An integrated modelling approach for estimating grain truck activity in the Canadian Prairie Region

By

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ABSTRACT

Agriculture-related trucking has been a major part of rural road use in areas with intensive agricultural production since the development of the road network. Grain movement is heavily influenced by the economic activity of rural areas and by the development of transportation systems serving those areas. Because the agricultural sector relies so heavily on the rural road network, network resiliency is foundational for the economic well-being of the agricultural industry in the Canadian Prairie Region. This makes it important to understand the movement of agricultural truck traffic in the region.

Truck traffic monitoring data and methodologies offer one approach to model truck activity. While useful for most engineering applications, these data are not well-suited for planning or forecasting purposes, particularly when there is interest in specific industries, like the agricultural sector. In contrast, freight demand modelling approaches are designed to forecast future activity and are often tailored to specific industries. However, these approaches tend not to provide the level of detail required for engineering applications, such as road design, asset management, or understanding how road closures impact a sector's supply chain.

This research develops and applies an integrated modelling approach to estimate grain truck activity in the Canadian Prairie Region (CPR). The modelling approach integrates methodologies from the truck traffic monitoring and freight demand modelling fields to establish sector-specific activity patterns. The approach consists of a 3-step commodity model, the Grain Tonnage Demand (GTD) model, which is then converted to the Hopper Bottom Truck Demand (HBTD) model using truck body type data. The results of the HBTD are then compared to those obtained using the Hopper Bottom Truck Traffic (HBTT) model, which is independently developed from truck traffic monitoring data.

The comparison of the HBTD and HBTT results considers the truck kilometres travelled (TKT) by hopper bottom trucks normalized by network distance and focusing on activity in southwestern Manitoba. This research found the HBTD model to underestimate the HBTT model by 39 percent (in terms of normalized TKT). When broken down by highway type the HBTD model overestimates hopper bottom truck traffic on provincial roads and weight class 2 and 3 highways. Since neither model can be considered as ground truth, the difference should not be interpreted as an error, but rather as a way to assess the relative strengths and limitations of the different modelling approaches. For the HBTD model, these limitations relate to challenges in modelling grain activity in urban areas, the exclusion of dump trucks from the model, an inability to include all segments of the grain supply chain, trip assignment assumptions, and the limited number of commodities considered. Likewise, for the HBTT model, limitations relate to data collection approaches, sampling methods, data processing techniques, the assignment of counts to the network, and the assumption that all hopper bottom trucks carry grain. Further integration of the approaches and resolution of the limitations could yield better agreement in the future.

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CREDITS

All maps presented in this thesis are produced with ArcGIS Pro® software by Esri, using the Universal Transverse Mercator (UTM) Zone 14 projection and the North American 1983 (NAD 83) geodetic datum. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. For more information about Esri® software, please visit www.esri.com.

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LIST OF ABBREVIATIONS

AADT – Annual Average Daily Traffic

AADTT – Annual Average Daily Truck Traffic

AVC – Automatic Vehicle Classifier

BNSF – Burlington Northern Santa Fe

CGC – Canadian Grain Commission

CN – Canadian National

CP – Canadian Pacific

CPR – Canadian Prairie Region

CWB – Canadian Wheat Board

FHWA – Federal Highway Administration

GTD – Grain Tonnage Demand

GVW – Gross Vehicle Weight

HBTD – Hopper Bottom Truck Demand

HBTT – Hopper Bottom Truck Traffic

KCS – Kansas City Southern

MHTIS – Manitoba Highway Traffic Information System

MoU – Memorandum of Understanding

MTI – Manitoba Transportation and Infrastructure

NCHRP – National Cooperative Highway Research Program

NS – Norfolk Southern

O-D – Origin-Destination

PCS – Permanent Count Station

PR – Provincial Road

PTH – Provincial Truck Highway

RTAC – Roads and Transportation Association of Canada

SADR – Small Area Data Region

SHM – Structural Health Monitoring

TAC – Transportation Association of Canada

TKT – Truck Kilometers Travelled

TTCG – Truck Traffic Classification Group

TTMS – Telemetric Traffic Monitoring Sites

TTPG – Truck Traffic Pattern Group

UMTIG – Urban Mobility Transportation Informatics Group

UP – Union Pacific

WCHSP – Western Canadian Highway Strengthening Program

WIM – Weigh-in-motion

1. INTRODUCTION

1.1. PURPOSE

The purpose of this research is to develop, apply, and assess an integrated modelling approach to estimate grain truck activity in the Canadian Prairie Region (CPR). The modelling approach integrates methodologies from the truck traffic monitoring and freight demand modelling fields to establish sector-specific activity patterns. The modelling results support highway planning and engineering decisions vis-à-vis the agriculture industry, including highway infrastructure investment programming, asset maintenance and management, geometric design, and the analysis of the impacts of risks and hazards on network reliability and resiliency.

1.2. BACKGROUND AND NEED

Agriculture-related trucking has been a major part of rural road use in areas with intensive agricultural production since the development of the road network. Trucks transport grain from field to storage facility, from storage facility to elevator, and from elevator to market. How producers choose where to deliver their grains is heavily influenced by the economic activity of rural areas and has historically been affected by the development of transportation systems serving those areas. Over the past 40 years in North America, this inter-relationship has been influenced by the following (Enns et al., 2012):

- Increasing crop yields resulting in a larger volume of commodities being produced for a given area of land
- Changes in the types of crops being planted
- A transition to fewer, but higher throughput grain handling facilities, operated by a smaller number of grain handling companies
- Increases in the size of farming operations and decreases in the number of farms
- Changes in truck regulations, which have enabled the use of larger, heavier, and more productive truck configurations on denser road networks
- Mergers within the rail industry, rationalization of rail networks serving rural areas, and the introduction of shuttle train service for grain transportation.

In Canada, the abolishment of the Canadian Wheat Board (CWB), changes in cross-border agricultural transportation, and possible expansion of grain transportation with northern rail and marine networks show that agriculture-related trucking will continue to play a pivotal role in rural economies (Enns et al., 2012).

Road infrastructure and network resiliency, defined by Adams et al., (2012) as “the capacity to absorb the effects of a disruption and to quickly return to normal operating levels,” is foundational for the economic well-being of the agriculture industry in the CPR, since the industry is heavily reliant on trucks to transport agricultural commodities. The rural road network in the CPR is a vast network featuring low redundancy, high speed operations, at grade intersections, and numerous network segments that are subject to seasonal changes in regulations (Regehr & Mehran, 2020). These characteristics make it prone to extreme weather events, flooding, on road incidents, and other disruptions that lead to road closures which interrupt the flow of agriculture-related trucking and other commodities in the supply chain (Transportation Research Board, 2021).

The volume and nature of truck activity in the CPR is currently estimated by traditional traffic monitoring methods, using data obtained from permanent count stations (PCSs), axle-based and length-based automatic vehicle classifiers (AVCs), weigh-in-motion (WIM) devices, short-duration sample counts, video counts, and manual surveys. Truck traffic monitoring programs provide information that characterizes the use of roads by trucks, which is sufficient to support many engineering applications (e.g., pavement design) (Maranchuk, 2016). and to analyze temporal trends. However, this information is not well-suited for planning or scenario analysis applications, especially those that rely on an understanding of the demands of specific industry sectors.

To support planning decisions, there is a need to characterize future transportation demands and the extent to which the physical transportation system can meet those demands (Manheim, 1980). Estimates of future commodity flows or truck volumes are typically made using demand models. Specifically, most freight demand models use origin-destination (O-D) data for selected commodities to estimate commodity movement between O-D pairs (Fekpe, 2011). To convert these commodity flows from tons to truck trips, Fekpe (2011) recommends the following four steps:

1. Identify primary truck configurations and body types
2. Allocate commodities to appropriate truck body types that are used to haul those commodities

3. Estimate average payloads by vehicle class and body type
4. Calculate truck equivalency factors to convert commodity tonnages between origins and destination into truck volumes

Truck traffic monitoring and truck demand modelling are both used by transportation agencies to estimate current and future truck traffic volumes. While the two methods are inherently different, there is opportunity to combine the two methods to create an integrated modelling approach to estimate truck activity generated by specific industries or commodity flows. Hernandez et al. (2016) discuss the use of axle configuration, truck body type data, and average payload information to integrate the two methods. Axle configuration data is used to determine the truck class, truck body type data is used to determine the type of commodity the truck can carry, and average payloads indicate the average load of a commodity in a specific truck class and body type.

The primary motivation of this research is to use an integrated modelling approach to estimate the extent and nature of grain truck traffic on the rural road network. Knowing where and when grain truck traffic is moving would allow agencies to better manage road assets in agriculture-intensive areas and to understand how road closures impact the sector’s supply chain. While the integrated approach focuses on the agriculture industry in this thesis, the concepts could be expanded to other sectors and commodities.

1.3. OBJECTIVES AND SCOPE

The main purpose of the thesis is to develop, apply, and assess an integrated modelling approach to estimate grain truck activity in the Canadian Prairie Region. More specifically, the objectives for this research are as follows:

1. Determine what publicly available data sources can be used to support the development and application of an integrated modelling approach, and what key data gaps are evident.
2. Apply a demand modelling approach to understand what key network (functional class, load class), vehicle (regulations), and land use characteristics (delivery points, crop production statistics) underpin the modelling of grain truck activity.
3. Estimate the magnitude (volume) and nature (spatial, temporal, vehicle classification distributions) of grain truck activity on the highway network and contextualize those estimates with respect to existing data.

The following points constrain the scope of the research:

- The geographic scope of the research includes the provinces of Manitoba, Saskatchewan, and Alberta.
- The research defines 2019 as the analysis year. This pre-dates the effects of the COVID-19 pandemic and ensures the useability of existing data sets.
- For this research, the agricultural sector comprises crop production (subsector 111), as defined by the North American Industry Classification System (NAICS) Canada 2017 Version 2.0, which is used by Industry Canada. Animal production

and aquaculture (subsector 112), support activities for agriculture and forestry (subsector 115), and fertilizer manufacturing (subsector 325) are beyond the scope of this research.

- This research focuses on the storage to elevator segment of the supply chain. Field to storage and elevator to elevator movements are beyond the scope of this research.
- The analysis utilizes four principal data types: (1) truck volume data from vehicle classification equipment (i.e., WIM devices, AVCs) and manual classification studies, (2) agricultural commodity flow data, (3) origin-destination data, and (4) transportation network data (principally highway, but also rail as required).

1.4. APPROACH

Truck traffic monitoring and traffic demand modelling can both be used to estimate truck traffic volumes, however, they use distinctly different methodologies. Figure 1 conceptualizes the overall analytical approach applied in this research and in so doing, illustrates the differences and complementarities between these two methodologies.

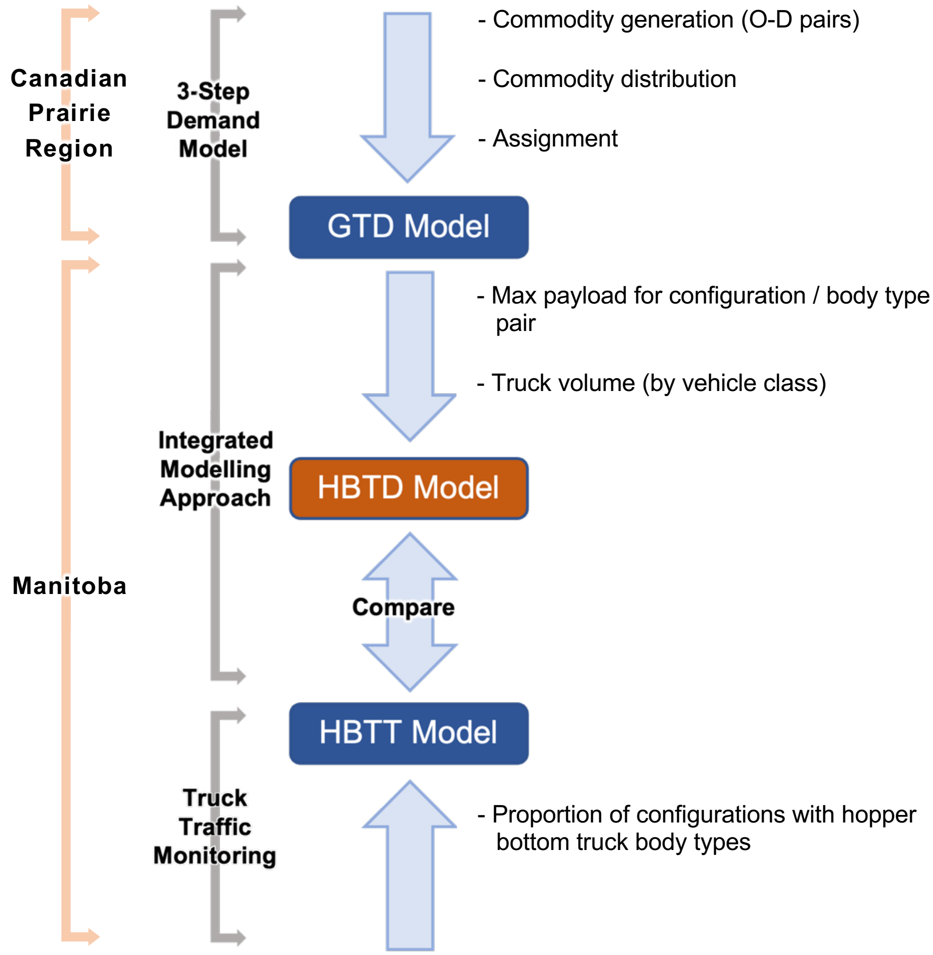


Figure 1 – Conceptualization of the analytical approach used in this research

First, this research applies develops a three-step commodity-based grain tonnage demand (GTD) model. Commodity generation uses grain production data and township centroids as origins and grain elevator locations as destinations. Commodity distribution applies the gravity model with distance as the primary decision parameter. The assignment of commodity flows to network links uses ArcGIS® routing software to find the shortest path from township origin to the assigned elevator destination. Given the focus on roads in this thesis, the mode choice step included in typical four-step demand models is excluded. The GTD model is developed and applied for the entire Canadian Prairie Region.

Second, following work by Fekpe and Hernandez et al., the integrated modelling approach of this research uses truck body type classification data to calculate the proportion of trucks that are classified as having a hopper bottom body type. The axle configurations used in this research include five-axle tractor semitrailers (3-S2s), six-axle tractor semitrailers (3-S3s), and eight-axle B-train doubles (3-S3-S2s). With the proportion of hopper bottom trucks, five grains, barley, canola, oats, soybeans, and wheat, are loaded into trucks to the truck's capacity, creating the hopper bottom truck demand (HBTD) model. Due to the limited availability of truck body type data, the geographic scope of the HBTD model is constrained to Manitoba.

Finally, this research comparatively assesses the HBTD model's truck volume estimates and the hopper bottom truck traffic (HBTT) model. The HBTT model was developed from truck traffic monitoring data through a separate research initiative, following the approach documented by Reimer and Regehr (2013). The HBTT model applied the same hopper bottom truck proportions to existing estimates of truck volume (by vehicle class). This final comparison focused on an agriculture intensive region in Manitoba.

1.5. THESIS ORGANIZATION

This thesis is organized into five chapters including this introductory chapter.

Chapter 2 – Environmental Scan: This chapter discusses ways of estimating truck traffic related to this thesis. Specifically, the environmental scan focuses on (1) agricultural transportation in the Canadian Prairie Region, (2) traffic monitoring methodologies, (3) freight demand modelling methodologies, and (4) approaches to modelling agriculture freight activity. This chapter also summarizes the findings of the environmental scan.

Chapter 3 – Research Methodology: This chapter describes the data sources used to develop the integrated modelling approach. It also describes the methodologies applied to create the GTD model, the HBTD model, and the HBTT model.

Chapter 4 – Analysis: This chapter presents and discusses the results of the three models discussed in chapter 3, namely the GTD model, the HBTD model, and the HBTT model. The chapter provides a comparison between the HBTD and HBTT models, summarizes the limitations of this work, and explores the implications for freight planning and data collection.

Chapter 5 – Conclusions and Recommendations: This chapter summarizes the key contributions and findings from this research and discusses recommendations for future work.

1.6. TERMINOLOGY

The following terms are used throughout this research:

Annual average daily traffic (AADT) – the number of vehicles passing a point on a highway in an average day of the year (TAC, 2017)

Annual average daily truck traffic (AADTT) – the number of trucks passing a point on a highway in an average day of the year (TAC, 2017)

Automatic vehicle classifier (AVC) – a permanently installed device designed to continuously count and classify vehicles passing a point on a highway

Canadian Wheat Board (CWB) – a Canadian agricultural marketing board established in 1935 and abolished in 2012 which oversaw grain sales, purchases, and exports

Cube out – the condition in which a truck reaches its maximum volumetric capacity before reaching its gross vehicle weight (GVW) limit

Demand modelling – a method used to estimate traffic volumes based on origins and destinations consisting of four steps: (1) generation, (2) distribution, (3) mode choice, and (4) assignment

Gross vehicle weight (GVW) – the total vehicle load

Hopper bottom – a truck body type designed to enable unloading of granular commodities (e.g., grains) from the bottom of a trailer or semitrailer

Mode choice – a step in the demand modelling approach which specifies the mode (road, rail, etc.) utilized to move a commodity

Permanent count station (PCS) – a type of permanently-installed equipment designed to continuously monitor vehicles passing a point on a highway

Commodity/trip assignment – a step in the demand modelling approach in which commodities or trips are attributed to the road network (Ortúzar & Willumsen, 2011)

Commodity/trip distribution – a step in the demand modelling approach in which commodities or trips are distributed between origins and destinations, normally by applying a gravity model (Ortúzar & Willumsen, 2011)

Commodity/trip generation – a step in the demand modelling approach in which the quantity of commodities or trips generated by origins and destinations are estimated (Ortúzar & Willumsen, 2011)

Truck traffic monitoring – the practice of observing on-road truck traffic activity to estimate volume, vehicle classification, and vehicle weight

Weigh-in-motion (WIM) – the process of measuring vehicle axle loads, axle group loads, and gross vehicle weight by measuring the dynamic tire forces

Weigh out – the condition in which a truck reaches its gross vehicle weight (GVW) limit before reaching its volumetric capacity

3-S2 – a five-axle tractor semitrailer combination consisting of a three-axle power unit and a semitrailer with a tandem axle group

3-S3 – a six-axle tractor semitrailer combination consisting of a three-axle power unit and a semitrailer with a tridem axle group

3-S3-S2 – an eight-axle truck configuration consisting of a three-axle power unit, a semitrailer with a rigidly connected tridem axle group, and a second semi-trailer with a tandem axle group connected to the lead trailer using a B-dolly

2. ENVIRONMENTAL SCAN

This chapter discusses ways of estimating truck traffic related to this thesis. Specifically, the environmental scan focuses on (1) agricultural transportation in the Canadian Prairie Region, (2) traffic monitoring methodologies, (3) freight demand modelling methodologies, and (4) approaches to modelling agriculture freight activity. This chapter also summarizes the findings of the environmental scan.

2.1. AGRICULTURAL TRANSPORTATION IN THE CANADIAN PRAIRIE REGION

As discussed in section 1.2, agricultural transportation has been influenced by six main factors over the last 40 years. An understanding of the ongoing evolution of these influences underpins the development of the integrated modelling approach described in this thesis. These six factors are discussed further in this section.

2.1.1. Increasing crop yields

Crop yields have increased over the last few decades resulting in a larger volume of commodities being produced for a given area of land (Enns et al., 2012). In the United States, over the last 70 years, the yields of soybeans and winter wheat have approximately tripled (Burchfield et al., 2020). In Canada, over the last 60 years, the average yields of canola, corn, and soybeans have increased by over 100% (Statistics Canada, 2022a).

The literature reveals evidence of various types of advances in agricultural production. For example, Karlen et al. (1994) described how the use of crop rotation increased yield and profit and allowed for sustained production. Approximately 15 years later, Smith et al., (2008) reported results of a three-year experiment, manipulating the number of crop species grown in rotation and in the winter, without any fertilizer or pesticides, to test if varying the species impacted crop yields. The results of this experiment provided insights into how grain diversity without the use of fertilizer and pesticides does not decrease grain production and helps with the sustainability of agroecosystems, leading to higher grain yields long term (Smith et al., 2008). More recent literature indicates that crop genetics and information-intensive innovations in farm management, such as precision farming, have led to increased crop production (Burchfield et al., 2020). The increase of crop yields directly impacts the number of truck trips generated.

2.1.2. Changes in the types of crops being planted

The types of crops being planted and produced has changed over time. For example, in Manitoba, there is less land used to grow wheat today than there has been historically (Enns et al., 2012). This can be seen in wheat production trends. In 1976, Canada produced 23.5 million tonnes of wheat, compared to 22.3 million tonnes in 2021 (Statistics Canada, 2022a). While these numbers are similar, given the improvements in farming technology, the slight decline over 45 years suggests that less land is being used to produce the same amount of wheat. In the same time period, canola grew from 836,000 tonnes to 13.8 million tonnes, corn grew from 3.8 million tonnes to 14 million tonnes, and soybeans increased from 250,000 tonnes in 1976 to 6.3 million tonnes, indicating producers are replacing wheat crops with canola, corn, and soybeans (Statistics Canada, 2022a).

2.1.3. Transition to fewer, but higher throughput grain handing facilities

The way grain has been handled has changed over the years. When the CWB was operating prior to 2012, grain sales, purchases and exports were run through a single-desk system. This allowed for the Canadian government to reportedly maximize returns to grain producers. The CWB created a freight adjustment factor to reflect the value of grain at each grain delivery location. The adjustment factor was signaled to farmers indicating the lowest cost direction to move their grain. This system minimized the cost of grain transport for all producers simultaneously, while pricing away any farm-specific location advantages by dividing prairie producers into east and west catchment areas to eventually deliver to either Thunder Bay or Vancouver and Prince Rupert, respectively (Gleim & Nolan, 2015). The CWB logistics were "designed to minimize collective, not individual, freight rate payouts across all farmers in the region (Gleim & Nolan, 2015, p. 100)."

Since the abolishment of the CWB in 2012, the grain transportation market has become competitive among a small number of grain handlers (i.e., Cargill, Federal Grain, G3, Parrish and Heimbecker, Paterson Grain, Richardson Pioneer, and Viterra, along with a few other smaller companies) with a smaller number of grain handing facilities (Canadian Grain Commission, 2022). These grain handlers incur both the benefits and costs of delivering grain to port within a specified time frame. This has led to a focus on reducing the risks of additional delivery costs and maintaining reliability instead of focusing on reducing the collective costs to producers for grain transportation (Gleim & Nolan, 2015).

2.1.4. Increase in the size of farming operations and decrease in the number of farms

The number of farms in Canada has decreased significantly over time. From 1986 to 2016, Canada lost one third of its total number of farms (Qualman et al., 2018). Statistics Canada (2021) shows that in 1986, there were a total of 293,089 farms in Canada, and by 2016, that number had reduced to 193,492. However, from the 1970s to 2000s, farm sizes have been increasing (Deininger & Byerlee, 2012). One main factor contributing to the growth in farm size has been rising wages in non-agricultural sectors, leading farm operators to search for ways to obtain incomes similar to what they could obtain in other sectors. This has led to farm operators increasing the average size of the operational land they own (Deininger & Byerlee, 2012). The improvement of technology, investment in land, and investment in better machinery have also been drivers of larger farm sizes (Deininger & Byerlee, 2012).

2.1.5. Changes in truck regulations enabling the use of larger, heavier, and more productive truck configurations

Over the last 50 years in Canada, three main policy changes enabling the use of larger, heavier, and more productive trucks have been made: the 1974 Western Canadian Highway Strengthening Program (WCHSP), the 1988 Roads and Transportation

Association of Canada Memorandum of Understanding on Heavy Vehicle Weights and Dimensions (RTAC MoU) and permitting of longer combination vehicles. The 1974 WCHSP used federal funding for the Prairie provinces to help strengthen pavements and bridges, thereby facilitating an increase in the size and weight limits for trucks operating on the primary road network. The regulatory changes allowed single axle weights to increase to 9,100 kg, tandem axles to increase to 16,000 kg, and total gross vehicle weights (GVWs) to increase to 50,000 kg.

The RTAC MoU, signed in 1988, developed vehicle weights, dimensions, and configurations to be used on major highways across Canada based on a technical analysis of the impacts on pavements and bridges, and the dynamic performance of trucks (Pushka & Regehr, 2021). The RTAC MoU recommended the implementation of a tridem axle group, not previously recognized in the WCHSP, with a maximum weight between 21,000 kg and 24,000 kg depending on the axle spread. The majority of agricultural products fall under weigh-out commodities (Harvard, n.d.), and hopper bottom trucks exhibit a loading pattern of trucks being either empty or fully loaded (Regehr et al., 2020), indicating that these changes in truck weight regulations have allowed hopper bottom trucks to carry more grain for their fully loaded trips.

Longer combination vehicles, which are specially permitted truck configurations consisting of a tractor and two or three trailers or semi-trailers that exceed basic length restrictions, have become increasingly utilized in the prairie region (Pushka & Regehr, 2021). While offering important productivity advantages for low-density commodities, they are seldom used to haul bulk agricultural commodities (Regehr et al., 2020). These changes ended up having little impact on the transportation of agricultural products, since these trucks are principally designed to haul cube-out commodities (Wood & Regehr, 2017).

2.1.6. Mergers within the rail industry, rationalization of rail networks serving rural areas, and the introduction of shuttle train service for grain transportation

Mergers in the rail industry in North America since the 1960s have led to a marked reduction in the number of rail companies operating in North America—from about 70 to seven Class I railroads today (Canadian National (CN), Canadian Pacific (CP), Burlington Northern Santa Fe (BNSF), Union Pacific (UP), CSX, Norfolk Southern (NS), and Kansas City Southern (KCS)) (Madar, 1999). In Canada specifically, CN and CP are the only trans-continental freight railroads in the country.

Further mergers have also been contemplated. In 1999, there were talks of Canadian National (CN) and BNSF merging; however, this merger did not go through (Madar, 1999). As of 2022, there were talks of Canadian Pacific (CP) and KCS merging, creating the first rail line in North America to span all three countries (Canada, the United States, and Mexico) (Canadian Pacific, 2021).

Since deregulation in 1980 with the passage of the Staggers Act, it appears that softer competition amongst Class I railroads due to mergers has resulted in the ability for railroads to raise rates (United States Department of Agriculture and United States Department of Transportation, 2010). Simultaneously, the share of grain moved by rail has decreased, and the number of truck shipments of grain has increased (United

States Department of Agriculture and United States Department of Transportation, 2010).

Hyland et al. (2016) explain that the introduction of shuttle train service has had a direct impact on the size of elevators. Shuttle trains allow for rail companies to move a large number of railcars directly from origin (typically a high throughput elevator) to destination (i.e., a marine port), bypassing rail classification yards. However, for this to happen, grain elevators need to have enough storage capacity to fill 100 railcars efficiently, leading rail companies to incentivize elevator owners and other grain industry stakeholders to either retrofit their existing smaller elevators, or build new larger, more efficient ones. The shift from single or multi-car shipments from small elevators to 100 or more railcar shipments from terminal elevators, increased the efficiency of grain hauling for trains; however, it has led to longer truck trips from farm to elevator.

2.2. TRUCK TRAFFIC MONITORING METHODOLOGIES

Transportation agencies routinely use truck traffic monitoring programs to estimate the volume and nature of truck activity on their road network. Understanding truck traffic monitoring methodologies is essential for an integrated modelling approach. The principal truck data types discussed in this chapter are:

1. Truck volume and classification data: Volume (or count) data provide an indication of the number of vehicles (per unit time) that pass a point on a road. Classification data provide information about the type of vehicle (e.g., axle or trailer configuration, truck body type). As such, these data represent a

disaggregation of volume data. Classification data can be collected automatically or manually (FHWA, 2016; Maranchuk, 2016).

2. Weight data: Weight data are collected automatically using weigh-in-motion (WIM) devices or by on-road officers at fixed or portable static weigh scales.

Traffic monitoring programs generate site-specific data, which are valuable for engineering measures of truck volume and weight at those locations. However, there are many instances where this site-specific data needs to be extended to a system-wide level (Regehr & Reimer, 2013). To estimate volumes on an entire system, a methodology to apply the site-specific data to larger road sections is required. Regehr and Reimer (2013) developed a hierarchical methodology using traffic monitoring data to estimate system-wide truck volumes in Manitoba, using 49 continuous count sites and various short-term turning movement counts. The methodology defines continuous count sites (AVC and WIM sites) with at least 12 consecutive months of data as level 1 sites, sites with classification data for less than 12 consecutive months as level 2 sites, and sites with truck volume data but no classification data as level 3 sites. The methodology estimates annual average daily truck traffic (AADTT) directly at level 1 sites, through the application of truck traffic pattern groups (TTPGs) at level 2 sites, and through the application of truck traffic classification groups (TTCGs) at level 3 sites. These estimates are then assigned to the network using a decision algorithm.

The following sections provide a summary of truck traffic monitoring practices and innovations in the field.

2.2.1. Volume and Classification Data

The need for truck volume has been well-established in existing practice (FHWA, 2016; TAC, 2017). Vehicles can be classified in many ways; however, the most common vehicle classification scheme in North America is the FHWA 13-class system, which categorizes vehicles by the number of wheels, the number and arrangement of axles, the functional use of the vehicle, and the number of trailers. Classification data can be obtained from numerous sources, including in-road strip sensors, inductive loops, video-based systems, non-intrusive side-fire sensors (e.g., radar), and through manual observation. Classification data are necessary for many applications that require disaggregate traffic volume by vehicle class (FHWA, 2016; TAC, 2017).

In response to the various challenges of estimating truck volume, researchers have pursued alternative methods for acquiring this data type. Perhaps the most active area of emerging research in the traffic monitoring field relates to the use of probe data to estimate vehicle (and truck) volumes. To date, much of the work has focused on vehicle volumes, but several studies have recently examined truck volume estimation from probe data. In the Canadian context, Grande et al. (2022) investigated the potential use of vehicle probe data to strengthen conventional traffic monitoring methods for generating network wide AADT. This was done by looking at the relationship between vehicle probe data and site-specific traffic volume data in Manitoba. This study used probe data sourced from HERE Technologies' Traffic Analytics data set for 2018. The speed-based probe data were aggregated by hour and road segment. This data was compared to traffic volume data from the Manitoba Highway Traffic Information System

(MHTIS), obtained from 2018 by hour. A key finding was that the volume of probes correlated more strongly with truck volumes than with total volumes. This offers a potential to leverage this data to obtain truck volumes at a network-wide scale.

Other studies using probe data include a study by Stanley Young et al., 2018 in Maryland using INRIX® Trip Records, another by Kaushik et al., 2018 in the United States using TomTom® geospatial data and speed profiles, and a study by Yi et al., 2021 in Utah using INRIX® probe trajectory data and HERE speed data.

StreetLight Data expands on probe data by adding in location-based services, OpenStreetMap data, U.S. Census data, and weather data to produce truck volume models. This data is currently limited to the United States. The model is made up of five StreetLight Truck Volume Metrics that link together to predict total vehicle volumes, as well as the three vehicle classes used by StreetLight (light-duty, medium-duty, and heavy-duty) (StreetLight, 2022).

Beyond the use of probe data, several other truck volume monitoring innovations have arisen from the literature. For example, Wattana and Nishio (2017) used a structural health monitoring system (SHM) consisting of accelerometers, temperature sensors, and a traffic counting system to create a model from on an active cable-stayed bridge in Bangkok, Thailand. The assessment of the model determined that the constructed regression model was applicable in estimating the number of equivalent trucks from the dynamic responses. However, traffic conditions including the number of passing vehicles and the speed of traffic flow slightly affected the accuracy of the estimations.

Satellite imagery has also been studied as a possible new data set. Kaack et al. (2019) created a proof of concept to show that an object detection network can be used to count trucks in satellite images and predict annual average daily truck traffic from those counts using machine learning. The intended use for this concept was for regions where no AADTT data exists. This framework consisted of a truck detection model and a traffic monitoring model. The truck detection model counts the number of trucks on roadways in a satellite image, while the traffic monitoring model translates those counts into an AADTT estimate.

Until recently, classification data has focused on axle configuration; however, there is a need to extend vehicle classification data to include truck body type. In response to the need for body type classification data, researchers have been pursuing efforts to obtain these data. For example, in the United States, body type classification data allow for commodity-based modelling (Fekpe, 2011), as has been done through the Freight Analysis Framework. In the Canadian context, Maranchuk (2016) collected body type data at four locations using a combination of manual roadside surveys and video-based monitoring in conjunction with WIM data.

In addition to manually reviewed video data at weigh scales, He et al. (2019) created an automated system to detect, classify and recognize various truck body types from video recordings. Videos captured from roadside passive cameras were used to develop deep learning algorithms to determine: (1) the location of a truck in the video along with whether it was a truck or not, (2) the classification of the truck into FHWA classes 5 through 13, (3) the classification of attributes such as tractor types, trailer types and refrigeration units, and (4) techniques for extracting vendor information using logo and text detection.

Options other than video data have also been studied in the literature. Hernandez et al. (2016) used existing traffic sensor infrastructure to develop an approach to monitor truck traffic body types, using WIM devices and advanced inductive loop detectors. For each vehicle that crossed the WIM site, an inductive signature was collected along with the usual WIM measurements such as axle loads and spacing, all of which were then used as inputs to determine the truck body classification through models that contained all 13 FHWA classes. A multiple classifier systems method was then added to classify the body type of each truck.

Asborno et al. (2019) investigated the potential use of lidar as a non-intrusive traffic sensor to classify truck body type. This was done by creating a classification model, using lidar and machine learning, capable of classifying 3-S2 trucks. The 3-S2 trucks were classified into five body types: van and container, platform, low-profile trailer, tank, and hopper and end dump.

2.2.2. Weight Data

Truck weight data are the hardest and most costly form of traffic monitoring data to collect, however they are also considered to be the most important (FHWA, 2016). Truck weight data are used for many transportation engineering functions, including pavement design, congestion cost estimates, and commodity-based modelling approaches, among others (FHWA, 2016; Fekpe, 2011). Other than at weigh bridges, the gross vehicle weight is determined by summing individual axle or wheel loads measured by a WIM or at fixed or portable weigh scales (FHWA, 2016).

In response to various challenges related to weight data collection, researchers have pursued alternative methods to collect these data. Two recent examples are particularly instructive when considering opportunities to estimate truck loads at a system-wide level. Liu et al. (2020) proposed a method to cluster WIM data in response to the challenge of increasingly growing truck traffic volume data and limited weight data. The proposed method groups traffic sites with similar traffic patterns to a WIM site, with the expectation that the clustered truck traffic data is smaller than the sum of all data from all traffic sites. This would allow for the cluster to be fully utilized by transportation agencies to evaluate freight tonnage. A case study was conducted in Florida using k-means clustering, WIM data from 2012 and 2017, and Telemetric Traffic Monitoring Sites (TTMS) for volume data, allocating each TTMS to the most appropriate WIM site based on distance, AADTT and truck volume distribution by vehicle class.

Hernandez and Hyun (2020) used position data from GPS equipped trucks in combination with weight data from WIM sites to create a methodology for estimating GVW distributions for 3-S2 trucks at traffic count sites. Using the GPS data from the trucks, traffic patterns were determined and used to find the degree to which the traffic count site was spatially related to a WIM site. A GVW distribution estimated by Gaussian mixture models was then estimated at the WIM sites defined to be spatially related to the traffic count site.

2.3. FREIGHT DEMAND MODELLING METHODOLOGIES

Freight demand modelling represents an alternative approach to traffic monitoring for estimating truck traffic volumes, with the noted difference that demand modelling is typically used as a planning or forecasting tool. Although there are conceptual similarities, it is difficult to directly apply passenger demand modelling techniques to the freight transportation context. This is because of the multi-dimensional nature of the freight demand unit and the importance of multiple stakeholders in the freight transportation process (Mishra et al., 2014). To address these differences, many types of freight demand models are used throughout Canada and the United States. This section reviews the three main categories of models: (1) activity-based models, (2) commodity-based models, and (3) factoring models. An understanding of the current state of freight demand modelling reinforces the use of the integrated modelling approach described in this thesis.

Horowitz et al. (2008) and Fischer et al. (2005) have summarized the freight demand modelling methodologies used throughout Canada, the United States, and Europe and provide the principal sources for this review. The NCHRP Report 606 *Forecasting Statewide Freight Toolkit* (Horowitz et al., 2008) lists five model classes used in the United States:

- The Direct Facility Flow Factoring Method
- The Origin-Destination Factoring Method
- The Truck Model
- The Four-Step Commodity Model

- The Economic Activity Model

Fischer et al. (2005), conducted a review of freight modeling methodologies used in the United States, Canada and Europe. The authors describe the following methods:

- Link-level factoring methods
- Factored truck trip tables
- Commodity-based freight models
- Three-step truck models
- Hybrid Models
- Supply chain and logistics chain models
- Tour-based models

Two other sources examined new methods for modelling freight:

- Fischer-Kowalski et al. (2006) looked into Materials flow analysis
- Fekpe (2011) looked into commodity truck equivalency factors

This review summarizes these methods according to three main categories, as shown in Figure 2.

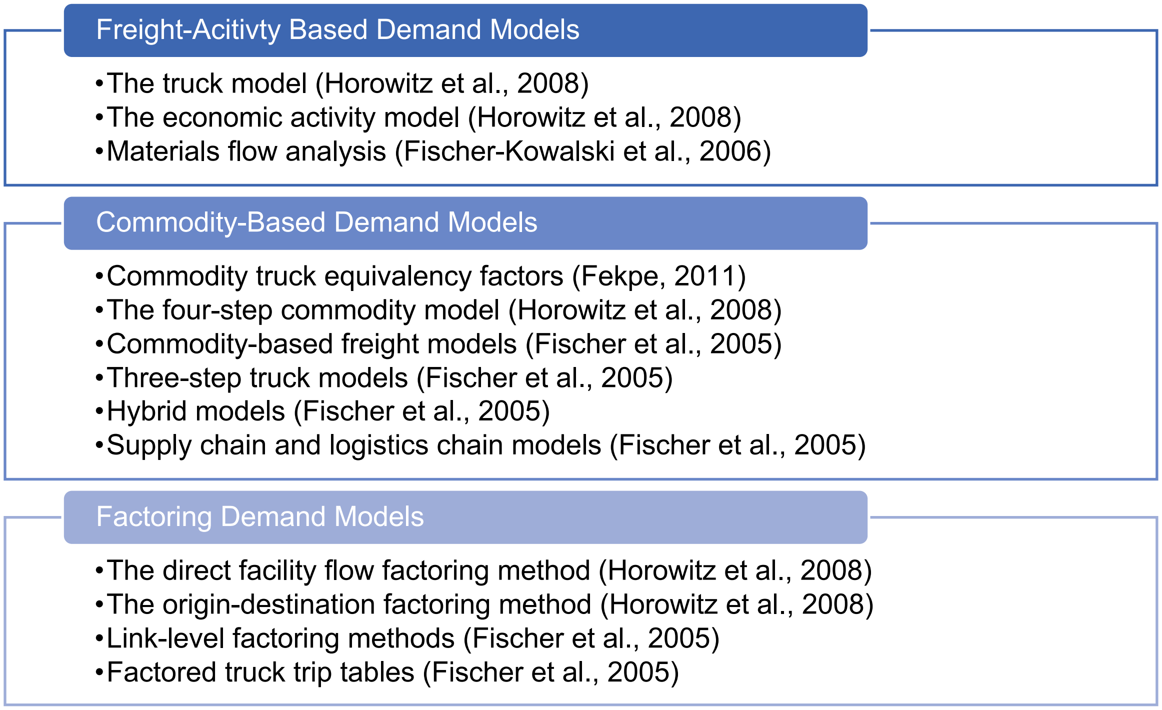


Figure 2 – Three categories of freight demand modelling methodologies

2.3.1. Freight Activity-Based Demand Models

According to Ortuzar (2011), an activity is defined as a “continuous interaction with the physical environment, a service or person, within the same socio-spatial environment, which is relevant to the sample/observation unit.” Activity-based models take known activities of a vehicle and link them to travel by understanding that travel is derived from the need to participate in activities (Rasouli & Timmermans, 2014). The literature contains many examples of different freight activity-based models being used with different methodologies. Relevant examples follow:

- Case studies in New Jersey and the Southern California Association of Governments discussed in the *Forecasting Statewide Freight Toolkit* use the truck model. The truck model uses the generation and distribution components of a traditional demand model to produce a table of truck trips and then uses the assignment component to assign truck trips to the table, without requiring a mode split component. This model follows a three-step process for trip generation, trip distribution and assignment with the truck types generally being considered in the model as light, medium, and heavy trucks based on gross vehicle weights (Horowitz et al., 2008).

- Case studies in Oregon and the Cross-Cascades economic activity model are discussed in the *Forecasting Statewide Freight Toolkit* use the economic activity model. This model uses all four components of a traditional demand model to produce freight forecasts for transportation facilities. The data used as input for the economic activity model are economic forecasts that are modified based on their performance determined by the model. Freight economic activity models are usually integrated with passenger forecasting models as the performance of highway truck traffic depends on the demand and usage of passenger vehicles (Horowitz et al., 2008).
- Fischer-Kowalski et al. (2006) looked to explain the volume of freight to be transported, or the scale of transport activity by combining the ideas of materials flow analysis generating highly aggregated indicators for the material “scale” of national economies, and transport statistics operating with indicators for the scale of freight transport activity. Materials flow analysis is a way to quantify the use, reuse, and loss of materials that enable modern society (i.e., metal and polymer) (Graedel, 2019). Materials flow analysis generates indicators for the material scale of national economies in Europe. One example of a standard material flow

indicator is the direct material input. Direct material input is made up of the total volume of materials extracted from the domestic environment to enter economic processing plus the total volume of imports, reported in metric tonnes per year. This indicator of direct material input is the main connection Fischer-Kowalski used to reconstruct what materials were required for one commodity and to identify system characteristics. Their model found the relation between transportation volumes and the materials flow analysis was casually established on a physical level, meaning a transport volume could be generated from a given level of material input into a socioeconomic system, and a given structure of economic division of labor.

2.3.2. Commodity-Based Demand Models

Commodity-based demand models focus on modelling the amount of freight, by weight, being transported to capture the economic mechanisms creating freight movements more accurately (Horowitz et al., 2008). Commodity-based models estimate the total number of tons (or tonnes) produced and attracted by each zone in the study area, then distribute the tons moving between origins and destinations usually using gravity models. Once the tons have been distributed, they are split into modes to estimate the number of tons moved by each available mode, then the tons are converted to vehicle trips (Holguín-Veras & Thorson, 2000). Within the reviewed literature, there are many examples of commodity-based models being used with different methodologies. Pertinent examples follow:

- Fekpe (2011) converted commodity flow from tons to truck trips by completing four steps: identifying the main truck configurations and major truck body types, allocating commodities to those truck body types based on typical body types used for specific commodities, estimating the average payload of each vehicle type, and calculating the truck equivalency factors and applying them to commodity origin-destination data. Fekpe used this process for loaded trucks only. However, empty trucks would need to be accounted for to analyze the transportation system performance.
- Case studies in Wisconsin and Cambridge discussed in the *Forecasting Statewide Freight Toolkit* use the four-step commodity model. The four-step commodity model resembles the typical four-step travel demand model for passenger vehicles, both using generation, distribution, mode split, and assignment. What differs between the four-step commodity model and the four-step travel demand model for passenger vehicles is that commodity models can analyze the impact of changes in employment, modal utility, trip patterns, and network infrastructure (Horowitz et al., 2008).
- Fischer et al (2005) discuss four model types that are related to commodity-based models: hybrid models, commodity-based freight models, three-step truck models, and supply chain and logistics chain models. Hybrid models combine features from commodity-based freight models and three-step models. Commodity-based freight models use or develop commodity flow forecast databases and can convert commodity tonnage to vehicle trips as part of the modelling process; however, they typically lack information on local pickup and

delivery trips. Three-step truck models use traditional trip generation, trip distribution and trip assignment, but these models can present issues with trip chaining characteristics of truck trips. Supply chain and logistics chain models apply analytical methods that simulate logistics choices throughout the whole supply chain for specific industries.

2.3.3. Factoring Demand Models

Factoring demand models use direct factoring of some part of their model to estimate future truck trips. Direct factoring uses information about existing flows and forecasts of economic data to produce forecasts of link volumes on roads. Factors are developed and applied to estimate changes in flow due to growth or changes in transportation service on a certain road or on a competing road (Horowitz et al., 2008). Examples of factor demand modelling in the literature follow:

- Case studies in Minnesota and Florida discussed in the *Forecasting Statewide Freight Toolkit* look at using the flow factoring method for modelling. The flow factoring method provides freight volumes on roadways and requires information on the facility itself and forecasts of the factors that affect the facility. Flow factoring does not provide overall transportation system forecasts or many important factors in freight forecasting; therefore, it is typically used to rapidly apply existing data to determine one or several short-term forecast volumes (Horowitz et al., 2008).
- Two case studies in the *Forecasting Statewide Freight Toolkit*, Oklahoma and the Kentucky Corridor, used the origin-destination factoring method. This method

uses existing factored freight origin-destination tables as the input for mode split and trip assignment rather than using tables created from trip generation and trip distribution model components. The tables used for this method are generally made from truck counts or from disaggregated Commodity Flow Survey data. Growth rates are generally developed from economic indicators (Horowitz et al., 2008).

- Fischer et al (2005) discuss two factoring methods: link-level factoring and factored truck trip tables. Link-level factoring methods use historical trends or economic growth forecasts to develop growth factors to be applied to base-year traffic volumes. Factored truck trip tables are similar to link-level factoring methods with the exception that the growth factors are applied to a base-year trip table. Factored truck trip tables have the advantage of being able to address network configuration changes, however they cannot address changes in freight movements.

2.4. APPROACHES TO MODELLING AGRICULTURAL FREIGHT ACTIVITY

The literature includes numerous examples of modelling agriculture-related activity. Some examples include:

- A commodity-based methodology for freight forecasting on rural road networks (Mruss, 2004)
- Development of a grain transportation model for Saskatchewan (Gienow, 2007)

- A simulation model for rationalizing the grain transportation and handling system in western Canada on a regional basis (Tosterud, 1973)
- A discrete event simulation model for analysis of farm scale grain transportation systems (Turner et al., 2019)
- Modelling and analysis of intermodal food grain transportation under hub disruption towards sustainability (Maiyar & Thakkar, 2019)
- An artificial fish swarm algorithm for a multi-objective grain transportation problem (Jia et al., 2020)

This section discusses the two most relevant approaches used to model agriculture freight activity in Canada, to understand what work has been done previously in relation to this thesis.

2.4.1. Manitoba Forecasting Model for Grain Movement

Mruss (2004) developed, applied, and evaluated a methodology for forecasting specific commodity movements and related truck traffic on a rural highway network. This methodology used a three-step freight forecasting model with grain production data from Manitoba for freight generation, a gravity model for freight distribution, and the all-or-nothing method for assignment (Mruss, 2004).

When determining freight generation, Mruss did not have true production or attraction data available. Grain production information was available for rural municipalities in Manitoba. Mruss determined that rural municipalities in Manitoba were too large to act as origin freight analysis zones, so the municipalities were split into smaller townships, and production information for municipalities was split accordingly into townships. Attraction data used in this model was estimated based on delivered tonnage information at grain delivery points (Mruss, 2004).

Freight distribution applied the gravity model singly constrained to attractions. Friction factors for the gravity model were estimated using the impedance between origin-destination pairs and an impedance function. Transport cost was chosen to test the measure of impedance for this model. Transport cost consisted of truck haul rates in dollars per tonne (when multiplied by the distance from origin to destination in kilometers), rail costs in dollars per tonne, elevation charges in dollars per tonne, and trucking incentives in dollars per tonne (Mruss, 2004).

The assignment step used the all-or-nothing assignment method, as the majority of roads in Manitoba were operating below the link capacity. The assignment of freight was based on travel cost which can be based on distance, travel time, or capacity. Because capacity was not an issue for freight movement in Manitoba, travel cost was based on travel time and differences in road links, including whether it was divided or undivided, surface type, surface condition, weight class and bridge restrictions (Mruss, 2004).

2.4.2. Grain Transportation Model for Saskatchewan

Gienow (2007) developed a grain transportation model that estimated the current and past grain flow in tonnes across the province of Saskatchewan on both highways and rural municipal roads using linear programming optimization. This grain transportation model used a three-step system of route optimization, system optimization and optimized route accumulation. Gienow also conducted a sensitivity analysis on friction factors affecting the routing of grain (Gienow, 2007).

To conduct route optimization, Gienow used grain facility locations for destination points, township locations for origin points, and road geometry and roadway attributes for the routable network. The roadway attributes included were weight limit, surface type, urban type, road condition, roadway type and divided or undivided. Friction factors were assigned to each attribute. Using these friction factors an adjusted length was calculated for each township to the closest 35 grain delivery points to allow for a large amount of choice for the linear programming optimization model (Gienow, 2007).

Gienow then determined the specific destinations of the grain using system optimization. The programming software used by Gienow for this model used the simplex method for system optimization. The simplex method is an iterative process that "fixes the variables at their limits and moves along the edges from variable to variable until the optimum solution is found" to determine the optimum routing of grain from township to grain elevator (Gienow, 2007).

For the final step of the model, the optimized route accumulation, the optimized origin-destination pairs were processed to determine the route from origins to destinations. This led Gienow to a final output database of tonnes hauled in each direction on each roadway in the model (Gienow, 2007).

2.5. SUMMARY

The agriculture sector in Canada has experienced several inter-related trends over the past decades. These include: increasing crop yields, changes to the types of crops being planted, transitions to fewer but higher throughput grain handling facilities, increases in the size of farms but decreases in the number of farms, changes in truck regulations to allow more productive trucks, and various market and infrastructure adjustments within the rail industry. The ongoing and complex nature of these trends necessitate a comprehensive understanding of the industry to support the modelling of grain activity, as is done in this thesis.

Truck traffic monitoring data and methodologies offer one approach to model grain truck activity. Such methodologies rely on site-specific truck volume, vehicle classification, truck body type, and truck weight data to characterize the extent and nature of truck activity. Extending site-specific observations to system-wide estimates requires further analytical effort. While useful for most engineering applications, these data are not well-suited for planning or forecasting purposes, particularly when there is interest in specific industries, like the agricultural sector.

In contrast, freight demand modelling approaches are specifically designed to forecast future activity and are often tailored to specific industries. Current modelling approaches used to estimate truck traffic can be summarized into three main categories: freight-activity based demand models, commodity-based demand models, and factoring demand models. Freight-activity based demand models include the truck model, and the economic activity model, both described by the NCHRP 606 *Forecasting Statewide*

Freight Toolkit. Commodity-based demand models include the four-step commodity model as described by the NCHRP 606 *Forecasting Statewide Freight Toolkit,* and commodity-based freight models, three-step truck models, hybrid models, and supply chain and logistics chain models, as described by Fischer et al., 2005. Factoring demand models include the direct facility flow factoring method, and the origin-destination factoring method as described by the NCHRP 606 *Forecasting Statewide Freight Toolkit,* and link-level factoring methods, and factored truck trip tables as described by Fischer et al. (2005). While the foregoing methods are useful for forecasting, on their own, they seldom offer the spatial, temporal, or vehicle-level specificity required for many engineering applications (e.g., pavement design).

Table 1 summarizes the use of truck traffic monitoring data in current demand modelling approaches. Of the 14 total demand modelling approaches discussed in this chapter, only four use any kind of truck traffic data. Fischer-Kowalski et al. (2006) used traffic data to relate to materials flow analysis numbers, Fekpe (2011) used classification and weight data to convert commodity flows to truck trips, the flow factoring method factors existing truck traffic data to determine short-term forecast volumes, and the link-level factoring method applies growth factors to existing truck traffic data. Moreover, the two efforts to model agriculture-related freight activity in the Canadian Prairie Region made no use of truck traffic monitoring data (Gienow, 2007; Mruss, 2004).

Table 1 - Use of truck traffic data in demand modelling approaches

Study	Traffic monitoring data used				How is truck traffic data used?
	Volume Data	Classification Data	Weight Data	None	
Freight Activity-Based Demand Modelling					
Fischer-Kowalski et al. (2006)	✓				Related materials flow analysis numbers to traffic volume data
New Jersey Truck Model				✓	
Economic activity model				✓	
Tour-based model				✓	
Commodity-Based Demand Modelling					
Fekpe 2011		✓	✓		Used classification and weight data to convert commodity flows to truck trips
Four-step commodity model				✓	
Hybrid models				✓	
Commodity-based freight models				✓	
Three-Step truck models				✓	
Supply chain and logistics chain models				✓	
Factoring Demand Models					
Flow Factoring method	✓				Factor existing truck traffic data to determine short-term forecast volumes
Origin-destination factoring method				✓	
Link-level factoring	✓				Apply growth factors to existing truck traffic data
Factored truck trip tables				✓	

Despite some level of integration evident in the literature, based on the findings from the environmental scan reported in this chapter, there appears to be a need to better utilize available resources and data from both truck traffic monitoring and demand modelling approaches to gain a comprehensive understanding of truck activity at a system-wide level. The integrated modelling approach developed and applied to the agriculture sector in this thesis helps fill this need.

3. METHODOLOGY

This chapter describes the methodology applied in this research, including (1) the data sources used to develop the integrated modelling approach, (2) the methods used to create the grain tonnage demand (GTD) model, (3) the methods used to create the hopper bottom truck demand (HBTD) model, and (4) the methods used to create the truck traffic model and in turn the hopper bottom truck traffic (HBTT) model.

3.1. DATA SOURCES

To develop the integrated model, this research uses data from the government of Canada, truck traffic data, and spatial data.

3.1.1. Government of Canada Data

There are two main government sources for agriculture data in the Canadian Prairie Region: Statistics Canada and the Canadian Grain Commission (CGC), a division of Agriculture Canada.

3.1.1.1. Grain Production Data

Data available from Statistics Canada is collected through different survey methods, including paper, telephone, in-person, and online surveys, along with crowd sourcing. Available grain data includes crop production, grain deliveries, land use, number of farms, animal production, farm businesses, farm population, and food (Statistics Canada, 2022).

Annual grain yield data are available from Statistics Canada via a table titled *Estimated areas, yield and production of principal field crops by Small Area Data Regions* (SADRs). This table summarizes the production of barley, canola, corn for grain, oats, soybeans, and wheat in each SADR, in metric tonnes. Figure 3 shows a map of the SADRs in the study region.

Figure 3 - Small area data regions in the Canadian Prairie Region

3.1.1.2. Grain Elevator Delivery Data

The CGC regulates grain handling in Canada and establishes standards of quality for Canadian grain. The CGC provides weekly grain statistics, grain deliveries at prairie points, annual Canadian grain exports, historical information on licensed grain elevators, elevator charge summaries, grain varieties by acreage, and weekly producer car allocations (Canadian Grain Commission, 2022).

The CGC publishes annual grain delivery data to grain elevators in Canada in thousands of metric tonnes. These data consist of deliveries of wheat, amber durum, oats, barley, rye, flaxseed, canola, sunflower, buckwheat, soybeans, peas, corn, safflower, canary seed, mustard seed, triticale, beans, lentils, chickpeas, and faba beans to each grain elevator in the country.

3.1.2. Truck Traffic Data

3.1.2.1. Truck Body Type Classification Data

Truck body type classification data were obtained from work done by Maranchuk (2016). This data consists of truck body type counts from the Headingly weigh scale, disaggregated by axle configuration and body type. The data are split into 28 different axle configurations and 12 different body types. The 12 body types tracked include bobtails, cherry pickers, concrete trucks, containers, dump trucks, flat decks, hoppers, livestock, other, refrigerated vans, tankers, and vans. These data were collected at the weigh scale on the TransCanada Highway in Headingly, Manitoba in September and October 2014.

3.1.2.2. Truck Volume and Classification Data

Truck volume and classification data were obtained from WIM devices, AVC sites, and turning movement counts. Traffic volume data (without classification data) were obtained from PCSs and short-duration counts obtained from tubes and inductive loops. As discussed in Section 3.4, these data were used to develop the truck traffic model following a methodology developed by Reimer & Regehr (2013). Figure 4 shows the continuous classification sites (WIM and/or AVC), Figure 5 shows the short duration classification sites (turning movement counts), and Figure 6 shows sites with only volume data. These data sets were collected for 2019.

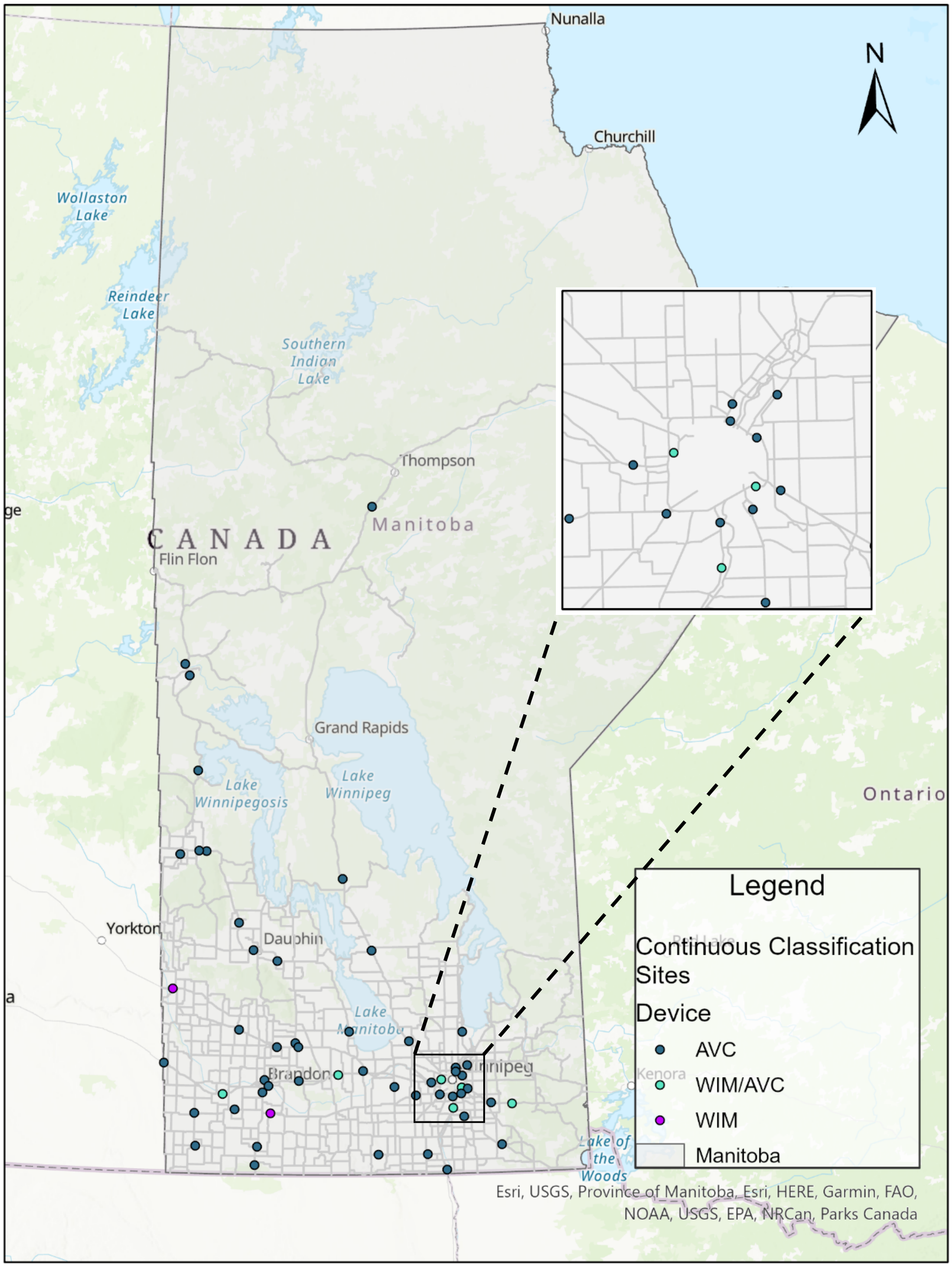


Figure 4 – Continuous classification sites in 2019

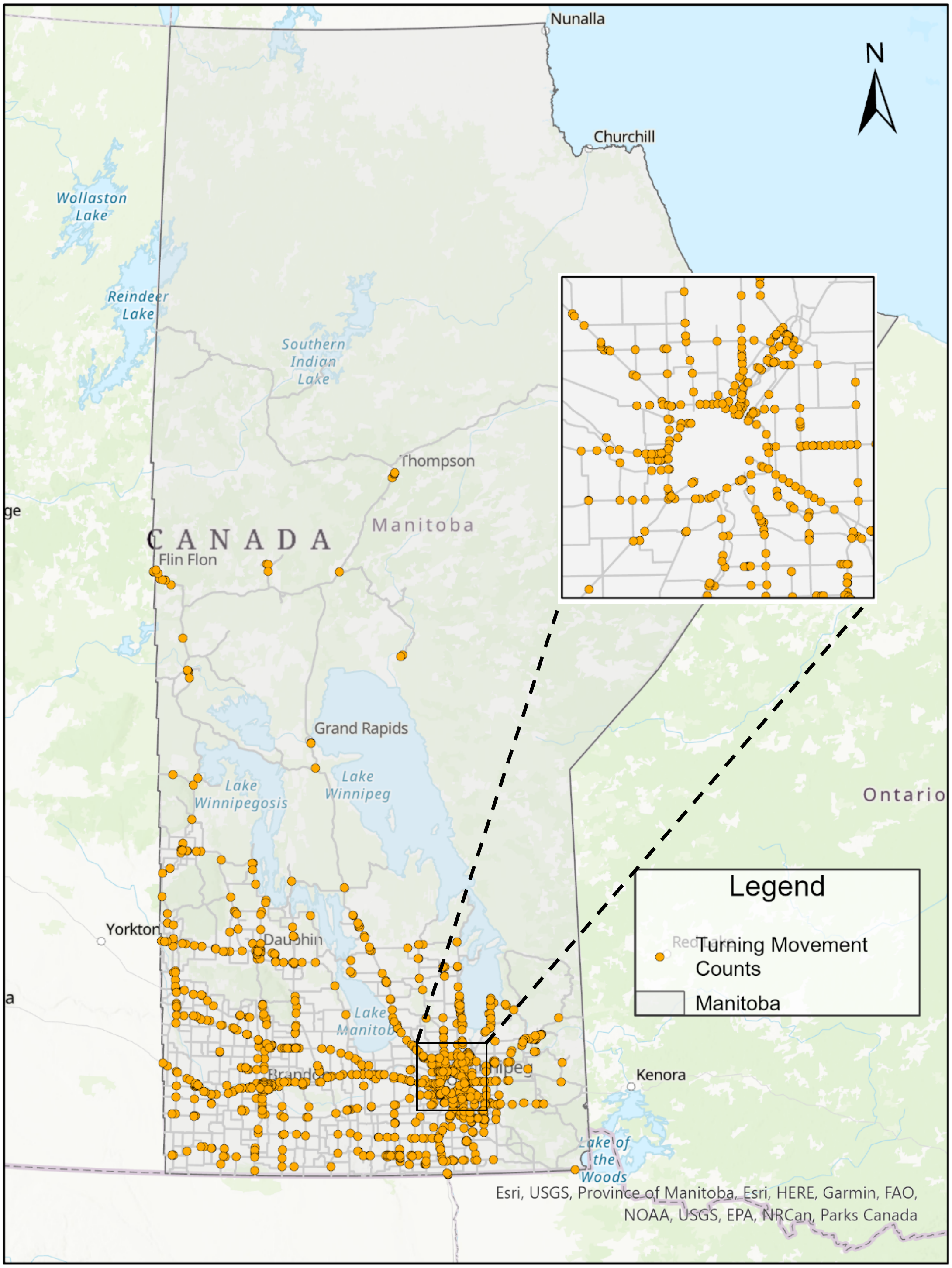


Figure 5 - Turning movement count sites in 2019

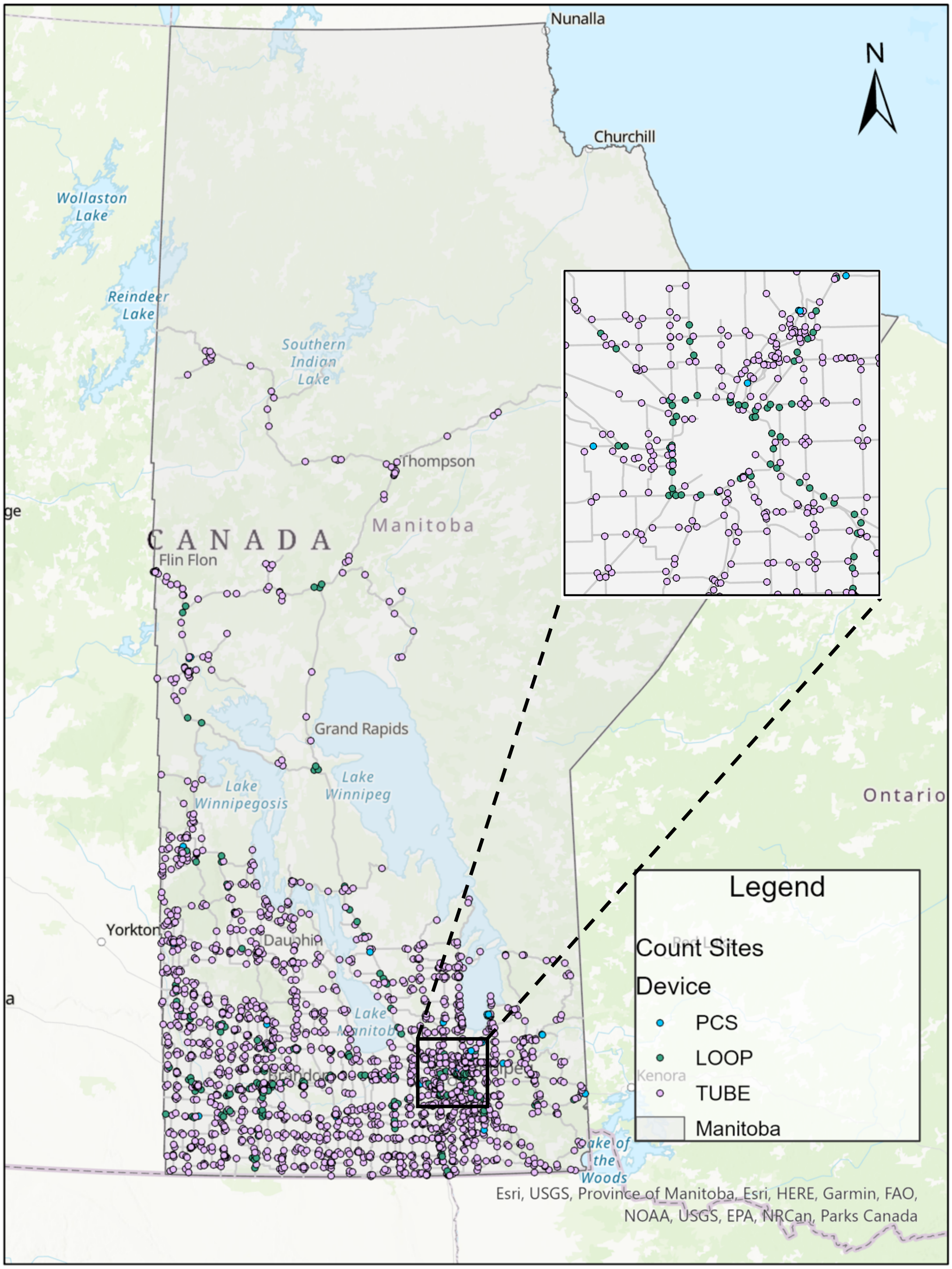


Figure 6 – Volume count sites in 2019

3.1.3. Spatial Data

3.1.3.1. Census road file

The census road file was obtained from Statistics Canada for the year 2019. The shapefile consists of 2,233,140 polylines of various length, each ending at an intersection with another polyline. Each polyline is assigned a rank along with regulatory data. The rank of the roads is classified as 1 through 5, with 1 corresponding to the Trans-Canada Highway, 2 representing the national highway network, 3 representing major highways, 4 representing secondary highways or major roads, and 5 representing all other roads. Figure 7 shows a map of the road network with rankings across Canada.

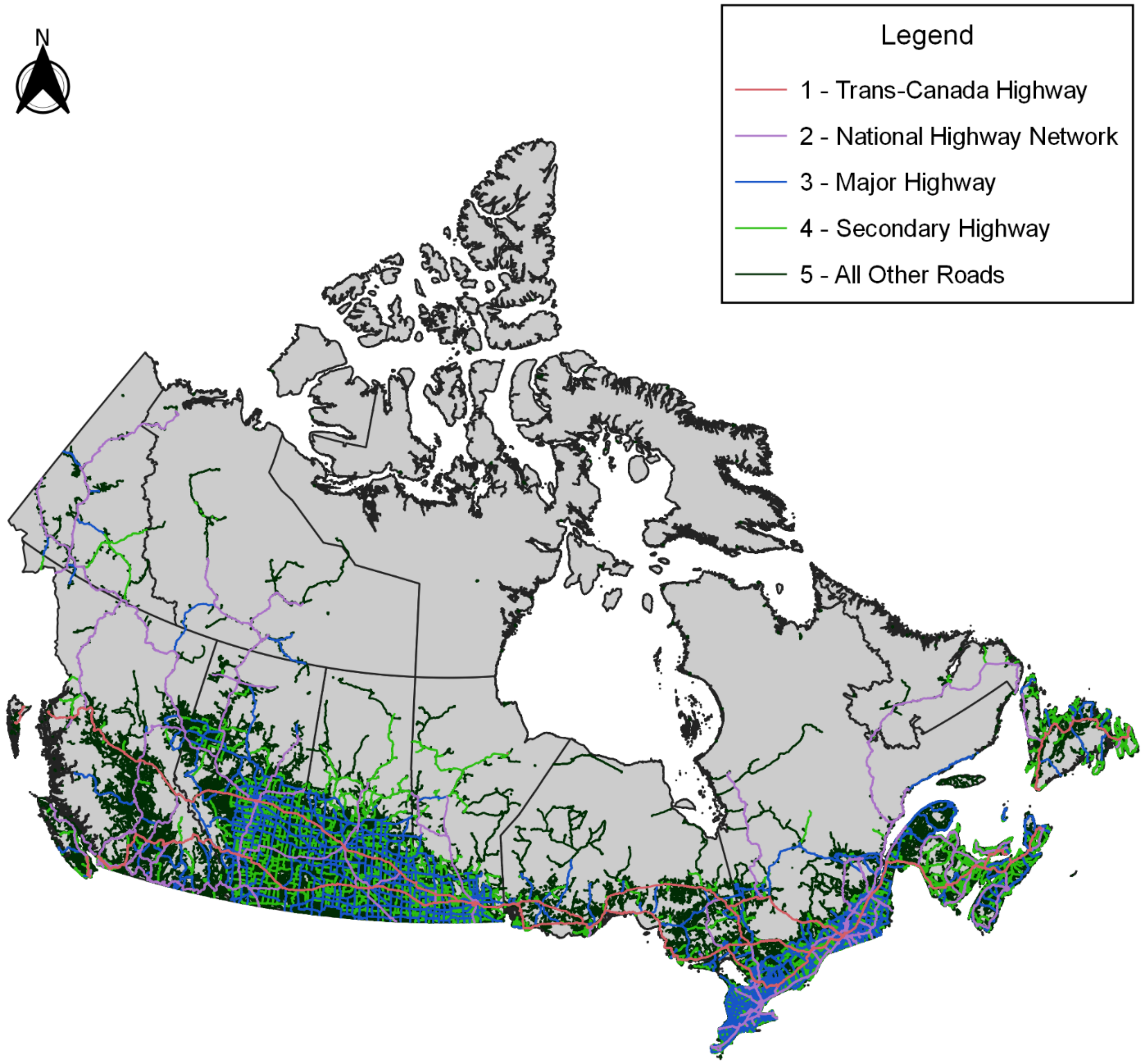


Figure 7 - Census road network 2019

Source: Statistics Canada

3.1.3.2. Speed Limit Data

Manitoba speed limit data were obtained from Manitoba Transportation and Infrastructure (MTI) in 2021. The shapefile consists of 1954 polylines of various lengths. Saskatchewan speed limit data were obtained from the Government of Saskatchewan in 2022. The shapefile consists of 25,063 polylines of various lengths. Each polyline in both shapefiles is assigned a speed limit between 10 km/h and 110 km/h, with most roads having a speed limit of 90 km/h or 100 km/h as expected on provincial roads. A map of Manitoba speed limits is shown in Figure 8. Figure 9 shows a map of the speed limits in Saskatchewan.

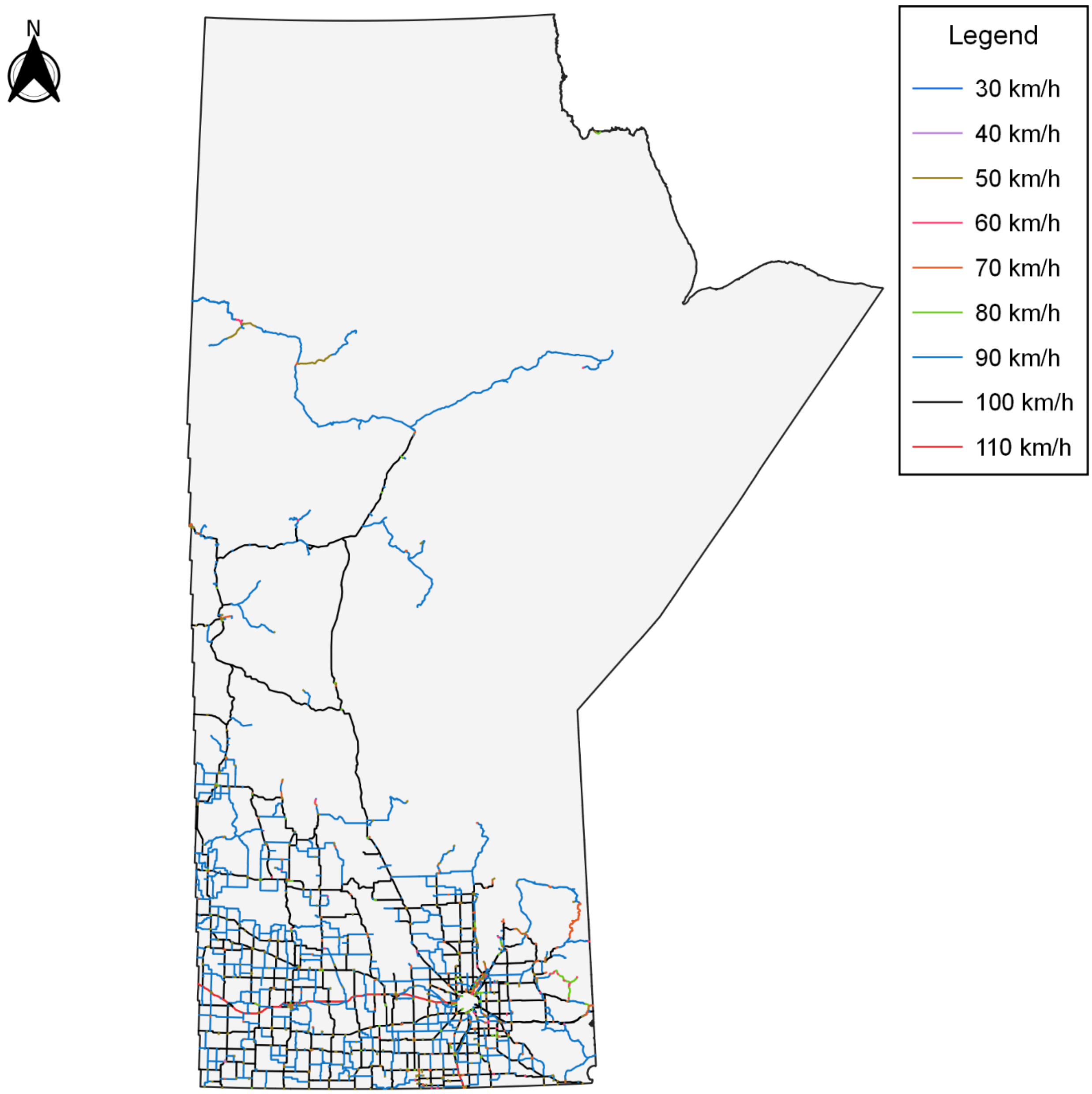


Figure 8 - Manitoba speed limits 2021

Source: Manitoba Transportation and Infrastructure

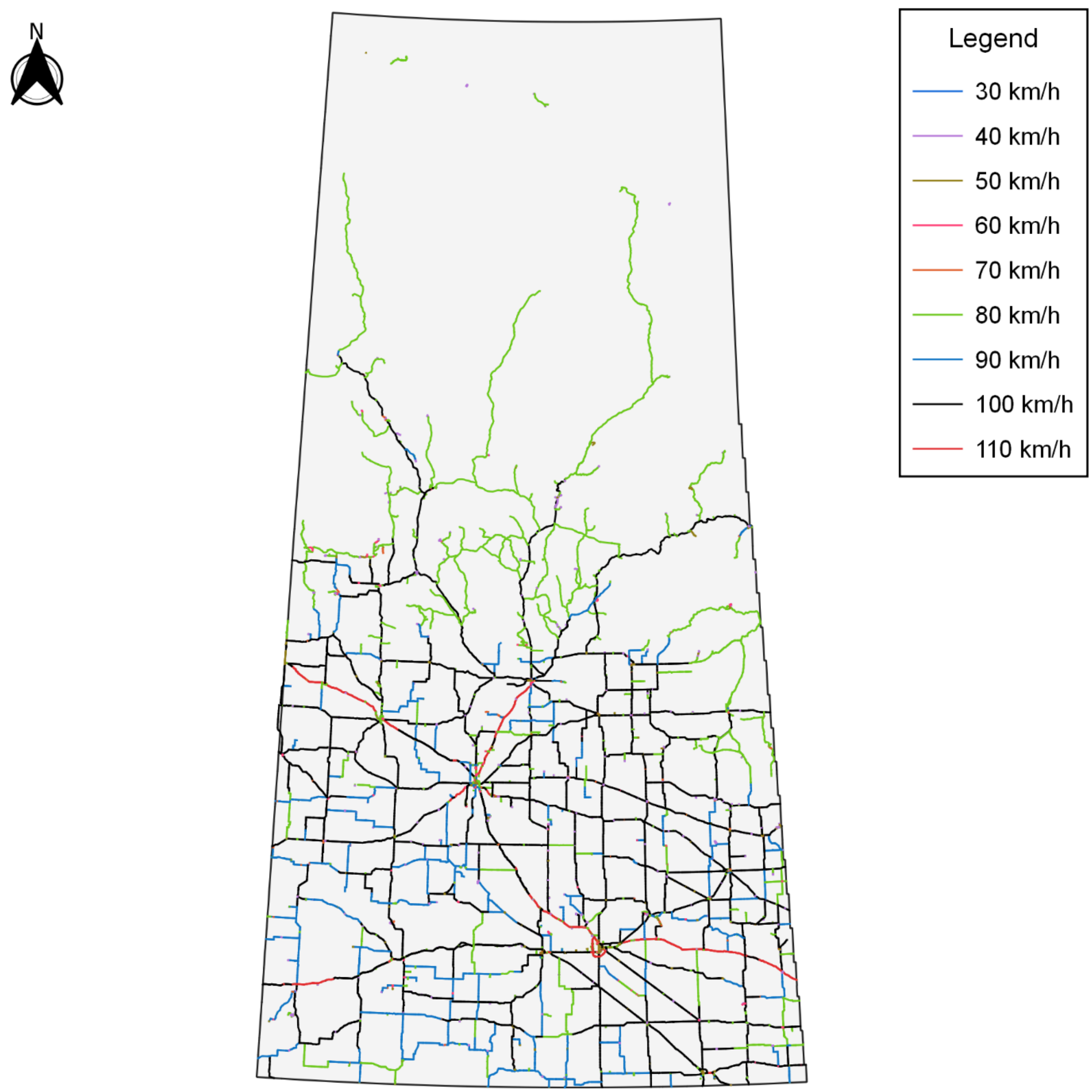


Figure 9 - Saskatchewan speed limits 2022

Source: Saskatchewan Government

Alberta speed limit data were obtained from the Alberta Government in 2021. The shapefile contains 1768 polylines of various length. Each polyline is assigned a speed limit between 30 km/h and 110 km/h. The shapefile provided for Alberta differs from Manitoba and Saskatchewan shapefiles, as it is a map of speed zones rather than speed limits. This means the shapefile contains portions of roadways that are not listed as 100 km/h. Any roadway not in the provided shapefile has a speed limit of 100 km/h. A map of Alberta's speed zones is shown in Figure 10.

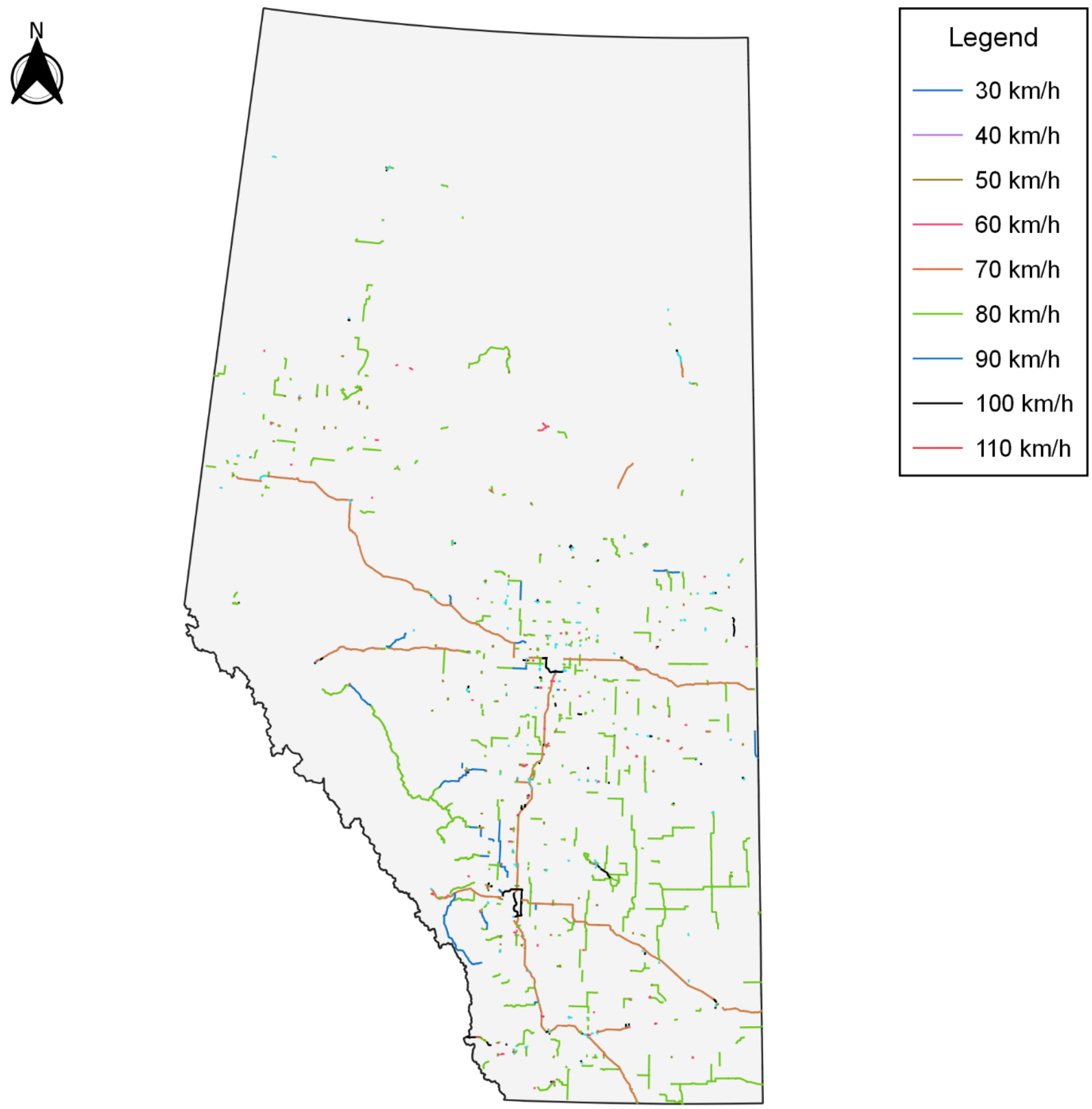


Figure 10 - Alberta speed zones 2021

Source: Alberta Government

3.1.3.3. Weight Limit Data (RTAC network)

Manitoba weight limit data were obtained from the province of Manitoba as pdf files. Manitoba's weight classification system is as follows:

- RTAC Routes (63,500 kg)
- RTAC Routes (62,500 kg)
- Class A1 Highways
- Class B1 Highways

Saskatchewan weight limit data were obtained from the province of Saskatchewan as a pdf file. Saskatchewan's weight classification system is as follows:

- B-Train (63,500 kg)
- Primary Weight
- GVW Limited Highway
- 75% of Primary Weight Highway
- 8,000 kg Restricted Highway
- Secondary Weight Highway

Alberta does not have designated weight limits on highways and therefore all highways in Alberta are assumed to allow 63,500 kg.

These documents were then used to create a shapefile to be used in the model. To standardize the weight classes across the region, a ranking from 1 to 4 was used. Weight class 1 represents RTAC Routes (63,500 kg), RTAC Routes (62,500 kg), B-

Train (63,500 kg) and all Alberta highways. Weight class 2 represents Class A1 Highways and Primary Weight roads, weight class 3 represents Class B1 Highways and Secondary Weight Highways, and weight class 4 represents all other weight restrictions.

3.1.3.4. Townships

Manitoba townships were obtained from the Manitoba Land Initiative in 2022. The shapefile contains 7204 polygons. Saskatchewan townships were obtained from the Government of Canada in 2022. The shapefile contains 7756 polygons. Alberta townships were obtained from the Alberta Government in 2022. The shapefile contains 7254 polygons. All three shapefiles contain polygons of generally uniform size with some variation based on land characteristics. All shapefiles assign a township, range, and direction from prime meridian for each polygon. Figure 11 shows a map of townships in the region.

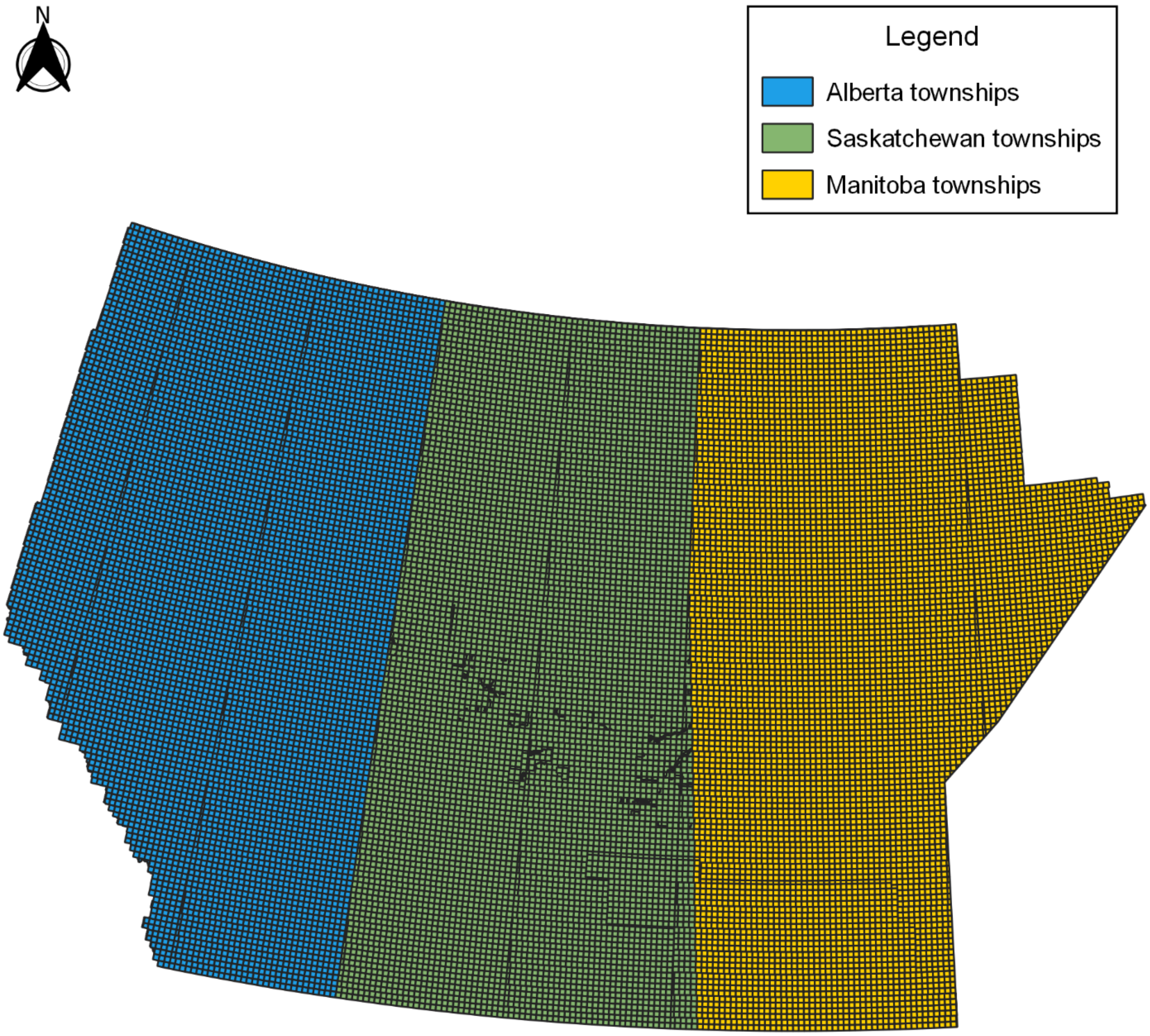


Figure 11 – Townships 2022

Source: Manitoba Land Initiative

3.1.3.5. Land Use Data

Land use data for the year 2000 was obtained from the government of Canada in 2021. The data comprises 146 shapefiles, 54 in Manitoba, 44 in Saskatchewan, and 48 in Alberta. These shapefiles consist of polygons of various shapes and sizes. Each polygon is assigned a land use cover classification number based on Table 2. A map of the region’s land use is shown in Figure 12.

Table 2 - Land use cover classification

Number	Classification
0	No Data
10	Unclassified
11	Cloud
12	Shadow
20	Water
30	Barren
31	Snow/Ice
32	Rock/Rubble
33	Exposed Land
34	Developed
35	Sparsely vegetated bedrock
36	Sparsely vegetated till-colluvium
37	Bare soil with cryptogam crust - frost boils
40	Bryoids
50	Shrubland
51	Shrub - Tall
52	Shrub - Low
53	Prostrate dwarf shrub
80	Wetland
82	Wetland Shrub
83	Wetland Herb
100	Herb
101	Tussock graminoid tundra
102	Wet sedge
103	Moist to dry non-tussock graminoid/dwarf shrub tundra
104	Dry graminoid prostrate dwarf shrub tundra
110	Grassland
120	Cultivated agricultural Land
121	Annual crops
122	Perennial crops and pasture

200	Forest/Trees
210	Coniferous
211	Coniferous - Dense
212	Coniferous - Open
213	Coniferous - Sparse
220	Broad Leaf
221	Broad Leaf - Dense
222	Broad Leaf - Open
223	Broad Leaf - Sparse
230	Mixed Wood
231	Mixed Wood - Dense
232	Mixed Wood - Open
233	Mixed Wood - Sparse

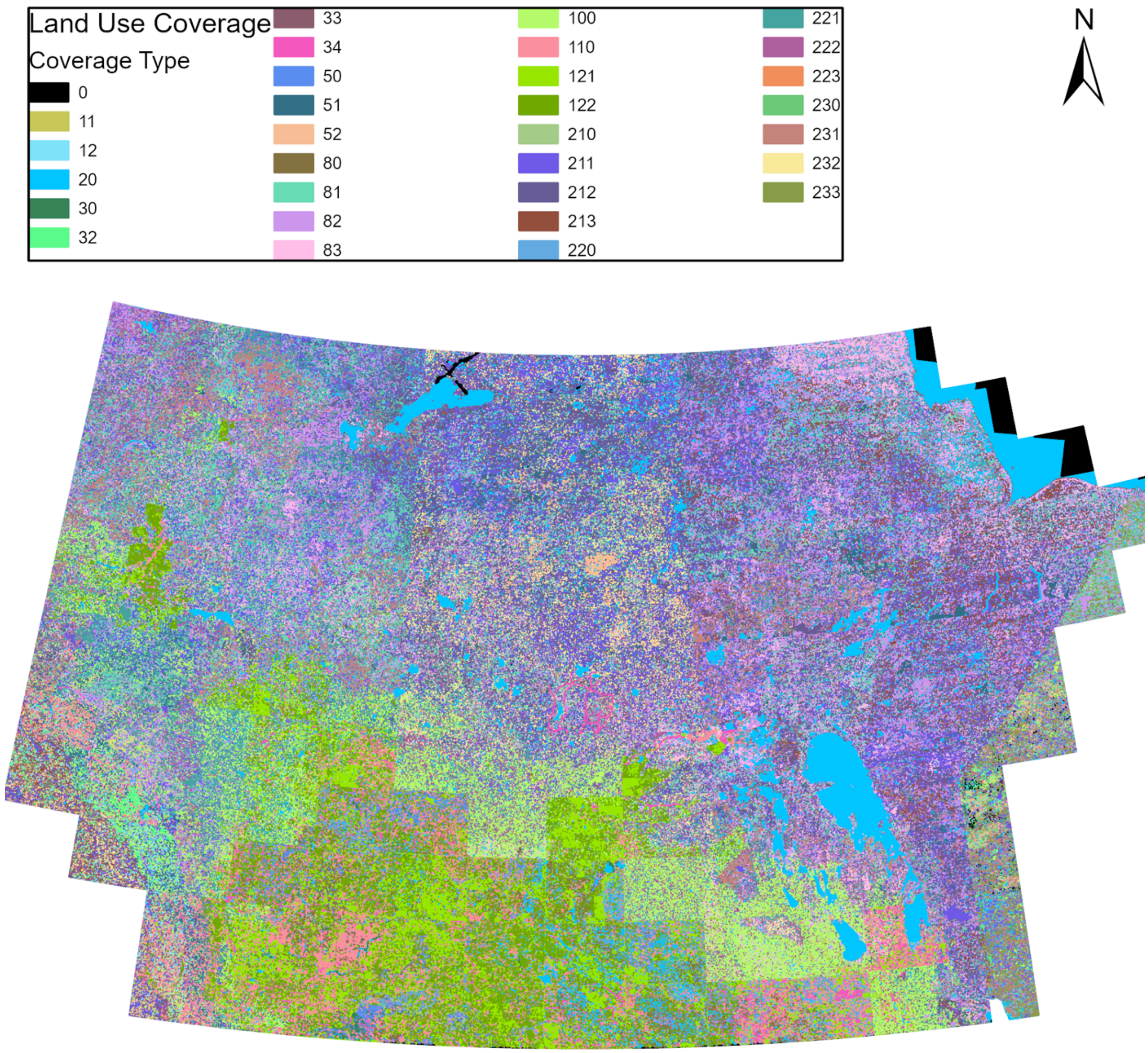


Figure 12 - Land use in 2000

Source: Government of Canada

3.1.3.6. Elevators

Elevator spatial data for the year 2019 was obtained from the Government of Canada in 2022. The shapefile contains 432 points. Each point indicates the location of a grain elevator, the station name, the province the elevator is located in, the railway servicing the elevator, the company owning the elevator, the elevator type, and the elevator capacity in tonnes. A map of the elevators is shown in Figure 13.

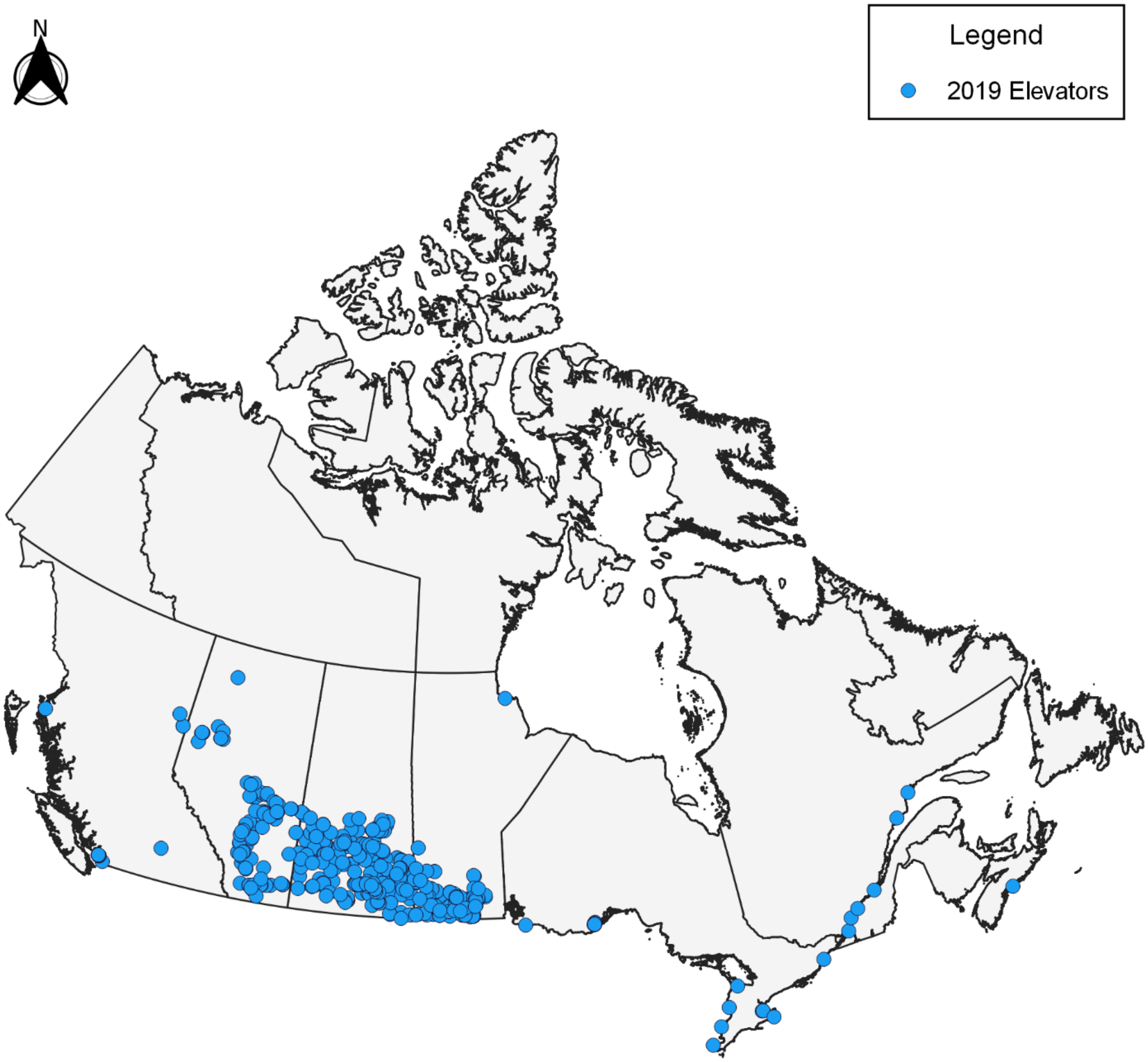


Figure 13 - Canadian Grain Commission elevators 2019

Source: Canadian Grain Commission

3.2. GRAIN TONNAGE DEMAND (GTD) MODEL

This section describes the methodology used to develop the GTD model for this thesis. This model focuses on the storage to elevator segment of the supply chain. The modelling approach comprises three steps: generation, distribution, and assignment.

3.2.1. Generation

3.2.1.1. Origins

The model defined origins as the centroids of agricultural townships in the region. The initial step to obtain these origins is to determine where in the region agricultural land is located. This is done by overlaying the agricultural land use data shown in Figure 15 and the townships in the region, shown in Figure 11. Taking both layers in ArcGIS and running the *Clip* geoprocessing tool leaves only the townships containing agricultural land shown in Figure 16. Once the relevant townships are determined, the centroids of each township are calculated using the *Feature to point* geoprocessing tool in ArcGIS, as shown in Figure 17. Figure 14 illustrates the process of obtaining origin points.

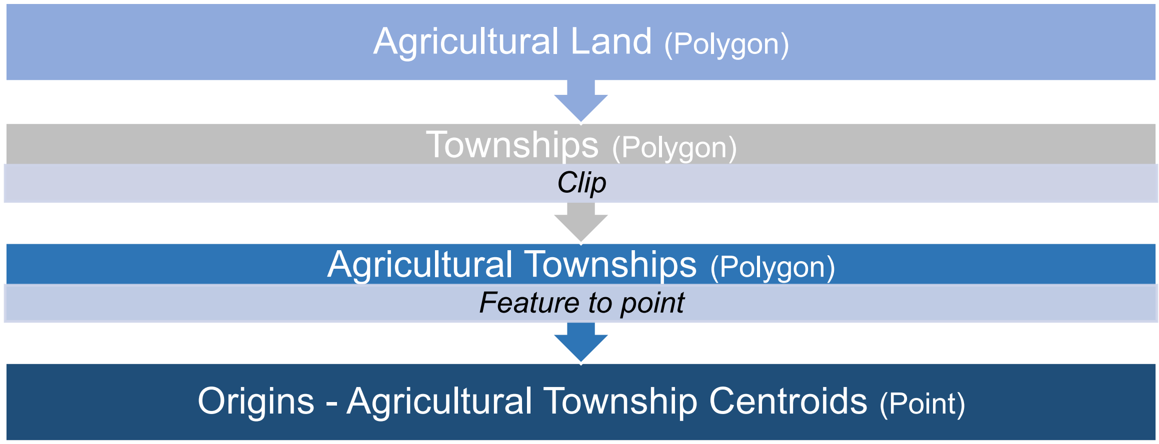


Figure 14 - Process to obtain origin points

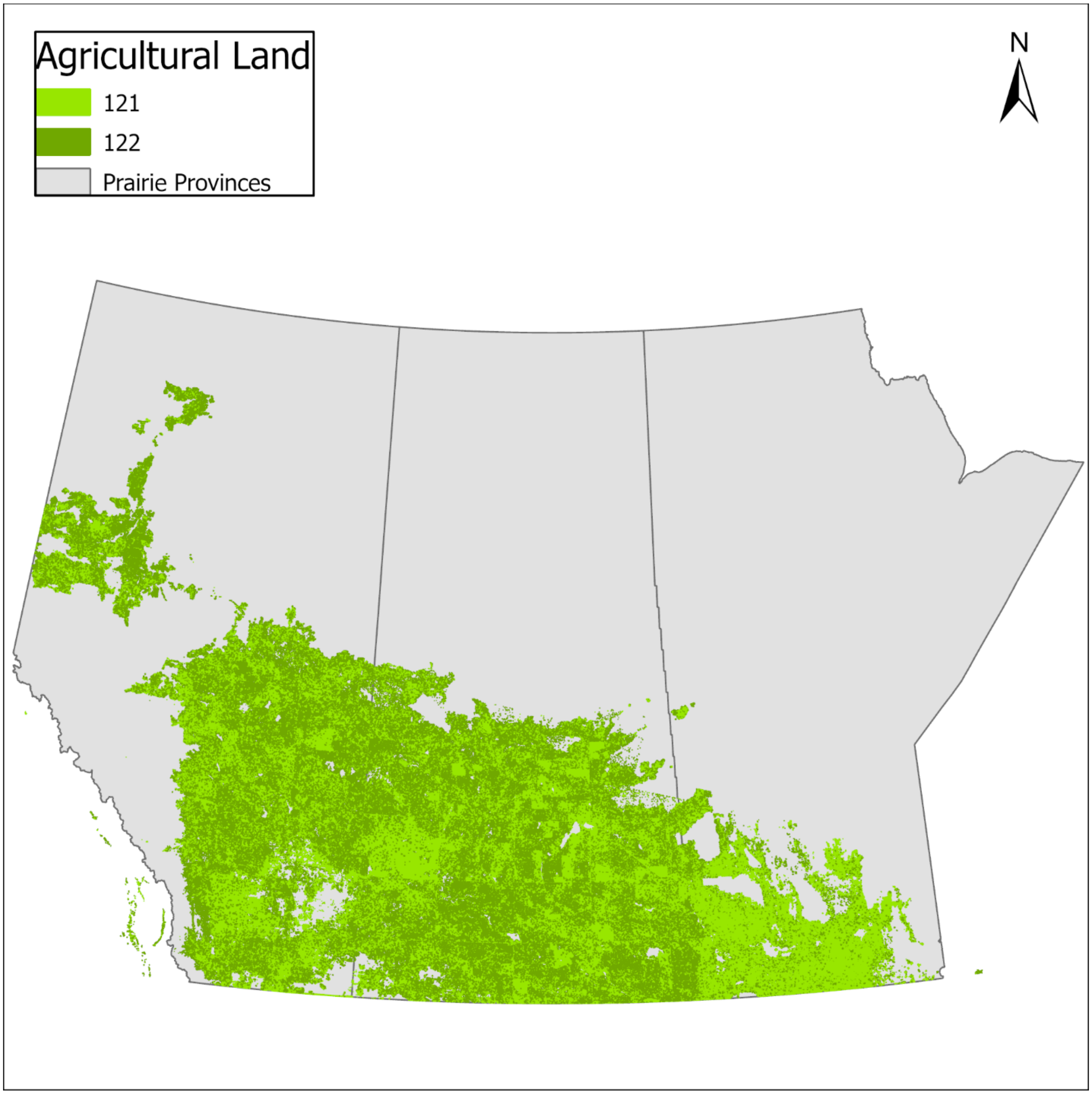


Figure 15 - Agricultural land use

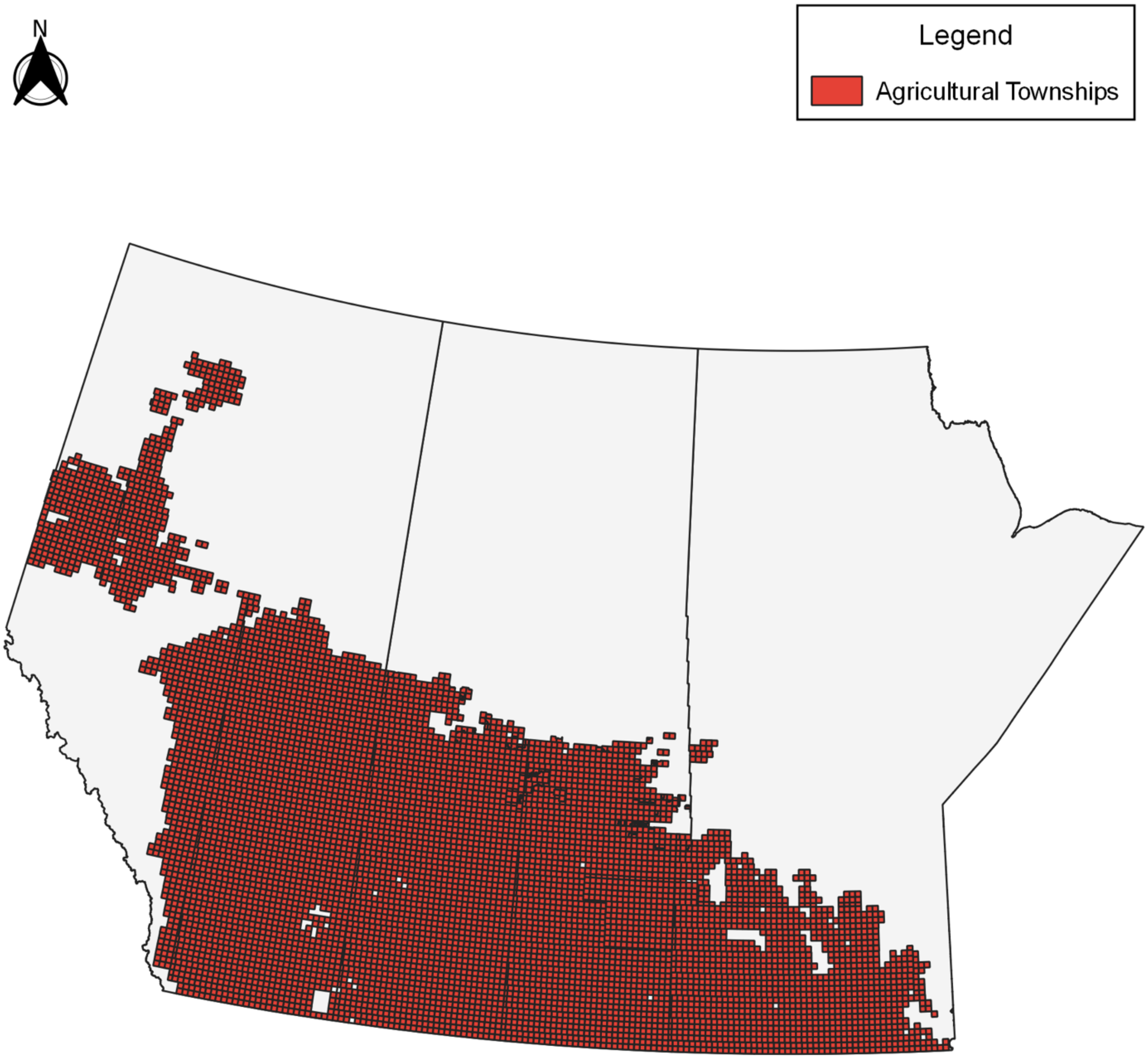


Figure 16 - Agricultural townships

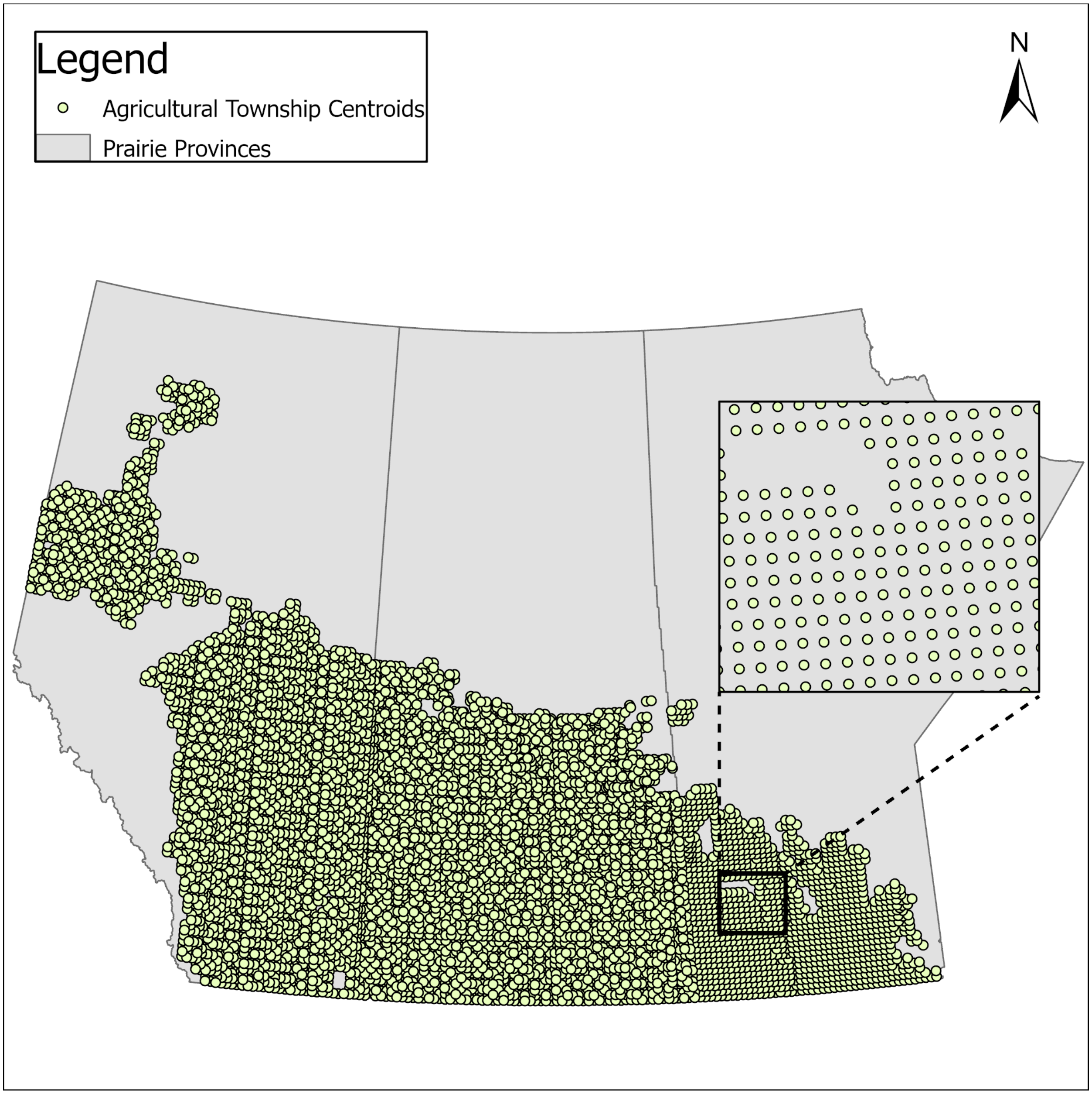


Figure 17 - Agricultural township centroids

Grain production data are then added to the centroids in order to route tonnes later in the model. To estimate the proportion of the crop yield that was produced in each township, the production rate of each SADR, i, is determined by dividing the crop yield in the SADR by the area of that SADR (Equation 1).

$$(1) \quad Crop\ Production\ Rate\ in\ SADR\ i\ = \frac{(Crop\ yield)_i}{Area_i}$$

Each agricultural township, j, is then assigned an SADR by using the *Select layer by location* feature in ArcGIS to select the townships within each SADR. Once each township has an assigned SADR, the crop production rate of the SADR is multiplied by the area of the township, shown in Equation 2, to determine the quantity of grain produced in each township in metric tonnes.

$$(2) \quad Crop\ produced\ in\ township\ j\ = (Crop\ Production\ Rate\ in\ SADR)_i \times\ Area_{\ j}$$

3.2.1.2. Destinations

Grain elevator locations in the region are the destinations for this model. The locations of these destinations can be seen in Figure 18. The quantities of grain delivered to the elevators, including barley, canola, oats, soybeans, and wheat, are obtained from the CGC table titled *Licensed elevator charge summaries,* reported in thousands of metric tonnes. These data are added to the grain elevators by joining the table obtained from the CGC, matching the station names. Each of the five grains are joined to the shapefile, then the sum of the five grains is calculated to give a total deliveries value in thousands of metric tonnes.

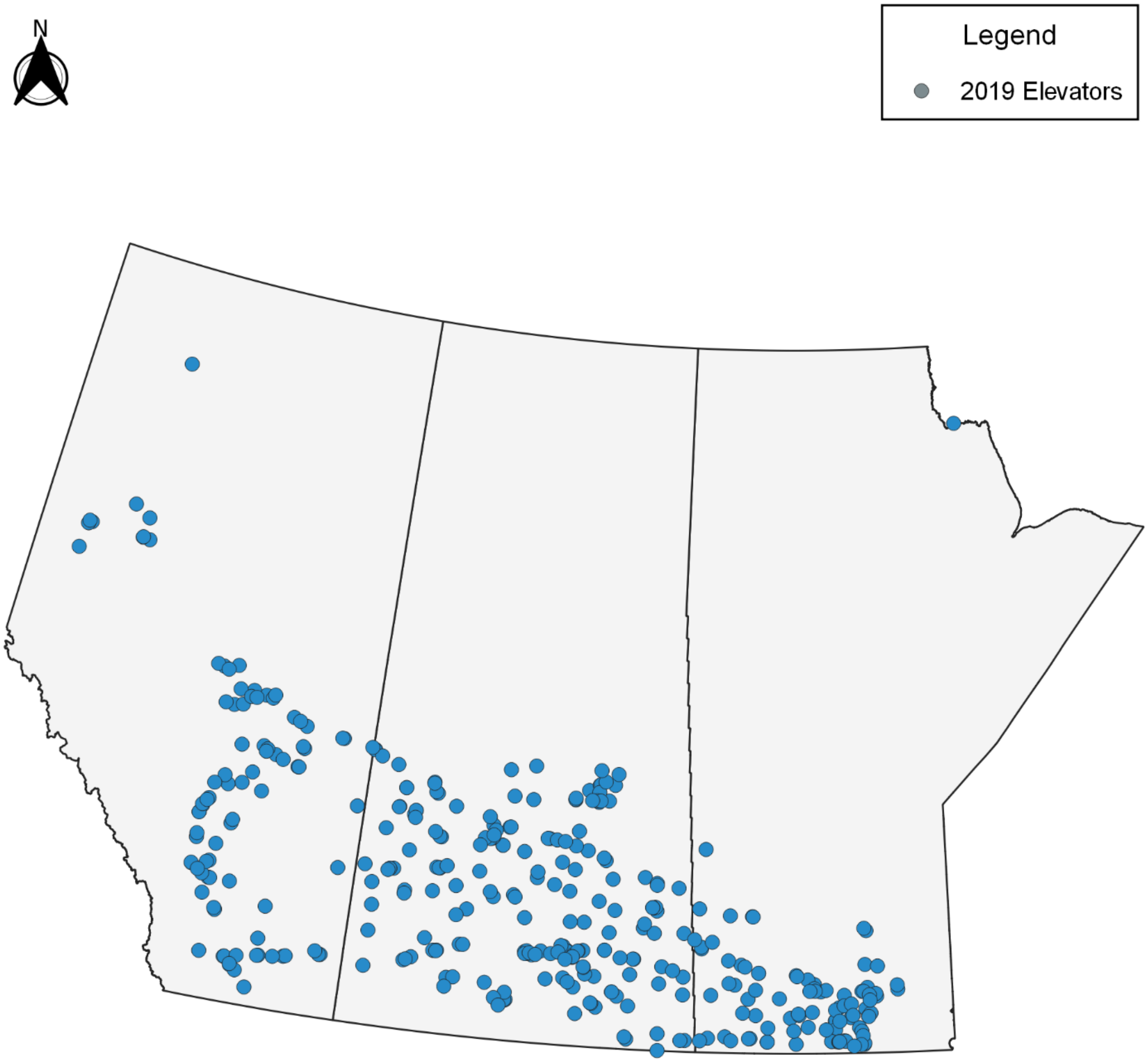


Figure 18 - Canadian Grain Commission elevators in the study region

3.2.2. Distribution

The distribution step is accomplished using a singly constrained gravity model by productions. This step uses the *Gravity Model* geoprocessing tool from an opensource ArcGIS geoprocessing toolbox from ESRI called *Gravity, Spatial Interaction, Movement, and Centrality Modeling Tools*. This tool requires the following parameters:

- Destination Features
- Destination Name Field
- Destination Attractiveness Field
- Origin Features

As previously mentioned, the Destination Features are the grain elevators, and the Origin Features are the township centroids. The Destination Name Field is the Station field in the grain elevators shapefile, and total deliveries to each elevator are used as the Destination Attractiveness Field.

The gravity model resulted in each township being assigned to a grain elevator, as shown in Figure 19, with the map legend in Figure 20.

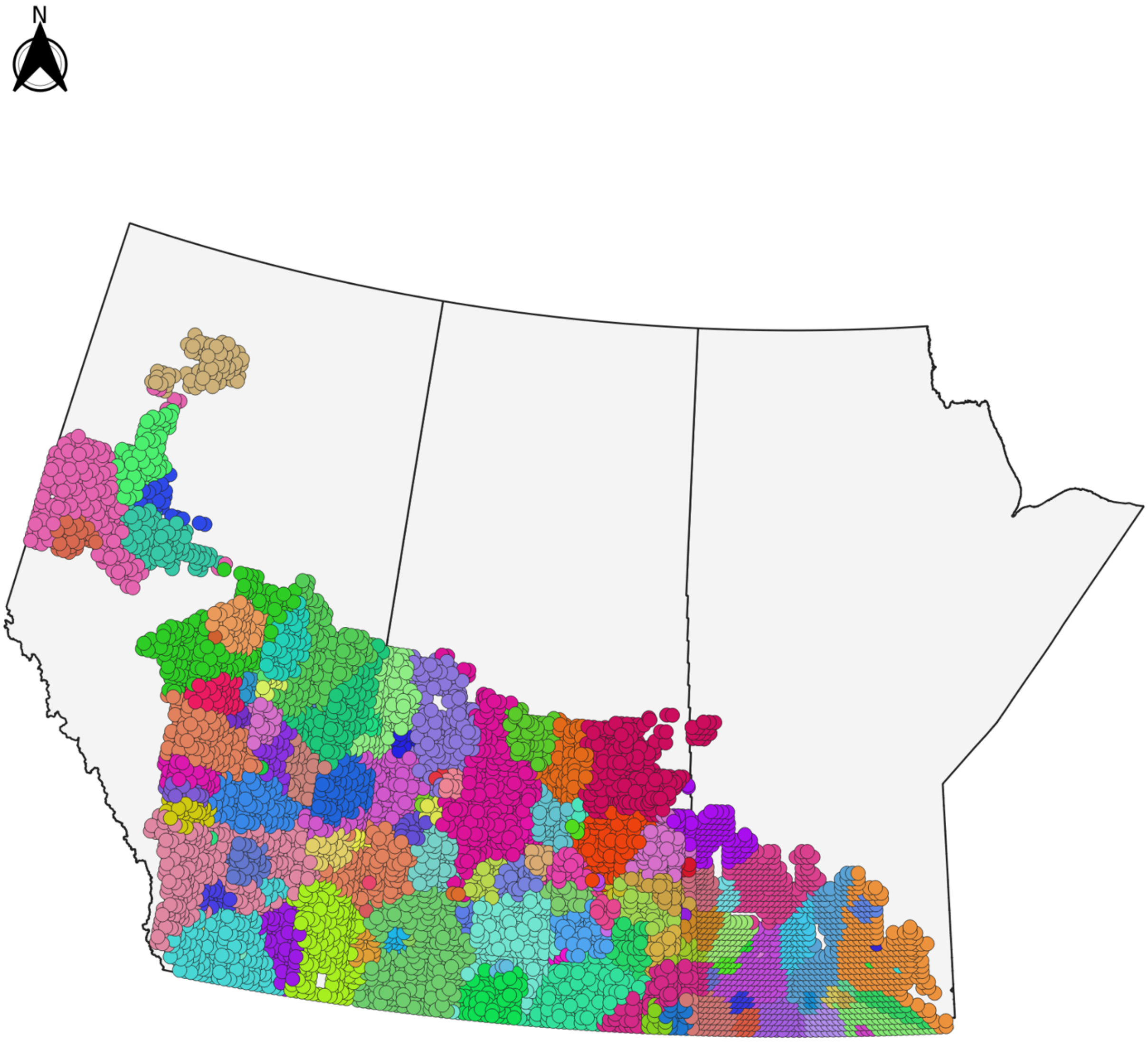


Figure 19 - Gravity model results

Legend

Acheson	Daysland	Lethbridge	Roblin
Agassiz	Dinsmore	Lloydminster	Rosetown
Amazon	Dixon	Long Plain	Rycroft
Antelope	Dunmore	Lucky Lake	Saskatoon
Arborg	Dutton	Lyalta	Sexsmith
Assiniboia	Edmonton	Maidstone	Shoal Lake
Balcarres	Elm Creek	Maple Creek	Smoky River
Balgonie	Elva	Marengo	Souris East
Barrhead	Estevan	Marshall	South Lakes
Beausejour	Fairlight	Maymont	Star
Beechy	Fort Macleod	Melfort	Starbuck
Biggar	Fox Valley	Melville	Stettler
Binscarth	Gaudin	Minnedosa	Stirling
Blackie	Gladstone	Mollard	Strongfield
Bloom	Glenlea	Moose Jaw	Swan Rv Valley
Boissevain	Glossop	Moosomin	Swift Current
Booth Siding	Grenfell	Morinville	Tisdale
Bow Island	Grimshaw	Morris	Trochu
Bowden	Gull Lake	N Battleford	Unity
Brada	Hamlin	Naicam	Vegreville
Brandon	High Level	Nampa	Vermilion
Camrose	Indian Head	Netley	Viking
Canora	Ituna	Northgate	Virden
Carlea	Kamsack	Oakner	Vulcan
Carnduff	Kegworth	Oban	Wadena
Carseland	Killam	Olds	Watson
Cassils	Killarney	Oyen	Westlock
Clavet	Kindersley	Prairie West	Wetaskiwin
Colonsay	Lacombe East	Provost	Weyburn
Congress	Lamont	Quill Lake	White Star
Corinne	Langenburg	Rathwell	Whitewood
Crossfield	Last Mountain S	Red River South	Winnipeg
Cupar	Lavoy	Redcoat	Yorkton
Dauphin	Leader	Reed Lake	
Davidson	Leross	Reford	

Figure 20 - Gravity model results legend

3.2.3. Assignment

This section discusses the methodology used to generate the assignment step of the demand model.

3.2.3.1. Road Network

The road network for the model is derived from the census road file by removing rank 5 roads and city roads to create a highway network. The highway road file is then reduced from double centerlines to single centerlines by labelling northbound and eastbound roads as A and southbound and westbound roads as B, then turning off the roads labelled as B. The highway network is then attributed with the speed limit and weight restriction data.

3.2.3.2. Network Dataset

The initial network dataset is created using the highway road network attributed with speed limit and weight restriction data. The network dataset includes time and distance as costs for the model, and weight restrictions as a hierarchy. Time, in hours, is a function of the speed limit and distance as shown in equation 3, and distance is calculated by ArcGIS as the length of the segment in kilometres. The hierarchy for weight restrictions is as follows: weight classes 1 and 2 are primary roads, weight classes 3 and 4 are secondary roads, and roads with weight class 5 are considered local roads.

$$(3) \quad FreeFlowTime\ (hr) = {Distance\ (km)} \Big/ {Speed\ limit\ (\tfrac{km}{hr})}$$

This dataset, however, leads to issues when trying to use the routing tool in ArcGIS. For example, as shown in Figure 21, given the time, distance, and a weight restriction hierarchy as the set costs of the network dataset, the path chosen by ArcGIS from the Reed Lake township point to the Reed Lake elevator is not the logical choice. In the example the logical route, based on posted speed limits, distance, and road weight restrictions, is north from the Reed Lake township, then west to the elevator.

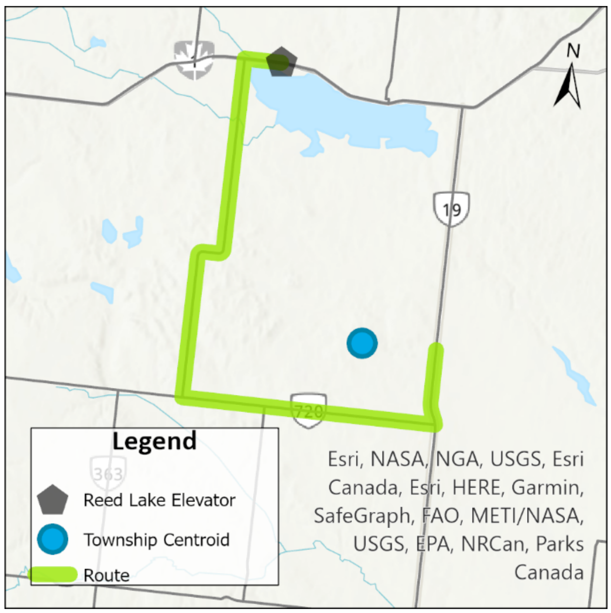


Figure 21 - Initial network dataset Reed Lake example

To resolve the routing issues on the initial network dataset, time, as a function of the speed limit, is removed from the costs, leaving distance and the weight restrictions hierarchy. As demonstrated in Figure 22, the use of these costs creates a more accurate route for the Reed Lake township to the Reed Lake elevator based on the true posted speed limits, distance, and road weight restrictions.

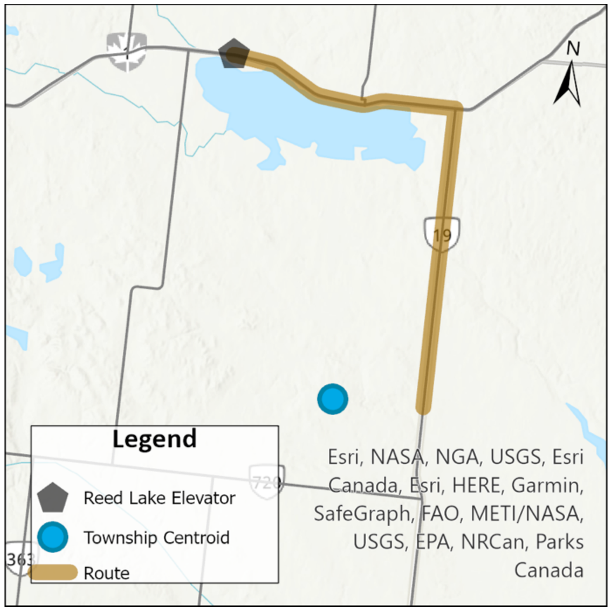


Figure 22 - Final network dataset Reed Lake example

3.2.3.3. Routing

Using the results from the gravity model, each township is routed to the elevator specified by the gravity model using the *Route Network Analyst.* The tonnes were added to the routes with an all-or-nothing approach as there is no risk of reaching the capacity of any road segment due to hopper bottom trucks being an overall small portion of the total AADT on any road segment. The first step in the network analysis is creating a *stop* on the road closest to the township centroid, then creating a second *stop* at the specified elevator for each township assigned to the elevator. Once the stops have been created for all the townships specified by the gravity model for the specific elevator (e.g., see Figure 23 for all townships assigned to the Reed Lake elevator), the network analyst is run. Running the network analyst determines the shortest path, with the given costs in the network dataset, between the township stops and the elevator, as shown for Reed Lake in Figure 24.

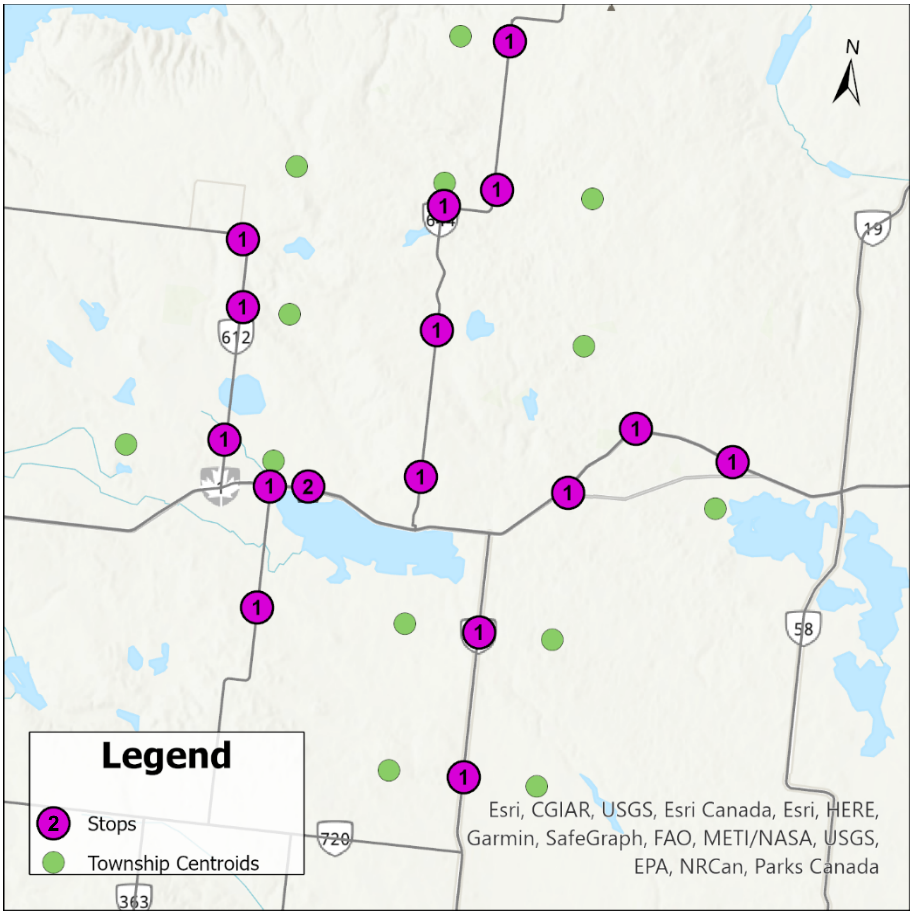


Figure 23 - Reed Lake route stops

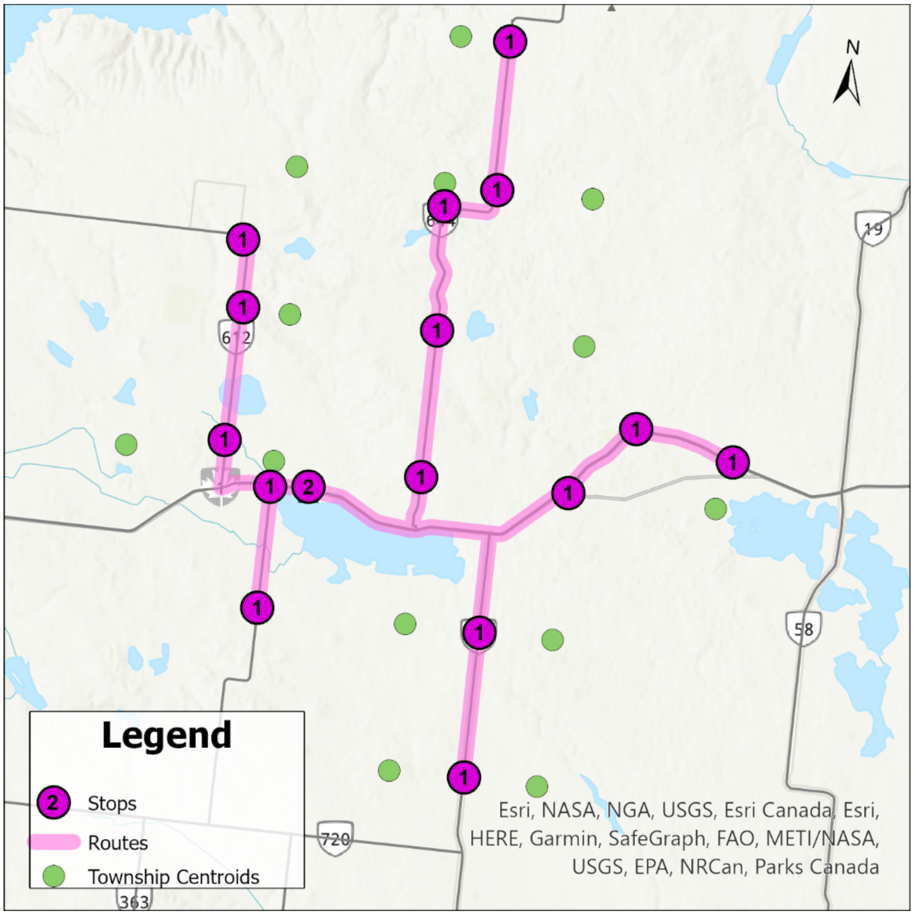


Figure 24 - Reed Lake routes

Each township for the given elevator is assigned a route number. The stop used on the network analyst is given the same route number, along with a sequence number. Each township stop is given the sequence number 1, and each elevator stop is given the sequence number 2, as shown in Figure 23. These sequence numbers direct the route to run from the township to the elevator. The route determined between the township and elevator will be assigned the same route number as the stop when the network analyst is run.

3.2.3.4. Assigning Tonnes

The routes are then *joined* to the township centroids based on the assigned route number. This allows for the routes to be attributed with the produced grain volumes from each township, including barley, canola, oats, soy, wheat, and the total tonnes produced. The routes from an elevator with a completed join can then be added to a new shapefile containing all the routes from all the elevators in the region. Figure 25 shows the completed shapefile with the routes from all elevators in the region.

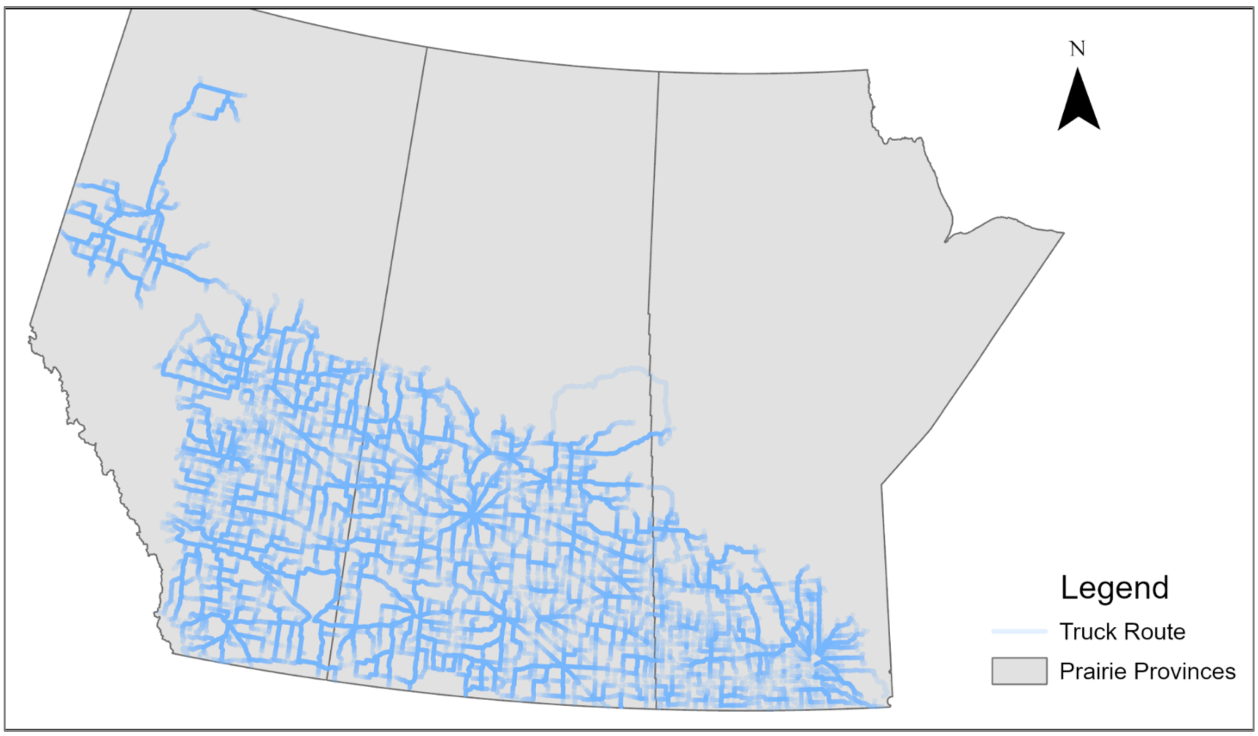


Figure 25 - Map of assigned truck routes, overlapping where routes share road segments

Using the *spatial join* geoprocessing tool and the join operation of *share a line segment with,* all of the routes that overlap an individual segment of the road network are summed together in terms of barley production, canola production, oats production, soy production, wheat production, and total production.

3.3. HOPPER BOTTOM TRUCK DEMAND (HBTD) MODEL METHODOLOGY

This section discusses the methodology used to calculate hopper bottom truck traffic on the road network to create the HBTD model as an extension from the GTD model.

3.3.1. Hopper Bottom Truck Body Type

The proportion of hopper bottom trucks on Manitoba highways in relation to total trucks is calculated from body type and vehicle class distribution data obtained from the Headingley weigh scale on Highway 1 in Manitoba (Maranchuk, 2016). These data are broken down into 28 axle configurations and 16 body types. For the HBTD model, hopper bottom trucks with 3-S2, 3-S3, and 3-S3-S2 axle configurations are considered. The proportion of trucks that are hopper bottom for each axle configuration is determined using equation 4.

$$(4) \qquad (PT_i) = \frac{(T_H)_i}{(T_T)_i}$$

Where:

PT_i = *proportion of trucks that are hopper bottom for axle configuration i*

$(T_H)_i$ = *hopper bottom trucks with axle configuration i*

$(T_T)_i$ = *total trucks with axle configuration i*

The proportion of hopper bottom trucks with each axle configuration is then determined using equation 5.

$$(5) \qquad PHB_i = \frac{(T_H)_i}{\sum_{i=1}^{3}(T_H)_i}$$

Where:

PHB_i = *proportion of hopper bottom trucks with axle configuration i*

$(T_H)_i$ = *hopper bottom trucks with axle configuration i*

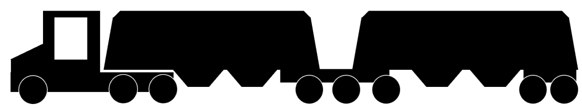
3.3.2. Loading Trucks

To calculate the amount of grain each truck type can carry, the density of each grain, the maximum volumetric capacity of each truck type, and the maximum weight of each truck type are determined. The model uses the values shown in Table 3 and Table 4.

Table 3 - Grain densities in tonne/m³

Grain Densities (tonne/m³) (Harvard, n.d.)	
Barley	0.615
Canola	0.705
Oats	0.410
Soybeans	0.769
Wheat	0.769

Table 4 - Maximum payload, maximum volumetric capacity, and schematics of the three axle configurations

Axle Configuration	Maximum Payload (tonnes) (Maranchuk, 2016)	Maximum Volumetric Capacity (m^3) (Lode King, 2022)	Schematic
3-S2	27.24	51.76	
3-S3	32.74	61.36	
3-S3-S2	44.22	83.28	

Once the truck specifications are determined, the grain densities and maximum volumetric capacity and payload are used to calculate the design density to determine if each grain type will cause the truck to weigh out or cube out. The design density is the density at which the vehicle both weighs-out and cubes-out (Regehr et al., 2009). The design density is determined by dividing the vehicle's maximum volumetric capacity by the maximum payload. If the density of the commodity is higher than the design density, the truck weighs-out. If the density of the commodity is lower than the design density, the truck cubes-out. This determines the maximum number of tonnes each axle configuration can carry. The final step in the model is to calculate the total number of trucks on each road segment using equation 6. Equation 6 is multiplied by two to include empty truck trips, which are assumed to utilize the same route when they return from the delivery point.

$$(6) \qquad Hopper\ Bottom\ Trucks\ on\ Road\ Segment =$$

$$2 * \sum_{g=1}^{5} \frac{t_g}{\left(t_{P_{3-S2(g)}} * PHB_{3-S2}\right) + \left(t_{P_{3-S3(g)}} * PHB_{3-S3}\right) + \left(t_{P_{3-S3-S2(g)}} * PHB_{3-S3-S2}\right)}$$

$Where$:

$g \ = \ grain\ type_{(1=barley, 2=canola, 3=oats, 4\ =\ soybeans, 5\ =\ wheat)}$

$t_g = tonnes\ of\ grain\ type\ g\ on\ road\ segment$

$t_{P_{i,g}} = payload\ of\ configuration\ type\ i\ for\ grain\ type\ g\ in\ tonne$

$PHB = percentage\ of\ hopper\ bottoms\ trucks\ with\ the\ specified\ configuration\ type$

The following is a sample calculation using the methodology discussed above.

Known:

	3-S2	**3-S3**	**3-S3-S2**
Max payload (tonnes)	27.24	32.74	44.22
Max volume (m³)	51.24	61.36	83.28

Grain	**Density (tonnes/m³)**
Barley	0.615
Canola	0.705
Oats	0.410
Soybeans	0.769
Wheat	0.769

Percentage of hopper bottom trucks (p):

$$PHB_{3-S2} = 21\%$$

$$PHB_{3-S3} = 14\%$$

$$PHB_{3-S3-S2} = 65\%$$

To determine maximum payloads for each axle configuration and grain, the design density must be calculated.

Using the maximum payload and volume for 3-S2's:

$Design\ Density = \frac{27.24\ tonnes}{51.24\ m^3} = 0.532\ tonnes/m^3$

Therefore, barley, canola, soybeans, and wheat weigh out, while oats cube out. This leads to the following loads for each axle configuration and grain type in tonnes:

	3-S2 payloads (tonnes)	3-S3 payloads (tonnes)	3-S3-S2 payloads (tonnes)
Barley	27.24	32.74	44.22
Canola	27.24	32.74	44.22
Oats	$0.41 \times 51.24 = 21\ .0$	$0.41 \times 61.36 = 25.2$	$0.41 \times 83.28 = 34.1$
Soybeans	27.24	32.74	44.22
Wheat	27.24	32.74	44.22

Tonnes of each grain on the road segment:

$$t_1 = 5901\ tonnes$$

$$t_2 = 20{,}262\ tonnes$$

$$t_3 = 2850\ tonnes$$

$$t_4 = 2538\ tonnes$$

$$t_5 = 31{,}152\ tonnes$$

Plugging everything into equation 6:

$$Hopper\ Bottom\ Trucks\ on\ Road\ Segment$$
$$= 2 * \sum_{g=1}^{5} \frac{t_g}{\left(t_{P_{3-S2(g)}} * PHB_{3-S2}\right) + \left(t_{P_{3-S3(g)}} * PHB_{3-S3}\right) + \left(t_{P_{3-S3-S2(g)}} * PHB_{3-S3-S2}\right)}$$

$$= 2 * (\frac{5901}{(27.24 * 0.21) + (32.74 * 0.14) + (44.22 * 0.65)} +$$

$$\frac{20{,}262}{(27.24 * 0.21) + (32.74 * 0.14) + (44.22 * 0.65)} +$$

$$\frac{2850}{(21 * 0.21) + (25.2 * 0.14) + (34.1 * 0.65)} +$$

$$\frac{2538}{(27.24 * 0.21) + (32.74 * 0.14) + (44.22 * 0.65)} +$$

$$\frac{31{,}152}{(27.24 * 0.21) + (32.74 * 0.14) + (44.22 * 0.65)})$$

$$= 3255\ hopper\ bottom\ trucks\ on\ the\ road\ segment\ in\ a\ year$$

3.4. HOPPER BOTTOM TRUCK TRAFFIC (HBTT) MODEL

Network-level estimates of truck traffic flows (expressed as annual average daily truck traffic volumes) are produced using a hierarchical approach adapted from Regehr and Reimer (2013). This section summarizes the approach used to create the truck traffic model along with the steps taken to convert this model into the hopper bottom truck traffic (HBTT) model. In this way, the HBTT model can be used as an independent comparator to the HBTD model. The total truck traffic model essentially provides an upper bound to the number of trucks on any road in the province of Manitoba, limiting the scope of this portion of the research to the province of Manitoba.

The hierarchical approach leverages the relatively strong classification and temporal monitoring capabilities at permanently installed AVCs to compensate for the sparsely collected classification data on Manitoba's highway network. Data from these sites are supplemented by available data from short duration counts and existing AADT estimates.

All traffic data sites are classified into one of three levels:

- Level 1 sites are those that continuously classify vehicles. In the Manitoba context, these are exclusively sites with AVC and/or WIM technology. Data for these sites must satisfy the requirements to estimate AADT for each vehicle class (that is, at least one full day of data exist for each day of week within each month). Thus, in some cases, the data are taken from previous years to satisfy this requirement, as far back as the 2015 data year.

- Level 2 sites are those that provide short duration classification data (i.e., they have some period of classification data that do not satisfy the requirements to estimate AADT for each vehicle class). For this research, this is limited to turning movement counts with full classification data (Manitoba also conducts limited classification turning movement counts that are unusable in this case). These are further subdivided into level 2A sites – those which contain data for at least 48 hours – and level 2B sites, which contain data for 6 to 47 hours.
- Level 3 sites are those that have traffic volume data but do not have any available classification data. These are subdivided into level 3A and level 3B sites. Level 3A sites are near level 1 or 2 sites without major intersecting roads. The classification distribution at the nearby higher-level sites is assumed to be applicable to the level 3A sites. Remaining level 3 sites are classified as level 3B sites, where the vehicle classification distribution is assigned by truck traffic classification group (TTCG).

Data from level 1 sites are used to generate truck traffic pattern groups (TTPGs) that are applied to level 2 sites to generate truck traffic flow estimates by class. TTPGs consider the variation of single-unit trucks, single-trailer trucks, and multiple-trailer trucks by day-of-week, hour-of-day, and month-of-year at each level 1 site. Cluster analysis using Euclidean distance between each data vector is used to group the sites with similar temporal trends in these three subdivisions of vehicle classifications. Engineering judgment is used to define the TTPGs in terms of identifiable roadway and operational characteristics of the contained sites (e.g., all sites on PTH 6 fall into TTPG

2). Finally, an assignment algorithm is developed and applied to assign level 2 sites to the appropriate TTPG.

Using a similar process, TTCGs are created using Level 1 site classification data. This begins with a cluster analysis using the classification distribution of classes 5, 6, 9, 10, and 13, as well as the total proportion of trucks to all vehicles at each Level 1 site, based on Euclidean distances. These classes are selected because they are the most prominent vehicle classes in the Manitoba context. Engineering judgment is used to define the TTCGs in terms of identifiable roadway and operational characteristics of the contained sites (e.g., all sites on PTH 6 fall into TTCG 3) (Reimer & Regehr, 2013). Finally, an assignment algorithm is developed and applied to assign level 3B sites to the appropriate TTCG.

Truck traffic volume is estimated at all sites using a hierarchical approach. Roadways are divided into truck traffic sequences, based on an assumption of homogeneity along the segment (Ominski et al., 2022). Truck traffic sequences are classified as level 1, 2, or 3, based on the available data on the sequence. Level 1 sequences adopt the truck traffic flows of the level 1 site. Truck traffic flows on level 2 sequences are estimated by applying temporal factors from the associated TTPG to the short duration classification data produced at the level 2 site. Truck traffic flows on level 3A sequences are estimated by multiplying the classification distribution at a nearby level 1 or 2 sequence by the existing traffic volume estimate (AADT) at the level 3A site. Finally, truck traffic flows on level 3B sequences are estimated by multiplying the classification distribution of the assigned TTCG by the existing traffic volume estimate (AADT) at the level 3B site.

To calculate the HBTT model volumes to compare to the HBTD model results, the AADTT values from the truck traffic model are multiplied by 365 to give a total annual volume of trucks. To determine the number of hopper bottom trucks represented in this truck traffic model, the same proportions of hopper bottom trucks used in the HBTD model, as discussed in section 3.3, are used. However, the truck traffic model has vehicle classification broken down into the 13 FHWA classes. On divided highways, class 13 consists of more axle configurations than solely 3-S3-S2s since considerable LCV traffic is present on these routes. Therefore, to determine the number of hopper bottom trucks on these routes, the total number of class 13 vehicles is first disaggregated to estimate the number of 3-S3-S2s within class 13, and then the volume of 3-S3-S2s is multiplied by the proportion of hopper bottom trucks for that configuration.

4. ANALYSIS RESULTS

This chapter presents and discusses the results of the (1) the grain tonnage demand (GTD) model, (2) the hopper bottom truck demand (HBTD) model, and (3) the hopper bottom truck traffic (HBTT) model. The chapter provides a comparison between the HBTD and HBTT models, summarizes the limitations of this work, and explores the implications for freight planning and data collection.

4.1. GRAIN TONNAGE DEMAND (GTD) MODEL RESULTS

This section discusses the results of the GTD model. Figure 26 shows the total flow of tonnes of grain (i.e., barley, canola, oats, soybeans, and wheat) along highways in the Canadian Prairie Region. The tonnages reported in this section refer to the payload of the truck, excluding the tare weight of the truck.

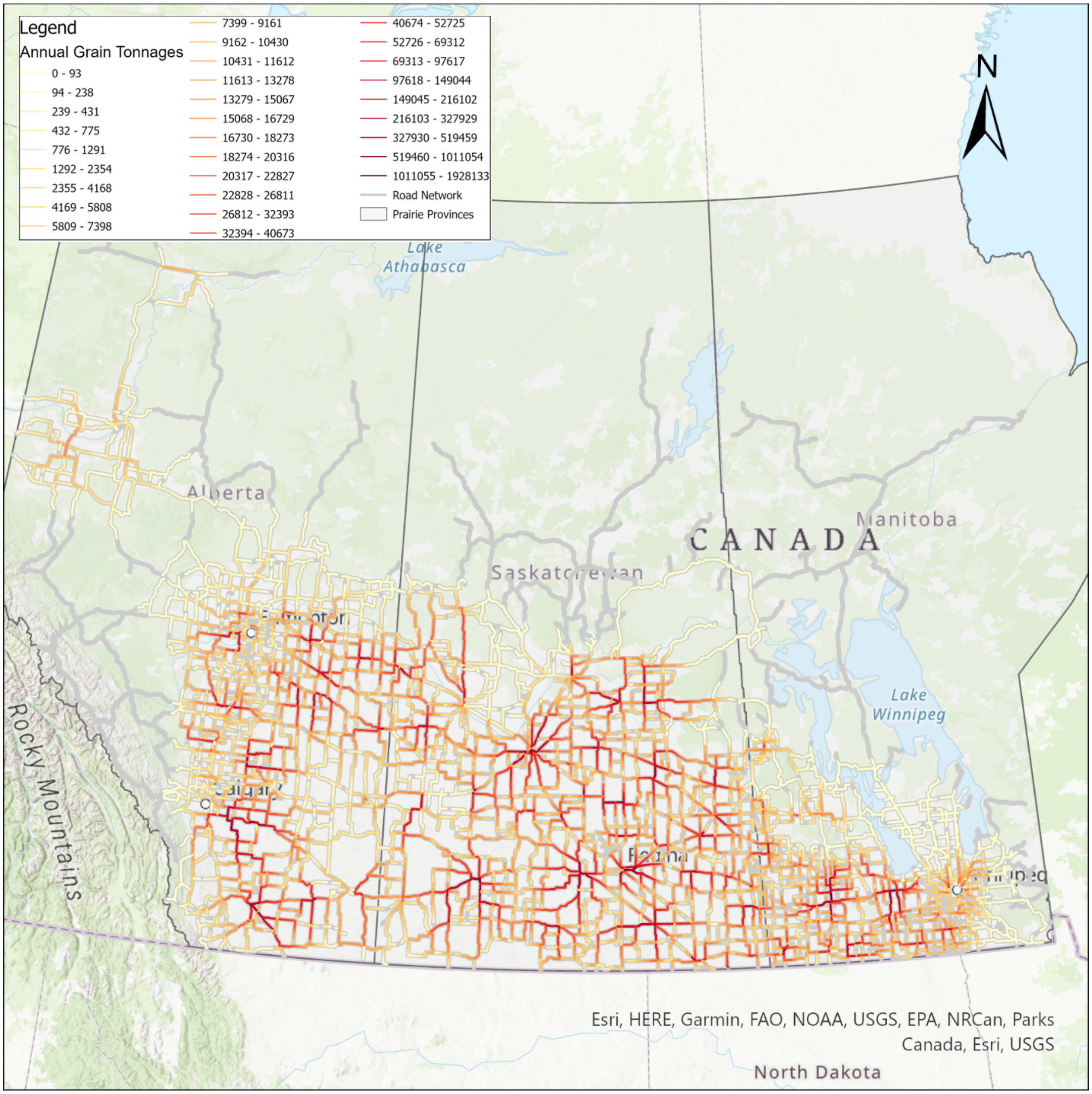


Figure 26 – Total annual flow of grain in the Canadian Prairie Region

Figure 26 shows the following:

- The highest quantity of grain movement in the region, with total tonnages between approximately 1 million and 2 million tonnes annually, occurs on two segments in Manitoba (Highway 1 near Portage la Prairie, Highway 10 near

Brandon), five segments in Saskatchewan (Highway 1 near Regina, Highway 1 near Moose Jaw, Highway 1 near Swift Current, Highway 15 near Last Mountain Lake, Highway 35 near Wadena), and two segments in Alberta (Highway 3 near Lethbridge, Highway 24 near Calgary).

- The areas with the lowest quantity of grain movement in the region, while still having some grain movement, are the southeastern corner of Manitoba, the Interlake region of Manitoba, the northern region of Saskatchewan, and the western region of Alberta, just east of the Rocky Mountains. Roads in these areas saw less than 100 tonnes of grain moved in 2019.

Table 5 summarizes grain tonnages by province. It shows the following:

- Of the three prairie provinces, Saskatchewan has the highest total tonne-kilometers of grain on the road network in 2019, at 1,220 million tonne-kilometers. The maximum tonnes carried on a single road segment in the province is 1,574 thousand tonnes and the average tonnage on the Saskatchewan road network is 62 thousand tonnes. The average tonnes on a road segment are calculated by dividing the load on every road segment in Saskatchewan by the number of road segments.
- Alberta is second among the prairie provinces in terms of tonne-kilometers carried on the road network in 2019, with 620 million tonne-kilometers. The maximum tonnes carried on a single road segment in Alberta is 1,088 thousand tonnes and the average tonnage on the Alberta road network is 33 thousand tonnes.

- Manitoba carries the fewest tonne-kilometers of the prairie provinces with 344 million tonne-kilometers. However, the maximum tonnage in Manitoba (1928 thousand tonnes) exceeds the maximum tonnages in Alberta and Saskatchewan, and the average tonnage on the Manitoba road network (37 thousand tonnes) is higher than the average tonnage in Alberta.

Table 5 – Annual tonnages in the Canadian Prairie Region by province

Province	Tonne-km (millions)	Maximum tonnes on any segment (thousands of tonnes)	Average tonnes on a segment (thousands of tonnes)
Alberta	620	1,088	33
Saskatchewan	1,220	1,574	62
Manitoba	344	1,928	37
Total	2,184	4,590	133

Table 6 summarizes grain tonnages by grain type. It shows the following:

- Of the five grain types studied, wheat generates the most tonne-kilometers on the network at 1,076 million tonne-kilometers, with a maximum load on a single road segment of 989 thousand tonnes of wheat and an average load on the network of 22 thousand tonnes of wheat.
- Canola creates the second most tonne-kilometers on the network at 642 million tonne-kilometers, with a maximum load on a single road segment of 628 thousand tonnes of canola and an average load on the network of 13 thousand tonnes of canola.
- Barley creates the third most tonne-kilometers on the network at 323 million tonne-kilometers, with a maximum load on a single road segment of 312

thousand tonnes of barley, and an average load on the network of seven thousand tonnes of barley.

- Fourth among the five grain types studied, oats create 105 million tonne-kilometers on the network, with a maximum load on a single road segment of 171 thousand tonnes of oats and an average load on the network of two thousand tonnes of oats.
- Soybeans create the fewest tonne-kilometers on the network at 39 million tonne-kilometers, with a maximum load on a single road segment of 213 thousand tonnes of soybeans and an average load on the network of one thousand tonnes of soybeans.

Table 6 – Annual tonnages in the Canadian Prairie Region by grain type

Grain	Tonne-km (millions)	Maximum tonnes on any segment (thousands)	Average tonnes on a segment (thousands)
Wheat	1,076	989	22
Canola	642	628	13
Barley	323	312	7
Oats	105	171	2
Soybeans	39	213	1
Total	2,184	1,928	46

Table 7 summarizes grain tonnages by the weight restrictions used as the hierarchy for the GTD model. It shows that the highest weight class roads (class 1) carry the most tonne-kilometers with 1,561 million tonne-kilometers. Class 1 roads make up 34,522 km of the total 56,326 km of roadway being used in this GTD model. Class 2 roads make up 7,079 km, class 3 roads make up 6,254 km, and the final 8,472 km are class 4 roads.

Table 7 – Annual tonnages in the Canadian Prairie Region by highway weight restriction class

Highway weight restriction class	Tonne-km (millions)	Maximum tonnes on any segment (thousands)	Average tonnes on a segment (thousands)
1	1,561	1,928	52
2	236	566	39
3	142	400	24
4	244	1,228	36
Total	2,184	4,122	151

Table 8 summarizes grain tonnages on specific highways. It shows the following:

- When ranked by tonne-kilometers, national highways 1 and 16 rank first and second overall, respectively. Highway 1 carries a total of 163 million tonne kilometers, has a maximum load of 1,590 thousand tonnes on a segment, and has an average load of 125 thousand tonnes across the entire highway. Highway 16 carries a total of 62 million tonne-kilometers, has a maximum load of 864 thousand tonnes on a segment, and has an average load of 58 thousand tonnes across the entire highway.
- The top two highways in Manitoba in the top 35 when ranked by tonne-kilometers are highways 10 and 3, ranked 8th and 18th overall, respectively. Highway 10 carries a total of 37 million tonne kilometers, has the highest maximum load on a segment in the region with 1,928 thousand tonnes, and has an average load of 101 thousand tonnes across the entire highway. Highway 3 carries a total of 22 million tonne kilometers, has a maximum load of 246 thousand tonne kilometers, and an average load of 74 thousand truck kilometers across the entire highway.
- The top two highways in Saskatchewan when ranked by tonne-kilometers are highways 35 and 4, ranked third and fourth overall, respectively. Highway 35 carries a total of 60 million tonne-kilometers, has a maximum load of 528

thousand tonnes on a segment, and has an average load of 124 thousand tonnes across the entire highway. Highway 35 also carries a total of 60 million tonne-kilometers but has a maximum load of 561 thousand tonnes on a segment and has an average load of 106 thousand tonnes across the entire highway.

- The top two highways in Alberta when ranked by tonne-kilometers are highways 24 and 4, ranked 12th and 19th overall. Highway 24 carries a total of 32 million tonne kilometers, has a maximum load of 1,024 thousand tonnes on a segment, and has an average load of 417 thousand tonnes across the entire highway. Highway 4 carries a total of 21 million tonne-kilometers, has a maximum load of 434 thousand tonnes on a segment, and has an average load of 215 thousand tonnes across the entire highway.

Table 8 – Annual tonnages in the Canadian Prairie Region by top 35 highways ranked by tonne-kilometers

Rank	Highway*	Tonne-km (millions)	Maximum tonnes on any segment (thousands of tonnes)	Average tonnes on a segment (thousands of tonnes)
1	**1**	163	1,590	125
2	**16**	62	864	58
3	**35**	60	528	124
4	**4**	60	561	106
5	**13**	56	413	97
6	**2**	47	385	79
7	**15**	40	1,228	86
8	**10**	37	1,928	101
9	**21**	36	216	65
10	**5**	33	698	106
11	**3**	32	300	60
12	**24**	32	1,024	417
13	**11**	30	473	106
14	**6**	29	407	77
15	**14**	27	691	118
16	**9**	25	635	65
17	**48**	23	593	123
18	**3**	22	246	74
19	**4**	21	434	215
20	**13**	20	442	70
21	**363**	19	206	100
22	**242**	19	400	168
23	**21**	18	901	51
24	**20**	18	214	75
25	**36**	18	279	37
26	**7**	17	446	92
27	**39**	17	1,283	99
28	**3**	16	362	73
29	**12**	15	605	76
30	**10**	15	1,236	95
31	**14**	14	669	65
32	**41**	14	551	41
33	**47**	14	170	42
34	**41**	14	277	119
35	**22**	13	465	72

*National Highway, Alberta, Saskatchewan, Manitoba

4.2. HOPPER BOTTOM TRUCK DEMAND (HBTD) MODEL RESULTS

This section reports the results of applying the methods described in Section 3.3 for the HBTD model. Due to data limitations, HBTD model results are only provided in Manitoba, since truck body type distributions were only available for trucks in Manitoba. Figure 27 shows the total number of loaded and empty hopper bottom trucks on roads in Manitoba in the year 2019.

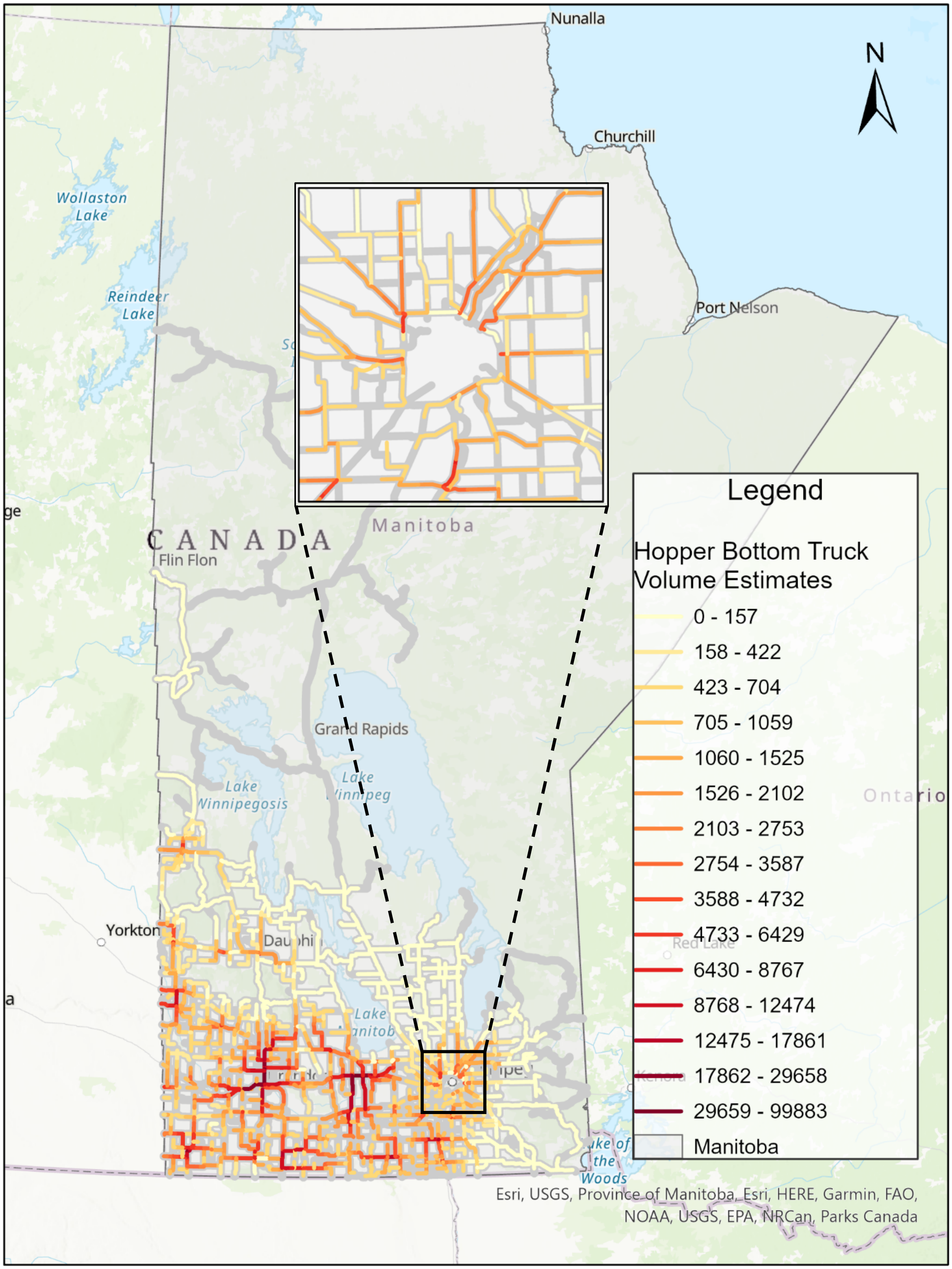


Figure 27 - Total annual volume of hopper bottom trucks in Manitoba

Figure 27 shows the following:

- The highways with the highest volume of hopper bottom trucks on the road in Manitoba are Highway 10, with the highest volume near Brandon of 99,883 trucks (274 trucks per day), followed by Highway 1, with the highest volume near Portage La Prairie of 83,587 trucks (229 trucks per day) and Highway 18, with the highest volume near Killarney of 29,658 trucks (81 trucks per day). Based on the total truck traffic model, this section of Highway 10 has an AADTT of 364, this section of Highway 1 has an AADTT of 2015, and this section of Highway 18 has an AADTT of 196.
- The lowest volume of hopper bottom trucks on the road, while still experiencing hopper bottom truck traffic in 2019, occurs mainly to the northwest of Winnipeg, with a limited number of locations along the eastern edge of the province, near the Whiteshell, and further north in the Interlake region.

Table 9 summarizes hopper bottom truck kilometers travelled (TKT) by truck configuration. It shows the following:

- Of the total 18 million TKT, 3-S3-S2s travel the most at 12 million TKT in Manitoba in the year 2019.
- 3-S2s travel the second most at four million TKT in Manitoba in 2019.
- Of the truck configuration types, 3-S3s travel the least at a total of three million TKT in Manitoba in 2019.

Table 9 – Annual hopper bottom truck kilometers travelled (TKT) by truck configuration in Manitoba

Truck configuration	TKT (millions)
3-S2	4
3-S3	3
3-S3-S2	12
Total	18

Table 10 summarizes hopper bottom TKT by grain type. This is calculated by using the proportions of each grain type produced. It can be noted that the rankings of grain on the road network are different from the regional results presented in Section 4.1 as follows:

- Of the five grain types being studied, wheat remains the highest ranked by TKT in Manitoba at 8.7 million TKT on the network, with 5.7 million TKT by 3-S3-S2s, 1.8 million TKT by 3-S2s, and 1.2 million TKT by 3-S3s in 2019.
- Canola remains the second ranked at 5.2 million TKT on the network in Manitoba, with 3.4 million TKT by 3-S3-S2s, 1.1 million TKT by 3-S2s, and 0.7 million TKT by 3-S3s in 2019.
- Soybeans are more prominent when looking at grain produced in Manitoba alone, as they create the third most TKT in Manitoba at 1.8 million total on the network, with 1.2 million TKT by 3-S3-S2s, 0.4 million TKT by 3-S2s, and 0.3 million TKT by 3-S3s trucks in 2019.
- Fourth among the five grain types studied, oats create 1.2 million TKT on the network in Manitoba, with 0.8 million TKT by 3-S3-S2s, 0.3 million TKT by 3-S2s, and 0.2 million TKT by 3-S3s in 2019.

- Unlike tonne kilometers across the region, barley creates the least TKT in Manitoba at one million total on the network, with 0.6 million TKT by 3-S3-S2s, 0.2 million TKT by 3-S2s, and 0.1 million TKT by 3-S3s in 2019.

Table 10 – Annual truck kilometers travelled (TKT) in Manitoba by grain type

Grain type	3-S2 TKT (millions)	3-S3 TKT (millions)	3-S3-S2 TKT (millions)	Total TKT (millions)
Barley	0.2	0.1	0.6	1.0
Canola	1.1	0.7	3.4	5.2
Oats	0.3	0.2	0.8	1.2
Soybeans	0.4	0.3	1.2	1.8
Wheat	1.8	1.2	5.7	8.7
Total	3.8	2.5	11.7	18.0

Table 11 summarizes hopper bottom TKT by the weight class restrictions used as the hierarchy for the HBTD model. It shows that weight class 1 roads see half of the total TKT in the province with a total of nine million TKT in 2019. Class 1 roads make up 3,812 km of the total 11,425 km of road network used in the HBTD model. Class 2 roads make up 1,783 km, class 3 roads make up 5,766 km, and class 4 roads make up a small proportion with 64 km.

Table 11 – Annual truck kilometers travelled (TKT) in Manitoba by highway weight restriction class

Highway weight restriction class	3-S2 TKT (millions)	3-S3 TKT (millions)	3-S3-S2 TKT (millions)	Total TKT (millions)
1	1.9	1.3	5.8	9.0
2	0.6	0.4	1.8	2.7
3	1.3	0.9	4.1	6.3
4	0.01	0.01	0.03	0.04
Total	4	3	12	18

Table 12 summarizes hopper bottom TKT on specific highways. It shows the following:

- The top ranked highway overall in Manitoba, excluding national highways, when looking at TKT is Highway 10 near Brandon. Highway 10 has a total TKT of 1,901 thousand with 1,236 thousand of those TKT by 3-S3-S2s, 399 thousand TKT by 3-S2s, and the final 266 thousand TKT by 3-S3s.
- The two national highways running through Manitoba, highways 1 and 16, rank first and fifth, respectively. Highway 1 has a total TKT of 2,396 thousand, with 1,557 thousand TKT by 3-S3-S2s, 503 thousand TKT by 3-S2s, and 335 thousand TKT by 3-S3s. Highway 16 has a total TKT of 756 thousand, with 492 thousand TKT by 3-S3-S2s, 159 thousand TKT by 3-S2s, and 106 thousand TKT by 3-S3s.
- The top ranked highway in the southern region of the province is Highway 3, ranked third overall with a total TKT of 1,488 thousand. Of those, 967 thousand truck kilometers are travelled by 3-S3-S2s, 312 thousand are travelled by 3-S2s, and the final 208 thousand are travelled by 3-S3s.
- The highway with the largest total TKT in the western portion of the province is Highway 83 near the Saskatchewan border. Highway 83 is ranked seventh overall with a total TKT of 495 thousand. Of those TKT, 322 thousand are travelled by 3-S3-S2s, 104 thousand are travelled by 3-S2s, and the final 69 thousand are travelled by 3-S3s.
- In the eastern portion of the province, Highway 59 running from the United States border to Lake Winnipeg is the highest ranked highway. Highway 59 is ranked 17th overall, with a total TKT of 165 thousand. Of those TKT, 107

thousand are travelled by 3-S3-S2s, 35 thousand are travelled by 3-S2s, and the final 23 thousand are travelled by 3-S3s.

Table 12 – Annual truck kilometers travelled (TKT) in Manitoba on top 20 highways ranked by total TKT

Rank	Highway	3-S2 TKT (thousands)	3-S3 TKT (thousands)	3-S3-S2 TKT (thousands)	Total TKT (thousands)
1	1	503	335	1,557	2,396
2	10	399	266	1,236	1,901
3	3	312	208	967	1,488
4	242	209	139	647	996
5	16	159	106	492	756
6	305	118	79	367	564
7	83	104	69	322	495
8	23	93	62	289	444
9	2	86	57	266	409
10	5	85	57	264	407
11	253	82	55	255	392
12	353	55	37	171	263
13	21	50	33	155	238
14	25	49	33	151	233
15	75	44	30	137	211
16	240	35	24	109	168
17	59	35	23	107	165
18	34	34	23	105	161
19	270	33	22	102	156
20	478	31	21	97	150
Total		2,519	1,679	7,796	11,994

4.3. HOPPER BOTTOM TRUCK TRAFFIC (HBTT) MODEL RESULTS

This section reports the HBTT model results, which are based on the total truck traffic model developed by the Urban Mobility and Transportation Informatics Group (UMTIG) at the University of Manitoba in 2022. The total truck traffic model is shown in Figure 28. The HBTT model results were calculated from the truck traffic model by applying the truck body type classification proportions of hopper bottom trucks to the total volumes of class 9, 10, and 13 trucks, as discussed in Section 3.4. Geographically, the HBTT model is constrained to the southwest region of Manitoba where agriculture is the main industry. This region consists of four SADRs, as shown in Figure 29. The results presented in this section are for the highlighted region in Figure 29 only.

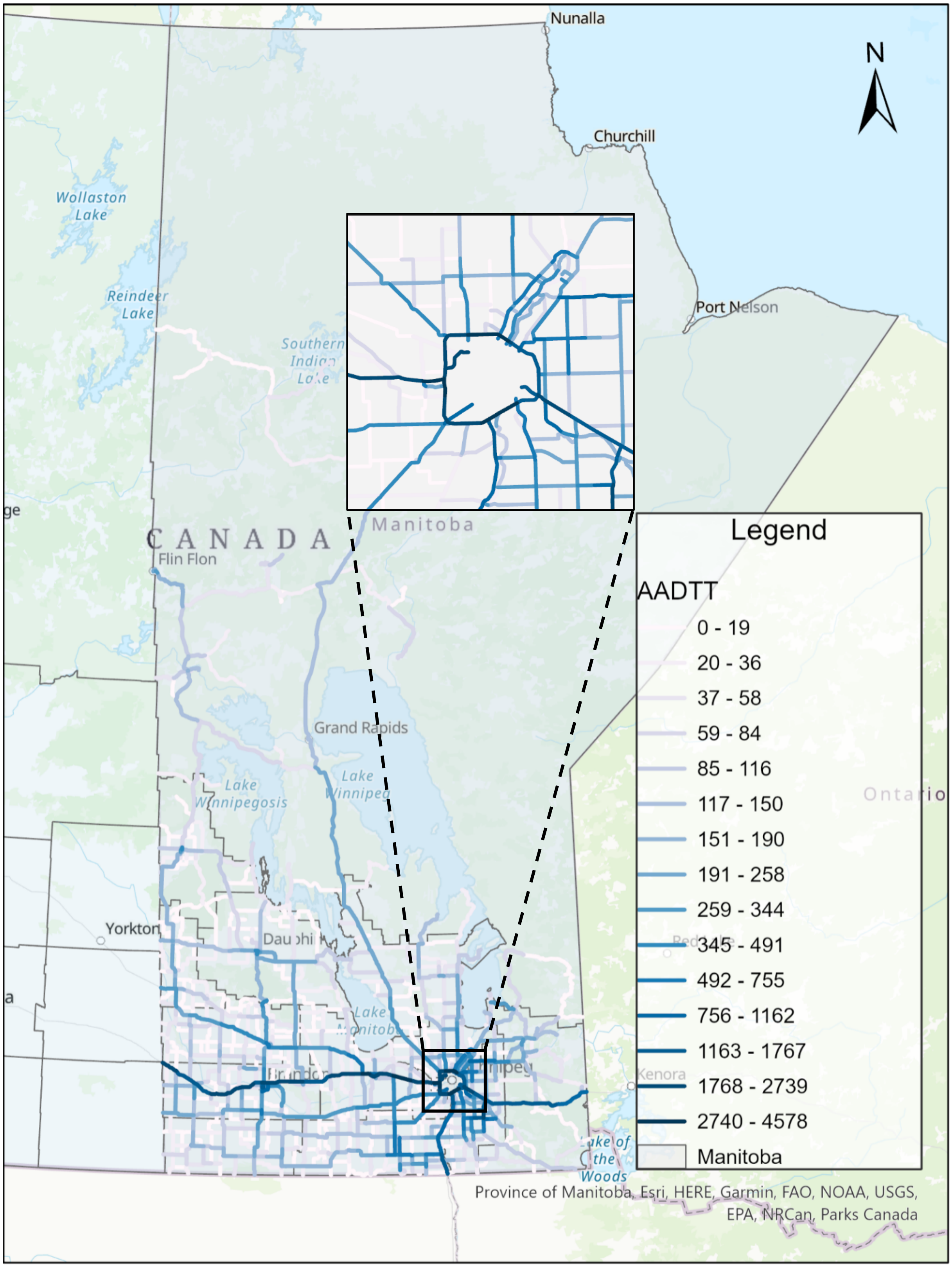


Figure 28 – Truck traffic model results (Expressed as AADTT)

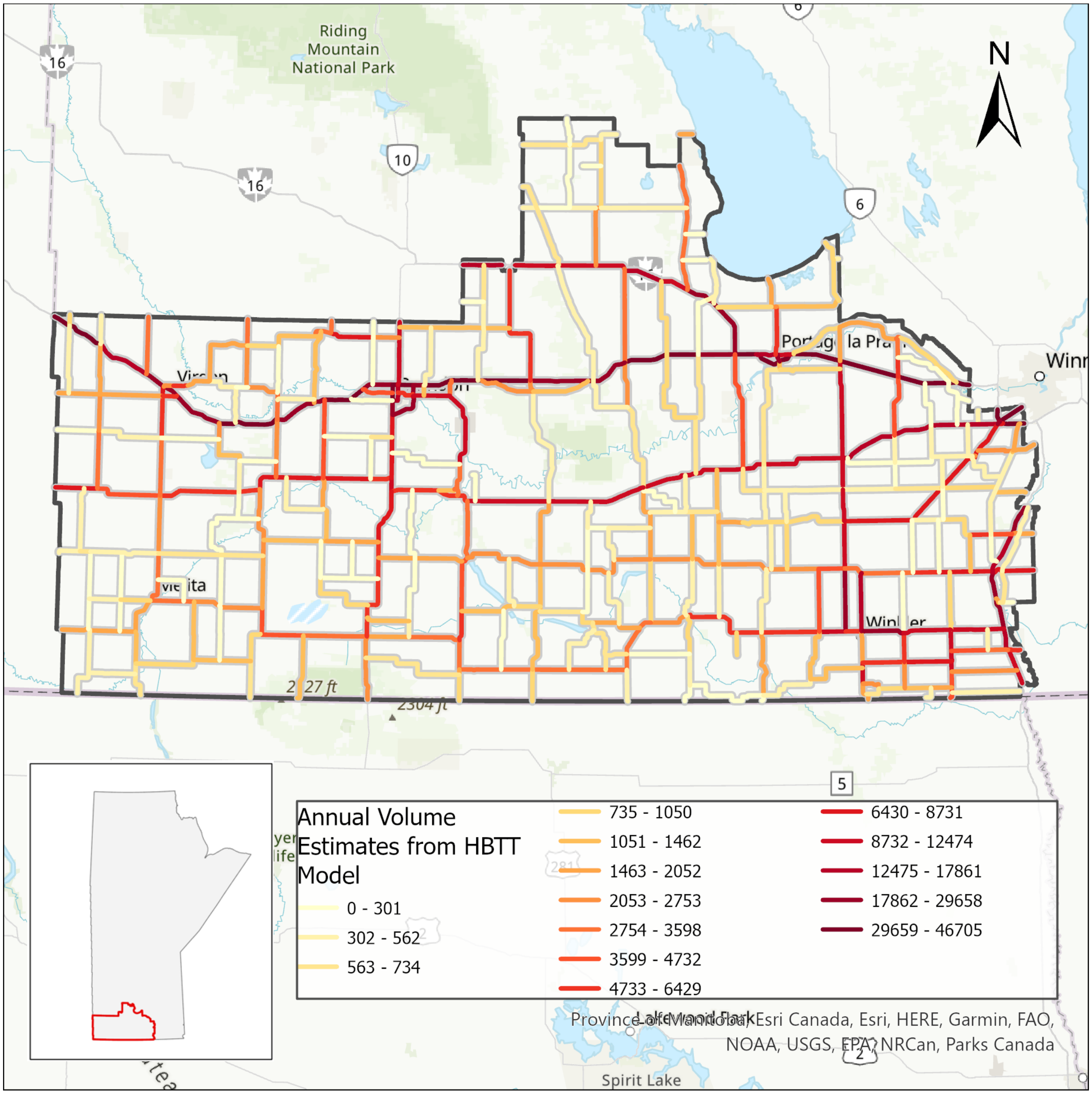


Figure 29 - HBTT model results in annual truck volumes

Figure 29 shows the following:

- Based on the HBTT model, the three highest volumes of hopper bottom trucks in the study area in 2019 occur on Highway 1. Highway 1 west of Portage la Prairie saw the most hopper bottom trucks with 46,705 (128 trucks per day). The second busiest portion of Highway 1 when looking at hopper bottom truck activity was near Headingley with 45,562 trucks (125 trucks per day), followed by the portion of Highway 1 east of Portage la Prairie, with 43,230 trucks (118 trucks per day). Based on the total truck traffic model, these sections of Highway 1 have AADTT values of 3256, 3176, and 2633, respectively.

- The lowest volume of hopper bottom trucks in the study area in 2019, while still experiencing hopper bottom truck traffic, occur near Headingley on Highway 270, between Highways 1 and 2, with a total of 24 hopper bottom trucks per year, and west of Portage la Prairie on Highway 242 between Highways 1 and 16, with a total of 55 hopper bottom trucks per year.

Table 13 summarizes hopper bottom TKT by truck configuration. The table shows that, of the total 35 million TKT in the study area in 2019, 3-S3-S2s travel the most at 23 million TKT, 3-S2s travel 7 million TKT, and 3-S3s travel 5 million TKT.

Table 13 – Annual truck kilometers travelled by truck configuration in Manitoba based on traffic monitoring

Truck configuration	TKT (millions)
3-S2	7
3-S3	5
3-S3-S2	23
Total	35

Table 14 summarizes hopper bottom TKT by highway type. It shows the following:

- Provincial trunk highways (PTHs) carry the majority of the hopper bottom trucks in the study area compared to provincial roads (PRs), with a total of 30 million

TKT. Of those TKT, 3-S3-S2s travel 20 million TKT, 3-S2 trucks travel 6 million TKT, and 3-S3s travel 4 million TKT.

- Provincial roads (PR) carry 5 million TKT in the study area in 2019. Three million TKT are travelled by 3-S3-S2s, 1 million by 3-S2s, and 0.7 million by 3-S3s.

Table 14 – Annual truck kilometers travelled in Manitoba by highway type based on traffic monitoring

Highway type	3-S2 TKT (millions)	3-S3 TKT (millions)	3-S3-S2 TKT (millions)	Total TKT (millions)
PTH	6	4	20	30
PR	1	0.7	3	5
Total	7	5	23	35

Table 15 summarizes hopper bottom TKT by the weight class restrictions used as the hierarchy for the HBTT model. Class 1 roads make up 3075 km of the total 7701 km of road network used in the HBTT model. Class 2 roads make up 1104 km, and class 3 roads make up 3523 km. While Table 15 shows that weight class 1 roads see 80 percent of the total TKT in the province with a total of 35 million TKT in 2019, weight class 1 roads only make up 40 percent of the road network used.

Table 15 – Annual truck kilometers travelled in Manitoba by highway weight restriction class based on traffic monitoring

Highway weight restriction class	3-S2 TKT (millions)	3-S3 TKT (millions)	3-S3-S2 TKT (millions)	Total TKT (millions)
1	6	4	18	28
2	0.7	0.5	2	3
3	1	0.5	2	3
4	0.0	0.0	0.0	0.0
Total	7	5	23	35

Table 16 summarizes hopper bottom TKT on specific highways. It shows the following:

- The top ranked highway in terms of TKT in the study area, excluding national highways, is Highway 2. Highway 2 has a total TKT of 4,299 thousand with 2,794 thousand of those TKT by 3-S3-S2s, 903 thousand TKT by 3-S2s, and the final 602 thousand TKT by 3-S3s.
- The two national highways running through Manitoba, highways 1 and 16, rank 1st and 4th, respectively. Highway 1 has a total TKT of 12,660 thousand, with 8,229 thousand TKT by 3-S3-S2s, 2,659 thousand TKT by 3-S2s, and 1,772 thousand TKT by 3-S3s. Highway 16 has a total TKT of 2,083 thousand, with 1,354 thousand TKT by 3-S3-S2s, 438 thousand TKT by 3-S2s, and 292 thousand TKT by 3-S3s.

Table 16 – Annual truck kilometers travelled in Manitoba on top 20 highways ranked by total TKT based on traffic monitoring

Rank	Highway	3-S2 TKT (thousands)	3-S3 TKT (thousands)	3-S3-S2 TKT (thousands)	Total TKT (thousands)
1	**1**	2,659	1,772	8,229	12,660
2	**2**	903	602	2,794	4,299
3	**3**	555	370	1,718	2,643
4	**16**	438	292	1,354	2,083
5	**75**	249	166	771	1,186
6	**23**	237	158	733	1,128
7	**10**	235	157	728	1,120
8	**14**	152	101	470	723
9	**13**	130	87	403	621
10	**100**	117	78	361	556
11	**5**	99	66	307	472
12	**83**	89	59	275	423
13	**18**	82	55	254	390
14	**201**	80	53	246	379
15	**110**	76	51	235	361
16	**340**	67	45	209	321
17	**428**	62	41	191	293
18	**34**	60	40	186	287
19	**21**	59	40	184	283
20	**305**	53	35	165	253
Total		43	29	134	206

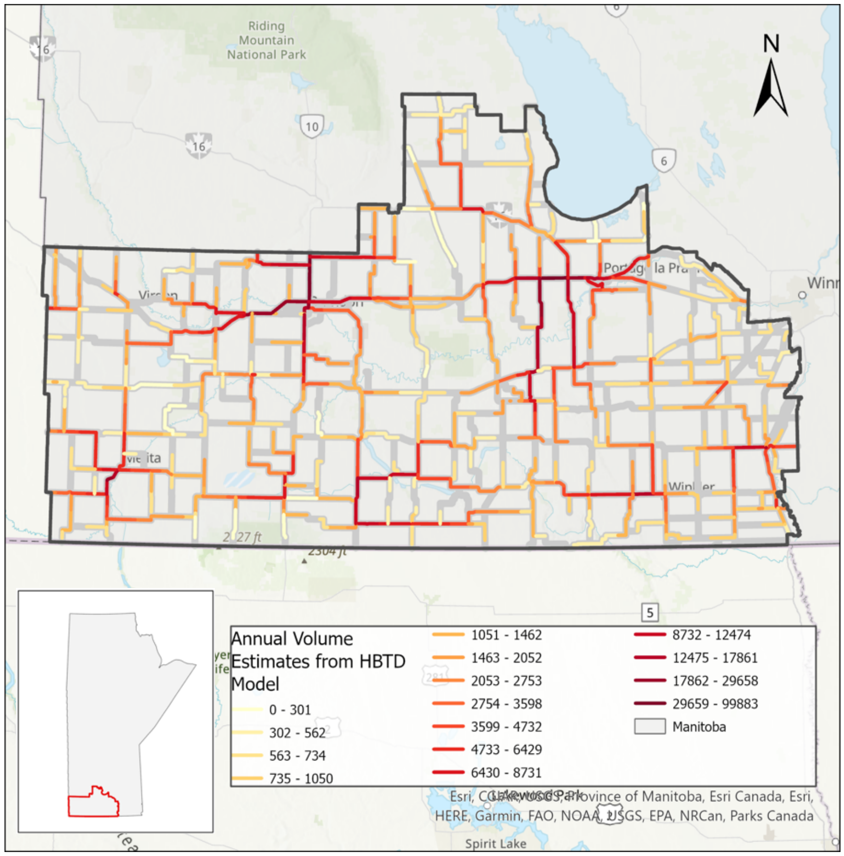
4.4. DISCUSSION OF RESULTS

This section compares the results of the HBTD model and the HBTT model in southwestern Manitoba, discusses limitations of this work, and explores the implications for freight planning and data collection.

4.4.1. Comparison

As shown in the results sections, publicly available data (land use data, grain production data, grain elevator delivery data, highway weight restrictions) are used to develop the GTD model. Truck body type classification data for Manitoba is then applied to the GTD model to develop hopper bottom truck volume estimates. In this section the HBTT model results from section 4.3 are used to compare and assess the results of the HBTD model estimates from section 4.2. To use the HBTT model results from section 4.3, a map of the HBTD model for the same southwestern region is shown in Figure 30(a). Figure 30(b) shows the HBTT model results in comparison. Because the HBTD model does not assign trucks to roadways in the same manner as the HBTT model, the results in this section present TKT divided by total kilometers to normalize the data by distance.

(a)



(b)

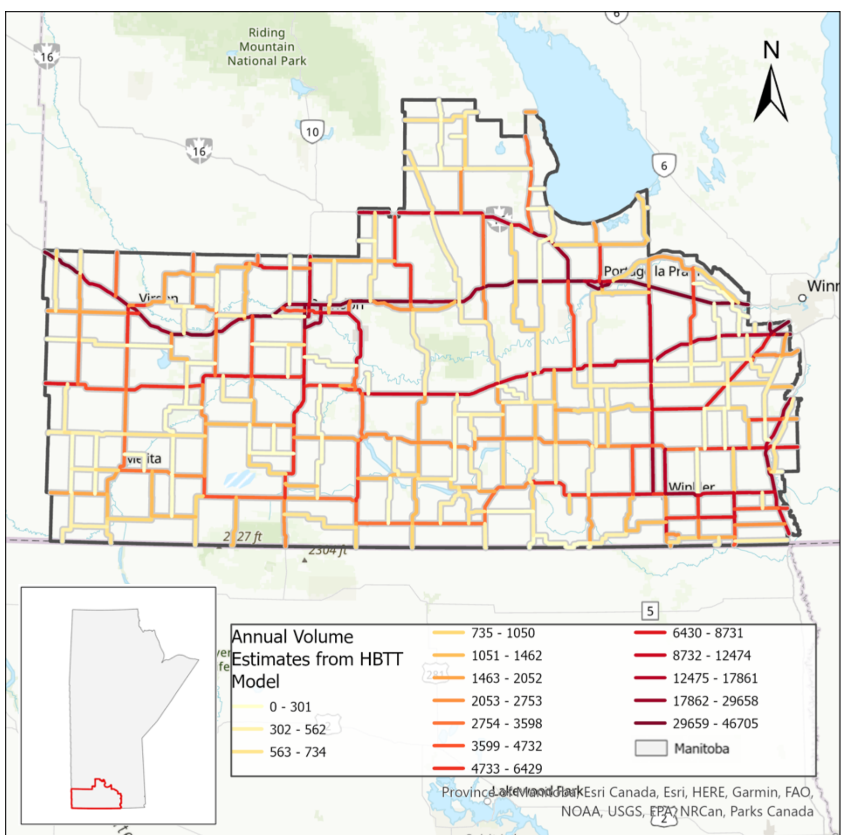


Figure 30- HBTD (a) and HBTT (b) model results for southwestern Manitoba

In this section, comparisons between the normalized TKT estimates produced by the HBTD and HBTT models are made in four ways: (1) by truck configuration; (2) by highway type; (3) by highway weight restriction class; and (4) by the trend between the models when highways are ranked by normalized TKT. Table 17 shows the normalized TKT by the three different truck configurations being studied over the entire highway network, and the comparisons between highway type and highway weight restriction class.

Table 17 - Comparison of results in terms of normalized TKT

	Truck Configuration	Highway Type			Highway Weight Restriction Class				
		PTH	PR	∑	1	2	3	4	∑
HBTD Model	3-S2	150	533	683	347	138	198	0	683
	3-S3	100	355	455	231	92	132	0	455
	3-S3-S2	464	1650	2114	1074	427	613	0	2114
	Total	715	2538	3252	1652	657	943	0	3252
HBTT Model	3-S2	467	484	951	767	89	95	0	951
	3-S3	311	323	634	511	59	63	0	634
	3-S3-S2	1444	1499	2943	2375	275	293	0	2943
	Total	2222	2306	4528	3653	423	451	0	4528
% Difference	3-S2	211%	-9%	39%	121%	-36%	-52%	0%	39%
	3-S3	211%	-9%	39%	121%	-36%	-52%	0%	39%
	3-S3-S2	211%	-9%	39%	121%	-36%	-52%	0%	39%
	Total	211%	-9%	39%	121%	-36%	-52%	0%	39%

Based on truck configuration, all three truck types have a percent difference of 39%. In other words, the HBTT normalized TKT estimates exceed the HBTD normalized TKT estimates by 39%. The consistency between the three truck types is due to use of the same proportions in both the HBTD model and the HBTT model. To determine the proportion of each truck configuration on the network in the HBTD model, the proportion of hopper bottom trucks in the data from the Headingley weigh scale on Highway 1 in Manitoba is used. Likewise, to determine the proportion of hopper bottom trucks in the HBTT model, the same proportion of hopper bottom trucks in the data from the Headingley weigh scale on Highway 1 in Manitoba is used. This leads to the consistent differences observed among the truck types in Table 17.

The Highway Type portion of Table 17 shows the normalized TKT by highway type and truck configuration. This comparison shows the same overall results with a difference of 39%. However, the difference between each highway type shows that, relative to the HBTT model, the HBDT model underestimates the normalized TKT on PTHs by 211%. Notably, the difference between the normalized estimates on PRs was smaller in magnitude (-9%) and opposite in direction. That is, the normalized TKT estimate for PRs was higher based on the HBTD compared to the HBTT model.

The Highway Weight Restriction Class portion of Table 17 shows the normalized TKT by highway weight restriction class and truck configuration. Again, the overall results for this comparison have the same difference of 39%. However, on weight restriction class 1 highways the difference is larger at 121%. Class 2 and class 3 highways have differences of -36% and -52%, respectively. These negative percent difference values indicate that class 2 and 3 highway use is overestimated in the HBTD model compared to the HBTT model.

Figure 31 compares the results of the two models when highways are ranked by normalized TKT. Perfect agreement (by rank) would be indicated by all data points falling on the diagonal line. While perfect agreement is not evident (nor expected), the figure shows that there is no consistent bias between the two models, as the data points are reasonably distributed above and below the diagonal line. Overall, as has already been shown, highways tend to rank relatively higher when considering the HBTT model compared to the HBTD model. However, there are also a small number of extreme lower rank values for the HBTT model where the HBTD model is modelling higher ranks. Both discrepancies are likely due to the HBTT model giving preference to PTHs while the HBTD model does not, which is consistent with results shown in Table 17, when looking at highway type.

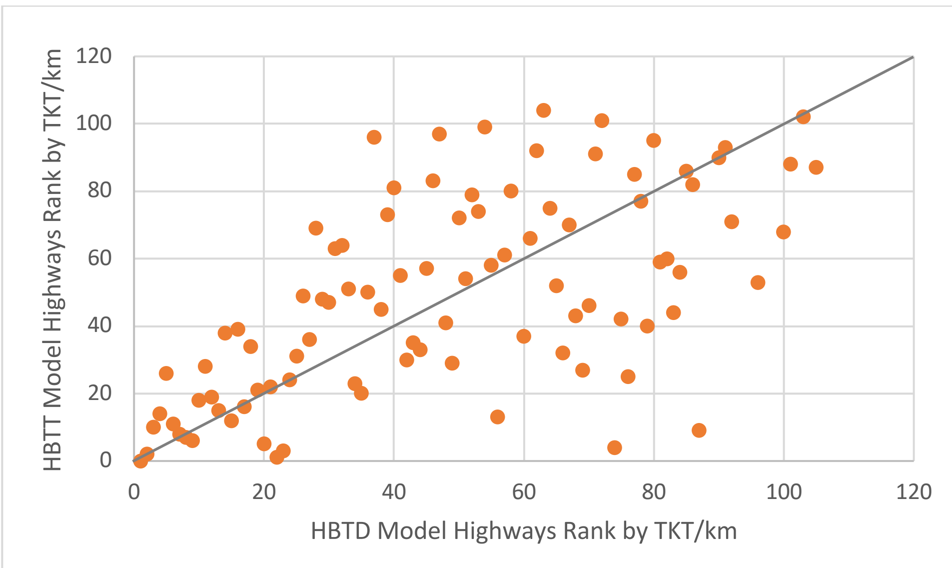


Figure 31 – Comparison of the HBTD and HBTT models when highways are ranked by TKT/km

4.4.2. Limitations

While there is no way to validate the results of the grain truck volume estimates from the integrated model with respect to ground truth values, the comparison presented in this research has provided insight into limitations affecting both the HBTD and HBTT models.

4.4.2.1. Hopper Bottom Truck Demand Model Limitations

There are five main limitations impacting the validity of the HBTD model. The first limitation occurs in urban settings due to shortcomings in traffic monitoring and truck body type classification data, as well as the elevator delivery data. In large urban areas, such as Winnipeg for example, there are four elevators with capacity for grain deliveries. However, in the grain delivery data supplied by Statistics Canada, all the Winnipeg elevators are combined into one delivery station. This means the gravity model uses the delivery data to attract trips to Winnipeg but does not specify to which Winnipeg elevator the trips were attracted. For this reason, trips are assumed to be split evenly between the four elevators. In addition to this delivery station assumption, the truck body type classification data cannot be applied to urban areas because traffic within city limits is not monitored by the province. Thus, urban roadways were removed from the model. Removing urban roadways, creates anomalies in truck volumes near urban areas with ring roads. In Winnipeg, there are four elevators within the limits of its ring road (PTH 100 and PTH 101), but all roads within the ring road were considered urban and removed from the model. This causes the trucks to be routed to the ring road using other highways but no further. These two assumptions particularly impacted the cities of Winnipeg and Edmonton, but also applied to other urban areas with ring roads.

The second limitation impacting the HBTD model is the exclusion of dump trucks. Dump trucks were not included because they carry a wide variety of commodities and there is no publicly available data to determine the proportion of dump trucks carrying grain. The addition of dump trucks would potentially add a significant number of trucks carrying grain to the model results, as dump trucks carry fewer tonnes than the largest truck studied, 3-S3-S2s. When loaded, 3-S3-S2s can carry a total of 44.22 tonnes or 83 m^3 of grain. In contrast, dump trucks can only carry a maximum of 10 tonnes or 9 m^3 of grain, based on a three-axle configuration. When weighed out (as is usually the case when hauling grain) every 3-S3-S2 is equivalent to approximately four dump trucks (Lynch Truck Center, 2023). Depending on the proportion of dump trucks on the road compared to the number of hopper bottom trucks, there could be a significant change to the number of total trucks on the road network, along with the number of each truck configuration on the road network. Adding dump trucks to the model would also change the HBTT results by adding to the total volume of grain carrying trucks.

The third limitation of the HBTD model is that two segments of the grain supply chain, elevator to elevator transfers and the exporting of grain, are excluded. Grain is transferred by a grain handling company from one elevator to another to optimize the quality of grain available for shipment by rail at a particular elevator. These truck trips would add additional trips to the road network and would occur on different roadways than the HBDT model is currently using. When it comes to exports, according to Statistics Canada, of the 2,400 million tonnes of barley, canola, oats, soybeans, and wheat produced in 2019, prairie elevators exported 2,031,600 tonnes to the United States and Mexico (Statistics Canada, 2022c). While many of these exports would be transported by rail, some would be transported by truck, which would add truck trips to the network on different roadways than the HBDT model trips currently occupy. Figure 32 shows the national highway network, which comprises the main export routes in the Canadian Prairie Region. For example, consider Highway 75, Manitoba's main export corridor to the United States. In the HBTT model, Highway 75 has a total of 761 thousand TKT by hopper bottom trucks, while the HBTD model estimates 211 thousand TKT by hopper bottom truck traffic. This is a difference of 550 thousand truck kilometers travelled, or 261%. If truck traffic created by exports was included, the HBTD model results would likely increase.

Figure 32 – National highway network in the Canadian Prairie Region

The fourth limitation of the HBTD model is the method that the truck traffic is assigned to the roadway. The model is only partially representative of how producers would select roads to use to transport their grain from storage to elevator. While an attempt was made to use time (as a function of speed) as the assignment variable, this tended to produce unreasonable results. Consequently, the assignment relied on distance as the only impedance used for assignment, with weight restriction classes used as the hierarchy. While weight restriction classes are used as the hierarchy, there is also the limitation that trucks were not loaded onto the network in a way that accounted for highway weight limits. Table 17 shows the HBTD model is overestimating the number of hopper bottom trucks on class 2 and 3 roadways compared to the HBTT model, and the HBTD model is overestimating truck traffic on PRs. This is due to the lack of speed data used in the HBTD model and a lack of acknowledgment to highway weight limits, as higher weight restriction class roads and PTHs typically have higher set speed limits than lower class roads and PRs. The comparison shown in Figure 31 can also be explained by this limitation. If it had been possible to include speed limit data and accurately represent highway weight limits in the HBTD model, it is likely that the number of trucks on class 1 roads and PTHs would have increased in the HBTD model, which would decrease the number of trucks on class 2 and 3 roads, and PRs.

The final limitation of the HBTD model is the scope of the agricultural sector being considered in this research. This research focusses solely on the storage to elevator truck trips created by the agricultural sector for certain grains; it does not include truck trips from field to storage, or storage to value added processing facilities. This research also does not include every type of crop grown in the Canadian Prairie Region and does not include fertilizer. These limits to the scope reduce the number of truck trips included in the HBTD model. Storage to value added processing facilities trips, for example, occur when producers deliver their grains to value added processing facilities instead of grain elevators. This would add hopper bottom truck trips that do not follow the same patterns as storage to elevator truck trips to the road network. The same can be said for field to storage trips.

4.4.2.2. Hopper Bottom Truck Traffic Model Limitations

The estimation of system-wide truck volumes is subject to numerous data related limitations, as discussed in detail by Reimer and Regehr (2013). In short, these limitations relate to data collection approaches, sampling methods, data processing techniques, and the assignment of counts to the network. In addition to those limitations, the HBTT model developed in this thesis is limited by the assumption that all hopper bottom trucks on the network are carrying grain. Since the truck body type classification does not specify what the trucks are carrying, the HBTT model assumes that all hopper bottom trucks carry only the grains studies in this research (barley, canola, oats, soybeans, and wheat). Hopper bottom trucks do not only carry these grains; they also carry fertilizer, seed, other grains, and even non-agricultural commodities, depending on geographic and temporal considerations. This assumption leads to the proportion of class 9, 10, and 13 truck carrying the five types of grain to be higher than the actual proportion. This causes an overestimation of hopper bottom trucks compared to the HBTD results.

4.4.3. Implications for Freight Planning and Data Collection

Freight demand modelling is a well-accepted approach to estimating the level of freight (and truck) activity across a network. Alternatively, truck traffic monitoring programs generate data that can also be used to estimate system-wide truck volumes. This research focused on integrating these two concepts, using demand modelling without mode choice for the specific industry sector of agriculture, and integrating traffic monitoring methods by using truck body type classification data. This research also uses the same truck body classification data to factor truck volumes estimated from truck traffic monitoring programs, providing a high-level comparison of the two methods, and offering insights into a more integrated approach to estimating system-wide volumes. While there are certain limitations to this research, the results appear to indicate that with improved data collection, this approach would be a useful way to determine truck traffic generated by different industry sectors. The results of this research lead to the following implications for freight planning and data collection:

- The results indicate a need for more truck body type classification studies across the region to be able to apply different proportions to different areas or road types. Truck body type factors could be developed using similar concepts as those underpinning the establishment of traffic pattern groups. Likewise, such samples should be conducted to capture seasonal patterns likely to exist for specific truck body types. For example, agriculture related truck traffic typically peaks in spring and fall, so the proportions of hopper bottom trucks observed during those seasons would likely be higher than during summer and winter.
- Based on the lower estimates provided by the HBTD compared to the HBTT model, there appears to be a need to include a broader distribution of grain types and movements beyond those between a farm and a delivery point.
- This work could be made more reliable with the addition of roadside surveys that could more accurately assess the relationship between truck body type and commodity. As the results indicate, being able to include some dump trucks (which may haul grain) and exclude some hopper bottom trucks (that may not carry grain) could improve the model results.

- Being able to estimate truck traffic by commodity would allow jurisdictions to make network planning decisions based on how sectors would be affected by certain industry-specific trends and decisions. Geographic areas home to particular industry sectors would benefit from this type of data product, since it would support better road asset management decisions and resiliency assessments.

5. CONCLUSIONS AND RECOMMENDATIONS

This chapter summarizes the key contributions and findings from this research and discusses recommendations for future work.

5.1. SUMMARY OF KEY CONTRIBUTIONS AND FINDINGS

The purpose of this research was to develop, apply and assess an integrated modelling approach to estimate grain truck activity in the Canadian Prairie Region. The modelling of tonnage flow across the Canadian Prairie Region, creating the GTD model, was completed using publicly available grain production data, land use data, elevator delivery data, and road weight class data. The conversion from tonnages to hopper bottom truck volume estimates, creating the HBTD model, was completed using truck body type classification data available in Manitoba. The results of the HBTD model were assessed by comparing them to hopper bottom truck volume estimates developed from the HBTT model, which was developed from truck traffic monitoring rather than demand modelling principles.

The key contributions and findings from this research are as follows:

- A key contribution of this research was the development of the GTD model for the entire Canadian Prairie Region. This appears to be the first time that such a model has been developed at the regional scale. Moreover, this model enables disaggregation by grain type, which does not appear to have been available in prior work. The GTD model estimated the busiest roads in the Canadian Prairie

Region in regard to annual grain tonnage to be Highway 1 with 163 million tonne kilometers, Highway 16 with 62 million tonne kilometers, and Highway 35 in Saskatchewan with 60 million tonne kilometers. The GTD model estimated the busiest highway in Manitoba to be Highway 10 with 37 million tonne kilometers, and the busiest highway in Alberta to be Highway 24 with 32 million tonne kilometers.

- Another key contribution of this research was the development of the HBTD model in that it extends a typical three-step commodity model for grain, such as those produced for Manitoba and Saskatchewan by Mruss (2004) and Gienow (2007), respectively, by estimating actual truck trips disaggregated by grain and truck configuration. The knowledge that can be obtained with this step can be particularly useful for engineering related decisions related to network connectivity, pavement design, network reliability, and network resiliency.
- The thesis utilized a relatively unique data set to convert the GTD model results into the HBTD model results. Manually collected truck body type data provided information on the proportion of predominant truck configurations that operated as hopper bottoms, and thus were likely carrying grain. The HBTD model estimated the busiest roads in Manitoba in regard to hopper bottom trucks in 2019 to be Highway 1 with 2,396 thousand TKT, Highway 10 with 1,901 thousand TKT, and Highway 3 with 1,488 thousand TKT.
- To assess the results of the HBTD model, the results from four SADRs were compared to the HBTT model, extracted from the total truck traffic model in the same SADRs in the southwestern portion of Manitoba. This comparison found

the HBTD model to underestimate hopper bottom truck traffic by 39%. Since neither model can be considered as ground truth, the difference should not be interpreted as an error, but rather as a way to assess the relative strengths and limitations of the different modelling approaches. Further integration of the approaches could yield better agreement in the future.

- Two key publicly available data sources supported the development of the HBTD model: the Canadian Grain Commission and Statistics Canada. There were also four main data sources for the network data used to create the road network used by the HBTD model: Statistics Canada and the governments of Alberta, Saskatchewan, and Manitoba. There were, however, some data gaps that limited the scope of the HBTD model. The lack of data in regard to grain movements between field to storage, elevator to elevator, and storage to value added processing facilities limited the scope and the number of truck trips the model was able to predict. There were two key data sources used to support the development of the HBTT model: observations by Maranchuk (2016) and the Province of Manitoba.
- This research demonstrated the need to integrate various types of data in the industry-oriented demand modelling approach. Activity-related data, such as land use characteristics, grain production statistics, and grain delivery quantities and delivery points were foundational to generating commodity flows and applying the gravity model. Network-related data, such as highway functional class and highway weight restrictions supported the assignment process. Truck body type data and information about the capacity of typical hopper bottom truck

configurations enabled the use of loading factors to convert tonnages into truck volumes.

- There were five main limitations for the HBTD model that reduced the accuracy of the model. The limitations for this research were the lack of data for urban areas with ring roads (e.g., Winnipeg and Edmonton), the exclusion of dump trucks from the scope of this research, exports of grain and elevator to elevator trips being excluded from the scope, speed limit data being excluded from trip assignment due to unreasonable routing, not assigning truck trips to highways in a way that included highway weight limits, and the exclusion of field to storage, and storage to value added processing facility truck trips. There was one main limitation for the HBTT model: that all hopper bottom trucks carried grain. Hopper bottom trucks can also carry fertilizer, seed, and grains not studied in this research. Many limitations also exist for the total truck traffic model that formed the foundation for the HBTT model. The resolution of the limitations affecting both models would incline the models toward better agreement.
- To improve the results of the HBTD model, more data, some that is not as readily available, would be required. Data sources that would make the use of integrated models to commodity-specific truck volume estimates more useful include export data, more spatially and temporally diverse truck body type data, and data from roadside surveys that could reveal what commodities trucks are carrying.

5.2. RECOMMENDATIONS FOR FUTURE WORK

The findings in this thesis and the noted limitations point to the need for future work, as follows:

- While agriculture makes up a large portion of Canada's economy, other sectors are also important to research. Using an integrated approach to model truck traffic similar to this work for other industry sectors such as petroleum, mining, forestry, or manufacturing would support more reliable transportation engineering and planning decisions.
- The HBDT model could be refined and extended with export data, roadside surveys, other types of truck trips (such as exports, elevator to elevator, field to storage, and storage to value added processing facilities), and speed limit data. However, the key need to make this model more accurate is better, more expansive truck body type data. The data used in this research were obtained in 2014 by manual roadside observation. Today there have been advancements in body type classification technologies. The advancements in inductive loop signatures and automated video detection as discussed in Chapter 2 could be used to develop a much more robust vehicle classification data set. The more accurate model with these additions could then be used to support more reliable transportation engineering and planning decisions.
- Transportation engineering methods are always advancing, and artificial intelligence (AI) is just one aspect of this continuous improvement. Initial research has been done to estimate origin-destination (O-D) matrices using road

link volumes and AI (Lorenzo & Matteo, 2013)—essentially reversing the typical demand modelling approach. Initial research on this topic uses machine learning under the assumption that the O-D matrices to be estimated have similar structure to the matrices used to teach the AI algorithms. This initial research is limited by not being able to estimate special cases of unpredictable changes in supply or demand (Lorenzo & Matteo, 2013). With the use of AI, this thesis could be used to teach machine learning technology to determine the original O-D matrix based on the given routes, or links, produced from the HBTD model. Training like this could be aided by industry-specific knowledge, as has been presented for the agriculture industry in this thesis.

6. REFERENCES

Adams, T. M., Bekkem, K. R., & Toledo-Durán, E. J. (2012). Freight resilience measures. Journal of Transportation Engineering, 138(11), 1403–1409. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000415

Asborno, M. I., Burris, C. G., & Hernandez, S. (2019). Truck Body-Type Classification using Single-Beam Lidar Sensors. Transportation Research Record, 2673(1), 26–40. https://doi.org/10.1177/0361198118821847

Burchfield, E., Matthews-Pennanen, N., Schoof, J., & Lant, C. (2020). Changing yields in the Central United States under climate and technological change. Climatic Change, 159(3), 329–346. https://doi.org/10.1007/s10584-019-02567-7

Canadian Grain Commission. (2022). Canadian Grain Commission. https://www.grainscanada.gc.ca/en/grain-research/statistics/

Canadian Pacific. (2021, September 15). Canadian Pacific and Kansas City Southern Execute Agreement to Combine, Creating First Single-Line Rail Network Linking U.S-Mexico-Canada. https://www.cpr.ca/en/media/canadian-pacific-and-kansas-city-southern-execute-agreement-to-combine-creating-first-single-line-rail-network

Deininger, K., & Byerlee, D. (2012). The rise of large farms in land abundant countries: Do they have a future? World Development, 40(4), 701–714. https://doi.org/10.1016/j.worlddev.2011.04.030

Enns, G., Reimer, M., & Regehr, J. (2012). Methodology to characterize agriculture-related trucking on low-volume rural roads to support asset management.

Federal Highway Administration. (2016). Traffic Monitoring Guide.

Fekpe, E. (2011). Truck equivalency factors to convert commodity flow data to truck trips. TRB 2011 Annual Meeting.

Fischer, M. J., Outwater, M. L., Cheng, L. L., Ahanotu, D. N., & Calix, R. (2005). Innovative Framework for Modeling Freight Transportation in Los Angeles County.

Fischer-Kowalski, M., Gaube, V., & Rainer, G. (2006). A Model Predicting Freight Transport from Materials Flows, and Transport Activity in Europe (Vol. 10, Issue 4). www.mitpressjournals.org/jie

Gienow, W. G. Wayne G. (2007). Development of a grain transportation model for Saskatchewan. Library and Archives Canada = Bibliothèque et Archives Canada.

Gleim, S., & Nolan, J. (2015). Canada's Grain Handling and Transportation System: A GIS-based Evaluation of Potential Policy Canada's Grain Handling and Transportation System: A GIS-based Evaluation of Potential Policy Changes. In Source: Journal of the Transportation Research Forum (Vol. 54, Issue 3).

Graedel, T. E. (2019). Material Flow Analysis from Origin to Evolution. Environmental Science and Technology, 53(21), 12188–12196. https://doi.org/10.1021/acs.est.9b03413

Grande, G., Lesniak, M., Tardif, L. P., & Regehr, J. (2022). Exploring vehicle probe data as a resource to enhance network-wide traffic volume estimates. Canadian Journal of Civil Engineering, 49(4), 558–568. https://doi.org/10.1139/cjce-2020-0656

Harvard. (n.d.). Weight per bushel and bulk densities of grain and seeds.

He, P., Wu, A., Rangarajan, A., & Ranka, S. (2019). Truck Taxonomy and Classification Using Video and Weigh-In Motion (WIM) Technology Final Report.

Hernandez, S., & Hyun, K. (2020). Fusion of weigh-in-motion and global positioning system data to estimate truck weight distributions at traffic count sites. In Journal of Intelligent Transportation Systems: Technology, Planning, and Operations (Vol. 24, Issue 2, pp. 201–215). Taylor and Francis Inc. https://doi.org/10.1080/15472450.2019.1659793

Hernandez, S. v., Tok, A., & Ritchie, S. G. (2016). Integration of Weigh-in-Motion (WIM) and inductive signature data for truck body classification. Transportation Research Part C: Emerging Technologies, 68, 1–21. https://doi.org/10.1016/j.trc.2016.03.003

Holguín-Veras, J., & Thorson, E. (2000). Trip Length Distributions in Commodity-Based and Trip-Based Freight Demand Modeling Investigation of Relationships.

Horowitz, A., Cohen, H., & Pendyala, R. (2008). Forecasting Statewide Freight Toolkit. National Academies Press. https://doi.org/10.17226/14133

Hyland, M. F., Mahmassani, H. S., & Bou Mjahed, L. (2016). Analytical models of rail transportation service in the grain supply chain: Deconstructing the operational and economic advantages of shuttle train service. Transportation Research Part E: Logistics and Transportation Review, 93, 294–315. https://doi.org/10.1016/j.tre.2016.06.008

Jia, S., Zhou, K., Zhou, S., Fang, H., Zhen, Y., & Zou, Y. (2020). An artificial fish swarm algorithm for a multi-objective grain transportation problem. Evolutionary Intelligence, 13(1), 9–19. https://doi.org/10.1007/s12065-019-00228-3

Kaack, L. H., Chen, G. H., & Morgan, M. G. (2019). Truck traffic monitoring with satellite images. 155–164. https://doi.org/10.1145/3314344.3332480

Karlen, D. L., Varve1, G. E., Bullock, D. G., & Cruse4, R. M. (1994). Crop Rotations for the 21st century.

Kaushik, K., Wood, E., & Gonder, J. (2018). Coupled Approximation of U.S. Driving Speed and Volume Statistics using Spatial Conflation and Temporal Disaggregation. Transportation Research Record, 2672(43), 1–11. https://doi.org/10.1177/0361198118758391

Liu, D., Deng, Z., Yinhai, W., & Kaiser, E. I. (2020). Method for identifying truck traffic site clustering using weigh-in-motion (WIM) data. IEEE Access.

Lode King. (2022). DISTINCTION ALUMINUM HOPPER SPECIFICATIONS. https://www.lodeking.com/hoppers/aluminum/specifications/

Lorenzo, M., & Matteo, M. (2013). OD matrices network estimation from link counts by neural networks. Journal of Transportation Systems Engineering and Information Technology, 13(4), 84–92. https://doi.org/10.1016/S1570-6672(13)60117-8

Lynch Truck Center. (2023). How much can a dump truck carry? https://www.lynchtruckcenter.com/how-much-can-a-dump-truck-carry/

Madar, D. (1999). Rail Mergers, Trade, and Federal Regulation in the United States and Canada. https://academic.oup.com/publius/article/32/1/143/1906867

Maiyar, L. M., & Thakkar, J. J. (2019). Modelling and analysis of intermodal food grain transportation under hub disruption towards sustainability. International Journal of Production Economics, 217, 281–297. https://doi.org/10.1016/j.ijpe.2018.07.021

Manheim, M. L. (1980). UNDERSTANDING “SUPPLY” IN TRANSPORTATION SYSTEMS.

Maranchuk, K. L. (2016). Using Axle Configuration, Body Type, and Payload Data to Benchmark Truck Traffic Trends on Highway Networks Serving Freight-Intensive Developments.

Mishra, S., Iseki, H., & Moeckel, R. (2014). Multi entity perspective freight demand modeling technique: Varying objectives and outcomes. Transport Policy, 35, 176–185. https://doi.org/10.1016/j.tranpol.2014.05.002

Mruss, K. L. P. (2004). A Commodity Based Methodology for Freight Forecasting on Rural Road Networks.

Ominski, A., Paramita, P., & Regehr, J. (2022). Development and attribution of a linear referencing system for managing and disseminating traffic volume data on rural highway networks. Canadian Geographer, 66(2), 337–352. https://doi.org/10.1111/cag.12707

Ortúzar, J. de D., & Willumsen, L. G. (2011). Modelling Transport (Fourth). Wiley.

Pushka, A., & Regehr, J. (2021). Retrospective longitudinal study of the impact of truck weight regulatory changes on operating gross vehicle weights. In Transportation Research Record (Vol. 2675, Issue 8, pp. 34–47). SAGE Publications Ltd. https://doi.org/10.1177/0361198121995502

Qualman, D., Akram-Lodhi, A. H., Desmarais, A. A., & Srinivasan, S. (2018). Forever young? The crisis of generational renewal on Canada’s farms. Canadian Food Studies / La Revue Canadienne Des Études Sur l’alimentation, 5(3), 100–127. https://doi.org/10.15353/cfs-rcea.v5i3.284

Rasouli, S., & Timmermans, H. (2014). Activity-based models of travel demand: Promises, progress and prospects. International Journal of Urban Sciences, 18(1), 31–60. https://doi.org/10.1080/12265934.2013.835118

Regehr, J., Maranchuk, K., Vanderwees, J., & Hernandez, S. (2020). Gaussian mixture model to characterize payload distributions for predominant truck configurations and body types. Journal of Transportation Engineering, Part B: Pavements, 146(2), doi: 10.1061/JPEODX.0000174.

Regehr, J., & Mehran, B. (2020). "Applying artificial intelligence to improve the resilience, fluidity, and safety of road freight transport in the Canadian Prairie and Northern Region." Proposal submitted to the AI for Logistics Program of the National Research Council of Canada.

Regehr, J., Montufar, J., & Clayton, A. (2009). Options for exposure-based charging for long multiple trailer truck permits. Transportation Research Record, 2097, 35–42. https://doi.org/10.3141/2097-05

Regehr, J., & Reimer, M. J. (2013). Methodology to Estimate the Distance Traveled by Trucks on Rural Highway Systems. https://doi.org/10.1061/(ASCE)TE.1943-5436

Reimer, M., & Regehr, J. (2013). Hybrid approach for clustering vehicle classification data to support regional implementation of the mechanistic-empirical pavement design guide. Transportation Research Record, 2339, 112–119. https://doi.org/10.3141/2339-13

Smith, R. G., Gross, K. L., & Robertson, G. P. (2008). Effects of crop diversity on agroecosystem function: Crop yield response. Ecosystems, 11(3), 355–366. https://doi.org/10.1007/s10021-008-9124-5

Stanley Young, P. E., Hou, Y., Sadabadi, K., Sekuła, P., & Markow, D. (2018). Estimating Highway Volumes Using Vehicle Probe Data - Proof of Concept: Preprint. www.nrel.gov/publications.

Statistics Canada. (2021). Table 32-10-0156-01 Farms classified by total farm area, Census of Agriculture historical data. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3210015601&pickMembers%5B0%5D=1.1&cubeTimeFrame.startYear=1976&cubeTimeFrame.endYear=2021&referencePeriods=19760101%2C20210101

Statistics Canada. (2022a). Table 32-10-0359-01 Estimated areas, yield, production, average farm price and total farm value of principal field crops, in metric and imperial units. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3210035901&cubeTimeFrame.startYear=1950&cubeTimeFrame.endYear=2022&referencePeriods=19500101%2C20220101

Statistics Canada. (2022b). Statistics Canada. https://www.statcan.gc.ca/en/subjects-start/agriculture_and_food

Statistics Canada. (2022c, December 31). Exports of Canadian grain and wheat flour. https://www.grainscanada.gc.ca/en/grain-research/statistics/exports-grain-wheat-flour/

StreetLight. (2022). Truck Volume Methodology and Validation.

TAC. (2017). Traffic Monitoring Practices Guide for Canadian Provinces and Municipalities.

Tosterud, R. J. (1973). A Simulation model for rationalizing the grain transportation and handling system in western Canada on a regional basis.

Transportation Research Board. (2021). Measuring and Managing Freight System Resilience Workshop. Transportation Research Circular.

Turner, A. P., Sama, M. P., McNeill, L. S. G., Dvorak, J. S., Mark, T., & Montross, M. D. (2019). A discrete event simulation model for analysis of farm scale grain transportation systems. Computers and Electronics in Agriculture, 167. https://doi.org/10.1016/j.compag.2019.105040

United States Department of Agriculture and United States Department of Transportation. (2010). Study of Rural Transportation Issues.

Wattana, K., & Nishio, M. (2017). Traffic volume estimation in a cable-stayed bridge using dynamic responses acquired in the structural health monitoring. Structural Control and Health Monitoring, 24(4). https://doi.org/10.1002/stc.1890

Wood, S., & Regehr, J. (2017). Regulations governing the operation of longer combination vehicles in Canada. Canadian Journal of Civil Engineering, 44(10), 838849.

Yi, Z., Liu, X. C., Markovic, N., & Phillips, J. (2021). Inferencing hourly traffic volume using data-driven machine learning and graph theory. Computers, Environment and Urban Systems, 85. https://doi.org/10.1016/j.compenvurbsys.2020.101548