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Title: Exploring the Relationship between Bicycle Level of Traffic Stress and Reported Bicycle Collisions

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Transportation agencies need efficient methods to determine how to improve bicycle facilities in order to improve connectivity and safety. Many studies have used standalone methods such as level of traffic stress (LTS) and bicycle level of service (BLOS) to better understand bicycle mode share and network connectivity for a region while other studies rely on collision severity models to explain what variables attribute to bicycle related collisions. This research looks at comparing bicycle LTS networks with bicycle collisions for four cities in New Hampshire. The LTS measurements of the road and the collision point are compared visually and collision severity models are developed incorporating the LTS measurements. Results of the visual analysis show some clustering patterns and geospatial correlation between higher LTS roads and 'Injury" type bicycle collisions. Using an ordered probit model, LTS 2 is found to be the only significant LTS with bicycle collisions. These results indicate that the assumption of LTS 2 being a safe route may be premature and bicycle ridership data plays a bigger role in bicycle safety.

Exploring the Relationship between Bicycle Level of Traffic Stress and Reported Bicycle Collisions

by
Rachel Vogt

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Rachel Vogt, Author

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CHAPTER 1: INTRODUCTION

RESEARCH BACKGROUND

Secretary of Transportation Anthony Foxx has declared bicyclist safety a top priority for the USDOT and launched "Safer People Safer Streets" initiative and it is being called "the most innovative, forward-leaning, biking-walking safety initiative ever" (Foxx 2014). The initiative will include increased funding for bicycle infrastructure and research focusing on aspects such as behavioral safety and education, vehicle safety, and infrastructure safety (Foxx 2014).

Transportation agencies across the nation are seeing an increase in bicycle ridership and need efficient tools to improve bicycle safety while staying within limited budgets. Bicycle safety models are based on several factors, one of which is collision data. Many studies are beginning to look toward stress level analysis methods to determine at risk bicycle facilities. One such method includes the level of traffic stress (LTS) criteria proposed by Mekuria et al. (2012), which is primarily used to predict how various facility improvements will impact connectivity. Although this method is starting to become more commonly used among transportation agencies, it has not been used exclusively for safety purposes or in combination with collision data.

NATIONAL TRENDS IN BICYCLE COLLISIONS

Nationally, bicycle collisions have increasingly become a bigger part of the total fatalities recorded each year. In 2004, the percentage of total bicycle fatalities was 1.7% and in 2013 it was 2.3%; however the number of bicycle fatalities remained approximately the same at 727 in 2004 and 743 in 2013 (USDOT 2015). This relationship indicates that while total fatalities are decreasing across the nation, bicycle fatalities remain the same meaning that safety improvements are not being applied for cyclist facilities. The 2013 collision data also revealed that 68% of all cyclists who died in a collision, died in an urban area, that from 2004 to 2013, the age of the cyclist involved in the collision increased from 39 to 44 years old, that males are 7 times more grater to be involved in a fatal collision in 2013, and alcohol involvement was reported for more than 34% of fatalities (USDOT 2015). The USDOT reports that bicycle fatalities "have steadily increased since 2009" as shown in Table 1(USDOT 2015).

TABLE 1: NATIONAL BICYCLE FATALITIES IN TRAFFIC COLLISIONS, 2008-2012 (USDOT 2015)

Year	Total Fatalities	Bicycle Fatalities	Percentage
2004	42,836	727	1.7%
2005	43,510	786	1.8%
2006	42,708	772	1.8%
2007	41,259	701	1.7%
2008	37,423	718	1.9%
2009	33,883	628	1.9%
2010	32,999	623	1.9%
2011	32,479	682	2.1%
2012	33,782	734	2.2%
2013	32,719	743	2.3%
Total	**330,762**	**7114**	**2.2%**

In the Pacific Northwest (Alaska, Idaho, Oregon, and Washington), 18 bicyclist fatalities occurred in 2013. Bicycle fatalities were the highest in California (141), Florida (133) and Texas (48) (USDOT 2015). The U.S. rate of bicycle fatalities is double that of Germany and triple that of the Netherlands, both in terms of number of trips and in distance travelled (Pucher & Dijkstra 2003).

OREGON BICYCLE COLLISIONS AND SAFETY TRENDS

The State of Oregon is a leader in bicycle and pedestrian activity. Pedestrian and bicyclist fatalities comprise more than 15% (17.7% in 2010) of all fatalities and are of primary concern for many communities in Oregon. The State of Oregon has identified pedestrian and bicycle collisions as a primary focus area for investing infrastructure funding.

Pedestrian and bicycle collisions are sporadic, it is difficult to predict where they will occur next, and it is even difficult to identify future high collision locations and corridors. The occurrence of one or two collisions at a location in a given period may or may not be a good indicator of future collisions. Because of the sporadic nature of bicycle and pedestrian collisions, ODOT needs to improve methods to identify and prioritize locations with increased risk, rather than simply a collision history, so they can be proactively treated.

Although this study considers bicycle collision data over a 10-year span for four cities in New Hampshire, the method used can be applied to other regions and states to improve safety. The collision dataset was produced by the NH Department of Transportation Bike Ped Team and provided by the Bike-Walk Alliance of NH (BWANH) for all Bicycle and Pedestrian collisions between 2002 and 2013. The New Hampshire Department of Transportation (NHDOT) Level of Traffic Stress (LTS) data collection was a pilot project done for a proof of concept and it has not been endorsed by NHDOT or the NH Bicycle & Pedestrian Advisory Committee (NH BPTAC).

OBJECTIVE AND SCOPE

The purpose of this study is to explore the geospatial and statistical relationship between LTS measurements and bicycle collisions to show how LTS models can assist collision prediction models. There are three goals for this study; (1) determine if stress levels provide an insight to the bicycle collision patterns, (2) determine the correlation between high stress levels and high collision severity, and (3) determine the correlation between high stress levels and high collision frequencies. By using a stress level analysis to aid in predicting where collisions may occur, communities can allocate funds more effectively for infrastructure safety improvements.

This research strives to show the impact of LTS models on bicycle safety models and demonstrate that more complicated and data intensive models are not required to effectively improve bicycle safety for a community. This research highlights a use of LTS models that are currently unfamiliar to bicycle safety by starting to predict bicycle collisions resulting in a simpler method for agencies to improve bicycle safety.

MOTIVATION/PROBLEM DEFINITION

As stated above, bicycle ridership is steadily increasing and therefor fatalities and injuries related to bicyclists are increasing. Using only collision data limits a bicycle safety models due to bicycle collisions being sporadic in nature and could be significantly underreported. Additionally, models that rely solely on bicycle collisions require several years of data resulting in several years of social and economic impacts for a community.

This research uses Level of Traffic Stress measurements as an additional layer to identify where bicycle collisions are occurring and at what severity level. If LTS measurements can help predict where bicycle collisions will occur or where the most dangerous collisions will occur, then many injuries and lives can be saved.

Contribution and Thesis Structure

This thesis provides a new method of analysis bicycle safety by using Level of Traffic Stress measurements. Previously, LTS has been used to determine connectivity of regions and promote ridership by improving connectivity. By adding bicycle collisions as an additional layer to LTS maps, agencies can easily visual where bicycles are most at risk. Additionally, a better understanding of the relationship between LTS and bicycle collisions is considered by using an ordered probit model.

This paper starts with a review of the literature focusing on bicycle collision studies, including severity models and predictive studies, as well as a review of the literature for Level of Stress Analysis. Chapter 3 describes the data sets used for this particular study as well as the methodology used to analyze the data. Chapter 4 summarizes the results of the study and Chapter 5 discusses the main conclusions that are drawn from those results.

CHAPTER 2: LITERATURE REVIEW

This literature review first looks at the impact bicycle collisions have on a community. It then covers the different statistical analysis tools that are used to determine what factors contribute to bicycle collisions and their severity. The review then goes on to discuss the different factors attributed to bicycle collisions and concludes with a discussion on stress measurement tools that are currently available.

CRITICAL FACTORS ASSOCIATED WITH BICYCLE COLLISIONS

From the studies discussed previously, several critical factors were found to be associated with bicycle collisions including roadway and intersection characteristics, traffic characteristics, land-use, demographic and behavioral patterns, and lighting and weather. Once identified, these factors will help determine what aspects might be missing in a LTS analysis.

Roadway and intersection factors include the roadway geometry, cross section, and operations of the intersection. The traffic characteristics include speed limit, peak hour traffic, and traffic volumes. The land-use discusses the impact different land-use types such as residential and commercial, have on bicycle collisions. The demographic and behavioral section includes the age of the bicyclist, their conditions while riding, drivers' condition when driving, type of vehicle involved in the collision, type of collision, the age of the driver, and the speed of the vehicle. Finally, the last subsection includes weather conditions and the lighting condition at the time of the collision.

Roadway Geometry

Geometry plays a huge role in collision of vehicles-bicycles. In published literature, researchers have analyzed factors such as number of traffic lanes adjacent to bicycle traffic, road curvature, and the shoulder characteristics or the presence of a bike lane in depth.

Greibe (2003) found that when there were 2 lanes there were more accidents. In addition, there were more accidents in the same direction on single lane with no centerline markings. This study also noted that many of the roadways geometry characters had strong correlation with each other. When considering pedestrian-vehicle collisions, Lee & Abdel-Aty (2005) found that 1 lane reduced the amount of pedestrian collisions when it is the pedestrian's fault by 4 times and 2 lanes reduced by nearly 0.75 times. It was also found that more collisions occurred on undivided roads with more number of lanes than divided roads with less number of lanes (Lee & Abdel-Aty 2005). Petritsch et al. (2006) considered a side path safety model design and found that the more lanes that are on the roadway, the more motorists focus on the opposing travel lanes and turning traffic as oppose to the activity on a side path. Additionally, on two lane roads, motorists look for cyclists on the side of the street and the roadway and cyclists using a side path may only concern themselves with traffic in the nearest travel lanes (Petritsch et al. 2006).

Pai (2011) found that horizontal and vertical curves contribute to bicycle accidents. Schepers & den Brinker (2011) considered potential visual barriers that different road geometry causes cyclists and found that cyclists collide with a bollard or road narrowing or rides off the road in a curve. This type of collision was found to occur more than when cyclists hit an obstacle because they were looking at something on the side of the road but not more than cyclists looking behind them. The biggest takeaway from the study was that focal operations play a more important role in collisions involving a curve. Dixon et al. (2012) found that 'no horizontal curves' should be a SPF that is included when calculating the unadjusted collision prediction model for the base conditions for a rural two-lane, two-way road segment. Eluru et al. (2008) found that collisions at curved/non-flat roadways tend to have more severe injury. Using a multinomial logit model, Kim et al. (2007) found that curved rounds significantly increase the chance that a fatal or incapacitating injury will occur during a vehicle-bicycle accident.

There are a number of different types of facility designs for bicycles and each has an impact on bicycle safety such as the presence of bicycle lanes, the grade of the roadways/bicycle track, and if there are any different pavement markings or colors (Oh et al. 2008; Vandenbulcke et al. 2014). Vandenbulcke et al. (2014) considered different cycle facilities and found that there is an increased risk of accident when associated with a specific type of intersection. This study found that right-of-way intersections equipped with cycle lanes tends to have higher accident risk for cyclists, due to vehicles not respecting the right-of-way (i.e. right-hook collisions). The researchers also found that cyclists riding on marked cycle lanes in roundabouts and signalized intersections with marked cycle lanes had higher accident risks for cyclists and attributed the higher risk to the cyclists being in drivers' blind spots (Vandenbulcke et al. 2014).

Schepers et al. (2011) found that more collisions where the bicycle has the right-of-way on a through movement occur at intersections with two-way bicycle tracks that are well marked and are reddish in color. However, this study found a cycle track where the approach is deflected 2-5 meters (6-10ft) from the intersection decreased the risk for the cyclist. Walker

(2007) considered the effect of lanes on how drivers overtake bicyclists on the road and discussed that more narrow roads might lead to vehicles passing cyclists closer which might cause more risk.

Petritsch et al. (2006) created the Sidepath Safety Model in order to determine if a side-path, or separated bicycle track, would be a viable option for a given road segment or how to improve an existing side-path with multiple collisions. This model found that the path width has an impact on the safety and recommends that paths be built wide enough to accommodate multiple users along a segment but restricted at conflict points to calm traffic. It also found that the distance between the side-path and the roadway, the speed of the adjacent roadway, and the number of lanes on the adjacent roadway were also key safety factors.

Intersection

The design of the intersection has an impact on bicycle safety in multiple ways as concluded by Wang & Nihan (2004). For intersection and network movement, hazardous crossings, right hook, left sneak, and complicated interactions are potentially dangerous to cyclists. Intersection safety was influenced by vehicle volume, vehicle speed, percent of heavy vehicle, and many other factors for both the major and minor roads (Dixon, Monsere, et al. 2012).

Oh et al. (2008) conducted a study based on surveys collected at 151 signalized intersections and found that average daily traffic volume, presence of bus stops, sidewalk widths, number of driveways, presence of speed restrict devices, and presence of crosswalks are all statistically significant factors that influence the risk level of bicycles. It has also been found that complex intersections (high number of road legs, road users, high number of signs, dense traffic crossings, etc.), and therefore complex traffic situations, increase the risk for bicycles (Vandenbulcke et al. 2014)

Abdel-Aty & Keller (2005) considered three types of variables in different probit models for signalized intersections; (1) based on collision types, (2) based on intersection characteristics, and (3) based on a complete set of significant variables. These models found that the division of the minor road, as well as a higher speed limit on the minor road, was found to lower the expected injury level while a median on the minor road may prevent more head-on collisions, which were found to be more severe collisions (Abdel-Aty & Keller 2005). Additionally, a higher speed limit on the minor road may cause the speed differential between vehicles on intersecting roads to be smaller, likely resulting in a decrease in the collision severity level (Abdel-Aty & Keller 2005).

Another study looked at two types of collisions across 540 un-signalized intersections; (1) through bicycle related collisions where the cyclist has right of way, and (2) through motor vehicle related collisions where the motorist has right of way (J. P. Schepers et al. 2011). The results showed that Type 1 collisions occurred more when the two-way bicycle tracks is well marked, and there are reddish colored bicycle crossing. Fewer collisions occur when there are raised bicycle crossings (speed humps) or other speed reduction measures (J. P. Schepers et al. 2011). Haleem & Abdel-Aty (2010) considered the number of lanes for un-signalized intersection and found that the traffic volume on the major approach, the number of through lanes on the minor approach (surrogate measure for traffic volume), the upstream and downstream distance to the nearest signalized intersection, left and right shoulder width, number of left turn movements on the minor approach, and number of right and left turn lanes on the major approach were significant factors that influence bicycle risk.

TRAFFIC CHARACTERISTICS

Many studies have recognized that traffic characteristics such as speed limit, peak hour traffic, and traffic volumes such as AADT and ADT are risk factors for cyclists. Greibe, (2003) found that higher speed limits relate to lower accident risks, but clarifies that it does not mean that high speeds in general are safer, rather that high-speed roads tend to have few vulnerable road users. Wang & Nihan, (2004) also found that speed limit decreases the risk or bicycle accidents but states that it could be related to the turn maneuvers or right-turning vehicles. Similarly, Abdel-Aty & Keller, (2005) determined that higher speed limits on the minor road lowered the expected injury level and Eluru et al., (2008) found that higher speed limits lead to higher injury severity levels. On the other hand, Haleem & Abdel-Aty, (2010) found that lower speed limits (less than 45 mph) reduced fatal injury probability when compared to greater than 45 mph. Kim et al., (2007) found that any speed greater than 20 mph and heavy vehicle traffic increased the risk of fatal injury.

Kim et al. (2007) also considered the peak hour effects and found that during the a.m. peak hour (6AM-9:59AM) there is an increased risk in fatal injury for bicycles. Nordback et al., (2014) found that collisions were equally sensitive to both AADT and AADB (average annual daily bicycles). Haleem & Abdel-Aty (2010) determined that AADT on the major approach decreased the effect on fatal injury when a natural logarithm was used but that the effect was increased when a surrogate measure for AADT was used to represent one, two, and three through lanes on a minor road. Dixon et al. (2012) found that AADT increased the risk for cyclists in an urban environment.

LAND-USE

Land-use impacts, though not very detailed in the literature, do influence the overall safety of bicyclists because it affects the amount and type of traffic and facilities of the road. Common distinctions of land-use types are urban, rural, residential, industry, farmland, institution, and commercial (Kim et al. 2007; Dixon, Monsere, et al. 2012; Haleem and Abdel-Aty 2010). Dixon, et al. (2012) found that land-use is a key factor that affects driveway safety and Schepers et al. (2014) stated that land-use has an effect on the distribution of traffic (bicycles included) over time and space. Oh et al. (2008) determined that the presence of industrial areas near intersections was associated with higher bicycle collisions. This is due to the more complicated traffic activities when compared with non-industrial areas.

Nordback et al. (2014) concludes that land-use types are variables that should be considered for SPFs as they may influence cyclist safety. One study analyzed the descriptive statistics of land-use and found that higher severity collisions occurred outside of urban areas and at farm/wood/pasture or residential areas (Kim et al. 2007). Greibe, (2003) used a dataset where land-use proved to be one of the most important variables in the models generated and land-use and speed limit explain the level of vulnerable road users exposed to a certain extent. In the model used for this study, it was found that shops, blocks of flats (or apartments), and industrial/residential/neighborhood were significantly influence to bicycle safety (Greibe 2003).

DEMOGRAPHIC AND BEHAVIOR

As expected, several factors are specific to the bicyclist when considering their risk level. The most impactful factor according to the literature is the age of the cyclist. Several studies found that riders over the age of 45 were more likely to be involved in a more severe collision (Kim et al. 2007; Boufous et al. 2012; Schepers & den Brinker 2011; Tin Tin et al. 2013; Noland & Quddus 2004). Bíl et al. (2010) found that cyclists 65 years and older were most at risk. Specifically, Schepers and den Brinker (2011) found that cyclists over 60 years old were more likely to be involved in collisions due to their low visible capability. Kröyer (2015) found that fatalities increased for riders above the age 55 and that there was an extreme increase in fatality risk between the age groups of 55-64 and 65-74. Alternatively, one study found that riders between the age of 10 and 19 were more likely to be involved in a higher severity collision (Martínez-Ruiz et al. 2013) and another discovered that children 9-11 years old are also at a higher risk (Maring & Van Schagen 1990). Other studies reported that age was an important factor, however they did not specify which age group was most at risk (Haleem & Abdel-Aty 2010).

Kim et al. (2007) found that bicyclist without a helmet were more likely to have an incapacity or non-incapacity injury. Several other studies also found that when cyclists who were not wearing a helmet they were at a higher risk (Andersson & Bunketorp, 2002; Martínez-Ruiz et al., 2013; Moahn et al., 2006; Noland & Quddus, 2004; Räsänen & Summala, 1998; Tin Tin et al., 2013). Additionally the location of the collision was an important feature to the risk level, although it was not determined if there was a specific location that led to higher risk levels

(Abdel-Aty & Keller 2005; Eluru et al. 2008). Several study found that males are more at risk for higher severity of collisions (Boufous et al., 2012; Ekman et al., 2001; Eluru et al., 2008; Kim et al., 2007; Noland & Quddus, 2004; P. Schepers & den Brinker, 2011; Tin Tin et al., 2013).

Another factor that several studies found to contribute to high risk levels was if the bicyclist was intoxicated (Olkkonen and Honkanen 1990; Rodgers 1995; Boufous et al. 2012; P. Schepers and den Brinker 2011; Martínez-Ruiz et al. 2013; Andersson and Bunketorp 2002; Eluru, Bhat, and Hensher 2008; Kim et al. 2007; Haleem and Abdel-Aty 2010; Noland and Quddus 2004). Other factors that were found included failure to follow traffic rules such as right of way, cyclist familiarity with the area, brake defeats, and if there were 2 riders (Schepers & den Brinker 2011; Martínez-Ruiz et al. 2013; Bíl et al. 2010; Kim et al. 2007).

Driver characteristics also directly affect the risk level for bicyclist. The most influential factor based on several studies is if the driver is intoxicated (Eluru et al. 2008; Noland & Quddus 2004). Additional factors that were found in many studies were; that the risk of the bicyclist increased if a truck was involved in the collision (Kim et al. 2007; Walker 2007; Greibe 2003; de Geus et al. 2012; Boufous et al. 2012) or if the collision was a head-on collision (Greibe 2003; Abdel-Aty & Keller 2005; Lenguerrand et al. 2006; Bíl et al. 2010; Dixon, Avelar, et al. 2012; Kim et al. 2007).Räsänen & Summala (1998) pointed out that attention of drivers greatly influence accidents or that the improper allocation of attention may lead drivers to ignore a cyclist who comes from an unexpected direction such as drivers turning right hit cyclists coming from left. Drivers do not allocate enough attention to cyclists and in some cases, cyclists do not feel or notice that they are in danger (Räsänen & Summala 1998).

Other factors include vehicles speeding, the age of the vehicle, if a bus is involved in the collision, if there are parked vehicles along the side of the road, and if the age of the driver is above 60 years old (Walker 2007; Vandenbulcke et al. 2014; Parkin et al. 2007; Pai 2011; Martínez-Ruiz et al. 2013; Bíl et al. 2010; Eluru et al. 2008; Kim et al. 2007; Noland & Quddus 2004).

Weather and Lighting

Bicycle collisions inherently have their own factors that are specific to bicycle collisions. The two more impactful factors are bad weather such as fog, snow, or rain, and the lighting of the road when it is dark outside. Moahn et al., (2006) recognizes that weather conditions and darkness are risk factors that influence collision involvement. One study found that bad weather (e.g. rain, snow, fog, etc.) increases the probability of fatality by 128% and darkness with no streetlights increases the probability of fatality by 110% (Kim et.al, 2007).

Pai, (2011) found that adverse weather, wet roads, and unlit streets in darkness were most common in rear-end collisions. Mountain and Jarrett (1996) stated that weather, quality of street lighting, and condition of the road surface used in a regression model will still have different underlying mean accident frequencies due to unique and unmeasured site characteristics. Stone & Broughton, (2003) found that darkness increased the accident incidence rates and fatality rates. Martínez-Ruiz et al. (2013) considered bicycle defects and found that bicycles with brake defects were at a higher risk of being involved in a collision with a vehicle.

ANALYZING BICYCLE COLLISIONS USING STATISTICAL MODELS

This section explores the different models that have been used to determine which factors influence the frequency and severity of bicycle collisions. The most common models used include the negative binomial models, linear regression models, logit models, and probit models. Some studies used simple summary statistics as well as a model and other models created their own model to overcome some model shortcomings. This research specifically considers Poisson and negative binomial models, linear regression models, and logit models to review which factors have the most potential for affecting bicycle collisions.

POISSON AND NEGATIVE BINOMIAL

The Poisson distribution was used to analyze the relationship of collisions and the variables that influenced the frequency of collisions. In their study, Oh et al. (2008) used the Poisson distribution to analyze bicycle collisions at urban signalized intersections. However, only bicycle variables were considered and there could be more risk factors found if driver characteristics had been considered (Oh et al. 2008). Nordback et al. (2014) focused on finding Safety Performance Functions (SPFs) for bicycles in cities in the United Stated and used the Poisson distribution because of its ability to create a logical fit for the accident data provided. Finally, the Poisson distribution was used for a study of the largest cycling event held in New Zealand to determine what factors play into risk level for bicyclists from incident rates (Tin Tin et al. 2013).

There are several studies that use negative binomial model or some variation of the model in order to determine the frequency of collisions. Oh et al. (2008) considered a negative binomial model when analyzing bicycle collision at signalized intersections in an urban area. In a study that considered collisions involving a bicycle and motor vehicle at a signalized intersection, Wang et al. (2004) used three different negative binomial models to estimate the risk of such collisions. Noland & Quddus (2004) used a fixed-effect negative binomial model to analyze the risk factors of pedestrians and bicycles casualties for various regions in England. Finally, a negative binomial regression model was used to study various factors, both road and bicycle, which influence bicycle risk factors at un-signalized intersections in order to try and prioritize their safety levels (J. P. Schepers et al. 2011).

LINEAR REGRESSION & LOGIT MODELS

Linear regression and logit models have been used to determine the impact factors have on collision severity levels, however linear regression models were generally accompanied by another modeling approach. Dixon et al. (2012) used Safety Performance Functions (SPFs) along with two linear regression models, one applied to urban and the other to rural, in order to quantify SPFs of driveways on state highways. These SPFs were mainly focused and applied to vehicles (Dixon, Avelar, et al. 2012). Another study used a linear model in conjunction with an empirical Bayes procedure to develop and validate a method for predicting expected accidents on main roads with minor junctions where traffic counts on the minor approaches were not available (Mountain & Jarrett 1996).

Logit models were very commonly used in previous studies concerning bicycle related collisions due to the models' ability to examine discrete choices, which are the level of severities of the collisions. Eluru et al. (2008) created a variation of the logit model, termed as a mixed generalized ordered response logit model due to the limitations of a standard ordered response logit model, to study pedestrian and bicycles injury severities in collisions. Kim et al. (2007) used a multinomial logit model to predict the probability of different severity levels for bicycle-motor vehicle collisions in North Carolina. Another study used a mixed multinomial model to predict the likelihood of a non-junction collision being a certain collision type (out of three possible types) (Pai 2011). The multimodal model was chosen because it allowed for the individuals within the observation to have different parameter estimates (Pai 2011).

Boufous et al. (2012) used a logit model to determine the risk factors for bicycles in Victoria, Australia. The logistic regression was used to identify predictor variables of severe injury. Schepers & den Brinker (2011) used a logit model to determine visual risk factors perceived by bicycles through a questionnaire. In order to find the perceived cycling risks and route acceptability of cyclists, Parkin et al. (2007) also used a logit model and a non-linear least squares model. Finally, Lenguerrand et al. (2006) used three different models, a multilevel logistic model, generalized estimating equation models, and logistics models, to model the hierarchical structure of road collisions. However, the results from the logistic models are not consistent with other studies (Lenguerrand et al. 2006).

STRESS MEASUREMENTS

Stress measurements have been used for several decades starting with the Bicycle Safety Index Rating in 1987 (Lowry, Callister, Gresham, & Moore, 2012). These measurements consider the impact different environmental characteristics have on a bicyclist's emotional stress level. Stress levels have then been attributed to safety ratings as higher levels of stress indicate that the bicyclist has a low feeling of safety. These measurements have been used to analyze the connectivity of communities and to promote bicycle ridership by reducing the stress levels of specific routes.

THE CASE FOR LEVEL OF TRAFFIC STRESS

Prior research on the effectiveness of level of traffic stress (LTS) measurements in explaining travel behavior rely on stated and observed data of how cyclists' route choices respond to changes in the built environment. Mekuria et al., (2012) produced the LTS criteria because it provides consistent criteria for network links and nodes that policy makers and the public can readily understand.

The classification's provided by LTS utilizes a popular four-group classification of urban bicyclists to define their LTS system (Geller 2013). This classification categorizes residents based on their cycling comfort levels rather than skill level thus enabling planners to think about stress level classifications as catering to three groups. The first group is a small, fearless section of the population that will choose to cycle in any conditions along any road-way. The second is typical, confident adult bicyclists who are comfortable on major arterials with bike lanes or small, slower roads without bike lanes. The last group consists of the vast majority of the population that has very low tolerance levels for negotiating vehicle traffic above small, residential street speeds. Links and nodes classified as LTS 1 are those Mekuria et al., (2012) suggest a rider would feel safe riding on with children and LTS 1 and LTS 2 roads are designed to represent the third group of riders with a low tolerance for vehicle traffic and speeds (Geller 2013).

Automobile speeds, number of lanes, and cycling infrastructure improvements define the LTS (Mekuria et al. 2012) and jurisdictions looking to develop maps for bicycle safety and policy evaluation would likely have ready access to each of these variables. In multiple countries, scholars report the importance of automobile speeds and number of lanes in determining subjects' perceptions of service levels (Kang & Lee, 2011; Providelo & da Penha Sanches, 2011). In mixed traffic, cyclists appear to prefer riding along residential streets to riding on major streets with higher speeds and more lanes (Caulfield, Brick, & McCarthy, 2012; Habib, Mann, Mahmoud, & Weiss, 2014). Infrastructure improvements correlate with higher cycling rates at the household, neighborhood and municipal level *(4, 5)* and determine route choice, with individuals willingly taking longer routes to stay on lower stress, higher infrastructure paths (Arentze & Molin, 2013; Hood, Sall, & Charlton, 2011; Tilahun, Levinson, & Krizek, 2007).

THE CASE AGAINST LTS

The literature offers several reasons to doubt the effectiveness of LTS accessibility in predicting cycling mode share or trip production. Some of the latest research on route choice using GPS data found that traffic volumes, which is left out of the LTS to minimize the data intensiveness, are critically important to understanding route choice (Broach, Dill, & Gliebe, 2012). Traveler awareness of connectivity is just as important as the availability of bicycle connectivity of a network itself (Lundberg & Weber 2014). Several studies have also included other aspects of a cycle trip that may play a significant role in route such as wayfinding (Wierda & Brookhuis 1991; Campbell & Lyons 2008), trip difficulty measures (Milakis & Athanasopoulos 2014), signalization, (Providelo & da Penha Sanches 2011; Broach et al. 2012; Titze et al. 2008; Sener et al. 2009), built and natural environment variables (Cervero & Duncan 2003), and accessibility to a variety of activities and transit stations.

LTS networks exclude traffic volumes, which are understood in the literature as an important factor to cyclists. Volume data may be costly to obtain across an entire network (Mekuria et al. 2012) yet volumes can increase stress and significantly alter riders' route decisions (Winters et al. 2011; Li et al. 2012). Larsen, Patterson, & El-Geneidy (2013) provide a geographic information science (GIS) based approach to prioritizing bicycle network investments that includes additional variable not covered by Mekuria et al., (2012). Their approach allowed for a spatial comparison of different criteria to prioritize infrastructure improvements, illustrating the different trade-offs inherent in including different criteria. While volume data is undoubtedly beneficial, it represents yet another layer of data cities may not be able to afford. A simple stand-in variable that correlates with collision rates may emerge as research continues to grow allowing small jurisdictions to account for missing data.

A Review of Alternatives

One alternative to the LTS modelling approach is the 2011 Highway Capacity Manual's Bicycle Level of Service (BLOS). This method is based on ten attributes to generate a numeric score representing bicyclist "perceptions" of comfort and safety is determined and the resulting score is then translated into a letter grade (Lowry et al. 2012). Lowry et al., (2012) uses this method to demonstrate how BLOS and bikeability can be calculated across an entire community and to determine various improvement scenarios for the community of Moscow, Idaho (Lowry et al. 2012).

Rybarczyk & Wu, (2010) overlay supply and demand models for bicycling in Milwaukee, Wisconsin and apply LTS to categorize and analyze bicycle supply. The system computes a six-level categorization which downgrades the LTS as the volume of directional traffic, the percentage of heavy vehicles, and the road surface conditions rise and increases the LTS as the effective width of the outside through lane increases (Rybarczyk & Wu 2010).

While these approaches may be more effective in predicting outcomes, the LTS framework offers criteria that cyclists, citizens, and local officials may readily understand. Additionally, data on vehicle volumes, the percentage of volumes from heavy vehicles, and road conditions may not be available or feasible to collect for small and medium sized jurisdictions.

SUMMARY

The literature review discusses the importance that different environmental factors such as land-use, weather, and roadway design affect a bicyclist's safety. The majority of previous studies used methods such as linear regression or binomial models to determine how impactful the different variables were. When considering the level of traffic stress method developed by Mekuria et al. (2012), there are conflicting views in the literature regarding how detailed the dataset should be to get accurate results. Using a more robust dataset requires more resources do not drastically improve the results of a stress level analysis. However, simple methods are missing key factors such as traffic volume. The following section will discuss the collision dataset and LTS measurement method used in this research.

CHAPTER 3: MATERIALS & METHODS

To determine if there is any correlation between LTS measurements and collision data both visual analysis and statistical analysis methods were used. The data were provided by the State of New Hampshire and the New Hampshire Bicycle and Pedestrian Transportation Advisory Committee with the help of the NH Department of Transportation.

DATA AND STUDY LOCATION

In order to address all the research purposes proposed, four cities in New Hampshire were chosen based on the available bicycle collision data and LTS dataset. The cities that were included were Concord, Manchester, Nashua, and Portsmouth. The following sections describe each data set, how they were combined, and the variables used in the visual and statistical analysis.

COLLISION DATA

The collision data used in this study includes all reported bicycle and pedestrian collisions from the State of New Hampshire between 2002 and 2013. The dataset includes the location of the accident, the roadway alignment, surface condition, lighting and weather at the time of the accident, day and time of time the accident occurred, the traffic control, and the level of severity including Fatal, Injury, and Property Damage Only, and unknown. It should be noted that common collision data information such as age, gender, and intoxication were not included in the dataset and therefor were not analyzed in the final models.

To visual analysis the collision data, collisions involving a bicycle were imported into ArcGIS. The severity levels included Fatal, Injury, and Property Damage Only. 'Unknown' collisions were included in the visual analysis but not in the statistical analysis as assumptions made regarding the "unknown" collisions could lead to misleading results.

CITY CHARACTERISTICS

Each city has unique characteristics, which give way to varying amounts and types of bicycle collisions. The City of Concord Bicycle Master Plan (2010) describes the bicycle and street network facilities within the city stating that

> "Streets are mostly narrow with limited space for bicycle lanes or shoulders, especially when competing for space with automobile parking...few off-street paved shared-use paths exist in the City."

The plan discusses the improvements for bicycle facilities through the downtown area of Concord, connection between various neighborhoods, and stripped bicycle lanes. The City of Manchester's Master Plan (2009) does not focus on bicycle facilities or improvements and states that design should encourage bicycling. The plan is more focused on improving walking and sidewalks. The City of Nashua's Master Plan (2001) includes a Regional Bicycle Transportation Plan that was developed to facilitate non-motorized travel within the region and identifies several key routes for inter-regional travel. The City of Portsmouth Bicycle and Pedestrian Plan (2014) identifies specific roads that require bicycle and shared lane improvements and wayfinding plans for the city to include walking and bicycling routes. The plan strives to improve safety for bicycles on streets and intersections within the City of Portsmouth.

Figure 1 shows the location and population of each city and the number of bicycle collisions from the 2002-2013 collision dataset.

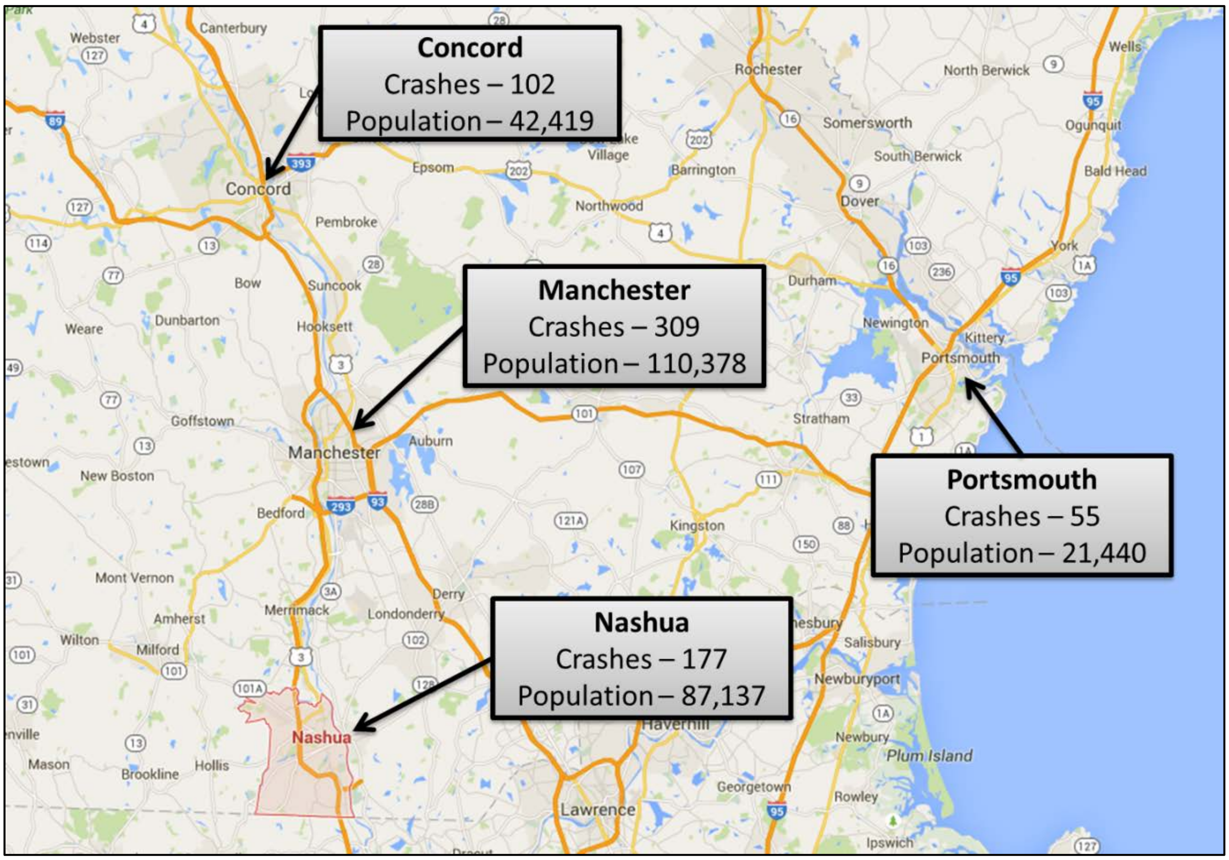

FIGURE 1 CASE STUDY LOCATIONS AND STATISTICAL INFORMATION

Figure 2 show the severity levels of the collision by each city. The City of Concord has the highest percentage of both Injury collisions and Property Damage Only collisions, although the distribution between Injury and Property Damage Only collisions is similar for all cities. The City of Portsmouth has the highest percentage of low stress bicycle routes (76%) and continues to make improvements to its bicycle facilities. The City of Concord has the highest percentage of high stress bicycle routes (65%) and is working towards improvements to their bicycle facilities in the new Bicycle Master Plan (Central New Hampshire Regional Planning Commission 2010).

Figure 3 and Figure 4 show the roadway and environmental attributes for the dataset. The majority of collisions were at an intersection or along a road, on normal, straight and level, two-way roads, during the day on clear days with dry surface conditions. Collisions were fairly even across the days of the week, but Friday and Monday had the highest percentages. More charts are included in the Appendices.

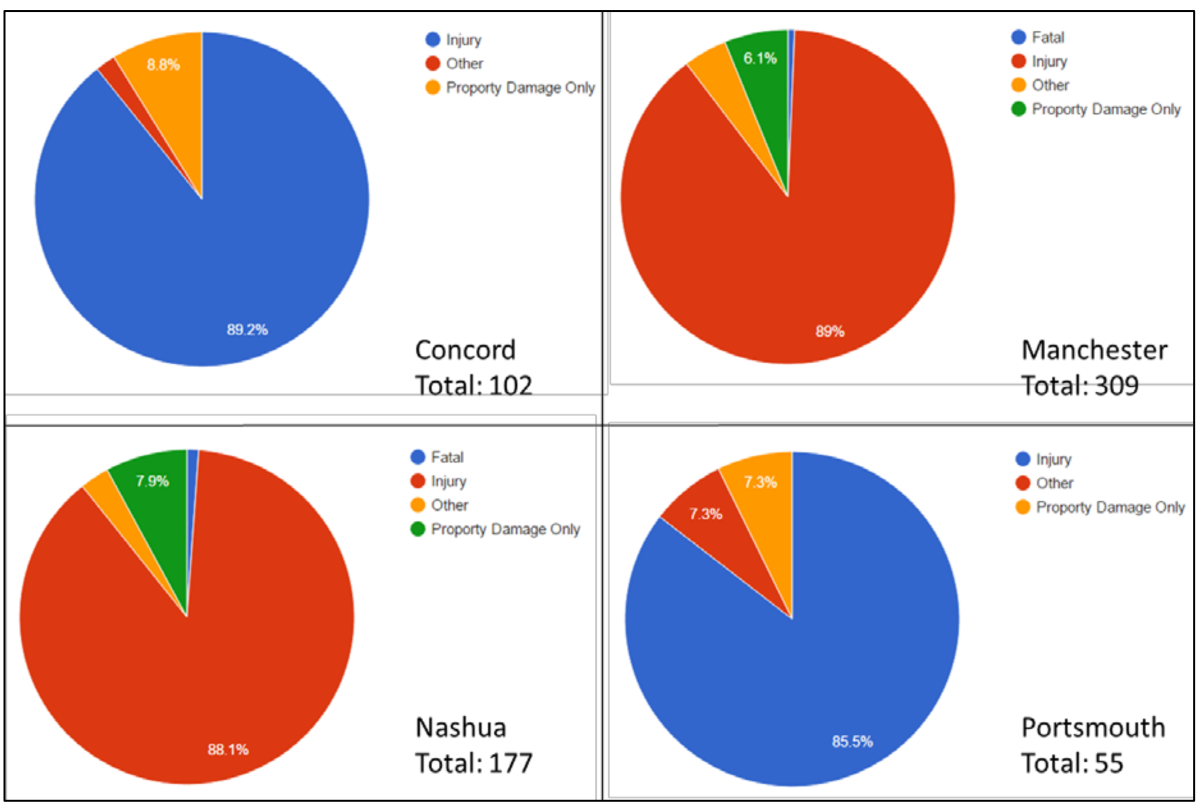

FIGURE 2: SEVERITY OF COLLISION BY CITY

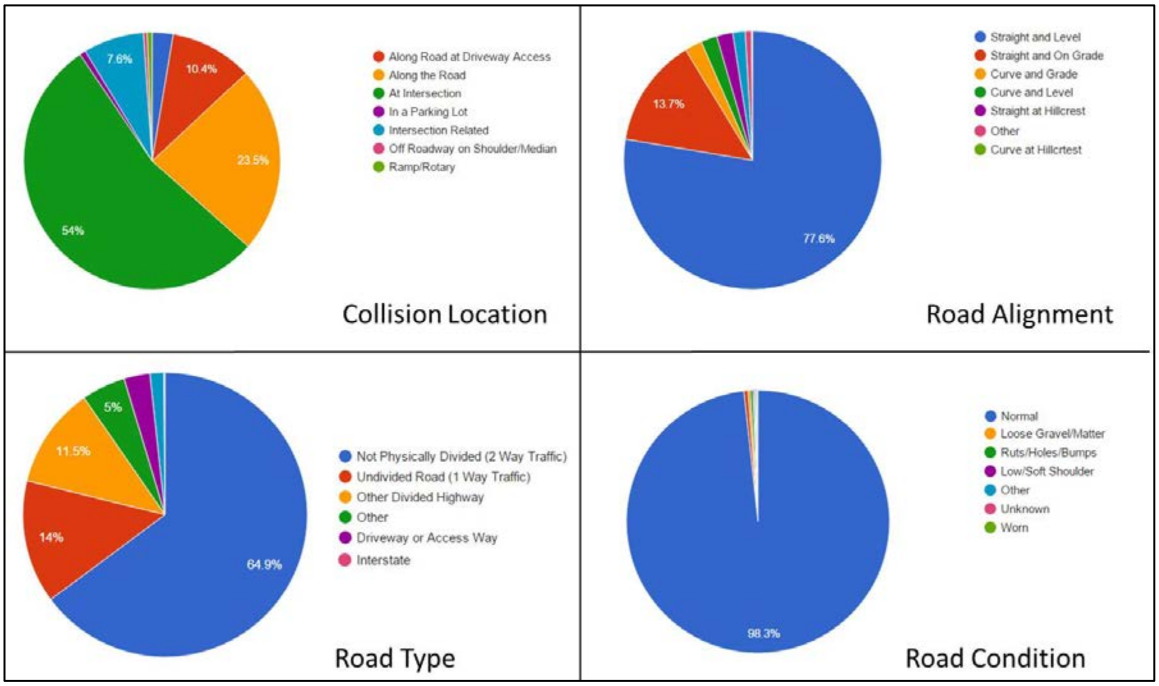

FIGURE 3: COLLISION ROADWAY ATTRIBUTES

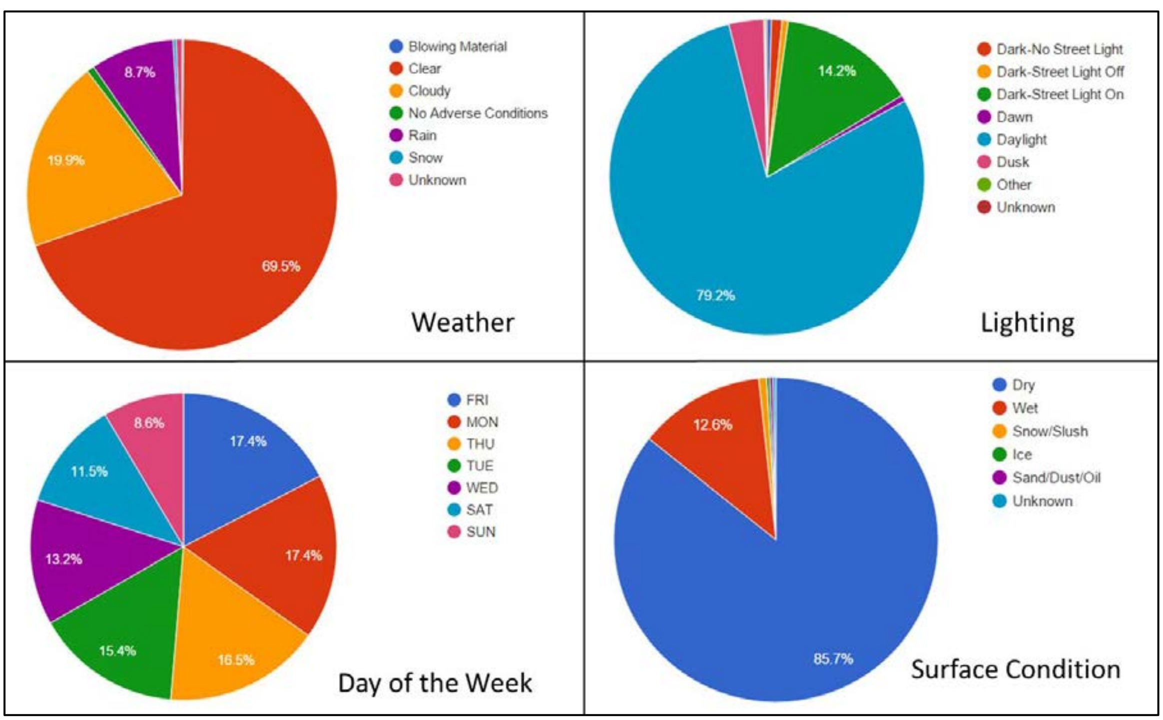

FIGURE 4: COLLISION ENVIRONMENT ATTRIBUTES

STRESS LEVEL DATA

The LTS dataset was a pilot project done as a proof of concept by the New Hampshire Bicycle Pedestrian Transportation Advisory Committee with the help of NH Department of Transportation in 2014 and has not yet been endorsed by NHDOT or NH BPTAC. The dataset includes bike lane presence and width, speed limit, parking presence and width, residential indicator, midblock crossing, and the number of right turn lanes and the bike lane configuration at an intersection approach. It should be noted that bike lane and parking data was collected for both the left and right side of the road, however due to the LTS recorded being different for less than 5% of the dataset, the right side LTS measurement was used for analysis.

Figure 5 shows the LTS of the road related to the collision for each city. The City of Concord has the highest percentage of LTS 4 road segments while the City of Portsmouth has the highest percentage of LTS 1 and 2 road segments. Figure 6 shows the LTS of the road for each severity level. ‘Injury’ and ‘Property Damage Only’ type collisions occurred the most on LTS 2 roads. All collisions occurred the least on LTS 1 classified road.

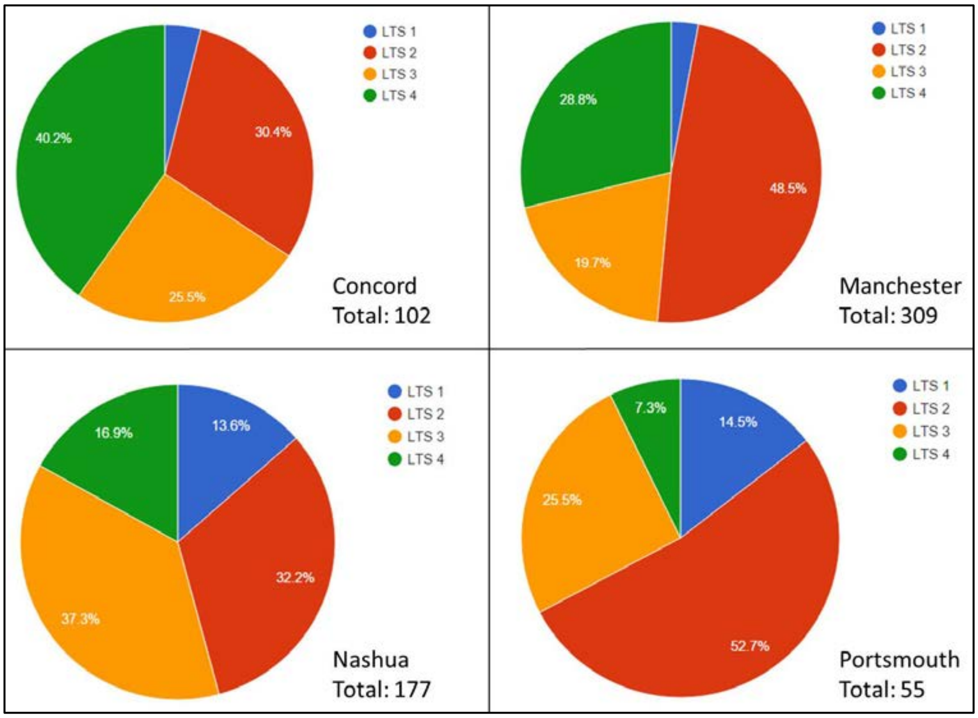

FIGURE 5: NUMBER OF COLLISIONS ON LTS ROAD SEGMENTS BY CITY

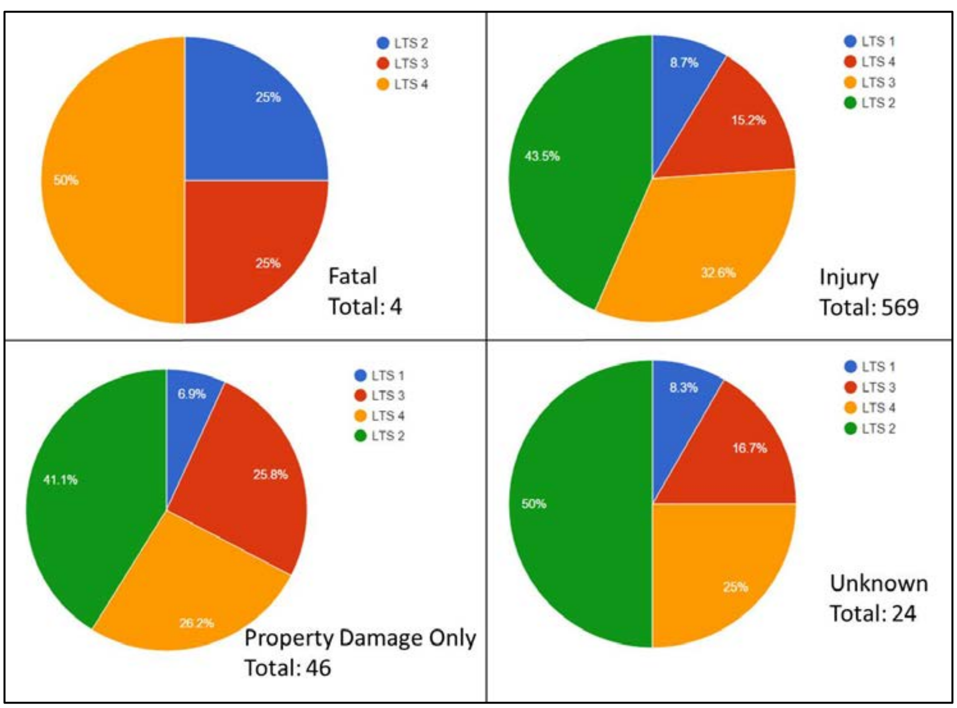

FIGURE 6: COLLISIONS ON LTS ROAD SEGMENTS BY SEVERITY

METHODS

To perform a visual analysis of the collision data and LTS data set, both data sets were imported into ArcGIS and each layer was modified to show a specific attribute; bicycle collision severity levels for the collision data and each LTS for the roadway data. A 'join' function was used multiple times to merge the excel dataset of collision data, which included all the accident information, with the geocoded collision data and a corresponding LTS measurement for each collision. There were nine cases where a collision occurred on a LTS 0 segments. LTS 0 segments include turnpikes, ramps, and all private roads, or unknown and these collisions were excluded from further analysis. The final data set was used for the statistical analysis as well as the visual analysis.

LIMITATIONS OF THE DATASET

The dataset has a few limitations, which prevent other methods of analysis to be successful. The first limitation is that the dataset only consists of some type of collision. The means that there are no "zero" values preventing any type of prediction analysis to be done. Additionally, the collision data includes only bicycle and pedestrian related collisions so any predictive analysis using this dataset predicts weather the collision is a bicycle or pedestrian collision occurs when a bicycle or pedestrian is involved.

The second limitation of the dataset is that there is no data on the user or victim of the collision. Many studies have found that user variables such as age or the cyclists, if alcohol is involved, and sex of the rider are significant to bicycle collisions. However, these variables were not collected in the collision dataset. For any type of statistical analysis, these variables are capture in the error term and the constant, which is not ideal.

Other limitations include the simplicity of the LTS data and not being able to capture traffic or bicycle volumes, the irregularity time intervals between observations, which prevent a time series analysis, and inherit skewness of the data towards "Injury" type collisions due to under-reporting.

DESCRIPTIVE STATISTICS

To understand the impact on bicycle crashes that the roadway and environmental characteristics had, the combined datasets were used in an ordered-probit modeling framework in Limdep (NLOGIT 5.0). The descriptive statistics of the key variables and variables of interest are shown in TABLE. The dependent variable represented the injury severity of the bicycle collision – Serious Injuries (Killed and Incapacitated Injuries), Non-serious Injuries (Non-incapacitating Injuries and Possible Injuries), and Property Damage Only (PDO), which represented 44 (6.84%), 529 (82.27%), and 70 (10.89%) of the data considered in this study.

A qualitative analysis of the dataset shows some trends of bicycle collisions and figures for the variables are included in the Appendices. As expected, 'Non-Serious Injury' type collisions are the most common in all four cities accounting for about 88% of all collision types. In New Hampshire, any motor vehicle accident causing death, personal injury, or combined vehicle property damage in excess of $1,000 must be reported as stated by the New Hampshire Division of Motor Vehicles. For bicycle collisions, it is less likely to be reported if the collision is property damage only because the total damage does not exceed $1,000. However, bicycle collisions that result in an injury are more likely to require medical attention, which leads to those crashes being reported.

TABLE 2: DESCRIPTIVE STATISTICS OF KEY VARIABLES IN THE MODEL

Key Variable	Meaning of variables in the model	Mean	Standard Deviation
2WAYTRAFFIC	Road design of segment (1 for 2 way traffic, 0 otherwise)	0.6485	0.4774
STOPSIGN	Traffic control at intersection (1 for Stop Sign, 0 otherwise)	0.2255	0.4179
CONDITION	Road condition of segment (1 for Normal, 0 otherwise)	0.9829	0.1297
TOD2	Time of day of collision (1 if between 1600 and 2000, 0 otherwise)	0.4199	0.4939
DAY2	Day of week of collision (1 if Thursday or Friday, 0 otherwise)	0.3390	0.4738
LTS4	Level of Traffic Stress of road segment (1 if LTS 4, 0 otherwise)	0.2551	0.4359
GRADE	Alignment of road segment (1 for segments with grade, 0 otherwise)	0.1586	0.3653
INTERSECTION	Location of collision (1 if at or related to an intersection, 0 otherwise)	0.6159	0.4864
DARKSTREETLIGHT	Light condition of collision (1 for dark with a street light, 0 otherwise)	0.1415	0.3486
WEATHER	Weather at time of collision (1 for clear weather, 0 otherwise)	0.6952	0.4603
OVERCAST	Weather at time of collision (1 for cloudy or rain, 0 otherwise)	0.2862	0.4523
LTS1	Level of Traffic Stress of road segment (1 if LTS 1, 0 otherwise)	0.0700	0.2551
LTS2	Level of Traffic Stress of road segment (1 if LTS 2, 0 otherwise)	0.4152	0.4928
LTS3	Level of Traffic Stress of road segment (1 if LTS 13 0 otherwise)	0.2597	0.4385

Of the reported collisions, the most common location of the collision was at an intersection and along the road (77%). This is expected for bicycle collisions because drivers may not be expecting a bicycle at an intersection and when not at an intersection, the bicyclist is riding along the side of the roadway. The other common collision location is along the road at a driveway, which similar to at an intersection is likely caused by drivers not expecting a bicycle or a bicycle not behaving erratically.

The most common road type and alignment was a two-way (65%), straight and level road (77%). This trend is likely because they are the most common routes used by cyclists. One-way roads had the next highest percentage of collisions (14%) and these types of roads were found in downtown areas of the cities. Straight and On Grade was the next highest roadway alignment (14%). Other studies found that 'Grade' was an important variable and it is an aspect that is not considered in many stress level analysis.

Normal road conditions accounted for almost all of the collision (98%) and dry road surfaces accounted for a large number of collisions (86%). Wet road surfaces accounted for 13% of collision. The majority of the collisions occurred during the day (79%) and on clear days (70%). Other environmental situations included dark with a streetlight on (14%), cloudy (20%), and rain (9%). At night, bicyclists are more difficult to see and bicycles do not always use lights. Collisions occur near a streetlight because more bicyclists ride of streets that are well lit.

More collisions occurred on Mondays and Fridays (17%) than any other day and the fewest collisions occurred on Sunday (7%). More collisions occurred during non-peak hours (69%). These trends are likely due to the behaviors of drivers and cyclists during daily commuting trips. On the weekend, there is less bicycle trips made and during the peak hours, traffic is usually slower and drivers are more aware of their surroundings.

ORDERED-PROBIT MODEL METHODOLOGY

Given the limitations of the dataset, the ordered-probit model was carefully chosen to better understand the relationship between the roadway and environmental characters. This model intends to capture different levels of injury severity while accounting for any unobserved heterogeneity (Islam & Hernandez 2013). To avoid or reduce the bias and variability introduced in the parameter estimations through the underreporting tendencies of bicycle collisions, the severity levels were given a value in descending order of injury severity level 0 for Serious Injury, 1 for Non-serious Injuries, and 2 for PDO collisions (Ye & Lord 2011).

The ordered-probit model is formulated by defining and unobserved variable y* as a modeling basis of ordinal ranking of the data, with y* specified as a latent and continuous measure of injury severity of each observation (Washington et al. 2011).

$$y* = \boldsymbol{\beta X} + \varepsilon \tag{1}$$

where y* = dependent variable (specified as a latent and continuous measure of injury severity of each bicycle collision *n*); **β** = vector of estimable parameters; **X** = vector of explanatory variables (ie. roadway alignment, weather conditions, and time of day); and ε = random error term, which is assumed to be normally distributed with 0 mean and a variance of 1.

Using Eq. (1) under the order-probit framework, the observed ordinal data *y*, or injury severity, for each observation can be represented as (Washington et al. 2011)

$$\begin{array}{ll} y = 0 \quad if \;\; \infty \leq y^* \leq \; \mu_0 & y = 1 \quad if \;\; \mu_0 \leq y^* < \mu_1 \\ y = 2 \quad if \;\; \mu_1 \leq y^* < \; \mu_2 & y = \cdots \\ y = I - 1 \quad if \;\; \mu_{I-2} \leq y^* < \mu_{I-1} & y = I \quad if \;\; \mu_{I-1} \leq y^* < \infty \end{array} \tag{3}$$

where μ = estimable parameters or thresholds between two adjacent injury categories that define y and are estimated jointly with the model parameters **β**, which corresponds to integer ordering; and *I* = highest integer ordered response, (e.g., for PDO, the value is 2).

To estimate the probability of *I* for a specific ordered response for each collision or observation *n*, ε is assumed to be normally distributed with 0 mean and variance of 1. The ordered section probabilities of the ordered-probit model are then defined as:

$$P_n(y = 0) = \Phi(-\boldsymbol{\beta X})$$

$$P_n(y = 1) = \Phi(\mu_1 - \boldsymbol{\beta X}) - \Phi(-\boldsymbol{\beta X})$$

$$P_n(y = 2) = \Phi(\mu_2 - \boldsymbol{\beta X}) - \Phi(\mu_1 - \boldsymbol{\beta X})$$

$$\ldots$$

$$P_n(y = 1) = 1 - \Phi(\mu_{I-1} - \boldsymbol{\beta X}) \tag{3}$$

where $P_n(y=1)$ is the probability that observation *n* has *I* as the highest order response index (for instance, the injury severity of the crash), given a collision occurred; and Φ (.) = a standard normal cumulative distribution function.

$$\frac{P_n(y=1)}{\partial X} = [\phi(\mu_{I-2} - \boldsymbol{\beta X}) - (\mu_{I-1} - \boldsymbol{\beta X})]\boldsymbol{\beta} \tag{4}$$

where Φ (.) = the probability mass function of the standard normal distribution.

Some potential limitations are created by using only a fixed-ordered probit model, such as bias estimates and negates unobserved heterogeneity (Islam & Hernandez 2013). These limitations are created in part because some assumptions of the standard probit model limits its applicability, the marginal probability effects change their sign while moving from the smallest to the largest outcome, and possible unobserved factors (e.g., helmet use, age, and gender) are not properly addressed. The assumptions are as follows:

1. Independent variables **β** are fixed over the observations;
2. Threshold μ's are fixed across observations;
3. Probability functions (Eq. 3) are fixed in a single direction; and
4. The error terms are normally distributed.

One method to avoid these potential limitations is to include random parameters to provide a mechanism to minimize the inconsistent, inefficient, and biased parameters (Washington et al. 2011). These random parameters would allow for partial flexibility of fixed-parameters. Random parameters were not analyzed for this study because bicycle collisions do not have as many variables which potentially random parameters such as air bag deployment or seatbelt use; which decrease the likelihood of a fatality but increase minor injuries.

SUMMARY

Using the collision and LTS dataset, visual models were created with GIS software and an ordered probit model was developed to explore the relationships between the collision locations and their relative LTS measurement. An ordered-probit was chosen based on the ordinal nature of the collision severity and due to the limitation of the dataset. The following section describes the results of the visual analysis and ordered probit model.

CHAPTER 4: RESULTS

This section discusses the results from the visual analysis of the collisions and LTS analysis and the results from the ordered probit model analysis.

Two conclusions can be cautiously made from the visual analysis of collision types compared to LTS values. First, there is likely a relationship between LTS 4 and fatal bicycle collisions and secondly, LTS 2 may have a larger impact on collision severity than previously thought. These general results should be considered with caution, as collision rates alone do not consider the percentage of bicycle traffic on the network. To demonstrate, Strava data (a running and cycling trip-tracking app) was available for the city of Nashua, as seen in Table 3, for each LTS road classification. Although the collision data shows that LTS 2 has the highest number of collisions and may be less safe than previous believed, the bicycle trip rates show that LTS 2 routes are the most used. This relationship strongly suggests that collision data alone is not sufficient to explain the impact of LTS measurements of safety and any conclusions made should be considered with caution.

TABLE 3 CITY OF NASHUA BICYCLE TRIP DATA

LTS	Bike Miles Traveled	BMT per Day	Total Miles %	Total Trip %
0	2,889,522	7,916.50	29.60%	6.10%
1	2,830,179	7,753.91	14.80%	12.10%
2	34,070,217	93,343.06	**44.40%**	**48.40%**
3	2,687,017	7,361.69	7.40%	23.00%
4	623,510	1,708.25	**3.80%**	**10.40%**

GIS-BASED VISUAL RESULTS

In addition to the basic relationships stated above, the maps generated using ArcGIS provide further insight into potential patterns and a geospatial relationship between the LTS measurements and collision severity. Figure 7 shows the central area of the city of Concord and one can observe that the majority of "Injury" type collisions occurred on three or 4 specific roads that were classified as LTS 3 or LTS 4.

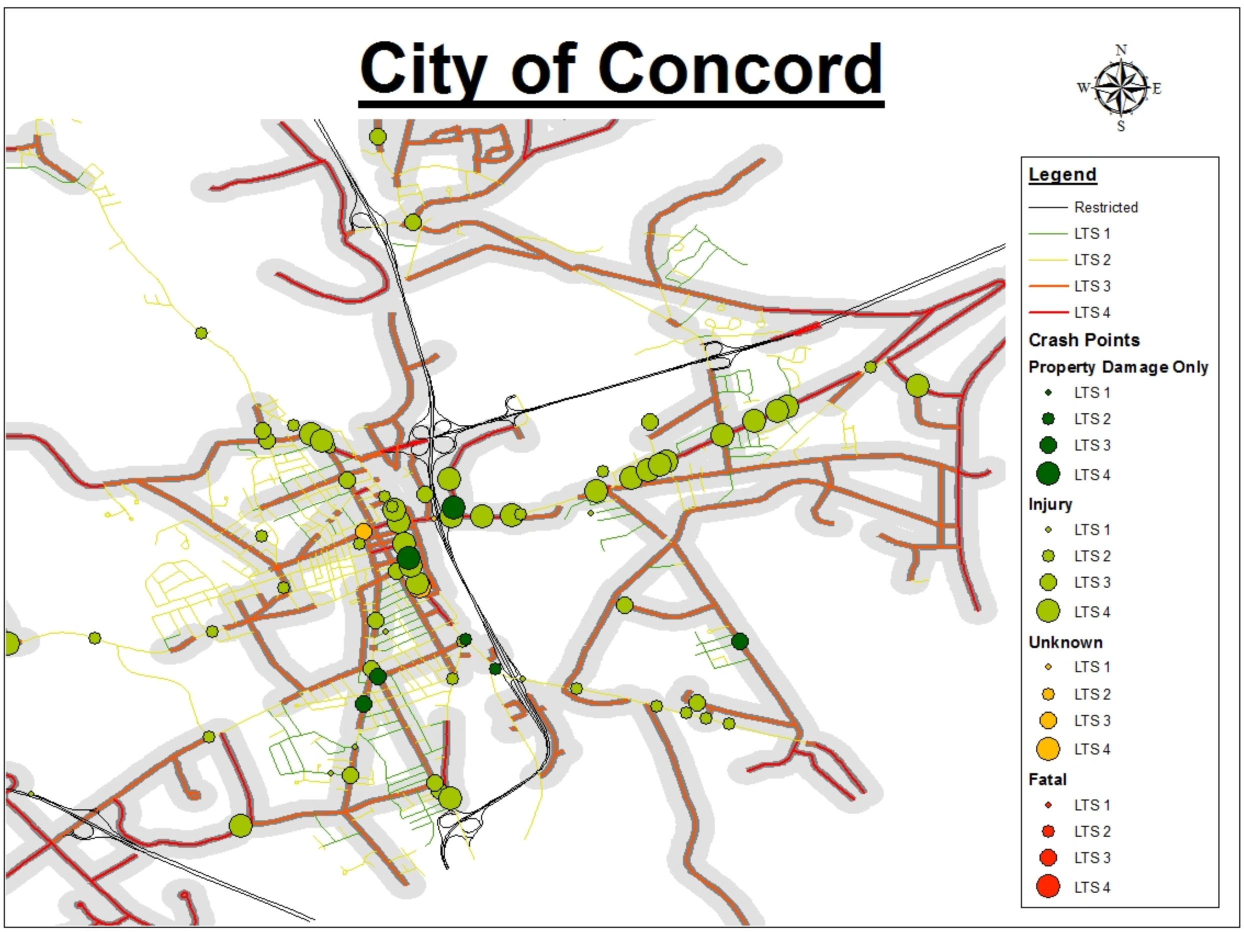

FIGURE 7 CITY OF CONCORD

The apparent cluster patterns highlight particular stretches of road that are less safe for cyclists. These roads predominantly include two-way 4 lane roads with an average AADT of approximately 10,000 vehicles per day. These roads did not have bike lanes and most did not have parking with the exception of some angled parking along segments of Main St. These roads were not in residential areas and had high traffic volumes or vehicles speeds of 35 mph or more. An observation to note is that there are many roads that are classified as LTS 3 or LTS 4 have no reported accidents on them, which is likely due to the low frequency of bicycle trips taken on these routes.

Figure 8 shows the central area of the city of Manchester, which much like Concord, the majority of "Injury" type collisions occurred on three or 4 specific roads that were classified as LTS 3 or LTS 4. The clustering patterns here are along roads that have between 2 to 4 lanes and are a mix of one and two ways. The average AADT along these roads is approximately 12,000 vehicles per day. These roads did not have bicycle lanes, were considered to be in residential areas, and approximately half had parking along the side of the roadway. The only reported fatality occurred of a road segment classified as LTS 3.

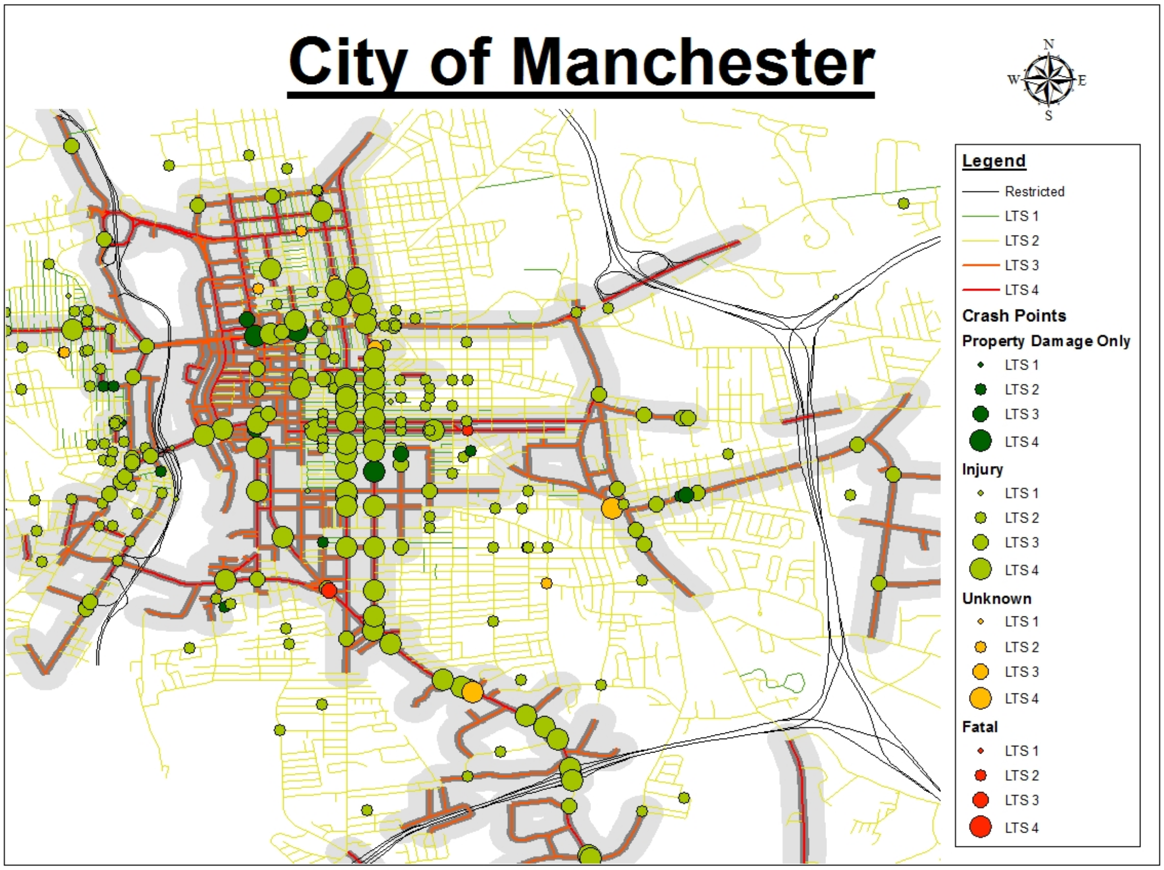

FIGURE 8 CITY OF MANCHESTER

Figure 9 shows the city of Nashua and that again the majority of “Injury” type collisions are along roads with LTS 3 or four. The majority of collisions took place in downtown Nashua, which is where Hwy 11 and Hwy 101 A come together to cross the Merrimack River. The road segments here are predominantly two-way, 2 to 4 lanes with an approximate average AADT of 21,000 vehicles per day. Most of the road segments have a speed limit of 30 mph and are non-residential roads. They also do not have a bike lane or parking along the side of the road. The two reported fatalities occurred on road segments classified as LTS 4.

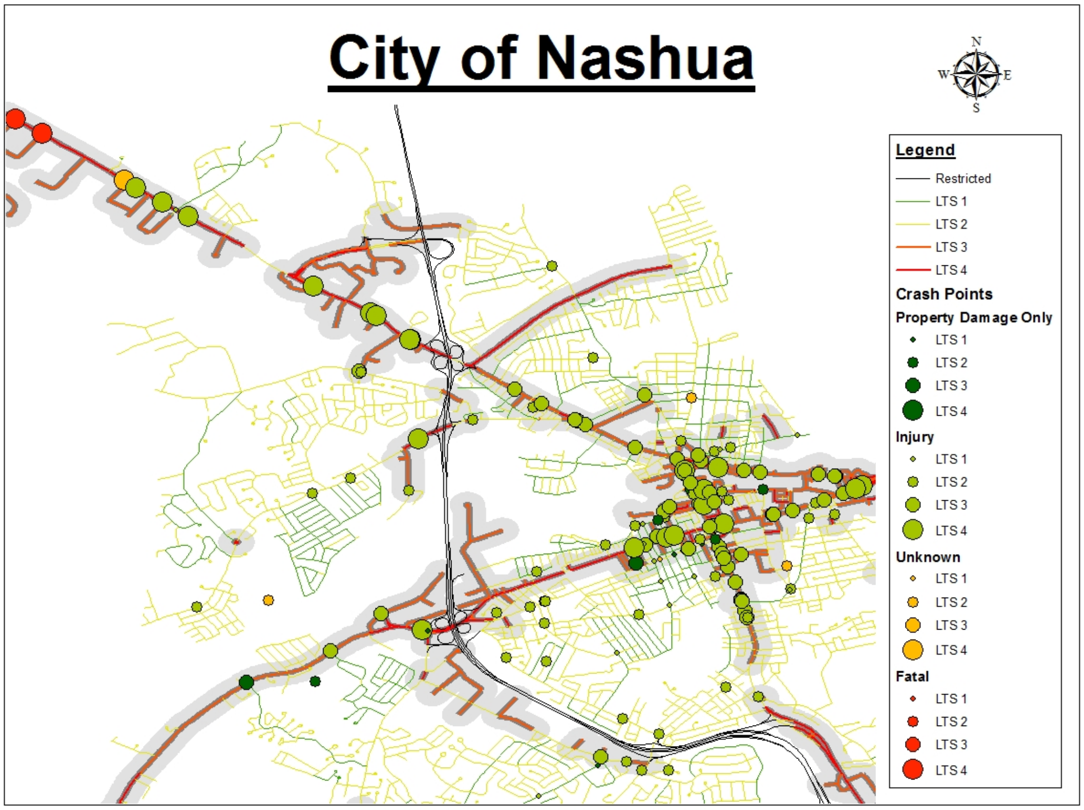

FIGURE 9 CITY OF NASHUA

Figure 10 shows the city of Portsmouth and it is difficult to distinguish a relationship between the bicycle collision data and LTS measurements due to the low number of reported collisions. Portsmouth is also one of the most bike-friendly cities in New Hampshire (Szczepanski 2014). The majority of collisions took place in downtown Portsmouth or along Hwy 1/Lafayette Rd. The road segments are two-way, 2 to 4 lanes with an approximate average AADT of 14,000 vehicles per day. Most of the road segments have a speed limit of 30 to 35 mph and are non-residential roads without bike lanes. There are a few areas, especially in the downtown area, where there is parking along the side of the road.

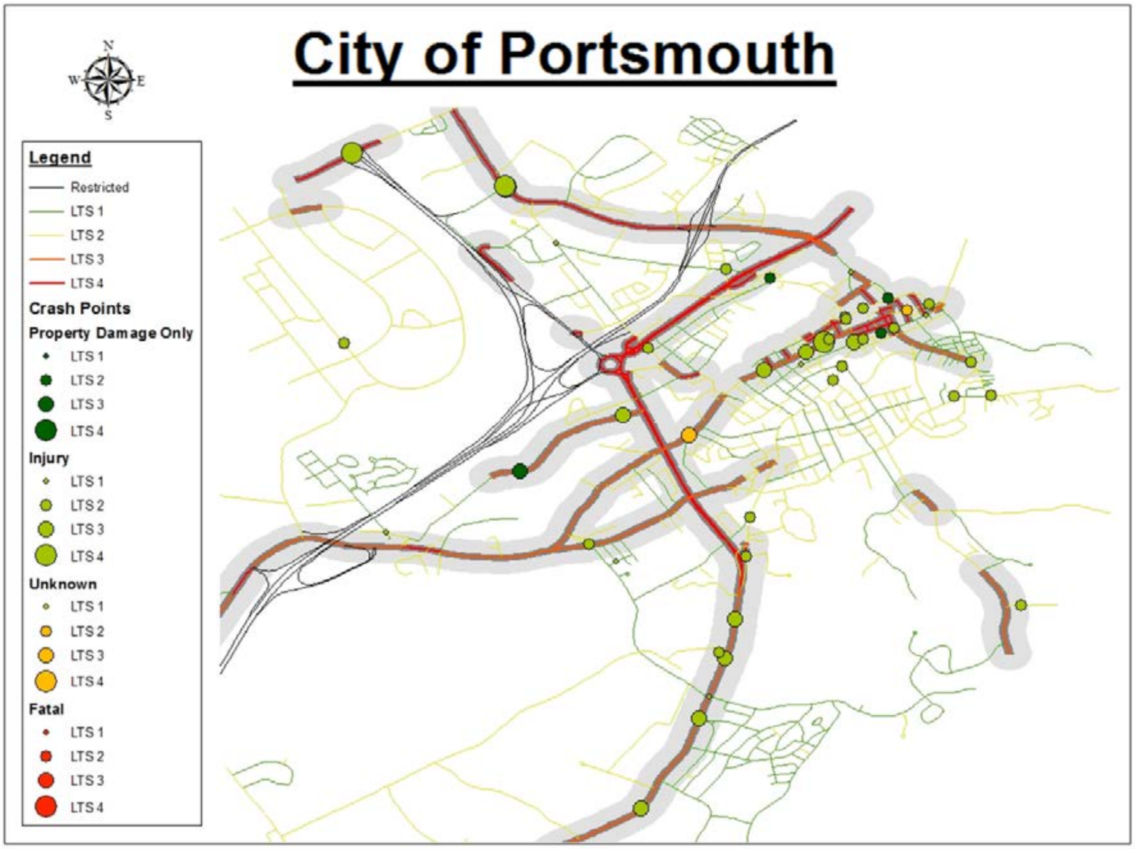

FIGURE 10 CITY OF PORTSMOUTH

ORDERED-PROBIT RESULTS

A fixed-parameter ordered probit model is estimated and the marginal effects of the model provide additional information regarding what is occurring within the injury severity categories. Table 4 provides the results of the fixed-parameter ordered probit model and Table 5 given the additional information of the marginal effects. For the results in Table 4, the constant term was found to be significant and the variability in the constant term is likely capturing the unobserved heterogeneity in bicycle collisions potentially cause in part by underreporting.

A negative coefficient (Table 4) represents an increased impact on injury severity probability. An example in the context of the coefficient and marginal effects (Table 5) is that the variable indicating two-way traffic (2WAYTRAFFIC where 1 represents two-way traffic, 0 otherwise) for PDO (*Y=2*) with a negative sign (-0.031) indicates that on average, the probability of a severe injury is higher given the crashes that occurred on a two-way road. Alternatively, the other injury severity categories are positive and their probability is lower on average.

TABLE 4: BICYCLE COLLISION INJURY SEVERITY MODEL RESULTS

	Fixed-parameters model	
Variable	*Coefficient*	*t-stat*
Constant	2.339	5.701
Road design of segment (1 for 2 way traffic, 0 otherwise)	-0.166	-1.459
Traffic control at intersection (1 for Stop Sign, 0 otherwise)	-0.252	-1.982
Road condition of segment (1 for Normal, 0 otherwise)	-0.733	-1.891
Time of day of collision (1 if between 1600 and 2000, 0 otherwise)	0.117	1.094
Day of week of collision (1 if Thursday or Friday, 0 otherwise)	0.184	1.647
Level of Traffic Stress of road segment (1 if LTS 4, 0 otherwise)	-0.198	-1.567
Threshold, $\mu1$	2.771	28.049
Log-likelihood at zero, LL(0)	-369.5241	
Log-likelihood at convergence, LL(β)	-376.4792	
Chi-square	0.03065	
Number of observations, N	643	

TABLE 5: MARGINAL EFFECTS ASSOCIATED TO THE FIXED-PARAMETERS MODEL

	Marginal Effects		
Variable	*Y = 0*	*Y = 1*	*Y = 2*
Road design of segment (1 for 2 way traffic, 0 otherwise)	0.0204	0.0107	-0.0311
Traffic control at intersection (1 for Stop Sign, 0 otherwise)	0.0355	0.0063	-0.0418
Road condition of segment (1 for Normal, 0 otherwise)	0.0539	0.1397	-0.1936
Time of day of collision (1 if between 1600 and 2000, 0 otherwise)	-0.0146	-0.0068	0.0214
Day of week of collision (1 if Thursday or Friday, 0 otherwise)	-0.0223	-0.0122	0.0345
Level of Traffic Stress of road segment (1 if LTS 4, 0 otherwise)	0.0271	0.0067	-0.0338

ROADWAY VARIABLES

Previous studies have found that roadway factors such as two-way roads and collisions occurring at intersections are the cause of varying level of severity in bicycle collisions. A probably explanation to such factors may be the complexity that these types of roads or intersections have and the driver or bicyclist's behavior.

More sever collisions occurred on two-way roads, which may be due to the higher number of bicycle ridership on these types of roads. Two-way roads also lead to head-on collisions, which are more likely to have a higher severity. More severe collisions occurred at intersections with stop signs. This is likely due to the behavior of cyclists or a driver to ignore or run through a stop sign. Additionally, collisions at intersections are likely to be angle crashes, which are more likely to be more severe collisions. Finally, when the pavement was considered "normal," that is in good condition, more severe collisions were likely to occur. This may be due to the high number of roadways in normal condition (98%) and drivers and bicycles may use caution on roads with ruts or in bad condition.

The marginal effects show that two-way roads are more likely to lead to fatal or serious injury collision, likely because of the possibility for a head-on collision. Intersections with stop signs were also more likely to be fatal or serious injury collusions, likely because of the possibility for angle-type collisions. Finally, roadways in “normal” condition were more likely to be less serious injury type collisions and PDO collisions.

TIME OF COLLISION VARIABLES

Time based variables, such as the time of the day of the collision and the day of the week the collision occurred on, have been found to be significant in some previous studies, however these variables are often captured in the lighting condition of the collision. For example, there is the potential for correlation between collisions that occur after 8pm and those that occur with “dark” lighting conditions. This study considered the lighting conditions and time based variables in different models and the lighting conditions were not found to be significant.

If the collision occurred between 4:00 p.m. and 8:00 p.m., it was more likely to be a less severe injury collision. This is likely due to the commuter behavior of traffic during that time of day. The congestion that is created during the p.m. peak hour causes vehicles to drive more slowly, reducing the risk of a high-speed, high severity collision. If the collision occurred on a Thursday or Friday, it was also less likely to be a severe injury collision. This may be caused by the driving behaviors towards the end of the workweek as compared to the beginning of the week and the weekend (recreational drivers).

Level of Traffic Stress Variables

The only stress level variable that was found to be significant was LTS 4, or the high stress roads. Collisions that occurred on these roads were more likely to have higher injury severity. This is consistent with the expected result of these roads, as the variables that cause higher stress (narrow roads and high traffic speeds) lead to more severe injury type collisions. The marginal effects show that the collisions on LTS 4 roadways are more likely to be fatal or serious injury type collisions.

Summary

From the visual results, there appears to be clustering patterns in downtown areas of cities and along specific corridors. These roads have similarities in their characteristics including speed limits of 30 to 35 mph, more than two lanes, two-way roads, and a majority of the roads had on street parking and did not have bicycle lanes. The ordered probit model results reveal that roadway factors such as two-way roads, stop sign controlled intersections, and roadways with normal conditions lead to more severe injuries and fatalities in bicycle-related collisions, collisions occurring in the evening time and on Thursday or Friday were less likely to be severe collisions, and LTS 4 roads lead to higher severity injuries and fatalities.

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

This research looked at the level of traffic stress (LTS) analysis and its impact of bicycle safety through a visual and statistical. The LTS method developed by Mekuria et al (2012) was chosen because of its simple and easy to acquire data, making it ideal for smaller communities that have limited finances. Visual maps for each city and an ordered probit model were used to determine the relationship between bicycle collisions and LTS classifications. The data used included reported bicycle collision data from 2002-2013, roadway LTS classifications, and trip rate information for four cities in New Hampshire. This section discusses the qualitative results of the data, the visual conclusion that can be made from the LTS and collision maps, and the statistical results from the Ordered Probit model.

USING LTS AND COLLISIONS IN A VISUAL ANALYSIS

Results from visually comparing LTS models and collision data suggest that LTS models can be useful in predicting where collisions are going to occur. Collisions of all types were clustered around roadways classified as LTS 3 and each city has specific corridors where collision patterns are visible. Additionally, roadway segments without bike lanes, speed limits of 30 mph to 35 mph, 2-4 lanes, more than 10,000 AADT, and parking were more likely to have “injury” type collisions. Using the LTS data and collision data separately may provide a good starting base to visualize where collisions are occurring or what route may be potentially dangerous for bicycle riders, however by combining these tools on a visual map, high-risk areas can be identify that tell not only where the collisions are occurring, but if it is the stress level variables such as speed and lane width that are contributing to the high number of collisions.

ORDERED PROBIT MODEL

The ordered probit model results reveal that roadway factors such as two-way roads, stop sign controlled intersections, and roadways with normal conditions lead to more severe injuries and fatalities in bicycle-related collisions. Two-way roads have more conflict points between bicyclist and vehicles and the most dangerous type of collisions include head-on collisions and sideswipe collisions, which have the high potential of occurring on two-way roads. Intersections with stop signs lead to angle type collisions when the driver or bicyclists disregard the stop sign. Bicycles tend to disregard the stop sign because on the difficulty in starting from a stop. Drivers may miss the stop sign if they are not familiar with the area or are distracted. When the road condition is not normal, drivers and bicyclists may use more caution when driving, thus driving at slower speeds and reducing the likelihood of a more severe collisions.

The results also found that bicycle collisions occurring in the evening time and on Thursday or Friday were less likely to be severe collisions. During the p.m. peak period, drivers may be more aware to the surrounding and driving more slowly due to congestion. During the week, the commuting drivers and bicyclists typically do not encounter unexpected behaviors which may be the reason collisions occurring on Thursday or Friday are more likely to be less severe.

Finally, LTS 4 was found to lead to higher severity injuries and fatalities, likely due to the variables such as speed and number of lanes that increase the stress level of the road. This is important because it confirms that using LTS models to begin to improve bicycle safety by targeting high stress roadways is a viable method.

SUMMARY AND FUTURE WORK

It can be concluded that LTS provides some insight into where bicycle collisions will occur and is a viable option for agencies to consider when looking at bicycle safety models, especially when no other analysis has been done and limited resources are available. Without collision data, the visual LTS models provide some insight into potentially dangerous corridors or road segments. Additionally, the results suggest that LTS 2 may not be as safe as previous thought as over half of the collisions occurred on roads classified as LTS 2. This finding is likely due to the increased ridership along roadways classified as LTS 2 and future safety analysis using LTS should include bicycle ridership to account for this fact.

The potential for LTS models to influence bicycle safety models is something that can be further explored in many different ways. Other collision data from different regions can be used to validate the behavior and characteristics of LTS 2 and if similar clustering patterns are visible. Additionally, other dataset may not have the limitations of this dataset so other model types such as probit or passion models can be used to investigate further the statistical relationship between the variables. Alternatively, different stress level analysis methods could be used to include variables like traffic volumes. The results from this study also show that bicycle ridership data is an important aspect when it comes to safety analysis. By including additional variables such as bicycle ridership and roadway elevation in the LTS maps, agencies gain more information about the safety of the roadway network for bicyclists.

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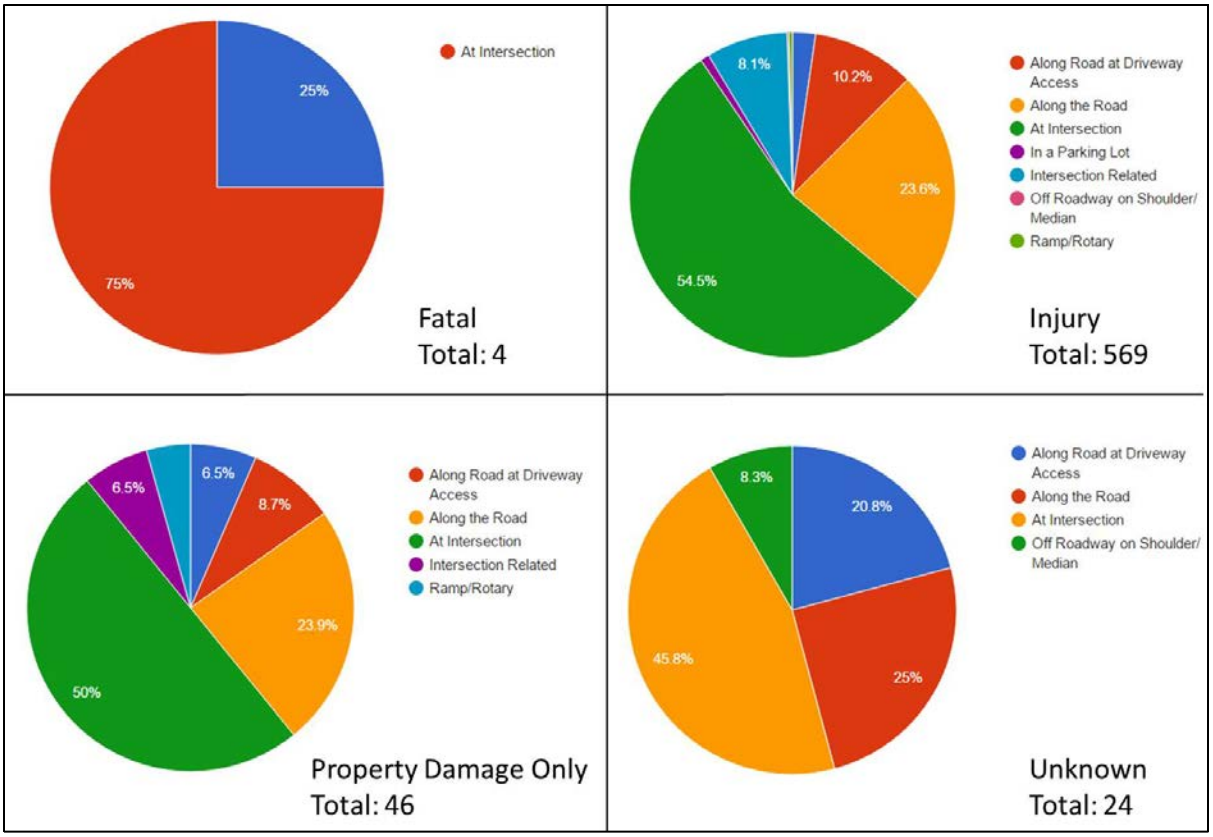
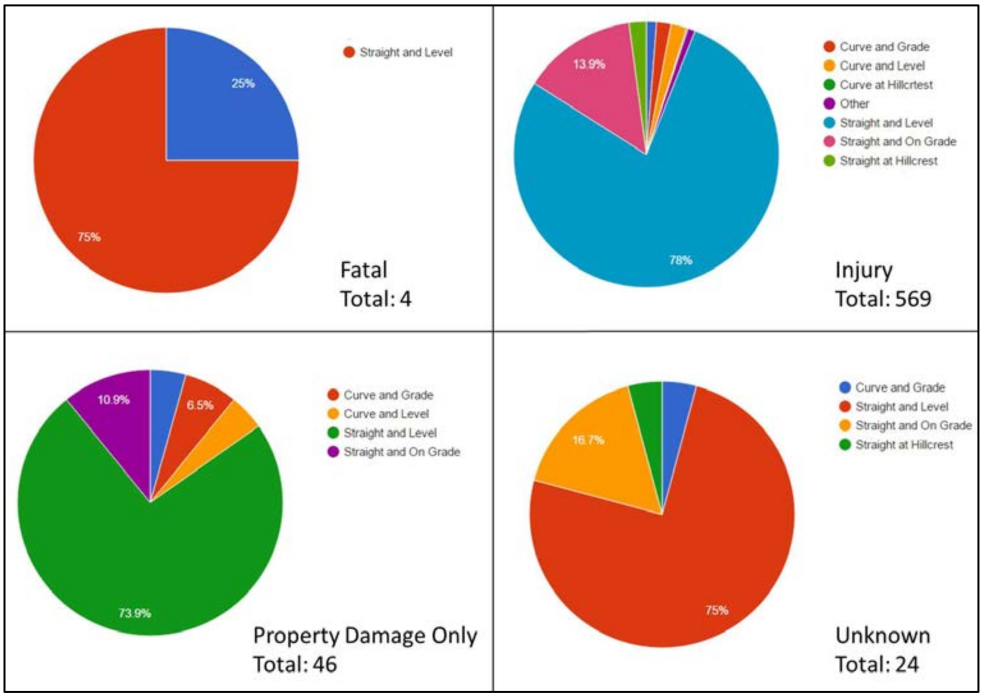
APPENDICES

VARIABLE DISTRIBUTION BY SEVERITY

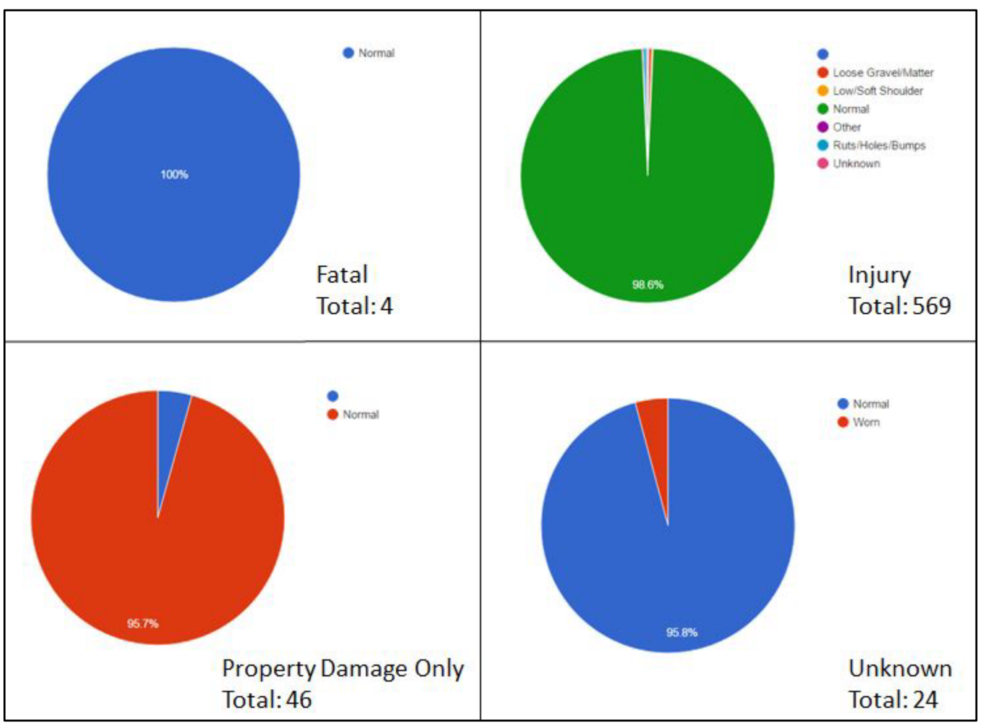
The following figures show the distribution of each variable for each severity level.



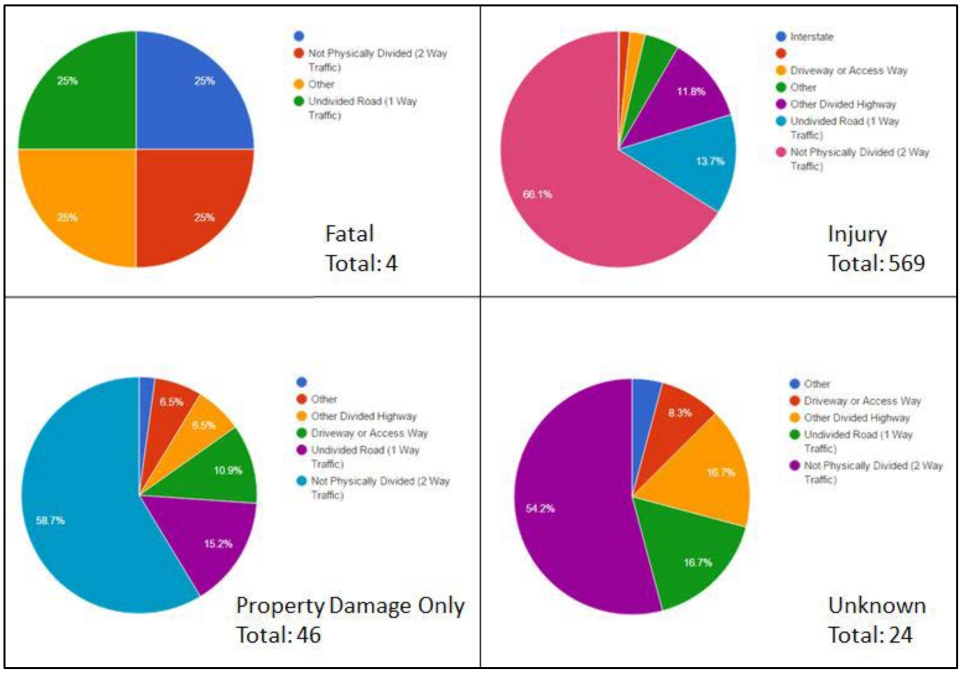
A1: COLLISION LOCATION BY SEVERITY



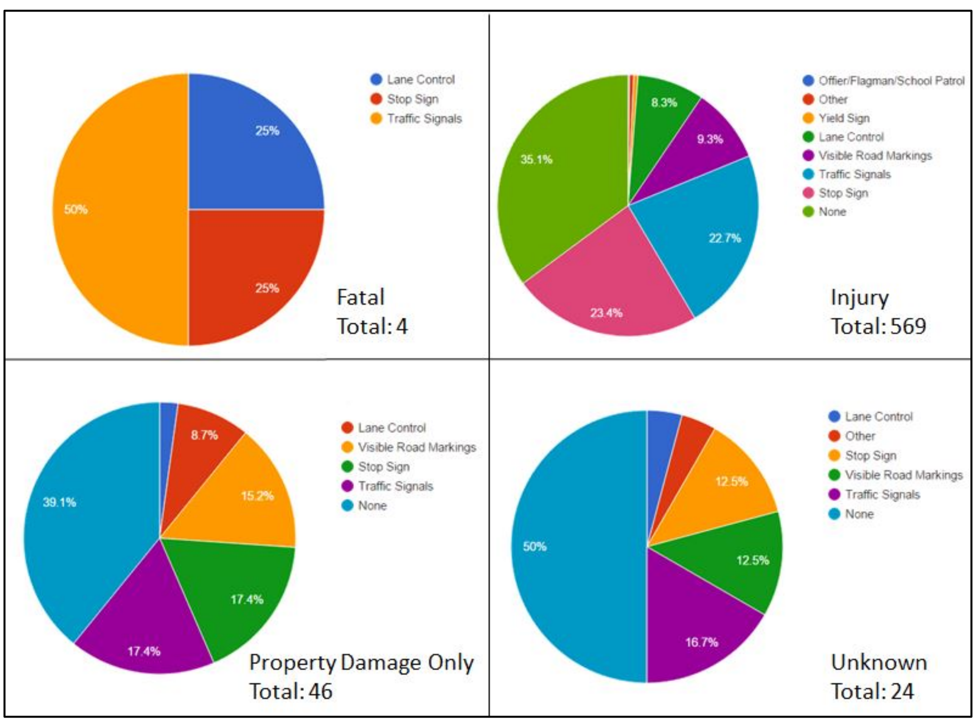
A2: ROAD ALIGNMENT BY SEVERITY



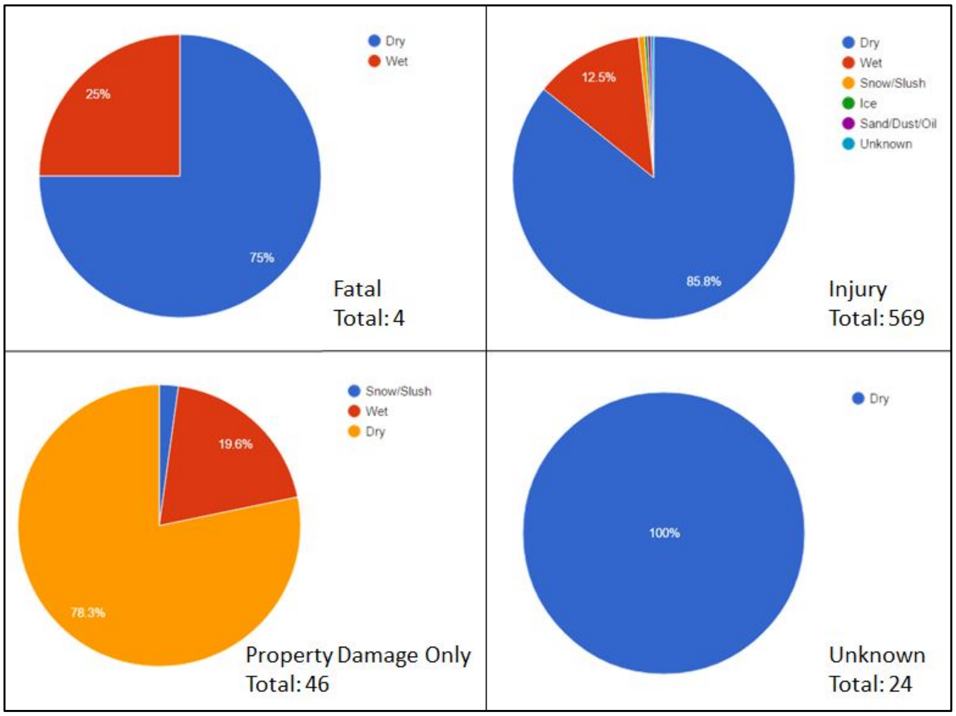
A3: ROAD CONDITION BY SEVERITY



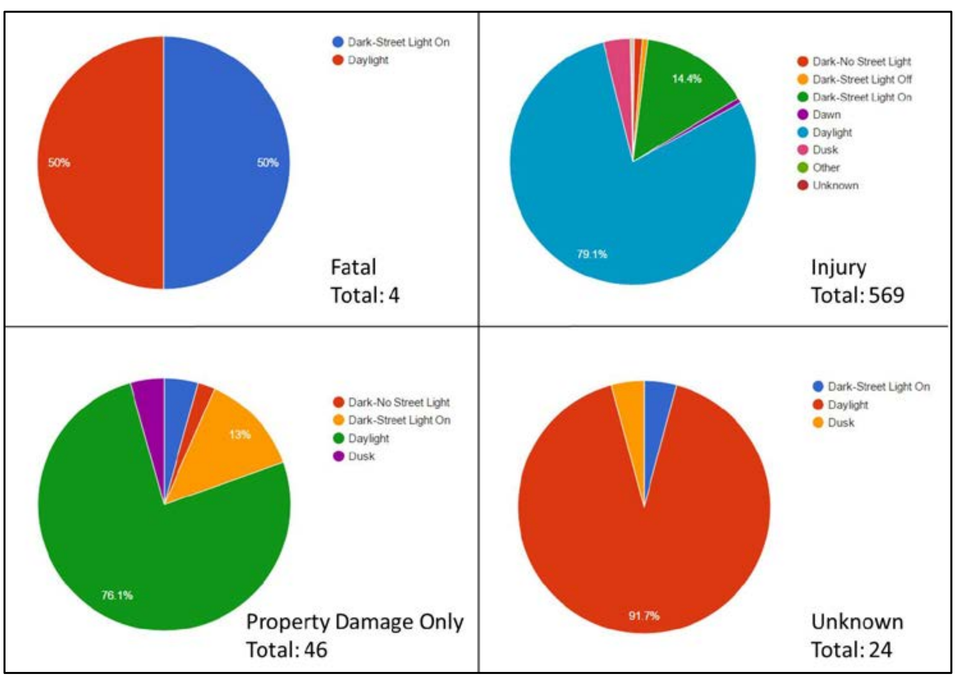
A4: ROAD DESIGN BY SEVERITY



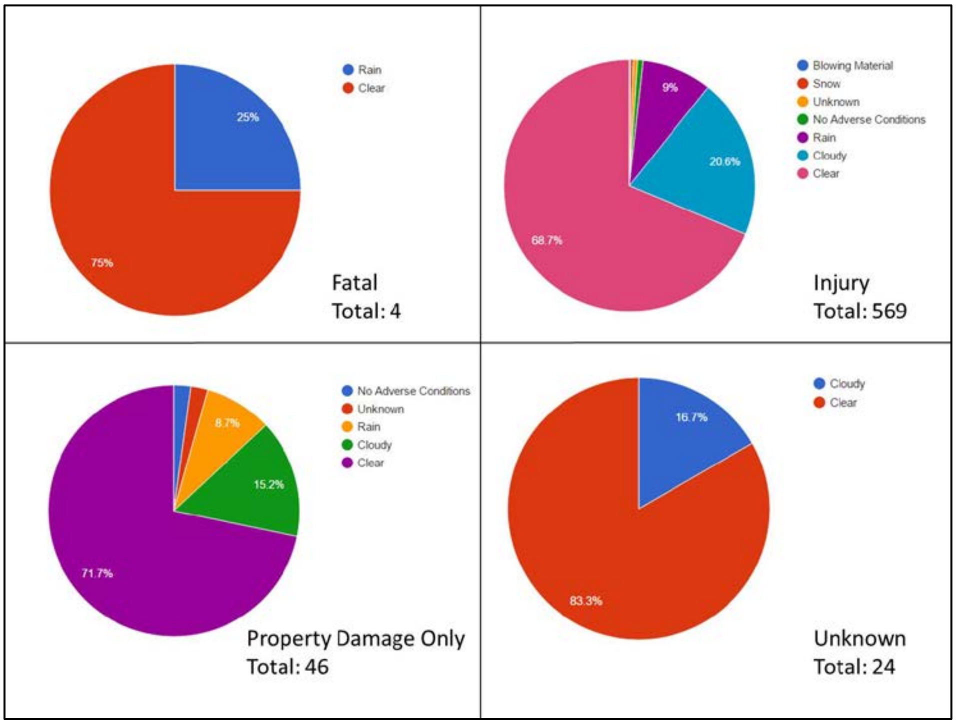
A5: TRAFFIC CONTROL BY SEVERITY



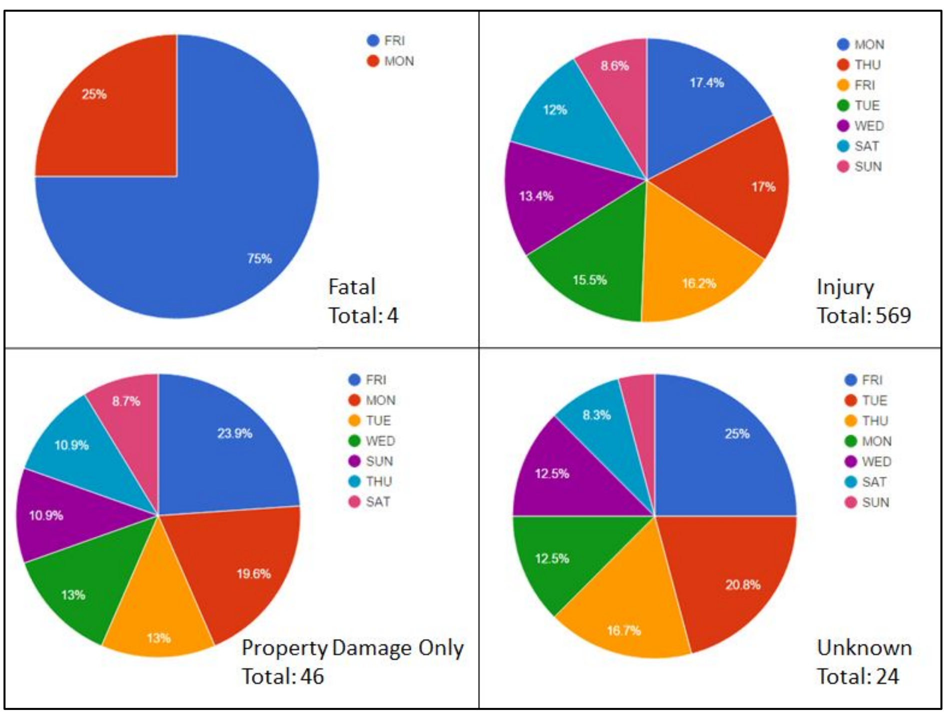
A6: SURFACE CONDITION BY SEVERITY



A7: LIGHTING CONDITION BY SEVERITY



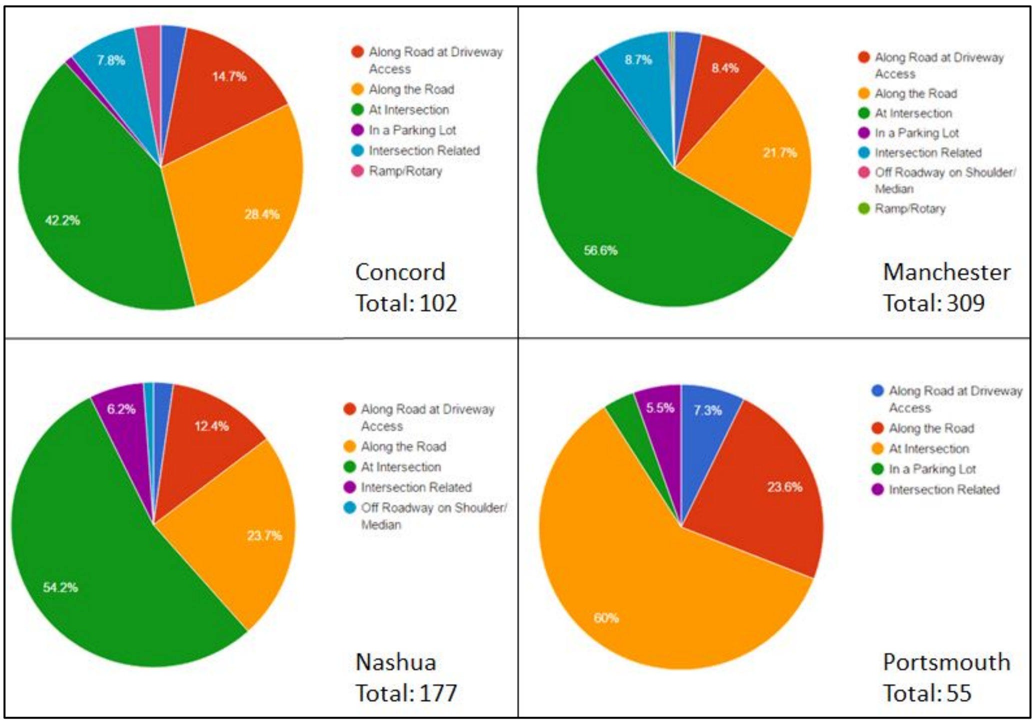
A8: WEATHER BY SEVERITY



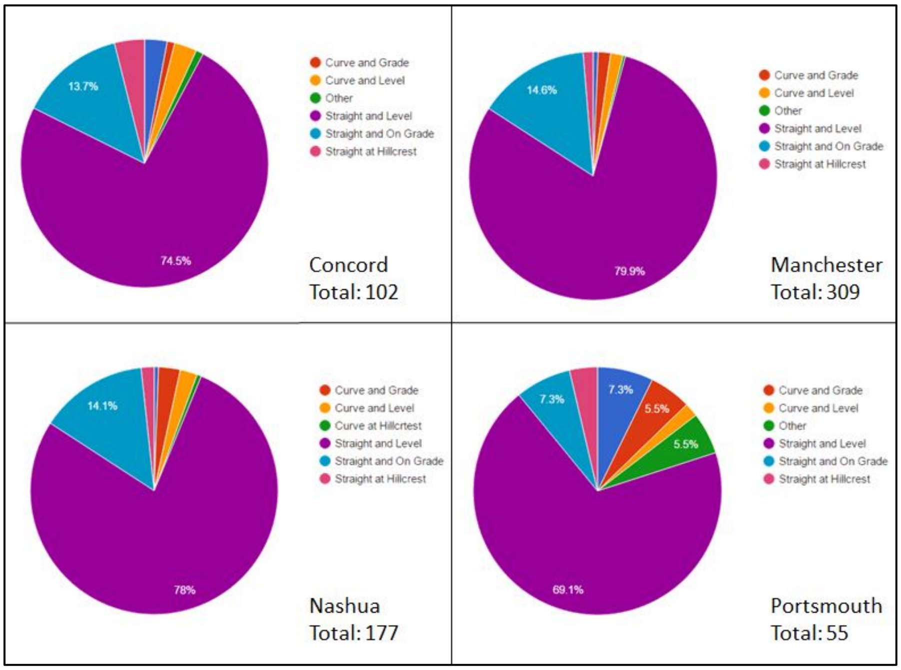
A9: DAY OF COLLISION BY SEVERITY

VARIABLE DISTRIBUTION BY CITY

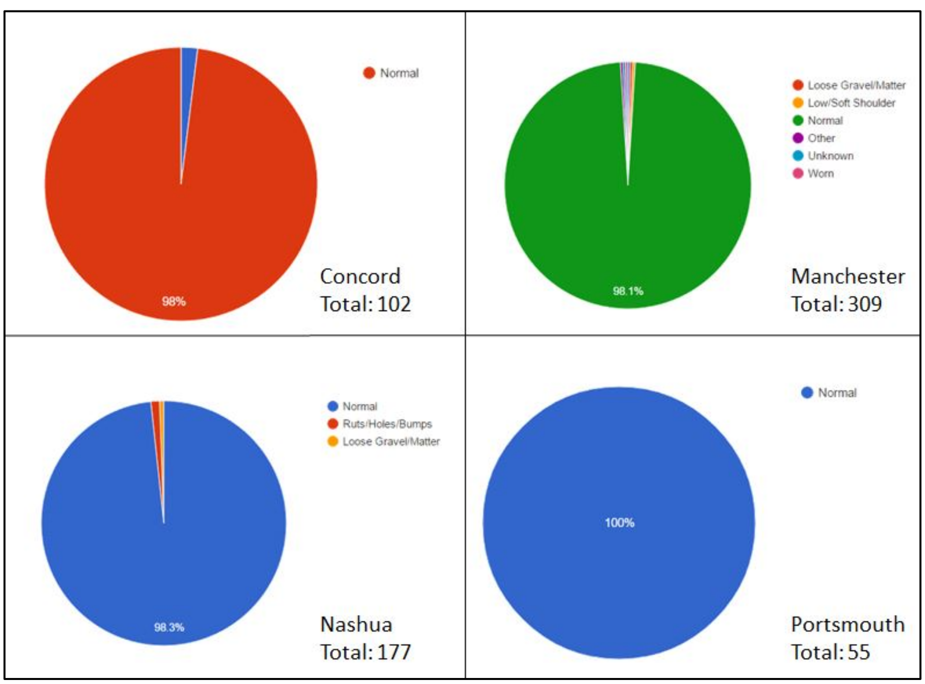
The following figures show the distribution of each variable for each city.



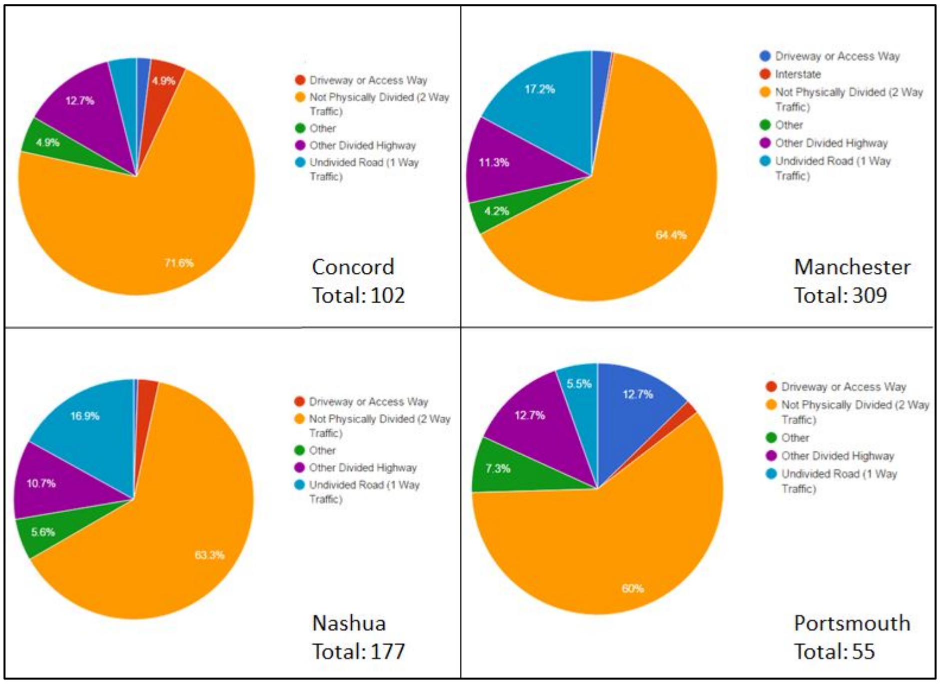
A10: LOCATION OF COLLISION BY CITY



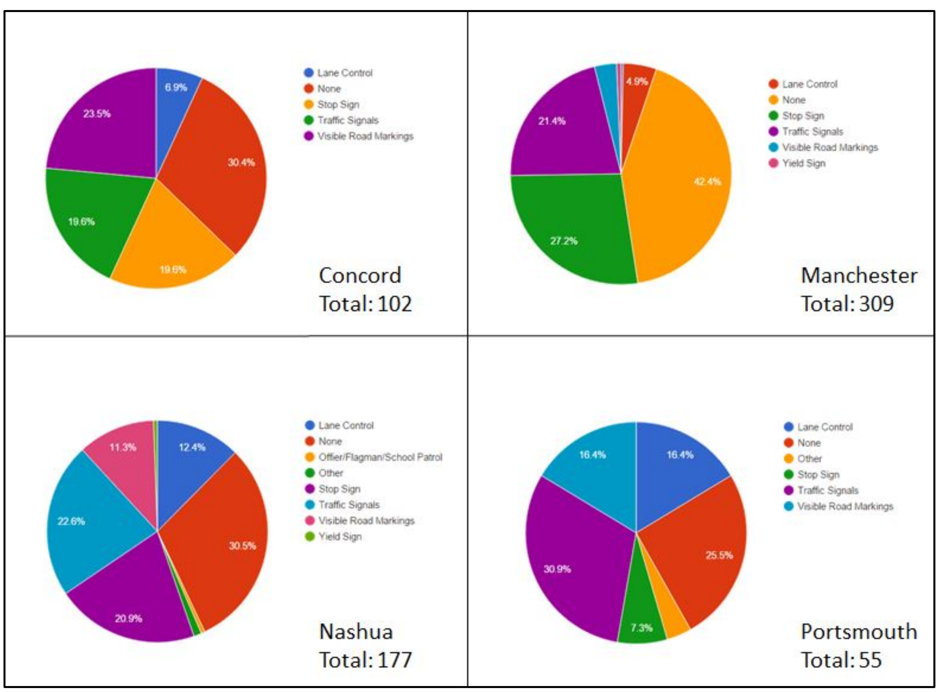
A11: ROAD ALIGNMENT BY CITY



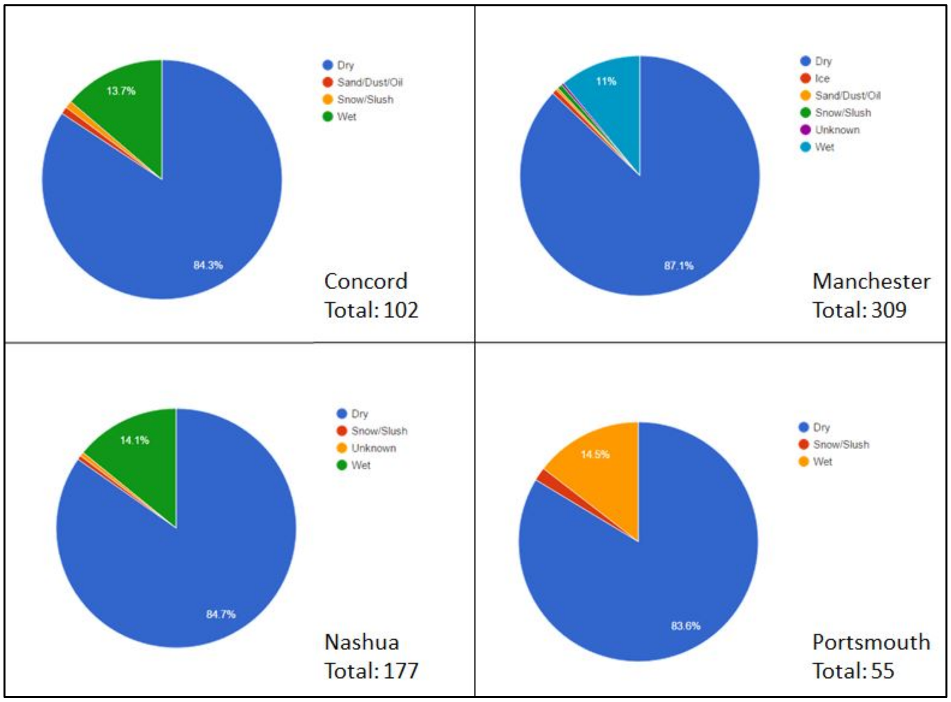
A12: ROAD CONDITION BY CITY



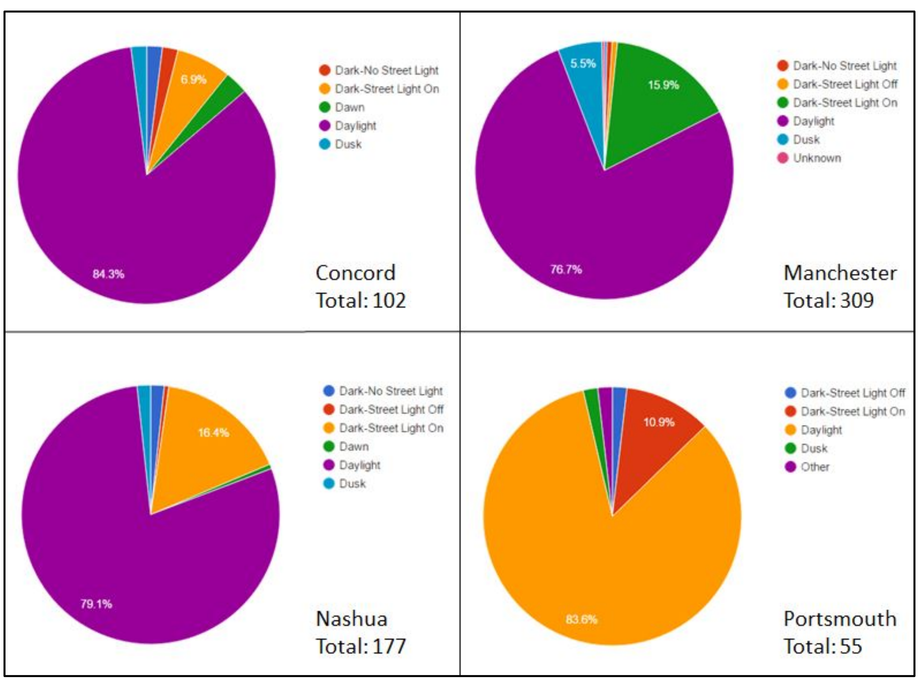
A13: ROAD DESIGN BY CITY



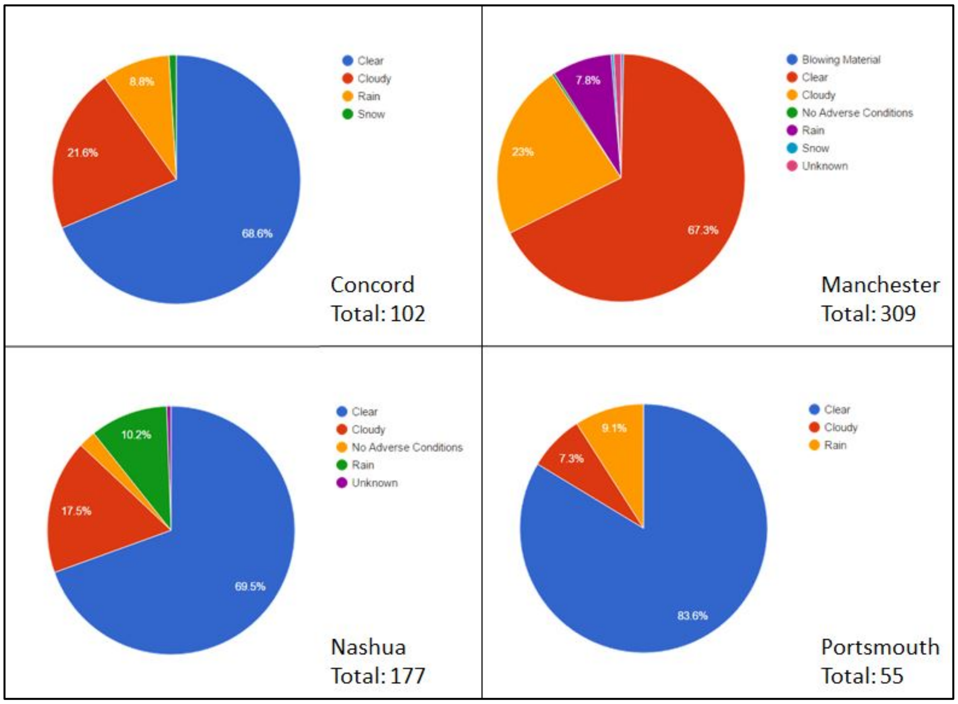
A 14: TRAFFIC CONTROL BY CITY



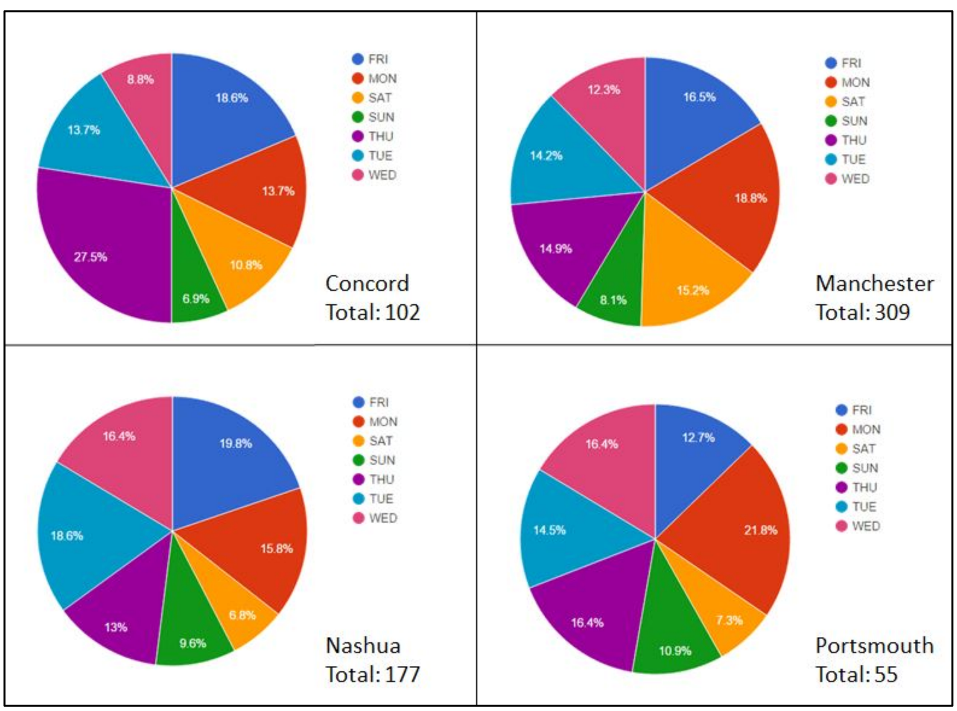
A15: SURFACE CONDITION BY CITY



A16: LIGHTING CONDITION BY CITY



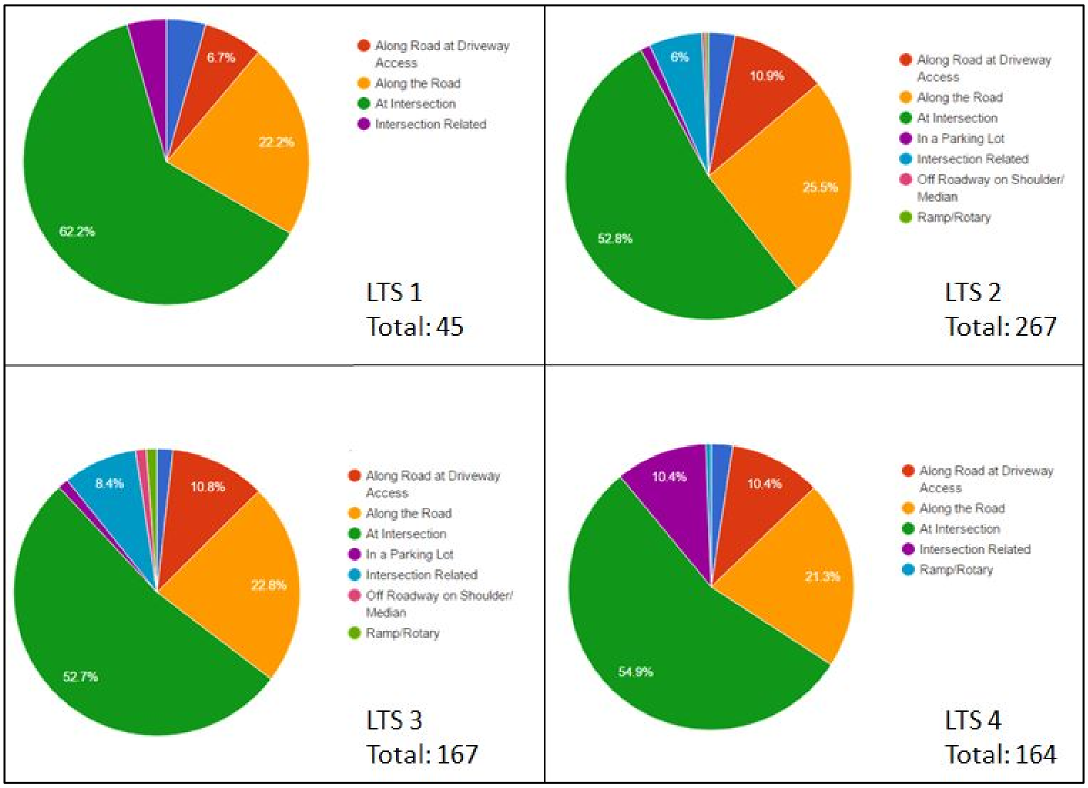
A17: WEATHER BY CITY



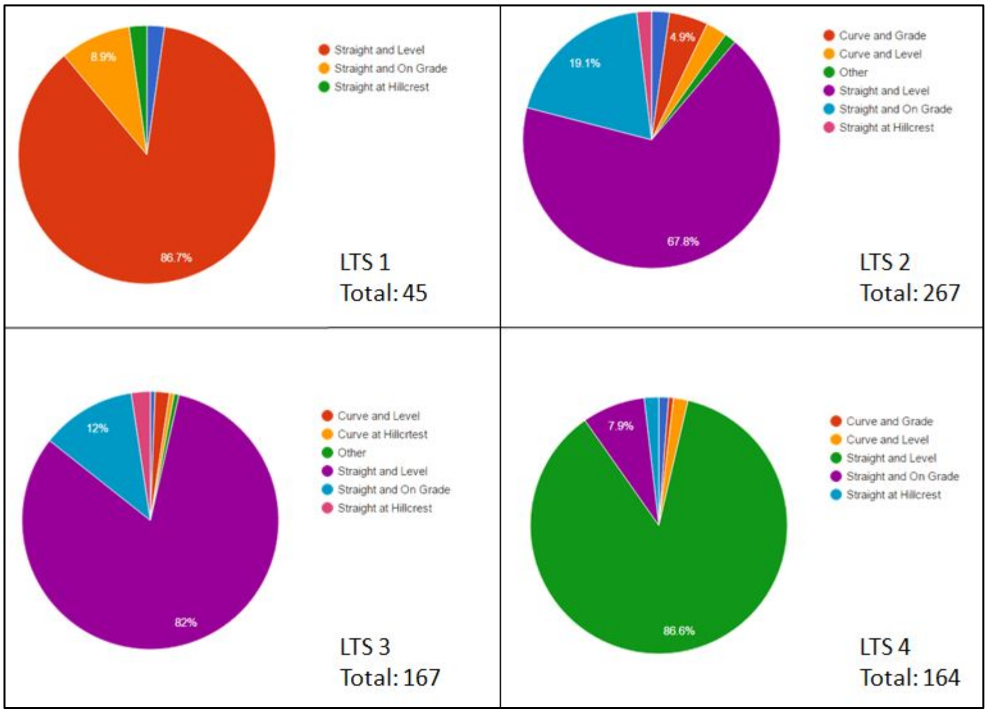
A18: DAY OF COLLISION BY CITY

VARIABLE DISTRIBUTION BY LTS

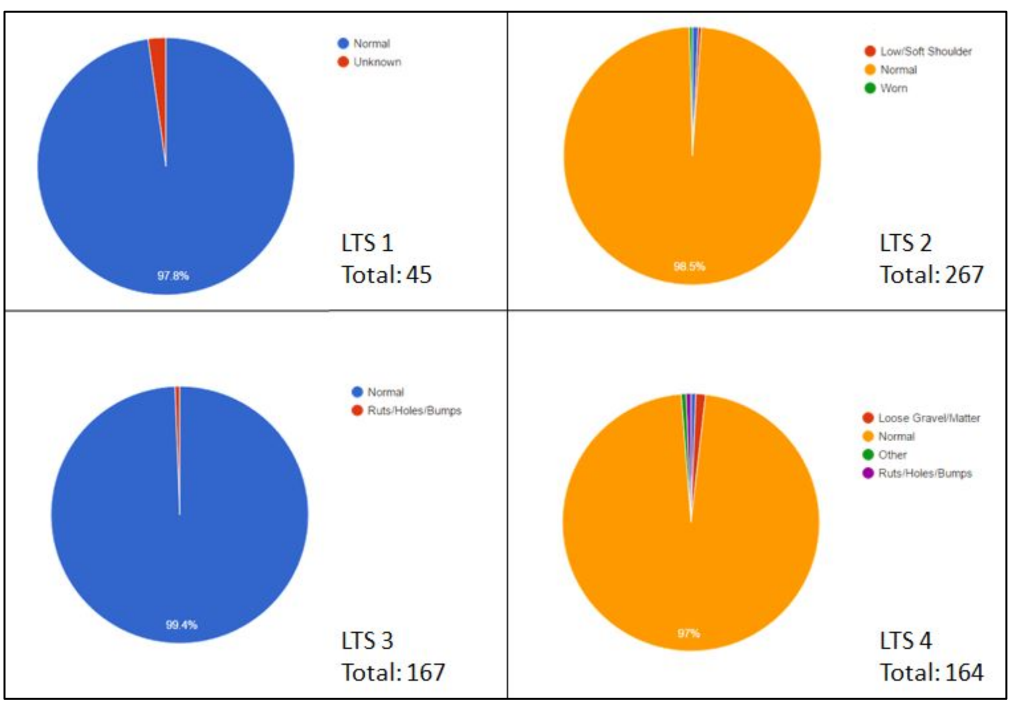
The following figures show the distribution of each variable for each city.



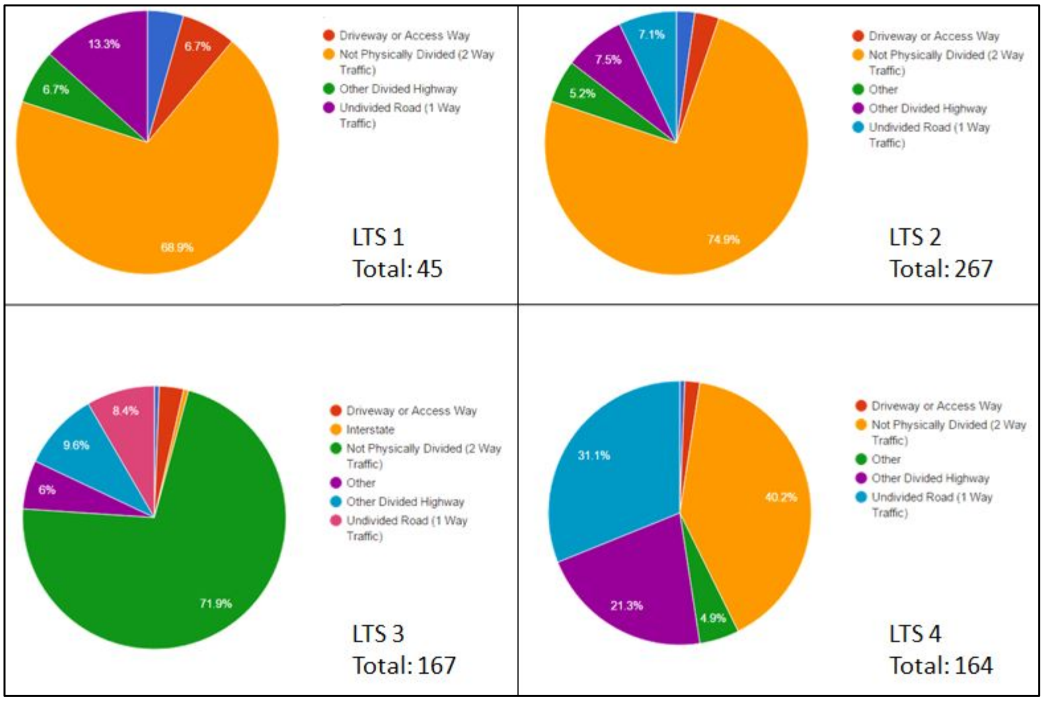
A19: COLLISION LOCATION BY LTS



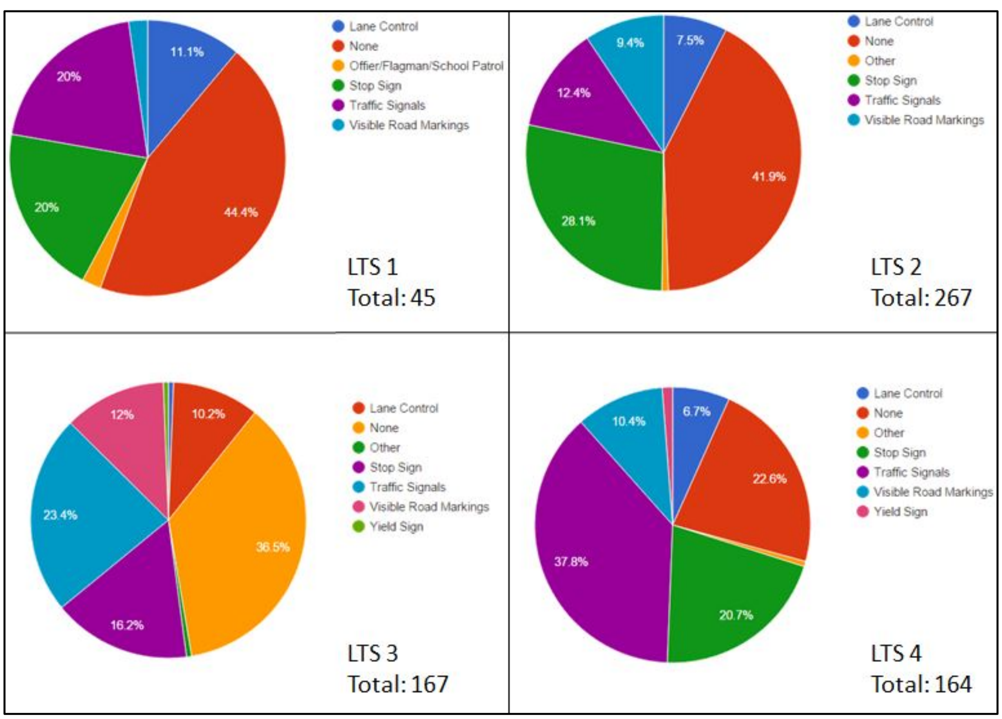
A20: ROAD ALIGNMENT BY LTS



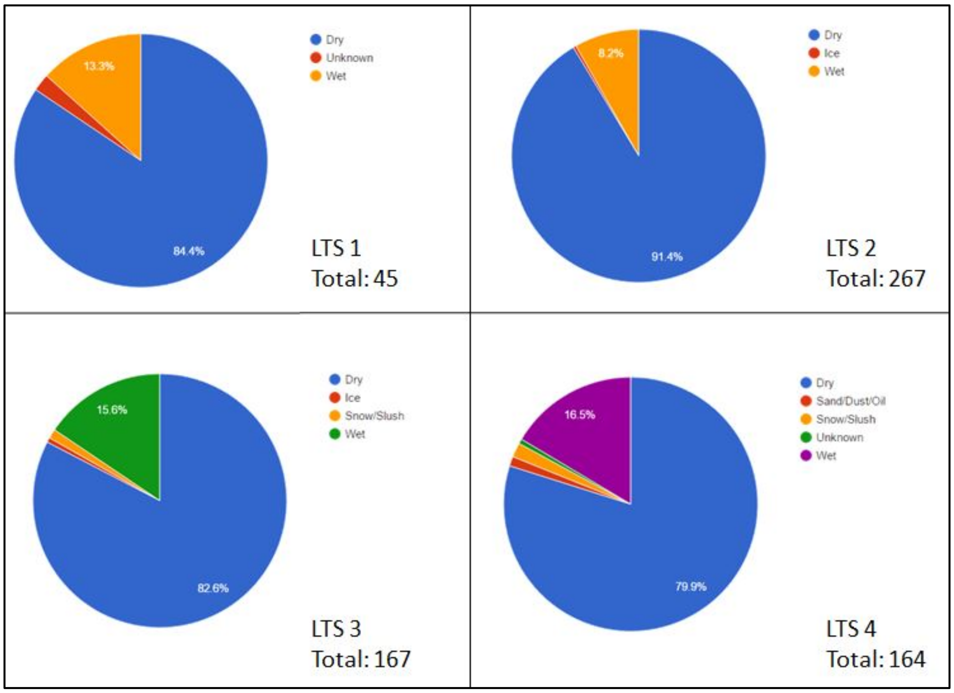
A21: ROAD CONDITION BY LTS



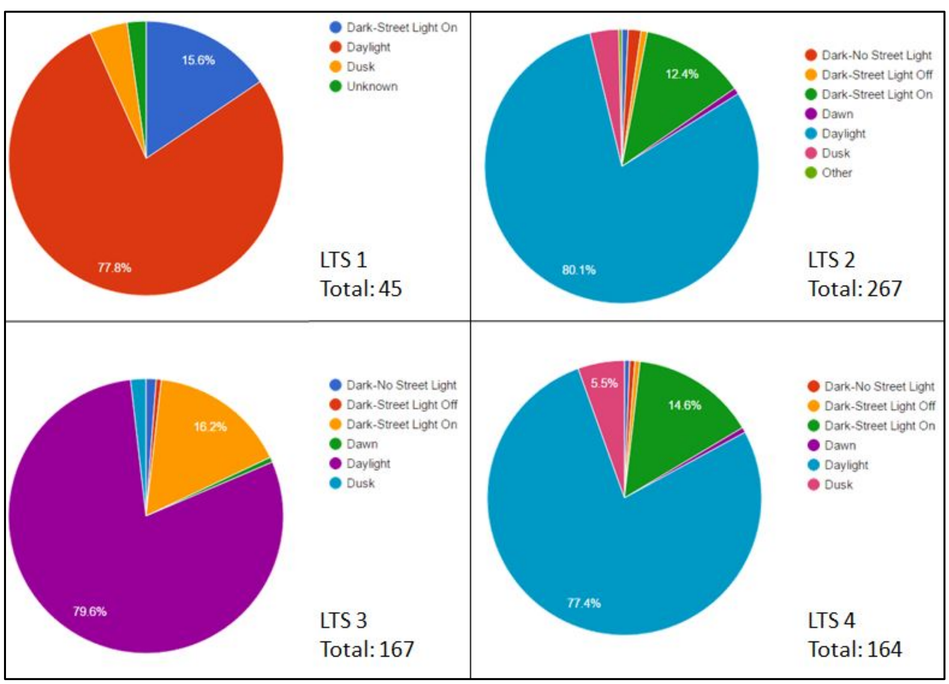
A22: ROAD DESIGN BY LTS



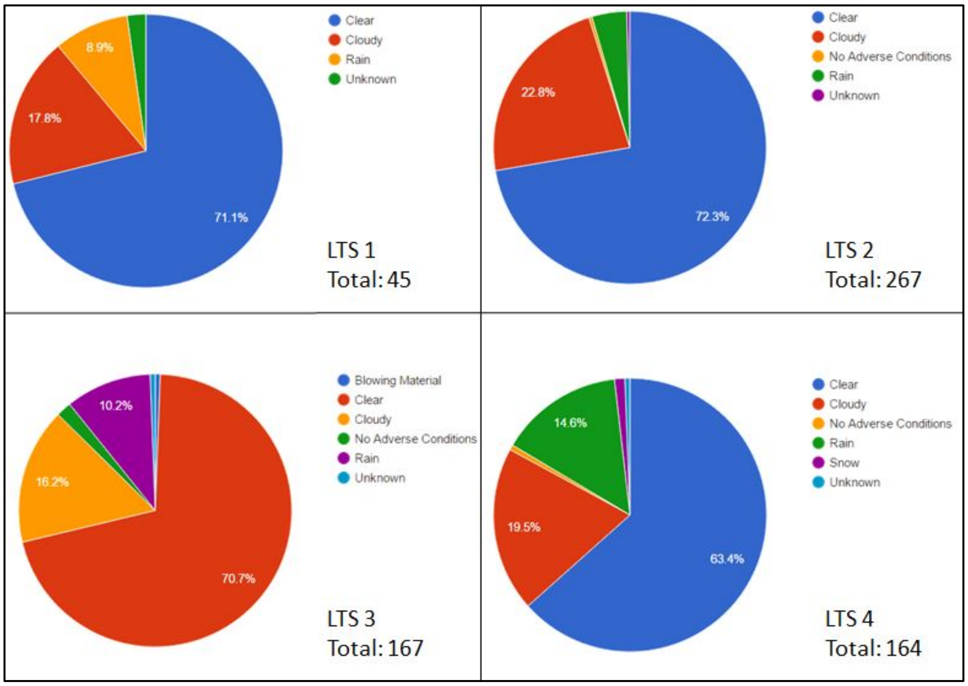
A23: TRAFFIC CONTROL BY LTS



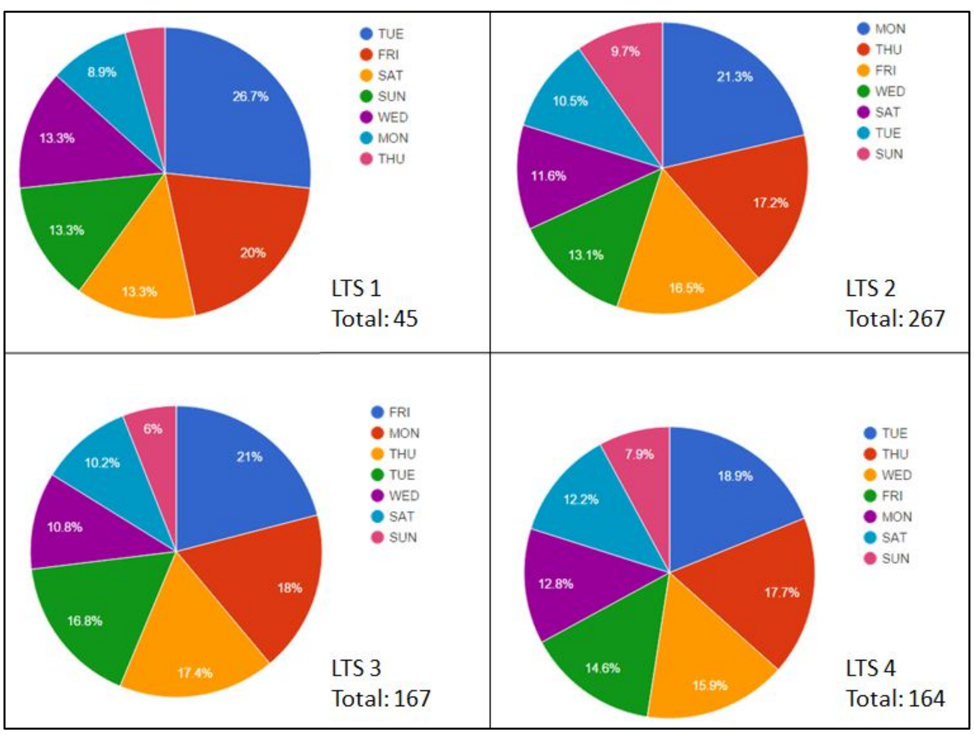
A24: SURFACE CONDITION BY LTS



A25: LIGHTING CONDITION BY LTS



A26: WEATHER BY LTS



A27: DAY OF COLLISION BY LTS