 focus on weight and volumes, the descriptive analysis also focuses on these two metrics. Additional metrics, including average monthly observed truck weight, average monthly observed median truck weight, and average monthly observed 95th percentile truck weight was also assessed and can be viewed in Unnikrishnan et al. (2019).[19] Additionally, plots for the total number of trucks and average monthly observed combined (truck and cargo) weights can be viewed in Unnikrishnan et al. (2019).[19]

This descriptive analysis considered four specific groups of trucks as follows (also summarized in Table 6.1):

1. ODOT Class 03 to ODOT Class 10 trucks (*excluding ODOT Class 04 and ODOT Class 07, these are classified as 2-axle and 3-axle buses, respectively*). This group was selected based on inputs used by Oregon's Statewide Integrated Model (SWIM), in which the lower threshold is a single unit truck of greater than 10,000 pounds (Parsons Brinckerhoff, 2010; WSP Parsons Brinckerhoff, 2017).

2. ODOT Class 11 trucks. As stated previously, these account for the largest proportion of freight-related vehicles and are the primary focus of WIM-related research.

3. ODOT Class 12 to ODOT Class 19 trucks. These represent the truck configurations in which heavier loads can be carried and can account for a moderate proportion of observed weights at Oregon WIM stations.

4. All truck, considering ODOT Class 03 to ODOT Class 19 (excluding ODOT Class 04 and ODOT Class 07).

Table 6.1also shows the proportion of trucks relative to all trucks (i.e., trucks that fall within the four aforementioned classification groups). These proportions are generated considering all WIM data and each WIM station. Referring to Table 6.1, ODOT Class 11 consistently account for the highest proportion of trucks, followed by ODOT Class 03.

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[19] Summary statistics for average monthly observed truck weight, average monthly observed median truck weight, average monthly observed 95th percentile truck weight, and plots for volume and average monthly observed combined (truck and cargo) weight can be viewed here.

Table 6.1: Summary of Classification Groups and Proportion of Total Number of Trucks

ODOT Class 03 to ODOT Class 10 Trucks		Proportion of Total Number of Trucks			
Class	**Definition**	**2015**	**2016**	**2017**	**2018**
ODOT Class 03	2-axle, Single Unit	32.01%	34.17%	29.19%	28.63%
ODOT Class 05	3-axle, Single Unit	2.80%	3.18%	3.68%	2.92%
ODOT Class 06	3-axle Combination	2.29%	2.40%	2.76%	2.88%
ODOT Class 08	4-axle Combination (2-axle Truck, 2-axle Trailer)	5.94%	6.02%	6.66%	7.32%
ODOT Class 09	4-axle Combination (3-axle Truck, 1-axle Trailer)	0.64%	0.66%	0.67%	0.70%
ODOT Class 10	4-axle Single Unit	0.04%	0.07%	0.11%	0.05%
ODOT Class 11 Trucks		**Proportion of Total Number of Trucks**			
Class	**Definition**	**2015**	**2016**	**2017**	**2018**
ODOT Class 11 Trucks	5-axle, Single Trailer Semi	41.52%	38.95%	41.76%	42.03%
ODOT Class 12 to ODOT Class 19 Trucks		**Proportion of Total Number of Trucks**			
Class	**Definition**	**2015**	**2016**	**2017**	**2018**
ODOT Class 12	5-axle Twins	1.43%	1.37%	1.45%	1.45%
ODOT Class 13	Other 5-axle Combinations	0.58%	0.64%	0.62%	0.67%
ODOT Class 14	6-axle Combinations	1.25%	1.19%	1.30%	1.28%
ODOT Class 15	Other 6-axle Combinations	3.02%	3.05%	3.26%	3.37%
ODOT Class 16	Triples	1.07%	0.98%	0.98%	1.15%
ODOT Class 17	Other 7-axle Combinations	3.41%	3.31%	3.44%	3.45%
ODOT Class 18	8-axle Combinations	3.83%	3.72%	3.80%	3.83%
ODOT Class 19	9-axle or More Combinations	0.16%	0.31%	0.32%	0.28%

Table 6.2 summarizes the WIM stations and associated months/years in which WIM data was unavailable. All I-5 WIM stations had available data for each month and year considered for analysis. Of the remaining WIM stations with unavailable data, potential reasons may include construction, WIM system replacement, or the WIM station was offline for some time.

Table 6.2: Summary of Data Unavailability and WIM Stations

WIM Station	Highway	Unavailable Data	
		Months	Year
Bend (NB)	US-97	July	2017
Cold Springs (EB)	I-82	May	2017
Cold Springs (WB)	I-82	June	2015
		May	2017
		January	2018
Emigrant Hill (WB)	I-84	April, May, October, November	2017
		September	2018
Juniper Butte (NB)	US-97	August, September, October, November, December	2017
		All Months	2018
Juniper Butte (SB)	US-97	June, July, August, September, October, November, December	2018
Lowell (WB)	OR-58	May, June, July, August, September, October, November, December	2017
		All Months	2018
Umatilla (SB)	US-730	All Months	2018

6.1 ODOT CLASS 03 TO ODOT CLASS 10 TRUCKS

As stated previously, the first group considered for the descriptive analysis consisted of ODOT Class 03 to ODOT Class 10 trucks (excluding ODOT Class 04 and ODOT Class 07). Definitions for these classifications are as follows:

- ***ODOT Class 03***: 2-axle, Single Unit
- ***ODOT Class 05***: 3-axle, Single Unit
- ***ODOT Class 06***: 3-axle Combination
- ***ODOT Class 08***: 4-axle Combination (2-axle Truck, 2-axle Trailer)
- ***ODOT Class 09***: 4-axle Combination (3-axle Truck, 1-axle Trailer)
- ***ODOT Class 10***: 4-axle Single Unit

The first descriptive analysis is to assess the total number of ODOT Class 03 to ODOT Class 10 trucks by WIM station and year, as illustrated in Table 6.3. As observed, the Woodburn WIM stations account for the highest volume of trucks, which remains fairly consistent for each year of WIM data. In 2017, however, Rocky Point and Booth Ranch had marginally higher volumes over the southbound Woodburn station. The Bend WIM station also accounts for a large volume of ODOT Class 03 to ODOT Class 10 trucks. Outside of Booth Ranch, Rocky Point, and Bend, WIM stations located at points of entry/exit experience the largest truck volumes. In addition, the WIM stations located at points of entry/exit have data for all months and years of WIM data. Of note, Woodburn (SB) in 2016 experiences the highest truck counts. Upon further investigation, for the first half of the year in 2016 (January through July), the number of trucks in the southbound direction were substantially larger than the northbound direction, therefore resulting in Woodburn (SB) experiencing, annually, higher truck volume than Woodburn (NB) in 2016.

The next statistic assessed was the average monthly observed combined (truck and cargo) weight. Observed weight refers to the weight recorded at the WIM station, likely differing from the registered weight or declared weight at the time of the trip. The average monthly observed combined weight was determined by summing the total observed weight for a given year of WIM data and dividing by 12. A summary of the average monthly observed combined weights by year, and WIM station is presented in **Error! Reference source not found.**. As with the total number of trucks, the Woodburn WIM stations consistently account for the largest average monthly observed combined weights. Other stations accounting for high average monthly observed combined weights include the Booth Ranch and Bend WIM stations.

Table 6.3: Total Number of ODOT Class 03 to ODOT Class 10 Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	**Total Number of Trucks**	**WIM Station**	**Total Number of Trucks**	**WIM Station**	**Total Number of Trucks**	**WIM Station**	**Total Number of Trucks**
Woodburn (NB)	1,280,109	Woodburn (SB)	1,809,807	Woodburn (NB)	1,175,497	Woodburn (NB)	1,195,265
Woodburn (SB)	1,138,596	Woodburn (NB)	1,423,073	Rocky Point (WB)	833,700	Woodburn (SB)	830,019
Booth Ranch (NB)	659,861	Booth Ranch (NB)	729,293	Booth Ranch (NB)	726,727	Booth Ranch (NB)	786,659
Bend (NB)	538,267	Bend (NB)	697,351	Woodburn (SB)	706,494	Rocky Point (WB)	752,547
Booth Ranch (SB)	518,737	Rocky Point (WB)	604,486	Bend (NB)	521,610	Bend (NB)	559,604
Umatilla (SB)	455,900	Booth Ranch (SB)	512,475	Ashland (NB)	461,544	Booth Ranch (SB)	558,176
Wyeth (WB)	448,230	Wyeth (WB)	480,044	Juniper Butte (SB)	452,239	Ashland (NB)	452,477
Ashland (SB)	447,505	Umatilla (SB)	449,894	Wyeth (WB)	419,313	Cascade Locks (EB)	424,290
Juniper Butte (SB)	397,640	Juniper Butte (SB)	442,951	Booth Ranch (SB)	395,322	Ashland (SB)	389,661
Ashland (NB)	390,723	Cascade Locks (EB)	431,503	Ashland (SB)	380,488	Wyeth (WB)	386,528
Rocky Point (WB)	361,854	Ashland (NB)	428,618	Cascade Locks (EB)	377,423	Klamath Falls (SB)	348,706
Cascade Locks (EB)	355,329	Ashland (SB)	402,000	Klamath Falls (SB)	364,534	Olds Ferry (EB)	249,735
La Grande (EB)	322,903	Juniper Butte (NB)	387,750	Juniper Butte (NB)	250,183	Klamath Falls (NB)	248,268
Juniper Butte (NB)	317,644	Emigrant Hill (WB)	329,697	Umatilla (SB)	241,763	Juniper Butte (SB)	221,818
Klamath Falls (SB)	282,089	Klamath Falls (SB)	269,859	Klamath Falls (NB)	193,124	La Grande (EB)	191,435
Farewell Bend (WB)	238,071	Klamath Falls (NB)	250,707	Farewell Bend (WB)	188,596	Farewell Bend (WB)	180,717
Emigrant Hill (WB)	212,447	Lowell (WB)	204,223	Olds Ferry (EB)	185,211	Emigrant Hill (WB)	104,698
Klamath Falls (NB)	175,300	La Grande (EB)	187,577	La Grande (EB)	181,041	Cold Springs (EB)	94,890
Lowell (WB)	160,471	Farewell Bend (WB)	161,234	Emigrant Hill (WB)	92,905	Cold Springs (WB)	69,386
Olds Ferry (EB)	105,815	Olds Ferry (EB)	126,349	Cold Springs (EB)	55,128	Juniper Butte (NB)	NA
Cold Springs (EB)	26,981	Cold Springs (EB)	51,204	Cold Springs (WB)	46,220	Lowell (WB)	NA
Cold Springs (WB)	14,674	Cold Springs (WB)	41,350	Lowell (WB)	36,573	Umatilla (SB)	NA

Table 6.4: Average Monthly Observed Combined (Truck and Cargo) Weight for ODOT Class 03 to ODOT Class 10 Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***
Woodburn (NB)	725,611	Woodburn (SB)	889,822	Woodburn (NB)	647,590	Woodburn (NB)	677,660
Woodburn (SB)	569,352	Woodburn (NB)	789,838	Woodburn (SB)	436,295	Woodburn (SB)	502,787
Booth Ranch (NB)	344,482	Booth Ranch (NB)	400,883	Booth Ranch (NB)	416,193	Booth Ranch (NB)	453,531
Booth Ranch (SB)	251,486	Bend (NB)	321,902	Bend (NB)	256,434	Rocky Point (WB)	312,055
Bend (NB)	251,034	Booth Ranch (SB)	261,441	Rocky Point (WB)	244,249	Booth Ranch (SB)	299,538
Ashland (SB)	232,664	Wyeth (WB)	242,064	Ashland (NB)	232,010	Bend (NB)	265,156
Umatilla (SB)	229,855	Umatilla (SB)	241,397	Wyeth (WB)	223,159	Juniper Butte (SB)	241,618
Wyeth (WB)	224,679	Cascade Locks (EB)	236,596	Juniper Butte (SB)	216,018	Cascade Locks (EB)	235,265
Cascade Locks (EB)	195,689	Rocky Point (WB)	223,160	Booth Ranch (SB)	215,465	Ashland (NB)	229,879
Ashland (NB)	194,677	Ashland (NB)	213,729	Cascade Locks (EB)	206,903	Wyeth (WB)	212,278
Juniper Butte (SB)	185,032	Juniper Butte (SB)	208,674	Ashland (SB)	198,145	Ashland (SB)	205,269
Farewell Bend (WB)	184,662	Emigrant Hill (WB)	208,311	Juniper Butte (NB)	193,264	Klamath Falls (SB)	160,761
Rocky Point (WB)	174,381	Ashland (SB)	207,164	Umatilla (SB)	169,445	Klamath Falls (NB)	136,636
La Grande (EB)	169,657	Juniper Butte (NB)	177,945	Klamath Falls (SB)	167,304	Olds Ferry (EB)	134,909
Juniper Butte (NB)	148,305	Klamath Falls (SB)	125,669	La Grande (EB)	109,319	La Grande (EB)	116,147
Emigrant Hill (WB)	139,411	La Grande (EB)	122,970	Olds Ferry (EB)	102,000	Farewell Bend (WB)	94,050
Klamath Falls (SB)	129,982	Klamath Falls (NB)	121,694	Farewell Bend (WB)	99,073	Emigrant Hill (WB)	77,843
Lowell (WB)	86,365	Lowell (WB)	99,490	Klamath Falls (NB)	96,153	Cold Springs (EB)	53,440
Klamath Falls (NB)	85,764	Farewell Bend (WB)	86,376	Emigrant Hill (WB)	95,666	Cold Springs (WB)	45,663
Olds Ferry (EB)	59,242	Olds Ferry (EB)	66,254	Lowell (WB)	48,307	Juniper Butte (NB)	NA
Cold Springs (EB)	15,701	Cold Springs (EB)	29,382	Cold Springs (EB)	34,113	Lowell (WB)	NA
Cold Springs (WB)	9,788	Cold Springs (WB)	25,330	Cold Springs (WB)	30,398	Umatilla (SB)	NA

* Combined Weight Refers to the Weight of the Truck and the Weight of the Cargo

6.2 ODOT CLASS 11 TRUCKS

The second group considered for the descriptive analysis consisted of ODOT Class 11 trucks. As stated previously, this classification accounts for the largest proportion of freight-related vehicles and is commonly the primary focus of WIM-related research. The definition for this classification is as follows:

- ***ODOT Class 11***: 5-axle, single trailer semi.

The first measure assessed was the total number of trucks. A summary of ODOT Class 11 truck counts by year, and WIM station is presented in Table 6.5. The total number of trucks was determined by summing the number of WIM records. As anticipated, the Woodburn WIM stations experienced the largest number of ODOT Class 11 trucks for each year of WIM data. The remaining I-5 WIM stations, as well as WIM stations along I-84, account for the next tier of truck counts. Of the non-interstate routes, the Klamath Falls WIM stations account for the largest number of ODOT Class 11 trucks. Outside of Emigrant Hill (WB), each of these WIM stations have data for all years of WIM data.

The next statistic is the average monthly observed combined (truck and cargo) weight. A summary of ODOT Class 11 trucks and the average monthly observed combined weight is presented in Table 6.6. As with the total number of trucks, outside of 2015, the Woodburn WIM stations experienced the highest monthly averages of observed combined weight. Following the Woodburn WIM stations are the other I-5 WIM stations (Ashland and Booth Ranch). After the I-5 WIM stations, the I-84 WIM stations experienced the highest monthly averages, followed by the US-97 WIM stations. Of the US-97 WIM stations, Klamath Falls is the only WIM station to have complete data for each year.

Table 6.5: Total Number of ODOT Class 11 Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	Total Number of Trucks	WIM Station	Total Number of Trucks	WIM Station	Total Number of Trucks	WIM Station	Total Number of Trucks
Woodburn (NB)	1,261,192	Woodburn (NB)	1,272,732	Woodburn (NB)	1,034,184	Woodburn (NB)	1,071,975
Woodburn (SB)	885,969	Woodburn (SB)	947,598	Woodburn (SB)	948,897	Woodburn (SB)	919,433
Ashland (NB)	693,321	Ashland (NB)	711,400	Ashland (NB)	730,383	Ashland (NB)	728,319
Booth Ranch (NB)	673,045	Booth Ranch (SB)	674,747	Booth Ranch (SB)	699,236	Booth Ranch (SB)	698,266
Booth Ranch (SB)	648,149	Booth Ranch (NB)	656,675	Booth Ranch (NB)	698,455	Ashland (SB)	668,234
Ashland (SB)	620,838	Ashland (SB)	654,820	Ashland (SB)	661,275	Booth Ranch (NB)	619,647
Olds Ferry (EB)	441,974	Farewell Bend (WB)	454,997	La Grande (EB)	461,969	La Grande (EB)	490,665
Wyeth (WB)	401,669	Olds Ferry (EB)	444,003	Farewell Bend (WB)	461,704	Olds Ferry (EB)	490,025
Cascade Locks (EB)	394,662	Wyeth (WB)	414,574	Cascade Locks (EB)	374,680	Farewell Bend (WB)	477,385
Farewell Bend (WB)	389,034	Cascade Locks (EB)	409,002	Olds Ferry (EB)	354,743	Wyeth (WB)	426,485
La Grande (EB)	370,231	La Grande (EB)	383,408	Wyeth (WB)	342,171	Cascade Locks (EB)	417,860
Umatilla (SB)	353,753	Umatilla (SB)	377,880	Umatilla (SB)	253,144	Emigrant Hill (WB)	297,321
Emigrant Hill (WB)	332,480	Emigrant Hill (WB)	333,135	Emigrant Hill (WB)	217,143	Klamath Falls (SB)	196,257
Klamath Falls (SB)	200,624	Klamath Falls (SB)	198,241	Klamath Falls (SB)	206,121	Klamath Falls (NB)	112,504
Juniper Butte (SB)	169,282	Juniper Butte (SB)	168,882	Juniper Butte (SB)	170,929	Bend (NB)	109,826
Juniper Butte (NB)	118,720	Juniper Butte (NB)	121,798	Klamath Falls (NB)	120,987	Cold Springs (WB)	80,373
Klamath Falls (NB)	118,057	Klamath Falls (NB)	117,413	Bend (NB)	89,574	Cold Springs (EB)	69,757
Bend (NB)	110,614	Bend (NB)	115,488	Cold Springs (WB)	69,106	Juniper Butte (SB)	64,821
Lowell (WB)	68,761	Cold Springs (WB)	71,625	Juniper Butte (NB)	67,268	Rocky Point (WB)	42,744
Cold Springs (EB)	59,058	Cold Springs (EB)	68,612	Cold Springs (EB)	59,265	Juniper Butte (NB)	NA
Cold Springs (WB)	54,453	Lowell (WB)	64,607	Rocky Point (WB)	44,504	Lowell (WB)	NA
Rocky Point (WB)	47,286	Rocky Point (WB)	47,674	Lowell (WB)	10,136	Umatilla (SB)	NA

Table 6.6: Average Monthly Observed Combined (Truck and Cargo) Weight for ODOT Class 11 Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***
Woodburn (NB)	2,875,058	Woodburn (NB)	2,844,319	Woodburn (NB)	2,266,836	Woodburn (NB)	2,295,466
Ashland (NB)	1,710,429	Woodburn (SB)	1,966,155	Woodburn (SB)	1,929,698	Woodburn (SB)	1,968,765
Woodburn (SB)	1,590,416	Ashland (NB)	1,752,529	Ashland (NB)	1,826,986	Ashland (NB)	1,837,117
Ashland (SB)	1,582,497	Booth Ranch (SB)	1,565,499	Booth Ranch (NB)	1,674,592	Booth Ranch (SB)	1,656,939
Booth Ranch (NB)	1,580,602	Booth Ranch (NB)	1,561,848	Ashland (SB)	1,518,718	Ashland (SB)	1,560,370
Booth Ranch (SB)	1,543,339	Ashland (SB)	1,560,510	Booth Ranch (SB)	1,485,549	Booth Ranch (NB)	1,517,653
La Grande (EB)	1,016,696	Cascade Locks (EB)	1,009,466	La Grande (EB)	1,155,484	La Grande (EB)	1,221,092
Wyeth (WB)	979,544	Farewell Bend (WB)	1,003,474	Farewell Bend (WB)	1,054,996	Olds Ferry (EB)	1,176,185
Olds Ferry (EB)	953,825	Emigrant Hill (WB)	1,003,220	Olds Ferry (EB)	924,284	Farewell Bend (WB)	1,071,269
Cascade Locks (EB)	934,584	Wyeth (WB)	1,002,676	Cascade Locks (EB)	906,567	Cascade Locks (EB)	1,017,800
Umatilla (SB)	877,734	La Grande (EB)	943,514	Wyeth (WB)	818,719	Wyeth (WB)	1,001,742
Farewell Bend (WB)	860,028	Umatilla (SB)	941,115	Umatilla (SB)	804,377	Emigrant Hill (WB)	769,548
Emigrant Hill (WB)	760,604	Olds Ferry (EB)	906,435	Emigrant Hill (WB)	768,182	Klamath Falls (SB)	511,372
Klamath Falls (SB)	558,081	Klamath Falls (SB)	517,014	Klamath Falls (SB)	539,512	Juniper Butte (SB)	455,925
Juniper Butte (SB)	452,165	Juniper Butte (SB)	475,390	Juniper Butte (SB)	485,932	Klamath Falls (NB)	287,736
Bend (NB)	299,612	Bend (NB)	320,954	Klamath Falls (NB)	287,493	Bend (NB)	280,375
Klamath Falls (NB)	276,918	Klamath Falls (NB)	303,219	Juniper Butte (NB)	268,089	Cold Springs (WB)	192,860
Juniper Butte (NB)	272,772	Juniper Butte (NB)	280,929	Bend (NB)	257,747	Cold Springs (EB)	157,011
Lowell (WB)	177,900	Lowell (WB)	176,004	Cold Springs (WB)	144,598	Rocky Point (WB)	95,273
Rocky Point (WB)	98,338	Cold Springs (EB)	125,499	Cold Springs (EB)	121,697	Juniper Butte (NB)	NA
Cold Springs (EB)	83,062	Cold Springs (WB)	125,410	Rocky Point (WB)	85,075	Lowell (WB)	NA
Cold Springs (WB)	72,768	Rocky Point (WB)	96,219	Lowell (WB)	79,669	Umatilla (SB)	NA

* Combined Weight Refers to the Weight of the Truck and the Weight of the Cargo

6.3 ODOT CLASS 12 TO ODOT CLASS 19 TRUCKS

The third group considered for the descriptive analysis consisted of ODOT Class 12 to ODOT Class 19 trucks. Definitions for these classifications are as follows:

- ***ODOT Class 12***: 5-axle twins.
- ***ODOT Class 13***: Other 5-axle combinations.
- ***ODOT Class 14***: 6-axle combinations.
- ***ODOT Class 15***: Other 6-axle combinations.
- ODOT Class 16: Triples.
- ***ODOT Class 17***: Other 7-axle combinations.
- ***ODOT Class 18***: 8-axle combinations.
- ***ODOT Class 19***: 9-axle or more combinations.

As with the previous classification groups, the first aspect assessed was the total number of trucks. A summary of total truck counts by WIM station and year is provided in Table 6.7. Once more, the Woodburn WIM stations experienced the largest volumes of trucks. Following the Woodburn WIM stations are the westernmost I-84 WIM stations (nearest Portland) of Cascade Locks (EB) and Wyeth (WB). When considering WIM stations with complete years of data, the Ashland WIM stations and the easternmost I-84 WIM stations of Olds Ferry (EB) and Farewell Bend (WB) also experienced a high number of trucks. Klamath Falls WIM stations have a low number of trucks compared to the other WIM stations.

As with the previous two classification groups, the next statistic assessed was the average monthly observed combined (truck and cargo) weight. A summary of the average monthly observed combined weights by WIM station and year is provided in Table 6.8. In terms of average monthly observed combined weight, the Woodburn WIM stations experienced the highest averages, followed by the remaining I-5 WIM stations, I-84 WIM stations, and then the US-97 WIM stations.

Table 6.7: Total Number of ODOT Class 12 to ODOT Class 19 Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	**Total Number of Trucks**	**WIM Station**	**Total Number of Trucks**	**WIM Station**	**Total Number of Trucks**	**WIM Station**	**Total Number of Trucks**
Woodburn (NB)	510,740	Woodburn (NB)	537,276	Woodburn (SB)	421,800	Woodburn (SB)	485,744
Woodburn (SB)	409,628	Woodburn (SB)	418,807	Woodburn (NB)	417,426	Woodburn (NB)	443,795
Cascade Locks (EB)	205,875	Cascade Locks (EB)	221,101	Wyeth (WB)	271,452	Cascade Locks (EB)	232,925
Wyeth (WB)	198,411	Wyeth (WB)	213,719	Cascade Locks (EB)	213,716	Wyeth (WB)	231,415
Booth Ranch (SB)	190,817	Booth Ranch (NB)	211,822	Booth Ranch (SB)	201,648	Booth Ranch (SB)	206,359
Umatilla (SB)	184,657	Umatilla (SB)	190,416	Booth Ranch (NB)	175,046	Booth Ranch (NB)	176,988
Booth Ranch (NB)	177,754	Booth Ranch (SB)	190,307	Farewell Bend (WB)	145,561	Olds Ferry (EB)	170,379
Farewell Bend (WB)	136,334	La Grande (EB)	161,147	La Grande (EB)	145,230	Farewell Bend (WB)	160,836
Olds Ferry (EB)	131,689	Olds Ferry (EB)	153,433	Rocky Point (WB)	123,297	La Grande (EB)	153,206
La Grande (EB)	124,408	Farewell Bend (WB)	149,970	Umatilla (SB)	123,185	Rocky Point (WB)	104,138
Emigrant Hill (WB)	110,436	Emigrant Hill (WB)	138,328	Olds Ferry (EB)	117,845	Emigrant Hill (WB)	99,862
Cold Springs (EB)	85,077	Rocky Point (WB)	105,351	Ashland (SB)	81,249	Cold Springs (EB)	93,867
Ashland (SB)	80,397	Cold Springs (EB)	93,870	Ashland (NB)	80,327	Cold Springs (WB)	91,525
Ashland (NB)	80,131	Cold Springs (WB)	87,387	Cold Springs (WB)	79,843	Ashland (SB)	81,544
Rocky Point (WB)	75,884	Ashland (SB)	81,486	Cold Springs (EB)	76,521	Ashland (NB)	80,702
Cold Springs (WB)	68,669	Ashland (NB)	79,886	Emigrant Hill (WB)	69,771	Klamath Falls (SB)	34,908
Juniper Butte (SB)	43,840	Juniper Butte (SB)	46,848	Juniper Butte (SB)	47,426	Klamath Falls (NB)	29,434
Juniper Butte (NB)	42,577	Juniper Butte (NB)	44,399	Klamath Falls (SB)	34,813	Bend (NB)	28,118
Lowell (WB)	32,336	Lowell (WB)	34,179	Klamath Falls (NB)	28,624	Juniper Butte (SB)	18,260
Klamath Falls (SB)	30,267	Klamath Falls (SB)	32,183	Juniper Butte (NB)	23,173	Juniper Butte (NB)	NA
Bend (NB)	26,948	Bend (NB)	29,308	Bend (NB)	21,110	Lowell (WB)	NA
Klamath Falls (NB)	26,181	Klamath Falls (NB)	27,535	Lowell (WB)	7,241	Umatilla (SB)	NA

Table 6.8: Average Monthly Observed Combined (Truck and Cargo) Weight for ODOT Class 12 to ODOT Class 19 Trucks by WIM Station

2015		2016		2017		2018	
WIM Station	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***
Woodburn (NB)	1,438,578	Woodburn (NB)	1,479,566	Woodburn (SB)	1,124,970	Woodburn (SB)	1,372,092
Woodburn (SB)	959,791	Woodburn (SB)	1,137,880	Woodburn (NB)	1,116,788	Woodburn (NB)	1,149,266
Cascade Locks (EB)	666,091	Cascade Locks (EB)	744,398	Wyeth (WB)	792,314	Cascade Locks (EB)	777,271
Wyeth (WB)	579,368	Wyeth (WB)	610,677	Cascade Locks (EB)	703,942	Wyeth (WB)	647,298
Booth Ranch (SB)	544,039	Booth Ranch (NB)	602,019	Booth Ranch (SB)	534,232	Booth Ranch (SB)	610,665
Umatilla (SB)	531,173	Umatilla (SB)	562,783	Booth Ranch (NB)	489,399	Booth Ranch (NB)	510,912
Booth Ranch (NB)	497,813	Booth Ranch (SB)	541,724	Umatilla (SB)	470,827	Olds Ferry (EB)	500,952
La Grande (EB)	380,823	Emigrant Hill (WB)	488,744	La Grande (EB)	426,791	La Grande (EB)	447,990
Farewell Bend (WB)	343,651	La Grande (EB)	391,175	Farewell Bend (WB)	383,921	Farewell Bend (WB)	416,006
Olds Ferry (EB)	331,718	Olds Ferry (EB)	383,562	Olds Ferry (EB)	379,206	Rocky Point (WB)	320,527
Emigrant Hill (WB)	329,284	Farewell Bend (WB)	383,002	Rocky Point (WB)	313,332	Emigrant Hill (WB)	312,194
Rocky Point (WB)	227,577	Rocky Point (WB)	302,795	Emigrant Hill (WB)	296,693	Cold Springs (WB)	309,321
Ashland (NB)	206,723	Cold Springs (EB)	222,982	Cold Springs (WB)	241,553	Cold Springs (EB)	277,521
Ashland (SB)	201,810	Cold Springs (WB)	222,284	Ashland (NB)	209,270	Ashland (NB)	212,753
Cold Springs (EB)	158,371	Ashland (NB)	205,616	Cold Springs (EB)	204,905	Ashland (SB)	189,004
Juniper Butte (SB)	131,294	Ashland (SB)	191,612	Ashland (SB)	185,647	Juniper Butte (SB)	146,225
Cold Springs (WB)	128,594	Juniper Butte (SB)	148,826	Juniper Butte (SB)	152,569	Klamath Falls (SB)	111,132
Juniper Butte (NB)	106,611	Juniper Butte (NB)	112,068	Klamath Falls (SB)	110,417	Bend (NB)	82,514
Lowell (WB)	98,490	Lowell (WB)	107,256	Juniper Butte (NB)	99,977	Klamath Falls (NB)	75,687
Klamath Falls (SB)	97,514	Klamath Falls (SB)	99,098	Lowell (WB)	70,696	Juniper Butte (NB)	NA
Bend (NB)	83,578	Bend (NB)	91,946	Bend (NB)	70,463	Lowell (WB)	NA
Klamath Falls (NB)	60,850	Klamath Falls (NB)	71,933	Klamath Falls (NB)	68,158	Umatilla (SB)	NA

* Combined Weight Refers to the Weight of the Truck and the Weight of the Cargo

6.4 ALL TRUCKS (ODOT CLASS 03 TO ODOT CLASS 19)

The final group considered includes all trucks (ODOT Class 03 to ODOT Class 19, excluding ODOT Class 04 and ODOT Class 07). The same two statistics presented for the previous three classification groups are once more presented for the final classification group. A summary of truck counts considering all trucks is provided in Table 6.9. As with the previous three classification groups, the Woodburn WIM stations and other I-5 WIM stations experienced the largest truck volumes each year. Following the I-5 WIM stations were the I-84 WIM stations and the US-97 WIM stations.

The next statistic assessed was the average monthly observed combined (truck and cargo) weight. A summary of the average monthly observed combined weight considering all trucks is presented in Table 6.10. As with the total number of trucks, the average monthly observed combined weight averages were highest at the Woodburn WIM stations and the other I-5 WIM stations. This was again followed by the I-84 WIM stations and the US-97 WIM stations.

Table 6.9: Total Number of Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	Total Number of Trucks	WIM Station	Total Number of Trucks	WIM Station	Total Number of Trucks	WIM Station	Total Number of Trucks
Woodburn (NB)	3,052,041	Woodburn (NB)	3,233,081	Woodburn (NB)	2,627,107	Woodburn (NB)	2,711,035
Woodburn (SB)	2,434,193	Woodburn (SB)	3,176,212	Woodburn (SB)	2,077,191	Woodburn (SB)	2,235,196
Booth Ranch (NB)	1,510,660	Booth Ranch (NB)	1,597,790	Booth Ranch (NB)	1,600,228	Booth Ranch (NB)	1,583,294
Booth Ranch (SB)	1,364,747	Booth Ranch (SB)	1,385,232	Booth Ranch (SB)	1,304,546	Booth Ranch (SB)	1,471,140
Ashland (NB)	1,164,175	Ashland (NB)	1,219,904	Ashland (NB)	1,272,254	Ashland (NB)	1,261,498
Ashland (SB)	1,148,740	Ashland (SB)	1,138,306	Ashland (SB)	1,123,012	Ashland (SB)	1,139,439
Wyeth (WB)	1,048,310	Wyeth (WB)	1,108,337	Wyeth (WB)	1,032,936	Cascade Locks (EB)	1,075,075
Umatilla (SB)	994,310	Cascade Locks (EB)	1,061,606	Rocky Point (WB)	1,001,501	Wyeth (WB)	1,044,428
Cascade Locks (EB)	955,866	Umatilla (SB)	1,018,190	Cascade Locks (EB)	965,819	Olds Ferry (EB)	910,139
La Grande (EB)	817,542	Bend (NB)	856,340	Farewell Bend (WB)	795,861	Rocky Point (WB)	899,429
Farewell Bend (WB)	763,439	Emigrant Hill (WB)	832,283	La Grande (EB)	788,240	La Grande (EB)	835,306
Bend (NB)	687,268	Farewell Bend (WB)	766,201	Bend (NB)	684,389	Farewell Bend (WB)	818,938
Olds Ferry (EB)	679,478	Rocky Point (WB)	757,511	Juniper Butte (SB)	670,594	Bend (NB)	720,585
Emigrant Hill (WB)	655,363	La Grande (EB)	732,132	Olds Ferry (EB)	657,799	Klamath Falls (SB)	579,871
Juniper Butte (SB)	610,762	Olds Ferry (EB)	723,785	Umatilla (SB)	618,064	Emigrant Hill (WB)	501,881
Klamath Falls (SB)	512,980	Juniper Butte (SB)	658,681	Klamath Falls (SB)	605,468	Klamath Falls (NB)	390,206
Rocky Point (WB)	485,024	Juniper Butte (NB)	553,947	Emigrant Hill (WB)	379,819	Juniper Butte (SB)	304,899
Juniper Butte (NB)	478,941	Klamath Falls (SB)	500,283	Klamath Falls (NB)	342,735	Cold Springs (EB)	258,514
Klamath Falls (NB)	319,538	Klamath Falls (NB)	395,655	Juniper Butte (NB)	340,624	Cold Springs (WB)	241,284
Lowell (WB)	261,568	Lowell (WB)	303,009	Cold Springs (WB)	195,169	Juniper Butte (NB)	NA
Cold Springs (EB)	171,116	Cold Springs (EB)	213,686	Cold Springs (EB)	190,914	Lowell (WB)	NA
Cold Springs (WB)	137,796	Cold Springs (WB)	200,362	Lowell (WB)	53,950	Umatilla (SB)	NA

Table 6.10: Average Monthly Observed Combined (Truck and Cargo) Weight for All Trucks by WIM Station and Year

2015		2016		2017		2018	
WIM Station	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***	**WIM Station**	**Observed Combined Weight (tons)***
Woodburn (NB)	5,039,247	Woodburn (NB)	5,113,723	Woodburn (NB)	4,031,214	Woodburn (NB)	4,122,392
Woodburn (SB)	3,119,560	Woodburn (SB)	3,993,857	Woodburn (SB)	3,490,964	Woodburn (SB)	3,843,643
Booth Ranch (NB)	2,422,897	Booth Ranch (NB)	2,564,749	Booth Ranch (NB)	2,580,183	Booth Ranch (SB)	2,567,142
Booth Ranch (SB)	2,338,863	Booth Ranch (SB)	2,368,664	Ashland (NB)	2,268,266	Booth Ranch (NB)	2,482,096
Ashland (NB)	2,111,829	Ashland (NB)	2,171,874	Booth Ranch (SB)	2,235,246	Ashland (NB)	2,279,749
Ashland (SB)	2,016,972	Cascade Locks (EB)	1,990,460	Ashland (SB)	1,902,510	Cascade Locks (EB)	2,030,336
Cascade Locks (EB)	1,796,364	Ashland (SB)	1,959,286	Wyeth (WB)	1,834,193	Ashland (SB)	1,954,643
Wyeth (WB)	1,783,592	Wyeth (WB)	1,855,417	Cascade Locks (EB)	1,817,412	Wyeth (WB)	1,861,318
Umatilla (SB)	1,638,762	Umatilla (SB)	1,745,295	La Grande (EB)	1,691,593	Olds Ferry (EB)	1,812,046
La Grande (EB)	1,567,176	Emigrant Hill (WB)	1,707,739	Farewell Bend (WB)	1,537,991	La Grande (EB)	1,785,230
Farewell Bend (WB)	1,388,341	Farewell Bend (WB)	1,472,852	Umatilla (SB)	1,444,649	Farewell Bend (WB)	1,581,324
Olds Ferry (EB)	1,344,785	La Grande (EB)	1,457,659	Olds Ferry (EB)	1,405,490	Emigrant Hill (WB)	1,159,584
Emigrant Hill (WB)	1,229,299	Olds Ferry (EB)	1,356,251	Emigrant Hill (WB)	1,160,541	Juniper Butte (SB)	843,767
Klamath Falls (SB)	785,576	Juniper Butte (SB)	832,890	Juniper Butte (SB)	854,519	Klamath Falls (SB)	783,265
Juniper Butte (SB)	768,492	Klamath Falls (SB)	741,781	Klamath Falls (SB)	817,233	Rocky Point (WB)	727,854
Bend (NB)	634,224	Bend (NB)	734,802	Rocky Point (WB)	642,656	Bend (NB)	628,045
Juniper Butte (NB)	527,688	Rocky Point (WB)	622,175	Bend (NB)	584,644	Cold Springs (WB)	547,844
Rocky Point (WB)	500,296	Juniper Butte (NB)	570,942	Juniper Butte (NB)	561,330	Klamath Falls (NB)	500,060
Klamath Falls (NB)	423,532	Klamath Falls (NB)	496,846	Klamath Falls (NB)	451,805	Cold Springs (EB)	487,972
Lowell (WB)	362,754	Lowell (WB)	382,750	Cold Springs (WB)	416,549	Juniper Butte (NB)	NA
Cold Springs (EB)	257,133	Cold Springs (EB)	377,864	Cold Springs (EB)	360,716	Lowell (WB)	NA
Cold Springs (WB)	211,150	Cold Springs (WB)	373,025	Lowell (WB)	198,672	Umatilla (SB)	NA

* Combined Weight Refers to the Weight of the Truck and the Weight of the Cargo

6.5 SUMMARY

Regardless of the classification group, the Woodburn WIM stations consistently account for the highest truck volumes. Further, the remaining I-5 WIM stations (Ashland and Booth Ranch) consistently account for high truck volumes relative to other WIM stations. Outside of the I-5 WIM stations, stations that account for a large number of total trucks are contingent on the classification group. And, although there are slight variations by year, the WIM stations that account for the largest volumes remain relatively consistent for each classification group. For ODOT Class 03 to ODOT Class 10 trucks, Bend (NB) on US-97 and Rocky Point (WB) on US-30 also experience high volumes. Although these two WIM stations experience high volumes, there are months in which no data is available at Bend (NB). As for Rocky Point (WB), all data is available, but it is difficult to distinguish what lower classifications are freight-related vehicles and which ones are not (this is true at all WIM stations when considering the lower classification group, ODOT Class 03 to ODOT Class 10 trucks). For ODOT Class 11 trucks, outside of the Woodburn WIM stations, WIM stations at points of entry or exit experience high volumes; specifically, the Ashland WIM stations, Cascade Locks (EB), Wyeth (WB), Olds Ferry (EB), and Farewell Bend (WB). Considering ODOT Class 12 to ODOT Class 19 trucks, outside of the Woodburn WIM stations, the westernmost I-84 WIM stations of Cascade Locks (EB) and Wyeth (WB) experience the highest volume of trucks. Lastly, when considering all trucks, Ashland and Booth Ranch WIM stations on I-5, along with the westernmost and easternmost I-84 WIM stations, experience the highest volumes.

When focusing on the total observed combined (truck and cargo) weight, similar trends are observed. That is, the Woodburn WIM stations consistently account for the largest observed combined weights and the remaining WIM stations that experience high total observed combined weight are contingent on classification group. Being that Woodburn sees a large proportion of empty trucks (see Table 7.13), this finding may simply be related to the sheer volume of truck traffic the Woodburn WIM stations experience. However, as is the case with the total number of trucks, there are slight variations by year, but the WIM stations that experience high observed combined weights remain relatively consistent. As with truck volumes, Bend (NB) and Rocky Point (WB) experience high observed combined weights of ODOT Class 03 to ODOT Class 10 trucks. For ODOT Class 11 trucks, the Ashland WIM stations, the I-84 border stations, and the Klamath Falls WIM stations experience the largest observed combined weights. For ODOT Class 12 to ODOT Class 19 trucks, the westernmost I-84 WIM stations of Cascade Locks (EB) and Wyeth (WB) experience the largest observed combined weights outside of the Woodburn WIM stations. Lastly, when considering all trucks, Ashland and Booth Ranch WIM stations on I-5, along with the westernmost and easternmost I-84 WIM stations, experience the highest observed combined weights. Of the non-interstate WIM stations, the Klamath Falls WIM stations consistently experience high observed combined weights.

In summary, the Woodburn WIM stations account for the largest volumes and observed combined (truck and cargo) weights across all classification groups and years of data. Outside of Woodburn, although there are slight variations, the WIM stations at points of entry or exit experience the largest volumes and observed combined weights. These results are expected, as these WIM stations capture freight destined to Oregon, originating from Oregon, or traveling through Oregon (north-south direction). As such, these WIM stations are selected for further analysis; specifically, Ashland WIM stations, Woodburn WIM stations, Cascade Locks and Wyeth WIM stations, Olds Ferry and Farewell Bend WIM stations, and Klamath Falls WIM stations

7.0 DESCRIPTIVE ANALYSIS OF SELECT WIM STATIONS

This chapter presents a focused descriptive analysis of select WIM stations. The select WIM stations considered for this descriptive analysis were chosen based on the quality control analysis, data availability (i.e., no months or years in which data was unavailable), and the descriptive analysis presented in Chapter 6.0. Therefore, based on these aspects, ten WIM stations were chosen for further analysis. The ten select WIM stations are shown in Table 7.1.

Table 7.1: Select WIM Stations

WIM Station	Highway	Direction
Ashland	I-5	Northbound
Ashland	I-5	Southbound
Woodburn	I-5	Northbound
Woodburn	I-5	Southbound
Cascade Locks	I-84	Eastbound
Wyeth	I-84	Westbound
Olds Ferry	I-84	Eastbound
Farewell Bend	I-84	Westbound
Klamath Falls	US-97	Northbound
Klamath Falls	US-97	Southbound

To build upon the statistics in Chapter 6.0, the descriptive analysis for the select WIM stations focuses on directional trends and seasonal trends at each WIM station. The same truck classification groups are applied to this descriptive analysis. As to not overlap years of WIM data, the seasonal trends are based on the following:

- January to April
- May to August
- September to December

In addition to directional and seasonal trends, monthly percentages of volume and combined (truck and cargo) weight are presented and analyzed to determine monthly trends. Additionally, day-of-week trends are presented. After detailing these temporal trends, annual growth rates in terms of volume and combined weight are computed for each WIM station, as well as an overall annual growth rate considering all select WIM stations. The final assessment consists of a summary table detailing truck counts, weight, and proportion of empties by WIM station.

7.1 ASHLAND WIM STATIONS

The first WIM stations assessed were the Ashland stations, located at the Oregon-California border. Directional trends and seasonal trends are presented based on the four classification groups previously defined. Classification-specific directional and seasonal trend plots can be viewed in Unnikrishnan et al. (2019).[20] For Figure 7.1 and Figure 7.2, truck volume and average monthly observed combined (truck and cargo) weight were normalizedt o values between 0 and 1 to show seasonal patterns using the same scale. Value were normalized by taking the value of weight or volume, subtracting the minimum value, then dividing by the difference between the maximum and minimum value. As a result, any white space observed does not correspond to missing data. This normalization procedure was applied to all succeeding WIM stations in Chapter 0.

For ODOT Class 03 to ODOT Class 10 truck directional trends based on volumes, refer to Table 7.2 Other than 2015, larger ODOT Class 03 to ODOT Class 10 truck volumes were experienced in the northbound direction, indicating more traffic headed into or through Oregon. Being that the combined (truck and cargo) weight trends were the same, this also indicates more freight (in terms of weight) is heading into or through Oregon. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.1. In terms of both volumes and combined weight, the summer months account for the largest proportion, with the early and late parts of the years accounting for comparable proportions. These trends were consistent in both directions, Ashland (NB) and Ashland (SB), for each year of WIM data.

For ODOT Class 11 truck directional trends based on truck volumes, refer to Table 7.2. For each year of WIM data, higher volumes and average monthly observed combined (truck and cargo) weight are observed in the northbound direction, indicating more traffic and combined weight headed into or through Oregon. However, the average monthly observed combined truck weight was highest in the southbound direction in 2015. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.1. In terms of both volumes and combined weight, the summer months account for the largest proportion, with the early and late parts of the years accounting for comparable proportions. At the Ashland (NB) WIM station, higher volumes and observed combined weights were experienced in recent years, 2017 and 2018.

For ODOT Class 12 to ODOT Class 19 truck directional trends, refer to Table 7.2. For each year of WIM data, higher volumes are observed in the southbound direction, and higher average monthly observed combined (truck and cargo) weights are observed in the northbound direction. In 2015, the difference in combined weight was less than 10,000 tons, and the difference in volume is less than 1,000. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.2. In terms of volumes, the summer months account for the largest proportion, with the early and late parts of the years accounting for comparable proportions. However, the range between seasons is less than 5,000 trucks. In terms of combined weight, there is also a spike in the summer months, in which the range from the other seasons is significantly greater.

For all trucks, directional trends are shown in Table 7.2. For each year of WIM data, higher volumes, and average monthly observed combined (truck and cargo) weights are observed in the northbound direction. In 2015, however, the difference in volumes was substantially less compared to other years. Seasonal volume and combined weight trends were also determined,

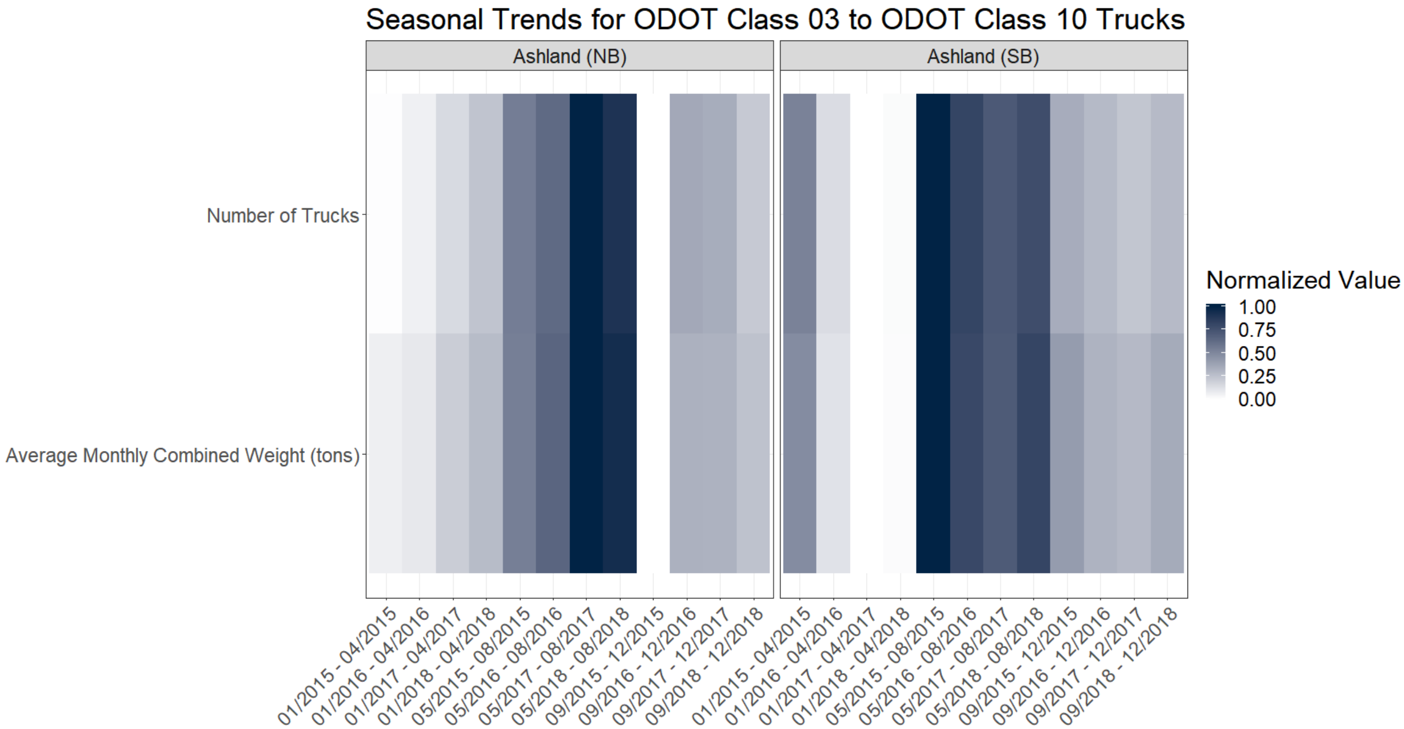
[20] All directional and seasonal trend plots by classification group can be viewed here.

where these trends can be observed in Figure 7.2. In terms of volumes and average monthly observed combined weights, the summer month's account for the largest proportion, with the early and late parts of the years accounting for comparable proportions. In the northbound direction, 2017 and 2018 experienced moderately higher volumes and average monthly observed combined weights compared to 2015 and 2016.

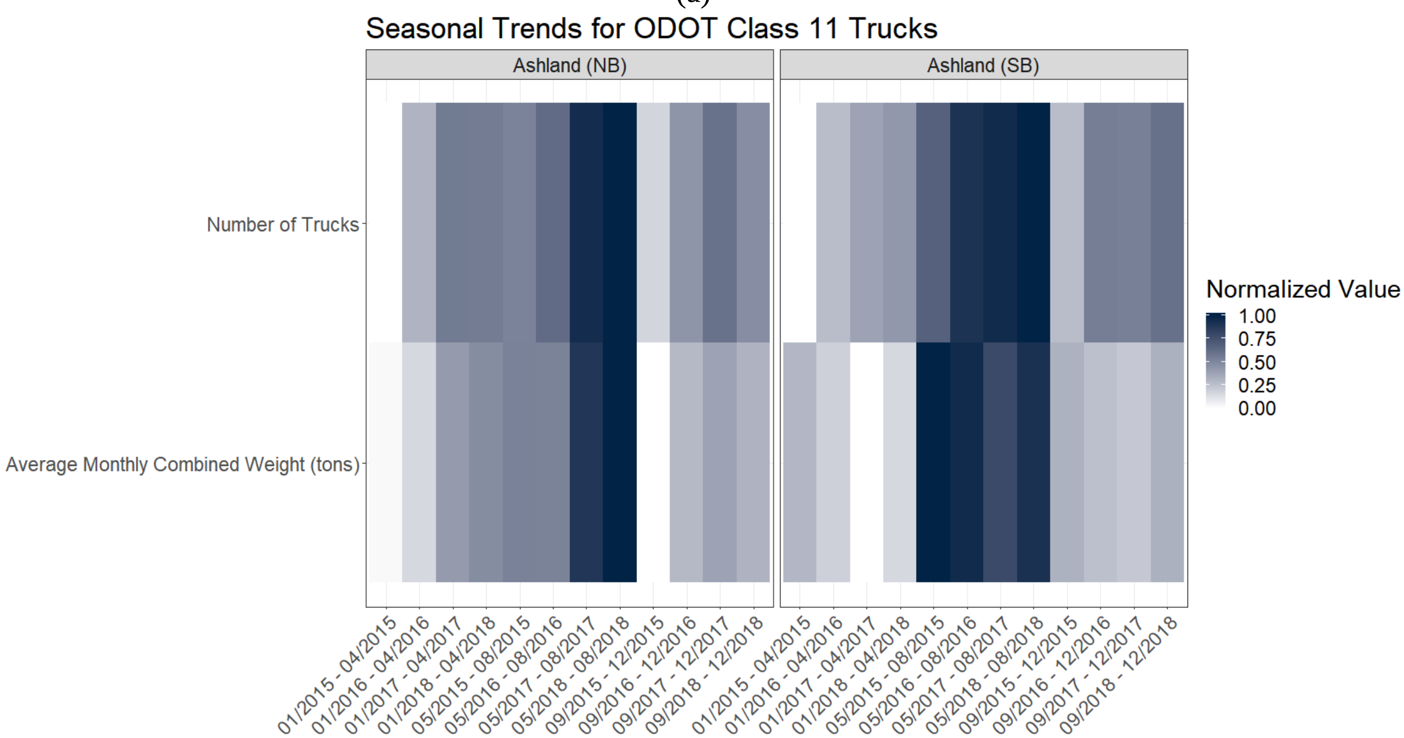
Table 7.2: Summary of Directional Trends by Classification Group at Ashland WIM Stations

		Northbound				Southbound			
Classification	Year	Number of Trucks	Percent of Annual Total[1]	Average Monthly Observed Combined Weight (tons)[2]	Percent of Annual Total[1]	Number of Trucks	Percent of Annual Total[1]	Average Monthly Observed Combined Weight (tons)[2]	Percent of Annual Total[1]
ODOT Class 03 to ODOT Class 10	2015	390,723	33.56%	194,677	9.22%	447,505	38.96%	232,664	11.54%
	2016	428,618	35.14%	213,729	9.84%	402,000	35.32%	207,164	10.57%
	2017	461,544	36.28%	232,010	10.23%	380,488	33.88%	198,145	10.41%
	2018	452,477	35.87%	229,879	10.08%	389,661	34.20%	205,269	10.50%
ODOT Class 11	2015	693,321	59.55%	1,710,429	80.99%	620,838	54.05%	1,582,497	78.46%
	2016	711,400	58.32%	1,752,529	80.69%	654,820	57.53%	1,560,510	79.65%
	2017	730,383	57.41%	1,826,986	80.55%	661,275	58.88%	1,518,718	79.83%
	2018	728,319	57.73%	1,837,117	80.58%	668,234	58.65%	1,560,370	79.83%
ODOT Class 12 to ODOT Class 19	2015	80,131	6.88%	206,723	9.79%	80,397	7.00%	201,810	10.01%
	2016	79,886	6.55%	205,616	9.47%	81,486	7.16%	191,612	9.78%
	2017	80,327	6.31%	209,270	9.23%	81,249	7.23%	185,647	9.76%
	2018	80,702	6.40%	212,753	9.33%	81,544	7.16%	189,004	9.67%
All Trucks (ODOT Class 03 to ODOT Class 19)	2015	1,164,175	-	2,111,829	-	1,148,740	-	2,016,972	-
	2016	1,219,904	-	2,171,874	-	1,138,306	-	1,959,286	-
	2017	1,272,254	-	2,268,266	-	1,123,012	-	1,902,510	-
	2018	1,261,498	-	2,279,749	-	1,139,439	-	1,954,643	-

[1] Percent Reflects the Proportion of Total Number of Trucks (e.g., ODOT Class 11 Trucks Account for 59.55% of Truck Volume and 80.99% of Average Monthly Observed Combined Weight in the Northbound Direction in 2015)
[2] Combined Weight Refers to the Weight of the Truck and the Cargo

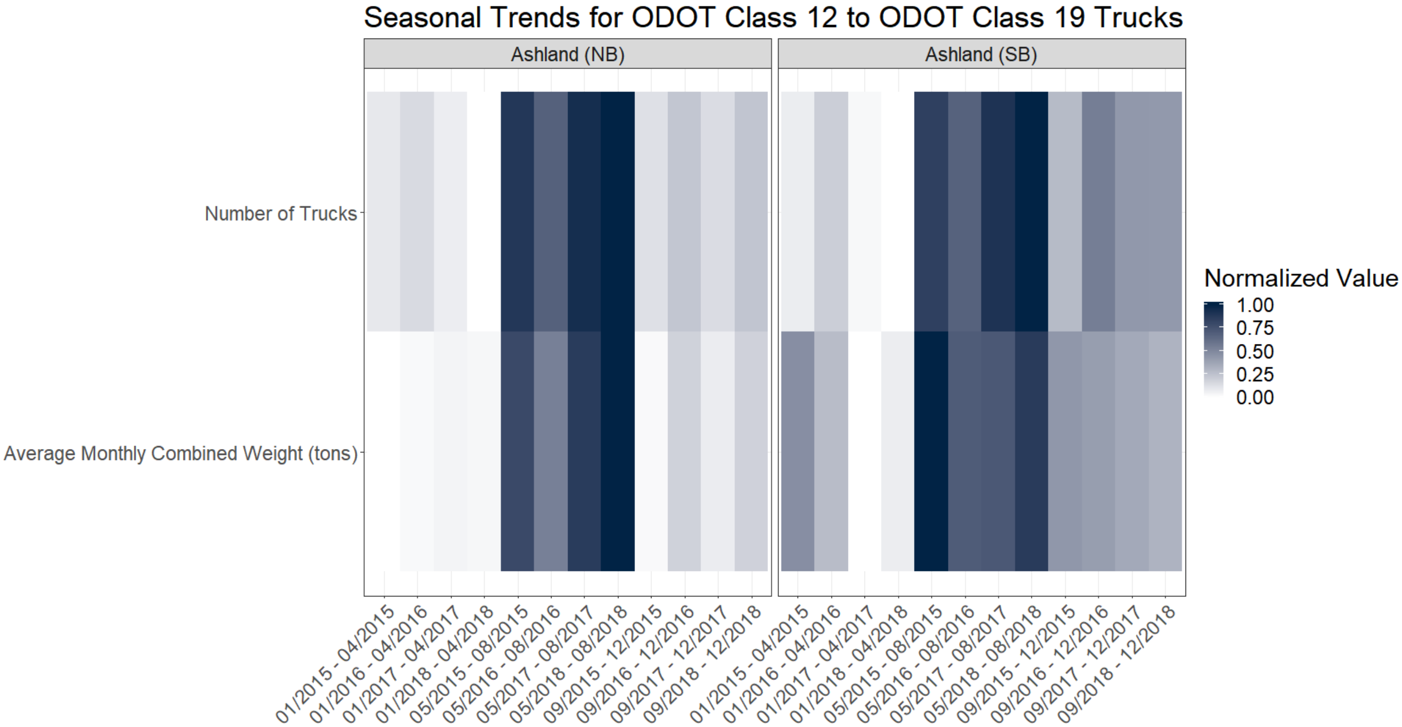


(a)

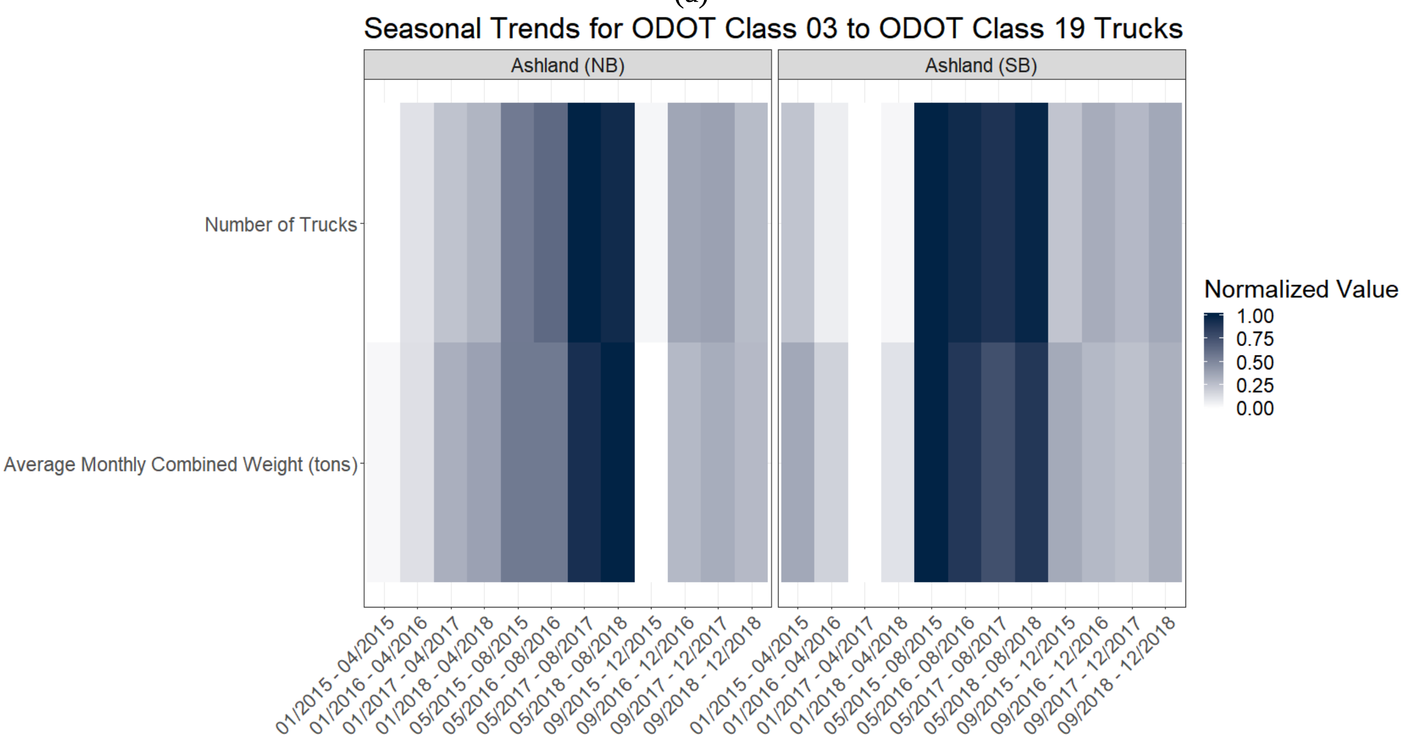


(b)

Figure 7.1: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 03 to ODOT Class 10 and (b) ODOT Class 11 trucks at Ashland WIM stations



(a)



(b)

Figure 7.2: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 12 to ODOT Class 19 and (b) ODOT Class 03 to ODOT Class 19 trucks at Ashland WIM stations

7.2 WOODBURN WIM STATIONS

The second set of WIM stations assessed were the Woodburn stations, the northernmost WIM stations along the I-5 corridor. Directional trends and seasonal trends are presented based on the four classification groups previously defined. For Figure 7.3 and Figure 7.4, truck volume and average monthly observed combined (truck and cargo) weight were normalized to show seasonal patterns using the same scale. As a result, any white space observed does not correspond to missing data.

For ODOT Class 03 to ODOT Class 10 truck directional trends, refer to Table 7.3. Other than 2016, in which a spike in southbound volumes and average monthly observed combined (truck and cargo) weights were experienced, larger volumes and average monthly observed combined weights were experienced in the northbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.3. Unlike Ashland, seasonal trends vary. In the northbound direction, summer accounts for higher volumes except in the year 2017, in which there was a decrease in truck volume. This year also had little observations in the month of July, possibly contributing to this trend. The small number of observations in the month of July may be due to closure. In the southbound direction, the early year and summer months were comparable, with the fall months also being comparable in 2017 and 2018. In the previous two years, there was a decrease in 2016 and an increase in 2015. As stated previously, the same trends are observed in terms of average monthly observed combined weight.

For ODOT Class 11 truck directional trends, refer to Table 7.3. For each year, the northbound direction experienced higher volumes and average monthly observed combined (truck and cargo) weight. However, in 2017 and 2018, the differences in direction were not as profound as the previous two years. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.3. In the northbound direction, there were minor differences between seasons in terms of volume; however, there was a negative spike in the summer months in 2017 and moderately lower volumes in 2018. The same trend in terms of average monthly observed combined weight was also observed in the northbound direction. In the southbound direction, similar volume trends were observed, but with higher summer spikes and higher fall volumes and combined weight. In the southbound direction, however, combined weight trends were quite different. There was a slight spike in the summer months in 2016 and 2017, a slight decrease in the summer months in 2018, and an increasing trend throughout the year in 2015.

For ODOT Class 12 to ODOT Class 19 truck directional trends, refer to Table 7.3. In 2015 and 2016, volume and average monthly observed combined (truck and cargo) weight values were higher in the northbound direction. In 2017, volume and average monthly observed combined weight values were approximately the same. Then, in 2018, volume and combined weight values were higher in the southbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.4. In the northbound direction, trends varied by year. In 2015, there was a steady decrease in volumes throughout the year. In 2016, the trend followed that of Ashland, as there was a spike during the summer months, and the other parts of the year were comparable. In 2017 there was a slight spike during the summer months.

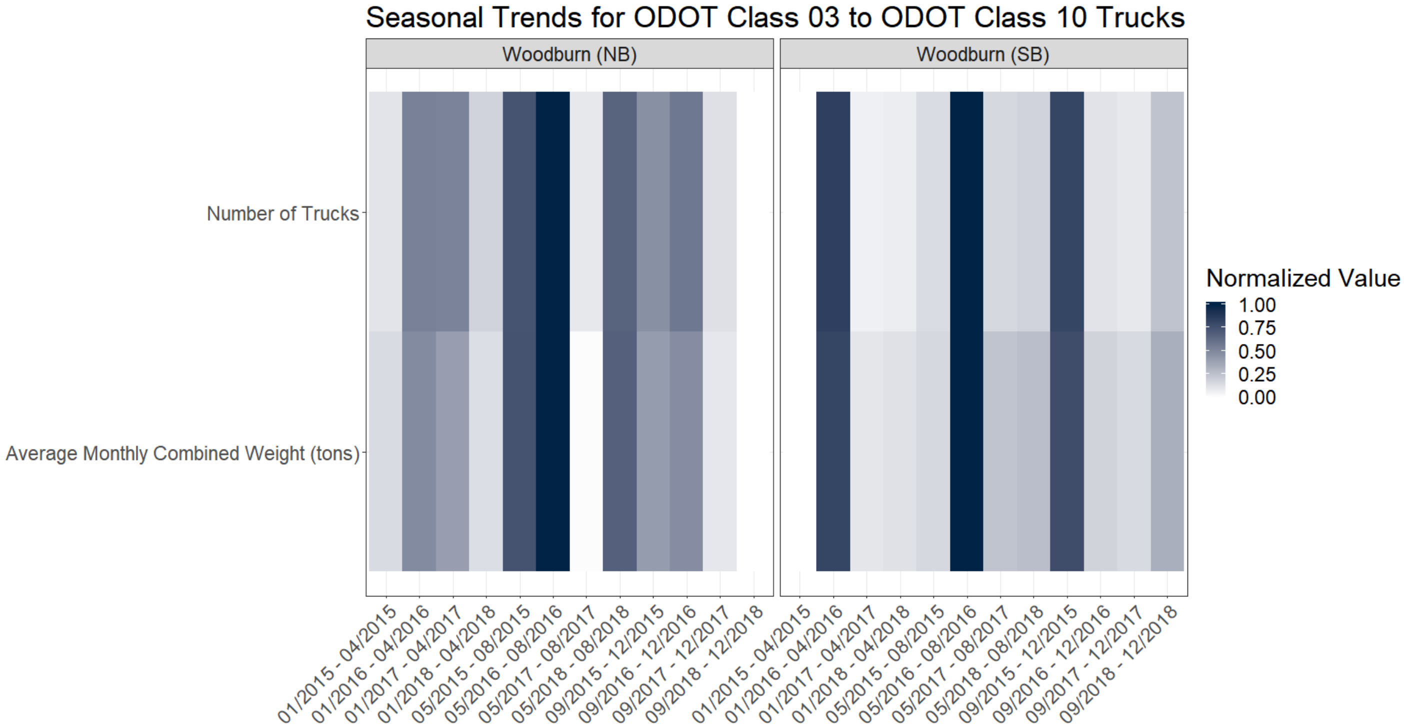
Lastly, in 2018, there was a decrease during the summer months and higher volumes in the early parts of the year. The same trends were observed in the northbound direction in terms of combined weight. In the southbound direction, volumes were consistent throughout the year for all years but 2018, in which there was a moderate spike during the summer months. Combined weight trends in the southbound direction were tantamount to volume trends in the southbound direction.

For all trucks, directional trends are shown in Table 7.3. For each year, higher volumes and average monthly observed combined (truck and cargo) weights are observed in the northbound direction, with a slight difference in volumes in 2016. Seasonal trends are shown in Figure 7.4. In the northbound direction, there were slight spikes in volume during the summer months in 2015, 2016, and 2018, while there was a slight decrease in 2017. Similar trends in the northbound direction were observed in terms of combined weight. In the southbound direction, volumes in the early part of the year and during the summer were fairly consistent, with 2016 having a substantially higher number of trucks. In the later parts of the year, trends varied based on year. In 2015, there was a sharp increase in volume in the later part of the year. In 2016, there was a significant decrease in volume in the later part of the year. Lastly, in 2017 there was a slight increase, and in 2018 there was a slight decrease. Combined weight trends in the southbound direction were equivalent to the volume trends.

Table 7.3: Summary of Directional Trends by Classification Group at Woodburn WIM Stations

		Northbound				Southbound			
Classification	**Year**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	Percent of Annual Total[1]
ODOT Class 03 to ODOT Class 10	2015	1,280,109	41.94%	725,611	14.40%	1,138,596	46.78%	569,352	18.25%
	2016	1,423,073	44.02%	789,838	15.45%	1,809,807	56.98%	889,822	22.28%
	2017	1,175,497	44.74%	647,590	16.06%	706,494	34.01%	436,295	12.50%
	2018	1,195,265	44.09%	677,660	16.44%	830,019	37.13%	502,787	13.08%
ODOT Class 11	2015	1,261,192	41.32%	2,875,058	57.05%	885,969	36.40%	1,590,416	50.98%
	2016	1,272,732	39.37%	2,844,319	55.62%	947,598	29.83%	1,966,155	49.23%
	2017	1,034,184	39.37%	2,266,836	56.23%	948,897	45.68%	1,929,698	55.28%
	2018	1,071,975	39.54%	2,295,466	55.68%	919,433	41.13%	1,968,765	51.22%
ODOT Class 12 to ODOT Class 19	2015	510,740	16.73%	1,438,578	28.55%	409,628	16.83%	959,791	30.77%
	2016	537,276	16.62%	1,479,566	28.93%	418,807	13.19%	1,137,880	28.49%
	2017	417,426	15.89%	1,116,788	27.70%	421,800	20.31%	1,124,970	32.23%
	2018	443,795	16.37%	1,149,266	27.88%	485,744	21.73%	1,372,092	35.70%
All Trucks (ODOT Class 03 to ODOT Class 19)	2015	3,052,041	-	5,039,247	-	2,434,193	-	3,119,560	-
	2016	3,233,081	-	5,113,723	-	3,176,212	-	3,993,857	-
	2017	2,627,107	-	4,031,214	-	2,077,191	-	3,490,964	-
	2018	2,711,035	-	4,122,392	-	2,235,196	-	3,843,643	-

[1] Percent Reflects the Proportion of Total Number of Trucks (e.g., ODOT Class 11 Trucks Account for 41.32% of Truck Volume and 57.05% of Average Monthly Observed Combined Weight in the Northbound Direction in 2015)
[2] Combined Weight Refers to the Weight of the Truck and the Cargo



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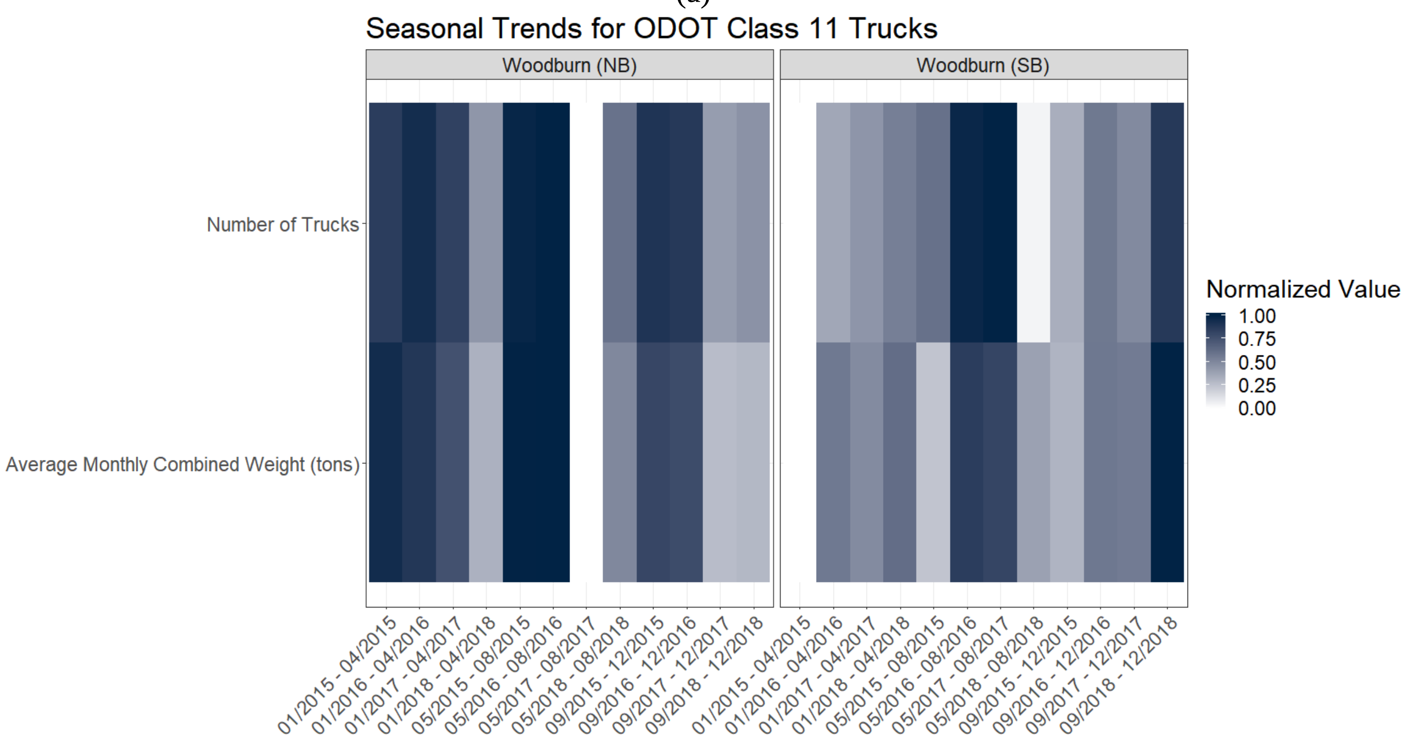
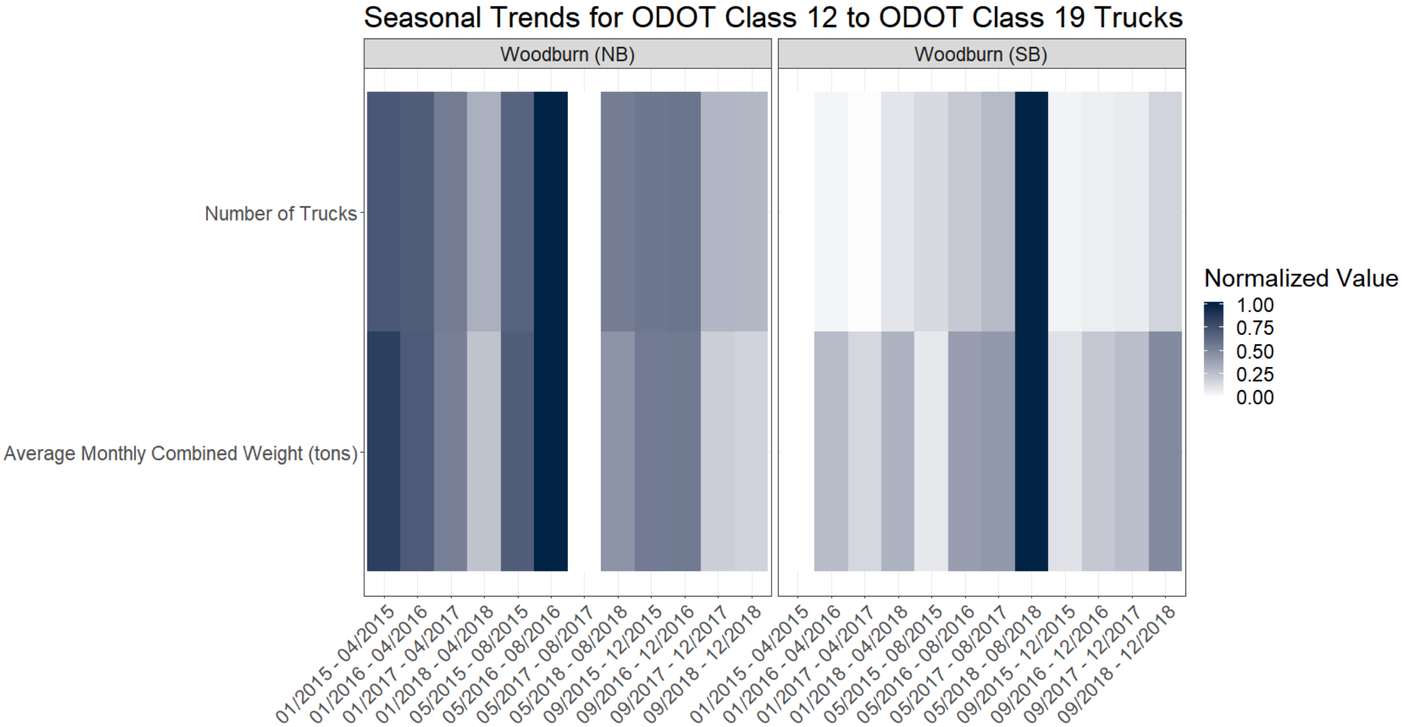


(b)

Figure 7.3: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 03 to ODOT Class 10 and (b) ODOT Class 11 trucks at Woodburn WIM stations



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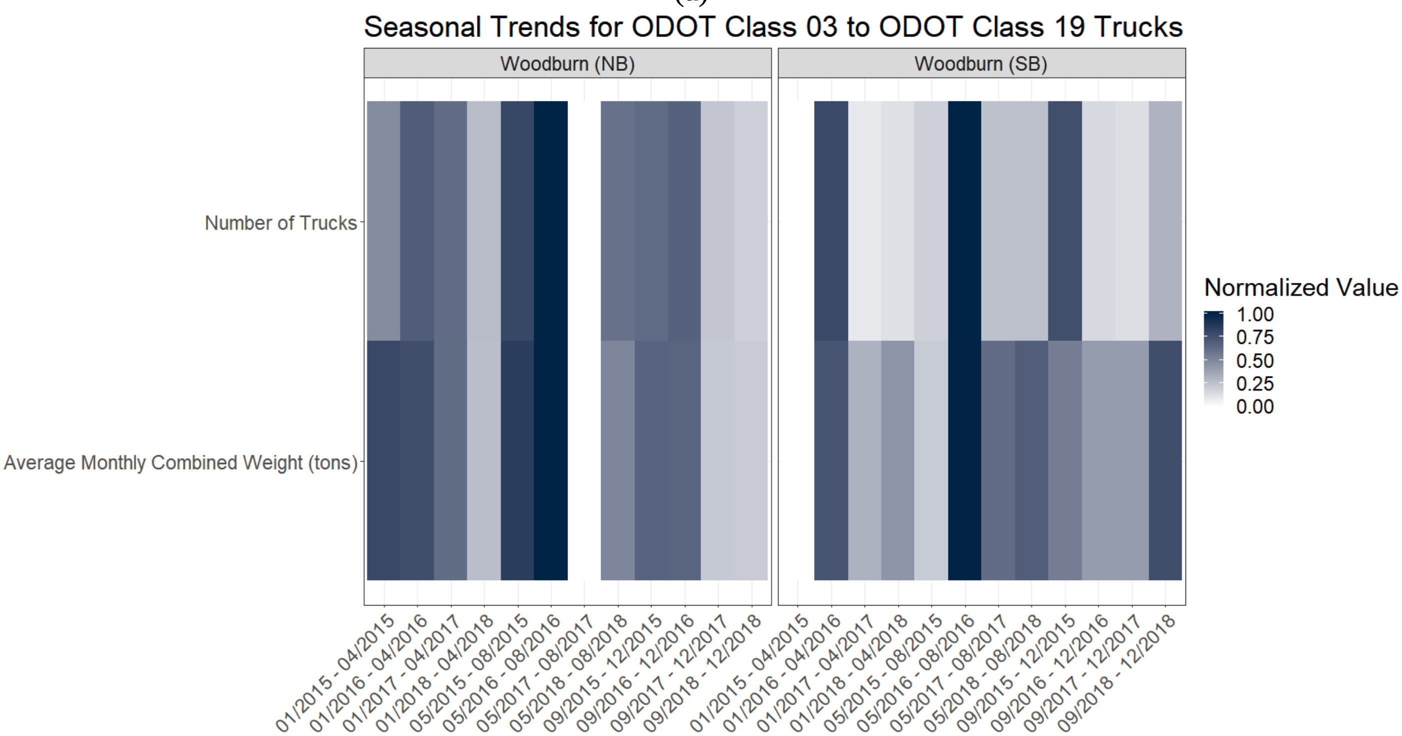


Figure 7.4: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 12 to ODOT Class 19 and (b) ODOT Class 03 to ODOT Class 19 trucks at Woodburn WIM stations

7.3 CASCADE LOCKS AND WYETH WIM STATIONS

The next pair of WIM stations assessed were the Cascade Locks and Wyeth WIM stations, the westernmost WIM stations along the I-84 corridor. Directional trends and seasonal trends are presented based on the four classification groups previously defined. For Figure 7.5 and Figure 7.6, truck volume and average monthly observed combined (truck and cargo) weight were normalized to show seasonal patterns using the same scale. As a result, any white space observed does not correspond to missing data.

For ODOT Class 03 to ODOT Class 10 truck directional trends, refer to Table 7.4. Other than 2018, larger truck volumes and average monthly observed combined (truck and cargo) weights were experienced in the westbound direction (Wyeth). In 2018, the eastbound direction (Cascade Locks) experienced higher truck volumes and average monthly observed combined weight. Seasonal volume and combined weight trends were also determined, where these trends can be seen in Figure 7.5. The seasonal trends at these WIM stations follow that of Ashland, where there are spikes in volumes and average monthly observed combined weight in the summer months. Different from Ashland, the later part of the year accounted for higher volumes and average monthly observed combined weights compared to the early part of the year. These trends are true in both the eastbound and westbound directions.

For ODOT Class 11 truck directional trends, refer to Table 7.4. In 2015, 2016, and 2018, volumes were slightly higher in the westbound direction (Wyeth) but had a sharp decrease in 2017. In terms of average monthly observed combined (truck and cargo) weight, the eastbound direction (Cascade Locks) accounted for marginally more in 2016, 2017, and 2018 (Cascade Locks had lower volumes in 2016 and 2018, yet higher average monthly observed combined weights). Seasonal volume and average monthly observed combined weight trends were also determined, where these trends can be seen in Figure 7.5. In terms of volumes, the trends in both directions are similar. Of interest is the volume trend in 2018, in which there was a substantial decrease in volumes in the later part of the year. This was observed in both directions. In terms of average monthly observed combined weight, the same trends observed for volumes were observed.

For ODOT Class 12 to ODOT Class 19 truck directional trends, refer to Table 7.4. In 2015, 2016, and 2018 slightly higher volumes were observed in the eastbound (Cascade Locks) direction, while in 2017, higher volumes were experienced in the westbound (Wyeth) direction. In terms of combined (truck and cargo) weight, higher combined weights were observed in the eastbound direction in 2015, 2016, and 2018, while higher combined weights were observed in the westbound direction in 2017. Seasonal volume and average monthly observed combined weight trends were also determined, where these trends can be seen in Figure 7.6. Volume trends by season varied by direction. In the eastbound direction, there were slight spikes during the summer months in each year, with there being a sharp decrease in volume in the later part of the year in 2017. In the westbound direction, there were minimal spikes in the summer in 2015, 2016, and 2018. In 2017, volumes steadily increased throughout the year. The directional season volume trends were also observed for average monthly observed combined weight.

For all trucks, directional trends are shown in Table 7.4. In terms of volume, higher volumes are observed in the westbound (Wyeth) direction in 2015, 2016, and 2017, while the eastbound

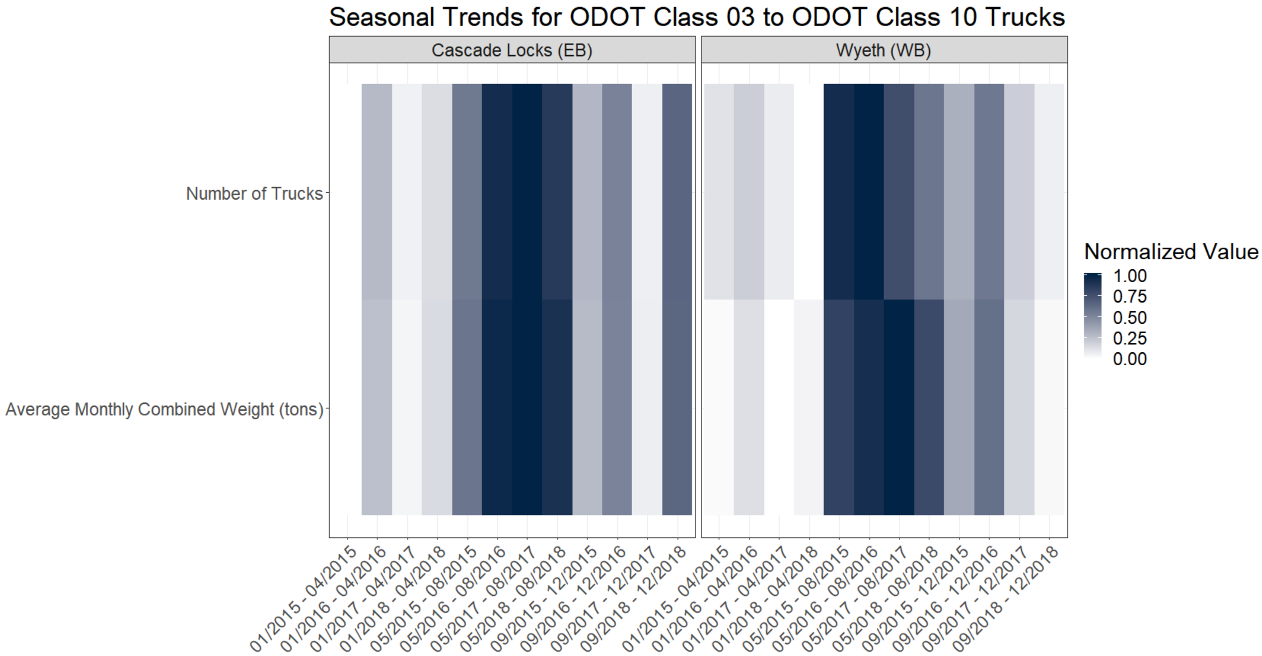
(Cascade Locks) had higher volumes in 2018. As for average monthly observed combined (truck and cargo) weight, although higher volumes were observed in the westbound direction, higher average monthly observed combined weights were experienced in the eastbound direction in 2015 and 2016. In 2017, average monthly observed combined weights were marginally higher in the westbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be seen in Figure 7.6. In the eastbound direction, there were slight spikes in volume during the summer months in 2015, 2016, and 2018, while there was a sharp decrease in 2017. Similar trends in the eastbound direction were observed in terms of average monthly observed combined weight. In the westbound direction, volumes in the early part of the year and the later part of the year were comparable, with each year having a spike in the summer months. The same trend was observed in terms of average monthly observed combined weight, with 2017 experiencing the largest average monthly observed combined weights in the summer months.

Table 7.4: Summary of Directional Trends by Classification Group at Cascade Locks and Wyeth WIM Stations

		Cascade Locks (Eastbound)				Wyeth (Westbound)			
Classification	**Year**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**
ODOT Class 03 to ODOT Class 10	2015	355,329	37.17%	195,689	10.89%	448,230	42.76%	224,679	12.60%
	2016	431,503	40.65%	236,596	11.89%	480,044	43.31%	242,064	13.05%
	2017	377,423	39.08%	206,903	11.38%	419,313	40.59%	223,159	12.17%
	2018	424,290	39.47%	235,265	11.59%	386,528	37.01%	212,278	11.40%
ODOT Class 11	2015	394,662	41.29%	934,584	52.03%	401,669	38.32%	979,544	54.92%
	2016	409,002	38.53%	1,009,466	50.72%	414,574	37.41%	1,002,676	54.04%
	2017	374,680	38.79%	906,567	49.88%	342,171	33.13%	818,719	44.64%
	2018	417,860	38.87%	1,017,800	50.13%	426,485	40.83%	1,001,742	53.82%
ODOT Class 12 to ODOT Class 19	2015	205,875	21.54%	666,091	37.08%	198,411	18.93%	579,368	32.48%
	2016	221,101	20.83%	744,398	37.40%	213,719	19.28%	610,677	32.91%
	2017	213,716	22.13%	703,942	38.73%	271,452	26.28%	792,314	43.20%
	2018	232,925	21.67%	777,271	38.28%	231,415	22.16%	647,298	34.78%
All Trucks (ODOT Class 03 to ODOT Class 19)	2015	955,866	-	1,796,364	-	1,048,310	-	1,783,592	-
	2016	1,061,606	-	1,990,460	-	1,108,337	-	1,855,417	-
	2017	965,819	-	1,817,412	-	1,032,936	-	1,834,193	-
	2018	1,075,075	-	2,030,336	-	1,044,428	-	1,861,318	-

[1] Percent Reflects the Proportion of Total Number of Trucks (e.g., ODOT Class 11 Trucks Account for 41.29% of Truck Volume and 52.03% of Average Monthly Observed Combined Weight in the Eastbound Direction in 2015)

[2] Combined Weight Refers to the Weight of the Truck and the Cargo



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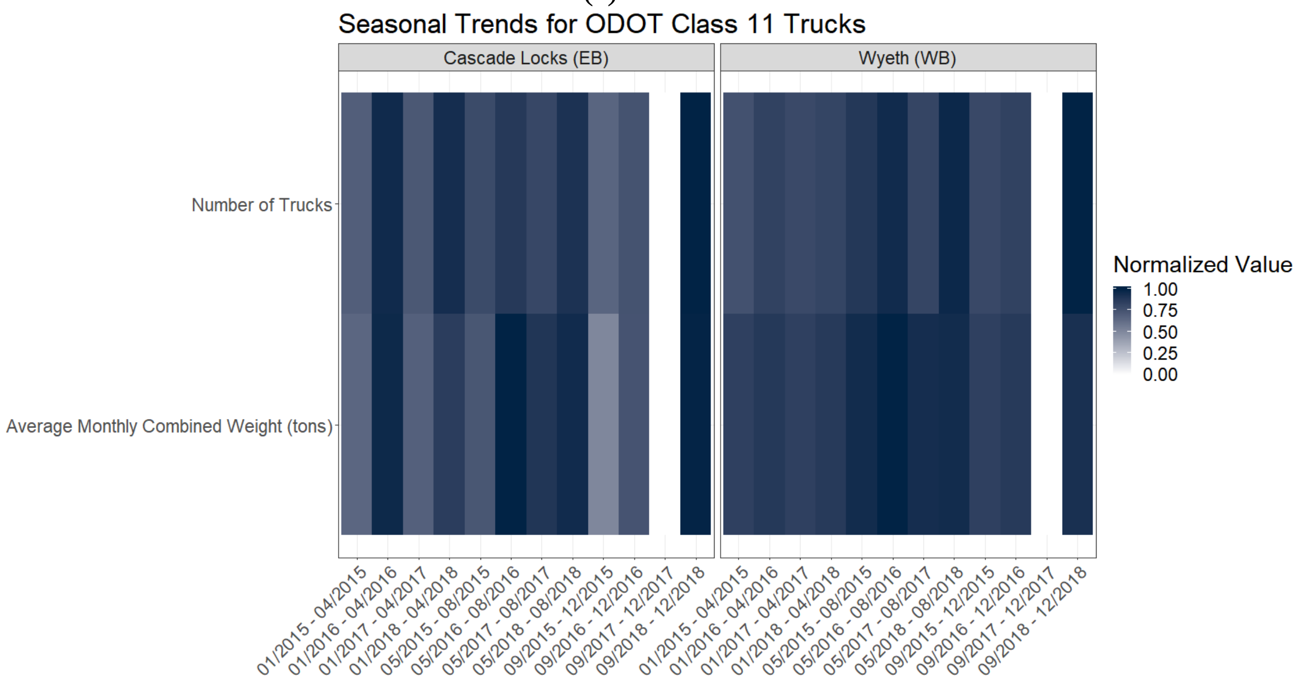

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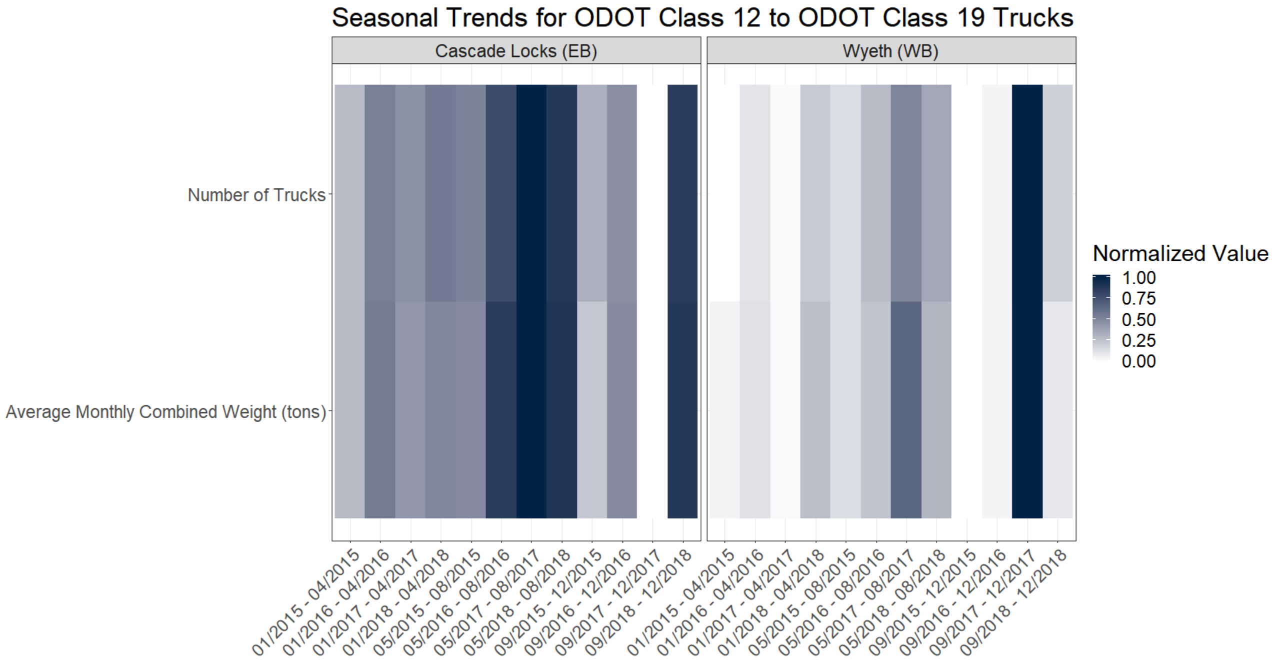
Figure 7.5: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 03 to ODOT Class 10 and (b) ODOT Class 11 trucks at Cascade Locks (EB) and Wyeth (WB) WIM stations



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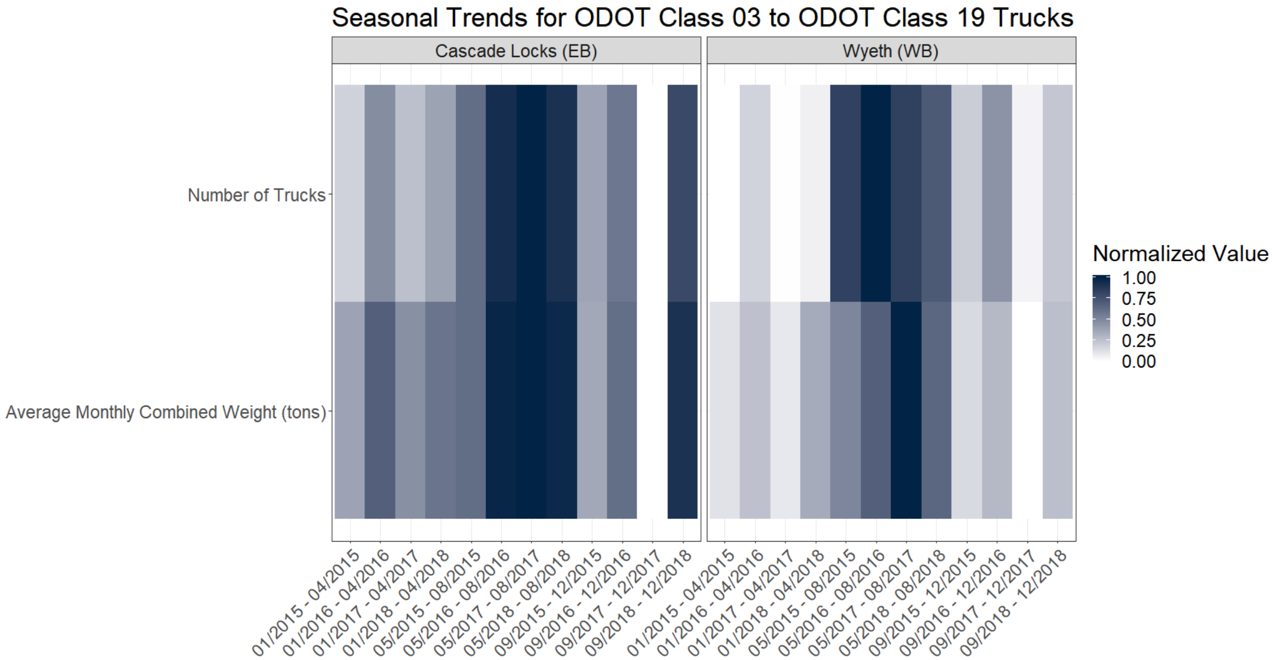

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Figure 7.6: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 12 to ODOT Class 19 and (b) ODOT Class 03 to ODOT Class 19 trucks at Cascade Locks (EB) and Wyeth (WB) WIM stations Olds Ferry and Farewell Bend WIM stations

The fourth pair of WIM stations assessed were the Olds Ferry and Farewell Bend WIM stations, the easternmost WIM stations along the I-84 corridor, specifically, located on the Oregon-Idaho border. Directional trends and seasonal trends are presented based on the four classification groups previously defined. For Figure 7.7 and Figure 7.8, truck volume and average monthly observed combined (truck and cargo) weight were normalized to show seasonal patterns using the same scale. As a result, any white space observed does not correspond to missing data.

For ODOT Class 03 to ODOT Class 10 truck directional trends, refer to Table 7.5. In terms of volume, higher volumes are observed in the westbound (Farewell Bend) direction in 2015, 2016, and 2017, while higher volumes were observed in the eastbound (Olds Ferry) direction in 2018. In terms of average monthly observed combined (truck and cargo) weight, trends are the same with 2017 as an exception. In 2017, slightly larger average monthly observed combined weights are observed in the eastbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be seen in Figure 7.7. For volumes, the trends vary based on direction. In 2015 and 2016, in the eastbound direction, volumes remain fairly consistent throughout the year. In 2017, there is a downward trend during the summer months, and in 2018 there is a significant upward trend during the summer months. In the westbound direction, volumes steadily increased throughout the year in 2015. In 2016 and 2017, there are slight spikes during the summer months. In 2018, volumes remained consistent in the early part of the year and through summer, but decrease in the later part of the year.

For ODOT Class 11 truck directional trends, refer to Table 7.5. In 2016 and 2017, volumes are higher in the westbound (Farewell Bend) direction, and in 2015 and 2018, volumes are higher in the eastbound (Olds Ferry) direction. The same trends are observed in terms of average monthly observed combined (truck and cargo) weight. Seasonal volume and average monthly observed combined weight trends were also determined, where these trends can be seen in Figure 7.7. In terms of volumes, trends vary based on direction. In the eastbound direction, volumes remain fairly consistent throughout the year. However, in 2017, there is a significant decrease in volumes during the summer months. In the westbound direction, 2016, 2017, and 2018 have spikes during the summer months. In 2015, volumes remained consistent through the early year and summer months, and then there is a sharp decrease in the later part of the year. The average monthly observed combined weight trends follow the same patterns as the volumes in both directions.

For ODOT Class 12 to ODOT Class 19 truck directional trends, refer to Table 7.5. In terms of volume, higher volumes are observed in the westbound (Farewell Bend) direction in 2015 and 2017, while higher volumes are observed in the eastbound (Olds Ferry) direction in 2016 and 2018. In terms of average monthly observed combined (truck and cargo) weight, higher combined weights are observed in 2015 and 2017 in the westbound direction, while higher average monthly observed combined weights are observed in 2018 in the eastbound direction. In 2016, the average monthly observed combined weights in both directions were approximately the same. Seasonal volume and combined weight trends were also determined, where these trends can be seen in Figure 7.8. As with the other two I-84 WIM stations, volumes trends vary by direction. In the eastbound direction, 2015 volumes remain consistent throughout the year, 2016, and 2018 volumes experience a spike during the summer months, and 2017 volumes experience a decrease during the summer months. In the westbound direction, volume trends in 2016, 2017, and 2018 remain fairly consistent throughout the year with slight increases in the summer. In 2015, volumes decreased throughout the year. The directional season volume trends were also observed for average monthly observed combined weight.

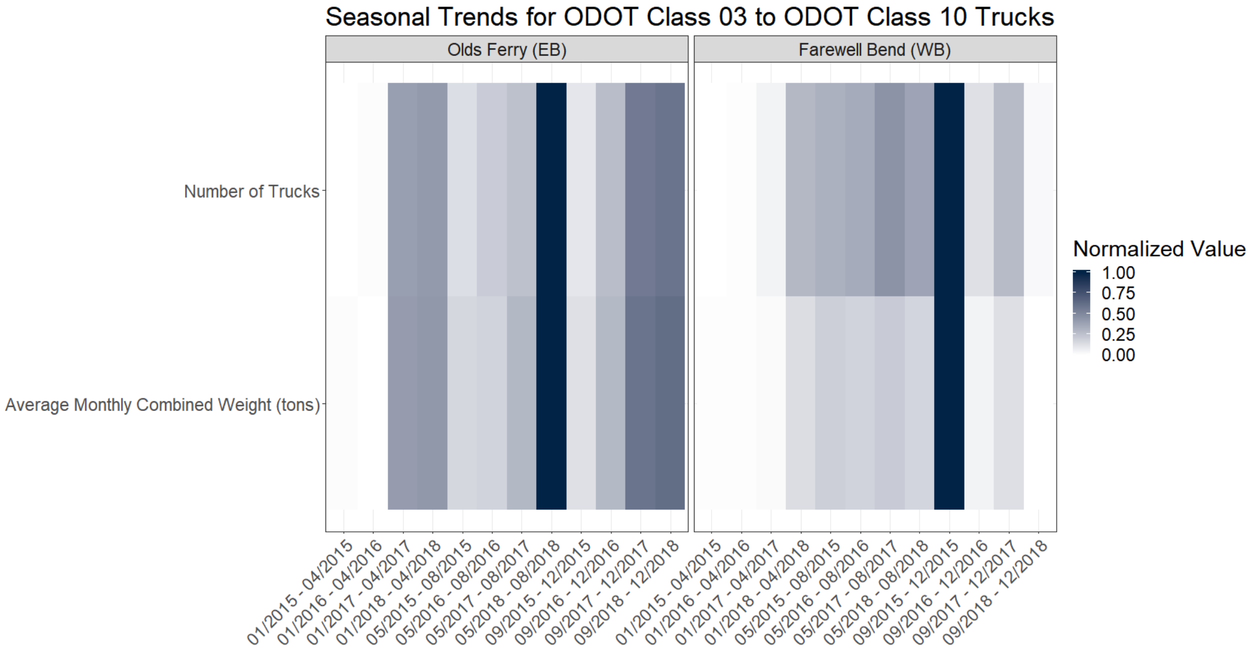
For all trucks, directional trends based on truck volumes are shown in Table 7.5. In terms of volume, higher volumes are observed in the westbound (Farewell Bend) direction in 2015, 2016, and 2017, while higher volumes were observed in the eastbound (Olds Ferry) direction in 2018. These same trends are observed in terms of average monthly observed combined (truck and cargo) weight. Seasonal trends are shown in Figure 7.8. In 2015 and 2016, in the eastbound direction, volumes remain consistent throughout the year. In 2017, there is a decrease during the summer months, and in 2018 there is an increase during the summer months. In the westbound direction, 2016, 2017, and 2018 experienced an increase during the summer months. In 2015, volumes steadily increased throughout the year. In terms of average monthly observed combined weight, the same trends are observed.

Table 7.5: Summary of Directional Trends by Classification Group at Olds Ferry and Farewell Bend WIM Stations

		Olds Ferry (Eastbound)				Farewell Bend (Westbound)			
Classification	**Year**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**
ODOT Class 03 to ODOT Class 10	2015	105,815	15.57%	59,242	4.41%	238,071	31.18%	184,662	13.30%
	2016	126,349	17.46%	66,254	4.89%	161,234	21.04%	86,376	5.86%
	2017	185,211	28.16%	102,000	7.26%	188,596	23.70%	99,073	6.44%
	2018	249,735	27.44%	134,909	7.45%	180,717	22.07%	94,050	5.95%
ODOT Class 11	2015	441,974	65.05%	953,825	70.93%	389,034	50.96%	860,028	61.95%
	2016	444,003	61.34%	906,435	66.83%	454,997	59.38%	1,003,474	68.13%
	2017	354,743	53.93%	924,284	65.76%	461,704	58.01%	1,054,996	68.60%
	2018	490,025	53.84%	1,176,185	64.91%	477,385	58.29%	1,071,269	67.75%
ODOT Class 12 to ODOT Class 19	2015	131,689	19.38%	331,718	24.67%	136,334	17.86%	343,651	24.75%
	2016	153,433	21.20%	383,562	28.28%	149,970	19.57%	383,002	26.00%
	2017	117,845	17.92%	379,206	26.98%	145,561	18.29%	383,921	24.96%
	2018	170,379	18.72%	500,952	27.65%	160,836	19.64%	416,006	26.31%
All Trucks (ODOT Class 03 to ODOT Class 19)	2015	679,478	-	1,344,785	-	763,439	-	1,388,341	-
	2016	723,785	-	1,356,251	-	766,201	-	1,472,852	-
	2017	657,799	-	1,405,490	-	795,861	-	1,537,991	-
	2018	910,139	-	1,812,046	-	818,938	-	1,581,324	-

[1] Percent Reflects the Proportion of Total Number of Trucks (e.g., ODOT Class 11 Trucks Account for 65.05% of Truck Volume and 70.93% of Average Monthly Observed Combined Weight in the Eastbound Direction in 2015)

[2] Combined Weight Refers to the Weight of the Truck and the Cargo



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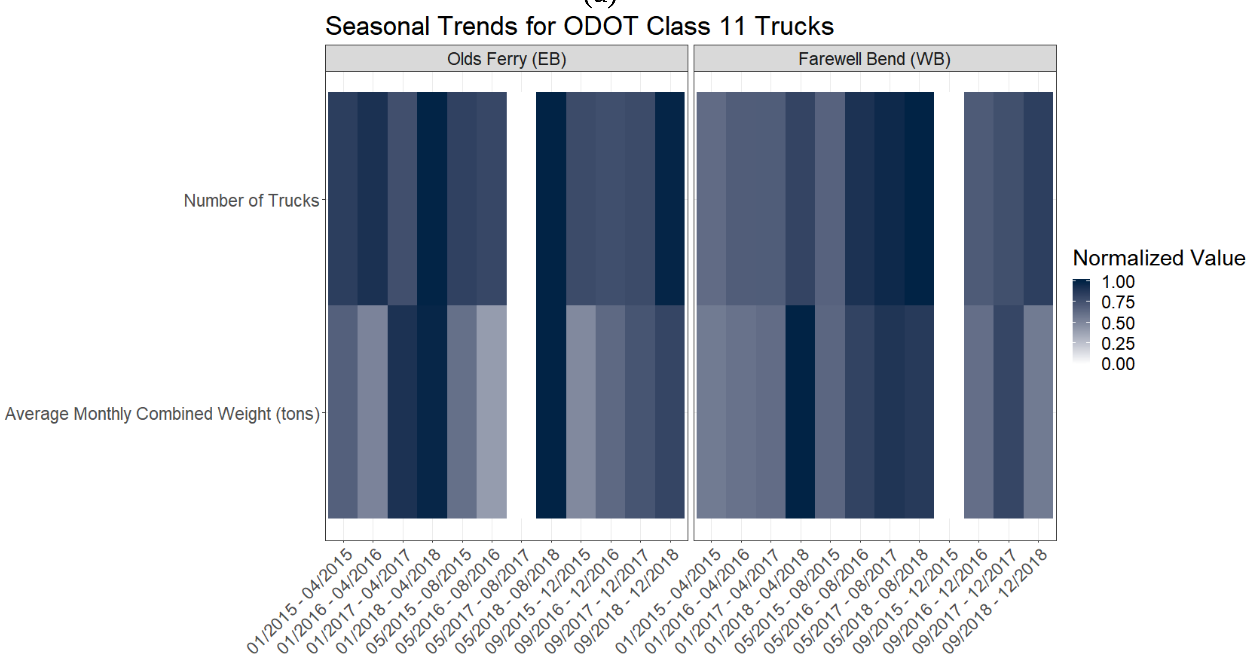

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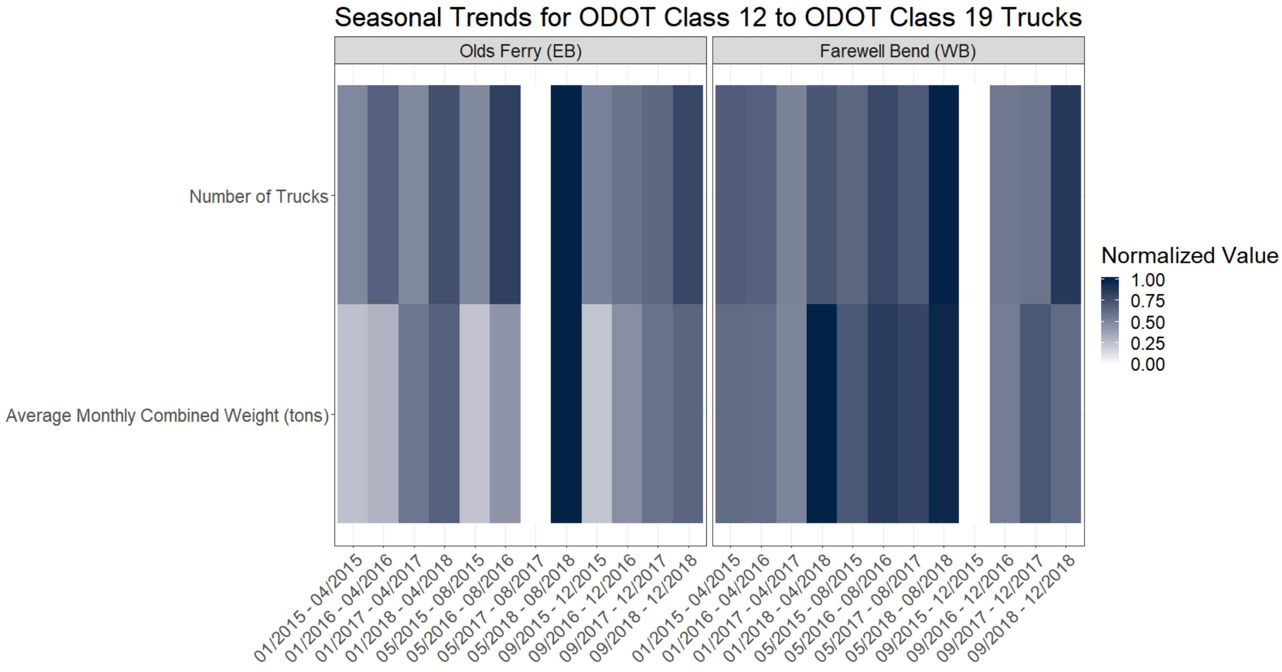
Figure 7.7: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 03 to ODOT Class 10 and (b) ODOT Class 11 trucks at Olds Ferry (EB) and Farewell Bend (WB) WIM stations



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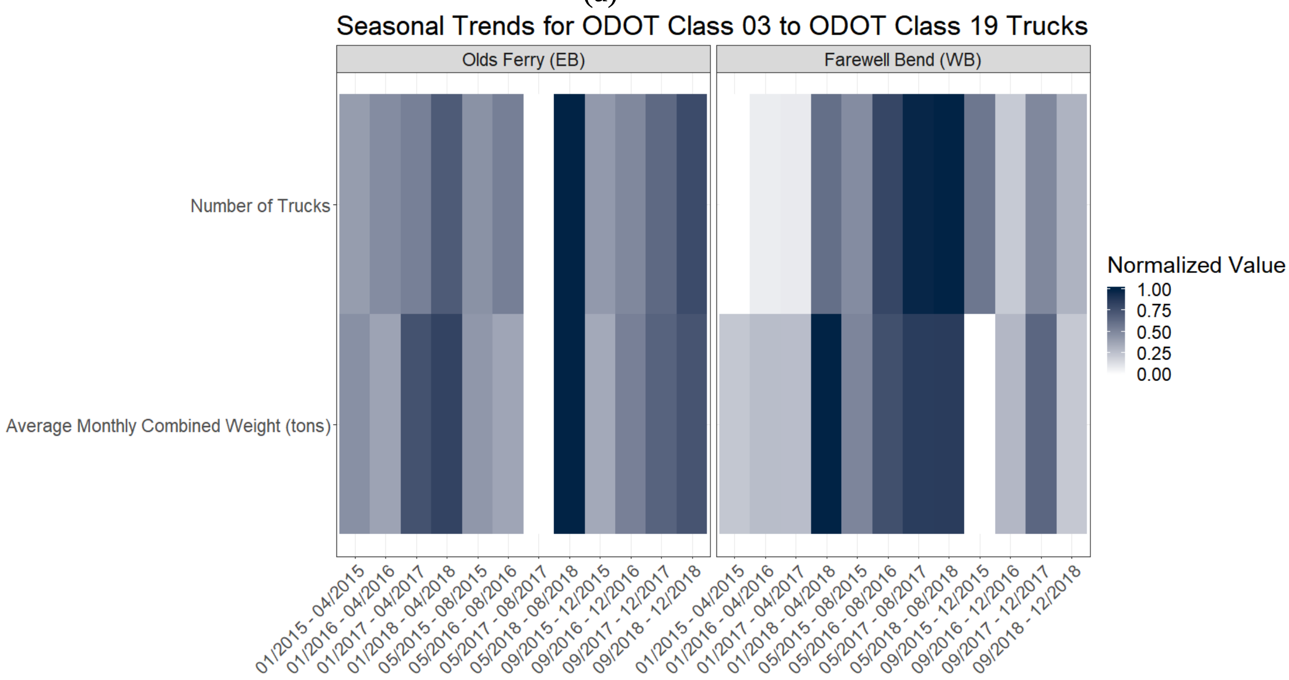

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Figure 7.8: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 12 to ODOT Class 19 and (b) ODOT Class 03 to ODOT Class 19 trucks at Olds Ferry (EB) and Farewell Bend (WB) WIM stations

7.4 KLAMATH FALLS WIM STATIONS

The final pair of WIM stations assessed were the Klamath Falls WIM stations, the southernmost WIM stations along the US-97 corridor, specifically, located on the Oregon-California border. Directional trends and seasonal trends are presented based on the four classification groups previously defined. For Figure 7.9 and Figure 7.10, truck volume and average monthly observed combined (truck and cargo) weight were normalized to show seasonal patterns using the same scale. As a result, any white space observed does not correspond to missing data.

For ODOT Class 03 to ODOT Class 10 truck directional trends, refer to Table 7.6. In terms of both volume and combined (truck and cargo) weight, higher values are observed in the southbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.9. As with the Ashland WIM stations, both directions in terms of volume and combined weight experience a spike during the summer months and have comparable values for early and later parts of the year. The outlier is Klamath Falls (NB), in which volumes and observed combined weights remain fairly consistent throughout 2017 (i.e., no significant upward trend in the summer months). In addition, higher volumes and combined weights are observed in 2016 and 2018 in the northbound direction, while higher volumes and combined weights are observed in 2017 and 2018 in the southbound direction. The directional season volume trends were also observed for combined weight.

For ODOT Class 11 truck directional trends, refer to Table 7.6. The volume and combined (truck and cargo) weight directional trends for ODOT Class 11 trucks are tantamount to that of ODOT Class 03 to ODOT Class 10 trucks; that is, moderately higher volumes and combined weights are observed in the southbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.9. In terms of volumes, each year experienced a spike during the summer months and had higher volumes in the later part of the year. This was observed in both directions. The combined weight trends are similar; however, the extreme parts of the year vary by year and direction. For instance, in 2018 in the northbound direction, higher combined weights were observed in the later part of the year compared to the early part of the year, while they were approximately the same in the southbound direction.

For ODOT Class 12 to ODOT Class 19 truck directional trends, refer to Table 7.6. As with the previous classification groups, higher volumes and combined (truck and cargo) weights are observed in the southbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.10. For both volume and combined weight in both directions, patterns are the same. There is a spike during the summer months, while the volume and combined weight values during the early and later parts of the year are comparable.

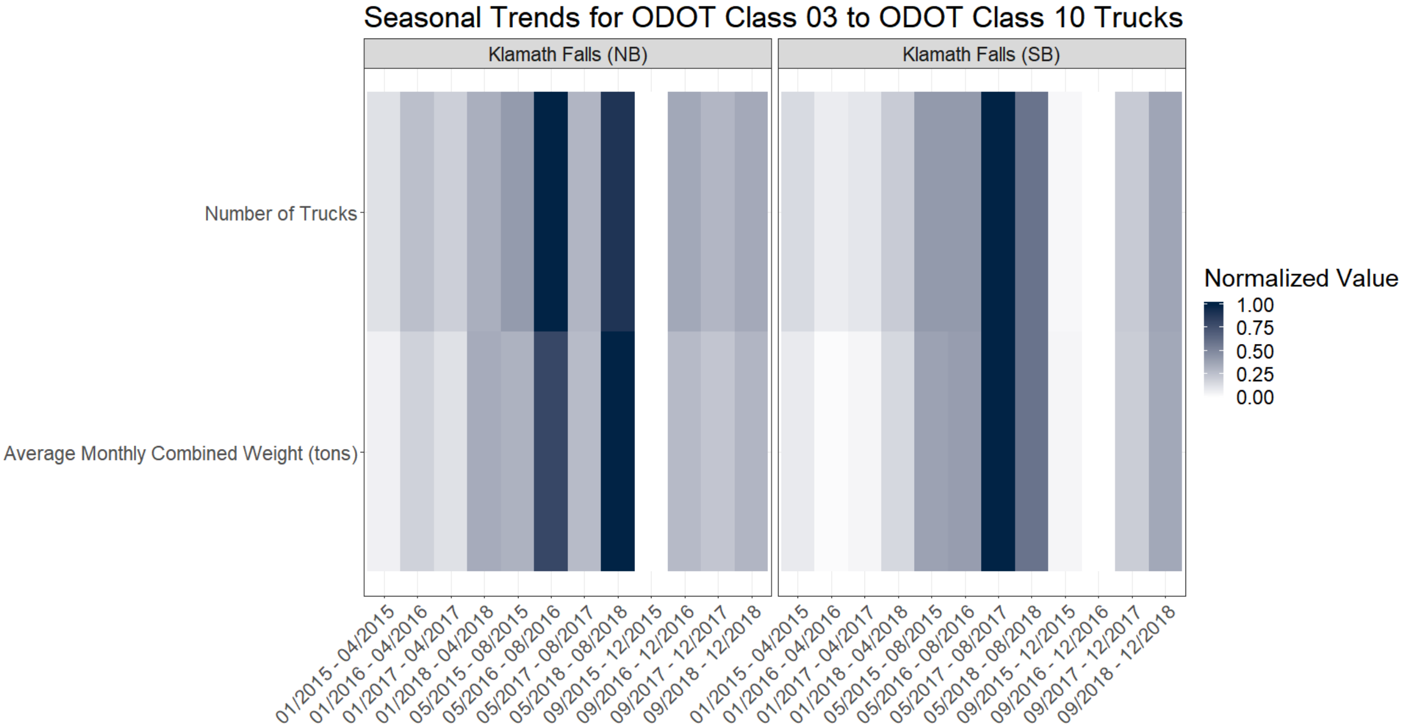
For all trucks, directional trends are shown in Table 7.6. Once more, higher volumes and combined (truck and cargo) weight were observed in the southbound direction. Seasonal volume and combined weight trends were also determined, where these trends can be observed in Figure 7.10. As was the case with the previous classification groups, each direction experienced the same trends for both volume and combined weight: an increase during the summer months and comparable values at the early and later parts of the year. However, in the northbound direction, larger summer spikes were experienced in 2016 and 2018, while in the southbound direction, a larger summer spike was experienced in 2017.

Table 7.6: Summary of Directional Trends by Classification Group at Klamath Falls WIM Stations

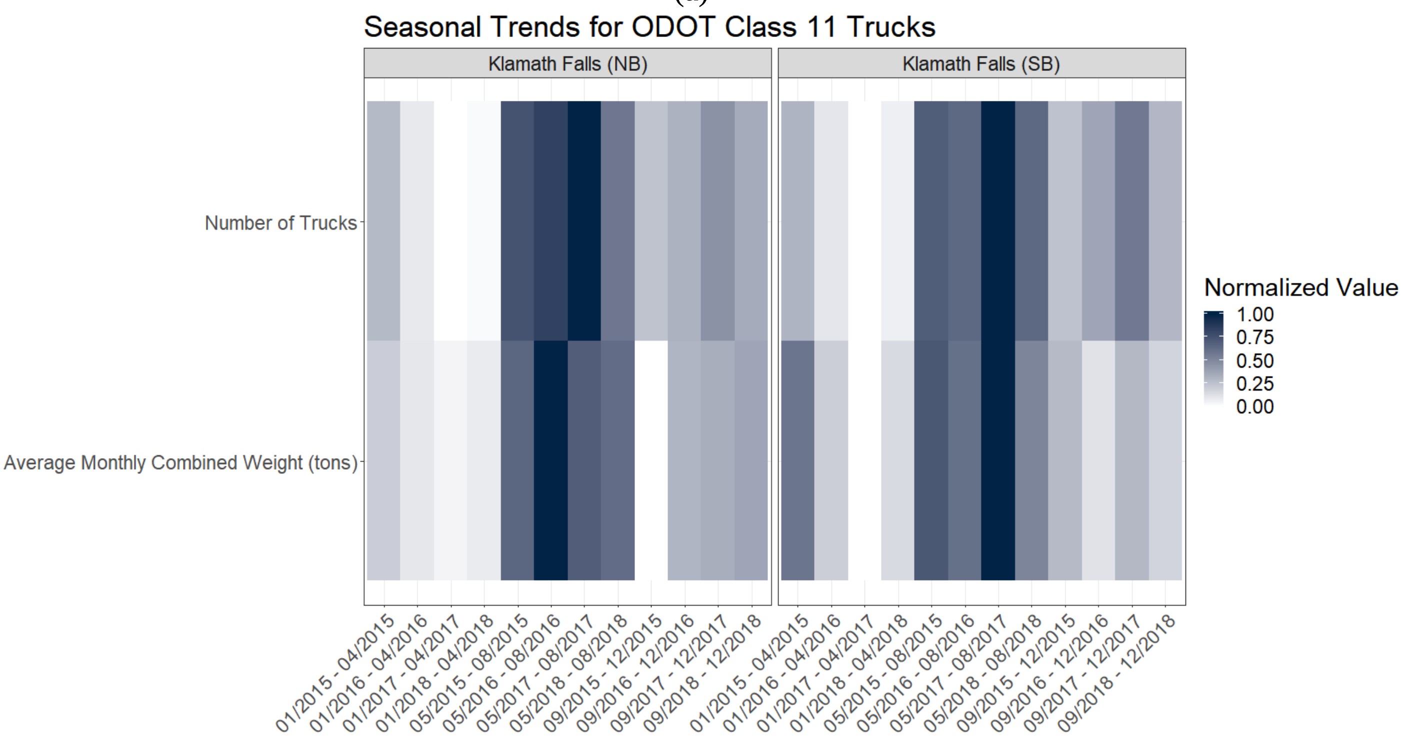
		Northbound				Southbound			
Classification	**Year**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**	**Number of Trucks**	**Percent of Annual Total[1]**	**Average Monthly Observed Combined Weight (tons)[2]**	**Percent of Annual Total[1]**
ODOT Class 03 to ODOT Class 10	2015	175,300	54.86%	85,764	20.25%	282,089	54.99%	129,982	16.55%
	2016	250,707	63.37%	121,694	24.49%	269,859	53.94%	125,669	16.94%
	2017	193,124	56.35%	96,153	21.28%	364,534	60.21%	167,304	20.47%
	2018	248,268	63.62%	136,636	27.32%	348,706	60.14%	160,761	20.52%
ODOT Class 11	2015	118,057	36.95%	276,918	65.38%	200,624	39.11%	558,081	71.04%
	2016	117,413	29.68%	303,219	61.03%	198,241	39.63%	517,014	69.70%
	2017	120,987	35.30%	287,493	63.63%	206,121	34.04%	539,512	66.02%
	2018	112,504	28.83%	287,736	57.54%	196,257	33.84%	511,372	65.29%
ODOT Class 12 to ODOT Class 19	2015	26,181	8.19%	60,850	14.37%	30,267	5.90%	97,514	12.41%
	2016	27,535	6.96%	71,933	14.48%	32,183	6.43%	99,098	13.36%
	2017	28,624	8.35%	68,158	15.09%	34,813	5.75%	110,417	13.51%
	2018	29,434	7.54%	75,687	15.14%	34,908	6.02%	111,132	14.19%
All Trucks (ODOT Class 03 to ODOT Class 19)	2015	319,538	-	423,532	-	512,980	-	785,576	-
	2016	395,655	-	496,846	-	500,283	-	741,781	-
	2017	342,735	-	451,805	-	605,468	-	817,233	-
	2018	390,206	-	500,060	-	579,871	-	783,265	-

[1] Percent Reflects the Proportion of Total Number of Trucks (e.g., ODOT Class 11 Trucks Account for 36.95% of Truck Volume and 65.38% of Average Monthly Observed Combined Weight in the Eastbound Direction in 2015)

[2] Combined Weight Refers to the Weight of the Truck and the Cargo

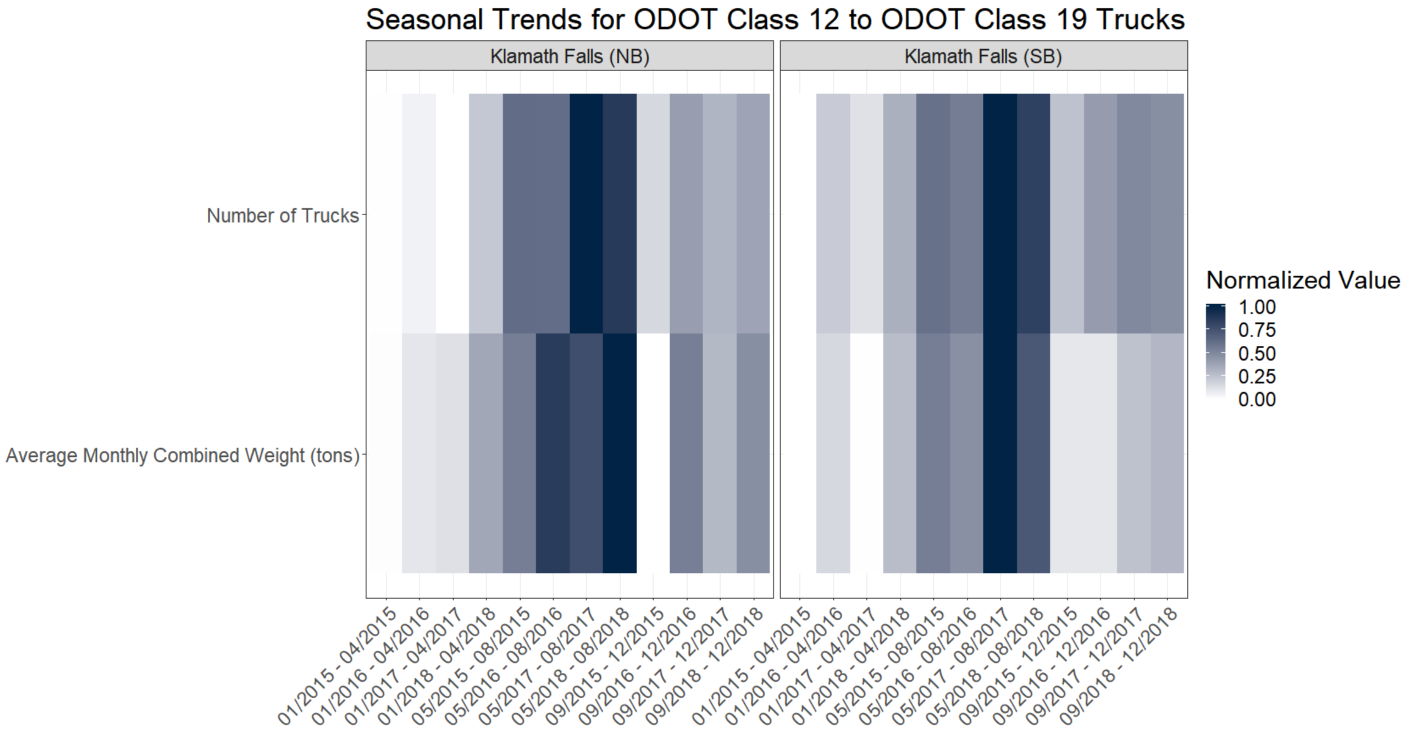


(a)

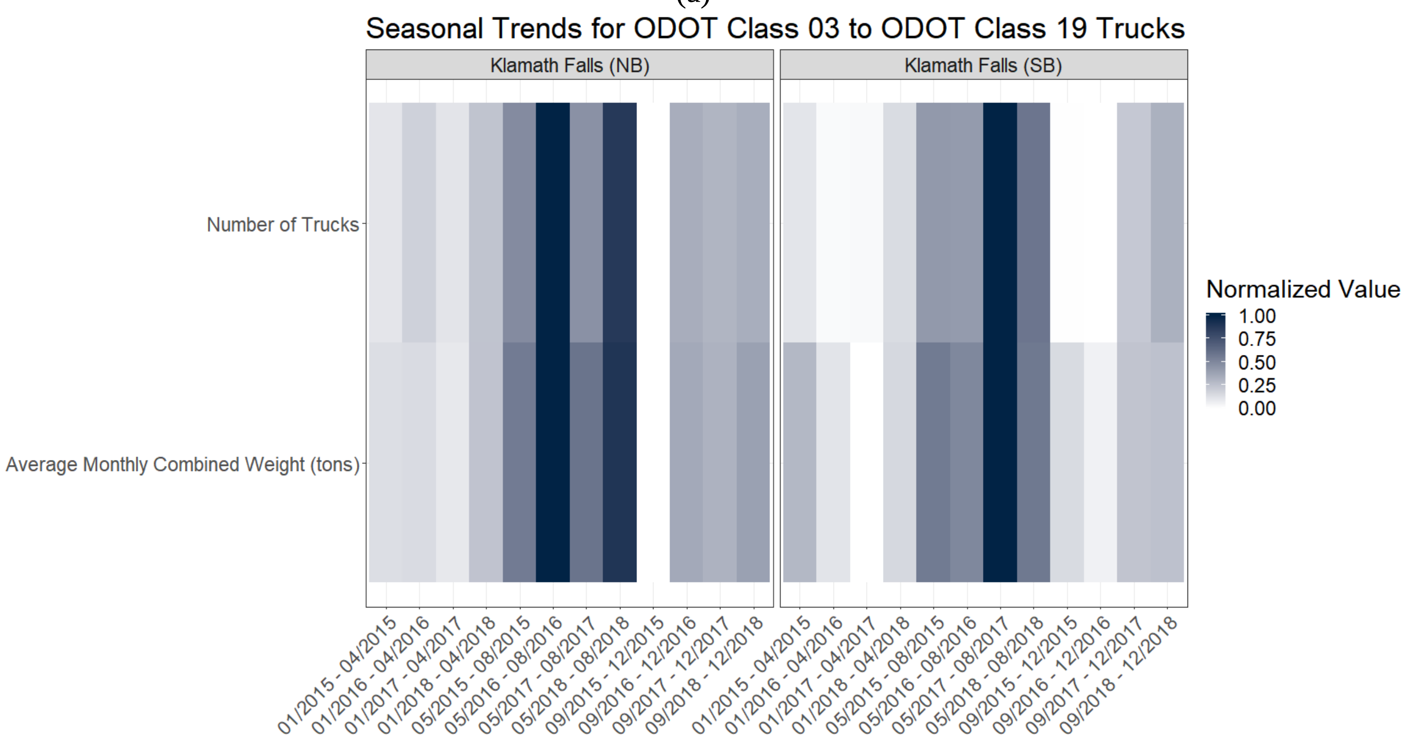


(b)

Figure 7.9: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 03 to ODOT Class 10 and (b) ODOT Class 11 trucks at Klamath Falls WIM stations



(a)



(b)

Figure 7.10: Volume and average monthly combined weight seasonal trends for (a) ODOT Class 12 to ODOT Class 19 and (d) ODOT Class 03 to ODOT Class 19 trucks at Klamath Falls WIM stations

7.5 MONTHLY PERCENTAGES AT SELECT WIM STATIONS

The next step in the select descriptive analysis was to provide quantitative measures of total truck volumes, and average observed combined (truck and cargo) weights by month and year. An example of the total number of trucks is provided in Table 7.7. As observed, the highest proportion of trucks are consistently observed from May to August. This remains true for all WIM stations and all years. With that in mind, however, there are notable differences. In 2015 at the Woodburn (SB) WIM station, the highest proportions of trucks are observed from September to December. In March 2017, at the Woodburn (NB) WIM station, the highest proportion of trucks was observed. At the Cascade Locks (EB) WIM station, the highest proportions are observed from May to August, with 2017 having significantly higher proportions relative to other years (this is not observed at Wyeth, the westbound WIM station at this location). Also of note are the monthly proportions at Olds Ferry (EB) in 2017. Specifically, the highest proportions are observed at the start of the year (March to May) and the end of the year (October to December). Interestingly, June, July, and August account for substantially small proportions, relative to other years, at 7.51%, 2.57%, and 0.89%, respectively. The same tables are presented in terms of total observed combined weight, in which trends follow that of the truck volumes. Monthly percentages for both the total number of trucks and observed combined weight at all WIM stations can be seen in Unnikrishnan et al. (2019).[21]

In addition to the monthly trends at each WIM station, aggregated monthly trends were calculated. These aggregated trends represent the average percent of observed combined (truck and cargo) weight and volume in a given month over the four years of WIM data. A summary of aggregated monthly volume percentages is shown in Table 7.8, and a summary of aggregated monthly combined weight percentages is shown in Table 7.9. Of interest are the months that account for the highest, 2nd highest, and 3rd highest proportions of volume and combined weight at each WIM station. These months are indicated in Table 7.8 and Table 7.9 by rank (e.g., 1, 2, or 3) and by color (green being the highest proportion, yellow being the second highest proportion, and orange being the third highest proportion). Regarding volumes, June has the highest proportion of observed volume at four WIM stations: Ashland (SB), Woodburn (NB), Farewell Bend (WB), and Klamath Falls (NB). June also accounts for the third highest proportion of volumes at four WIM stations: Ashland (NB), Woodburn (SB), Wyeth (WB), and Klamath Falls (SB). Also accounting for large proportions of volume are July and August. In July, the highest proportion of volume is observed at Ashland (NB), Wyeth (WB), and Klamath Falls (SB), while Cascade Locks (EB) experiences the highest proportion of volume in August. Additionally, July experiences the second highest proportion of volume at Ashland (SB), Cascade Locks (EB), and Klamath Falls (NB), while August experiences the second highest proportion of volume at Ashland (NB), Wyeth (WB), Farewell Bend (WB), and Klamath Falls (SB). Also of note, four WIM stations have the third highest proportion of volume in May: Woodburn (NB), Cascade Locks (EB), Olds Ferry (EB), and Klamath Falls (NB). As observed, the summer months experience the highest proportions of volumes, with June accounting for at least the third highest proportion for eight of the 10 WIM stations.

[21] Monthly percentages of volume and combined weight by WIM station and classification can be viewed here.

In terms of combined (truck and cargo) weight, monthly proportions are similar. For example, seven of the 10 WIM stations experience their highest proportion of combined weight in June. Specifically, Ashland (SB), Klamath Falls (NB), and Klamath Falls (SB) experience their highest proportion in June, Ashland (NB) and Woodburn (NB) experience their second highest proportion in June, and Woodburn (SB) and Farewell Bend (WB) experience their third highest proportion in June. Observed combined weight proportions in August account for at least the second highest proportion for six of the 10 WIM stations, with Ashland (NB), Woodburn (SB), Cascade Locks (EB), and Wyeth (WB) having the highest proportion of combined weight in August. In March, Woodburn (NB), Olds Ferry (EB), and Farewell Bend (WB) have their highest proportion of combined weight, in which Woodburn (NB) and Olds Ferry (EB) also experienced their second highest proportion of volume in March. Outside of the aforementioned WIM stations and their March proportions, the majority of high proportions of combined weight are observed in the summer months (June, July, and August), which follows the high proportions observed for volumes.

Table 7.7: Total Number of Trucks at Ashland WIM Stations by Month

Northbound												
	Total Number of Trucks				Percent of Total				Comparison Across Years			
Month	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	86,051	88,653	87,966	92,914	7.37%	7.24%	6.89%	7.34%	7.37%	6.89%	0.48%	7.21%
February	82,036	87,943	90,338	90,792	7.02%	7.19%	7.08%	7.17%	7.19%	7.02%	0.16%	7.11%
March	99,485	103,024	107,617	108,459	8.52%	8.42%	8.43%	8.57%	8.57%	8.42%	0.15%	8.48%
April	100,916	101,337	108,301	108,291	8.64%	8.28%	8.48%	8.55%	8.64%	8.28%	0.36%	8.49%
May	103,799	105,125	113,249	118,150	8.89%	8.59%	8.87%	9.33%	9.33%	8.59%	0.74%	8.92%
June	109,174	110,855	118,019	115,177	9.35%	9.06%	9.25%	9.10%	9.35%	9.06%	0.29%	9.19%
July	109,922	108,640	120,519	118,141	9.41%	8.88%	9.44%	9.33%	9.44%	8.88%	0.57%	9.27%
August	104,405	111,153	121,157	116,831	8.94%	9.08%	9.49%	9.23%	9.49%	8.94%	0.55%	9.18%
September	93,296	106,184	105,617	103,739	7.99%	8.68%	8.27%	8.19%	8.68%	7.99%	0.69%	8.28%
October	98,683	100,913	107,199	107,687	8.45%	8.25%	8.40%	8.51%	8.51%	8.25%	0.26%	8.40%
November	89,969	101,030	101,187	91,449	7.70%	8.25%	7.93%	7.22%	8.25%	7.22%	1.03%	7.78%
December	90,350	99,031	95,269	94,444	7.73%	8.09%	7.46%	7.46%	8.09%	7.46%	0.63%	7.69%
Total	**1,168,086**	**1,223,888**	**1,276,438**	**1,266,074**								

Southbound												
	Total Number of Trucks				Percent of Total				Comparison Across Years			
Month	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	85,628	82,230	80,643	82,086	7.42%	7.19%	7.15%	7.17%	7.42%	7.15%	0.27%	7.23%
February	81,513	80,289	77,149	78,575	7.06%	7.02%	6.84%	6.87%	7.06%	6.84%	0.23%	6.95%
March	96,239	90,666	91,850	91,075	8.34%	7.93%	8.14%	7.96%	8.34%	7.93%	0.41%	8.09%
April	98,350	92,857	90,099	91,148	8.52%	8.12%	7.99%	7.96%	8.52%	7.96%	0.56%	8.15%
May	104,851	102,403	99,663	104,181	9.09%	8.95%	8.83%	9.10%	9.10%	8.83%	0.27%	8.99%
June	113,453	108,543	108,718	108,791	9.83%	9.49%	9.64%	9.51%	9.83%	9.49%	0.34%	9.62%
July	108,748	109,402	107,000	108,769	9.42%	9.57%	9.48%	9.50%	9.57%	9.42%	0.14%	9.50%
August	103,546	106,367	106,975	107,251	8.97%	9.30%	9.48%	9.37%	9.48%	8.97%	0.51%	9.28%
September	93,808	96,470	95,205	95,507	8.13%	8.44%	8.44%	8.35%	8.44%	8.13%	0.31%	8.34%
October	96,396	93,156	97,518	100,206	8.35%	8.15%	8.64%	8.76%	8.76%	8.15%	0.61%	8.48%
November	86,503	91,086	89,050	90,835	7.50%	7.97%	7.89%	7.94%	7.97%	7.50%	0.47%	7.82%
December	84,812	90,082	84,234	86,003	7.35%	7.88%	7.47%	7.51%	7.88%	7.35%	0.53%	7.55%
Total	**1,153,847**	**1,143,551**	**1,128,104**	**1,144,427**								

Table 7.8: Aggregated Monthly Observed Volume Averages by WIM Station

WIM Station	January	February	March	April	May	June	July	August	September	October	November	December
Ashland (NB)	7.21%	7.11%	8.48%	8.49%	8.92%	9.19%[3]	9.27%[1]	9.18%[2]	8.28%	8.40%	7.78%	7.69%
Ashland (SB)	7.23%	6.95%	8.09%	8.15%	8.99%	9.62%[1]	9.50%[2]	9.28%[3]	8.34%	8.48%	7.82%	7.55%
Woodburn (NB)	7.67%	7.76%	9.32%[2]	8.79%	9.16%[3]	9.35%[1]	6.96%	8.87%	8.59%	8.34%	7.83%	7.37%
Woodburn (SB)	6.96%	7.08%	8.28%	7.89%	8.81%	8.92%[3]	8.89%	8.89%	8.99%[1]	8.96%[2]	8.28%	8.05%
Cascade Locks (EB)	6.57%	6.79%	8.52%	8.66%	9.21%[3]	9.05%	9.60%[2]	9.71%[1]	7.75%	9.01%	7.98%	7.15%
Wyeth (WB)	6.61%	6.68%	8.39%	8.56%	9.21%	9.42%[3]	9.63%[1]	9.59%[2]	8.32%	8.84%	7.76%	6.98%
Olds Ferry (EB)	7.54%	7.10%	9.56%[2]	9.21%	9.27%[3]	8.55%	7.18%	6.77%	7.87%	9.90%[1]	9.10%	7.95%
Farewell Bend (WB)	6.78%	6.97%	8.64%	8.64%	8.98%	9.16%[1]	8.93%	9.10%[2]	8.97%	9.09%[3]	7.78%	6.96%
Klamath Falls (NB)	5.36%	6.05%	8.35%	8.95%	10.10%[3]	10.58%[1]	10.24%[2]	9.85%	8.91%	8.60%	7.30%	5.71%
Klamath Falls (SB)	5.92%	6.15%	7.99%	8.75%	9.80%	10.35%[3]	10.53%[1]	10.43%[2]	8.87%	8.50%	7.04%	5.67%
Average	6.79%	6.86%	8.56%	8.61%	9.25%[2]	9.42%[1]	9.07%	9.17%[3]	8.49%	8.81%	7.87%	7.11%

[1] Month with highest proportion of observed volume (highlighted in green)
[2] Month with 2nd highest proportion of observed volume (highlighted in yellow)
[3] Month with 3rd highest proportion of observed volume (highlighted in orange)

Table 7.9: Aggregated Monthly Observed Combined (Truck and Cargo) Weight Averages by WIM Station

WIM Station	January	February	March	April	May	June	July	August	September	October	November	December
Ashland (NB)	7.57%	7.37%	8.60%	8.48%	8.87%	9.05%[2]	8.89%[3]	9.06%[1]	8.15%	8.36%	7.77%	7.82%
Ashland (SB)	7.38%	7.11%	8.23%	8.18%	8.99%	9.43%[1]	9.17%[3]	9.41%[2]	8.39%	8.43%	7.78%	7.50%
Woodburn (NB)	8.00%	8.00%	9.64%[1]	8.86%	9.10%[3]	9.25%[2]	6.80%	8.64%	8.37%	8.27%	7.76%	7.31%
Woodburn (SB)	7.11%	7.21%	8.45%	7.95%	8.73%	8.77%[3]	8.58%	9.20%[1]	8.71%	8.78%[2]	8.17%	8.33%
Cascade Locks (EB)	7.00%	7.27%	9.10%[3]	8.87%	9.20%[2]	8.78%	8.99%	9.28%[1]	7.29%	8.86%	7.97%	7.39%
Wyeth (WB)	7.16%	7.33%	8.82%	8.62%	8.99%[3]	8.97%	9.07%[2]	9.35%[1]	7.82%	8.72%	7.90%	7.26%
Olds Ferry (EB)	7.86%	7.42%	10.06%[1]	9.60%[2]	9.26%	8.21%	6.76%	6.54%	7.52%	9.49%[3]	9.29%	8.00%
Farewell Bend (WB)	7.29%	7.53%	9.12%[1]	8.85%	9.10%[2]	9.08%[3]	8.73%	8.90%	7.97%	8.35%	7.93%	7.15%
Klamath Falls (NB)	5.41%	6.03%	8.31%	9.01%	10.15%[2]	10.65%[1]	9.82%[3]	9.79%	8.98%	8.81%	7.43%	5.60%
Klamath Falls (SB)	6.53%	6.66%	8.30%	8.79%	9.49%	9.91%[1]	9.61%[3]	9.90%[2]	8.96%	8.84%	7.23%	5.77%
Average	7.13%	7.19%	8.86%	8.72%	9.19%[2]	9.21%[1]	8.64%	9.01%[3]	8.22%	8.69%	7.92%	7.21%

[1] Month with highest proportion of observed volume (highlighted in green)
[2] Month with 2nd highest proportion of observed volume (highlighted in yellow)
[3] Month with 3rd highest proportion of observed volume (highlighted in orange)

7.6 DAY OF THE WEEK TRENDS

To assess day-of-week trends, 2018 WIM data was used to summarize truck volumes by WIM station and day-of-week. Trends by WIM station and day of the week are shown in Table 7.10 (counts) and Table 7.11 (proportions). As observed, regardless of classification group, Wednesday accounts for at least the third highest volume at each WIM station (Cascade Locks with ODOT Class 11 trucks is the only exception), and consistently accounts for the highest volume at the I-5 WIM stations of Ashland and Woodburn. Additionally, considering the I-5 WIM stations, Thursdays account for the second highest volumes and Tuesdays the third highest volumes. The only exception is for ODOT Class 11 trucks at Woodburn (SB), where Mondays account for the third highest volumes.

On the I-84 WIM stations (Cascade Locks, Wyeth, Olds Ferry, and Farwell Bend), Fridays, Mondays, and Sundays account for at least the third highest volumes. When considering all trucks, Fridays account for the highest volume at Cascade Locks (EB) and Olds Ferry (EB), while accounting for the third highest volume at Wyeth (WB). When considering ODOT Class 11 trucks, Fridays account for the highest volume at Cascade Locks (EB) and the second highest volume at Olds Ferry (EB). Mondays, considering all trucks, account for the second highest volume at Farewell Bend (WB). When considering ODOT Class 11 trucks, Mondays account for the second highest volume at Wyeth (WB) and the highest volume at Farwell Bend (WB). Sundays account for the second highest volume at Farewell Bend (WB).

On US-97, Klamath Falls WIM stations, considering all trucks, the second highest volume is observed on Fridays. This is the only case in which Wednesdays, Thursdays, or Tuesdays do not account for the top three volumes across all classifications groups.

When considering ODOT Class 12 to ODOT Class 19 trucks, Wednesdays, Thursdays, or Tuesdays are all top three in terms of volume, where the majority of WIM stations experience the highest volume on Wednesday, the second highest volume on Thursday, and the third highest volume on Tuesday.

Table 7.10: Summary of Truck Volume Counts by Day of the Week, WIM Station, and Classification Group in 2018

Number of Observed Trucks by Day of the Week (ODOT Class 03 to ODOT Class 19)							
WIM Station	Weekday					Weekend	
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Ashland (NB)	151,888	199,646	216,049	207,991	174,670	153,600	157,654
Ashland (SB)	163,909	180,046	190,080	185,069	168,038	134,565	117,732
Woodburn (NB)	397,215	441,063	472,044	468,831	425,430	247,827	258,625
Woodburn (SB)	355,731	368,837	388,890	388,464	365,462	205,768	162,044
Cascade Locks (EB)	163,362	166,470	167,898	177,296	182,740	114,504	102,805
Wyeth (WB)	158,331	160,214	164,917	172,038	160,865	109,012	119,051
Olds Ferry (EB)	108,960	146,544	145,273	142,920	151,372	131,590	83,480
Farewell Bend (WB)	130,639	124,556	130,175	131,463	103,548	86,204	112,353
Klamath Falls (NB)	53,588	62,549	64,161	63,577	58,768	43,221	44,342
Klamath Falls (SB)	83,416	90,601	89,811	89,653	89,889	74,222	62,279
Number of Observed Trucks by Day of the Week (ODOT Class 11)							
WIM Station	Weekday					Weekend	
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Ashland (NB)	74,344	124,404	139,468	128,459	84,224	81,482	95,938
Ashland (SB)	95,723	110,933	118,864	112,135	91,357	73,686	65,536
Woodburn (NB)	140,910	172,503	196,880	195,942	152,167	91,892	121,681
Woodburn (SB)	156,353	155,851	165,895	156,909	143,862	77,947	62,616
Cascade Locks (EB)	66,356	69,016	68,252	70,395	73,680	39,118	31,043
Wyeth (WB)	70,614	69,176	69,282	71,257	61,653	38,153	46,350
Olds Ferry (EB)	50,473	84,281	80,786	76,304	82,809	79,440	35,932
Farewell Bend (WB)	78,406	70,861	75,805	75,625	50,788	50,005	75,895
Klamath Falls (NB)	12,781	19,995	20,968	19,408	13,180	11,641	14,531
Klamath Falls (SB)	24,555	34,216	34,157	31,898	28,391	27,813	15,227
Number of Observed Trucks by Day of the Week (ODOT Class 12 to ODOT Class 19)							
WIM Station	Weekday					Weekend	
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Ashland (NB)	7,662	14,681	15,852	15,318	14,618	8,997	3,574
Ashland (SB)	9,177	14,808	15,494	15,300	14,460	8,610	3,695
Woodburn (NB)	71,034	83,351	87,610	82,058	75,387	25,596	18,759
Woodburn (SB)	75,053	89,142	92,792	92,127	80,849	33,048	22,733
Cascade Locks (EB)	36,458	43,070	44,074	43,199	37,962	15,968	12,194
Wyeth (WB)	34,648	40,867	42,514	43,675	36,642	17,607	15,462
Olds Ferry (EB)	22,070	30,686	32,091	30,536	28,620	16,288	10,088
Farewell Bend (WB)	26,207	29,238	29,697	29,980	22,725	10,531	12,458
Klamath Falls (NB)	4,445	5,546	5,664	5,608	4,582	2,179	1,410
Klamath Falls (SB)	5,401	6,736	6,581	6,555	5,535	2,436	1,664

Green Indicates the Day with the Highest Number of Observed Trucks
Yellow Indicates the Day with the Second Highest Number of Observed Trucks
Orange Indicates the Day with the Third Highest Number of Observed Trucks

Table 7.11: Summary of Truck Volume Proportions by Day of the Week, WIM Station, and Classification Group in 2018

Number of Observed Trucks by Day of the Week (ODOT Class 03 to ODOT Class 19)							
WIM Station	**Weekday**					**Weekend**	
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Ashland (NB)	12.04%	15.83%	17.13%	16.49%	13.85%	12.18%	12.50%
Ashland (SB)	14.39%	15.80%	16.68%	16.24%	14.75%	11.81%	10.33%
Woodburn (NB)	14.65%	16.27%	17.41%	17.29%	15.69%	9.14%	9.54%
Woodburn (SB)	15.91%	16.50%	17.40%	17.38%	16.35%	9.21%	7.25%
Cascade Locks (EB)	15.20%	15.48%	15.62%	16.49%	17.00%	10.65%	9.56%
Wyeth (WB)	15.16%	15.34%	15.79%	16.47%	15.40%	10.44%	11.40%
Olds Ferry (EB)	11.97%	16.10%	15.96%	15.70%	16.63%	14.46%	9.17%
Farewell Bend (WB)	15.95%	15.21%	15.90%	16.05%	12.64%	10.53%	13.72%
Klamath Falls (NB)	13.73%	16.03%	16.44%	16.29%	15.06%	11.08%	11.36%
Klamath Falls (SB)	14.39%	15.62%	15.49%	15.46%	15.50%	12.80%	10.74%
Number of Observed Trucks by Day of the Week (ODOT Class 11)							
WIM Station	**Weekday**					**Weekend**	
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Ashland (NB)	10.21%	17.08%	19.15%	17.64%	11.56%	11.19%	13.17%
Ashland (SB)	14.32%	16.60%	17.79%	16.78%	13.67%	11.03%	9.81%
Woodburn (NB)	13.14%	16.09%	18.37%	18.28%	14.20%	8.57%	11.35%
Woodburn (SB)	17.01%	16.95%	18.04%	17.07%	15.65%	8.48%	6.81%
Cascade Locks (EB)	15.88%	16.52%	16.33%	16.85%	17.63%	9.36%	7.43%
Wyeth (WB)	16.56%	16.22%	16.24%	16.71%	14.46%	8.95%	10.87%
Olds Ferry (EB)	10.30%	17.20%	16.49%	15.57%	16.90%	16.21%	7.33%
Farewell Bend (WB)	16.42%	14.84%	15.88%	15.84%	10.64%	10.47%	15.90%
Klamath Falls (NB)	11.36%	17.77%	18.64%	17.25%	11.72%	10.35%	12.92%
Klamath Falls (SB)	12.51%	17.43%	17.40%	16.25%	14.47%	14.17%	7.76%
Number of Observed Trucks by Day of the Week (ODOT Class 12 to ODOT Class 19)							
WIM Station	**Weekday**					**Weekend**	
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Ashland (NB)	9.49%	18.19%	19.64%	18.98%	18.11%	11.15%	4.43%
Ashland (SB)	11.25%	18.16%	19.00%	18.76%	17.73%	10.56%	4.53%
Woodburn (NB)	16.01%	18.78%	19.74%	18.49%	16.99%	5.77%	4.23%
Woodburn (SB)	15.45%	18.35%	19.10%	18.97%	16.64%	6.80%	4.68%
Cascade Locks (EB)	15.65%	18.49%	18.92%	18.55%	16.30%	6.86%	5.24%
Wyeth (WB)	14.97%	17.66%	18.37%	18.87%	15.83%	7.61%	6.68%
Olds Ferry (EB)	12.95%	18.01%	18.84%	17.92%	16.80%	9.56%	5.92%
Farewell Bend (WB)	16.29%	18.18%	18.46%	18.64%	14.13%	6.55%	7.75%
Klamath Falls (NB)	15.10%	18.84%	19.24%	19.05%	15.57%	7.40%	4.79%
Klamath Falls (SB)	15.47%	19.30%	18.85%	18.78%	15.86%	6.98%	4.77%

Green Indicates the Day with the Highest Number of Observed Trucks
Yellow Indicates the Day with the Second Highest Number of Observed Trucks
Orange Indicates the Day with the Third Highest Number of Observed Trucks

7.7 ANNUAL GROWTH RATES

Utilizing the total number of trucks for each WIM station and each year, a summary annual growth rates by WIM station are presented. The annual growth rate for each WIM station is computed as:

$$\left[\left(\frac{\textbf{Number of Trucks in 2018}_i}{\textbf{Number of Trucks in 2015}_i}\right)^{\left(\frac{1}{y}\right)} - 1\right] \times 100$$

(7-1)

Where:

> Number of Trucks in 2018_i is the total number of trucks in 2018 at WIM station i (e.g., Woodburn, Ashland, etc.), Number of Trucks in 2015_i is the total number of trucks in 2015 at WIM station i, and y is equal to four (the number of years of data).

Using Eq. (7-1), the annual growth rates shown in Table 7.12 were calculated. In terms of volume, six of the WIM stations have an increasing annual growth rate, and four WIM stations have a decreasing annual growth rate. Based on the WIM data, Ashland (SB), Woodburn (NB), Woodburn (SB), and Wyeth (WB) have decreasing annual growth rates. These results are unexpected based on two factors: (1) the continued growth in freight delivered by truck and (2) these are key WIM stations based on volumes and locations. Each of these WIM stations are located at a point of entry or exit. Of the WIM stations with increasing annual growth rates, Olds Ferry (EB) has the largest at 7.58%. This WIM station is located on the Oregon-Idaho border, indicating (based on the recorded WIM data) that freight leaving Oregon and headed east is growing annually. Also, with a moderate annual growth factor, relative to the other WIM stations, is Klamath Falls (NB) and Klamath Falls (SB). Although Ashland (NB) is also increasing annually (annual growth rate of 2.03%), there is larger growth along US-97, according to the recorded WIM data; specifically, an annual growth rate of 5.12% at Klamath Falls (NB) and an annual growth rate of 3.11% at Klamath Falls (SB).

In terms of combined (truck and cargo) weight, annual growth differs compared to volume. Three of the WIM stations have decreasing annual growth rates: Ashland (SB), Woodburn (NB), and Klamath Falls (SB). Regarding Klamath Falls (SB), the annual growth rate is approximately zero, while the annual growth rate at Ashland (SB) is roughly -0.78%. The third WIM station with a decreasing annual growth rate is Woodburn (NB) at -4.90%. Of the remaining WIM stations, all with increasing annual growth rates, the largest rate is observed at Olds Ferry (EB) at 7.74%. Also, with moderate annual growth rates in terms of weight are Woodburn (SB) at 5.36% and Klamath Falls (NB) at 4.24%.

In comparing annual growth rates for volume and combined (truck and cargo) weight, three WIM stations have opposite growth rates. For instance, at Woodburn (SB) there is an annual growth rate for volume of -2.11%, and a +5.36% annual growth rate for combined weight, at Wyeth (WB) there is a -0.09% annual growth rate for volume and a +1.07% annual growth rate for combined weight, and at Klamath Falls (SB) there is a +3.11% annual growth rate for volume and a -0.07% annual growth rate for combined weight. A potential reason for the decreasing rate in volume and increasing rate in combined weight may be attributed to more double and triple trailers hauling freight, possibly reducing the number of single trailers. However, further analysis is necessary to determine why these annual growth rates are being observed at these WIM stations. Lastly, an overall annual growth rate for volume and combined weight was calculated considering the total number of trucks and observed combined weight for all 10 WIM stations. When considering all WIM stations, there is an overall annual growth rate of 0.18% for volume and a 1.19% annual growth rate for combined weight. This indicates that, according to the recorded WIM data, freight volume and combined weight are growing annually, albeit marginally. To further assess the overall annual growth rates, additional WIM stations, and years of WIM data is recommended.

Table 7.12: Annual Growth Rates by WIM Station

WIM Station	Number of Trucks		Annual Growth Rate	Combined Weight (tons)[1]		Annual Growth Rate
	2015	2018		2015	2016	
Ashland (NB)	1,168,086	1,266,074	2.03%	25,341,945	27,356,984	1.93%
Ashland (SB)	1,153,847	1,144,427	-0.20%	24,203,659	23,455,716	-0.78%
Woodburn (NB)	3,052,041	2,711,035	-2.92%	60,470,967	49,468,701	-4.90%
Woodburn (SB)	2,434,193	2,235,196	-2.11%	37,434,716	46,123,721	5.36%
Cascade Locks (EB)	955,866	1,075,075	2.98%	21,556,363	24,364,035	3.11%
Wyeth (WB)	1,048,310	1,044,428	-0.09%	21,403,103	22,335,817	1.07%
Olds Ferry (EB)	679,478	910,139	7.58%	16,137,426	21,744,549	7.74%
Farewell Bend (WB)	763,439	818,938	1.77%	16,660,091	18,975,888	3.31%
Klamath Falls (NB)	319,538	390,206	5.12%	5,082,383	6,000,722	4.24%
Klamath Falls (SB)	512,980	579,871	3.11%	9,426,914	9,399,178	-0.07%
Overall[2]	12,087,778	12,175,389	0.18%	237,717,566	249,225,312	1.19%

[1] Combined Weight Refers to the Weight of the Truck and the Cargo
[2]` Overall growth rate includes truck and weight values at all 10 WIM stations

7.8 TRUCK VOLUMES, WEIGHT, AND PROPORTION OF EMPTIES

The final assessment of the select WIM stations consisted of summarizing truck counts and proportions, combined weight (truck and cargo), average cargo weight (observed combined weight minus the weight of the truck), and proportion of empty trucks by WIM station. A summary is provided in Table 7.13 to Table 7.15 for the 2018 WIM data. To present metrics related to cargo weight and proportion of empties, the weight of the truck must be known. For ODOT Class 11 trucks, a weight of 32,000 pounds was used (this value is widely known and commonly used in WIM-related research). For ODOT Class 12 to ODOT Class 19, weight density plots were generated at each WIM station. Seven of the 10 WIM stations had a weight distribution in which there was a lower peak and upper peak; Ashland (NB), Cascade Locks (EB), and Wyeth (WB) did not have clear lower and upper peaks. For the seven WIM stations with lower and upper peaks, the weight value at the lower peak was determined and assumed to be the truck weight. To approximate these metrics at all WIM stations, the average of the seven WIM stations was taken to be the truck weight: 41,902 pounds. It was also discovered that the weight distributions of ODOT Class 13 trucks were vastly different compared to the other classifications in this group. As a result, the empirical weight of ODOT Class 13 trucks was computed separately following the same process, in which a truck weight of 22,533 pounds was determined and used. Distribution plots of cargo weight for ODOT Class 11 trucks, assuming a truck weight of 32,000 pounds, can be seen in Appendix B.

It should be noted, these values are approximate and based solely on the distribution of the observed combined weights. For future assessments, it is recommended to calculate each value for each classification individually for the year of interest and by WIM station, tantamount to what had to be done for ODOT Class 13 trucks. This stems from the calculations being based on observed combined weight distributions, which vary by year and vary by WIM station. This is evident in the succeeding chapter, in which a different year of WIM data resulted in different empirical truck weights. This premise holds for ODOT Class 03 to ODOT Class 10 trucks as well, as observed combined weights between these classifications vary substantially from class-to-class. Therefore, for this report, cargo weight and proportion of empties are not reported for ODOT Class 03 to ODOT Class 10 trucks.

Referring to the Ashland WIM stations, the average cargo weight in the northbound direction is 31,305 pounds. As for the proportion of empty trucks, the average proportion of empties in the northbound direction is 5.88%. In the southbound direction, the average cargo weight is less at 22,258 pounds, and the average proportion of empties is higher at 10.11%. Also, in the southbound direction, Class 12, Class 13, Class 15, and Class 17 all have a proportion of empties of greater than 10%.

Referring to the Woodburn WIM stations, the average cargo weight in the northbound direction is 19,000 pounds, and the average proportion of empties is 21.42%. In the northbound direction, Class 11, Class 16, and Class 18 are the only classifications to have proportions less than 10%, while the remaining classifications have a substantially high number of observed empties. In the southbound direction, the average observed cargo weight is higher at 25,425 pounds, and the proportion of empties is significantly lower at 10.45%.

At Cascade Locks (EB) and Wyeth (WB), the average cargo weight at Cascade Locks is 33,849 pounds, and the average proportion of empties is 2.40%. At Wyeth, the average cargo weight is 27,342 pounds, and the average proportion of empties is 9.15%. Also on I-84 are the Olds Ferry (EB) and Farewell Bend (WB) WIM stations. At Olds Ferry, the average cargo weight is 27,584 pounds and the average proportion of empties is 10.02%. At Farewell Bend, the average cargo weight is 22,208 pounds and the average proportion of empties is 18.39%.

At Klamath Falls, the average cargo weight in the northbound direction is 25,054 pounds, and the average proportion of empties is 7.55%. In the southbound direction, the average cargo weight is 33,255 pounds, and the average proportion of empties is 4.90%.

Based on the following, considering the I-84 WIM stations, higher cargo weights and fewer empties are observed in the eastbound direction. On the other hand, lower cargo weights and a higher proportion of empties are observed in the westbound direction. These trends indicate that more cargo is headed east leaving Oregon than headed west into Oregon. This is in-line with findings presented in the descriptive analysis. As for the I-5 WIM stations, the trends are opposite. That is, at Ashland, higher cargo weights and fewer empties are observed in the northbound direction (headed to or through Oregon), while lower cargo weights and higher empties are observed in the southbound direction. At Woodburn, higher cargo weights and fewer empties are observed in the southbound direction, while lower cargo weights and more empties are observed in the northbound direction. Lastly, at Klamath Falls, higher cargo weights and fewer empties are observed in the southbound direction. This finding is also in-line with findings in the descriptive analysis and annual growth rate calculations.

Additionally, ODOT Class 11 trucks were examined further considering the following weight thresholds:

- Percent of ODOT Class 11 trucks less than or equal to 32,000 pounds.
- Percent of ODOT Class 11 trucks less than or equal to 36,000 pounds.
- Percent of ODOT Class 11 trucks greater than or equal to 76,000 pounds.
- Percent of ODOT Class 11 trucks greater than or equal to 80,000 pounds.

A summary of ODOT Class 11 proportions under these thresholds is given in Table 7.16. Based on weight distributions for 2018 WIM data, very few Class 11 trucks have an observed combined (truck and cargo) weight of less than 32,000 pounds. The highest proportions are observed at Woodburn (NB), Wyeth (WB), and Farewell Bend (WB) at 3.34%, 3.17%, and 8.09%, respectively.

Considering the threshold of less than or equal to 36,000 pounds, moderately higher proportions are observed for most WIM stations (Ashland (NB), Cascade Locks (EB), and the Klamath Falls WIM stations did not increase much). The proportion at the Woodburn WIM stations have the highest increase; specifically, 3.34% to 12.36% (northbound) and 2.22% to 12.73% (southbound).

For Class 11 trucks greater than or equal to 76,000 pounds, the highest proportion is observed at Klamath Falls (SB) with 12.98%. Also with moderate proportions are Klamath Falls (SB) at 8.00%, Wyeth (WB) at 7.35%, and Farewell Bend (WB) at 5.28%.

For the final threshold, percent of Class 11 trucks greater than or equal to 80,000 pounds, Klamath Falls (SB) has the highest proportion at 3.79%. The only other WIM station with a proportion of greater than 2.00% is Wyeth (WB) at 2.30%.

Table 7.13: Summary of Truck Counts, Truck Weight (Truck and Cargo), Cargo Weight, and Empty Trucks at I-5 WIM Stations

Ashland WIM Stations										
	Northbound					Southbound				
ODOT Classification	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**
ODOT Class 03	341,107	26.94%	9,185	-	-	270,782	23.66%	9,255	-	-
ODOT Class 05	10,834	0.86%	28,740	-	-	17,708	1.55%	25,657	-	-
ODOT Class 06	22,283	1.76%	15,732	-	-	20,399	1.78%	15,275	-	-
ODOT Class 08	74,362	5.87%	19,803	-	-	77,835	6.80%	18,612	-	-
ODOT Class 09	5,818	0.46%	41,441	-	-	5,146	0.45%	38,822	-	-
ODOT Class 10	224	0.02%	37,179	-	-	147	0.01%	40,766	-	-
ODOT Class 11	728,319	57.53%	60,538	28,538	0.17%	668,234	58.39%	56,042	24,042	0.70%
ODOT Class 12	46,797	3.70%	62,544	20,642	2.30%	46,133	4.03%	53,862	11,960	10.95%
ODOT Class 13	7,551	0.60%	30,464	7,931	26.43%	7,769	0.68%	28,799	6,266	32.81%
ODOT Class 14	19,152	1.51%	67,975	26,073	1.97%	20,986	1.83%	58,504	16,602	2.57%
ODOT Class 15	5,701	0.45%	65,228	23,326	4.33%	4,842	0.42%	57,825	15,923	12.06%
ODOT Class 16	21	0.00%	87,996	46,094	9.52%	23	0.00%	65,599	23,697	8.70%
ODOT Class 17	2,651	0.21%	61,768	19,866	4.34%	2,036	0.18%	61,371	19,469	16.90%
ODOT Class 18	914	0.07%	76,975	35,073	2.41%	1,858	0.16%	79,330	37,428	3.12%
ODOT Class 19	340	0.03%	116,109	74,207	1.47%	529	0.05%	86,839	44,937	3.21%
Woodburn WIM Stations										
	Northbound					Southbound				
ODOT Classification	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**
ODOT Class 03	836,545	30.86%	10,114	-	-	540,403	24.18%	10,831	-	-
ODOT Class 05	80,673	2.98%	25,641	-	-	48,613	2.17%	26,173	-	-
ODOT Class 06	67,036	2.47%	17,133	-	-	94,804	4.24%	17,132	-	-
ODOT Class 08	188,251	6.94%	19,660	-	-	129,141	5.78%	20,462	-	-

Ashland WIM Stations										
ODOT Class 09	20,878	0.77%	38,375	-	-	16,117	0.72%	38,998	-	-
ODOT Class 10	1,882	0.07%	44,662	-	-	941	0.04%	48,942	-	-
ODOT Class 11	1,071,975	39.54%	51,392	19,392	3.34%	919,433	41.13%	51,391	19,391	2.22%
ODOT Class 12	19,912	0.73%	49,598	7,696	26.33%	18,118	0.81%	57,815	15,913	7.14%
ODOT Class 13	20,987	0.77%	35,204	12,671	27.99%	10,973	0.49%	31,671	9,138	36.64%
ODOT Class 14	23,552	0.87%	56,973	15,071	10.49%	22,134	0.99%	58,876	16,974	3.85%
ODOT Class 15	94,040	3.47%	47,845	5,943	40.35%	156,873	7.02%	52,599	10,697	29.87%
ODOT Class 16	37,818	1.39%	72,346	30,444	1.34%	34,691	1.55%	82,549	40,647	0.08%
ODOT Class 17	115,955	4.28%	59,149	17,247	36.15%	100,298	4.49%	69,389	27,487	10.07%
ODOT Class 18	127,274	4.69%	79,641	37,739	4.28%	117,030	5.24%	84,676	42,774	3.41%
ODOT Class 19	4,257	0.16%	66,696	24,794	42.54%	25,627	1.15%	87,708	45,806	0.75%

Table 7.14: Summary of Truck Counts, Truck Weight (Truck and Cargo), Cargo Weight, and Empty Trucks at Cascade Locks/Wyeth and Olds Ferry/Farewell Bend WIM Stations

Cascade Locks and Wyeth WIM Stations										
	Eastbound (Cascade Locks)					Westbound (Wyeth)				
ODOT Classification	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**
ODOT Class 03	305,278	28.40%	9,814	-	-	263,859	25.26%	9,593	-	-
ODOT Class 05	10,388	0.97%	29,841	-	-	12,807	1.23%	28,532	-	-
ODOT Class 06	23,032	2.14%	16,710	-	-	22,658	2.17%	14,792	-	-
ODOT Class 08	78,180	7.27%	20,799	-	-	79,853	7.65%	19,642	-	-
ODOT Class 09	7,007	0.65%	44,176	-	-	6,976	0.67%	39,702	-	-
ODOT Class 10	405	0.04%	49,391	-	-	375	0.04%	46,622	-	-
ODOT Class 11	417,860	38.87%	58,458	26,458	0.18%	426,485	40.83%	56,372	24,372	3.17%
ODOT Class 12	16,375	1.52%	62,508	20,606	0.81%	15,799	1.51%	53,906	12,004	17.90%
ODOT Class 13	5,212	0.48%	34,803	12,270	18.53%	11,495	1.10%	43,282	20,749	15.45%
ODOT Class 14	20,408	1.90%	70,269	28,367	0.18%	21,341	2.04%	62,979	21,077	6.28%
ODOT Class 15	40,205	3.74%	66,205	24,303	1.17%	55,067	5.27%	57,252	15,350	12.26%
ODOT Class 16	19,036	1.77%	88,435	46,533	0.03%	18,462	1.77%	75,890	33,988	2.37%
ODOT Class 17	39,420	3.67%	81,007	39,105	0.41%	63,547	6.08%	65,649	23,747	18.66%
ODOT Class 18	90,383	8.41%	91,722	49,820	0.06%	41,596	3.98%	90,235	48,333	2.63%
ODOT Class 19	1,886	0.18%	99,078	57,176	0.27%	4,108	0.39%	88,360	46,458	3.60%
Olds Ferry and Farewell Bend WIM Stations										
	Eastbound (Cascade Locks)					**Westbound (Farewell Bend)**				
ODOT Classification	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**
ODOT Class 03	155,573	17.09%	9,009	-	-	104,098	12.71%	8,266	-	-
ODOT Class 05	13,368	1.47%	16,096	-	-	4,248	0.52%	21,486	-	-
ODOT Class 06	13,174	1.45%	14,252	-	-	12,018	1.47%	13,550	-	-

Cascade Locks and Wyeth WIM Stations										
ODOT Class 08	63,240	6.95%	20,198	-	-	54,945	6.71%	17,757	-	-
ODOT Class 09	4,314	0.47%	35,536	-	-	5,323	0.65%	30,716	-	-
ODOT Class 10	66	0.01%	41,128	-	-	85	0.01%	40,699	-	-
ODOT Class 11	490,025	53.84%	57,606	25,606	1.72%	477,385	58.29%	53,857	21,857	8.09%
ODOT Class 12	17,495	1.92%	55,716	13,814	8.85%	16,103	1.97%	47,703	5,801	26.16%
ODOT Class 13	8,238	0.91%	26,180	3,647	48.34%	5,786	0.71%	32,692	10,159	29.90%
ODOT Class 14	15,287	1.68%	60,384	18,482	7.14%	17,954	2.19%	54,785	12,883	16.29%
ODOT Class 15	31,992	3.52%	56,175	14,273	18.48%	28,363	3.46%	53,645	11,743	36.66%
ODOT Class 16	17,380	1.91%	80,799	38,897	0.03%	18,537	2.26%	64,951	23,049	2.86%
ODOT Class 17	40,122	4.41%	79,711	37,809	4.34%	42,401	5.18%	66,629	24,727	23.91%
ODOT Class 18	37,063	4.07%	87,758	45,856	0.50%	30,655	3.74%	78,083	36,181	9.95%
ODOT Class 19	2,802	0.31%	91,771	49,869	0.75%	1,037	0.13%	95,376	53,474	11.67%

Table 7.15: Summary of Truck Counts, Truck Weight (Truck and Cargo), Cargo Weight, and Empty Trucks at Klamath Falls WIM Stations

Klamath Falls WIM Stations										
	Northbound					Southbound				
ODOT Classification	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**	**Number of Trucks**	**Percent**	**Average Truck Weight (lbs.)**	**Average Cargo Weight (lbs.)**	**Proportion of Empty Trucks**
ODOT Class 03	192,584	49.35%	9,690	-	-	299,152	51.59%	9,211	-	-
ODOT Class 05	9,750	2.50%	26,044	-	-	8,262	1.42%	28,159	-	-
ODOT Class 06	11,915	3.05%	18,216	-	-	10,401	1.79%	15,359	-	-
ODOT Class 08	28,076	7.20%	23,434	-	-	27,968	4.82%	20,866	-	-
ODOT Class 09	5,768	1.48%	47,950	-	-	2,565	0.44%	42,846	-	-
ODOT Class 10	175	0.04%	43,805	-	-	358	0.06%	47,162	-	-
ODOT Class 11	112,504	28.83%	61,382	29,382	0.57%	196,257	33.84%	62,535	30,535	0.37%
ODOT Class 12	2,137	0.55%	57,500	15,598	11.42%	2,167	0.37%	59,111	17,209	9.14%
ODOT Class 13	1,829	0.47%	36,273	13,740	22.58%	2,178	0.38%	35,578	13,045	20.89%
ODOT Class 14	5,462	1.40%	60,059	18,157	4.38%	5,751	0.99%	63,168	21,266	2.43%
ODOT Class 15	5,727	1.47%	53,583	11,681	15.03%	5,703	0.98%	62,304	20,402	8.31%
ODOT Class 16	596	0.15%	83,348	41,446	0.00%	685	0.12%	80,008	38,106	0.00%
ODOT Class 17	7,646	1.96%	60,487	18,585	7.38%	4,873	0.84%	80,801	38,899	1.79%
ODOT Class 18	5,924	1.52%	79,512	37,610	0.39%	13,464	2.32%	95,442	53,540	0.04%
ODOT Class 19	113	0.03%	81,186	39,284	6.19%	87	0.02%	108,194	66,292	1.15%

Table 7.16: Summary of Proportions of ODOT Class 11 Trucks by Weight in 2018

WIM Station	Proportion Less Than 32,000 lbs.	Proportion Less Than 36,000 lbs.	Proportion Greater Than 76,000 lbs.	Proportion Greater Than 80,000 lbs.
Ashland (NB)	0.17%	0.43%	0.68%	0.08%
Ashland (SB)	0.70%	4.13%	2.12%	0.22%
Woodburn (NB)	3.34%	12.36%	0.15%	0.01%
Woodburn (SB)	2.22%	12.73%	1.28%	0.14%
Cascade Locks (EB)	0.18%	0.41%	1.43%	0.25%
Wyeth (WB)	3.17%	8.03%	7.35%	2.30%
Olds Ferry (EB)	1.72%	6.48%	1.83%	0.64%
Farewell Bend (WB)	8.09%	13.63%	5.28%	1.01%
Klamath Falls (NB)	0.57%	1.96%	8.00%	1.20%
Klamath Falls (SB)	0.37%	1.40%	12.98%	3.79%

7.9 SUMMARY OF DESCRIPTIVE ANALYSIS AT SELECT WIM STATIONS

Through the descriptive analysis of select WIM stations, it was determined that direction plays a role in the number of trucks and the total combined (truck and cargo) weight observed. At the border WIM stations of Ashland and Olds Ferry (EB)/Farewell Bend (WB), it was determined that volumes and combined weights headed into Oregon are greater than volumes and combined weights leaving Oregon. However, in 2018, higher volumes and combined weights were observed leaving Oregon at the Olds Ferry (EB)/Farewell Bend (WB). Interestingly, the opposite trends were observed at Klamath Falls. In particular, higher volumes and combined weights were observed leaving Oregon (southbound). The trends at Klamath Falls in the southbound direction may be related to findings from Hernández & Anderson (2017), in which it was found that truck drivers often prefer to take US-97 when traveling south to “make-up time” by avoiding the topography that is present on Southern I-5 (the Ashland WIM stations). Most notably, this includes the Siskiyou Pass on I-5. This section of I-5 has a grade of approximately 6% in both directions and is the highest point on the I-5 corridor. On the other hand, US-97 crossing the Oregon-California border remains relatively flat in terms of elevation changes.

As for seasonal trends, the common theme observed was an increase during the summer months. With that in mind, however, Woodburn (SB) experienced some interesting trends. When considering all trucks, no year followed the trend of another. In 2016, there was a slight spike during the summer months, in 2015 there was a steady increase throughout the year, and in 2017 there was essentially a constant trend throughout the year. In one direction, Woodburn (NB), there was even a sharp decrease during the summer months in terms of both volume and combined (truck and cargo) weight in 2017. The variations were not as profound when considering only ODOT Class 11 trucks, but were still present. The most consistent trends observed at Woodburn were in the northbound direction for ODOT Class 03 to ODOT Class 10 trucks.

In regards to monthly percentages and volumes, June accounts for at least the third highest proportion for eight of the 10 WIM stations: (1 - highest proportion) Ashland (SB), Woodburn (NB), Farewell Bend (WB), and (2 - 3rd highest proportion) Klamath Falls (NB), Ashland (NB), Woodburn (SB), Wyeth (WB), and Klamath Falls (SB). As observed, monthly proportions are contingent on direction, in which directional trends were also observed in the descriptive analysis. August accounts for at least the third highest proportion for seven of the 10 WIM stations and July for six of the 10 WIM stations. When considering combined (truck and cargo) weight, similar trends are observed. In particular, June accounts for at least the third highest proportion for seven of the 10 WIM stations, while August accounts for six of the 10 WIM stations. Unlike the volume monthly percentages, three WIM stations experienced their highest proportion of combined weight in March: Woodburn (NB), Olds Ferry (EB), and Farewell Bend (WB). When considering the average of all WIM stations by month, June accounts for the highest proportion, May the second highest proportion, and August the third highest proportion. Lastly, both Klamath Falls WIM stations have higher proportions from May to August when compared to the other select WIM stations.

For day-of-the-week trends, it was determined that the highest volumes across all WIM stations are consistently observed on Wednesdays, Thursdays, and Tuesdays. Other days of the week experienced high volumes contingent on the classification group. For example, considering all trucks, Friday accounted for the highest, second highest, and third highest volume at Cascade Locks (EB) and Olds Ferry (EB), Klamath Falls (SB), and Wyeth (WB), respectively. When considering ODOT Class 11 trucks, Sundays accounted for the second highest volume at Farewell Bend (WB). Mondays also account for high volumes, where the highest volume at Farewell Bend (WB), second highest volume at Wyeth (WB), and third highest volume at Woodburn (SB) were observed on Mondays. When considering ODOT Class 12 to ODOT Class 19 trucks, Wednesdays, Thursdays, and Tuesdays were the top three days.

Annual growth rates for each WIM station were computed. Of the ten select WIM stations, six WIM stations resulted in an increasing annual growth rate, none of which were the Woodburn WIM stations. The WIM station with the highest annual growth rate, for both volume and combined (truck and cargo) weight, is Olds Ferry (EB) at 7.58% and 7.74%, respectively. This WIM station is located on the Oregon-Idaho border, indicating (based on the recorded WIM data) that freight leaving Oregon and headed east is growing annually. Also, with a moderate annual growth factor, relative to the other WIM stations, is Klamath Falls (NB). Although Ashland (NB) is also increasing annually (annual growth rate for volume of 2.03% and annual growth rate for combined weight of 1.93%), there is larger growth along US-97, according to the recorded WIM data. Klamath Falls (SB) truck traffic is also growing, which corresponds to the trends observed when compared to Ashland (SB). Also of interest, three WIM stations had opposite annual growth rates. Woodburn (SB) has a negative annual growth rate in terms of volume (-2.11%) and a positive annual growth rate in terms of combined weight (+5.36%). Similar to Woodburn (NB), Wyeth (WB) has a negative annual growth rate in terms of volume (-0.07%) and a positive annual growth rate in terms of combined weight (+1.07%). The third WIM stations with opposite annual growth rates is Klamath Falls (SB), where there is a positive annual growth rate in terms of volume (+3.11%) and a negative annual growth rate in terms of combined weight (-0.07%). Lastly, an overall annual growth rate for volumes and combined weight was determined using values from all ten select WIM stations. The overall annual growth rate for volume was determined to be +0.18%, and the overall annual growth rate for combined weight was determined to be +1.19%.

In terms of cargo weight and empty trucks, higher cargo weights and fewer empties are observed in the eastbound direction on I-84. These trends indicate that more cargo is headed east leaving Oregon than headed west into Oregon. This is in-line with findings presented in the descriptive analysis. As for the I-5 WIM stations, the trends are the opposite. That is, at Ashland, higher cargo weights and fewer empties are observed in the northbound direction (headed to or through Oregon), while lower cargo weights and higher empties are observed in the southbound direction (leaving Oregon). At Woodburn, higher cargo weights and fewer empties are observed in the southbound direction, while lower cargo weights and more empties are observed in the northbound direction. Lastly, at Klamath Falls, higher cargo weights and fewer empties are observed in the southbound direction. This finding is also in-line with findings in the descriptive analysis and annual growth rate calculations.

Additionally, three different thresholds considering only ODOT Class 11 trucks were assessed. The first threshold was the proportion of ODOT Class 11 trucks below 36,000 pounds, the second was the proportion above 76,000 pounds, and the third was the proportion above 80,000 pounds. Using these thresholds, moderately higher proportions of ODOT Class 11 trucks under 36,000 pounds (compared to under 32,000 pounds) are observed for most WIM stations (Ashland (NB), Cascade Locks (EB), and the Klamath Falls WIM stations did not increase much). The proportion at the Woodburn WIM stations have the highest increase; specifically, 3.34% to 12.36% (northbound) and 2.22% to 12.73% (southbound). For the second threshold, greater than or equal to 76,000 pounds, the highest proportion is observed at Klamath Falls (SB) with 12.98%. Also with moderate proportions are Klamath Falls (SB) at 8.00%, Wyeth (WB) at 7.35%, and Farewell Bend (WB) at 5.28%. For the final threshold, greater than or equal to 80,000 pounds, Klamath Falls (SB) has the highest proportion at 3.79%. The only other WIM station with a proportion of greater than 2.00% is Wyeth (WB) at 2.30%.

8.0 DATA COMPARISON

To determine if Oregon WIM data can be used for planning analyses (e.g., use in Oregon's SWIM model), Oregon WIM data at the select WIM stations is compared to various data sources. In each case, the comparisons and methods vary based on the data being compared. The data sources selected for comparison include the Freight Analysis Framework (FAF) data and traffic volume obtained from two 24-hour traffic counts adjacent to two WIM stations located near ATRs.

Being that FAF data reports cargo weight only, truck weights must be subtracted from the observed combined (truck and cargo) WIM weights to make comparisons as accurate as possible. For ODOT Class 11 trucks (tantamount to FHWA Class 09 trucks), the weight of an empty truck is widely known to be approximately 32,000 pounds. Therefore, for WIM records of ODOT Class 11 trucks, truck weights were subtracted from the total observed weight using 32,000 pounds. For ODOT Class 12 to ODOT Class 19 truck weight, a different approach was taken, as configurations differ. The approach consisted of generating density plots of the observed weights for ODOT Class 12 to ODOT Class 19 trucks, in which the lower peak was assumed to be the empirical truck weight. This was done using 2016 data. An example of a generated density plot is shown in Figure 8.1. These plots were generated for each classification at the most trafficked WIM station, Woodburn.[22] It was determined that the average of the lower peaks equaled 39,751 pounds and was assumed to be the truck weight (weight of truck only) for ODOT Class 12 to ODOT Class 19 trucks. Weights at the lower peaks of the density curves were determined by identifying the density value at the highest point of the lower peak, then associated that value with the corresponding weight. A tabulated summary of lower peaks for ODOT Class 12 to ODOT Class 19 trucks is presented in Table 8.1.

[22] Density plots by classification for ODOT Class 11 to ODOT Class 19 trucks can be found here.

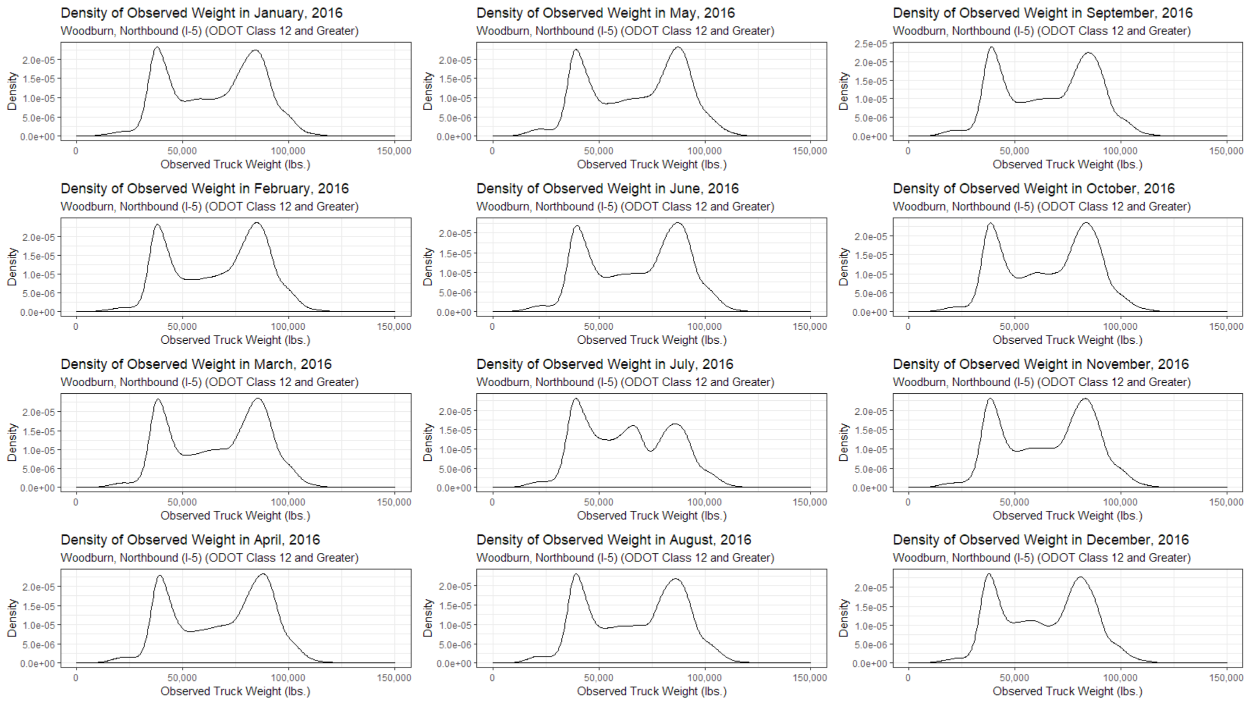


Figure 8.1: Example of density plot used to determine truck weight (weight of truck only) for ODOT Class 12 to ODOT Class 19 trucks

Table 8.1: Observed Low Peaks at Woodburn WIM Stations by Classification in 2016 (lbs.)

Month	Class 12*		Class14*	Class 15*		Class 17*		Class 18*		Class 19*	Average
	Woodburn (NB)	Woodburn (SB)	Woodburn (SB)	Woodburn (NB)	Woodburn (SB)	Woodburn (NB)	Woodburn (SB)	Woodburn (NB)	Woodburn (SB)	Woodburn (NB)	
January	36,860	40,310	43,819	40,444	38,210	36,929	40,415	39,593	37,464	37,948	39,199
February	37,551	40,279	43,846	40,676	37,926	37,370	41,086	37,833	38,352	38,313	39,323
March	37,091	39,902	43,975	40,977	38,306	37,735	40,865	38,299	37,559	38,579	39,329
April	37,977	40,675	44,246	42,135	38,556	38,389	41,216	42,250	38,564	40,017	40,402
May	38,153	40,176	44,313	42,333	38,610	38,594	41,035	42,625	39,554	40,072	40,547
June	38,214	40,048	43,886	42,414	38,648	38,719	41,254	43,603	39,016	39,939	40,574
July	38,604	40,244	44,401	42,394	38,646	38,872	40,625	43,211	37,778	39,440	40,421
August	38,276	41,519	46,641	41,860	40,266	38,791	42,699	40,477	41,517	40,392	41,244
September	38,229	39,439	44,451	41,671	38,607	38,419	41,043	41,220	39,356	38,309	40,075
October	37,314	39,200	42,975	41,392	37,735	37,743	40,068	38,317	36,758	38,822	39,033
November	37,070	39,017	42,994	40,519	37,345	37,438	39,413	37,679	36,327	39,196	38,700
December	36,464	38,010	41,909	40,035	36,956	36,663	38,814	38,678	35,832	38,318	38,168
Average	37,650	39,902	43,955	41,404	38,318	37,972	40,711	40,315	38,173	39,112	**39,751**
Number of Trucks	22,579	18,740	23,651	109,775	126,963	137,819	82,717	160,555	115,005	5,762	

* Included classes were based on their observed weight distributions having a clear lower and upper peak. Therefore, ODOT Class 13 and ODOT Class 16 trucks were not included, as the observed weight distributions did not have clear lower and upper peaks.

8.1 FREIGHT ANALYSIS FRAMEWORK (FAF) COMPARISON

For the FAF data comparison, four comparisons are made based on WIM records of ODOT Class 11 to ODOT Class 19 trucks. The weights reported in FAF data represent the weight of the commodity only (i.e., cargo weight). Therefore, the weight of the truck was subtracted from the combined (truck and cargo) weight observed in the WIM data. This was done based on a truck weight of 32,000 lbs. for ODOT Class 11 trucks and a weight of 39,751 pounds for ODOT Class 12 to ODOT Class 19 trucks. The choice to include ODOT Class 12 to ODOT Class 19 trucks for this comparison stems from their configuration and potential cargo weight, as FAF weights are in terms of the commodity only. This premise is based on the inclusion of additional observed cargo weight resulting in more accurate comparisons.

The first comparison is with the base year of the FAF data, 2012. The other three comparisons are based on the predicted values in the FAF data; specifically, for years 2015, 2016, and 2017. For the FAF comparison, only WIM stations at the southern border of Oregon are used: Ashland and Klamath Falls. The selection of just these WIM stations stems from assumptions regarding freight origins and destinations. In the case of these two WIM stations, three different assumptions are made and assessed:

- ***Assumption 1***: Shipments originating in Washington or Oregon and destined to California, Nevada, Arizona, or Mexico, are passing through the Ashland or Klamath Falls WIM stations. The same assumption is being applied if shipments are originating in California, Nevada, Arizona, or Mexico, and destined to Oregon or Washington.

- ***Assumption 2***: Shipments originating in Washington or Oregon and destined to California or Arizona are passing through the Ashland or Klamath Falls WIM stations. The same assumption is being applied if shipments are originating in California or Arizona and destined to Oregon or Washington. For this, shipments including Nevada and Mexico have been removed.

- ***Assumption 3***: Shipments originating in Washington or Oregon and Destined to California are passing through the Ashland or Klamath Falls WIM stations. The same assumption is being applied if shipments are originating in California and destined to Oregon or Washington.

Under these three assumptions, comparisons are made for each year. Considered FAF regions and the southern Oregon WIM stations are shown in Figure 8.2.
For proceeding tables in which percent differences are presented, the following is used:

$$\frac{\boldsymbol{W_{id} - F_{id}}}{\left[\frac{\boldsymbol{W_{id} + F_{id}}}{\mathbf{2}}\right]} \times \mathbf{100} \tag{8-1}$$

Where:

> W_{id} represents WIM weight in year i and direction d, and F_{id} represents FAF weight in year i and direction d.

The choice to calculate percent difference as opposed to percent change stems from the weight values being from different data sources (i.e., a WIM weight does not have a percent change to a FAF weight). If comparing weight values within-weight sources, a percent change calculation would serve appropriate. Additionally, in the succeeding tables where this information is presented, all percent differences are presented as WIM data relative to FAF data (i.e., the percent difference of the WIM data when compared to the FAF data). This occurs as the WIM data is listed first in Eq. **(8-1)**. For example, if the percent difference is negative, it is due to the WIM data being less than the FAF data; whereas, if the value is positive, it is due to the WIM data being greater than the FAF data. To demonstrate an example, refer to Table 8.6. In the northbound direction, there is a WIM weight of 3,597,377 tons and a FAF weight of 4,025,671 tons (WIM weight is less than FAF weight). Inserting these weights into Eq. **(8-1)** results in a value of -11.24%, indicating the WIM weight is 11.24% less than the FAF weight. This remains true for all tables in which percent differences are presented, including the percent differences presented in Chapter 8.2.

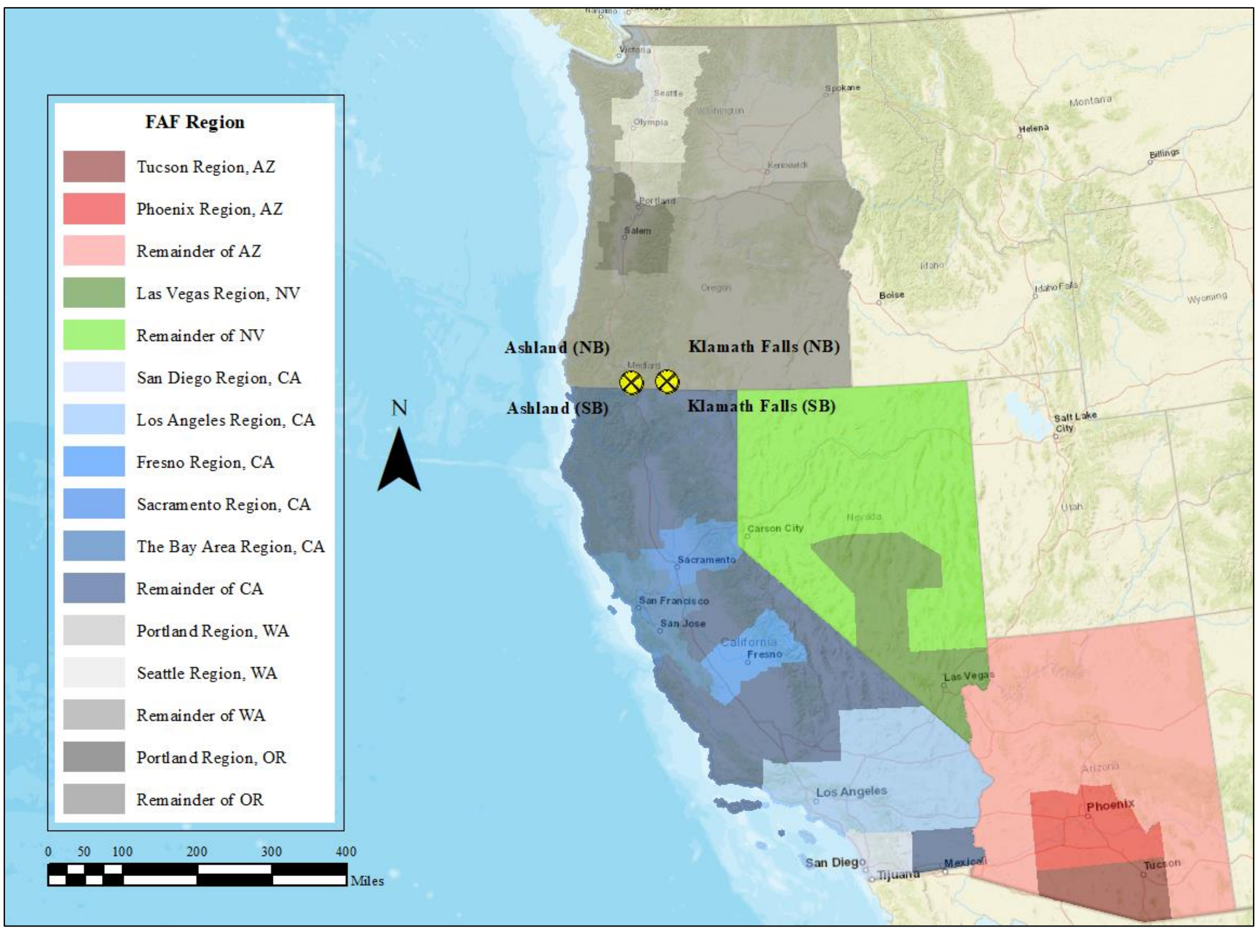


Figure 8.2: FAF regions and southern Oregon WIM stations

8.1.1 2012 FAF Comparison

The first FAF comparison is for the year 2012. For 2012, the base year of the FAF data and year used for all future projections, WIM data was only available for just over four months of the year. Therefore, for the most accurate comparison, only the four months of complete data were used: September, October, November, and December.

Due to FAF data being aggregated at an annual level, and only four complete months of WIM data available, monthly percentages were computed using the four complete years of WIM data (2015 to 2018). This was done to assess the consistency of the observed combined (truck and cargo) weights across the years. A summary of monthly observed combined weight totals for ODOT Class 11 trucks by year and WIM station are shown in Table 8.2 and Table 8.3. The same process was completed for ODOT Class 12 to ODOT Class 19 trucks, as shown in Table 8.4 and Table 8.5. Referring to the northbound Ashland WIM station for ODOT Class 11 trucks (Table 8.2), the monthly observed combined weights for September, October, November, and December remain fairly consistent from 2015 to 2018. To illustrate, the range (the difference between maximum and minimum proportions) in September is 0.60%, 0.31% in October, 1.23% in November, and 0.90% in December. In the southbound direction, the same consistency is observed. The range in September is 0.51%, 1.11% in October, 0.61% in November, and 0.33% in December. Based on this, the average percentage across the years is used to disaggregate the FAF data. For example, the average percentages of total combined weight at the northbound Ashland WIM station in September, October, November, and December are 8.08%, 8.23%, 7.62%, and 7.70%, respectively. These monthly averages are summed to obtain an aggregated average during these four months. The same process is done for the northbound Klamath Falls WIM station. On this premise, the average observed cargo weight for ODOT Class 11 trucks over this four month period at the northbound Ashland and Klamath Falls WIM stations are 31.63% and 30.18%, respectively, resulting in an average of 30.91% (average of the two WIM stations). The same process for ODOT Class 12 to ODOT Class 19 trucks results in 31.45% and 30.60%, resulting in an average of 31.03%. Therefore, aggregating the averages results in 30.97% (average of 30.91% and 31.03%), where this is the percentage of the FAF data that is compared to the four months of WIM data. In the southbound direction, following the same process, the aggregated average was determined to be 29.92%. The comparison is then made based on these two aggregated averages. A comparison of WIM and FAF weights based on these aggregated averages is shown in Figure 8.3 and Table 8.6.

Table 8.2: Monthly Observed Cargo Weights for ODOT Class 11 Trucks at Ashland WIM Stations

Northbound														
		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	**2012**	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	NA	724,900	738,380	778,501	797,378	7.69%	7.65%	7.60%	7.67%	7.69%	7.60%	0.08%	7.65%
February	NA	679,539	714,046	772,266	770,332	7.20%	7.40%	7.54%	7.41%	7.54%	7.20%	0.34%	7.39%
March	NA	806,253	818,685	883,132	902,268	8.55%	8.49%	8.63%	8.68%	8.68%	8.49%	0.20%	8.59%
April	NA	832,994	805,738	855,324	899,529	8.83%	8.35%	8.35%	8.66%	8.83%	8.35%	0.48%	8.55%
May	NA	847,521	844,074	903,704	1,003,943	8.99%	8.75%	8.83%	9.66%	9.66%	8.75%	0.91%	9.06%
June	NA	882,935	880,293	938,314	937,404	9.36%	9.12%	9.17%	9.02%	9.36%	9.02%	0.34%	9.17%
July	NA	885,419	803,982	908,827	934,377	9.39%	8.33%	8.88%	8.99%	9.39%	8.33%	1.05%	8.90%
August	361,483	829,778	861,803	965,732	949,279	8.80%	8.93%	9.43%	9.13%	9.43%	8.80%	0.64%	9.07%
September	742,212	740,517	815,472	814,352	835,998	7.85%	8.45%	7.95%	8.04%	8.45%	7.85%	0.60%	8.08%
October	793,954	770,940	780,587	845,142	873,246	8.17%	8.09%	8.26%	8.40%	8.40%	8.09%	0.31%	8.23%
November	663,902	698,393	787,816	818,435	720,718	7.40%	8.17%	7.99%	6.94%	8.17%	6.94%	1.23%	7.62%
December	651,553	732,819	797,072	753,978	767,828	7.77%	8.26%	7.36%	7.39%	8.26%	7.36%	0.90%	7.70%
Total	NA	9,432,008	9,647,950	10,237,709	10,392,299								

Southbound													
		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	**2012**	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	NA	681,449	614,491	545,658	561,941	7.52%	7.45%	7.14%	7.00%	7.52%	7.00%	0.53%	7.28%
February	NA	665,993	611,566	522,353	551,681	7.35%	7.41%	6.83%	6.87%	7.41%	6.83%	0.58%	7.12%
March	NA	783,553	684,905	620,910	671,629	8.65%	8.30%	8.12%	8.36%	8.65%	8.12%	0.53%	8.36%
April	NA	796,201	695,939	592,871	668,693	8.79%	8.44%	7.76%	8.32%	8.79%	7.76%	1.04%	8.33%
May	NA	842,304	773,239	694,571	742,780	9.30%	9.37%	9.09%	9.25%	9.37%	9.09%	0.29%	9.25%
June	NA	879,111	794,172	704,023	745,886	9.71%	9.63%	9.21%	9.29%	9.71%	9.21%	0.50%	9.46%
July	NA	817,402	753,771	724,712	749,641	9.03%	9.14%	9.48%	9.33%	9.48%	9.03%	0.45%	9.24%
August	274,225	825,716	820,467	777,465	801,189	9.12%	9.95%	10.17%	9.97%	10.17%	9.12%	1.05%	9.80%
September	545,826	742,793	705,213	664,006	700,170	8.20%	8.55%	8.69%	8.72%	8.72%	8.20%	0.51%	8.54%
October	525,641	756,152	619,822	659,011	685,545	8.35%	7.51%	8.62%	8.53%	8.62%	7.51%	1.11%	8.25%
November	434,768	648,401	593,721	594,060	607,847	7.16%	7.20%	7.77%	7.57%	7.77%	7.16%	0.61%	7.42%
December	523,267	617,481	581,697	544,577	545,690	6.82%	7.05%	7.12%	6.79%	7.12%	6.79%	0.33%	6.95%
Total		9,056,557	8,249,003	7,644,219	8,032,692								

Table 8.3: Monthly Observed Cargo Weights for ODOT Class 11 Trucks at Klamath Falls WIM Stations

Northbound													
		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	2012	2015	2016	2017	2018	2015	2016	2017	2018	Max %	Min %	Range	Average
January	NA	94,796	56,408	71,828	107,025	6.61%	3.20%	4.74%	6.48%	6.61%	3.20%	3.41%	5.26%
February	NA	101,047	82,128	94,694	103,276	7.05%	4.67%	6.25%	6.25%	7.05%	4.67%	2.38%	6.05%
March	NA	136,035	152,876	134,007	120,769	9.49%	8.69%	8.85%	7.31%	9.49%	7.31%	2.18%	8.58%
April	NA	136,333	168,635	150,567	137,274	9.51%	9.58%	9.94%	8.31%	9.94%	8.31%	1.64%	9.33%
May	NA	147,706	188,747	193,201	131,325	10.30%	10.72%	12.76%	7.95%	12.76%	7.95%	4.81%	10.43%
June	NA	161,773	205,094	179,930	152,265	11.28%	11.65%	11.88%	9.21%	11.88%	9.21%	2.67%	11.01%
July	NA	157,099	190,425	95,183	176,463	10.95%	10.82%	6.29%	10.68%	10.95%	6.29%	4.67%	9.68%
August	66,432	137,947	197,458	96,400	175,953	9.62%	11.22%	6.37%	10.65%	11.22%	6.37%	4.85%	9.46%
September	133,637	116,497	164,676	113,456	150,897	8.12%	9.36%	7.49%	9.13%	9.36%	7.49%	1.86%	8.53%
October	131,605	112,809	137,631	160,223	160,911	7.87%	7.82%	10.58%	9.74%	10.58%	7.82%	2.76%	9.00%
November	97,316	82,173	131,520	122,973	131,623	5.73%	7.47%	8.12%	7.96%	8.12%	5.73%	2.39%	7.32%
December	63,942	49,888	84,418	101,667	104,989	3.48%	4.80%	6.71%	6.35%	6.71%	3.48%	3.24%	5.34%
Total	NA	1,434,104	1,760,015	1,514,129	1,652,771								

Southbound													
		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	2012	2015	2016	2017	2018	2015	2016	2017	2018	Max %	Min %	Range	Average
January	NA	297,614	201,873	163,198	234,846	8.54%	6.66%	5.14%	7.84%	8.54%	5.14%	3.40%	7.04%
February	NA	291,258	226,621	170,601	230,087	8.35%	7.47%	5.37%	7.68%	8.35%	5.37%	2.98%	7.22%
March	NA	330,718	280,597	248,324	264,790	9.48%	9.25%	7.82%	8.84%	9.48%	7.82%	1.67%	8.85%
April	NA	313,798	296,604	303,763	249,485	9.00%	9.78%	9.56%	8.33%	9.78%	8.33%	1.46%	9.17%
May	NA	310,062	297,615	364,150	248,890	8.89%	9.81%	11.46%	8.31%	11.46%	8.31%	3.16%	9.62%
June	NA	324,304	304,683	346,339	265,283	9.30%	10.05%	10.90%	8.85%	10.90%	8.85%	2.05%	9.78%
July	NA	292,699	273,139	318,238	278,808	8.39%	9.01%	10.02%	9.30%	10.02%	8.39%	1.63%	9.18%
August	84,221	301,290	282,379	318,747	291,291	8.64%	9.31%	10.04%	9.72%	10.04%	8.64%	1.40%	9.43%
September	207,507	290,954	251,391	289,544	270,253	8.34%	8.29%	9.12%	9.02%	9.12%	8.29%	0.83%	8.69%
October	242,737	318,556	245,720	272,260	264,661	9.14%	8.10%	8.57%	8.83%	9.14%	8.10%	1.03%	8.66%
November	203,381	244,578	215,003	208,189	213,899	7.01%	7.09%	6.55%	7.14%	7.14%	6.55%	0.58%	6.95%
December	157,664	171,151	156,686	172,855	184,060	4.91%	5.17%	5.44%	6.14%	6.14%	4.91%	1.23%	5.42%
Total	NA	3,486,982	3,032,311	3,176,209	2,996,353								

Table 8.4: Monthly Observed Cargo Weights for ODOT Class 12 to ODOT Class 19 Trucks at Ashland WIM Stations

Northbound

		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	**2012**	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	NA	59,494	59,020	58,833	65,083	6.74%	6.76%	6.48%	6.91%	6.91%	6.48%	0.43%	6.72%
February	NA	58,026	62,801	67,085	64,698	6.58%	7.19%	7.39%	6.87%	7.39%	6.58%	0.81%	7.01%
March	NA	75,458	73,271	79,149	77,546	8.55%	8.39%	8.71%	8.23%	8.71%	8.23%	0.48%	8.47%
April	NA	78,002	75,124	76,215	78,459	8.84%	8.60%	8.39%	8.33%	8.84%	8.33%	0.51%	8.54%
May	NA	81,994	74,001	84,994	94,188	9.29%	8.47%	9.36%	10.00%	10.00%	8.47%	1.52%	9.28%
June	NA	87,818	79,363	94,115	89,072	9.95%	9.09%	10.36%	9.46%	10.36%	9.09%	1.27%	9.72%
July	NA	84,252	70,164	80,774	85,557	9.55%	8.04%	8.89%	9.08%	9.55%	8.04%	1.52%	8.89%
August	34,254	85,124	88,765	86,935	96,817	9.65%	10.17%	9.57%	10.28%	10.28%	9.57%	0.71%	9.92%
September	71,777	81,303	82,028	75,758	81,159	9.22%	9.39%	8.34%	8.62%	9.39%	8.34%	1.05%	8.89%
October	72,808	77,252	74,103	74,607	84,181	8.76%	8.49%	8.21%	8.94%	8.94%	8.21%	0.72%	8.60%
November	59,745	56,798	69,922	68,444	64,988	6.44%	8.01%	7.54%	6.90%	8.01%	6.44%	1.57%	7.22%
December	50,807	56,669	64,649	61,288	60,247	6.42%	7.40%	6.75%	6.40%	7.40%	6.40%	1.01%	6.74%
Total	NA	882,190	873,212	908,197	941,995								

Southbound

		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	**2012**	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	NA	60,912	46,062	33,252	39,894	7.48%	6.89%	5.52%	6.27%	7.48%	5.52%	1.96%	6.54%
February	NA	61,874	47,573	35,960	38,961	7.60%	7.12%	5.97%	6.12%	7.60%	5.97%	1.63%	6.70%
March	NA	72,249	56,905	46,816	50,199	8.87%	8.51%	7.77%	7.89%	8.87%	7.77%	1.10%	8.26%
April	NA	72,485	57,566	45,913	52,773	8.90%	8.61%	7.62%	8.29%	8.90%	7.62%	1.28%	8.36%
May	NA	76,070	57,730	55,491	62,037	9.34%	8.64%	9.21%	9.75%	9.75%	8.64%	1.11%	9.23%
June	NA	85,438	64,525	58,873	68,832	10.49%	9.65%	9.77%	10.81%	10.81%	9.65%	1.16%	10.18%
July	NA	75,598	60,189	57,774	62,448	9.28%	9.01%	9.59%	9.81%	9.81%	9.01%	0.80%	9.42%
August	22,839	72,594	76,141	65,724	68,590	8.91%	11.39%	10.91%	10.77%	11.39%	8.91%	2.48%	10.50%
September	47,159	67,593	61,400	58,022	59,267	8.30%	9.19%	9.63%	9.31%	9.63%	8.30%	1.33%	9.11%
October	37,134	71,483	49,696	58,696	54,688	8.78%	7.44%	9.74%	8.59%	9.74%	7.44%	2.31%	8.64%
November	26,645	50,405	50,229	44,842	43,107	6.19%	7.52%	7.44%	6.77%	7.52%	6.19%	1.33%	6.98%
December	37,742	47,746	40,371	41,048	35,780	5.86%	6.04%	6.81%	5.62%	6.81%	5.62%	1.19%	6.08%
Total	NA	814,445	668,386	602,410	636,576								

Table 8.5: Monthly Observed Cargo Weights for ODOT Class 12 to ODOT Class 19 Trucks at Klamath Falls WIM Stations

Northbound

		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	**2012**	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	NA	16,149	8,835	13,060	20,850	7.70%	2.80%	5.25%	6.45%	7.70%	2.80%	4.90%	5.55%
February	NA	15,921	12,384	18,100	21,197	7.59%	3.92%	7.27%	6.56%	7.59%	3.92%	3.67%	6.34%
March	NA	17,914	29,104	28,554	24,575	8.54%	9.22%	11.47%	7.61%	11.47%	7.61%	3.87%	9.21%
April	NA	19,978	27,999	26,431	31,874	9.53%	8.87%	10.62%	9.87%	10.62%	8.87%	1.75%	9.72%
May	NA	20,727	30,050	31,608	30,245	9.88%	9.52%	12.70%	9.36%	12.70%	9.36%	3.34%	10.37%
June	NA	27,353	33,256	30,556	29,233	13.04%	10.53%	12.28%	9.05%	13.04%	9.05%	3.99%	11.22%
July	NA	19,178	31,238	11,214	26,997	9.14%	9.89%	4.51%	8.36%	9.89%	4.51%	5.39%	7.97%
August	9,878	18,492	36,300	8,999	39,298	8.82%	11.49%	3.62%	12.16%	12.16%	3.62%	8.55%	9.02%
September	18,002	16,357	36,469	17,531	32,165	7.80%	11.55%	7.04%	9.96%	11.55%	7.04%	4.50%	9.09%
October	19,055	16,271	26,777	22,604	26,165	7.76%	8.48%	9.08%	8.10%	9.08%	7.76%	1.32%	8.35%
November	14,628	12,517	25,880	22,389	23,474	5.97%	8.20%	9.00%	7.27%	9.00%	5.97%	3.03%	7.61%
December	12,434	8,866	17,509	17,812	17,029	4.23%	5.54%	7.16%	5.27%	7.16%	4.23%	2.93%	5.55%
Total	NA	209,723	315,800	248,857	323,102								

Southbound

		Total Cargo Weight (tons)				Percent of Total				Comparison Across Years			
Month	**2012**	**2015**	**2016**	**2017**	**2018**	**2015**	**2016**	**2017**	**2018**	**Max %**	**Min %**	**Range**	**Average**
January	NA	35,174	33,818	21,568	43,262	6.19%	6.16%	3.41%	6.76%	6.76%	3.41%	3.36%	5.63%
February	NA	39,719	37,137	25,297	40,782	6.99%	6.76%	4.00%	6.38%	6.99%	4.00%	2.99%	6.03%
March	NA	44,139	53,872	46,895	47,173	7.76%	9.81%	7.41%	7.38%	9.81%	7.38%	2.43%	8.09%
April	NA	49,480	58,963	61,245	67,827	8.70%	10.73%	9.68%	10.60%	10.73%	8.70%	2.03%	9.93%
May	NA	53,089	59,550	84,874	58,848	9.34%	10.84%	13.41%	9.20%	13.41%	9.20%	4.21%	10.70%
June	NA	69,581	55,957	84,243	57,430	12.24%	10.19%	13.31%	8.98%	13.31%	8.98%	4.33%	11.18%
July	NA	52,699	52,030	69,957	61,210	9.27%	9.47%	11.05%	9.57%	11.05%	9.27%	1.78%	9.84%
August	18,011	60,641	53,371	65,301	75,277	10.67%	9.71%	10.32%	11.77%	11.77%	9.71%	2.05%	10.62%
September	37,854	50,214	48,567	54,821	61,836	8.83%	8.84%	8.66%	9.67%	9.67%	8.66%	1.01%	9.00%
October	38,520	50,545	38,352	52,017	50,001	8.89%	6.98%	8.22%	7.82%	8.89%	6.98%	1.91%	7.98%
November	27,821	34,586	32,932	34,857	42,317	6.08%	5.99%	5.51%	6.62%	6.62%	5.51%	1.11%	6.05%
December	20,600	28,589	24,835	31,845	33,654	5.03%	4.52%	5.03%	5.26%	5.26%	4.52%	0.74%	4.96%
Total	NA	568,456	549,382	632,921	639,615								

8.1.1.1 Assumption 1

Under Assumption 1, the comparisons to the base year of FAF data result in a 11.24% difference in the northbound direction and a 33.81% difference in the southbound direction (see Figure 8.3 and Table 8.6). In both directions, the reported cargo weight in the FAF data is higher than the recorded cargo weight in the ODOT WIM data. With these assumptions assuming various FAF regions, it may be a contributing factor to the percent differences. As such, comparisons to the other two assumptions were made.

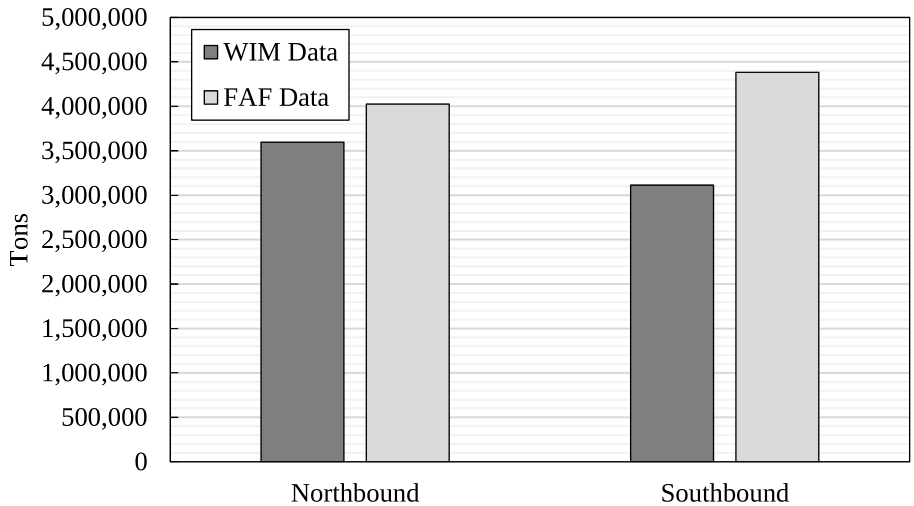


Figure 8.3: WIM and FAF weight comparison at Ashland and Klamath Falls WIM stations in 2012 under assumption 1

Table 8.6: WIM and FAF Weight Comparison at Ashland and Klamath Falls WIM Stations in 2012 Under Assumption 1

Direction	WIM Data (tons)	FAF Data (tons)	Percent Difference (WIM Relative to FAF)
Northbound	3,597,377	4,025,671	- 11.24%
Southbound	3,114,267	4,381,558	- 33.81%

8.1.1.2 Assumption 2

Results from the WIM and FAF comparison under Assumption 2 are shown in Figure 8.4 and Table 8.7. As observed, by removing FAF regions from the first assumption, comparisons have improved. In the northbound direction, comparisons have substantially improved with a difference of just 3.37%. In the southbound direction, although the difference is still high, it has improved to 29.44%. As was the case with Assumption 1, the reported cargo weight in the FAF data is higher than the recorded cargo weight in the ODOT WIM data in both directions. Based on these results, a comparison is made under one last assumption.

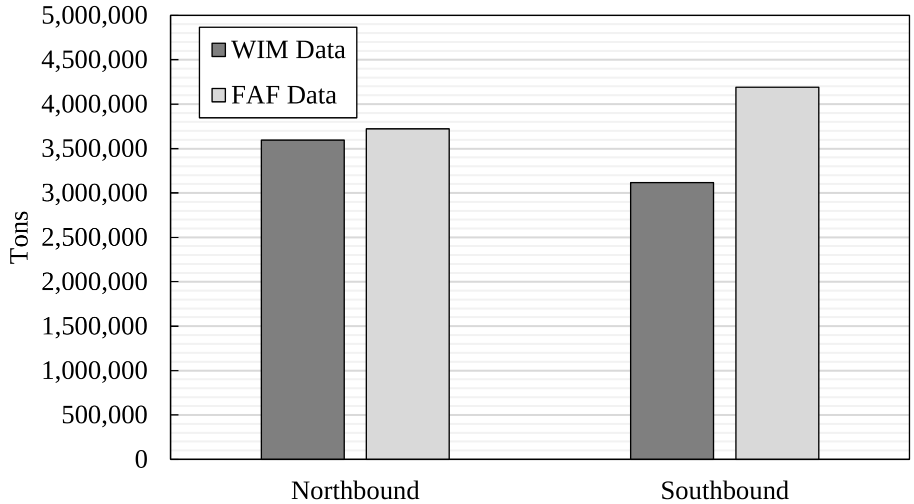


Figure 8.4: WIM and FAF weight comparison at Ashland and Klamath Falls WIM stations in 2012 under assumption 2

Table 8.7: WIM and FAF Weight Comparison at Ashland and Klamath Falls WIM Stations in 2012 Under Assumption 2

Direction	WIM Data (tons)	FAF Data (tons)	Percent Difference (WIM Relative to FAF)
Northbound	3,597,377	3,720,536	- 3.37%
Southbound	3,114,267	4,189,293	- 29.44%

8.1.1.3 Assumption 3

Results from WIM and FAF comparisons under Assumption 3 are shown in Figure 8.5 and Table 8.8. Of the three assumptions, Assumption 3 has the best results. Assumption 1 assumes only California FAF regions south of the Oregon border. As such, the difference in the northbound direction has improved to 1.97% and the difference in the southbound direction has improved to 20.99%. In the northbound direction, unlike the previous assumptions, the recorded cargo weight in ODOT's WIM data is greater (+ 1.97%). In the southbound direction, however, the reported FAF cargo weight is once more higher than the recorded cargo weight in the ODOT WIM data.

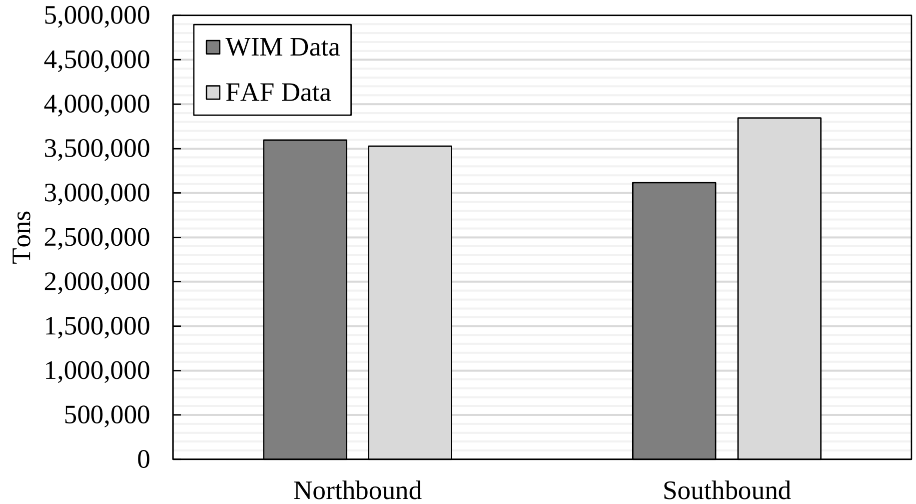


Figure 8.5: WIM and FAF weight comparison at Ashland and Klamath Falls WIM stations in 2012 under assumption 3

Table 8.8: WIM and FAF Weight Comparison at Ashland and Klamath Falls WIM Stations in 2012 Under Assumption 3

Direction	WIM Data (tons)	FAF Data (tons)	Percent Difference (WIM Relative to FAF)
Northbound	3,597,377	3,527,113	+ 1.97%
Southbound	3,114,267	3,844,577	- 20.99%

8.1.2 2015, 2016, and 2017 FAF Comparison

8.1.2.1 Assumption 1

The first comparisons made were based on Assumption 1. These comparisons are shown in Figure 8.6 and Figure 8.7. Tabulated values and percent differences are shown in Table 8.9. In relation to the comparisons of 2012 in which partial data was used, these comparisons **are markedly better**. In the northbound direction, the smallest difference between WIM and FAF data is observed in 2017 at a difference of 4.47%. In the southbound direction, the smallest difference is observed in 2015 at a difference of 10.93%. A potential reason for the variability among years may be attributed to the forecasted nature of the FAF data; specifically, the assumed growth rate used to forecast FAF cargo weight values. The assumed growth rate in the FAF forecasts may be contributing to the improved comparisons. For all years and directions, the reported FAF cargo weight is higher than the recorded cargo weight in the ODOT WIM data.

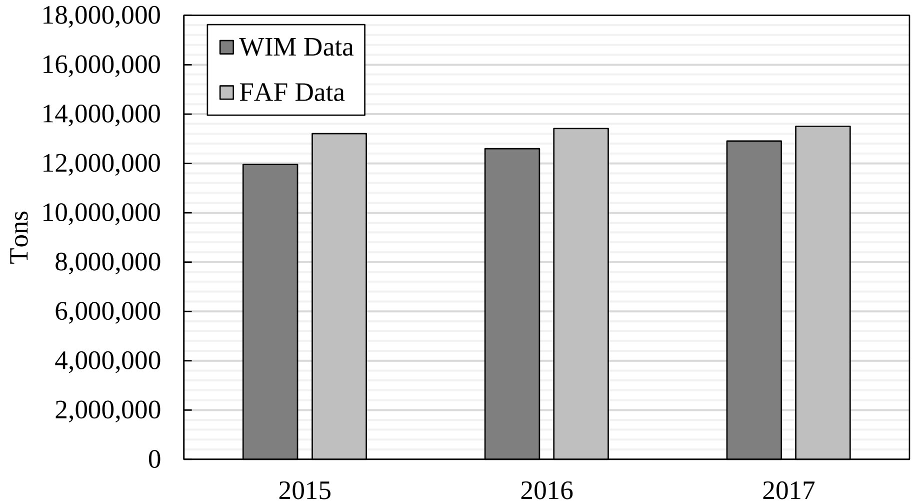


Figure 8.6: WIM and FAF comparison by year at Ashland (NB) and Klamath Falls (NB) WIM stations under assumption 1

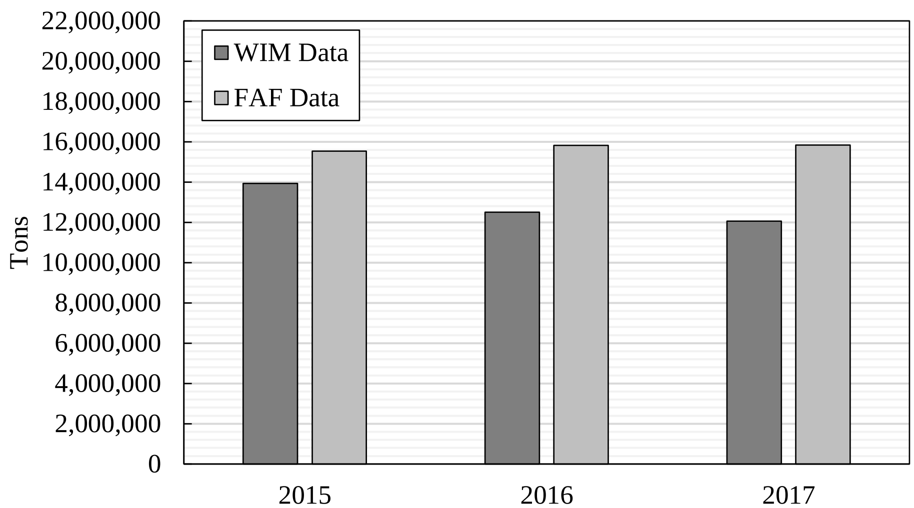


Figure 8.7: WIM and FAF comparison by year at Ashland (SB) and Klamath Falls (SB) WIM stations under assumption 1

Table 8.9: WIM and FAF Comparison at Ashland and Klamath Falls WIM Stations Under Assumption 1

Year	Direction	WIM Data (tons)	FAF Data (tons)	Percent Difference (WIM Relative to FAF)
2015	Northbound	11,958,024	13,202,052	- 9.89%
	Southbound	13,926,441	15,536,850	- 10.93%
2016	Northbound	12,596,977	13,410,425	- 6.26%
	Southbound	12,499,082	15,813,422	- 23.41%
2017	Northbound	12,908,892	13,499,005	- 4.47%
	Southbound	12,055,759	15,837,359	- 27.11%

8.1.2.2 Assumption 2

For WIM and FAF comparisons under Assumption 2, see Figure 8.8 and Figure 8.9. Tabulated differences are presented in Table 8.10. As with the comparisons using the base year of FAF data, comparison under Assumption 2 has improved. Considering both directions, the best results are for that of 2015, where the northbound difference is 4.03%, and the southbound difference is 6.65%. When considering the best results by direction, the smallest difference in the northbound direction is observed in 2016 at a difference of 0.46%. In the southbound direction, the smallest difference is observed in 2015 at a difference of 6.65%. Other than the northbound direction in 2017, in which the WIM data is higher, the reported FAF cargo weights are greater than the cargo weights recorded in the ODOT WIM data. A potential reason for the variability among years may be attributed to the forecasted nature of the FAF data; specifically, the assumed growth rate used to forecast FAF weight values.

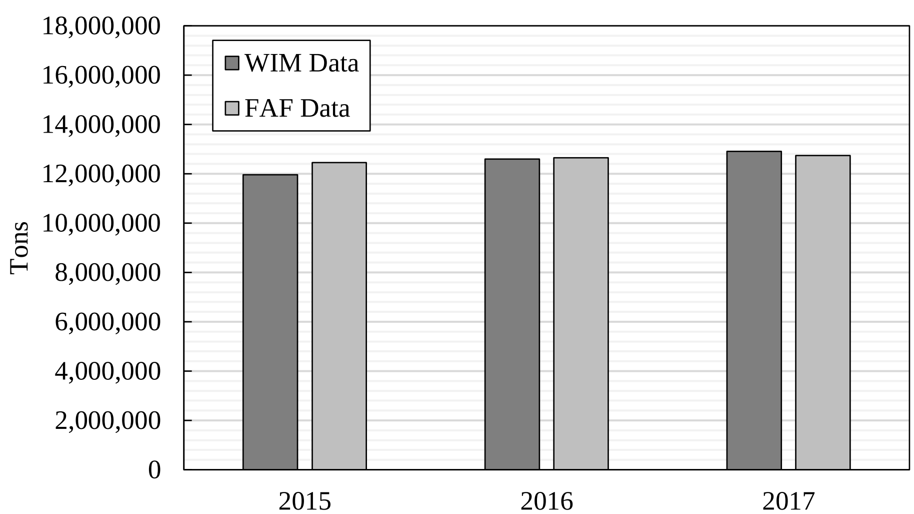


Figure 8.8: WIM and FAF comparison by year at Ashland (NB) and Klamath Falls (NB) WIM stations under assumption 2

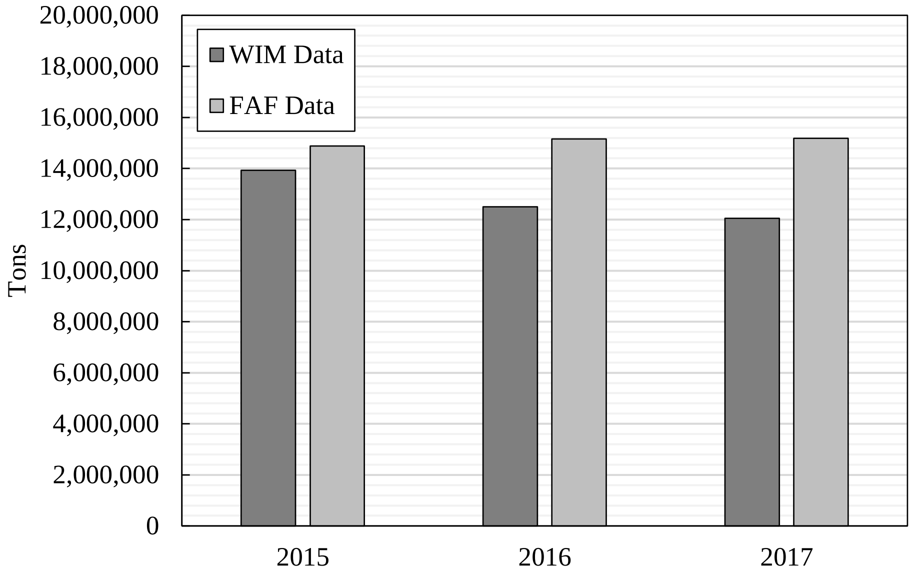


Figure 8.9: WIM and FAF Comparison by year at Ashland (SB) and Klamath Falls (SB) WIM stations under assumption 2

Table 8.10: WIM and FAF Comparison at Ashland and Klamath Falls WIM Stations Under Assumption 2

Year	Direction	WIM Data (tons)	FAF Data (tons)	Percent Difference (WIM Relative to FAF)
2015	Northbound	11,958,024	12,449,559	- 4.03%
	Southbound	13,926,441	14,883,767	- 6.65%
2016	Northbound	12,596,977	12,654,985	- 0.46%
	Southbound	12,499,082	15,161,329	- 19.25%
2017	Northbound	12,908,892	12,740,924	+ 1.31%
	Southbound	12,055,759	15,180,003	- 22.94%

8.1.2.3 Assumption 3

For WIM and FAF comparisons under Assumption 3, see Figure 8.10 and Figure 8.11. A tabulation of differences is presented in Table 8.11. Assumption 3 had the best results across the board. When considering both directions in the same year, 2015 had the best results with 1.27% in the northbound direction and 1.46% in the southbound direction. This difference in the southbound direction was the lowest observed. Unlike the previous assumptions, the majority of comparisons under Assumption 3 resulted in cases where the recorded WIM cargo weight was higher than the reported FAF cargo weight (the southbound direction in 2016 and 2017 have higher FAF cargo weights). As with the previous comparisons, a potential reason for the variability among years may be attributed to the forecasted nature of the FAF data; specifically, the assumed growth rate used to forecast FAF weight values.

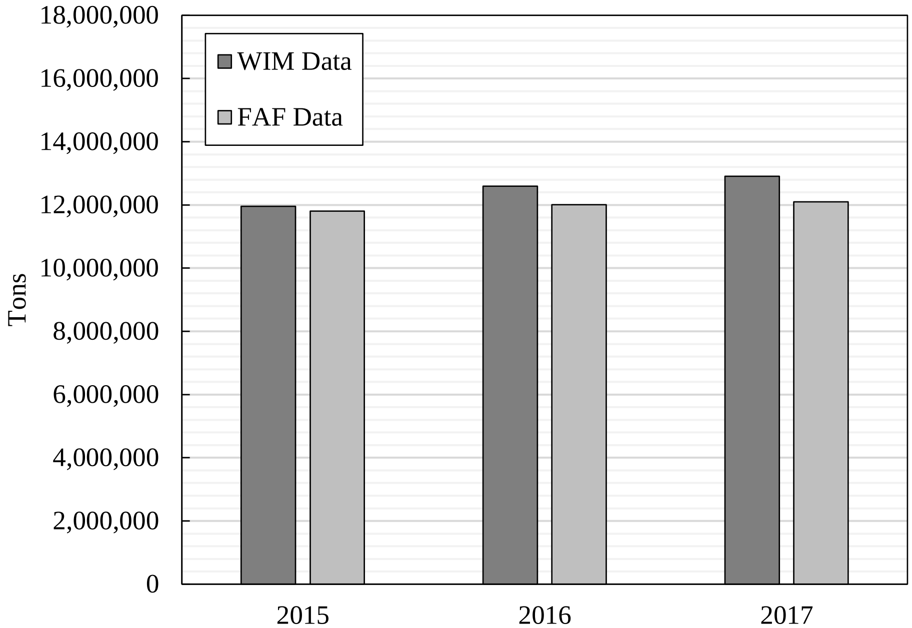


Figure 8.10: WIM and FAF comparison by year at Ashland (NB) and Klamath Falls (NB) WIM stations under assumption 3

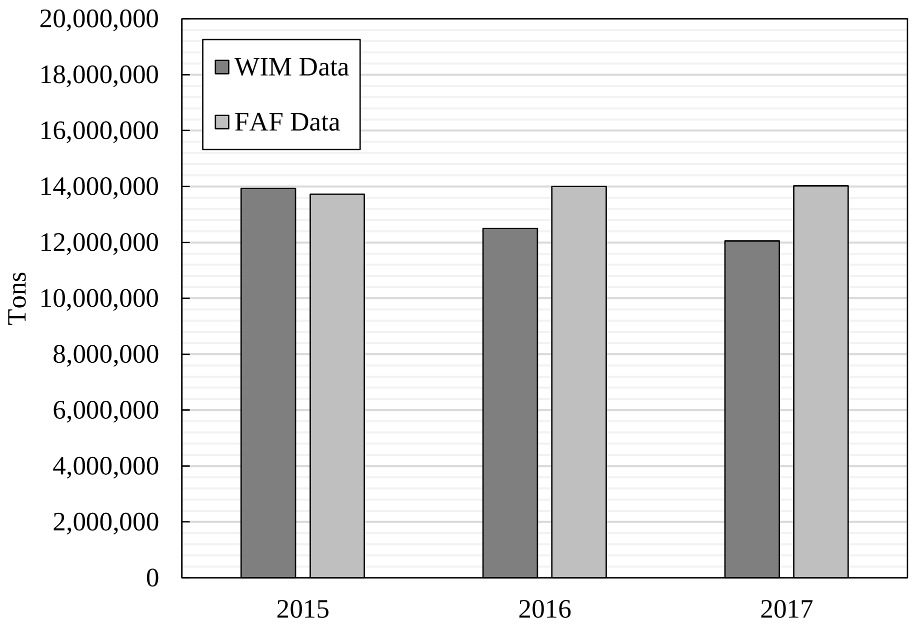


Figure 8.11: WIM and FAF comparison by year at Ashland (SB) and Klamath Falls (SB) WIM stations under assumption 3

Table 8.11: WIM and FAF Comparison at Ashland and Klamath Falls WIM Stations Under Assumption 3

Year	Direction	WIM Data (tons)	FAF Data (tons)	Percent Difference (WIM Relative to FAF)
2015	Northbound	11,958,024	11,807,414	+ 1.27%
	Southbound	13,926,441	13,724,344	+ 1.46%
2016	Northbound	12,596,977	12,006,162	+ 4.80%
	Southbound	12,499,082	13,999,099	- 11.32%
2017	Northbound	12,908,892	12,102,318	+ 6.45%
	Southbound	12,055,759	14,022,745	- 15.09%

8.2 WIM AND ODOT TRAFFIC COUNT COMPARISON

To compare WIM truck counts to traffic counts from ATRs, four WIM stations located near ATRs with directional volumes were selected. For these comparisons all trucks are used, as all trucks are included in the ODOT traffic counts (i.e., ODOT Class 03 to ODOT Class 19). The first selected WIM stations are Cascade Locks (EB) and Wyeth (WB), located near the Cascade Locks ATR. In the provided traffic data for the Cascade Locks ATR, traffic counts were conducted over a 24-hour period: April 24, 2017 at 3:00 a.m. to April 25, 2017 at 3:00 a.m. Using this time, WIM truck counts were extracted from the 2017 WIM data based on these conditions. Likewise, traffic data provided for the Huntington ATR (located near Olds Ferry and Farewell Bend) was collected over a 24-hour period: October 10, 2017 at 10:00 a.m. to October 11, 2017 at 10:00 a.m. Once more, WIM truck counts were extracted from the 2017 WIM data based on these conditions. Results from these comparisons are shown in Table 8.12. Percent differences are determined as discussed in Chapter 8.1. As observed, WIM data records have higher truck counts at each location, with the closest comparison at Wyeth (EB) at a different of +1.43% (WIM data relative to the 24-hr traffic count). It was anticipated that comparisons would be closer; therefore, further investigation into truck counts by individual classes is recommended.

Table 8.12: WIM and Truck Count Comparison in 2017

WIM Station	WIM Data	24-hr Count Data	Percent Difference (WIM Relative to 24-hr Count)
Cascade Locks (EB)	3,250	2,819	+ 14.20%
Wyeth (WB)	2,684	2,646	+ 1.43%
Olds Ferry (EB)	3,163	2,613	+ 19.04%
Farewell Bend (WB)	2,680	2,291	+ 15.65%

8.3 SUMMARY

As part of the data comparisons, two comparisons were made. The first of these was to FAF data. To compare, only Ashland and Klamath Falls WIM stations were used based on limiting assumptions of freight origins and destinations. In response to this, three specific assumptions were compared, where results improved with each assumption. In each case, the northbound comparisons had better results compared to its southbound counterpart. In 2012, this was illustrated in the comparisons under Assumption 3, where the difference in the northbound direction was approximately 2%, and the difference in the southbound direction was approximately 21%. In addition, the most consistent year in terms of minimal differences was 2015. For example, under Assumption 3, the difference in the northbound and southbound directions were 1.27% and 1.46%, respectively. That said, some northbound comparisons for the years 2016 and 2017 also produced good results, specifically, 4.80% and 6.45% differences under Assumption 3. This indicates that based on the assumptions being made, WIM data can be used to approximate cargo weight traveling through or to Oregon, as well as cargo weight leaving Oregon.

The second data comparison was to that of ODOT's traffic counts. In the provided traffic data for the Cascade Locks ATR, traffic counts were conducted over a 24-hour period: April 24, 2017, at 3:00 a.m. to April 25, 2017, at 3:00 a.m. Using this time, WIM truck counts were extracted from the 2017 WIM data based on these conditions. Likewise, traffic data provided for the Huntington ATR (located near Olds Ferry and Farewell Bend) was collected over a 24-hour period: October 10, 2017, at 10:00 a.m. to October 11, 2017, at 10:00 a.m. Once more, WIM truck counts were extracted from the 2017 WIM data based on these conditions. Results from these comparisons are shown in Table 8.12. As observed, WIM data records higher truck counts at each location, with the closest comparison at Wyeth (EB) at a different of -1.43% (relative to WIM data). It was anticipated that comparisons would be closer; therefore, further investigation into truck counts by individual classes is recommended.

9.0 EROAD DATA

To supplement the ODOT WIM data, freight data from EROAD was obtained (EROAD, 2020). EROAD is a fully integrated regulatory technology, tolling, and services provider based in Auckland, New Zealand. In recent years, there has been an increasing presence of EROAD in the United States. This has been accomplished by developing products in response to the various freight-related regulatory changes, such as the mandate for electronic logging devices. Through EROAD services, several freight-related data fields are collected.

The EROAD data request consisted of trips that passed through the 10 select WIM stations (see Table 7.1 for a list of the select WIM stations). To ensure anonymity, these trips were aggregated at a quarterly level for the year 2018. Geocoordinates of the 10 select WIM stations were provided to EROAD, in which they extracted trip information of trucks that traveled through these 10 WIM stations. Per EROAD, the data was extracted as follows:

- With no deterministic method of matching ODOT WIM data to EROAD GPS data (i.e., common identifier, such as license plate numbers), EROAD matched trips based on timestamps.
- Timestamp matching can result in a degree of error as there may be a need to interpolate the data to find a match.
- Data limited to trucks traveling through the 10 select WIM stations in 2018.
- Origins and destinations provided at the county-level.
    - Origins and destinations were determined by trucks’ on-and-off events and intersection with a WIM station.
    - Trip chains were not employed.

For the current project, the following EROAD data fields for 2018 were obtained as described in Table 9.1.

Table 9.1: Variable Names and Descriptions for EROAD Data

Variable	Description
Quarter	The Quarter of the Year in Which the Trips Occurred
WIM Name	WIM Site That the Trip Passed Through
Highway	Highway the WIM Site is Located On
Direction	Direction of Travel
Origin County	Origin County of the Trip
Origin State	Origin State of the Trip
Destination County	Destination County of the Trip
Destination State	Destination State of the Trip
Declared Weight	Declared Weight, in Pounds, for Truck[a]
Industry Type	Industry Type of the Organization in Which the Truck Belongs To[b]
Total Number of Trips	Number of Trips Given the Above Aggregations

[a] Declared Weight is recorded as “NA” When Weight for Trip is Unknown
[b] Industry Category is recorded as “NA” if No Industry Category is Assigned to Organization

During analysis, various oddities were found in the EROAD data. Most notably, these oddities were related to origins and destinations. For example, there were roughly 620 easily identifiable observations in which both the origin and destination were not located in Oregon, and the trip between locations does not go through Oregon (it is likely that upon further investigation, this value is much higher). Additionally, when creating the origin-destination maps presented in Chapter 9.5, many origin and destination locations are located near the WIM station of interest, as well as origin-destination clusters being present in geographically counterintuitive locations (i.e., in the opposite direction of travel based on the direction of the WIM station). As noted, trip chains were not employed for the current study, which could result in origins and destinations that do not fully depict where the freight is originally originating from or destinated to. As a result, trips over a specific length that correspond to the maximum allowable drive hours are originating or destined to locations closer to Oregon and resulting in origin and destination locations that are counterintuitive. However, there were observations in which the origin or destination was cross-country, indicating that some trip chains may have been included.

With this in mind, and being that each origin and destination must be manually checked to identify all of these problematic instances, these cases, and cases that may be discovered through a manual check, were left in the data and included in the analyses conducted. As such, when inferring from the presented results, this limitation must be considered.

The following analyses were completed utilizing the EROAD data:

- Descriptive analysis, specifically focusing on the number of trips and WIM stations.
- Declared weight distributions and how they compare to ODOT WIM data.
- Industry type.
    - Total number of trips by industry type and WIM station.

    - Most observed industry types at each WIM station based on total number of trips.

- Driving distance by WIM station based on provided origin and destination locations.
- Origin-destination summary.
    - All trips.
    - Summary by industry type.

9.1 DESCRIPTIVE ANALYSIS

Data obtained from EROAD was for the year 2018 and included 107,980 observations with 525,503 total trips through the select WIM stations (see Table 7.1). Henceforth, it is assumed that an EROAD trip is equal to a truck count and trips and truck counts are compared directly. Observations refer to the number of data points provided in the data (i.e., rows). In regards to the number of trips, this was a variable provided, in which a total number of trips was associated with each observation. For example, if ten trips share the same industry type, declared weight, origin-destination, and passed through the same WIM station, EROAD aggregated this to a single observation with an associated number of trips equal to 10. A summary of the number of observations and the total number of trips by WIM station is presented in Table 9.2. As shown in Table 9.2, the Woodburn WIM stations have both the highest number of observations and the highest number of trips. The second highest number of observations and trips are observed at the Cascade Locks (EB) and Wyeth (WB) WIM stations, the westernmost WIM stations along I-84. The third highest number of observations are at the Olds Ferry (EB) and Farewell Bend (WB) WIM stations. Although the Olds Ferry (EB) and Farewell Bend (WB) WIM stations had the third highest number of observations, the third highest number of trips are observed at the Ashland WIM stations.

Table 9.2: Summary of WIM Data by WIM Station, Number of Observations, and Number of Trips in 2018

WIM Station	Number of Observations	WIM Station	Number of Trips Through WIM Station
Woodburn (NB)	24,238	Woodburn (NB)	163,215
Woodburn (SB)	22,404	Woodburn (SB)	143,952
Cascade Locks (EB)	14,295	Cascade Locks (EB)	50,002
Wyeth (WB)	13,888	Wyeth (WB)	48,448
Olds Ferry (EB)	7,661	Ashland (NB)	28,876
Farewell Bend (WB)	7,425	Ashland (SB)	28,664
Ashland (NB)	6,165	Olds Ferry (EB)	18,946
Ashland (SB)	5,580	Farewell Bend (WB)	17,991
Klamath Falls (NB)	3,789	Klamath Falls (NB)	14,901
Klamath Falls (SB)	2,535	Klamath Falls (SB)	10,508

In comparing the total number of trips in the EROAD data to the recorded number of trucks in the ODOT WIM data, some differences were observed (see Table 9.3 and Table 9.4). Referring to Table 9.3, the most observed truck counts in both datasets occurred at the Woodburn WIM stations. However, for the second highest observed truck counts, EROAD data indicates Cascade Locks (EB) and Wyeth (WB), while ODOT WIM data indicates the Ashland WIM stations. For the third highest observed truck counts, the former was reversed; that is, EROAD data indicates the Ashland WIM stations have the third highest truck counts, and ODOT WIM data indicates Cascade Locks (EB) and Wyeth (WB) have the third highest truck counts. In addition to comparing the observed truck counts, a ratio is provided, defined as the number of EROAD trips divided by the number of observed trucks in the WIM data. The premise behind this ratio is to assess EROAD coverage at the select WIM stations relative to the total number of trucks observed in the WIM data. Once more, referring to Table 9.3, the highest ratio of EROAD counts to WIM counts is observed at the Woodburn WIM stations, followed by Cascade Locks (EB) and Wyeth (WB). As for the third highest, this was observed at two different stations in alternate directions, albeit both are located along the Oregon-California border. Specifically, Klamath Falls (NB) at 3.82% and Ashland (SB) at 2.50% had the third highest. In general, WIM stations with the highest number of trips observed in the EROAD data appear to follow WIM stations with the highest number of truck counts in the WIM data.

Table 9.3: ODOT WIM and EROAD Truck Count Comparison in 2018

EROAD Data		WIM Data		
WIM Station	**Trips**	**WIM Station**	**ODOT Class 03 to ODOT Class 19**	**Ratio**
Ashland (NB)	28,876	Ashland (NB)	1,266,074	1:44
Ashland (SB)	28,664	Ashland (SB)	1,144,427	1:40
Woodburn (NB)	163,215	Woodburn (NB)	2,711,035	1:17
Woodburn (SB)	143,952	Woodburn (SB)	2,235,196	1:16
Cascade Locks (EB)	50,002	Cascade Locks (EB)	1,075,075	1:22
Wyeth (WB)	48,448	Wyeth (WB)	1,044,428	1:22
Olds Ferry (EB)	18,946	Olds Ferry (EB)	910,139	1:48
Farewell Bend (WB)	17,991	Farewell Bend (WB)	818,938	1:46
Klamath Falls (NB)	14,901	Klamath Falls (NB)	390,206	1:26
Klamath Falls (SB)	10,508	Klamath Falls (SB)	579,871	1:55

* Values in green indicate the WIM station with the highest number of trucks and ratio
* Values in yellow indicate the WIM station with the second highest number of trucks and ratio
* Values in orange indicate the WIM station with the third highest number of trucks and ratio

In an additional comparison, only EROAD records with a declared weight equal to 80,000 pounds were compared to ODOT Class 11 truck counts in the WIM data, as seen in Table 9.4. Similar comparisons are observed. Woodburn WIM stations have the highest number of truck counts in both the EROAD data and WIM data, as well as the highest ratio. For the second highest number of truck counts, once more, the EROAD data indicates Cascade Locks (EB) and Wyeth (WB), while the WIM data indicates the Ashland WIM stations. Considering the third highest number of truck counts, the EROAD data indicates the Ashland WIM stations. However, in the WIM data, the third highest truck counts are observed at Olds Ferry (EB) and Farewell

Bend (WB). In regards to the ratio of EROAD truck trips to trucks observed in the WIM data, the same is observed, as was observed in Table 9.3.

Table 9.4: ODOT WIM and EROAD Truck Count Comparison in 2018 Using Declared Weight Equal to 80,000 lbs. and ODOT Class 11 Trucks

EROAD Data		WIM Data		Ratio
WIM Station	**Trips**	**WIM Station**	**ODOT Class 11**	
Ashland (NB)	3,944	Ashland (NB)	728,319	1:185
Ashland (SB)	3,985	Ashland (SB)	668,234	1:168
Woodburn (NB)	27,952	Woodburn (NB)	1,071,975	1:38
Woodburn (SB)	24,801	Woodburn (SB)	919,433	1:37
Cascade Locks (EB)	6,670	Cascade Locks (EB)	417,860	1:63
Wyeth (WB)	6,411	Wyeth (WB)	426,485	1:67
Olds Ferry (EB)	1,924	Olds Ferry (EB)	490,025	1:255
Farewell Bend (WB)	1,728	Farewell Bend (WB)	477,385	1:276
Klamath Falls (NB)	2,005	Klamath Falls (NB)	112,504	1:56
Klamath Falls (SB)	1,166	Klamath Falls (SB)	196,257	1:168

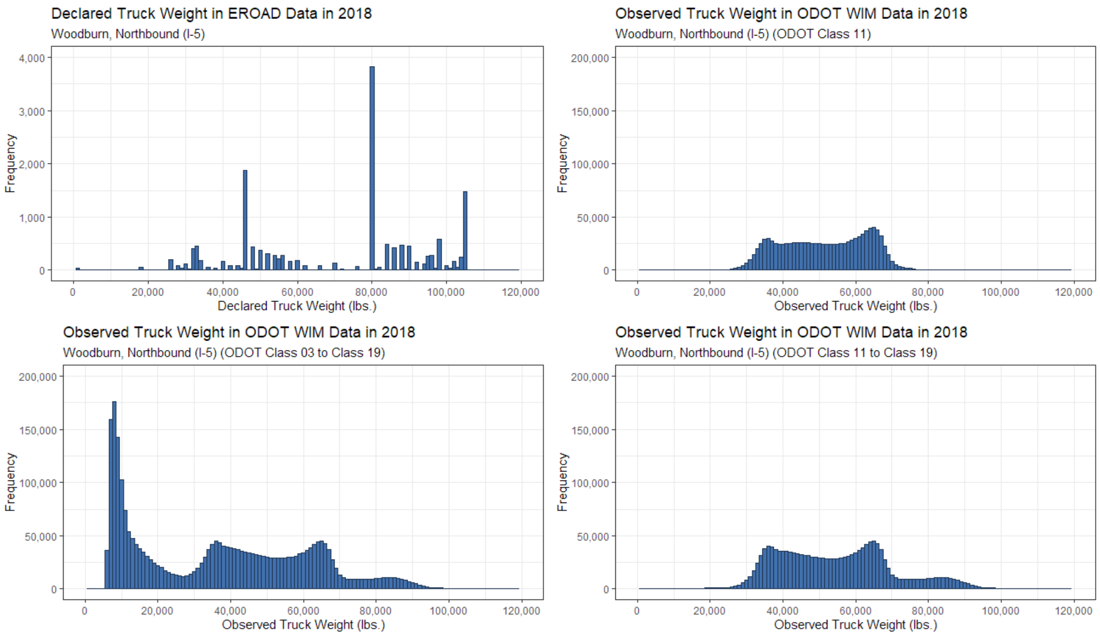
* Values in green indicate the WIM station with the highest number of trucks and ratio
* Values in yellow indicate the WIM station with the second highest number of trucks and ratio
* Values in orange indicate the WIM station with the third highest number of trucks and ratio

9.2 WEIGHT COMPARISONS

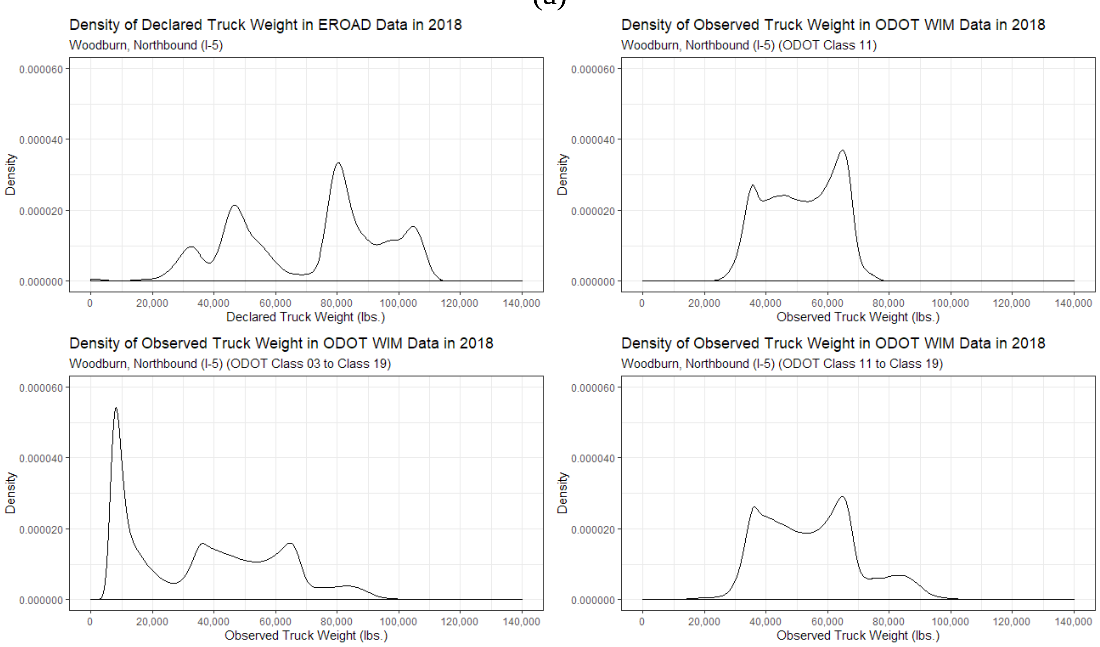
When preparing the EROAD data, declared weight for a number of observations was unknown or not reported. Specifically, roughly 40% of the observations did not have a declared weight, or the declared weight was unknown. As a result, a visual inspection of the weight distributions was assessed before comparing descriptive statistics in regards to weight. This was done by assessing both the distribution based on a histogram plot and a smoothed density plot. Figure 9.1 and Figure 9.2 show an example of the weight distribution plots at the Woodburn WIM stations. For weight distribution plots at the other select WIM stations, refer to Unnikrishnan et al. (2019).[23] As observed in the plots, due to the nature of the weight in the EROAD data (i.e., it is declared, not observed), the distributions between the EROAD and WIM datasets are vastly different. Due to these ample differences in weight distributions, no further weight comparisons were made.

It should be noted that for ODOT records, declared weight categories occur within 2,000 lb. increment. Per EROAD, for Oregon configuration and weight-mile-tax calculation, EROAD uses the ODOT tax tables (these tables are in increments of 2,000 lbs. Therefore, the definition of declared weight for both ODOT and EROAD is assumed to be the same.

[23] EROAD and WIM weight distribution plots by WIM station can be viewed here.

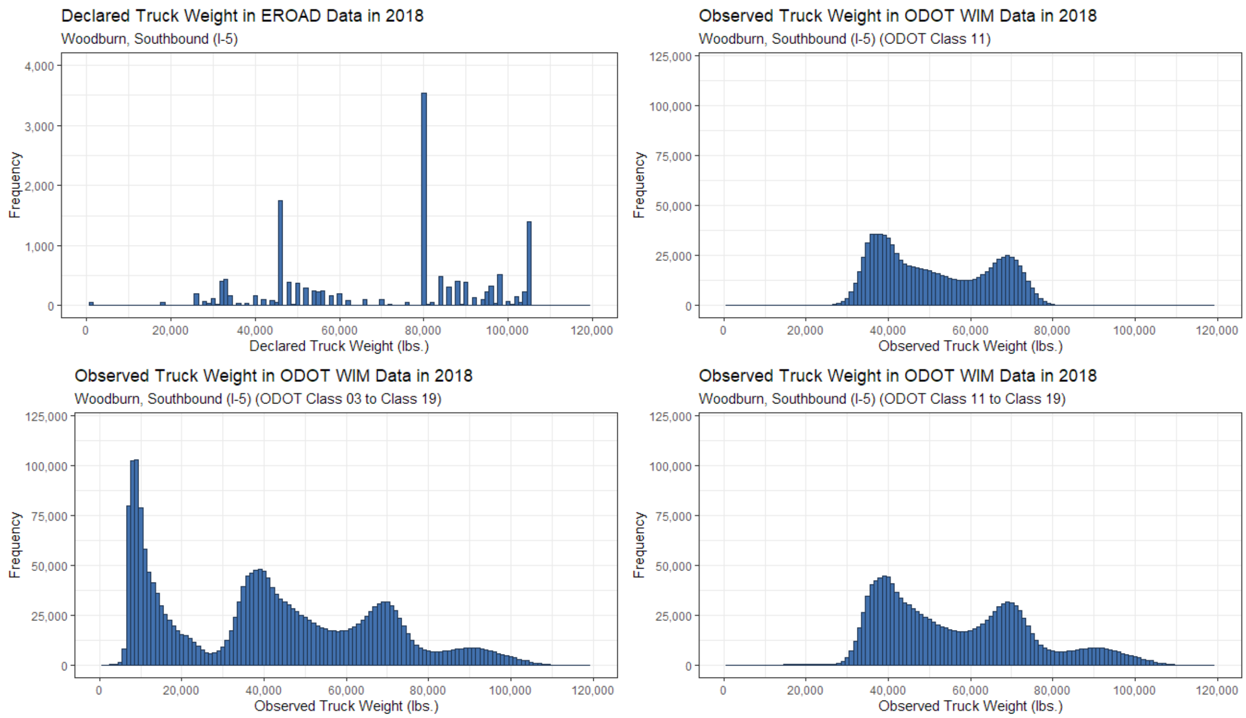


(a)

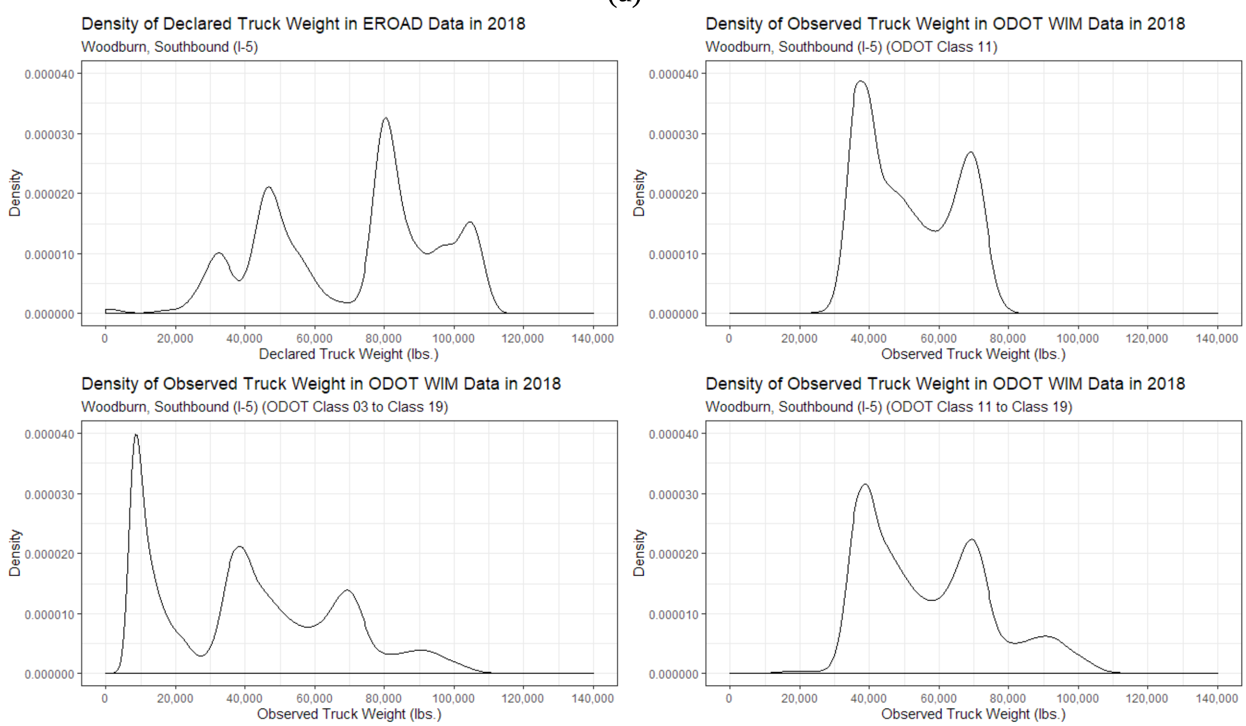


(b)

Figure 9.1: (a) EROAD and WIM weight distribution comparison at Woodburn (NB) in 2018 and (b) EROAD and WIM weight density comparison at Woodburn (NB) in 2018



(a)



(b)

Figure 9.2: (a) EROAD and WIM weight distribution comparison at Woodburn (SB) in 2018 and (b) EROAD and WIM weight density comparison at Woodburn (SB) in 2018

9.3 INDUSTRY TYPE

As presented in Table 9.1, the industry type associated with the truck (as reported by the company) was included in the EROAD data. The industry types are based on the North American Classification System (NAICS); however, EROAD uses an internal classification system that is a simplified version of NAICS. In general, all industry types were observed at each WIM station; however, some industry types were WIM-station-specific. A summary of all industry types and the number of trips included in the EROAD data by WIM stations are shown in Table 9.5. Additionally, Table 9.6 shows industry types and their proportion of the total number of trips. The industry type of Electricity, Gas, Water, and Waste Services was observed only at the Woodburn WIM stations but did not account for a large number of trips. Also of note is the industry type Arts and Recreation Services, as this type did not account for a high number of trips and was observed at just five WIM stations; specifically, both Woodburn WIM stations, Cascade Locks (EB), Wyeth (WB), and Ashland (SB). Excluding Ashland (SB), these are the WIM stations located nearest to the Portland Metropolitan area. Likewise, the industry type Furniture and Other Manufacturing was observed only at the WIM stations nearest to the Portland Metropolitan area.

Two interesting observations include the industry types of Information Media and Telecommunications, and Milk and Dairy. Specifically, Information Media and Telecommunications was observed at the WIM stations closest to the Portland Metropolitan area (Woodburn WIM stations, Cascade Locks, and Wyeth), but was also observed at the Klamath Falls WIM stations (this industry type was not observed at the Ashland WIM stations). Regarding Milk and Dairy, this industry type was observed at all WIM stations except Klamath Falls (SB).

On the other end of the spectrum, three industry types were consistently observed at each WIM station and accounted for a high number of trips:

- General Freight
- Other Agriculture
- Transport Equipment, Machinery, and Equipment Manufacturing

Regarding the industry type General Freight, per NAICS, potential industry types include bulk mail transportation, container services, among others. In the United States, Other Agriculture consists of one of the following: (1) growing crops (except oilseeds and/or grains; vegetables and/or melons; fruits and/or tree nuts; greenhouse, nursery and/or floriculture products; tobacco; cotton; sugarcane; hay; sugar beets; or peanuts), (2) growing a combination of crops (except a combination of oilseed(s) and grain(s); and a combination of fruit(s) and tree nut(s)) with no one crop or family of crop(s) accounting for one-half of the establishment's agricultural production (i.e., value of crops for market), and (3) gathering tea or maple sap.

To further assess industry type and WIM station, the top five industry types passing through each WIM station were determined based on the total number of trips in the EROAD data. These industry types are presented in Table 9.7. At the I-5 WIM stations, the top three industry types are the same at each WIM station: Ashland and Woodburn. At the Woodburn WIM stations, the fourth and fifth industry types are also the same, making the top five industry types identical. At the Ashland WIM stations, however, the fourth and fifth highest industry types differ by direction. At Ashland (NB), the fourth and fifth highest industry types are Other Agriculture, and Food, Beverage, and Tobacco Product Manufacturing, respectively. At Ashland (SB), the fourth and fifth highest industry types are Rental, Hiring, and Real Estate Services, and Construction, respectively.

Table 9.5: Summary of Industry Types and WIM Station by Total Number of Trips

Industry Type[1]	Ashland (NB)	Ashland (SB)	Woodburn (NB)	Woodburn (SB)	Cascade Locks (EB)	Wyeth (WB)	Olds Ferry (EB)	Farewell Bend (WB)	Klamath Falls (NB)	Klamath Falls (SB)
Accommodation and Food Services	135	115	376	362	404	458	215	193	64	45
Aggregates	145	134	702	608	169	157	43	42	70	52
Arts and Recreation Services	-	1	8	11	2	4	-	-	-	-
Construction	186	211	1,167	1,103	516	532	42	52	96	73
Electricity, Gas, Water, and Waste Services	-	-	47	41	-	-	-	-	-	-
Fishing, Aquaculture and Agriculture, Forestry, and Fishing Support Services	136	111	563	512	334	312	228	223	59	62
Food, Beverage, and Tobacco Product Manufacturing	241	170	587	606	339	369	5	5	92	76
Forestry and Logging	105	122	1,411	1,215	479	462	159	162	67	58
Furniture and Other Manufacturing	-	-	46	36	3	1	-	-	-	-
General Freight	2,599	2,416	6,735	6,265	4,520	4,416	3,180	3,198	1,737	1,138
General Haulage	107	95	492	450	264	264	182	184	21	14
Horticulture	31	32	444	436	518	455	23	18	7	8
Information Media and Telecommunications	-	-	37	58	21	25	-	-	22	24
Livestock: Meat and Wool	4	6	561	423	235	205	227	229	21	11
Metal Product Manufacturing	79	60	302	305	119	115	1	1	19	5
Milk and Dairy	10	14	7	31	2	8	19	11	4	-
Mining	9	8	103	82	58	54	26	27	12	9

Industry Type[1]	Ashland (NB)	Ashland (SB)	Woodburn (NB)	Woodburn (SB)	Cascade Locks (EB)	Wyeth (WB)	Olds Ferry (EB)	Farewell Bend (WB)	Klamath Falls (NB)	Klamath Falls (SB)
Other Agriculture	263	95	974	732	1,190	1,157	1,023	976	313	198
Other Services	183	143	1,004	993	565	453	324	152	162	111
Owner-Occupied Property Operation (National Accounts Only)	15	2	20	2	6	4	24	7	4	2
Petroleum, Chemical, Polymer, and Rubber Product Manufacturing	46	46	295	313	127	111	12	12	62	58
Private Transport	165	150	698	668	418	388	368	381	36	29
Professional, Scientific, and Technical Services	9	7	16	11	6	6	5	2	1	1
Refrigerated Haulage	68	21	318	228	214	172	104	112	109	69
Rental, Hiring, and Real Estate Services	212	212	700	678	249	266	86	85	59	42
Retail Trade	29	24	273	252	74	87	10	13	45	5
Steel and aluminum	11	8	320	311	324	318	75	85	11	6
Transport Equipment, Machinery, and Equipment Manufacturing	520	488	1,709	1,681	1,477	1,490	961	948	371	262
Transport, Postal, and Warehousing	20	19	405	381	213	235	7	9	13	9
Wholesale Trade	51	69	263	288	262	216	1	1	5	2
Wood and Paper Products Manufacturing	637	645	2,263	2,083	649	619	154	151	195	110

[1] Industry types are based on EROAD's internal classification system, which is a simplified version of NAICS.

Table 9.6: Summary of Industry Types and WIM Station by Percentage of Trips

Industry Type[1]	Ashland (NB)	Ashland (SB)	Woodburn (NB)	Woodburn (SB)	Cascade Locks (EB)	Wyeth (WB)	Olds Ferry (EB)	Farewell Bend (WB)	Klamath Falls (NB)	Klamath Falls (SB)
Accommodation and Food Services	2.24%	2.12%	1.65%	1.71%	2.94%	3.43%	2.87%	2.65%	1.74%	1.82%
Aggregates	2.41%	2.47%	3.07%	2.87%	1.23%	1.18%	0.57%	0.58%	1.90%	2.10%
Arts and Recreation Services	-	0.02%	0.04%	0.05%	0.01%	0.03%	-	-	-	-
Construction	3.09%	3.89%	5.11%	5.21%	3.75%	3.98%	0.56%	0.71%	2.61%	2.94%
Electricity, Gas, Water, and Waste Services	-	-	0.21%	0.19%	-	-	-	-	-	-
Fishing, Aquaculture and Agriculture, Forestry, and Fishing Support Services	2.26%	2.05%	2.46%	2.42%	2.43%	2.34%	3.04%	3.06%	1.60%	2.50%
Food, Beverage, and Tobacco Product Manufacturing	4.01%	3.13%	2.57%	2.86%	2.46%	2.76%	0.07%	0.07%	2.50%	3.07%
Forestry and Logging	1.75%	2.25%	6.18%	5.74%	3.48%	3.46%	2.12%	2.23%	1.82%	2.34%
Furniture and Other Manufacturing	-	-	0.20%	0.17%	0.02%	0.01%	-	-	-	-
General Freight	43.20%	44.54%	29.48%	29.60%	32.86%	33.06%	42.38%	43.93%	47.24%	45.91%
General Haulage	1.78%	1.75%	2.15%	2.13%	1.92%	1.98%	2.43%	2.53%	0.57%	0.56%
Horticulture	0.52%	0.59%	1.94%	2.06%	3.77%	3.41%	0.31%	0.25%	0.19%	0.32%
Information Media and Telecommunications	-	-	0.16%	0.27%	0.15%	0.19%	-	-	0.60%	0.97%
Livestock: Meat and Wool	0.07%	0.11%	2.46%	2.00%	1.71%	1.53%	3.03%	3.15%	0.57%	0.44%
Metal Product Manufacturing	1.31%	1.11%	1.32%	1.44%	0.87%	0.86%	0.01%	0.01%	0.52%	0.20%
Milk and Dairy	0.17%	0.26%	0.03%	0.15%	0.01%	0.06%	0.25%	0.15%	0.11%	-
Mining	0.15%	0.15%	0.45%	0.39%	0.42%	0.40%	0.35%	0.37%	0.33%	0.36%
Other Agriculture	4.37%	1.75%	4.26%	3.46%	8.65%	8.66%	13.63%	13.41%	8.51%	7.99%
Other Services	3.04%	2.64%	4.39%	4.69%	4.11%	3.39%	4.32%	2.09%	4.41%	4.48%

Industry Type[1]	Ashland (NB)	Ashland (SB)	Woodburn (NB)	Woodburn (SB)	Cascade Locks (EB)	Wyeth (WB)	Olds Ferry (EB)	Farewell Bend (WB)	Klamath Falls (NB)	Klamath Falls (SB)
Owner-Occupied Property Operation (National Accounts Only)	0.25%	0.04%	0.09%	0.01%	0.04%	0.03%	0.32%	0.10%	0.11%	0.08%
Petroleum, Chemical, Polymer, and Rubber Product Manufacturing	0.76%	0.85%	1.29%	1.48%	0.92%	0.83%	0.16%	0.16%	1.69%	2.34%
Private Transport	2.74%	2.77%	3.06%	3.16%	3.04%	2.90%	4.90%	5.23%	0.98%	1.17%
Professional, Scientific, and Technical Services	0.15%	0.13%	0.07%	0.05%	0.04%	0.04%	0.07%	0.03%	0.03%	0.04%
Refrigerated Haulage	1.13%	0.39%	1.39%	1.08%	1.56%	1.29%	1.39%	1.54%	2.96%	2.78%
Rental, Hiring, and Real Estate Services	3.52%	3.91%	3.06%	3.20%	1.81%	1.99%	1.15%	1.17%	1.60%	1.69%
Retail Trade	0.48%	0.44%	1.19%	1.19%	0.54%	0.65%	0.13%	0.18%	1.22%	0.20%
Steel and aluminum	0.18%	0.15%	1.40%	1.47%	2.36%	2.38%	1.00%	1.17%	0.30%	0.24%
Transport Equipment, Machinery, and Equipment Manufacturing	8.64%	9.00%	7.48%	7.94%	10.74%	11.15%	12.81%	13.02%	10.09%	10.57%
Transport, Postal, and Warehousing	0.33%	0.35%	1.77%	1.80%	1.55%	1.76%	0.09%	0.12%	0.35%	0.36%
Wholesale Trade	0.85%	1.27%	1.15%	1.36%	1.90%	1.62%	0.01%	0.01%	0.14%	0.08%
Wood and Paper Products Manufacturing	10.59%	11.89%	9.91%	9.84%	4.72%	4.63%	2.05%	2.07%	5.30%	4.44%

[1] Industry types are based on EROAD's internal classification system, which is a simplified version of NAICS.

Table 9.7: Top Five Industry Types by WIM Station Based on Number of Trips

Ashland (NB)			Ashland (SB)		
Industry Type	**Number of Trips**	**Percent of Total**	**Industry Type**	**Number of Trips**	**Percent of Total**
General Freight	2,599	43.20%	General Freight	2,416	44.54%
Wood and Paper Products Manufacturing	637	10.59%	Wood and Paper Products Manufacturing	645	11.89%
Transport Equipment, Machinery and Equipment Manufacturing	520	8.64%	Transport Equipment, Machinery and Equipment Manufacturing	488	9.00%
Other Agriculture	263	4.37%	Rental, Hiring and Real Estate Services	212	3.91%
Food, Beverage and Tobacco Product Manufacturing	241	4.01%	Construction	211	3.89%
Woodburn (NB)			**Woodburn (SB)**		
Industry Type	**Number of Trips**	**Percent of Total**	**Industry Type**	**Number of Trips**	**Percent of Total**
General Freight	6,735	29.48%	General Freight	6,265	29.60%
Wood and Paper Products Manufacturing	2,263	9.91%	Wood and Paper Products Manufacturing	2,083	9.84%
Transport Equipment, Machinery and Equipment Manufacturing	1,709	7.48%	Transport Equipment, Machinery and Equipment Manufacturing	1,681	7.94%
Forestry and Logging	1,411	6.18%	Forestry and Logging	1,215	5.74%
Construction	1,167	5.11%	Construction	1,103	5.21%
Cascade Locks (EB)			**Wyeth (WB)**		
Industry Type	**Number of Trips**	**Percent of Total**	**Industry Type**	**Number of Trips**	**Percent of Total**
General Freight	4,520	32.86%	General Freight	4,416	33.06%
Transport Equipment, Machinery and Equipment Manufacturing	1,477	10.74%	Transport Equipment, Machinery and Equipment Manufacturing	1,490	11.15%

Ashland (NB)			Ashland (SB)		
Other Agriculture	1,190	8.65%	Other Agriculture	1,157	8.66%
Wood and Paper Products Manufacturing	649	4.72%	Wood and Paper Products Manufacturing	619	4.63%
Other Services	565	4.11%	Construction	532	3.98%
Olds Ferry (EB)			**Farewell Bend (WB)**		
Industry Type	**Number of Trips**	**Percent of Total**	**Industry Type**	**Number of Trips**	**Percent of Total**
General Freight	3,180	42.38%	General Freight	3,198	43.93%
Other Agriculture	1,023	13.63%	Other Agriculture	976	13.41%
Transport Equipment, Machinery and Equipment Manufacturing	961	12.81%	Transport Equipment, Machinery and Equipment Manufacturing	948	13.02%
Private Transport	368	4.90%	Private Transport	381	5.23%
Other Services	324	4.32%	Livestock: Meat and wool	229	3.15%
Klamath Falls (NB)			**Klamath Falls (SB)**		
Industry Type	**Number of Trips**	**Percent of Total**	**Industry Type**	**Number of Trips**	**Percent of Total**
General Freight	1,737	47.24%	General Freight	1,138	45.91%
Transport Equipment, Machinery and Equipment Manufacturing	371	10.09%	Transport Equipment, Machinery and Equipment Manufacturing	262	10.57%
Other Agriculture	313	8.51%	Other Agriculture	198	7.99%
Wood and Paper Products Manufacturing	195	5.30%	Other Services	111	4.48%
Other Services	162	4.41%	Wood and Paper Products Manufacturing	110	4.44%

9.4 DISTANCE TRAVELED

As presented in Table 9.1, the obtained EROAD data included information on origin and destination at the county-level. The county seat of each county was identified to approximate a driving distance for each of the observations in the EROAD data. Utilizing the Google Maps API, the geographic coordinates of each county seat (i.e., latitude and longitude values) were used to determine the driving distance between origins and destinations. The driving distance determined via Google Maps was also compared to the geodesic distance between origins and destinations (i.e., the shortest distance between two points on an ellipsoid). A brief comparison and correlation between these two distances is also provided.

Table 9.8 shows the shortest distance (geodesic distance) and driving distance summary statistics for each WIM station. In addition, Table 9.9 shows the percent difference between the geodesic and driving distances. Regarding the summary statistics, the highest mean, median, and 95th percentile driving distances are observed at Olds Ferry (EB), the easternmost WIM station on I-84 near the Oregon-Idaho border, while the highest maximum driving distance is observed at Wyeth (WB). As it pertains to the lowest mean, median, and 95th percentile driving distances, these are observed at Woodburn (SB), while the lowest maximum driving distance is observed at Klamath Falls (SB). Additionally, figures showing the distance distribution when considering all WIM stations are presented in Figure 9.5. Figure 9.5 shows that when considering all WIM stations, the average driving distance is approximately 215 miles, the 25th percentile driving distance is approximately 74 miles, the median driving distance is approximately 174 miles, the 75th percentile driving distance is approximately 290 miles, and the 95th percentile driving distance is approximately 559 miles. Additionally, although not shown in Figure 9.5, the 99th percentile driving distance is approximately 972 miles. These plots have been generated for each WIM station and can be found in Unnikrishnan et al. (2019).[24] Lastly, the correlation between the two distance types was assessed. This was completed through four steps: (1) computing Pearson's Product-Moment Correlation coefficient, (2) computing Kendall's Rank Correlation coefficient, (3) computing Spearman's Rank Correlation coefficient, and (4) plotting the ratios of driving distance to geodesic distance. A summary of the correlation tests is shown in Table 9.10, and a plot is shown in Figure 9.3. In Figure 9.3, R represents the correlation coefficient and p is the associated p-value. As observed, there is a significantly high positive correlation between the two distances, essentially a correlation coefficient of practically one based on two of the correlation tests. The final assessment was the plot of distance ratios, as illustrated in Figure 9.4. The plot shows that there is an average distance ratio of 1.24.

[24] Driving distance distribution plots for each WIM station can be viewed here.

Table 9.8: Summary Statistics for Shortest Distance and Driving Distance Between Origins and Destinations

Shortest Distance (Geodesic Distance)				
WIM Station	**Mean Distance (mi)**	**Median Distance (mi)**	**95th Percentile Distance (mi)**	**Max Distance (mi)**
Ashland (NB)	249	223	544	2,300
Ashland (SB)	232	223	513	1,218
Woodburn (NB)	125	92	330	2,300
Woodburn (SB)	117	89	296	2,104
Cascade Locks (EB)	163	138	368	2,384
Wyeth (WB)	158	136	348	2,684
Olds Ferry (EB)	288	245	664	2,384
Farewell Bend (WB)	286	239	656	2,684
Klamath Falls (NB)	203	175	467	2,471
Klamath Falls (SB)	201	176	471	981
Driving Distance (Google Maps API)				
WIM Station	**Mean Distance (mi)**	**Median Distance (mi)**	**95th Percentile Distance (mi)**	**Max Distance (mi)**
Ashland (NB)	302	279	650	2,787
Ashland (SB)	282	272	594	1,602
Woodburn (NB)	150	109	420	2,787
Woodburn (SB)	140	102	379	2,534
Cascade Locks (EB)	218	192	473	2,892
Wyeth (WB)	211	192	462	3,268
Olds Ferry (EB)	356	299	842	2,892
Farewell Bend (WB)	353	292	834	3,268
Klamath Falls (NB)	262	236	570	2,908
Klamath Falls (SB)	260	235	588	1,291

Table 9.9: Percent Difference (Relative to Geodesic Distance)

WIM Station	Mean Distance (mi)	Median Distance (mi)	95th Percentile Distance (mi)	Max Distance (mi)
Ashland (NB)	19.35%	22.40%	17.66%	19.15%
Ashland (SB)	19.56%	20.03%	14.68%	27.23%
Woodburn (NB)	18.22%	16.94%	24.04%	19.15%
Woodburn (SB)	17.35%	13.10%	24.40%	18.54%
Cascade Locks (EB)	28.80%	32.89%	24.91%	19.25%
Wyeth (WB)	28.52%	34.19%	28.26%	19.63%
Olds Ferry (EB)	21.19%	19.94%	23.71%	19.25%
Farewell Bend (WB)	21.00%	20.05%	23.86%	19.63%
Klamath Falls (NB)	25.49%	29.67%	19.79%	16.24%
Klamath Falls (SB)	25.55%	28.50%	21.99%	27.34%

Table 9.10: Summary of Correlation Tests for Driving and Geodesic Distances

Pearson's Product-Moment Correlation		
t-statistic	*p*-value	Coefficient
3,456.30	0.000	0.996
Kendall's Rank Correlation		
z-statistic	*p*-value	Coefficient
458.7	0.000	0.937
Spearman's Rank Correlation		
S	*p*-value	Coefficient
1×10^{12}	0.000	0.994

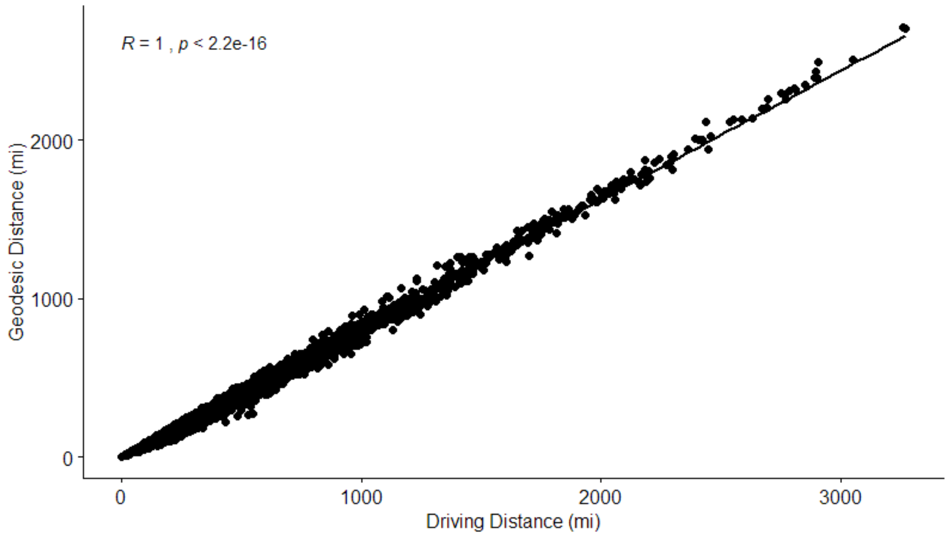


Figure 9.3: Correlation between driving distance and geodesic distance

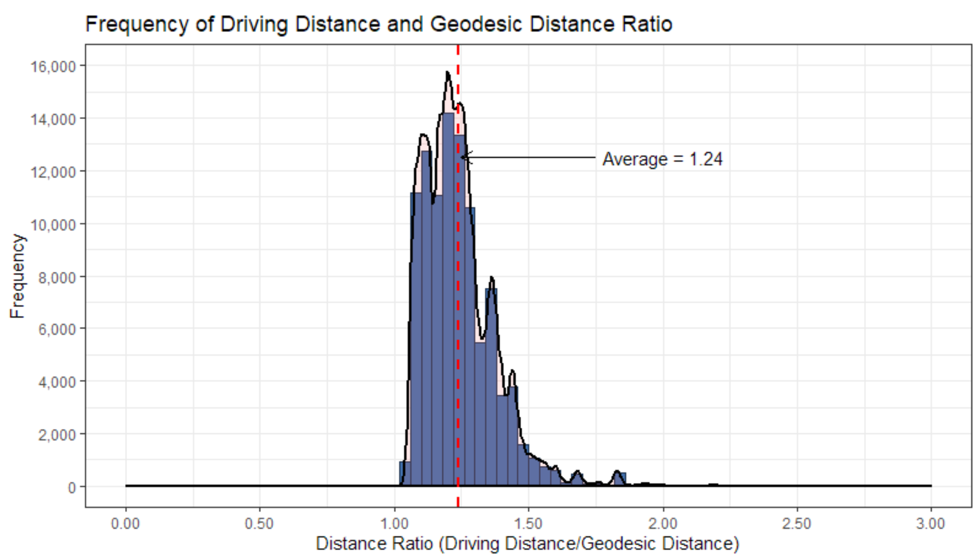
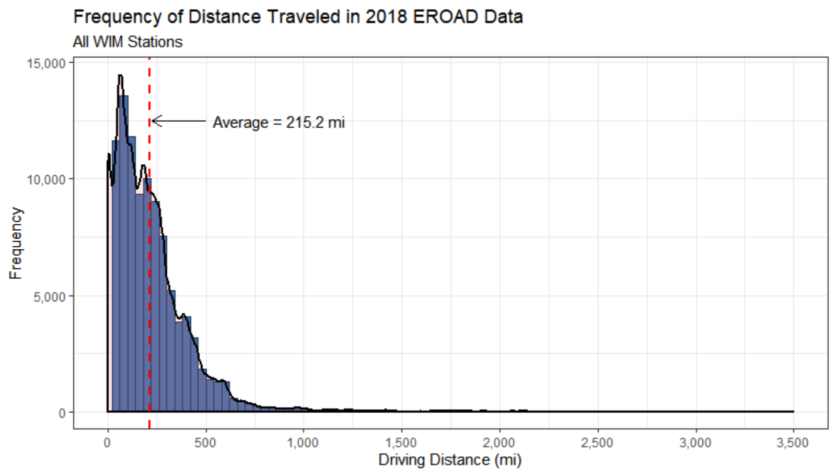


Figure 9.4: Distribution of distance ratio



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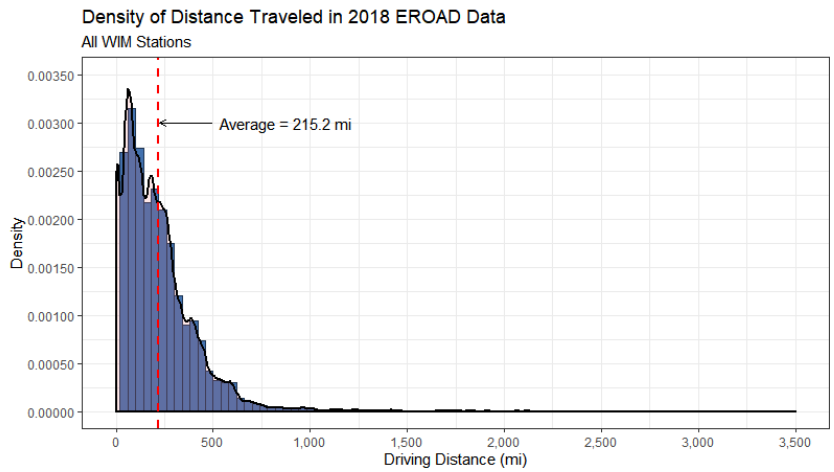

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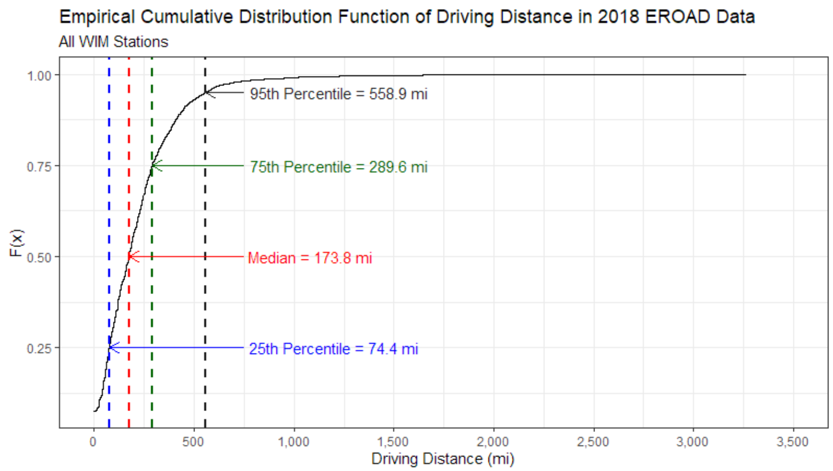


(c)

Figure 9.5: (a) Count distribution, (b) density, and (c) emprical CDF of driving distance considering all WIM stations

9.5 ORIGIN-DESTINATION

The final analysis using the EROAD data was investigating the origins and destinations. This was done by looking at the origins and destinations for all EROAD observations and the origins and destinations by WIM station. Per WIM station, a series of maps were created to illustrate origins and destinations for all industry types and tables to breakdown origins and destinations for the main industry types.

9.5.1 All WIM Stations

For origins and destinations considering all WIM stations, refer to Figure 9.6 and Figure 9.7, respectively. The figures show that the majority of trips originate and/or are destined to the Pacific Northwest, albeit there are moderate concentrations of origins and destinations in Central California and Northern California. Holistically, the majority of origins and destinations are in Oregon, with the top five origins and destinations as: Marion County, OR; Multnomah County, OR; Linn County, OR; Clackamas County, OR; and, Lane County, OR. A summary of top origins and destinations when considering all WIM stations is presented in Table 9.11. Regarding origins, the locations furthest away from Oregon include New York, Florida, Tennessee, and Coahuila, Mexico. For destinations, the locations furthest from Oregon include New Jersey, Virginia, and North Carolina. However, considering both origins and destinations, not one accounting for more than four trips.

To look at origins and destinations at a higher resolution, a series of maps are presented by WIM station in the subsequent sub-chapters.

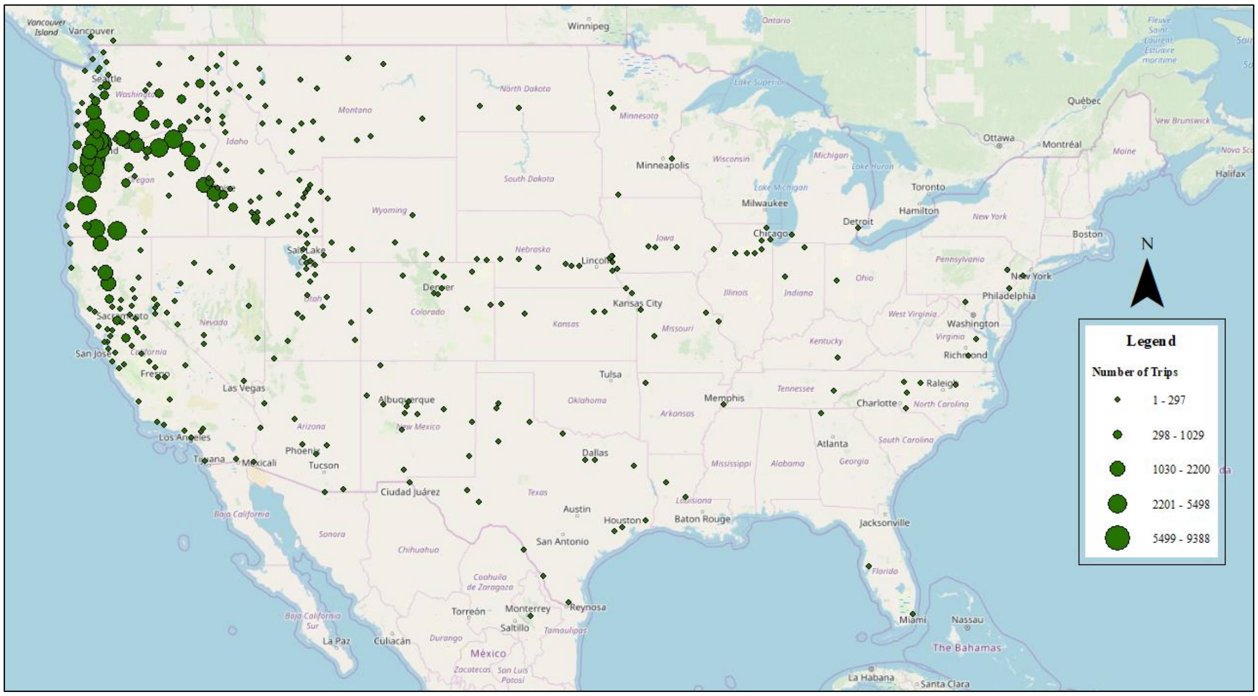


Figure 9.6: Origins as reported in EROAD considering all WIM stations

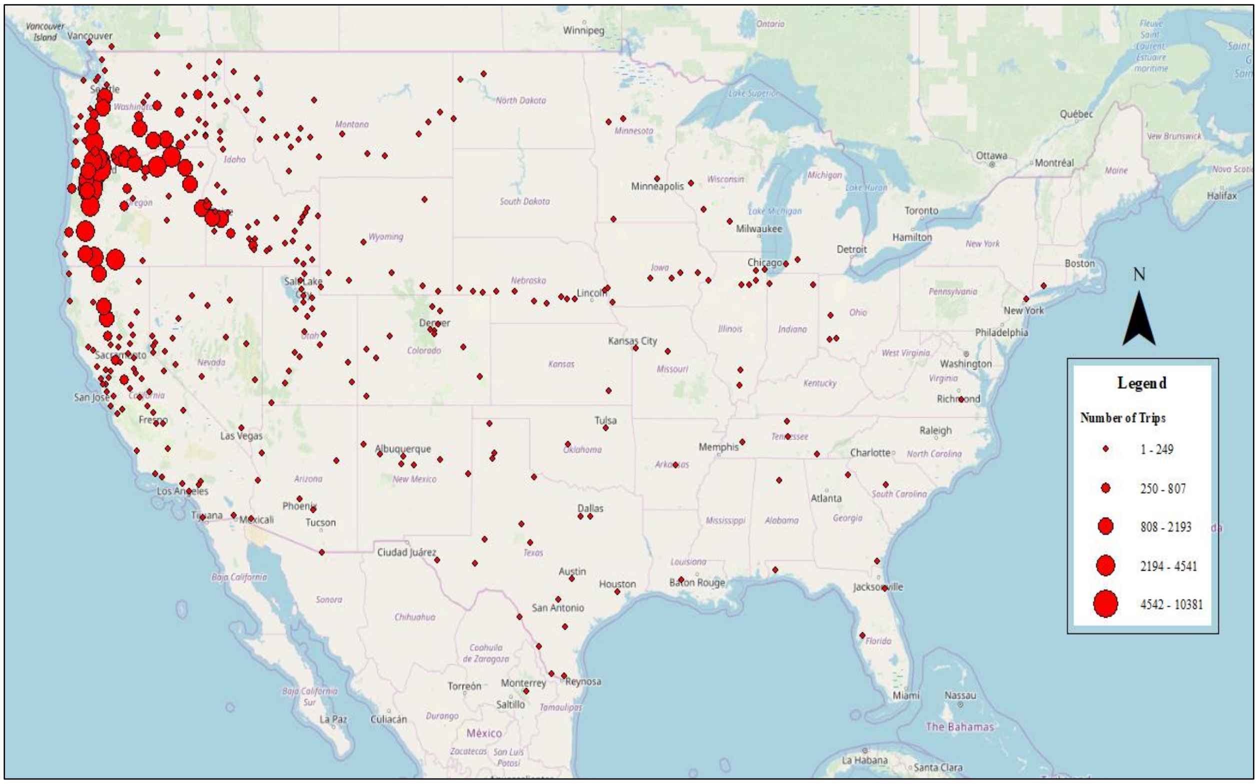


Figure 9.7: Destinations as reported in EROAD data considering all WIM stations

Table 9.11: Top Origins and Destinations as Reported in EROAD Data *

Origin (County Seat)	Number of Trips	Destination County (County Seat)	Number of Trips
Marion County, OR (Salem)	9,388	Marion County, OR (Salem)	10,381
Multnomah County, OR (Portland)	9,299	Multnomah County, OR (Portland)	9,055
Linn County, OR (Albany)	6,859	Linn County, OR (Albany)	6,535
Clackamas County, OR (Oregon City)	5,498	Clackamas County, OR (Oregon City)	6,025
Lane County, OR (Eugene)	4,848	Lane County, OR (Eugene)	4,541
Umatilla County, OR (Pendleton)	3,835	Clark County, WA (Vancouver)	3,745
Clark County, WA (Vancouver)	3,620	Jackson County, OR (Medford)	3,612
Jackson County, OR (Medford)	3,588	Umatilla County, OR (Pendleton)	3,584
Washington County, OR (Hillsboro)	3,446	Washington County, OR (Hillsboro)	3,386
Douglas County, OR (Roseburg)	3,146	Douglas County, OR (Roseburg)	2,968
Cowlitz County, WA (Kelso)	3,091	Cowlitz County, WA (Kelso)	2,843
Morrow County, OR (Heppner)	2,731	Klamath County, OR (Klamath Falls)	2,623
Klamath County, OR (Klamath Falls)	2,640	Morrow County, OR (Heppner)	2,566
Wasco County, OR (The Dalles)	2,200	Hood River County, OR (Hood River)	2,399
Hood River County, OR (Hood River)	1,920	Wasco County, OR (The Dalles)	2,193

* Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

9.5.2 Ashland WIM Stations

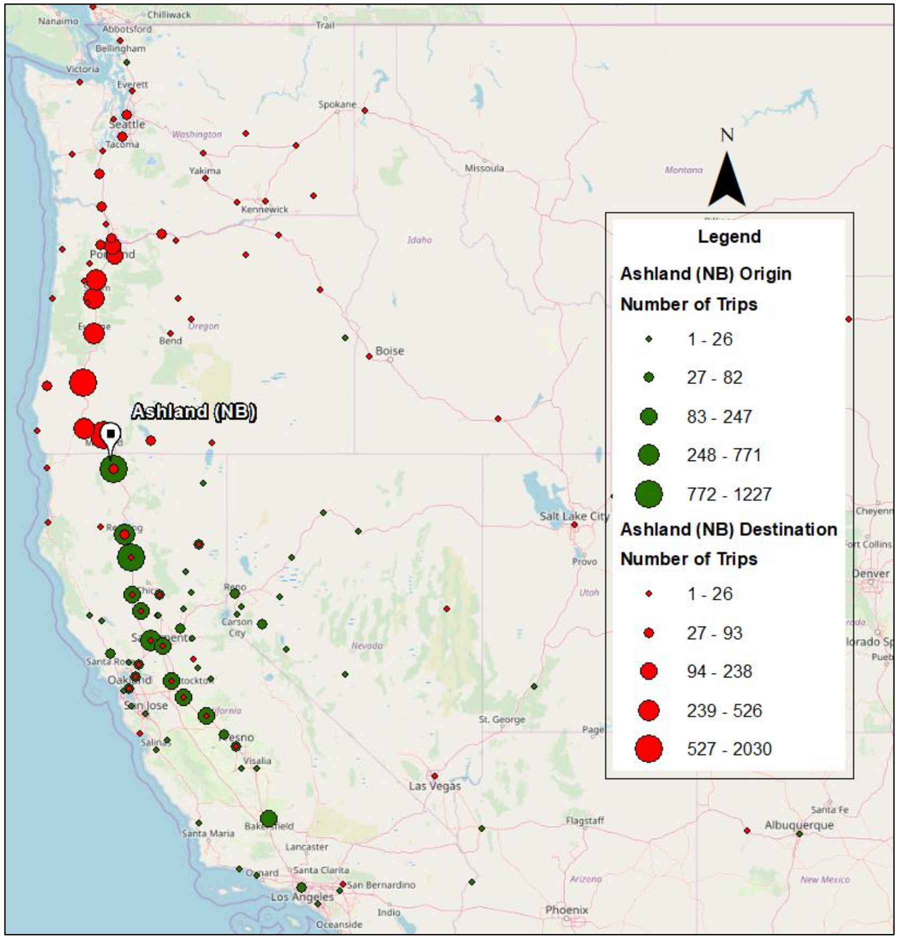
Origins and destinations considering the Ashland (NB) and Ashland (SB) WIM stations are shown in Figure 9.8. Considering Ashland (NB), the majority of trips originate in Northern California However, there are some clusters in Central California, spanning from Sacramento, to Stockton, to Fresno, and Bakersfield; there is also a small cluster (27 to 82 trips) near Los Angeles. As for destinations, the majority of trips are destined to Southern Oregon (Medford, Ashland, and Roseburg areas). In addition, there are moderate clusters near Eugene, Albany, and Salem, each ranging from 239 trips to 526 trips. For destinations, clusters are also observed in the Portland Metropolitan area (94 trips to 238 trips) and the Seattle-Tacoma area (29 trips to 93 trips).

Additionally, the top five industry types (based on trips) at Ashland (NB) and the corresponding origins and destinations were identified, see Table 9.12. Table 9.12 shows that, in general, the top five industry types are originating in Northern California counties; specifically, counties near the Oregon border. However, there are three locations that are a moderate distance from the border. For Wood and Paper Products Manufacturing, the fifth highest origin is Contra Costa County, CA, located in the East Bay Area, CA (just east of Oakland). For Transport Equipment, Machinery, and Equipment Manufacturing, the fifth highest origin is San Joaquin County, CA, located just south of Sacramento. Lastly, for Other Agriculture, the fourth and fifth highest origins are Glenn County, CA, and San Joaquin, CA. In regard to Glenn County, CA, this is located just west of Chico.

As it pertains to destinations and the top industry types at Ashland (NB), most industry types are headed to Jackson, Josephine, and Douglas counties, all in Southern Oregon. However, for some industry types, the top destinations are Lane and Linn counties (Central Oregon in the areas of Eugene and Albany, respectively). Of note are the destinations of Marion County and Clackamas County. Marion County is the third highest destination for Transport Equipment, Machinery, and Equipment Manufacturing, the third highest destination for Other Agriculture, and the fourth highest destination for Food, Beverage, and Tobacco Manufacturing. Clackamas County is the fourth highest destination for Other Agriculture.

Considering Ashland (SB), the majority of trips originate in Oregon at locations along the I-5 corridor. The highest number of trips originate in Southern Oregon, in the Ashland and Medford areas, with trip clusters of 988 to 1,938 and 176 to 447. The second highest cluster of originating trips is near Roseburg, with the number of trips ranging from 448 to 987. Continuing north on I-5, there are trip clusters of 176 to 447 in the Eugene, Albany, and Salem areas. Lastly, there are trip clusters of 36 to 175 originating in the Portland Metropolitan area and Southern Washington.

As for top origins and destinations as it pertains to top industry types, a summary for Ashland (SB) is shown in Table 9.13. Table 9.13 shows that that, in general, the top five industry types are originating in Southern Oregon counties; specifically, counties near the Oregon border (i.e., Jackson, Josephine, and Douglas counties). Lane County is in the top five origins for four of the five industry types, ranking as high as third (General Freight). Marion County is in the top five for three of the five industry types: Transport Equipment, Machinery, and Equipment Manufacturing (3rd); Rental, Hiring, and Real Estate Services (5th); and, Construction (4th). The furthest north origin is Clackamas County, which is the fourth highest origin for Rental, Hiring, and Real Estate Services.
As it pertains to destinations and the top industry types, most industry types are headed to Siskiyou, Tehama, Shasta, and Yolo counties (all located between Red Bluff, CA and the Oregon-California border). Two destinations of interest are Butte County and Glenn County, although they are still located fairly north in California (both are located near Chico).



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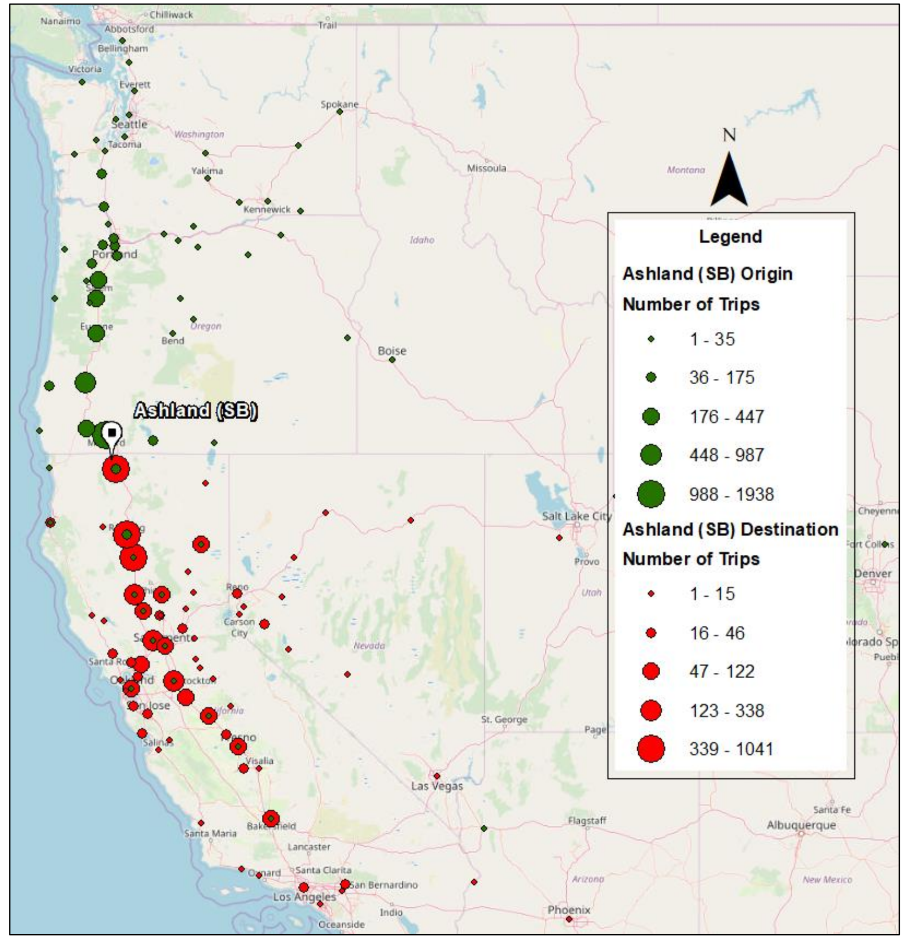


(b)

Figure 9.8: Origins and destinations as reported in EROAD data at (a) Ashland (NB) and (b) Ashland (SB) WIM stations

Table 9.12: Top Origins and Destinations by Most Observed Industry Types at Ashland (NB) WIM Station *

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Siskiyou County, CA (425)	Jackson County, OR (814)
	Tehama County, CA (377)	Douglas County, OR (408)
	Shasta County, CA (282)	Linn County, OR (203)
	Yolo County, CA (182)	Josephine County, OR (195)
	Jackson County, OR (177)	Lane County, OR (151)
Wood and Paper Products Manufacturing	Siskiyou County, CA (144)	Jackson County, OR (321)
	Shasta County, CA (98)	Douglas County, OR (115)
	Tehama County, CA (90)	Josephine County, OR (60)
	Jackson County, OR (68)	Lane County, OR (33)
	Contra Costa County, CA (42)	Linn County, OR (27)
Transport Equipment, Machinery, and Equipment Manufacturing	Tehama County, CA (111)	Douglas County, OR (119)
	Siskiyou County, CA (97)	Jackson County, OR (112)
	Shasta County, CA (63)	Marion County, OR (74)
	Jackson County, OR (35)	Linn County, OR (43)
	San Joaquin County, CA (30)	Lane County, OR (39)
Other Agriculture	Siskiyou County, CA (59)	Jackson County, OR (68)
	Tehama County, CA (59)	Douglas County, OR (46)
	Jackson County, OR (18)	Marion County, OR (22)
	Glenn County, CA (15)	Clackamas County, OR (17)
	San Joaquin County, CA (15)	Josephine County, OR (15)
Food, Beverage, and Tobacco Product Manufacturing	Siskiyou County, CA (57)	Jackson County, OR (108)
	Tehama County, CA (39)	Douglas County, OR (41)
	Jackson County, OR (33)	Josephine County, OR (38)
	Shasta County, CA (33)	Marion County, OR (19)
	Yolo County, CA (15)	Linn County, OR (17)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

Table 9.13: Top Origins and Destinations by Most Observed Industry Types at Ashland (SB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Jackson County, OR (869)	Siskiyou County, CA (370)
	Douglas County, OR (338)	Tehama County, CA (348)
	Lane County, OR (187)	Shasta County, CA (261)
	Josephine County, OR (159)	Yolo County, CA (189)
	Linn County, OR (158)	Jackson County, OR (174)
Wood and Paper Products Manufacturing	Jackson County, OR (335)	Siskiyou County, CA (111)
	Douglas County, OR (131)	Tehama County, CA (99)
	Josephine County, OR (51)	Shasta County, CA (92)
	Lane County, OR (31)	Jackson County, OR (51)
	Coos County, OR (26)	Butte County, CA (34)
Transport Equipment, Machinery, and Equipment Manufacturing	Douglas County, OR (116)	Tehama County, CA (90)
	Jackson County, OR (92)	Siskiyou County, CA (87)
	Marion County, OR (82)	Shasta County, CA (63)
	Lane County, OR (62)	Jackson County, OR (41)
	Josephine County, OR (36)	Yolo County, CA (35)
Rental, Hiring, and Real Estate Services	Jackson County, OR (68)	Siskiyou County, CA (36)
	Douglas County, OR (51)	Jackson County, OR (23)
	Clackamas County, OR (28)	Shasta County, CA (23)
	Josephine County, OR (26)	Tehama County, CA (17)
	Marion County, OR (17)	Glenn County, CA (13)
Construction	Jackson County, OR (55)	Shasta County, CA (70)
	Lane County, OR (44)	Siskiyou County, CA (63)
	Douglas County, OR (34)	Jackson County, OR (31)
	Marion County, OR (17)	Tehama County, CA (12)
	Shasta County, OR (17)	Yolo County, CA (6)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

9.5.3 Woodburn WIM Stations

Origins and destinations passing by the Woodburn (NB) and Woodburn (SB) WIM stations are shown in Figure 9.9. Considering Woodburn (NB), the majority of trips originate in areas near the WIM station, such as Salem and Albany, both with trip clusters of 1,749 trips to 4,835 trips. Also with a large number of originating trips is the Eugene area with 1,749 trips to 4,835 trips, Roseburg area with 806 trips to 1,748 trips, and the Medford area with 440 trips to 805 trips. There is also a cluster of 147 trips to 439 trips originating in the Red Bluff, CA area just north of Chico. As for destinations, the majority of trips are destined to Northern Oregon (clusters of 861 trips to 1,955 trips and 1,956 trips to 3,705 trips), Southern Washington (861 trips to 1,955 trips) and the Seattle-Tacoma area (multiple clusters of 317 trips to 860 trips).

Also, the top five industry types (based on trips) and their corresponding origins and destinations at Woodburn (NB) were identified (shown in Table 9.14). Table 9.14 shows that origins for the top five industry types traveling through Woodburn (NB) span Oregon, ranging from southern counties of Jackson and Douglas, to central and coastal counties of Lane, Linn, and Coos, to northern counties of Marion, Polk, Clackamas, and Multnomah.

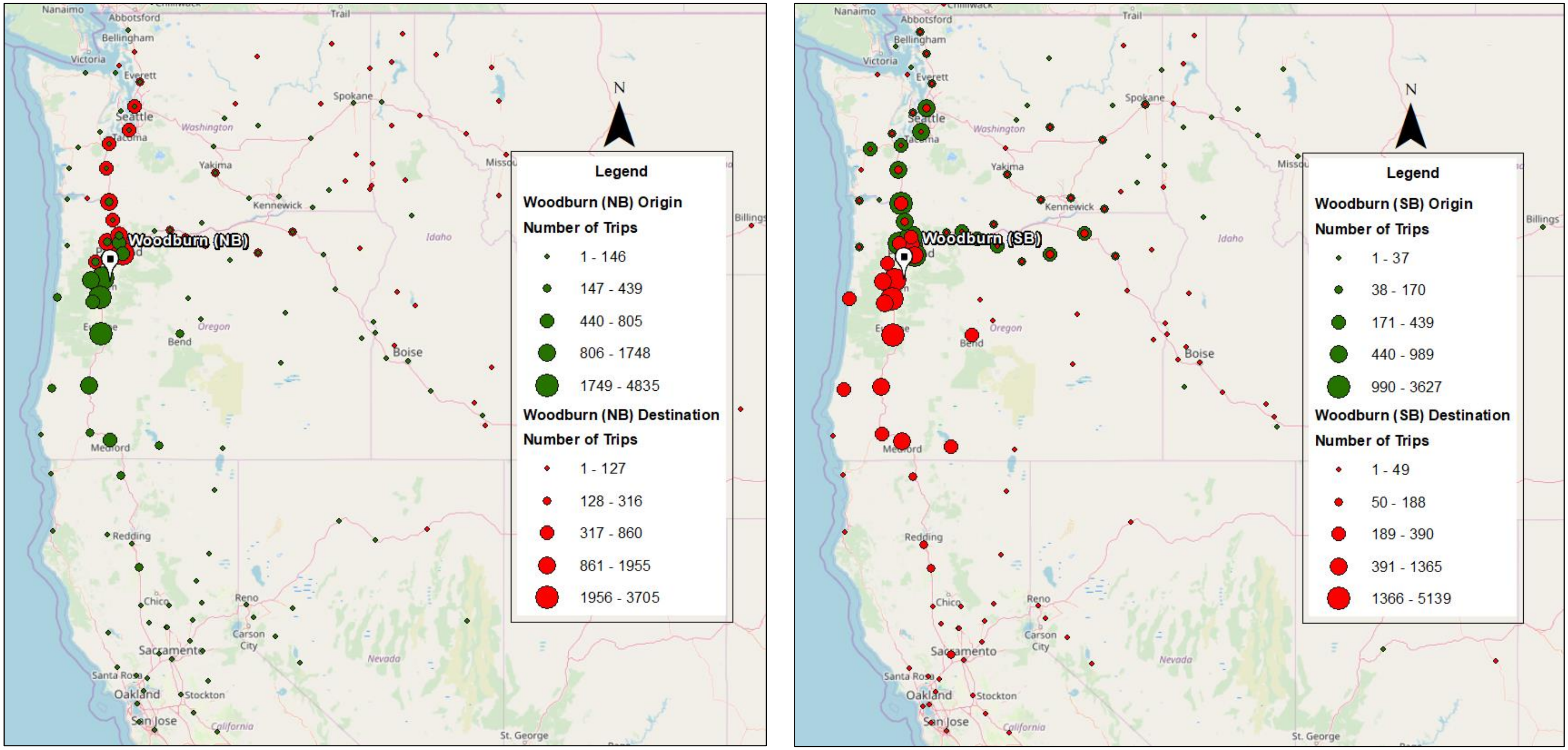
In regards to destinations and the top industry types, most industry types are headed to Multnomah, Clackamas, and Washington counties. Of the destinations outside of Oregon, there are Clark and Cowlitz counties in Southern Washington along the Oregon border. For Clark County, it is the fourth highest destination for General Freight, the third highest destination for Wood and Paper Products Manufacturing, the fifth highest destination for Transport Equipment, Machinery, and Equipment Manufacturing, the fourth highest destination for Forestry and Logging, and the fifth highest destination for Construction. Regarding Cowlitz County, it is the top destination for Wood and Paper Products Manufacturing and the second highest destination for Forestry and Logging.

Considering Woodburn (SB), the majority of trips originate in Northern Oregon, Eastern Oregon (along I-84), Southern Washington, and Central Washington near the Seattle-Tacoma area. In Northern Oregon, trip clusters of 440 trips to 989 trips and 990 trips to 3,627 trips are observed. In Eastern Oregon, all origin locations have originating trips between 171 and 439. In Southern Washington, there are originating trips of 990 to 3,627 and 440 to 989. Lastly, in Central Washington, there are clusters of trips in the Seattle-Tacoma area of 440 trips to 989 trips and 171 trips to 439 trips. Regarding destinations, the majority of trips are destined for Salem and Albany areas. For the Salem area, there are trip clusters of 1,366 trips to 5,139 trips, 391 trips to 1,365 trips, and 189 trips to 390 trips. In Eugene, there is a single cluster of 1,366 trips to 5,139 trips. Also with clusters along the I-5 corridor are the Roseburg (391 trips to 1,365 trips), Grants Pass (189 trips to 390 trips), and Ashland areas (391 trips to 1,365 trips). Of the I-5 corridor, there are destination clusters at Lincoln City (189 trips to 390 trips), Coos Bay (189 trips to 390 trips), Bend (189 trips to 390 trips), and Klamath Falls (189 trips to 390 trips).

Additionally, the top five industry types (based on trips) were identified, as were the locations of origin and destination for these industries. A summary of top industry types and associated origin-destinations for Woodburn (SB) is shown in Table 9.15.

Looking at origins for the top five industry types, the majority of trips originate in Multnomah, Clackamas, and Washington counties, where their ranking depends on the industry type. For example, Multnomah County is the top origin for General Freight and Transport Equipment, Machinery, and Equipment Manufacturing; the third highest origin for Wood and Paper Products Manufacturing, and Construction; and, the fifth highest origin for Forestry and Logging. As for Clackamas County, it is the top origin for Construction; the second highest origin for General Freight, Wood and Paper Products Manufacturing, and Forestry and Logging; and, the fourth highest origin for Transport Equipment, Machinery, and Equipment Manufacturing. Of the origins outside of Oregon, when considering the top five industry types, trips are originating in Clark, Cowlitz, and Lewis counties of Washington. As discussed previously, Clark and Cowlitz counties are located on the border of Oregon, while Lewis County is located just north of Clark and Cowlitz counties.

Regarding destinations and top industry types, all top destinations are in Oregon. Consistently, Linn (Albany area), Marion (Salem area), and Lane (Eugene area) counties are top destinations for all industry types.



(a) (b)

Figure 9.9: Origins and destinations as reported in EROAD data at (a) Woodburn (NB) and (b) Woodburn (SB) WIM stations

Table 9.14: Top Origins and Destinations by Most Observed Industry Types at Woodburn (NB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Linn County, OR (1289)	Multnomah County, OR (900)
	Marion County, OR (1020)	Clackamas County, OR (732)
	Lane County, OR (961)	Marion County, OR (659)
	Douglas County, OR (488)	Clark County, WA (513)
	Jackson County, OR (336)	Washington County, OR (420)
Wood and Paper Products Manufacturing	Linn County, OR (446)	Cowlitz County, WA (319)
	Douglas County, OR (362	Clackamas County, OR (292)
	Lane County, OR (295)	Clark County, WA (225)
	Coos County, OR (256)	Marion County, OR (204)
	Marion County, OR (235)	Multnomah County, OR (198)
Transport Equipment, Machinery, and Equipment Manufacturing	Marion County, OR (286)	Multnomah County, OR (417)
	Linn County, OR (242)	Marion County, OR (346)
	Lane County, OR (197)	Clackamas County, OR (162)
	Douglas County, OR (160)	Washington County, OR (140)
	Multnomah County, OR (100)	Clark County, WA (95)
Forestry and Logging	Linn County, OR (605)	Clackamas County, OR (201)
	Marion County, OR (177)	Cowlitz County, WA (134)
	Lane County, OR (124)	Marion County, OR (111)
	Polk County, OR (78)	Clark County, WA (95)
	Douglas County, OR (72)	Linn County, OR (85)
Construction	Marion County, OR (376)	Clackamas County, OR (227)
	Lane County, OR (258)	Washington County, OR (170)
	Linn County, OR (175)	Marion County, OR (147)
	Polk County, OR (51)	Multnomah County, OR (129)
	Clackamas County, OR (49)	Clark County, WA (68)

* Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

Table 9.15: Top Origins and Destinations by Most Observed Industry Types at Woodburn (SB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Multnomah County, OR (881)	Linn County, OR (1,200)
	Clackamas County, OR (657)	Marion County, OR (1,147)
	Marion County, OR (510)	Lane County, OR (856)
	Clark County, WA (433)	Douglas County, OR ((364)
	Washington County, OR (372)	Polk County, OR (299)
Wood and Paper Products Manufacturing	Cowlitz County, WA (355)	Linn County, OR (417)
	Clackamas County, OR (279)	Lane County, OR (364)
	Multnomah County, OR (179)	Marion County, OR (303)
	Clark County, WA (162)	Douglas County, OR (266)
	Marion County, OR (151)	Coos County, OR (146)
Transport Equipment, Machinery, and Equipment Manufacturing	Multnomah County, OR (375)	Marion County, OR (302)
	Marion County, OR (319)	Linn County, OR (236)
	Washington County, OR (146)	Lane County, OR (215)
	Clackamas County, OR (137)	Douglas County, OR (150)
	Lewis County, WA (120)	Multnomah County, OR (130)
Forestry and Logging	Cowlitz County, WA (178)	Linn County, OR (507)
	Clackamas County, OR (133)	Marion County, OR (230)
	Clark County, WA (110)	Lane County, OR (101)
	Linn County, OR (100)	Clackamas County, OR (61)
	Multnomah County, OR (88)	Polk County, OR (44)
Construction	Clackamas County, OR (201)	Marion County, OR (373)
	Washington County, OR (161)	Lane County, OR (266)
	Multnomah County, OR (156)	Linn County, OR (142)
	Marion County, OR (110)	Polk County, OR (49)
	Lewis County, WA (74)	Benton County, OR (47)

* Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

9.5.4 Cascade Locks (EB) and Wyeth (WB) WIM Stations

Origins and destinations considering the Cascade Locks (EB) and Wyeth (WB)Figure 9.10 WIM stations are shown in Figure 9.10. Considering Cascade Locks, the majority of trips originate in areas located along the I-5 corridor, including the Portland area (clusters of 1,476 trips to 3,888 trips and 455 trips to 1,475 trips), Salem area (455 trips to 1,475 trips), Albany area (455 trips to 1,475 trips), and Eugene area (192 trips to 454 trips). There is also a small cluster in the Roseburg area of 57 trips to 191 trips. Outside of Oregon, there are origin trip clusters in Southern Washington (455 trips to 1,475 trips), Chehalis, WA area (192 trips to 454 trips), the Olympia, WA area (57 trips to 191 trips), and the Seattle-Tacoma area (57 trips to 191 trips). In regards to destinations, most trips are destined to Eastern Oregon near the area of Biggs Junction (670 trips to 1,529 trips), Morrow County (Heppner area) (670 trips to 1,529 trips), Pendleton area (670 trips to 1,529 trips), and as for east as Ontario (144 trips to 346 trips). Outside of

Oregon, there are destination clusters near Boise, ID (144 trips to 346 trips), Yakima, WA (347 trips to 669 trips), Richland, WA (347 trips to 669 trips), Walla Walla, WA (347 trips to 669 trips), Ritzville, WA (144 trips to 346 trips), and Spokane, WA (144 trips to 346 trips).

Further, the top five industry types (based on trips) and their corresponding origins and destinations were identified. A summary of top industry types and associated origin-destinations for Cascade Locks is shown in Table 9.16.

Referring to the origins of the top industry types at Cascade Locks, Multnomah, Clackamas, Washington, and Marion counties are consistently top origins. Noteworthy origins include Tillamook County (located near the coast) and Linn County (located in Central Oregon in the Albany area). In regards to Tillamook County, it is the fifth highest origin for Wood and Paper Products Manufacturing, while Linn County is the fourth highest origin for General Freight, fourth highest origin for Wood and Paper Products Manufacturing, and the fifth highest origin for Other Services.

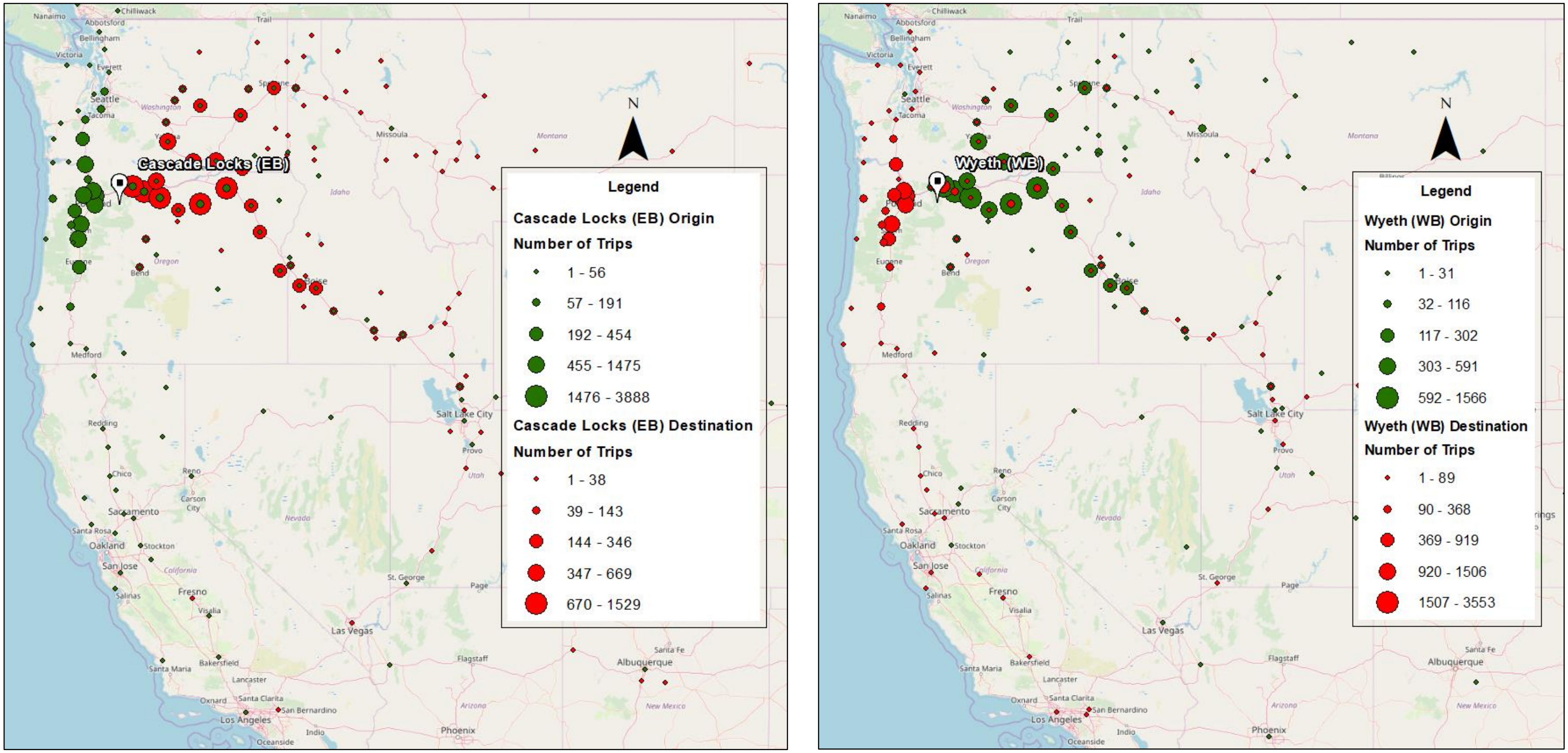
As it pertains to destinations for top industry types at Cascade Locks, the majority of trips are consistently destined to Sherman County, Hood River County, Umatilla County, Morrow County, and Wasco County regardless of industry type. Just one top destination is located outside Oregon; specifically, Franklin County, WA (located in Pasco, WA, just north of Umatilla) and is the fourth highest destination for Wood and Paper Products Manufacturing, and the fifth highest destination for Other Agriculture.

Origins and destinations considering the Wyeth WIM station are nearly a mirror image of the origins and destinations observed at Cascade Locks. For instance, as it pertains to origins, the majority of trips originate in the area of Biggs Junction (several clusters of 592 trips to 1,566 trips), Morrow County (Heppner area) (592 trips to 1,566 trips), Pendleton area (592 trips to 1,566 trips), and as for east as Ontario (117 trips to 302 trips). Outside of Oregon, there are origin clusters near Boise, ID (117 trips to 302 trips), Yakima, WA (303 trips to 591 trips), Richland, WA (303 trips to 591 trips), Walla Walla, WA (117 trips to 302 trips), Ritzville, WA (117 trips to 302 trips), and Spokane, WA (117 trips to 302 trips). The same holds true for destinations, with the exception of the Olympia, WA area, and the Seattle-Tacoma area. The majority of trips are destined to areas located along the I-5 corridor, including the Portland area (clusters of 1,507 trips to 3,553 trips, and 920 trips to 1,506 trips, and 369 trips to 919 trips), Salem area (920 trips to 1,506 trips), Albany area (369 trips to 919 trips), and Eugene area (90 trips to 368 trips). There is also a small cluster in the Roseburg area of 90 trips to 368 trips. Outside of Oregon, there are destination trip clusters in Southern Washington (369 trips to 919 trips), and the Chehalis, WA area (90 trips to 368 trips).

Additionally, the top five industry types (based on trips) and their corresponding origins and destinations at Wyeth were identified. A summary of top industry types and associated origin-destinations for Wyeth is shown in Table 9.17.

As for origins, the top origins are the top destinations that were observed at the Cascade Locks WIM station: Sherman County, Hood River County, Umatilla County, Morrow County, and Wasco County, regardless of industry type. The one non-Oregon origin is Franklin County, WA, located near Pasco, WA, just north of Umatilla.

Regarding destinations, top destinations are the top origins that were observed at the Cascade Locks WIM station: Multnomah County and Clackamas County. Other destinations include Clark County, WA (located on the Oregon border) for General Freight (4th), Transport Equipment, Machinery, and Equipment Manufacturing (3rd); Marion County, OR for General Freight (3rd), Transport Equipment, Machinery, and Equipment Manufacturing (2nd), Other Agriculture (2nd), and Wood and Paper Products Manufacturing (4th); and, Linn County, OR for General Freight (5th), and Wood and Paper Products Manufacturing (5th).



(a) (b)

Figure 9.10: Origins and destinations as reported in EROAD data at (a) Cascade Locks (EB) and (b) Wyeth (WB) WIM stations

Table 9.16: Top Origins and Destinations by Most Observed Industry Types at Cascade Locks (EB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Multnomah County, OR (890)	Hood River County, OR (473)
	Clackamas County, OR (466)	Morrow County, OR (368)
	Marion County, OR (402)	Umatilla County, OR (350)
	Linn County, OR (383)	Wasco County, OR (336)
	Clark County, WA (347)	Sherman County, OR (375)
Transport Equipment, Machinery, and Equipment Manufacturing	Multnomah County, OR (509)	Umatilla County, OR (182)
	Marion County, OR (219)	Morrow County, OR (154)
	Clark County, WA (129)	Wasco County, OR (129)
	Washington County, OR (100)	Sherman County, OR (122)
	Clackamas County, OR (70)	Hood River County, OR (65)
Other Agriculture	Multnomah County, OR (253)	Umatilla County, OR (186)
	Washington County, OR (137)	Sherman County, OR (144)
	Yamhill County, OR (119)	Morrow County, OR (136)
	Marion County, OR (110)	Wasco County, OR (95)
	Clackamas County, OR (103)	Franklin County, WA (81)
Wood and Paper Products Manufacturing	Clackamas County, OR (154)	Wasco County, OR (86)
	Multnomah County, OR (126)	Hood River County, OR (82)
	Cowlitz County, WA (108)	Morrow County, OR (61)
	Linn County, OR (45)	Franklin County, WA (36)
	Tillamook County, OR (38)	Umatilla County, OR (35)
Other Services	Multnomah County, OR (103)	Umatilla County, OR (55)
	Marion County, OR (94)	Morrow County, OR (54)
	Clackamas County, OR (74)	Wasco County, OR (49)
	Clark County, WA (53)	Hood River County, OR (44)
	Linn County, OR (53)	Sherman County, OR (39)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

Table 9.17: Top Origins and Destinations by Most Observed Industry Types at Wyeth (WB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Hood River County, OR (429)	Multnomah County, OR (851)
	Umatilla County, OR (387)	Clackamas County, OR (496)
	Morrow County, OR (361)	Marion County, OR (396)
	Wasco County, OR (316)	Clark County, WA (347)
	Sherman County, OR (291)	Linn County, OR (322)
Transport Equipment, Machinery, and Equipment Manufacturing	Umatilla County, OR (200)	Multnomah County, OR (482)
	Morrow County, OR (179)	Marion County, OR (216)
	Wasco County, OR (139)	Clark County, WA (121)
	Sherman County, OR (138)	Washington County, OR (101)
	Union County, OR (61)	Clackamas County, OR (84)
Other Agriculture	Umatilla County, OR (190)	Multnomah County, OR (213)
	Morrow County, OR (161)	Marion County, OR (142)
	Sherman County, OR (155)	Washington County, OR (122)
	Wasco County, OR (101)	Yamhill County, OR (119)
	Franklin County, WA (78)	Clackamas County, OR (104)
Wood and Paper Products Manufacturing	Wasco County, OR (99)	Clackamas County, OR (151)
	Hood River County, OR (81)	Multnomah County, OR (94)
	Morrow County, OR (67)	Cowlitz County, WA (70)
	Cowlitz County, WA (58)	Marion County, OR (45)
	Umatilla County, OR (55)	Linn County, OR (39)
Construction	Wasco County, OR (132)	Multnomah County, OR (104)
	Hood River County, OR (76)	Clackamas County, OR (93)
	Morrow County, OR (43)	Hood River County, OR (78)
	Sherman County, OR (43)	Clark County, WA (47)
	Umatilla County, OR (39)	Wasco County, OR (43)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

9.5.5 Olds Ferry (EB) and Farewell Bend (WB) WIM Stations

Origins and destinations considering the Olds Ferry (EB) and Farewell Bend (WB) WIM stations are shown in Figure 9.11. Considering Olds Ferry, most trips originate in Eastern Oregon, Southeastern Washington, and the Portland area. For Eastern Oregon, trips are originating near Wasco (96 trips to 285 trips), Morrow County (Heppner area) (286 trips to 533 trips), Pendleton (534 trips to 1,529 trips), the La Grande area (534 trips to 1,529 trips), the Pleasant Valley area (534 trips to 1,529 trips), and as far east as the Ontario area (96 trips to 285 trips). For origins in Washington, there are clusters in the Seattle-Tacoma area with 96 trips to 285 trips and 31 trips to 95 trips, the Yakima area with 96 trips to 285 trips, Walla Walla area with 96 trips to 285 trips, and Pasco area with 286 trips to 533 trips. As for destinations, the majority of trips are destined to Eastern Oregon in the Ontario area (clusters of 598 trips to 1,325 trips and 186 trips to 597 trips), the Boise-Nampa area (clusters of 598 trips to 1,325 trips and 101 trips to 185 trips), near Twin Falls, ID (clusters of 186 trips to 597 trips and 101 trips to 185 trips), and the Salt Lake City area (101 trips to 185 trips).

As with the previous WIM stations, the top five industry types (based on trips) and their corresponding origins and destinations were identified. A summary of top industry types and their associated origin-destinations for Olds Ferry is shown in Table 9.18.

For top origins of the top industry types, most trips originate in Eastern Oregon counties, including Umatilla, Baker, Morrow, and Union. Outside of these Eastern Oregon counties, there is Franklin County, WA, Multnomah County, OR, and Clackamas County Oregon. Franklin County, WA is the fifth highest origin for General Freight and the second highest origin for Other Agriculture. Multnomah County, OR is the fifth highest origin for Transport Equipment, Machinery, and Equipment Manufacturing, and the fourth highest origin for Private Transport. Lastly, Clackamas County, OR is the fourth highest origin for Other services.

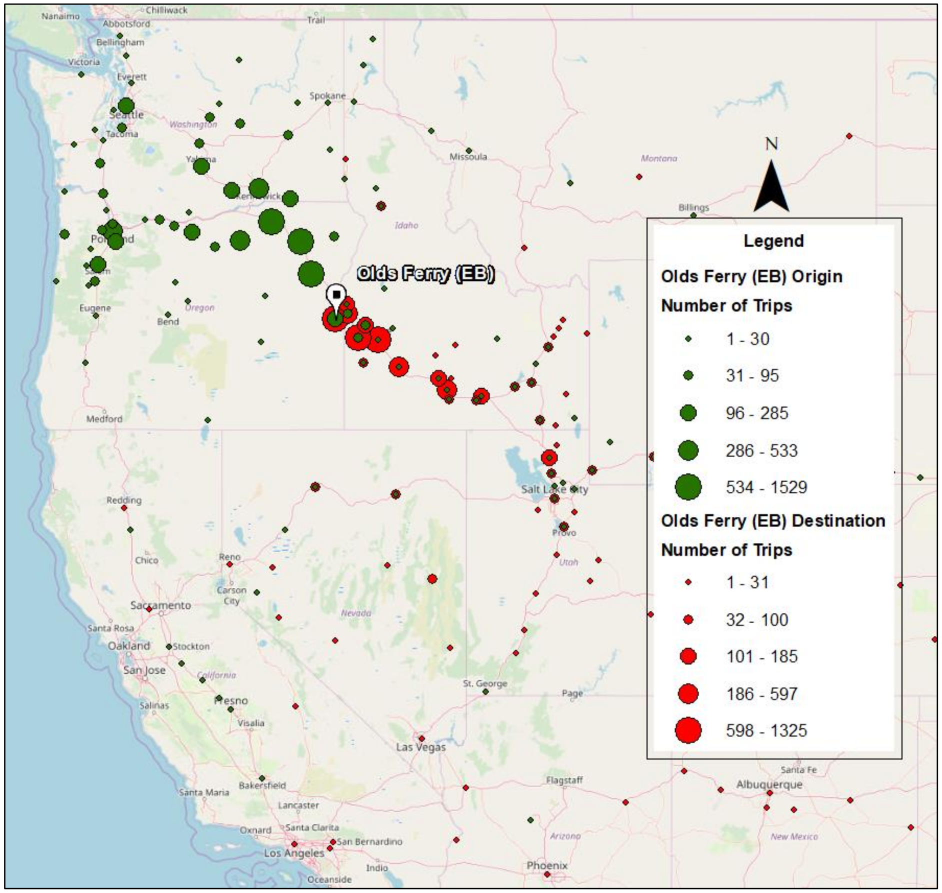
As for destinations for top industry types, the only Oregon county is Malheur (located on the Idaho border). All other destinations, considering the top industry types, are in Idaho. These destinations are most often Ada (East Boise), Canyon (West Boise), and Payette (Northwest Boise area) counties. Ada County, ID is the second highest destination for General Freight, the fourth highest destination for Other Agriculture, the second highest destination for Transport Equipment, Machinery, and Equipment Manufacturing, the top destination for Private Transport, and the third highest destination for Other Services. Canyon County, ID is the third highest destination for General Freight, the third highest destination for Other Agriculture, the third highest destination for Transport Equipment, Machinery, and Equipment Manufacturing, the fourth highest destination for Private Transport, and the top destination for Other Services. Lastly, Payette County, ID is the fourth highest destination for General Freight, the second highest destination for Other Agriculture, the fourth highest destination for Transport Equipment, Machinery, and Equipment Manufacturing, the fifth highest destination for Private Transport, and the fifth highest destination for Other Services.

As was the case with the Cascade Locks and Wyeth WIM stations, origins and destinations considering the Farewell Bend WIM station are nearly a mirror image of the origins and destinations observed at Olds Ferry. For example, as it pertains to origins, the majority of trips originate in Eastern Oregon in the Ontario area (clusters of 436 trips to 1,373 trips and 205 trips to 435 trips), the Boise-Nampa area (clusters of 436 trips to 1,373 trips), near Twin Falls, ID (clusters of 205 trips to 435 trips and 113 trips to 204 trips), and the Salt Lake City area (113 trips to 204 trips). The same holds true for destinations. The majority of trips are destined to Eastern Oregon near Pleasant Valley (544 trips to 1,513 trips), La Grande (544 trips to 1,513 trips), Pendleton (544 trips to 1,513 trips), Morrow County (Heppner) (240 trips to 543 trips), and Wasco (97 trips to 239 trips). Other destinations in Oregon include the Portland area (clusters of 240 trips to 543 trips and 97 trips to 239 trips) and Salem area (97 trips to 239 trips). Outside of Oregon, there is a cluster of trips in the Seattle-Tacoma area (97 trips to 239 trips), Yakima, WA (97 trips to 239 trips), Walla Walla, WA (97 trips to 239 trips), Pasco, WA (240 trips to 543 trips), and Spokane, WA (27 trips to 96 trips).

In addition, the top five industry types (based on trips) and their corresponding origins and destinations were identified. A summary of top industry types and their associated origin-destinations for Farewell Bend is shown in Table 9.19.

Looking at origins of the top five industry types, there is one origin not located in Idaho or Utah: Malheur County, OR. Specifically, Malheur County, OR is the top origin for General Freight, the top origin for Other Agriculture, the top origin for Transport Equipment, Machinery, and Equipment Manufacturing, the second highest origin for Private Transport, and the top origin for Livestock: Meat and Wool. As for the top origin in Utah, Box Elder County, UT is the fifth highest origin for Transport Equipment, Machinery, and Equipment Manufacturing. For origins in Idaho, these are primarily in Ada, Canyon, Payette, and Elmore counties, all in the Boise, ID area.

Moving to top destinations for the top industry types, the majority of trips are destined to Eastern Oregon counties, such as Umatilla, Baker, Union, and Morrow, and Franklin County, WA. The top destination not in these areas is Multnomah County, OR, which is the fifth highest destination for Transport Equipment, Machinery, and Equipment Manufacturing, and the second highest destination for Private Transport.



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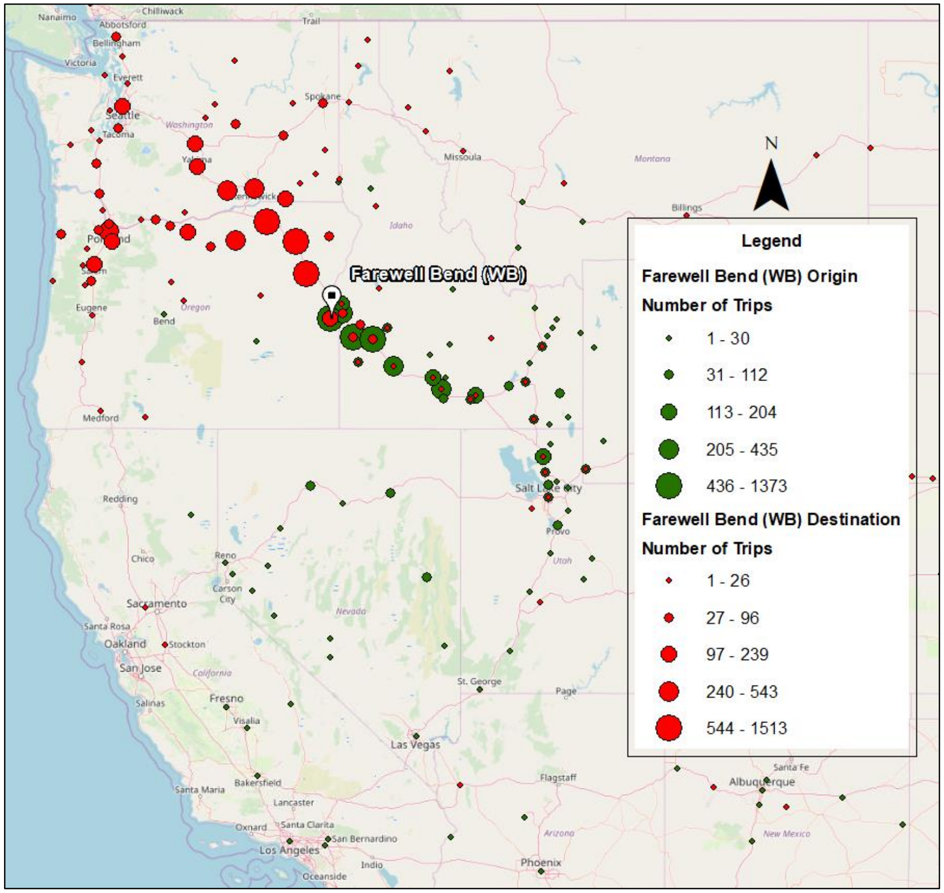


(b)

Figure 9.11: Origins and destinations as reported in EROAD Ddata at (a) Olds Ferry (EB) and (b) Farewell Bend (WB) WIM stations

Table 9.18: Top Origins and Destinations by Most Observed Industry Types at Olds Ferry (EB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Umatilla County, OR (558)	Malheur County, OR (414)
	Baker County, OR (319)	Ada County, ID (365)
	Union County, OR (288)	Canyon County, ID (335)
	Morrow County, OR (162)	Payette County, ID (260)
	Franklin County, WA (153)	Jerome County, ID (170)
Other Agriculture	Umatilla County, OR (299)	Malheur County, OR (208)
	Franklin County, WA (134)	Payette County, ID (77)
	Union County, OR (111)	Canyon County, ID (75)
	Baker County, OR (69)	Ada County, ID (67)
	Morrow County, OR (57)	Elmore County, ID (50)
Transport Equipment, Machinery, and Equipment Manufacturing	Umatilla County, OR (171)	Malheur County, OR (198)
	Union County, OR (147)	Ada County, ID (95)
	Baker County, OR (126)	Canyon County, ID (90)
	Morrow County, OR (101)	Payette County, ID (63)
	Multnomah County, OR (78)	Elmore County, ID (51)
Private Transport	Umatilla County, OR (63)	Ada County, ID (71)
	Baker County, OR (51)	Malheur County, OR (45)
	Union County, OR (51)	Gem County, ID (44)
	Multnomah County, OR (49)	Canyon County, ID (36)
	Morrow County, OR (20)	Payette County, ID (27)
Other Services	Umatilla County, OR (39)	Canyon County, ID (65)
	Union County, OR (39)	Malheur County, OR (55)
	Baker County, OR (34)	Ada County, ID (54)
	Clackamas County, OR (26)	Idaho County, ID (28)
	Jefferson County, OR (21)	Payette County, ID (26)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

Table 9.19: Top Origins and Destinations by Most Observed Industry Types at Farewell Bend (WB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Malheur County, OR (438)	Umatilla County, OR (517)
	Canyon County, ID (375)	Baker County, OR (325)
	Ada County, ID (296)	Union County, OR (267)
	Payette County, ID (214)	Morrow County, OR (182)
	Elmore County, ID (151)	Franklin County, WA (169)
Other Agriculture	Malheur County, OR (206)	Umatilla County, OR (266)
	Canyon County, ID (92)	Union County, OR (122)
	Ada County, ID (68)	Franklin County, WA (104)
	Payette County, ID (54)	Morrow County, OR (94)
	Jerome County, ID (51)	Baker County, OR (91)
Transport Equipment, Machinery, and Equipment Manufacturing	Malheur County, OR (221)	Umatilla County, OR (199)
	Canyon County, ID (111)	Union County, OR (130)
	Ada County, ID (100)	Baker County, OR (111)
	Elmore County, ID (44)	Morrow County, OR (78)
	Box Elder County, Utah (37)	Multnomah County, OR (62)
Private Transport	Ada County, ID (65)	Umatilla County, OR (62)
	Malheur County, OR (55)	Multnomah County, OR (56)
	Canyon County, ID (38)	Union County, OR (53)
	Gem County, ID (34)	Baker County, OR (47)
	Payette County, ID (32)	Gen County, ID (22)
Livestock: Meat and Wool	Malheur County, OR (78)	Umatilla County, OR (70)
	Payette County, ID (25)	Baker County, OR (40)
	Umatilla County, OR (22)	Union County, OR (25)
	Baker County, OR (19)	Morrow County, OR (23)
	Ada County, ID (12)	Malheur County, OR (18)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

9.5.6 Klamath Falls WIM Stations

Origins and destinations considering the Klamath Falls (NB) and Klamath Falls (SB) WIM stations are shown in Figure 9.12. Considering Klamath Falls (NB), most trips are originating in the Reno, NV area (67 trips to 167 trips), Redding, CA area (67 trips to 167 trips), Red Bluff, CA area (168 trips to 273 trips), and Weed, CA area (168 trips to 273 trips). Regarding destinations, locations span Oregon into areas of Washington. For destinations in Oregon, there are 337 trips to 1,121 trips destined to the Klamath Falls area, 163 trips to 336 trips destined to the Bend area, 62 trips to 162 trips destined to Madras and Mitchell areas, and 62 trips to 162 trips destined to the Wasco area. Each of the aforementioned destinations is located along the US-97 corridor. Additional noteworthy destinations are those located along the I-5 corridor, specifically, the

Eugene area (163 trips to 336 trips), the Albany area (163 trips to 336 trips), the Salem area (62 trips to 162 trips), and the Portland Metropolitan area (clusters of 62 trips to 162 trips and 18 trips to 61 trips).

As with each of the previous WIM stations, the top five industry types (based on trips) and their corresponding origins and destinations were identified. A summary of top industry types and their associated origin-destinations for Klamath Falls (NB) is shown in Table 9.20.

For top origins of top industry types, the majority fall within Northern California: Siskiyou, Shasta, and Tehama counties. The one origin not in Northern California is Washoe County, NV, where trips are likely originating from the Reno, NV area. Specifically, Washoe County, NV is the fifth highest origin for Other Agriculture.

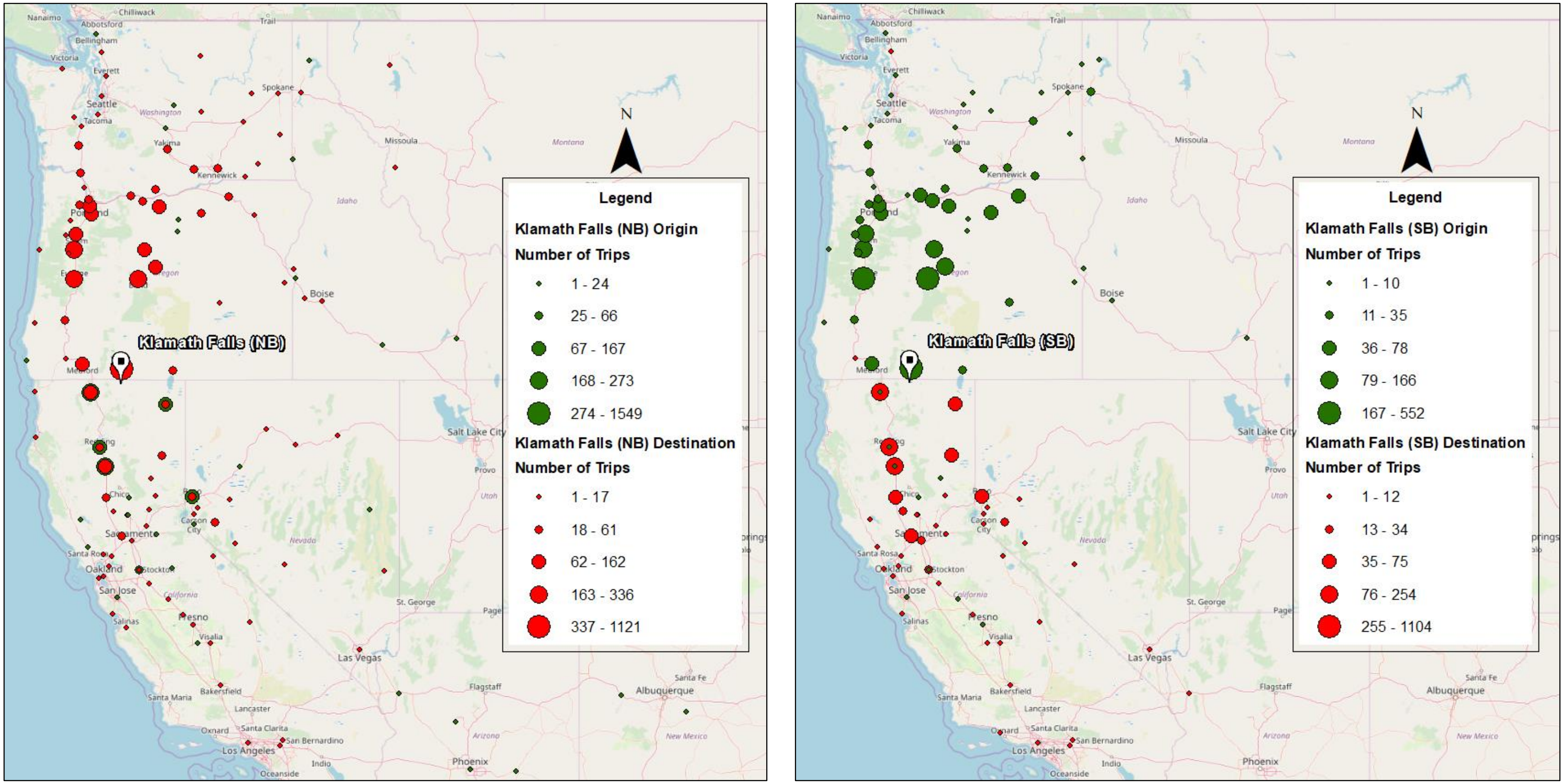
In terms of destinations, the top industry types are most often destined to Southern Oregon and Central Oregon. As for Southern Oregon, Klamath County is the top origin for all top five industry types. Central Oregon destinations include Lane, Linn, and Marion counties. Also of note are Deschutes County and Sherman County. Deschutes County, located off the US-97 corridor, is in the top five for each industry type. Sherman County, located at the northernmost section of US-97 near Wasco and Biggs Junction, is the fourth highest destination for Other Services.

Considering Klamath Falls (SB), origins and destinations are nearly a mirror image when compared to Klamath Falls (NB). For origins in Oregon along the US-97 corridor, there are 167 trips to 552 trips originating in the Klamath Falls area, 167 trips to 552 originating in the Bend area, 79 trips to 166 trips originating in the Madras and Mitchell areas, and 36 trips to 78 trips originating in the Biggs Junction and Condon areas. For origins in Oregon along the I-84 corridor, there are 36 trips to 78 trips originating in the Hood River area and 36 trips to 78 trips originating in the Pendleton area. Off of I-84, there are also 36 trips to 78 trips originating in the Heppner area. The remaining origins of note are along the I-5 corridor, including 167 trips to 552 originating in the Eugene area, 79 trips to 166 trips originating in the Albany and Salem areas, and clusters of 79 trips to 166 trips and 11 trips to 35 trips originating in the Portland Metropolitan area. In regards to destinations, the majority of destinations are along the I-5 corridor in California. There are 76 trips to 254 trips destined to the Weed, CA area, 76 trips to 254 trips destined to the Redding, CA area, 76 trips to 254 trips destined to the Red Bluff, CA area, 35 trips to 75 trips destined to the Chico, CA area, and clusters of 35 trips to 75 trips and 13 trips to 34 trips destined to the Sacramento area. In addition to these clusters along the I-5 corridor in California, there are two clusters in the northeast part of the state; specifically, 35 trips to 75 trips are destined to the Alturas and Susanville areas. Outside of California, there is a cluster of trips (35 trips to 75 trips) destined to the Reno, NV area.

As with each of the previous WIM stations, the top five industry types (based on trips) and their corresponding origins and destinations were identified. A summary of top industry types and their associated origin-destinations for Klamath Falls (SB) is shown in Table 9.21.

As it pertains to origins and the top industry types, all origins but two are in Oregon, with Klamath County being the top origin for all industry types. The two origins outside of Oregon are Cowlitz County, WA (located on the Oregon-Washington border), and Franklin County, WA (located just north of Umatilla). Deschutes County is consistently a top origin regardless of industry type.

Regarding destinations and top industry types, the majority of trips are destined to Northern California counties, such as Siskiyou, Shasta, and Tehama. Other top destinations in California include Glenn County and Fresno County. As for Glenn County (located just west of Chico), it is the fifth highest destination for General Freight. In regards to Fresno County (located nearly at the midpoint between Sacramento and Los Angeles when considering the county seat of Fresno), it is the fifth highest destination for Other Services.



(a) (b)

Figure 9.12: Origins and destinations as reported in EROAD data at (a) Klamath Falls (NB) and (b) Klamath Falls (SB) WIM stations

Table 9.20: Top Origins and Destinations by Most Observed Industry Types at Klamath Falls (NB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Klamath County, OR (546)	Klamath County, OR (431)
	Siskiyou County, CA (134)	Lane County, OR (137)
	Tehama County, CA (134)	Deschutes County, OR (136)
	Shasta County, CA (83)	Linn County, OR (106)
	Lane County, OR (67)	Crook County, OR (76)
Transport Equipment, Machinery, and Equipment Manufacturing	Klamath County, OR (131)	Klamath County, OR (119)
	Siskiyou County, CA (38)	Crook County, OR (39)
	Tehama County, CA (22)	Deschutes County, OR (33)
	Crook County, OR (17)	Lane County, OR (28)
	Shasta County, CA (16)	Marion County, OR (26)
Other Agriculture	Klamath County, OR (110)	Klamath County, OR (85)
	Siskiyou County, CA (21)	Deschutes County, OR (37)
	Deschutes County, OR (16)	Clackamas County, OR (18)
	Tehama County, CA (15)	Linn County, OR (17)
	Washoe, NV (15)	Marion County, OR (16)
Wood and Paper Products Manufacturing	Klamath County, OR (87)	Klamath County, OR (67)
	Jackson County, OR (30)	Deschutes County, OR (24)
	Shasta County, CA (12)	Jackson County, OR (18)
	Tehama County, CA (11)	Lane County, OR (18)
	Siskiyou County, CA (8)	Lincoln County, OR (15)
Other Services	Klamath County, OR (83)	Klamath County, OR (64)
	Lane County, OR (30)	Lane County, OR (31)
	Siskiyou County, CA (12)	Marion County, OR (12)
	Franklin County, WA (3)	Sherman County, OR (8)
	Jackson County, OR (3)	Deschutes County, OR (5)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

Table 9.21: Top Origins and Destinations by Most Observed Industry Types at Klamath Falls (SB) WIM Station*

Industry Type	Top Five Origins (Number of Trips)	Top Five Destinations (Number of Trips)
General Freight	Klamath County, OR (187)	Klamath County, OR (375)
	Lane County, OR (131)	Tehama County, CA (131)
	Deschutes County, OR (116)	Siskiyou County, CA (128)
	Linn County, OR (80)	Shasta County, CA (85)
	Hood River County, OR (52)	Glenn County, CA (49)
Transport Equipment, Machinery, and Equipment Manufacturing	Klamath County, OR (72)	Klamath County, OR (88)
	Crook County, OR (46)	Siskiyou County, CA (31)
	Deschutes County, OR (29)	Shasta County, CA (24)
	Lane County, OR (20)	Tehama County, CA (23)
	Marion County, OR (20)	Washoe County, NV (10)
Other Agriculture	Klamath County, OR (44)	Klamath County, OR (77)
	Deschutes County, OR (33)	Tehama County, CA (15)
	Jefferson County, OR (17)	Washoe County, NV (14)
	Clackamas County, OR (14)	Siskiyou County, CA (11)
	Linn County, OR (13)	Jefferson County, CA (9)
Other Services	Klamath County, OR (33)	Klamath County, OR (57)
	Lane County, OR (32)	Lane County, OR (12)
	Marion County, OR (11)	Siskiyou County, CA (9)
	Deschutes County, OR (8)	Shasta County, CA (6)
	Franklin County, WA (4)	Fresno County, CA (4)
Wood and Paper Products Manufacturing	Klamath County, OR (29)	Klamath County, OR (57)
	Cowlitz County, WA (15)	Douglas County, OR (11)
	Jackson County, OR (13)	Siskiyou County, CA (10)
	Deschutes County, OR (12)	Deschutes County, OR (8)
	Marion County, OR (7)	Jackson County, OR (7)

*Origins and Destinations are Independent (Each Top Origin Does Not Necessarily Correspond to a Top Destination) of Each Other

9.6 EROAD SUMMARY

Using the data obtained from EROAD, a series of analyses were conducted. The EROAD data contains information on origin and destination (at the county-level), declared weight, industry type, and the total number of trips. Utilizing these characteristics, the first analysis was descriptive, with a focus on truck count comparisons to ODOT's WIM data. A total of 107,980 observations were included in the EROAD data, resulting in 525,503 total trips through the select WIM stations. In assessing truck counts, the Woodburn WIM stations, Cascade Locks (EB) and Wyeth (WB) WIM stations, and Ashland WIM stations had the highest number of trips in the EROAD data. This differed slightly from the WIM data, where the Ashland WIM stations had the second highest truck volume, and the Cascade Locks (EB) and Wyeth (WB) WIM stations had the third highest truck volume. These slight differences may simply be a result of EROAD coverage. Coverage in neighboring states to the east, such as Idaho, has shown to be high, which may be contributing to the higher number of trips at the Cascade Locks (EB) and Wyeth (WB). At this time, coverage in California is unknown.

The following analysis assessed weight distributions in both the EROAD and WIM datasets. In the EROAD data, approximately 60% of the observations did have a declared weight (40% of the declared weight was unknown). In addition, the declared weight figure may not be a proxy for actual vehicle weight (tare plus payload) and, therefore, not directly comparable against WIM data. The majority of declared weight values were reported as 80,000 pounds. After visually assessing the large differences between WIM and EROAD weight distributions, no further weight analysis was conducted.

The next analysis focused on industry type and WIM station. The industry type is defined and reported to EROAD by the company, no specific information on industry type was obtained at the truck level (e.g., commodities being transported on a given truck). The number of industry types observed at the WIM stations ranged from 27 to 31, with both Woodburn WIM stations having the highest number of observed industry types. Regardless of WIM station, two industry types consistently accounted for a high number of trips: (1) General Freight and (2) Transport Equipment, Machinery, and Equipment Manufacturing. These two industry types, along with Other Agriculture, were the top three industry types based on the number of trips on the I-84 and US-97 WIM stations. At the I-5 WIM stations, these industry types, along with Wood and Paper Products Manufacturing, were the top three industry types based on the number of trips.

Of interest, Woodburn observed an industry type that was not found at any other WIM station in Oregon: Electricity, Gas, Water, and Waste Services. Also noteworthy is the industry type Arts and Recreation Services. Although this industry type did not account for a high number of trips, it was primarily observed at the WIM stations located nearest to the Portland Metropolitan area (one trip was observed at the Ashland (WB) WIM station). This is likely associated with the various art centers (e.g., the Portland Art Museum, Oregon Symphony) located in the Portland Metropolitan area. Likewise, the industry type Furniture and Other Manufacturing was observed only at the WIM stations nearest to the Portland Metropolitan area.

Next, using the county origins and destinations, driving distances and their corresponding descriptive statistics were computed. It was determined that Cascade Locks (EB) had the highest mean, median, and 95th percentile driving distances, while Wyeth (WB) had the highest maximum driving distance. On the other end, the lowest mean, median, and 95th percentile driving distances were observed at Woodburn (SB), while Klamath Falls (SB) had the lowest maximum driving distance. Additionally, Olds Ferry (EB) and Farewell Bend (WB) (the WIM stations on the Oregon-Idaho border) had the highest 25th and 75th percentile driving distances of all WIM stations.

In addition to assessing driving distance, a brief comparison and correlation between driving distance and geodesic distance (shortest distance) was presented. It was determined through a series of correlation tests that the two distances are highly positively correlated with a high level of confidence, and the average ratio between distance is approximately 1.24.

The final analysis focused on origins and destinations at the aggregated level and broken down by WIM station. In addition, summary tables were provided to illustrate the top origins and destinations based on the top five industry types observed at each WIM station. In general, the majority of origins and destinations for the top industry types were in neighboring counties relative to the WIM station. Additionally, there were approximately 620 observations that were easily identified as having origins and destinations that do not consist of a trip through Oregon. Regardless of the easily identified locations in which a trip would not go through Oregon, the overall picture in terms of origin and destination looks realistic. Each dataset has its own advantages and limitations, where the EROAD data can be advantageous in its ability to complement other data sources, such as WIM. EROAD, specifically, is unique in that it has industry type information. Such information can link trucks and industries to the economy, which is a vital component for analyses.

10.0 SUMMARY AND RECOMMENDATIONS

The objective of the current study was to evaluate Oregon WIM data for use by ODOT for short-term and long-term highway investment prioritization and tools/methods to conduct freight analyses. First, an overview of WIM systems was presented with a focus on key advantages and disadvantages of the most commonly used WIM systems. Additionally, ASTM WIM functional performance requirements were identified (see Table 2.1). Next, an extensive and comprehensive review of WIM-related research was conducted. Through the literature review, it was found that freight flow, installation, calibration, and quality checks are the most common WIM-related studies. In regards to freight flow, the methods used across studies are similar, where the most common include distribution fitting and truck matching/re-identification.

Upon completing the literature review, WIM in Oregon was specifically discussed. This focused explicitly on WIM systems in Oregon and WIM-related research in Oregon. Currently, Oregon has 21 WIM sites used for enforcement, three virtual WIM sites used only for data collection, and three locations with license plate reading capabilities. Of the 21 sites used for enforcement, more than half are located on Oregon’s three primary freight corridors: I-5, I-84, and US-97. The early WIM-related works in Oregon focus on implementation and accuracy of WIM systems, and the effects of closed weigh stations on evasion behavior. In later years, work concentrated on using WIM data for design procedures; specifically, structural live load parameters for bridge design and ESAL estimation for pavement design. Only in recent years have WIM data been used in Oregon to analyze freight behavior. Next, potential data sources to be used along with Oregon’s WIM data in the analysis were inventoried.

The remaining tasks consisted of a data-driven analysis using Oregon WIM data. Using four years of WIM data (2015 to 2018), a quality control analysis was conducted for ODOT Class 11 (FHWA Class 09) trucks. This was based on previous WIM-related research and that quality control checks for ODOT Class 11 trucks have been widely used and established. In addition to the characteristics of these trucks being widely known, they also account for the greatest proportion of freight-related vehicles. Unfortunately, being that characteristics of other classification are less established, a quality control analysis on other truck classifications could not be conducted. Next, two sets of descriptive analyses were conducted considering four truck classification groups: (1) ODOT Class 03 to ODOT Class 10 trucks (excluding Class 04 and Class 07), (2) ODOT Class 11 trucks only, (3) ODOT Class 12 to ODOT Class 19 trucks, and (4) all trucks (ODOT Class 03 to ODOT Class 19, excluding Class 04 and Class 07). For the descriptive analyses, one analysis focused on all WIM stations and one focused on select WIM stations. Based on data availability, truck volume, and average observed combined (truck and cargo) weight, 10 WIM stations were selected for further analysis: Ashland (NB), Ashland (SB), Woodburn (NB), Woodburn (SB), Cascade Locks (EB), Wyeth (WB), Olds Ferry (EB), Farewell Bend (WB), Klamath Falls (NB), and Klamath Falls (SB). Following the descriptive analysis, data comparisons were made; specifically, WIM data was compared to FAF weights, and ODOT traffic volume counts. The final analysis used EROAD data. Analyses included truck volume comparisons, driving distance, industry type, and origin-destination by WIM station.

The following sub-chapters summarize the results of the data analyses. Following these summaries are recommendations.

10.1 DATA QUALITY

In general, the data quality was consistent across WIM stations, overall less than 1.0% of observations were removed. The WIM stations at Ashland, Booth Ranch (SB), Bend (NB) in 2017 and 2018, and Rocky Point (WB) in 2017 and 2018 experienced higher data reduction after completion of the quality control analysis. Specifically, data reduction at the Ashland WIM stations ranged from 1.32% to 2.28% in the northbound direction and 2.23% to 2.46% in the southbound direction. At Booth Ranch (SB), data reduction ranged from 1.89% to 2.39%. Lastly, at Bend (NB) and Rocky Point (WB), data reduction ranged from 2.29% to 5.30% and 1.83% to 3.10%, respectively. Although moderate data reductions were observed, these percent reductions meet the ASTM requirements presented in Table 2.1.

10.2 DESCRIPTIVE ANALYSIS

Included in the descriptive analysis were the following metrics: total number of trucks and average monthly observed combined (truck and cargo) weight. It was determined that Woodburn consistently experiences the largest truck volumes and combined weights according to the WIM data. After the Woodburn WIM stations, truck volumes and weights are contingent on the classification group. However, with that in mind, it was determined that all I-5 WIM stations and WIM stations located at points of entry or exit experience high truck volumes and combined weights relative to other WIM stations (Cascade Locks, Wyeth, Olds Ferry, Farewell Bend, and Klamath Falls). As such, the following WIM stations were identified for further analysis based on the presented statistics and data availability: Ashland (NB), Ashland (SB), Woodburn (NB), Woodburn (SB), Cascade Locks (EB), Wyeth (WB), Olds Ferry (EB), Farewell Bend (WB), Klamath Falls (NB), and Klamath Falls (SB).

10.3 DESCRIPTIVE ANALYSIS OF SELECT WIM STATIONS

Utilizing only the main WIM stations, a series of descriptive analyses were conducted. The first of these analyses was based on directional and seasonal trends in terms of volume and average monthly observed combined (truck and cargo) weight. Although trends varied based on WIM station and direction, the most common trends were increasing volumes and combined weights during the summer months. This remained true for nearly all WIM stations, with the Woodburn WIM stations exhibiting a large amount of variation in trends across years and classification groups. It was also determined that higher truck volumes and combined weights were observed entering Oregon (Ashland WIM stations and Olds Ferry/Farewell Bend WIM stations). However, an opposite trend was observed at the Klamath Falls WIM stations, in which higher truck volumes and combined weights were observed leaving Oregon (southbound Klamath Falls WIM station).

Next, monthly percentages of truck volume and combined (truck and cargo) weight were presented. It was found that June accounts for at least the third highest proportion for eight of the 10 WIM stations: (1 - highest proportion) Ashland (SB), Woodburn (NB), Farewell Bend (WB), and (2 - 3rd highest proportion) Klamath Falls (NB), Ashland (NB), Woodburn (SB), Wyeth

(WB), and Klamath Falls (SB). August accounts for at least the third highest proportion for seven of the 10 WIM stations and July for six of the 10 WIM stations. When considering combined weight, similar trends are observed. When considering the average of all WIM stations by month, June accounts for the highest proportion, May the second highest proportion, and August the third highest proportion. Also of note, the proportion of trucks and combined weight from May to August were highest at the Klamath Falls WIM stations.

For day-of-week trends, it was determined that the highest volumes across all WIM stations are consistently observed on Wednesdays, Thursdays, and Tuesdays. Other days of the week experienced high volumes contingent on the classification group. For example, considering all trucks, Friday accounted for the highest, second highest, and third highest volume at Cascade Locks (EB) and Olds Ferry (EB), Klamath Falls (SB), and Wyeth (WB), respectively. When considering ODOT Class 11 trucks, Sundays accounted for the second highest volume at Farewell Bend (WB). Mondays also account for high volumes, where the highest volume at Farewell Bend (WB), second highest volume at Wyeth (WB), and third highest volume at Woodburn (SB) were observed on Mondays. When considering ODOT Class 12 to ODOT Class 19 trucks, Wednesdays, Thursdays, and Tuesdays were the top three days.

As for annual growth rates, six of the WIM stations experienced an increasing annual rate based on the recorded WIM data. Of these, Olds Ferry (EB) has the highest annual growth rate in terms of volume and combined (truck and cargo) weight (7.58% for volume and 7.74% for combined weight). Also, of note, the Klamath Falls WIM stations experienced more annual growth when compared to the Ashland WIM stations. In comparing annual growth rates for volume and combined weight, three WIM stations have opposite growth rates. At Woodburn (SB) there is an annual growth rate for volume of -2.11%, and a +5.36% annual growth rate for combined weight, at Wyeth (WB) there is a -0.09% annual growth rate for volume and a +1.07% annual growth rate for combined weight, and at Klamath Falls (SB) there is a +3.11% annual growth rate for volume and a -0.07% annual growth rate for combined weight. Lastly, an overall annual growth rate for volume and combined weight was calculated considering the total number of trucks and observed combined weight for all 10 WIM stations. When considering all WIM stations, there is an overall annual growth rate of 0.18% for volume and a 1.19% annual growth rate for combined weight.

The final part of the select descriptive analysis consisted of a summary table that presents the number of trucks by classification, their proportion of the total, average truck weight, average cargo weight, and proportion of empty trucks. In general, the larger proportion of empty trucks are observed at WIM stations exiting Oregon (westbound and southbound directions) and consist of ODOT Class 13, ODOT Class 15, ODOT Class 17 trucks. The exception is Woodburn (NB), where the proportion of empties is greater than its southbound counterpart. Additionally, three different thresholds considering only ODOT Class 11 trucks were assessed. The first threshold was the proportion of ODOT Class 11 trucks below 36,000 pounds, the second was the proportion above 76,000 pounds, and the third was the proportion above 80,000 pounds. Using these thresholds, moderately higher proportions of ODOT Class 11 trucks under 36,000 pounds (compared to under 32,000 pounds) are observed for most WIM stations (Ashland (NB), Cascade Locks (EB), and the Klamath Falls WIM stations did not increase much). The proportion at the Woodburn WIM stations have the highest increase; specifically, 3.34% to 12.36% (northbound) and 2.22% to 12.73% (southbound).

For the second threshold, greater than or equal to 76,000 pounds, the highest proportion is observed at Klamath Falls (SB) with 12.98%. Also with moderate proportions are Klamath Falls (SB) at 8.00%, Wyeth (WB) at 7.35%, and Farewell Bend (WB) at 5.28%. For the final threshold, greater than or equal to 80,000 pounds, Klamath Falls (SB) has the highest proportion at 3.79%. The only other WIM station with a proportion of greater than 2.00% is Wyeth (WB) at 2.30%.

10.4 DATA COMPARISONS

The first data comparison was to FAF data. To compare, only Ashland and Klamath Falls WIM stations were used based on limiting assumptions of freight origins and destinations. In response to this, three specific assumptions were compared, where results improved with each assumption. In each case, the northbound comparisons had better results compared to the southbound direction. In 2012, this was illustrated in the comparisons under Assumption 3, where the difference in the northbound direction was approximately 2%, and the difference in the southbound direction was approximately 21%. In addition, the most consistent year in terms of minimal differences was 2015. For example, under Assumption 3, the difference in the northbound and southbound directions were 1.27% and 1.46%, respectively. This indicates that based on assumptions being made, WIM data can be a viable resource for approximating cargo weight traveling through or to Oregon, as well as commodity weight leaving Oregon in the north- and southbound directions.

The second data comparison consisted of WIM and ODOT's traffic count data at ATR locations near Cascade Locks/Wyeth and Olds Ferry/Farwell Bend. Results from these comparisons showed that WIM data records have higher truck counts at each location, with the closest comparison at Wyeth (EB) at a difference of -1.43% (relative to WIM data). It was anticipated that comparisons would be closer; therefore, further investigation into truck counts by individual classes is recommended.

10.5 EROAD DATA

A total of 107,980 observations were included in the EROAD data, resulting in 525,503 total trips through the select WIM stations (observations refer to the number of data points, and trips is a variable associated with each observation indicating the total number of trips). In assessing truck counts, the Woodburn WIM stations, Cascade Locks (EB) and Wyeth (WB) WIM stations, and Ashland WIM stations had the highest number of trips in the EROAD data. This differed slightly from the WIM data, where the Ashland WIM stations had the second highest truck volume, and the Cascade Locks (EB) and Wyeth (WB) WIM stations had the third highest truck volume. These slight differences may simply be a result of EROAD coverage. Coverage in neighboring states to the east, such as Idaho, has shown to be high, which may be contributing to the higher number of trips at the Cascade Locks (EB) and Wyeth (WB). At this time, coverage in California is unknown. However, in general, WIM stations with the highest number of trips observed in the EROAD data appear to follow WIM stations with the highest number of truck counts in the WIM data.

The following analysis assessed weight distributions in both the EROAD and WIM datasets. In the EROAD data, the weight metric is declared weight. Due to this, there was little variation in weight, as reported in the EROAD data. When computing summary statistics, metrics were identical across all WIM stations. This stemmed from the majority of observations being reported as 80,000 pounds. Additionally, approximately 40% of the observations did have a declared weight, or the declared weight was unknown. Therefore, after visually assessing the weight distributions and summary statistics, no further analysis was conducted in terms of weight.

The next analysis focused on industry type and WIM station. The number of industry types observed at the WIM stations ranged from 27 to 31, with both Woodburn WIM stations having the highest number of observed industry types. Regardless of WIM station, two industry types consistently accounted for a high number of trips: (1) General Freight and (2) Transport Equipment, Machinery, and Equipment Manufacturing. These two industry types, along with Other Agriculture, were the top three industry types based on the number of trips on the I-84 and US-97 WIM stations. At the I-5 WIM stations, these industry types, along with Wood and Paper Products Manufacturing, were the top three industry types based on the number of trips. Of interest, Woodburn observed an industry type that was not observed at any other WIM station in Oregon: Electricity, Gas, Water, and Waste Services. Also noteworthy is the industry type Arts and Recreation Services. Although this industry type did not account for a high number of trips, it was primarily observed at the WIM stations located nearest to the Portland Metropolitan area. This is likely associated with the various art centers (e.g., the Portland Art Museum, Oregon Symphony) located in the Portland Metropolitan area.

Next, using the county origins and destinations, driving distances and their corresponding descriptive statistics were computed. It was determined that Cascade Locks (EB) had the highest mean, median, and 95th percentile driving distances, while Wyeth (WB) had the highest maximum driving distance. On the other end, the lowest mean, median, and 95th percentile driving distances were observed at Woodburn (SB), while Klamath Falls (SB) had the lowest maximum driving distance. In addition to assessing driving distance, a brief comparison and correlation between driving distance and geodesic distance (shortest distance) were presented. It was determined through a series of correlation tests that the two distances are highly positively correlated with a high level of confidence, and the average ratio between distance is approximately 1.24.

The final analysis focused on origins and destinations, both holistically and by WIM station. In addition, summary tables were provided to illustrate the top origins and destinations based on the top five industry types observed at each WIM station. Most often, the majority of origins and destinations were located in neighboring counties relative to the WIM station. There were approximately 620 observations that were easily identified as having origins and destinations that do not consist of a trip through Oregon (it is plausible that upon further investigation, this value may be much higher). Although there were observations that did not consist of a trip through Oregon, the overall picture in terms of origin and destination looks realistic. Each dataset has its own advantages and limitations, where the EROAD data can be advantageous in its ability to complement other data sources, such as WIM.

10.6 RECOMMENDATIONS AND FUTURE WORK

Based on the analysis, the following recommendations are made.

10.6.1 Quality Control

With the inclusion of all truck classifications, it is possible that erroneous observations are present that cannot be detected without a rigorous quality control analysis. At WIM stations the threshold for incorrect measurements can vary from 15% to 30%, therefore it is recommended that each truck classification is analyzed independently. There are logical checks that can be implemented, but specific truck characteristics must be investigated further. ODOT Class 11 has a more established quality control procedure but it may be necessary to adjust some parameters to accommodate local truck type characteristics and commodities. Overall Oregon WIM data quality is very good, but data quality checks are always necessary to detect faulty sensors or missing data.

Being that the quality control analysis showed that all WIM stations are well within the compliance threshold for 95% tolerance, ODOT WIM data can be used as-is. Quality control analyses ensure that 95% tolerance is being met, allowing ODOT WIM to be continued to use as-is.

10.6.2 Weight Distributions

Although a comprehensive quality control check was conducted for ODOT Class 11 trucks, weight distribution plots showed that lower (unloaded) and upper (loaded) peaks often did not fall within the thresholds found in other studies. Oregon truck weight distribution peaks may differ as weight distributions can be a function of the type of products/commerce specific to trucks passing through a WIM station. In other words, commodities passing through, or within, Oregon may result in different weight distributions than have been observed in other research studies. It is recommended that researchers and ODOT staff can readily access information related to the periodic calibration of WIM stations (to ensure that dynamic forces are properly estimating the static weight) and their accuracy. Ensuring each WIM sensor is accurately estimating static weight impacts the number of trucks identified as unloaded or loaded. It also recommended to compare Oregon weight distributions with that of other neighboring states to assess similarities or differences, particularly near the state border. To assess this, additional research on this topic is recommended.

10.6.3 Cargo Weight and Percentage of Empty Trucks

The percentage of empty trucks varies by WIM location and direction of travel. The threshold utilized to determine percentage of empty trucks can be a function of WIM station and truck class. It is recommended to continue monitoring and studying ODOT Class 11 weight distributions to detect changes in freight patterns. The distribution of weight for the other truck classes is less understood and it is recommended that weight distributions of each truck classification be analyzed individually by year and WIM station and direction of travel. Additionally, it is recommended that several years of WIM data and WIM stations be included with the intention of identifying truck empty and loaded thresholds by truck class. Another option can include surveying trucking firms in regards to empty weights of various truck configurations. With these recommendations in mind, weight distributions may simply be different for Oregon based on commodity types. The percentage of empty trucks and fully loaded trucks vary widely across locations and direction of travel. It is likely that commodity/product type and origin-destination are responsible for the variations. To assess this, additional research on this topic is recommended.

10.6.4 Data Comparisons

Through the comparison with FAF data, it was determined that WIM data could match FAF data contingent on assumptions being made in the north- and southbound directions. However, it is recommended that further investigation into the east- and westbound direction be done to understand the cause of the differences between WIM and FAF estimates. Combining cargo weight values obtained for each truck classification individually (i.e., Chapter 10.6.3) and FAF-identified networks may result in more realistic freight flows than the values estimated by FAF alone. For example, FAF estimates are projected for future years while WIM data can provide actual measurements for the year of interest and at a specific location and direction of travel.

10.6.5 EROAD Data

The primary recommendation as it pertains to EROAD data is to utilize this data source to better understand origins and destinations of freight movement to and from Oregon. As stated previously, industry information in EROAD data is unique, making it a more attractive data source compared to other avenues. It is also recommended that the viability of a long-term public-private partnership be assessed, where a focus can be on expanding coverage and obtaining information on commodities. EROAD data currently does not include truck-specific cargo information but surveys can be carried to complete some data gaps. An additional comparison is recommended; specifically, to motor carrier citation records that include origin-destination information. Further, it is recommended, if considering private data sources, to explore additional datasets. One such option could be Transearch (HIS). Transearch data includes information on commodity, volume, and units of shipments by economic area, counties, state-level for Mexico, and province/municipal area for Canada. With the current study showing the workability of using WIM data for freight analyses, integration with Transearch data may serve useful for the commodity portion. Albeit, Transearch has its own limitations, including price and transparency of data processing. Oregon WIM datasets can be utilized to assess the value and accuracy of Transearch or any other truck freight data source.

10.7 NEXT STEPS

Based on recommendations for OMSC freight priorities, current freight priorities include the need for accurate and detailed freight data related, but not limited, to commodity, weight, value, distance, origins and destinations, and seasonal patterns (Oregon Modeling Steering Committee, 2019). The current study has detailed many of these priorities through the use of readily available ODOT WIM data and EROAD data (a possible data opportunity for OMSC). Moving forward, to address the OMSC Action Plan, these data sources can be further evaluated to inventory light commercial and heavy commercial truck patterns (D.1 and D.2). The methodology implemented also provides a framework to assess the quality of new data sources, which can be applied to other data sources of interest (R.1). Findings from the current work also indicate that WIM data can be used to address, through additional research, OMSC Action Plan R.6: “How trucks adjust movements in response to highway travel impediments.” WIM data can be used to identify freight patterns and movement concerning locations of impediments.

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APPENDIX A

This appendix provides a full summary of reviewed literature by study objective.

Table A.1: Summary of WIM-Related Research by Purpose/Objective

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Authors	**Location**	**Objective**	**Data**	**Results**
Selezneva & Wolf (2017)	Arizona	• Survey other state DOTs and develop a WIM Guidebook.	NA	• Identified most important site selection criteria according to surveyed DOTs. • Although similar, each agency performs its own state-specific quality checks. • Developed guidebook for site location and assessment, installation, calibration, maintenance, and quality assurance.
Oskarbski & Kaszubowski (2016)	Gdynia	• Use WIM locations to control truck access. • Analyze access through a simulation-based approach.	• Truck traffic data (2012).	• Based on three scenarios, WIM systems can be used to control truck access.
New York City Department of Transportation (2016)	New York	• Disseminate information on strategic freight plans in New York.	NA	• New York plans to expand the number of WIM systems across the city to address the high percentage of overweight trucks.
New York City Department of Transportation (2015)	New York	• Serve as a newsletter for future freight initiatives, including WIM.	NA	• Recommends use of WIM to inform future policies and regulations regarding truck route management.
Martin et al. (2014)	Kentucky	• Survey other state DOTs to identify WIM sensor types and usage.	NA	• Several suggestions and recommendations based on survey responses from other state DOTs.
AMEC Earth and Environmental (2012)	United States	• Develop guidelines for traffic data collection at WIM sites.	NA	• Specific guidelines regarding site assessment, site validation for weight, site validation for classification, pavement smoothness, installation, and calibration auditing.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Clough Harbour and Associates (2012)	New York	• Research and design a prototype roadside commercial vehicle electronic screening system. • Develop design guidelines, standards, and specifications to be used for data collection and roadside enforcement.	NA	• Several recommendations based on the results from the prototype implemented.
Miller & Sharafsaleh (2010)	California	• Identify issues related to planning and development of virtual weigh stations in California.	NA	• Issues associated with design and architecture, operations, site selection, data collection, functional requirements, and technology requirements were identified and discussed.
Cambridge Systematics, Inc. (2009)	United States	• Detail concept of operations for virtual WIM stations. • Provide benefits and costs.	NA	• • Virtual WIM stations can improve safety and reduce congestion. • Reduction in overweight trucks can save states tens of millions of dollars.
Hahn & Pansare (2009)	Maryland	• Implement and evaluate quartz WIM sensor for Virtual WIM station. • Done as pilot study.	NA	• Practical test. • Calibration and maintenance method for Virtual WIM system. • Flexible, cost-effective, and rapid deployment model for future Virtual WIM systems.
Ramseyer, Nghiem, & Swyden (2008)	Oklahoma	• Determine best combination of weight enforcement systems and procedures.	NA	• Recommendations to build new WIM facilities at specific locations.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Hunsucker & Graves (2004)	Kentucky	• Evaluate data collection equipment, calibration, and sampling techniques. • Standardize procedures to collect weight data.	• WIM data collected at a single site on US-27 • 1998 to 2001	• A calibration worksheet to inform WIM technicians of optimum settings. • Systems can be calibrated for a target vehicle type. • Maintenance is key to keeping a system that can perform well over a long period of time. • A refined data collection process should be implemented to ensure sufficient traffic data is being collected for each class of highway.
Data Quality Control and Accuracy				
Authors	**Location**	**Objective**	**Data**	**Results**
Stephens et al. (2017)	Montana	• Develop strategy for collecting reliable traffic data.	NA	• Identified key quality control checks for ATR and WIM data collection.
Southgate (2015)	United States	• Develop methodology to determine quality of WIM data. • Identify guidelines for making judgement calls on whether to keep or exclude WIM data observations.	• Not Disclosed	• Step-by-step procedure to replicate the quality control checks. • Recommends a program be written to conduct the quality control analyses with more efficiency.
Mai et al. (2013)	Alabama	• Investigate quality control of WIM data by incorporating threshold values and rational procedures.	• WIM data collected from 12 bending plate WIM sensor locations (2006 to 2008).	• Proposed rational checks should be implemented in future WIM data quality checks. • Rational check is recommended to be integrated with the data collection process.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Fei (2014)	Oklahoma	• Conduct rigorous data quality checks. • Determine variability of traffic characteristics. • Determine required number of WIM sites based on variability in traffic characteristics. • Evaluate WIM data in Oklahoma using the proposed framework.	• WIM data from 23 WIM locations in Oklahoma. • 2008 to 2012	• Proposed data quality check can assess data by direction and lane for any WIM site following a specified criteria. • Variation level between roadway classification is high. • Need to develop more rigorous grouping method to characterize traffic patterns.
Bell & Figliozzi (2013)	Oregon	• Evaluate accuracy of Oregon's TRUE data. • Show ability of TRUE data for addressing freight modeling, performance measures, and planning needs.	• TRUE data obtained from 17 pilot vehicles (2011). • WIM data for the 17 pilot vehicles.	• TRUE axle count was higher than the WIM axle count. • Smaller different in terms of GVW, but there could be an accuracy issue. • TRUE data, integrated with WIM data, can greatly improve freight emission estimates.
Brogan, Tarefder, Ruiz, & Ababio (2011)	New Mexico	• Identify measures to ensure high-quality traffic data is collected, processed and analyzed.	NA	• WIM network should be expanded by 21 new sites. • Hire new WIM techs. • Replace existing WIM sensor technologies. • WIM data must be retrieved daily and stored as specific file types.
Quinley (2010)	United States	• Develop a WIM data analyst's manual. • Recommend procedures to perform validation and quality control checks of WIM data.	NA	• Some agencies use their own systems to perform validation checks, while the remaining agencies use third-party software. • Developed steps to validate WIM data, assess individual vehicle records, and recommendations for automated validation programs.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Ramachandran (2009)	North Carolina	• Identify manual quality control checks.	• WIM data. • 12 consecutive months, between 1997 and 2007, collected from 45 WIM sites.	• Can use graphical displays, distributions, summary statistics, etc., to perform manual quality control checks.
Estimate Truck Traffic Flow Characteristics				
Authors	**Location**	**Objective**	**Data**	**Results**
Eluru et al. (2018)	Florida	• Develop fused database using various freight data sources. • Use econometric and optimization methods to estimate county-level commodity flows. • Develop algorithm to disaggregate FAF data.	• FAF[4] data. • TRANSEARCH data (2011). • ATRI data (March, April, May, and June of 2010) • WIM data (2010 to 2015). • Land use data.	• A fused database to help planning agencies. • Algorithm to disaggregate FAF data. • Framework to use WIM data to generate origin-destination flows by weight category.
Faruk et al. (2016)	Texas	• Deploy a portable WIM system to collect data and identify traffic flow trends, GVW trends, and overweight trends. • Week-by-week comparison of traffic characteristics.	• WIM data from the deployed portable WIM system on Highway FM 1016. • Data collected over 21 days.	• Loss of sensitivity to detect light-weight vehicles over time. • Truck volumes remained consistent from week-to-week. • Trends for traffic flow and vehicle classification followed historical trends.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Hyun et al. (2015)	California	• Develop modified decision tree model to estimate truck volumes. • Use Gaussian mixture model to fit GVW distributions. • Determine spatial and temporal transferability of proposed models.	• WIM data collected at four locations in California. • 10,904 records were collected over "multiple days."	• Model estimates differed from actual volumes by just 8% when averaged over all configurations. • Gaussian mixture model capture the actual GVW of each configuration. • Proposed models are spatially and temporally transferrable.
Pigman et al. (2015)	Kentucky	• Update processing of traffic characteristics through various quality control and analytical programs. • Estimate truck traffic parameters. • Regression analysis to smooth and predict truck flow growth rate.	• WIM data from 41 WIM sites in Kentucky. • 2007, 2011, 2012, and 2013. •	• The proposed methodology adequately estimated the truck traffic characteristics. • Step-by-step procedure and computer code to replicate the analysis.
Abdullah (2011)	Malaysia	• Use WIM data to investigate traffic flow characteristics.	• WIM data from single site on Federal Road 54. • Four Months of data (October, 2009 to January, 2010).	• Vehicle classification and GVW have significant effects on speed. • Majority of trucks were traveling below the posted speed limit.
Mitchell (2010)	Australia	• Estimate models to identify freight traffic trends. • Use estimates to derive corridor-specific freight traffic trends.	• WIM data collected from sites on the National Land Transportation Network (1997 to 2009).	• Mixed effects models predict actual values at an adequate rate. • Freight trends for corridors of interest were identified using model estimates.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Figliozzi et al. (2001)	Texas	• Derive truck flows from two methods of estimation.	• Truck numbers from border bridge systems and U.S. Customs (1997). • U.S. international trade data. • Transborder Surface Freight Database. • Commodity densities. • Trailer data. • Standard International Trade Code data.	• Identified cities with largest truck volumes. • Truck weight per commodity is calculated based on commodity densities. • Truckload values vary by commodity group. • First method can better estimate truck volumes if more data on density and volumes by commodity group is available.
Figliozzi et al. (2000)	Texas	• Use WIM data to calibrate trade-derived estimates of truck volumes.	• WIM data from nine sites across Texas, which were complemented with three additional sites.	• Trends and characteristics related to overloaded trucks, empty trucks, cube out and weight out trucks, effects due to direction of travel, seasonal effects, and time-of-day effects are observed. • Axle loads measured at WIM sites and along NAFTA highway corridors have substantial differences.
Estimate Truck Loading Characteristics				
Authors	**Location**	**Objective**	**Data**	**Results**

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Florida Transportation Data and Analytics Office (2018)	Florida	• Quantify truck empty backhaul using WIM data. • Validate WIM data using range and constrain validation. • Derive variables from WIM data.	• WIM data obtained from WIM sites on interstates only (2015 to 2017). • Only Class 09 trucks.	• Freight commodity movement was determined using the derived variables. • Direction of travel with greatest flow was identified. • Pattern of imports and exports.
Hernandez (2017)	California	• Derive empty and loaded weights using a Gaussian mixture model. • Analyze truck body type distributions, loaded weights, and empty weights. • Enhance the TEF method.	• WIM data from four locations in California. • Data collected during "several 2- to 3-day periods" during fall, winter, and spring, as well as various time periods (2012 to 2013).	• VISU data may be underestimating empty weights and overestimated loaded weights.
Schmidt et al. (2016)	France	• Analyze loading and behavior patterns. • Analyze axle load distributions by axle rank and truck category. • Utilize the R package Mixtools.	• WIM data from three WIM sites on high traffic volume highways and motorways. • One year of data (September, 2013 to August, 2014).	• Just 20% of trucks were fully loaded. • Frontward center of gravity gives semi-trailers an understeering tendency. • Two modes accurately described the Gaussian PDFs for axle loading.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Ghosn et al. (2015)	New York	• Estimate effects of different categories of overweight trucks on New York infrastructure. • Use data mining algorithm to categorize trucks obtained from WIM data.	• WIM data from one site on I-90 near Albany, NY. • One year of data (2009). • WIM data from several sites along I-88 (2011).	• 11% of trucks may be carrying divisible load permits. • 1% of trucks may be carrying special hauling permits. • 6% of trucks may be illegally overweight. • The cost of trucks with divisible load permits, special hauling permits, and overweight trucks may be totaling in $95M per year in bridge infrastructure costs and $145M on pavements.
Estimate Truck Travel Time				
Authors	**Location**	**Objective**	**Data**	**Results**
Monsere et al. (2009)	Oregon	• Use truck transponder data to generate freight corridor travel times and real-time travel information.	• WIM data (2007 to 2008). • Washington State WIM data (March, 2008). • Probe data from eight specific routes/trips.	• Freight travel times at the corridor-level could be generated. • Relationship between passenger vehicle travel time and truck travel time. • Long distances between WIM stations were challenging in regards to directly adapting WIM data to real-time use.
Truck Re-Identification, Tracking, Matching, etc.				
Authors	**Location**	**Objective**	**Data**	**Results**
Hyun et al. (2017)	California	• Use WIM data and data from inductive loop sensors to develop algorithm to correctly match trucks. • Use selective weighted Bayesian model to track trucks.	• WIM data from sites spanning 26 miles on I-5 in California. • Data was collected for 5.5 hours over two days.	• Proposed methodology correctly matched 81% of trucks.

Implementation and Operations (Performance, Calibration, Installation, Maintenance, etc.)				
Cetin & Nichols (2009)	Indiana	• Use WIM data and the assignment problem to improve accuracy or re-identification algorithms.	• WIM data at a single site on I-70. • Two days of data in July, 2004.	• By decomposing process into two stages, re-identification was substantially improved.
Cetin et al. (2011)	Oregon	• Use re-identification methods to match trucks between two WIM sites in Oregon.	• WIM from two WIM sites in Oregon that are 145 miles apart (October, 2007).	• Several approaches are developed to allow for trade-off of total matched vehicles and the acceptable error. • Mismatch error can be reduced to as low as 1% with associated mismatching of 25%.

APPENDIX B

Appendix B shows cargo weight distributions for ODOT Class 11 trucks. The presented distributions are based on the assumption that an ODOT Class 11 truck weighs 32,000 pounds. Therefore, to generate the plots, 32,000 pounds was subtracted from the observed weight in the WIM data. Cargo weight distribution plots are shown for the 10 select WIM stations only: Ashland (NB), Ashland (SB), Woodburn (NB), Woodburn (SB), Cascade Locks (EB), Wyeth (WB), Olds Ferry (EB), Farewell Bend (WB), Klamath Falls (NB), and Klamath Falls (SB).

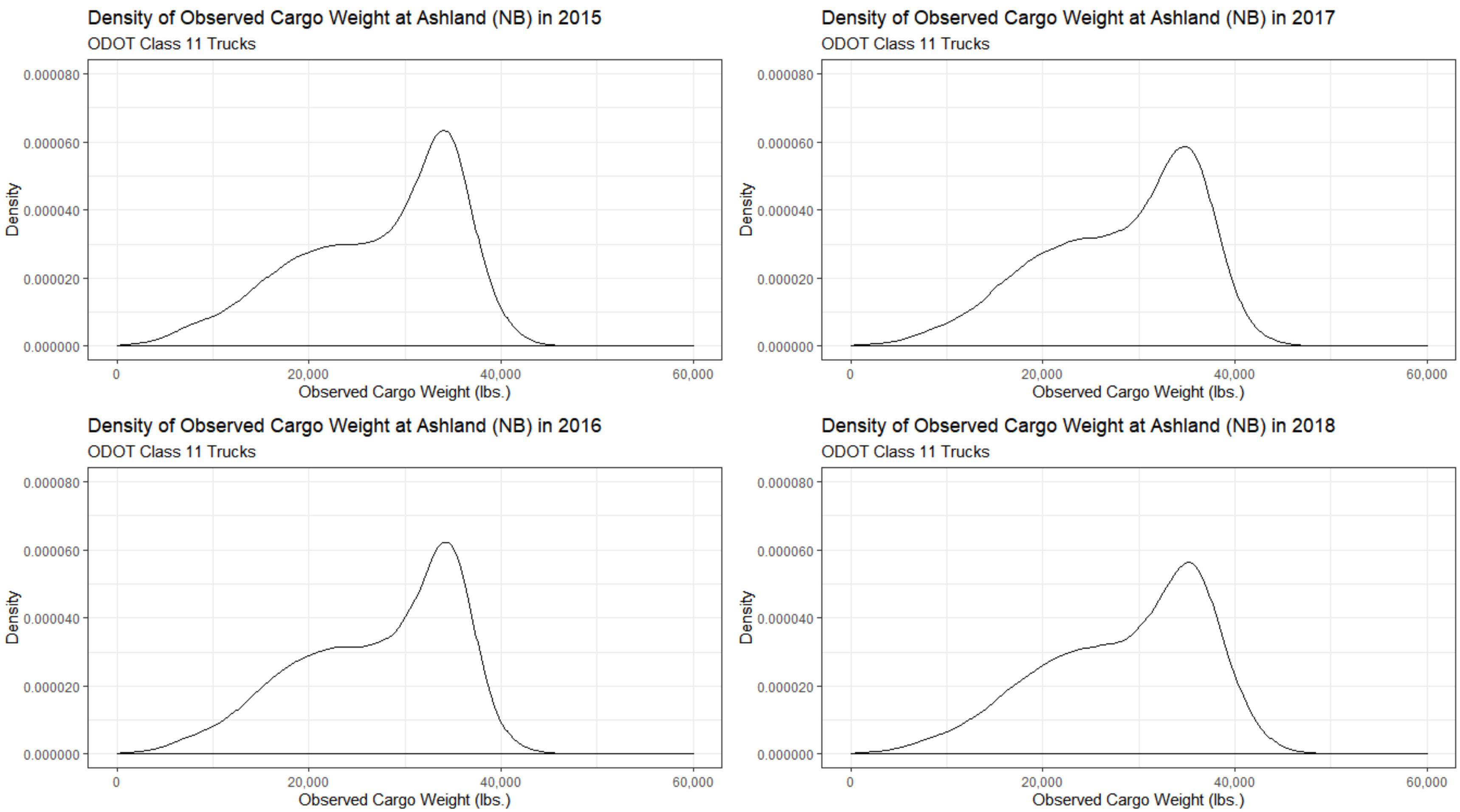

Figure B.1: Cargo weight distributions for ODOT Class 11 trucks at Ashland (NB) by year

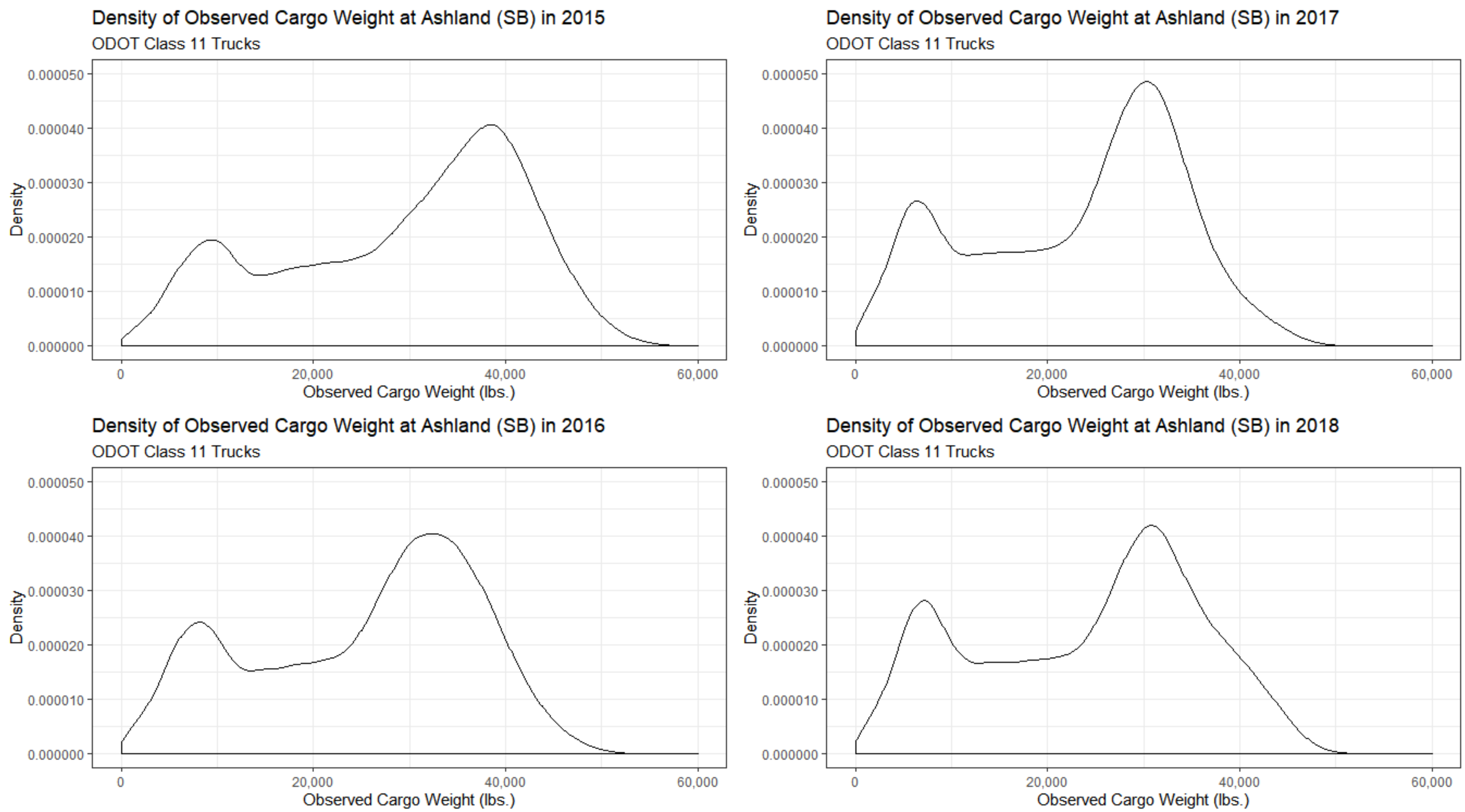

Figure B.2: Cargo weight distributions for ODOT Class 11 trucks at Ashland (SB) by year

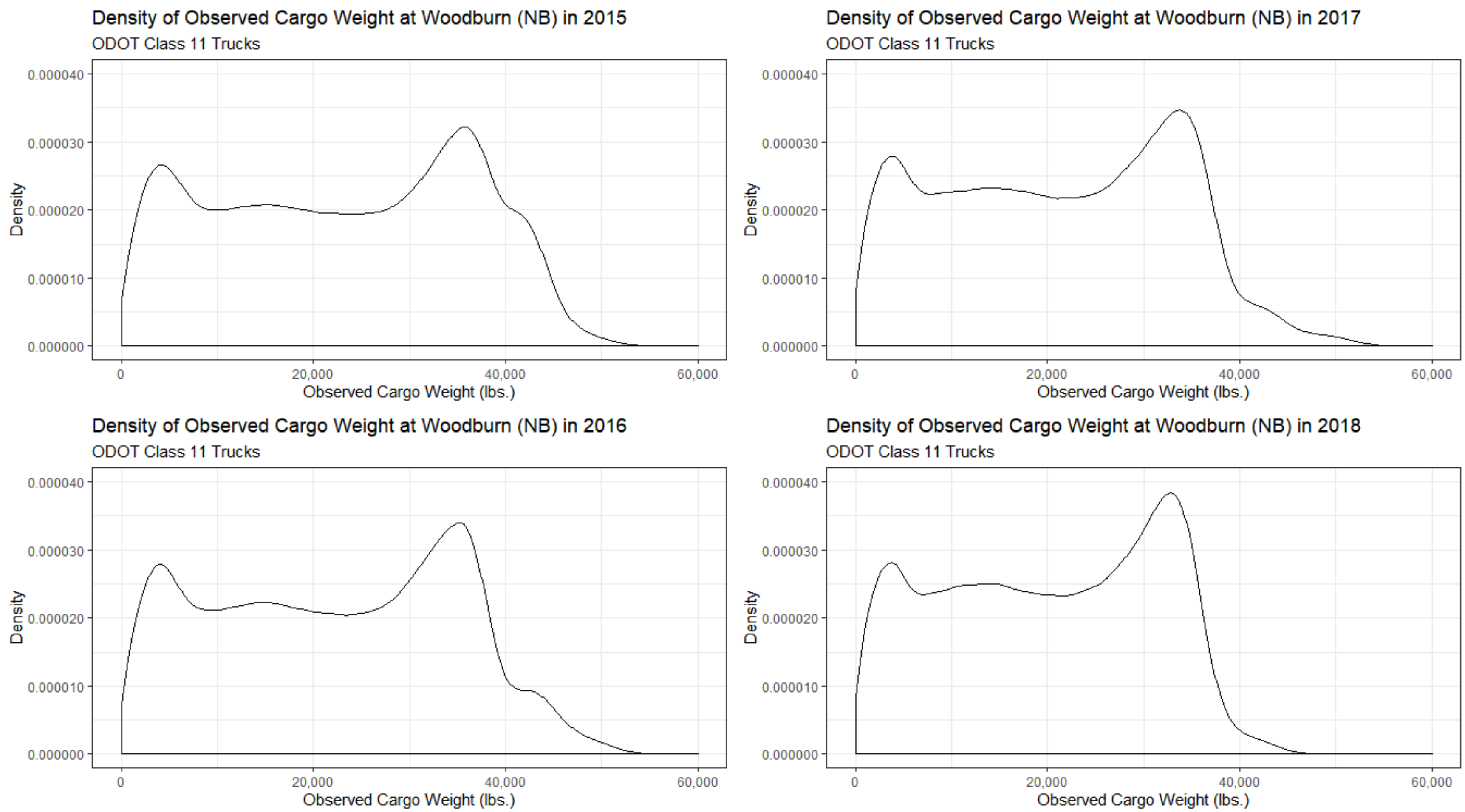

Figure B.3: Cargo weight distributions for ODOT Class 11 trucks at Woodburn (NB) by year

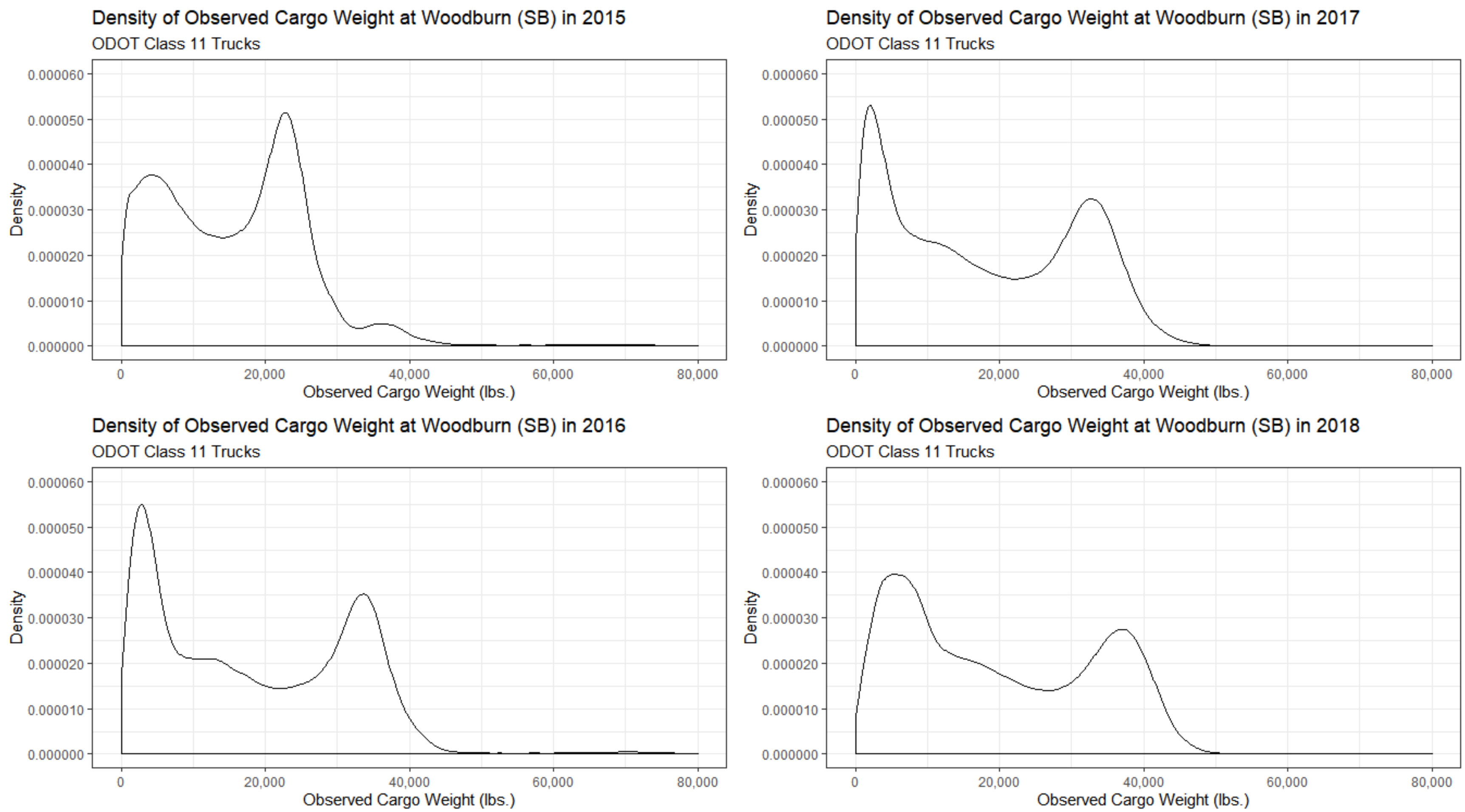

Figure B.4: Cargo weight distributions for ODOT Class 11 trucks at Woodburn (SB) by year

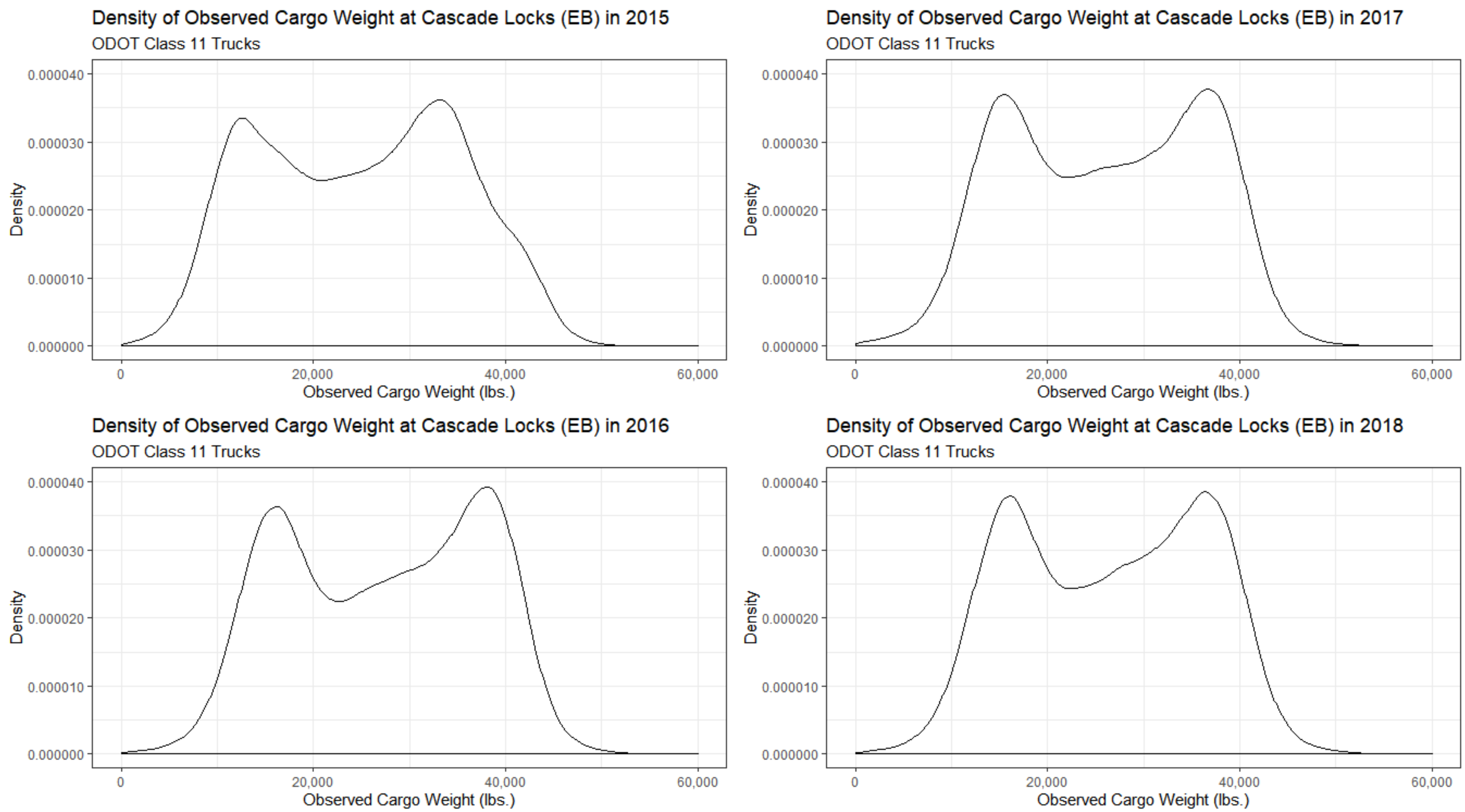

Figure B.5: Cargo weight distributions for ODOT Class 11 trucks at Cascade Locks (EB) by year

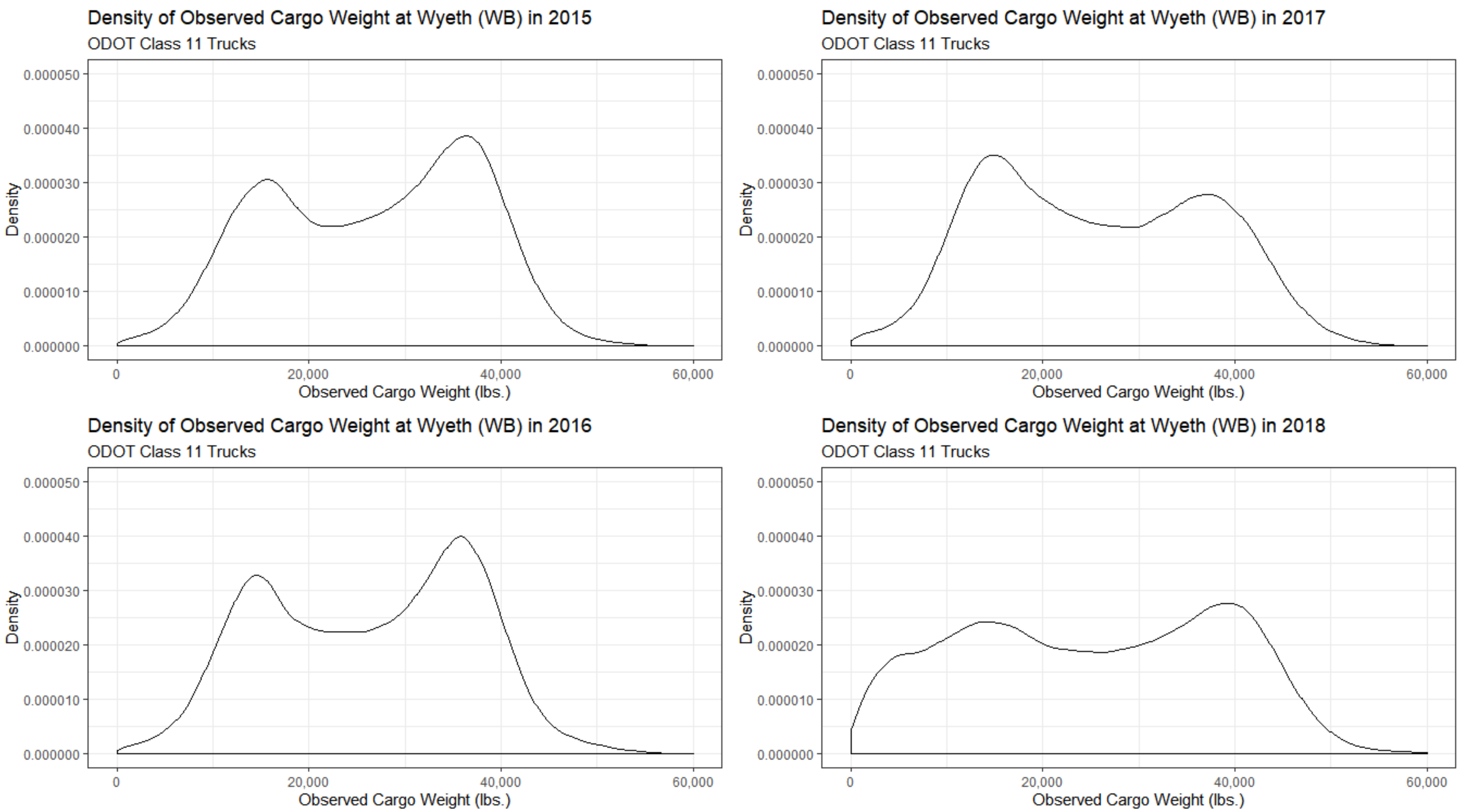

Figure B.6: Cargo weight distributions for ODOT Class 11 trucks at Wyeth (WB) by year

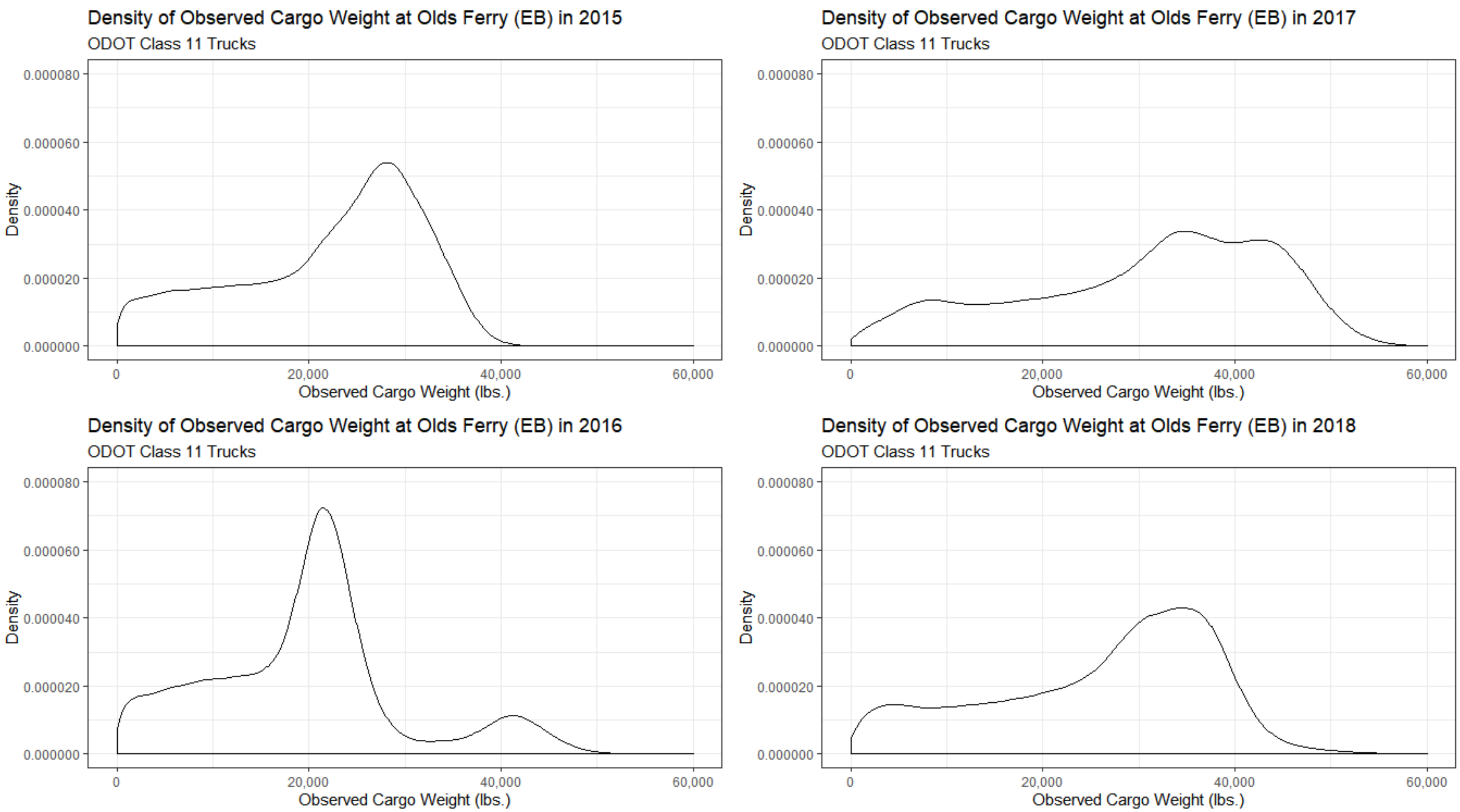

Figure B.7: Cargo weight distributions for ODOT Class 11 trucks at Olds Ferry (EB) by year

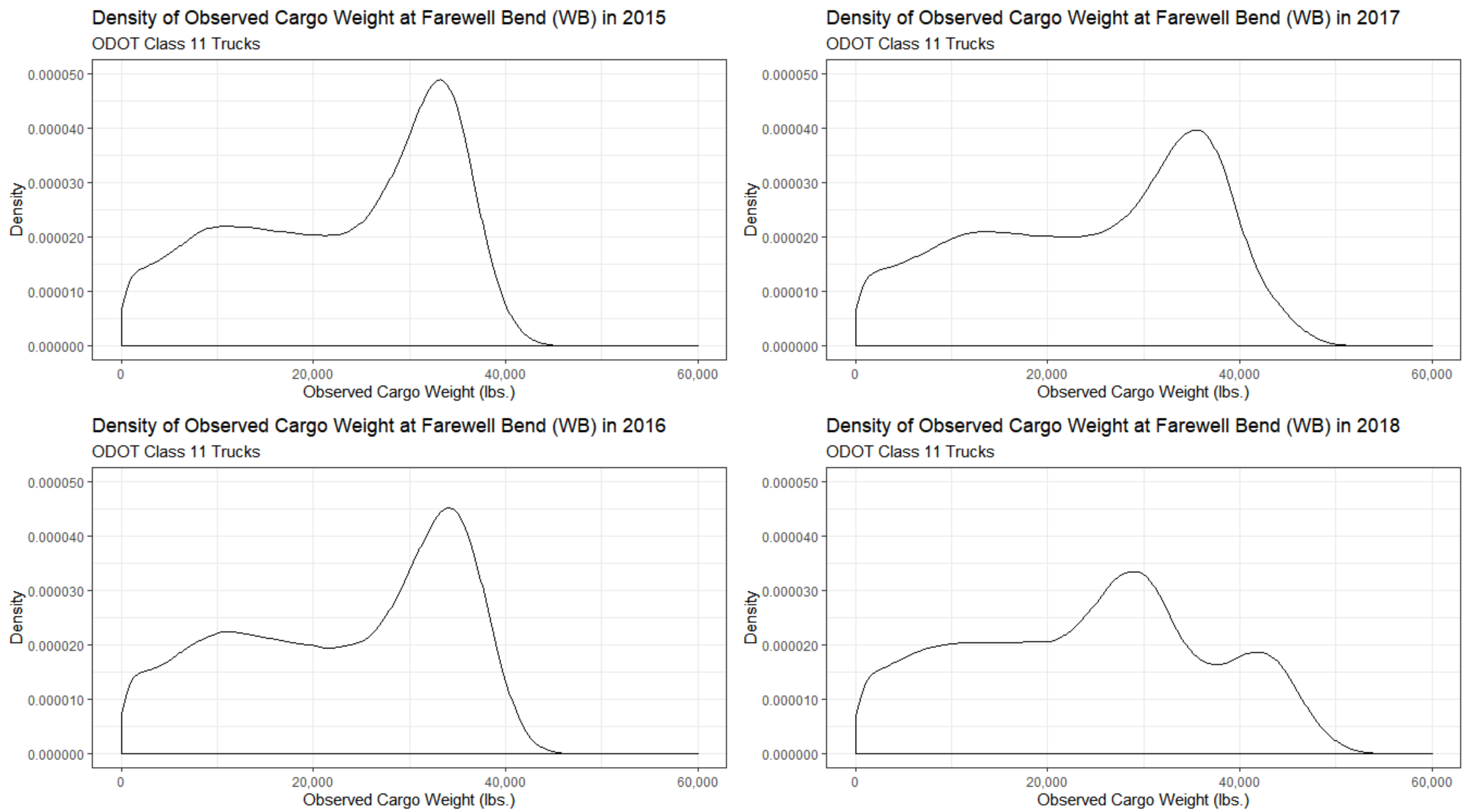

Figure B.8: Cargo weight distributions for ODOT Class 11 trucks at Farewell Bend (WB) by year

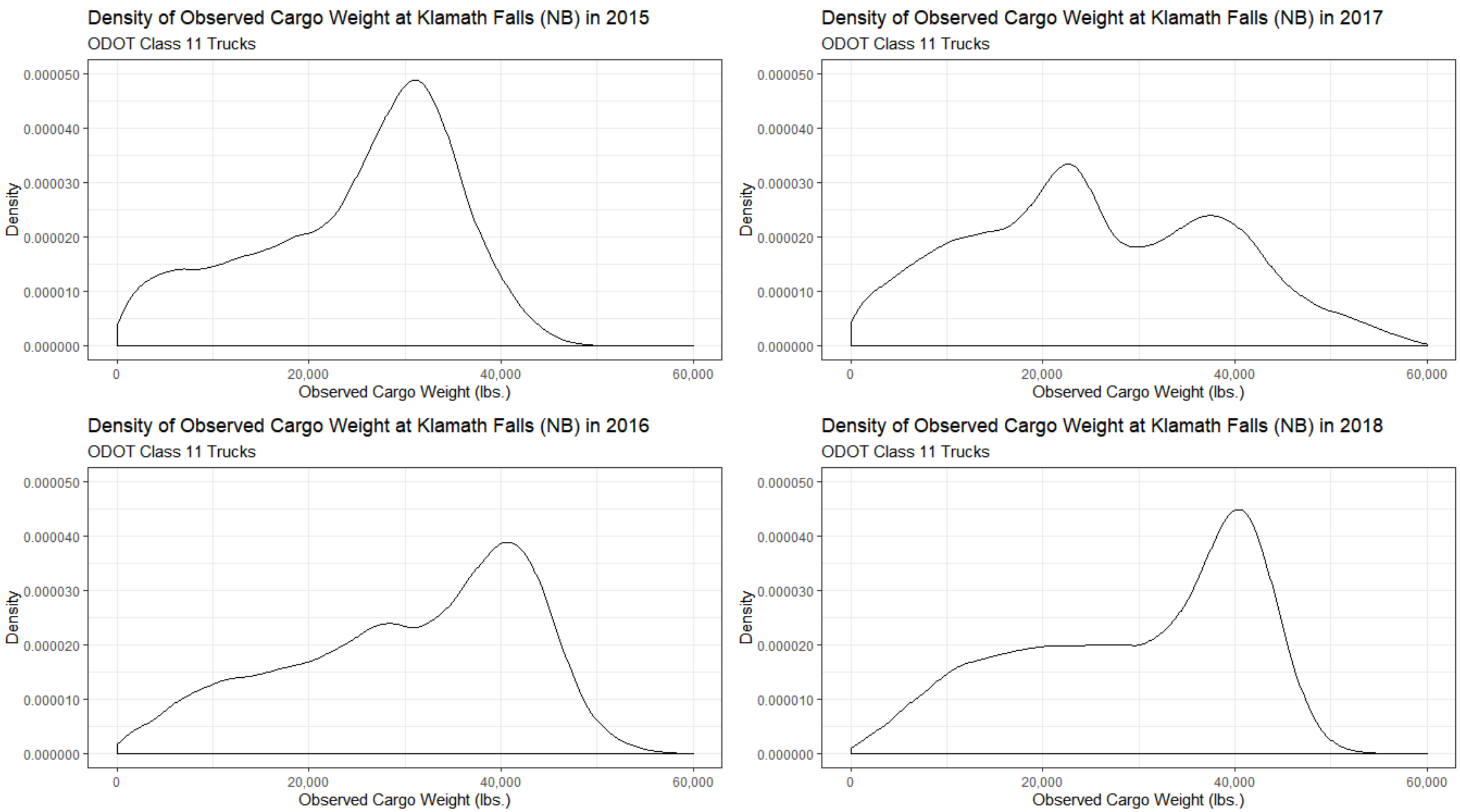

Figure B.9: Cargo weight distributions for ODOT Class 11 trucks at Klamath Falls (NB) by year

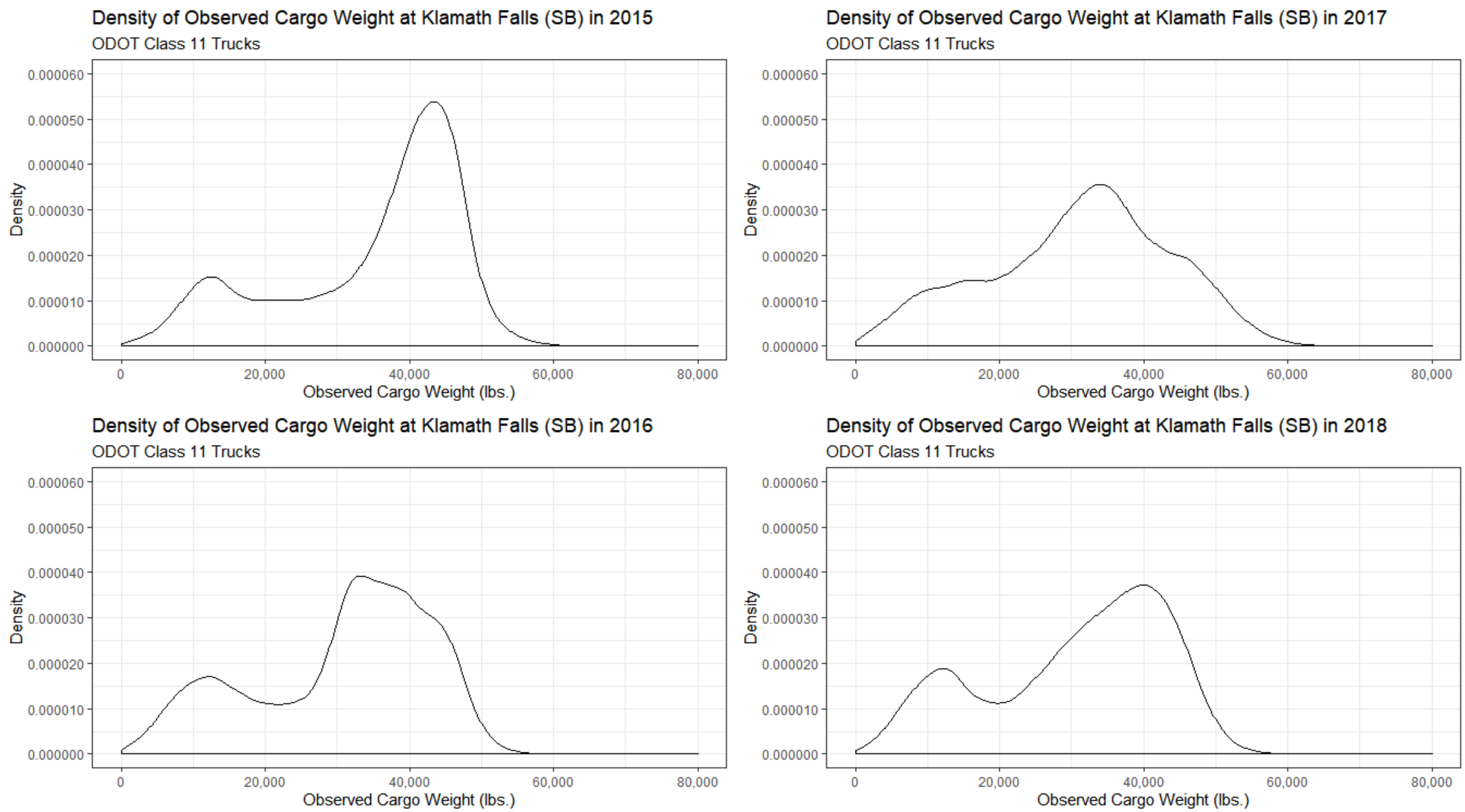

Figure B.10: Cargo weight distributions for ODOT Class 11 trucks at Klamath Falls (SB) by year