Truck Parking Utilization Analysis Using GPS data

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Abstract: Unavailability of sufficient parking spaces during various time periods at rest areas results in illegal and unsafe parking at On/Off ramps, and other unauthorized areas which may lead to traffic safety hazards. In this research, the authors attempt to understand truck parking utilization by developing econometric models using truck GPS data for predicting truck parking utilization at rest areas in order to improve truck parking management and ensure proper utilization of the parking spaces. Count models including Poisson and Negative binomial models were developed in addition to generalized ordered response probit (GORP) models to understand the factors that affect the truck parking utilization. The GORP model that subsumes Poisson model as a special case was found to provide the best data fit. The model results suggest that several factors positively contribute to the truck parking utilization (example, truck volume on the adjacent roadway, number of lanes etc.) at rest areas whereas factors such as on ramp and off-ramp violation decreases the truck utilization. Also, parking utilization was found to be varying considerably by time-of-day.

Author Keywords: Truck parking utilization; Count models; GORP models; Rest area; Truck GPS data.

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Introduction

The freight transportation system in the United States (U.S.) makes one of the most valuable contributions to the nation's economy and growth. In this system, truck traffic is expected to increase by 45% by 2040 (FHWA, Freight Facts and Figures 2013). Long term economic growth is expected to result in even greater demand for truck traffic transportation mode. However, there is a huge gap between the demand and supply of truck parking facilities in many states (Dowling et al. 2014). Also, truck traffic does not get access to all roadways because cities and counties regulate truck traffic either by restricting parking, prohibiting trucks from using certain roads, and/or designating specific routes for truck use. This leads truck drivers to search for parking areas for rest and if parking is not available, they tend to park in non-designated areas such as ramps leading to spillover parking that is a significant safety concern to other road users. Moreover, truck parking has been indicated as the most influential factor for route selection decisions (Dowling et al. 2014). Lack of truck parking is also indicated as a characteristic of an unreliable route as the truck drivers do not get the required amount of rest or sleep and this may lead to safety concerns during travel for the truck driver as well as other modes.

The combination of increased truck traffic and tighter delivery schedules is one of the primary reasons for the increased demand for truck parking in the U.S. (Fleger et al. 2002). The growing economy demands truck drivers to continue driving for longer hours, even when they are fatigued. This situation has severe consequences for highway safety, and the U.S. Department of Transportation (DOT) has hours of service regulations, which necessitate drivers to pause for rest and sleep after specified hours of continuous driving. According to Federal Motor Carrier Safety Administration (FMCSA) drivers can be on duty for 14 hours, out of which they are allowed to drive for 11 hours. After driving for 11-hours drivers' must have at least 10 hours of rest until they are allowed to drive again. Furthermore, 2013 FMCSA hours of service rule requires truck drivers to take a 30-minute break during the first eight hours of a shift. Although there are facilities for resting and sleeping at public rest areas along major highways, many truck drivers cannot take advantage of these facilities because of unavailability of truck parking especially during peak resting

periods. This leads the truck driver to either keep driving without rest which increases the risk of accidents or park at undesignated areas, such as the shoulders along the on- and off-ramps of rest areas and other interchange ramps (Chatterjee and Wegmann 2000). Chatterjee et al. (Chatterjee and Wegmann 2000) conducted an extensive survey of truck accumulation and utilization at all public rest areas in Tennessee to understand the usage characteristics of truck parking in public rest areas at night and to assess the nature and magnitude of the problem. In order to understand and ensure proper utilization of the truck parking at the rest areas at specific periods of time, research is needed to understand utilization during different time periods and the factors associated with this utilization.

The primary objective of this paper is to develop truck parking utilization models using GPS truck data and understand the associated factors that affect truck parking utilization. This study extends the work done by Golias et al. (Golias et al. 2012) who used truck GPS data to evaluate the performance of roadways in Memphis, TN using truck stop and rest stop demand analysis. All truck stops with duration between eight to twelve hours were considered. The authors provided frequency of truck stops based on the time of the day for major TN rest stop areas. If truck-drivers know the truck parking areas (TPAs) utilization along their route, they can better plan when and where to park (van de Ven et al. 2012). This will lead to less TPA over-crowding and less off-site parking, and thus increase road safety, and in general enable more efficient use of existing TPA capacity (van de Ven et al. 2012). While the study by Golias et al. (Golias et al. 2012) provided a descriptive overview of the problem, a system state prediction model that can forecast TPA utilization was not developed. In this context, the objectives of the proposed research are four-fold: 1) Assemble a comprehensive dataset for analyzing TPA utilization in TN; 2) Develop econometric models that encompass recent advances in choice modeling literature to estimate the effects of various factors on truck parking utilization; and 3) Evaluate the developed models using model fit and predictive performance criteria; and 4) Compute elasticity effects to quantify the magnitude of impact of different factors on parking utilization.

The rest of the paper is organized as follows. The next section presents an up-to-date literature review on truck parking utilization using truck GPS data. The third section describes the econometric methodology of models used in this study for predicting the truck parking utilization. The fourth section presents the data collection procedure used to process the GPS truck data and obtain the hourly truck utilization for the 24-hour period for all the rest area locations within the case study area along with a brief description of additional data collected for this research. The fifth section presents the model estimation results along with model fit comparison, elasticity effects, and model validation results. The last section concludes the paper and proposes future research opportunities.

Literature Review

In this section, the relevant literature on application of econometric models to evaluate the truck parking utilization, use of GPS data for truck research, and use of different types of data and methodologies to develop truck parking utilization models is presented.

Statistical and Econometric methods for truck parking utilization

Simple regression models have been used for estimating large truck parking on interstates (Golias et al. 2012; Van de Ven et al. 2012). The main significant factors were percent of large truck, total truck volume, parking duration, distance to I-81, distance to nearest truck stop, distance to nearest rest area and service provided. The models developed were then used to estimate demand in 10 and 20 years. Any shortfall in supply with respect to the estimated demand was then determined for each truck stop and the entire highway. The results indicated that the existing maximum demand exceeds the supply. This excess demand will keep increasing if the number of parking spaces for large trucks does not increase. Moreover, mathematical models like simplified demand model have been used to develop national commercial vehicle parking demand model which estimates final demand of commercial vehicle parking for the National Highway System (NHS) in order to investigate the adequacy of truck parking facilities (Fleger et al. 2002). The model predicts truck parking demand for a highway segment based on total truck-hours of travel and the time and duration of the stops. Some of the model parameters were seasonal peaking factor, short haul

to long haul ratio, short term parking duration, time driving for long haul drivers, time at home for long haul drivers and long haul parking ratio. Also, Real-time parking data (count the number of arrivals and departure vehicles) along with driver behavior and demographics and AADT have been used to develop truck parking information system for highway corridors using discrete choice and linear regression model (Garber et al. 2004). Car park utilization/choice model is used to estimate time-dependent demand for truck parking facilities along an interstate highway (Heinitz and Hesse 2009).

Use of Truck GPS Data for Truck Research

Truck GPS data was used to analyze truck parking problems in urban areas (Kawamura et al. 2014) and also to study impact of tolling on truck speed and routing (Wang and Goodchild 2014). Flaskou et al. (Flaskou et al. 2015) developed methodology for processing raw GPS data and developed freight performance measures. Thakur et al. (Thakur et al. 2015) developed algorithms to convert large streams of raw GPS data into more useable truck trip databases. GPS data was also used to study trucks travelling between transportation hubs in Toronto and Chicago (Gingerich et al. 2015). Several researches have used truck GPS data for evaluating performance measures such as truck trip reduction strategy (Fischer et al. 2006), improvement for growing freight demand (Liao 2009), improving truck corridors (McCormack and Hallenbeck 2006), roadway system reliability (McCormack and Northwest 2010) and in transportation planning applications such as truck travel time estimation in urban networks (Morgul et al. 2013). Other have used prediction models to determine commercial vehicle demand and supply characteristics using count and survey data (Bayraktar et al. 2014) and also using truck parking inventory data and crash data (Goods Movement Planning 2001). Moreover, Gaber et al. (Gaber et al. 2005) discussed various literatures and argued that varying methodologies yield different results in the assessment of commercial vehicle parking. Some have used unique approaches such as step by step segment model (Pecheux et al. 2002) calibrated from field surveys and growth factor (Parametrix 2005) developed for the study corridors to predict future truck parking demand.

Data and Methodologies Used for Truck Parking

In some research, survey of truck drivers and truck stop owners was used along with traffic information and duration data (Garber et al. 2002, 2004). A similar kind of survey was done at 31 rest areas in Tennessee on truck accumulation and utilization to understand the usage characteristics of truck parking at night (Chatterjee and Wegmann 2000). This survey data was analyzed to generate a variety of statistics useful for the assessment of the nightly truck parking situation in Tennessee. Floating vehicle data (FVD) which are position measurements from a fleet of vehicles equipped with Global Navigation Satellite System (GNSS) enabled smart-phones have also been used for estimating and forecasting parking utilization (van de Ven et al. 2012).

There have been several studies that assessed the use of technology to detect truck parking availability (Andersson et al. 2013; Fallon and Howard 2011; Gertler and Murray 2011; Haghani et al. 2013; Mbiydzenyuy et al. 2012). These technologies are evaluated to identify their capability of collecting data and to determine whether a truck parking facility is full and if not, to indicate the number of parking spaces available. Others have used low-cost strategy and geo-spatial analysis to rank truck parking areas for identifying parking issues in order to increase truck parking (Adams et al. 2009). Some research sought to address a perceived need for additional truck parking space along U.S interstates highway (Davis 1997).

There have been few different approaches to address the growing demand for truck parking. For example, nighttime observational studies at all public rest areas were done to learn about the parking space utilization characteristics of trucks. The availability of space in private truck stops near interchanges was examined. Results showed that the rest areas were swarming with trucks at night, since a lot of trucks were found parked along the shoulders of highway exit and entrance ramps, as well as on interchange ramps. On the other hand, around 30% of the private truck parking spaces remained vacant (Pecheux et al. 2002). Interview was also held to understand why some truck drivers parked along the highway when there were available private parking spaces. However, it was a preliminary study and it does not explain the utilization or shortage during the various time periods.

From the review of various literatures, it can be understood that roughly 42% of the literature mentioned about using truck GPS data for evaluating parking utilization/demand, about 33% mentioned different methodologies like surveys, to collect truck data and additional data and about more or less 20% mentioned about technological usage of implementing safe and easier truck parking. It has been found that the prediction of parking utilization in the rest areas that is dependent on several factors has not been addressed. This research intends to estimate the parking utilization, and identify factors affecting parking utilization for design and improvement purposes and also identify locations which require rest areas or truck parking so that the truck drivers get ample rest thus increasing safety and efficiency.

Methodology

In this section we present the econometric framework for count data models as a special case of generalized ordered-response models. The generalized ordered response (GOR) model is the generalization of the ordered response (OR) model allowing the threshold values in the OR to vary across the different outcome categories (Eluru et al., 2008).

Count Modeling Framework

Frequency of trucks parked at a rest area is an example of count data and is typically modeled using count models that assume a parametric distribution for the frequency outcomes. The parameters of the underlying distribution (e.g., mean and variance) are specified as a function of different covariates to capture their influence on the count dependent variable. The two most commonly used count models in the literature are the Poisson and Negative Binomial (NB) models. The Poisson model has the *equi-dispersion* property *i.e.;* the expected mean is equal to the variance. However, this is a restrictive assumption and past literature found evidence for both under-dispersion (although less common) and over-dispersion in certain empirical contexts. The NB model is particularly suited for cases when there is over-dispersion in the count data being modeled. The NB model is a generalization of the Poisson model in which the expected mean parameter is assumed to be gamma distributed (Greene 2008). Another aspect of considerable importance while modeling count data is over-representation of zeroes beyond the probability mass implied by the standard

count models – a property referred to as the *excess zeroes* problem. Several variants of standard models including the zero-inflated count models and hurdle count models were developed in the past to address the excess zeroes problem (Gurmu 1998; Lord et al. 2005, 2007). However, extending these methods to cases when there can be over or under representation of several count outcomes (not just zero) can result in complex model structures that are difficult to estimate. Recently, Castro *et al.* developed Generalized Ordered Response (GOR) models that subsume standard count models including Poisson and NB models as special cases and can easily handle deviations in probability profile imposed by standard models (Castro et al. 2012). In this study, these different count models in the literature were estimated and compared to identify the best model for analyzing the number of trucks parked. A brief discussion of alternate modeling methods follows.

Poisson Model

Assuming the truck parking data to be realizations from Poisson distribution, the probability of observing a count outcome *y* conditional on the expected mean parameter λ is given by:

$$P(Y = y) = \frac{e^{-\lambda} \times \lambda^{y}}{y!} \tag{1}$$

As indicated earlier, the Poisson model has the *equi-dispersion* property which implies that the variance of the Poisson distribution is equal to the expected mean parameter λ. So, to ensure that the λ parameter is always greater than 0 during model estimation, it is parameterized as $e^{LOG(\lambda)}$ and $LOG(\lambda)$ is specified as a linear function of different exogenous variables as follows: $LOG(\lambda) = \boldsymbol{\beta}'\boldsymbol{X}$ where $\boldsymbol{X}$ is the vector of exogenous variables and $\boldsymbol{\beta}$ is the corresponding vector of coefficients that were estimated using maximum likelihood inference approach.

Negative Binomial Model

In the NB model, the probability of observing count outcome y conditional on the expected mean parameter λ and dispersion parameter $r > 0$ is given by:

$$P(Y=y)=\left(\frac{r}{r+\lambda}\right)^{r}\times\frac{\Gamma(r+y)}{\Gamma(y+1)\Gamma(r)}\times\left(\frac{\lambda}{r+\lambda}\right)^{y} \tag{2}$$

Where Γ is the gamma function defined as follows:

$$\Gamma(t)=\begin{cases}\int_{x=0}^{\infty}x^{t-1}e^{-x}dx \text{ for positive non}-\text{integer } t\\ (t-1)!\text{ for positive integer } t\end{cases} \tag{3}$$

The expected mean of the NB model is λ whereas the variance is $\lambda+\frac{\lambda^2}{r}$ making the model particularly suited for handling over-dispersion. In the NB model, the dispersion parameter *r* must also be estimated in addition to the β parameters in the $LOG(\lambda)$ specification.

Generalized Ordered Response Probit (GORP) Framework

In the GORP framework, a latent risk propensity y^* is mapped into observed count outcomes *y* by threshold parameters ψ_k where *k* is the index for all possible count outcomes. Assuming specific functional forms for these threshold parameters will result in the GORP framework replicating standard count models. The latent risk propensity y^* in the standard ordered response framework can be written as:

$$y^*=\boldsymbol{\gamma}'\boldsymbol{Z}+\varepsilon \tag{4}$$

Where $\boldsymbol{Z}$ is a vector of all exogenous variables and $\boldsymbol{\gamma}$ is the corresponding vector of coefficients; ε is the stochastic error term that represents all unobserved factors (not captured in the exogenous variables) that can impact y^* and is assumed to be an independent realization from a standard normal distribution, *i.e.*, $\varepsilon\sim N(0,1)$. In the GORP framework, the probability that the observed outcome is *y* is given by:

$$P(Y=y)=P\left(\psi_{y-1}<y^*<\psi_y\right)=P\left(\psi_{y-1}<\boldsymbol{\gamma}'\boldsymbol{Z}+\varepsilon<\psi_y\right) \tag{5a}$$

$$=P\left(\psi_{y-1}-\boldsymbol{\gamma}'\boldsymbol{Z}<\varepsilon<\psi_y-\boldsymbol{\gamma}'\boldsymbol{Z}\right)$$

$$=\Phi\left(\psi_y-\boldsymbol{\gamma}'\boldsymbol{Z}\right)-\Phi\left(\psi_{y-1}-\boldsymbol{\gamma}'\boldsymbol{Z}\right) \tag{5b}$$

Where $\Phi(.)$ is the cumulative distribution function of standard normal random variable.

Standard count models including the Poisson and NB models can be obtained by imposing certain constraints on the GORP model, *i.e.*, the implied probability expressions for different count outcomes would be identical for the GORP (Eq. (5)) and standard count models (Eq. (3) and Eq. (4)). To see this, consider the constraints and functional forms imposed on ψ_k parameters below:

Generalized Poisson Model

$$\psi_k = \Phi^{-1}\left(\sum_{s=0}^{k} \frac{e^{-\lambda} \times \lambda^s}{s!}\right) + \alpha_k \; \forall \; k \geq 0 \tag{6}$$

If (1) ψ_k is parameterized as shown in Eq. (6), (2) all γ parameters in the propensity equation are equal to 0, and (3) all α_k parameters are equal to 0, then the GORP model collapses to the standard Poisson model.

Generalized Negative Binomial Model

$$\psi_k = \Phi^{-1}\left(\sum_{s=0}^{k} \left(\frac{r}{r+\lambda}\right)^r \times \frac{\Gamma(r+s)}{\Gamma(s+1)\Gamma(r)} \times \left(\frac{\lambda}{r+\lambda}\right)^s\right) + \alpha_k \; \forall \; k \geq 0 \tag{7}$$

If (i) ψ_k is parameterized as shown in Eq. (6), (ii) all γ parameters in the propensity equation are equal to 0, and (iii) all α_k parameters are equal to 0, then the GORP model collapses to the standard NB model.

Although theoretically one could estimate one α_k parameter specific to each count outcome *k*, from a practical standpoint, α_k can be fixed as α_K where *K* is a pre-determined count outcome depending on the empirical context, *i.e.*, $\alpha_k = \alpha_K \; \forall \; k \geq K$. Also, the α_k parameters control for any additional probability mass that is not captured by the parameters in the λ and y^* specifications. So, the GORP versions of Poisson and NB models can easily handle over or under-representation of multiple count outcomes without necessitating a hurdle or inflated model set-up.

In the GORP versions of Poisson and NB models, the analyst must also estimate the γ parameters in propensity y^* and the α_k parameters in thresholds ψ_k in addition to the β parameters in $LOG(\lambda)$ specification and dispersion parameter *r* (in case of NB models).

Data Collection

In this section we present the methodology for the data preparation. First we present the steps to identify the truck parking rest areas for the case study area. Second, we explain the procedure for extracting the polygon area of a rest area sample and how to utilize these polygons to extract the truck parking counts. Finally, we explore the additional dataset that was collected for analysis and model development.

Identification of Rest Area

The first step is to identify the truck parking areas for the study area. This is done by obtaining the rest area map that features the locations of over 2000 highway rest areas across the U.S. The locations are the coordinates for the entrance to the off ramp for the rest areas. From this shape file, the rest areas that belong to the required study area were obtained. A total of 46 rest areas are found within the case study area (shown in Fig. 1). Once the rest areas were identified, the base map of the U.S. with imagery was loaded and the rest area locations were identified. Next, three types of polygons were created over the rest area of each location which includes parking area, off-ramp and on-ramp (shown in Fig. 2). The size of the polygons is approximately scaled to the rest area as revealed by the base map of ArcGIS. Moreover, the location of the truck GPS points is not 100% accurate and precise. Hence some consideration was given across the capturing of the truck GPS point using the constructed polygon. For example, some of the GPS points were found to be located above the field or tress beside the on and off ramp which did not make sense. This was an error of the GPS point and in order to capture those points, the polygons were extended.

<<Figure 1 Here>>

<< Figure 2 Here>>

Identification of Parked Trucks

The next step is to determine the number of trucks parked within the three polygons of a particular rest area (shown in Fig. 3). The major steps for this procedure are as follows:

Step 1: First, the truck GPS data (shown in Fig. 3a) from ATRI (American Transportation Research Institute) was processed for the study area using Vehicle Probe GPS Data Processing Tool. This

tool provides functions to produce refined set of data from a large data set to be used in other modules.

Step 2: The refined truck dataset was loaded in ArcGIS and trucks with the speed being less than or equal to five miles per hour (Flaskou et al. 2015) were identified using SQL tool.

Step 3: The stopped trucks data were exported in Microsoft Excel and then coordinate pairs (latitude and longitude combinations) of those stopped trucks were identified using a common identification number called TRUCKID.

Step 4: Once the unique stopped trucks were identified using the TRUCKID, their coordinates were projected in ArcGIS.

Step 5: Finally, using the rest area polygons, the number of trucks parked in the respective locations was identified and recorded (shown in Fig. 3b).

<<Figure 3 Here>>

Since GPS receiver readings can vary slightly, even for stationary objects, the precision of the latitude and longitude fields was rounded down to one decimal place (resulting in 6 decimal places rather than 7). The 7th decimal place of latitude/longitude represents a foot or less of geography precision. The trucks parked on the on ramp and off ramp were needed to find the on/off ramp violation criteria which is used as a categorical variable in the model presented. These are indicator variables that indicated whether the truck was parked on ramp or off-ramp at that particular time period. When the truck drivers see trucks parked off-ramp, in order to avoid congestion and save time, sometimes they choose not to park thinking that the parking space might be full. It is also difficult to maneuver trucks when plenty of them are parked off ramp. On the other hand, when the truck drivers park on ramp, it means either the parking space was full or to save time maneuvering from the parking spot, they park on ramps so that they can exit and hit the road as quickly as possible. Moreover, some of the trucks might have met with crash or collision thus forcing them to park on and off ramp.

The ATRI data used in this paper consists of 3 months of data for the year 2014. Each month comprises of two weeks of truck data. A total of 46,368 (i.e. 46x42x24) observations were collected, spanning across 46 unique parking locations for 42 days and 24 hours a day. Table 1 shows the frequency distribution of the number of trucks parked on all the 46 rest areas which shows the predominance of zero number of trucks parked at the locations (50%). This is because of lower number of samples in the truck GPS data. The truck GPS data used in this study constitutes a subset of the truck population with various penetration rates ranging from 3% to 20% (not evenly distributed) across the state of Tennessee. With increasing sample size and higher penetration rate of truck GPS data, the model results will improve further. According to ATRI, the percentage of truck data collected in the years 2015 and 2016 has increased to over 50% in some of the states in the US. The research presented in this paper is a general methodology to model truck parking utilization, to explore the factors associated with truck parking using truck GPS data considering the fact that lower percentage of GPS data are available now but their penetration will only grow in future.

<<Table 1 Here>>

Collection of Additional Data

Additional data was collected such as average speed of the truck traffic passing on the adjacent roadway of that particular rest area, the number of lanes of the roadway adjacent to the rest area, and hourly precipitation of the location in concern from the National Climatic Data Center (NCDC). Rest area characteristics such as availability of rest rooms, vending machines, pets' facilities, picnic tables, phone services and handicapped facilities were also collected. These variables were used as categorical variables where unavailability of these features indicated 0 and availability was indicated as 1. The reason why average speed is included is because there might be congestion at the road beside the rest area which might affect the truck parking. If the average speed of the trucks passing the rest area is lower, it indicates congestion and hence might affect truck parking. Hence the effect of average speed was included in the model. The hourly precipitation would help identify if precipitation has any significant effect on the truck utilization, that is, if the truck drivers prefer to park at the rest area during rain or continue to drive. Similarly, the rest

area characteristics such as size, capacity, and available amenities would also give valuable information as to whether these have any effect on the truck utilization. However, most of these variables were insignificant in the estimated models since there was not enough variation the parking area characteristics across different observations to infer the effect on parking demand.

Table 2 and 3 shows the descriptive statistics and frequency distribution of the response and explanatory variables used in the model. These are, (a) Speed – whether the average speed of the trucks passing the rest area location is 35 miles per hour or greater. 35 miles per hours was chosen because it is the 85th percentile speed. (b) Number of lanes – whether the number of lanes of the roadway adjacent to the rest area in consideration were 2 or more than 2 (c) On ramp – whether there were any trucks parked on the on ramp of the rest area during that time period (d) Off ramp – whether there were any trucks parked on the off ramp of the rest area during that time period (e) Days of the week when the trucks were parked at the rest area. Table 3 shows that about 86.3 % of the time, the trucks passing the rest area usually travel at an average speed of 65 miles per hour or less. In addition, it can be seen that the on ramp and off ramp violation are evenly distributed and 82.62% of the observations had trucks parked at the rest area adjacent to the 2 lane roadway. Also, about 71.43% of the trucks were parked during weekdays.

<<Table 2 Here>>

<<Table 3 Here>>

Results

The models coefficients are estimated using 75% of the dataset and validation is done using the remaining 25% of the data set. In this section, we first discuss the effects of explanatory variables on the number of trucks parked, then the variable effects on the propensity and on the thresholds that affect the translation of propensity to whether or not a truck is parked at any given time. Next we discuss the model fit comparisons and finally discuss the elasticity effects and model validation.

Model Estimation Results

The results section presents the statistically significant explanatory variables along with their estimated coefficients and t-statistics (in parenthesis) for each of the developed models as shown in Table 4. Four models are developed: Poisson (Model 1), negative binomial (NB) (Model 2), Poisson with propensity (Model 3), and Poisson with propensity and threshold specific constant (Model 4). Given that there is no a priori reason for the mean and variance in any practical context to be equal, the use of a NB distribution for Model 2 is an important empirical generalization over the Poisson distribution (Model 1). Model 2 is a regular NB model whereas Model 3 and 4 are Poisson models that include threshold parameters which take heterogeneity across observations into account by allowing some of the parameters to vary across observations. Model 4 is similar to Model 3 except it contains threshold specific constants to allow more flexibility and better predictive accuracy.

<<Table 4 Here>>

By comparing the model results, it can be observed that due to significance of the dispersion parameter, the negative binomial model is more effective in prediction than the Poisson model. However, as the variable *"number of lanes (=2)"* is added to the propensity equation, there is no longer dispersion in the model. Therefore, the negative binomial is collapsing back to Poisson model with Propensity. The dispersion parameter becomes large (implying low dispersion) with the variable *"number of lanes (=2)"* in the propensity. Hence, the model is able to explain variance using explanatory variables without dispersion parameters and therefore Poisson with propensity performs better than the NB model. Hence Model 3 and Model 4 are Poisson with propensity and propensity with threshold respectively.

The variables that have significant effect on truck parking utilization include *truck volume*, *on ramp*, *off ramp*, *average speed*, *number of lanes*, *hour 1*, *hour 3*, *hour 16*, *hour 17*, *hour 22*, and *Thursday*. It can be noticed that the mean values of parameter estimates are similar in sign in all the four models. The results indicate that higher truck volume is more likely to increase the truck parking utilization at the rest areas. The *on ramp* and *off ramp* variables indicate that with on ramp and off ramp parking violation, the truck

parking utilization will likely to decrease. This is intuitive because when truck drivers enter a rest area for parking and when they observe trucks being parked on the ramps, it becomes difficult for them to maneuver the vehicle and they will likely to avoid such rest areas. Moreover, they may also assume that the truck parking might be full and continue driving to find the next location. On the other hand, it can also be instinctive that the parking capacity must be full which lead the drivers to park on the ramps. It is also conceivable that the truck drivers park on the on ramps for easy and quick exit on the roadway. The *speed* indicates that with the average speed of trucks passing the rest area being equal to or lower than 35 mph are more likely to decrease the truck parking utilization on the rest area. The *number of lanes* indicate that the roadway adjacent to the rest area having two lanes have more likelihood to increase the truck parking utilization at the rest area because higher number of lanes is usually accompanied with high traffic flow. The positive coefficient of *hour 1 & hour 3* suggests that truck parking utilization increases during the period 12 AM – 1 AM and 2 AM – 3 AM which is intuitive since the truck drivers at this time tries to find spots for parking and resting. On the other hand, the results show negative coefficients for *hour 16*. This suggests that during the period 3 PM – 4 PM (*hour 16*), truck parking utilization reduces which is also intuitive since the truck drivers prefer to travel during this period. Moreover, positive coefficients for *hour 17* suggest truck drivers tend to stop at a rest area during the period 4 PM – 5 PM due to personal needs like dinner or restroom facility. In addition to this, positive coefficients of *hour 22* suggests that some truck drivers tend to rest early and therefore some of the parking spots are usually filled during this hour. During the period 1 AM – 2 AM (hour 2), truck parking utilization decreases since most of the spots are usually filled at this period and the drivers either park on the ramps or try to move ahead and search for a spot at the next location. During the period 5 AM – 6 AM (hour 6), truck parking utilization decreases since most truck drivers start their trip either early or during this period from the parking spot after having a good night's rest. Similarly, during the period 12 PM – 1 PM (*hour 13*), truck parking utilization reduces because the truck drivers usually stop at a gas station for food and gas since these facilities are usually not available at a rest area. Finally, during the period 5 PM – 6 PM (*hour 18*), the utilization reduces which is also

intuitive since the truck drivers like to drive during these periods and do not stop and park at the rest area unless encountered by an emergency like mechanical fault or accidents because they usually like to rest at late night periods mostly after 12 am as indicated by *hour 1*.

Threshold parameters

The threshold parameters include the threshold specific constants ($\boldsymbol{\alpha_k}$ values), as well as variables associated with *off ramp* and *Number of lanes (=2)* as part of $\boldsymbol{\gamma}$ vector. The thresholds are responsible for the ‘‘instantaneous’’ translation of the truck parking utilization propensity to whether or not the truck driver will park at any given time at any location (that is, they determine the mapping of the latent propensity to the observed count outcome). The threshold specific constants ($\boldsymbol{\alpha_k}$) do not have any substantive interpretations. However, their presence provides flexibility in the count model to accommodate high or low probability masses for specific outcomes. The $\boldsymbol{\alpha_k}$ parameters are identified by specifying $\boldsymbol{\alpha_0} = 0$ and $\boldsymbol{\alpha_k} = \boldsymbol{\alpha_k}\ \forall k \geq K$. We, initially set K=4 and with multiple trials K is reduced based on statistical significance and general data fit.

The elements in the $\boldsymbol{\gamma}$ vector are presented next in Table 4. For the other variables, a positive coefficient shifts all the thresholds toward the left of the truck parking utilization propensity scale, which has the effect of reducing the probability of zero trucks parked. The effect of *off ramp* suggests that, given two observations with same truck parking utilization propensity, the segment with off ramp violation is more likely to have a non-zero truck parking utilization occurrence compared to the other. This is an intuitive result since off ramp violation will likely mean truck parking area is full which may not be the case. The effect of *number of lanes (=2)* indicates an increase in non-zero truck parking utilization at rest areas adjacent to two lane roadway, for a given truck parking propensity. That is, the translation of probability into the occurrence of truck parking is elevated for 2 lane roadway adjacent rest areas, most likely because it is easy for truck drivers to enter a rest area adjacent to two lanes where as they may need to change multiple lanes, or maneuver in a different direction before entering a rest area which is difficult and risky.

Model Selection and Statistical fit

The Generalized Poisson count model with propensity and threshold is superior to the other models, as should be clear from the highest log-likelihood value and presence of several additional statistically significant coefficients in Table 4. However, all the models developed in this study were compared formally using the Bayesian Information Criterion (BIC) that penalizes models that attain better fit at the cost of additional parameters. According to the BIC criterion, a model with lower BIC value is preferred. It can be seen from the table that the Generalized Poisson model has the least BIC value of 86,682 among all models suggesting superior data fit. This underscores the importance of using GORP model structures that provide additional flexibility to standard count models for analyzing count outcomes (for instance, parking utilization in the current empirical context).

Elasticity Effects

The elasticity computed is a measure of the aggregate percentage change in the response variable due to a change in an exogenous variable (Castro et al. 2012). By computing the elasticity effects of the exogenous variables, the magnitude of effects of these variables on the truck parking utilization can be determined. In this paper, we computed the percentage change in the expected number of trucks that park in a rest area because of a unit change in each exogenous variable. However, since standard elasticity calculations are not applicable to categorical variables, pseudo-elasticity effects were calculated for such variables. The pseudo-elasticity of an indicator variable essentially represents the average percent change in average truck parking utilization when the value of that particular variable is changed from 0 to 1 for all rest areas.

For brevity, the elasticity effects are only presented for the best model, *i.e.*, Poisson model with propensity and threshold parameters (model 4) (see Table 5). From the Table 5, it can be observed that the elasticity effects are consistent with the coefficient estimates. The first entry in the table indicates 100% increase in truck volume is likely to increase truck parking by 1.33% whereas presence of on ramp and off ramp violations decrease truck parking utilization by 1.921% and 0.109%, respectively. One additional lane to an existing two-lane roadway increases parking utilization in adjacent rest areas by 3.338%. Parking areas that are adjacent to roadways with average truck speeds greater than 35 mph have 13.561% lower

utilization than parking areas adjacent to roadways with lower truck speeds. Similarly, parking areas have 11.218% more utilization during the hour past midnight compared to other non-peak rest hours Also, interestingly; parking utilization on Thursdays is 3.195% more than on other days of the week. Other numbers in the table can be interpreted similarly.

<<Table 5 Here>>

Model Validation

In order to examine the prediction power of the models, a validation exercise was undertaken in which the predicted truck parking counts were compared with the observed count in the data. Then, Absolute Percentage Difference (APD) between predicted and observed counts was calculated. Lastly, Average Absolute Percentage Difference (AAPD) across all truck utilization levels was computed. A model with lower AAPD has better predictive ability than models with higher AAPD values. The results of the prediction analysis are presented in Table 6. It can be seen from the table that the Generalized Poisson model with propensity and threshold parameters (model 4) best has the best predictive performance with an AAPD value of 1.50%. The simple Poisson model that ignores dispersion has a very high AAPD value. Even NB model that accounts for dispersion has higher AAPD value than the Generalized Poisson model. So, Poisson model with propensity and threshold parameters is better suited to capture dispersion in count data than NB model in the context of truck parking utilization.

<<Table 6 Here>>

Conclusions

Past studies that analyzed truck parking utilization have been mostly descriptive. The primary objective of this paper was to develop a set of econometric models that can predict truck parking utilization as a function of geometric and traffic characteristics of adjacent roadways and the rest area characteristics. All the models in this study were estimated using Truck GPS data for rest areas in Tennessee. Given the count nature of parking utilization data, count modeling methods were used in this study. To be specific, standard count models including Poisson and Negative Binomial (NB) models and generalized ordered response probit

(GORP) models that subsume standard count models as special cases were estimated. Among the different models estimated in this study, the Generalized Poisson model with propensity and threshold parameters (Model 4) was found to provide the best statistical fit as well as predictive performance. The main contributing factors towards truck parking utilization were found to be truck volume, on ramp and off ramp violations, higher average speeds of the trucks passing the rest area, presence of a two lane roadway adjacent to the rest area. Also, among different hours of the night, the hour past midnight had higher parking demand. Going beyond simple parameter estimates, elasticity effects that indicate percentage change in parking utilization due to unit change in different factors were computed. For instance, a 100% increase in truck volume was found to increase truck parking utilization by 1.33%.

One of the primary drawbacks of this research is lower sample size of the truck GPS data. With private sector competitiveness in an emerging economy and adaptation of GPS units by truck drivers, in the future it will be possible to obtain large samples of truck GPS data. With availability of more sample GPS data, mixing models that allow random heterogeneity in the impact of different factors on parking utilization and spatial models that control for dependencies in parking utilization rates across proximal rest areas can be developed. This study was performed only on the rest areas of Tennessee and may not represent drivers' decision to park in other states. However, the proposed methodology can be applied for estimating demand of other rest areas of the country; however, it would be interesting to study the transferability of the models developed in this study to other regions.

Acknowledgement

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Table 1. Frequency distribution of Truck Parking Utilization

No. of Parked Trucks	Count	(%)
0	23,185	50.00%
1	7,666	16.53%
2	7,659	16.52%
>= 3	7,858	16.95%
Total	46,368	100.00%

Table 2. Descriptive Statistics of Explanatory Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Number of trucks parked per hour	1.0043	1.1596	0	7.0
Volume (Vph)	32.0887	18.9001	1.0	259.0
Average speed (mph)	23.0612	10.2253	6.0	84.0
On ramp (if parked=1, 0 otherwise)	0.5016	0.5000	0	1.0
Off ramp (if parked=1, 0 otherwise)	0.4991	0.5000	0	1.0

Table 3. Frequency distribution of Explanatory Variables (categorical)

Explanatory Variable	(%)
Speed	
Less than or equal to 35 mph	86.3%
Greater than 35 mph	13.7%
Number of Lanes	
2 Lanes	82.61%
> 2 Lanes	17.39%
On ramp	
No	49.84%
Yes	50.16%
Off ramp	
No	50.09%
Yes	49.91%
Weekday	
Mon-Fri	71.43%
Sat-Sun	28.57%

Table 4. Model Results

Variables	*Poisson (Model 1)*	*Neg. Bin (Model 2)*	*Poisson (with γ) (Model 3)*	*Poisson (with γ & α) (Model 4)*
	Coefficient (t-stat)	*Coefficient (t-stat)*	*Coefficient (t-stat)*	*Coefficient (t-stat)*
Constant	-0.0663	-0.0723	0.4675	-0.3167
	(-2.406)	(-2.063)	(21.335)	(-2.89)
Log(Volume)	0.0163	0.0166	0.3048	0.0201
	(2.286)	(1.819)	(20.962)	(2.365)
On Ramp	-0.016	-0.0159	-0.1527	-0.0196
	(-1.493)	(-1.181)	(-3.959)	(-1.531)
Off Ramp			-0.2197	-0.1047
			(-5.449)	(-1.796)
Average Speed (<= 35mph)				-0.1931
				(-1.822)
Number of Lanes (= 2)	0.0268	0.031	0.3274	0.086
	(1.878)	(1.725)	(6.095)	(1.465)
12 am – 1 am (hour 1)	0.0981	0.0997	0.0454	0.1062
	(3.741)	(2.969)	(3.364)	(3.382)
1 am – 2 am (hour 2)	-0.0387	-0.0362		
	(-1.418)	(-1.058)		
2 am – 3 am (hour 3)	0.0441	0.0462	0.0222	0.0525
	(1.66)	(1.37)	(1.641)	(1.656)
5 am – 6 am (hour 6)	-0.0494	-0.0476	-0.017	
	(-1.782)	(-1.376)	(-1.219)	
12 pm – 1 pm (hour 13)	-0.0479	-0.0455	-0.0162	
	(-1.755)	(-1.334)	(-1.18)	
3 pm – 4 pm (hour 16)	-0.0533	-0.0513	-0.02	-0.0381
	(-1.938)	(-1.496)	(-1.457)	(-1.385)
4 pm – 5 pm (hour 17)	0.0388	0.0416	0.0184	0.0564
	(1.46)	(1.234)	(1.354)	(1.779)
5 pm – 6 pm (hour 18)	-0.0276			
	(-1.002)			
9 pm – 10 pm (hour 22)	0.0527	0.0548	0.0265	0.0601
	(1.971)	(1.612)	(1.953)	(1.884)
Thursday	0.033	0.0315	0.0135	0.035
	(2.177)	(1.64)	(1.748)	(1.923)
Dispersion parameter		1.6991		
		(36.366)		
γ Vector				

Table 4. Model Results (Continued)

Log(Volume)			-0.6325	
			(-20.728)	
On Ramp			0.3535	
			(4.182)	
Off Ramp			0.4857	0.0982
			(5.499)	(1.795)
Number of Lanes			0.6648	-0.1054
(= 2)			(6.151)	(-1.466)
Threshold Specific Constants				
α_1				-0.6166
				(-50.13)
α_2				-0.9154
				(-43.799)
α_3				1.3192
				(6.724)
Number of Observations	34,776	34,776	34,776	34,776
Number of Parameters Estimated	14	13	17	17
Log-composite likelihood at convergence	-1.419	-1.384	-1.361	-1.244
Log-likelihood	-49,332	-48,113	-47,324	-43,252
BIC	98,810	96,312	94,826	86,682

Table 5. Elasticity Effects of the Generalized Poisson Model

Variables	*Poisson (with γ & α) (Model 4)*
Volume (100% increase)	1.330
On Ramp	-1.921
Off Ramp	-0.109
Average Speed (<= 35mph)	-13.561
Number of Lanes (= 2)	3.338
12 am – 1 am (hour 1)	11.218
1 am – 2 am (hour 3)	5.124
5 am – 6 am (hour 16)	-3.417
12 pm – 1 pm (hour 17)	4.214
8 pm – 9 pm (hour 22)	5.549
Thursday	3.195

Table 6. Model Validations

Truck Utilization	Observed Count	Expected Count							
		Poisson (Model 1)		*Neg. Bin (Model 2)*		*Poisson (with γ) (Model 3)*		*Poisson (with γ & α) (Model 4)*	
		Count	APD (%)	Count	APD (%)	Count	APD (%)	Count	APD (%)
0	5838	4193	28.18	6686	14.53	5402	7.47	5776	1.06
1	1896	4222	122.68	2157	13.77	2934	54.75	1891	0.26
2	1907	2268	18.93	1152	39.59	1835	3.78	1944	1.94
3 or more	1951	909	53.41	1597	18.14	1421	27.17	2004	2.72
AAPD (%)			55.80		21.51		23.29		1.50

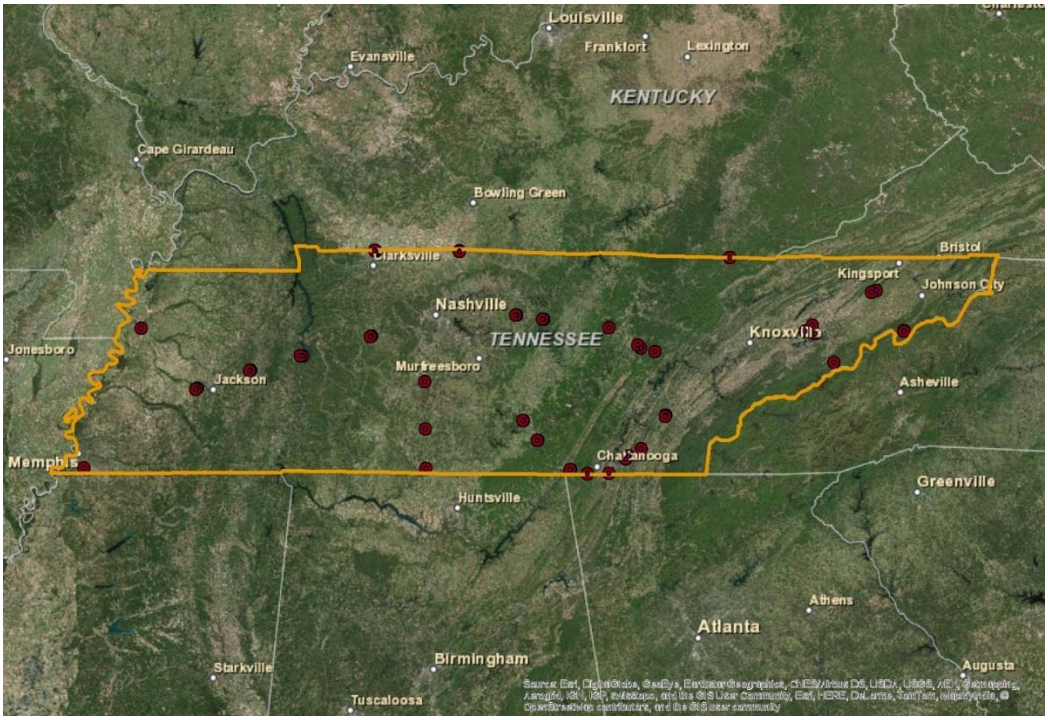
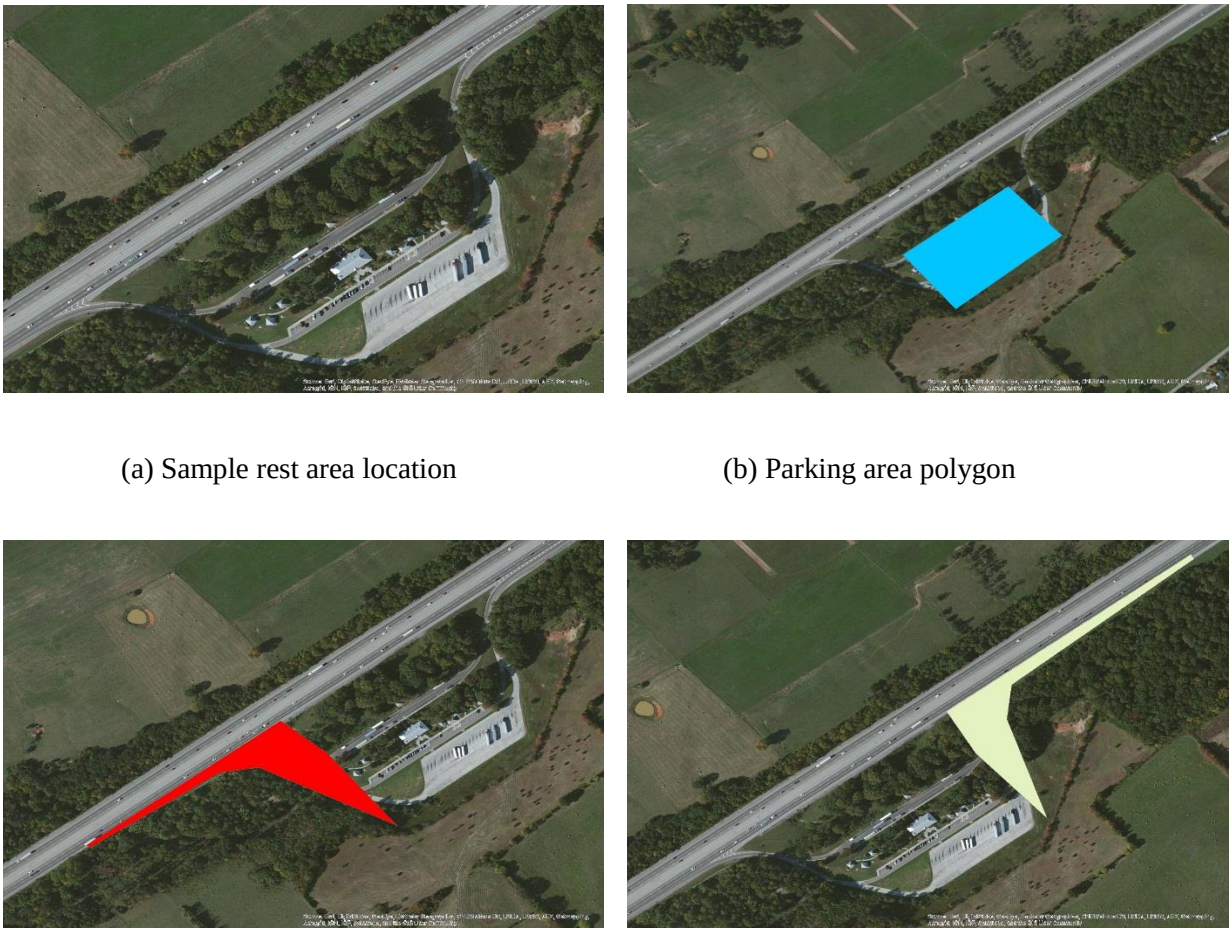


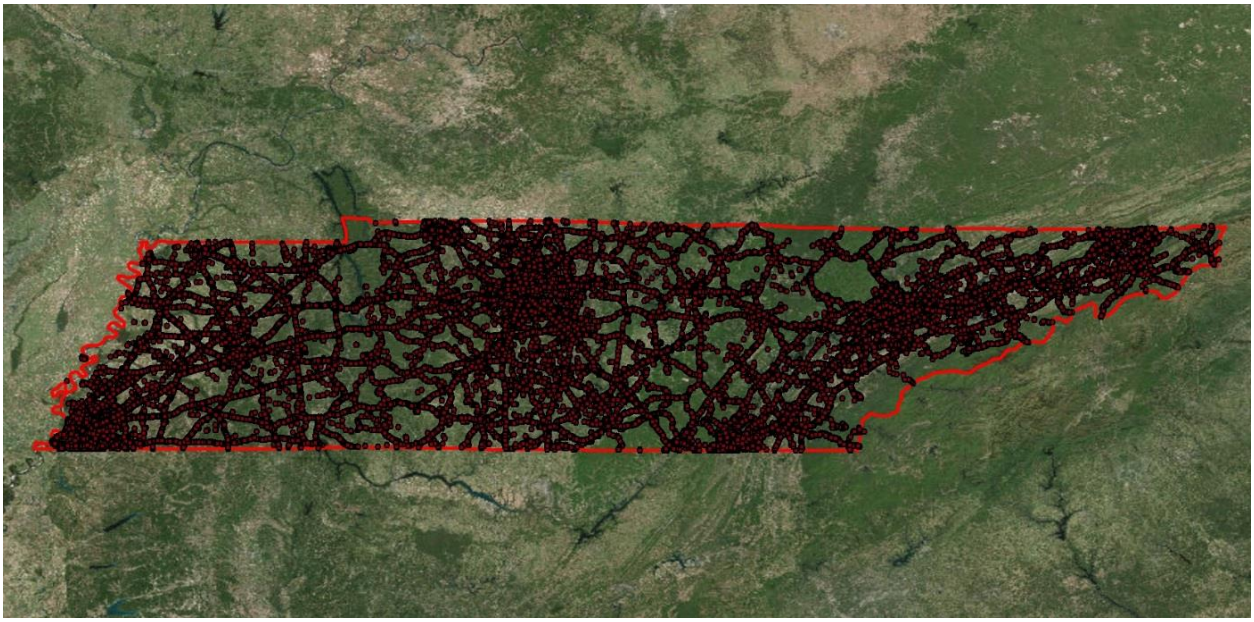
Fig. 1. Rest areas in Tennessee



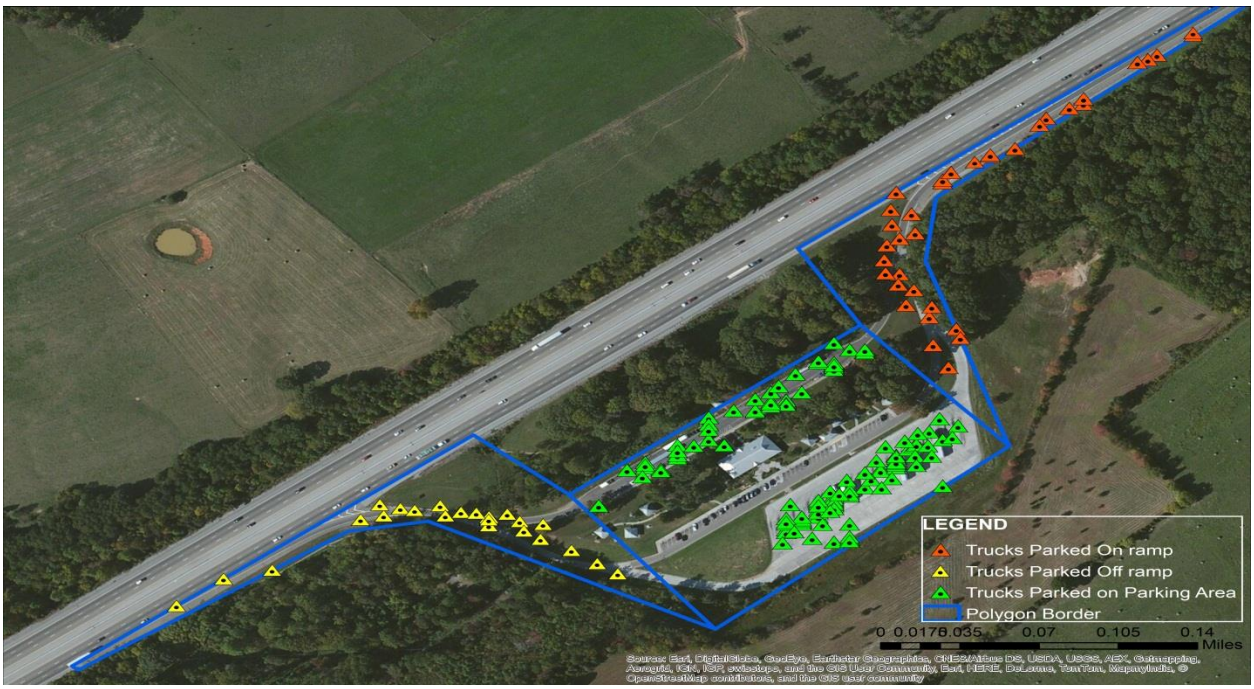
(a) Sample rest area location (b) Parking area polygon

(c) Off-ramp polygon (d) On-ramp polygon

Fig. 2. Polygon extraction from rest area location



(a) Sample truck GPS data



(b) Parked trucks on rest area location

Fig. 3. Extraction of parked truck data from raw GPS data

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