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Probe vehicle performance measures for assessing travel time reliability

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Probe vehicle performance measures for assessing travel time reliability

by

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NOMENCLATURE

AASHTO	American Association of State Highway and Transportation Officials
BTI	Buffer Time Index
DOT	Department of Transportation
FHWA	Federal Highway Administration
FOTM	Failure/On-Time Measures
HDFS	Hadoop Distributed File System
IQR	Interquartile Range
LOTTR	Level of Travel Time Reliability
MI	Misery Index
MPO	Metropolitan Planning Organization
NPMRDS	National Performance Management Research Data Set
PHTTR	Peak Hour Travel Time Reliability
PR	15th-85th Percentile Range
PTI	Planning Time Index
SD	Standard Deviation
SHRP	Strategic Highway Research Program
SS	Skew Statistic
TRB	Transportation Research Board
TTI	Travel Time Index

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ABSTRACT

Travel time reliability reflects the degree to which the amount of time needed for a trip is predictable. Metrics that quantify travel time reliability are emerging as a fundamental part of assessing the performance of transportation networks. Many states and municipalities are starting to incorporate travel time reliability into their transportation assessments and planning processes. Probe vehicle data is a prevalent data source which can be utilized to compute many of these travel time reliability metrics. This study used probe vehicle data from INRIX to compute, compare, and apply travel time reliability metrics on interstate segments in Iowa. It also looked at the concept of utilizing composite travel time reliability metrics to more concisely but still comprehensively convey travel time reliability.

Different travel time reliability metrics were gathered from past literature and current FHWA rulemaking. These reliability metrics were computed and outcomes from each were compared. From ten different metrics, three groups of similar metrics were identified: the standard deviation of segment travel time index (TTI), the 15^{th}-85^{th} percentile range of TTI, and the buffer time index. These metrics, along with the level of travel time reliability and peak hour travel time reliability metrics from the FHWA, were applied at a segment level to the interstate network in the Des Moines area as well as across Iowa. Choropleth maps and identification of the most unreliable segments in the network emerged as useful ways to assess travel time reliability. It was observed that each metric would identify different segments as being unreliable because the metrics were sensitive to different characteristics of the TTI distribution.

To concisely and comprehensively convey multiple aspects of travel time reliability, a method was developed for creating composite travel time reliability metrics using different combinations of the three key metrics identified earlier. Composite metrics were compared with each other as well as with the original travel time reliability metrics using choropleth maps and route progression plots. A composite metric combining the standard deviation of TTI and the 15^{th}-85^{th} percentile range of TTI emerged as a feasible composite metric to apply to assess travel time reliability at scale.

CHAPTER 1. INTRODUCTION

1.1 Mobility Reporting

Before examining travel time reliability metrics in detail, it is important to first go through a brief summary of the more recent history of performance monitoring on transportation highway systems.

1.1.1 Background on Freeway Performance Assessment and Traffic Data Collection

As urban freeway systems developed in the US, agencies became aware of the need for traffic management, and traffic monitoring systems began to be developed in the 1960s and 1970s. These utilized sensors in fixed locations that could measure traffic volumes and speeds in real time. Today, many of these fixed-location sensor networks remain on major freeway routes in urban areas. Some common types of fixed-location sensors are inductive loop detectors, radar sensors, and video monitoring systems. At a basic level, they can typically provide data such as traffic volumes and vehicle speeds for selected points on a freeway. In addition, some other uses for fixed-location sensors include estimating travel times for small highway sections, estimating vehicle trajectories, assisting in the classification of vehicles, and automatically estimating traffic density (Coifman, 2002; Ki and Baik, 2006; Ozkurt and Camci, 2009).

Fixed-location sensors have some limitations regarding performance monitoring at a larger scale. As with all infrastructure owned by agencies, they require an investment for installation and maintenance. As a consequence, such systems have primarily been installed in areas experiencing heavy recurring congestion, typically urban areas. Thus, fixed-location sensor networks usually lack coverage in more rural areas. Due to these limitations, finding alternative data sources would be very useful for performance monitoring of freeways on a larger and more comprehensive scale.

In the past ten years, some rapid advancements in performance monitoring strategies and techniques were made. This has mainly been due to new data sources becoming available, which have inspired many studies that have explored how to fully utilize these newer data sources to properly assess the performance of highway systems at a large scale.

One of the more important research initiatives along these lines was the Strategic Highway Research Program (SHRP) 2 program. SHRP 2 was a major research program sponsored by the FHWA and AASHTO and it was managed by TRB. It took place from 2006 to 2015. Its principal goals were to improve highway safety, reduce congestion, and improve methods for renewing roads and bridges. To address these goals, research was focused into four areas: safety, renewal, reliability, and capacity, with over 132 research reports being generated. The reliability and capacity focus areas both addressed freeway performance and congestion. The capacity focus area mainly addressed the need for more physical capacity to help mitigate congestion, whereas the reliability focus area narrowed down more on assessing characteristics of highway performance affecting travel time reliability. The SHRP 2 reliability projects documented numerous techniques for performance measurement and provided guidance to agencies nationwide to implement highway performance measurement strategies.

Many performance measures for freeway systems developed under SHRP 2 and other studies have made use of new data sources that have emerged in the past decade. SHRP 2 Reliability Project L02 (Establishing Monitoring Programs of Travel Time Reliability) discussed data sources that could be used for travel time reliability monitoring. These include

AVI (automated vehicle identification) sensor data, such as Bluetooth device MAC address matching, and AVL (automated vehicle location) probe vehicle data.

AVI data consists of vehicle identifiers, such as the MAC addresses of electronic devices which have Bluetooth capabilities, to estimate travel times on freeway segments by comparing the time of detection at multiple locations where the same identifier is recorded (Sharifi et al., 2011). This data collection technique can only sample vehicles transporting devices that have Bluetooth capabilities enabled during the trip. AVI data collection also has one of the same disadvantages as traditional fixed-sensors, the requirement to install and maintain physical sensors along the roadway.

AVL or "probe vehicle" data consists of a stream of timestamped vehicle position information (latitudes and longitudes) recorded by an electronic device with the ability to use the Geographic Positioning System (GPS) to determine its location. Starting around the year 2010, several vendors began compiling this type of data into roadway information, the most common product being a record of average speeds for predefined roadway segments. Initially, the data was somewhat sparse. However, by 2012 the data quality and quantity had improved significantly with the increase of noncommercial probe sources in the form of GPS units and cell phone users (Bullock et al., 2014). Today, probe vehicle data is collected from cell phones, navigation devices, commercial fleet management services, and other similar products, and is available from several different vendors such as INRIX, NAVTEQ, HERE, Traffic Cast, and others (Sharma et al., 2017). Unlike sensor-based data, probe vehicle data does not require installation and maintenance of infrastructure. Therefore, probe vehicle data can be a cheaper alternative for agencies to utilize for performance assessment. Also, since probe vehicle data is not limited in its geographic distribution to where sensors have been installed, it is able to cover virtually the entire expanse of all freeway systems, in both urban and rural areas. This paper will utilize probe vehicle data from INRIX, with further discussion of the data itself and its potential drawbacks and limitations presented in Chapter

In 2017, the FHWA published a rule requiring state agencies and Metropolitan Planning Organizations (MPOs) receiving federal funds to begin assessing the reliability of their roadway systems. This requirement originated in the Moving Ahead for Progress in the 21st Century Act (MAP-21). One of the goals of this rule is to provide a nationally consistent means of the reporting of condition and performance of roadway systems. In this rule, state DOTs are required to make use of the National Performance Measurement Research Data Set (NPMRDS), a probe vehicle data set consisting of 5-minute average segment speeds, to calculate a series of specific performance measures defined in the rulemaking language. This data set utilizes TMC segments. TMC segments typically lie between interchanges for highways can vary from less than mile to multiple miles. However, INRIX has recently started providing average speeds for XD segments. XD segments are typically much shorter than TMC segments, often between 0.1 miles and 1.5 miles. This study uses INRIX's XD segments.

1.1.2 State-Level Mobility Reports

Even before the federal rulemaking on national performance measures, some State DOTs had begun to commission reports on the performance of their highway systems based on probe vehicle data. Some states in the Midwest that have already begun publishing such performance reports are Indiana and Iowa. These reports both make use of probe vehicle data from INRIX.

Indiana released its first interstate mobility report in 2011, predating the recent rulemaking from the FHWA. The Indiana Interstate Mobility Report was precipitated by the closure of the I-64 bridge across the Ohio River in the Louisville area, which diverted traffic to the I-65 crossing. The need to monitor traffic congestion across the region, where very little monitoring infrastructure was available, led Indiana DOT to invest in probe data. The following year, the first mobility report was published, which used probe data to assess the extent of congestion across the entire state.

Indiana's most recent interstate mobility report was released in 2015 (Day et al.). This mobility report assessed the interstate system using a few different approaches. The primary metric used for quantifying the amount of freeway congestion is distance weighted congestion hours (DWCH). Each roadway segment is considered to be congested if its speed fell below a certain threshold (in Indiana, 45 mph was used). The total amount of time that a segment is congestion could therefore be calculated in terms of congested hours (CH). Multiplying CH by the segment length yields DWCH. This step is useful because the segment lengths are heterogeneous.

The Indiana Mobility Reports presented DWCH as a series of stacked bar graphs with data from individual months across a span of years clustered together so that seasonal trends in congestion could be assessed as well as trends from year to year. Each bar on the figure was broken down by route. A direct example of this is shown in Figure 1.1. Similar charts were also provided using total delay (in vehicle hours) as an alternative to DWCH.

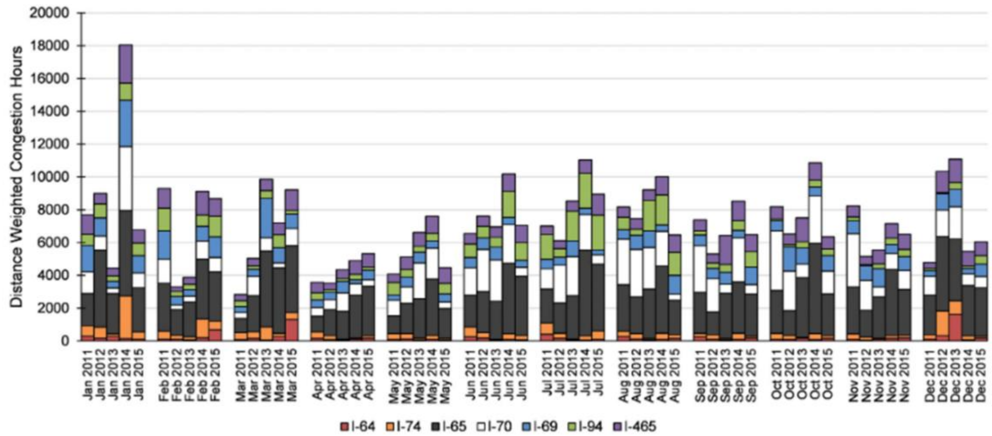

Figure 1.1 *Distance weighted congestion hours, 2011-2015 (Day et. al.).*

Speed profiles were also presented for every interstate, with separate plots per direction. These speed profiles show the distribution of speeds along each mile of the route for each month, allowing the location and severity of speed reductions to be visually assessed. A direct example of this is shown in Figure 1.2, which displays speed profile of I-65N.

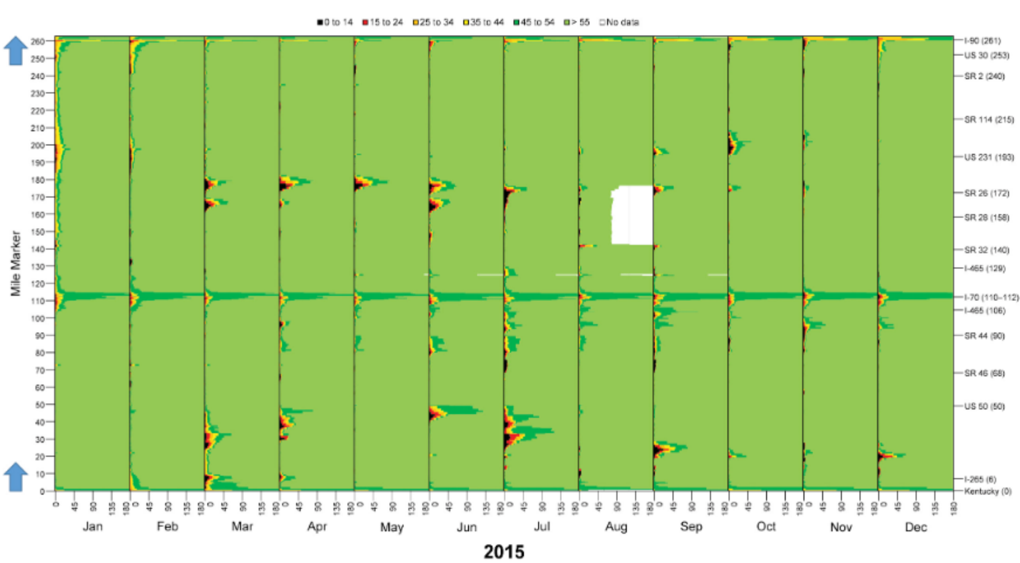

Figure 1.2 *I-65 northbound speed profile (Day et. al.).*

The report also presented several online mobility dashboards that allow users to view performance for specific locations and time periods. Some of these dashboards include the following:

- The “traffic ticker” provides a view of congestion and distribution of speeds at a state-wide level which can filtered down to individual roadways.
- Congestion profiles show locations of congestion along any defined route
- Segment travel times can be used to compare the cumulative frequency distributions of travel times in two different time periods for predefined routes

Finally, the latest mobility report from Indiana acknowledges the ongoing discussion on national policy for the reporting of performance measures and states that many of the proposed metrics are oriented towards the analysis of speed data records similar to those already used in the Indiana mobility report. Although many of the graphics imply the system reliability, as of 2019 the Indiana mobility report series has not included metrics specifically oriented toward directly quantifying reliability.

Iowa began publishing similar annual reports around the same time frame. Its most recent edition is the 2016 Interstate Congestion Report. Iowa’s report shows the number of congestion hours, both in the form of total congestion hours, as well as a distance-weighted approach, a delay cost which converts total delay into user costs, and speed performance (using speed profiles similar to Indiana’s report). Iowa’s report also goes into a congestion causation analysis. The 2016 report also included a report on the sources of congestion, which was based on an analysis that cross-referenced the delay cost data against other data sources on workzones, incidents, and weather, and against itself to identify recurring congestion.

Unlike the Indiana mobility report, Iowa's report does include a travel time reliability metric: the "percent increase in typical travel time". This metric is more commonly known as the buffer time index (BTI). It is calculated by taking the difference between the 95th percentile of travel times and the average travel time for a given segment and dividing that by the average travel time as shown in the following equation.

$$BTI = \frac{TT_{95\%} - TT_{avg.}}{TT_{avg.}}$$

This metric is meant to reflect the increase in travel time necessary for 95 percent of trips to arrive on time. The Iowa congestion report computed travel time reliability for three time periods each year (AM peak, PM peak, and the entire year). In addition to the yearly assessment, they also did a daily assessment in order to examine seasonal trends. A direct example of this daily assessment for I-29N is shown in Figure 1.3. Lastly, they performed a segment-level reliability analysis and visualized it using bar plots showing both directions for each route. This allows for quick identification of which segments along a route are unreliable. A direct example for I-35 is shown displaying progressions for BTI along each direction (Figure 1.4).

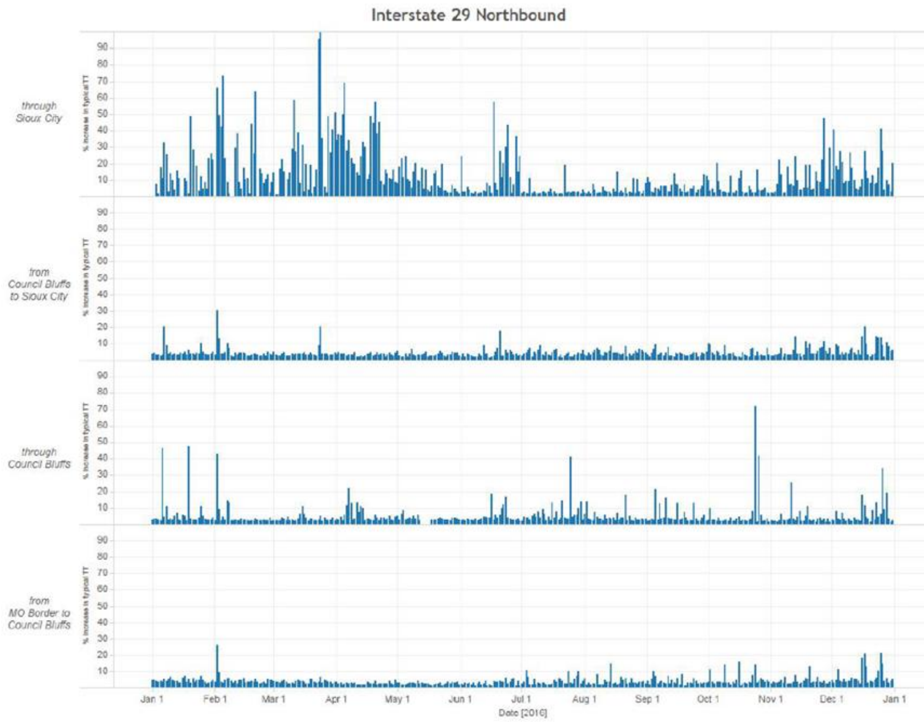

Figure 1.3 *Daily BTI for I-29N (Iowa DOT).*

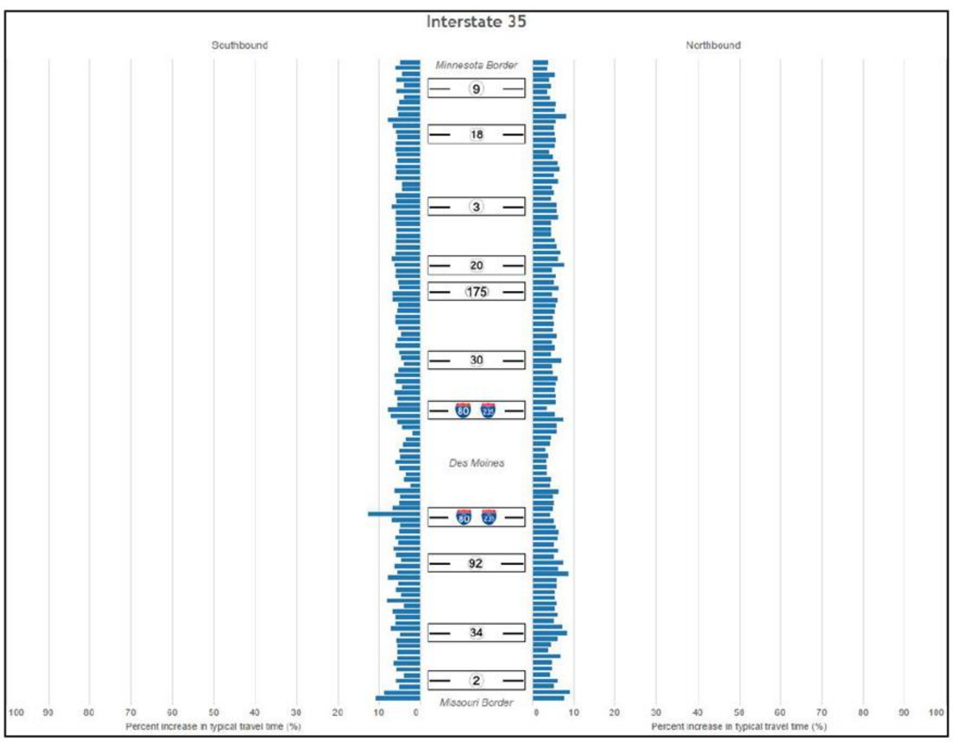

Figure 1.4 *I-35 BTI progression (Iowa DOT).*

Although the present suite of mobility metrics in the Iowa congestion report does feature a reliability metric, there are several different metrics that could be used for this assessment, as identified by SHRP 2 and other studies, and in the FHWA rulemaking. The primary purpose of the present study is to compare these metrics and offer recommendations on other metrics for inclusion in future reports. The next section will introduce travel time reliability concepts and provide a list of travel time reliability metrics that have been developed.

1.2 Travel Time Reliability Metrics

Travel time reliability is a relatively recent emphasis area in transportation performance monitoring. Its importance is underscored by the FHWA rulemaking requiring reliability assessments. Reliability was one of the four principal focus areas under SHRP 2. One simple definition of travel time reliability is that it is the consistency of travel time over time. Under the general SHRP2 reliability focus, one of the thematic groupings was the area of data, metrics, analysis, and decision support (Establishing Monitoring Programs for Travel Time Reliability, 2014). This study will mostly focus on the areas under this thematic grouping.

A technical report, *Incorporating Reliability Performance Measures into the Transportation Planning and Programming Processes*, was released in 2014. This reference is useful for both explaining what travel time reliability is and providing insight into the different reliability metrics that currently exist and how to calculate them. It states that reliability is often defined in two widely held ways, each one being valid. The first is that reliability is the variability of travel times on a facility or trip over the course of time. This definition is the same as the previously mentioned one. The other definition is that reliability can be quantified by the number of times a trip's travel time either fails or succeeds to meet some predetermined threshold. No matter how reliability is defined, it is always subject to the factors that influence travel time itself. These include changes in demand, traffic control, weather, work zones, and the capacity of the roadway itself.

This SHRP 2 technical reference then provides definitions of various reliability performance metrics. These include the standard deviation of travel times, Planning Time Index, Buffer Time Index, Skew Statistic, Misery Index, Failure/On-Time Measures, and 80th Percentile TTI. A summary of these metrics is presented in Table 1.1.

Many of these metrics make use of travel time index (TTI) values. TTI is calculated by taking the travel time measurement and dividing it by the free-flow travel time of that segment. For this study, the 85th percentile of observed speed measurements was used to estimate the free-flow travel time of each segment.

The metrics can be applied to a specific highway section, a subset of a transportation network, or a travelers' origin and destination. The present study will apply these metrics to specific highway segments. The same metrics, except for the standard deviation of travel times, are also mentioned in *Road Traffic Congestion: A Concise Guide* by Falcocchio and Levinson (2015).

Table 1.1 *Summary of travel time reliability metrics in literature.*

Travel Time Reliability Metric	Metric Abbreviation	Formula/Description
Standard Deviation	SD_{tt}	The standard deviation of travel times.
Planning Time Index	PTI	95th percentile TTI
Buffer Time Index	BTI	$\frac{TT_{95\%} - Avg.TT}{Avg.TT}$
Skew Statistic	SS	$\frac{TTI_{90\%} - Median\ TTI}{Meidan\ TTI - TTI_{10\%}}$
Misery Index	MI	The average of the highest 5% of travel times divided by free flow travel time. (Simplification: 97.5th percentile TTI)
Failure/On-Time Measures	FOTM	Percentage of trip with travel times <1.1 the mean travel time or <1.25 the mean travel time. Percentage of trips with space mean speed less than 50, 45, or 30 mph.
80th Percentile TTI	TTI_{80}	80th percentile TTI.
*Where Travel Time Index (TTI) = Travel Time / Free-Flow Travel Time		

It is important to note that for the MI, the average of the highest 5% of travel times divided by the free flow travel time can simply be approximated to the 97.5^{th} percentile of TTI. This approach is less calculation intensive than using the classic definition and will therefore be used in this study when computing MI.

The SHRP 2 technical reference also mentioned that SHRP 2 Project L03 found that the BTI and PTI can be an unstable indicator of changes in reliability, as it can move in a direction opposite of the mean and percentile-based measures. The reference believes that this is because the percent change in these values can be different from year to year and if one changes more in relation to the other, counterintuitive results could appear. Also, while not specifically tested, the SS may also suffer from the same instability phenomenon.

In addition to the SHRP 2 metrics, the national performance measures defined by the 2017 FHWA rulemaking includes two metrics oriented toward travel time reliability on highway segments. These two metrics are the Level of Travel Time Reliability (LOTTR) and the Peak Hour Travel Time Reliability (PHTTR).

LOTTR is meant to represent the difference between longer travel times (80^{th} percentile of travel times) and normal travel times (50^{th} percentile of travel times). It is computed by taking the 80^{th} percentile of travel times and dividing by the 50^{th} percentile of travel times for each road segment. A threshold of 1.5 has been set for LOTTR. If the LOTTR metric exceeds 1.5 on a given segment, that segment is considered unreliable".

For PHTTR, average travel times are computed for every peak hour (which are established in the rulemaking as the 6^{th}, 7^{th}, 8^{th}, 16^{th}, 17^{th}, and 18^{th} hours of the day) and the maximum of these six average values is then divided by the desired travel time. Like LOTTR, a threshold of 1.5 is used to determine which segments are unreliable. This metric is meant to represent a way to check where the observed travel times in large urban areas are more than 50 percent higher than would be desired in during any given peak hour.

These two metrics are meant to be utilized in large urban areas with a population of around one million. A quick summary of these two metrics and their formula/description is shown in Table 1.2. Note that LOTTR is meant to be computed over certain time periods, which are shown in Table 1.3. The max of these computed LOTTR values for the given time periods is meant to be used as the annual LOTTR value for that segment. PHTTR, by definition, is computed using the average travel time values for the peak hours of the day. These metrics are also meant to be computed using the National Performance Management Research Data Set (NPMRDS). NPMRDS contains speed data aggregated over 5-minute bins. However, alternative travel time/speed datasets can also be used, such as the INRIX data used in this study, for example.

Table 1.2 *Summary of FHWA travel time reliability metrics.*

Travel Time Reliability Metric	Metric Abbreviation	Formula/Description
Level of Travel Time Reliability	LOTTR	$\frac{TT_{80\%}}{TT_{50\%}}$ (LOTTR < 1.50 is "reliable")
Peak Hour Travel Time Reliability	PHTTR	$\frac{1}{TT_D}\max\{TT_6, TT_7, TT_8, TT_{16}, TT_{17}, TT_{18}\}$ (PHTTR <1.50 is "reliable")

Table 1.3 *LOTTR analysis time periods.*

Analysis Time Period
6 a.m. – 10 a.m. on Weekdays
10 a.m. – 4 p.m. on Weekdays
4 p.m. – 8 p.m. on Weekdays
6 a.m. – 8 p.m. on Weekends

In summary, travel time reliability is currently a newly emerging way to approach assessing the performance of interstate and highway networks. Various metrics have recently been developed through research (such as SHRP 2 projects) as well as by the FHWA directly that attempt to quantify travel time reliability. These metrics can be computed using probe vehicle data from providers such as INRIX. This makes travel time reliability metrics very viable for inclusion with other performance metrics into items such as mobility reports from state DOTs.

1.3 Research Objectives

The following is a list of the primary research objectives this study aims to achieve:

Objective 1: Identify a number of travel time reliability metrics which can be computed with utilization of probe vehicle data.

Objective 2: Compare the different travel time reliability metrics with one another to attempt to both to see the different aspects of reliability these metrics show as well as to group similar metrics together.

Objective 3: Apply these travel time reliability metrics to interstates in Iowa.

Objective 4: Develop metrics based on combinations of travel time reliability metrics to determine if these can better describe travel time reliability.

1.4 Thesis Structure

This thesis contains five chapters. A basic description of each chapter is as follows:

Chapter 1: Introduction – This chapter goes through a background of the more recent history of mobility reporting. It touches on the recent performance assessment strategies for freeway networks as well as the data used for these assessments. It also discusses a couple recent mobility reports that states have produced. The background concludes with providing an overview of travel time reliability and its various metrics. The background is followed by the research objectives.

Chapter 2: Data Summary – This chapter discusses the INRIX and Iowa DOT data used for this study in detail. It discusses an overview of the data, how the data was processed, and reviews what the INRIX data looks like (how complete the data is both temporally and spatially, as well as how the observed speeds look in comparison to the speed limit).

Chapter 3: Travel Time Reliability Analysis – This chapter discusses the computation of the travel time reliability metrics. It also contains an overview of all the different analyses and assessments conducted with regards to these computed travel time reliability metrics. Discussions on all these different analyses are provided.

Chapter 4: Development of Composite Reliability Metrics – This chapter reviews the combining of different existing travel time reliability metrics together into single composite metrics. Explanation on the methodology used for doing this is discussed. Network performance visualizations are utilized with these new composite metrics and compared with that of the original metrics.

Chapter 5: Conclusions – This chapter summarizes all important findings from this study. It also briefly discusses potential areas for future research as well as reiterates any limitations of this study.

CHAPTER 2. DATA SUMMARY

2.1 Data Overview

Two primary sources of data were used for this study. The first primary data source that was used was probe vehicle speed data from INRIX. The second primary data source was the Iowa DOT's open data available to the public online.

The probe vehicle speed and travel time dataset for Iowa provided by INRIX is quite large and therefore requires a proper way of both storing the data and processing it. As such, it is initially stored on a high-performance cluster which makes use of the Hadoop Distributed File System (HDFS). The dataset covers all the interstates throughout Iowa (the focus of this study) as well as other highways and some arterials. INRIX provides both real-time and historical speed and travel time data in 1-minute time periods for its defined XD segments. For the XD segments used in this study, the typical segment length varies from 0.1 miles to slightly over 1 mile with an average segment length overall of just under 0.6 miles. Shapefiles (which can be mapped and visualized spatially in software such as ArcGIS) of these XD segments are also provided. Data included for the XD segments include attributes such as segment ID, segment length, associated route number, and directional bearing. XD segments are typically updated by INRIX yearly. The speed data stored on the cluster covers 2016 through present (mid-2019 at the writing of this paper). For this study, only 2018 data will be utilized.

Sharma et al., in their 2017 report discussing the opportunities and challenges of utilizing INRIX data for performance monitoring, provide an overview of the sources INRIX uses for its data as well as the format for the INRIX data itself. In brief, INRIX gets some of its probe vehicle data from sources such as trucks, taxis, buses, and passenger cars which have GPS units onboard. In fact, INRIX has agreements with several fleets to obtain their speed and location data anonymously. The INRIX data itself is delivered in CSV format with each row corresponding to a minute of data from a particular XD segment. A sample of an instant of INRIX data is shown in Figure 2.1. The key data columns from this INRIX data used for this study include the XD segment ID, the timestamp of the particular speed/travel time measurement, the speed measurement (average speed for the XD segment for the minute of the given timestamp), the travel time (based on the aggregation of data from GPS probes), and the confidence (a value of 10, 20, or 30). How the confidence value was used will be discussed shortly in the data processing section of this report.

```
Code,C-Value,SegmentClosed,Score,Speed,Average,Reference,Travel,CentralTime,Time
1450489749,87,,30,67,66,66,0.526,2018-09-07 00:04:20 CDT,2018-09-07T05:10:11Z
1450489735,79,,30,67,66,66,0.526,2018-09-07 00:04:20 CDT,2018-09-07T05:10:11Z
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```

Figure 2.1 *Snapshot of raw INRIX data in csv format.*

It is important to note that INRIX data does have some potential limitations. There can be a speed difference between INRIX probe data and traditional infrastructure-based data sources. For example, one study found that there is around a 6-mph difference between INRIX probe data and ground truth (Lattimer and Glotzbach, 2012). Additionally, Kim and Coifman in their 2014 report pointed out two issues when comparing INRIX data to loop detector data. First, INRIX speeds lagged loop detector measurements by almost 6 minutes.

Second, there are many instances of reported speeds being identical to the previous sample. Their study observed that the effective average sampling period for INRIX data is 3-5 minutes despite being reported in 1-minute intervals typically. Sometimes these repeated speeds even exceed 10 minutes. This certainly could have an impact on travel time reliability calculations, as having repetitions of the same measurement would promote higher reliability. Another study highlights multiple findings regarding INRIX data including that INRIX had more reliable coverage during the day (especially during peak hours), that real-time data is much better to use for travel time estimation than historical data, and that there is always speed bias between probe data and benchmarked sensors (Ahsani et. al., 2017).

From Iowa DOT's open source data, a shapefile was downloaded which contained information about a large majority of road segments throughout Iowa. These include all the interstates throughout Iowa (the focus of this study). Like the INRIX XD segment shapefile, this shapefile can be uploaded into software such as ArcGIS to be better viewed spatially. Some important information shown for each section of highway that would be important for performance monitoring was the AADT, Truck AADT, and the posted speed limit. It is important to note that these segments defined by the Iowa DOT do not line up with the XD segments provided by INRIX, despite covering the same interstates. In addition to the road network shapefile, other shapefiles outlining MPO boundaries and Iowa DOT district boundaries were also downloaded.

2.2 Data Processing

In order to prepare for computing travel time reliability metrics, INRIX data needed to be obtained from the HDFS on the cluster. First, the INRIX data was obtained in csv file format from the cluster using scripts utilizing the Pig scripting language, which works well with Apache Hadoop. These scripts helped to narrow down the initial data to include only include data from 2018, real-time data, and data from only interstate XD segments. In order to only use real-time data and not any historical data, the confidence value, which was briefly discussed earlier, was utilized. The confidence value can either be 10, 20, or 30. A confidence value of 30 indicates the speed measurement for that data row was from real-time data, therefore a simple filter can be applied to remove any historical data. There is also an additional data column INRIX provides known as the confidence score. This score can range from 0 to 100 and can help agencies determine whether that INRIX data row meets their criteria for real-time data (Sharma et. al., 2017). For this study, a minimum threshold was not set for the confidence score, so essentially all real-time data from INRIX was accepted.

For this study, the subset of 2018 interstate data was moved into a SQL Server database table for prototyping of different performance measures. The data was initially available in its original format as it is received from INRIX. This provided a record for each individual minute. With there being 525,600 minutes in the year, the number of records for an entire statewide highway system could easily number in the billions. It is a common practice to aggregate the data to a larger bin size to reduce the computational effort and storage need; the NPMRDS, for example, uses 5-minute bins. However, this will obviously have an impact on the travel time reliability metric values. One question this poses is how much the INRIX data can be aggregated before it compromises the travel time reliability metric values. This is examined in Chapter 3. To prepare for assessing this question, the INRIX data was aggregated at the following levels using SQL: 5-minute bins, 15-minute bins, and 1-hour bins. To aggregate, the average speed of all measurements within the time bins were taken for each segment.

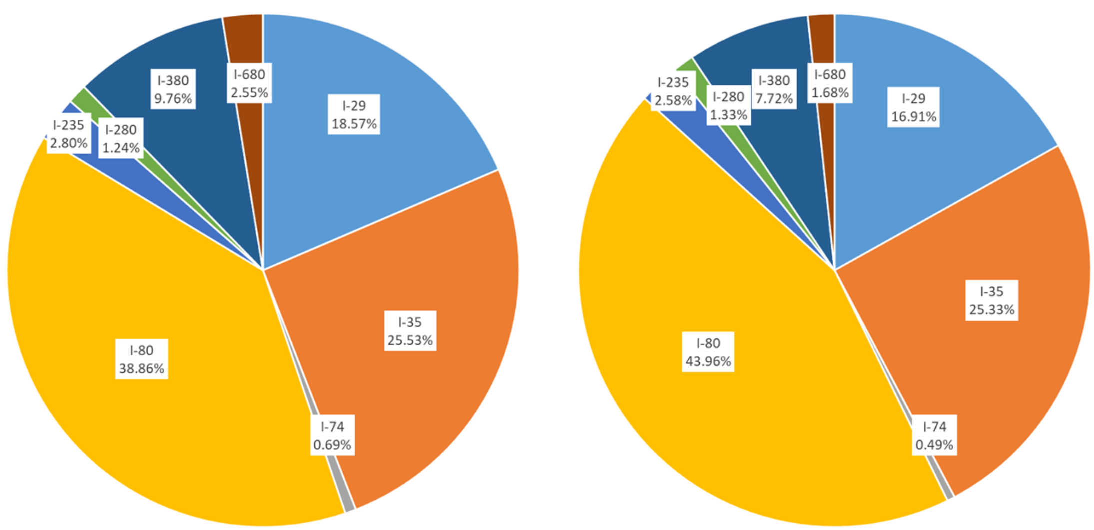
One primary task that needed to be completed was to join the INRIX XD segment information with the segment information from the Iowa DOT open data. This was necessary because the INRIX XD segment definitions do not contain information about the posted speed limit or about traffic volumes. As previously mentioned, the start and end locations of the XD segments do not line up with the Iowa DOT segments. However, ArcGIS was used to be able to spatially join the XD segments to the most adjacent Iowa DOT segment. With the INRIX XD segment definitions now linked to information about the speed limit, this information was added to the SQL database as a new table that could be joined to the INRIX speed data.

2.3 Data Review

Before discussing the computation of travel time reliability metrics, it is important to first review the INRIX data. Several previous studies have assessed the quality of the INRIX data through comparison with alternative data sources (Haghani et. al., 2009; Wang et. al., 2014; Hu et. al., 2016; Sharifi et. al., 2016). Therefore, it was not considered necessary to further examine data accuracy for the present study. This discussion provides an overview of the scale and coverage quality of the data in the Iowa roadway network.

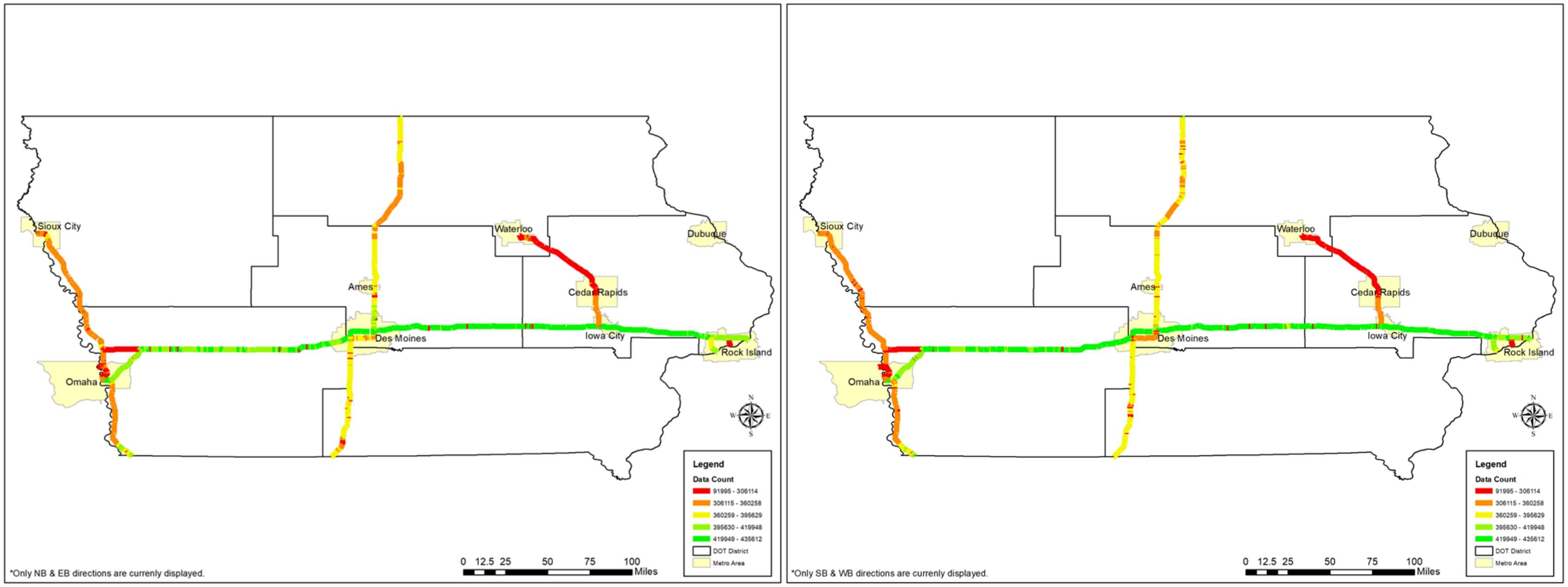
Figure 2.2 (a) shows what percentage of the 2,746 XD segments are associated with each different interstate route in Iowa. I-80, which stretches east-west across the entirety of Iowa, unsurprisingly has the most segments. Other routes which have a sizable chunk of segments include are I-35, which runs north-south across central Iowa, and I-29, which runs along the western border. Figure 2.2 (b) shows the percentage of all the data rows for the INRIX dataset each route contains. Most of the routes have a similar proportion of the total data rows and the total number of XD segments. However, there are subtle differences. One example is that I-80 contains 38.86% of the total XD segments but has 43.96% of the total

INRIX dataset. Perhaps a better way to compare and visualize the data quantity of various segments with respect to one another is to use a choropleth (color-scaled) map of Iowa showing the data quantity of each segment. This map was generated in ArcGIS and is shown in Figure 2.3 with (a) showing the northbound and southbound directions and (b) showing the southbound and westbound directions. These maps confirm that I-80 does appear to have a higher quantity of data for most of its segments when compared to other routes. It is likely that the prominence of I-80 as a major freight corridor leads to its superior data coverage. There are several segments in urban areas that do not have a better quantity of data than some rural segments on I-80. It also appears that the bearing (direction) on each route does not have a significant impact on data quantity as both (a) and (b) in Figure 2.3 display similar visualizations.



(a) % of XD Segments Per Route (b) % of Data Rows Per Route

Figure 2.2 *Percentage of total XD segments and total data rows for each route.*



(a) Northbound and Eastbound directions

(b) Southbound and Westbound directions

Figure 2.3 *Choropleth maps displaying the quantity of data per segment.*

Another way to visualize the completeness of data was developed through the definition of a "completeness ratio", which is defined as the number of segments with data measurements for a given timestamp, divided by the total number of segments. This is plotted over time in Figure 2.4. This plot encompasses the entire year. There a few conclusions that can be drawn from this visualization.

- Until the start of May, a few segments are missing data entirely, as shown by the completeness ratio failing to attain a value of 1.
- The completeness typically fluctuates between about 0.6 and 1.0 for most of the year, representing variation throughout individual days. Unusual fluctuations begin to occur in November and December, with the completeness ratio never reaching 1 during those time periods, and with a greater range of variation compared to most of the year.
- Lastly, there are some periods of missing data during the year where no segments across the state have any data. The most notable instance of this is the last two thirds of October. However, there are also some gaps in December, late June/early July, and late January/early February.

A similar plot was also made that shows a similar concept for the different data aggregation levels (5 min., 15 min., and 1 hr.) in Figure 2.5. The previous observations made using the raw data are also apparent from the aggregated datasets. An additional observation is that as the aggregation level is increased (the time bin sizes are increased) the completeness ratio of each timestamp increases. This is expected, as when a time bin becomes larger, there is a higher chance for individual data measurements to be present within that bin.

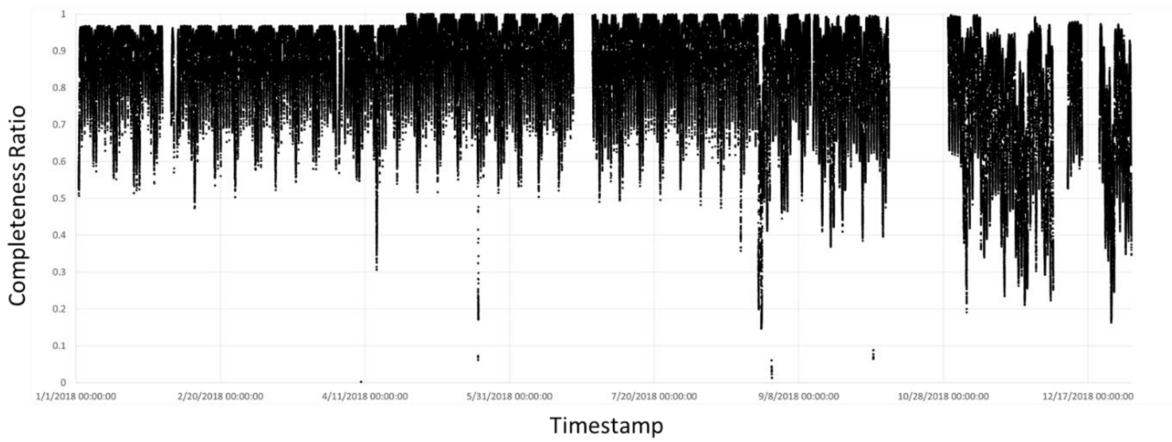


Figure 2.4 *Completeness ratio plot with the raw data.*

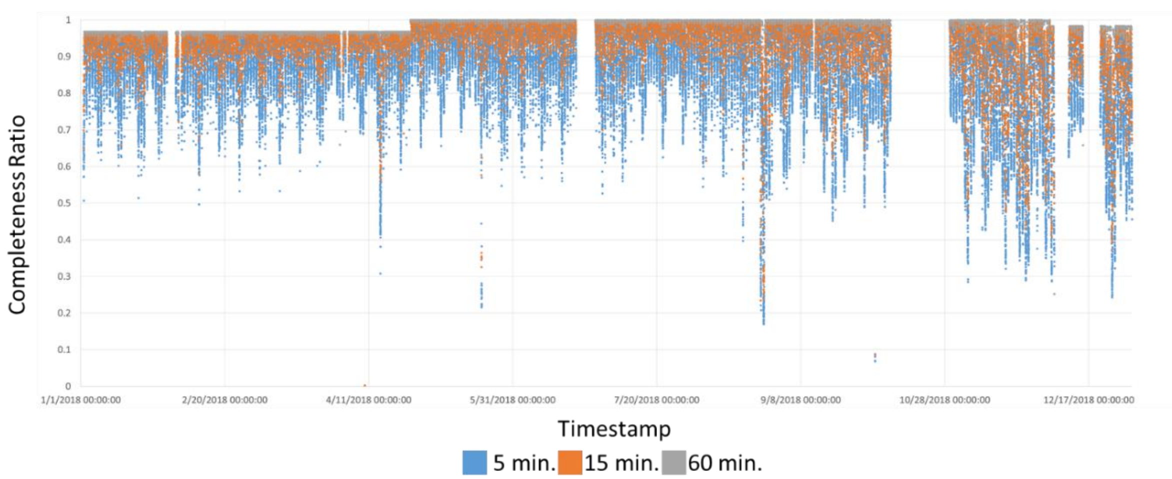


Figure 2.5 *Completeness ratio plot with the aggregated datasets.*

Another aspect of the INRIX dataset which was examined was to assess how the observed speeds compared to the segment's speed limit. Figure 2.6 shows every observed speed throughout the year for each different speed limit. This illustrates the range of variation within each speed limit range. The 60 mph, 65 mph, and 70 mph ranges show that as the speed limit increases, both the minimum and maximum speed limits increase. Meanwhile, the 55 mph speed range shows a very wide range of speeds, going against this trend.

Figure 2.7 shows the distribution of different speed measurements across the segments. The median, average, and 85th percentile speed (what this study considers the free-flow speed) for each segment was calculated over the entire year. The distribution shows how many segments had that speed measurement with respect to their average speed, median speed, and 85th percentile speed.

Figure 2.7 (a) shows that there are almost no segments with a speed limit of 55 mph whose average or median values are 55 mph. There are many more segments with higher average/median speeds, with the peak occurring around 67 mph. At a speed limit of 55 mph, the observed speeds far exceed the speed limit. In fact, the peaks for the distribution of average, median, and 85th percentile segments almost more closely resemble that of the 70mph speed limit distribution.

For the other speed limits, the 85th percentile speed for a given segment typically is about 3-6mph faster than the posted speed limit. The pronounced difference in the 55 mph segment data suggests that some segments may be improperly labeled as 55mph instead of 70mph by the segment definition dataset. This may be due to errors in the spatial join process, incorrect labels in the Iowa DOT open data speed limit values, or a combination of the two. Fortunately, the travel time reliability metrics assessed in this report do not use speed limit in their computational process except for PHTTR. For PHTTR, the speed limit will be used as the desired travel time for the segment. Therefore, it’s worth noting that PHTTR could be affected if the speed limit for a given segment in the segment definition dataset is not correct. If higher speed segments are improbably labeled with a speed limit of 55 mph, their PHTTR will appear to have a more desirable value. However, this issue is unlikely to be a problem in urban areas, where PHTTR is meant to be primarily used.

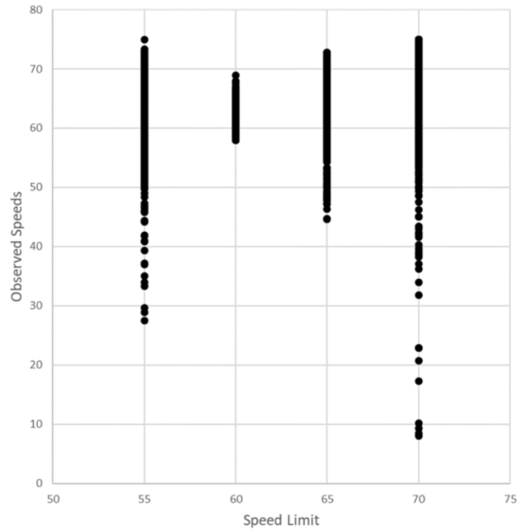


Figure 2.6 *Observed speeds for each speed limit.*

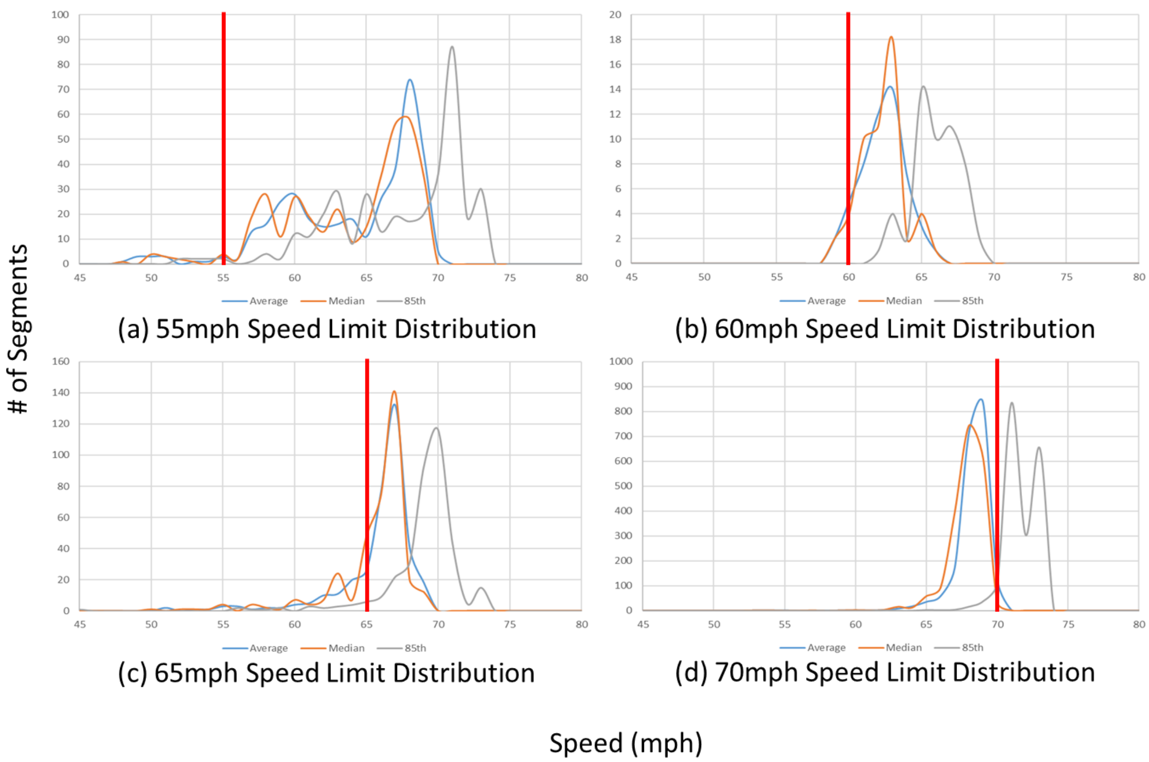


Figure 2.7 *Distribution of different segment speed statistics at each speed limit.*

CHAPTER 3. TRAVEL TIME RELIABILITY ANALYSIS

3.1 Computation of Travel Time Reliability Metrics

Before discussing the actual computational process for the travel time reliability metrics, it is important to summarize the travel time reliability metrics considered in this study as well as the analysis time periods over which these metrics will be computed. Table 3.1 summarizes all the travel time reliability metrics used in this study, including the metric name, the metric's abbreviation, and the formula and/or description of the metric. Most of these metrics are found in the literature and the FHWA rulemaking noted back in Chapter 1. Some additional metrics are included. These are the interquartile range (IQR), based on the 25^{th} and 75^{th} percentiles; the percentile range (PR), using the 15^{th} and 85^{th} percentiles, the standard deviation of TTI (SD_{tti}), and the standard deviation of travel time (SD_{tt})

Percentile ranges express the range of variability in a dataset and are relatively simple to calculate. Other travel time reliability metrics (such as SS) already make use of the difference in percentile values for TTI as a part of their computational formulas. For TTI, free-flow travel time for each segment is estimated as the travel time traveling at the 85^{th} percentile speed over the year through the length of that segment. Additionally, for MI, a simplification can be made to use the 97.5^{th} percentile of TTI values which is less computationally intensive than the traditional definition but provides similar results.

Table 3.2 displays the analysis time periods that will be used in the computation of the travel time reliability metrics. Notice that time periods are consistent with what is recommended by the FHWA rulemaking when computing LOTTR. In addition to these time periods, the metrics were also computed using data over the entire year regardless of time of day.

Table 3.1 *Summary of travel time reliability metrics considered in this study.*

Travel Time Reliability Metric	Metric Abbreviation	Formula/Description
Standard Deviation	SD_{tt} or SD_{tti}	The standard deviation of either raw travel times or TTI values.
25th-75th Percentile Range (IQR) of TTI	IQR	The 25th-75th percentile range (IQR) of the TTI values.
15th-85th Percentile Range of TTI	PR	The 15th-85th percentile range of the TTI values.
Planning Time Index	PTI	95th percentile TTI
Buffer Time Index	BTI	$\frac{TT_{95\%} - Avg.TT}{Avg.TT}$
Skew Statistic	SS	$\frac{TTI_{90\%} - Median\ TTI}{Meidan\ TTI - TTI_{10\%}}$
Misery Index	MI	The average of the highest 5% of travel times divided by free flow travel time. (Simplification: 97.5th percentile TTI)
Level of Travel Time Reliability	LOTTR	$\frac{TT_{80\%}}{TT_{50\%}}$ (LOTTR < 1.50 is "reliable")
Peak Hour Travel Time Reliability	PHTTR	$\frac{1}{TT_D}\max\{TT_6, TT_7, TT_8, TT_{16}, TT_{17}, TT_{18}\}$ (PHTTR <1.50 is "reliable")
*Where Travel Time Index (TTI) = Travel Time / Free-Flow Travel Time		

Table 3.2 *Analysis time periods used for travel time reliability metric computation.*

Analysis Time Period	Abbreviation
6 a.m. – 10 a.m. on Weekdays	AM Peak
10 a.m. – 4 p.m. on Weekdays	Mid-Day
4 p.m. – 8 p.m. on Weekdays	PM Peak
6 a.m. – 8 p.m. on Weekends	Weekend

For the computation of the travel time reliability metrics, SQL queries were used with the results being uploaded to Excel for future assessment. These SQL queries followed the general process displayed in Figure 3.1. This process was followed using all the different aggregation-levels of the dataset (raw (1 min.), 5 min., 15 min., and 1 hr.).

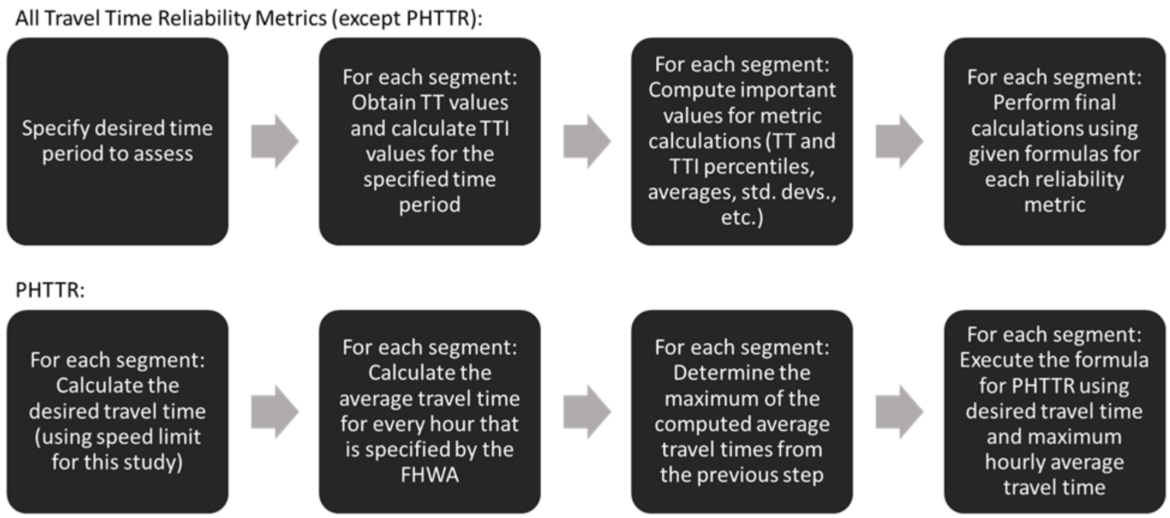


Figure 3.1 *General calculation process for travel time reliability metrics.*

3.2 Comparison and Selection of Metrics

With all metrics computed for every segment for the different analysis time periods, it was possible to compare these metrics with each other. This comparison was done for all the travel time reliability metrics except for PHTTR, since its calculation process is more unique, and it does not share the same analysis time periods with the other metrics. This comparison was done in two stages using the raw INRIX data.

The first stage was to perform a series of linear regressions between all possible comparison pairs of the 9 metrics. This can be visualized as a series of scatterplots in a matrix format. Figure 3.2 shows this scatterplot-based comparison for all the data, regardless of time period. Figure 3.3 shows this scatterplot-based comparison for the four analysis time periods. A scatterplot with a more linear trend and higher R^2 value resulting from linear regression suggests that the two metrics are more strongly correlated. There are some metrics that are well-correlated and others that are weakly correlated. This shows that different metrics are likely to show different segments as being unreliable, despite all of the metrics having been developed for the purpose of quantifying reliability.

This analysis allows metrics to be grouped into families that display similar results and strong correlation. The scatterplots seem to agree on a grouping of like metrics as indicated by the different colored circles in the figures. The groups are as follows: SD_{tti} & SD_{tt}; IQR, PR, SS, & LOTTR; PTI, BTI, & MTI.

For SD_{tti} and SD_{tt}, both make use of standard deviation, which both would be sensitive to outliers, as standard deviation considers the full range of outliers and can tend to find where there may be a high number of outliers. For IQR, PR, SS, and LOTTR, all these metrics make use of percentiles. IQR and PR both assess both ends of the distribution of travel times while SS and LOTTR both primarily focus on the upper half of the distribution. However, all these metrics utilize percentiles which are high enough to detect wide central tendencies in the dataset, but generally not high enough to be strongly affected by outliers or extreme travel time observations. However, PTI, BTI, and MTI all utilize more extreme percentiles such as the 95th percentile in the case of PTI and BTI and the 97.5th percentile in the case of MTI. Therefore, these metrics will be identifying segments with a high number of more extreme travel time observations.

The second stage of comparison was a way to verify the scatterplot-based groupings from the first stage by comparing some visualizations from all the different metrics. The first visualization used was showing choropleth (color-scaled) maps of the Des Moines area for each metric and comparing them with one another. These maps were created for all data (Figure 3.4), PM peak (Figure 3.5), and weekends (Figure 3.6). Red on these maps indicates a higher level of unreliability (more variability) while green indicates low unreliability (less variability). Colored boxes are placed next to the metric names which correspond to the groupings developed with the scatterplots. This helps assessing whether these grouping hold true in terms of metrics within a group showing similar results to one another. In summary, it appeared that the groupings held up well across the different time periods with only minor differences seen between metrics within a group and more major differences seen with metrics in different groups.

The second visualization used was comparing the progressions of segment travel time reliability across I-80E (Figure 3.7). This was again done for all data, PM peak, and weekends. The different colors on the plots correspond to the original groupings from the scatterplots. Once again, it appears that the original groupings mostly hold up in these progression plots. Metrics within a group mostly present relatively similar progression trends while metrics in different groups present more distinctive trends.

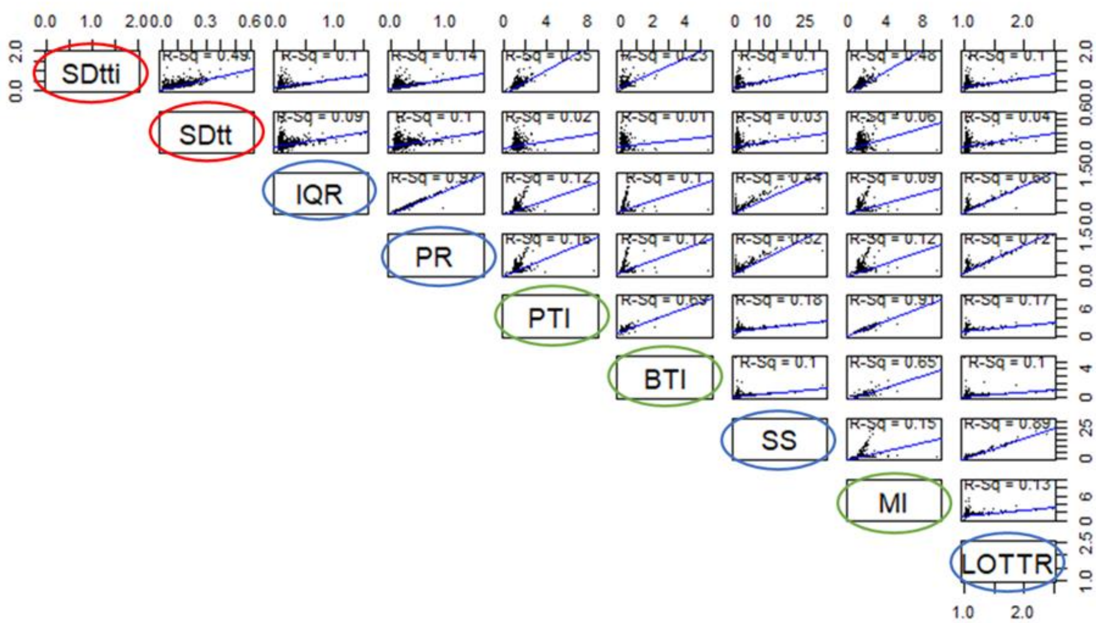


Figure 3.2 *Scatterplot-based comparison of metrics using all the data.*

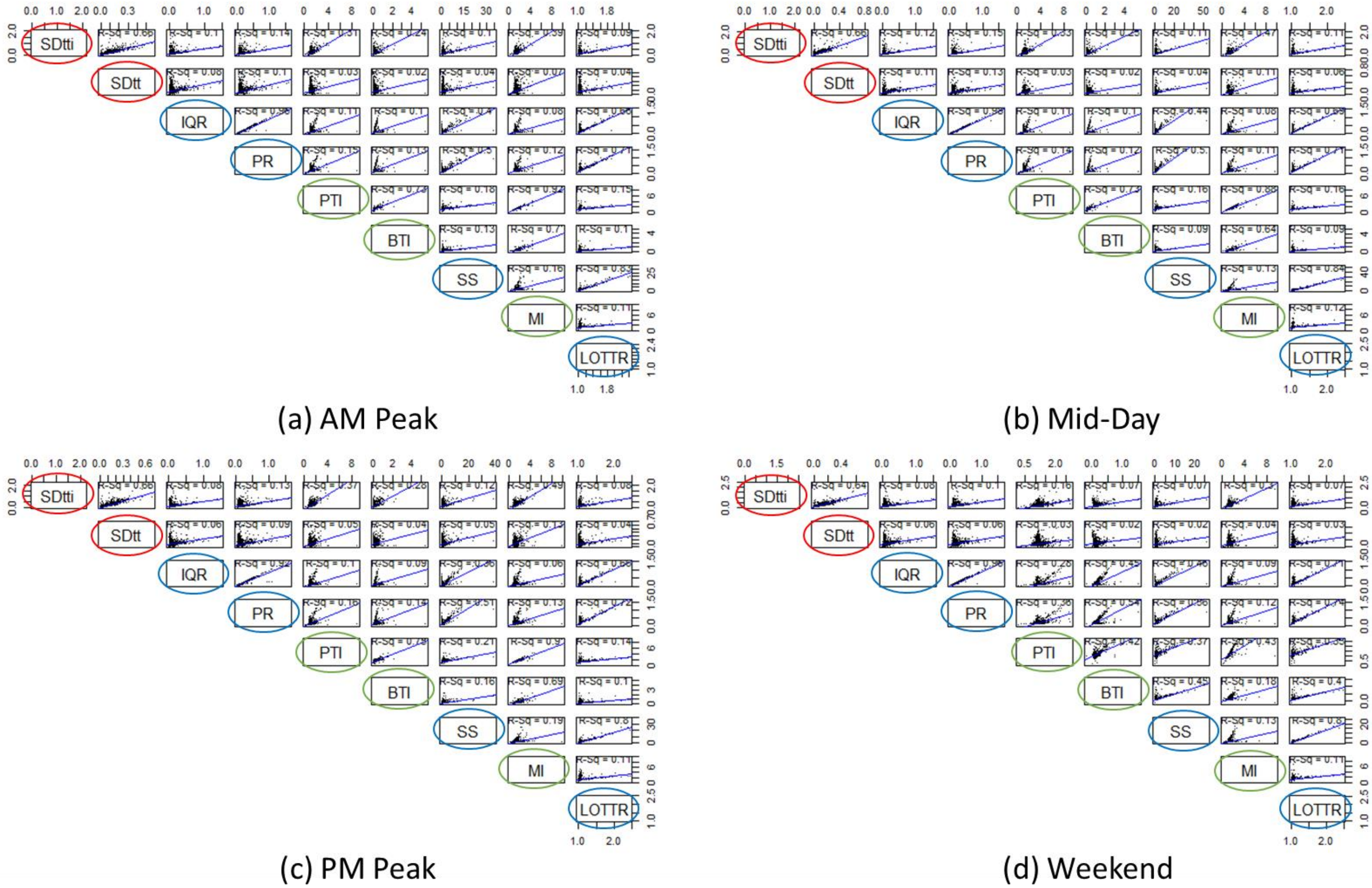


Figure 3.3 *Scatterplot-based comparison of metrics for each of the different time period.*

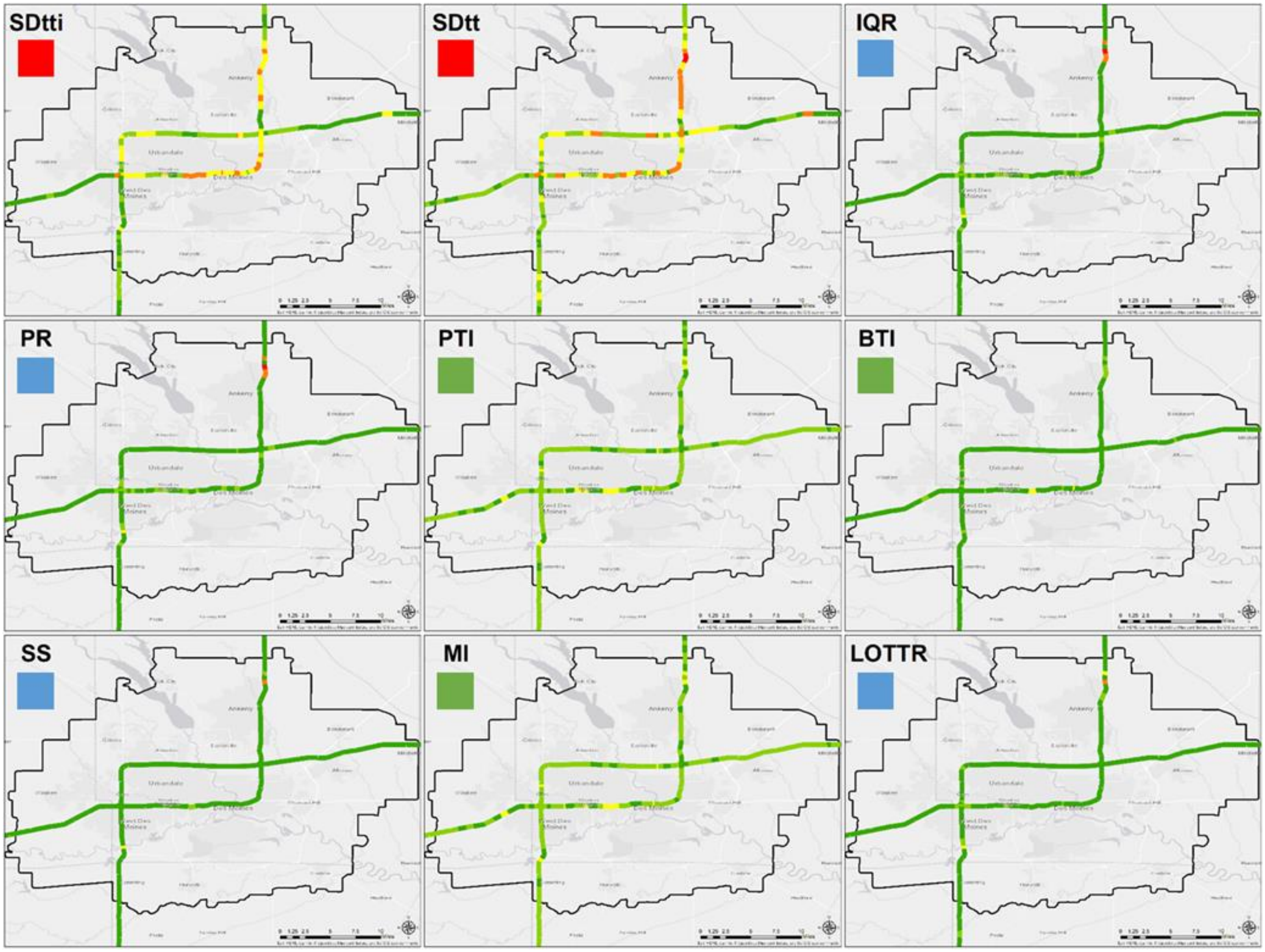


Figure 3.4 *Des Moines area visual comparison of metrics using all data.*

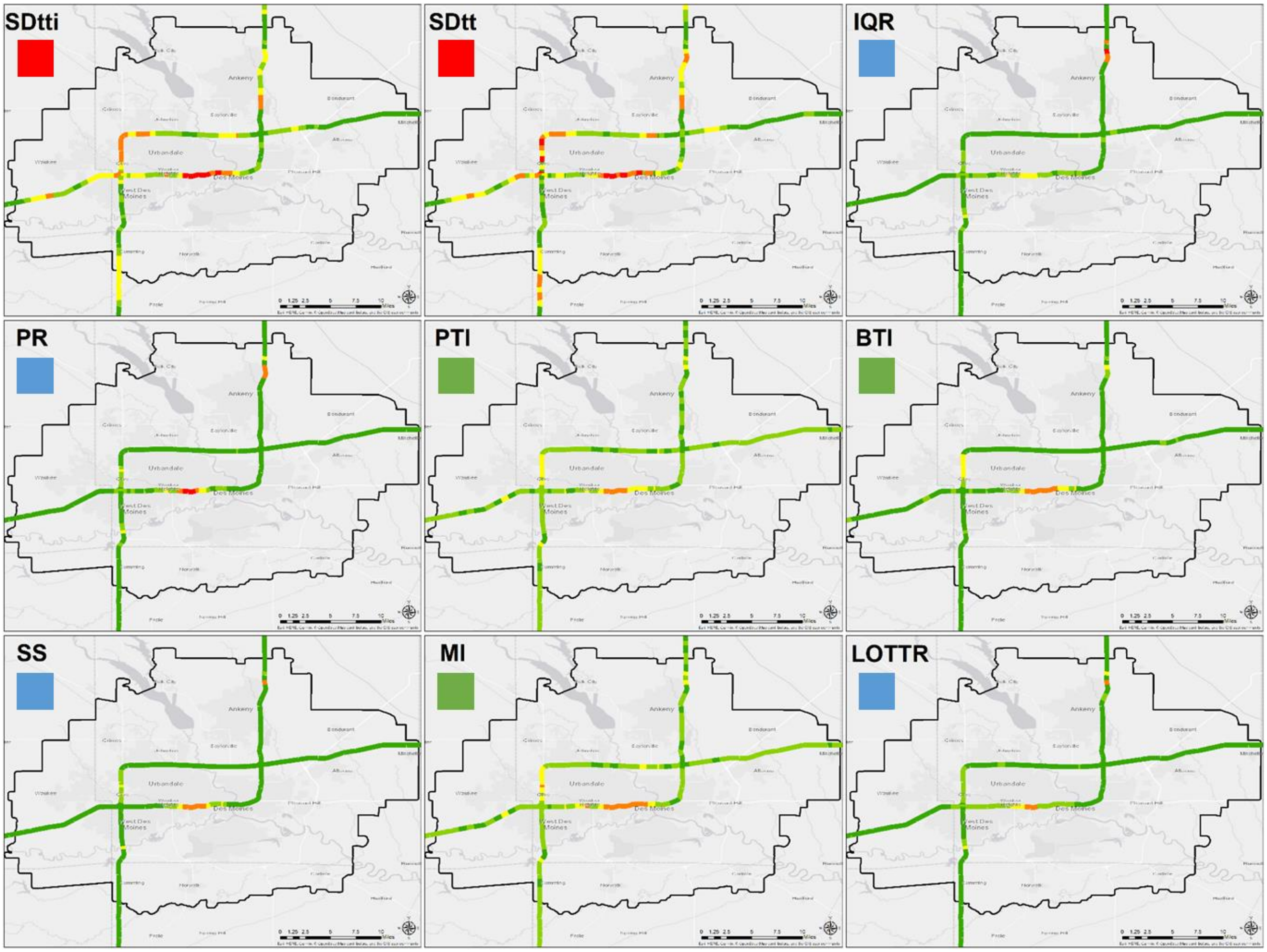


Figure 3.5 *Des Moines area visual comparison of metrics using PM peak.*

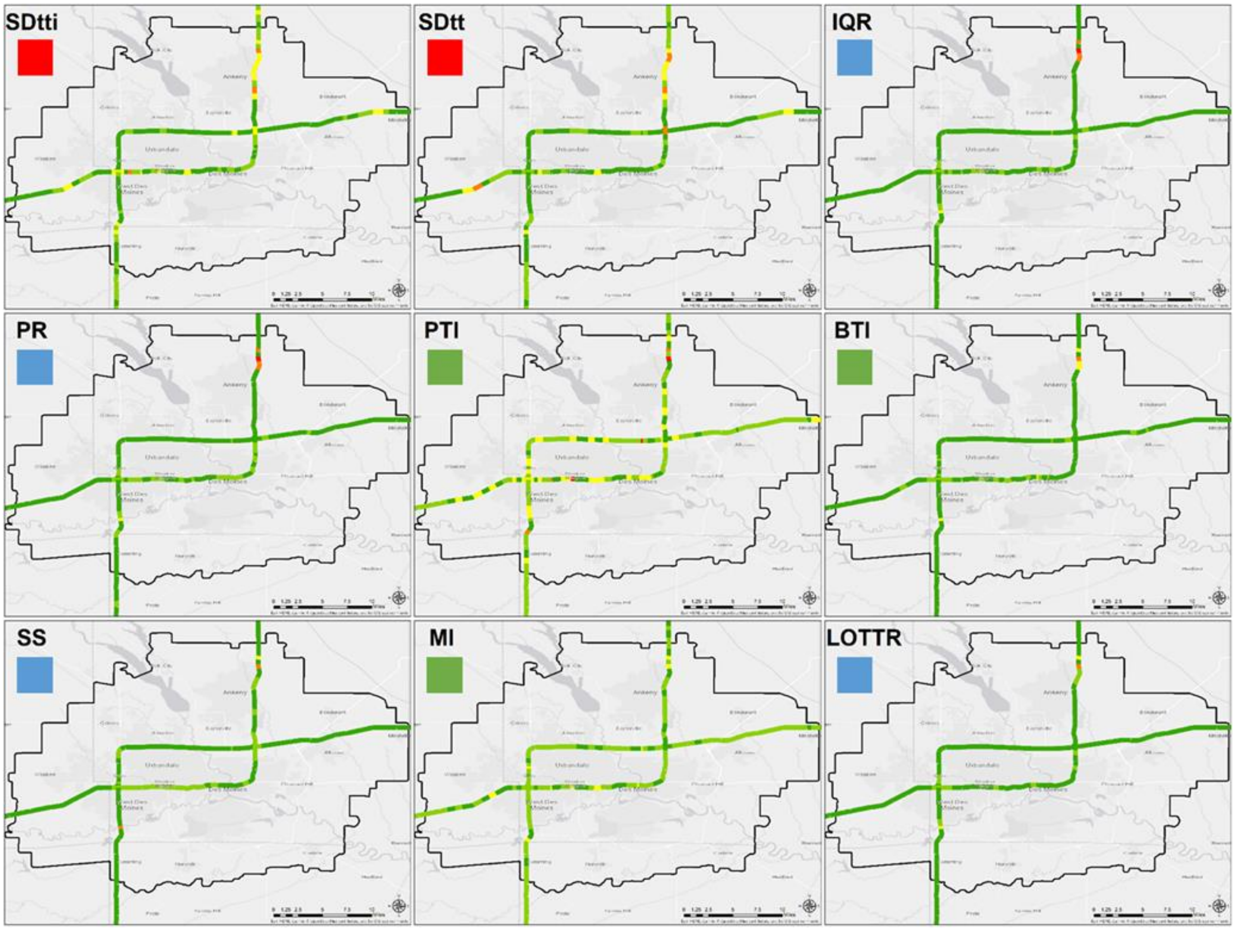


Figure 3.6 *Des Moines area visual comparison of metrics using weekends.*

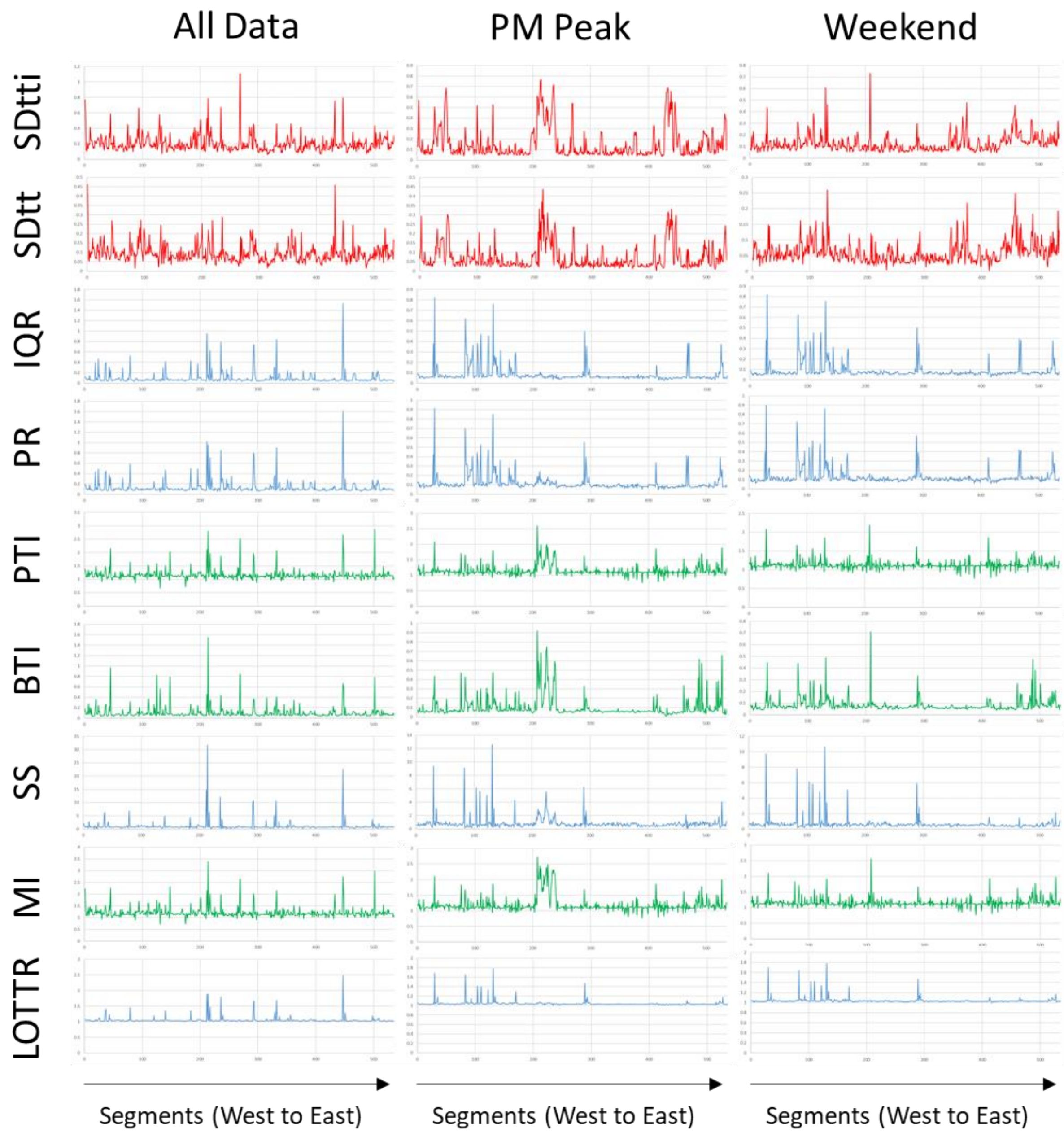


Figure 3.7 *I-80 Eastbound progression plot comparisons.*

The next step was to select metrics for further assessment. Since travel time reliability metrics in a group produce very similar results, it made sense to select a metric from each group for further evaluation, rather than comparing multiple similar metrics.

From the "red" group (SD_{tti} and SDtt), SD_{tti} was selected. The reason is that TTI values are normalized by free-flow travel time and are therefore not influenced by segment length. TT values, however, are not normalized and presumably can be biased by segment length. Longer segment lengths could have more standard deviation in travel time when compared to shorter segment lengths. SD_{tti} considers the whole range of TTI values, and therefore will be sensitive to outliers.

For the "blue" group (IQR, PR, SS, and LOTTR), PR was selected. PR and IQR produce extremely similar results to one another, so realistically either metric could be selected. PR was selected based on the idea it would better capture a wider spread in TTI values than IQR, but still without being influenced by extreme outliers. The SS places heavy influence on the upper half of the TTI distribution, with the difference between the 90th percentile and median in the numerator of the computational formula. However, PR can capture both sides of the distribution of TTI values. LOTTR will still be separately assessed along with PHTTR since it is directly noted in FHWA rulemaking.

For the "green" group (PTI, BTI, and MI), BTI was selected. These three metrics provided similar results to one another, however occasionally BTI yielded just slightly different results from PTI and MTI. This could be because it is the only metric of the three that normalizes using average travel time instead of free flow travel time. This metric was also selected because it was previously implemented in Iowa's 2016 Interstate Congestion Report, and because it normalizes by average travel time instead of TTI, which sets it apart from the other two selected metrics (SDtt and PR). BTI truncates some outliers, but with its higher threshold it can locate where there is an excessive number of unusually high travel times. Unlike SDtti and PR, BTI only considers one side of the distribution of travel time observations.

Table 3.3 displays the selected travel time reliability metrics for further assessment. The three selected metrics from each group that were just discussed are present along with LOTTR and PHTTR from FHWA rulemaking.

Table 3.3 *Selected travel time reliability metrics for further assessment.*

Metric	Abbreviation
Standard Deviation of TTI	SD_{tti}
15^{th}-85^{th} Percentile Range of TTI	PR
Buffer Time Index	BTI
Level of Travel Time Reliability	LOTTR
Peak Hour Travel Time Reliability	PHTTR
*Red denotes directly noted in FHWA rulemaking.	

3.3 Effect of Aggregating Speed Data

While the speed and travel time data INRIX provides utilizes 1-minute time bins, the dataset can be rather large and can be more computationally demanding with regards to calculating travel time reliability metrics. Also, LOTTR and PHTTR were developed to be used with the NPMRDS which utilizes speed data aggregated into 5-minute time bins. This leads to two questions. At what point do the travel time reliability metrics begin to deviate significantly from their values using the raw INRIX data? Also, how much does aggregating the data further reduce the overall data storage and computational time to calculate travel time reliability metrics? Answering these two questions could help provide a nice middle-ground between data storage, computation time, and travel time reliability metric integrity.

To answer the latter question, Figure 3.8 shows both how data size and SQL querying time change as the aggregation level is increased (time bins sizes are increased). The SQL query time was for calculating all the travel time reliability metrics (except PHTTR) for PM peak and the data size is simply the number of data rows in each dataset in total across all time periods. There is a similar downwards trend with an increase in aggregation level for both data size and the SQL query time. The trend appears to be roughly negatively exponential and while there is a significant reduction in data size switching from raw INRIX data (1-minute time bins) to 5-minute time bins, this reduction become much more minimal with further aggregation.

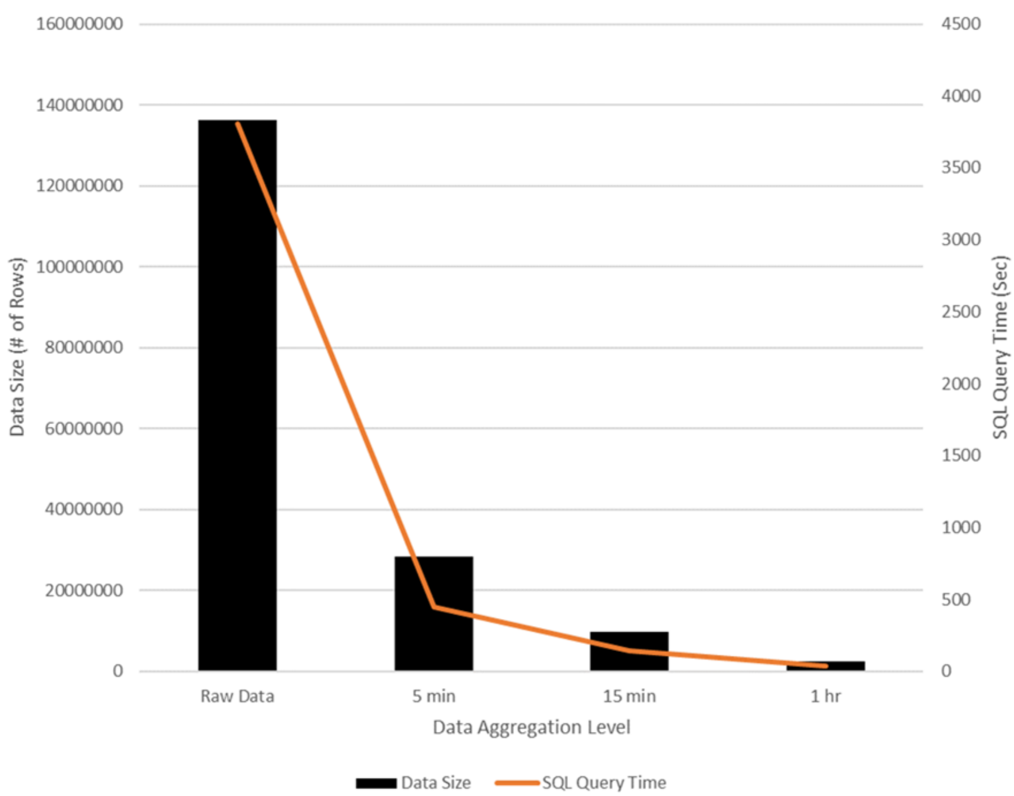


Figure 3.8 *Aggregation level's effect on data size and SQL query time.*

To assess when travel time reliability metrics based on aggregated data begin to deviate from values based on the unaggregated data, scatterplots were made comparing each aggregation level (5 min., 15 min, and 1 hr.) to the raw dataset. Each point on the scatterplot represents the reliability metric at a certain aggregation level vs. the reliability metric derived from the raw data for each segment. A linear progression with an R^2 very close to 1 implies that the metrics are not deviating much from their raw data value at that given aggregation level. PM peak data was used for these scatterplots. Figure 3.9 (5 min.) Figure 3.10 (15 min.), and Figure 3.11 (60 min.) show these scatterplots.

The 5-minute aggregations show R^2 values of 0.98 or greater, showing strong agreement between results from aggregated and unaggregated data. As the aggregation level increases, the R^2 values decrease. Both SD_{tti} and BTI fall below a R^2 value of 0.98 when a 15-minute aggregation level is used. LOTTR and PR do not fall below a R^2 value of 0.98 until a 1-hour aggregation level is used. SD_{tti} and BTI appear to be more sensitive to the impacts of aggregation than PR. This is likely because these two metrics would be more sensitive to measurements that are the extremes of the TT and TTI distributions. These more extreme measurements would be more likely captured when aggregating using small time bins vs. when using large time bins.

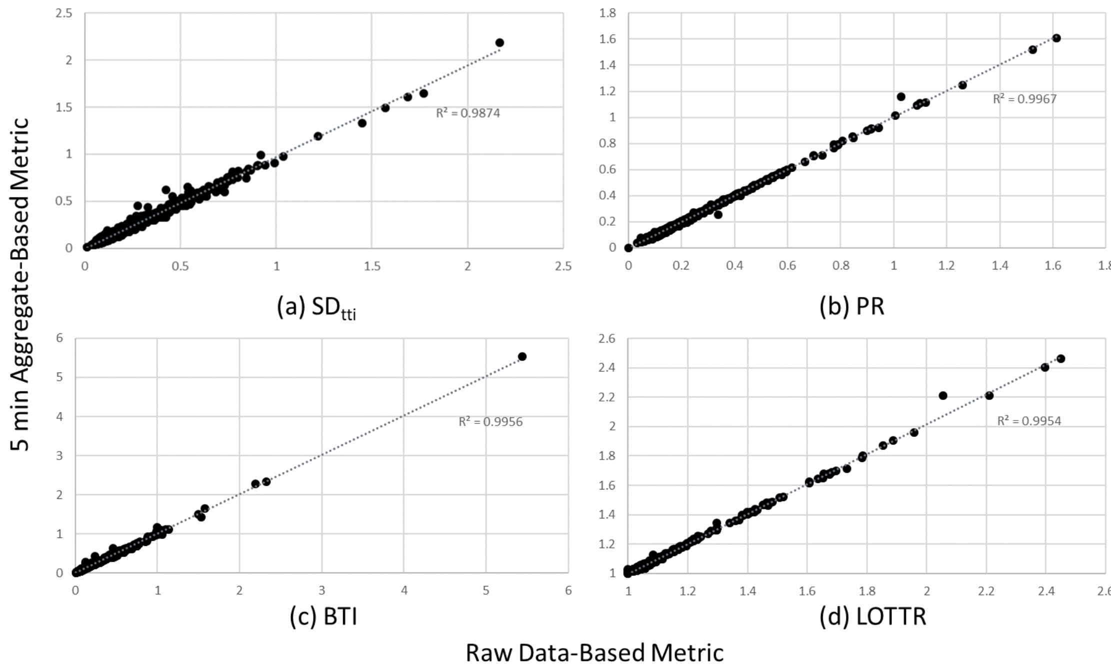


Figure 3.9 *Scatterplot-based comparison of 5-minute aggregation vs. raw data.*

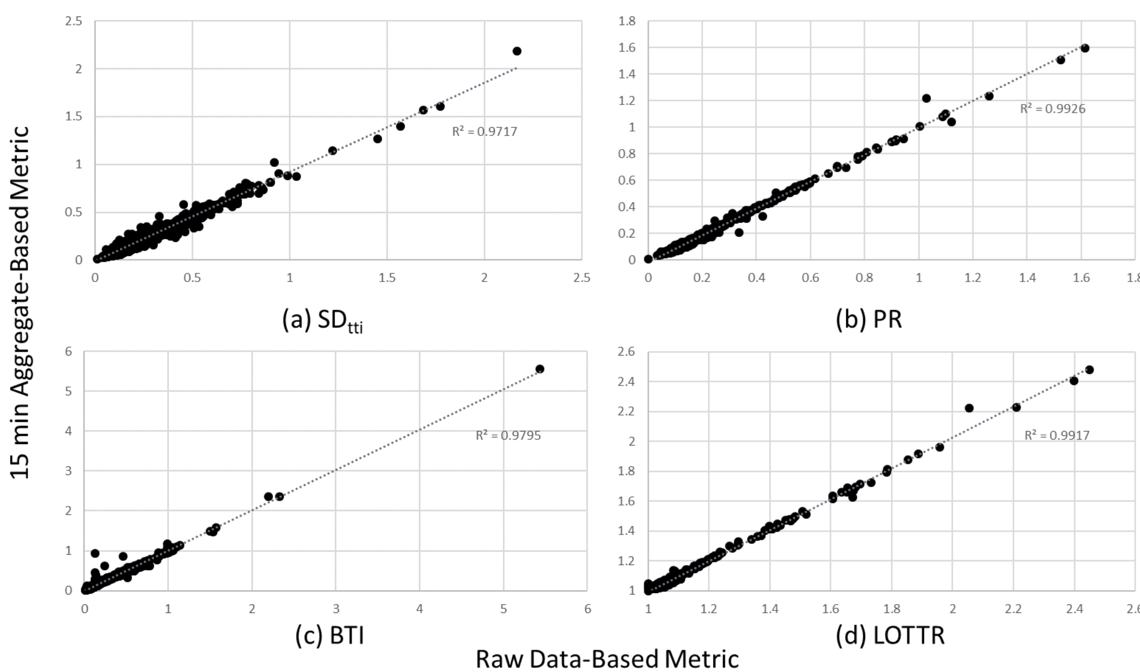


Figure 3.10 *Scatterplot-based comparison of 15-minute aggregation vs. raw data.*

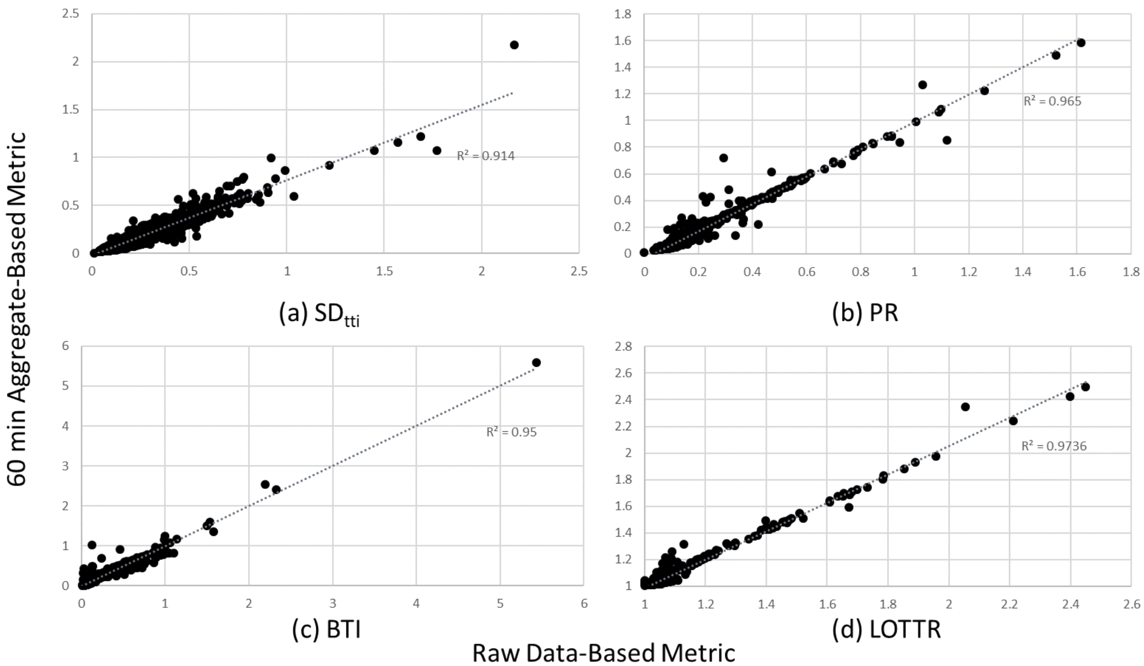


Figure 3.11 *Scatterplot-based comparison of 1-hour aggregation vs. raw data.*

For the rest of this study, the 5-minute aggregation speed and travel time data were used for travel time reliability metric applications for three primary reasons. First, the computational time and storage space reduction seen from moving from the raw 1-minute data to aggregated 5-minute data is substantial, with further aggregation not providing much more benefit. Second, the travel time reliability metrics do not appear to deviate substantially when aggregating using 5-minute time bins from using raw data. Lastly, LOTTR and PHTTR were developed for use with the NPMRDS dataset, which utilizes a 5-minute aggregation level.

3.4 Pre-Application

3.4.1 Comparing Reliability for the Different Analysis Time Periods

Highway performance, including travel time reliability, is well known for varying by time of day and day of week. The degree to which this variation can be observed by a metric offers a means of comparing different metrics with each other. This section performs such a comparison.

Figure 3.12 shows three different pie charts. Each chart displays results for the three different selected reliability metrics (SD_{tti}, PR, and BTI). These show what percentage of segments report a certain time period as being the worst recorded time period (i.e., where travel time was the most unreliable during the time period, according to the metric). Interestingly, all three metrics indicate that most segments experience the worst reliability performance during the weekend. This is typically followed by PM peak, AM peak, and then mid-day. This is most pronounced when using PR, which shows that 82% segments experience the worst reliability performance (i.e., the highest PR score) during the weekend. SD_{tti} and BTI have similar proportions between the time periods, with BTI having slightly more segments with their worst reliability seen during AM and PM peak periods.

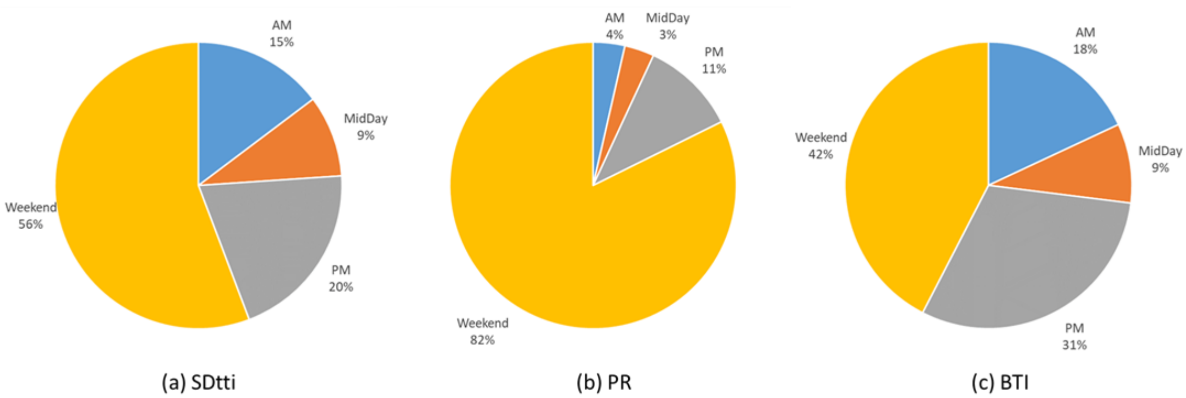


Figure 3.12 *Comparison of which time period was the worst per segment for SD_{tti}, PR, and BTI.*

Simply looking at which time period has the worst reliability masks a few details. For one, the magnitude of the difference in reliability between the different time periods is not accounted for. Second, there is no way to distinguish between unreliable segments and reliable segments. For example, a segment might have its worst reliability values occurring during weekend time periods, but its overall level of reliability may be superior.

To address these details, different percentiles were assessed across the different time periods for the same three reliability metrics. Figure 3.13 shows SD_{tti}, Figure 3.14 shows PR, and Figure 3.15 shows BTI. The different colored bars represent a percentile of reliability metrics seen for a given analysis time period. For example, the yellow bar for the weekend in Figure 3.13 shows the 85th percentile of the SD_{tti} values seen during the weekend. This approach shows both the difference in magnitude between time periods and how “reliable” and “unreliable” segments are distributed across the different time periods according to different metrics. What is perhaps the most important percentile to look at here is the 95th percentile. This illustrates how unreliable the worst 5% of segments are during any given time period. Given that there are 2,746 interstate XD segments in Iowa, this number approximately represents what the 137th most unreliable segment looks like. Using the 95th percentile, the PM peak typically has equal or slightly more extreme reliability readings when compared to weekends. Interestingly Figure 3.14 shows that for PR, the analysis time period had little influence on reliability metric results, as all of the different analysis time periods are roughly similar, even considering all data as an analysis time period.

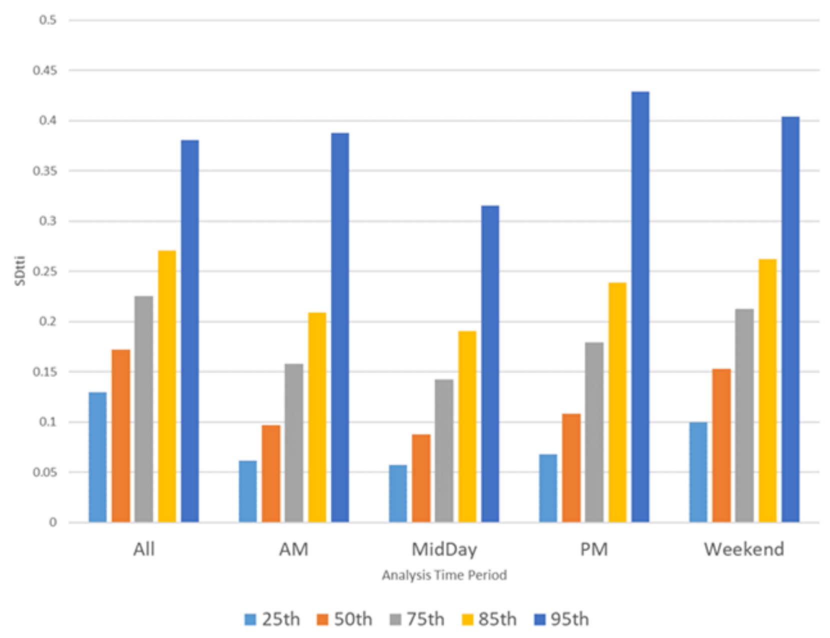


Figure 3.13 *Comparison of percentiles for* SD_{tti} *across different time periods.*

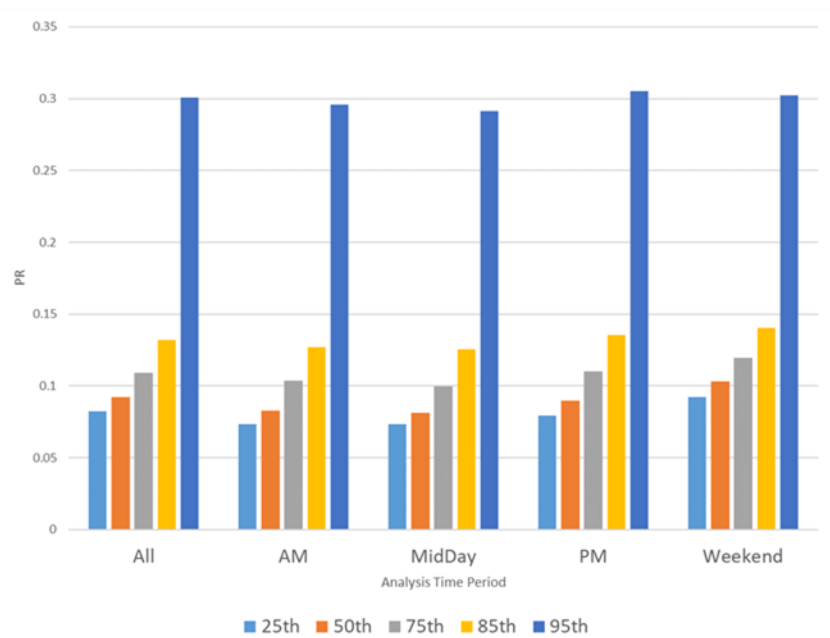


Figure 3.14 *Comparison of percentiles for PR across different time periods.*

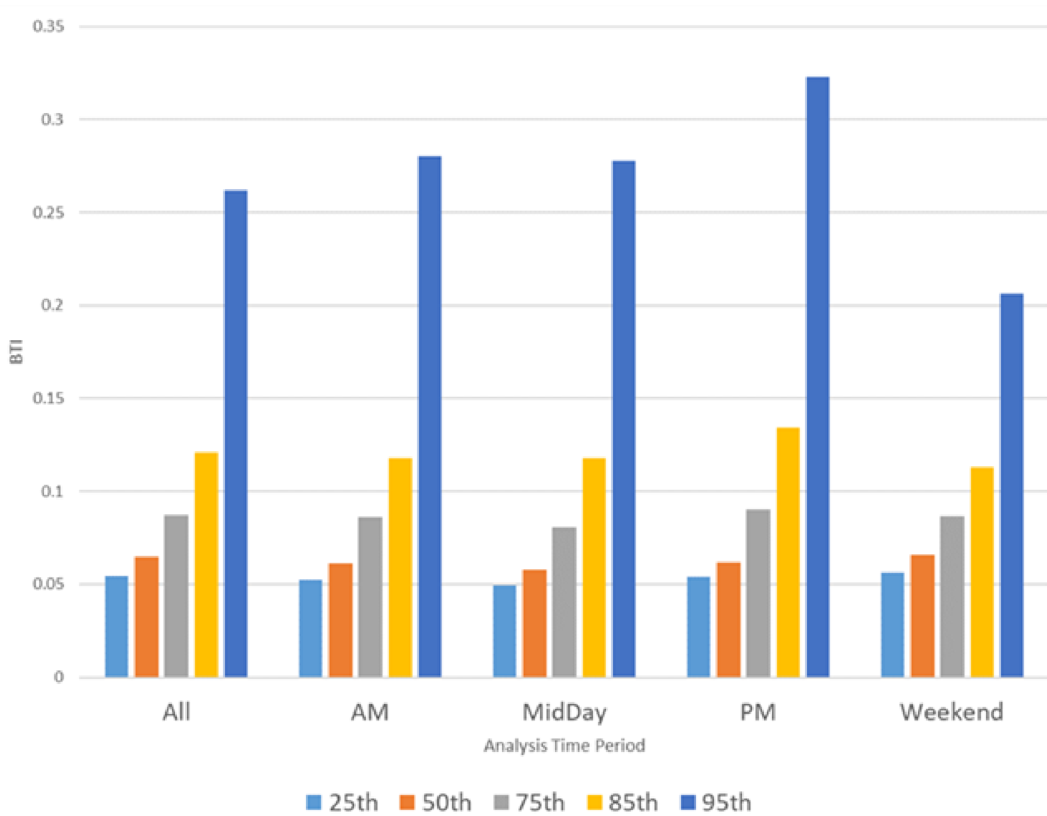


Figure 3.15 *Comparison of percentiles for BTI across different time periods.*

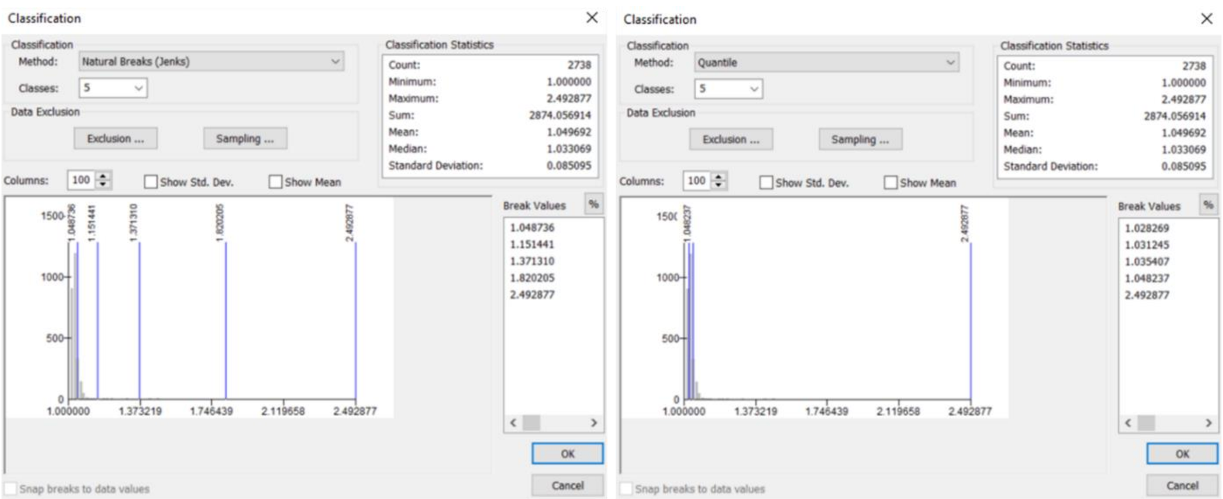
In summary, while the weekend analysis time period has the most unreliable reading for a greater proportion of the total segments, the PM peak has the most extreme unreliable values for the most unreliable segments. The remainder of this study focuses on data from the PM peak. For preparation of a mobility report or other comprehensive analysis, it would be appropriate to repeat this analysis for all time periods.

3.4.2 Quantile vs. Natural Data Classifications for Choropleth Maps

When trying to visually display results for any performance metric with spatial definitions, choropleth (color-scaled) maps are often used. These maps are very useful to quickly make a general assessment of an entire network. For this reason, they are used frequently in this study to help effectively convey results. However, the data classifications (the breakpoints for the different color-scales) used for these choropleth maps can dramatically change the perception of the network's performance. The two different types of data classifications that were considered for this study are quantile breaks and Jenks natural breaks. Both options are readily available to use when creating maps in ArcGIS. Quantile breaks, as the name suggested, simply use evenly spaced percentiles. This study uses five color-scales for map creation, so four breakpoints are needed. For quantile breaks, the 20th percentile, 40th percentile, 60th percentile, and 80th percentile are utilized for breakpoints. Jenks data classification method is a data clustering method designed to determine the best arrangement of values into different classes by finding natural breakpoints in the dataset (Jenks, 1967). This is the default data classification method in ArcGIS when creating choropleth maps.

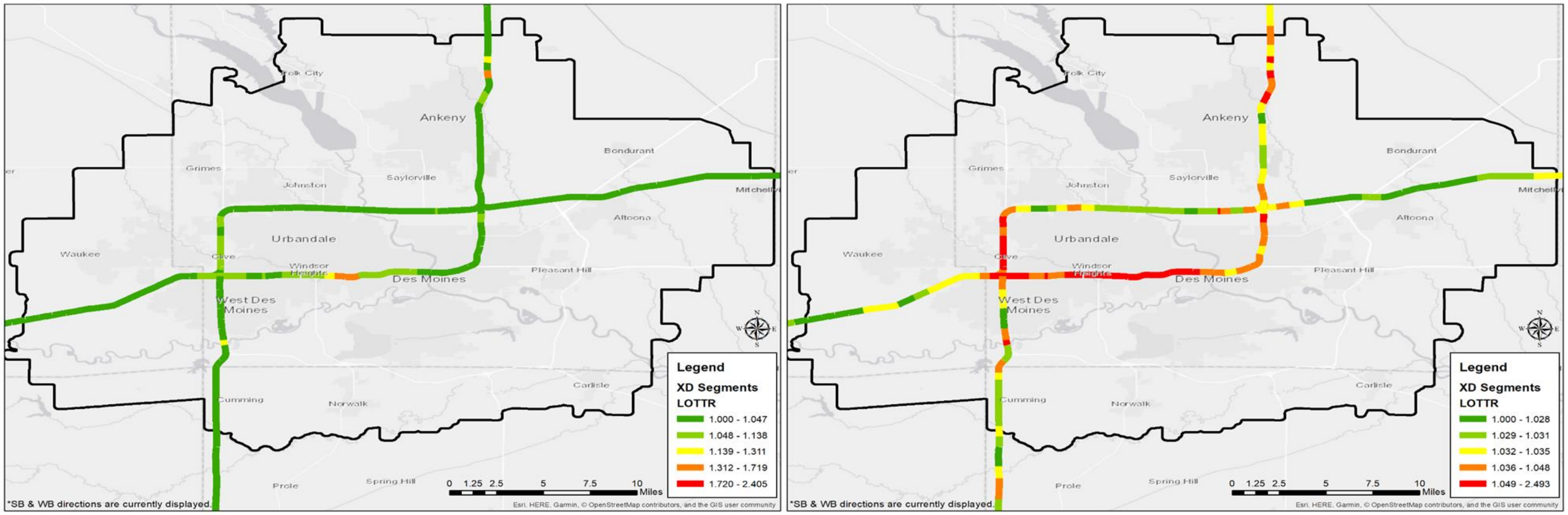
To help see what data classification appears to work best for the travel time reliability metric values in this study, screenshots taken from ArcGIS were compared. These screenshots help visualize were the breakpoints are in relation to the dataset's distribution. Another way to help compare the two methods is to create the choropleth maps themselves using each method for the different reliability metrics.

The first metric that used for comparison was LOTTR. LOTTR is useful for this comparison because it is asserted by the FHWA rulemaking that a value of 1.5 is considered unreliable. This provides a reference point to see if the breakpoints from each data classification method suggest a value close to 1.5 as a breakpoint. Figure 3.16 shows the ArcGIS screenshots for LOTTR and Figure 3.17 shows the two choropleth maps for LOTTR. It appears that the Jenks classification method does a more effective job at displaying the data. Its breakpoints seem more reasonable overall than the breakpoints derived from using quantile breaks. When looking at quantile breaks, all the breakpoints are extremely close together, usually only separated by about 0.01. Additionally, any segment with a LOTTR value over 1.047 appears as red on the map. Given that 1.047 is actually a relatively reliable value for LOTTR, it is not desirable that it should appear as red on a map. The Jenks classification method, meanwhile, displays segments with a value of 1.37 or higher as orange, and over 1.82 as red. These values seem far more reasonable. The sharp difference in perception when using these two data classification methods is vividly apparent in the maps shown in Figure 3.17.



(a) Natural Breaks (Jenks) (b) Quantile Breaks

Figure 3.16 *Jenks vs. Quantile breaks for LOTTR (Screenshot from ArcGIS).*

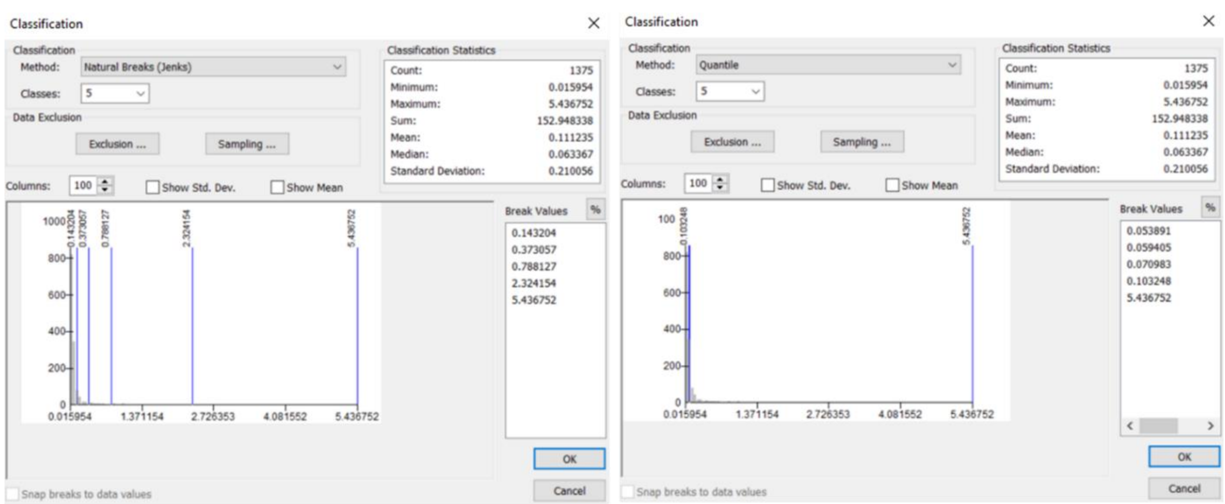


(a) Natural Breaks (Jenks)

(b) Quantile Breaks

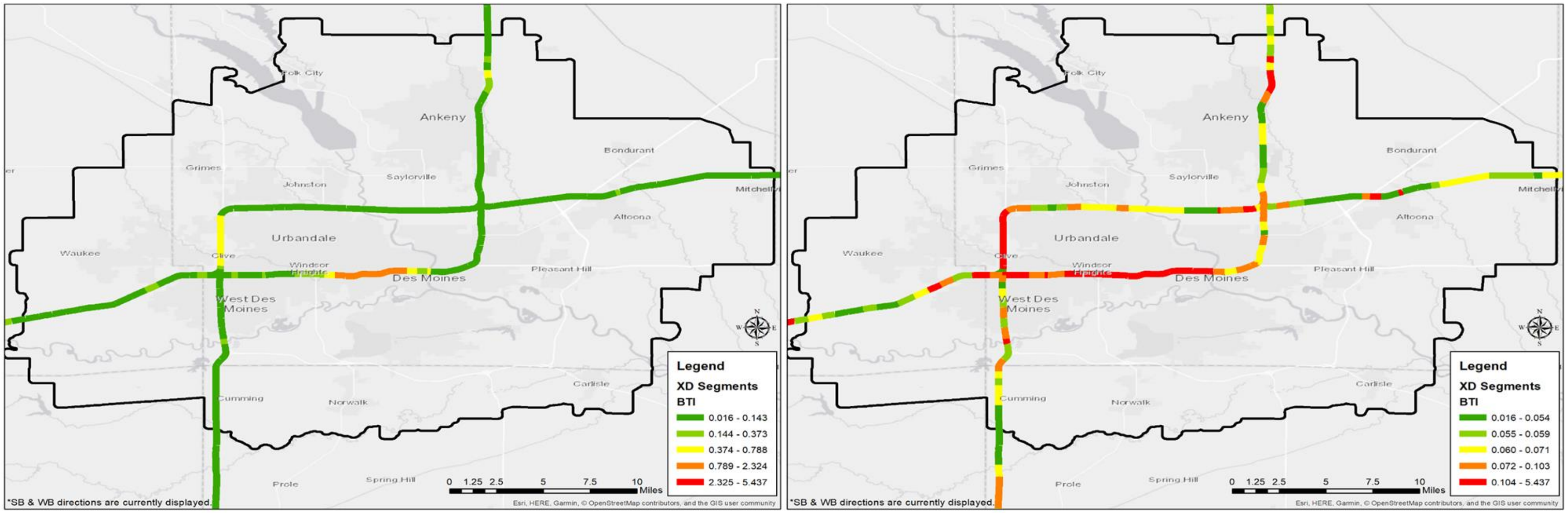
Figure 3.17 *Jenks vs. Quantile breaks LOTTR choropleth maps.*

Similar comparisons between the data classification techniques were made for the other reliability metrics. Figure 3.18 shows a comparison of the ArcGIS screenshots for BTI while Figure 3.19 shows a comparison between the resulting choropleth maps for BTI. Similar to LOTTR, there is a clear visual difference between the choropleth maps for BTI. When using quantile breakpoints, all of the values are again relatively close together, with a value of 0.103 being the lower-bound for displaying red on the map. This doesn't seem appropriate, as a value of 0.103 for BTI is usually regarded as still quite reliable. However, Jenks classification method shows a wider spread for the breakpoints, with higher more reasonable values used for breakpoints for the orange and red display groups.



(a) Natural Breaks (Jenks) (b) Quantile Breaks

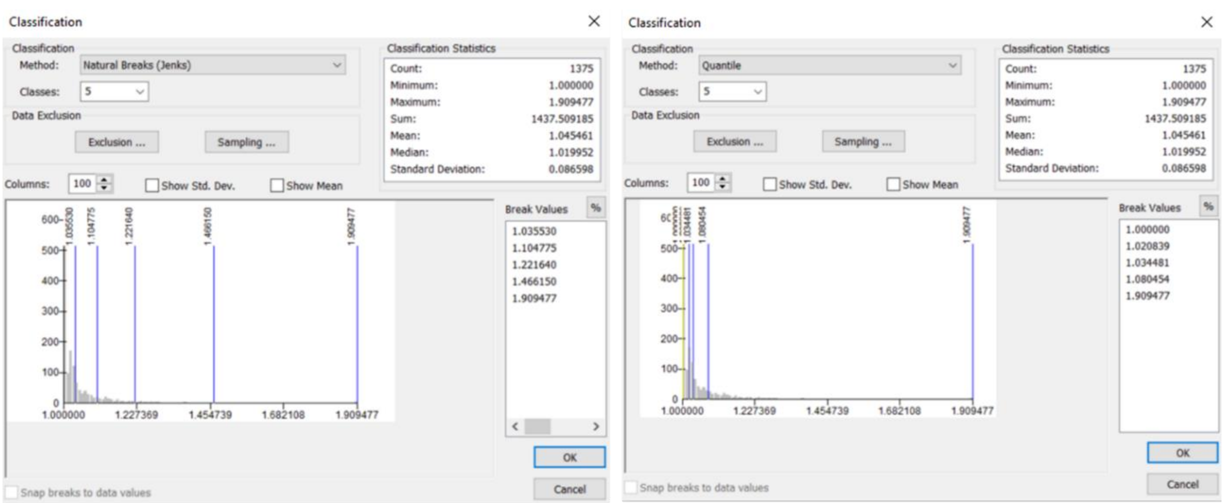
Figure 3.18 *Jenks vs. Quantile breaks for BTI (Screenshot from ArcGIS)*



(a) Natural Breaks (Jenks) (b) Quantile Breaks

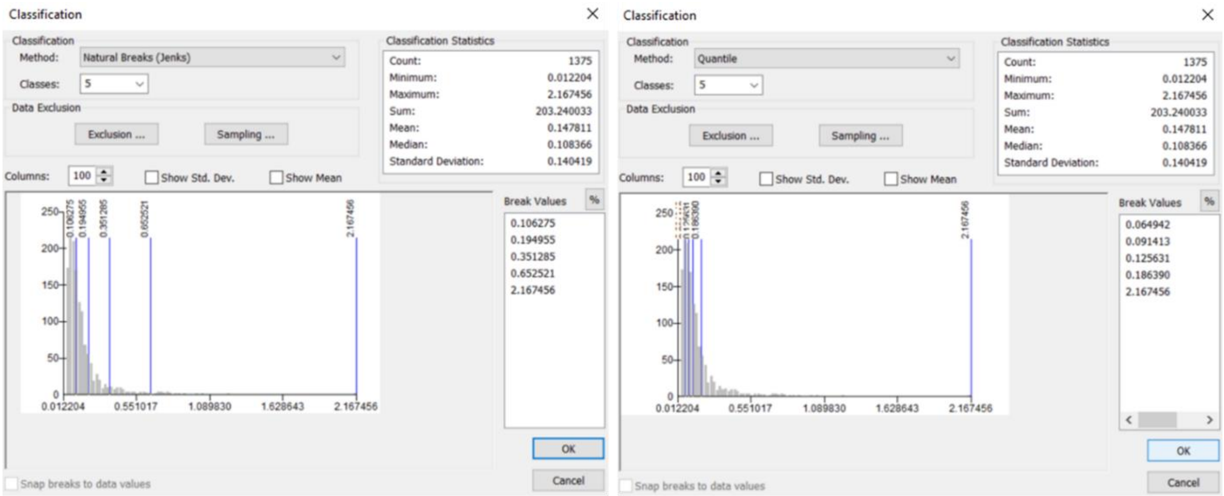
Figure 3.19 *Jenks vs. Quantile breaks BTI choropleth maps.*

Again, a similar comparison process was followed for PHTTR, SD_{tti}, and PR. For these metrics, only the screenshots from ArcGIS have been included. Figure 3.20 shows the ArcGIS screenshots for PHTTR. Similar points can be made for the comparisons made through the lens of the PHTTR metric than where made when looking at LOTTR and BTI. In fact, notice that the Jenks breakpoint for beginning the red color scale is 1.466. This value is extremely close to the FHWA set threshold for unreliability of 1.5. Looking at the quantile breakpoints, they are again all very close to one another and are also values that seem to reliable, with 1.080 being the value used to begin the red color scale. Figure 3.21 shows the comparison between quantiles and Jenks classifications for SD_{tti} and Figure 3.22 shows the comparison between quantiles and Jenks classifications for PR. The observations made from SD_{tti} and PR-based comparison are essentially the same as for the other three metrics.



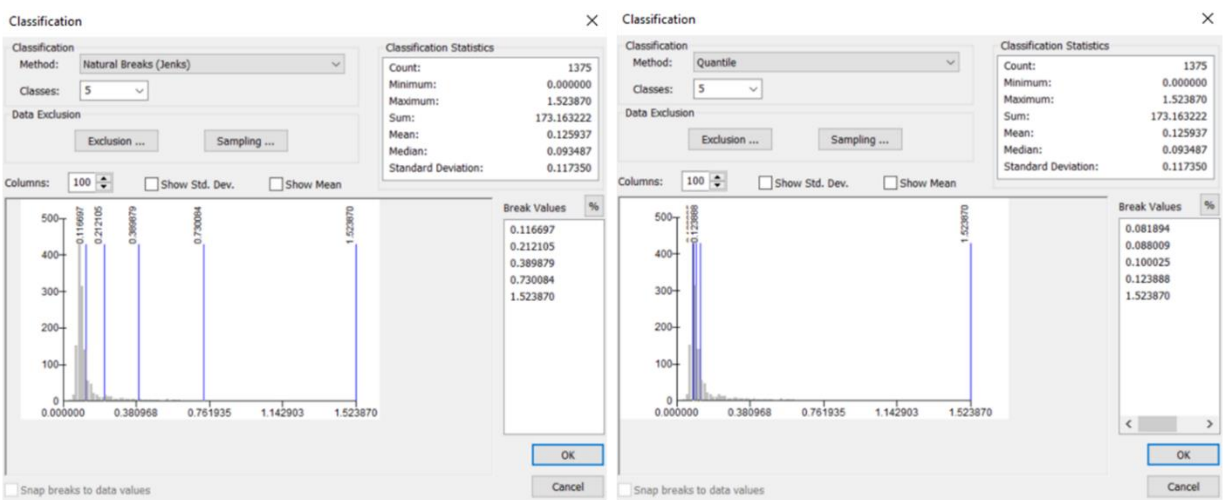
(a) Natural Breaks (Jenks) (b) Quantile Breaks

Figure 3.20 *Jenks vs. Quantile breaks for PHTTR (Screenshot from ArcGIS).*



(a) Natural Breaks (Jenks) (b) Quantile Breaks

Figure 3.21 *Jenks vs. Quantile breaks for SD_{tti} (Screenshot from ArcGIS).*



(a) Natural Breaks (Jenks) (b) Quantile Breaks

Figure 3.22 *Jenks vs. Quantile breaks for PR (Screenshot from ArcGIS).*

In summary, the Jenks data classification method seems to do a better job at more appropriately visualizing travel time reliability on roadway segments on a choropleth map than using quantiles for data classification. Therefore, Jenks data classification method will continue to be utilized for all the choropleth maps in this report.

3.5 Application to the Des Moines Area

The Des Moines metropolitan area is the most populated urban area in Iowa with a population of 645,911 people in 2017 with projections having the population reach nearly 1 million in coming years, according to the Greater Des Moines Partnership (2018). Large urban areas are typically focus areas for transportation performance assessments due to their higher levels of population and economic activity, which generate higher volumes of traffic demand. Therefore, the first application of the selected reliability metrics uses the Des Moines area as a case study. The next section of the report details a statewide application.

Application of the travel time reliability metrics was performed in two stages for the Des Moines area. The first stage utilized the FHWA reliability metrics of LOTTR and PHTTR. The second stage utilized the three selected reliability metrics of SD_{tti}, PR, and BTI.

3.5.1 LOTTR and PHTTR

The FHWA sets a threshold of 1.5 and higher for identifying segments as unreliable for both LOTTR and PHTTR. As a reminder, LOTTR is computed for four different time periods (AM peak on weekdays, mid-day on weekdays, PM peak on weekdays, and weekends). If values for any of the four analysis time periods are above 1.5, the segment is deemed unreliable. Essentially, the max LOTTR value can be found for each segment across the four time periods and checked against the threshold of 1.5 to identify whether it is reliable. PHTTR uses a similar process, but instead of using four analysis time periods, it utilizes the maximum average travel time value of the different peak hours throughout the day and divides this by the desired travel time. For this study, the speed limit was used as each segment's desired travel time.

Figure 3.23 shows the segments identified as unreliable in the Des Moines area according to LOTTR or PHTTR. Two segments were identified by LOTTR and eleven segments were identified by PHTTR. There was not a segment which was identified by both LOTTR and PHTTR together. Nine of the eleven segments identified by PHTTR are located on I-235, suggesting that stretch of highway could be the most unreliable in the Des Moines area. Table 3.4 shows these same identified segments in a table. This table provides additional information, including the segment ID, unreliability rank, the route, the reliability metric value, and the other reliability metric values along with what rank that segment would be for using other reliability metric. This table highlights that LOTTR and PHTTR do not provide the same results, which is not unexpected since they approach identifying unreliability in different ways. The most unreliable segment according to PHTTR, for example, had a PHTTR of 2.09 yet a LOTTR of only 1.21, which falls well under the 1.5 threshold.

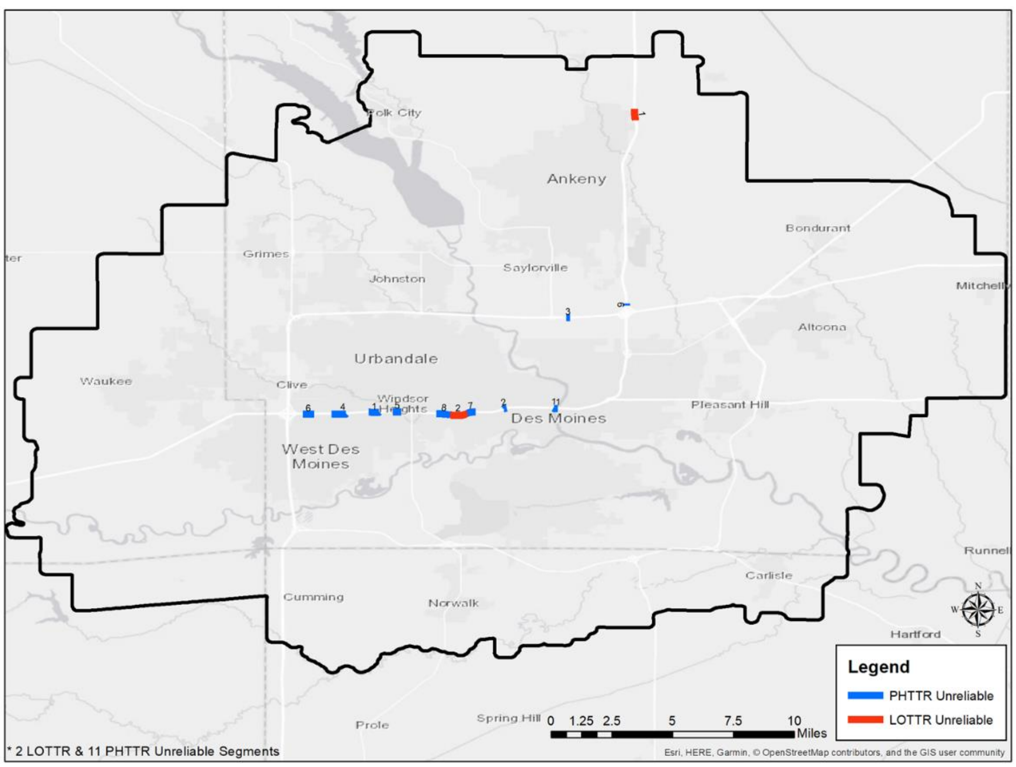


Figure 3.23 *Unreliable segments in the Des Moines area according to PHTTR and LOTTR.*

Table 3.4 *Summary of unreliable segments in the Des Moines area according to PHTTR and LOTTR.*

LOTTR Unreliable Segments				
Rank	Segment ID	Route	LOTTR	*PHTTR (Rank)*
1	1485754798	I-35S	1.69	*1.21 (33)*
2	1485852747	I-235S	1.68	*1.38 (16)*
PHTTR Unreliable Segments				
Rank	Segment ID	Route	PHTTR	*LOTTR (Rank)*
1	1485859264	I-235N	2.09	*1.21 (9)*
2	1485852299	I-235S	1.91	*1.06 (31)*
3	1485517139	I-80W	1.91	*1.05 (37)*
4	1485764384	I-235N	1.82	*1.09 (17)*
5	1485852719	I-235S	1.73	*1.09 (18)*
6	1485520730	I-235N	1.67	*1.06 (35)*
7	1485648363	I-235S	1.64	*1.13 (12)*
8	1485852735	I-235S	1.61	*1.40 (3)*
9	1485700549	I-235N	1.60	*1.06 (45)*
10	1485849307	I-235N	1.55	*1.05 (55)*
11	1485573408	I-235N	1.51	*1.04 (103)*
*Rank out of 283 segments in the Des Moines Metro.				

Another way to visualize the results from LOTTR and PHTTR is to create choropleth maps. Figure 3.24 shows choropleth maps for LOTTR and Figure 3.25 shows choropleth maps for PHTTR. Two choropleth maps were created for each metric to display each set of highway directions more effectively without any issue of overlapping. The left map always shows northbound and eastbound highway directions while the right map always shows southbound and westbound highway directions. Looking at these maps, it is a bit easier to see the difference in reliability metric results between LOTTR and PHTTR as well as the difference in reliability metric results for each highway direction. PHTTR appears to show that the Des Moines area is more unreliable overall whereas LOTTR appears to show that the majority of the Des Moines area exhibits fairly reliable performance. Both metrics indicate that I-235 has lower reliability closer to the interchange with I-35 in West Des Moines for the northbound direction, but lower reliability closer to downtown Des Moines in the southbound direction. Both LOTTR and PHTTR show pockets of higher unreliability on I-35 in both directions in the Ankeny area. PHTTR also shows some segments with higher unreliability on I-80 around Urbandale whereas LOTTR does not.

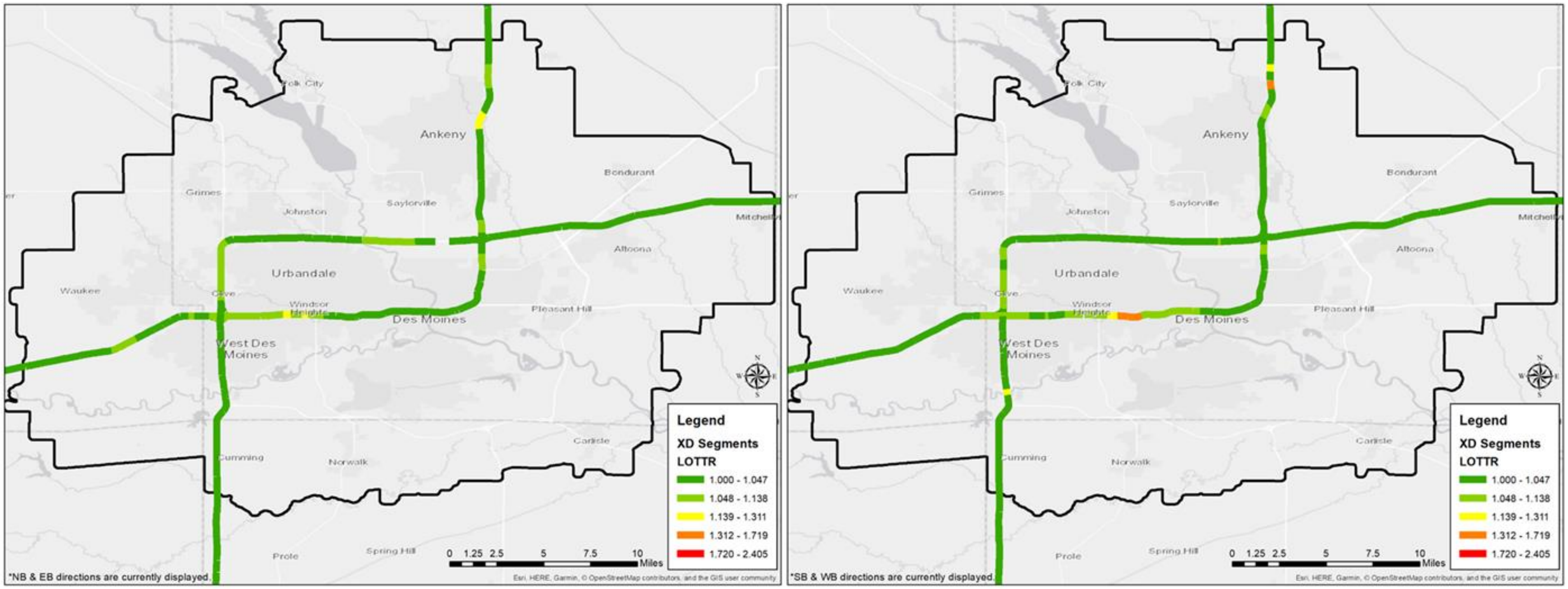


Figure 3.24 *Choropleth maps of LOTTR in the Des Moines area (NB/EB & SB/WB).*

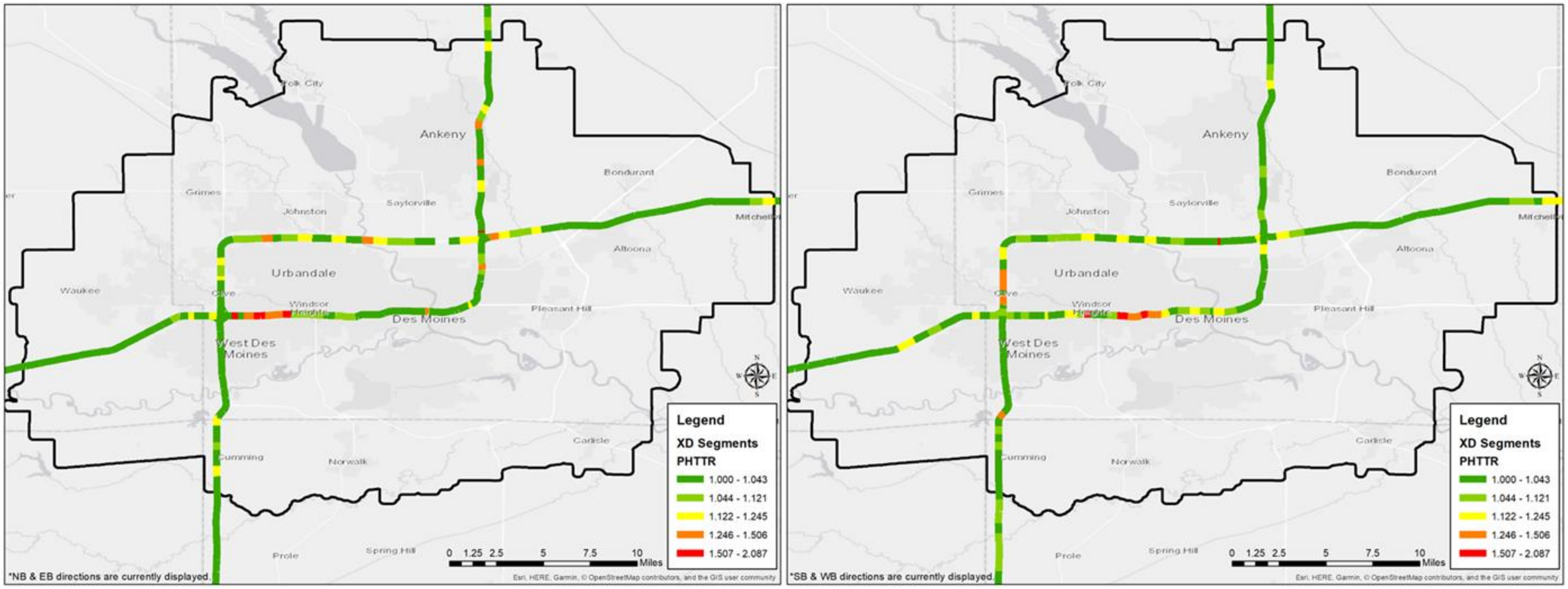


Figure 3.25 *Choropleth maps of PHTTR in the Des Moines area (NB/EB & SB/WB).*

Up to this point, travel time reliability metric values have simply been computed according to their specific definition and set calculation procedure. It is also worth looking at what the travel times observed for segments identified as the most reliable and the most unreliable segments looked like throughout the year. This might provide a way to better characterize how “reliable” or “unreliable” performance looks on a day-to-day basis. It can also potentially provide a way to see any differences between segments identified by different reliability metrics. For now, this will be done for the two most unreliable segments and the two most reliable segments as identified by LOTTR and PHTTR. Later in this report, similar travel time data visualizations will be performed for SD_{tti}, PR, and BTI as well.

Figure 3.26 shows detailed travel time data views for the two most reliable and the two most unreliable segments according to LOTTR. Figure 3.27 shows similar visualizations but utilizing segment identified using PHTTR instead. Each data point represents an individual travel time measurement across that segment. The most unreliable segment identified by LOTTR (Figure 3.26 (a)) clearly had a shift in baseline travel times in late April as there is a sudden jump in travel times. LOTTR was obviously sensitive to this jump in baseline, as the variability in travel times do not look that remarkably different when compared to the two most reliable segments. However, the second most unreliable segment according to LOTTR (Figure 3.26 (b)) clearly has more variability in its observed travel times indicating it is actually more unreliable. Even this segment, though, as a jump in the baseline for travel times around the beginning of December at the end of the year. For PHTTR, there does seem to be an elevated variability in travel times for the two most unreliable segments vs. the two most reliable segments.

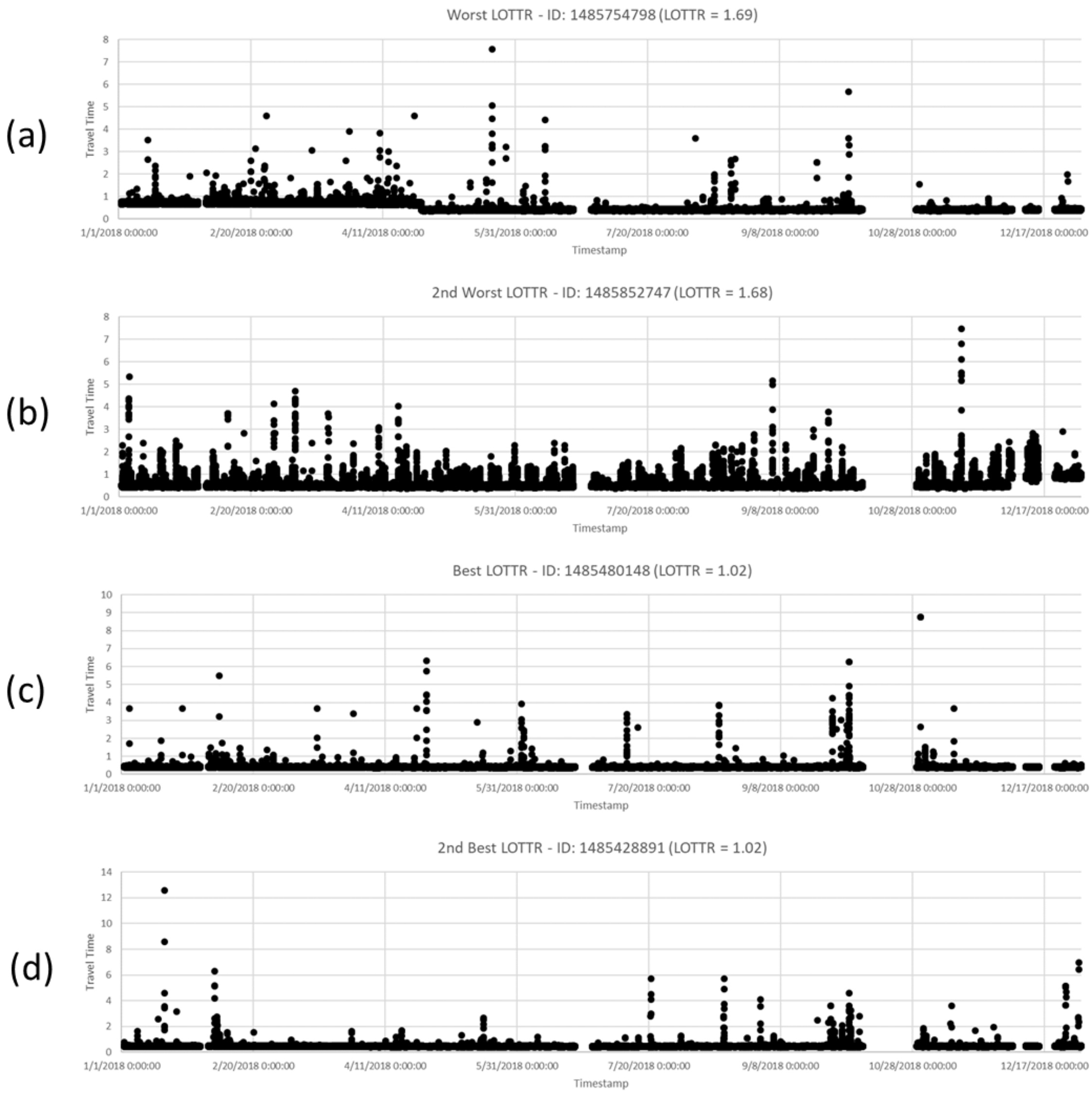


Figure 3.26 *Detailed travel time data views for the best and worst LOTTR segments.*

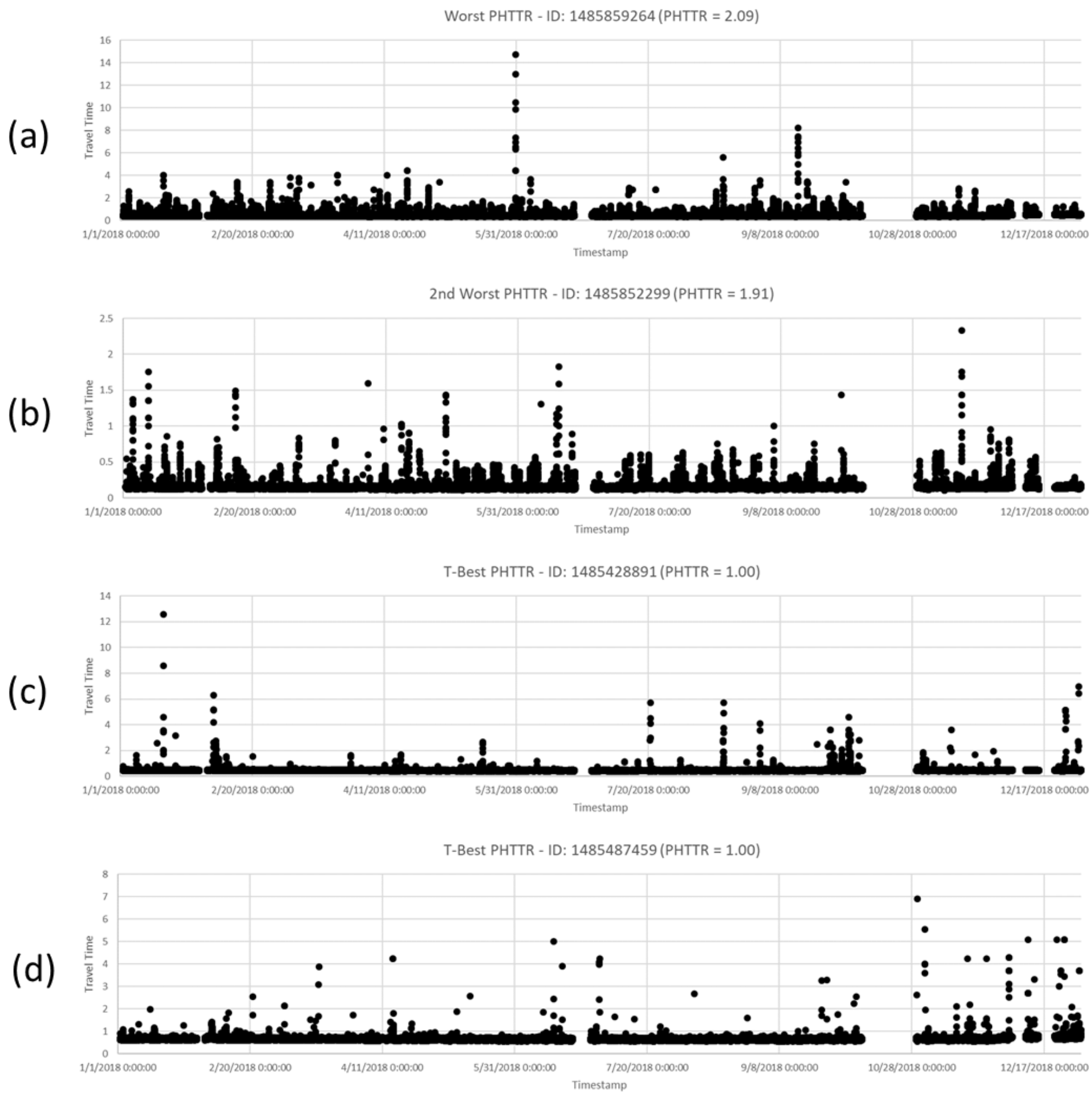


Figure 3.27 *Detailed travel time data views for the best and worst PHTTR segments.*

3.5.2 SD_{tti}, PR, and BTI

Unlike LOTTR and PHTTR, SD_{tti}, PR, and BTI do not have predefined thresholds to identify segments as unreliable or reliable. Also, unlike LOTTR and PHTTR, a maximum value across time periods is not used. This section presents results in the form of choropleth maps, segment ranking, and best/worst segment detail based on these metrics.

Figure 3.28 shows choropleth maps for the Des Moines area using SD_{tti}. Similar to PHTTR, shows the Des Moines area having generally elevated levels of unreliability. SD_{tti} identified I-235 as particularly unreliable in certain stretches in areas, also similar to PHTTR. However, SD_{tti} also identified I-80 (particularly eastbound) as somewhat unreliable throughout its bypass of the inner Des Moines metro area. I-35 in Ankeny appears to have some elevated levels of unreliability as well.

Figure 3.29 shows choropleth maps for PR. The PR results show the Des Moines are as more reliable overall, especially when compared to SD_{tti}. However, it does identify a hotspot of unreliability slightly west of downtown Des Moines on I-235W. This same stretch was identified as unreliable by PHTTR and SD_{tti}, but PR seems to highlight this area a little more strongly. PR also does identify a portion I-35S in Ankeny as unreliable.

Figure 3.30 shows choropleth maps for BTI. BTI almost seems to show levels of reliability roughly between SD_{tti} and PR for the Des Moines area. The inner loop has elevated levels of unreliability, particularly when looking at the northbound/eastbound directions. The same area of I-235W identified by SD_{tti} and strongly by PR appears as unreliable. Again, a small stretch of I-35N in Ankeny has some higher levels of unreliability.

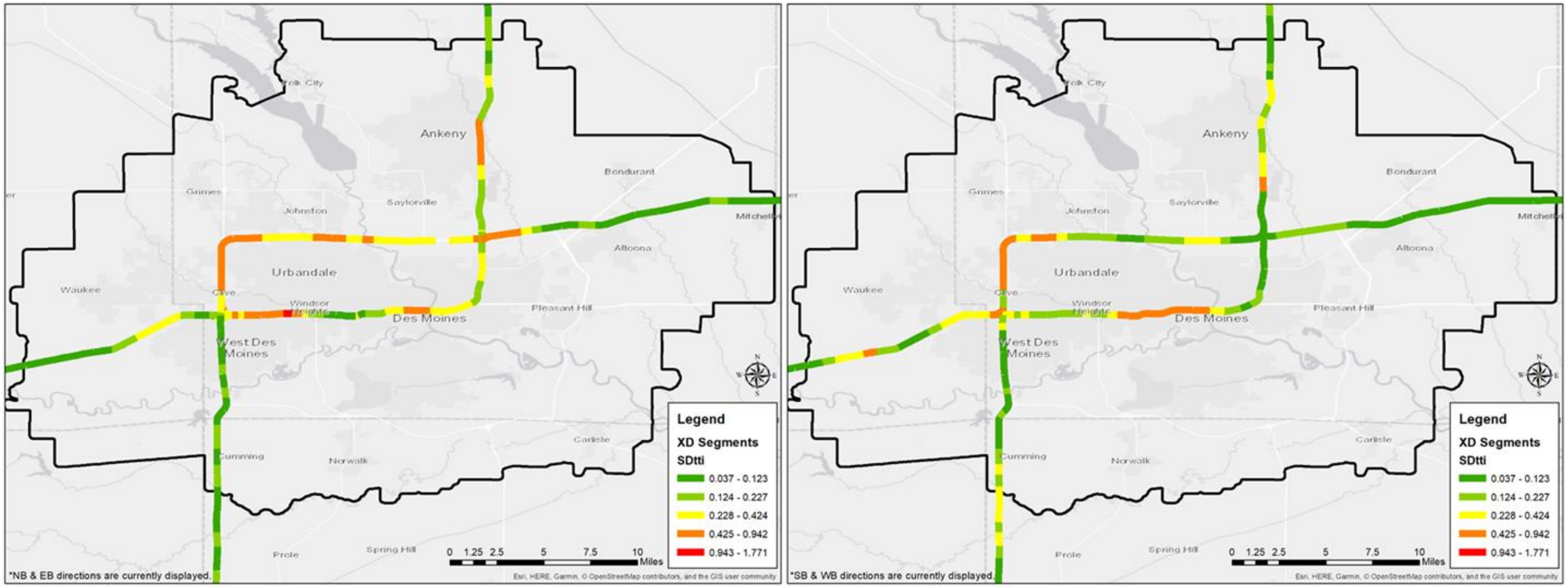


Figure 3.28 *Choropleth maps of SD_{tti} in the Des Moines area (NB/EB & SB/WB).*

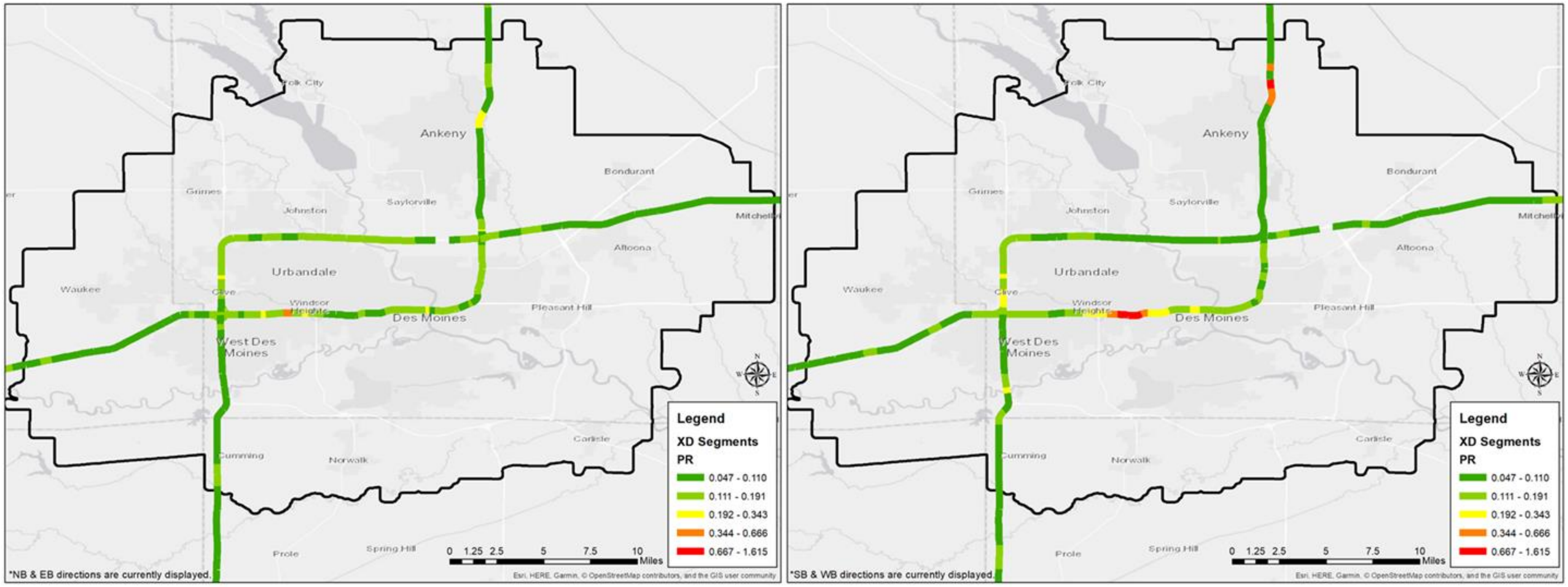


Figure 3.29 *Choropleth maps of PR in the Des Moines area (NB/EB & SB/WB).*

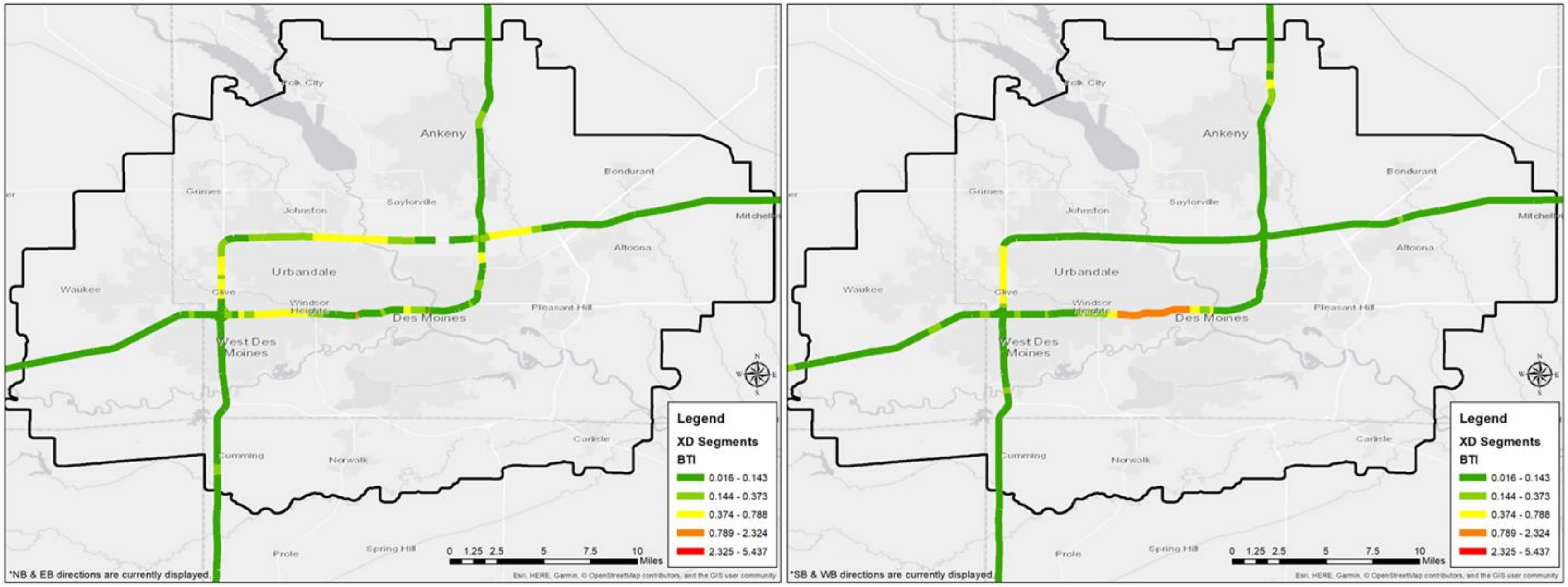


Figure 3.30 *Choropleth maps of BTI in the Des Moines area (NB/EB & SB/WB).*

To identify specific segments with high levels of unreliability, the top 5 most unreliable segments were identified in the Des Moines area according to each of the three different metrics (SD_{tti}, PR, and BTI). A map showing the top 5 most unreliable segments in the Des Moines are is shown in Figure 3.31. Table 3.5 shows more information about these five segments including their rank, ID, route, SD_{tti} value, and their values and ranks for PR and BTI. Four of the five segments were located on I-235 with the other segment (the most unreliable one) being located on I-35S at the interchange with I-235 and I-80 in West Des Moines. These segment locations are in essentially the same locations identified as unreliable in the choropleth maps shown previously. Both SD_{tti} and BTI agreed on which segment was the most unreliable segment in the Des Moines area. However, this same segment had a relatively low PR value, which ranked 166th out of 283 segments. Other than this segment and one other (which was 3rd for SD_{tti} and 4th for BTI), no other segments which appear in the top 5 for SD_{tti} appear in the top 5 list for PR or BTI. This shows that SD_{tti} tends to identify different segments than PR and BTI as unreliable. However, the top 5 most unreliable segments that SD_{tti} identified do usually rank within the top 30 for the other two metrics.

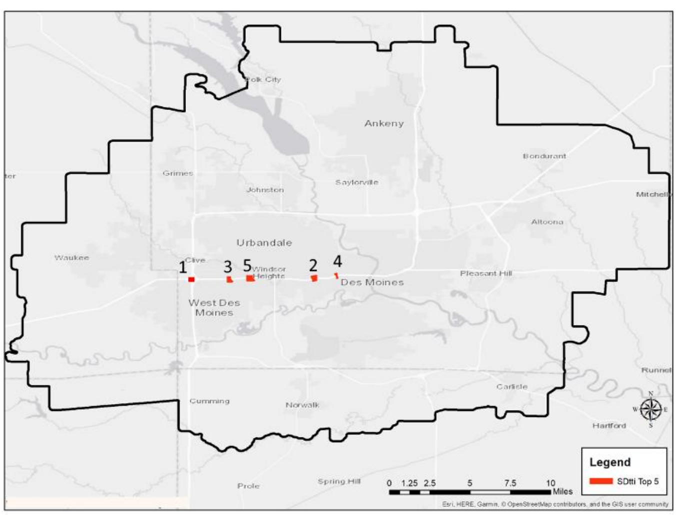


Figure 3.31 *Top 5 most unreliable segments map of the Des Moines area according to SD_{tti}.*

Table 3.5 *Top 5 most unreliable segments summary for the Des Moines area (SD_{tti}).*

Rank	Segment ID	Route	SDtti	*PR (Rank)*	*BTI (Rank)*
1	1485465513	I-35S	2.17	*0.10 (166)*	*5.44 (1)*
2	1485859264	I-235N	1.45	*0.36 (8)*	*0.70 (19)*
3	1485852299	I-235S	1.22	*0.29 (14)*	*1.05 (4)*
4	1485764384	I-235N	0.90	*0.22 (20)*	*0.59 (29)*
5	1485648363	I-235S	0.80	*0.47 (6)*	*0.95 (8)*

*Rank out of 283 segments in the Des Moines Metro.

Similar to SD_{tti}, the top 5 most unreliable segment according to PR were identified. Figure 3.32 shows a map displaying the 5 segment's location and Table 3.6 provides a summary of additional information about these 5 segments. 3 of the top 5 most unreliable segments were located on I-235S and 2 of the top 5 segments were located on I-35S in Ankeny. These 5 segments are in the same 2 areas that were prominently identified as unreliable earlier in the choropleth map for PR. While the top 2 most unreliable segments identified by PR are ranked within top 11 most unreliable segments for SD_{tti} and BTI, the other 3 segments on the list rank 70^{th} or higher for SD_{tti} and outside the top 20 for BTI.

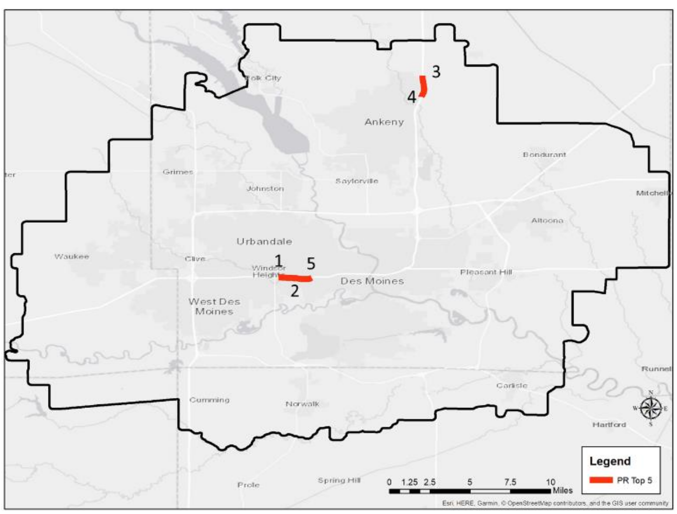


Figure 3.32 *Top 5 most unreliable segments map of the Des Moines area according to PR.*

Table 3.6 *Top 5 most unreliable segments summary for the Des Moines area (PR).*

Rank	Segment ID	Route	PR	SDtti (Rank)	BTI (Rank)
1	1485852735	I-235S	1.12	0.75 (10)	0.89 (11)
2	1485852747	I-235S	0.94	0.76 (8)	1.01 (6)
3	1485754798	I-35S	0.79	0.36 (70)	0.44 (39)
4	1485754787	I-35S	0.56	0.26 (102)	0.28 (58)
5	1485483204	I-235S	0.47	0.33 (75)	0.66 (23)
*Rank out of 283 segments in the Des Moines Metro.					

Like SD_{tti} and PR, the top 5 most unreliable segments for BTI were also identified. Figure 3.33 displays a map highlighting the locations of these 5 segments and Table 3.7 provides additional information about these 5 segments. Similar to SD_{tti}, the BTI results show that four of the five segments came from I-235 with the other segment being located on I-35S at the interchange with I-80 and I-235 in West Des Moines. As previously mentioned, the I-35S segment was identified as the most unreliable in the Des Moines area by both BTI and SD_{tti}. However, the difference between this segment and the rest of the segments is much more pronounced with BTI than it was with SD_{tti}. This segment had a BTI of 5.44, far greater than the second most unreliable segment with a BTI of 1.50. The top 3 most unreliable segments identified by BTI do not even appear in top 60 for PR. However, all the top 5 segments identified by BTI do appear to be relatively highly ranked by SD_{tti}, with the two metrics even sharing 2 segments amongst their top 5.

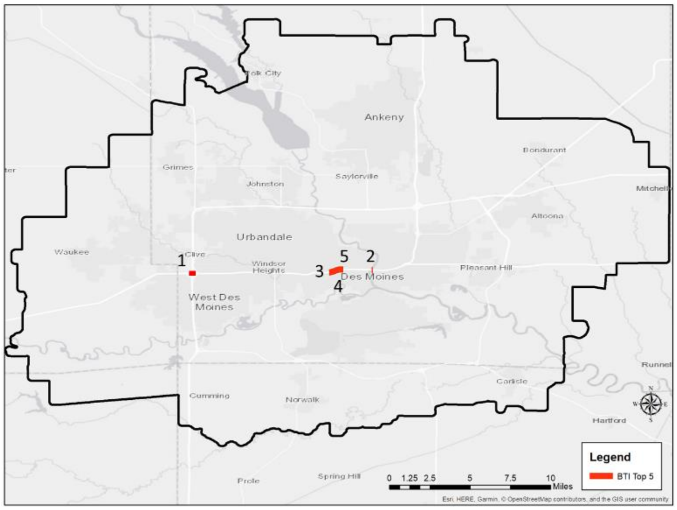


Figure 3.33 *Top 5 most unreliable segments map of the Des Moines area according to BTI.*

Table 3.7 *Top 5 most unreliable segments summary for the Des Moines area (BTI).*

Rank	Segment ID	Route	BTI	*SDtti (Rank)*	*PR (Rank)*
1	1485465513	I-35S	5.44	*2.17 (1)*	*0.10 (166)*
2	1485604287	I-235N	1.50	*0.58 (34)*	*0.14 (61)*
3	1485852313	I-235S	1.10	*0.65 (18)*	*0.14 (62)*
4	1485852299	I-235S	1.05	*1.22 (3)*	*0.29 (14)*
5	1485852283	I-235S	1.04	*0.7 (15)*	*0.22 (22)*
*Rank out of 283 segments in the Des Moines Metro.					

Figure 3.34 shows detailed travel time data views for the two most reliable and the two least reliable segments in the Des Moines area according to SD_{tti}. The two most reliable segments (a and b) appear to have consistent travel times most of the year with a few outliers. It's worth noting that the second most reliable segment (b) was missing data through the end of April. The second most unreliable segment (b) appears to have a greater variable in travel times throughout the year as would be expected. The most unreliable segment (a), however, had extremely consistent travel time throughout most of the year except for the month of December. During the month of December, there is a spike in travel times and the variability of the travel times appears to increase. SD_{tti} was clearly sensitive to this odd spike in the travel time dataset at the end of the year. It is worth noting that this segment is very short, but this does not explain why there is a sudden spike in travel times at the end of the year.

Whether this was due to a real-world cause, or due to some sort of data anomaly, the SD_{tti} metric was clearly sensitive to it. This same segment was also identified by BTI and this will be discussed further shortly in this report when looking at BTI specifically.

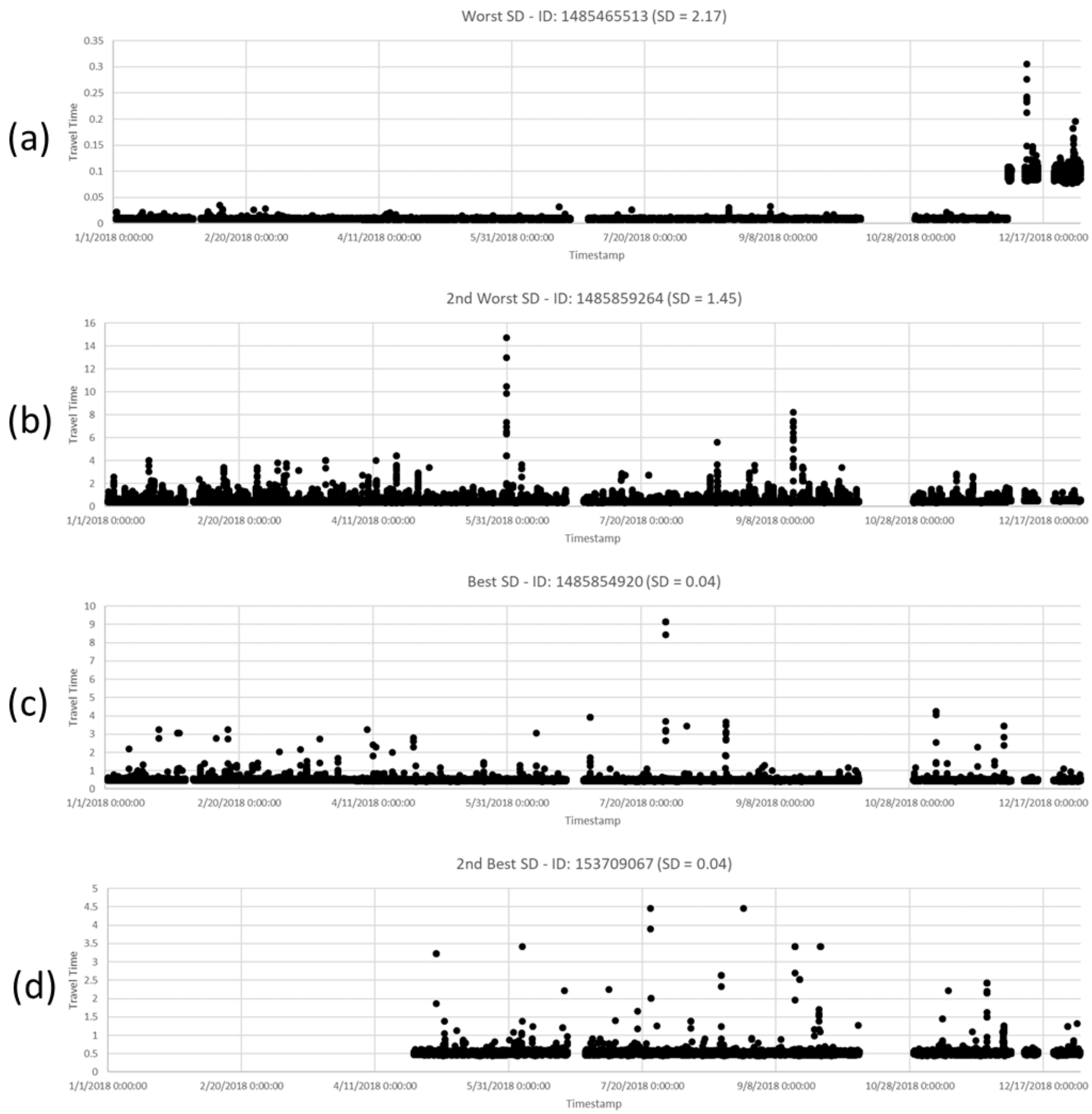


Figure 3.34 *Detailed travel time data views for the best and worst SD_{tti} segments.*

The detailed travel time data views for the top 2 most reliable and the top 2 most unreliable segments in the Des Moines area as identified by PR are shown in Figure 3.35. The segments identified by PR provide an excellent example of differences in travel times between unreliable and reliable segments. Both segments identified as unreliable (a and b) show considerable variability in travel times throughout the year. There is a slight jump in the base travel times seen in the second most unreliable segment (b) but given the vast variability in travel times clearly seen throughout the year, this did not seem to have much influence on why this segment's unreliability appeared to be so high. The two most reliable segments (c and d) both seem to have consistent travel times throughout the year.

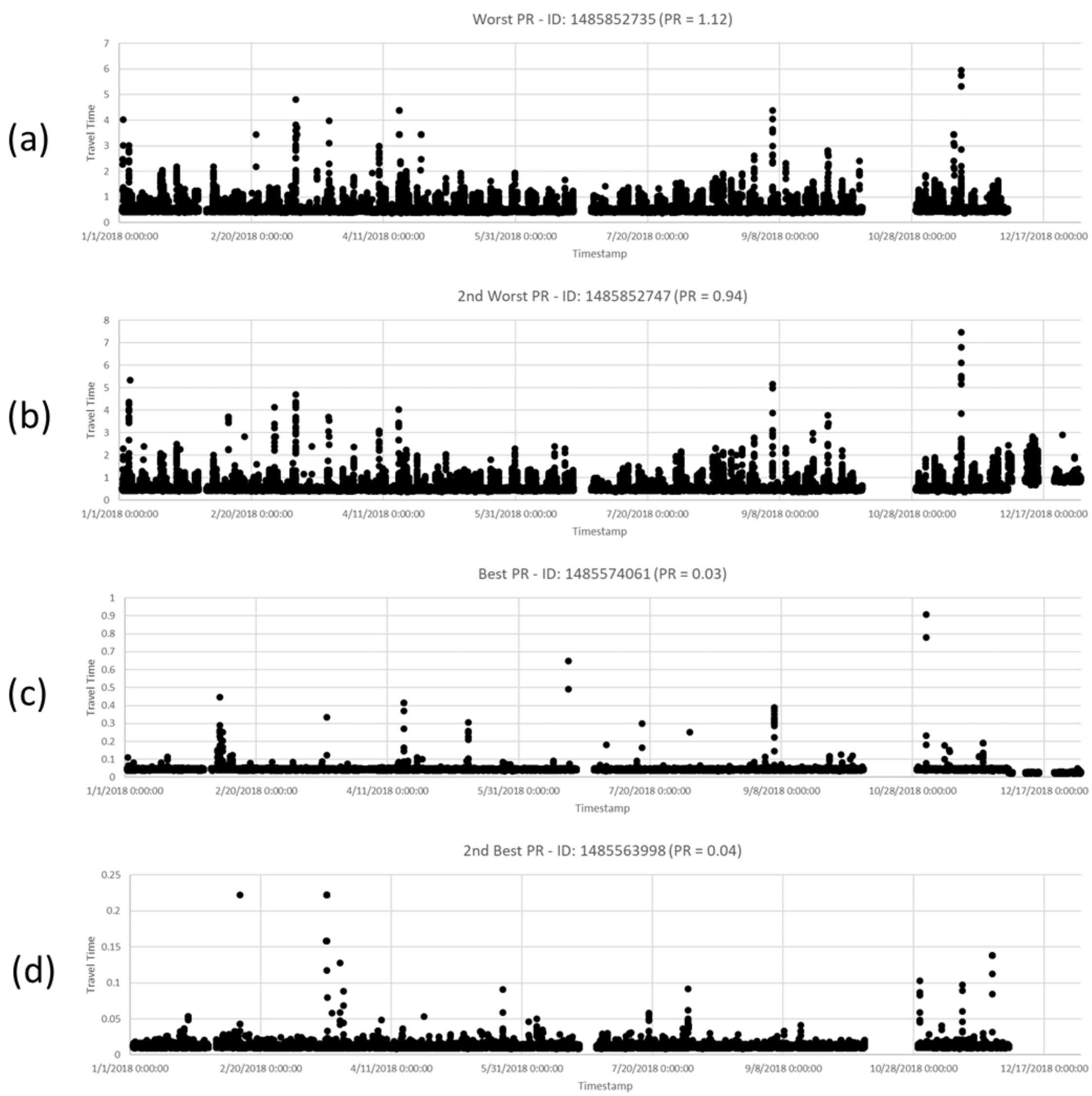


Figure 3.35 *Detailed travel time data views for the best and worst PR segments.*

Figure 3.36 shows the detailed travel time data views for the top 2 most unreliable and the top 2 most reliable segments in the Des Moines area according to BTI. The most unreliable segment (a) identified is the same segment that was discussed with SD_{tti}. The sudden jump in travel times seen in December clearly had a pronounced effect on the BTI value. In fact, the BTI reading of 5.44 is far greater the second most unreliable segment which has a reading of just 1.50. This same segment, while also ranking as the most unreliable segment by SD_{tti}, ranked just 166th out of the 283 segments for PR in the Des Moines area. This emphasizes how the different travel time reliability metrics approach quantifying different aspects of reliability. Both SD_{tti} and BTI will be influenced more by a batch of outliers (like what is seen in this segment) whereas PR will not be since it only considered the difference between the 15th percentile and 85th percentile of the dataset. The segment identified as the second most unreliable segment (b) also had a slight jump in travel times seen at the end of the year in December. The rest of the year does have some variability in travel time values, but this jump at the end of the year still seems to have had an impact on the BTI value. The two most reliable segments identified by BTI (c and d) both have outliers, but for the most part most the travel time values do appear to be consistent throughout the year.

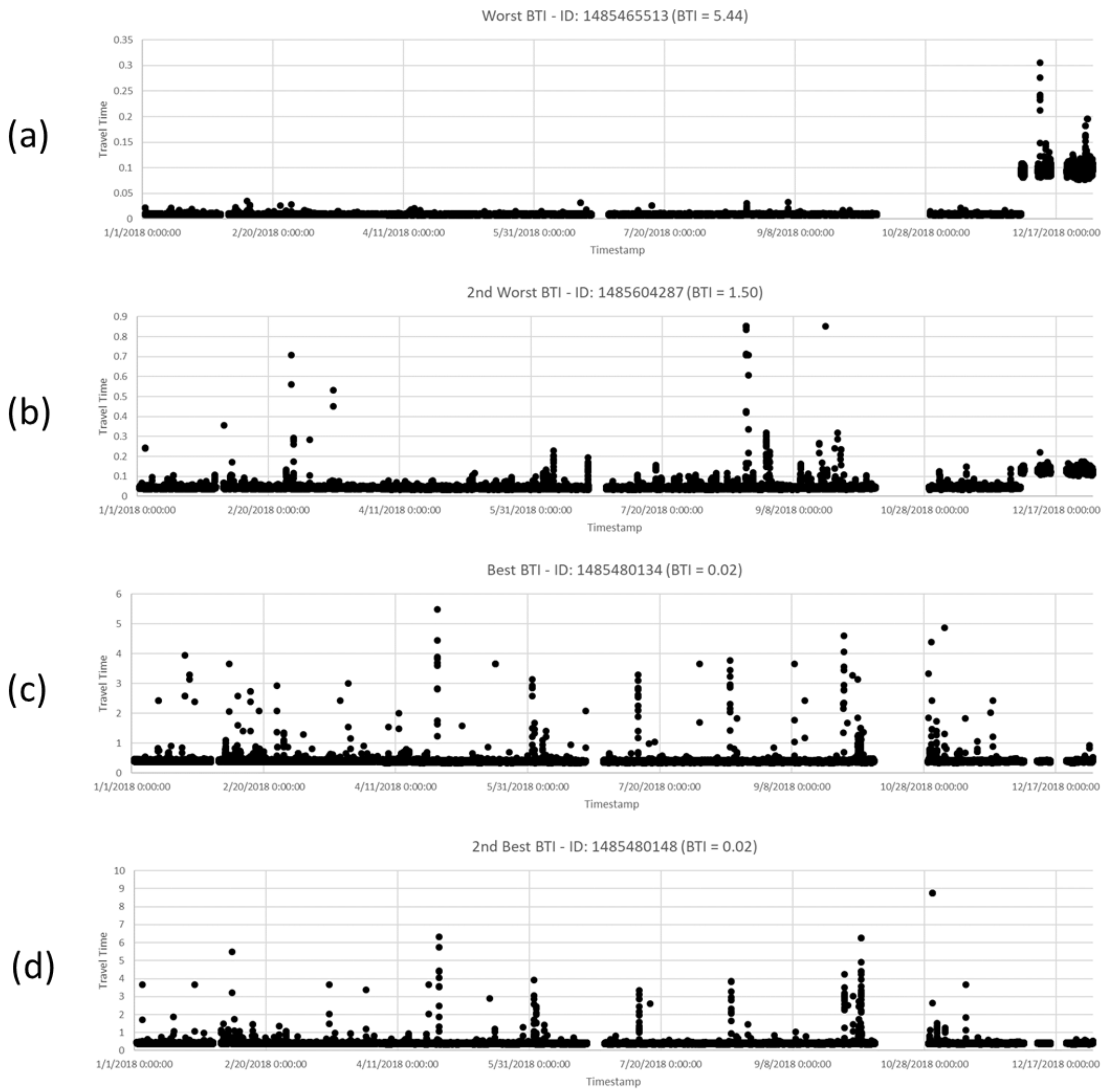


Figure 3.36 *Detailed travel time data views for the best and worst BTI segments.*

3.6 Application Statewide in Iowa

In this section, the travel time reliability metrics which were applied previously to the Des Moines area are applied to the entire state of Iowa using the same procedures as before.

3.6.1 LOTTR and PHTTR

While LOTTR and PHTTR are meant to be used in urban areas, they can still be relatively easily applied statewide. In fact, it is interesting to see whether these metrics are able to identify unreliable segments in more rural locations as well. Figure 3.37 shows a map displaying all the segments which were identified by LOTTR and PHTTR as unreliable using the FHWA threshold of 1.5. Across the state, 22 segments were identified by LOTTR as unreliable, while 23 segments were identified as unreliable by PHTTR. Segments identified by LOTTR appear to be more dispersed between urban and rural areas, whereas the unreliable segments according to PHTTR appear to be in urban areas most of the time. In fact, 11 of the 23 segments identified by PHTTR are in Des Moines. Table 3.8 shows additional information about the top 10 most unreliable segments across Iowa according to LOTTR and PHTTR. Most of the segments in top 10 for LOTTR are typically around the top 50 for PHTTR as well. However, only 1 segment in the top 10 for PHTTR even appears in the top 100 for LOTTR. I-380 segments appeared the most in the LOTTR top 10 with 4 segments. I-235 segments appeared the most in the PHTTR top 10, with 5 segments.

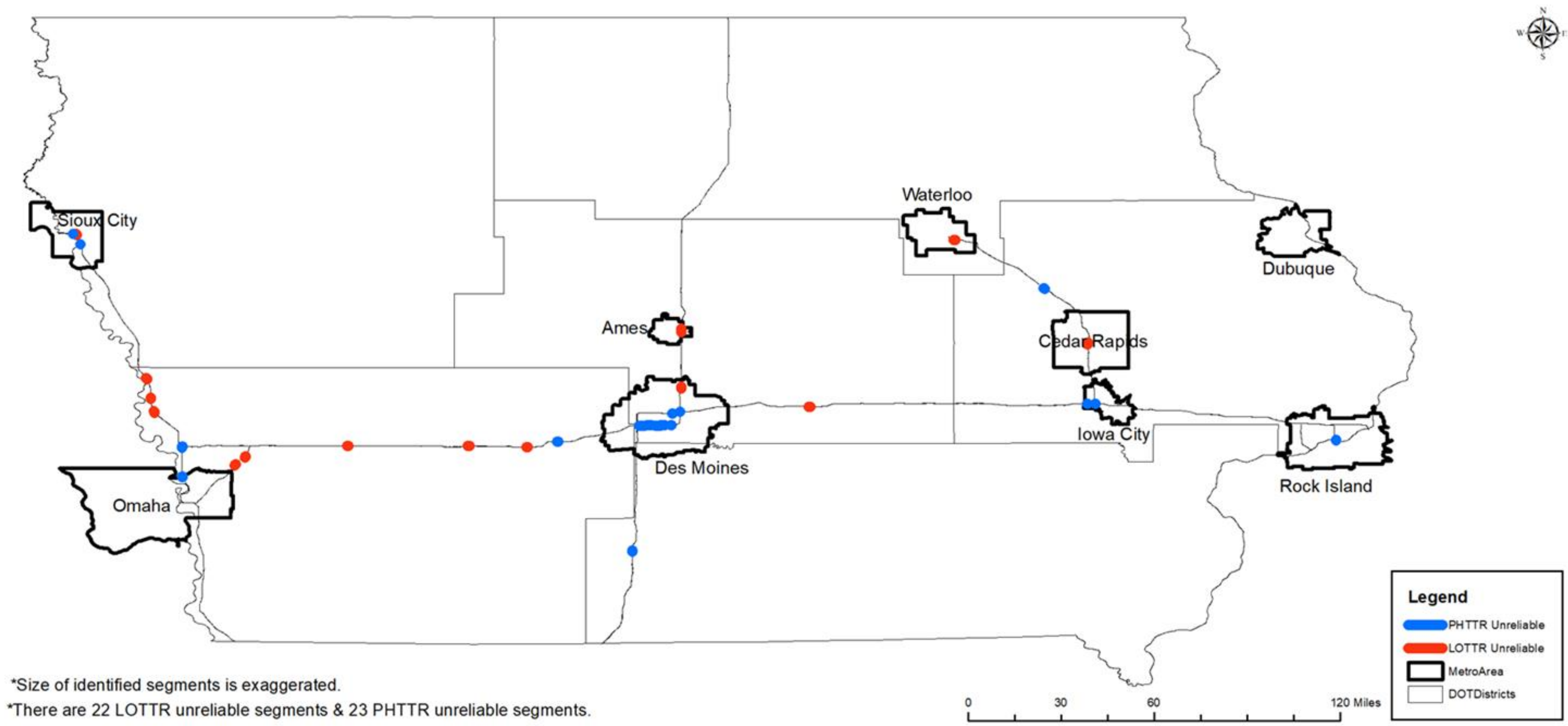


Figure 3.37 *Unreliable segments in Iowa according to PHTTR and LOTTR.*

Table 3.8 *Summary of the top 10 unreliable segments in Iowa according to PHTTR and LOTTR.*

Top 10 Most Unreliable Segments (LOTTR)				
Rank	Segment ID	Route	LOTTR	*PHTTR (Rank)*
1	1485698310	I-380S	2.46	*1.53 (21)*
2	1485513416	I-35S	2.41	*1.56 (18)*
3	1485616120	I-35S	2.21	*1.41 (31)*
4	1485817663	I-380S	2.21	*1.15 (225)*
5	1485690186	I-80W	1.96	*1.43 (28)*
6	1485696970	I-380S	1.90	*1.40 (30)*
7	1485697849	I-380S	1.87	*1.34 (40)*
8	1485581318	I-380N	1.80	*1.27 (68)*
9	1485770672	I-80E	1.79	*1.30 (52)*
10	1485715216	I-29N	1.72	*1.32 (46)*
*Rank out of 2746 segments across Iowa.				

Top 10 Most Unreliable Segments (PHTTR)				
Rank	Segment ID	Route	PHTTR	*LOTTR (Rank)*
1	1485859264	I-235N	2.09	*1.08 (120)*
2	1485852299	I-235S	1.91	*1.06 (170)*
3	1485517139	I-80W	1.91	*1.04 (510)*
4	1485737932	I-29S	1.90	*1.04 (751)*
5	1485698144	I-380S	1.90	*1.08 (122)*
6	1485897987	I-680E	1.88	*1.08 (110)*
7	1485764384	I-235N	1.82	*1.05 (346)*
8	1485852719	I-235S	1.73	*1.09 (105)*
9	1485520730	I-235N	1.67	*1.05 (385)*
10	1485521372	I-29N	1.66	*1.11 (91)*
*Rank out of 2746 segments across Iowa.				

Figure 3.38 (LOTTR) and Figure 3.39 (PHTTR) show choropleths maps of Iowa for each metric. Each figure shows the southbound and westbound directions. Northbound and eastbound directions can be displayed using the same methodology. LOTTR has an interesting “ring” of unreliability appear around an approximately 30-40 radius around the Des Moines area. I-80 (both east and west of Des Moines) and I-35 (both north and south of Des Moines) have small patches of unreliability. Much of the state appears to be quite reliable according LOTTR, with mainly isolated unreliable segments scattered throughout the state. PHTTR has a much “choppier” look in its choropleth maps, with many more unreliable segments sprinkled throughout the state. The Sioux City area and, to a much greater extent, the Des Moines area appear to have slightly more concentrated areas of unreliability compared to other areas of the state.

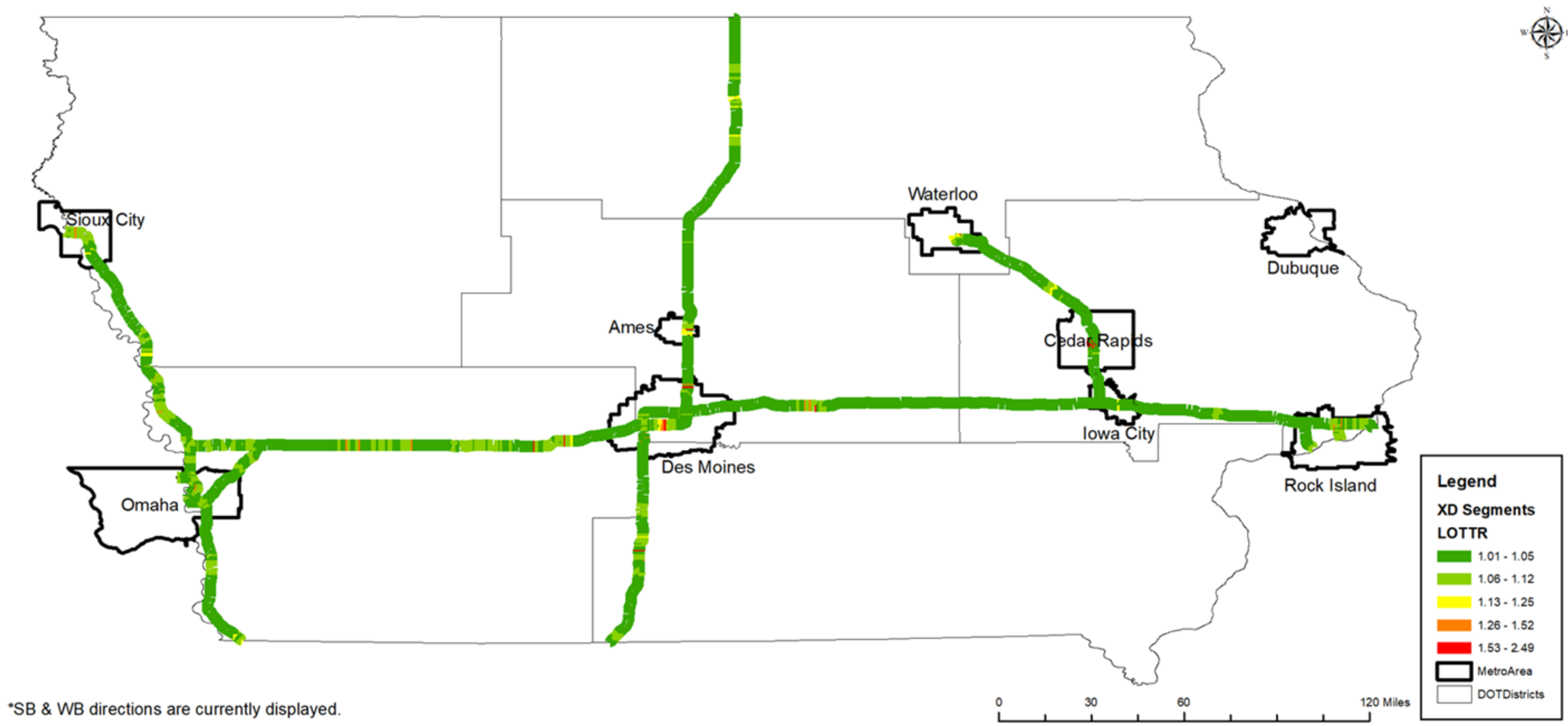


Figure 3.38 *Choropleth map of LOTTR for Iowa.*

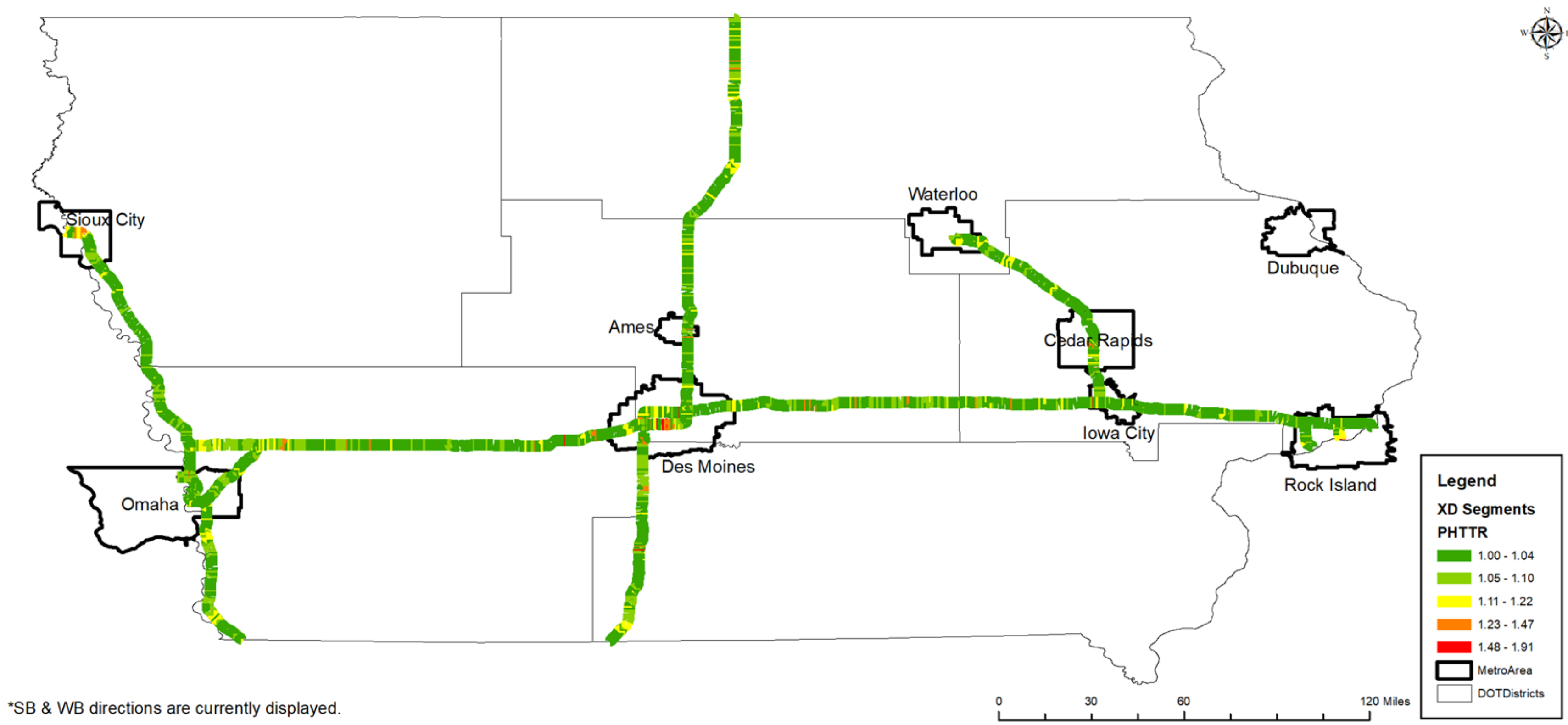


Figure 3.39 *Choropleth map of PHTTR for Iowa.*

3.6.2 SD_{tti}, PR, and BTI

Like that of the Des Moines area application, choropleth maps and the identification of the most extreme unreliable segments will be displayed for each of the three different reliability metrics (SD_{tti}, PR, and BTI). For the choropleth maps, it is worth noting that, since they show the entire state, individual segments with high unreliability may or may not show up clearly. However, larger stretches of unreliability can be detected.

Figure 3.40 shows a choropleth map of Iowa for SD_{tti} (for southbound and westbound directions). Many of the urban areas throughout Iowa appear to have higher levels of unreliability than the rural areas. Des Moines, the quad cities (Rock Island area), and I-380 in the Iowa City appear to be particularly unreliable according to SD_{tti}.

Figure 3.41 shows a similar choropleth map of Iowa for PR. There does not appear to be as long of stretches of highway identified as unreliable when compared to SD_{tti}. Instead, there seems to be specific hot-spots of unreliability scattered around the state. I-80W to the west of Des Moines does appear to have many stretches identified as at least moderately unreliable.

Figure 3.42 shows a choropleth map of Iowa for BTI. BTI shows most of Iowa as very reliable except for some of the Des Moines area and a few isolated small stretches throughout the state. Other than Des Moines, it does not appear that rural areas are any more or less reliable than urban areas.

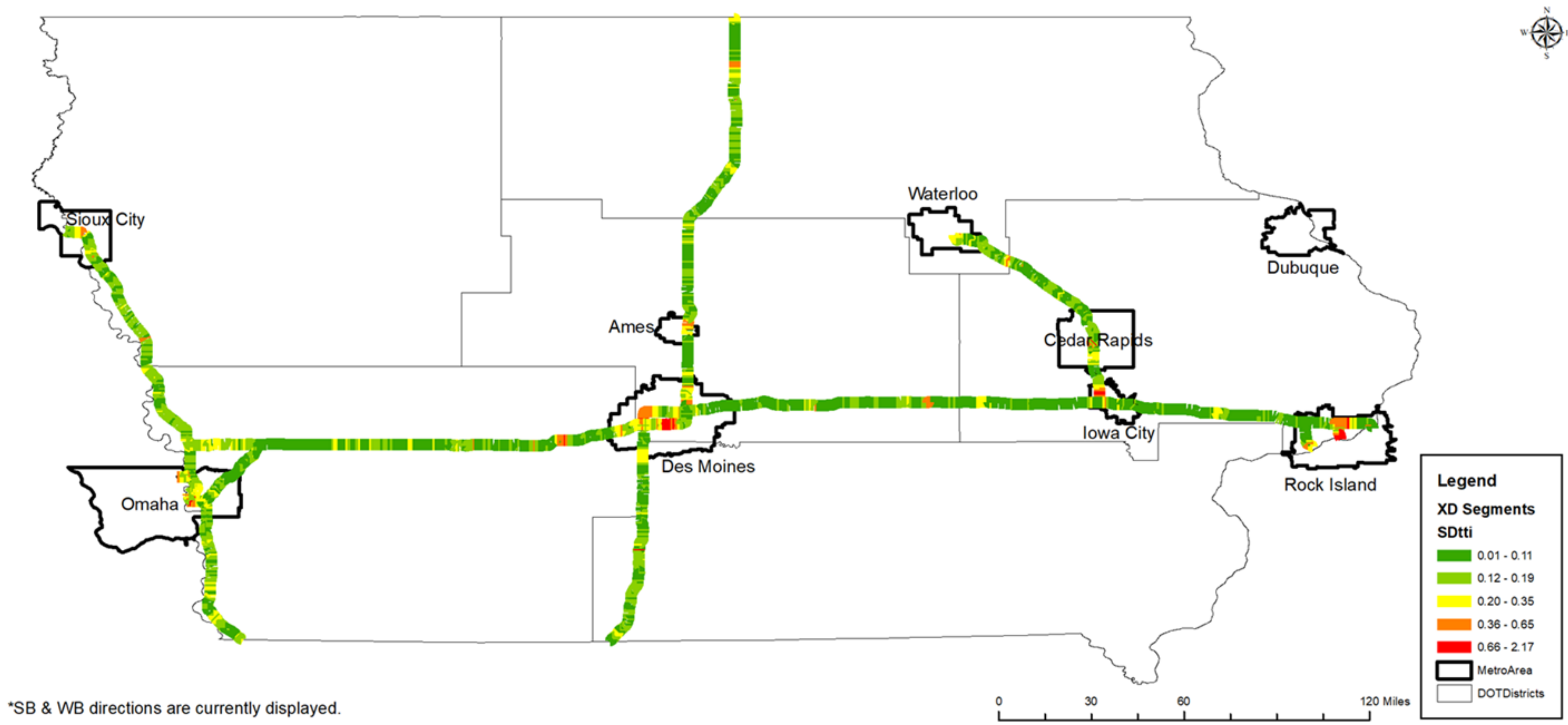


Figure 3.40 *Choropleth map of SD_{tti} for Iowa.*

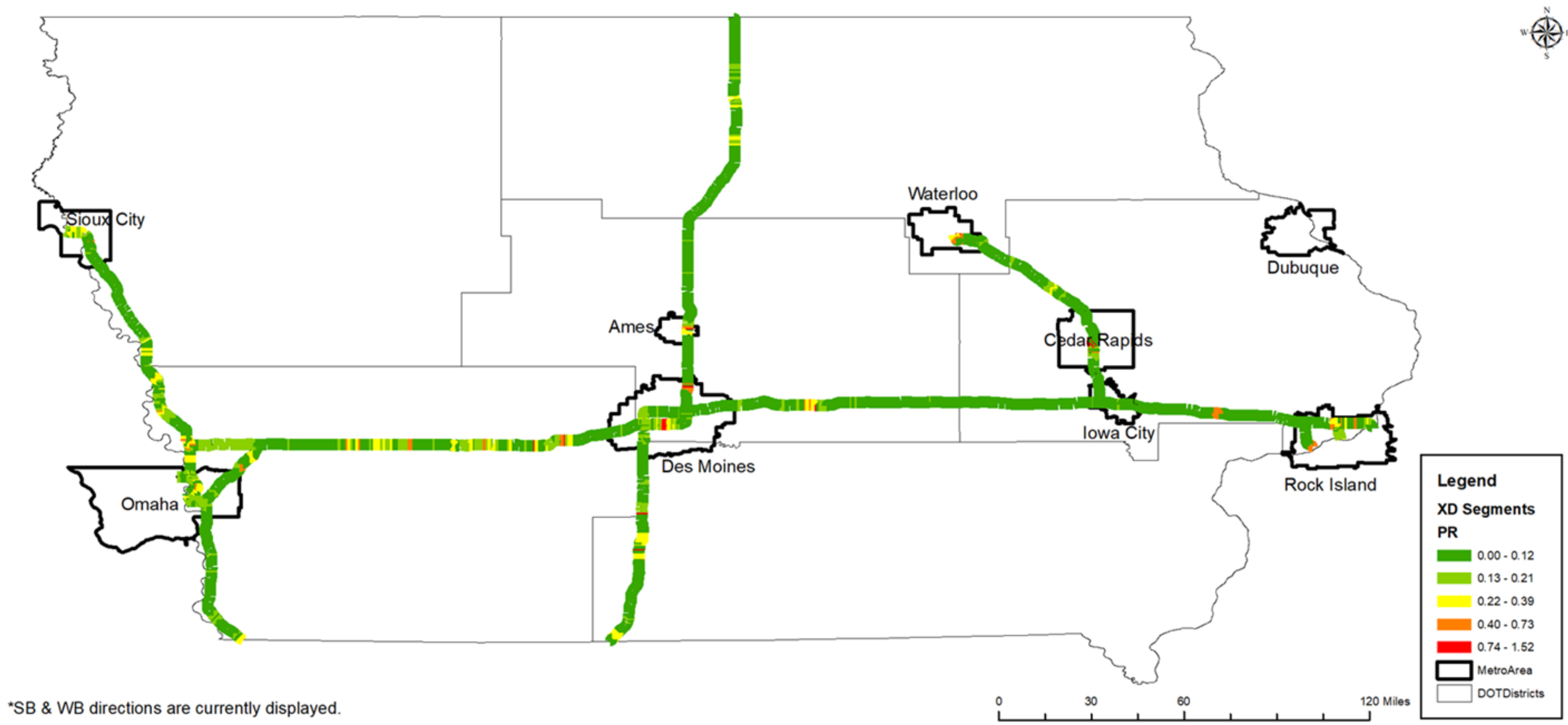


Figure 3.41 *Choropleth map of PR for Iowa.*

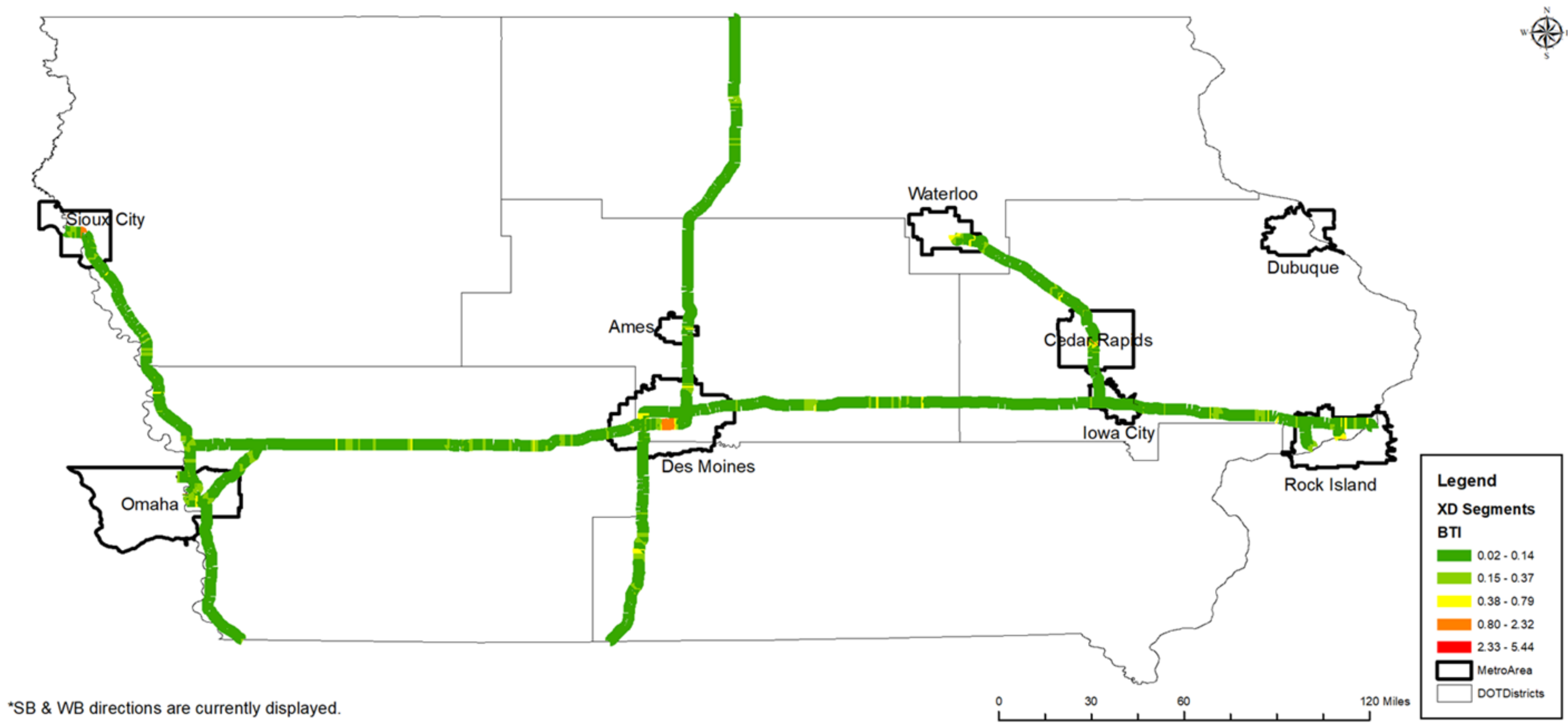


Figure 3.42 *Choropleth map of BTI for Iowa.*

Similar to the Des Moines area, the segment with the most extreme unreliability metric values in relation to other segments in the analysis zone were identified. For the state of Iowa, the top 10 most unreliable segments were identified according to SD_{tti}, PR, and BTI.

Figure 3.43 identified the top 10 most unreliable segments in Iowa according to SD_{tti} on a map. Table 3.9 provides additional information about these 10 segments. All 10 segments appear in or near urban areas. Three of the top 10 segments appear on I-680 near Omaha, despite I-680 not being a particularly long interstate in relation to interstates such as I-80, I-35, and I-29. The Des Moines area has 3 of the top 10 most unreliable segments in the state, with the segment on I-35S identified earlier as the most unreliable segment in the Des Moines metro also being the most unreliable segment across the state. None of the segments appearing the top 10 for SD_{tti} are even in the top 100 for PR. The second most reliable segment according to SD_{tti} actually ranks as the 10^{th} most reliable segment in the state according to BTI. However, SD_{tti} and BTI do share 2 segments in their top 10 most unreliable lists.

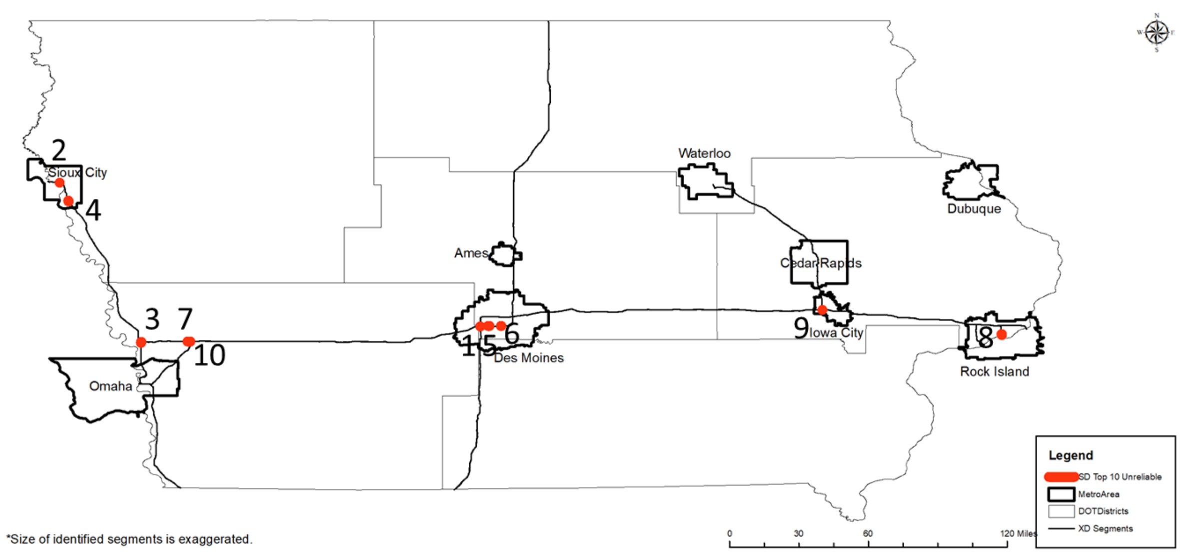


Figure 3.43 *Top 10 most unreliable segments map for Iowa according to SD_{tti}.*

Table 3.9 *Top 10 most unreliable segments information for Iowa (SD_{tti}).*

Rank	Segment ID	Route	SDtti	*PR (Rank)*	*BTI (Rank)*
1	1485465513	I-35S	2.19	*0.12 (548)*	*5.53 (1)*
2	1485737932	I-29S	1.65	*0.13 (457)*	*0.02 (2736)*
3	1485897987	I-680E	1.61	*0.26 (171)*	*0.48 (69)*
4	153882812	I-29N	1.50	*0.27 (168)*	*0.63 (39)*
5	1485859264	I-235N	1.33	*0.36 (103)*	*0.67 (35)*
6	1485852299	I-235S	1.19	*0.3 (141)*	*1.10 (10)*
7	1485621159	I-680E	0.99	*0.17 (294)*	*0.15 (376)*
8	1485780063	I-74E	0.97	*0.17 (303)*	*0.15 (379)*
9	1485698144	I-380S	0.91	*0.36 (101)*	*1.43 (6)*
10	1485676686	I-680E	0.89	*0.24 (194)*	*0.17 (326)*
*Rank out of 2746 segments across Iowa.					

Figure 3.44 shows the top 10 most unreliable segments in Iowa according to PR with Table 3.10 providing additional information about these segments. Most of the segments were located in or around urban areas with the exception of a few rural segments. 7 of the 10 segments were located roughly in the central Iowa area in and surrounding Des Moines. The only segment in the PR top 10 list which is shared with another metric's top 10 list is an I-380S segment which ranked 4th for BTI and 4th for PR. However, all of top 10 most unreliable segments identified by PR rank in at least the top 100 for both SD_{tti} and BTI with one minor exception (the 10th ranked PR segment ranks 120th using BTI).

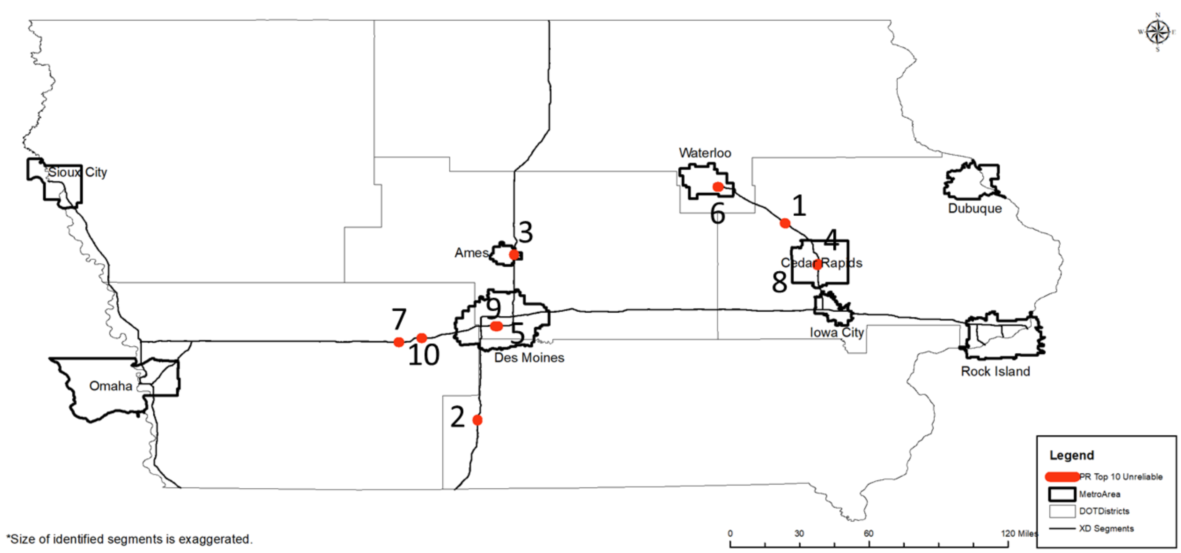


Figure 3.44 *Top 10 most unreliable segments map for Iowa according to PR.*

Table 3.10 *Top 10 most unreliable segments information for Iowa (PR).*

Rank	Segment ID	Route	PR	*SDtti (Rank)*	*BTI (Rank)*
1	1485698310	I-380S	1.61	*0.76 (20)*	*0.69 (31)*
2	1485513416	I-35S	1.52	*0.72 (29)*	*0.67 (36)*
3	1485616120	I-35S	1.25	*0.59 (57)*	*0.56 (56)*
4	1485817663	I-380S	1.16	*0.81 (16)*	*1.65 (4)*
5	1485852735	I-235S	1.11	*0.75 (23)*	*0.9 (21)*
6	1485696970	I-380S	1.11	*0.52 (90)*	*0.52 (61)*
7	1485690186	I-80W	1.09	*0.51 (94)*	*0.5 (66)*
8	1485697849	I-380S	1.02	*0.54 (81)*	*0.45 (75)*
9	1485852747	I-235S	0.92	*0.77 (19)*	*0.99 (14)*
10	1485689862	I-80W	0.92	*0.75 (21)*	*0.36 (120)*

*Rank out of 2746 segments across Iowa.

Figure 3.45 shows a map of Iowa displaying the location of the top 10 most unreliable segments according to BTI. Table 3.11 shows additional information regarding these 10 segments. All of the top 10 segments are located in urban areas with 4 of them being located in Des Moines and 4 of them being located in the Iowa City and Cedar Rapids corridor. The segment with the abnormally high BTI value that was examined in detail in the Des Moines area application ranks number 1 in the state again. It has a BTI value nearly double that of the second most unreliable segment in the state. SD_{tti} and BTI share 3 segments in their top 10 segment lists. However, many of the segments in the top 10 list for BTI do not rank very highly when utilizing PR, with two segments even ranking below 2000th for PR out of 2,756 segments across the state.

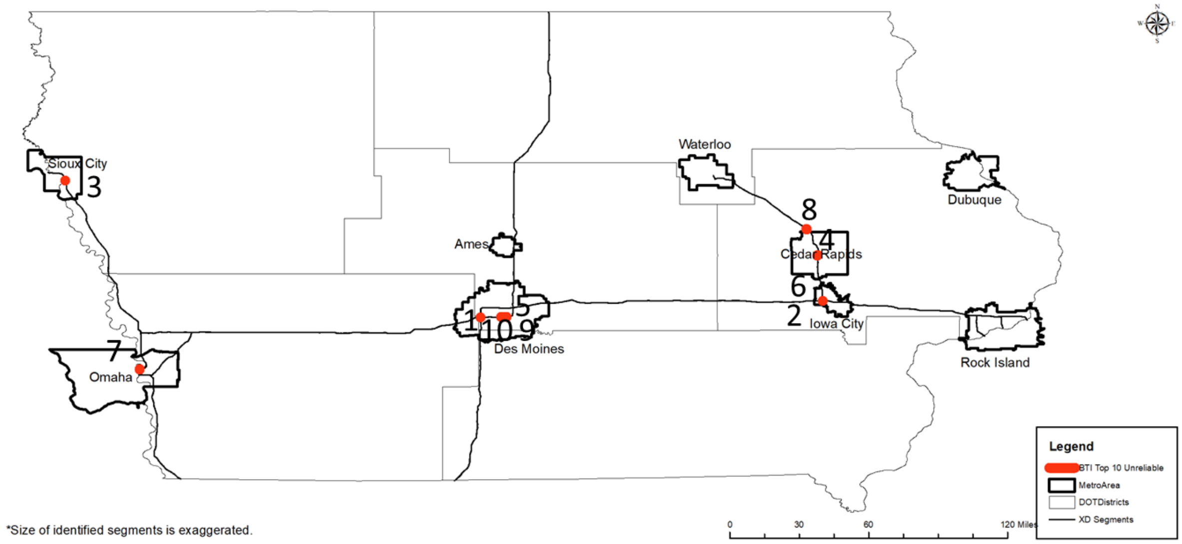


Figure 3.45 *Top 10 most unreliable segments map for Iowa according to PR.*

Table 3.11 *Top 10 most unreliable segments information for Iowa (BTI).*

Rank	Segment ID	Route	BTI	*SDtti (Rank)*	*PR (Rank)*
1	1485465513	I-35S	5.53	*2.19 (1)*	*0.12 (548)*
2	1485710503	I-80W	2.34	*0.79 (18)*	*0.08 (2284)*
3	1485715404	I-29N	2.28	*0.48 (113)*	*0.27 (164)*
4	1485817663	I-380S	1.65	*0.81 (16)*	*1.16 (4)*
5	1485604287	I-235N	1.51	*0.58 (62)*	*0.14 (393)*
6	1485698144	I-380S	1.43	*0.91 (9)*	*0.36 (101)*
7	1485540064	I-29S	1.18	*0.29 (286)*	*0.07 (2554)*
8	1485698562	I-380S	1.11	*0.35 (201)*	*0.10 (846)*
9	1485852313	I-235S	1.11	*0.63 (42)*	*0.13 (422)*
10	1485852299	I-235S	1.10	*1.19 (6)*	*0.30 (141)*

*Rank out of 2746 segments across Iowa.

3.7 Summary

In Chapter 3, the computational process used for calculating 10 different travel time reliability metrics was explained. Once these travel time reliability metrics were computed, they were subjected to direct comparison with each other using a variety of approaches including graphical and spatial visualizations. As a result of this comparison process, three distinct groups emerged where the metrics exhibited similar results to one another within their own group. This allowed for three specific metrics to be selected for further application which all quantified uniquely different aspects of travel time reliability. These metrics included the standard deviation of travel time indexes (SD_{tti}), the 15^{th} to 85^{th} percentile range of travel time indexes (PR), and the buffer time index (BTI).

In addition to these three metrics, the level of travel time reliability and the peak hour travel time reliability metrics from the FHWA were also utilized in further application. These metrics were applied to the Des Moines area specifically as well as to the entire state of Iowa using PM peak data. Assessments were made using a variety of techniques including identifying unreliable segments according to a set threshold (for LOTTR and PHTTR), displaying choropleth maps, and identifying the top 5 (in the case of the Des Moines area) or the top 10 (in the case of the state of Iowa) most unreliable segments according to each metric. Choropleth maps seemed to be particularly useful tools for effectively assessing travel time reliability.

When applying the travel time reliability metrics to the Des Moines area, detailed travel time data views were utilized. These data views display all the observed travel times throughout the year for some of the most unreliable and most reliable segments according to the different metrics. These data views helped display why some segments had high unreliability. SD_{tti} and BTI seemed to be particularly sensitive to any abrupt changes in the base travel time during the year and are also more sensitive to outliers.

Given that choropleth maps were such a crucial visualization tool utilized in this report, examining the way the data was classified into different categories in these maps (i.e. what metric value constitutes being displayed as green, yellow, orange, red, etc.) was important. Just comparing two different data classification techniques (quantiles and Jenks) showed that data classification methodology has a profound impact on how the network performance is perceived. It was found that using Jenks data classification method provided the most appropriate visualizations of travel time reliability when compared to using quantiles.

The effect of aggregating the probe vehicle data from INRIX on computational time, data storage, and travel time reliability metric integrity was assessed. It was found that aggregating the speed and travel time data in 5-minute time bins struck an optimal balance between greatly reducing data storage and computation time while still mostly maintain travel time reliability metric integrity.

A short comparison between the travel time reliability metric assessments across the different analysis time periods was conducted. This comparison found that many segments had their worst reliability during the weekends. However, the PM peak had some of the worst reliability values for the top 5% of segments. More in depth review of travel time reliability values across different time periods is certainly possible in future research. Additionally, this study only fully applied travel time reliability metrics across the Des Moines area and Iowa using the PM peak time period. Performing some of the same application techniques used in this study for PM peak for other time periods might produce interesting results. It is also possible to adjust the times of day these analysis time periods cover, as this study just drew from FHWA defined time periods used for computing LOTTR.

CHAPTER 4. DEVELOPMENT OF COMPOSITE RELIABILITY METRICS

4.1 Introduction

In Chapter 3, various travel time reliability metrics were compared with one another. Through this process, three groups of similar metrics were identified that yielded similar outcomes when applied to segment-level assessment of travel time reliability on Iowa's interstate network. These three metrics, when used independently to assess reliability, clearly displayed different looking results from one another. This is because, through their different definitions and computational formulas, they quantify different but equally important aspects of travel time reliability. Rather than trying to assess reliability for a network using several different metrics independently, it might be easier to convey reliability more efficiently through the use of a single composite reliability metric. This study will develop, apply, and compare composite reliability metrics using the three unique travel time reliability metrics there were extensively applied in Chapter 3. These three metrics were the standard deviation of travel time indexes (SD_{tti}), the 15^{th}-85^{th} percentile range of travel time indexes (PR), and the buffer time index (BTI). PM peak data will be used.

4.2 Computing Composite Reliability Metrics

A previous study was done which ranked the performance of arterial corridors by creating a composite index incorporating both average travel time and travel time reliability characteristics (Day et al., 2015). The methodology that was used for developing composite indexes in that study directly inspired the methodology conducted in this study for developing composite travel time reliability metrics.

First, all segment values for each of the different travel time reliability metrics were normalized using the maximum observed value on a segment in the state of Iowa for the given travel time reliability metric. After doing so, each of the three metrics was transformed such that its values fell within a range between 0 and 1.

Figure 4.1 shows a scatterplot of PR vs. SD_{tti}, with both metrics being normalized. Figure 4.2 shows a similar scatterplot for PR vs. BTI and Figure 4.3 shows a scatterplot of BTI vs. SD_{tti}. A point on one of these plots, Figure 4.1 for example, represents one segment's SD_{tti} value on the x-axis and PR value on the y-axis. It is assumed that the farther a segment's point on one of these scatterplots lies from the origin, the more unreliable that segment is according to both metrics utilized in the scatterplot. From this principle, using the equation for the length of a line between two points on a coordinate system, an equation can be developed for a composite reliability metric. That equation looks like the following when utilizing 2 metrics:

$$\text{Composite Metric} = \sqrt{x^2 + y^2}$$

In this equation, x and y would represent the value of each of the different reliability metrics for that segment. A similar process could be followed for combining three different reliability metrics by simply adding a z^2 term under the radical. Figure 4.4 shows a 3D scatterplot of SD_{tti}, PR, and BTI, again with all metrics being normalized.

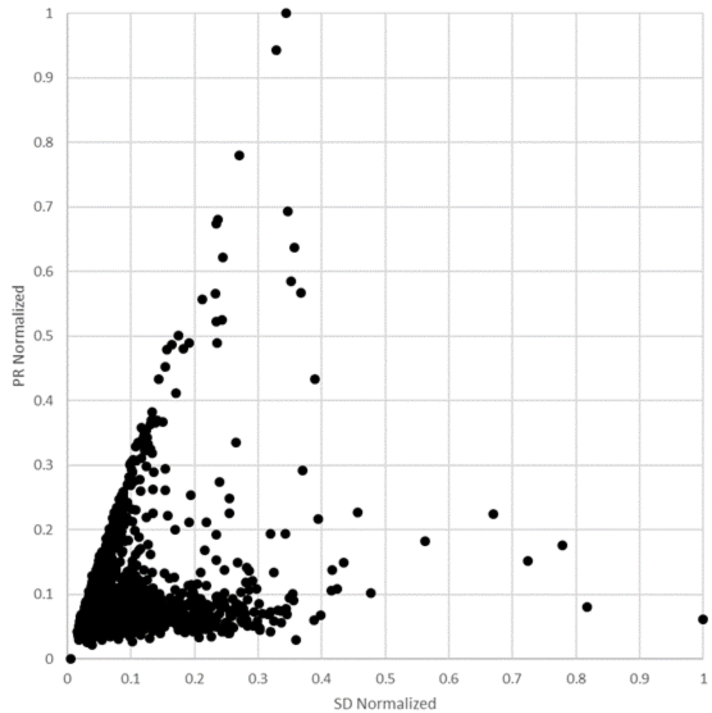


Figure 4.1 *Scatterplot of normalized PR vs. normalized SD_{tti}.*

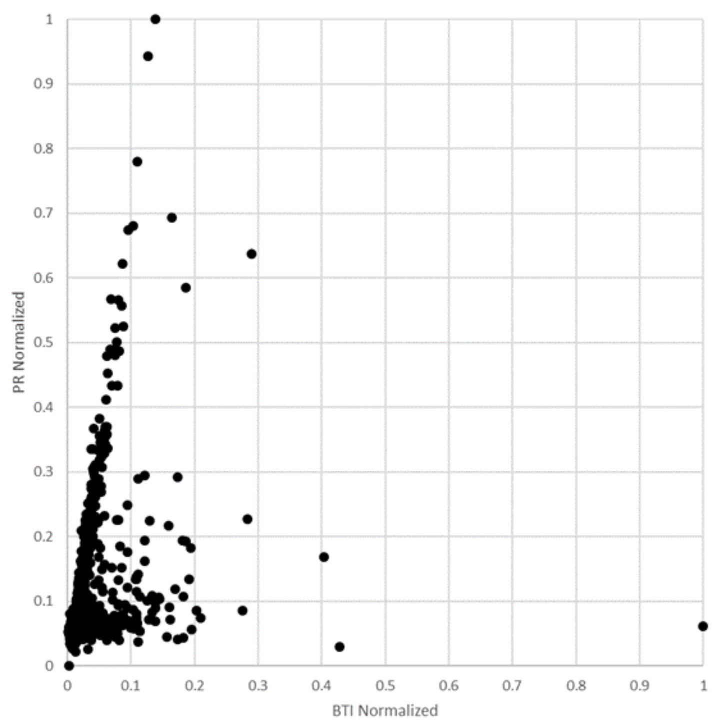


Figure 4.2 *Scatterplot of normalized PR vs. normalized BTI.*

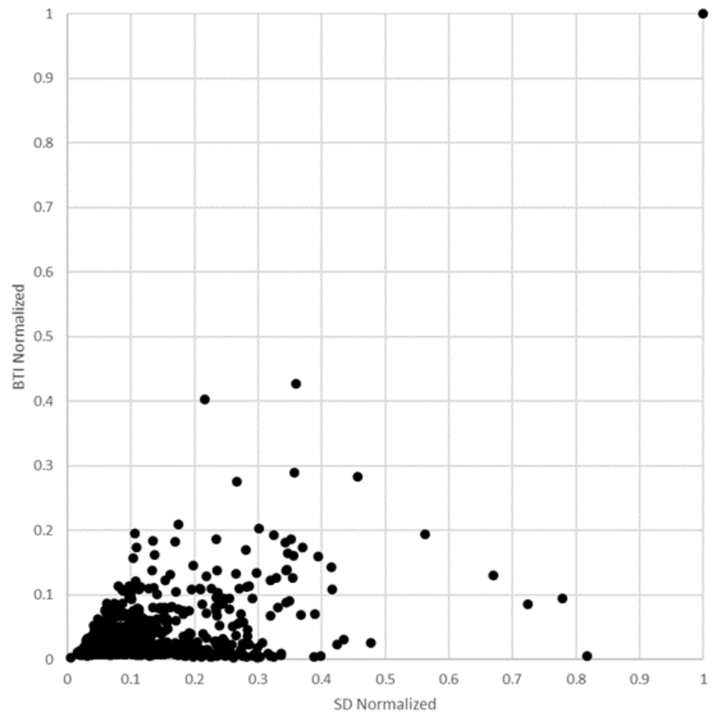


Figure 4.3 *Scatterplot of normalized BTI vs. normalized SD_{tti}.*

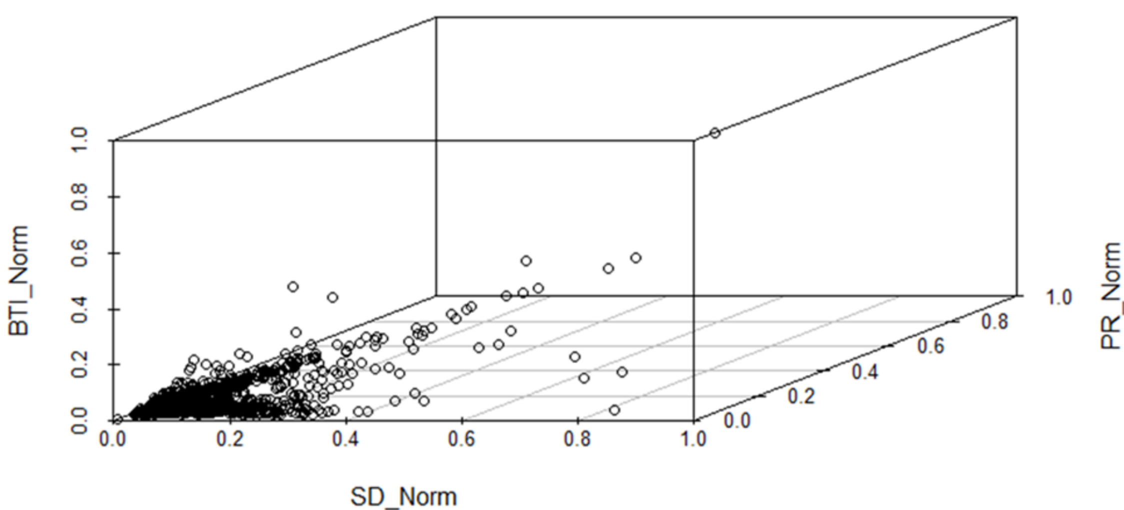


Figure 4.4 *3D Scatterplot of normalized SD_{tti}, normalized PR, and normalized BTI.*

4.3 Assessing and Visualizing the Composite Metrics

Four composite reliability metrics were developed in this study. These four composite reliability metrics are SD-PR, PR-BTI, BTI-SD, and 3M (which stands for 3 metric composite). Perhaps the best way to assess and compare these composite reliability metrics is to apply them to real-world segments both in the Des Moines area and throughout Iowa.

Figure 4.5 shows a choropleth map of Iowa displaying SD-PR for southbound and westbound directions during PM peak. According to SD-PR, the urban areas usually have sections of higher unreliability. I-235 in Des Moines appears to have abnormally high amounts of unreliability in comparison to routes in other portions of Iowa. There are isolated segments with higher unreliability, particularly in portions of I-80W between Omaha and Des Moines.

Figure 4.6 shows a similar choropleth map of Iowa for PR-BTI. PR-BTI seems to show slightly less unreliable portions in urban areas when compared to the map of SD-PR, but overall the two maps look somewhat similar. I-235 in Des Moines still has some high levels of unreliability.

Figure 4.7 shows a choropleth map of SD-BTI. SD-BTI seems to identify the Des Moines area as slightly more unreliable again, like that which was seen with SD-PR. However, overall the map looks very similar to the two previous maps of SD-PR and PR-BTI.

Figure 4.8 shows a choropleth map of the 3-metric composite (3M). Note how extremely similar this map appears to be in comparison to the SD-PR map. In fact, the two maps appear to be almost undisguisable. The relationship between these two composite metrics will be more closely examined shortly through other applications.

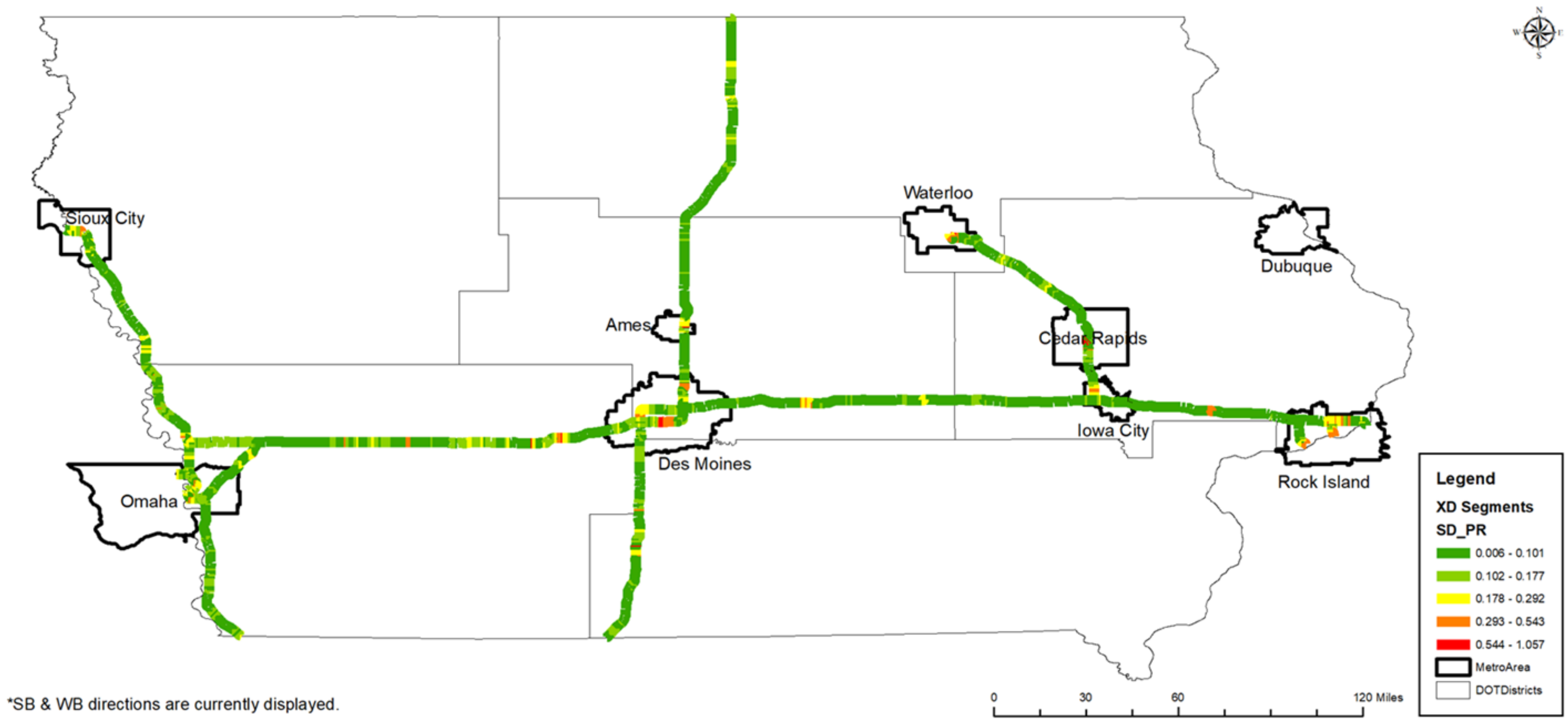


Figure 4.5 *Choropleth map of SD-PR in Iowa.*

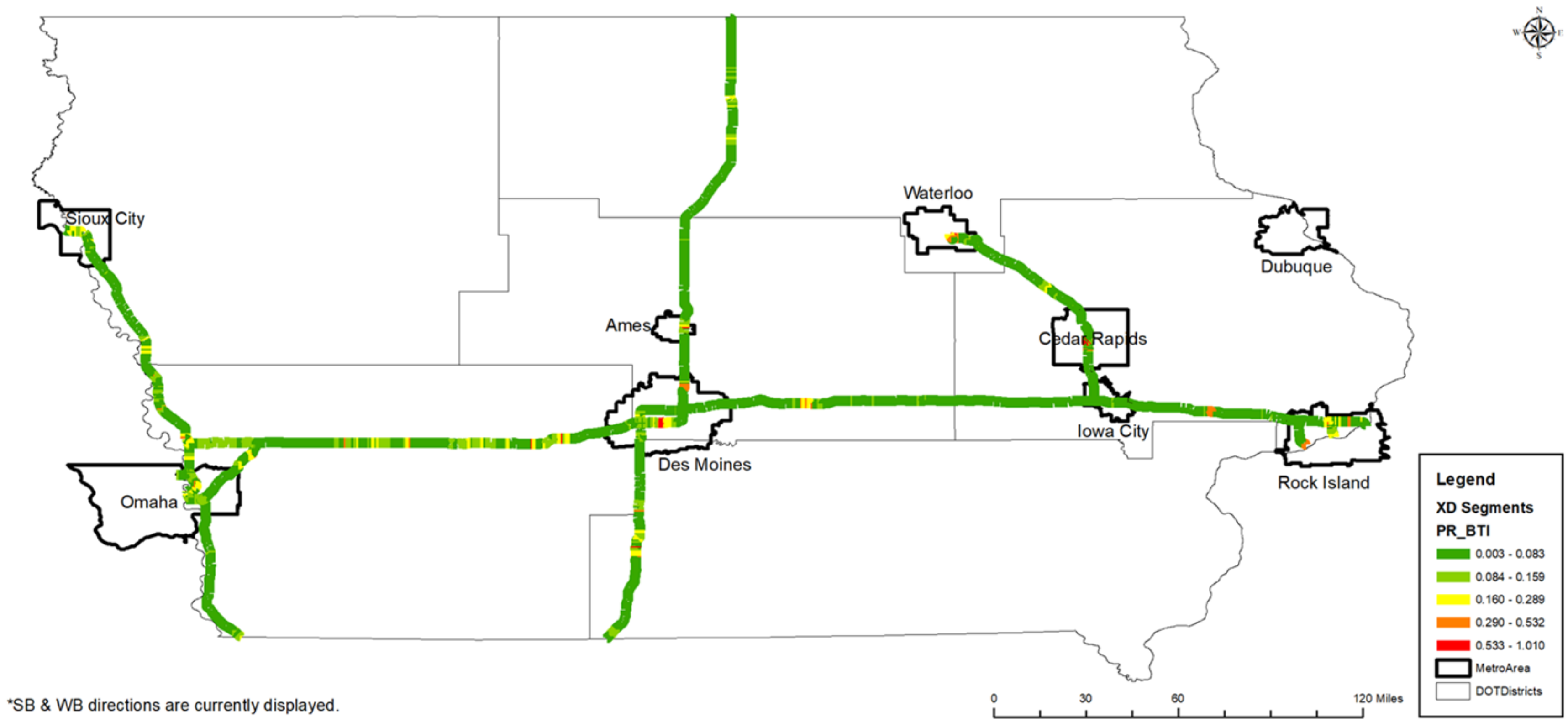


Figure 4.6 *Choropleth map of PR-BTI in Iowa.*

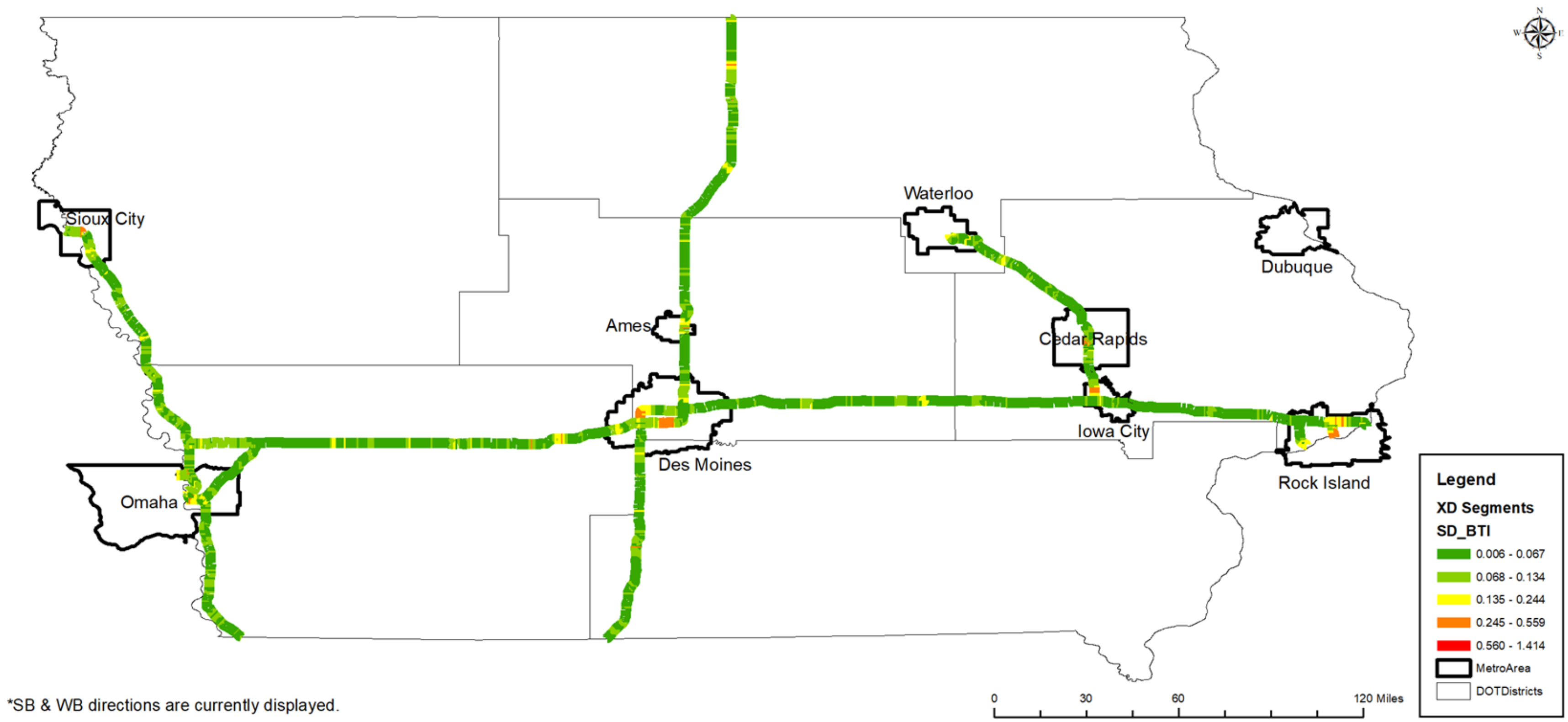


Figure 4.7 *Choropleth map of SD-BTI in Iowa.*

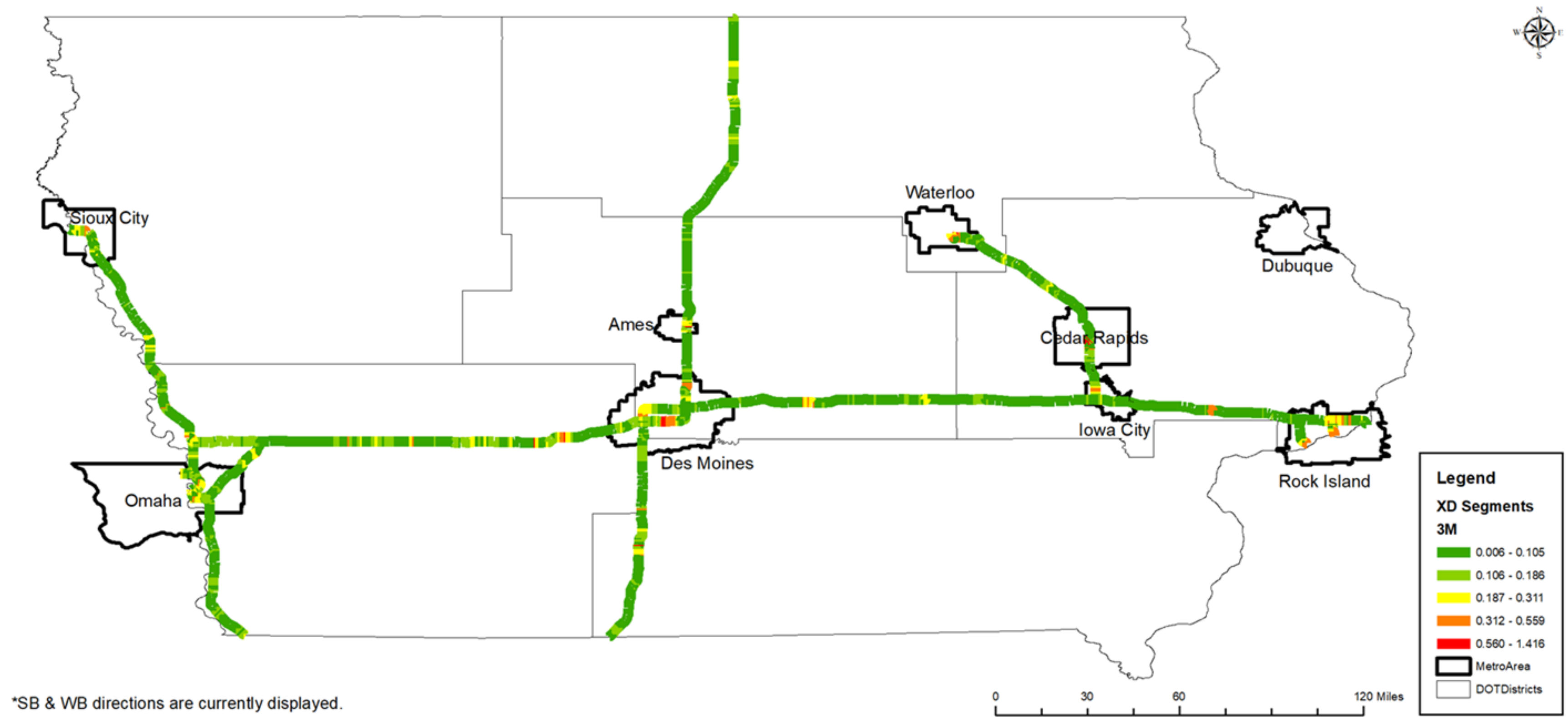


Figure 4.8 *Choropleth map of 3M in Iowa.*

An effective way to compare the new composite metrics with not only each other, but also against the original metrics, is to show side-by-side comparisons of travel time reliability choropleths maps of Des Moines. This is shown in Figure 4.9, which displays the northbound and eastbound directions. When looking at the original metrics, it appears that BTI is showing levels of reliability roughly between that of SD_{tti} (which shows higher levels of unreliability) and PR (which shows very low amounts of unreliability). This could explain why the three-metric composite (3M) results look very similar to the SD-PR composite. If BTI typically gives reliability estimates roughly between that of SD_{tti} and PR, it could explain why there is not much difference between 3M and SD-PR. However, if this were the case, SD-PR would have the potential to look very similar to the BTI on its own. Upon comparing the choropleth maps for SD-PR and BTI, while they do appear to be roughly similar, SD-PR shows higher spikes of unreliability when compared to BTI. The PR-BTI composite metric exhibits different outcomes from the other composite metrics, showing generally low levels of unreliability in the Des Moines area.

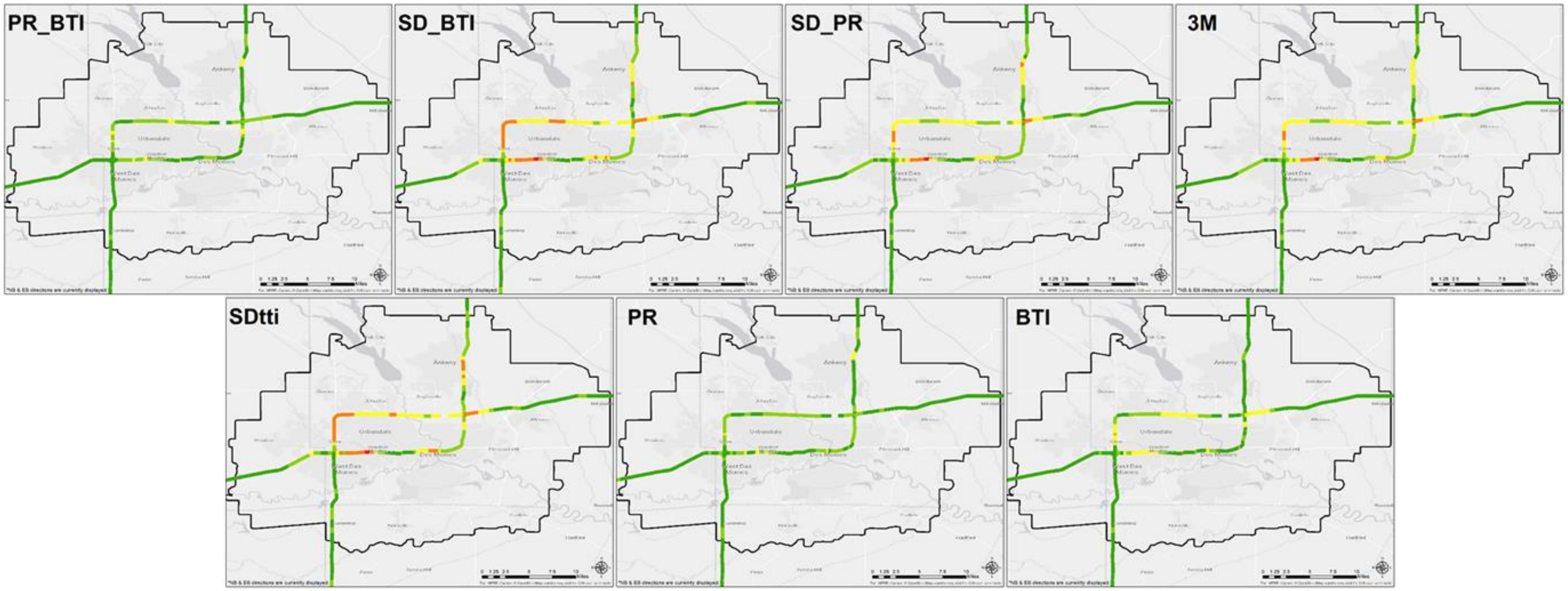


Figure 4.9 *Comparison of the new composite metrics and original metrics using choropleth maps of the Des Moines area.*

Figure 4.10 shows how reliability progresses along I-80E segments for the three-original metrics (in red) and the four different composite metrics (in blue). Similar to the choropleth maps, 3M and SD-PR exhibit considerable similarity. Figure 4.11 shows a scatterplot of 3M vs. SD-PR that shows how similar the two different composite metrics are to one another. Most of the points in the scatterplot are along a 45-degree line, and the R^2 value is 0.985. In other words, 3M is almost identical to SD-PR, meaning there is no value to combining a third metric. It is also clear that SD-PR does not provide similar results to BTI alone, as the two progression lines for I-80E have clear differences. Since the composite of SD_{tti} and PR looks nearly identical to that of the composite where all three metrics are considered, this will be the selected composite metric moving forward for some further assessments.

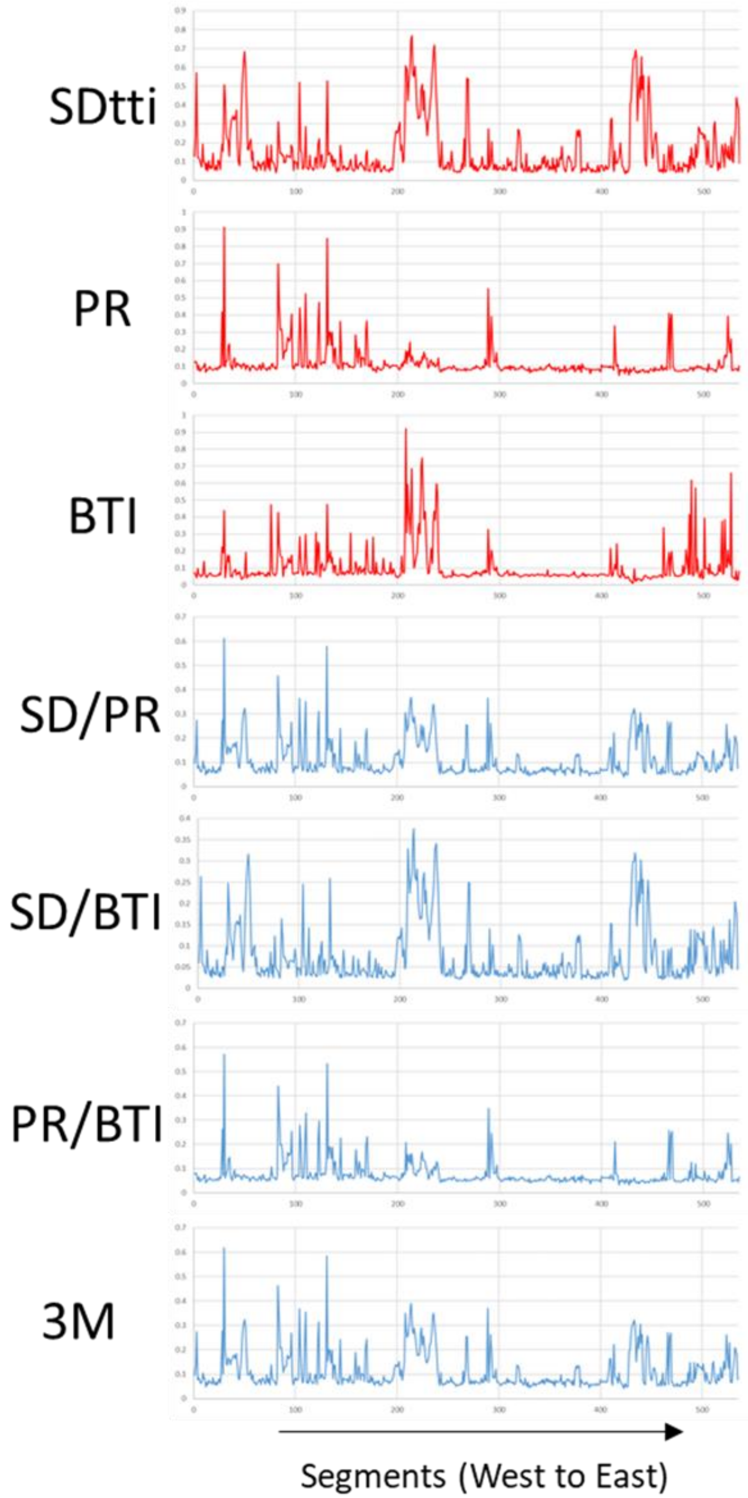


Figure 4.10 *Comparison of the new composite metrics and original metrics using progression along I-80E.*

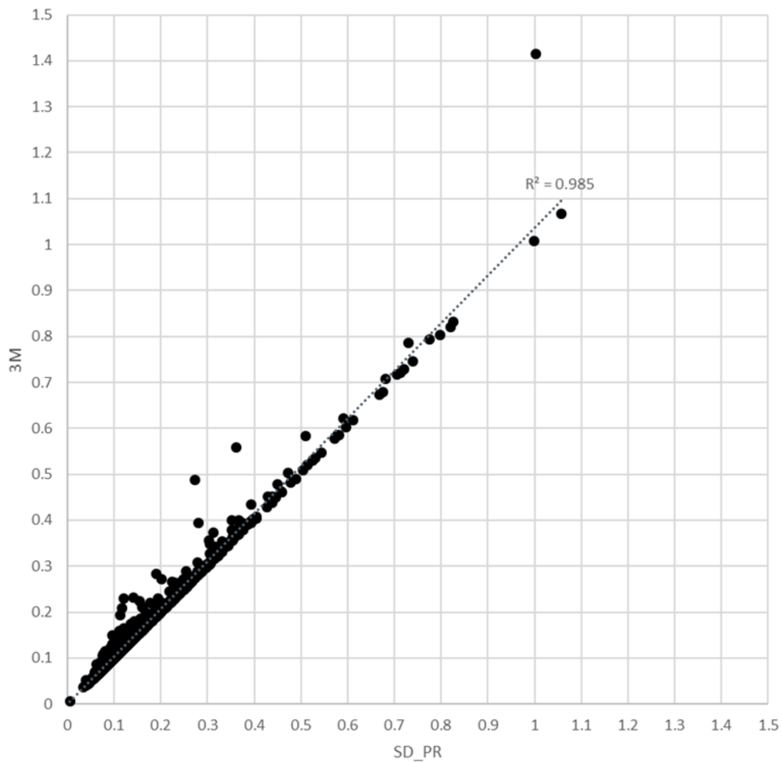


Figure 4.11 *Scatterplot of 3M vs. SD-PR.*

Figure 4.12 shows a map of the top 10 most unreliable segments in Iowa according to SD-PR. Table 4.1 shows additional information about these 10 segments, including what their values and statewide ranks were for the original 3 reliability metrics. Most of the top 10 unreliable segments in Iowa are in or near urban areas dispersed around the state. Most of the segments listed in the top 10 for SD-PR are also ranked in the top 100 for at least 2 of the original metrics. Several of the top 10 ranked segments for the individual metrics made the top 10 for SD-PR including the top 6 for PR, the top 4 for SD_{tti}, and 3 of the top 4 for BTI. Table 4.2 (SD_{tti}), Table 4.3 (PR), and Table 4.4 (BTI) revisit the top 10 most unreliable segments identified by each of those metrics and display their new reliability value and rank with the SD-PR composite metric. All the segments in the top 10 for SD_{tti} and PR appear in the top 40 for the new composite metric. However, 4 of the top 10 segments for BTI appear outside the top 100 for the SD-PR composite metric, with 2 segments even appearing outside the top 300 for SD-PR.

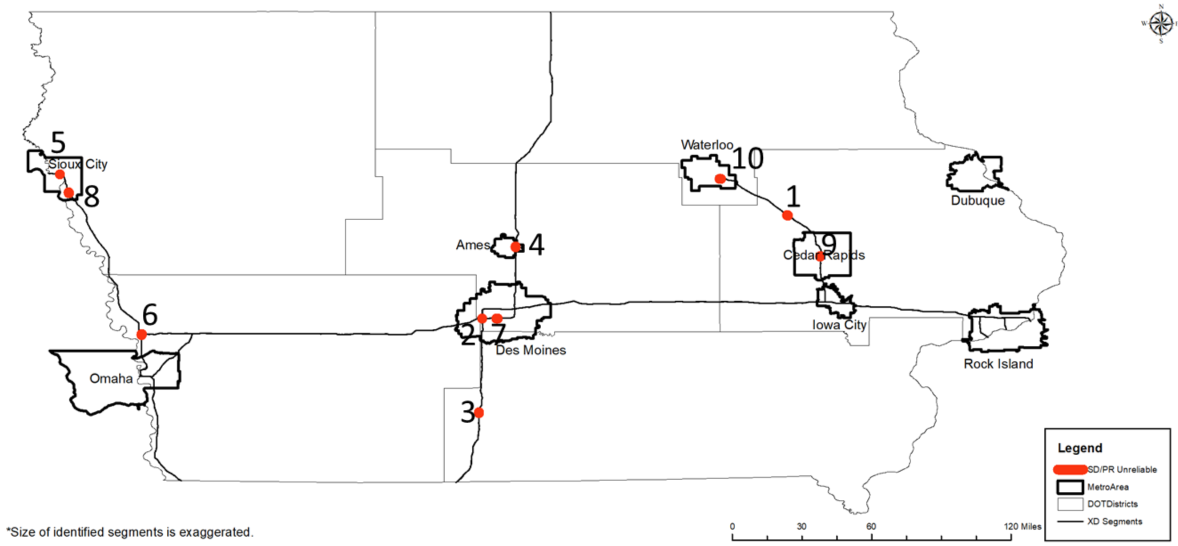


Figure 4.12 *Top 10 most unreliable segments in Iowa map according to SD-PR.*

Table 4.1 *Summary of the top 10 most unreliable segments in Iowa (SD-PR).*

Rank	Segment ID	Route	SD/PR	*SDtti (Rank)*	*PR (Rank)*	*BTI (Rank)*
1	1485698310	I-380S	1.06	*0.76 (20)*	*1.61 (1)*	*0.69 (31)*
2	1485465513	I-35S	1.00	*2.19 (1)*	*0.12 (548)*	*5.53 (1)*
3	1485513416	I-35S	1.00	*0.72 (29)*	*1.52 (2)*	*0.67 (36)*
4	1485616120	I-35S	0.83	*0.59 (57)*	*1.25 (3)*	*0.56 (56)*
5	1485737932	I-29S	0.82	*1.65 (2)*	*0.13 (457)*	*0.02 (2736)*
6	1485897987	I-680E	0.80	*1.61 (3)*	*0.26 (171)*	*0.48 (69)*
7	1485852735	I-235S	0.78	*0.75 (23)*	*1.11 (5)*	*0.90 (21)*
8	153882812	I-29N	0.74	*1.5 (4)*	*0.27 (168)*	*0.63 (39)*
9	1485817663	I-380S	0.73	*0.81 (16)*	*1.16 (4)*	*1.65 (4)*
10	1485696970	I-380S	0.72	*0.52 (90)*	*1.11 (6)*	*0.52 (61)*

*Rank out of 2746 segments across Iowa.

Table 4.2 *New composite metrics ranks for SD_{tti} top 10 most unreliable segments.*

Rank	Segment ID	Route	SDtti	*SD/PR (Rank)*
1	1485465513	I-35S	2.19	*1.00 (2)*
2	1485737932	I-29S	1.65	*0.82 (5)*
3	1485897987	I-680E	1.61	*0.8 (6)*
4	153882812	I-29N	1.50	*0.74 (8)*
5	1485859264	I-235N	1.33	*0.71 (12)*
6	1485852299	I-235S	1.19	*0.59 (18)*
7	1485621159	I-680E	0.99	*0.44 (37)*
8	1485780063	I-74E	0.97	*0.49 (29)*
9	1485698144	I-380S	0.91	*0.51 (27)*
10	1485676686	I-680E	0.89	*0.46 (32)*

*Rank out of 2746 segments across Iowa.

Table 4.3 *New composite metrics ranks for PR top 10 most unreliable segments.*

Rank	Segment ID	Route	PR	*SD/PR (Rank)*
1	1485698310	I-380S	1.61	*1.06 (1)*
2	1485513416	I-35S	1.52	*1.00 (3)*
3	1485616120	I-35S	1.25	*0.83 (4)*
4	1485817663	I-380S	1.16	*0.73 (9)*
5	1485852735	I-235S	1.11	*0.78 (7)*
6	1485696970	I-380S	1.11	*0.72 (10)*
7	1485690186	I-80W	1.09	*0.71 (11)*
8	1485697849	I-380S	1.02	*0.67 (15)*
9	1485852747	I-235S	0.92	*0.68 (13)*
10	1485689862	I-80W	0.92	*0.68 (14)*

*Rank out of 2746 segments across Iowa.

Table 4.4 *New composite metrics ranks for PR top 10 most unreliable segments.*

Rank	Segment ID	Route	BTI	*SD/PR (Rank)*
1	1485465513	I-35S	5.53	*1.00 (2)*
2	1485710503	I-80W	2.34	*0.36 (59)*
3	1485715404	I-29N	2.28	*0.27 (140)*
4	1485817663	I-380S	1.65	*0.73 (9)*
5	1485604287	I-235N	1.51	*0.28 (134)*
6	1485698144	I-380S	1.43	*0.51 (27)*
7	1485540064	I-29S	1.18	*0.14 (536)*
8	1485698562	I-380S	1.11	*0.19 (324)*
9	1485852313	I-235S	1.11	*0.31 (98)*
10	1485852299	I-235S	1.10	*0.59 (18)*

*Rank out of 2746 segments across Iowa.

In Chapter 3, detailed travel time data views were used to visualize individual travel time records for segments identified as the most or least reliable according to various travel time metrics. A similar inspection will be conducted here. Figure 4.13 shows detailed travel time data views for 2 of the top 3 most unreliable segments in Iowa and the 2 most reliable segments in Iowa according to SD-PR. The third most unreliable segment (b) was shown instead of the second because the second most unreliable segment's detailed data view was already presented in Chapter 3 as it was the most unreliable segment for both SD_{tti} and BTI in Des Moines.

The unreliable segments shown here (a and b) exhibit a similar feature to that segment identified in Chapter 3. Both segments experience a decrease in the base travel time around the end of April, about a third of the way through the year. This clearly impacted the reliability assessment of these segments. Both segments also appear to have more travel time variability during the first third of the year when the base travel time is higher. The two most reliable segments (c and d) both appear to have relatively consistent travel times throughout the year. The second most reliable segment (d) does have some outliers, but most of the travel time measurements appear to be clustered close together. This segment is missing travel time data for the first third of the year.

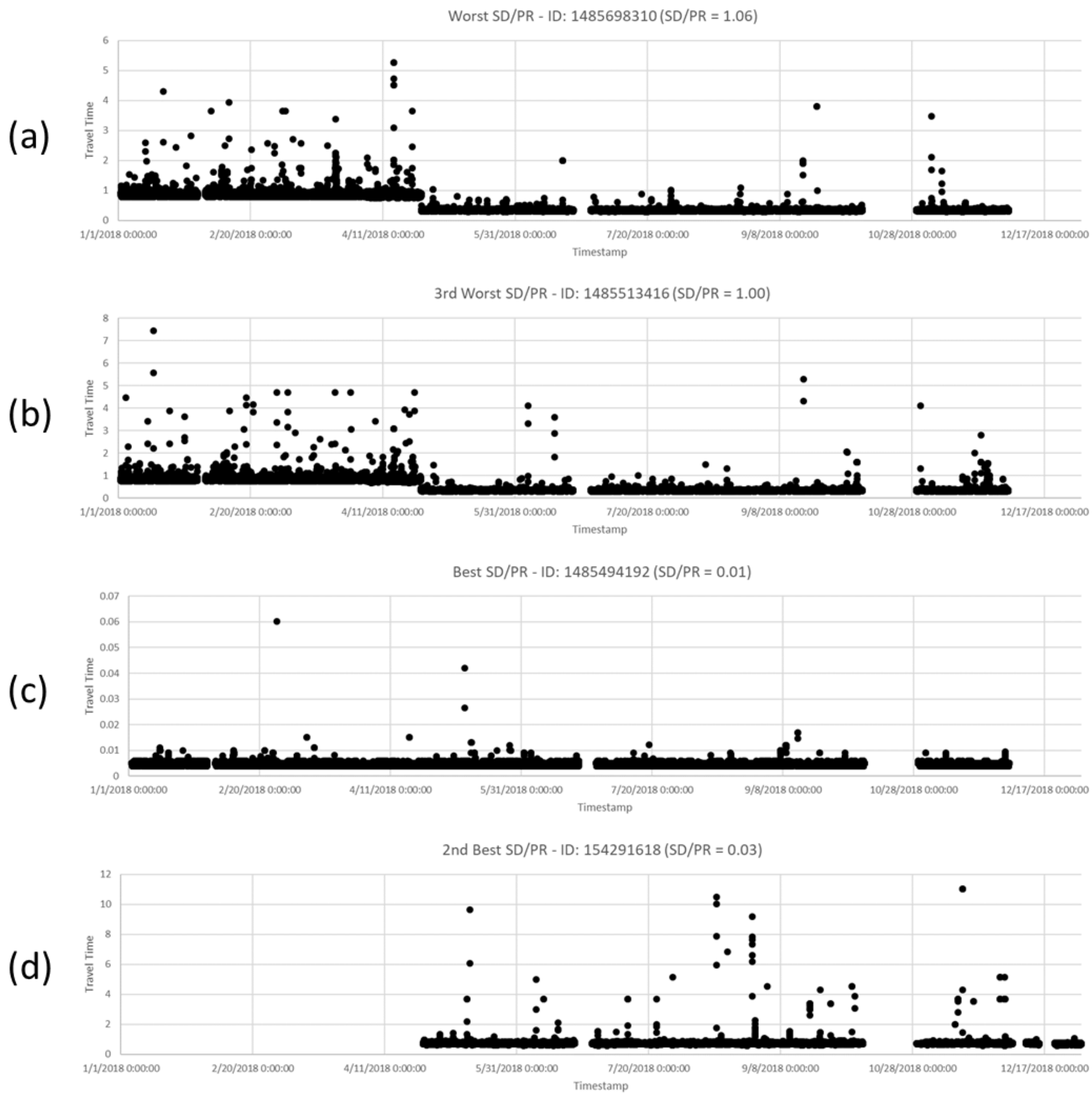


Figure 4.13 *Detailed travel time data view of the most reliable and least reliable segments in Iowa according to SD-PR.*

4.4 Summary

As observed in Chapter 3, different travel time reliability metrics identify different groups of segments as being unreliable. Therefore, an analysis using different metrics yields different outcomes. The analysis in this chapter examined potential methods of combining these metrics into a composite measure that is able to identify segments that would be considered unreliable under the individual metrics. The objective was to yield a single metric that could serve as a performance measure for broadly assessing travel time reliability. SD_{tti}, PR, and BTI were used in different combinations to generate these different composite metrics. The composite metrics were applied and visualized for all interstate segments throughout Iowa. Comparisons were made between both the composite metrics themselves and the original three independent reliability metrics. These comparisons utilized choropleth maps of the Des Moines area and I-80E reliability progression plots.

The composite metric of SD_{tti} and PR emerged as a feasible composite metric to apply to fully assess reliability across Iowa. The top 10 most unreliable segments in Iowa were identified using SD-PR. Additionally, the original top 10 most unreliable segment lists from the original three reliability metrics were revisited to see what those segments now rated using SD-PR. Lastly, some of the worst reliable and most reliable segments were examined in more detail by observing travel time data measurement progression throughout the year. Two of the most unreliable segments identified by SD-PR had major jumps in the base travel time readings about a third of the way through the year, which revealed that SD-PR is still sensitive to segments which have a jump in their baseline travel time during the year, which was also observed for the independent travel time reliability metrics back in Chapter 3.

CHAPTER 5. CONCLUSIONS

5.1 Summary

Travel time reliability reflects the predictability of the amount of time needed to complete a trip. Metrics which attempt to quantify travel time reliability are emerging as a fundamental part of assessing the performance of transportation networks. With many states and municipalities beginning or planning to utilize travel time reliability in their reports and assessments of their transportation networks, additional research on assessing and implementing these reliability metrics is valuable. Additionally, probe vehicle data is a prevalent data source which can be utilized to compute many of these travel time reliability metrics. This study used probe vehicle data from INRIX to compute, compare, and apply travel time reliability metrics on interstate segments throughout Iowa. It also looked at the concept of utilizing composite travel time reliability metrics to more concisely but still comprehensively convey travel time reliability.

Many different travel time reliability metrics were gathered through a review of current literature and current FHWA rulemaking. Metrics identified from these sources were then computed and compared against each other. Three distinctive groups of similar metrics emerged, with the standard deviation of travel time indexes, the 15^{th}-85^{th} percentile range of travel time indexes, and the buffer time index selected as representative metrics from each group. These three metrics were applied for both the Des Moines area and the state of Iowa as a whole. Peak hour travel time reliability (PHTTR) and the level of travel time reliability (LOTTR), developed by the FHWA, were also calculated for comparison.

SD_{tti}, PR, and BTI were used to assess the impact of changing the impact of aggregating the probe vehicle data from INRIX. The raw data (1 min.), 5 min., 15 min., and

60 min. levels of aggregation were examined. It was determined that using 5-minute time bins to aggregate the probe vehicle data greatly reduced computational time, required storage space, and still maintained the integrity of the travel time reliability metric values.

Before fully applying the travel time reliability metrics to any transportation networks, simple comparisons were made between the different analysis time periods. The analysis time periods used in this study were derived from the analysis time periods defined by the FHWA for computing and assessing LOTTR. Weekends were found to have the worst travel time reliability for a majority of segments across the state. However, the reliability of the worst 5% of segments was actually found to be slightly worse for PM peak when compared to the other time periods. PM peak data was utilized for the majority of the remainder of the study.

Choropleth (color-scaled) maps are an effective way to quickly visualize reliability across a network. However, before utilizing these maps in a full-scale application, assessing the impact different data classification methods have was crucial. Jenks data classification, which attempts to find natural breakpoints in a dataset, was compared with using the quantiles from the distribution of the travel time reliability metric values. It was found that Jenks data classification was more appropriate to use for visualizing travel time reliability on a choropleth map.

The selected travel time reliability metrics were fully applied to both the Des Moines area and the state of Iowa as a whole. The primary ways of visualizing and assessing reliability on segments in these networks were the use of choropleth maps and the identification of the top 5 (Des Moines area) or top 10 (Iowa) most unreliable segments, and the identification of segments classified as unreliable using a set threshold (when using LOTTR and PHTTR).

A method was developed for creating composite travel time reliability metrics. These composite metrics were developed using different combinations of SD_{tti}, PR, and BTI. The goal of developing composite metrics was to more concisely but still comprehensively convey all of the different aspects of travel time reliability. These composite metrics were compared with each other as well as with the original three travel time reliability metrics through the use of choropleth maps and route progressions plots. SD-PR emerged as a feasible composite metric to apply to fully assess reliability across Iowa.

During the application of the independent travel time reliability metrics as well as the composite travel time reliability metrics, detailed views of travel times observed on the segment throughout the year were assessed for some of the most unreliable and most reliable segments according to each of the different metrics. The key observation made from this assessment was that many of the original travel time reliability metrics as well as the SD-PR composite metrics, are sensitive to any jump in the base travel times in a segment throughout the year. Real-world scenarios that could potentially cause these travel time baseline jumps include construction on that segment either beginning or ending during the year, a change in the speed limit during the year, or another modification to the capacity of the roadway. The exact cause of the travel time changes seen in this study was not examined.

5.2 Limitations and Future Research

The analysis presented here was limited to segments of Interstate highways in the state of Iowa. Iowa is a mostly rural state with any urban areas being relatively small or moderately sized. Utilizing data from a wider area or from an area with much larger urban areas might be useful to see if the outcomes of this study are transferable. Also, adding additional roadway types other than interstates would be useful for future analysis. In particular, non-limited-access roadways where traffic control devices are used to stop traffic will likely have very different reliability outcomes. Additional studies that incorporate data from densely-populated areas and use data for multiple highway types could be useful.

The probe vehicle data used from INRIX itself has some inherent limitations, as past studies have highlighted. There is a slight time lag seen when comparing INRIX data to alternative speed data sources. Also, INRIX data might sometimes be sampled at longer rates than 1 minute on some segments, which could lead to repetitions of the same speed measurement being recorded in the dataset (Kim and Coifman, 2014). This would have a direct impact on travel time reliability. Lastly, INRIX speed data can be around 6 mph slower than ground truth on average (Lattimer and Glotzbach, 2012). This would certainly have a direct impact on PHTTR in this study, as the speed limit of the segment was used for establishing the desired travel time.

Static choropleth maps utilized in this study can be somewhat difficult to fully assess reliability for the independent segments of a network. An interactive online tool that allows the viewer to zoom in on particular regions, routes, and individual segments would be very powerful. Future states, municipalities, or other transportation agencies could utilize such an interactive tool in their reports and assessments. A mapping scheme that can present the two directions of the roadway within the same map view would also be a useful addition.

This study only examined results at the segment level and relied exclusively on the XD segment definitions provided by INRIX. Using travel time estimation techniques or using a way to aggregate the segment-level metrics across entire corridors or routes could be worth exploring in future studies.

This study included a basic comparison of travel time reliability across different analysis time periods. However, more comprehensive studies could be conducted. Additionally, the analysis time periods used in this study came directly from the FHWA in their computational process for LOTTR. Utilizing different time periods for analysis could be worth exploring in future studies. This study also primarily used PM peak data for the majority of full-scale applications of the travel time reliability metrics. Trying the different analysis time periods could be useful for these applications.

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