Title: Canadian commercial trucking movements: Improving the identification of stop locations from continuously streaming GPS data.

By: Kristina Kwiatkowski
Adviser: J Blanford

Abstract

Continuous data captured by GPS systems are used to monitor Canadian trucking movements. Trucks can make multiple stops for varying durations therefore making it difficult to identify stops that represent a delivery or a destination. In order to use these data for determining trucking routes and estimating time-to-market it is necessary to identify stops between a point of origin and a destination. Identifying a point of origin and destinations are a challenge. In this study we analyzed trucking data collected for one month throughout North America and examined time stopped at a location, density of GPS points at a location and both time and density to identify stops. Identified stops were validated against imagery and GIS methods used to highlight key movement corridors and distribution locations visited by each of the trucks. The methods presented here are useful for monitoring truck movements and identifying areas in need of investments when examining fluidity indicators (time-to-market) between two locations.

Keywords: trucking, GPS, GIS-T, commercial transport, traffic management, supply-chain logistics, fluidity indicator, origin-destination, mobility data, routing analysis

1.0 Introduction

The Canadian-American border is the largest shared border in the world, spanning over 8000 kilometres (Gibbins, 2005). Canada and the United States also share the world's largest bilateral trading agreement. Commercial trucking plays a major role in the transportation of goods over the border accounting for 57% of the value of Canada's trade with the United States (Transport_Canada, 2011) . During 2013, over 5 million trucks crossed the border into Canada with imports valuing in excess of CAD $239.8 million and exports valuing in excess of CAD $157.3 million (Transport_Canada, 2011, 2014) (Table 1). As trade volumes continue to increase, safe movement of freight through the environment is important to avoid accidents (e.g. train explosion due to flammable cargo, such as oil, in Quebec 2013 (CBC, 2013)) and minimize pollution (e.g. along main transport routes (NACEC, 2001) and areas of high wait-times (CCPP, 2005)). Infrastructure will also be affected resulting in the need for enhancements to existing transport systems and changes in the frequency at which roads need to be repaired (Gillen, 2012). Trucking delays can be costly resulting in increased inventory costs due to additional fuel consumption coupled with rising fuel prices (Gillen, 2012). Therefore understanding how goods travel between locations is important for ensuring safe, efficient and sustainable movement of freight both now and in the future. Knowing where high volume routes and bottlenecks occur within the transport system are important for investment planning (Figliozzi et al., 2011) to maintain efficiency and minimizing costs.

In Canada, Transport Canada's Gateways and Trade Corridors Initiative (TCGTCI) have developed a fluidity indicator that evaluates how trade corridors operate and determines the reliability (i.e. the ability for a trade corridor to yield a consistent transit time) associated with a trade corridor (Eisele et al., 2013). The fluidity indicator captures "time-to-market", essentially the time it takes for goods to travel from a source location to its final destination as the goods move through the supply chain (Transport_Canada, 2011). The indicator value quantifies the variability and reliability of freight movements through the system, therefore the value is used to set transport performance targets (i.e. transit and dwell time benchmarking by mode of transport (e.g. road, rail, air, water)), guide national trade policy, monitor improvement of policies, ensuring asset management accountability by measuring return on infrastructure investments and marketing (Transport_Canada, 2011) as well as assess the monetary impact of variability (Tardif, 2009).

Capturing "time-to-market" requires calculating how realistically an object, in this case a truck, can get between two locations, an origin and destination within a specified time. The analysis of commercial trucking movements is not new (see (Figliozzi et al., 2011; Greaves and Figliozzi, 2008; Gregory and Kwiatkowski, 2011; Leore et al., 2003)). Data from a variety of sources such as driver surveys (Klein and Goodchild, 2011), third party Global Positioning System (GPS) data providers (Gregory and Kwiatkowski, 2011) and in house GPS data loggers (Greaves and Figliozzi, 2008) have been used to assess trucking movement. Data captured through GPS provide spatial accuracy but may be semi-continuous depending on whether the collection method is change-based (i.e. change in speed or direction of the object) or collected at set time intervals (Andrienko et al., 2013). These data provide trajectories of movement and lack additional levels of detail such as information of source and destination, purpose of trip and road/route that was taken.

To make sense of these data and improve upon these limitations several studies have developed a variety of methods that enable analysts to identify where concentrations of movement occur (Rinzivillo et al., 2008); identify where flow of movement may be affected (e.g. bottlenecks) (McCormack and Zhao, 2011) and determine the source and destination of movement (Gregory and Kwiatkowski, 2011). For example, Figliozzi et al. (2011) and McCormack and Zhao (2011) joined commercial truck GPS data to segmented road networks to determine trucking corridors and identify bottlenecks of trucking freight corridors and measure the reliability of truck movement.

Stop time has been used to determine the purpose of a trip and hence origin and destination(Axhausen et al., 2003; Greaves and Figliozzi, 2008; Sharman and Roorda, 2011). Axhausen et al. (Axhausen et al., 2003) correlated destinations with trip purpose by utilizing GPS tracks. During this study the duration of stop time at each location was compared to a number of points of interest within a 200-metre radius of a cluster centre. Similarly, Sharman and Roorda (2011) used a 5 minute stop time to determine destinations of trucking movements. Gregory and Kwiatkowski (2011) determined the origin, destination and trip length of GPS trucking movements through the use of 'geofences ' or virtual city boundaries based on the Census Metropolitan Area of select major Canadian cities (Canada, 2011) Thus, origin/destination locations were determined when a truck passed a geofence and entered a city. A trip was determined based on the time taken for a truck to travel between two geofence locations. Greaves and Figliozzi (2008) used a combination of vehicle heading, stop time and distance travelled to determine the origin and destination of trucks. A destination was determined if the distance from the previous GPS point was less than six metres, the heading did not change, travel speed was zero and a stop time of four minutes was recorded.

Although, these methods are useful for identifying the source and destination of a trip, there are several limitations. The method by Sharman and Roorda (2011) only utilized 5 minute stop times to capture the source and destination of a trip. This could result in the misclassification of destinations since these short stop times may only be capturing refueling, restroom or meal breaks. The method by Gregory and Kwiatkowski (2011) only calculates travel routes between paired cities therefore locations that are not included in this pairing will be omitted resulting in misclassification of trips

Currently Transport Canada assesses the fluidity of truck movements between locations by estimating the travel time between the source and destination of truck movement between 48 cities, 96 city pairs within Canada as described by (Gregory and Kwiatkowski, 2011). The key top 12 Canadian cities are based on the population of census metropolitan areas as identified by Statistics Canada (2013) . For each paired city an origin-destination matrix (OD) capturing the average distance and travel time between each location was determined using surveys (Gregory and Kwiatkowski, 2011). These were then used to determine the reliability/fluidity of the road network by comparing the time it takes for a truck to pass between a source (geofence location) and destination (geofence location) to the OD matrix for the same two locations (Tardif, 2009). As highlighted in the previous paragraph there are limitations to using this method. Therefore, the objective of this study was to enhance the existing OD matrix currently used by Transport Canada by developing a methodology that can be used to identify origin/destinations from GPS trucking data. Once identified these locations can be used for developing estimates of "time-to-market" between new origin-destination pairings.

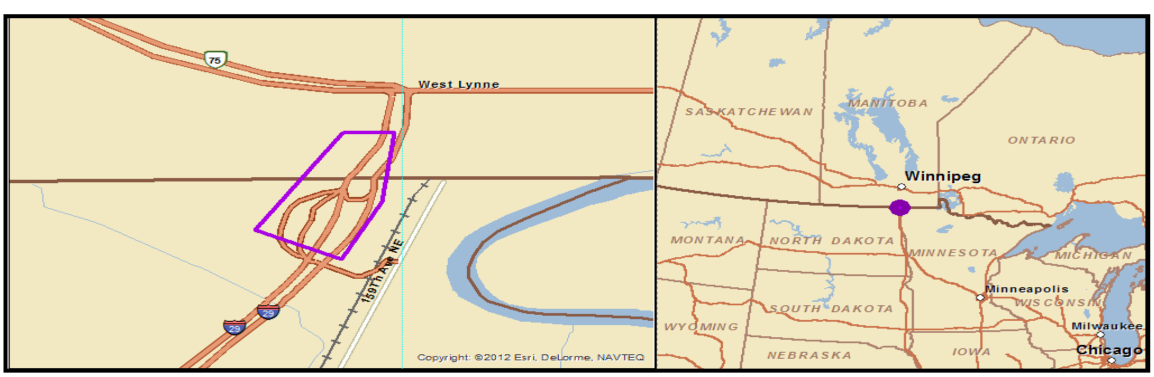
2.0 Methodology

To develop the methodologies we used GPS trucking data for one month. The data and methods are described next.

2.1 Data

The GPS data used in this study was collected from a third party vendor and consisted of data from 846 different class 8 commercial trucking carriers (e.g. trucks weighing over 33,000 lbs.). The information associated with each record was the carrier id, truck id, latitude, longitude, date and time. The GPS receiver is installed on the trucks and collected at various interval depending on trucking company. Each week Transport Canada Data Services Centre receives an update and stores the data as a table in an SQL Server database. GPS data for 62,742 unique trucks have been collected. For a single truck the number of GPS points collected in a day can range from 1 to 655, therefore the dataset can grow quite large very quickly, particularly when trying to analyze movement of 62,742 trucks. Due to the large number of trucks tracked daily (N=30,770; GPS points N = 2.9 million) for the purpose of this study, a subset of trucking data was selected for analysis. Trucks crossing the border at Emerson, Manitoba, were isolated by geofencing (an area of 46,256 metres squared) and used to select both inbound (to Canada) and outbound (to USA) trucks (Figure 1). Data was extracted for February 15 - April 15, 2013. However, only the month of March was analyzed.

Figure 1: Geofence at Emerson border crossing used to select GPS trucks. Map created in ArcGIS 10.2 with ESRI background map.



Data was error checked and duplicates removed. Date and times were provided in an integer format and converted to a date time stamp for the purpose of easily ordering the data. A unique id was created for every record based on the truck id and date time stamp chronologically. Three additional fields were created to capture the speed, distance and elapsed time between each consecutive GPS point for each unique truck. Distances were calculated using the Haversine formula (Gregory and Kwiatkowski, 2011). Elapsed time between two locations were calculated by taking the difference in time between the current GPS point and last known GPS point. Distance and time were then used to calculate the speed between consecutive points in kilometres per hour and used to error check the GPS data. Trucks travelling at speeds greater than 150km/h were removed since it is not feasible for trucks to travel at this velocity (Greaves and Figliozzi, 2008).

2.2 Spatial and temporal movement of trucks

To understand the movement of trucks during March, tracks for each truck were created by date and time. Each track was stored as a geography data type in an SQL database and imported into ArcGIS 10.2 using a database connection.

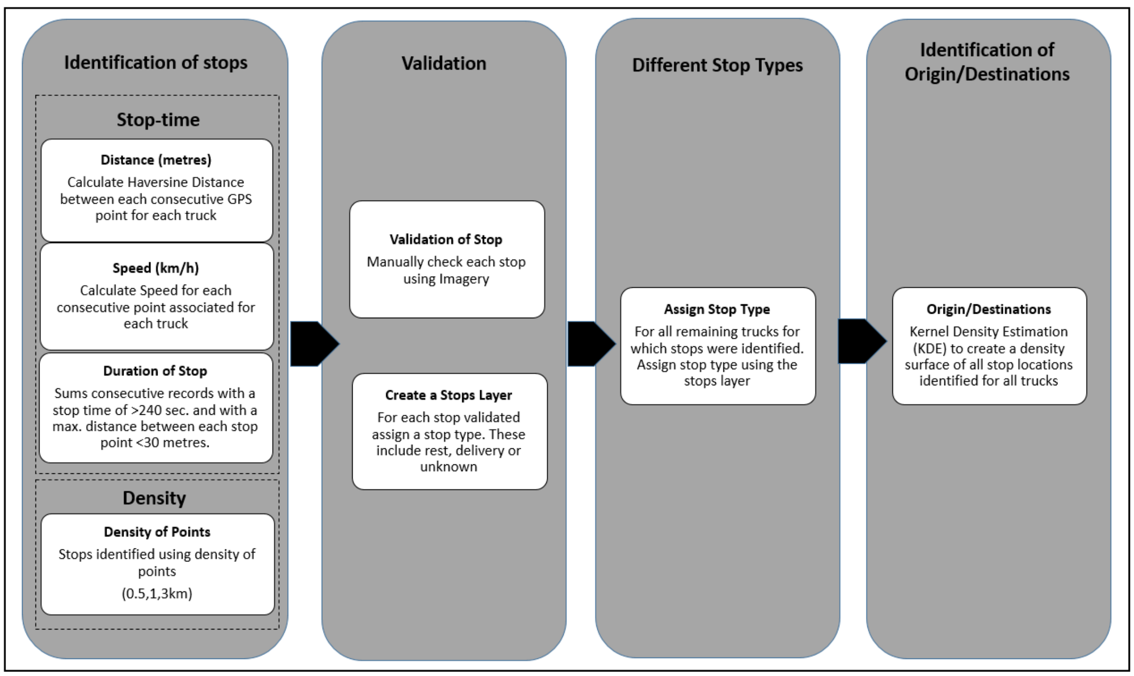
Most frequently used routes were identified using Kernel Density Estimation (KDE). This method has been widely used for visualizing point data and been useful for identifying traffic accident hotspot locations (Anderson, 2009; Xie and Yan, 2008), delineating urban areas (Borruso, 2003) and discovering spatial patterns in origin-destination mobility data (Guo et al., 2012). The Kernel Density tool works by calculating the amount of lines located in an area, or 'kernel'. The kernel is defined as a circular area around each line (Anderson, 2009). The lines were then examined based on their distance from the weighted mean centre of all lines in the study area. The distances for each kernel from the mean centre are summed and the density estimate is created for the trucks (Anderson, 2009). The GPS tracks were used as the input polyline feature and a search radius of 1km was used. The results of the Kernel Density calculation were compared to an ESRI road network layer using the Zonal Statistics tool in ArcGIS 10.2. By combining the density results with the road network data, the sections of roads with high truck traffic volumes were identified and visualized. This was performed to identify which highways the trucks in this dataset predominately use.

2.3 Determining Stop Locations

As described earlier the fluidity indicator captures "time-to-market" by comparing actual travel time to between two locations to the known travel time. Since the GPS data are a collection of points that are collected continuously these data do not contain trip information such as origin, destination and transit times. Truck drivers can make multiple stops throughout their journey that may include breaks (rest and food), borders or tolls, and pickup or delivery of goods. The process of delivery or picking up of goods varies by the type of goods, time of day. For example, a truck carrying a container from a marine terminal to a department store will need to pick up the goods at a specific time and deliver the goods at an allotted time. If the truck is late, it may need to park and wait until it can make the delivery, resulting in a variable and extended stop time. Conversely, if the truck arrives within the allotted time the delivery can take a matter of minutes. This variation in delivery times can make the identification of stops challenging.

Since we did not know the origin or destination of any trips within our dataset, stops were identified using stop-time (see 2.3.1) and density of GPS points (see 2.3.2). To validate our findings we developed a test dataset that was checked manually against imagery data. The test dataset was comprised of 10 randomly selected trucks. These were used to identify different stop types and create a stops layer that could then be used to classify stops for each of the remaining trucks. Once each of the stops were identified key origin/destination locations were identified, as summarized in **Figure 2**.

Figure 2: Process used to identify, validate and create a layer of different stop types such as rest, delivery and unknown. Once a layer containing stop types was created, this was used to classify different stop types for the remaining trucks.



2.3.1 Stop-time: Stop times were calculated for trucks that moved less than 30 metres within a time threshold of 240 seconds (Greaves and Figliozzi, 2008). Similar to other studies (Greaves and Figliozzi, 2008), who found that when a GPS unit was stationary, the GPS measurements fluctuated to within 30 metres of where the actual object was positioned. Therefore to account for this, we selected the threshold to isolate stop times and stop locations. The total time a truck was stopped was calculated by cumulating the sum of time elapsed for each unique truck for a distance travelled of 30 metres or less. Each stop was assigned a null value, unique id number and the total stop-time.

2.3.2 Density: Density of GPS points were calculated by converting the GPS points to a raster with a cell size of 0.5, 1 and 3km^2. In other words, each raster cell was assigned the total number of GPS points occurring within a 0.5, 1 and 3km sq. area, thus capturing the number of closely distributed point. To accomplish this, the GPS points for each unique truck was converted to a raster using count as the cell assignment in ArcGIS 10.2.

2.3.3 Validation of Stops: Each stop using method 2.3.1 and 2.3.2 was verified by comparing the density of points to imagery. Imagery was available as a basemap through ESRI's map services and added as a background layer in ArcGIS 10.2. For the purpose of this study we used 'Imagery with labels'. Each stop was classified as a rest/break (to represent stops at lay-by's, gas stations, and truck rest stops), delivery (to represent stops at distribution centers and shopping centers) and unknown (to represent locations that were unidentifiable). Examples of these stops are illustrated in Figure 3. For (ii), stops were assessed for cells with 50 or more points. Preliminary assessments found that cell values of 50 points or less across all cell sizes (0.5, 1 and 3km^2) represented congestion along major highways and therefore were not verified. The outputs from here were used in the combination of stop-time and density method that is described next.

Figure 3: Examples of the different stop types that were identified and classified using background imagery. Imagery was provided by ESRI and added to ArcGIS 10.2 as a basemap layer. The basemap layer selected was World Imagery.

The validated stops for the 10 trucks were converted to a raster dataset to create a points of interest (POI) layer. Each stop-type was assigned a unique value (1 = delivery, 4 =

rest/gas stop, 6 = border, 8 = unknown, 10 = unclassified) and the minimum value was assigned priority when converting from point to raster using a cell size of 10km to capture near points within a 10km by 10km area. The stops layer was then used to assign stops identified for the remaining trucks.

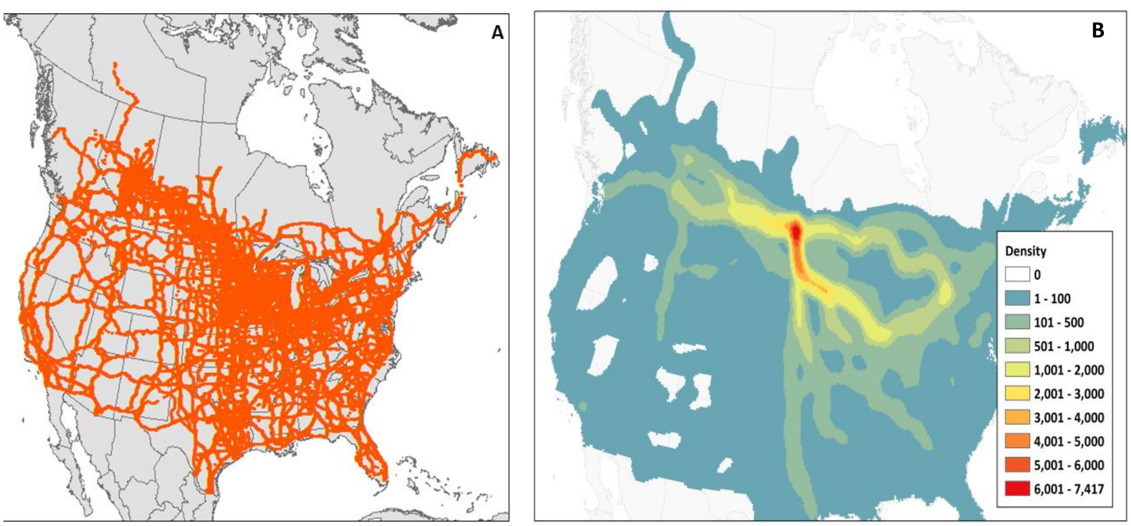
2.3.4 Identification of Origin/Destination: Once the final points were identified and stop-types determined we were able to identify key stop locations and stop-type by using KDE to highlight hotspots and density (point-to raster) to isolate stops based on the number of times a truck visited a location. Each cell was assigned the most frequent stop-type identified.

3.0 Results

3.1 Spatial and Temporal Movement of Trucks

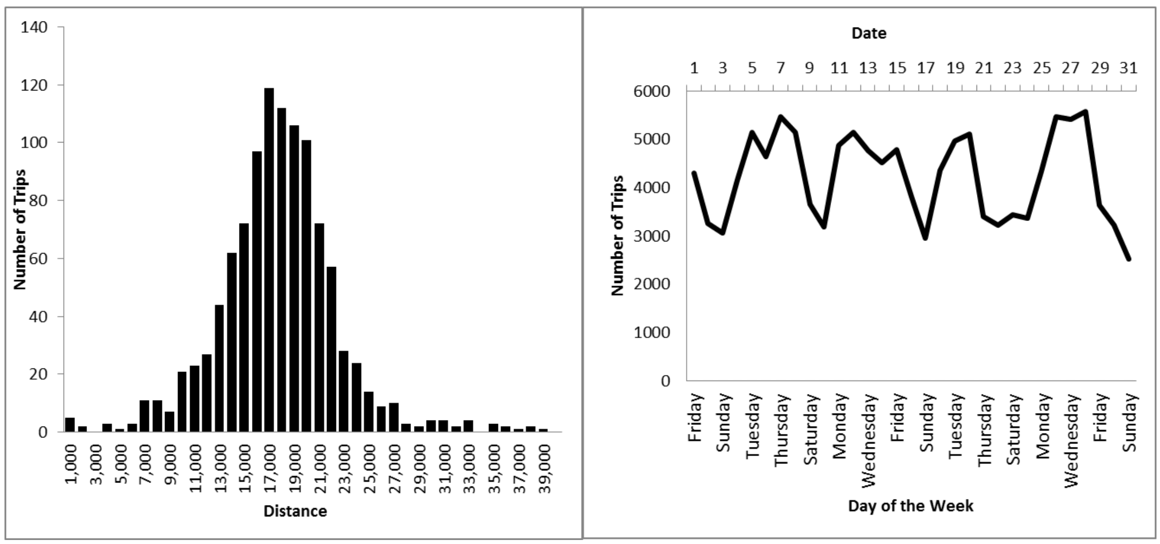
A total of 1069 trucks were recorded taking trips resulting in 3,774,281 GPS points being collected. Although trucks were only selected for the Emerson crossing, these trucks traveled extensively throughout the USA and Canada (Figure 4A). The densest location of trucks were found near the Emerson border (Figure 4B).

Figure 4: (A) Routes taken by all trucks (N=1,069) and (B) areas where the highest truck densities occurred during March, 2013.

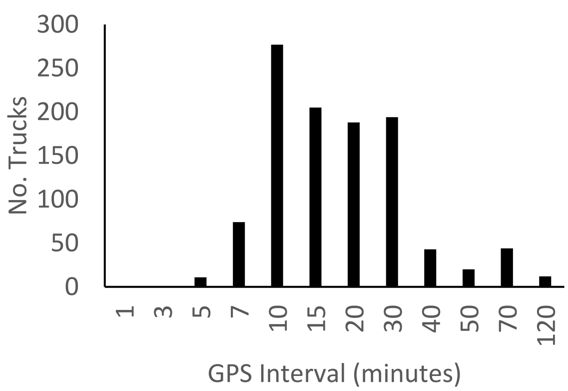


Trucks traveled between 1,000 and 39,000 km with the vast majority traveling between 17,000 and 18,000 km (Figure 5A) with daily trips averaging 556 km. Truck movement was cyclical with the highest number of trips being made during weekdays (Monday – Thursday) and diminished over the weekend (Saturday and Sunday) (Figure 5B). On average, trucks traveled at a speed of 82 km/h (SE +/- 0.24) GPS data was collected at various intervals (Figure 5C).

Figure 5: (A) Distances traveled by each truck in km and (B) the number of trips during each day of the week and (C) average time intervals (minutes) between GPS point for each truck during March, 2013.



C



3.2 Identification of Different Stop Types

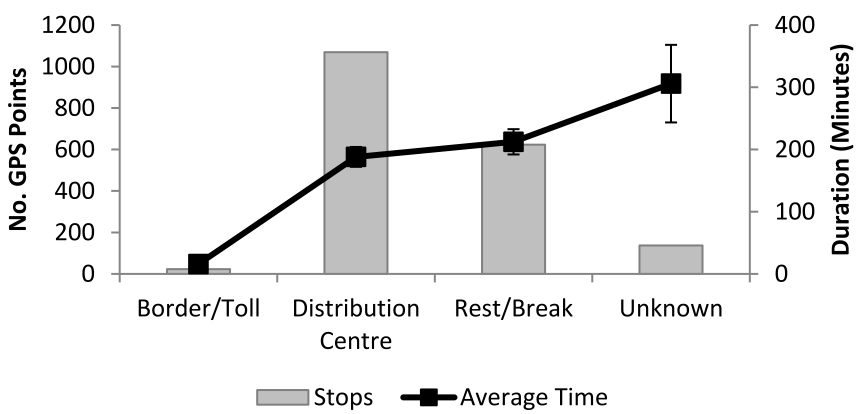
3.2.1 Identification of stops through the development of a training sample: A total of 52,219 GPS points were collected for the 10 trucks. The average intervals between GPS points for each truck ranged from 7m to 129m. A total of 1,852 stops with an average stop time of 3.73 hours were identified. When manually inspected against imagery we found that the majority of these were deliveries (N=1,065) followed by rest stops (N=623) (Table 1). The distribution of points were assessed at three different scales, 0.5km, 1km and 3km and stops analyzed. We identified more than 11,300 stops (N=11,377 (0.5km); N= 12,287 (1km); and N=14,675 (3km)) (Table 1).

Table 1: Summary of 10 randomly identified trucks and the number of stops identified using the density and stop-time method.

Truck ID	*No. GPS Points*	*Distance Travelled (km)*	*No. Stops Identified using Density Method (0.5km)*	*No. Stops Identified using Density Method (1km)*	*No. Stops Identified using Density Method (3km)*	*No. Stops Identified using Stop-time Method*	*Mean Interval (Minutes)*
2800	12,081	40,270	2,181	2,363	2,928	325	7
5193	12,060	45,281	2,921	3,090	3,363	337	7
3249	9,434	22,939	3,185	3,339	4,214	395	9
18155	3,105	27,112	110	111	165	171	20
24829	3,995	30,724	1,033	1,003	1,020	178	21
13299	3,602	28,508	726	821	1,082	179	24
19494	3,016	33,261	618	655	690	140	28
13571	2,688	39,398	278	485	688	20	31
10743	1,566	33,066	146	175	178	63	55
20561	672	15,565	179	245	347	44	129

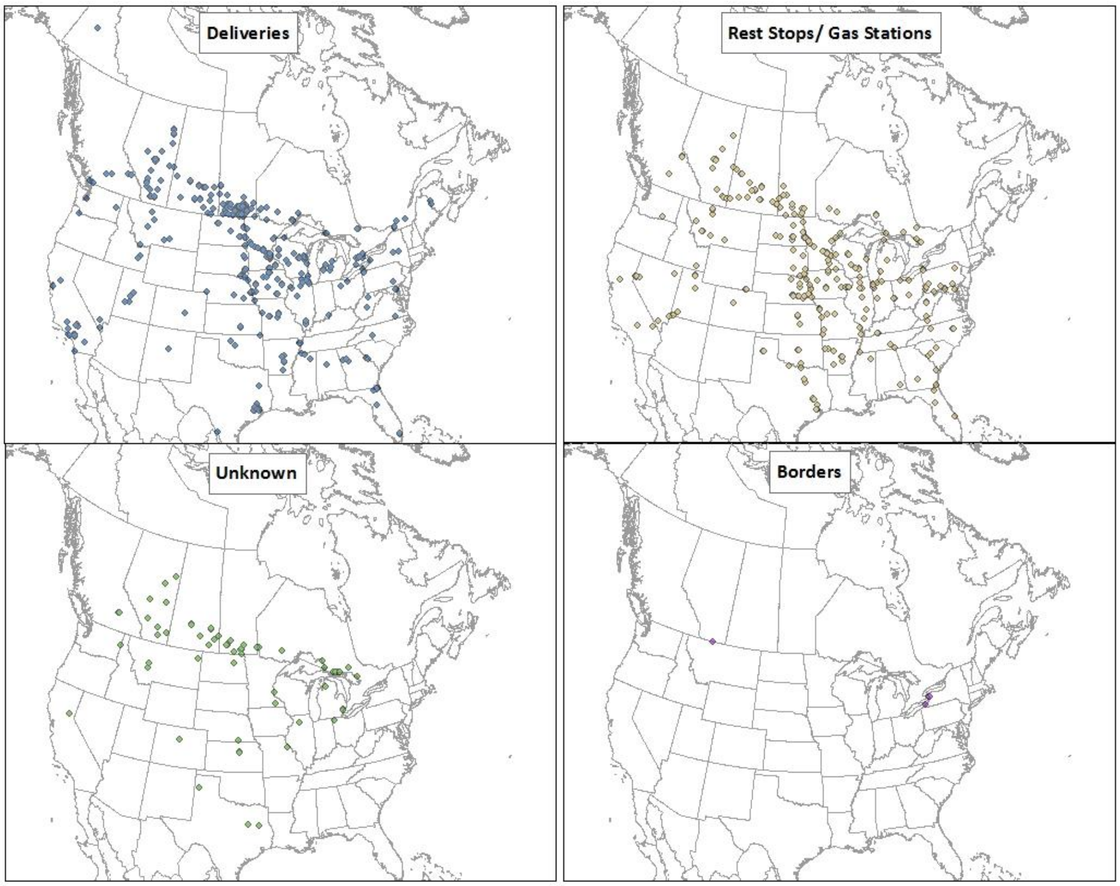
The time taken at rest stops and to make deliveries was highly variable and in many cases similar (Figure 6). For example, the shortest rest stop was recorded to be 4.03 minutes and the longest at 6,841.85 minutes, with an average stop time of 212.35 minutes. Similar times were also captured for deliveries with the quickest stop recorded at 4.02 minutes and the longest at 6,931.15 minutes with an average stop time of 188.09 minutes.

Figure 6: Average stop time associated with different stop types. N= 10 trucks.



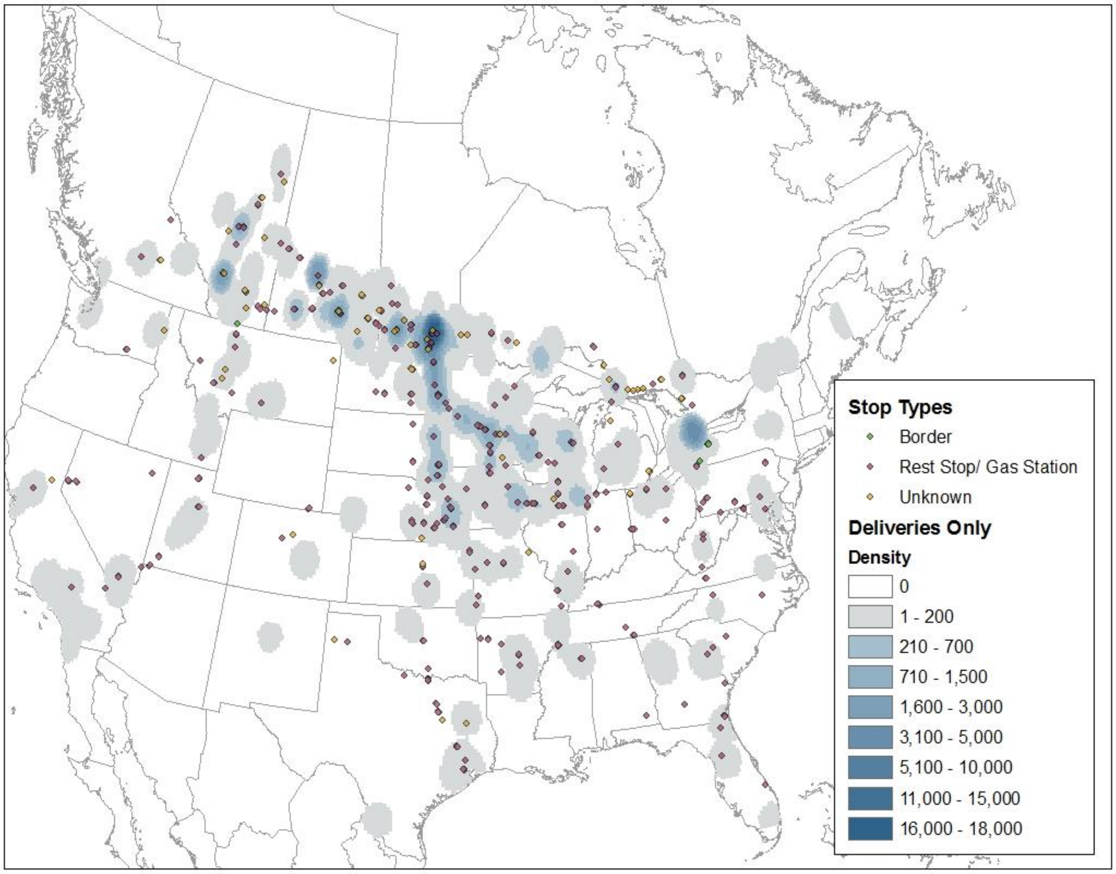
3.2.2 Identification of stops for all remaining trucks: For the remaining dataset a total number of 143,101 stops were identified using time alone. Of these, 44% were classified as deliveries, 15% as rest, 0.8% as unknown (the location where the stop occurred was obscure and not able to be categorized), 0.2% as Border crossing and the remaining 40% were unclassified.

Figure 7: Map of all stop-types (deliveries, rest stops/gas stations, unknown, border crossing) identified using stop-time.



The highest density of the stops (Figure 8) were located in southern Manitoba near the Emerson border and Winnipeg. The areas surrounding the Great Lakes, particularly, the Greater Toronto Area and Chicago also had high densities of stops.

Figure 8: Density of stop locations identified throughout North America.



4.0 Discussion

With a rise in the volume of trade between locations both within Canada and across the border with the USA, identifying key trade routes are important for the management of road infrastructure (McCormack and Zhao, 2011). In this study we analyzed GPS data collected for over a thousand trucks and were able to identify 143,101 stops that ranged from border/toll stoppages to rest stops and the delivery of goods to distribution centers. Our ultimate goal was to identify delivery locations so that these can be used to assess "time-to-market" and determine the reliability of freight movement throughout the system. 84,288 of locations were identified in Canada and 58,813 in the USA. Although scattered throughout the USA, the majority of the deliveries were to locations close to the border. This can be explained by the way in which the data was extracted (by selecting only vehicles that crossed at the Emerson border) as well as the way in which trans-border shipments can occur. Although a free trade agreement exists between Canada and the USA to eliminate trade barriers (NAFTA) truck movement may be restricted by cabotage regulations (e.g. the transportation services by a foreign firm between point to point moves within the same country) (Rodrigue, 2013)) and the location of distribution centres.

Although we were able to identify stops using stop-time and density, our ability to distinguish between the different stop-types was challenging. In this study, we clearly showed that stop-times can be highly variable. For example, we found a large overlap between the time taken to make deliveries and the time taken for rest-stops. Therefore, using stop-time on its own may result in the misidentification of stop types.

Using density of GPS points enabled us to identify where the locations with the highest concentrations of points were located. By manually identifying the type of stops, we were able to explore different relationships between the different stop types and concentration of points. For locations with consistently high density of points (e.g. > 150 points per 0.5, 1 and $3km^2$) delivery centers were easily identified. Although good for identifying key distribution centers, there are a number of limitations associated with this method. For one, the analysis of density alone does not provide any time-based data in the output. Secondly, it favours trucks with small intervals between GPS points. Finally, it does not account for deliveries at locations that occur less frequently. For example, a truck may only deliver goods to smaller centres where there is only need for one truck to deliver goods once per week or month.

Due to the variability in which trucks operate and the time they take to deliver goods (e.g. 4 minutes to in excess of 115 hours), the ability to identify delivery locations without some prior knowledge is limiting. Ashbrook and Starner (Ashbrook and Starner, 2002, 2003) identified significant places from GPS movement data by clustering GPS points within a specified radius of one another. Stopher, Clifford, Zhang & Fitzgerald (Stopher et al., 2008) as well as Bohte and Maat (Bohte and Maat, 2009) used trip surveys in conjunction with the GPS data collection to identify the trip purposes. In this study we had no prior knowledge of delivery locations and used a trained sample set of 10 trucks that were validated against imagery. By creating a POI layer, we were able to identify 143,101 stop locations (14.7% = rest; 46.1%=delivery, 1.0%=unknown, 38.1%=unclassified). In addition, we found that 38.1 percent of stops were not within the original POI stops file that was created from the 10 trucks. Thus, from 10 trucks we were able to identify 61.9% of stops.

The large amount of GPS trucking data can serve as a useful tool for determining key routes of trucks, calculating transit times between city pairs, or identifying where trucks stop; the lack of behavioural data makes identifying the type of stops difficult. This is due to supply chain logistics (e.g. multiple stops between origin-destination (Patil and Holguín-Veras, 2005)) and the different characteristics of trucks, trucking companies, number of drivers and the nature of the goods. For example, trucking company A may only be concerned with urban freight distribution and make frequent deliveries throughout the day within a particular urban area, whereas trucking company B may only be concerned with long haul freight from distribution centre A to B. The behaviour of the driver and the truck can also vary depending on the nature of the goods, the value of the goods, or whether or not the vehicle is empty or loaded.

Identifying destinations using GPS trucking data is challenging. By initially identifying and validating the stop locations of 10 trucks, we were able to create a POI layer that was useful for classifying different stop types for the remainder of trucks. Not only are the methods useful for building knowledge on known stops and trucking patterns over time, but can also be used to assess trucking patterns and the relationship along corridors (e.g. NAFTA corridors) (Rodrigue, 2013), identify key distribution centers and understand how these shape freight flow structures and port selection (Perrine et al.; Rodrigue, 2013).

Here we presented a methodology that can be used to identify different stop-types by developing a training dataset. In this study we only used one month of data. As more data is analyzed over time, key stops will become more apparent as trucking densities will increase in key locations. These can be matched with place names and used to enhance the existing OD matrix currently used by Transport Canada to include additional geographic locations.

References

Anderson, T.K., 2009. Kernel density estimation and K-means clustering to profile road accident hotspots. Accident; analysis and prevention 41, 359-364.

Andrienko, G., Andrienko, N., Bak, P., Keim, D., Wrobel, S., 2013. Visual Analytics of Movement. Springer Berlin Heidelberg., Berlin, Heidelberg.

Ashbrook, D., Starner, T., 2002. Learning Significant Locations and Predicting User Movement with GPS, IEEE Int. Symp. on Wearable Computing (ISWC'2002), Seattle, USA, pp. 101-108.

Ashbrook, D., Starner, T., 2003. Using GPS to learn significant locations and predict movement across multiple users. Personal and Ubiquitous Computing 7, 275-286.

Axhausen, K.W., Schönfelder, S., Wolf, J., Oliveira, M., Samaga, U., 2003. Eighty Weeks of GPS Traces : Approaches to Enriching Trip Information. Transport Res Rec 1870, 46-54.

Bohte, W., Maat, K., 2009. Deriving and validating trip purposes and travel modes for multi-day GPS-based travel surveys: A large-scale application in the Netherlands. Transportation Research Part C 17, 285-297.

Borruso, G., 2003. Network density and the delineation of urban areas. Transactions in GIS 7, 177-191.

Canada, S., 2011. 2011 Census - Boundary files, In: Canada, S. (Ed.), Canada.

Canada, S., 2013. Population of census metropolitan areas. Table 051-0056. Statistics Canada, Canada.

CBC, 2013. 50 feared dead in Lac-Mégantic train derailment. CBC News.

CCPP, 2005. Truckers Idling Reduction Program: Case Study. Candian Centre for Pollution Prevention.

Eisele, W., Tardif, L.-P., Villa, J.C., Schrank, D.L., Lomax, T., 2013. Evaluating Global Freight Corridor Performance for Canada. Journal of Transportation of the Institute of Transportation Engineers I, 39-58.

Figliozzi, M.A., Wheeler, N., Albright, E., Walker, L., Sarkar, S., Rice, D., 2011. Algorithms for Studying the Impact of Travel Time Reliability Along Multisegment Trucking Freight Corridors. Transport Res Rec, 26-34.

Gibbins, R., 2005. Meaning and Significance of the Canadian-American Border, In: Gangster, P., Lorey, D.E. (Eds.), Borders and Border Politics in a Globalizing World. Rowman & Littlefield, pp. 151–168.

Gillen, P.D., 2012. Building for the Future of British Columbia : The Importance of Transportation Infrastructure to Economic Growth and Employment.

Greaves, S.P., Figliozzi, M.A., 2008. Collecting Commercial Vehicle Tour Data with Passive Global Positioning System Technology Issues and Potential Applications. Transport Res Rec, 158-166.

Gregory, A., Kwiatkowski, K., 2011. The Fluidity of the Canadian Transportation System: A Commercial Trucking Perspective, CTRF Annual Conference, Gatineau, Quebec, pp. 1-12.

Guo, D., Zhu, X., Jin, H., Gao, P., Andris, C., 2012. Discovering spatial patterns in orign-destination mobility data. Transactions in GIS 16, 411-429.

Klein, M., Goodchild, A., 2011. Pacific Highway Commercial Vehicle Operations. . Transportation Research Record: Journal of the Transportation Research Board, 2238, 15-23.

Leore, B., Trent, M., Shallow, T., 2003. Using truck tractor logs to estimate travel times at canada-us border crossings in southern Ontario, CTRF Annual Conference, Ottawa, Canada.

McCormack, E., Zhao, W., 2011. GPS truck data performance measures program in Washington State. Washington State Transport Center, Washington, p. 17.

NACEC, 2001. North American Trade and Transportation Corridors : Environmental Impacts and Mitigation Strategies. North American Commission for Environmental Cooperation.

NAFTA, 1993. North American Free Trade Agreement Implementation Act, Public Law No. 103-182, 107 Stat. 2057.

Patil, G., Holguín-Veras, J., 2005. Observed trip chain behavior of commercial vehicles. Transp Res Rec 1906, 74-80.

Perrine, S., Kwiatkowski, K., Blanford, J.I., International food imports: Using visualization methods to identify vulnerabilities and risk. Journal of Transport Geography.

Rinzivillo, S., Pedreschi, D., Nanni, M., Giannotti, F., Andrienko, N., Andrienko, G., 2008. Visually driven analysis of movement data by progressive clustering. Inform Visual 7, 225-239.

Rodrigue, J.-P.e.a., 2013. The Geography of Transport Systems, . Hofstra University, Department of Global Studies & Geography, Hofstra University.

Sharman, B.W., Roorda, M.J., 2011. Analysis of Freight Global Positioning System Data. Transportation Research Record: Journal of the Transportation Research Board 2246, 83–91.

Stopher, P., Clifford, E., Zhang, J., FitzGerald, C., 2008. Deducing mode and purpose from GPS data, Working Paper ITLS-WP-08-06. INSTITUTE of TRANSPORT and LOGISTICS STUDIES, The Australian Key Centre in Transport and Logistics Management, The University of Sydney, Sydney, Australia, p. 13.

Tardif, L.-P., 2009. Application of Freight Flow Measurements. Vancouver TRB/OECD Workshop, Vancouver, Canada, p. 24.

Transport_Canada, 2011. Transportation in Canada. Transport Canada, Ottawa Canada, p. 149.

Transport_Canada, 2014. Transportation in Canada 2013: Statistical Addendum. Report No. TP 14816. . Transport Canada.

Xie, Z., Yan, J., 2008. Kernel density estimation of traffic accidents in a network space. Computers, Environment and Urban Systems 32, 396-406.