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Motivations for Speeding – Additional Data Analysis

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13. ABSTRACT (Maximum 200 words)

Speeding-related crashes continue to be a serious problem in the United States. A recently completed NHTSA project, *Motivations for Speeding*, collected data to address questions about driver speeding behavior. This naturalistic driving study used 1-Hz GPS units to collect data from 88 drivers in Seattle and 76 drivers in rural Texas to record how fast vehicles traveled on different roadways. Analysis identified four basic patterns of speeding behavior.

The project developed this data set to redefine speeding in terms of speeding episodes and create a new data set for analyses in terms of individual speeding episodes, and examined the influence of situational factors on the different types of speeding. Analyses of the speeding episodes identified types of speeding: speeding that occurs around speed-zone transitions, incidental speeding, casual speeding, cruising speeding, and aggressive speeding. Analyses also identified driver types: Unintentional Speeders, Situational Speeders, Typical Speeders, and Deliberate Speeders. Both types of speeding and driver types occurred across all demographic groups.

Data analyses on the relationships between situational factors and speeding was conducted at a high level due to the lack of available situational data, yielding the following conclusions: (1) general riskiness of different types of speeding was corroborated by the involvement of riskier elements in speeding episodes, (2) anecdotal evidence of location-specific characteristics affecting both the occurrence and non-occurrence of speeding was found, (3) there were indirect indicators that certain aspects of the driving environment affect speeding behavior, and (4) there were clear similarities between types of speeding at both the rural and urban data collection sites.

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EXECUTIVE SUMMARY

Speeding-related crashes continue to be a serious problem in the United States. The proportion of speeding-related fatal crashes has changed little in over a decade. In 2012, 30% of all fatal crashes had speeding as a contributing factor (NCSA, 2014), the same percentage as in 1996 (Liu, Chen, Subramanian, & Utter, 2005). Speeding is a complicated behavior that varies by driver and situation (Richard et al., 2013a). It is also a common behavior, with most drivers reporting that they drive over the speed limit at least some of the time (Schroeder, Kostyniuk, & Mack, 2012). Given the widespread occurrence of speeding and the high toll in injuries and lives lost in speed-related crashes, 10,219 fatalities in 2012 (NCSA, 2014), as well as the high economic costs of speed-related crashes (Blincoe et al., 2014), this is a safety issue that demands a great deal of attention.

The recently completed NHTSA project, *Motivations for Speeding* (Richard et al., 2013a), collected data that can be used to address questions about driver speeding behavior. This was a naturalistic driving study in which 1-Hz Global Positioning System (GPS) data were collected from 88 drivers in Seattle and 76 drivers in rural Texas (College Station) to record how fast vehicles traveled on different roadways. This effort resulted in a rich and unique data set that can provide a wide range of insights into speeding behavior. The current project further developed this data set and conducted additional analyses to expand upon the information already generated from this data set. A key activity was to operationalize speeding in terms of individual Speeding Episodes that capture driving characteristics during a particular speeding event. The specific study objectives in this research were to:

1. Redefine speeding in terms of Speeding Episodes and use the new data to identify underlying types of speeding and Driver Types.
2. Conduct additional data analyses on the relationships between situational factors and speeding.

GENERAL APPROACH

A key goal of the current research was to redefine speeding behavior in terms of holistic speeding events. To support this definition of speeding, time series of GPS driving data were parsed into Free-flow Episodes (FFEs), and Speeding Episodes (SEs), which represent short yet continuous segments or “snippets” of driving time extracted from a trip. Free-flow Episodes are used as a proxy for a driver’s *opportunity* to speed within a trip, and they exclude parts of a trip where a vehicle is stopped, trapped in traffic congestion, slowing to a stop for a traffic control device, etc.—situations in which it would be unlikely that a driver has a chance to speed. Speeding Episodes are used as the primary data element in the analysis of speeding, and they represent an interval of driving in which a vehicle is potentially speeding. In the current study, speeding conceptually represents a risk of getting a speeding ticket more than a clear risk of getting into a speed-related crash. The operational definitions of these data elements were as follows:

- A *Free-Flow Episode* (FFE), which represents the opportunity to speed, occurred when the driver was traveling at or above a threshold set at 5 mph below the posted speed limit. This speed criterion had to be maintained for at least 30 seconds to be included as a FFE.

- A *Speeding Episode (SE)* was defined as continuous driving at or above a threshold set at 10 mph above the posted speed limit. This speed criterion had to be maintained for at least 6 seconds to be included as a SE.

Time-series data were reduced into data structures summarizing trip, FFE, and SE characteristics. Examples of variables included in this reduction include descriptive statistics for speed and acceleration, duration, and percent time on a particular road type. Geographic Information System (GIS) maps of the Seattle and Texas sites were used to obtain posted speed limit, functional class, and other available road network data, which then were linked to driving data. In Seattle, there were a total of 4,754 separate SEs recorded across 6,137 trips with at least one FFE. In Texas, there were a total of 1,376 separate SEs recorded across 4,645 trips with at least one FFE.

ANALYSIS AND RESULTS

The underlying premise in these analyses is that speeding results from qualitatively different types of driving behaviors, or from different speeding choices. In this case, it is possible that SEs may take different forms depending on the underlying motivations or associated behaviors. Thus, a key objective of this project was to identify different types of speeding.

Cluster analyses were conducted to answer specific questions about driver speeding behavior. All analyses described below were conducted on variables calculated using time-series data within individual SEs (e.g., mean speed, total duration, etc.). In addition, cluster analyses were conducted separately for Seattle and rural Texas data because the roadway environments and driving patterns at these locations differed substantially. The specific speeding-behavior questions addressed with the cluster analysis included:

- Is it possible to characterize *types of speeding* based on characteristics of Speeding Episodes?
- Is it possible to classify subtypes of speeders (*Driver Types*) using patterns in their types of speeding?
- To what extent are Driver Types defined by demographics and/or attitudes and beliefs about speeding?

The basic process used to address these questions involved three steps. The first step was to conduct a cluster analysis on select SE variables to divide SEs into groups/types of speeding based on shared characteristics. The second step involved identifying relatively how often each driver engaged in the different types of speeding, thus creating a "speeding profile" for each driver. These speeding profiles were then used as the basis for a second cluster analysis to identify different Driver Types based on similarities in speeding profiles. The final step involved running a Chi-square test on the Driver Types to determine if category membership reflects demographics. In addition to this, patterns in responses to personal inventory items about attitudes and beliefs about speeding were examined for trends across Driver Types.

Seattle Cluster Analyses for Speeding Type

Variables representing different characteristics of SEs (e.g., duration, mean speed, etc.) were entered into a k-means cluster analysis. The most interpretable result was the 6-cluster solution described below:

Cluster 1 - Speeding Up: The characteristics of these SEs are consistent with speeding up that can occur immediately prior to an increase in the posted speed.

Cluster 2 – Speed Drop: The characteristics of these SEs are consistent with drivers slowing down after transitioning to a lower posted-speed zone.

Cluster 3 – Incidental Speeding: This is the most common type of speeding, and it likely represents unintentional or incidental speeding on the part of a driver.

Cluster 4 – Casual Speeding: This type of speeding is similar to Incidental speeding, but differs primarily in degree, with all variables having higher values. It seems to represent a more accepting or casual attitude towards speeding in the situations in which they occur.

Cluster 5 – Cruising Speeding: The defining aspect of this type of speeding is the long duration relative to the other types, akin to drivers "cruising" along a roadway at elevated speeds for a moderate duration.

Cluster 6 – Aggressive Speeding: This type of speeding represents more aggressive and/or riskier driving than other types.

Overall, the cluster analysis was effective at parsing SEs into groups whose members were similar across multiple dimensions. More importantly, the resulting clusters are interpretable.

Seattle Cluster Analysis to Identify Driver Types

A second cluster analysis was conducted to determine if it is possible to classify individuals into different Driver Types with respect to speeding. Table ES-1 below provides the median values for the proportion of each type of speeding by Driver Type.

Table ES-1. Driver Type by type of speeding for Seattle drivers.

Driver Type Label	N	Cluster 1 Speed Up	Cluster 2 Speed Drop	Cluster 3 Incidental	Cluster 4 Casual	Cluster 5 Cruising	Cluster 6 Aggressive
Deliberate	19	4%	4%	46%	33%	3%	5%
Typical	29	2%	3%	65%	25%	2%	0%
Situational	15	16%	3%	53%	3%	0%	0%
Unintentional	18	0%	0%	79%	17%	0%	0%
Average	*20*	*3%*	*2%*	*63%*	*24%*	*2%*	*1%*

The following sections summarize the characteristics of the Driver Types described above and provide the rationale for the labels assigned to each Driver Type.

Driver Type 1 – Deliberate: Drivers in this group had relatively more Casual, Cruising, and Aggressive SEs, but fewer Incidental SEs. Moreover, the Cruising and Aggressive types of speeding are the ones that most likely represent deliberate attempts to speed, and at relatively high speeds as well. Individuals in this group also had substantially more SEs than those in other groups. This group seemed to represent drivers that are most willing to engage in deliberate or intentional speeding behavior (i.e., with longer durations and at higher speeds).

Driver Type 2 – Typical Speeders: Drivers in this group are labeled as the Typical Driver Type primarily because, as Table 8 shows, the distribution of SEs closely matched the average distribution across all Driver Types. This group contained the largest number of drivers. Individuals in this Driver Type also occupied a middle range in terms of their speeding profiles and the overall frequency of SEs.

Driver Type 3 – Situational Speeders: This group is overrepresented in terms of the Speeding Up type of speeding (16% vs 5% on average) and, like the drivers in the Deliberate Driver Type, they have proportionately less Incidental speeding. The Speeding Up type occurred in specific situations, such as in advance of speed limit increases, and in sections where there seemed to be a mismatch between the roadway cues and the posted speed limit.

Driver Type 4 – Unintentional Speeders: In contrast to the other Driver Types, this last group was made up of drivers that mostly engaged in Incidental speeding, combined with a small amount of Casual speeding. The other types of speeding were uncommon in this group.

Extent to which Driver Types were Defined by Demographics

Another analysis was conducted on Seattle SE data to determine the extent to which Driver Types were defined by demographics. The previous cluster analyses made it possible to assign a Driver Type (using cluster membership) to individual drivers based upon the types of speeding events that they incurred (see Table ES-2).

Table ES-2. Demographic makeup of Driver Types in Seattle.

Driver Type	Older Female	Older Male	Younger Female	Younger Male	Total	Composition
Deliberate	4	4	4	7	19	More young males
Typical	5	7	11	6	29	More young females
Situational	5	6	2	2	15	More older drivers
Unintentional	5	6	4	3	18	More older drivers
Total	*19*	*23*	*21*	*18*	*81*	

A chi-squared test was run on the results to determine if any significant differences in group membership could be found between demographic groups. The chi-squared test with 9 degrees of freedom had a p-value of less than 0.001, which indicated that a significant difference was found in cluster memberships across demographic groups. Situational and Unintentional Driver Types had the highest frequency of Older drivers (male and female), while Typical Driver types were more frequently Younger females and Deliberate Driver Types were more frequently Younger Males; however, this difference was a matter of degree. All demographic groups were found in each driver type.

Trends in Beliefs and Attitudes across Driver Types

Participants in the original *Motivations for Speeding* study completed multiple personal inventory questions about their attitudes, motivations, and beliefs towards speeding (Richard et al., 2013b). Responses to these questions provided a way to obtain further insight about how the Driver Type groups may differ. Mean values for each question were calculated for all members of a particular Driver Type. The objective was to identify patterns in responses that might provide qualitative insight about how the Driver Types differed in terms of their attitudes and beliefs about speeding. Table ES-3 below summarizes the trends observed across questions.

Table ES-3. Trends across Driver Type in responses to personal inventory questions related to behaviors, beliefs, and attitudes towards speeding.

Question Type	Driver-Type Trends
Self-reported driving behaviors	*Deliberate* driver-types more frequently engage in riskier behaviors.
Attitudes towards not speeding	*Deliberate* driver-types are the least positive; *Unintentional* are the most positive on some questions.
Situational factors affecting speeding	*Deliberate* driver-types are the most likely to speed; *Unintentional* driver-types are the most likely to avoid speeding.
Social norms towards not speeding	*Unintentional* driver-types most likely to be influenced by others to not speed.
Control beliefs and intentions about not speeding	*Deliberate* driver-types are the least agreeable regarding not speeding; *Unintentional* driver-types are the most agreeable.
Self-reported speed	*Deliberate* driver-types reported faster speeds on each road type.
Most questions	*Typical* and *Situational* Driver Types generally overlapped each other.

A few consistent patterns occurred across the different types of questions in the surveys. The dominant trend was that responses from the Deliberate speeding driver group were on the aggressive end of the spectrum relative to other Driver Types. This pattern was evident for almost all questions. Another less prominent trend that occurred within certain sets of questions was that Unintentional Driver Types were on the more conservative/safer end of the response spectrum. Neither of these trends were surprising given the types of speeding that defined these Driver Types. With regard to the Typical and Situational Driver Types, they were usually not different from the Unintentional Driver Type, and they sometimes fell in between the Deliberate and Unintentional Driver Types in their responses to these questions. For almost all questions, differences between Typical and Situational Driver Types were minimal.

Texas Cluster Analyses for Type of Speeding

The data from Texas were analyzed in a manner parallel to that of the Seattle data. Most of the clusters identified for the Texas data were comparable to particular types of speeding clusters in Seattle. The only exception was Cluster 6. Rather than representing an Aggressive type of speeding, this cluster (Small Increase) seems to represent a shortened version of the Speeding Up cluster. Note that the Driver Type cluster analysis was not run in Texas. This is because over a quarter of Texas drivers had an insufficient number of SEs to compute the proportional distribution of types of speeding for those drivers.

Situational Analysis

To obtain a better understanding of situational aspects of speeding, we used road-network data to examine where different types of Speeding Episodes occurred in both Seattle and Texas. Specifically, SEs were mapped to identify the locations where SEs occurred more frequently to determine if there were roadway characteristics that systematically encouraged different types of speeding (identified as speeding "hot spots"). To do so, we employed an exploratory approach of using the proportion of SEs relative to FFEs at various locations to develop speeding "heat maps." The goal of this analysis was to determine if there were patterns with respect to where SEs occurred that could provide insight into the different speeding types identified in the cluster analysis. The findings regarding the different types of speeding are summarized below.

Speeding Up: These SEs mostly occurred on arterials and were tied to transition zones or roads with speed limit changes that are incongruent with perceived design speed.

Speed Drop: These SEs mostly occurred on arterials and were tied to speed limit transition zones.

Incidental: These SEs occurred across widespread regions of the road network. There were clear "hot spots," which may indicate locations in which the driving environment encouraged speeding, even when drivers were not intending to speed.

Casual: These SEs were slightly less widespread than Incidental speeding, but with fewer "hot spots."

Cruising: The majority of the SEs in the Cruising cluster occurred on the freeways and state highways.

Aggressive (Seattle Only): These SEs were distributed throughout the map with only a few "hot spots." This type of speeding also had the highest prevalence of riskier speeding characteristics, such as exceeding the speed limit by 20 mph and more speeding at night. The link between roadway characteristics and SEs seemed to be the weakest for Aggressive SEs, which suggested that driver-specific factors may play a more important role in this type of speeding.

Small Increase (Texas Only): These SEs were mostly tied to speed limit transition zones on lower-speed roads.

SUMMARY AND CONCLUSIONS

There were two primary objectives in this project. The first was to redefine speeding in terms of Speeding Episodes and use the new data to identify underlying types of speeding and Driver Types. The second objective was to conduct additional data analyses on the relationships between situational factors and speeding. Overall, we were successful in accomplishing the first objective in full; however, limited data on situational factors permitted us to only address the second objective at a high level. The key conclusions are described below.

The Cluster Analysis Approach was Useful for Identifying Types of Speeding

A primary objective in this project was to advance beyond the current notions of speeding as a monolithic and aggregate concept and develop a more nuanced understanding of the behavioral factors that comprise speeding. In this regard, the basic cluster analysis approach was quite successful. Specifically, it carved up the large number of individual Speeding Episodes (SEs) into sub-groups that had characteristics that could be meaningfully interpreted, and that were largely distinct from each other. The primary speeding types included the following:

1) *Speeding that Occurs around Speed-Zone Transitions*: This includes Speeding Up, Speed Drop, and Small Increase types of speeding observed in both Seattle and Texas. These SEs typically have short durations, a high maximum speed, and they occur on lower-speed roads. In these cases, the roadway environment in the lower posted speed segment may be similar enough to the higher posted speed limit segment that it supports faster driving.

2) *Incidental Speeding*: This is the most common type of speeding, and it involves low-exceedance, short-duration episodes that more likely represented the upper bound normal speed maintenance behavior, as opposed to a separate speeding behavior.

3) *Casual Speeding*: This is a common type of speeding. Although it is similar to Incidental speeding, it involved speeds that were high enough that drivers were likely aware that they were speeding. However, the durations were relatively brief, which suggests that drivers might not persist in this type of speeding for long (e.g., it could include passing behavior).

4) *Cruising Speeding*: The defining characteristic of this type of speeding was the relatively long duration. While the longer duration increased a driver's exposure to safety risk, this type of speeding was more likely to occur on controlled-access, high-speed roads, which reduced the likelihood of unexpected hazards. Another notable aspect of this type of speeding is that only a subset of drivers in Seattle engaged in this type of speeding. Specifically, the subset of drivers that had the highest prevalence of Cruising speeding (i.e., 8-25% of their trips) was limited to 10 drivers, representing all demographic groups

5) *Aggressive Speeding*: This type of speeding was characterized by relatively high speed exceedance, moderate duration, and a high level of speed variability. This cluster only occurred in Seattle and it generally encompassed riskier aspects of speeding than the other clusters. Similar to the Cruising speeding type, the subset of drivers that had the highest prevalence of Aggressive speeding (i.e., 15-50% of their trips) was limited to 10 drivers, representing all demographic groups.

The types of speeding listed above were also remarkably consistent across drivers and locations, with five of the six clusters identifiable in both Seattle and Texas.

Cluster Analysis to Identify Driver Types Suggest that these Types were not Defined Exclusively by Driver Demographics

The cluster analysis conducted using individual drivers' speeding profiles was successful in identifying four different Driver Types, including:

1) *Deliberate Speeders*: Drivers in this group averaged a higher proportion of Casual and Aggressive SEs, but lower levels of Incidental SEs than other groups. Individuals in this group also had substantially more SEs than those in other groups. In general, these drivers tended to engage in the more aggressive and deliberate types of speeding substantially more than other Driver Types. Deliberate speeders also reported engaging in risky driving behaviors more frequently than others, and they had the most favorable attitudes towards speeding.

2) *Typical Speeders*: The distribution of SEs within this group basically matched the distribution across all drivers. The Typical Driver Type was also comprised of the largest number of drivers, and Casual speeding was relatively more common in this group. Individuals in this Driver Type also occupied a middle range in terms of average speeding profiles and frequency of SEs.

3) *Situational Speeders*: This type was distinct in that these drivers had a much higher proportion of the Speeding Up type of speeding than other Driver Types, and they engaged in minimal amounts of Aggressive and Cruising speeding. Overall, this group only engaged in a little more speeding than the Unintentional Driver Type, but they did not share their favorable views regarding not speeding.

4) *Unintentional Speeders*: This group was comprised primarily of drivers that engaged mostly in Incidental speeding and some Casual speeding, but almost none of the other types of speeding. These drivers also had attitudes and beliefs that were the most favorable towards not speeding, and they likely represent non-speeders.

Analyses on the demographic composition of the groups listed above indicated that there were significant differences across the groups. However, the groups differed largely in terms of degree, since all of the demographic categories appeared in each Driver-Type cluster. Further examination of responses to personal inventory questions showed clear trends regarding attitudes and beliefs about speeding were observed across the Driver Types.

Additional Data Analyses on the Relationships between Situational Factors and Speeding

The second objective in this project was to conduct additional data analyses on the relationships between situational factors and speeding. A challenge for meeting this objective was the lack of situational data available to conduct the corresponding analyses. While we were able to address this objective at a high level, there are many questions that remained unanswered. Some of the key findings from the situational analyses are described below.

The first finding from the situational analysis was that the general "riskiness" of different types of speeding was corroborated by the involvement of riskier elements in Speeding Episodes. This analysis was done by examining how the types of speeding differed in terms of the best proxies for safety risk available in the data set (e.g., exceeding posted speed by more than 20 mph, nighttime speeding, etc.). In Seattle, the Aggressive and Cruising speeding types were associated with relatively higher prevalence of risky conditions, and longer exposure durations. In contrast, the Incidental and Casual speeding types were the least likely to involve risky aspects. The general pattern was similar in Texas, except that there was no Aggressive speeding type found there, so the Cruising cluster appeared to be the riskiest type of speeding in the Texas sample of drivers.

The second finding generated from the situational analysis was that there was at least anecdotal evidence of location-specific characteristics affecting both the occurrence and non-occurrence of speeding. Locations with posted speed changes, but where the roadway characteristics remained the same across zones, were a common example of where speeding occurred more often. Other locations where we commonly observed higher levels of speeding included those in which the roadway was more open and provided better separations from hazards, including divided roadways and sidewalks that were set apart from the curb.

Implications for Safety Countermeasures

A key practical implication that stems from this research is that there is converging evidence that the Deliberate speeder group represents a Driver Type that is notably distinct from other groups. In particular, their speeding behaviors are different in that they speed much more frequently and they tend to engage in the more aggressive and deliberate types of speeding, substantially more than other Driver Types. Moreover, individuals in the Deliberate Driver Type also report engaging in risky driving behaviors more frequently than others, and they have the most favorable attitudes towards speeding. The distinctiveness of the Deliberate Driver Type leads to an important practical implication, which is the possibility of specifically directing safety campaigns and countermeasures towards this group. Because their behaviors and attitudes are outside the norm, they can be identified both by their on-road behavior and by using personal inventory items, which may be a practical way to identify drivers from this group. This is also the most critical group to focus on because they engage in the most aggressive type of speeding, likely in conjunction with other risky driving behaviors. Therefore, changing their behavior may have disproportionately large benefits in terms of reducing speeding-related crashes.

A related implication pertains to the different types of speeding identified. Some of the analyses suggested that the relative riskiness of the types of speeding may differ. In particular, the Aggressive type in Seattle and Cruising type in Texas more frequently have characteristics that may increase crash risk in comparison to Incidental or even the Casual types of speeding. Further research is needed to more thoroughly characterize each type. However, if it becomes possible to identify distinct speeding behavior types that are linked to increased crash risk, then it opens up the possibility of making those types of speeding an enforcement priority, or more efficiently deploying resources to specifically target those behaviors, rather than the types of speeding that are less dangerous. This could be particularly effective if it is possible to determine where and when the most dangerous types of speeding are most likely to occur.

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List of Acronyms and Abbreviations

FFE	Free-flow Episode
FM	Farm-to-Market
GIS	Geographic Information System
GPS	Global Positioning System
IRB	Institutional Review Board
mph	Miles Per Hour
NHTSA	National Highway Traffic Safety Administration
PS	Posted Speed
SE	Speeding Episode
SHRP2	Strategic Highway Research Program
TS	Travel Speed

BACKGROUND

Speeding-related crashes[1] continue to be a serious problem in the United States, and the proportion of speeding-related fatal crashes has changed little in over a decade. In 2012, 30% of all fatal crashes had speeding as a contributing factor (NCSA, 2014), the same percentage as in 1996 (Liu, Chen, Subramanian, & Utter, 2005). Speeding is a complicated behavior that varies by driver and situation (Richard et al., 2013a). It is also a common behavior, with most drivers reporting that they drive over the speed limit at least some of the time. In the National Highway Traffic Safety Administration's (NHTSA) *2011 National Survey of Speeding Attitudes and Behaviors*, when asked how often they drove 10 or 15 miles per hour over the posted speed limit, over half of the respondents (52%) reported having driven 15 mph over the speed limit on multi-lane divided highways, over one-third (36%) reported having driven 15 mph over the posted speed limit on two-lane roads, and 36% also reported having driven 10 mph over the posted limit on neighborhood or residential streets (Schroeder, Kostyniuk, & Mack, 2012). Nine percent of those surveyed reported having been stopped by the police for speeding in the previous year, and eight percent reported receiving a speeding ticket through the mail for a violation recorded by a speed camera (Schroeder et al., 2012). Given the widespread occurrence of speeding and the high toll in injuries and lives lost in speed-related crashes, 10,219 fatalities in 2012 (NCSA, 2014), as well as the high economic costs of speed-related crashes, which was estimated at $59 billion in economic costs and $210 billion in comprehensive costs in 2010 (Blincoe et al., 2014), this is a safety issue that demands a great deal of attention.

The recently completed NHTSA project, *Motivations for Speeding* (Richard et al., 2013a), collected data that can be used to address questions about driver speeding behavior. This was a naturalistic driving study in which 1-Hz Global Positioning System (GPS) data were collected from 88 drivers in Seattle and 76 drivers in rural Texas (College Station) to record how fast vehicles traveled on different roadways. This study yielded important new insights into speeding behavior, such as identifying four basic speeding types (*incidental* speeding, *regular* speeding but in small amounts per trip, *occasional* speeding but in large amounts for these trips, and *habitual* speeding). The *Motivations for Speeding* project also provided a better understanding of the complexity of speeding behavior. This included findings showing the variation of speeding patterns across different road types, some of which were significantly associated with psychological factors.

However, there were some practical constraints in the *Motivations for Speeding* study that limited the information that could be gleaned from this dataset. In particular, the definition of "speeding" employed in that study was operationalized in a way that was practical and which supported the analyses, but which did not fully capture the dynamics of speeding events. Essentially, trips were segmented into successive 30-second epochs and speeding was counted if it occurred at any time within that epoch. Although this approach was effective for identifying predictors of speeding, it was less effective for identifying different types of speeding. The basic problem was that the epochs did not adequately capture the fundamental characteristics of speeding events (i.e., duration, speed profile, etc.) because the fixed 30-second duration

[1] NHTSA considers a crash to be speeding-related if the driver was charged with a speeding-related offense or if an officer indicated that racing, driving too fast for conditions, or exceeding the posted speed limit was a contributing factor in the crash.

overlapped imprecisely with speeding behavior that varied in terms of when it began and how long it lasted. Thus, the same speeding behavior was sometimes divided across multiple epochs, or only encompassed as a small part of one epoch. Consequently, the findings from analyses conducted to identify different types of speeding yielded an incomplete picture of the basic types of speeding.

The alternative approach, used in the analyses conducted for the current study, involved constructing a new data set based on Speeding Episodes (SEs), rather than fixed 30-second driving epochs. The new approach involved tracking the points at which: 1) the driver first exceeds the speeding thresholds, then 2) drops below it (for a minimum amount of time), which marked the start and end points of an SE. This approach provided information about the duration of a Speeding Episode, in addition to other useful characteristics, such as maximum and average speed, acceleration profile and speed variability.

The original *Motivations for Speeding* project produced a rich and unique data set that can provide a wide range of insights into speeding behavior. The current project further developed this data set and conducted additional analyses to expand upon the information already generated from this data set. A key activity was to operationalize speeding as Speeding Episodes that are more holistic. This new data set facilitated analyses to identify underlying types of speeding and Driver Types, in addition to examining the influence of situational factors on the different types of speeding. The specific study objectives in this project are described below.

STUDY OBJECTIVES

The purpose of this research is to use existing data from the *Motivations for Speeding* project to:

1. Redefine speeding in terms of Speeding Episodes and use the new data to identify underlying types of speeding and Driver Types.
2. Conduct additional data analyses on the relationships between situational factors and speeding.

OVERVIEW OF THE REPORT

This report consists of several sections, described below:

General Approach: This section provides a high-level description of how the original *Motivations for Speeding* driving data were processed and combined with GIS map data for this study.

Analysis and Results: This section summarizes how the data were analyzed and describes the: 1) results of the descriptive analyses to characterize the data, 2) cluster analyses investigating types of speeding and driver types, and 3) analyses of situational factors.

Summary and Conclusions: This section summarizes the overall findings of the project and describes the key conclusions that arise from the analyses.

Appendix A: Appendix A contains maps showing the road networks and key roadways by functional class within the data collection regions.

GENERAL APPROACH

This section provides a high-level overview of the general approach used to prepare the data for analysis. The reports describing the original *Motivations for Speeding* project provide details about how data were collected over a 23 week period for the 88 drivers in Seattle and 76 drivers in the College Station area of Texas (Richard et al., 2013a, 2013b).

A key goal of the current research was to redefine speeding behavior in terms of Speeding Episodes, rather than individual trips, as was done in the original *Motivations for Speeding* effort. To achieve this objective, two separate analyses were performed: a Speeding Episode analysis and an analysis of situational driving factors. The first analysis was comprised of a cluster analysis that examined the characteristics of each Speeding Episode to identify types of speeding and then different Driver Types. The second analysis used geospatial data to analyze situational factors—such as time of day and road functional class—that potentially influenced drivers' speed choices. The GPS data collected in *Motivations for Speeding* were processed into two types of data structures to support each analysis. Those data structures included: 1) data reductions of time series data for performing the cluster analysis, and 2) geospatial data for presentation and analysis using Geographic Information System (GIS) software.

To support this definition of speeding, time series of GPS driving data were parsed into Free-flow Episodes (FFEs) and Speeding Episodes (SEs), which represent short yet continuous segments or "snippets" of driving time extracted from a trip. Free-flow Episodes were used as a proxy for a driver's *opportunity* to speed within a trip. FFEs excluded parts of a trip where a vehicle was stopped, trapped in traffic congestion, slowing to a stop for a traffic control device, etc.—situations in which it would be unlikely that a driver had a chance to speed. Speeding Episodes were used as the primary data element in the analysis of speeding, and they represented an interval of driving in which a vehicle was speeding. In the current study, speeding conceptually represented a risk of getting a speeding ticket more than a clear risk of getting into a speed-related crash. Richard et al., 2013a provides a detailed discussion of the definitions and thresholds for FFEs and SEs. The operational definitions of these data elements were as follows:

- A *Free-Flow Episode*, which represented the opportunity to speed, occurred when the driver was traveling at or above a threshold set at 5 mph below the posted speed limit. This speed criterion had to be maintained for at least 30 seconds to be included.
- A *Speeding Episode* was defined as continuous driving at or above a threshold set at 10 mph above the posted speed limit. This speed criterion had to be maintained for at least 6 seconds to be included.

Figure 1 illustrates the definition of a FFE and an SE. Small dips below the FFE or SE threshold were ignored when parsing the episodes in order to more accurately represent driving behavior by minimizing spurious FFEs and SEs from occurring. This essentially prevented what is practically the same FFE or SE parsed into different episodes.

Custom software tools were developed for reducing the time-series data into a set of aggregate variables that identified the characteristics of each trip, FFE, and SE using a common data structure. Examples of variables included in this reduction are descriptive statistics for speed and acceleration, episode duration and timing, speed profile variables, percent time in speed bands above posted speed, and percent time on road feature. Table 1 lists the primary type of variables included in the data reduction with examples of each variable type.

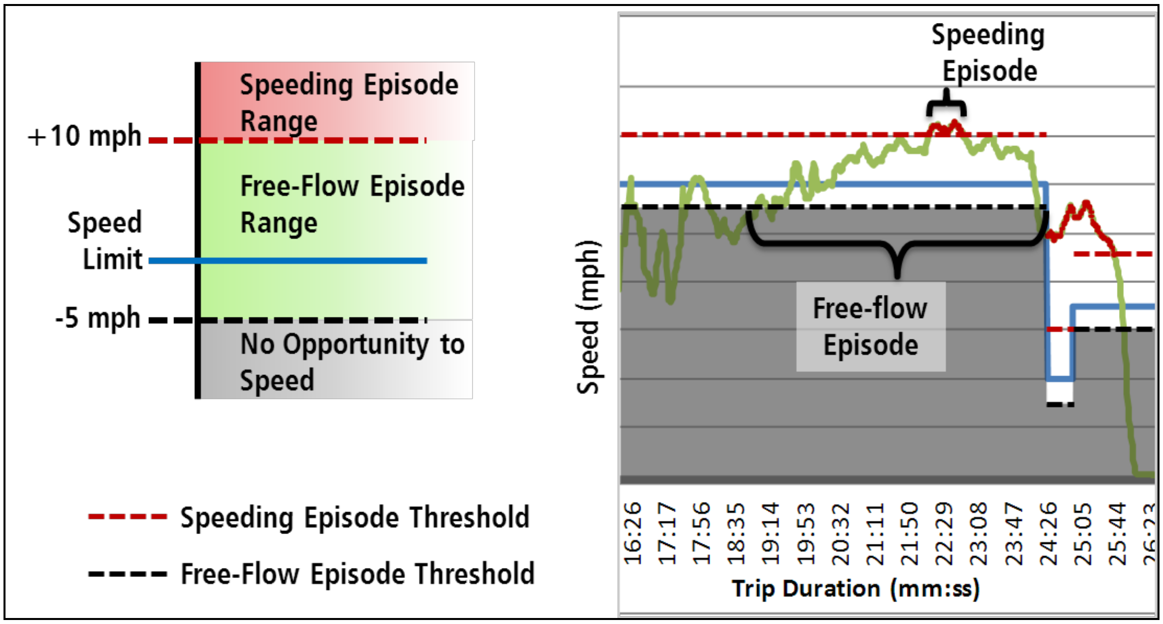


Figure 1. Definition of a Free-Flow Episode (FFE) and a Speeding Episode (SE) based on travel speed relative to the speed limit. The example on the right shows travel speed for part of a trip with the duration of an FFE and an SE indicated.

Table 1. Variable types with examples.

Variable Type	Examples
Speed and Acceleration	Min; max; mean; 1st, 2nd, 3rd quartile; 85th percentile; standard deviation; standard deviation of exponential moving average
Episode Duration and Timing	Start & end time, time in trip at FFE/SE start & end, distance in trip at FFE/SE start & end, FFE distance; FFE duration
Speed Profile Variables	Mean speed in 1st, 2nd, and 3rd segments of the episode (equal segments)
Percent Time in Speed Bands Above Posted Speed (PS)	Percent time above PS + n mph, percent time above n% of PS, percent time moving, percent time stationary; percent time in speed band (0 to 90 in 5 mph speed bands)
Percent Time on Road Feature	Percent time on: controlled access, bridge, tunnel, frontage road, etc.

DATA PROCESSING

A structured approach was used to reduce the data into a form that defined speeding in terms of SEs (see Figure 2). Data dictionaries were used to define the output variables that would be included in the data reduction that was developed. The source variables from which the data reduction would be compiled were also identified and codified in the data dictionaries.

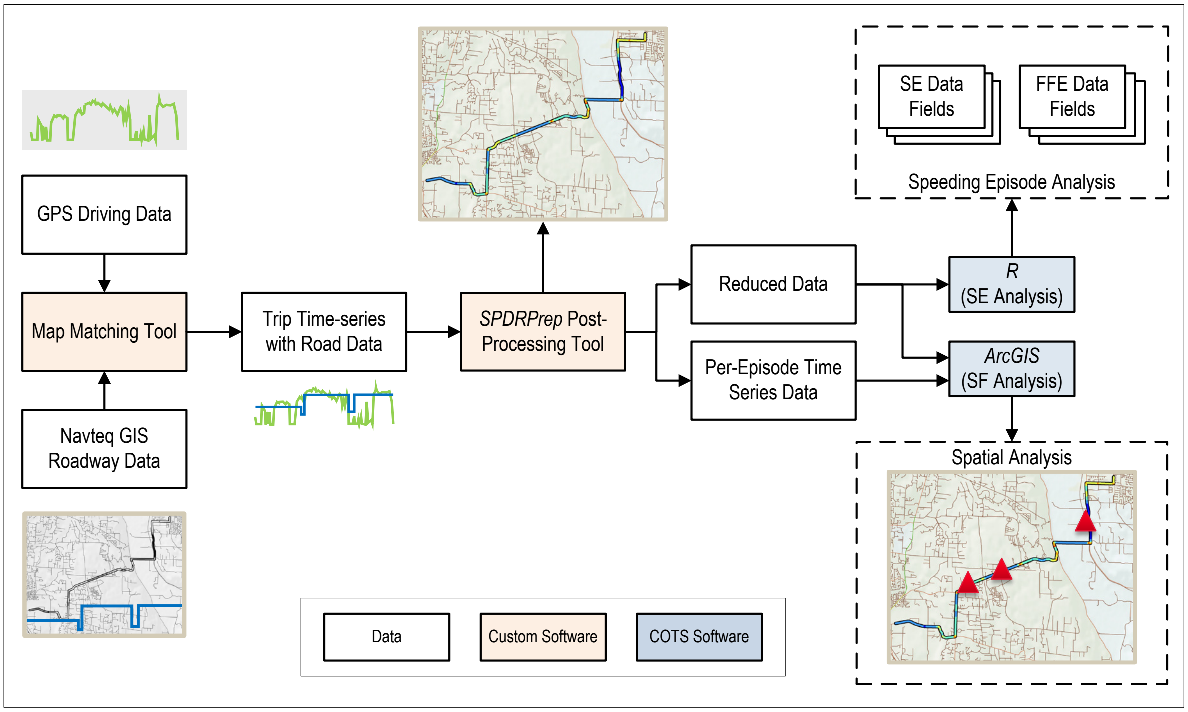


Figure 2. Illustration showing the data processing steps in preparing for analysis.

MAP-MATCHING TOOL

GIS maps of the Seattle and Texas sites, provided by NAVTEQ, were used to obtain posted speed limit, functional class and other available road network data. Once the maps were obtained, the GPS data were combined with the roadway data using custom-developed map-matching software for ArcGIS, which accurately matched each GPS point to the road on which the vehicle was traveling. Adapted from an algorithm by Quddus, Noland, and Ochieng (2006), the map-matching tool used fuzzy logic to estimate the most likely match based on vehicle speed, heading error with respect to the road, and previous matches. The matching was validated to determine accuracy; errors were generally rare and easy to detect, and were managed in later post-processing. The output was a set of time-series data with GPS data matched to the roadway.

POST-PROCESSING TOOL

The next step in data processing was to develop a data reduction software tool for parsing the matched GPS data into three types of episodes: trips,[2] FFEs, and SEs. The tool was written in C# and was based on the framework of the post-processing software previously developed for the *Motivations for Speeding* project. The matched GPS/GIS data were processed using this tool. The output was comprised of a series of data tables that included two types of data: 1) the data reductions described above and 2) per-episode time-series data. The data reductions (i.e., the FFEs and SEs) were used to perform a cluster analysis, in which Driver Types were

[2] For the efficiency in the data processing and to provide maximum flexibility for analysis, trips were considered as episodes. Specifically, the same statistics were calculated for trips as were calculated for FFEs and SEs.

identified (SE analysis). The per-episode time-series data, combined with the FFE/SE reductions and the results from the cluster analysis, were imported into ArcGIS to perform the situational factors analysis.

ANALYSIS AND RESULTS

This section describes the analyses conducted with the FFE and SE data. This includes descriptive analyses detailing high-level driving patterns, cluster analyses to identify speeding types and Driver Types, and analyses to identify situational factors that affect different types of speeding.

DESCRIPTIVE ANALYSES OF FREE-FLOW AND SPEEDING EPISODES

This section provides basic descriptive information about the SEs for Seattle and Texas.

Descriptive statistics were calculated using SE data to describe basic properties of the driver speeding. Overall, there were 6,995 trips recorded in Seattle and 5,666 trips recorded in Texas. For a small minority of those trips, drivers did not record any FFEs, which means that they did not have an opportunity to speed. For the remainder of the analyses, only trips in which drivers had FFEs were considered. In Seattle, there were a total of 4,754 separate SEs recorded across 6,137 trips with at least one FFE (see Figure 3). In Texas, there were a total of 1,376 separate SEs recorded across 4,645 trips with at least one FFE. Note that the range of speed limits along the x-axis in Figure 3 differs between the two locations.

In Seattle, the number of SEs varied substantially across posted speed limit, with the highest number of SEs occurring on 60 mph roads, which are typically interstate freeways or major highways in the Seattle area. There were also a high number of SEs on 30 and 35 mph roads. The overall number of SEs was much smaller in Texas, and the distribution across roads was more balanced than in Seattle.

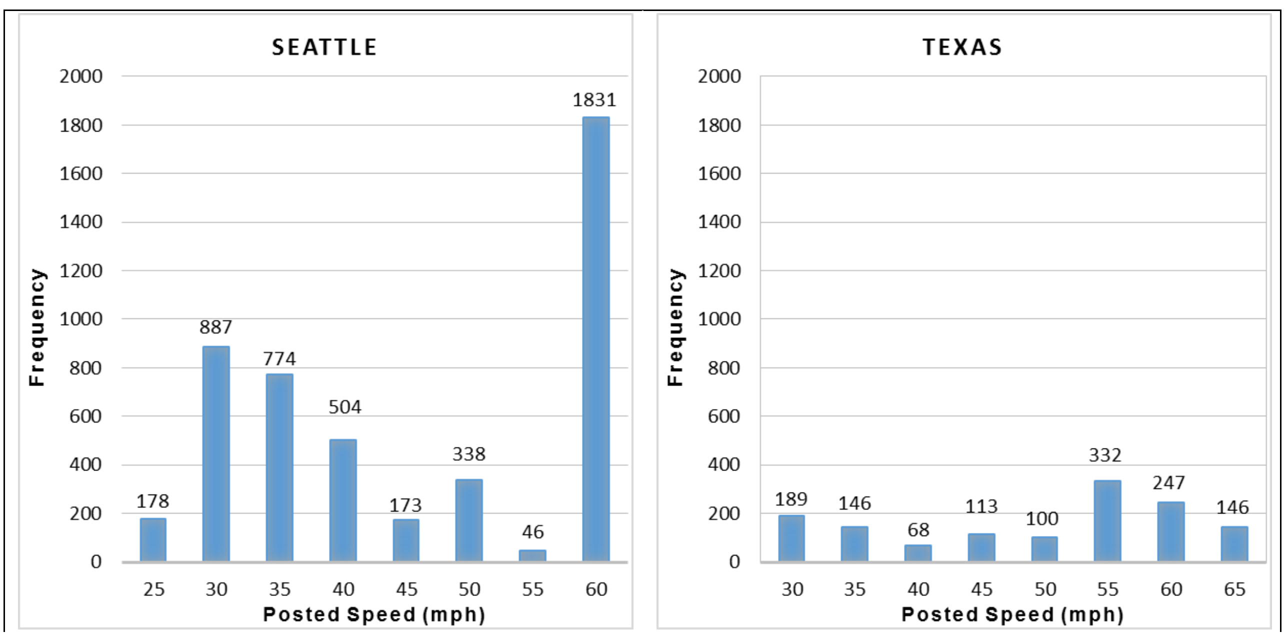


Figure 3. Frequency of Speeding Episodes (SEs) by posted speed for Seattle and Texas.

Figure 4 below shows the median duration for SEs across posted speed (see Table 2 and Table 3 for figure data). The interquartile range is also shown using the error bars. In Seattle, the typical duration of SEs was generally consistent across posted speed, ranging from 12 to 16 seconds long. The exception was SEs that occurred on 50 mph roads, which had a longer duration and wider interquartile range. In Texas, roads with posted speeds up to 40 mph showed a similar short-duration pattern as in Seattle. However, on higher-speed roads, SE durations tended to be longer and also more varied, as indicated by the wide interquartile ranges.

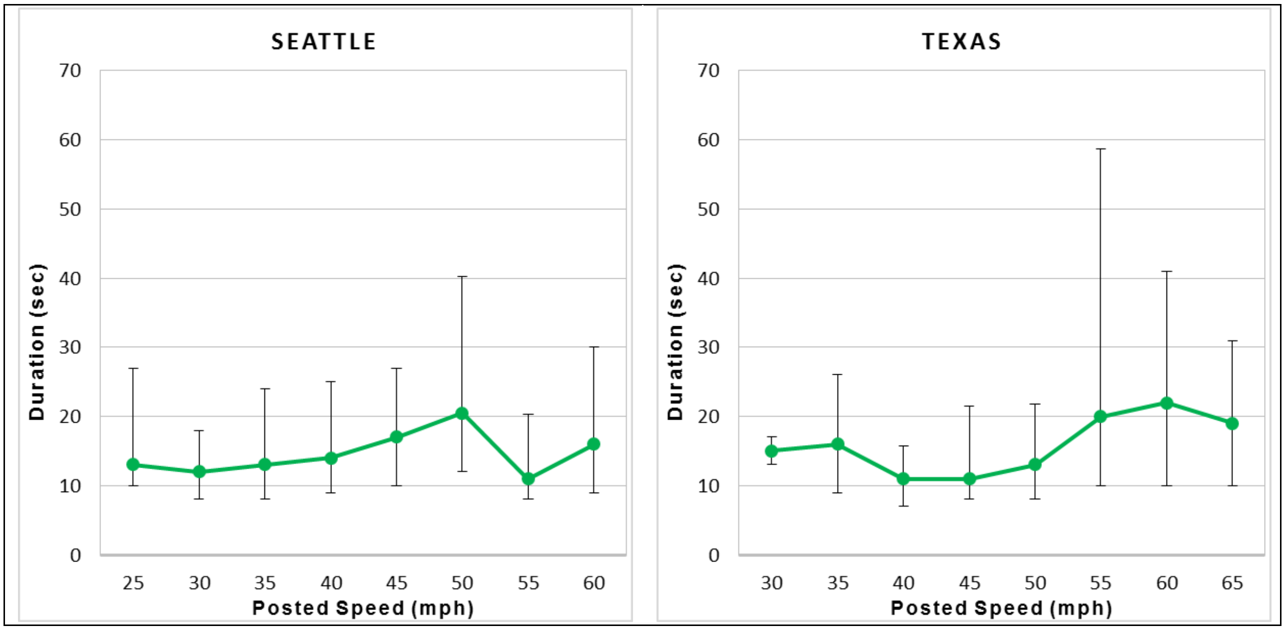


Figure 4. Median duration and inter-quartile range (error bars) of Speeding Episodes (SEs) by posted speed for Seattle and Texas.

Table 2. Median duration and median maximum exceedance of Speeding Episodes (SEs) by posted speed for Seattle (NA=Not Applicable).

	25 mph	30 mph	35 mph	40 mph	45 mph	50 mph	55 mph	60 mph	65 mph
n	178	887	774	504	173	338	46	1831	NA
Median Duration (sec)	13	12	13	14	17	21	11	16	NA
Median Maximum Speed Exceedance (mph)	14.7	13.8	13.3	14.0	14.7	13.3	11.9	12.8	NA

Table 3. Median duration and median maximum exceedance of Speeding Episodes (SEs) by posted speed for Texas (NA=Not Applicable).

	25 mph	30 mph	35 mph	40 mph	45 mph	50 mph	55 mph	60 mph	65 mph
N	NA	189	146	68	113	100	332	247	146
Median Duration (sec)	NA	15	16	11	11	13	20	22	19
Median Maximum Speed Exceedance (mph)	NA	19.0	15.0	13.2	14.2	13.7	13.6	12.9	12.0

There was a similar degree of consistency with regard to maximum speed exceedance (above the speed limit), which was the highest recorded speed within an SE. In Seattle, the median value for maximum speed exceedance and the corresponding interquartile range within SEs (see Figure 5, Table 2 and Table 3) ranged between 12 and 15 mph above the posted speed limit. There was also a slight trend towards lower maximum exceedance values at higher posted speeds. In Texas, the magnitude of the maximum speed exceedance was similar to in Seattle; the exception being 30 mph roads, which had substantially higher median values. Given that on 30 mph roads, the maximum exceedance was around 5 mph higher than on 35 mph roads, the pattern suggested that drivers might have treated both types of roads similarly and driven the same speed on each. The Texas maximum exceedance graph also exhibits a downward trend in exceedance levels with increasing posted speeds.

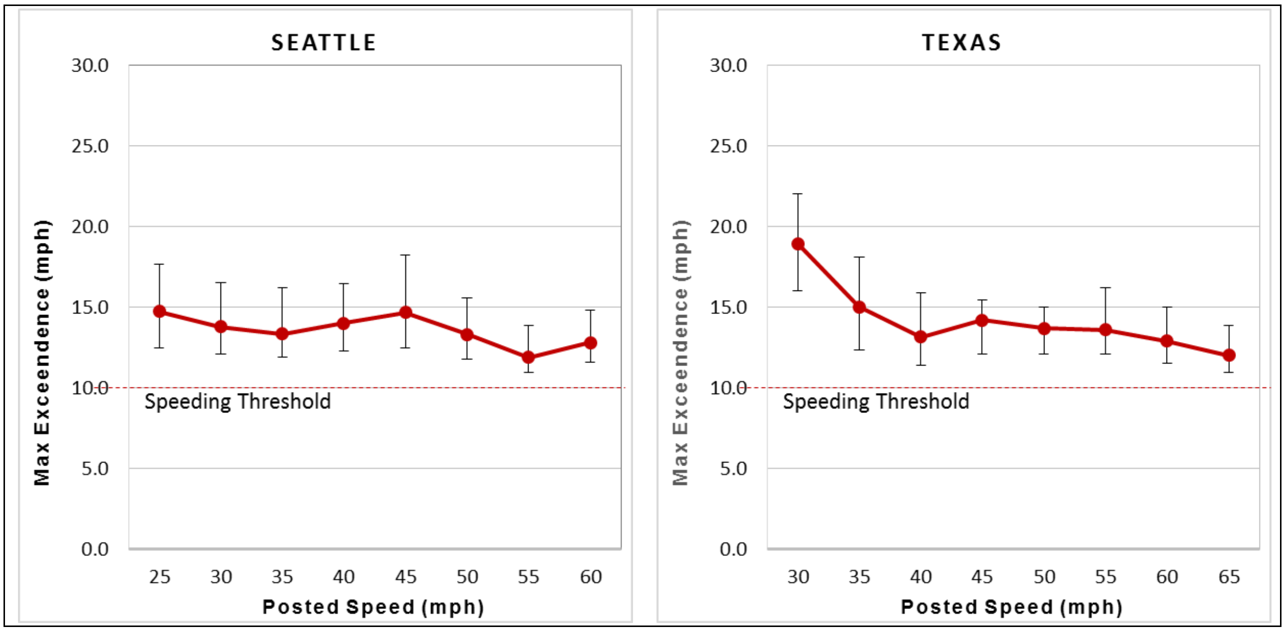


Figure 5. Median maximum exceedance and inter-quartile range (error bars) of Speeding Episodes (SEs) by posted speed for Seattle and Texas.

Figure 6, below, shows when trips and SEs were most likely to occur throughout the day in Seattle. The frequency of SEs increased steadily throughout the day, dropping after the evening rush hour. This pattern mirrored the distribution of trips throughout the day, and the ratio of SEs to trips was consistently between 40% and 50% for most of the day (lower dashed line). This ratio was elevated during the early morning hours; however, there were so few trips during that time that it is difficult to determine if this is a reliable pattern.

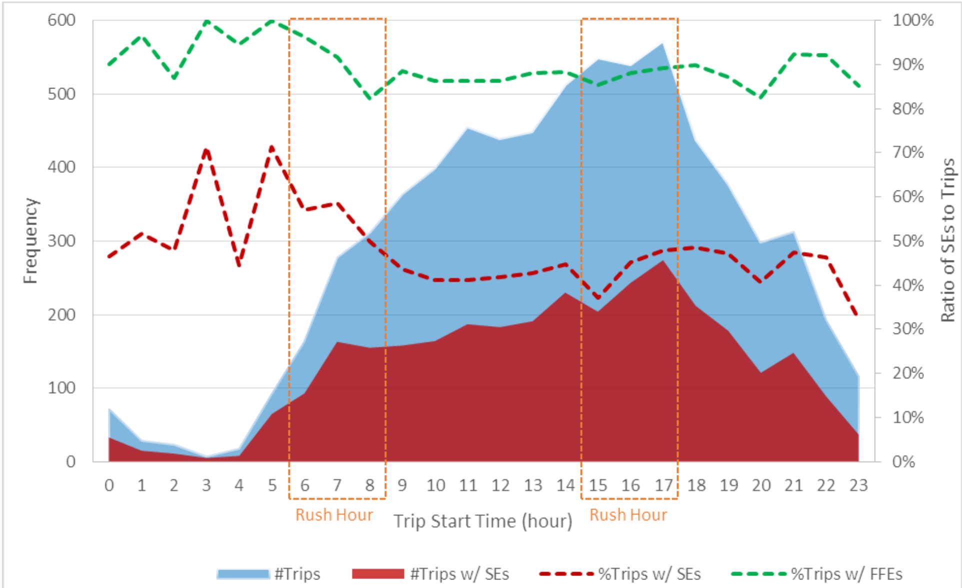


Figure 6. Frequency of all trips (top, blue shading) and trips with Speeding Episodes (SEs; bottom, red shading) in Seattle as a function of trip start time. Dashed lines indicate percentage of trips with free-flow and those with SEs.

Figure 7 below shows when trips and SEs were most likely to occur throughout the day in Texas. Unlike in Seattle, there were small peaks in the frequency of SEs during rush-hour periods as well as around the lunch hour. The ratio of SEs to trips was elevated in the morning and dropped steadily throughout the day.

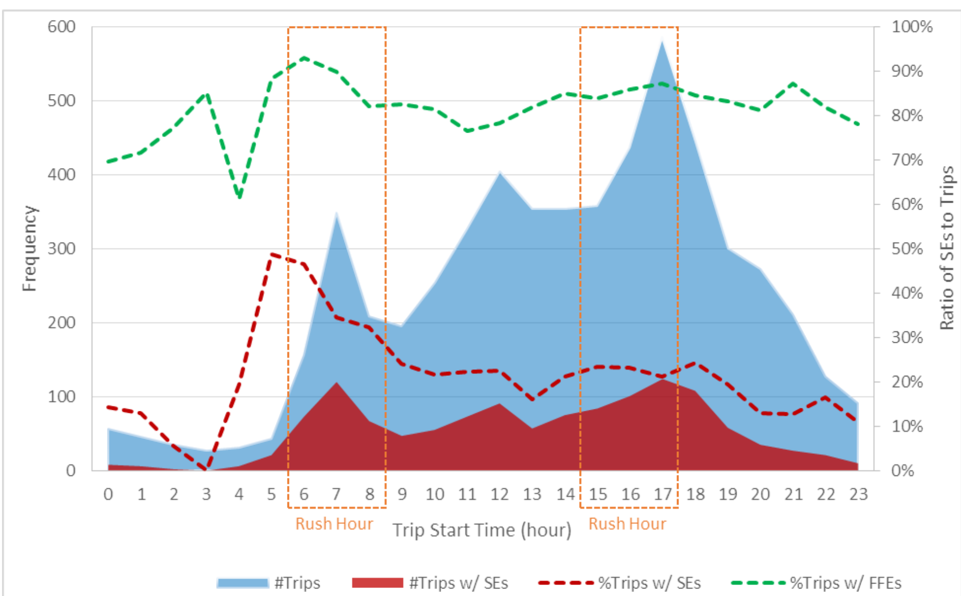


Figure 7. Frequency of all trips (top, blue shading) and trips with Speeding Episodes (SEs; bottom, red shading) in Texas as a function of trip start time. Dashed lines indicate percentage of trips with free-flow and those with SEs.

The next set of charts provides information about SEs across drivers. The histograms in Figure 8 address the question of how frequently SEs occurred for individual drivers, accounting for the number of trips taken (only trips with FFEs). Specifically, the figure shows driver counts of the ratio of SEs to trips. In Seattle, the histogram is positively skewed, with more than half of all drivers averaging less than 1 SE per trip taken. There was also a small group of drivers that averaged more than two SEs per trip. In Texas, the positive skew is substantially more pronounced, with most drivers averaging less than 0.8 SEs per trip taken.

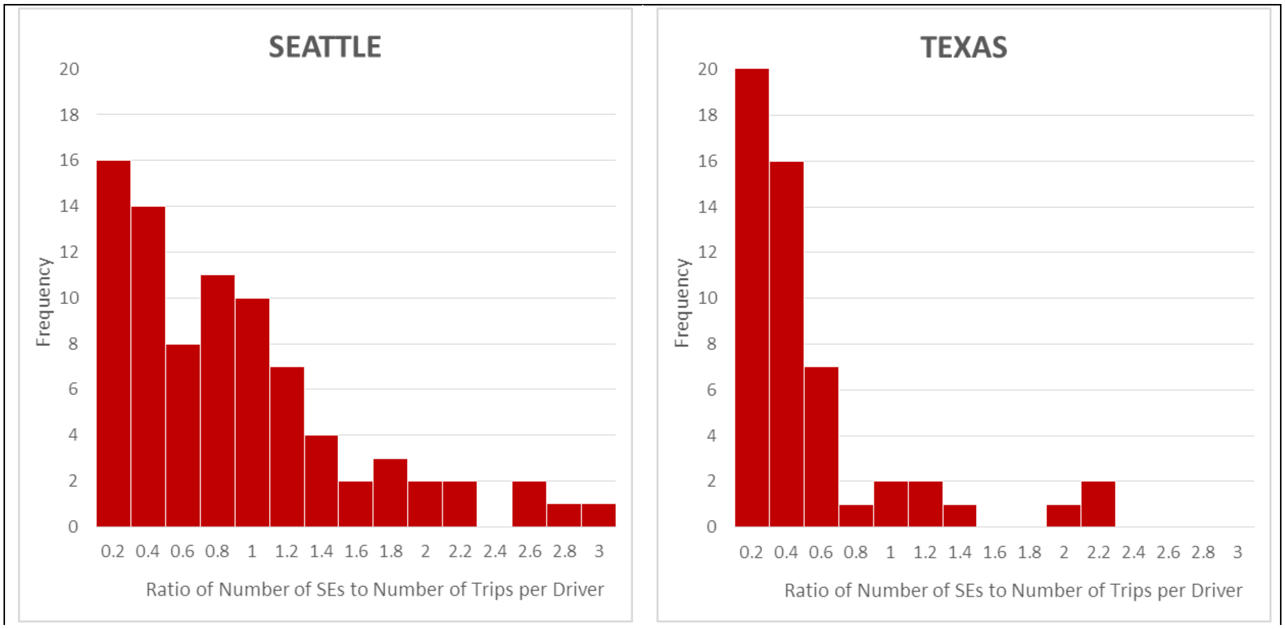


Figure 8. Ratio of Speeding Episodes (SEs) to free-flow trips enumerated across Seattle and Texas drivers.

Figure 9, below, provides a different view of the prevalence of SEs across trips. Specifically, it shows the percentage of trips that each driver made that had at least one SE, enumerated across drivers. The histogram indicates that in Seattle, most drivers sped on at least half of their trips. The opposite pattern seems to be true for Texas, where most drivers sped on less than half of their trips.

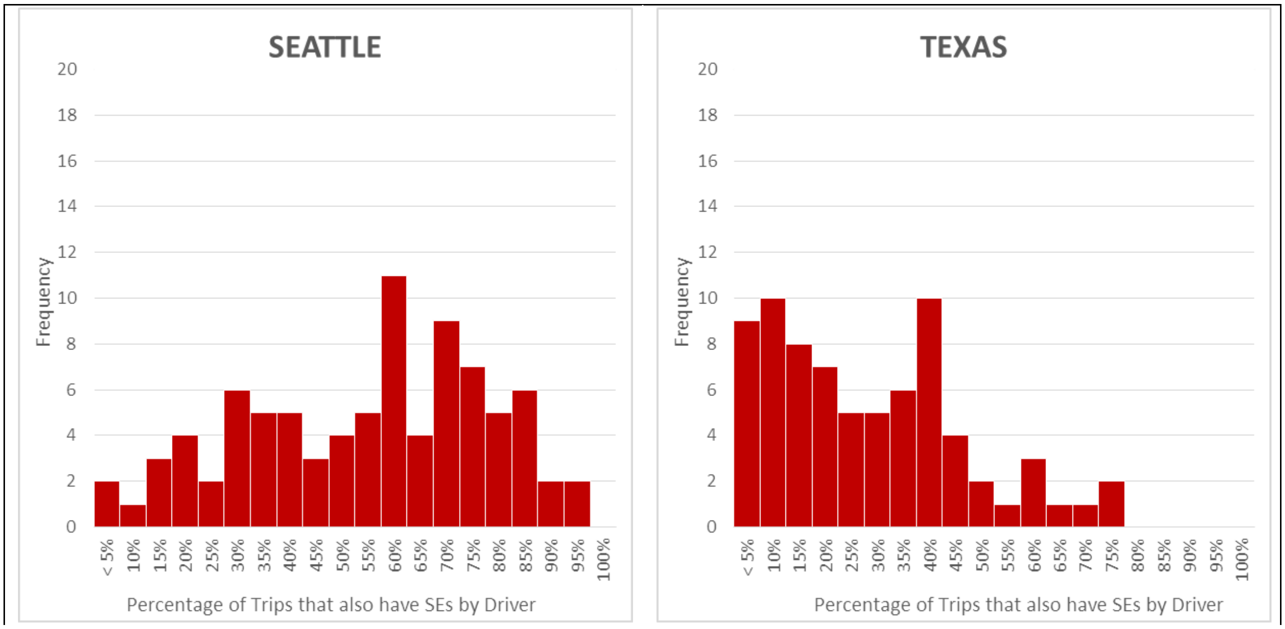


Figure 9. Percentage of free-flow trips with at least one Speeding Episode (SE) enumerated across Seattle and Texas drivers.

CLUSTER ANALYSIS OF SPEEDING EPISODES

This section describes how individual SEs were analyzed across all drivers to identify different types of speeding based on intrinsic characteristics of SEs. Following this analysis, the different types of speeding that resulted were then used to determine if different Driver Types could be identified by the types of speeding in which they typically engage.

The underlying premise in these analyses was that speeding resulted from qualitatively different types of driving behaviors, or from different speeding choices. While in some cases, speeding can result, unintentionally, from lack of vigilance, at other times speeding can occur because drivers are deliberately exceeding the posted speed limit, perhaps as “thrill seeking” or to reduce travel time when late. If speeding results from these different motivations, it is likely that SEs may take different forms depending on the underlying motivations or associated behaviors. Thus, a key objective of this project was to identify different types of speeding. If this could be done, then it could lead to the possibility of identifying riskier types of speeding and the development of countermeasures that can be targeted towards reducing these speeding types.

Cluster analyses were conducted to answer specific questions about driver speeding behavior. All analyses described below were conducted on variables calculated using time-series data within individual SEs (e.g., mean speed, total duration, etc.). In addition, cluster analyses were conducted separately for Seattle and rural Texas data because the roadway environments and driving patterns at these locations differed substantially. The specific speeding-behavior questions addressed with the cluster analysis included:

- Is it possible to characterize *types of speeding* based on characteristics of Speeding Episodes?

- Is it possible to classify subtypes of speeders (*Driver Types*) using patterns in their types of speeding?
- To what extent are Driver Types defined by demographics and/or attitudes and beliefs about speeding?

The basic process used to address these questions involved three steps. The first step was to conduct a cluster analysis on select SE variables to divide SEs into groups/types of speeding based on shared characteristics. The second step involved identifying, relatively, how often each driver engaged in the different types of speeding, thus creating a "speeding profile" for each driver. These speeding profiles were then used as the basis for a second cluster analysis to identify different Driver Types based on similarities in speeding profiles. The final step involved running a Chi-square test on the Driver Types to determine if category membership reflects demographics. In addition to this, patterns in responses to personal inventory items about attitudes and beliefs about speeding were examined for trends across Driver Types.

Selection of Variables for Speeding Type Analysis

A key objective for the selection of variables for the cluster analysis was to include variables that represented different intrinsic characteristics of SEs, which was not possible to do in the previous analyses of this speeding data (Richard et al., 2013a). Figure 10, below, illustrates four of these characteristics: magnitude, duration, variability, and form. These are also described in Table 4. One advantage of this approach was that these characteristics were defined mostly independently of situational factors, such as road type and time of day, which permitted these factors to be examined as predictor variables in separate analyses.

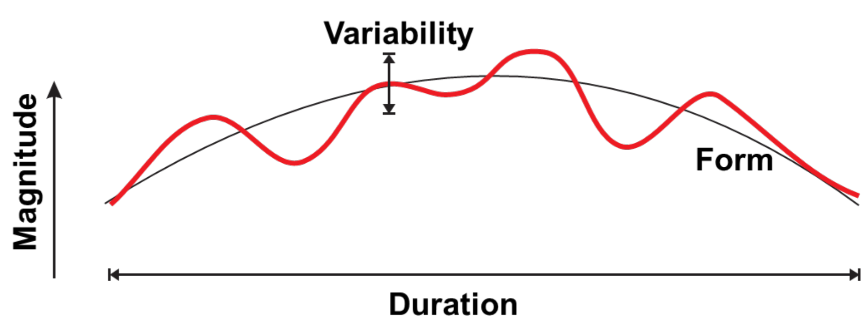


Figure 10. Basic characteristics of a Speeding Episode (SE).

Table 4. Description and relevance of the basic characteristics of Speeding Episodes (SEs).

Characteristic	Description	Relevance
Duration	Length of SE	Provides a measure of exposure to speeding risk
Magnitude	Extent to which drivers exceed the speed limit	Higher speed exceedance increases risk
Variability	Deviations from central speed trend	Captures certain behaviors, such as weaving around traffic
Form	Overall shape of SE time series	Global indication of how speed changes throughout the SE. Captures some situational aspects, such as driver response to speed limit changes

Another consideration for selecting the basic SE characteristics described in Table 4 was to select aspects that exhibited some degree of independence from each other, which helped increase the distinctiveness of groups in the cluster analysis. The characteristics described above were mostly independent; however, there was a notable exception to this at short SE durations. In this case, the characteristics were constrained by the kinematics of brief speed increases. That is, magnitude could only increase by a small amount in a short duration, variability would be largely driven by the corresponding increase then decrease in speed magnitude, and the general form will be slightly peaked, but rather flat compared to longer duration SEs that permit larger speed increases. Therefore, SEs that had a short duration tended to be relatively similar, likely resulting in these SEs being grouped together in a common cluster.

Table 5, below, shows the specific variables that were selected to capture the basic SE characteristics. We examined a larger number of variables than the ones in the table, in addition to transformations of these variables (e.g., standard deviation of speed with and without high-frequency smoothing). The set listed in Table 5 represents the variables that best reflect the SE characteristics we were trying to capture. Note that the magnitude variables were calculated as speed exceedances relative to the posted speed limit, rather than absolute speed. This was done to make this variable comparable for SEs that occurred on roadways with different posted speeds.

Table 5. Description of the variables included in the cluster analysis to identify types of speeding.

Characteristic	Variable	Description
Duration	Duration	Length of SE
Magnitude	Maximum Speed Exceedance	Peak magnitude minus posted speed
	Mean Speed Exceedance	Stable/global measure of magnitude as defined as the mean SE speed minus the posted speed
Variability	Standard Deviation of the Exponential Moving Average	Smoothed speed variability; this removes high-frequency oscillations in speed change that obscure the underlying speed change trends
	Standard Deviation of Acceleration	Variability in speed change
Form	Median Acceleration	Speed change trend
	Speed Change	Absolute speed change from beginning to end of SE
	Leg 1	Speed change in the first half of an SE; comparing it to Leg 2 provides general information about the SE shape (e.g., monotonic up or down vs. peak or valley)
	Leg 2	Speed change in the second half of an SE; comparing it to Leg 1 provides general information about the SE shape (e.g., Monotonic up or down vs. peak or valley)

General Approach for Conducting the Cluster Analysis

The substantial differences between Seattle and Texas in terms of driving environment and observed driving patterns motivated separate—but similar—cluster analyses for each location. For both locations, the variable values for SE data were entered into a k-means cluster analysis. The within-group sum of squares was calculated for cluster solutions that ranged from 1 to 15 cluster centers, and was used to identify an appropriate cluster solution. The resulting clusters identified each SE in the data set as belonging to a single cluster representing a unique type of speeding.

The following sections describe the results of the cluster analyses. The results from Seattle and Texas data analyses are discussed in separate sections.

Seattle Cluster Analyses for Speeding Type

The Seattle speeding type cluster analysis was run using the nine variables in Table 5 that describe different aspects of speeding behavior. Figure 11 shows scatterplots of the values of these variables for all of the SEs.[3] The variables were plotted as semitransparent dots and so the dark gray areas reflect multiple overlapping points.

The key data patterns apparent in each scatterplot are described below:

- *Top left*: Mean Exceedance vs. SE Duration – Although the points are concentrated at low exceedances and short durations, there is also a tendency for points to align along both axes, representing short duration high-speed SEs, and long duration SEs with speed exceedances on the low end.
- *Top right*: For the measures of variability, there is a stronger relationship at low values, which occurs because of the nature of the calculations for the variables. However, at larger values, the two measures become more disassociated.
- *Bottom left*: With regard to Speed Change vs. Median Acceleration, there is a clear, logical pattern evident. Specifically, negative Median Acceleration values coincide with speed drops, and positive Median Acceleration values coincide with speed increases.
- *Bottom right*: Although there is a fair degree of scatter, the dominant pattern is that speed increases in Leg 1 are associated with speed decreases in Leg 2. This is characteristic of Speeding Episode time series that have a peaked shape.

A general observation apparent in all of the scatter plots is that, while there is a fair degree of variability within each graph, there are also clear regions with a high concentration of data points, typically near the low range of each variable. It is likely that a substantial proportion of this concentration reflects the strong kinematic linkage between variables that occurs for short-duration SEs (as described in the previous sections). Another notable pattern—especially relevant to the cluster analysis—is that the distribution of points within each scatterplot is largely continuous. This absence of "natural" clustering suggests that some types of speeding are likely to be quite similar, differing primarily in terms of degree.

[3] The Maximum Speed Exceedance variable is not shown in Figure 11; however, its basic form is qualitatively similar as the Mean Speed Exceedance by Duration scatterplot, but shifted towards higher y-axis values.

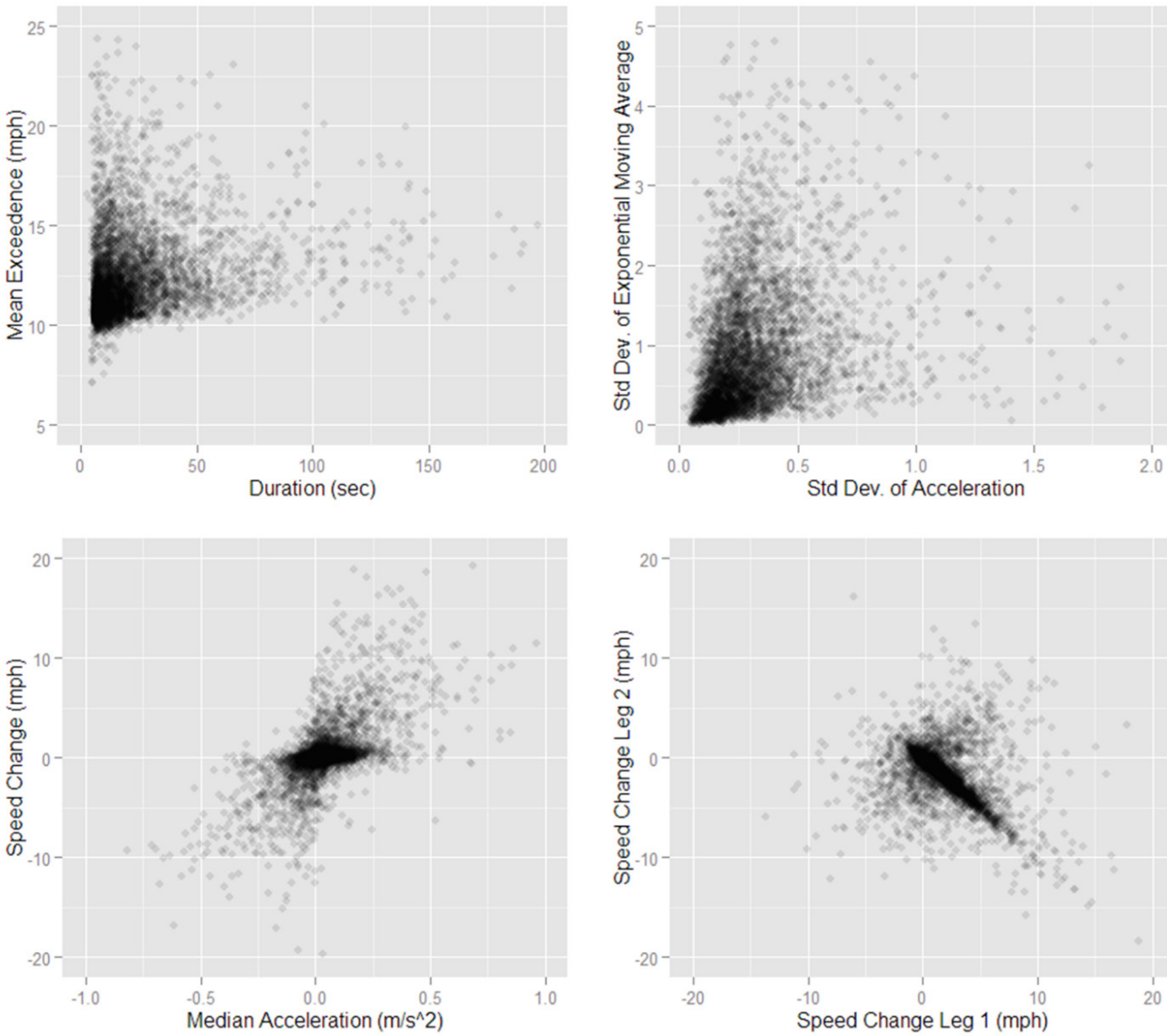


Figure 11. Variables used to cluster Speeding Episodes (SEs) for the Seattle sample.

The nine variables in Table 5 were used to cluster the SEs with the k-means clustering algorithm. The analysis was repeated with 1 to 15 cluster centers. Figure 12 shows how well each of these cluster solutions fit the data. Lower within-groups sum of squares indicate that members of each cluster are closer to its center. The inflection point around six clusters suggests that a six-cluster solution represents a point of diminishing returns, where adding more clusters provides diminishing benefit relative to the overall fit to the data. Cluster solutions from 4-9 were examined, and we determined the six-cluster solution to be the most interpretable, in addition to being comprised of the most distinct clusters. Thus, the six-cluster solution was selected for the full analysis of the Seattle SE data.

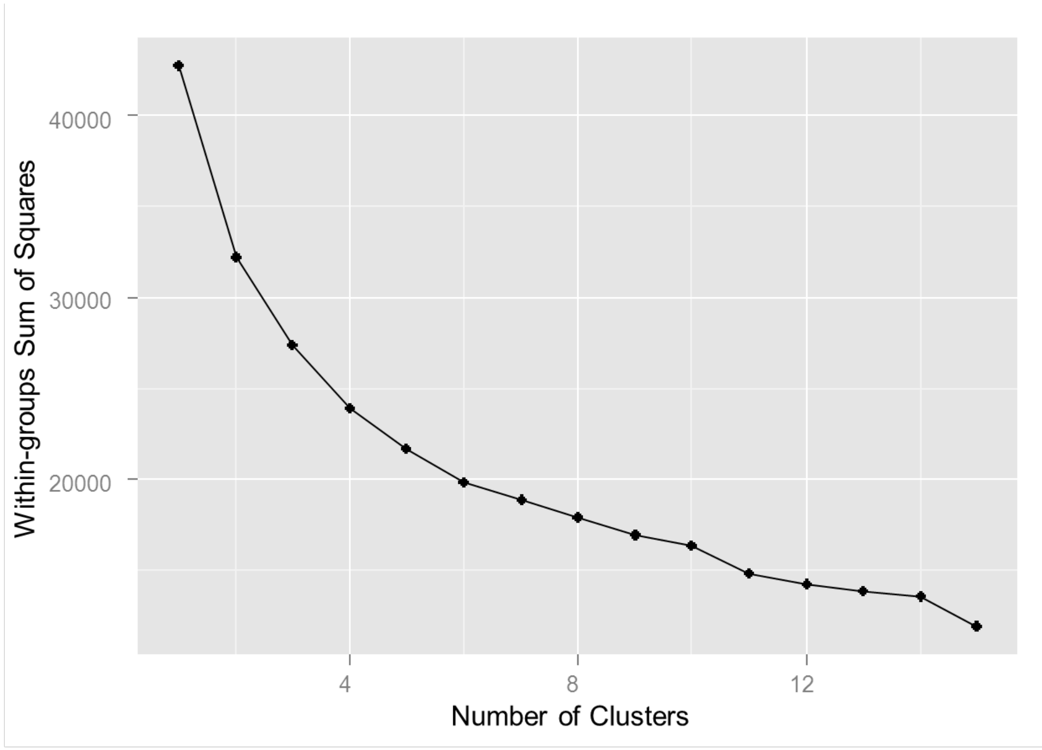


Figure 12. Within groups sum of squares for the Seattle sample.

An important objective during the analysis of speeding types was to end up with types of speeding that seemed to be plausibly tied to driving behaviors. In order to confirm this, we calculated descriptive statistics for the SE variables to characterize the underlying speeding behaviors, at least at a high level. Table 6 shows some of the properties of the clusters as defined by the median values of key variables. The variables describing the speed change in each leg were condensed into a description of the general form of the cluster time-series. The general form was also verified using visual inspection. Two variables that were not used in the cluster analysis (Maximum Acceleration and Maximum Deceleration[4]) are also shown in the table because they have explanatory value.

One notable outcome of the cluster analysis is that Clusters 3 and 4 contained substantially more SEs than the other clusters. The text below Table 6 discusses each of the clusters in detail.

[4] Note that Maximum Acceleration and Maximum Deceleration were not directly measured. There were instead computed using 1-Hz GPS speed values. This has the effect of smoothing the values, resulting in Acceleration/Deceleration levels that are lower than actual. Nevertheless, the computed values still provide useful information about general trends.

Table 6. Median values of key variables for Speeding Episodes (SEs) within each cluster for Seattle.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
N	218	204	2638	1263	187	244
Duration	14	13	11	20	98	28
Max Speed above Speed Limit	19	19	12	15	18	20
Mean Speed above Speed Limit	8	17	11	13	13	16
StdDev ExpMA	2.1	1.8	0.4	1	1.7	2.6
Speed Change	8.6	-7.1	0.0	0.0	0.2	0.1
Max Accel	0.8	0.3	0.4	0.6	0.7	1
Max Decel	-0.2	-0.7	-0.3	-0.6	-0.7	-1
General Form	Rising	Dropping	Flat	Slight Peak	Slight Peak / Flat	Sharper Peak
Label	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Aggressive

Cluster 1 - Speeding Up: The defining characteristics of Cluster 1 were the relatively large increase in speed from beginning and end, the generally rising form of the time series, high maximum exceedance, and high variability (StdDev ExpMA). These characteristics are consistent with speeding up that can occur immediately prior to an increase in the posted speed. Thus, this cluster is identified as representing "speeding up" behavior. Although visual inspection confirmed that most of these SEs occurred immediately preceding speed limit changes, there were also several Speeding Up SEs that occurred over longer stretches of roadway where the posted speed changed more than once, but the characteristics of the roadway remained generally the same. That is, the visual layout and geometry on the upstream lower-speed sections were nearly the same as the for the higher-speed sections, so drivers may have lacked the cues indicating that they should slow down.

Another interesting pattern is that a small number Speeding Up SEs occurred at locations without posted speed changes, such as midblock within an urban arterial. These SEs seem to represent instances in which an accelerating vehicle slowed abruptly, ending the SE within one or two seconds (this typically requires deceleration levels of 5 m/s^2 or higher, which exceed "comfortable" deceleration levels—i.e., 3.5 m/s^2).

Cluster 2 – Speed Drop: Cluster 2 represents the complementary behavior to the Speeding Up cluster. In particular, it is defined by a relatively large decrease in speed, the generally decreasing shape of the time series, high maximum exceedance, and high variability (StdDev ExpMA). Accordingly, these characteristics are consistent with drivers slowing down after transitioning to a lower posted-speed zone.

Cluster 3 – Incidental Speeding: The SEs in Cluster 3 represent the most common type of speeding, which occurs substantially more often than all other types. The values of most variables in this cluster are on the low end, particularly mean speed, which is just 1 mph over threshold for speeding. As discussed in the previous sections, this cluster captures the SEs that are bound by the kinematics of short-duration speeding. In terms of driver behavior, this cluster likely represents unintentional or incidental speeding on the part of a driver because it barely exceeds the threshold and the duration is in line with drivers coasting shortly after the exceedance occurs until the speed drops below the threshold. Note, however, that even though the mean speed is just slightly over the threshold for speeding, it is still 11 mph above the posted speed limit. Thus, it is likely that in these SEs, drivers were not overly concerned about trying to remain at or below the posted speed limit. They may be have been keeping up with fast-moving traffic or the driving environment may afford higher speeds, but there is at least some degree of acceptance on the part of the driver for exceeding the speed limit. It may also reflect attempts to stay below the perceived threshold at which they are more likely to get a speeding ticket.

Cluster 4 – Casual Speeding: This is the second-most common type of speeding. It is similar to Incidental speeding, but differs primarily in degree, with all variables having higher values. The median Maximum exceedance indicates that half of the SEs involved speeding that exceeded the posted speed by at least 15 mph, and the median duration of 20 seconds suggests that drivers were not in a hurry to reduce their speeds. Relative to the Incidental speeding cluster, the SEs in Cluster 4 seem to represent a more accepting or casual attitude towards speeding in the situations in which they occur.

Cluster 5 – Cruising Speeding: The defining aspect of Cluster 5 is the long duration relative to the other types of speeding, akin to drivers “cruising” along a roadway at elevated speeds for a moderate duration. It is likely that this represents a rather deliberate type of speeding. In particular, on at least half of SEs, drivers exceeded the speed limit by 18 mph or more, which is easily noticeable in urban driving. Moreover, the durations were long enough that the higher speed required active speed maintenance on the drivers’ part (i.e., as opposed to inadvertently reaching too high of a speed, then coasting back to a slower speed). Also, this is unlikely to represent speeding using a high cruise-control setting because the variability is moderate and the computed maximum acceleration and deceleration are at the high end.

Cluster 6 – Aggressive Speeding: The last cluster differs from the other clusters in that it has the highest speed variability in addition to consistently high values for most of the other variables, including high maximum and mean speed exceedance, duration, and the highest maximum acceleration and deceleration levels. In general, these values suggest that Cluster 6 represents more aggressive and/or riskier driving than that found in the other clusters. Visual inspection of a number of individual SEs indicated that while most have a generally peaked shape, there is a relatively high degree of speed undulation within the SEs. This suggests that drivers engaged in repeated speed adjustments, possibly related to traffic interactions, such as weaving around traffic.

To show the relationship between the different clusters, Figure 13, below, plots the distribution of SE in terms of mean exceedance and duration, as well as being color-coded and outlined by speeding cluster. The general regions occupied by each cluster are indicated in the annotation.

Visual inspection of Figure 13 indicates that several patterns are evident. The first is that the mean exceedance and duration dimensions are important for grouping the SEs into clusters. This is indicated by the general uniformity in color within most of the demarcated regions. Another pattern is that the highest concentration of data points occurs with median durations under 25 seconds and below approximately 13 mph above the posted speed. This indicates that a large majority of SEs recorded in the study were qualitatively similar, and that they also did not represent “extreme” levels in terms of magnitude and duration of the speeding-related risk.

A third pattern is simply that the cluster groupings make logical sense in terms of their speed and duration, and that they are generally consistent with their assigned labels. In particular:

- The bottom-right corner of the graph represents both low mean exceedance and short durations. The Unintentional SEs occupy this region. At higher speeds, and slightly longer durations are the Casual SEs.
- SEs related to Speeding Up and Speed Drops are concentrated along the upper end of the y-axis. These involve high speeds, but only for short durations, which can occur at speed zone transitions.
- The bottom-right region of the chart contains most of the SEs related to Cruising speeding. Speed exceedance levels are moderate, but the durations are long relative to the other types of speeding.
- Finally, the Aggressive speeding cluster is found predominately towards the central region, covering a broad area. SEs in this cluster vary substantially.

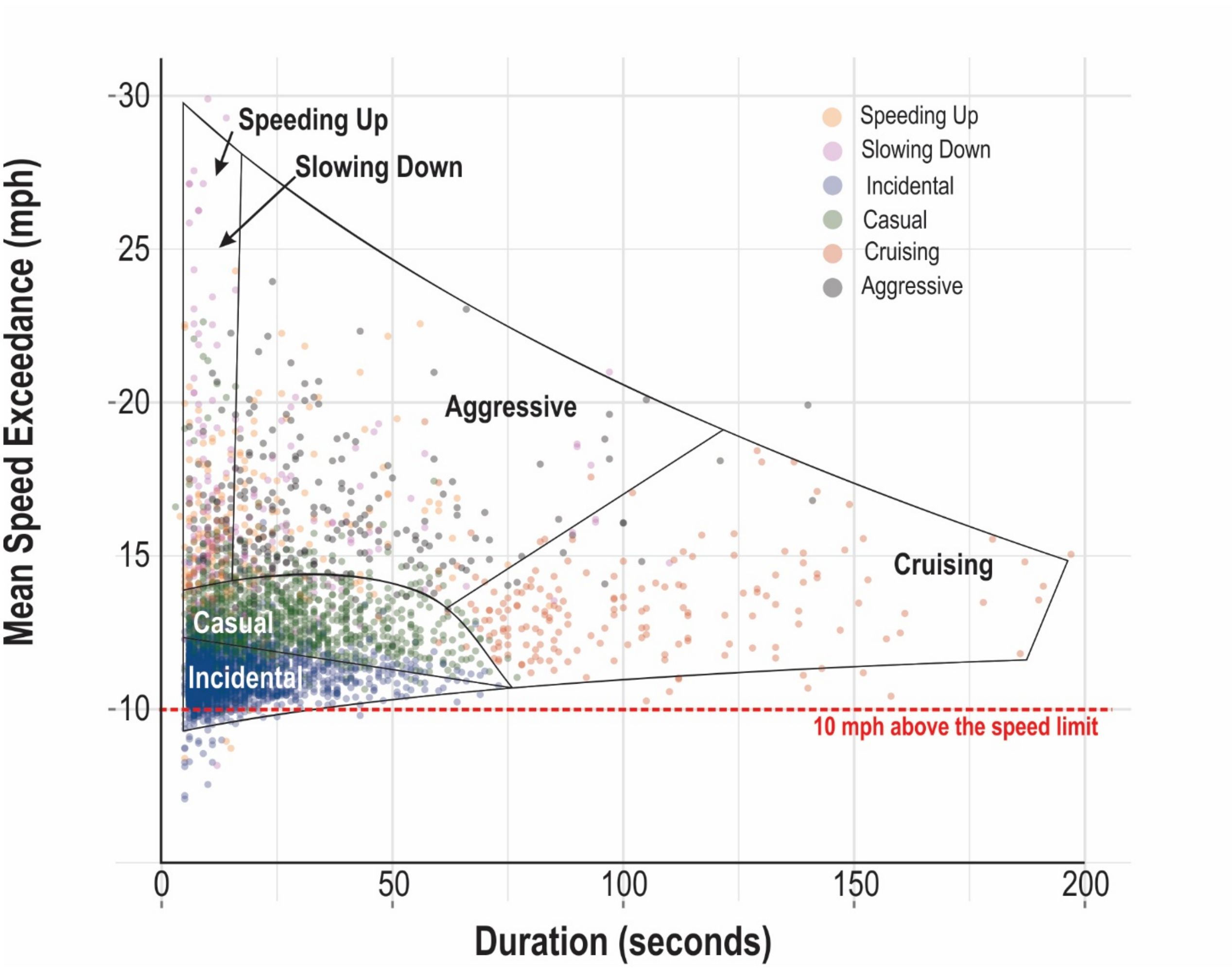


Figure 13. Scatter plot of mean speed exceedance by duration for all Seattle Speeding Episodes (SEs). Points are color-coded based on cluster membership. The general region occupied by each cluster is indicated.

Overall, the cluster analysis was effective at parsing SEs into groups whose members were similar across multiple dimensions. More importantly, the resulting clusters are clearly interpretable. However, it should be noted that the clusters were limited to describing largely high-level speeding behaviors. This was likely a result of the general nature of the variables used for clustering. In particular, the clustering variables largely represented outcomes arising from more specific behaviors (e.g., high speed variability caused by frequent accelerator and brake pedal presses when weaving through traffic, or slow responses to changes in elevation). Thus, it is possible that similar data patterns could be caused by more than one type of driver action, which cannot be distinguished by the limited variables available in the current data set. However, richer naturalistic driving data, such as those available in the Strategic Highway Research Program (SHRP2) dataset, could provide more details about driver actions (e.g., accelerator presses; lane changes), so that clusters could be better defined in terms of underlining behaviors that are more specific (e.g., weaving through traffic, etc.).

Seattle Cluster Analysis to Identify Driver Types

This section describes the second cluster analysis conducted to determine if it was possible to classify individuals into different Driver Types with respect to speeding. Note that the term Driver Types is synonymous with "speeder type" when referring to drivers. The term Driver Types is used in the remainder of this report to minimize confusion with the phrase "types of speeding," which is reserved for describing the speeding clusters in the previous section.

The clusters representing different types of speeding from the previous analyses were used to cluster drivers. In particular, a "speeding profile" was calculated for each driver, which simply represented how each driver's Speeding Episodes were distributed among the six types of speeding (see Table 7).

Table 7. Example "speeding profiles" for hypothetical drivers based on each driver's distribution of Speeding Episodes (SEs) across the types of speeding.

Example DATA	Speeding Up	Speed Down	Incidental	Casual	Cruising	Aggressive	Row Sum
Driver 1	5%	5%	50%	25%	10%	5%	100%
…	8%	7%	20%	35%	20%	10%	100%
Driver N	5%	0%	60%	30%	5%	0%	100%

Each driver's speeding profile was then used as the basis for clustering drivers into different groups. Ward's (1963) hierarchical clustering technique identified four clusters of drivers based on similarities in their distributions of SEs of different speeding types. Each of the four Driver-Type clusters is boxed in red in the dendrogram below, with the branches at the lowest level representing individual drivers (Figure 14). The dendrogram shows that one group is much larger than the others.

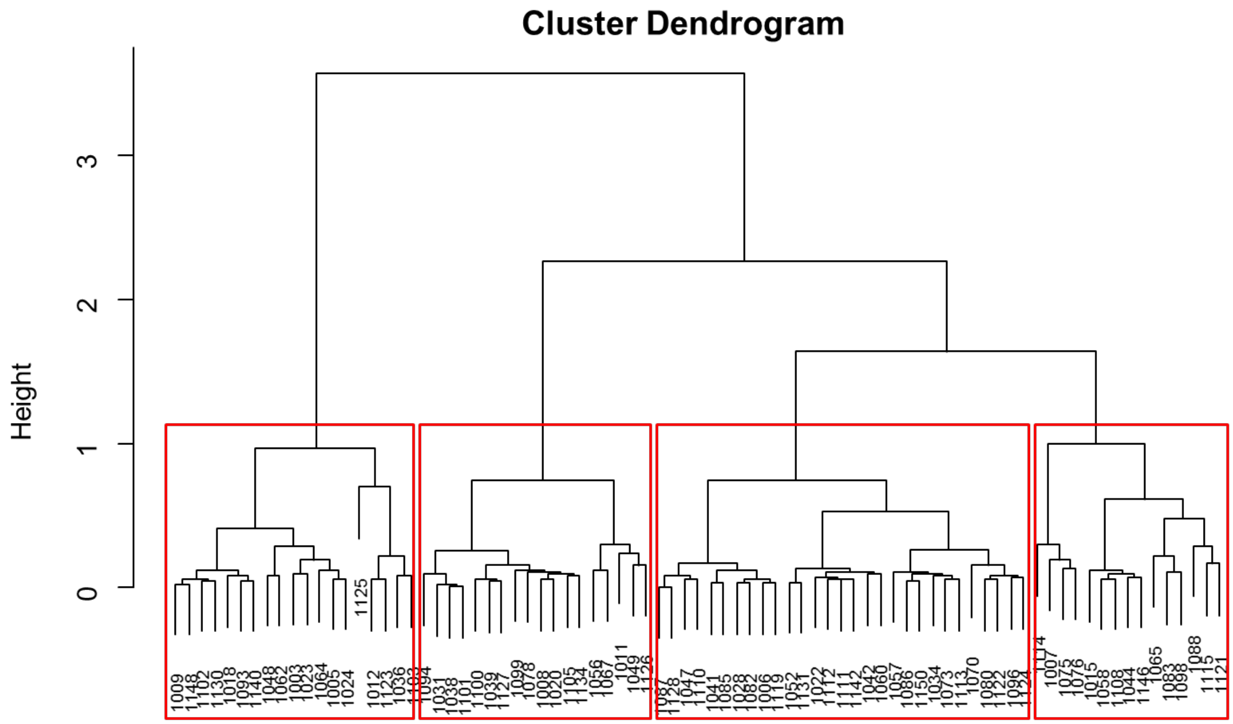


Figure 14. Results of Ward's (1963) hierarchical clustering for Seattle drivers.

Figure 15 provides four violin plots that show the average "speeding" profile across the drivers within each Driver Type cluster. The height of each "violin" distribution (indicated in white) shows the range of speeding-type proportions, and the width represents the frequency of data points at that particular value. For example, the plot for the Situational Driver Type in Figure 15 has a long, narrow shape for the Speeding Up type of speeding, which indicates that drivers in the group were evenly spread between 0.0 and 0.25. In contrast, the shape for the Aggressive type of speeding for the same group shows a wide base, which indicates that most drivers were concentrated near 0.0, but a couple points ranged up to around 0.10. Differences in the position and shape of the violin distributions across the Driver Types provide insight about what types of drivers are represented within each group, and they form the basis for assigning the corresponding group labels. The labels are discussed in more detail after Figure 16 below.

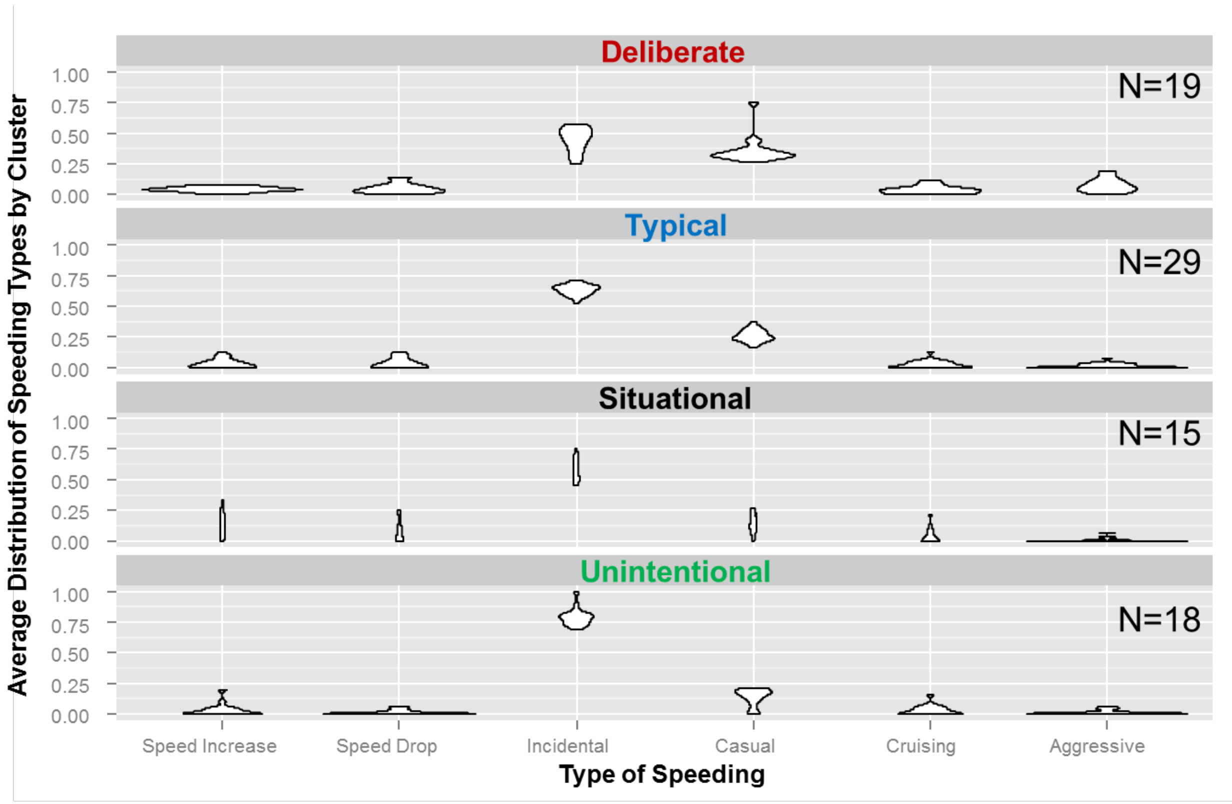


Figure 15. The proportion of the types of speeding for each of four Seattle Driver Types.

Table 8 below provides the median values for the proportion of each type of speeding by Driver-Type. The column averages are also provided to make possible to assess whether a particular type of speeding is over- or under- represented for a specific Driver Type relative to other Driver Types.

Table 8. Driver Type by type of speeding for Seattle drivers.

Driver Type Label	N	Cluster 1 Speed Up	Cluster 2 Speed Drop	Cluster 3 Incidental	Cluster 4 Casual	Cluster 5 Cruising	Cluster 6 Aggressive
Deliberate	19	4%	4%	46%	33%	3%	5%
Typical	29	2%	3%	65%	25%	2%	0%
Situational	15	16%	3%	53%	3%	0%	0%
Incidental	18	0%	0%	79%	17%	0%	0%
Average	*20*	*3%*	*2%*	*63%*	*24%*	*2%*	*1%*

Further information about the different Driver Types can be obtained by examining how often different Driver Types engaged in each type of speeding. To this end, Figure 16 shows how frequently individuals from different Driver Types engaged in each type of speeding. In particular, drivers in the Deliberate Driver Type engaged in the most of all types of speeding, except the Speed Up type, which occurred most often in the Situational Driver Type. Individuals in the Typical Driver Type were the second most frequent speeders, followed by Unintentional and Situational Driver Types, respectively. Another pattern apparent in Figure 16 is that the largest differences among Driver Types occurs with Incidental and Casual types of speeding, which make sense given how much more common these types of speeding are relative to the others.

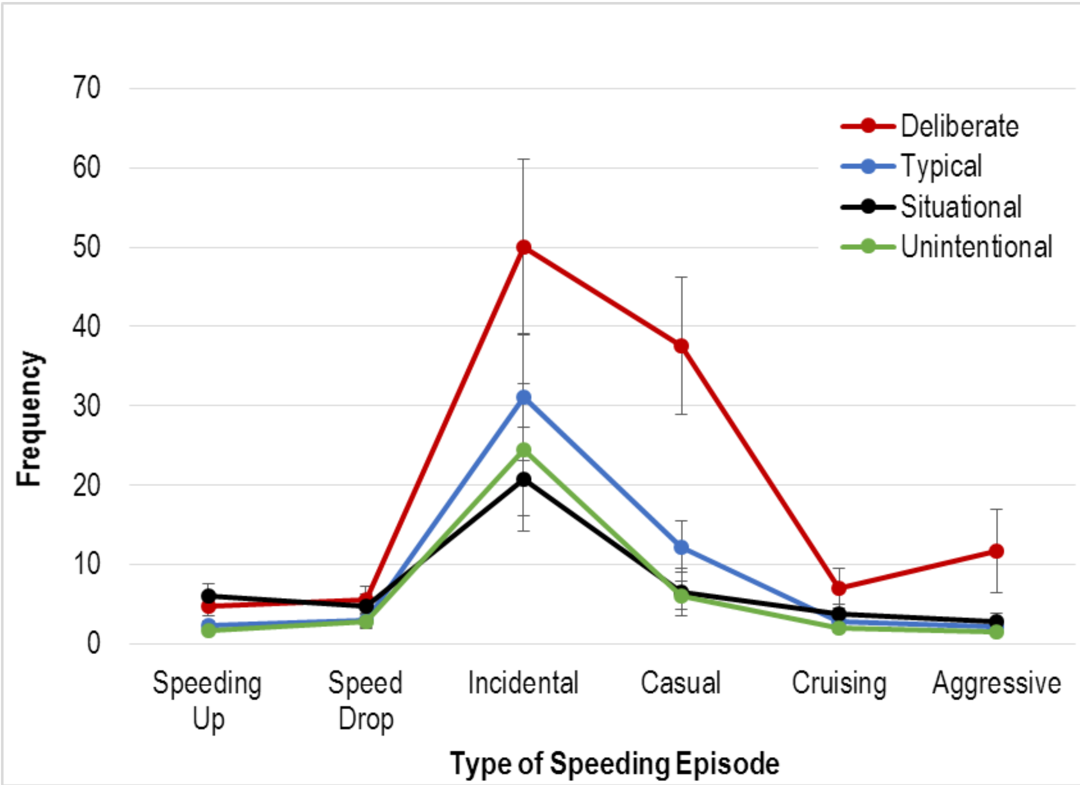


Figure 16. Average frequency of different types of Speeding Episodes (SEs) by Driver Types in Seattle.

The following sections summarize the characteristics of the Driver Types described above and provide the rationale for the labels assigned to each Driver Type.

Driver Type 1 – Deliberate: Drivers in this group had relatively more Casual, Cruising, and Aggressive SEs, but fewer Incidental SEs. Moreover, the Cruising and Aggressive types of speeding are the ones that most likely represent deliberate attempts to speed, and at relatively high speeds as well. As shown in Figure 16, individuals in this group also had substantially more SEs than those in other groups. Thus, out of all of the Driver Types, this group seemed to represent drivers that are most willing to engage in deliberate or intentional speeding behavior (i.e., with longer durations and at higher speeds).

Driver Type 2 – Typical Speeders: Drivers in this group are labeled as the Typical Driver Type primarily because Table 8 shows that the distribution of SEs closely matched the average distribution across all Driver Types. This group contained the largest number of drivers. Individuals in this Driver Type also occupied a middle range in terms of their speeding profiles and the overall frequency of SEs.

Driver Type 3 – Situational Speeders: This group is somewhat of a challenge to label. These drivers are overrepresented in terms of the Speeding Up type of speeding (16% vs 5% on average), and like the drivers in Deliberate Driver Type, they have proportionately less Incidental speeding. The Speeding Up type occurred in specific situations, such as: in advance of speed limit increases, sections where there seems to be a mismatch between the roadway cues and the posted speed limit, and in other instances in which getting up to speeding ended in an abrupt slowing—perhaps because of interactions with other traffic or road users. The label of "Situational" Driver Type loosely fits, but a more precise description is hindered by the fact that multiple types of speeding behavior are perhaps being captured by the Speeding Up type of speeding that primarily defines this Driver Type. Another notable characteristic is that individuals in this Driver Type were at the low end in terms of the frequency of SEs (see Figure 16), and are likely to be infrequent speeders overall.

Driver Type 4 – Unintentional Speeders: In contrast to the other Driver Types, the last group was made up of drivers that mostly engaged in Incidental speeding, combined with a small amount of Casual speeding. The other types of speeding were uncommon in this group. Since Incidental speeding typically has a relatively low maximum speed and short duration, it fits with the scenario of drivers unintentionally exceeding a speed target (that is below the 10 mph speeding threshold) and subsequently coasting back down to their target after realizing that they were driving faster than intended. Thus, the most fitting label for these drivers is that of Unintentional speeders.

These results demonstrate that the types of speeding identified in the initial cluster analysis reflect more than just the dynamics of speed control within a trip, but likely also reflect systematic differences between drivers. Further analysis is needed to assess whether other characteristics of drivers, such as demographic characteristics, define the types of drivers described in Figure 15. This analysis is described in the next section.

Extent to which Driver Types were Defined by Demographics

Another analysis was conducted on Seattle SE data to determine the extent to which Driver Types were defined by demographics. The previous cluster analyses made it possible to assign a Driver Type (using cluster membership) to individual drivers based upon the types of speeding events that they incurred. The demographic composition of the different Driver Types is shown in Figure 17 below for Seattle.

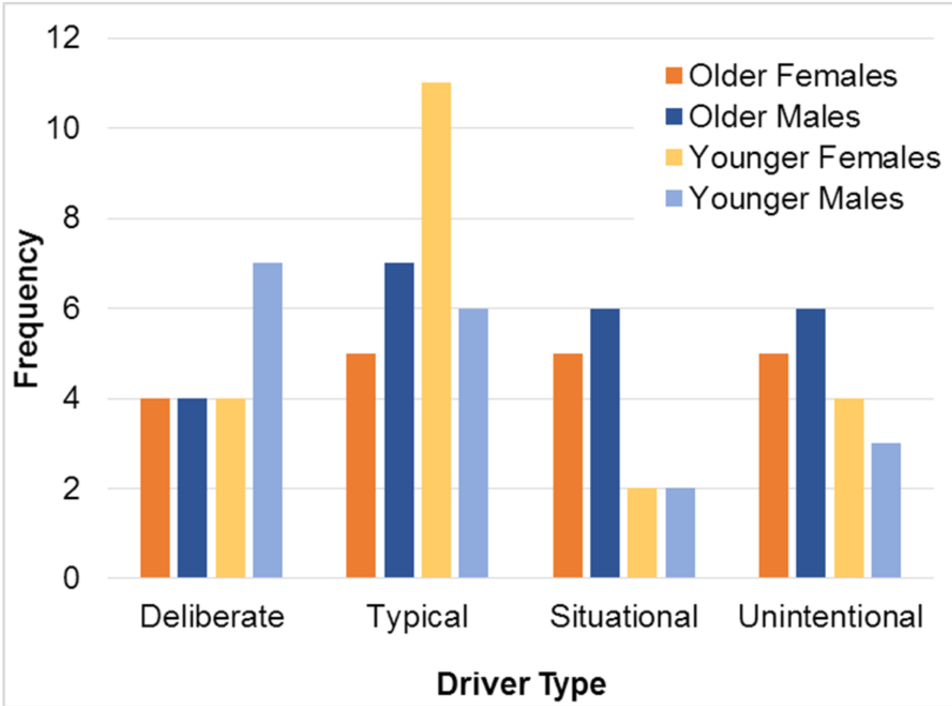


Figure 17. Driver Type by demographic group in Seattle (based on cluster membership).

Upon visual inspection, the most salient pattern appears to be that each Driver Type included drivers from all demographic categories; however, there are also differences across Driver Types. In particular, Young Males are more prevalent in the Deliberate driver category, whereas Young Females are more prevalent in the Typical driver category. Both the Situational and Unintentional Driver Types are comprised of a greater proportion of older drivers.

A chi-squared test was run on the results to determine if any significant differences in group membership could be found between demographic groups. The number of drivers from each demographic category for each Driver Type is shown in Table 9 below. The chi-squared test with 9 degrees of freedom had a p-value of less than 0.001, which indicates that a significant difference was found in cluster memberships across demographic groups. Despite the significant effects, it is the case that all of the different Driver Types include drivers from each demographic group, and the number of drivers in each group is still relatively small overall. Although these initial results are promising, it is still too early to draw conclusions about demographic differences across Driver Types. A more comprehensive analysis involving substantially more drivers is required to examine this question more reliably.

Table 9. Demographic makeup of Driver Types in Seattle.

Driver Type	Older Female	Older Male	Younger Female	Younger Male	Total	Composition
Deliberate	4	4	4	7	19	More young males
Typical	5	7	11	6	29	More young females
Situational	5	6	2	2	15	More older drivers
Unintentional	5	6	4	3	18	More older drivers
Total	*19*	*23*	*21*	*18*	*81*	

Driver Demographics for Riskier Speeding Types

A clear pattern in terms of driver demographics and Driver Type is that drivers from all demographic groups occurred within each Driver Type. While the demographic distributions across groups varied, there were too few drivers overall to make definitive claims about these patterns. As a second look at the issue of driver demographics, we examined the riskier types of speeding with regard to demographics, in particular, Cruising and Aggressive speeding. Figure 18 shows a scatterplot of the percentage of free-flow trips that also had the two "riskiest" speeding types ("Cruising" and "Aggressive" speeding). Each dot represents a single driver, color-coded by demographic category, as described below.

Two patterns were apparent in the scatterplot. First, there appears to be three tiers of drivers. The first is a group of three males that stand out from the rest because of a relatively high percentage of both types of speeding. The second group is a dense yet compact set of drivers closely grouped near the graph origin, which represents the majority of drivers that had little-to-no riskier Speeding Episodes. The last group occupies an intermediate range (between 8-25%), representing drivers that occasionally engaged in riskier speeding. The second pattern evident in the scatterplot is that the riskier speeding tiers are not clearly defined by demographics. Both younger and older drivers, and males and females are found in the intermediate tier. The highest-risk tier is all males; however, there are too few drivers in this group to draw solid conclusions. Overall, Figure 18 provides similar findings as the cluster analysis, which suggested that Driver Types were not exclusively defined by driver demographics.

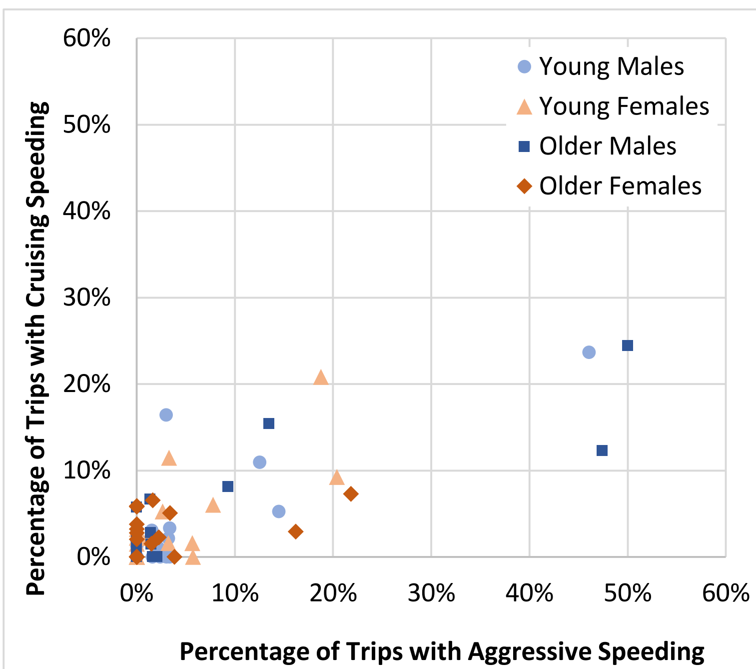


Figure 18. Percentage of free-flow trips on which "Cruising" and "Aggressive" Speeding Episodes (SEs) occurred for individual drivers in Seattle, coded by demographic group.

Trends in Beliefs and Attitudes across Driver Types

Participants in the original *Motivations for Speeding* study completed multiple personal inventory questions about their attitudes, motivations, and beliefs towards speeding (Richard et al., 2013b). Responses to these questions provided a way to obtain further insight about how the Driver Type groups may differ. In particular, since the Aggressive type of speeding was relatively common among the Deliberate Driver Type group, these drivers may have more permissive attitudes about speeding than other groups. Likewise, since members of the Unintentional Driver Type group engaged mostly in Incidental speeding, they may have more restrictive attitudes about speeding than other groups.

To examine if Driver Types differed in terms of their self-reported attitudes, behaviors, and beliefs about speeding, participant responses to the personal inventory items were examined. In particular, mean values for each question were calculated for all members of a particular Driver Type. The objective was to identify patterns in responses that might provide qualitative insight about how the Driver Types differed in terms of their attitudes and beliefs about speeding.

There were 91 personal inventory questions available for this investigation. Since this analysis was largely exploratory, trends in responses across questions were more important than patterns within specific questions. For most of the questions, mean responses did not differ noticeably across groups; however, for a sizable minority of questions, mean responses showed some separation across some Driver Types. To separate out questions in which mean responses were potentially different, a one-way ANOVA was run separately on each question. Only the questions for which the significance value was less than 0.10 were included in the current investigation.

Note that the ANOVA results were not intended to identify specific comparisons as being significant. This approach would be problematic because there were only a small number of participants within each group, and the likelihood of Type 1 errors would be high across the set of comparisons. Therefore, the ANOVA results were simply used to identify survey items for which at least one Driver Type differed from the others. This was a convenient method for reducing the number of survey items included in this analysis. The overall objective was just to look for qualitative, yet interpretable patterns in responses across Driver Types.

Personal Inventory Questions for Each Driver Type

The personal inventory questions were grouped into subsections based on the nature of the questions and the corresponding response scales. The sections below show the mean responses on the personal inventory questions for each Driver Type. Items are grouped by type of question (i.e., different sections of the personal inventory). Response patterns were examined within each subset of questions. For most of the subsets, at least a quarter of the questions could be used to identify Driver-Type trends. Graphs showing the response patterns for each question are provided below.

Self-reported Driving Behaviors

There were 45 questions related to self-reported driving behaviors included from the Driver-Behavior Questionnaire (DBQ; Reason et al., 1990) and DeJoy Risky-driving Questionnaire (DeJoy, 1992). Eleven of those questions had p-values of less than 0.1. The mean values by group and corresponding error bars for this subset are shown in Figure 19 and Figure 20. Of the items in which some differentiation between the groups occurred, a consistent pattern is evident among almost all of the items. Specifically, responses from the Deliberate Driver Type group are at the riskier end of the response scale relative to the other groups, which are largely undifferentiated. One interesting finding is that for the DBQ questions, differences only occurred on questions related to riskier driving behaviors. There were no differences across groups for questions about relatively harmless behaviors, such as mistakenly activating a turn signal when the driver was intending to activate the windshield wipers.

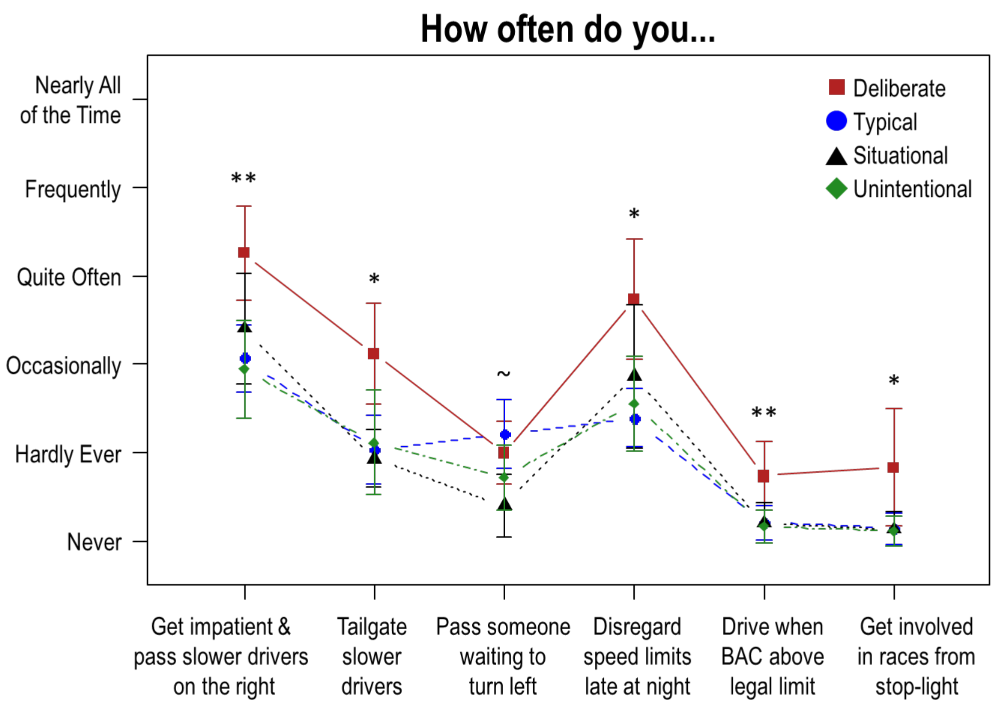


Figure 19. Mean responses by Driver Type for questions about driving self-reported driving behavior (Part 1; ~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

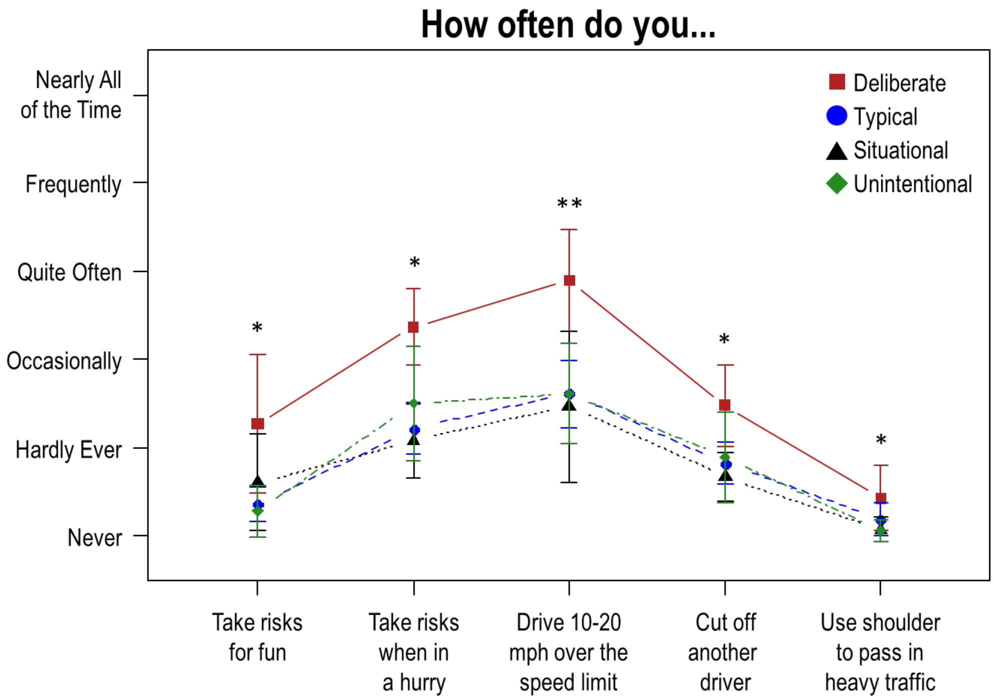


Figure 20. Mean responses by Driver Type for questions about driving self-reported driving behavior (Part 2; ~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

Beliefs about Speeding

The remaining personal inventory questions are from at driver speed questionnaire based on the Theory of Planned Behavior (Ajzen, 1985; Elliott, Armitage, & Baughan, 2005). Questions in this survey are divided into different sections addressing different types of driver beliefs and motivations. The first set involved 13 questions about general beliefs regarding driving within or near the speed limit. For most of these questions, there were minimal differences across Driver Types. For the questions shown in Figure 21, below, Deliberate Driver Types were separated from the other groups in the direction of more negative views about keeping to the speed limit. Another minor trend is that the Unintentional Driver Types were generally on the more positive end of responses related to keeping within the speed limit.

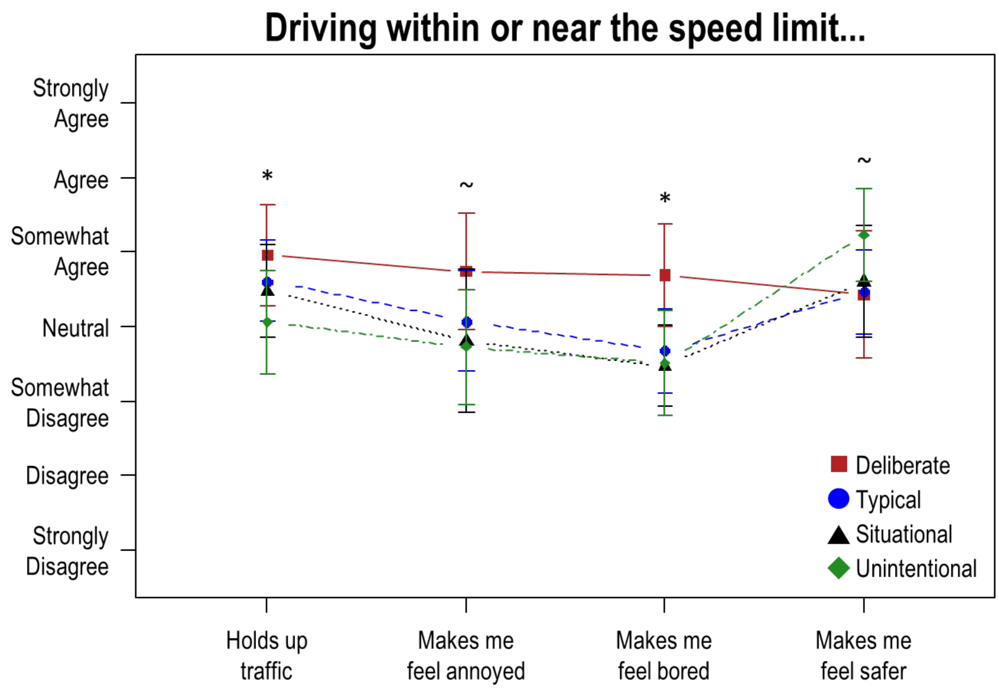


Figure 21. Mean responses to questions about speeding beliefs by Driver Type (~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

Situational Factors

There were 13 questions addressing how likely drivers would be to keep to the speed limit in different driving situations. Mean responses are shown in Figure 22 and Figure 23 for eight of these items. Two trends emerge. The first is that the Deliberate Driver Type group once again stands out in most of the questions. This group consistently reported being the least likely to keep to the speed limit in the different situations. The second trend is that drivers in the Unintentional Driver Type group tended to respond as being the most likely to keep to the speed limit. The other two groups were often in the middle range, and had similar means, with a few exceptions.

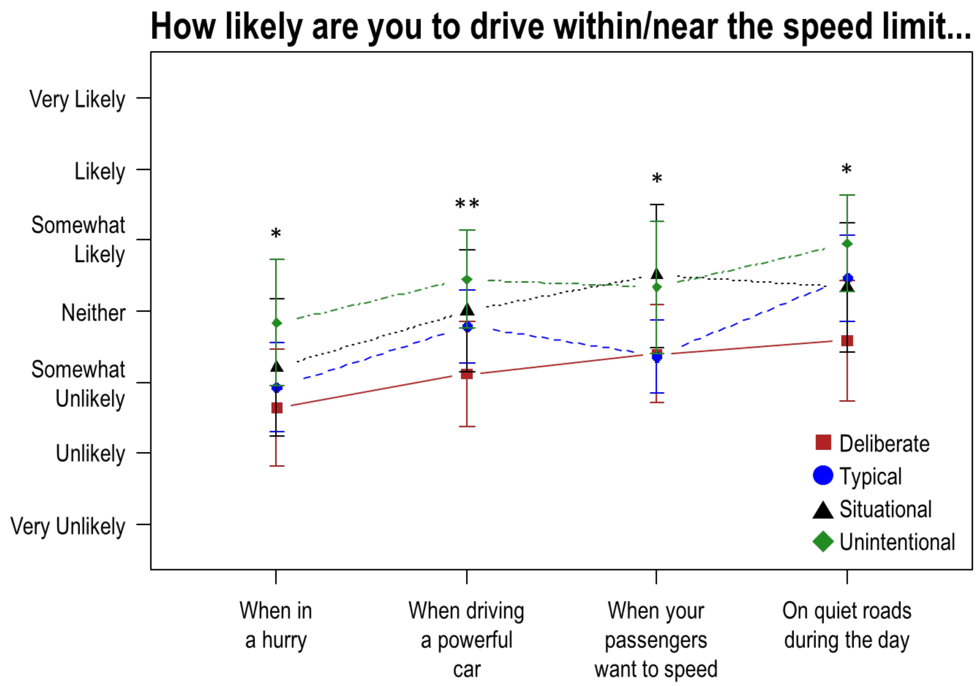


Figure 22. Mean responses by Driver Type for questions about situational factors and speeding (Part 1; ~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

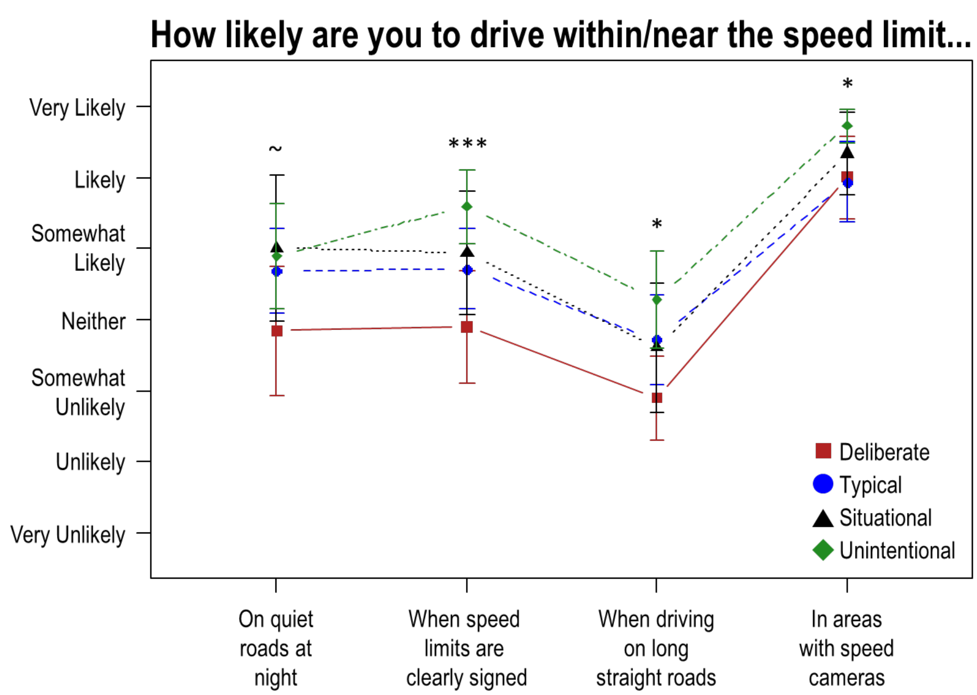


Figure 23. Mean responses by Driver Type for questions about situational factors and speeding (Part 2; ~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

Influence from Other Drivers and Control Beliefs

There were nine questions that covered social norms and the influence of others on participants' willingness to keep to the speed limit. For the questions that showed some degree of differentiation across groups, the only pattern apparent was that Unintentional Driver Types were more likely to report being influenced by others (see Figure 24).

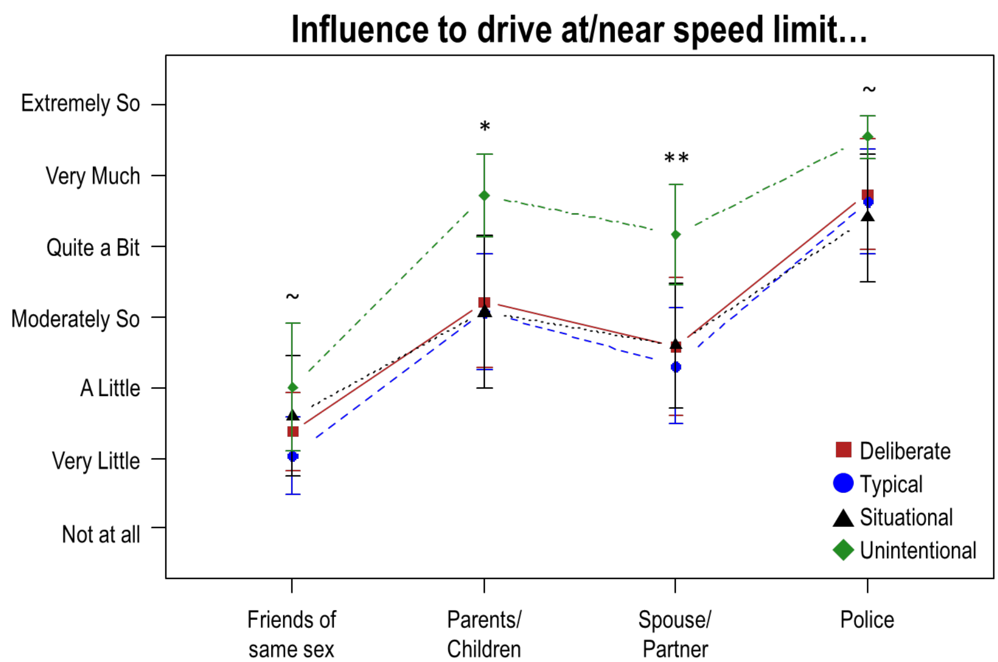


Figure 24. Mean responses by Driver Type for questions about the influence of others on speeding behavior (~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

Participants also responded to five questions about their control beliefs and intentions regarding driving at or near the speed limit. The consistent trends across the 3 questions shown in Figure 25 indicate that Unintentional drivers respond more positively with regard to keeping within the speed limit, while Deliberate Driver Types respond most negatively.

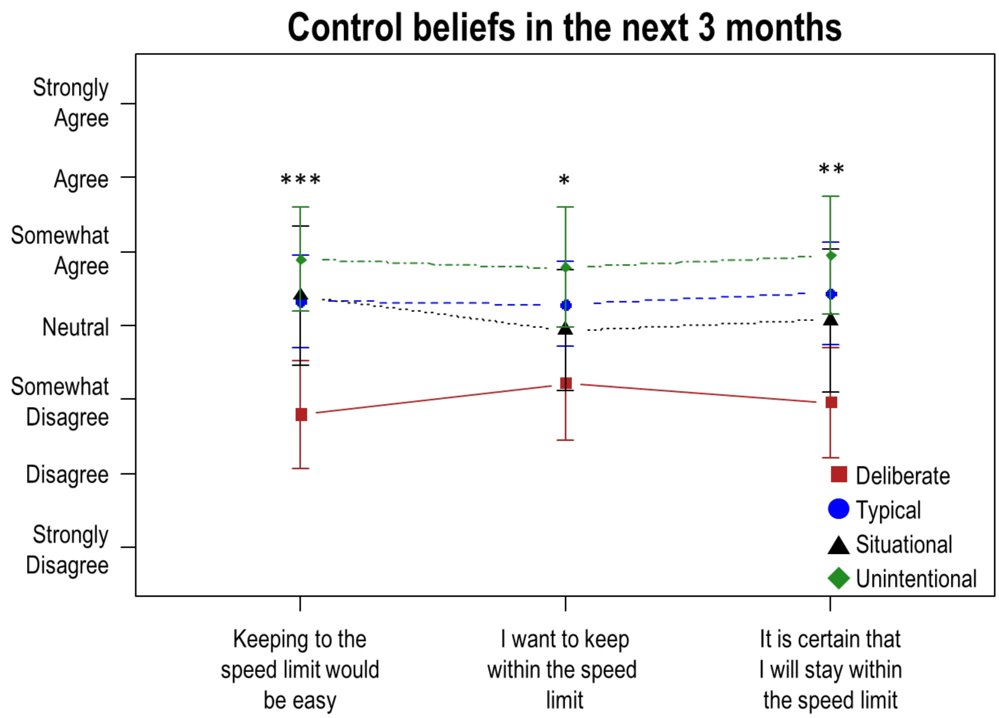


Figure 25. Mean responses by Driver Type for questions about driver control beliefs on speeding behavior (~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

Self-reported Speed

The personal inventory also had four questions that showed an image and description of an open-road scenario each with different posted speed limits, and asked participants how fast they would normally travel in the indicated scenario. As seen in Figure 26, mean responses for all groups are slightly above the posted speed limit. Although self-reported speeds are undifferentiated on 25 mph residential roads, the Deliberate Driver Type generally reported higher speeds on other road types. There were no differences among the other groups.

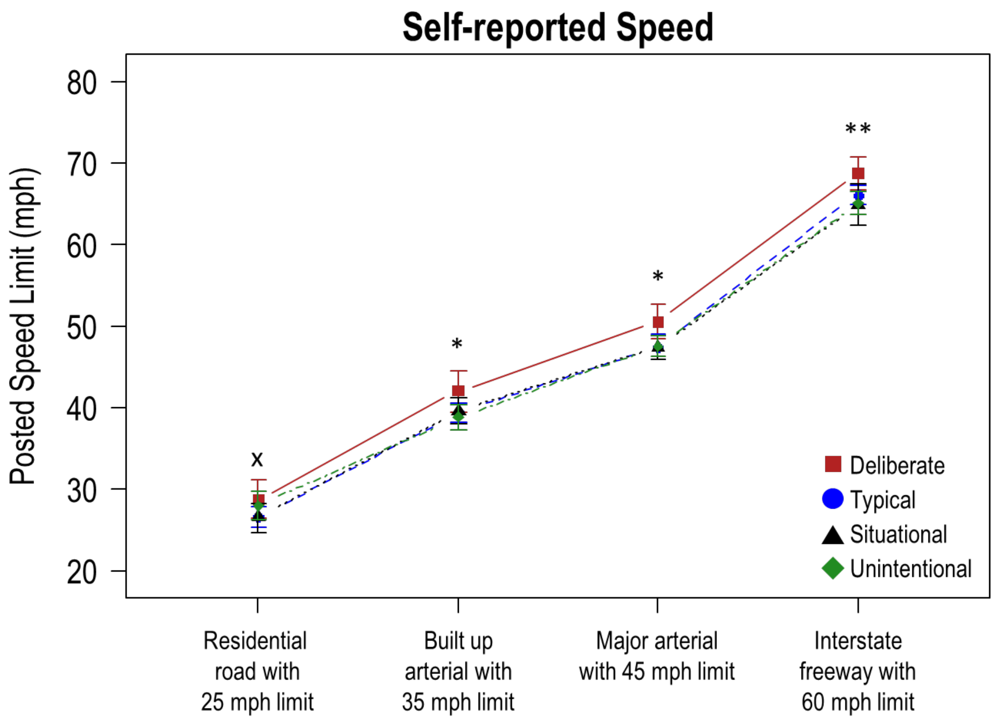


Figure 26. Mean responses by Driver Type for questions about driver self-reported speed (~ < 0.1; * < 0.05; ** < 0.01; * < 0.001).**

Table 10, below, summarizes the trends observed across questions. The table also indicates the number of questions that met the criterion for inclusion.

Table 10. Trends across Driver Type in responses to personal inventory questions related to behaviors, beliefs, and attitudes towards speeding.

Question Type	Number of Qs Included / Total Qs	Driver-Type Trends
Self-reported driving behaviors	11 / 47	*Deliberate* driver-types more frequently engage in riskier behaviors.
Attitudes towards not speeding	4 / 14	*Deliberate* driver-types are the least positive; *Unintentional* are the most positive on some questions.
Situational factors affecting speeding	8 / 12	*Deliberate* driver-types are the most likely to speed; *Unintentional* driver-types are the most likely to avoid speeding.
Social norms towards not speeding	4 / 9	*Unintentional* driver-types most likely to be influenced by others to not speed.
Control beliefs and intentions about not speeding	3 / 5	*Deliberate* driver-types are the least agreeable regarding not speeding; *Unintentional* driver-types are the most agreeable.
Self-reported speed	3 / 4	*Deliberate* driver-types reported faster speeds on each road type.
Most questions		*Typical* and *Situational* Driver Types typically overlapped each other.

Discussion

A few consistent patterns occurred across the different types of questions in the surveys. The dominant trend was that responses from the Deliberate speeding driver group are on the aggressive end of the spectrum relative to other Driver Types. This pattern is evident for almost all questions shown in the figures. Another less prominent trend that occurred within certain sets of questions was that Unintentional Driver Types were on the more conservative/safer end of the response spectrum. Neither of these trends were surprising given the types of speeding that defined these Driver Types. With regard to the Typical and Situational Driver Types, they were usually no different from the Unintentional Driver Type, and they sometimes fell in between the Deliberate and Unintentional Driver Types. For almost all questions, differences between Typical and Situational Driver Types were minimal. This suggests that these may not represent qualitatively different types of drivers.

Texas Cluster Analyses for Speeding Type

The data from Texas were analyzed in a manner parallel to that of the Seattle data. The same nine variables that captured speed-related characteristics were used in the Texas cluster analysis. Figure 27 shows scatter plots for eight of those variables. The pattern of results was generally similar to that of the Seattle data, but with a few exceptions. One notable difference was that the distribution of points was far less concentrated in Texas, which was because there were a third as many SEs as in Seattle. The basic forms of the scatter plot distributions in Figure 27 closely resemble those from Seattle. However, there are key differences in the top left-plot, which shows the Mean Exceedance by Duration. In Texas, there was a more pronounced concentration along both axes, including longer duration SEs at moderate speeds, and an apparent spike of higher exceedance SEs around 15-25 seconds in duration. Another difference in Texas is found in the top-right plot, which shows the two variables related to speed variability. For Texas, the Standard Deviation of Acceleration has a smaller range than in Seattle, which is at least partly attributable to the longer SE durations. The lower overall variability in this speed change measure may also reflect a greater use of cruise control during speeding, or it may be related to the longer, straighter roads that facilitate maintaining a steady speed.

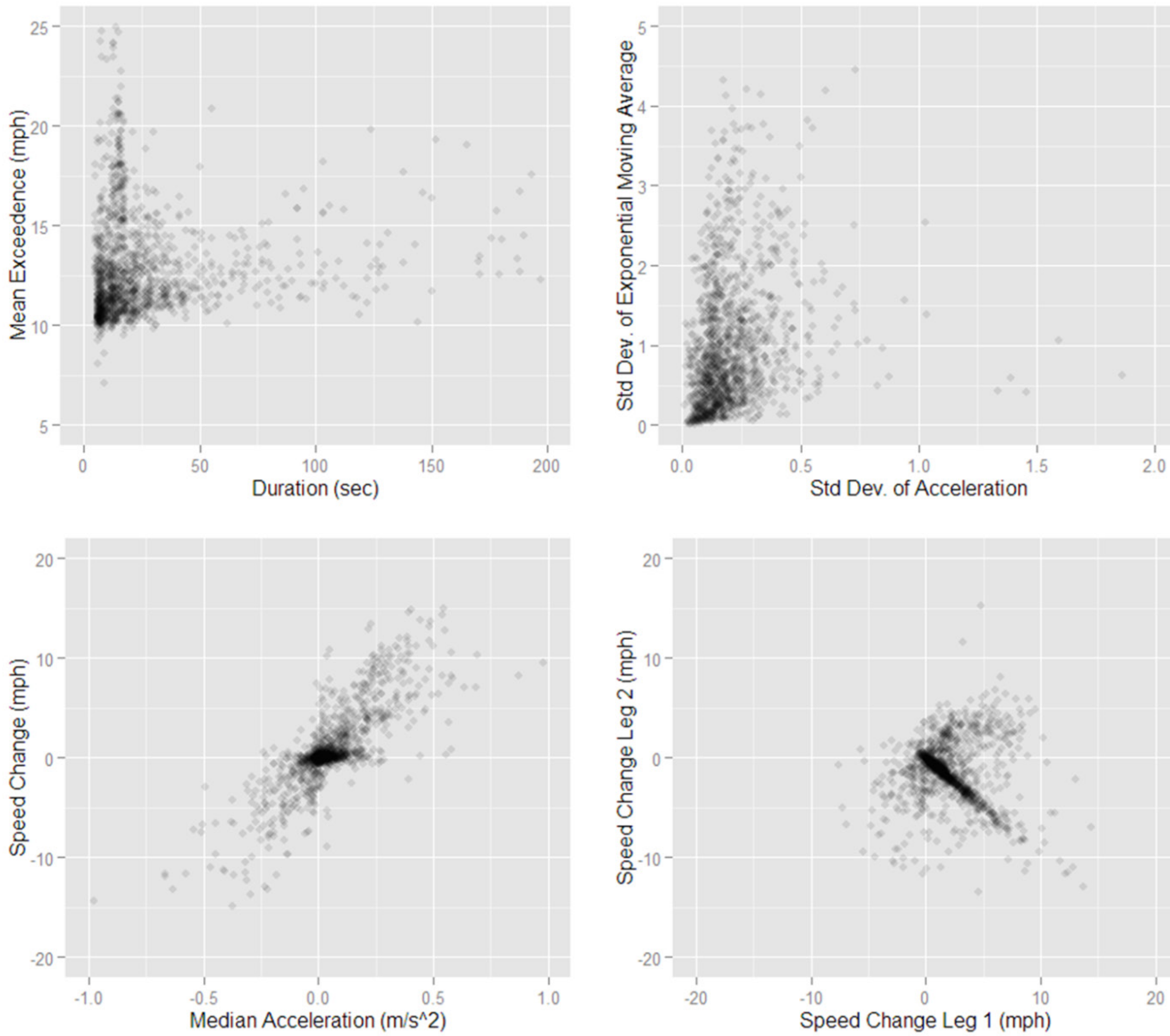


Figure 27. Variables used to cluster Speeding Episodes (SEs) for the Texas sample.

Characterizing Types of Speeding based on Speed Profile and Situational Variables

As with the Seattle data, the nine speed-related variables were used to cluster the SEs with the k-means clustering algorithm. The analysis was repeated with 1 to 15 cluster centers. Figure 28 shows how well each of these cluster analyses fit the data. Based on the within groups sum-of-squares, seven or eight cluster solutions appear to be optimal. However, inspection of the seven and eight cluster solutions indicated that these solutions frequently produced clusters comprised of less than a dozen SEs. Thus, we selected a six-cluster solution for Texas. This solution was also the most interpretable one.

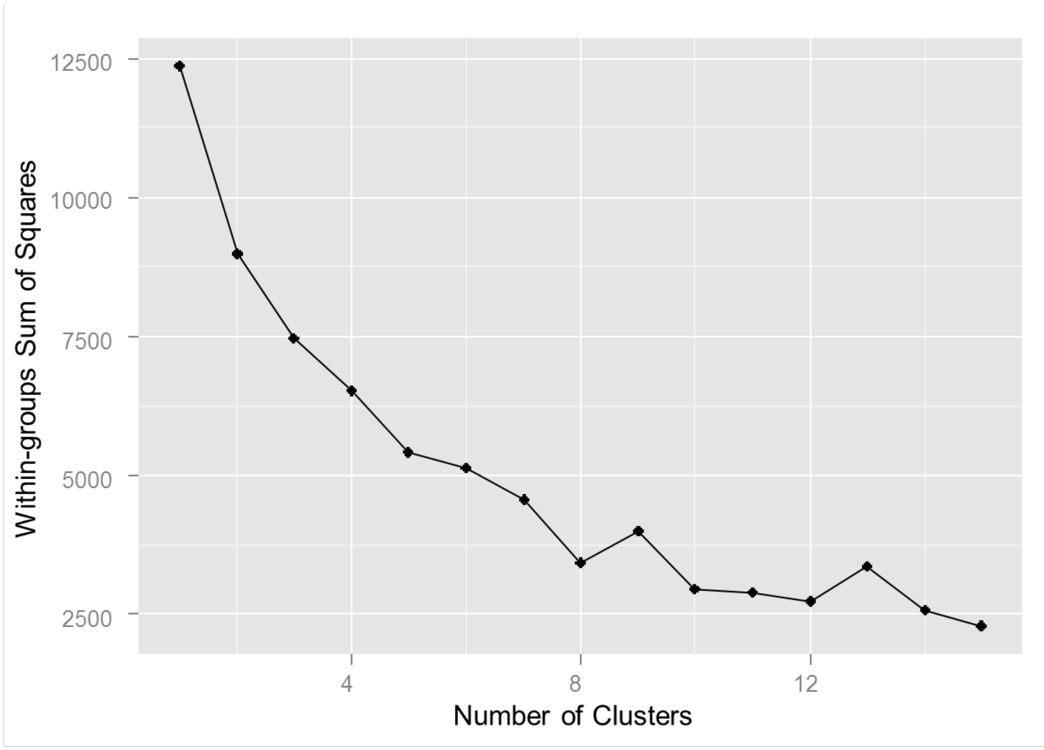


Figure 28. Within groups sum of squares for the Texas sample.

To characterize the speeding behaviors represented by the Texas SE clusters, we calculated descriptive statistics for the key SE variables. Table 11 shows some of the properties of the clusters as defined by the median values of key variables. The variables describing the speed change in each leg were condensed into a description of the general form of the cluster time-series. The general form was also verified using visual inspection. Two variables that were not used in the cluster analysis (Maximum Acceleration and Maximum Deceleration) are also shown in the table because they have explanatory value.

Similar to the Seattle data, more than half of the SEs were grouped into just two clusters (3 and 4); however, there is less disparity between these two clusters and the others. Another important observation is that most of the clusters were comparable to particular types of speeding clusters in Seattle. Each cluster is described below.

Table 11. Median values of key variables for Speeding Episodes (SEs) within each cluster in Texas.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
N	98	93	731	250	68	136
Duration	15	14	14	28	216	11
Max Speed above Speed Limit	21.3	18.4	12.1	15.9	18.1	15.4
Mean Speed above Speed Limit	17	15.9	11.1	13.2	14.3	12.9
StdDev ExpMA	2.6	1.2	0.4	1.3	1.7	1
Speed Change	9.1	-6.4	0	0.1	0.2	4.2
Max Accel	0.6	0.2	0.2	0.4	0.3	0.4
Max Decel	0	-0.6	-0.3	-0.5	-0.5	0
General Form	Rising	Dropping	Flat	Slight Peak	Slight Peak / Flat	Shallow Rise
Label	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Small Increase

Cluster 1 – Speeding Up: The defining characteristics of Cluster 1 were the relatively large increases in speed from beginning and end, the generally rising form of the time series, high maximum exceedance, and high variability (StdDev ExpMA). These values were quite similar to those of the Seattle Speeding Up cluster. The primary difference between the two was that the mean speed was higher in Texas than in Seattle (17 vs. 8 mph, respectively), although maximum speed exceedance was similar across locations. Behaviorally, this would suggest that Texas drivers may have gotten up to speed sooner, and the slightly higher computed Maximum Acceleration in Texas is consistent with this notion.

Cluster 2 – Speed Drop: As with Seattle, Cluster 2 represented the complementary behavior to the Speeding Up cluster. In particular, it was defined by a relatively large decrease in speed, the generally dropping shape of the time series, high maximum exceedance, and high variability (StdDev ExpMA). The values were very close to those in the corresponding Seattle cluster and these characteristics are consistent with drivers slowing down after transitioning to a lower posted-speed zone.

Cluster 3 – Incidental Speeding: This cluster closely matched the Incidental speeding cluster (Cluster 3) in Seattle. In addition to being the most common type of speeding, the values of most variables were on the low end. The biggest difference relative to its Seattle counterpart is that the duration was slightly longer in Texas.

Cluster 4 – Casual Speeding: This cluster had similar variable values as the Casual speeding cluster in Seattle (Cluster 4). In Texas, the duration, max speed exceedance, and speed variability were slightly higher. There was also a comparable relationship between the Casual and Incidental clusters in Texas, as in Seattle. Specifically, the variables in both clusters shared similar trends, but those in the Casual cluster had higher median values.

Cluster 5 - Cruising: The defining aspect of Cluster 5 was the long duration relative to the other speeding types, akin to drivers “cruising” along a roadway at elevated speeds for a moderate duration. This type of speeding also included some SEs that had very low variance, likely representing speeding when cruise control was activated. This cluster matched the Cruising cluster in Seattle; however, the median duration was over twice as long, which is to be expected given the prevalence of long stretches of straight roadway in rural Texas.

Cluster 6 – Small Increase: Cluster 6 is the only cluster in Texas that did not clearly match a Seattle cluster. It was defined by a small rising trend, the shortest overall duration, and speed levels comparable to the Casual speeding cluster. It was also on the low end in terms of speed variability, but this is still twice that of Incidental speeding. It could represent a shortened version of the Speeding Up cluster. In line with this notion, the 5-cluster solution combined this cluster with the Speeding Up cluster.[5]

One notable outcome of the cluster analysis of Texas speeding was the absence of an Aggressive speeding cluster. A potential explanation for this is that posted speeds are generally set higher in Texas, which results in less speeding overall. It is also possible that the roadway environments simply makes it uncomfortable for drivers to speed at excessive levels on many roads for more than brief durations. The lack of an Aggressive speeding cluster in Texas also provides an explanation for why the Casual and Cruising speeding clusters in Texas had generally higher median values than in Seattle. Specifically, Casual and Cruising clusters in Texas likely captured the SEs that were analogous to the Aggressive type in Seattle, since they were too uncommon to form their own cluster. This is somewhat apparent in Figure 29 below, which shows the distribution of SEs in terms of mean exceedance and duration, color-coded and outlined by speeding cluster. The general regions occupied by each cluster are indicated in the annotation.

Visual inspection of Figure 29 indicates that patterns are generally similar to the corresponding scatter plot for the Seattle data, but the region occupied by Aggressive speeding is relatively empty and the corresponding SEs were divided among the Casual and Cruising clusters.

[5] Note, while the 5-cluster solution improves the interpretability of the Speeding Up cluster, it also substantially changes most of the other clusters in ways that are at odds with consistent patterns obtained using higher-cluster solutions, and the results much less interpretable. For these reasons, we stayed with the 6-cluster solution in Texas.

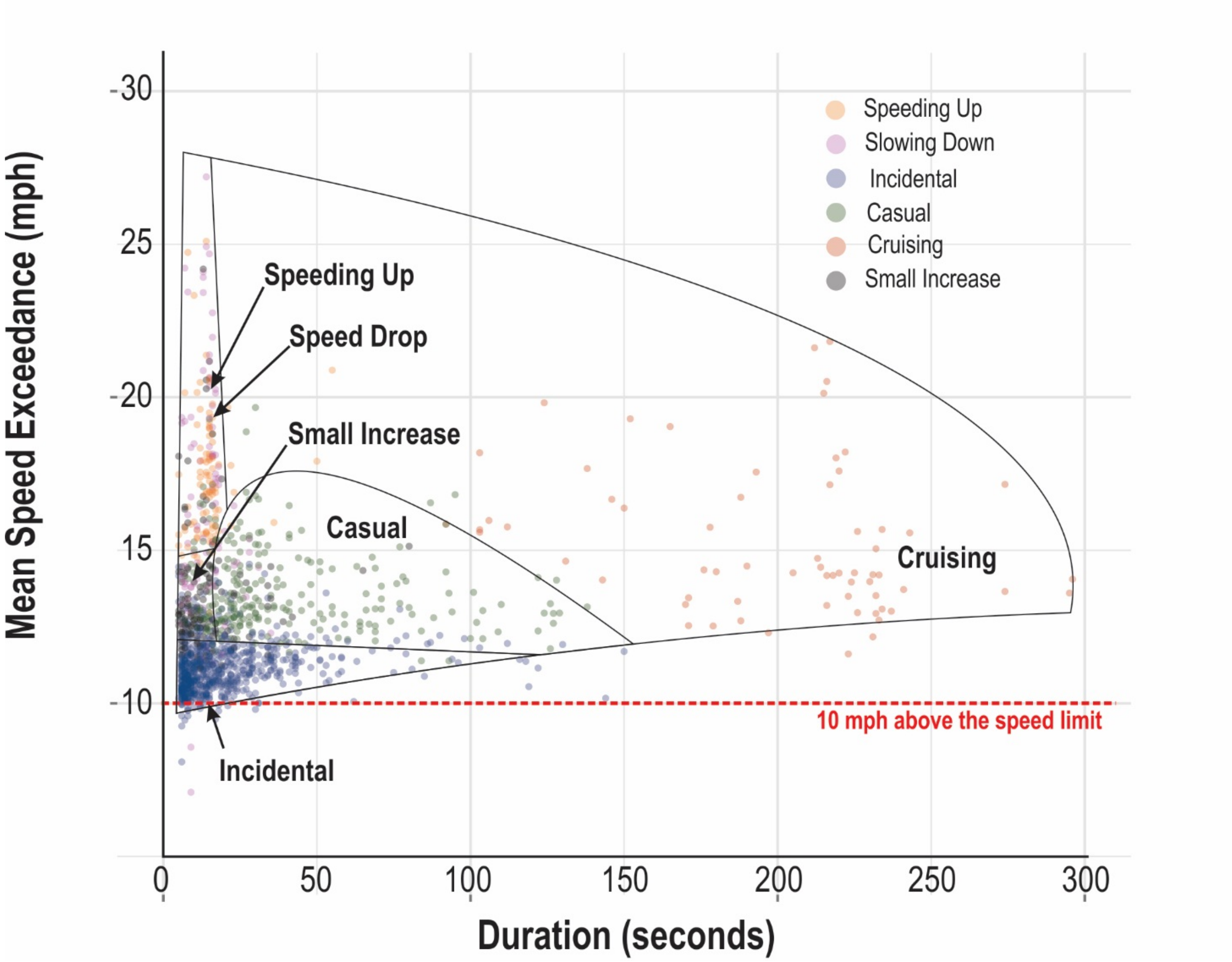


Figure 29. Scatter plot of mean speed exceedance by duration for all Texas Speeding Episodes (SEs). Points are color-coded based on cluster membership. The general region occupied by each cluster is indicated.

Driver Type Cluster Analysis

Note that the Driver Type cluster analysis was not run in Texas. This is because over a quarter of Texas drivers had an insufficient number of SEs to compute the proportional distribution of speeding-types for those drivers.

SITUATIONAL ANALYSIS

Overview and Rationale for Approach

The cluster analysis described in the previous section identified different types of speeding. This approach, however, was somewhat abstract because the grouping of SEs was done only using variables related to speed (e.g., magnitude, duration, etc.). While this was useful for capturing the characteristics that define speeding types at a fundamental level, it was also important to account for the broader driving situations that may also influence a driver's propensity and opportunity to speed. To obtain a better understanding of situational aspects of speeding, we used road-network data to examine where SEs occurred. We also had a limited number of variables that provided information about the driving context (e.g., time of day, type of road, etc.), and we examined the different types of speeding in terms of these situational variables.

To better understand the relationship between the roadway environment and speeding behavior, the first step was to identify the locations where SEs occurred more frequently to determine if there were aspects that systematically encouraged different types of speeding. To do so, we employed an exploratory approach of using the frequency of SEs at various locations to develop speeding "heat maps." Heat maps provide color-coded information about categories or quantities at specific locations or on specific road segments. The intensity of the color indicates the level of the category or the quantity, generally, the greater the intensity of the color (darker the color) the higher the frequency or greater the proportion of SEs on a particular road segment.

The goal of this analysis was to determine if there were patterns with respect to where SEs occurred that can provide insight into the different speeding types identified in the cluster analysis. The advantage of developing heat maps is that the maps can show trends with regard to where SEs occur, in general, which can then be used to identify specific roadway features across locations that might have contributed to this speeding. Since the speed characteristics of the speeding type clusters were generally different, it is likely that roadway factors associated with the various clusters also differ. Thus, using heat maps to identify where the SEs in each cluster occurred allowed us to compare and contrast the roadway factors across the different clusters.

As potentially useful as this approach was, there were limitations that we had to address. The first was that driving in this study was not uniform across the road types, and some roads were traversed substantially more frequently than others. This meant that using the absolute count of SEs to identify high-speeding locations can be misleading, since roads that are heavily traveled can have a high number of SEs, even if the overall rate of SEs is low. For example, in the Seattle region, a great deal of driving was done on the major freeways that traverse the city (I-5 and I-405), and the number of SEs on these roads is the highest. To compensate for the different amounts of driving on different roads, the number of SEs on a road segment was divided by the number of FFEs on the same road segment. This yielded a corresponding proportion of SEs on a road segment that was comparable to proportions at other locations. This also allowed us to identify specific locations where drivers were speeding at a higher rate when given the opportunity to speed (i.e. a higher proportion of free-flow trips at the location were speeding).

The second data limitation was that many of the locations identified as "hot spots" consisted of driving from a just small number of drivers at that location. Two factors potentially contributed to this. The first was that, except for a set of major roads, driving by individuals was generally spread throughout the study area, which meant that repeated traversals of a road segment by many different drivers was uncommon. Moreover, since most drivers tended to drive to many of the same locations repeatedly, the same few drivers end up contributing most of the traversal on specific road segments. Consequently, the small number of drivers in this study resulted in many of the "hot spots" on minor roads reflecting speeding behaviors that may be more specific to a single individual than to general roadway factors. This makes it difficult to disentangle the unique effects of situation-specific factors that might have contributed to driver speed choice from driver-specific effects and their interactions with the situational/location specific factors.

Thus, considering the limitation of the data set, we used the heat maps to identify high-level trends rather than specific location- and driver-specific effects. The situational analysis of SEs that follows presents heat-maps, and summaries of where speeding occurred for the different types of speeding clusters. An analysis of the relationships between the available roadway/situational factors and speeding types is also presented.

Descriptive Situational Analysis

This section provides an overview of the general driving patterns observed in the Seattle and Texas regions in this study. Specifically, patterns related to where drivers had the opportunity to speed, and the locations/roadways where SEs actually occurred were analyzed. We also examined where FFEs and SEs occurred during nighttime driving. The analysis that follows is presented separately for Seattle and Texas. This was done because the two regions have distinctively separate geospatial characteristics that could have a different influence on the speeding behavior of drivers. At the very basic level, the Seattle area is more urban and has more built-up spaces, whereas the region in Texas where most of the driving took place is rural and has more open spaces.

The maps that follow present color-coded information about the location and frequency of the FFEs and SEs. To develop these maps, we calculated the simple frequency of FFEs and SEs respectively for each roadway segment, and then displayed the frequencies on each segment using color-codes. Note that this approach loses information about the spatial extent of individual SEs and replaces them with the spatial extent of the road segment. This information loss is unavoidable, since it is the only way to aggregate separate SEs into heat maps. In the heat maps, the darker the color of the roadway segment, the greater the prevalence of Free-Flow and Speeding Episodes on those segments.

Seattle Situational Analysis

The section that follows presents maps showing the location of the FFEs and SEs in Seattle. In addition, maps showing where SEs from each type of speeding occurred are also presented. Finally, situational factors and their relationship to the types of speeding were analyzed and summarized. Note that Appendix A contains separate maps of the road networks and labels for the key roadways in Seattle and Texas. Most of these details were excluded from the driving data maps to improve their legibility. It is helpful to refer to the appendix maps when interpreting the driving data maps.

Free-flow Episodes

The map that follows (Figure 30) shows the frequency of FFEs for each roadway segment in the Seattle region. It highlights roadway segments where drivers were able to travel at free-flow speeds the most, and thus potentially had the opportunity to speed most often. The frequency of FFEs on the roadway segments is color-coded in shades of green, with the road segments that have the fewest FFEs (0-50 trips on a road segment) coded in light green, and road segments with most FFEs represented in dark green (200 – 250 trips on a road segment).

Overall, drivers covered a wide area and traversed roads throughout Seattle at free-flow speeds. Although FFEs are scattered across the study area, the general pattern seems to be that the central areas of the city had more FFEs that the outlying areas. This was probably due to regular commuting patterns from the suburbs into the city.

In the central areas, the highest number of FFEs occurred on freeways and state highways, i.e., the four major freeways that connect the suburbs in the North/South, and East/West of the Greater Seattle region. It is, therefore, not surprising that these roads had the most FFEs as they probably also had the most driving overall.

In the outlying areas, most of the FFEs occur on arterials and major roads. There was certainly a large amount of driving on residential roads in the outlying area; however, most residential roads were excluded because the posted speeds on residential and local streets were not typically available in the road-network database.

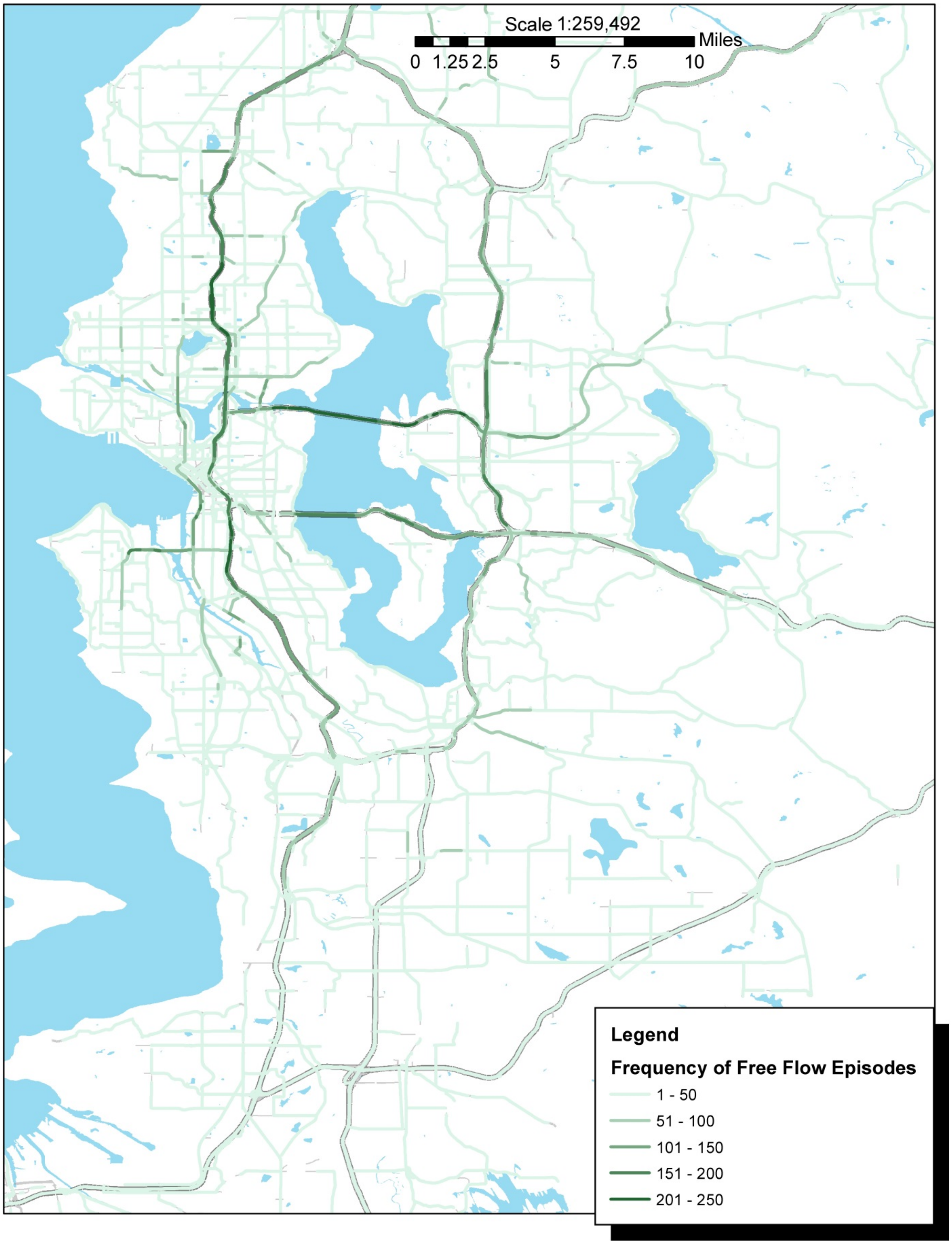


Figure 30. Frequency of Free-flow Episodes (FFEs) on road segments in Seattle.

Nighttime Free-flow Episodes

The following map (Figure 31) shows the frequency of FFEs at night. Nighttime driving was defined as trips started between 8pm and 6am. There were a total 1,224 FFEs at night, with the highest concentration of FFEs along two stretches of the Interstate 5, which is a major freeway route through Seattle. The general pattern that emerges indicates that only a small proportion of the FFEs occurred at night. While this is initially counterintuitive since traffic congestion is generally lighter at night than during the day, this is likely due to the comparatively small number of nighttime trips overall. Another possible explanation could be that the criterion for counting driving as free-flow (posted speed minus 5 mph) may have been too high if many drivers slowed down to mitigate reduced nighttime visibility.

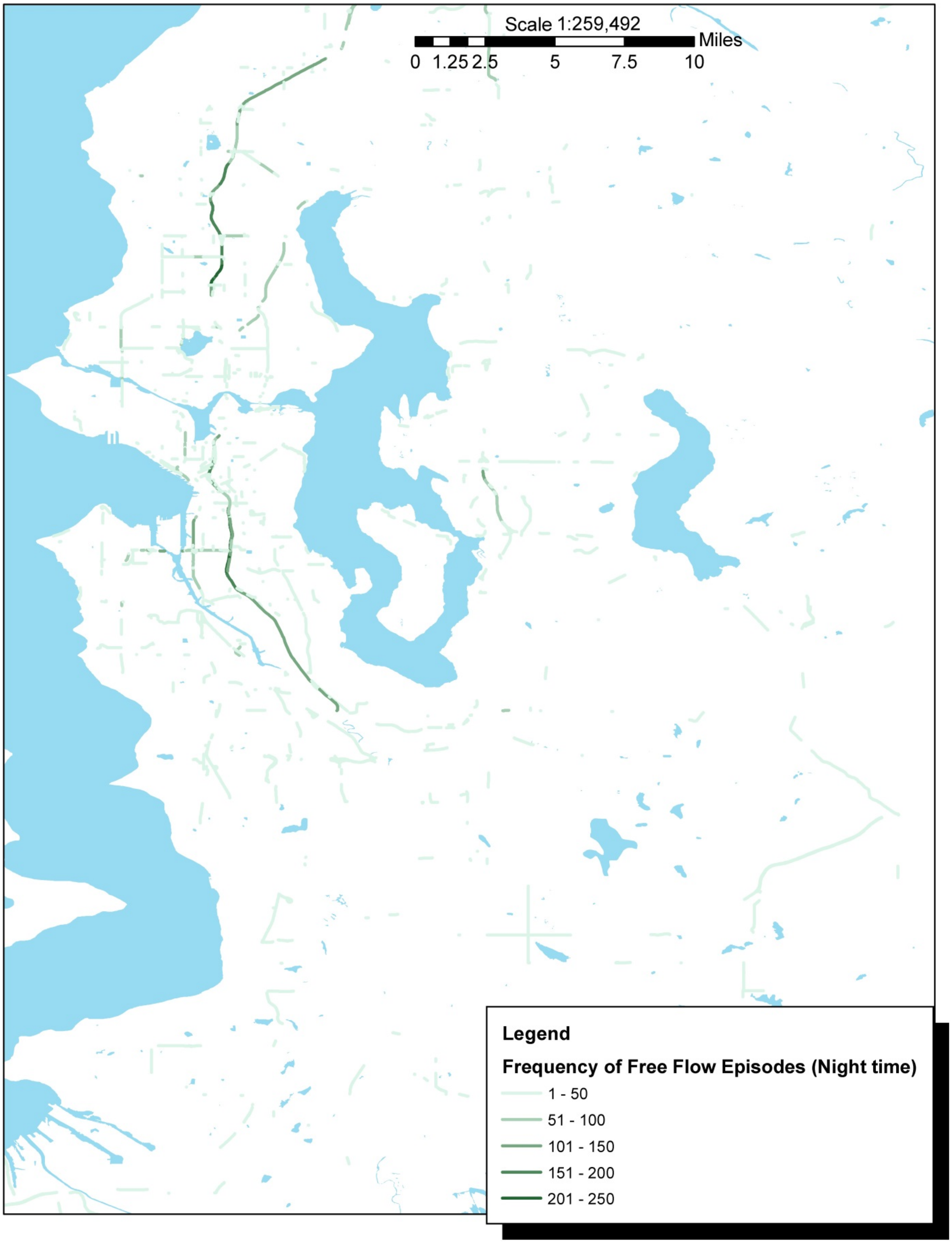


Figure 31. Frequency of Free-flow Episodes (FFEs) at night (8pm – 6am) in Seattle.

Count of Speeding Episodes

Figure 32, below, shows the frequency of SEs on each roadway segment in the Seattle region. The absolute count of SEs on the roadway segments are color-coded using a gradient that starts at yellow, for the road segment that had the fewest traversals with SEs, and increasing to dark red for road segments with the most SEs. Since this map is color-coded as a function of frequency of SEs, it highlights the roadway segments/locations that had high number of SEs overall.

As seen from the map, the road segments with high numbers of SEs are concentrated in and around the four major high-speed roads that either pass through the city or connect the suburbs to city. This finding is not at all surprising since the majority of the driving and FFEs were also on these roads. However, just looking at the count of SEs on segments provides an incomplete picture since it is confounded by the fact that these road segments also had the most FFEs. Nevertheless, at a high level, the map still indicates that SEs were widespread across the region.

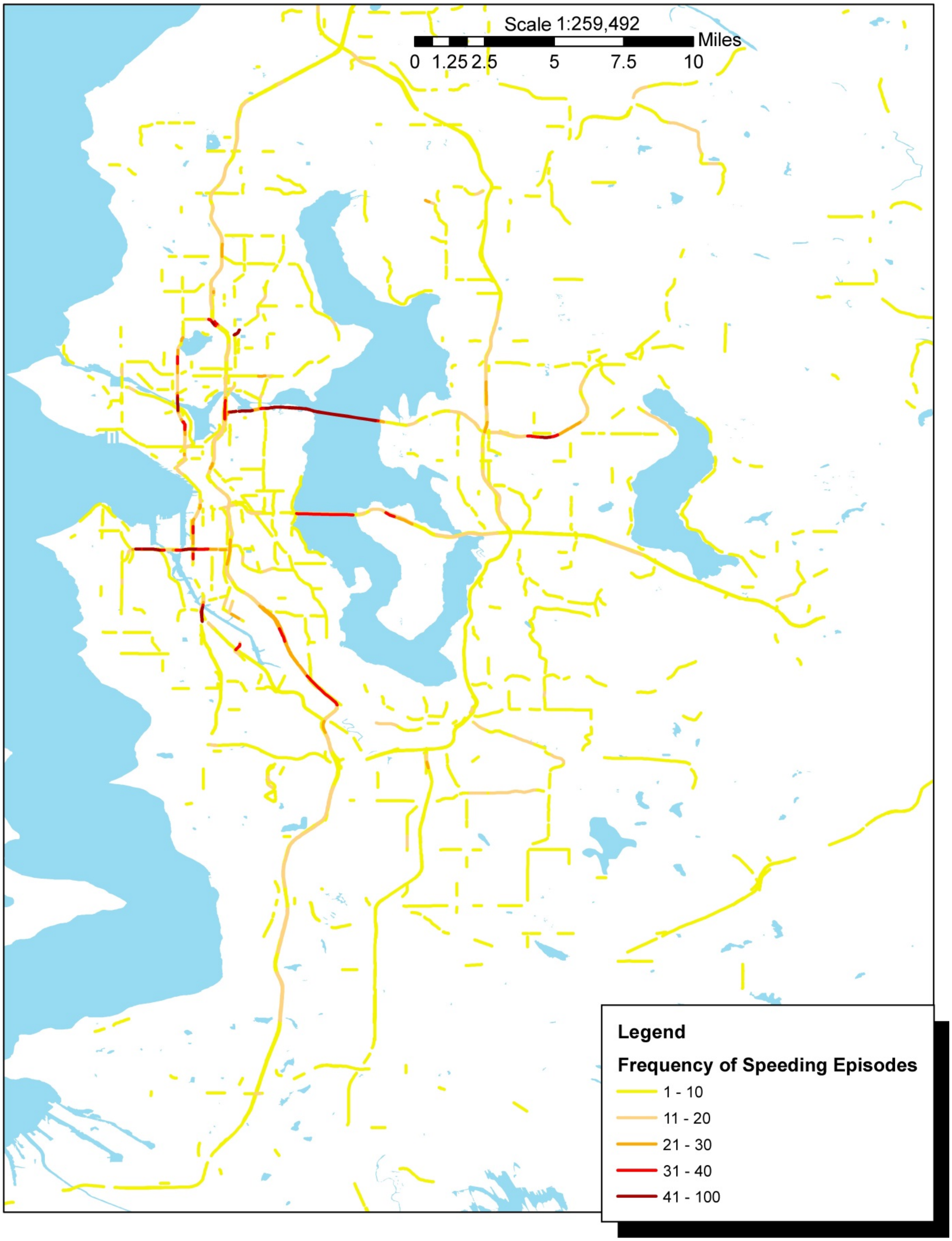


Figure 32. Frequency of Speeding Episodes (SEs) on road segments in Seattle.

Percentage of Free-flow Episodes that involved Speeding Episodes

The major limitation of examining absolute frequency of SEs is that roads that have the most driving are probabilistically most likely to have the most speeding, which could wash out indications of situational speeding at less frequently traversed locations. As a solution to this confound, we examined speeding relative to the opportunity to speed. That is, we developed heat maps in which the number of SEs on a segment was divided by the number of FFEs on the same segment. Using the percentage of SEs by FFEs for roadway segments allowed us to identify specific roadway locations where drivers were speeding at a higher rate when given the opportunity to speed, (i.e. a higher proportion of free-flow trips at the location involved speeding). One drawback of this approach is that roads with just a few traversals can more easily reach high proportions, which can lead to misleading hot spots. To minimize this, segments that had fewer than five FFEs were excluded from all of the maps based on percentage of SEs.

The resulting SE density map is shown in Figure 33. Again, similar to the previous Figure 32, it is clear that SEs are still widespread across the region; however, using this new measure it is apparent that the locations of the hot spots have changed significantly. Specifically, the roadway sections with the highest percentage (50% or greater) of FFEs seems to have shifted more to minor or arterial roadways instead of freeways. Note that in the remainder of this document, we will use the term “hot spot” to refer to road segments that have the highest proportion of SEs.

Apart from specific hot spots, freeway road segments generally still had a higher percentage of SEs overall. Closer examination of these sections indicated that many of these freeway sections were located between major exit junctions and had dedicated exit lanes for drivers exiting the freeway. Another observation was that several other hot spots occurred on small sections where speed limit transitions occur.

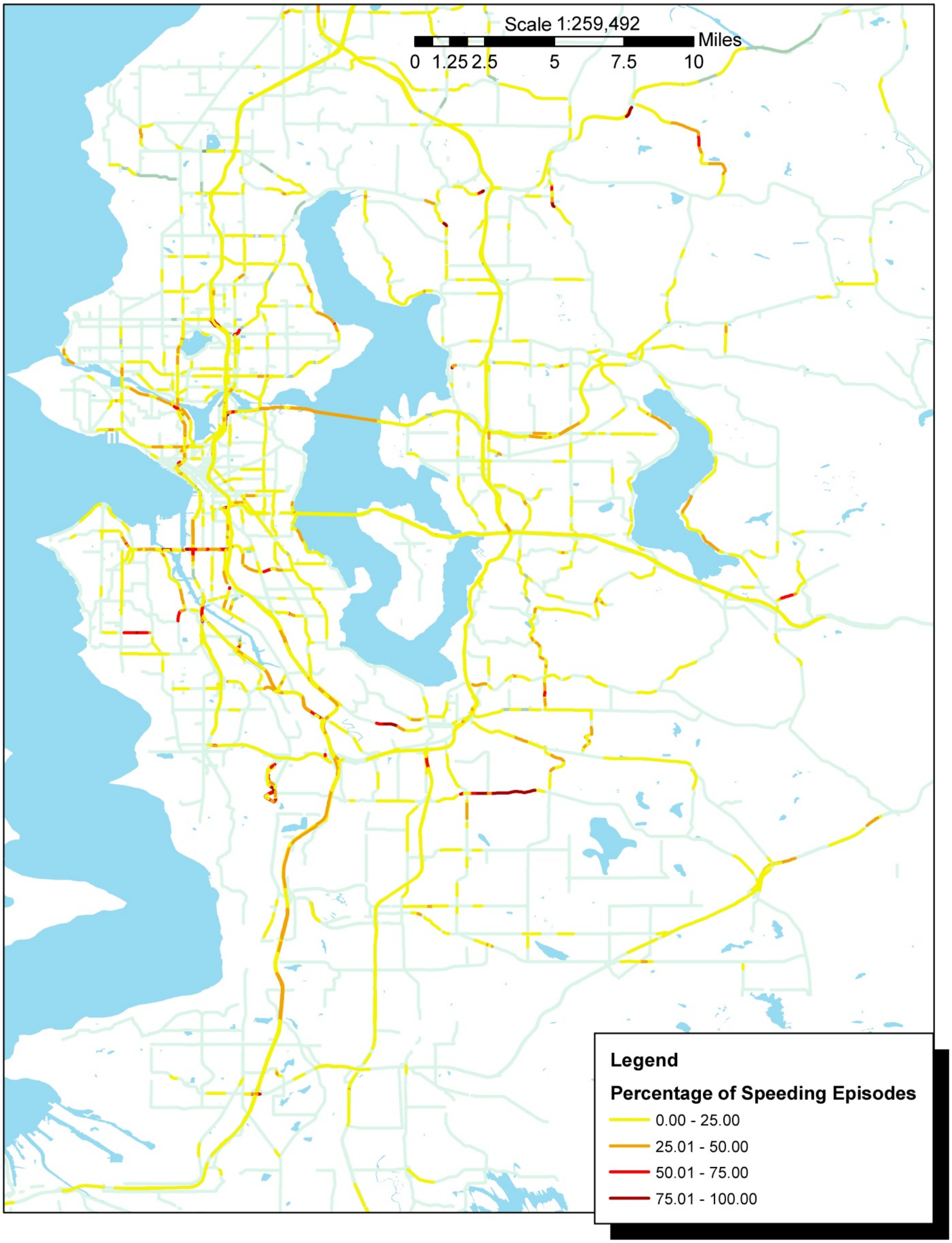


Figure 33. Percentage of Speeding Episodes (SEs) while free-flow driving in Seattle.

Relationship between Clusters and Location/Roadways where Drivers Speed

The previously described cluster analysis identified different types of speeding. While it was possible to assign labels to the clusters based on the values of the underlying speed-related variables, going further and examining the SEs in each cluster in the context of the broader road network can provide valuable insight regarding the underlying driving behaviors. This could also provide information about the relationship between the different types of speeding and any situational factors that may influence a driver's propensity to speed. To obtain a better understanding of these aspects, we examined the different types of speeding clusters in terms of situational and roadway factors.

The following sections provide heat maps based on SE density for each of the six speeding clusters in Seattle. The maps use the same measure based on how often drivers speed on a road segment relative to number of FFEs on that segment. However, in this case, the SEs used to calculate the percentage were restricted to the specific cluster being analyzed. This measure allowed us to examine whether there were any patterns that emerged that were specific to location or road types for each cluster.

Cluster 1: Speeding Up

Based on the speed-related variables in the cluster analysis, this cluster primarily represents drivers increasing their speed in advance of an upcoming speed limit increase. The spatial pattern of the SEs shown in the Figure 34 heat map is largely consistent with this notion. Specifically, Speeding Up episodes are mostly confined to short road segments on arterial roads that are immediately upstream of locations where the posted speed limit increases. Most of the hot spots (indicated in red) also occur at these locations. Note that the green lines in the map indicate road segments where free-flow travel occurred without any Speeding Up type of speeding (although other types of may have occurred on these segments). Darker shading indicates a greater number of free-flow trips.

Other groups of SEs in this cluster also occur on roadways where there are multiple posted speed changes. These are mostly arterial roads that have multiple speed transitions increasing or decreasing depending on the type of built-up area (e.g., shopping malls and residential sections). In many of these instances, visual inspection of the roadways revealed that the changes in posted speed limit were not accompanied by corresponding changes in roadway characteristics. That is, the visual layout and geometry on the lower-speed sections were nearly the same as the for the higher-speed sections, so drivers may have lacked the cues indicating that they should be driving more slowly. This had the effect of extending the duration of these Speeding Episodes.

Another observation is that a small proportion of Speeding-Up SEs occurred at locations without posted speed changes, such as midblock within an urban arterial. These SEs seem to represent instances in which an accelerating vehicle slowed abruptly, ending the SE within one or two seconds. Taken together, the collection of different patterns associated with this cluster suggests that it may represent a mix of multiple types of speeding behaviors.

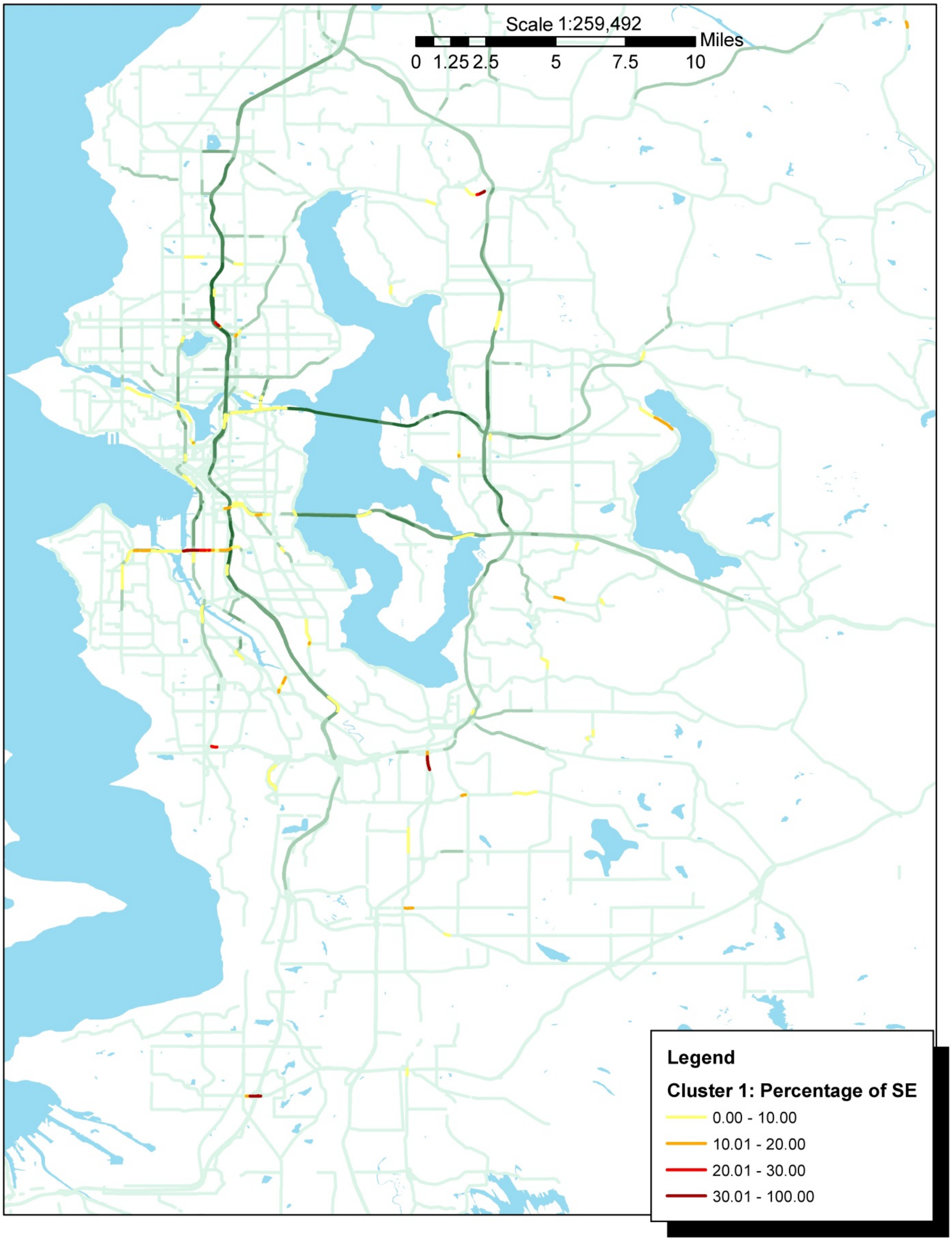


Figure 34. Percentage of Speeding Episodes (SEs) while free-flow driving for the Speeding Up cluster in Seattle.

Cluster 2: Speed Drop

The SEs in the Speed Drop cluster occurred most frequently on freeways and major arterials. Similar to the Speeding Up cluster, the majority of the SEs in this cluster also seem to be on roads near speed transitions; however, in this case, the transitions are reductions in posted speed limits, particularly on lower speed roads.

One pattern apparent in Figure 35 is that hot spots occurred on both short and long road segments. The short hot spot segments are consistent with drivers who were decelerating after the posted speed limit transitions downward, indicating that drivers likely wait until after the transition to begin slowing down. In the longer hot spot segments, it may be the case that drivers ignore the transitions and continue at higher speed until they are required to slow in response to traffic interaction or traffic control devices. These longer hot spot segments may represent situations where the posted speed reduction is inconsistent with the roadway environment, which may continue to afford travel at the higher speed. This is plausible in the sections of state highways that have the longer hot spot segments.

Some of the SEs in this cluster are also on freeway sections which do not have speed transitions. At this point, there is no clear explanation for these, and closer examination of these segments is required.

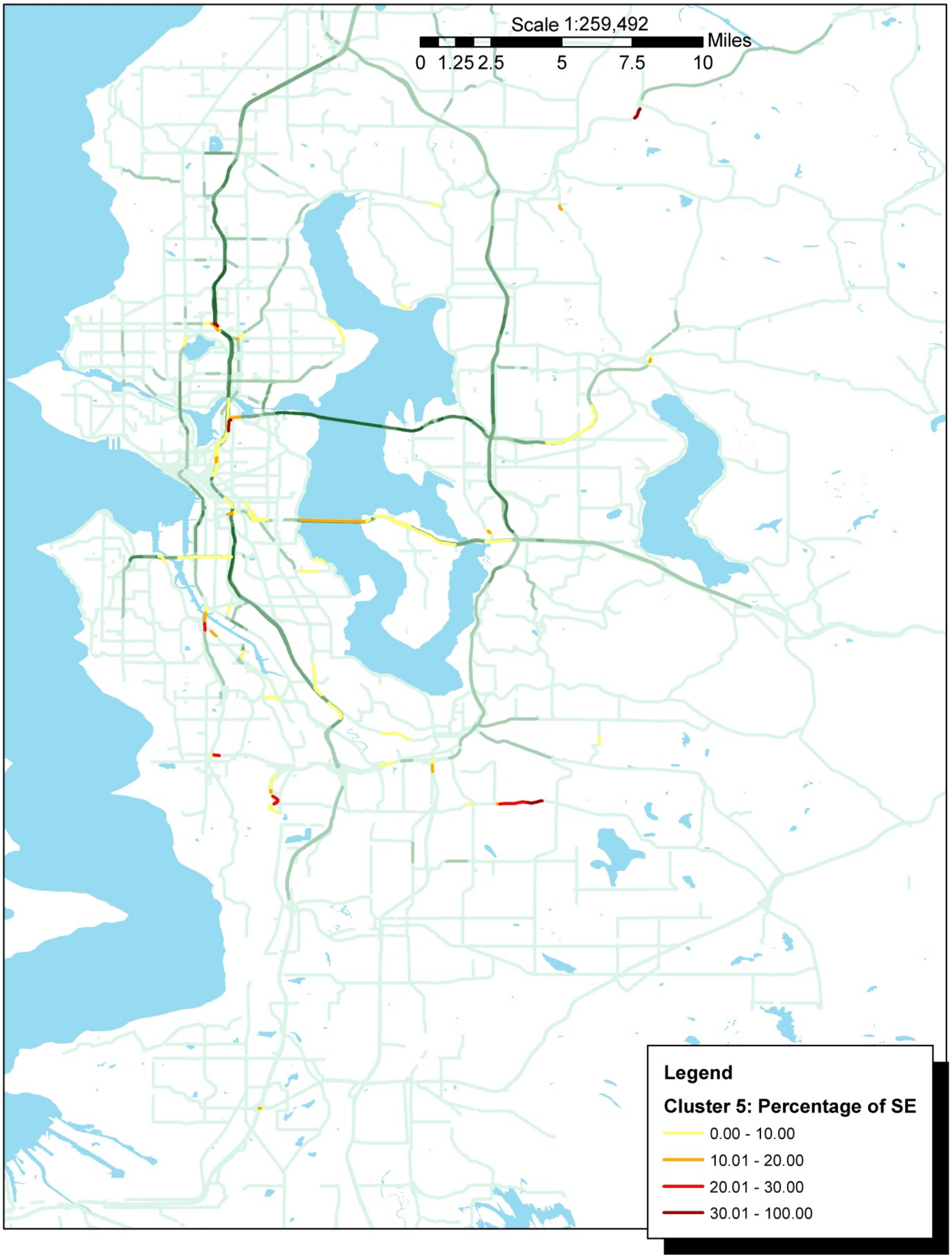


Figure 35. Percentage of Speeding Episodes (SEs) while free-flow driving for the Speed Drop cluster in Seattle.

Cluster 3: Incidental Speeding

The most notable aspect of the SEs on the Incidental speeding map (Figure 36) is how widespread they are across the Seattle region. In contrast, the hot spots and other areas with high SE concentrations are more limited to freeways and state highway sections, in addition to certain arterials. Even though the SEs are widely distributed, there are still clear hot spots throughout the map. Given the interpretation of this cluster as incidental or unintentional speeding, these hot spots may indicate locations in which the driving environment encourages speeding, even when drivers are not intending to speed. Although we examined these hot spots for trends with regard to roadway characteristics that may be associated with unintentional speeding, we had insufficient data about the road network to identify clear patterns.

Another observation is that, although the SEs in this cluster were widespread, there were still many lower-speed roads with FFEs on which Incidental speeding did occur. As mentioned earlier, we had insufficient road-network data to examine this pattern more closely, but it would be interesting to determine how those roads differ from other lower-speed roads on which SEs did occur.

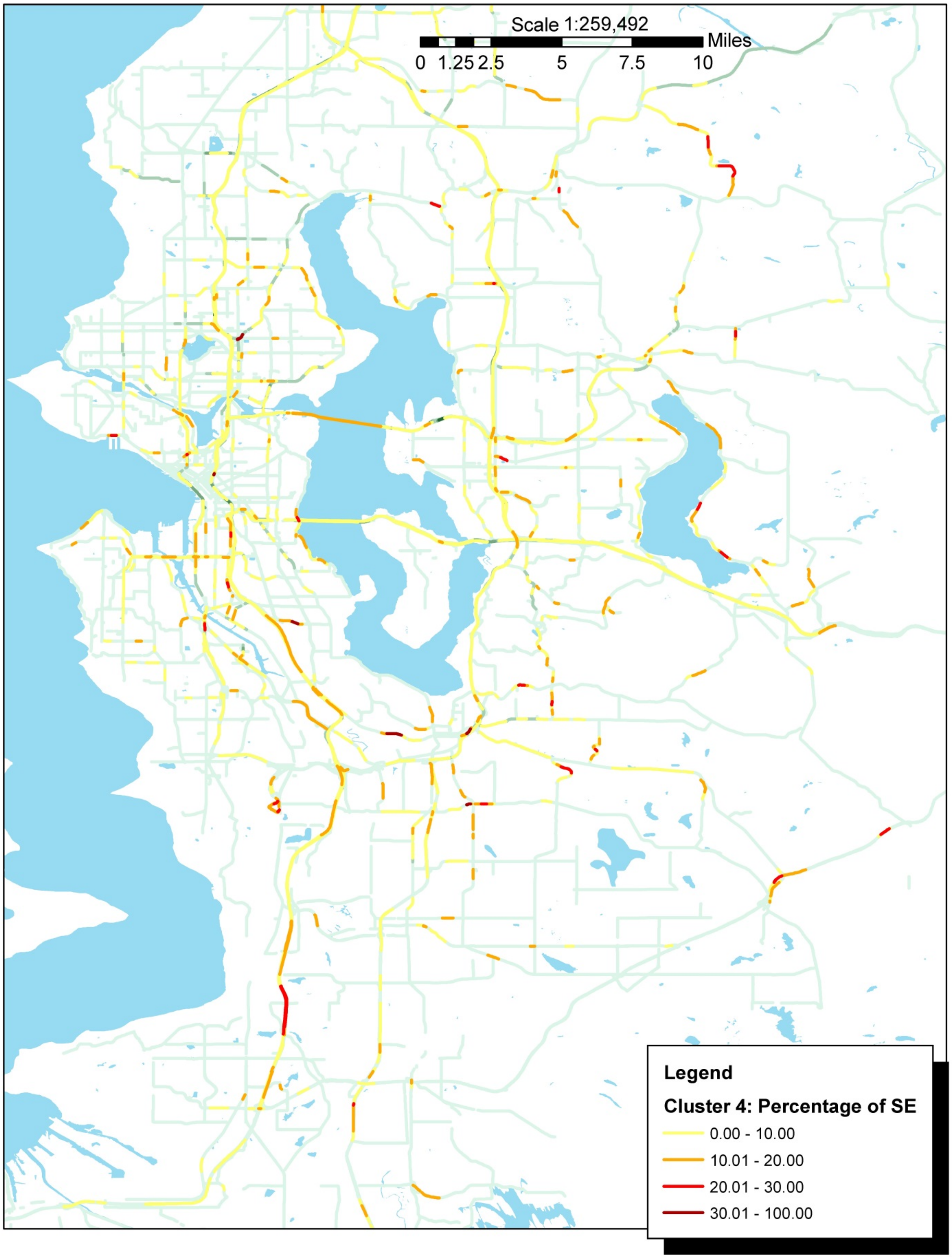


Figure 36. Percentage of Speeding Episodes (SEs) while free-flow driving for the Incidental speeding cluster in Seattle.

Cluster 4: Casual Speeding

Similar to the Incidental Speeding Episodes, Casual Speeding Episodes are distributed across the Seattle region (Figure 37). As compared to the Incidental cluster, there appears to be a generally higher concentration of SEs on freeways and state highways. However, there are also many arterial roads that had a high proportion of SEs, and most of the hot spots seen in the map are on arterial roads. Given the characteristics of Casual speeding as involving speeding where drivers may be unconcerned about exceeding the posted speed limit, it is likely that the hot spots identified in the maps have roadway characteristics that are conducive for speeding, such as wide roadway sections with no pedestrian traffic.

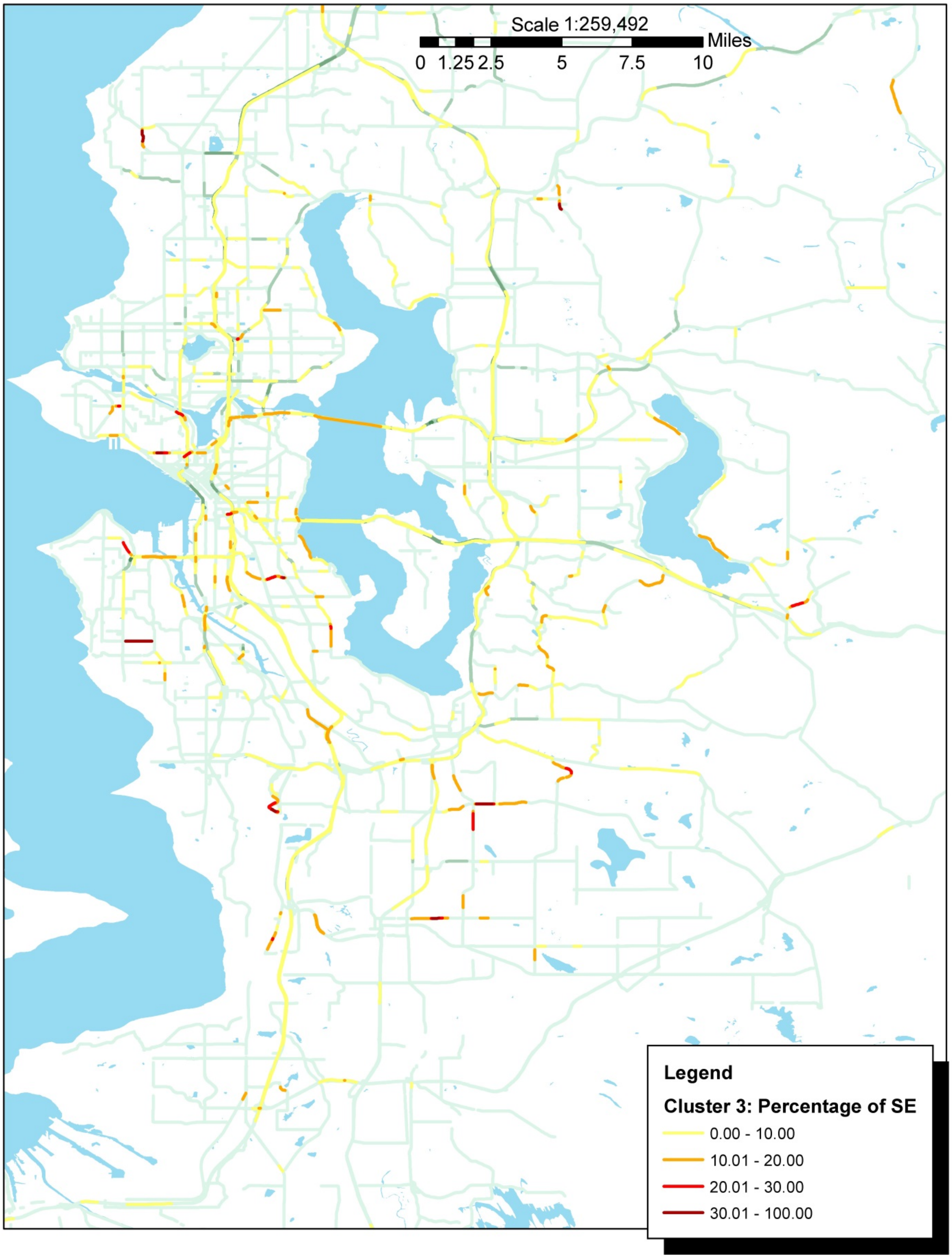


Figure 37. Percentage of Speeding Episodes (SEs) while free-flow driving for the Casual speeding cluster in Seattle.

Cluster 5: Cruising Speeding

The majority of the SEs in the Cruising cluster occurred on the freeways and state highways (Figure 38). This is not surprising since there are better opportunities to cruise for longer durations on these types of roadways, which have long stretches with little-or-no traffic control devices or access points to break the travel flow.

There were also a small number of arterial roads that seemed to have a fairly high proportion of SEs from this cluster. We investigated these locations and found that most of the trips on these roads were from a small number of participants; in several cases it was the same participant who had multiple trips on a specific road.

While the majority of SEs in the Cruising type of speeding occurred on the freeways and state highways, there were also certain freeway sections where SEs do not occur, even though those sections had a large number of free-flow driving. This suggests that these roadway sections have some characteristics (e.g., reduced line of sight, multiple merging lanes or exits) that make it challenging for drivers to speed for extended durations.

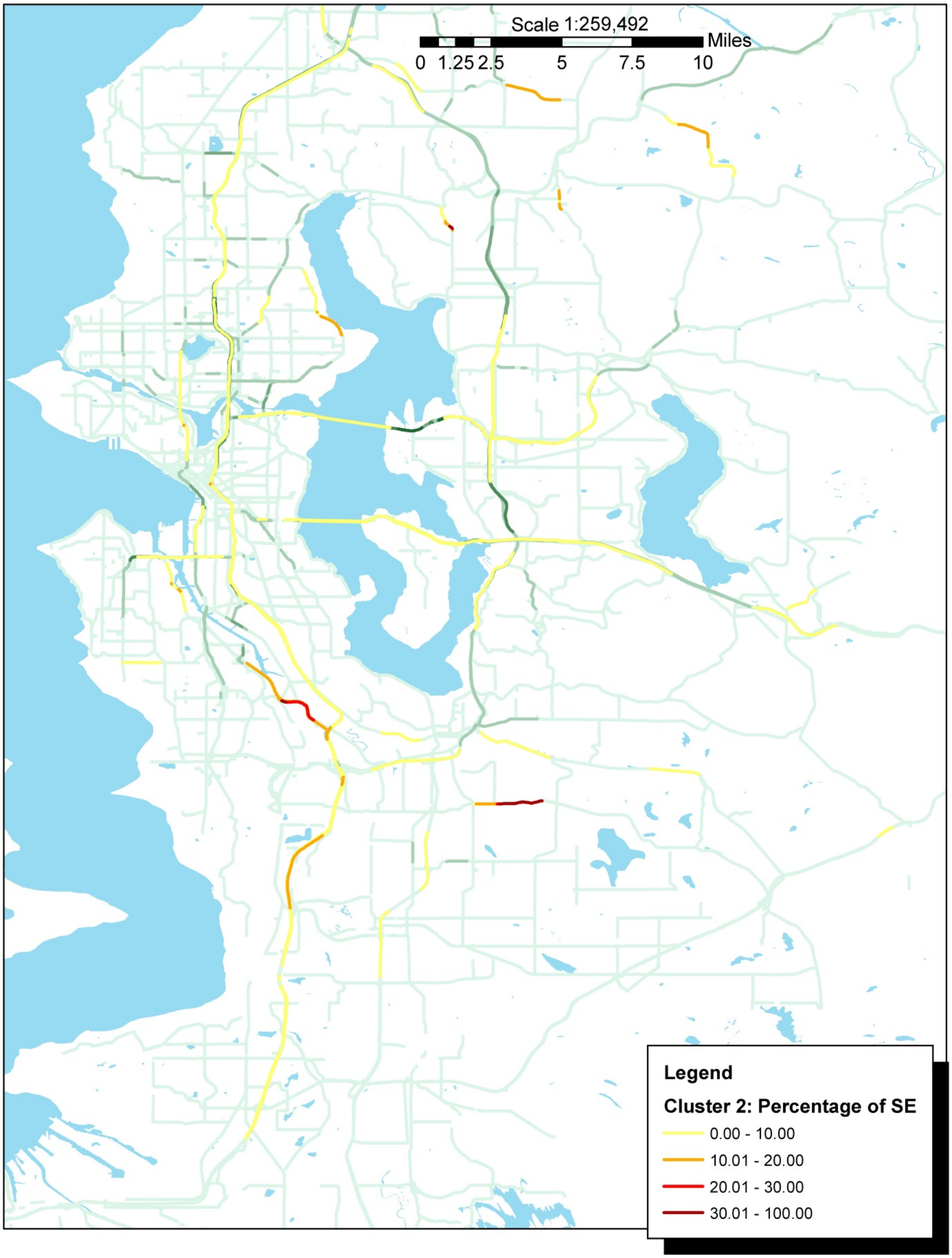


Figure 38. Percentage of Speeding Episodes (SEs) while free-flow driving for the Cruising speeding cluster in Seattle.

Cluster 6: Aggressive Speeding

The SEs for the Aggressive cluster seem to occur at many of the same locations as the SEs for the Cruising speeding cluster on freeways and state highways (Figure 39). However, the SEs in this cluster also occurred on a higher number of lower-speed roads in some of the more built-up parts of Seattle. One noticeable pattern that emerges from this map is that this cluster does not seem to have specific locations with relatively high concentrations of SEs. A possible explanation for this finding is that drivers who engage in Aggressive speeding are opportunistic and tend to speed wherever they can, regardless of the road type or geometry. Another finding that partially supports this explanation is that a comparatively higher percentage of SEs in this cluster occurred at night (16%) when drivers likely have a greater opportunity to speed than during the day. More generally, the link between roadway characteristics and SEs seems to be the weakest for Aggressive SEs, which suggests that driver-specific factors may play a more important role in this type of speeding.

As with the Cruising SEs, there were also road segment that had many FFEs, but no SEs. This, again, suggests that there are certain types of roadway geometries that discourage this type of speeding.

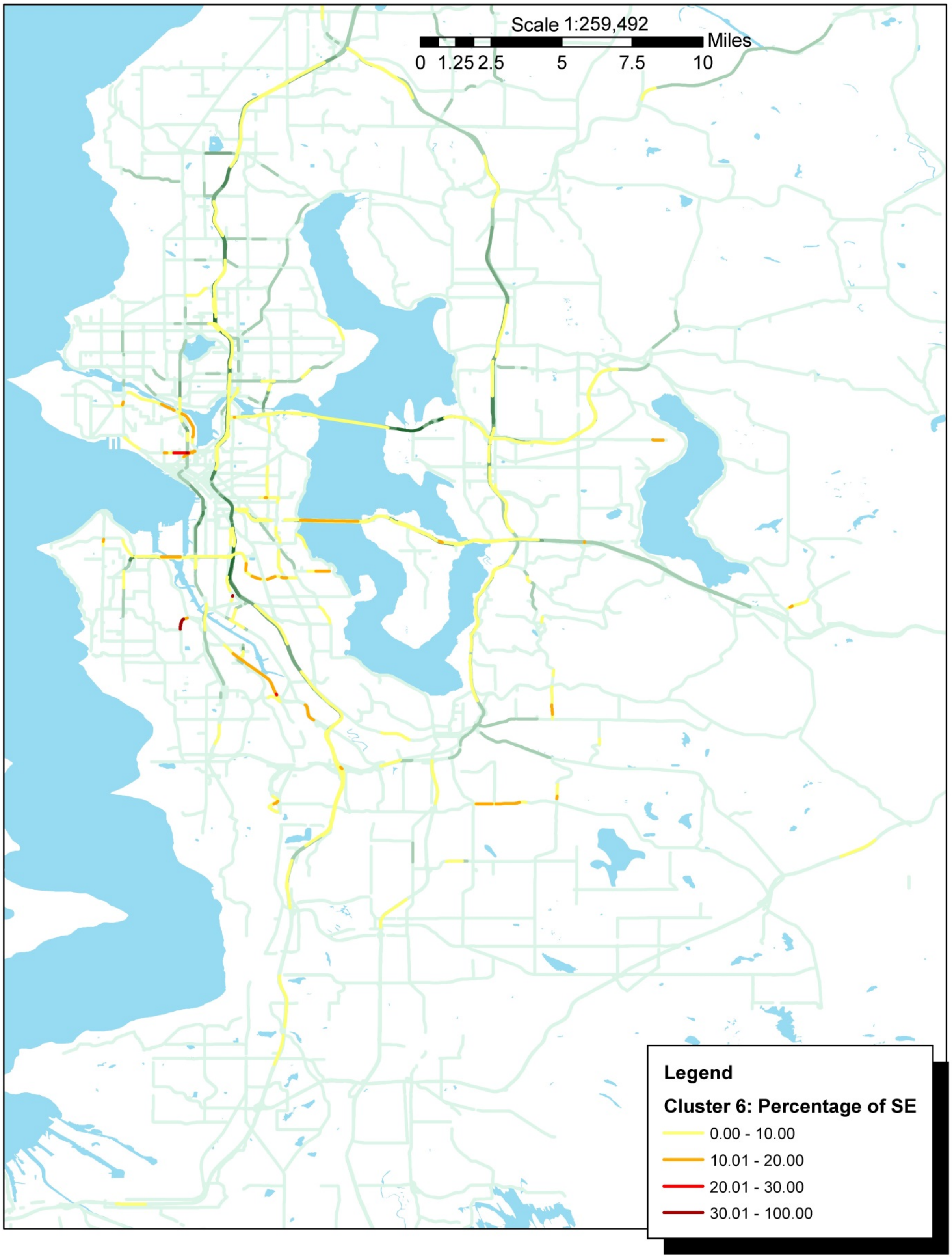


Figure 39. Percentage of Speeding Episodes (SEs) while free-flow driving for the Aggressive speeding cluster in Seattle.

Roadway and Situational Factors

The heat maps in the previous section indicated the high-level trends regarding where speeding occurred in each type of speeding, and also provided a general idea of the type of roads on which the corresponding SEs occurred. However, the maps provide minimal details about the specific characteristics of the roadway (e.g., posted speed limit) or driving situations (e.g., time of day) for the speeding clusters. To obtain a better understanding of the relationship between certain situational factors and SEs within clusters, we generated simple crosstabs between the types of speeding and the available situational variables. Note that only a small set of variables related to the roadway or driving situation were available, but these include key factors such as road function class and time of day.

Table 12, below, provides insight about which posted speeds were associated with different cluster types. In particular, the table shows the proportion of SEs within each cluster type that occurred on a roadway with the indicated posted speed. The last row and column in the table indicate the total number of SEs for each cluster (last row) and on each posted speed road (last column). Also, the cell highlighting in bold, red variant and italic, blue variant indicates how different a proportion in a cell was from the Posted Speed Total Proportion, which provides the expected proportion based on the sample means (second-to-last column). In other words, the cells highlighted in bold, red variants indicate that SEs within a cluster were overrepresented at the corresponding posted speed level relative to the sample proportion, and the cells highlighted in italics, blue variants indicate that SEs were underrepresented. The data patterns across posted speed for each cluster are discussed below.

Table 12. The proportion of each cluster on different posted speed roads in Seattle. (Cells highlighted in bold, red variants indicate that Speeding Episodes (SEs) within a cluster are overrepresented at the corresponding posted speed level relative to the sample proportion; cells highlighted in italic, blue variants indicate that SEs are underrepresented.)

Posted Speed	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Aggressive	Posted Speed Total	
							Proportion	N
25	**0.08**	**0.08**	0.03	0.04	**0.06**	0.03	0.04	178
30	**0.23**	**0.29**	0.17	0.20	*0.03*	**0.28**	0.19	887
35	**0.40**	*0.12*	0.17	0.14	*0.09*	*0.12*	0.16	774
40	0.11	**0.24**	0.09	0.12	*0.07*	*0.07*	0.11	504
45	**0.12**	**0.10**	0.03	0.04	*0.01*	0.03	0.04	173
50	*0.01*	*0.01*	0.07	0.08	**0.19**	0.06	0.07	338
55	0.00	0.00	0.01	0.01	0.01	0.00	0.01	46
60	*0.05*	*0.14*	**0.43**	*0.36*	**0.54**	0.40	0.39	1831
Cluster Total	218	204	2638	1263	187	244	1.00	4731

Speeding Up Cluster: The SEs in this cluster were overrepresented on lower speed roads—especially on 35 mph roads—and they were underrepresented on 60 mph roads. This pattern makes sense because speed increase-transitions are more common on lower speed roads. It should be noted that 60 mph was the maximum speed in the Seattle driving area, thus the Speeding Up SEs that occur on 60 mph roads do not arise from speed-limit transitions. Rather, they likely represent speeding that ends in abrupt deceleration, which should be uncommon enough to show up as being underrepresented.

Speed Drop Cluster: The SEs in this cluster were overrepresented on low speed roads, similar to the Speeding Up cluster. In this case, however, the SEs were relatively more frequent on 30 and 40 miles/hour roads, followed by 25 and 45 mph roads. Also, this cluster was underrepresented on 60 mph roads. This pattern makes sense since speed reduction transitions are generally on arterial or local streets within built-up areas.

Incidental Speeding Cluster: The SE distribution for Incidental speeding basically matches the overall sample distribution. This is because over half of the SEs occurred in this cluster, so it exerts a strong influence on the full-sample distribution. Despite this, Incidental SEs were slightly more overrepresented on 60 mph roads. This was not surprising since many of these road sections have a design speed that is higher than 60 mph. Also, a related factor may include drivers tending to match faster ambient traffic flow speeds, either because they were not vigilantly monitoring their own speed, or because they preferred to avoid slowing down the traffic flow.

Casual Speeding Cluster: The distribution of SEs in this cluster also matches the full-sample distribution, as well as the distribution of Incidental SEs. The latter finding is consistent with the notion that Casual SEs differ from Incidental SEs primarily in terms of degree. One difference, however, is that they seem to be slightly underrepresented on 60 mph roads relative to the Incidental speeding cluster.

Cruising Speeding Cluster: The SEs in this cluster were overrepresented on high speed roads, especially on 50 mph and 60 mph roads. The SEs in this cluster were underrepresented on 30 mph and 35 mph roads. This pattern is consistent with the notion that the higher speed roads provide better opportunities for long-duration speeding than lower-speed roads.

Aggressive Speeding Cluster: The SEs in this cluster were primarily overrepresented on 30 mph roads, and perhaps slightly less on 35-40 mph roads. Given the high speed exceedances associated with this cluster in general, the fact that SEs were occurring frequently on low-speed roads is consistent with the idea that this cluster represents a more aggressive and riskier type of speeding.

In addition to posted speed, the other key roadway variable available was road functional class. Since functional class is a determining factor for posted speed, we expected that the relative frequency of SEs in each cluster would corroborate the findings for posted speed. As seen in Table 13, below, the general pattern across clusters confirms this expectation (See Appendix A for a detailed description of the functional class levels). With regard to specific clusters, the Speeding Up and Speed Drop clusters were overrepresented on major arterials and underrepresented on state highways and freeways. On major arterials, it is possible that the changes in visual cues and geometry near the posted speed transitions were similar enough between the higher and lower speed sections that drivers did not feel compelled to keep to the lower speed. With the Casual and Incidental clusters, these were neither over- nor under-represented on any of the functional class types, which is basically the same pattern as shown in the posted speed table. The SEs in the Cruising cluster were overrepresented on freeways and state highways, which is similar to the posted speed findings. Finally, the pattern for the Aggressive cluster indicates an opposite pattern from the posted speed table, with freeways being overrepresented and major arterials being underrepresented. We have no explanation for this; however, it is consistent with the notion that driver-specific factors play a larger role in Aggressive SEs than roadway factors.

Table 13. The relative frequency of cluster on different roadway functional classes in the Seattle region. (Cells highlighted in bold, red variants indicate that Speeding Episodes (SEs) within a cluster are overrepresented at the corresponding roadway functional class relative to the sample proportion; the cells highlighted in italic, blue variants indicate that SEs are underrepresented.)

Posted Speed	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Aggressive	Posted Speed Total	
							Proportion	N
Residential	0.00	0.01	0.00	0.00	0.02	0.02	0.00	14
Arterial	**0.44**	*0.38*	0.41	0.40	*0.19*	0.40	0.40	1639
Major Arterial	**0.37**	**0.38**	*0.19*	*0.20*	*0.16*	*0.16*	0.21	883
State Highway	*0.15*	*0.11*	0.19	0.20	**0.25**	*0.17*	0.19	784
Freeway	*0.04*	*0.13*	0.20	0.20	**0.38**	**0.26**	0.20	826
Cluster Total	265	248	2015	1155	197	266	1.00	4146

Type of Speeding by Time-of-Day

One situational factor that is most frequently cited as a contributing factor to speeding crashes is nighttime driving (e.g., Liu et al., 2005). Accordingly, we examined the frequency of SEs in each cluster by time of day. Unsurprisingly, the majority of SEs occurred during the day, with the percentage of nighttime SEs for each cluster ranging from 10 % to 16 %. The Aggressive speeding cluster had the highest proportion of nighttime SEs (16%), followed by the Cruising speeding cluster (13%). In general, there were too few driving SEs to conclusively identify a relationship between type of speeding and time of day.

Table 14. Speeding Episodes (SEs) in each cluster by time of day and percentage of night time SEs in each cluster in the Seattle region.

	Day	Night	Total Speeding Episodes	Percentage of Nighttime Speeding Episodes
Speeding Up	196	22	218	10%
Speed Drop	180	24	204	12%
Incidental	2353	285	2638	11%
Casual	1123	140	1263	11%
Cruising	162	25	187	13%
Aggressive	205	39	244	16%

General "Riskiness" of Speeding Episodes

Speeding at night can be riskier than during the day. A major contributing factor to risk of speeding at night is reduced sight distance (Owens & Sivak, 1993). In general, sight distances are shorter at night due to reduced visibility, which gives drivers less time to react to unexpected events. The elevated risk of nighttime speeding leads to a broader question of whether it is possible to differentiate the speeding type clusters in terms of general "riskiness." In addition to time of day, we identified three other measures that could provide insight about the "riskiness" of speeding types. These included:

a) Proportion of SEs in each cluster that exceeded 20 mph over the posted speed limit.

b) Proportion of speeding on "Not Controlled Access" roads.

c) Average duration of the SE.

The three measures, in addition to the proportion of nighttime SEs, were selected because they generally imply a potentially higher level of risk. In particular, driving at an exceedingly high speed, such as 20 mph above the posted speed limit, reduces a driver's safety margin by reducing the time available to respond to hazards. Also, speeding on roads that do not have controlled or restricted access increases the potential for conflicts since drivers are more likely to encounter pedestrians, bicyclist, and also hazards from driveways. Finally, longer SE durations increase the exposure risk to potential speed-related hazards. The objective of the following analysis was to use these proxies for elevated safety risk to gain some insight on the general riskiness of each cluster.

Table 15, below, summarizes the findings related to riskiness of the different types of speeding. In the first three rows, the values indicate the percentage of Speeding Episodes within each type of speeding that contain the riskier speeding elements. For example, 39% of Aggressive SEs contained speeding that was more than 20 mph above the speed limit. The average duration variable is not a percent, but instead indicates how long average SEs were for each type of speeding. The highest values in each row are indicated with bold font, and the findings related to each are discussed below. The Riskiness and Riskiness by Duration rows generally characterize the relative riskiness of the SEs in each type of speeding (as explained below), which is also indicated by the color scale and numerical range of green (least risky; 0.0) to red (most risky; 1.093).

Table 15. Relative riskiness of Speeding Episodes (SEs) from each type of speeding in the Seattle region (higher values reflect higher relative risk).

	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Aggressive
Speed Exceed 20mph	31%	33%	0%	2%	8%	**39%**
Not Controlled Access	**70%**	55%	47%	51%	28%	50%
Nighttime SE (8-6)	10%	12%	11%	11%	13%	**16%**
Average Duration (seconds)	19.1	21.0	14.8	24.5	**109.6**	35.4
Riskiness	*0.022*	*0.021*	*0.000*	*0.001*	*0.003*	***0.031***
Riskiness by Duration	0.422	0.449	0.000	0.027	0.337	**1.093**

Speed Exceedance over 20 mph: The SEs in the Aggressive speeding cluster were more likely to exceed the posted speed limit by 20 mph as compared to other clusters. About 39% of the SEs in the Aggressive speeding cluster exceeded the posted speed by 20 mph. This cluster was closely followed on this measure by Speeding Up and Speed Drop clusters with 31% and 33%, respectively.

Not Controlled Access: The Speeding Up cluster had the highest percentage of SEs on "Not controlled access" roads (70%), which was in line with findings from the functional class data, which indicated that the majority of the SEs in these clusters were on arterials. The Cruising speeding cluster had the smallest proportion of SEs on "Not Controlled Access" roads (28%), as the opportunities for longer duration speeding are more limited on these roads.

***Nighttime SE*:** The percentage of nighttime SEs for each cluster ranged from 10% to 16 %, with the Aggressive speeding cluster having the highest proportion of nighttime SEs (16%), followed by the Cruising speeding cluster (13%).

Average Duration: The average duration of SEs was by far the highest for the Cruising speeding cluster. The average duration of SEs in this cluster was 109.6 seconds, which was substantially greater (almost 3 times) than the Aggressive speeding cluster, which was second with average duration of 35.4 seconds.

Riskiness and Riskiness by Duration (Exposure): As mentioned earlier, the goal of this analysis was to find a cursory way of characterizing the risk-level associated with the different types of speeding. To do so, we used the measures described above to calculate the general "Riskiness" of each type of speeding by multiplying the measured values together.[6] Also, as discussed above, the duration of SEs determines the drivers' exposure to the speeding risk. Thus, we calculated the associated risk as a product of "Riskiness'" and "Exposure" to get a sense of risk associated with each type of speeding.

The results indicated that the Aggressive speeding cluster was associated with the highest "risk" level relative to the other clusters. This is not surprising considering the fact that these types of SEs tended to exceed the posted speed by 20 mph, occurred almost half the time on arterials where there is a greater chance of interaction with pedestrians and bicyclists, and happened comparatively more often at nighttime, adding visibility constraints to the task of driving. They also tended to be longer in duration compared to the other clusters except the Cruising cluster.

While the Aggressive speeding cluster was clearly elevated relative to the other clusters, the Speeding Up, Speed Drop, and Cruising clusters were in the next tier down. The Cruising cluster appears in this group almost entirely because of the long duration, since the other risk-related measures for this cluster have values on the low end. Finally, the results suggested that the risky elements of Incidental and Casual speeding were minimal compared to the other types of speeding.

[6] Note that different schemes for weighting the relative contribution of the measures were investigated. For the most part, the general trends remained, and since there was no solid a priori basis for positing a particular weighting scheme, the measures were left unweighted.

Texas Situational Analysis

The section that follows presents maps showing the location of the free-flow and SEs in the Texas region. In addition, maps showing where SEs from each speeding cluster occurred are also presented. Finally, situational factors and their relationship to the types of speeding are analyzed and summarized.

Free-flow Episodes showing where driving occurred

The map that follows presents the frequency of FFEs for each roadway segment in the Texas region, highlighting roadway segments where drivers were able to travel at free-flow speeds and potentially had the opportunity to speed more frequently. The frequency of free-flow on the roadway segments is color-coded in shades of green, with the road segments that have the fewest FFEs (0-50 trips on a road segment) coded in light green, and road segments with most FFEs represented in dark green (200 – 250 trips on a road segment).

Overall, driving in Texas covered a substantially wider area than in Seattle. Consequently, the maps that follow show only a small window where the majority of the driving occurred (the Texas maps exclude approximately 30% of SEs that occurred outside of the mapped area). The map scale in Texas is also shown as smaller than in Seattle (covering a smaller geographic region). This was done because the density of arterial roads is greater within College Station, and the smaller scale was necessary to make the road segments with SEs visible.

In the map (Figure 40), the width of the roadway provides an indication of the functional class of the roadway. The widest roads are the freeways and state highways. A variety of roadways were traversed by Texas drivers at free-flow speeds, with a large number of FFEs on the major roads in and around town. Some routes clearly had more FFEs than others—especially; State Highway 6, FM 2776, US 190, and FM 2818 (see Appendix A). Similar to Seattle, there was a large amount of driving on residential roads in the area; however, this driving had to be excluded because the posted speeds for these roads were typically unavailable.

In the outlying areas, most of the FFEs occur on major roads, especially several of the farm-to-market (FM) roads that connect the towns in the region.

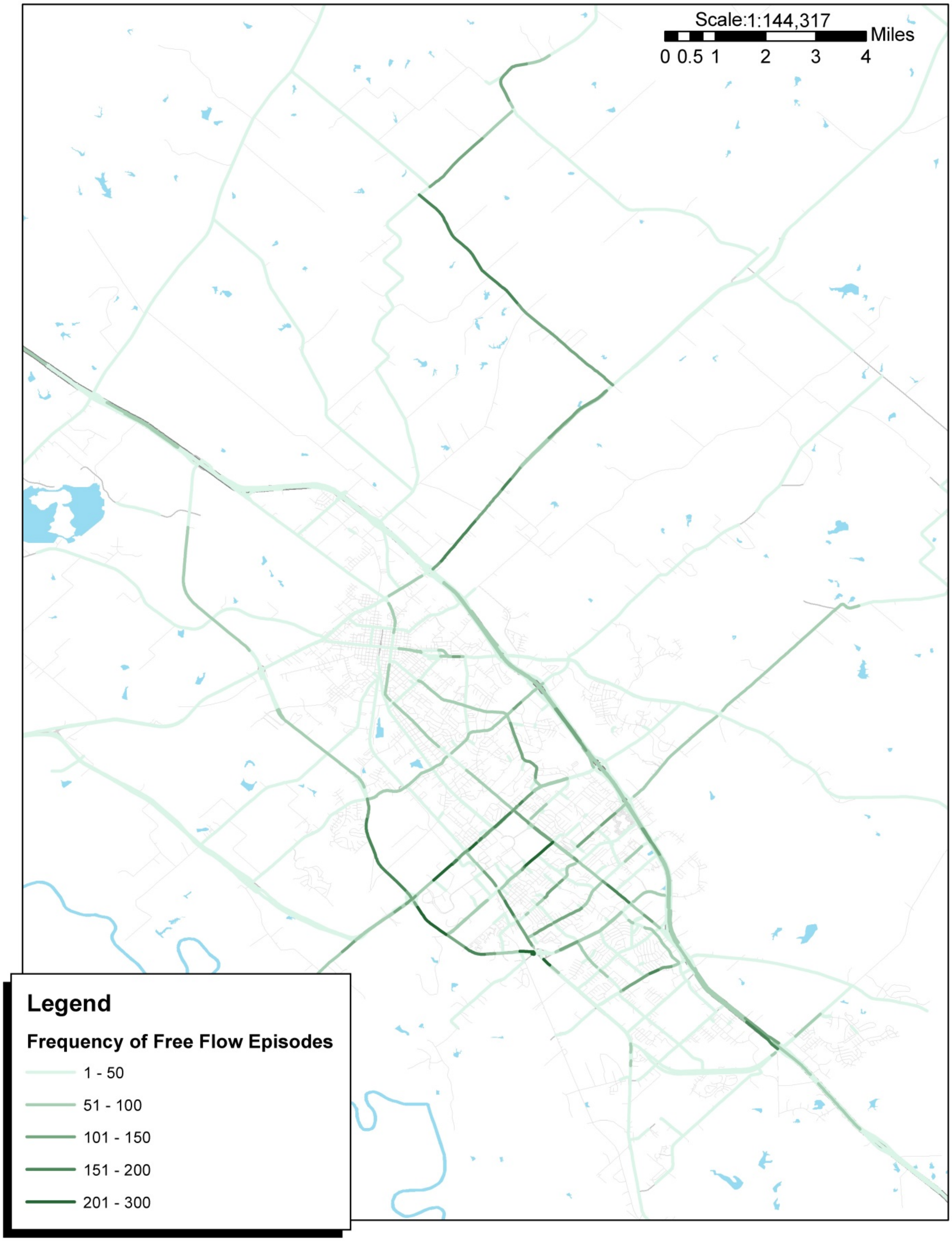


Figure 40. Frequency of Free-flow Episodes (FFEs) on road segments in Texas.

Nighttime Free-flow Episodes

The following map shows the frequency of FFEs at night. Nighttime was defined as trips started between 8pm and 6am. Overall, there were very few FFEs during the night with only 867 of them recorded during the entire study. A major contributing factor to this was the limited number of nighttime trips in the Texas sample. Also, nighttime posted speeds were in effect during the data collection, which meant that legal posted speeds were lower during this time than those used to calculate FFE in the current data set. Note that we did not recalculate our measures using adjusted nighttime speed limits because of the potential for introducing errors that would be prohibitive to trace and correct.

The remaining data plotted in Figure 41 show that the highest concentration of FFEs were on some of the major roads in town and also along the section of the state highway that passes on the outskirts of Bryan/College Station. Otherwise, there were very few nighttime FFEs that occurred outside of town and outside the region shown in the map.

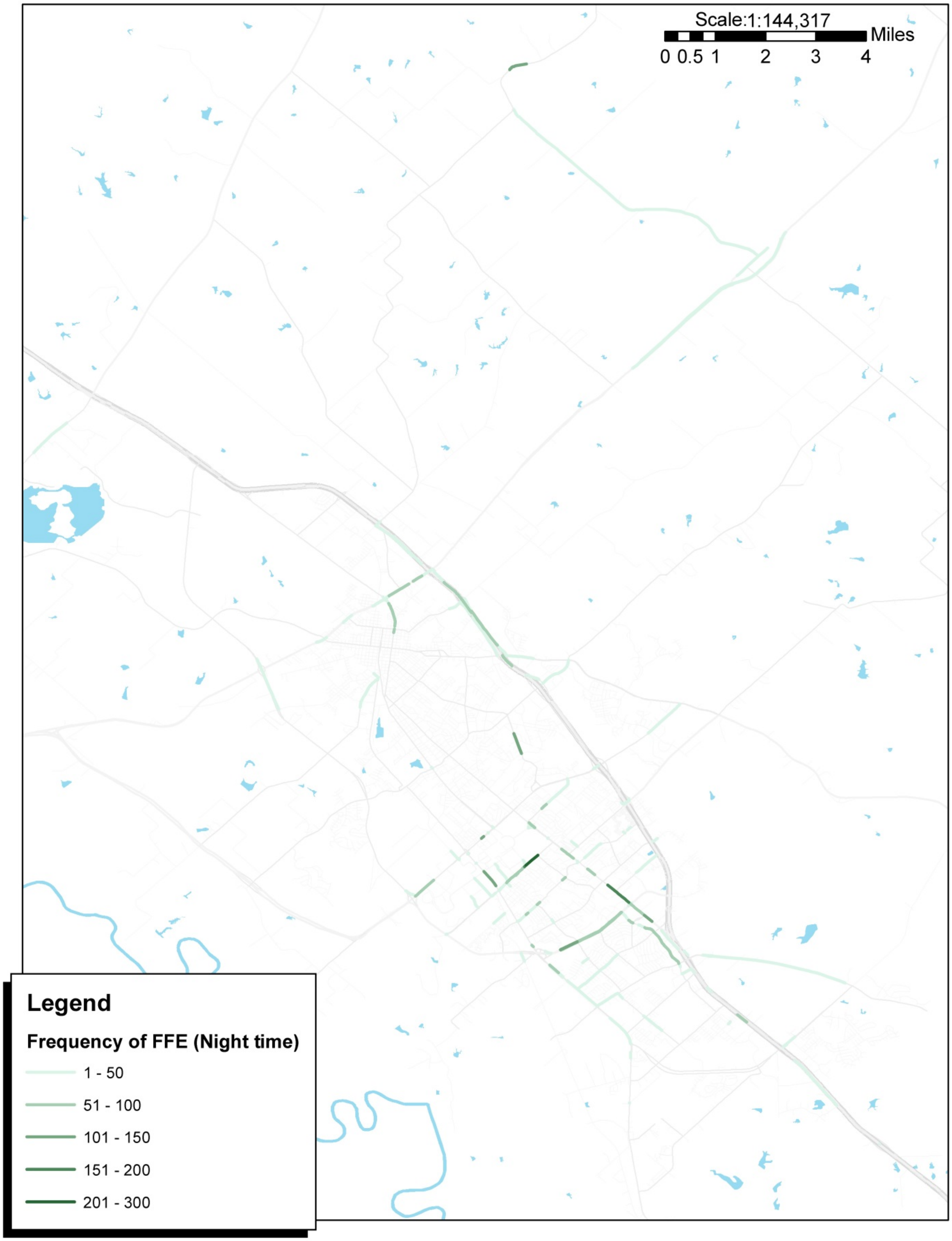


Figure 41. Frequency of Free-flow Episodes (FFEs) at night (8pm – 6am) in Texas.

Count of Speeding Episodes

Figure 42 below shows the absolute frequency of SEs for each roadway segment in the Bryan/College Station region. The absolute count of SEs on the roadway segments are color-coded using a gradient that starts at yellow, for the road segment that had the fewest traversals with SEs, and increasing to dark red for road segments with the most SEs. Since this map is color-coded as a function of frequency of SEs, it highlights the roadway segments/locations that had high number of SEs overall.

As seen from the map in Figure 42, there were very few road segments with a high number of SEs, and almost all of the roads have fewer than 50 SEs altogether. The one road that had the highest count of SEs is an FM road in the upper right quadrant (FM 2776). The overall pattern suggests that the SEs were generally infrequent. The ones that did occur were concentrated in and around the Bryan/College Station area, on a variety of road types.

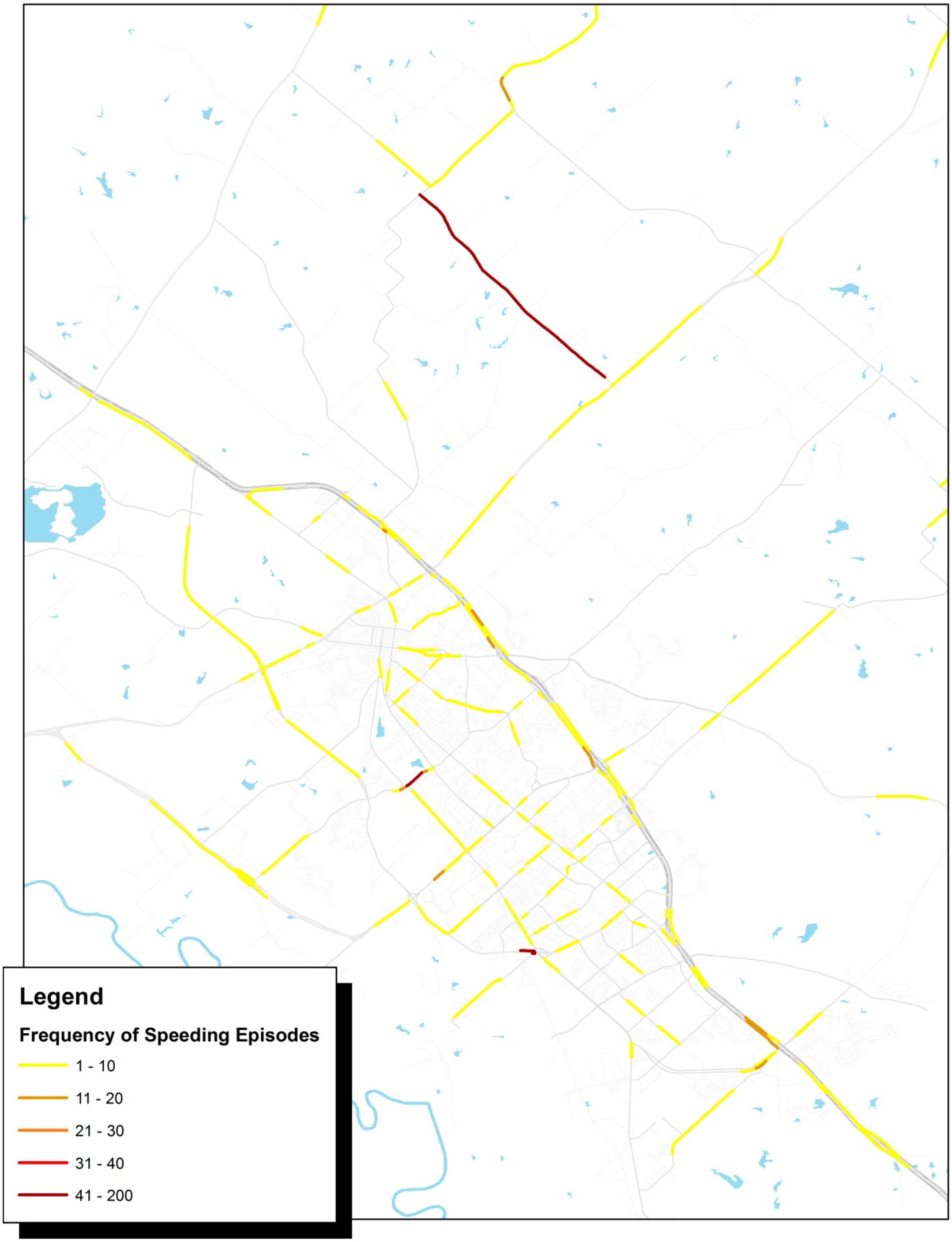


Figure 42. Frequency of Speeding Episodes (SEs) on road segments in Texas.

Percentage of Free-flow Episodes that involved Speeding Episodes

Figure 43, below, shows the percentage of SEs by FFEs for roadway segments. The color coding increases from yellow to red as the percentage of SEs increases. Note that the green lines in the map indicate road segments where free-flow travel occurred without any speeding. Darker shading indicates a greater number of free-flow trips.

In comparison to the absolute frequency of SEs shown in Figure 42, above, the map in Figure 43 shows that a small number of hot spots emerged using this approach. More of the major roads in and around town seem to have a higher percentage of SEs compared to the absolute frequency map. However, SEs were still relatively uncommon in Texas, given that SEs occurred on most of the road segments less than 10% of the time. Nevertheless, there were several longer segments (1 to 5 miles in length) that have relatively high percentage of SEs. These included parts of State Highway 6, State Highway 21, and FM 2776.

Closer examination of the hot spots provides some insight into the driving context. In particular, inspection of the hot spots that occur on state highways indicates that the corresponding sections were near exits or on sections between major exits. In contrast, the farm-to-market road (FM 2776) in the upper-right quadrant with a high proportion of SEs had multiple speed transitions within a short span—transitioning between 50 and 70 mph. In addition, this road had long stretches of open roadway that allowed for higher speed travel. It seems that given the long open road on this segment, the drivers were more willing to drive at higher speeds.

Another difference in Figure 43 relative to Figure 42 is that speeding which occurred on several roads is no longer included in Figure 43. This is because the corresponding road segments had fewer than five FFEs and were consequently excluded from the map.[7]

[7] To minimize the number of misleading hot spots that arise from a small denominator, segments that had five or fewer FFEs were excluded from all of the maps based on SE frequency. This is discussed in more detail in the corresponding Seattle section.

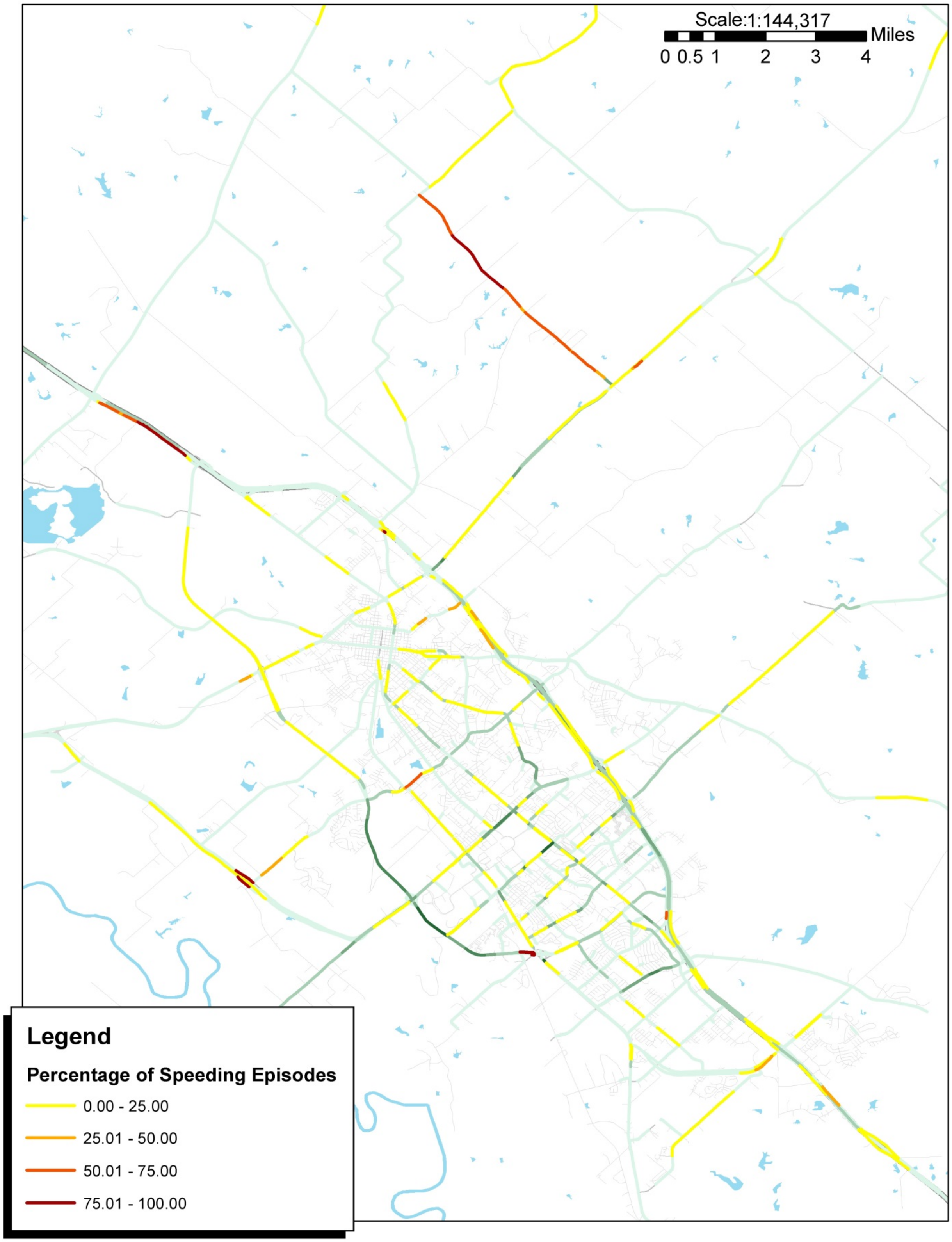


Figure 43. Percentage of Speeding Episodes (SEs) while free-flow driving in Texas.

Relationship between Clusters and Location/Roadways where Drivers Speed

Similar to the analysis done in Seattle, we examined the spatial distribution of SEs for the different types of speeding in terms of situational and roadway factors.

The following sections provide the heat maps based on SE density for a subset of the Texas clusters; specifically the Incidental, Casual, and Small Increase (Cluster 6) types of speeding. The heat maps for the other three clusters (Speeding Up, Speed Drop, and Cruising) are excluded because they had too few SEs within the map to identify any trends or patterns.

As with the Seattle analysis, the maps show the ratio of SEs to FFEs on a road segment, but only for the indicated cluster. This measure allowed us to examine whether there were any patterns that emerged specific to location or road types for each cluster.

Cluster 3: Incidental

Unlike Seattle, the SEs in the Incidental speeding cluster were not as widespread across the driving region (see Figure 44). Instead, these SEs were concentrated on certain stretches of the state highways, and in a few locations in town. The SEs on the highways typically covered much longer continuous stretches than those occurring in town. This is likely an artifact of highway road segments generally being longer than road segments in town (note: the entire road segment was color coded, even if the underlying SEs were much shorter). There were a few hot spots on the map, with the majority of them occurring on roads designed to accommodate high speed, such as State Highway 6.

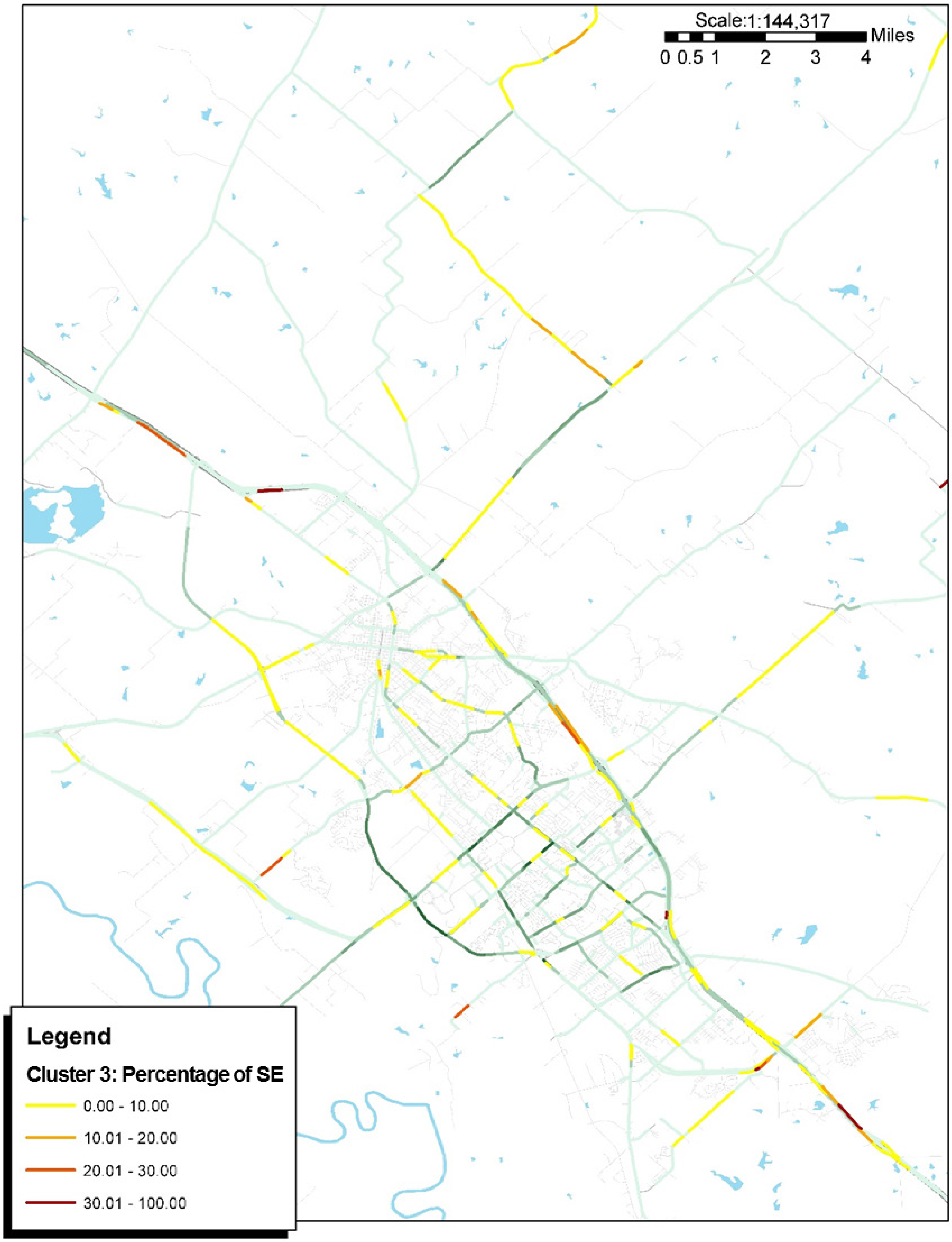


Figure 44. Percentage of Speeding Episodes (SEs) while free-flow driving for the Incidental speeding cluster in Texas.

Cluster 4: Casual

The Casual SEs, shown in Figure 45, seem to have slightly greater prevalence in town relative to the outlying areas. This is consistent with the greater amount of driving within Bryan/College Station. There were a few long stretches with SEs that occurred outside of town, specifically on the freeway (State Highway 6) that traverses from the upper left quadrant to the bottom right on the map. The other major concentration of SEs outside of town occurred on FM 2776 in the upper-right quadrant. These sections were clearly rural with limited or no built-up area next to the roadway. Also, these hot spots seem to overlap with the location of the hot spots in the Incidental speeding cluster. This finding suggests that these two segments may be locations that encourage unintentional speeding and/or support intentional speeding.

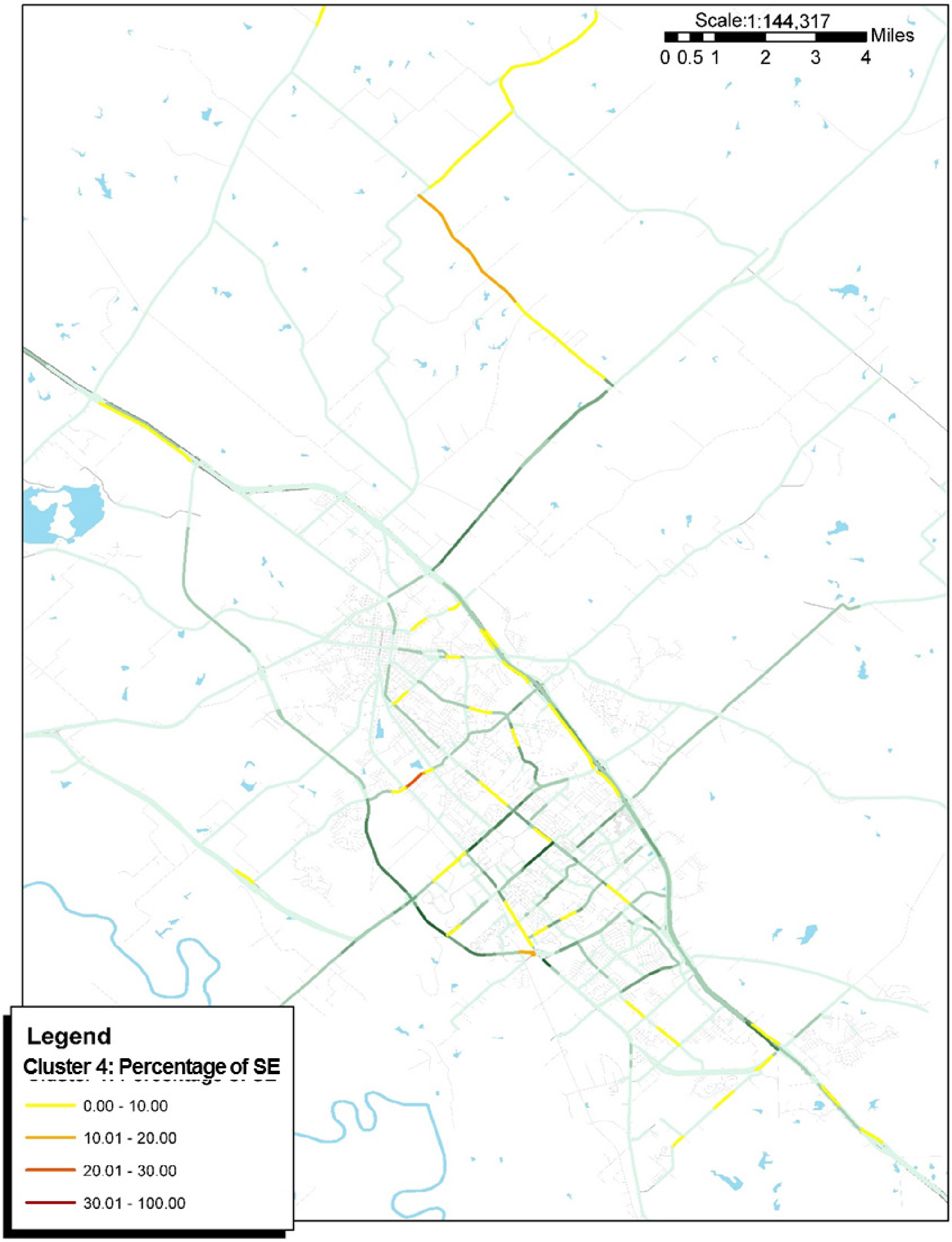


Figure 45. Percentage of Speeding Episodes (SEs) while free-flow driving for the Casual speeding cluster in Texas.

Cluster 6: Small Speed Increase

The Small Speed Increase cluster is unique to the Texas region, but it shares speed-related characteristics in common with the Speeding Up clusters in both Seattle and Texas. The SEs in this cluster mostly occurred on major arterials and regular arterials (see Figure 46). Another aspect is that many of the SEs in this cluster occurred on short segments of the roadways. A closer look at the areas with the highest proportions of SEs indicates that the SEs tended to be confined to locations where there were speed transitions. An exception to this was the long stretch that occurred on FM 2776 road in the upper right quadrant. On this road, posted speed transitioned from 50 to 55 and then to 70 mph; however, the roadway characteristics did not change markedly across this stretch, and drivers may largely be ignoring the posted speed.

There was only one hot spot visible in Figure 46. It occurred in a location on the state highway where the highway transitioned from undivided to divided lanes.

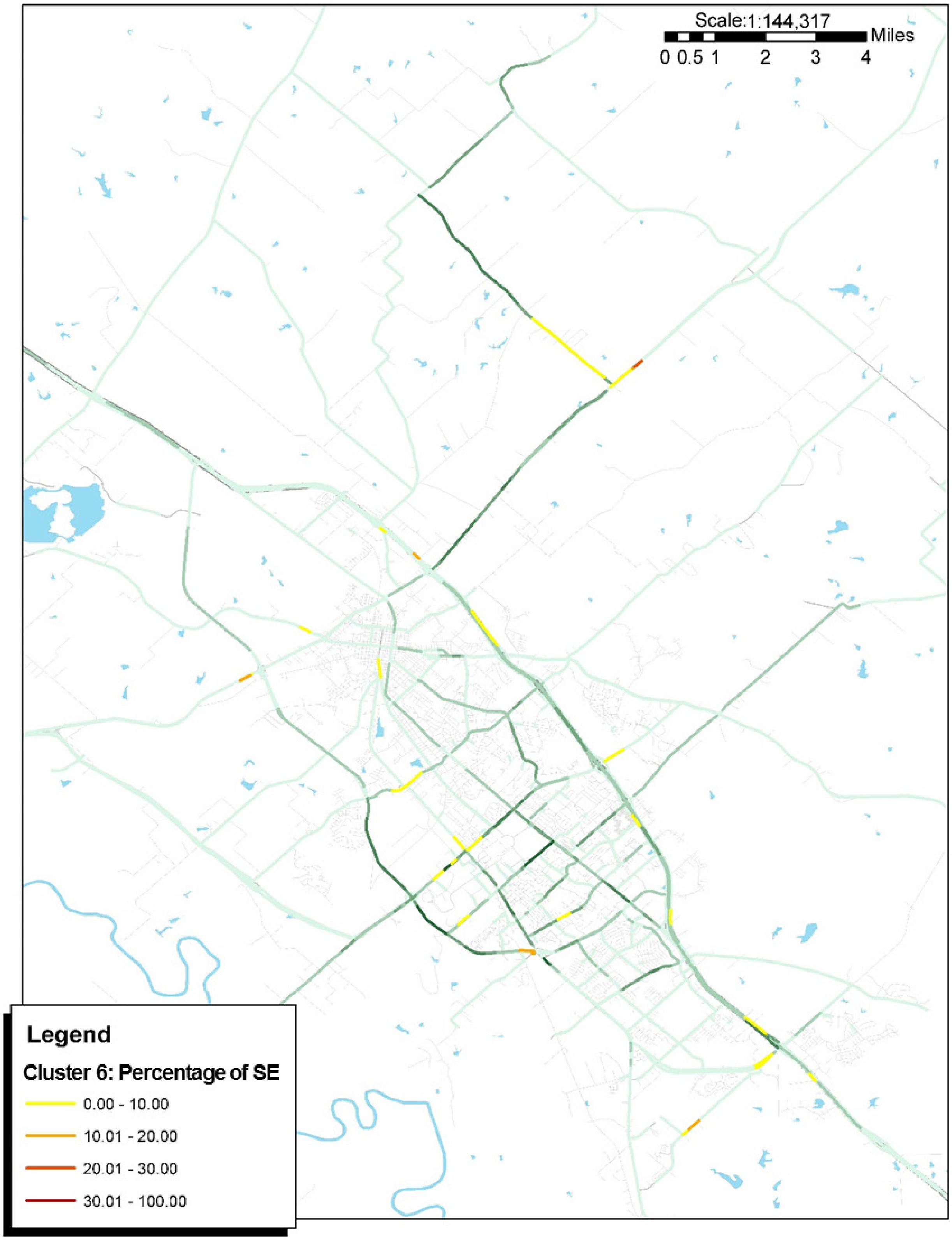


Figure 46. Percentage of Speeding Episodes (SEs) while free-flow driving for the Small Increase speeding cluster in Texas.

Roadway and Situational Factors

We used the same approach as in the Seattle analysis to examine the roadway and situational factors. Specifically, to obtain a better understanding of the relationship between certain situational factors and SEs, we generated simple crosstabs between the types of speeding and the available situational variables. Also, key roadway factors such as road functional class and time of day were included.

Table 16, below, provides insight about which posted speeds were associated with different cluster types. In particular, the table shows the proportion of SEs within each cluster type that occurred on a roadway with the indicated posted speed. The last row and column in the table indicate the total number of SEs for each cluster (last row) and on each posted speed road (last column). Also, the highlighted bold, red variants and italic, blue variants indicate how different the proportion in a cell is from the Posted Speed Total Proportion, which provides the expected proportion based on the sample means (shows as the second-to-last column). In other words, the cells highlighted in bold, red variants indicate that SEs within a cluster were overrepresented at the corresponding posted speed level relative to the sample proportion, and the cells highlighted in italic, blue variants indicate that SEs were underrepresented. The data patterns across posted speed for each cluster are discussed below.

Table 16. The proportion of each cluster on different posted speed roads in Texas. (Cells highlighted in bold, red variants indicate that Speeding Episodes (SEs) within a cluster are overrepresented at the corresponding posted speed level relative to the sample proportion; cells highlighted in italic, blue variants indicate that SEs are underrepresented.)

Posted Speed	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Small Increase	Posted Speed Total	
							Proportion	N
30	**0.66**	**0.44**	*0.04*	*0.10*	*0.00*	**0.21**	0.14	189
35	0.12	0.11	*0.08*	**0.19**	*0.00*	0.13	0.11	146
40	*0.02*	0.06	0.06	0.04	*0.00*	0.07	0.05	68
45	0.07	**0.12**	0.07	**0.10**	*0.00*	0.12	0.08	113
50	*0.02*	**0.10**	0.08	*0.05*	*0.01*	**0.14**	0.07	100
55	*0.10*	*0.15*	0.25	*0.16*	**0.71**	**0.29**	0.24	332
60	*0.00*	*0.01*	**0.23**	**0.22**	**0.21**	*0.04*	0.18	247
65	*0.00*	*0.00*	**0.16**	0.10	*0.07*	*0.00*	0.11	146
70	*0.00*	0.01	0.03	0.04	*0.00*	*0.00*	0.02	33
Cluster Total	98	93	729	250	68	136	100%	1374

Speeding Up Cluster: Relative to the full sample proportion, the SEs in this cluster were substantially overrepresented on 30 mph roads and underrepresented on high speed roads with posted speed limits of 55-65 mph. This is similar to the finding for Seattle.

Speed Drop Cluster: The SEs in this cluster were overrepresented on 30 mph roads similar to the Seattle cluster and the Speed-up cluster. Also, this cluster was underrepresented on 60 mph, 55 mph and 65 mph roads. Again, this pattern is consistent with the one found in Seattle.

Incidental Cluster: The SEs in this cluster were underrepresented on 30 mph roads but otherwise match sample proportions fairly closely. This is similar to Seattle.

Casual Cluster: The distribution of SEs across posted speed in this cluster were similar to the full sample proportion, with slightly fewer SEs on 55 mph roads. This pattern suggests that this type of speeding was common on most types of roads.

***Cruising Cluster**:* The SEs in this cluster were overrepresented on high speed roads—especially on 55 mph, and 60 mph roads. This is consistent with other characteristics of this cluster that suggest that it occurs on long stretches of the open road.

Small Increase Cluster: The SEs in this cluster were slightly overrepresented on lower speed roads and they were underrepresented on high speed roads with posted speed limits of 60 mph and above. Given this pattern and other characteristics about this cluster, it is probably the case that this type of speeding represents a special case of the more general Speeding Up cluster found in Texas and Seattle.

The relationship between type of speeding and roadway functional class was also examined for Texas driving (see Table 17). Appendix A provides a detailed description of the functional class levels. The overall trends were generally consistent with the posted speed table described above. Some notable findings were that Speeding Up SEs were substantially overrepresented on major arterials compared to the other clusters, including the Small Increase SEs. This suggests that there may be inherent differences in the driving environments associated with both types of speed increase clusters (Speeding Up and Small Increase). Another notable finding is that the Cruising SEs were overrepresented on arterials—specifically ones that had 55 mph speed limits. These tended to be in the outlying areas of College Station, and one interpretation is that speeding on these roads naturally tended to have a longer duration due to an absence of traffic interactions and traffic control devices (TCDs) that would require drivers to slow down.

Table 17. The relative frequency of cluster on different roadway functional classes in Texas. (Cells highlighted in bold, red variants indicate that Speeding Episodes (SEs) within a cluster are overrepresented at the corresponding roadway functional class relative to the sample proportion; cells highlighted in italic, blue variants indicate that SEs are underrepresented.)

Posted Speed	Speeding Up	Speed Drop	Incidental	Casual	Cruising	Small Increase	Posted Speed Total	
							Proportion	N
Residential	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0
Arterial	0.00	**0.80**	0.60	0.66	**0.83**	0.64	0.60	739
Major Arterial	**0.88**	*0.13*	0.15	*0.12*	*0.03*	0.30	0.21	259
State Highway	0.10	0.06	0.14	0.09	*0.01*	0.04	0.10	128
Freeway	*0.02*	*0.01*	0.11	0.14	0.13	*0.02*	0.09	114
Cluster Total	96	93	610	237	69	135	1	1240

Type of Speeding by Time-of-Day

We examined the frequency of SEs in each cluster by time of day (Table 18). The percentage of nighttime SEs across type of speeding was very low—ranging from 1% to 6 %. Since there were very few driving nighttime SEs, it is not possible to identify the relation between type of speeding and time of day.

Table 18. Speeding Episodes (SEs) in each cluster by time of day and percentage of night time SEs in each cluster in Texas.

	Night	Day	Total	Percentage
Speeding Up	1	97	98	1%
Speed Drop	6	87	93	6%
Incidental	35	696	731	5%
Casual	16	234	250	6%
Cruising	1	67	68	1%
Small Increase	5	131	136	4%

General "Riskiness" of SEs

We also analyzed the general riskiness of the type of speeding. The analysis was done on the same situational measures as the Seattle region. These included:

a) Proportion of SEs in each cluster that exceeded 20 mph over the posted limit.

b) Proportion of speeding on "Not Controlled Access" roads.

c) Average duration of the SE.

Table 19, below, summarizes the findings related to the riskiness of the different types of speeding. In the first three rows, the values indicate the percentage of Speeding Episodes within each type of speeding that contain the riskier speeding elements. The average duration variable is not a percent, but instead indicates how long, on average, that SEs were for each type of speeding. The highest values in each row are indicated with bold font, and the findings related to each are discussed below. The Riskiness and Riskiness by Duration rows generally characterize the relative riskiness of the SEs in each type of speeding (as explained below), which is also indicated by the color scale and numerical range of green (least risky; 0.0) to red (most risky; 0.569).

Table 19. Relative riskiness of Speeding Episodes (SEs) from each type of speeding in Texas (higher values reflect higher relative risk).

	Speed Up	Speed Drop	Incidental	Casual	Cruising	Slow Increase
Speed Exceed 20mph	**54%**	38%	0%	6%	22%	7%
Not Controlled Access	**99%**	96%	74%	78%	85%	98%
Nighttime SE (8-6)	1%	**6%**	5%	**6%**	1%	4%
Average Duration (seconds)	14.9	14.1	19.9	39.3	**210.5**	13.5
Riskiness	*0.005*	***0.022***	*0.000*	*0.003*	*0.003*	*0.003*
Riskiness by Duration	0.075	0.301	0.000	0.121	**0.569**	0.035

Speed Exceedance over 20 mph: The SEs in the Speeding Up cluster seemed to be more likely to exceed the posted speed limit by 20 mph as compared to other clusters. About 54% of the SEs in this cluster exceeded the posted speed by 20 mph. The percentage of SEs in the Speed drop cluster was also high at 38%. This is similar to Seattle.

Not Controlled Access: Most of the SEs in the Texas region were on arterials and major arterials, which are "Not Controlled Access" roads. The Casual and Incidental cluster had the lowest percentage of speeding, 78% and 74% respectively, on "Not Controlled Access" roads.

***Nighttime SE**:* The percentage of nighttime SEs for each cluster was very low. It ranged from 1% to 6%.

Average Duration: The average duration of SEs was highest for the Cruising cluster, similar to the Seattle region. The average duration of SEs in this cluster was 210.5 seconds, which was substantially greater than the Casual cluster which was a distant second with 39. 3 seconds. The average duration of the Cruising cluster in the Texas was 210.5 seconds, over 100 seconds greater than in the Seattle region (109.4 seconds). This is probably a product of the geography/terrain and the population density in the area.

Riskiness and Riskiness by Duration (Exposure): In general, this analysis is less informative than the Seattle analysis because the numeric ranges across variables makes them less comparable. Nevertheless, the results of the analysis indicate that, in the Texas region, the "Cruising" cluster was associated with the highest level of "risk." This is largely a result of the increase in exposure risk associated with the long average duration of the SEs in this cluster (210.5 seconds), and the high percentage of SEs on "Not Controlled Access" roads. However, before coming to a conclusion based on these findings, two factors should be considered. First, the sample size of the cruising cluster was significantly smaller, which probably skewed the average duration based on a few longer SEs. Second, considering the rural landscape of the region, the "Not Controlled Access" roads had longer stretches of open roadway, typically without sidewalks, traffic control devices and/or intersections. This likely reduced interactions with other vehicles and pedestrians in the environment (although animal hazards were still present), which may have reduced the overall risk level.

The analysis also found that the Speed Drop cluster was associated with an elevated level of risk as compared to Casual, Speed Up and Small Increase clusters. The Incidental cluster seemed to be the least associated with risk on this measure. One difference between Texas and Seattle is that the "risk" measure for Casual speeding is much higher than for Incidental speeding in Texas. This could be due to the Casual speeding cluster capturing some of the SEs with more aggressive characteristics.

SUMMARY AND CONCLUSIONS

This section discusses the major conclusions drawn from the analyses in this report. There were two primary objectives in this project. The first was to redefine speeding in terms of Speeding Episodes and use the new data to identify underlying types of speeding and Driver Types. The second objective was to conduct additional data analyses on the relationships between situational factors and speeding. Overall, we were successful in accomplishing the first objective in full; however, limited data on situational factors permitted us to only address the second objective at a high level. Each of these objectives is discussed in more detail in the following sections. This project also yielded additional conclusions that are also discussed below.

OBJECTIVE 1: REDEFINE SPEEDING IN TERMS OF SPEEDING EPISODES AND USE THE NEW DATA TO IDENTIFY UNDERLYING TYPES OF SPEEDING AND DRIVER TYPES

This objective was successfully accomplished. The dataset was fully developed and subsequent analyses provided information about several aspects of speeding. The key findings are listed below and discussed in separate sections that follow.

- Descriptive analyses identified high-level characteristics of SEs.
- The cluster analysis approach was useful for identifying types of speeding.
- Cluster analysis to identify Driver Types suggests that these types are not defined exclusively by driver demographics.

Descriptive Analyses Identified High-level Characteristics of Speeding Episodes

In this project, speeding was broadly defined as an episode in which drivers exceed the posted speed limit by 10 mph or more. One overall finding based on the descriptive analyses was that the corresponding SEs exhibited similar characteristics across posted speed and location. In particular, duration was relatively consistent across posted speed in urban and built-up areas, which was likely due to traffic control devices and interactions with other traffic being a consistent aspect of driving in town or in urban areas. It was only on higher-speed, rural roads in Texas that SEs become longer and span a much wider range. Another finding was that the median value for Maximum Speed Exceedance similarly showed a relatively small degree of variation across posted speed level. While there was still a small proportion of SEs that reached exceptionally high exceedance levels, it was clear that during most SEs, there was a limit to how fast drivers were willing to go. With regard to time of day, the data also showed that there were no clear spikes in terms of when SEs occurred, with a possible exception for early morning in Texas. Otherwise, SEs occurred basically whenever individuals were driving. In general, SEs were still rare, especially in comparison to the total number of opportunities to speed. Most drivers averaged fewer than one Speeding Episode per trip.

It should be noted that the descriptive analysis provides a rather basic view of the nature of Speeding Episodes that does not account for much of the complexity of speeding. Subsequent analyses identified different types of speeding that occurred with substantially different frequencies. It is clear that the summary values generated in the descriptive analyses were heavily influenced by the large proportion of Incidental and Casual SEs, which were themselves relatively similar.

The Cluster Analysis Approach was Useful for Identifying Types of Speeding

A primary objective in this project was to advance beyond the current notions of speeding as a monolithic and aggregate concept, and develop a more nuanced understanding of the behavioral factors that comprise speeding. In this regard, the basic cluster analysis approach was quite successful. Specifically, it carved up the large number of individual Speeding Episodes into sub-groups that had characteristics that could be meaningfully interpreted, and that were largely distinct from each other. The primary speeding types included the following:

1) *Speeding that Occurs around Speed-Zone Transitions*. This includes Speeding Up, Speed Drop, and Small Increase types of speeding observed in both Seattle and Texas. These SEs typically have short durations, a high maximum speed, and they occurred on lower-speed roadways. In these cases, the roadway environment in the slower segment may be similar enough to the higher-speed segment that it supports faster driving.

2) *Incidental speeding*. This is the most common type of speeding, and it involves low-exceedance, short-duration episodes that more likely represent the upper bound normal speed maintenance behavior, as opposed to a separate speeding behavior (see also the discussion in the Additional Conclusions section).

3) *Casual speeding*. This is another relatively common type of speeding. Although it is similar to Incidental speeding, it involves speeds that are high enough that drivers are likely to be aware that they are speeding. However, the durations are relatively brief, therefore drivers may not persist in this type of speeding for long (e.g., it could include passing behavior)

4) *Cruising speeding*. The defining characteristic of this type of speeding is the relatively long duration. While the longer duration increases a driver's exposure to safety risk, this type of speeding is more likely to occur on controlled-access, high-speed roads, which reduce the likelihood of unexpected hazards. Another notable aspect of this type of speeding is that only a subset of drivers in Seattle engaged in this type of speeding. Specifically, the subset of drivers that had the highest prevalence of Cruising speeding (i.e., 8-25% of their trips) was limited to 10 drivers, representing all demographic groups (see Figure 18).

5) *Aggressive speeding*. This type of speeding is characterized by relatively high speed exceedance, moderate duration, and a high level of speed variability. This cluster only occurred in Seattle and it generally encompassed riskier aspects of speeding than the other clusters. Similar to the Cruising speeding type, the subset of drivers that had the highest prevalence of Aggressive speeding (i.e., 15-50% of their trips) was limited to 10 drivers, representing all demographic groups.

The types of speeding listed above were also remarkably consistent across drivers and locations, with five of the six clusters identifiable in both Seattle and Texas. The primary difference, however, was that the Speeding Up cluster in Texas was distributed across two different clusters. The higher-speed cluster matched the characteristics of its counterpart in Seattle; however, the lower-speed version was a better match in terms of the type of roadway segments.

While the cluster analysis was successful in parsing Speeding Episodes into meaningful types of speeding, the overall approach was still limited by the variables available. Specifically, the different types of speeding are still rather general and abstract in comparison to speeding that can be more directly tied to actual driving behaviors (e.g., speeding to pass other vehicles). This outcome is not unexpected, since the analysis was based on variables that represent general aspects of high-speed driving over time, and the corresponding types of speeding were accordingly general in nature (e.g., speeding up, cruising, etc.). These types of variables were all that were available in the dataset. However, richer naturalistic driving data, such as those available in the SHRP2 dataset, could provide important proxies for driver actions (e.g., accelerator presses; lane changes), so it is possible that clusters could be better defined in terms of more specific underlining behaviors (e.g., weaving through traffic, etc.) in the future.

Cluster Analysis to Identify Driver Types Suggest that these Types are not Defined Exclusively by Driver Demographics

The cluster analysis conducted using individual drivers' speeding profiles was successful in identifying four different types of drivers. A key limitation of this analysis, however, was the small number of drivers at each location. In Texas, too few drivers had a sufficient number of Speeding Episodes to conduct the analysis at all. Nevertheless, in Seattle there were enough drivers to run the cluster analysis, and the corresponding Driver Types included the following:

5) *Deliberate speeders*: Drivers in this group averaged a higher proportion of Casual and Aggressive SEs, but lower levels of Incidental SEs than other groups. Individuals in this group also had substantially more SEs than those in other groups. In general, these drivers tended to engage in the more aggressive and deliberate types of speeding, substantially more than other Driver Types. Deliberate speeders also reported engaging in risky driving behaviors more frequently than others, and they had the most favorable attitudes towards speeding.

6) *Typical speeders*: The distribution of SEs within this group basically matched the distribution across all drivers. The Typical Driver Type was also comprised of the largest number of drivers, and Casual speeding was relatively more common in this group. Individuals in this Driver Type also occupied a middle range in terms of average speeding profiles and frequency of SEs.

7) *Situational speeders*: This Driver Type is challenging to label. This type is distinct in that these drivers had a much higher proportion of the Speeding Up type of speeding than other Driver Types, and they engaged in minimal amounts of Aggressive and Cruising speeding. Overall, this group only engaged in a little more speeding than the Unintentional Driver Type, but they did not share the same favorable views regarding not speeding.

8) *Unintentional speeders*: This group is comprised primarily of drivers that engaged mostly in Incidental speeding and some Casual speeding, but almost none of the other

types of speeding. These drivers also had attitudes and beliefs that were the most favorable towards not speeding. While this group may represent non-speeders, most of them still drove at sufficiently high speeds to exceed the speeding threshold on many occasions.

Analyses on the demographic composition of the groups listed above indicated that there were significant differences in the distribution of demographic groups across Driver Type. However, the groups differed largely in terms of degree, since all of the demographic categories appeared in each Driver-Type cluster. This finding is generally consistent with the results of the analysis into demographic predictors of speeding behavior from the previous *Motivations for Speeding* project. Specifically, that study found that demographic predictors, which initially were significantly associated with the occurrence of speeding on a trip, were subsequently displaced as significant predictors by variables related to beliefs and attitudes about speeding (Richard et al., 2013a). In the current project, clear trends regarding attitudes and beliefs about speeding were observed across the Driver Types.

A second way that we examined demographic aspects of speeding was by identifying which drivers engaged in the riskiest types of speeding. In particular, Figure 18 shows a scatterplot of the percentage of free-flow trips in which Aggressive and Cruising speeding occurred separately. While an outlier group of three frequent speeders is male-only, the remaining groups of drivers with elevated levels of both types of speeding included drivers from each demographic category. This, again, suggests that riskier speeding behavior is not exclusive to certain demographic groups.

OBJECTIVE 2: ADDITIONAL DATA ANALYSES ON THE RELATIONSHIPS BETWEEN SITUATIONAL FACTORS AND SPEEDING

The second objective in this project was to conduct additional data analyses on the relationships between situational factors and speeding. A challenge for meeting this objective was the lack of situational data available to conduct the corresponding analyses. While we were able to address this objective at a high level, there are many questions that remained unanswered. Some of the key findings from the situational analyses are described below.

The first finding from the situational analysis was that the general “riskiness” of different types of speeding was corroborated by the involvement of riskier elements in SEs. This analysis was done by examining how the types of speeding differed in terms of the best proxies for safety risk available in the data set (e.g., exceeding posted speed by more than 20 mph, nighttime speeding, etc.). In Seattle, the “Aggressive” and “Cruising” speeding types were associated with relatively higher prevalence of risky conditions, and longer exposure durations. In contrast, the Incidental and Casual speeding types were the least likely to involve risky aspects. The general pattern was similar in Texas, except that there was no Aggressive speeding type, so the Cruising cluster appeared to be the riskiest type of speeding.

The second finding generated from the situational analysis was that there is at least anecdotal evidence of location-specific characteristics affecting both the occurrence and non-occurrence of speeding. Although it was beyond the scope of the current project to conduct a systematic and detailed recording of the roadway features at many of the locations associated with SEs, we did examine the roadway environment at several locations where certain types of speeding occurred frequently. Locations with posted speed changes, but where the roadway characteristics remained the same across zones, were a common example of where speeding occurred more often. Other locations where we commonly observed higher levels of speeding included those in which the roadway was more open and provided better separations from hazards, including divided roadways and sidewalks that were set apart from the curb. While these anecdotal observations are suggestive, this topic can still benefit from analyses that include a more rigorous and systematic selection and cataloging of site characteristics.

There is also indirect evidence for the broad notion that certain aspects of the driving environment affect speeding behavior. In particular, there were certain locations that had a higher frequency of Incidental SEs, which suggests that the driving environment at these locations may unintentionally encourage speeding, even when drivers were not intending to speed. The converse of this was also apparent. In particular, while Cruising and Aggressive SEs covered most of the freeways, there were certain stretches of these roads in which SEs did not occur, even though those sections had a large number of Free-Flow Episodes. There is also overlap in the non-speeding zones across the two types of speeding. This suggests that these roadway sections may have some characteristics (e.g., reduced line of sight, multiple merging lanes or exits) that discourage speeding in some way.

A final minor finding regarding situational aspects of speeding was that there were clear similarities between types of speeding at both the rural and urban data collection sites. Similar patterns were found with regard to where different types of speeding occur across the two locations. With the exception of obvious differences, such as the longer durations associated with Cruising speeding, most of the clusters had remarkably similar median values on speed-related variables. This suggests that there are over-arching roadway design aspects that influence speeding behavior in similar ways.

ADDITIONAL CONCLUSIONS

In addition to the primary conclusions discussed above, there were some additional findings from this study that merit discussion. These are presented below.

Implications for Safety Countermeasures

A key practical implication that stems from this research is that there is converging evidence that the Deliberate speeder group represents a Driver Type that is notably distinct from other groups. In particular, their speeding behaviors are different in that they speed much more frequently and they tend to engage in the more aggressive and deliberate types of speeding substantially more than other Driver Types. Moreover, individuals in the Deliberate Driver Type also report engaging in risky driving behaviors more frequently than others, and they have the most favorable attitudes towards speeding. The distinctiveness of the Deliberate Driver Type leads to an important practical implication, which is the possibility of specifically directing safety campaigns and countermeasures towards this group. Because their behaviors and attitudes are outside the norm, they can be identified both by their on-road behavior and by using personal inventory items, which may be a practical way to identify drivers from this group. This is also the most critical group to focus on because they engage in the most aggressive type of speeding, likely in conjunction with other risky driving behaviors. Therefore, changing their behavior may have disproportionately large benefits in terms of reducing speeding-related crashes.

A related implication pertains to the different types of speeding identified. Some of the analyses suggested that the relative riskiness of the types of speeding may differ. In particular, the Aggressive type in Seattle and Cruising type in Texas more frequently have characteristics that may increase crash risk in comparison to Incidental or even the Casual types of speeding. Further research is needed to more thoroughly characterize each type. However, if it becomes possible to identify distinct speeding behavior types that are linked to increased crash risk, then it opens up the possibility of making those types of speeding an enforcement priority, or more efficiently deploying resources to specifically target those behaviors, rather than the types of speeding that are less dangerous. This could be particularly effective if it is possible to determine where and when the most dangerous types of speeding are most likely to occur.

Incidental Speeding may Not Represent True Speeding Behavior

Although Speeding Episodes were defined as being speeding because they involved driving at more than 10 mph above the speed limit, a majority of the SEs may have represented common speed maintenance behavior rather than deliberate speeding. In particular, Incidental speeding made up the largest proportion of all SEs; however, the underlying speed characteristics just barely met the criteria for speeding. It is more likely that Incidental speeding represents the high end of a deliberate and common speed-choice strategy in which drivers view the posted speed as a floor, with the ceiling being the speed beyond which they are at risk of getting a ticket (e.g., +10 mph). This was by far the most dominant speed-choice strategy reported by the study drivers that participated in follow-up focus group interviews, particularly since drivers perceived the safety risks of driving within this speed range typically as low (Richard et al., 2013a). This points to a fundamental disconnect between the literal meaning of the posted speed limit, and the practical interpretation of this information by drivers. Changing driver views about this belief is an obvious candidate for a speed-reduction countermeasure. However, this view is likely to be deeply engrained in the driving population and would require tremendous effort to change (however, previous successes with impaired driving and seatbelt use suggest that this is feasible).

Despite the possibility that Incidental speeding may not represent speeding of interest, identifying and characterizing this type of driving is still an important step forward in the effort to understand speeding behavior. A key objective that this achieves is that it identifies what regular/baseline high-speed events look like. Any analysis of naturalistic driving data will inevitably capture vast amounts of this type of high-speed driving, which largely represents uninteresting “noise” for studies that are investigating more dangerous types of speeding. Identifying this Incidental speeding allows researchers to filter out these episodes. Note that we did not attempt this in the current project because it was exploratory in nature, and documenting this Incidental speeding was important. Another practical constraint was that the occurrence of other types of speeding was too low to support separate, in-depth analyses.

Implications for Definition of Speeding

Another conclusion from this study, related to the previous one, is that it may be worthwhile to revisit the criteria for labeling fast driving as a speeding event. In the current study, SEs were defined by a simple 10 mph exceedance threshold, with the sole exception being that slight drops below this level were included if speed levels returned above 10 mph over the posted limit within a few seconds. This criterion was adequate in the *Motivations for Speeding* study and it had important connections to underlying driver beliefs and behaviors (Richard et al., 2013a). This approach was also suitable for the exploratory objectives in the current project. A key drawback, however, was that it resulted in the majority of SEs pertaining to Incidental speeding, which as the previous conclusion describes, may not represent a unique speeding-centric behavior at all.

There are multiple options for making the speeding criterion more stringent. The first is to simply increase the threshold required to qualify as speeding (i.e., from +10 mph to +15 mph). However, a key drawback of this approach is that it shortens the durations of other types of speeding that may indeed represent unique behaviors. Doing this also dilutes the connection between speed and perceptions of speeding risk, such as the common belief that drivers will get a speeding ticket above 10 mph.

Another option is to use compound criteria, such as pairing the 10 mph threshold with a minimum duration and/or a maximum speed exceedance criterion (i.e., maximum exceedance > 15 mph). In the case of an additional duration criterion, it would eliminate many of the Incidental SEs because they tended to have the shortest duration. However, speeding related to speed-zone transitions may also be lost using this approach.

Yet another option is to deal with this issue in a post hoc manner, similar to what was done in the current analyses. It is relatively simple to identify Incidental SEs based on their speed-related characteristics, and they can be filtered out after the fact. In this regard, it may even make sense to lower the speed threshold from 10 mph to 5 or 0 mph to more completely capture the driving episodes representing the common speed-choice strategy described above. This might actually improve the accuracy of identifying these uninteresting speeding events.

The precise approach taken likely depends on the specific data and study objectives. Nevertheless, future studies analyzing naturalistic driving data should carefully consider what implications the definition of speeding has for the speeding data extracted for analysis.

APPENDIX A – KEY ROADWAY MAPS

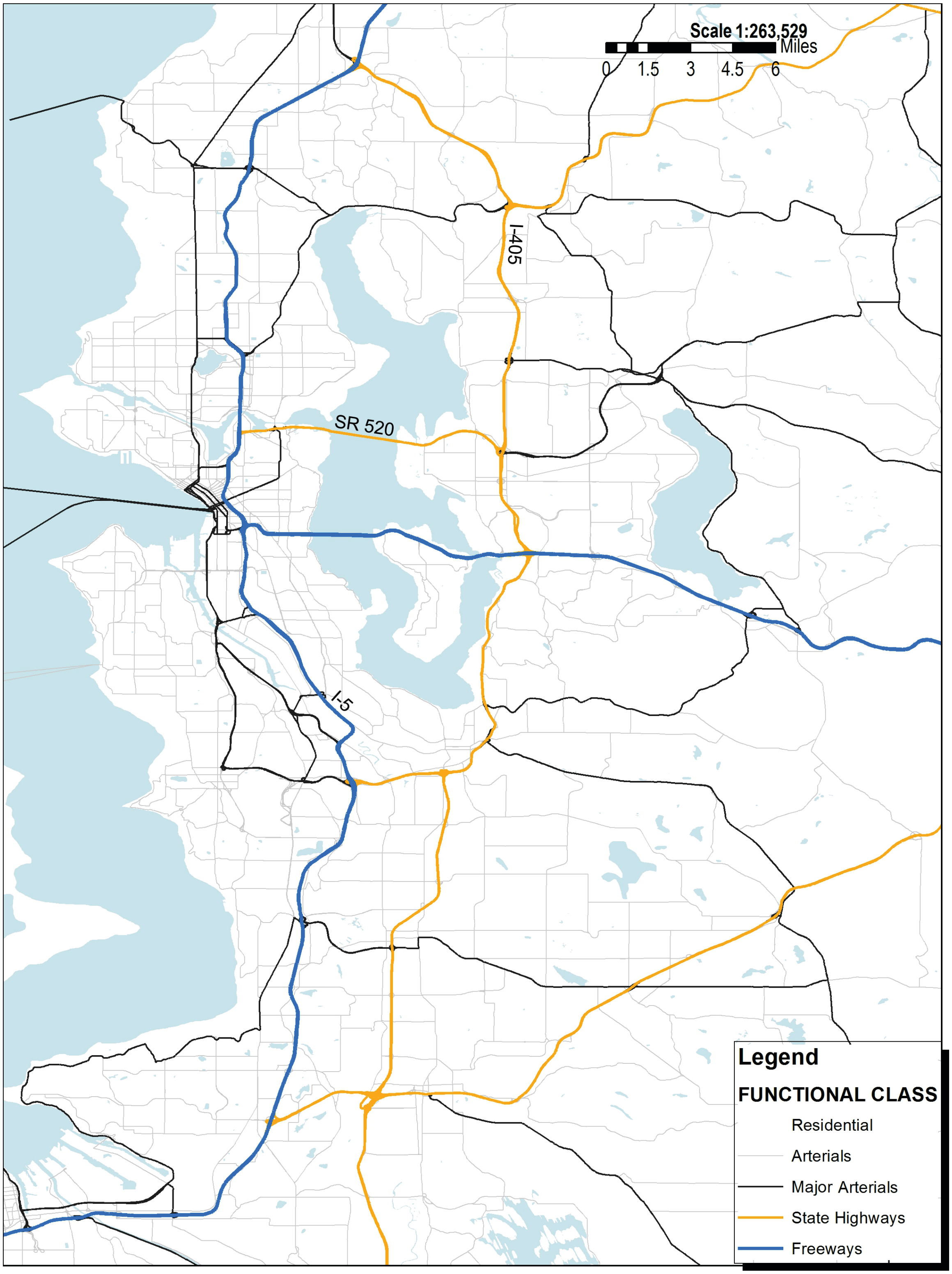
Table 20 provides a description of the roadway functional classes used in the analyses. The maps in this appendix indicate the locations of the major roadways/functional classes in the Seattle and Texas regions.

Table 20. Definitions for different roadway classes.

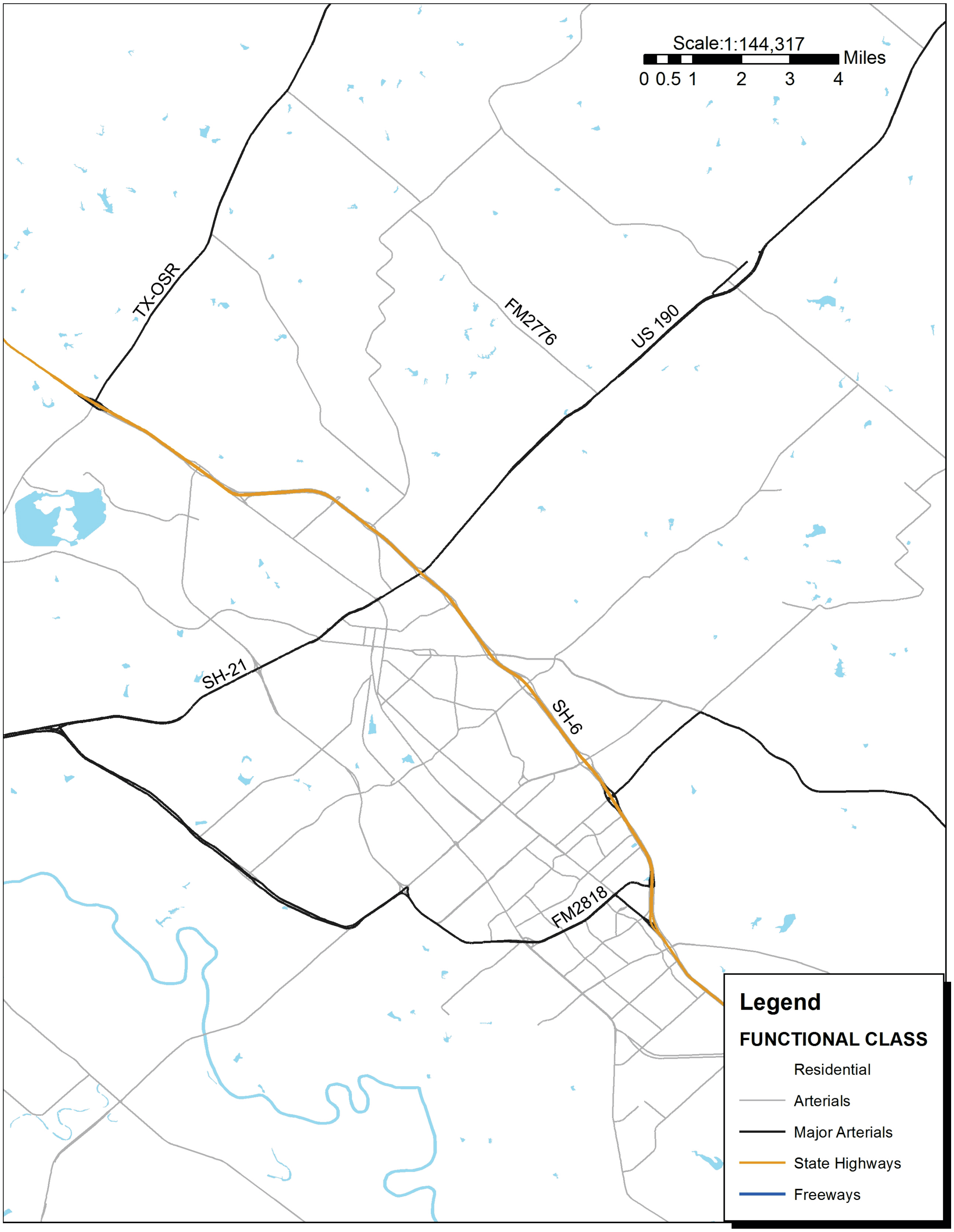
Road Class	Description
Residential	Roads that provide lower speed travel within neighborhoods. These roads have volume and traffic movement levels below those of any other functional class.
Arterial	Collector roads that provide moderate speed travel between neighborhoods. They provide for a high volume of traffic movement at moderate speeds, and they connect with higher functional class roads to collect and distribute traffic between neighborhoods.
Major Arterial	Collector roads that provide moderate speed travel within cities. They provide a high volume of traffic movement at a lower level of mobility than State Highways.
State Highway	Roads that provide quick travel between and through cities and are used to channel traffic to Freeways. These roads have very few, if any speed changes that allow for high volume, high speed traffic movement.
Freeway	Roads that allow for high volume, maximum speed traffic movement between and through major metropolitan areas. These roads typically have few, if any, speed changes, and access to the road is usually controlled.

Note that the maps below exclude approximately 30% of SEs that occurred outside of the mapped area. Also, although residential roads are listed in the map legend, they are not shown in the maps because the map scale is too large.

SEATTLE MAP


Scale 1:263,529
Miles
0 1.5 3 4.5 6
I-405
SR 520
I-5
Legend
FUNCTIONAL CLASS
Residential
Arterials
Major Arterials
State Highways
Freeways

TEXAS MAP


Scale:1:144,317
Miles
0 0.5 1 2 3 4
TX-OSR
FM2776
US 190
SH-21
SH-6
FM2818
Legend
FUNCTIONAL CLASS
Residential
Arterials
Major Arterials
State Highways
Freeways

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