RESEARCH & DEVELOPMENT

Impact of Development Density on K-Factors

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Abstract:
NCDOT's Transportation Planning Branch seeks to utilize a method to estimate the impact of peak spreading based on capacity constraints that is found in the latest national guidance for traffic forecasting. To fully understand peak spreading impacts, it is necessary to understand how K-factor data changes. A model that tests factors that affect K-factor data, including site and socioeconomic characteristics, provides a useful guide for estimating reasonable levels of peak spreading. The purpose of this project was to determine how K-factor data changes to estimate the impact of peak spreading across different area types. Exploratory models were developed for forecasting peak spreading using North Carolina traffic data where peak spreading was measured as change in the K-factor. Peak spreading studies conducted in cities in other states were also reviewed for comparison. The results of this research will be useful to inform efficient and cost-effective roadway project design and will help provide additional information to advise the NEPA process.

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Executive Summary

NCDOT's Transportation Planning Branch seeks to utilize a method to estimate the impact of peak spreading based on capacity constraints that is found in the latest national guidance for traffic forecasting. To fully understand peak spreading impacts, it is necessary to understand how K-factor data changes. A model that tests factors that affect K-factor data, including site and socioeconomic characteristics, provides a useful guide for estimating reasonable levels of peak spreading.

The purpose of this study was to determine how K-factor data changes to estimate the impact of peak spreading across different area types. Models were developed for forecasting peak spreading where peak spreading was measured as change in the K-factor. Peak spreading occurs when the K-factor, defined as the proportion of the 24-hour traffic volume that occurs during the peak hour, decreases in relation to an increase in traffic congestion. Peak spreading can result from change in the departure time of motorists to a non-peak hour in reaction to congested peak hour traffic conditions. Reliable estimates of K-factor change are important for the accurate estimation of travel demand and roadway performance, including travel speed and vehicle emissions.

The research team sought to replicate the peak spreading study developed by Miller (2012) for the Northern Virginia area, but with some modifications in data sources and modeling inputs. Data were collected from 54 continuous count stations located on North Carolina roadways representing 34 of the 100 counties in the state for the period 1995-2016. All stations gave two-directional counts, resulting in 108 station-direction combinations, or sites, for analysis purposes.

Two before-and-after periods were included in the analysis: 2000/2010 and 2005/2015. For all sites with available data for the 2000/2010 period, the average annual K-factor adjusted for months for which data were not available increased by 0.0002, from 0.1012 to 0.1014, during the period. The average annual 24-hour volume-to-capacity ratio, which was used as a surrogate for travel congestion, increased from 3.2838 to 3.2891. Neither change was statistically significant. For all sites with available data for the 2005/2015 period, the average annual K-factor adjusted for months for which data were not available decreased by 0.0004, from 0.0998 to 0.0994, during the period. The 24-hour volume-to-capacity ratio increased from 3.6808 to 3.9224. The change in average annual K-factor was not statistically significant. The change in average annual 24-hour volume-to-capacity ratio was statistically significant ($p<0.001$). The K-factor results for all sites with available data are to be expected since the annual K-factors are generated with data from many sites that experience random variation in the K-factor over time.

Since many of the 108 sites appeared to experience non-commute travel patterns that would generate more random variation in K-factors rather than predictable variation that could be captured by the socioeconomic factors and roadway attributes included in

statistical testing, a subset of sites was used in exploratory peak spreading modeling efforts. While the ANOVA results indicate that site characteristics (such as facility functional class) and socioeconomic characteristics (including population and employment) affect the K-factor, exploratory modeling did not indicate that land use density was a statistically significant factor in K-factor change when including other variables in the model.

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1. Introduction

NCHRP 765 is the latest guidance for traffic forecasting. NCHRP 765 includes documentation for a method to estimate the impact of peak spreading based on capacity constraints. NCDOT's Transportation Planning Branch seeks to use this method to help determine how traffic data used in the program development process may change in the future. To better understand the implications of the NCHRP 765 peak spreading documentation, it is necessary to understand how K-factor data changes. A model that tests factors that affect K-factor data, such as site and socioeconomic characteristics, provides a useful guide for estimating reasonable levels of peak spreading.

The purpose of this project was to determine how K-factor data changes to estimate the impact of peak spreading across different area types. This project utilizes North Carolina traffic data in its modeling effort, and it also reviews peak spreading studies conducted in cities in other states for comparison. The results of this research will be useful to inform efficient and cost-effective roadway project design and will help provide additional information to advise the NEPA process.

1.1. Background and Research Need

Chapter 8 of NCHRP 765 provides guidance for improving the temporal accuracy of traffic forecasts and includes information on peak spreading, defined as an adjustment in the temporal characteristics of travel in response to worsening traffic congestion that results in the flattening and widening of the peaks in diurnal distributions of travel. Peak spreading tools provide more realistic traffic forecasts that account for prolonged congestion effects since they constrain hourly traffic forecasts to available capacities. NCHRP 765 provides documentation for a basic approach to applying peak spreading to traffic forecasts based on a technique documented by the Ohio Department of Transportation (Smith et al., 2014). This approach involves shifting volumes in excess of capacity for the heaviest volume hours onto to the shoulder hours until there are no longer any hours of the day in which forecast volumes exceed capacity.

The NCHRP 765 documentation forms the foundation of an Excel-based tool that NCDOT's Transportation Planning Branch is developing to forecast peak spreading and K-factor impacts in North Carolina. The NCHRP 765 peak spreading approach can be improved as a forecasting tool by integrating findings concerning factors that affect K-factor data, such as rural/urban context and development density, in order to estimate reasonable levels of peak spreading. The Virginia Center for Transportation Innovation and Research recently completed research to generate a model for forecasting peak spreading that incorporates site characteristics (e.g., functional class, 24-hour volume-to-capacity ratio) and regional socioeconomic characteristics (e.g., jurisdictional employment growth) that may be used as a guide for the proposed project effort (Miller, 2012).

Research supports that traffic forecasters should be aware of potential changes in traffic peaking over time, particularly in rapidly developing areas where relatively small variations in peaking spreading can have a major impact (ITE, 2006). Research further suggests that inaccuracies in forecasting resulting from the exclusion of peak spreading in the process has consequences for the analysis of capital construction investments, air quality analysis, and analysis for transportation demand management (Barnes, 1998). Specifically, the failure to take into account peak spreading in the forecasting process can result in overestimation of forecasted traffic volumes in the peak hour and an underestimation of average speeds during this time as well as an underestimation of forecasted traffic volumes in the shoulders of the peak and an overestimation of average speed during these times (Barnes, 1998).

1.2. Objectives

The primary goal of this research effort is to determine how K-factor data changes in order to estimate the impact of peak spreading across different area types in North Carolina. The research results would provide a guide for estimating reasonable levels of peak spreading to inform more realistic traffic forecasts. The main study objectives were to:

- Determine and assess factors that affect K-factor data and compare North Carolina K-factor results with results from large cities in other states as a guide for determining reasonable levels of peak spreading
- Generate North Carolina-specific K-factor documentation that can accompany and provide context for the NCHRP 765 peak spreading method that will be utilized by NCDOT's Transportation Planning Branch

The results of this research will be used by NCDOT's Transportation Planning Branch as an input into an Excel-based tool that they are developing to forecast peak spreading in North Carolina. North Carolina-specific K-factor documentation will be included in the instructions for the peak spreading tool that will be used by traffic forecasters internal and external to NCDOT. The research product will provide traffic forecasters with data-driven guidance on what can be expected from potential urban population growth in relation to capacity on North Carolina roadways in order to inform future planning decisions.

2. Literature Review

An extensive literature review was conducted to determine the state of the practice regarding how peak spreading impacts are estimated and quantified and to inform an appropriate modeling approach for estimating K-factor changes in North Carolina. The review provides a summary of K-factor and peak spreading definitions, modeling approaches, and explanatory variables used to test variability in K-factors.

2.1. K-Factor and Peak Spreading Definitions

In general, the K-factor is defined as the proportion of annual average daily traffic (AADT) occurring in an hour. K-factors are typically generated using a year of data collected at a continuous count station. Two types of K-factors that are used in traffic planning and forecasting are the K_{30} and the K_{100}. The K_{30} is known as the Design Hour Factor and is calculated by dividing the 30th highest hourly volume by the AADT for the year in which data were collected. The K_{100} is known as the Planning Analysis Hour Factor and is calculated by dividing the 100th highest hourly volume by the AADT for the year in which data were collected.

The K_{30} was introduced in the 1950 Highway Capacity Manual (HCM). In the 2010 HCM, the K_{30} characteristics are described as follows:

- The K-factor generally decreases as the AADT on a highway increases;
- The reduction rate for high K-factors is faster than for lower values;
- The K-factor decreases as development density increases; and
- The highest K-factors generally occur on recreational facilities, followed by rural, suburban, and urban facilities, in descending order.

The HCM recommends that the K_{30} be determined from local data for similar facilities with similar demand characteristics. In their state traffic manual (2007), the Ohio Department of Transportation (ODOT) notes that the K_{30} does not change considerably from year to year unless there are major changes in land use served by the roadway under consideration.

As a part of their project level traffic forecasting process, several State Departments of Transportation (DOTs) utilize the K_{30} in forecast development and analysis, including ODOT and NCDOT. The Florida Department of Transportation (FDOT) is in the process of adopting standardized K-factors based on locations in the state where volumes are continuously monitored (FDOT, 2014). Standard K-factor values are fixed for roadways from planning through design and are set by the area type in which roadways are located and facility type (Exhibit 1).

FDOT Standard K Factors

Area *(Population) [Examples]*	**Facility Type**	**Standard K Factors*** (%AADT)	**Representative Time Period**
Large Urbanized Areas with Core Freeways *(1,000,000+) [Jacksonville, Miami]*	Freeways	8.0 - 9.0 ***	Typical weekday peak period or hour
	Arterials & Highways	9.0**	Typical weekday peak hour
Other Urbanized Areas *(50,000+) [Tallahassee, Ft. Myers]*	Freeways	9.0 **	Typical weekday peak hour
	Arterials & Highways	9.0 **	Typical weekday peak hour
Transitioning to Urbanized Areas *(Uncertain) [Fringe Development Areas]*	Freeways	9.0	Typical weekday peak hour
	Arterials & Highways	9.0	Typical weekday peak hour
Urban *(5,000-50,000) [Lake City, Key West]*	Freeways	10.5	100th highest hour of the year
	Arterials & Highways	9.0 **	Typical weekday peak hour
Rural *(<5,000) [Chipley, Everglades]*	Freeways	10.5	100th highest hour of the year
	Arterials	9.5 **	100th highest hour of the year
	Highways	9.5	100th highest hour of the year

*	Some smoothing of values at area boundaries/edges would be desirable.
**	Value is 7.5% in approved Multimodal Transportation Districts where automobile movements are deemphasized. Essentially, this lower value represents an extensive multi-hour peak period rather than a peak hour.
***	Value is 8.0% for FDOT-designated urbanized core freeways and may be either be 8.5% or 9.0% for non-core freeways. Values less than 9% essentially represent a multi-hour peak period rather than a peak hour.

Exhibit 1: FDOT Recommended Standard K-Factors by Area and Facility Type

Abundant literature exists on peak spreading that provides multiple definitions of the concept. Research concerns govern how peak spreading is defined as a dependent variable in the existing research. Peak spreading has been defined by the length of the peak period (Karl and Gaffney, 2008), the proportion of peak hour volume during the peak 3- or 4-hour period (Cambridge Systematics, Inc., 1997; Allen, 1991, 1996; Ivan, 2000, 2001), the proportion of travel demand during a peak period associated with a particular mode (Sall, et al., 2010), and peak period congested travel time (Purvis, 1999). In general, peak spreading is a phenomenon where the proportion of traffic demand decreases in the most severely congested part of a peak period when travel conditions deteriorate and the decreased proportion moves outward to the shoulders of the most severely congested part. Peak spreading causes the peak period travel demand profile to be flatter and wider over time, as shown in Exhibit 2.

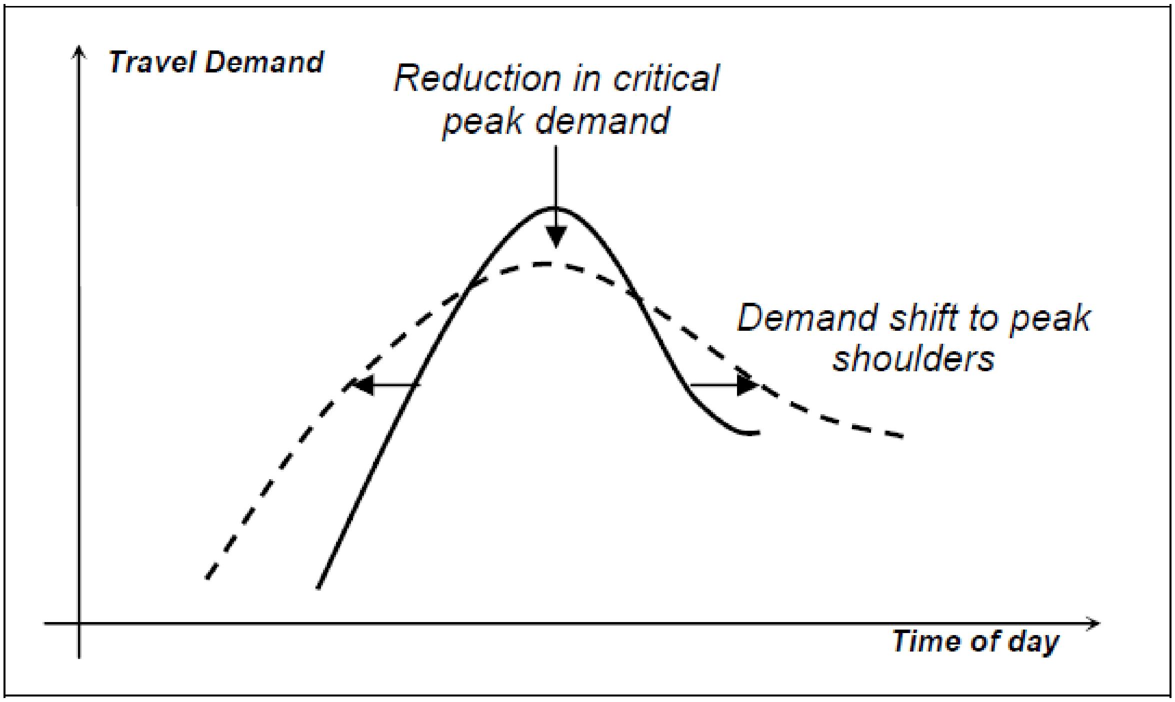

Exhibit 2: Demand Change in Peak Spreading

Peak spreading can be a result of reactive responses of travelers to deteriorated traffic conditions. However, implementation of policies such as flextime work schedules and temporal/dynamic road pricing can encourage peak spreading, if implemented appropriately. In either way, peak spreading leads to a more efficient use of urban roadway networks during the peak period. Failure to take peak spreading into account can result in overestimation of forecasted traffic volumes in the peak hour (and thus underestimation of average speeds) and an underestimation of forecasted traffic volumes in the shoulder periods (and thus an overestimation of average speeds), which can lead to problematic subsequent analysis such as air quality analysis for conformity requirements and capital investment analysis for new projects.

NCHRP 765 defines peak spreading as an adjustment in the temporal characteristics of travel in response to worsening traffic congestion that results in the flattening and widening of the peaks in diurnal distributions of travel (Smith, et al, 2014). However, several authors have made a distinction between “active” peak spreading and “passive” peak spreading. Jassmi and Ochieng (2015) defined active peak spreading as the peak spreading that occurs when the driver makes a conscious decision to make a trip at a time other than the most congested, eventually spreading the peak period. Passive spreading was defined as what occurs when the intensity of congestion during the peak period increases so that travel times become longer and therefore extends the peak period. Barnes (1998) also differentiates between active peak spreading and passive peak spreading. She defines active peak spreading as occurring when travelers purposely retime their trips to avoid all or part of the congested conditions of the peak period. This means that travelers may begin their trips earlier to arrive at the same time as typical, or they may retime their trips to completely avoid the most congested time. This change in traveler behavior results in spreading the peak over time. Passive peak spreading consists of trips extending beyond the height of the peak as a consequence of increased delays due to congestion and results in no change in the demand profile. As congestion increases, travel times increase so that the peak period becomes more spread out because travelers are spending more time on the roadway for the same trip. Citing Porter, et al., Barnes emphasizes that both active and passive peak spreading results from differential growth in peak period travel. In practice, active and passive peak spreading could occur simultaneously to various degrees in all peak spreading situations.

Holyoak (2007) defines peak spreading as a reduction in traffic proportions during the most congested part of the peak period with corresponding increases during the peak shoulders, and she distinguishes between passive and active peak spreading. The former is defined as the natural increase in the duration of peak travel as travel demand tests the capacity of a facility so that the levels of peak travel activity persist for a longer period, and the latter is defined as resulting from individual travelers deliberately changing their travel behavior to avoid peak periods or when transportation policies are enacted to encourage people to travel at times other than peak periods.

Johnston (1987, 1991) provides a series of findings on peak spreading from a survey conducted in London and several models that he developed. His findings include:

- Most peak-period trip retiming was reactive and marginal.
- Most of the retiming of departure times in the morning peak was due to the simple fact that increased congestion makes the journey longer and most morning peak travelers are arrival time constrained.
- Morning-peak travelers making a regular journey to work or education were those most likely to make departure time adjustments, while journeys for some other purposes (shopping, social) tended to avoid the peak period by retiming.
- Relatively few peak travelers deliberately changed both departure and arrival times.
- Short-journey travelers were much less inclined to change their journey patterns than long-journey travelers if congestion gets worse. This is simply because delays increase with distance.
- Travelers valued very highly the predictability of travel time and were very sensitive to deterioration in travel time reliability.
- Travelers were making trade-offs between retiming the travel and enduring prolonged travel time. The survey showed a wide variation in the willingness of

travelers to make such trade-offs and different types of travelers responded in quite different ways to changes in travel conditions.

- Generally travelers seemed to need quite large relative changes in travel time before they would deliberately retime their journeys.
- His model indicated that the utility value to travelers of traveling in the peak rather than in the off-peak is at least double the difference in travel time it takes to make the journey.
- Anecdotal evidence suggests that there is “peak contraction,” which is the reverse of peak spreading, when road networks are improved. Specifically, drivers may retime their trips back if conditions improve, which re-sharpen the peak-period profile.

Alternately, Gordon, et al. (1990) conducted a study which minimized the effect of congestion on peak spreading. Based on the National Personal Transportation Survey (NPTS) data for 1977 and 1983, the researchers concluded that there is no evidence to support active spreading as the consequence of increased congestion in major metropolitan areas. Instead, they found that adjustments in locations for both residences and workplaces provided a much more solid explanation for congestion relief than “spontaneous” adjustments to work schedules at an aggregate level. They indicated that potential benefits that resulted from changing departure time may not be enough to offset the costs of adjustment in the activity patterns in non-working hours.

2.2. Peak Spreading Modeling Approaches

Citing Jin and Chiao (2008), Miller (2012) provides three major approaches for forecasting peak spreading: 1) regional hourly proportion models, 2) link-specific hourly proportion models, and 3) choice models. Barnes (1998) suggests that link-based and trip-based methods allow for a peak spreading analysis to be implemented within the steps of the traditional four-step travel demand modeling process. She further concludes that peak spreading modeling approaches can: 1) adjust the traditional four-step forecasting process to better accommodate the effects of peak spreading, 2) consist of sub-models that run independently of the four-step process, but the output can be used as input for a traditional forecasting model, or 3) consist of models that are developed to stand alone with no connection to a more extensive forecasting model.

Barnes (1998) recommends a short-term and a long-term approach for peak spreading model development. The short-term approach consists of generating simple models from historic traffic data collected at key freeway locations representing a variety of area types with preference given to locations with the most historic data available. For the long-term approach, Barnes recommends that a departure time element be included in future research in order to understand future active peak spreading trends. She concludes that the most common approach to incorporating peak spreading into the forecasting process consists of adjusting the four-step modeling process to recognize the effects of congestion on peak conditions by constraining the trip matrix so demand cannot exceed capacity. She further suggests that peak spreading treatments do not require activity-based modeling and detail beyond what is included in most urban area models, but that a model developed outside of a traditional forecasting model will require a considerable amount of data.

The literature suggests that peak spreading is an aggregate phenomenon caused by complex individual motivations and behavior of travelers influenced/bounded by policies. Modeling peak spreading can therefore be very challenging, especially within the traditional four-step trip-based modeling framework. Numerous attempts have been made to model peak spreading and incorporate it into transportation planning and forecasting. It is worth noting that none of the methods presented in this report represent the single answer to peak spreading issues or address peak spreading issues fully. Most of the methods have considerable limitations.

The following sections provide a review of four major peak spreading modeling approaches recognized in the literature: 1) regional hourly proportion models, 2) link-based hourly proportion models, 3) trip-based models, and 4) choice models.

2.2.1. Regional Hourly Proportion Models

Regional hourly proportion models use factors derived from trip surveys or other data sources to assign a proportion of traffic to the peak hour. Traffic assignment is not link-specific, but is based on trip purpose and applies to an entire region. Regional hourly proportion models do not explicitly account for changes in congestion effects.

Ivan produced two studies that utilized regional hourly proportion models. In one study, Ivan, et al. (2000) researched the peak period profile of ten freeway locations in Connecticut based on number of lanes, commuting direction, congestion (v/c ratio for the peak period), and distance from a central business district (CBD). The authors used hourly volume counts from a five-year period from permanent continuous count stations at locations with extensive congestion along the corridors during the peak period. The CBD variable was important in formulating the area type and in categorizing between business and personal trips. The authors employed OLS linear regression to relate the explanatory variables to the peak hour proportion for an afternoon peak period of 3 PM to 7 PM.

Relative distance from a CBD for a given area to a site and the number of lanes at a site were found to be indicators of how the peak period profile is distributed at low levels of congestion. The CBD variable was found to be statistically significant, indicating that a count location which is further from the CBD for its area tends to have a peak period profile which is flatter at low levels of congestion than a site that is closer. The number of lanes variable was also found to be statistically significant, indicating that a site with more lanes will tend to have a peak period profile that is more peaked at low levels of congestion than a site with less lanes. The CBD variable was incorporated into area type and regional models, which were found to be the best in explaining scale and shape since they tend to consider overall differences between areas or regions rather than a single specific characteristic of the site or trip.

In a second study that builds on their previous research effort, Ivan, et al. (2001) attempted to enhance the four-step transportation planning procedure that traditionally predicts peak hour flow on links as a fixed percentage of the daily assignment by also considering congestion, region, and area type for predicting the K-factor. The authors use hourly volume counts from a five-year period to investigate peak spreading at ten freeway locations in Connecticut by using an exponential model transformed to OLS linear regression to relate a congestion measure and link-related variables to the peak hour proportion for a four-hour afternoon peak period of 3 PM to 7 PM. Nine of the 10 count locations were categorized as urban and the other was categorized as rural, and all the locations experienced high (greater than 0.5) v/c ratios during peak periods. The authors used the v/c ratio for each link as the congestion measure that was related to the ratio of the peak hour volume to the four-hour peak period volume for each link. Commuting direction was also included as an explanatory variable. The freeway count locations were grouped by region within the state (Capitol, Southeast, Southwest, and New York Metro) and by area type (urban, suburban, ex-urban, shoreline, New York City Metro) for the modeling effort. The authors hypothesize that peak spreading is best captured by the congestion measure.

The modeling results for the area type model indicated that peak spreading differs among the area types with change in the predictor variables associated with decreasing urbanization. For the regional model, peak spreading was not found to vary by direction for some of the regions included in the study. The authors point out that the use of an exponential model is ideal for capturing the diminishing benefit of commuting out of the peak as congestion increases and the four-hour peak period volume approaches saturation.

Moses (2015) used National Household Travel Survey (NHTS) data to determine peaking characteristics by trip type in Florida's large urbanized metropolitan areas – Jacksonville, Miami-Fort Lauderdale-Pompano Beach, Orlando-Kissimmee, and Tampa-St. Petersburg-Clearwater. Peaking characteristics were analyzed for work trips (home-based work trips and non-home-based work trips combined) and all trips (all trip types combined). The results showed that the highest proportion of work trips occurred during the morning peak, and that the evening peak had a lower proportion of work related trips compared to the morning peak but experienced broader post peak shoulder than the morning post peak shoulder. Moses explains that this indicates a more extended peak period during the evening compared to the morning peak period.

2.2.2. Link-Based Hourly Proportion Models

Link-based hourly proportion models use aggregate travel patterns to forecast the proportion of peak hour volume for individual links within the transportation network, and they can be integrated with the traditional four-step travel demand modeling process. This type of model aims at obtaining more realistic traffic assignments for the peak hour. It works as a post-assignment procedure, which applies link-specific peaking factors to three-hour peak period traffic volumes or area-and-roadway-functional-class specific peaking factors to daily traffic volumes to obtain peak hour traffic assignments. Link-based measures can be applied in the traffic assignment process to divert trips that exceed link capacity to the shoulders of the peak.

Moses (2015) conducted a study using historical traffic data from 1996 to 2012 collected at 26 permanent continuous count stations in large urbanized areas in Florida to analyze the relationship between 24-hour peaking characteristics and various performance measures. Two link-based models were generated to predict AM and PM peak volumes and hourly volume variations. The peak volume model included area type (urban, urbanized, large urbanized), facility type (freeways, divided arterials, undivided arterials, collectors, tollways, HOV lanes), speed limit of the roadway (30 mph to 70 mph in increments of 5 mph), and average daily traffic per lane (vehicles per hour) as predictor variables. The hourly volume model included area type, facility type, speed limit, and time of day (hour of day from 1 to 24). Moses chose not to include variables such as population, employment, or regional median income in the modeling effort since they were indirectly captured by the area type classification. Peak volume modeling was performed by AM and PM peak period using linear regression. High-fit linear models with R-square values of 0.86 and 0.87 were generated from the hourly data collected by lane. Facility type, ADT/lane, and speed limit were statistically significant variables in both the AM peak period and PM peak period models. Area type, however, was not a statistically significant variable, possibly due to the similarity of peaking characteristics in urban, urbanized, and large urbanized areas. Hourly volume modeling was performed using Gaussian functions to capture multiple peaks during the day. Gaussian models were found to model the weekday hourly volumes by reasonably replicating the peaking profiles with R-squared values higher than 0.95 for all facility types. The author notes that the hourly volume models do not represent actual travel demand on facilities during peak periods since the models are based on traffic counts which do not incorporate trip diversions to other routes due to demand exceeding facility capacity. The author suggests that Gaussian hourly volume models can be used to predict future traffic volumes if the characteristics of future trip making are known. Such characteristics can be used to modify or calibrate the amplitude, centroid, width and number of peak periods.

Allen (1991) presents a methodology for projecting peak spreading as change in temporal patterns associated with capacity limitations using a modified Poisson distribution to describe the spread of 4-hour volumes across each 15-minute period on the I-80 corridor in northern New Jersey, a major commuting and trucking route. The model forecasts the future flattening or shifting of the peak hour based on specific links by estimating the total volume during the 4-hour AM peak period (6-10 am) and by estimating the highest consecutive 60-minute volume during the peak period. Allen hypothesized that peaking patterns in the I-80 corridor are influenced by the extent to which employees have flexible working hours (flextime) that enable them to travel to work at nonstandard times and the level of traffic congestion.

Trip origin and destination information were gathered through a roadside survey of I-80 corridor motorists and used to develop both future estimates of eastbound AM 4-hour traffic and volume during the peak 60-minute period for each roadway link in the study area. The modeling approach related variables such as speed difference, downstream delay, average trip time, proximity to employment, work trip proportion, and average relative location to a congestion factor defined as the percentage of the 4-hour peak period volume that occurs in each 15-minute time interval. One Poisson model was fitted for all 13 links under study.

Louden, et al. (1988) implemented a link-based model based on data collected from 49 corridors in Arizona, Texas, and California that covered a period from 5 to 20 years. Relationships between peak hour volume and peak period (3-hour) volume were modeled as a function of link facility type and link volume/capacity ratio in the peak period. The functional form of the peak spreading model is as follows:

$$P = \frac{1}{3} + a \cdot e^{(b \cdot \frac{v}{c})}$$

Where,

P = the ratio of peak hour volume to peak period (3-hour) volume

v/c = the volume / capacity ratio for the peak period (3-hour) period

a, b = model parameters

The value of 1/3 in the model serves as a reasonable starting point, which assumes a uniform distribution of traffic volumes across the 3-hour peak period.

In his study for the Virginia Center for Transportation Innovation and Research, Miller (2012) used the K-factor, defined as the proportion of the 24-hour traffic volume that occurs during the peak hour, as a measure of peak spreading. Data were collected from 32 continuous count stations (52 sites by direction) in the six Northern Virginia counties for the period 1997-2010. The data collected showed that the average annual K-factor decreased from 0.103 to 0.097 during the period, while the 24-hour volume-to-capacity ratio increased from 7.3 to 8.0 on average. Both changes were statistically significant, according to the author.

Two models were developed in the Virginia study, with model #1 for existing roads and model #2 for new roads.

Model #1: $K_{new} = 0.019 + 0.758K_{old} + 0.022Emp - 0.011Two - 0.007Free - 0.012RuralMulti$

Where,

K_{new} = new K-factor to predict

K_{old} = historical K-factor

Emp = percentage change in number of filled jobs in a jurisdiction over the time period

Two = rural two-lane road dummy: 1 if yes, or 0 if not

Free = freeway or expressway dummy: 1 if yes, or 0 if not

RuralMulti = rural multilane road dummy: 1 if yes, or 0 if not

Model #2: $K_{new} = 0.080 + 0.059Emp - 0.010Circ - 0.002Freeway_{24vc}$

Where,

K_{new} = new K-factor to predict

Emp = percentage change in number of filled jobs in a jurisdiction over the time period

Circ = circuity road type dummy: 1 if yes, or 0 if not

Freeway_{24vc} = 24-hour volume divided by hourly capacity for freeway sites only

The two models rely on site characteristics (e.g. functional class and 24-hour volume-to-capacity ratio of freeways) and regional socioeconomic characteristics (e.g. jurisdictional employment change) to determine the value of K-factors. Except for new freeways, the models do not directly use a congestion measure (e.g. v/c ratio) as a predictor. However, employment changes may be a good indicator of the change of congestion level.

Both the Phoenix and Virginia models have significant limitations for use in regional travel forecasting. Since peaking factors are link-specific, there is no guarantee of continuity of flow in the peak hour prediction. Two adjacent links without intersections in between could end up with different peak hour flows due to different peaking factors applied. These two methods seem to fit project-level peak spreading forecasting better than regional or even sub-area forecasting.

2.2.3. Trip-Based Models

Trip-based models selectively reduce the trip table interchanges for those links in which demand exceeds capacity and allow continuity of flow between adjacent links. This approach requires time period trip tables, or a pre-assignment factoring procedure. A report authored by Cambridge Systematics, Inc. (1997) on time-of-day modeling procedures provides three examples of trip-based models for peak spreading: 1) a subarea model in the San Francisco Bay Area (Tri-Valley model), 2) a model applied for a study in Boston, Massachusetts (Central Artery/Tunnel project), and 3) a model applied for a study in Washington, DC.

The Tri-Valley model accounted for the overall constraint of the future highway network system capacity by time-of-day by limiting the assignment of trips to the present highway network based on the overall capacity of the future network at selected gateways. The model approach does not account for changes in traveler behavior due to congestion and does not assume that the excess trips on each congested interchange are not made. The model assumes that the excess trips cannot be completed in the peak hour and are forced to be taken outside of the peak hour.

The Boston area model reduced individual origin-destination cells of the trip table according to congestion levels in the corridor corresponding to the origin-destination pair. This iterative-factoring procedure was only applied to highway trips and attempted to account for and apply peak spreading to adjust impossibly high future peak hour travel estimates resulting from growth projections in downtown Boston. The model's selective reduction focuses on congested links and avoids changing uncongested corridors by unrealistic amounts. The Boston area model considered more links in its analysis than the Tri-Valley model, and it applies interchange-specific peak hour factors rather than a region wide factor. However, similarly to the Tri-Valley model, the Boston area model does not account for changes in traveler behavior due to congestion, and there is no explicit treatment of the trips being reduced.

The Washington, DC model is a post-mode choice procedure applied to AM peak period automobile trips that was calibrated using household travel survey data. The travel survey data was stratified by trip purpose, including home-based work, home-based university, and three non-home-based trip purposes. The model estimated the percentage of peak period travel during the 3-hour AM peak period at the vehicle trip interchange level occurring during the peak hour based on the congested travel time minus free-flow travel time and trip distance. A set of curves was used to relate the percentage share of peak period trips to congested travel time difference and trip distance. The modeling procedure may be transferable to other areas (Cambridge Systematics, Inc., 1997).

2.2.4. *Choice Models*

Choice models are based on the concept of individual utility maximization, require knowledge of individual travel behavior, and apply to an entire region.

Purvis (1999) suggests that peak spreading models are a great tool to moderate congestion forecasts in over-saturated situations and are a practical extension to traditional trip-based four step travel model systems. He discusses different methods for modeling peak spreading, including a time-of-day departure time choice model developed by the Metropolitan Transportation Commission (MTC) to estimate peak spreading for the San Francisco Bay Area. The time-of-day departure time choice model provided is a simple binomial logit choice model with the choices of two-hour AM peak period departure and non-AM peak period departure with the choice applied to daily home-to-work auto person trips. The model is estimated using data from the 1990 Bay Area household travel survey and includes variables such as free-flow travel time, AM peak period congested travel time, trip distance, household income, and dummy variables for bridge crossers, carpooling, and retail employment. The model shows that carpoolers are more likely to start their travel during peak periods, but bridge crossers are more likely to start outside of the peak period, and retail workers are more likely to start their commute after the AM peak period. Purvis discusses limitations to the model, including its tendency to divert trips from the peak period to the shoulders of the peak period due to increased congestion levels. In extreme cases, this results in higher shoulder hour travel demand than the peak period travel demand which, in turn, produces slower four-hour speeds than two-hour speeds. The author describes a “quick fix” to this issue whereby the lower of the two travel speeds was fed back into mode choice under the assumption that the lower speed is a more accurate and reasonable reflection of the AM peak two-hour period since the MTC mode choice models were estimated using AM peak two-hour travel times and costs.

Sall, et al. (2010) provides a choice model that considers mode choice and time of day within the regional travel demand planning process for the San Francisco area. The combined utility of five time periods (early morning, morning peak, midday, evening peak, and evening) and mode (including drive alone, a two-person auto trip, and transit) was estimated using a nested logit model. The time of day model was used at two levels, where the time of day and mode were determined (based on the combined utility of mode choice and time of day) and the specific half-hour in which automobile travel occurred was determined (based on congested auto travel times).

2.3. Explanatory Variables

The peak spreading modeling approaches offered by the available literature test a variety of variables in relation to K-factor change and peak spreading. The following sections provide a summary of several categories of factors that have been evaluated as predictors for peak spreading, including area type factors, congestion-related factors, socioeconomic factors, and seasonal factors.

2.3.1. Area Type Factors

Replogle (1990) discusses the calibration of a peak hour traffic model for planning use in Montgomery Country, Maryland. The model assumes that land use density/mix and the associated demographic character of an area along with the amount of peak hour congestion in the transportation system influence the peaking characteristics of traffic. Replogle further suggests that small towns, bedroom communities, and isolated industrial or office parks typically display higher peak hour factors since a greater portion of the total daily trips are made in the AM and PM peak hours of traffic compared to heterogeneous, high-density cosmopolitan urban centers. Replogle argues that homogenous land use areas such as office centers and residential communities attract or generate more of their daily trips in the peak hours than do places that attract human activity both day and night.

Using data from the 1980 COG Auto Use Survey and Montgomery County turning movement counts from the 1970s through the 1980s, Replogle created a density-based AM peak hour trip table splitting model which incorporated vehicle miles of travel (VMT) and congestion as the volume to capacity (V/C) ratio and accounted for changes in peak hour factors responding to urbanization as a function of area type, household density, and employment density. The final model results suggested that more transportation infrastructure per unit of development is needed when the development is put into low density areas than if it goes into already built up areas, and that heterogeneous land uses at a small scale, which permit more travel demand to be met by non-motorized means, similarly require less transportation infrastructure per unit of development.

2.3.2. Congestion-Related Factors

In several studies, the 24-hour volume-to-capacity ratio is used as a congestion factor to forecast the degree of peak spreading (Ivan, 2000, 2001; Miller, 2012). Liu, et al. (2007) used the availability of a parallel route as an independent variable related to congestion. In his congestion-based peak spreading model for northern New Jersey, Allen (1991) included a variable for the peak v/c ratio (highest 15-minute) and the average v/c ratio (averaged over four hours). For a different study based in the Washington, DC area, Allen (1996) employed two congestion measures – the ratio of the peak hour travel time to the off peak travel time and the difference between the peak hour travel time and the off peak travel time.

2.3.3. Socioeconomic Factors

Habib, et al. (2009) and Replogle (1990) accounted for socioeconomic factors when modeling peak spreading by including household and employment density as independent variables in their models. As previously mentioned, Replogle (1990) demonstrated that mixed land uses (e.g., an area containing residences, shopping destinations, and employers) show less peaking as lower K-factors than homogenous land uses. Applying data from the Greater Toronto Area to a choice and trip timing model, Habib, et al. (2009) showed that some variation in peak spreading occurs by industry type. Ivan (2001) and Sinha (2004) suggest that growth industry types should be included as independent variables since some industries, such as retail and food service, are more likely to have unconventional start times than others, such as finance. Additional variables that may influence work schedules include income, age, and area type. Purvis (2002) also considered travel time, distance, and income, as well as employment in the retail industry.

2.3.4. Seasonal Factors

Gunamardena, et al. (1996) used hourly volume counts from 1991 through 1993 collected at 60 permanent continuous count stations in Indiana to generate AM and PM peak hour and peak-directional factors by facility type (urban Interstate/freeway, urban arterial, rural Interstate, rural arterial, rural collector). Applying an ANOVA analysis, they found statistically significant factor effects for day of the week and season of the year for count station identification number, year, day of week, season of year, and month of season factor levels by roadway type. Liu and Sharma (2006) incorporated holiday traffic as a factor in their model for rural highways in Alberta, Canada and showed that holidays provide a substantial portion of the highest hourly volumes per year. Using statewide volume data from urban areas in Florida, Yang et al. (2009) showed that seasonal variation in peak spreading is also influenced by roadway type and socioeconomic characteristics such as number of retirees in an area.

2.4. Modeling Peak Spreading in the Triangle Region

ITRE's Triangle Regional Model Service Bureau (2013) tested three modeling techniques to develop peak spreading models for the Triangle Region, which were intended to be sensitive to congestion. These techniques were discrete choice modeling, peaking factor diversion curves, and trip matrix reduction. Developing models using the first two techniques relies heavily on local household travel survey data, while the last one needs effective matrix adjustment procedures. The discrete choice modeling technique was used to develop a set of peak hour versus shoulder choice models; however, no satisfactory models were achieved. The peaking factor diversion curves derived from the survey data reveal that there was no substantial region-wide peak spreading phenomena back in 2006 when the survey was conducted, which means the survey data do not support the development of peak spreading models for the study area. The idea of using an OD Matrix Estimation procedure in the trip matrix reduction process was later developed, which automatically constrains the trip matrix to peak hour highway network capacity. The approach worked well according to the preliminary testing. Based on the tests done on a few highway network scenarios in the study area, the results indicate that the method has great potential to handle peak spreading in large congested networks. Further research will be conducted in the future to optimize parameters in the method to improve convergence in a shorter run time.

3. Methodology

The research team developed a case study methodology informed by the literature review. The research team sought to replicate the peak spreading study developed by Miller (2012) for the Northern Virginia area, but with some modifications in data sources and modeling inputs. K-factors were generated from count data from the population of continuous traffic count stations installed on North Carolina roadways. These data were analyzed and models were developed to forecast how these K-factors may change based on previous trends. In particular, a measure of development density was defined and related with changes in time of day travel at the continuous traffic count stations.

3.1. Data Collection Plan for Generating K-Factors

Data were collected from 54 continuous traffic count stations located on North Carolina roadways representing 34 of the 100 counties in the state for the period 1995-2016 (Exhibit 3). The research team planned to generate K-factors for every station by direction for one Tuesday, Wednesday, and Thursday block for every month during the period where data were available. The research team sought to avoid days with snow or ice and federal/state holidays so that the K-factors would be comparable.

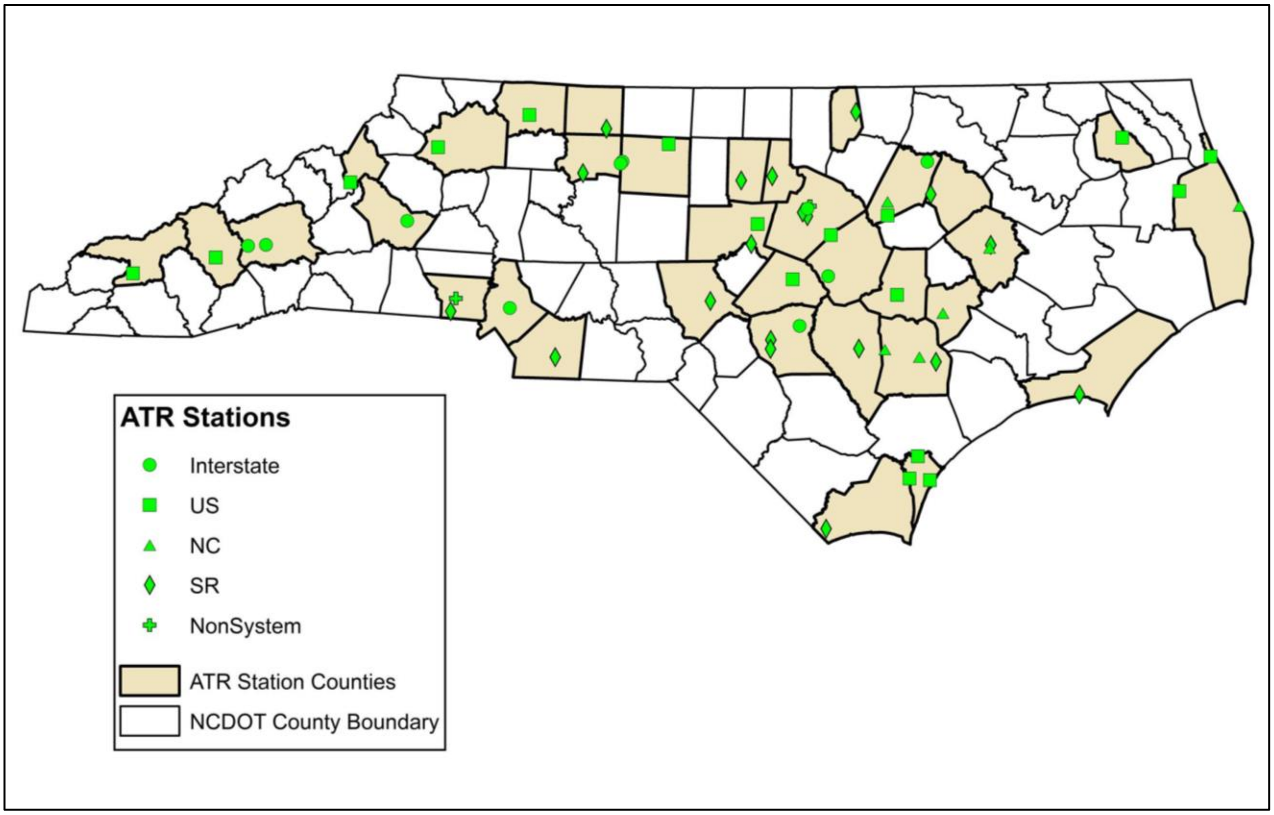

Exhibit 3: Continuous Count Stations with Available Data in North Carolina

Dates for North Carolina state holidays were obtained from the North Carolina Office of State Human Resources (NC-OHSR) and dates for federal holidays were obtained from the United States Office of Personnel Management (USOPM). Dates for snow and ice days were obtained from Weather Underground's historic monthly weather data archive. Exhibit 4 provides the years, months, and dates used as a guide for obtaining the K-factors.

Additional data were collected to perform the analyses, including socioeconomic data and roadway attributes for the links where the 54 continuous traffic count stations were located. A summary of the data sources is provided in the following:

1. Socioeconomic data: Population data were obtained from the 2000 and 2010 United States Census and employment data were obtained from the United States Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. The LEHD data are provided quarterly by the United States Census Bureau and cover longitudinal workforce indicator information by industry, work force living location and work location, and industry employment gain and loss. Data were aggregated by county and year for the continuous traffic count station locations.

2. Roadway attribute data: Characteristics of the roadway links associated with the continuous traffic count stations was obtained from NCDOT's GIS Unit in the form of a geospatial file that included attribute information such as functional classification,

number of lanes, posted speed limit, and presence of median. Area type and default per lane capacities were obtained from the NCDOT Comprehensive Transportation Planning Manual (NCDOT, 2012) which derives its capacities from the 2000 Highway Capacity Manual (HCM).

3. K-factors at the continuous traffic count stations for the period 1995-2016: NCDOT staff provided continuous traffic count data from the 54 stations by hour of day and direction for every date in the period 1995-2016 where data were available. Every station has some missing days of data, and some stations had a year or more of missing data. The data were provided in multiple Excel files that were aggregated into a single dataset with 672,681 records in total.

The analysis dataset was composed of data extracted for the dates listed in Exhibit 4. This dataset contained 66,084 records, with each record representing a single day of continuous traffic data and its corresponding K-factor at a given station in a particular travel direction in the period 1995-2016. Exhibit 5 provides a summary of partial and complete year data availability for this dataset by total number of stations and total number of sites, where a site represents a station by direction. For each record, a set of variables in addition to the K-factor were available for use in the analysis. These variables are listed and described in Exhibit 6. The research team attempted to include the variables that were used in the Miller (2012) study, which included the 24-hour volume-to-capacity (V/C) ratio defined as “the ratio of a link’s 24-hour volume divided by its hourly capacity” and used as a surrogate for travel congestion. The research team acknowledges that this is not a standard use of capacity and may have limited usefulness for forecasting due to issues such as aggregation error.

Month	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
January	10-12	9-11	7-9	6-8	5-7	4-6	9-11	8-10	7-9	6-8	4-6	10-12	9-11	8-10	6-8	5-7	11-13	10-12	8-10	7-9	6-8	5-7
February	14-16	13-15	11-13	10-12	9-11	8-10	13-15	12-14	11-13	10-12	8-10	7-9	13-15	12-14	10-12	9-11	15-17	7-9	5-7	4-6	3-5	2-4
March	14-16	12-14	11-13	10-12	9-11	7-9	13-15	12-14	11-13	9-11	8-10	7-9	13-15	11-13	10-12	9-11	8-10	6-8	5-7	4-6	3-5	8-10
April	11-13	16-18	15-17	14-16	13-15	11-13	17-19	16-18	15-17	13-15	12-14	11-13	17-19	15-17	14-16	13-15	12-14	10-12	9-11	8-10	7-9	5-7
May	16-18	14-16	13-15	12-14	11-13	9-11	15-17	14-16	13-15	11-13	10-12	9-11	15-17	13-15	12-14	11-13	10-12	8-10	14-16	13-15	12-14	10-12
June	20-22	25-27	24-26	23-25	22-24	20-22	26-28	25-27	24-26	22-24	21-23	20-22	26-28	24-26	23-25	22-24	21-23	19-21	18-20	24-26	23-25	21-23
July	11-13	16-18	15-17	14-16	13-15	18-20	17-19	16-18	15-17	13-15	12-14	11-13	17-19	15-17	14-16	13-15	12-14	10-12	9-11	8-10	14-16	19-21
August	15-17	13-15	12-14	11-13	10-12	8-10	14-16	13-15	12-14	10-12	9-11	8-10	14-16	12-14	11-13	10-12	9-11	14-16	13-15	12-14	11-13	9-11
September	12-14	17-19	16-18	15-17	14-16	12-14	18-20	17-19	16-18	14-16	13-15	12-14	18-20	16-18	15-17	14-16	20-22	11-13	10-12	9-11	15-17	13-15
October	17-19	22-24	21-23	20-22	19-21	17-19	23-25	22-24	21-23	19-21	18-20	17-19	23-25	21-23	20-22	19-21	25-27	23-25	22-24	21-23	20-22	25-27
November	14-16	12-14	18-20	17-19	16-18	14-16	27-29	19-21	18-20	16-18	15-17	14-16	27-29	18-20	17-19	16-18	15-17	6-8	5-7	4-6	3-5	1-3
December	5-7	10-12	9-11	8-10	7-9	5-7	11-13	10-12	9-11	7-9	6-8	5-7	11-13	9-11	8-10	7-9	6-8	4-6	3-5	2-4	8-10	6-8

Exhibit 4: Data Collection Months and Dates for 1995-2016 Period

Number of Partial Years Available	Number of Stations for Which Data Were Available	Number of Sites for Which Data Were Available	Number of Complete Years Available	Number of Stations for Which Data Were Available	Number of Sites for Which Data Were Available
22	28	56	18	1	2
21	9	18	17	2	4
20	3	6	16	2	4
19	2	4	15	7	14
18	2	4	14	8	16
17	3	6	13	7	14
13	1	2	12	9	18
11	4	8	11	3	6
10	2	4	10	6	12
			9	3	6
			8	2	4
			7	2	4
			6	2	4

Exhibit 5: Summary of Partial and Complete Years of Data Available for Stations and Sites

Variable	Definition
Station	A continuous count station that provides volume data for a specified segment of a roadway facility
Site	A combination of a station and a direction, e.g., if one station provides both northbound and southbound counts, the station would constitute two sites
Date	The date on which volume data were collected, formatted mm/dd/yy
Month	Calendar month during which volume data were obtained
Day	The Tuesday, Wednesday, or Thursday during which volume data were obtained
Year	Calendar year (1995 through 2016) for which traffic volume or a county's population, employment, or labor force was obtained
Direction	Direction for which volume data were obtained
County	North Carolina county in which volume data were collected
Area Type	Area type where the roadway is located (Rural, Suburban, or Urban)
Functional Class Code	Numeric functional classification of the roadway as defined by the FHA
Functional Class Description	Functional classification description as defined by the FHA
Median	Denotes whether the roadway is median divided (1) or not (0)
Number of Lanes	Denotes the number of lanes (number of lanes in both directions for undivided roadways; number of lanes in one direction for divided roadways)
Speed Limit	Posted speed limit on the roadway
Area and Functional Class Description	Concatenation of area type and functional classification description of the roadway
Functional Class Group	Grouping of roadways by functional classification into one of seven groups (see Appendix A)
Station Capacity PV/Hr/Ln	Hourly maximum passenger vehicle capacity of roadway (LOS E) per lane for the station defined according to the NCDOT Comprehensive Transportation Planning Manual (see Appendix B)
Site Capacity PV/Hr	Total hourly maximum passenger vehicle capacity of the roadway (LOS E) for the site defined according to the NCDOT Comprehensive Transportation Manual
24 Hour V/C	24-hour volume-to-capacity ratio as the ratio of a roadway segment's 24-hour volume divided by its hourly capacity
Population	US Census 2000 or 2010 total population for the county where a station/site is located (2000 county population totals assigned to data years 1995-2009 and 2010 county population totals assigned to data years 2010-2016)
LEHD Employment Q1	LEHD total employment for Quarter 1 for the county where a station/site is located and the calendar year
Daily K-Factor	Proportion of 24-hour volume that occurs during peak hour
Peak Hour Volume	The volume of the roadway segment during the peak hour of a 24-hour calendar day
Peak Hour	The single hour of a 24-hour calendar day with the highest traffic volume on a given roadway segment
Total Daily Volume	The total traffic volume over a 24-hour period

Exhibit 6: Definitions of Variables Used in Analyses

3.2. Data Analysis

Two data analyses were performed prior to the development of models to forecast changes in K-factors:

1. Variability in the K-factors for all sites and for a subset of sites were analyzed using analysis of variance (ANOVA) in order to identify which variables could potentially be used to forecast the change in K-factors over time.

2. In order to test the change in K-factors over time, annual adjusted K-factors were generated to account for variability resulting from months with missing data. Sites were included in the analysis if at least nine months of data were available for both the first year (before period) and last year (after period) used for the comparison.

3.2.1. *Variability in K-Factors – All Sites*

Data analyses were performed to determine the variability in the K-factors and whether the K-factors had changed over time.

An initial examination of the analysis dataset was performed using ANOVA to identify which variables were likely to explain variability in the K-factors and to be useful for forecasting the change in K-factors over time. This preliminary testing aids in showing the feasibility of forecasting a K-factor given the random variation in the data. Each daily K-factor for each site was treated as a single observation with no adjustments made to the dataset.

The ANOVA results show that when a site was defined as the station and the direction of traffic, the Site variable explained most (55.2%) of all variation in the K-factors. The Site variable was established as a block in the ANOVA so that the influence of other variables could be detected while controlling for the variation across sites. With the Site variable as a block and including the Month and Year variables as main effects along with the interaction effect of the Month variable crossed with the Year variable, the model explained the same amount of variation in the K-factors, while adding Day as a main effect increased the explained variation to 55.9%.

The effect of month but not year was statistically significant at $p<0.05$ in relation to variation in the K-factors when controlling only for the Site variable. Exhibit 7 provides the average K-factors and their 95% confidence intervals by year and Exhibit 8 provides the average K-factors and their 95% confidence intervals by month. The practical difference in annual average K-factors is small, and the reason for apparent variation in the factors is not accounted for in the charts. Exhibit 8 indicates significant seasonal variation in the K-factors that should be recognized when dealing with locations with missing months of data.

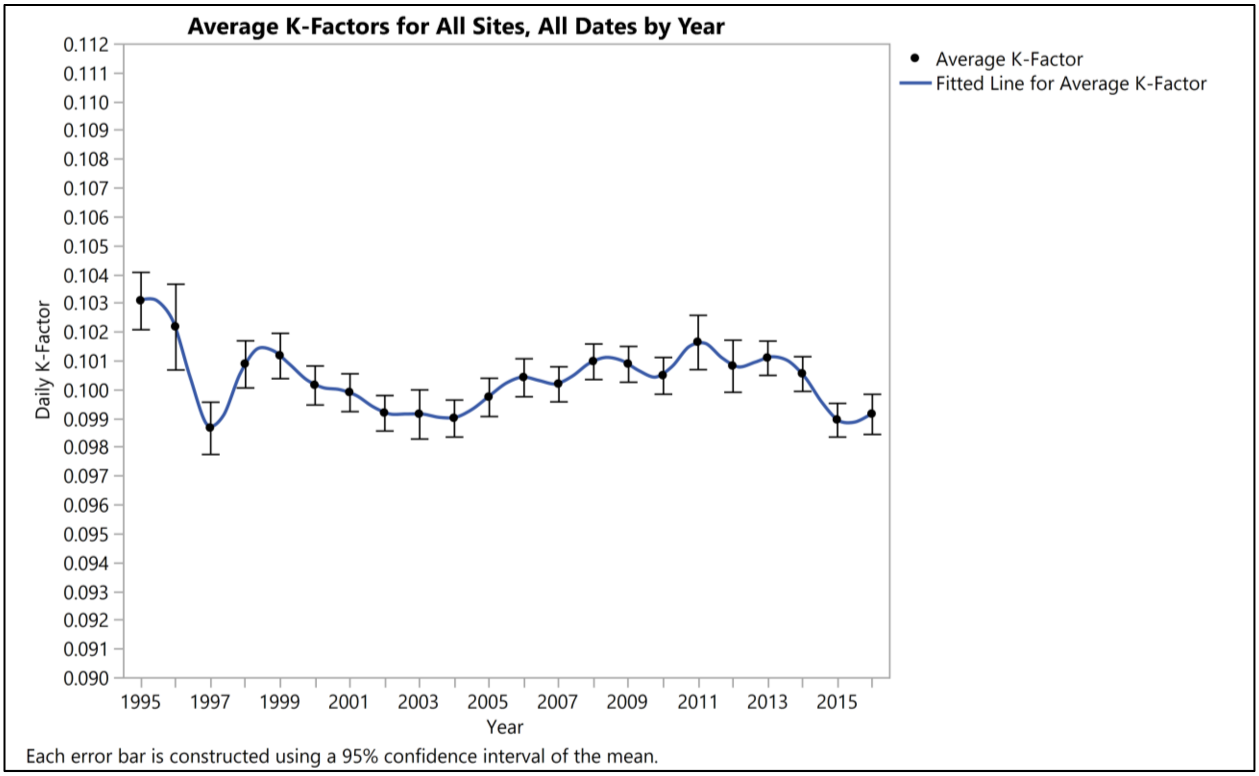

Exhibit 7: Average K-Factors for All Sites, All Dates by Year

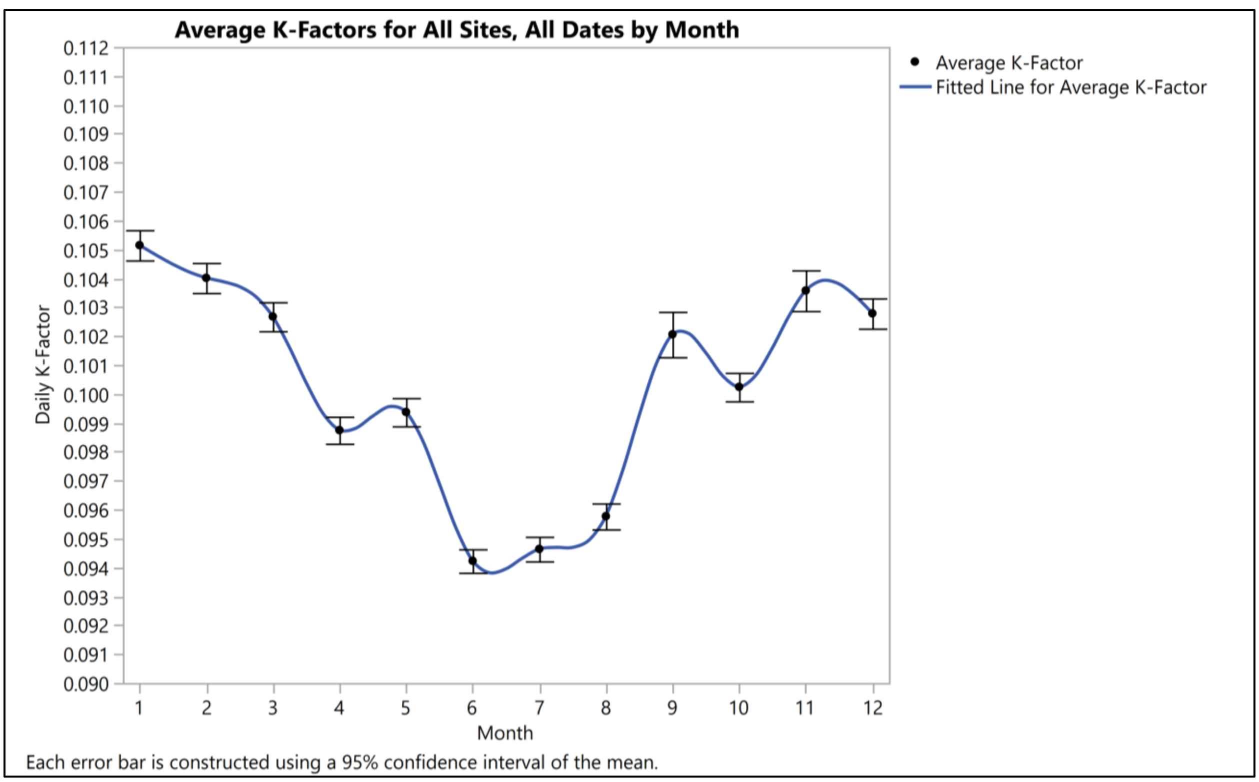

Exhibit 8: Average K-Factors for All Sites, All Dates by Month

When the Site variable was removed as an independent variable, less variation in the K-factors could be explained than when the Site variable was included. Exhibit 9 shows that the socioeconomic variables such as population and employment in combination with the roadway attribute variables could explain some variation in the K-factors where the Site variable was excluded from the model (4.2%). A model that includes the Site variable and the socioeconomic and roadway attribute variables explains 56.5% of the variation in the K-factors. This finding indicates that there is considerable amount of variation in K-factors between the sites that is not accounted for in the ANOVA.

Variables	% Variation Explained	Discussion
Site	55.2%	Most of the variation in K-factors can be explained by the Site variable. Socioeconomic variables can partially but not completely replace the Site variable.
Site, Month, Year, Month*Year	55.2%	
Site, Month, Year, Month*Year, Population, Employment (LEHD Q1), Functional Class Group	55.3%	
Month, Year, Month*Year, Population, Employment (LEHD Q1), Functional Class Group	4.0%	
Month, Year, Month*Year, Population, Employment (LEHD Q1)	<1%	
Month, Year, Month*Year, Functional Class Group, 24 Hour V/C as an integer	3.6%	Impact of congestion (defined as 24 Hour V/C) varies by facility in relation to K-factors when controlling for socioeconomic variables.
Same as previous but with Functional Class Group*24 Hour V/C as an integer added	3.6%	
Same as previous but with Population and Employment (LEHD Q1) added	4.2%	
Site, Month, Year, Month*Year, Population, Employment (LEHD Q1), Functional Class Group, 24 Hour V/C as an integer, Functional Class Group*24 Hour V/C as an integer	56.5%	Socioeconomic and roadway attribute variables in combination account for only a fraction of the variation in the K-factors relative to the influence of the Site variable.

Exhibit 9: Variation in K-Factors According to ANOVA Results for All Sites

3.2.2. Variability in K-Factors – Subset of Sites

Compared to the Northern Virginia study area analyzed by Miller (2012), the North Carolina study area appears to have more variation in roadway and area types in relation to the continuous traffic count station locations. The research team hypothesized that many stations contributing to the analysis dataset experience non-commute travel patterns that would generate more random variation in K-factors rather than predictable variation than could be captured by the socioeconomic and roadway attribute variables under consideration. To test this hypothesis, the research team focused on a subset of sites that, upon examination of their K-factors, peak hours, peak hour volumes, and county-level population and employment data plotted over time in years, appeared to show locations with commute patterns where the K-factor was negatively correlated with peak hour volumes, population, and employment.

Fifteen sites total were included in the subset of data that was further tested using ANOVA. The dataset was comprised of 9,150 records. The sites and their attributes are listed in Exhibit 10. A summary of the correlation results for these sites in relation to all sites is provided in Exhibit 11. The subset of sites are mostly located on interstates and arterial roadways in rural, urban, and suburban areas.

Site ID	County	Route	Area Type	Functional Classification
A0501_Northbound	Avery	US 19E	Rural	Principal Arterial - Other
A1001_Westbound	Buncombe	I-240	Urban	Interstate
A1101_Westbound	Burke	I-40	Urban	Interstate
A1801_Eastbound	Chatham	US 64	Rural	Principal Arterial - Other
A1801_Westbound	Chatham	US 64	Rural	Principal Arterial - Other
A2501_Northbound	Cumberland	SR 1007 (ALL AMERICAN EXPY)	Urban	Principal Arterial - Other Freeways and Expressways
A2702_Westbound	Dare	US 64	Rural	Principal Arterial - Other
A3303_Westbound	Forsyth	SR 1120 (CLEMMONSVILLE RD)	Urban	Major Collector
A4008_Southbound	Guilford	US 29	Urban	Principal Arterial - Freeways and Expressways
A4012_Eastbound	Guilford	I-40 BUS	Urban	Principal Arterial - Freeways and Expressways
A5001_Eastbound	Johnston	I-40	Suburban	Interstate
A5001_Westbound	Johnston	I-40	Suburban	Interstate
A5301_Westbound	Lenoir	NC 55	Rural	Major Collector
A5903_Northbound	Mecklenburg	I-277	Urban	Interstate
A5903_Southbound	Mecklenburg	I-277	Urban	Interstate

Exhibit 10: Subset of Sites Included in Additional ANOVA Analysis

Explanatory Variables	All Sites (108 total – 66,084 observations)	Subset of Sites (15 total – 9,150 observations)
	Daily K-Factor	
Month	-0.0254***	-0.049***
Year	-0.0039	-0.1153***
Functional Classification Group	0.1846***	0.5673***
24 Hour V/C	-0.1416***	-0.4566***
Population (2000, 2010)	-0.0299***	-0.3466***
LEHD Quarter 1 Employment	-0.0229***	-0.3018***
Peak Hour Volume	-0.2038***	-0.5287***

****Significance level: p<0.001*

Exhibit 11: Pairwise Pearson's Correlation Coefficient Results for All Sites and Subset of Sites

Exhibit 12 provides an example of the commuter-based attributes reflected in the subset of sites. This exhibit shows activity at a continuous count station located on I-40 in Johnston County. The daily K-factors recorded at this location show a significant decrease over time from 1995-2016, while peak hour volumes and county-level employment increase during the period. The two sites that comprise the station both display commute patterns, with the eastbound lanes showing an evening peaking pattern and the westbound lanes showing a morning and evening peaking pattern.

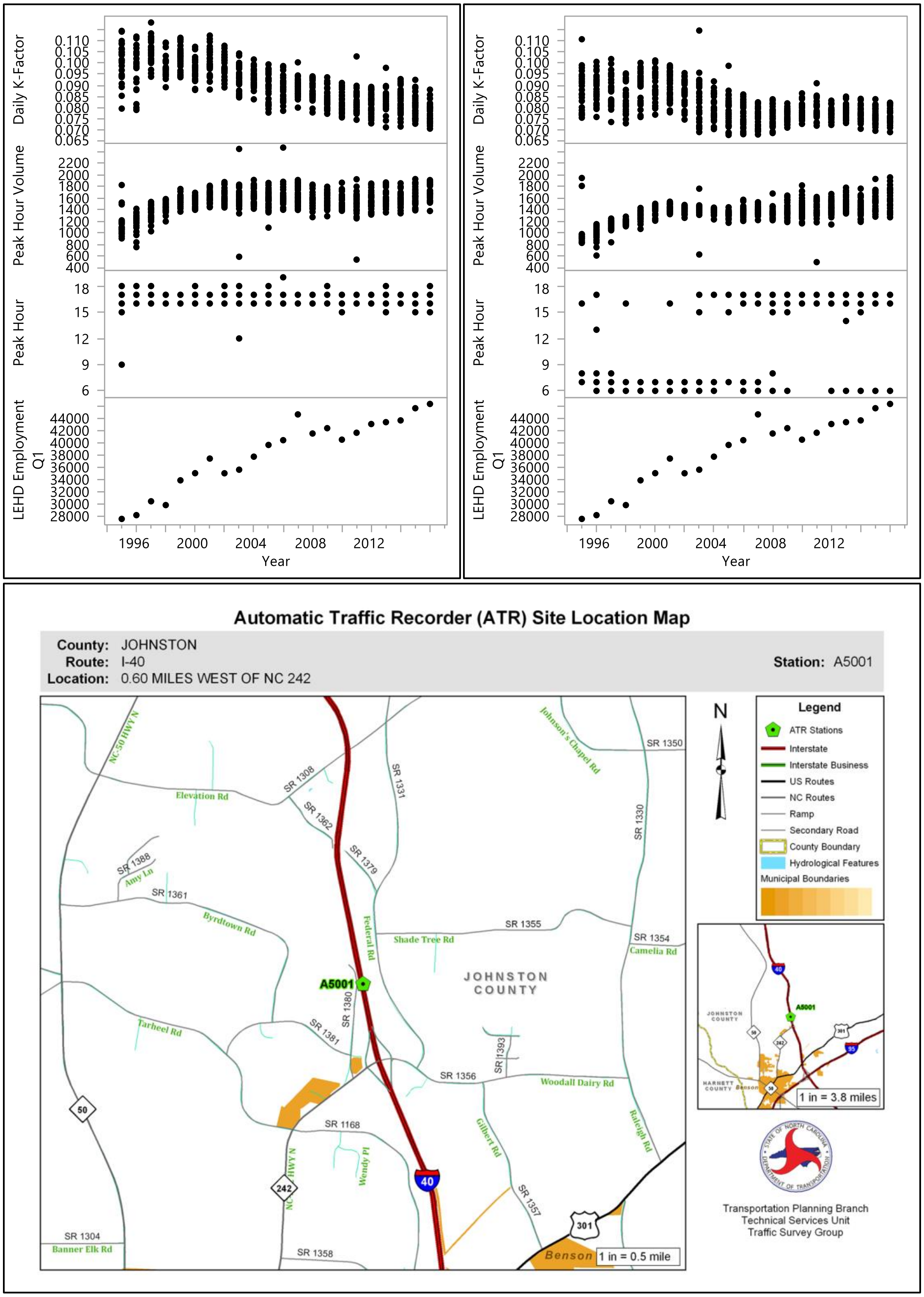

Exhibit 12: Station A5001 on I-40 in Johnston County, North Carolina with Eastbound Site Data (top left) and Westbound Site Data (top right)

The same variables were considered in relation to variation in the K-factors for the site subset as with the complete analysis dataset. The results are provided in Exhibit 13. The ANOVA results show that when a site was defined as the station and the direction of traffic, the Site variable explained the majority (73.0%) of all variation in the K-factors. With the Site variable as a block and including the Month and Year variables as main effects along with the interaction effect of the Month variable crossed with the Year variable, the model explained slightly more variation in the K-factors (77.5%), while adding Day as a main effect increased the explained variation to 78.7%.

When the Site variable was removed as an independent variable, less variation in the K-factors could be explained than when the Site variable was included. However, socioeconomic variables explain a greater portion of variation in the K-factors for the subset of sites compared to when all sites are included in the analysis. Exhibit 13 shows that the socioeconomic variables such as population and employment in combination with the roadway attribute variables could explain over a third (38.6%) of the variation in the K-factors where the Site variable was excluded from the model. A model that includes the Site variable and the socioeconomic and roadway attribute variables explains 79.2% of the variation in the K-factors. This finding indicates that a considerable amount of variation in K-factors for the fifteen sites included in the analysis can be explained by the variables included in the ANOVA.

Variables	% Variation Explained	Discussion
Site	73.0%	Most of the variation in K-factors can be explained by the Site variable. Socioeconomic variables can partially but not completely replace the Site variable.
Site, Month, Year, Month*Year	77.5%	
Site, Month, Year, Month*Year, Population, Employment (LEHD Q1), Functional Class Group	77.6%	
Month, Year, Month*Year, Population, Employment (LEHD Q1), Functional Class Group	34.0%	
Month, Year, Month*Year, Population, Employment (LEHD Q1)	15.1%	
Month, Year, Month*Year, Functional Class Group, 24 Hour V/C as an integer	33.4%	Impact of congestion (defined as 24 Hour V/C) varies by facility in relation to K-factors.
Same as previous but with Functional Class Group*24 Hour V/C as an integer added	37.5%	
Same as previous but with Population and Employment (LEHD Q1) added	38.6%	
Site, Month, Year, Month*Year, Population, Employment (LEHD Q1), Functional Class Group, 24 Hour V/C as an integer, Functional Class Group*24 Hour V/C as an integer	79.2%	Socioeconomic and roadway attribute variables in combination account for large portion of the variation in the K-factors relative to the influence of the Site variable.

Exhibit 13: Variation in K-Factors According to ANOVA Results for 15 Site Subset

The results of the two sets of ANOVA tests indicate that that the single best predictor of a K-factor was the Site variable. This variable accounted for the majority of the variation in the K-factors for all sites and for the subset of sites. The results also suggest that other variables may explain the variation in K-factors to a lesser extent, and that it may be possible to develop a measure that incorporates socioeconomic data such as employment and land use to use as a predictor for change in the K-factors.

A smaller dataset was used for exploratory modeling. This dataset was chosen based on data completeness, i.e., at least one decade between the first and last years that peak hour factors were available and at least nine months of data available for both the first year and the last year. The research team determined if the change in annual adjusted K-factors is statistically significant, then developed a linear model to forecast the change in the K-factor over the period as a function of a variety of independent variables. The research team then developed a second linear regression model to forecast a K-factor in the absence of an existing K-factor to be used for a site where a new facility is being constructed and for which there may be no historical data.

3.2.3. Change in Annual Adjusted K-Factors

In order to test the change in K-factors over time, annual adjusted K-factors were developed to account for variability resulting from months with missing data. Sites were included in the analysis of K-factor change over time if at least nine months of data were available for both the first year (before period) and last year (after period) used for the comparison. The analysis was performed using all sites that met this minimum data requirement and a subset of these sites that appeared to show locations with commute patterns where the K-factor was correlated with peak hour volumes and employment. This subset consists of those sites from the 15 site subset used in the previous ANOVA that fulfilled the minimum data requirement. Two time periods were considered when evaluating change in the annual adjusted K-factors:

1. 2000-2010: This time period was chosen in order to examine change in K-factors that may be correlated with extreme changes in socioeconomic conditions represented by the “Dotcom Bubble,” resulting “Dotcom Crash,” and the “Great Recession” (NBER, 2010). The height of the Dotcom Bubble occurred in the year 2000, with the subsequent crash beginning in 2001 onward. The Great Recession began in late 2007 and continued through 2009. Exhibit 14 provides a comparison of average K-factor trends for the 15 site subset that exhibits a relationship between the K-factor and peak hour volumes and employment and all other sites. Especially for the 15 site subset that shows the most change in the average K-factor between 2000 and 2010, it is hypothesized that socioeconomic conditions resulting from the Dotcom Bubble/Crash and the Great Recession affected K-factor data and derived statistics.

2. 2005-2015: This time period was chosen to examine moderate change in K-factors over a ten year time frame. While this time period contains the Great Recession, moderate change in average K-factors between 2005 and 2015 for the 15 site subset and for all other sites is reflected in Exhibit 14.

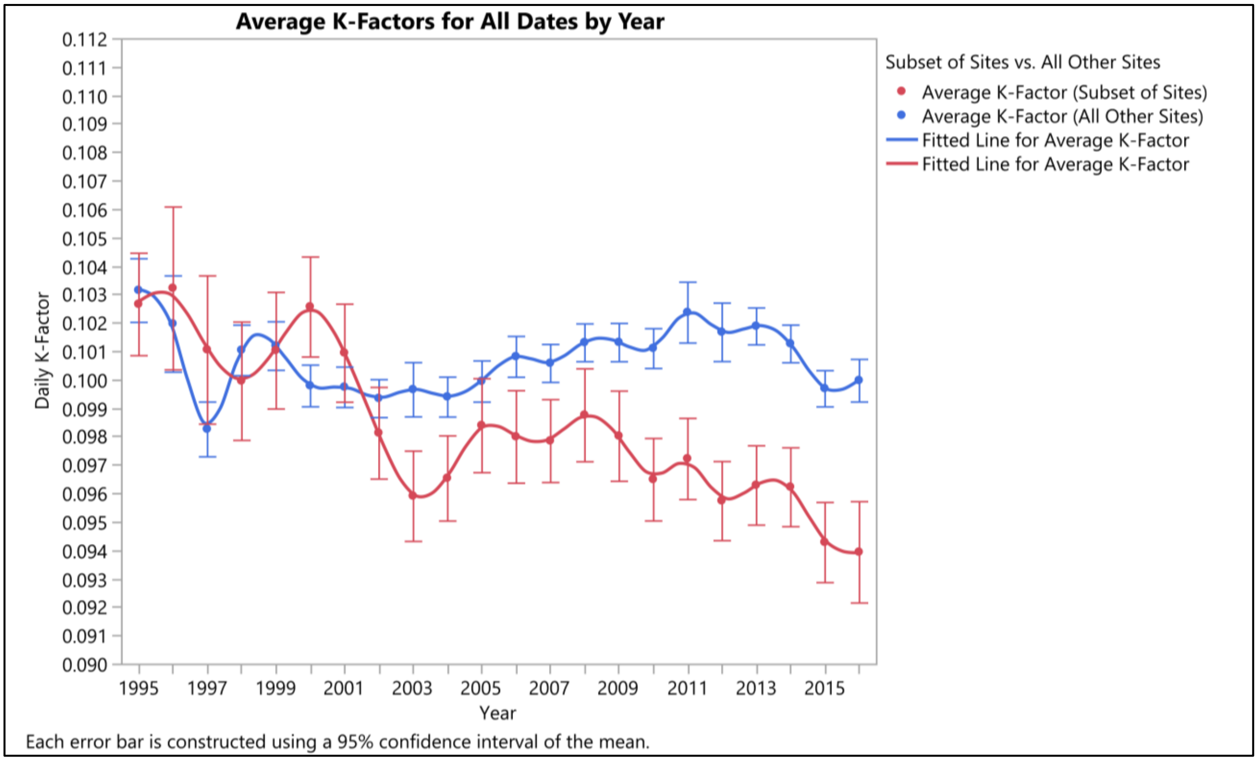

Exhibit 14: Average K-Factors Comparison, All Dates by Year

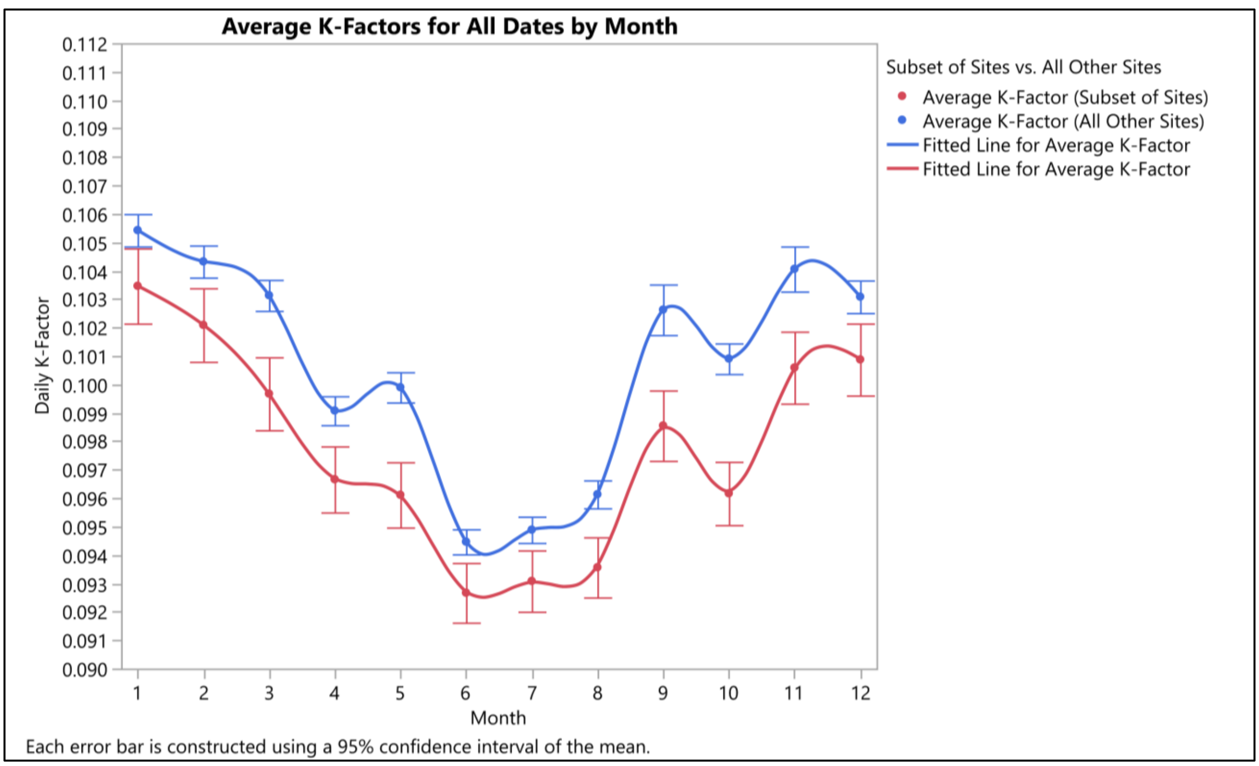

Exhibit 15: Average K-Factors Comparison, All Dates by Month

Exhibits 8 and 15 provide evidence of seasonal variation in K-factors which informed the development of annual K-factors that account for months with missing data. Annual adjusted K-factors were generated for sites with no more than three months of missing data, but less than twelve months of data available for generating an annual K-factor. The factor adjustments were achieved by applying monthly expansion factors for each year. The monthly expansion factors were based on all sites for each year and were calculated as follows:

$$ME_{month} = \frac{K_{year}}{K_{month}}$$

Where,

ME_{month} = monthly expansion factor for a given month for all sites

K_{year} = average K-factor for a given year

K_{month} = average K-factor for a given month

Annual adjusted K-factors for sites with no more than three months of missing data, but less than twelve months of data were calculated as follows:

$$adjK_{year} = \frac{K_{month\ 1} + K_{month\ 2} + \ \dots\ + \ K_{month\ 12}}{N}$$

Where,

$adjK_{year}$ = adjusted annual K-factor for a given year

$K_{month\ 1 \dots 12}$ = average K-factor for each month with available data

N = number of months for which an average K-factor was available (9, 10, or 11 months)

For sites where twelve months were available for a given year, the annual K-factor represents the average of all daily K-factors for the year.

For reference, Exhibit 16 provides a summary by year of available sites with no more than three months of missing data. Exhibit 17 provides a summary of the number of sites available for the years used in analysis (2000, 2005, 2010, and 2015) for all sites that met the minimum data requirement, while Exhibit 18 provides a summary of the number of sites available from the 15 site subset that fulfilled the minimum data requirement.

Year	Number of Sites with No More than (3) Months of Missing Data per Year	Percent of All Sites
1995	46	43%
1996	8	7%
1997	26	24%
1998	64	59%
1999	70	65%
2000	86	80%
2001	92	85%
2002	94	87%
2003	92	85%
2004	96	89%
2005	90	83%
2006	94	87%
2007	102	94%
2008	104	96%
2009	104	96%
2010	104	96%
2011	102	94%
2012	102	94%
2013	106	98%
2014	104	96%
2015	102	94%
2016	74	69%

Exhibit 16: Summary of Available Sites by Year

Year	No. of Months Used to Calculate Annual K-Factor	No. of Sites
2000	9	16
	10	18
	11	18
	12	32
	Total	**84 sites**
2010	9	2
	10	6
	11	12
	12	64
	Total	**84 sites**
2005	10	8
	11	16
	12	62
	Total	**86 sites**
2015	10	10
	11	10
	12	66
	Total	**86 sites**

Exhibit 17: All Sites Used for Annual K-Factor Analysis

Year	No. of Months Used to Calculate Annual K-Factor	No. of Sites
2000	10	4
	11	4
	12	2
	Total	**10 sites**
2010	9	1
	10	1
	11	1
	12	7
	Total	**10 sites**
2005	10	1
	11	1
	12	9
	Total	**11 sites**
2015	10	1
	12	10
	Total	**11 sites**

Exhibit 18: Subset of Sites Used for Annual K-factor Analysis

3.2.4. Pairwise Comparison of Annual K-Factors at Individual Sites

A smaller dataset was used to test whether the annual K-factor changed over time. 104 sites were available in the entire dataset. From these, sites were selected that fulfilled the minimum data requirement. The number of sites used in the comparison of annual K-factors for the years included in the analysis are summarized in Exhibits 17 and 18. A summary of the comparison results is provided in Exhibit 19.

Unpaired and paired two-tailed Student's t-tests were performed to determine if differences in the annual K-factors were statistically significant. A significance level of $p<0.05$ was used for the analyses. The results from the comparison of annual K-factors indicate the following:

- 2000/2010 Comparison
    - For the 84 sites included in the overall analysis, the average annual K-factor increased marginally by 0.0002, from 0.1012 to 0.1014. This change was not statistically significant (unpaired: $t(83)=0.08$, $p=0.92$; paired: $t(83)=0.17$, $p=0.86$). This result is to be expected since the annual K-factor in the overall analysis is generated with data from many sites that experience random variation in the K-factor over time. The annual K-factor decreased for 37 sites and increased for 47 sites. The average annual 24-hour volume-to-capacity ratio increased from 3.2838 to 3.2891. This increase was not statistically significant (unpaired: $t(83)=0.01$, $p=0.99$; paired: $t(83)=0.8$, $p=0.94$). The annual 24-hour volume-to-capacity ratio increased at 42 of the 84 sites.

    - For the subset of ten sites, the average annual K-factor decreased by 0.0094, from 0.1072 to 0.0977. This change was detected as statistically significant only when using the paired version of the Student's t-test (unpaired: $t(9)=1.56$, $p=0.14$; paired: $t(9)=6.09$, $p<0.001$). The annual K-factor decreased for all ten sites. The average annual 24-hour volume-to-capacity ratio increased from 3.6360 to 4.0150. This increase was statistically significant (unpaired: $t(9)=0.34$, $p=0.74$; paired: $t(9)=3.00$; $p<0.05$). The annual 24-hour volume-to-capacity ratio increased at eight of the ten sites.

- 2005/2015 Comparison
    - For the 86 sites included in the analysis, the average annual K-factor decreased by 0.0004, from 0.0998 to 0.0994. This change was not statistically significant (unpaired: $t(85)=0.15$, $p=0.88$; paired: $t(85)=0.38$, $p=0.70$). This result is to be expected since the annual K-factor in the overall analysis is generated with data from many sites that experience random variation in the K-factor over time. The annual K-factor decreased for 41 sites and increased for 45 sites. The annual average 24-hour volume-to-capacity ratio increased from 3.6808 to 3.9224. This increase was detected as statistically significant only when using the paired version of the Student's t-test (unpaired: $t(85)=0.48$, $p=0.63$; paired: $t(85)=2.93$;

$p<0.01$). The annual 24-hour volume-to-capacity ratio increased at 53 of the 86 sites.

- For the subset of eleven sites, the annual K-factor decreased by 0.0032, from 0.1008 to 0.0976. This change was not statistically significant (unpaired: $t(10)=0.47$, $p=0.64$; paired: $t(10)=1.39$, $p=0.19$). The annual K-factor decreased for seven sites and increased for four sites. The average annual 24-hour volume-to-capacity ratio increased from 4.0721 to 4.5697. This increase was statistically significant (unpaired: $t(10)=0.43$, $p=0.67$; paired: $t(10)=2.43$; $p<0.05$). The annual 24-hour volume-to-capacity ratio increased at ten of the eleven sites.

Variation in the annual K-factors across sites when the year was held constant and across periods when the site was held constant was tested. A significance level of $p<0.05$ was used for the testing. ANOVA testing showed that the period (before year or after year) and the site (1 to n) were significant ($p<0.001$) in terms of explaining the annual K-factors for the subset of sites for only the 2000/2010 comparison. The site was significant ($p<0.001$) for the subset of sites for the 2005/2015 comparison and for all sites for both comparisons. For all sites and for the subset of sites, the sample variance of the site-by-site annual K-factor difference from the before to the after period was smaller than the sample variance of the sites within the before year or within the after year.

No. of Sites	Period	Year	Average Annual K-Factor	Std Dev	Upper 95% CI	Lower 95% CI	Maximum	Minimum	% of Sites with Decrease in Annual K-Factor	Average Difference in Annual K-Factor from Before to After	Difference Significant?
84	Before	2000	0.1012	0.0167	0.1048	0.0976	0.1776	0.0704	44%	0.0002	No (unpaired two-tailed t-test: t(83)=0.08, p=0.92); No (paired two-tailed t-test: t(83)=0.17, p=0.86)
	After	2010	0.1014	0.0169	0.1051	0.0977	0.1788	0.0695			
86	Before	2005	0.0998	0.0174	0.1036	0.0961	0.1722	0.0711	48%	-0.0004	No (unpaired two-tailed t-test: t(85)=0.15, p=0.88); No (paired two-tailed t-test: t(85)=0.38, p=0.70)
	After	2015	0.0994	0.0161	0.1029	0.0960	0.1444	0.0718			
10	Before	2000	0.1072	0.0138	0.1171	0.0972	0.1245	0.0865	100%	-0.0094	No (unpaired two-tailed t-test: t(9)=1.56, p=0.14); Yes (paired two-tailed t-test: t(9)=6.09, p<0.001)
	After	2010	0.0977	0.0132	0.1071	0.0883	0.1157	0.0785			
11	Before	2005	0.1008	0.0167	0.1120	0.0896	0.1257	0.0769	64%	-0.0032	No (unpaired two-tailed t-test: t(10)=0.47, p=0.64); No (paired two-t-tailed test: t(10)=1.39, p=0.19)
	After	2015	0.0976	0.0156	0.1080	0.0871	0.1186	0.0764			

Std Dev = Standard Deviation of the Average Annual K-Factor; Upper 95% CI = Upper Bound of the 95% Confidence Interval for the Average Annual K-Factor; Lower 95% CI = Lower Bound of the 95% Confidence Interval for the Average Annual K-Factor; Maximum = Maximum Annual K-Factor; Minimum = Minimum Annual K-Factor

Exhibit 19: Summary of Annual K-Factor Comparison Results

3.3. Development of Exploratory Models to Forecast a K-Factor

As previously described, the results of the ANOVA tests indicate that it may be possible to develop a measure that incorporates socioeconomic data such as employment and land use to use as a predictor for change in the K-factors.

Measures at different scales can be used depending on the purpose in the study. For example, county level data may be useful for developing screening criteria, because a richer set of data is available for counties. However, a smaller geography may be more useful for studying the area around chosen count stations of interest.

Desirable characteristics of land use density measures for K-factor analysis include:

1. Be based on land use measures that are available at appropriate geographies across the state of North Carolina

2. Be available for and across appropriate time periods for analysis so they can show change in land use intensity

Some literature suggests that individual households do not change their travel based on changes in the built environment (Brownstone, 2008). This suggests that changes to the built environment in already developed areas may not change the behavior of individual households, but it is not clear how households in undeveloped areas are affected by development. The measures of change that are of interest for their effect on K-factors need to address not how neighborhoods compare to each other, but how to measure change that leads to differences in choice of time to travel.

Several possible methods for developing a suitable land use density measure were explored, including the use of USDA Urban Influence Codes (UIC) and the use of Rural-Urban Commuting Area Codes (RUIC). An evaluation of these methods are provided in Appendix C.

While the use of UIC or RUIC codes was not deemed feasible for use in this study, a possible candidate measure for land use density is based on a measure used in the Triangle Regional Model developed by ITRE as a tool for analyzing current and future travel in the Research Triangle region of North Carolina. This measure relates population and employment in the vicinity of a continuous count station to population and employment in a larger region surrounding a continuous count station. The vicinity is defined as within a two mile radius of a continuous count station. The region surrounding the continuous count stations is defined as within an eleven mile radius which equals the weighted average trip distance for both peak and off-peak daily home-based work trips derived from the 2006 Triangle Household Travel survey (ITRE, 2011).

The equation for calculating land use density in the vicinity of a continuous count station is:

$$Land\ use\ density_i = \frac{Population_i + \frac{\sum_j Total\ Population_j}{\sum_j Total\ Employment_j} \times Total\ Employment_i}{Area_i}$$

Where,

Land use $density_i$ = land use density for area within two miles of a continuous count station

$Population_i$ = US Census block-level population within two miles of a continuous count station

Total $Employment_i$ = total number of primary jobs for all workers in all sectors for US Census block groups within two miles of a continuous count station

$Area_i$ = combined US Census block area in square miles within two miles of a continuous count station

Total $Population_j$ = US Census block-level population within eleven miles of a continuous count station

Total $Employment_j$ = total number of primary jobs for all workers in all sectors for US Census block groups within eleven miles of a continuous count station

Population data were acquired from the 2000 and 2010 United States Census and employment data were obtained from the United States Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program through their On the Map web-based tool. Data were obtained for US Census blocks within two and within eleven miles of each continuous count station included in the analysis. Population is defined as all people living in a geographic area for the data year. Employment is defined as the total number of primary jobs for all workers in all sectors in a geographic area for the data year.

The subset of ten sites with annual K-factors for the years 2000 and 2010 were used to develop linear regression models to predict the K-factor as a function of several factors. Two exploratory models were generated: 1) a longitudinal model with an existing K-factor included as a predictor and 2) a longitudinal model that does not include an existing K-factor as a predictor. The explanatory variables that were considered in the model development are summarized in Exhibit 20.

Variable	Definition
Annual 24 Hour V/C	Adjusted average annual 24-hour volume-to-capacity ratio as the ratio of a roadway segment's 24-hour volume divided by its hourly capacity for the year 2000
Percent Change in Land Use Density	Percent change in the measure for land use density within two miles of a continuous count station that incorporates population and employment data between the before and after year
Rural Two-Lane Road	Denotes whether the facility's functional class is a rural two-lane road (1) or not (0)
Rural Multilane Road	Denotes whether the facility's functional class is a rural multilane road (1) or not (0)
Access Controlled	Denotes whether the facility is access controlled (freeway or interstate) (1) or not (0)
Old K-Factor	Adjusted average annual proportion of 24-hour volume that occurs during peak hour for the year 2000
New K-Factor	Adjusted average annual proportion of 24-hour volume that occurs during peak hour for the year 2010; also called a prediction because the variable is being predicted as the dependent variable by the independent variables in the models

Exhibit 20: Variables Included in Exploratory Model Development

3.3.1. *Longitudinal Model with Existing K-Factor*

Using the data from the subset of ten sites with annual K-factors for the years 2000 and 2010, a linear regression model was developed to predict the K-factor as a function of several variables described in Exhibit 20. The existing, old K-factor for 2000 was included in the exploratory model development to predict the future, new K-factor for 2010. Model building began by entering all variables into the linear regression model. Then variables that were not statistically significant were removed one at a time until only variables that were statistically significant at $p<0.05$ remained.

The final model (Model 1) is provided in the following equation:

$$New\ K\text{-}Factor = \ 0.89014889(Old\ K\text{-}Factor) + 0.0023386$$

Where,

New K-Factor = new K-factor in 2010

Old K-Factor = old K-factor in 2000

All terms represent variables that were statistically significant; $p<0.0001$ for Old K-Factor. With the inclusion of a previous, old K-factor, 86% of the variation was explained (adjusted R-square value was 0.8596).

3.3.2. *Longitudinal Model without Existing K-Factor*

Newly constructed facilities or facilities with limited historical data do not allow for a future year K-factor to be estimated from a previous K-factor. A second regression model was developed where the previous, old K-factor was excluded.

In the same manner as Model 1, the data from the subset of ten sites with annual K-factors for the years 2000 and 2010 was used and a linear regression model was developed to predict the

K-factor as a function of several variables described in Exhibit 20. Model building began by entering all variables into the linear regression model. Then variables that were not statistically significant were removed one at a time until only variables that were statistically significant at $p<0.05$ remained.

The final model (Model 2) is provided in the following equation:

$$New\ K\text{-}Factor = -0.0119969(Rural\ Two\text{-}Lane) - 0.0276329(Access\ Controlled) + 0.11237084$$

Where,

New K-Factor = new K-factor in 2010

Rural Two-Lane = facility's functional class is a rural two-lane road (1) or not (0)

Access Controlled = facility is access controlled (freeway or interstate) (1) or not (0)

All terms represent variables that were statistically significant; $p<0.05$ for Rural Two-Lane and $p<0.001$ for Access Controlled. Without a previous, old K-factor, 82% of the variation was explained (adjusted R-square value was 0.8172).

Percent Change in Land Use Density was found to be significant at $p<0.05$ only when all other variables were removed from the model. A model including only Percent Change in Land Use Density ($p<0.05$) captured 46% of the variation in the K-factor (adjusted R-square value was 0.4621) and indicated an increase in the K-factor associated with an increase in land use density. This suggests that the land use density measure used in the exploratory modeling efforts does not adequately capture the effect of development in relation to peak spreading for the subset of sites included.

As previously discussed, the ANOVA for all sites and the subset of sites indicated that the site variable was the strongest predictor of the K-factor. Model 1 indicates that the initial K-factor, which appears to be acting as a site variable, explains the majority of the future K-factor value variation. In the absence of the initial K-factor for use in modeling, ANOVA results showed that population and employment could explain variation to a lesser degree. However, Model 2 indicates that facility characteristics can explain variation in the K-factor to a greater degree than change in land use density as calculated from population and employment data.

4. Discussion and Conclusions

The purpose of this study was to determine how K-factor data changes in order to estimate the impact of peak spreading across different area types. Models were developed for forecasting peak spreading where peak spreading was measured as change in the K-factor. Peak spreading occurs when the K-factor, defined as the proportion of the 24-hour traffic volume that occurs during the peak hour, decreases in relation to an increase in traffic congestion. Active peak spreading can result from change in the departure time of motorists to a non-peak hour in reaction to congested peak hour traffic conditions. Reliable estimates of K-factor change are important for the accurate estimation of travel demand and roadway performance, including travel speed and vehicle emissions.

Data were collected from 54 continuous count stations located on North Carolina roadways representing 34 of the 100 counties in the state for the period 1995-2016. All stations gave two-directional counts, resulting in 108 station-direction combinations, or sites, for analysis purposes.

Two before-and-after periods were included in the analysis: 2000/2010 and 2005/2015. For all sites with available data for the 2000/2010 period, the average annual K-factor adjusted for months for which data were not available increased by 0.0002, from 0.1012 to 0.1014, during the period. The average annual 24-hour volume-to-capacity ratio, which was used as a surrogate for travel congestion, increased from 3.2838 to 3.2891. Both changes were not statistically significant. For all sites with available data for the 2005/2015 period, the average annual K-factor adjusted for months for which data were not available decreased by 0.0004, from 0.0998 to 0.0994, during the period. The 24-hour volume-to-capacity ratio increased from 3.6808 to 3.9224. The change in average annual K-factor was not statistically significant. The change in average annual 24-hour volume-to-capacity ratio was statistically significant ($p<0.001$). The K-factor results for all sites with available data are to be expected since the annual K-factors are generated with data from many sites that experience random variation in the K-factor over time.

Since many of the 108 sites appeared to experience non-commute travel patterns that would generate more random variation in K-factors rather than predictable variation that could be captured by the socioeconomic factors and roadway attributes included in statistical testing, a subset of sites was used in exploratory peak spreading modeling efforts. Two models to forecast K-factors were developed in this study. Model 1, for use with an established roadway with an existing K-factor, explained 86% of the variation in K-factors and is based on the previous K-factor only. Model 2, for use with a new roadway without an existing K-factor, explained 82% of the variation in K-factors and is based on whether the facility is a rural two-lane road or not and whether the facility is access controlled (freeway or interstate) or not. These factors are favorable for use in modeling since they are typically obtainable from publically available datasets for varying time periods.

While the ANOVA results indicate that site characteristics, such as facility functional class, and socioeconomic characteristics, including population and employment, affect the K-factor, exploratory modeling did not indicate that land use density was a statistically significant factor in K-factor change when including other variables in the model. In addition, the K-factor varies more across sites with the year held constant than across time periods with the site held constant.

The research team recommends a screening approach for incorporating K-factor data in the forecasting process that starts at the county level:

1. Examine population and employment change using US Census and LEHD data (if no or little change, expect little change in K-factor)

2. Examine road density change (if population and employment increase but road density does not, this could indicate areas where congestion will increase)

Where more detailed data are available at a smaller geography (i.e., the block group level), additional evaluation of land use and development in the surrounding area can be pursued as an alternative to assuming the K-factor will remain constant. However, given that variability is generally greater across sites for a single time period than across time periods for a single site, site-specific studies may be more suitable where data and local knowledge are available.

The land use density measure that was developed in this study was not found to be adequate when tested through exploratory modeling. The research team believes that a more accurate measure can be developed that takes into account proximity to employment centers. Further discussion on such a measure is provided in the following section.

Unlike the research that this study was modeled on (Miller, 2012), which examined locations in Northern Virginia that experienced substantial congestion in both the before and after periods, the North Carolina sites with available data typically experienced mild to moderate congestion in both the before and after periods included in the analysis. This poses a potential study limitation, since a significant change (increase) in congestion is needed to generate measurable peak spreading. The research team attempted to control for the variability in congestion levels across the 108 sites by analyzing a subset of locations were K-factor variation appeared predictable rather than random in relation to the socioeconomic factors of interest.

Additionally, the North Carolina sites with available data were more geographically dispersed than those included in Northern Virginia study (Miller, 2012). North Carolina count locations included those in rural and suburban areas, rather than almost entirely dense urban areas.

5. Future Research

The research team believes that modeling efforts can be improved in the future by incorporating an accessibility measure that takes into account proximity to employment centers. This measure may be useful for analyzing and understanding localized peak spreading since time-of-day departure decisions made relative to work arrival times are dependent on commuting distance and expected travel times. The land use density measure employed in this study focuses on the areas within two miles of the count station locations, and it may not accurately represent the entirety of the effect of employment on travel behavior that results in K-factor change.

While a detailed discussion of possible accessibility measures is outside of the scope of the present research, existing research shows that the development of such a measure is possible. For instance, the United States Department of Housing and Urban Development has developed a jobs proximity index that uses LEHD employment data (HUD, 2017). The index quantifies the accessibility of a given residential neighborhood as a function of its distance to all job locations within a Core Based Statistical Area (CBSA), with larger employment centers weighted more heavily. The index uses a gravity model, where the accessibility of a given residential block group is a summary description of the distance to all job locations, with the distance from any single job location positively weighted by the size of employment (job opportunities) at that location and inversely weighted by the labor supply (competition) to that location. The currently available jobs proximity index values are available at the block group level for the year 2014 only.

6. References

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7. Appendix A: Functional Classification Groupings

Description	Group
Rural - Interstate	1
Rural - Principal Arterial - Other Freeways and Expressways	1
Suburban - Interstate	1
Urban - Interstate	1
Urban - Principal Arterial - Other Freeways and Expressways	1
Urban - Minor Arterial	2
Urban - Principal Arterial - Other	2
Urban - Local	3
Urban - Major Collector	3
Suburban - Minor Arterial	4
Suburban - Principal Arterial - Other	4
Suburban - Local	5
Suburban - Major Collector	5
Rural - Minor Arterial	6
Rural - Principal Arterial - Other	6
Rural - Local	7
Rural - Major Collector	7
Rural - Minor Collector	7

8. Appendix B: LOS E Modeling Parameters

FACILITY TYPE	REGION	TERRAIN	AREA TYPE	TRUCKS	LOS E CAPACITY
Freeway	ALL	Level	Urban	Average	2045
Freeway	ALL	Level	Urban	High	2000
Freeway	ALL	Level	Suburban	Average	2055
Freeway	ALL	Level	Suburban	High	2005
Freeway	ALL	Level	Rural	Average	2060
Freeway	ALL	Level	Rural	High	2010
Freeway	PIED/MTNS	Rolling	Urban	Average	1950
Freeway	PIED/MTNS	Rolling	Urban	High	1825
Freeway	PIED/MTNS	Rolling	Suburban	Average	1960
Freeway	PIED/MTNS	Rolling	Suburban	High	1830
Freeway	PIED/MTNS	Rolling	Rural	Average	1965
Freeway	PIED/MTNS	Rolling	Rural	High	1835
Freeway	MTNS	Mountainous	Urban	Average	1785
Freeway	MTNS	Mountainous	Urban	High	1555
Freeway	MTNS	Mountainous	Suburban	Average	1795
Freeway	MTNS	Mountainous	Suburban	High	1560
Freeway	MTNS	Mountainous	Rural	Average	1800
Freeway	MTNS	Mountainous	Rural	High	1565
Expressway	ALL	Level	Urban	Average	1685
Expressway	ALL	Level	Urban	High	1645
Expressway	ALL	Level	Suburban	Average	1770
Expressway	ALL	Level	Suburban	High	1730
Expressway	ALL	Level	Rural	Average	1860
Expressway	ALL	Level	Rural	High	1815
Expressway	PIED/MTNS	Rolling	Urban	Average	1605
Expressway	PIED/MTNS	Rolling	Urban	High	1500
Expressway	PIED/MTNS	Rolling	Suburban	Average	1685
Expressway	PIED/MTNS	Rolling	Suburban	High	1575
Expressway	PIED/MTNS	Rolling	Rural	Average	1775
Expressway	PIED/MTNS	Rolling	Rural	High	1655
Expressway	MTNS	Mountainous	Urban	Average	1470
Expressway	MTNS	Mountainous	Urban	High	1280
Expressway	MTNS	Mountainous	Suburban	Average	1545
Expressway	MTNS	Mountainous	Suburban	High	1345
Expressway	MTNS	Mountainous	Rural	Average	1620
Expressway	MTNS	Mountainous	Rural	High	1410

FACILITY TYPE	REGION	DIVIDED	AREA TYPE	SPEED LIMIT	LOS E CAPACITY
Urban Arterial I	ALL	Yes	Urban	55	1140
Urban Arterial I	ALL	Yes	Suburban	55	1175
Urban Arterial I	ALL	Yes	Rural	55	1350
Urban Arterial I	ALL	Yes	Rural	45	1305
Urban Arterial II	ALL	Yes	Urban	45	1075
Urban Arterial II	ALL	Yes	Suburban	45	1080
Urban Arterial II	ALL	Yes	Suburban	35	1030
Urban Arterial III	ALL	Yes	Suburban	35	1005
Urban Arterial IV	ALL	Yes	Urban	35	770
Urban Arterial IV	ALL	Yes	Urban	25	720
Urban Arterial I	ALL	No	Urban	55	965
Urban Arterial I	ALL	No	Suburban	55	1025
Urban Arterial I	ALL	No	Rural	55	1140
Urban Arterial I	ALL	No	Rural	45	1105
Urban Arterial II	ALL	No	Urban	45	860
Urban Arterial II	ALL	No	Suburban	45	895
Urban Arterial II	ALL	No	Suburban	35	875
Urban Arterial III	ALL	No	Suburban	35	795
Urban Arterial IV	ALL	No	Urban	35	635
Urban Arterial IV	ALL	No	Urban	25	590
FACILITY TYPE	**REGION**	**TERRAIN**	**AREA TYPE**	**SPEED LIMIT**	**LOS E CAPACITY**
2-Lane Highway	ALL	Level	-	-	1235
2-Lane Highway	ALL	Rolling	-	-	1175

9. Appendix C: Review of Land Use Density Measures

One of the focuses of this project was to determine how change in land use can influence K-factors. This requires choosing an appropriate land use measure to which to compare K-factors over time. Measures can be used to compare areas to each other at the same point in time, or for one area across time periods. For this research project, it was desired to measure change across time. Some measures from the literature that were explored but not chosen are reviewed in the following and then a discussion of the measures is provided.

A set of categorical variables called Urban Influence Codes (UIC) were developed by the US Department of Agriculture (USDA) (USDA ERS, 2017). These capture both the size of a county and whether it is adjacent to a micropolitan or metropolitan area. While the codes are based only on population, they illustrate the idea of classifying areas by whether they are influenced by a nearby larger area. The measures are intended to capture relationships among economies and thus provide a finer level of rural-urban information. Twelve codes are provided, including three for non-metropolitan micropolitan counties, and seven non-metropolitan, non-core counties. Codes were developed for 1993, 2003, and 2013. Counties are divided into “large” with greater than 1 million population and “small” with less than 1 million population. The UIC can be used to analyze trends in non-metro areas related to population density and urban influence. A summary of the 2013 UIC codes is provided in Exhibit 21.

Code	Description
1	In large metro area of 1+ million residents
2	In small metro area of less than 1 million residents
3	Micropolitan area adjacent to large metro area
4	Noncore adjacent to large metro area
5	Micropolitan area adjacent to small metro area
6	Noncore adjacent to small metro area and contains a town of at least 2,500 residents
7	Noncore adjacent to small metro area and not contain a town of at least 2,500 residents
8	Micropolitan area not adjacent to a metro area
9	Noncore adjacent to micro area and contains a town of at least 2,500 residents
10	Noncore adjacent to micro area and does not contain a town of at least 2,500 residents
11	Noncore not adjacent to metro or micro area and contains a town of at least 2,500 residents
12	Noncore not adjacent to metro or micro area and does not contain a town of at least 2,500 residents

Exhibit 21: 2013 Urban Influence Codes (UIC)

A recent effort to identify the Impacts of Land Use on Travel Behavior in Small Communities and Rural Areas for NCHRP 25-36 (Morton, 2014) explored measures that could be used to capture levels of land use activity related to travel behavior and apply them to appropriate units of analysis. The Commuting zone was chosen as the unit of analysis to include the “typical pattern of commuting trips in a spatially-defined labor market.” The study used the following variables: population density calculated over developed or developable land, road density calculated as road miles per square mile of developed or developable land, land use mix that measures potential for interaction between residents and establishments, and variation in population density computed as the coefficient of variation for population density across census block groups in commuting zones.

Rural-Urban Commuting Area codes developed by the Economic Research Service use census tracts rather than counties (USDA ERS, 2017). The classification contains ten primary and twenty one secondary codes. The ten primary codes describe the largest commuting share. The twenty one secondary codes describe secondary flows. This allows for flexibility to describe areas for which the primary flow is local, but the secondary flow is to a metropolitan area. These codes were updated for the 2010 US Census using the 2006-2010 ACS commuting tabulations prepared for the Census Transportation Planning Products (CTPP). The primary RUCA codes are summarized in Exhibit 22 and the secondary RUCA codes are summarized in Exhibit 23.

Code	Description
1	Metropolitan area core: primary flow within an urbanized area (UA)
2	Metropolitan area high commuting: primary flow 30% or more to a UA
3	Metropolitan area low commuting: primary flow 10% to 30% to a UA
4	Micropolitan area core: primary flow within an urban cluster of 10,000 to 49,999 (large UC)
5	Micropolitan high commuting: primary flow 30% or more to a large UC
6	Micropolitan low commuting: primary flow 10% to 30% to a large UC
7	Small town core: primary flow within an urban cluster of 2,500 to 9,999 (small UC)
8	Small town high commuting: primary flow 30% or more to a small UC
9	Small town low commuting: primary flow 10% to 30% to a small UC
10	Rural areas: primary flow to a tract outside a UA or UC
99	Not coded: Census tract has zero population and no rural-urban identifier information

Exhibit 22: Primary Rural-Urban Commuting Area (RUCA) Codes

Code	Description
1.0	Metropolitan area core: primary flow with an urbanized area
1.1	Secondary flow 30% to 50% to a larger UA
2.0	Metropolitan area high commuting: primary flow 30% or more to a UA
2.1	Secondary flow 30% to 50% to a larger UA
3	Metropolitan area low commuting: primary flow 10% to 30% to a UA
4	Micropolitan area core: primary flow within an urban within an urban cluster
4.1	Secondary flow 30% to 50% to a UA
5.0	Micropolitan high commuting: primary flow 30% or more to a large UC
5.1	Secondary flows 30% to 50% to a UA
6.0	Micropolitan low commuting: primary flow 10% to 30% to a large UC
7.0	Small town core: primary flow within an urban cluster of 2,500 to 9,999 small UC
7.1	Secondary flow 30% to 50% to a UA
7.2	Secondary flow 30% to 50% to a large UC
8.0	Small town high commuting: primary flow 30% or more to a small UC
8.1	Secondary flow 30% to 50% to a UA
8.2	Secondary flow 30% to 50% to a large UC
9.0	Small town low commuting: primary flow 10% to 30% to a small UC
10.0	Rural areas: primary flow to a tract outside a UA or UC
10.1	Secondary flow 30% to 50% to a UA
10.2	Secondary flow 30% to 50% to a large UC
10.3	Secondary flow 30% to 50% to a small UC
99	Not coded

Exhibit 23: Secondary Urban-Rural Commuting Area (URCA) Codes

The Urban Influence Codes (UIC) were expected to be helpful for comparisons across years, since they were developed for counties and county boundaries are stable between census years. The UIC codes were developed for 1993, 2003, and 2013 (based on 1990, 2000, and 2010 census data). The example of Johnston County in North Carolina is useful for illustrating these codes. In 1993 and 2000, the county's code was 2 and in 2013 the county's code was 1. The map shown in Exhibit 24 indicates that this code may not help reveal the relationship of Johnston County to the Triangle region since the code shows the county as part of the same region.

The Rural Urban Commuting Area Codes (RUCA) were developed for census tracts and were expected to be more helpful for providing finer geographic detail, but less useful for comparisons across years since census tract boundaries are revised between census years, particularly for rapidly growing areas. The RUCA codes were developed for 1990, 2000, and 2010. Similarly to the UIC codes example, the RUCA codes are not useful for showing the relationship between the continuous count station locations and the broader commuting area since there is little variability in the RUCAs in the study areas (Exhibit 25).

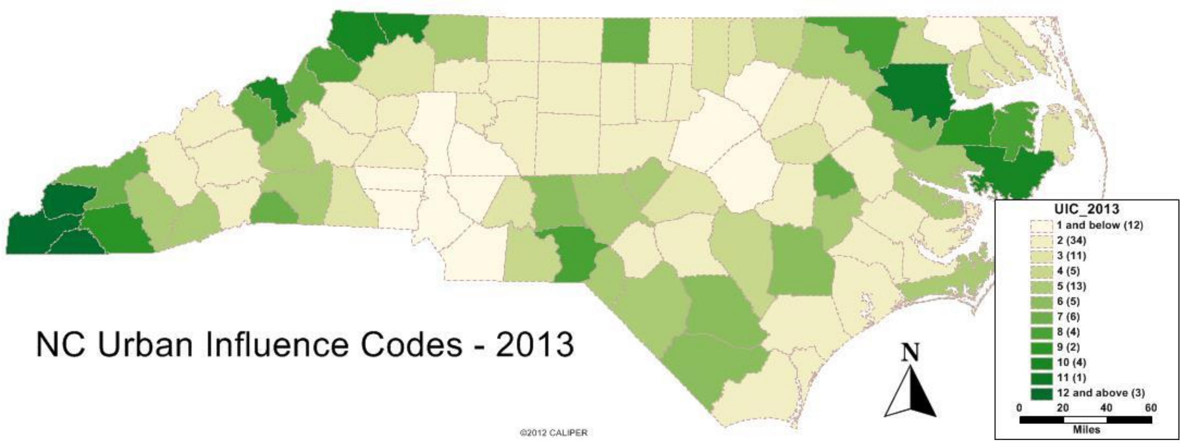

Exhibit 24: North Carolina Urban Influence Codes (UIC) for 2013

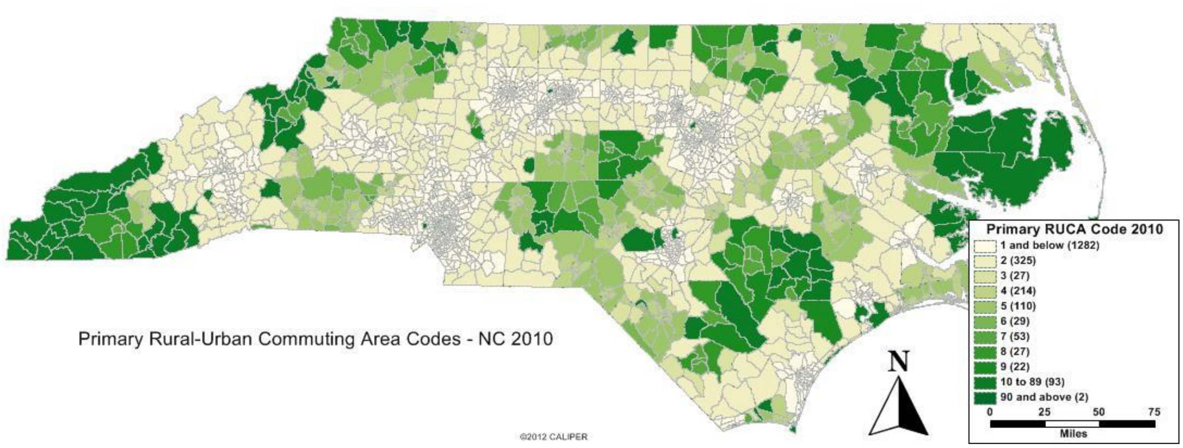

Exhibit 25: North Carolina Primary Rural-Urban Commuting Area Codes (RUCA) for 2010