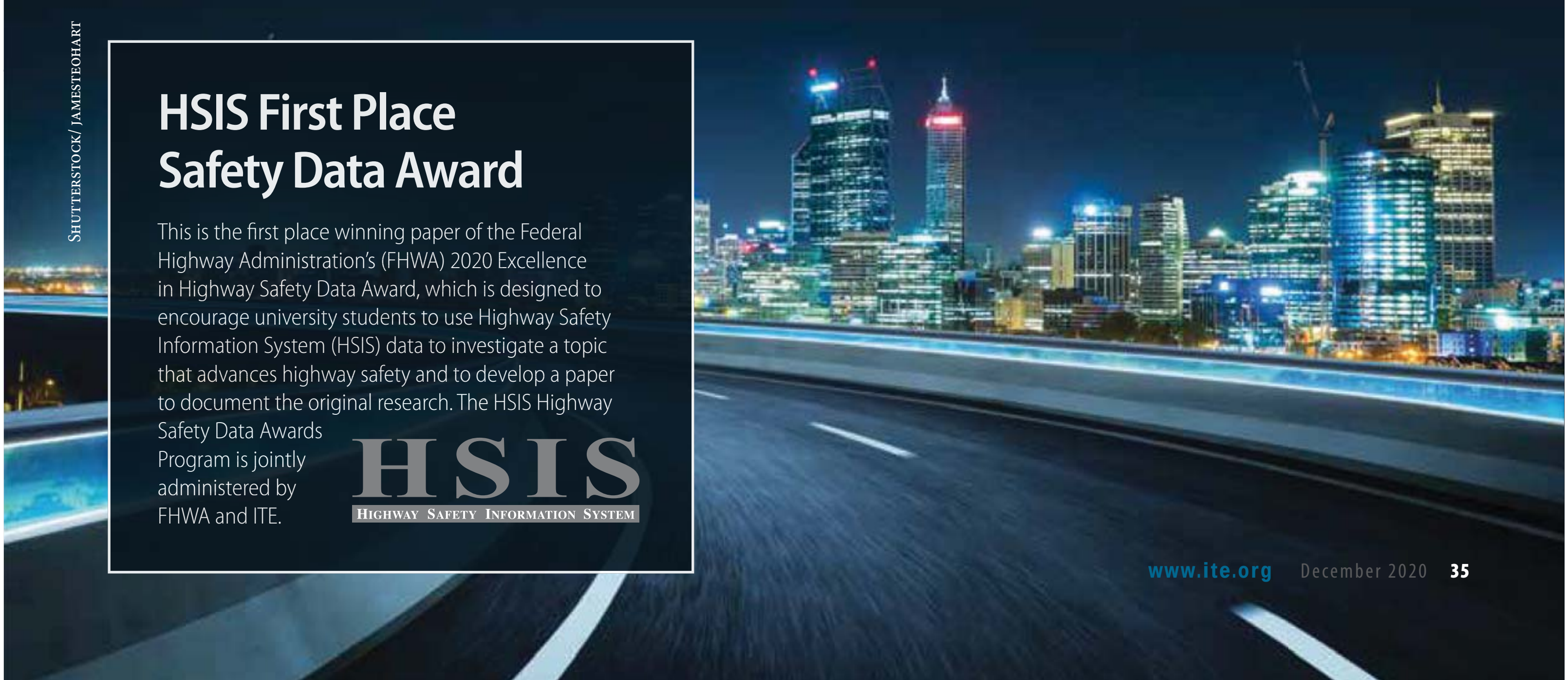
Safety Criteria for Selecting a Smart Corridor:

Random Forest Approach using HSIS Data from Washington State

By Xiaoyu Guo (S), Yongxin Peng, and Chaolun Ma

A roadway crash is a multifaceted event involving circumstances such as highway geometry, traffic exposure, operating speed, driver characteristics, vehicle factors, and the interactions among them. Determining the relationship between vehicle operating speed, roadway design elements, and traffic volume on crash outcomes would greatly benefit the road safety profession in general. There is both a need and an increasing trend to use data-driven procedures, such as machine learning approaches, artificial intelligence, and logistic regression methods to better understand the causes behind crashes.[1-12] Databases like the Highway Safety Information System (HSIS) contain quality data on a large number of crashes and their associated roadway and traffic records consistently across multiple years and states. These databases provide solid resources to perform innovative learnings.[13-16]



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HSIS First Place Safety Data Award

This is the first place winning paper of the Federal Highway Administration's (FHWA) 2020 Excellence in Highway Safety Data Award, which is designed to encourage university students to use Highway Safety Information System (HSIS) data to investigate a topic that advances highway safety and to develop a paper to document the original research. The HSIS Highway Safety Data Awards Program is jointly administered by FHWA and ITE.

HSIS
Highway Safety Information System

With the rise of the Intelligent Transportation Systems (ITS) and implementation of technologies in vehicles and infrastructures, various types of detectors, sensors, and cameras are being installed in cars and roadway systems. The ultimate aim of deploying technologies is to reduce crashes, improve safety, and achieve Vision Zero.[17, 18] Before implementing technologies, a smart corridor, testbed, or pilot site is an effective way to deploy technologies and test the impacts brought by them. Most of those ongoing smart corridors are constructed to practice and challenge the technology deployments, especially the Vehicle-to-Infrastructure (V2I) communications, i.e., the North Avenue Smart Corridor launched by the City of Atlanta and Georgia Tech in Georgia, USA. Moreover, there are pilot sites on a larger scale that implement Vehicle-to-Everything (V2X) on top of V2I. Take, for instance, the Connected Vehicle Pilot Deployment Program in New York City, NY, USA; Tampa, FL, USA; and Wyoming, USA supported by the U.S. Department of Transportation (USDOT). Although there are smart corridors built for both interstates, state highways, and urban streets, researchers have revealed that the frequency of crashes was higher when highways pass through the vicinity of major cities, pointing to heavy vehicular movement.[19] Hence, in this study, the selection range of smart corridor is on state highways only.

Recently, the American Association of State Highway and Transportation Officials (AASHTO) initialed the Signal Phase and Timing (SPaT) Challenge and promoted it through the National Operations Center of Excellent (NOCoE). A guideline along with the challenge suggested the state DOT and cities involve at least two high level types of decisions when selecting a SPaT enabled corridor: 1) Need for V2I applications; and 2) Infrastructure compatibility.[20] However, there is more to consider than these two decisions. The selection process is not only complex as suggested in the guideline, but also contains multitudinous options (i.e., potential routes). For instance, in Washington State, USA, if an agency only considers state routes, then there are 221 options; if an agency applied an additional filter over the length (i.e., in between 22 and 26 miles [35.4 and 41.9 kilometers]), then there are still more than 80 adequate options. Moreover, the cost of constructing a smart corridor can be expensive, due to the installation, deployment, and maintenance of equipment like radar, camera, and roadside units. As constructing and maintaining a smart corridor is costly and presents a technology challenge, it is important to choose the right site efficiently and effectively.[21]

Although there are existing frameworks, such as the Prioritization Criteria and Methodology Chapter in the Arterial Smart Corridor Projects Final Report, they are conducted purely from the state of the practice.[22] To the best of the authors' knowledge, there is not yet any work to determine important safety criteria for selecting a smart corridor via any machine learning approach. Random Forest (RF) is one of the well-known machine learning techniques for building multiple decision trees and merging them together to obtain a more accurate and stable prediction. RF is also widely applied, as it is a good indicator of the importance assigning to the features. In this study, the authors implement a RF model to identify 13 safety criteria out of 111 variables in the HSIS and the Highway Performance Monitoring System (HPMS) data from the State of Washington for selecting a smart corridor. The study then evaluates those criteria with its existing SPaT enabled corridor on WA 522. Lastly, this study predicts four potential smart corridors on WA 161, WA 99, and WA 202, and discusses their potentials in deploying connected technologies. The 13 criteria recommended in this study for selecting a smart corridor are generalized and ready to be adapted in other states. As the selection process of a smart corridor is time-consuming and expensive, the recommended criteria are efficient and effective ways for state and local agencies to identify potential smart corridors in their state route network.

Data Description

Data for the analyses in this study are composed of the HSIS (crash-based) and the HPMS (roadway-based) database in Washington State during 2015. The HSIS is a database managed by the University of North Carolina Highway Safety Research Center (HSRC) under contract with the Federal Highway Administration. Safety researchers have widely used the database to investigate various topics ranging from problem-identification, modeling to crash-prevention, and prediction.[23] Different from the conventional use of the HSIS data, the authors aim to identify the safety factors that could be used in the selection process of a smart corridor for implementing ITS related technologies and deploying connected and autonomous vehicles. With the HSIS database as the main source of data, the HPMS is a supportive database that includes data on the extent, condition, performance use, and operating characteristics of U.S. highways. The HPMS data is a roadway-based (or segment-based) data frame, which means each row is one segment in the road network. Thus, the authors integrated the HSIS data with the HPMS data based on route ID and the milepost.[24]

As one in the first group of state agencies that undertook the SPaT Challenge, WSDOT is assumed to choose the SPaT corridor on WA 522 by considering various transportation aspects (i.e., safety issues, traffic congestions) and carefully follow the guideline.[20] With this assumption, the authors developed a RF algorithm to determine safety criteria for corridor selection process. The RF algorithm was developed by using the data associated with those selected variables (see the Step 2 selection process in the next section, Two-Step Criteria Selection Method) on WA 522. Seventy-five percent in the dataset is randomly sampled as the training set, and the rest as the test set. Descriptive statistics of those selected variables are summarized in Table 1.

Table 1. Descriptive Statistics Summary on Selected Variables.

			Descriptive Statistics			
Aspect	**Variable name**	**Variable Type**	**Min.**	**Max.**	**Mean**	**S.D.**
Crash	Number of Crashes	Numerical	1	54	2.3	3.1
	Crash Severity	Categorical	1 = Property Damage Only, 2 = Injury, 3 = Fatal			
	Crash Type	Categorical	1 = Multi-Vehicle, 2 = Single Vehicle, 3 = Pedestrian/Bike, 4 = Others			
	Crash Location	Categorical	1 = Intersection, 2 = Driveway, 3 = Others			
	Time of Crash	Categorical	1 = AM Peak, 2 = PM Peak, 3 = Off Peak			
Road Inventory	Width of Right Shoulder	Numerical	0.0	22.0	1.3	2.1
	Width of Left Shoulder	Numerical	0.0	40.0	6.0	4.2
	Lane Width	Numerical	8.0	18.0	11.8	0.6
	Median Width	Numerical	0.0	99.0	20.2	30.6
	Grade	Categorical	1 = 0.0 – 0.4 percent, 2 = 0.4 – 2.4 percent, 3 = 2.5 - 4.4 percent, 4 = 4.5 - 6.4 percent, 5 = 6.5 - 8.4 percent, 5 = 8.5 or greater			
	Curve	Categorical	1 = Under 3.5 degrees, 2 = 3.5 - 5.4 degrees, 3 = 5.5 - 8.4 degrees, 4 = 8.5 – 13.9 degrees; 5 = 14.3 – 27.9 degrees, 6 = 28 degrees or more			
Traffic	AADT	Numerical	159	237,647	40,402	49,963
	AADT for Single-unit Trucks	Numerical	5	7,550	1,294	1,448
	Number of Signalized Intersection	Numerical	0.0	9.0	0.6	1.4
	Number of Intersection	Numerical	0.0	78.0	3.6	5.7
	Percentage of Single-unit Trucks and Buses in Peak Hour	Numerical	0.0	4.0	0.3	0.2

Note: min. = minimum; max. = maximum; S.D. = standard deviation.

Two-Step Criteria Selection Method

The following two subsections introduce the two steps, variable pre-selection and Random Forest, in our proposed Two-Step Criteria Selection Method. The flow of the methodology is illustrated in Figure 1.

Step 1: Variable Pre-selection

After integrating the HSIS and the HPMS datasets into one dataset, there are 111 variables in total to be evaluated. Twenty variables come from HSIS, while 91 variables come from HPMS, as shown in Layer 1, Figure 1. A series of data cleaning and checking procedures were considered in the variable pre-selection step, including:

- Eliminate the variables with either empty (i.e., more than 90 percent of N/A) or erroneous data;
- Eliminate the deterministic variables (i.e., with variance close to zero);
- Examine and eliminate the correlated numerical variables; and etc.

After the data cleaning and consistency checking procedures, 111 variables with 35,298 data points are reduced into 27 variables with 8,586 data points. These 27 variables are then categorized into three safety aspects, 12 crash related variables, 10 roadway inventory related variables, and five traffic related variables (see details listed in Layer 2 in **Figure 1**).

Step 2 Selection: Random Forest

With these 27 pre-selected variables, in Step 2, the Random Forest (RF) machine learning algorithm, a popular tree-based regression

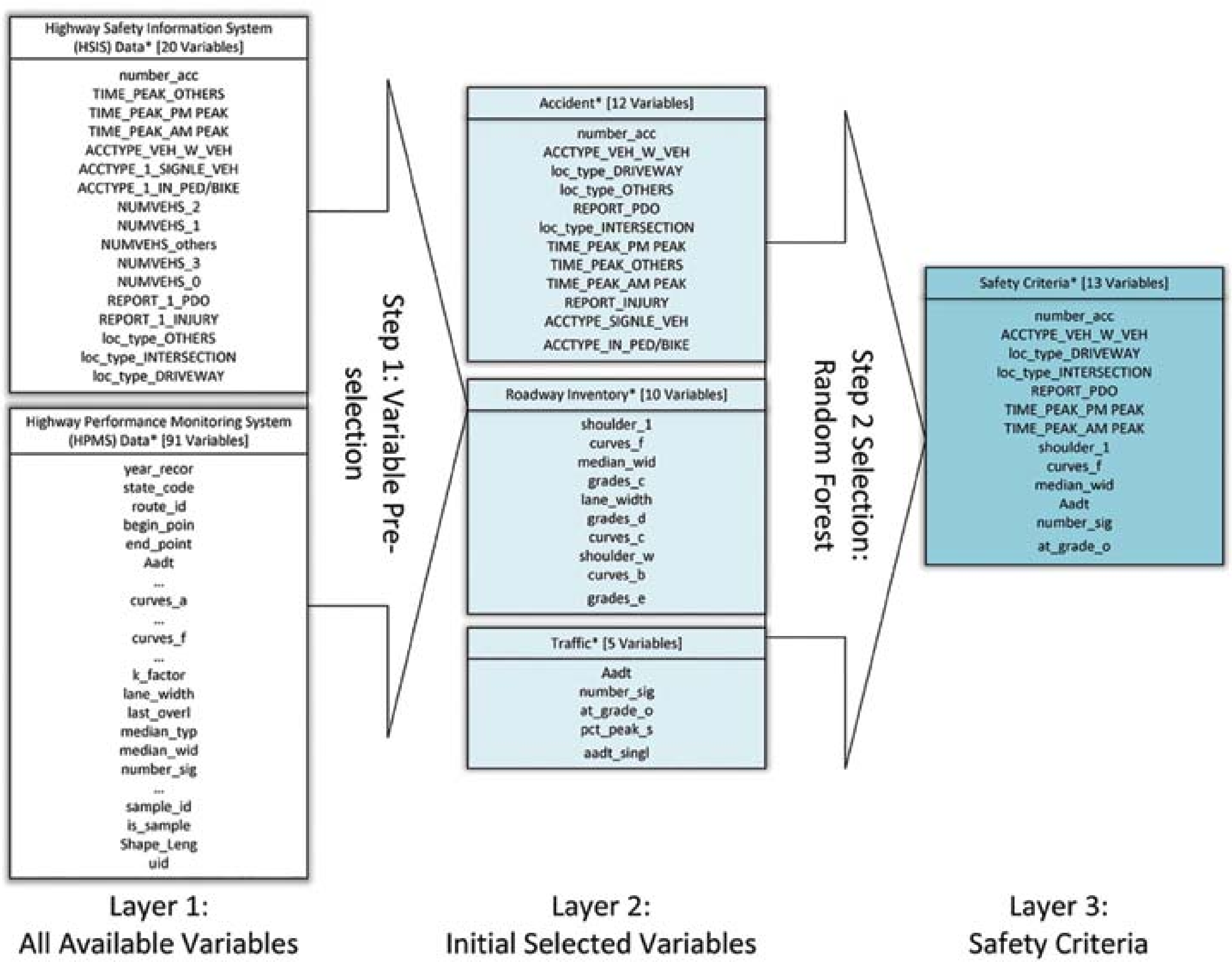

Figure 1. Two-Step Criteria Selection Method in Steps and Layers.

*: Abbreviations are from HSIS or HPMS

and classification method, is performed over these 27 variables list Layer 2, Figure 1.[25] The essential idea with using the RF algorithm is to grow an extensive collection of de-correlated trees based on different parts of the same training set and averaging the results. Thus, the algorithm can provide low variance results. Practically, each feature is sampled without replacement according to proportion of its maximum in RF algorithm. Gini index is a common tool to interpret and rank the feature outcomes from RF. It is defined in Equation 1 and denotes node impurity (the probability of a wrongly classified variable when randomly chosen). Predictors with largest Gini coefficient are chosen to make a binary split on the node,

$$Gini\ index = \sum_{i}^{n} p_i\,(1-p_i) \qquad 1$$

where n is the number of classes in the target variable and p_i is the probability of an object being classified to a particular class. In the RF algorithm, the Mean Decrease in Gini index is the weighted average of the predictor's decrease in node impurity. It is a measure of variable importance. A higher Mean Decrease in Gini index indicates higher variable importance. In the Step 2 Criteria Selection, the Gini index is computed as in Figure 2.

The RF algorithm performed with a 94.3 percent accuracy for the test data during pre-training process. Then, the 27 pre-selected variables are categorized into their aspects (i.e., crash, roadway inventory, and traffic) in Layer 2 and ranked per percentile calculated from Gini Index (i.e., relative importance). Details on the relative importance (i.e., percentile) of each variable is calculated and presented in Figure 3. Lastly, 13 safety criteria are then finalized by choosing those variables with a 50-percent percentile or above in their aspects. Those safety criteria are implemented for re-training the random forest model. A final model with those key safety criteria reached 95.3 percent accuracy for the test data.

Results and Discussions

Two types of comparisons are visualized on the heat maps and discussed in this section. One compares the performances of identified key safety criteria in each aspect on the existing smart corridor along WA 522. The primary purpose is to evaluate whether those safety criteria describes the characteristics of this existing smart corridor. The other comparison is between potential smart corridors on WA 161, WA 99, WA 202, and the existing one on

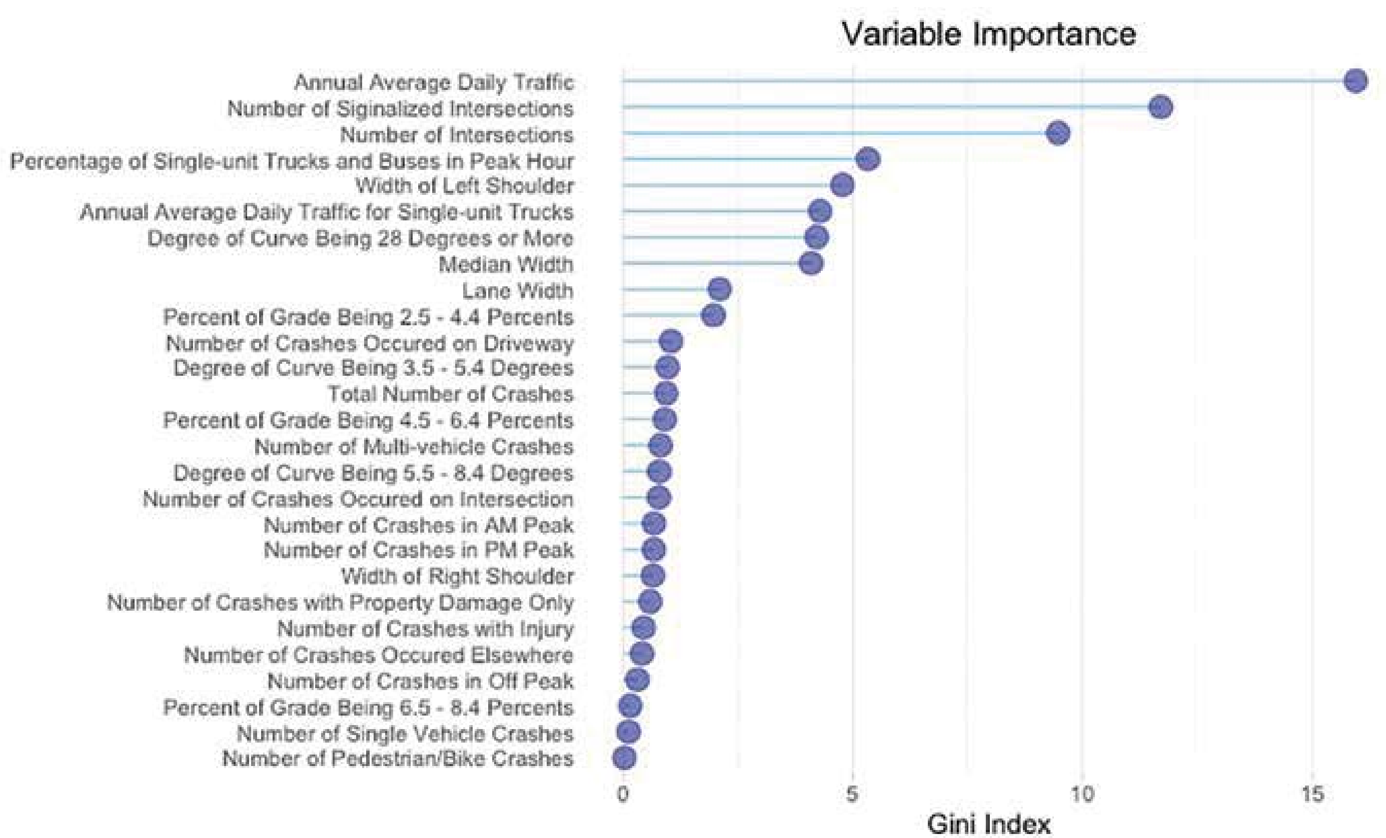

Figure 2. Step 2 Criteria Selection using Random Forest.

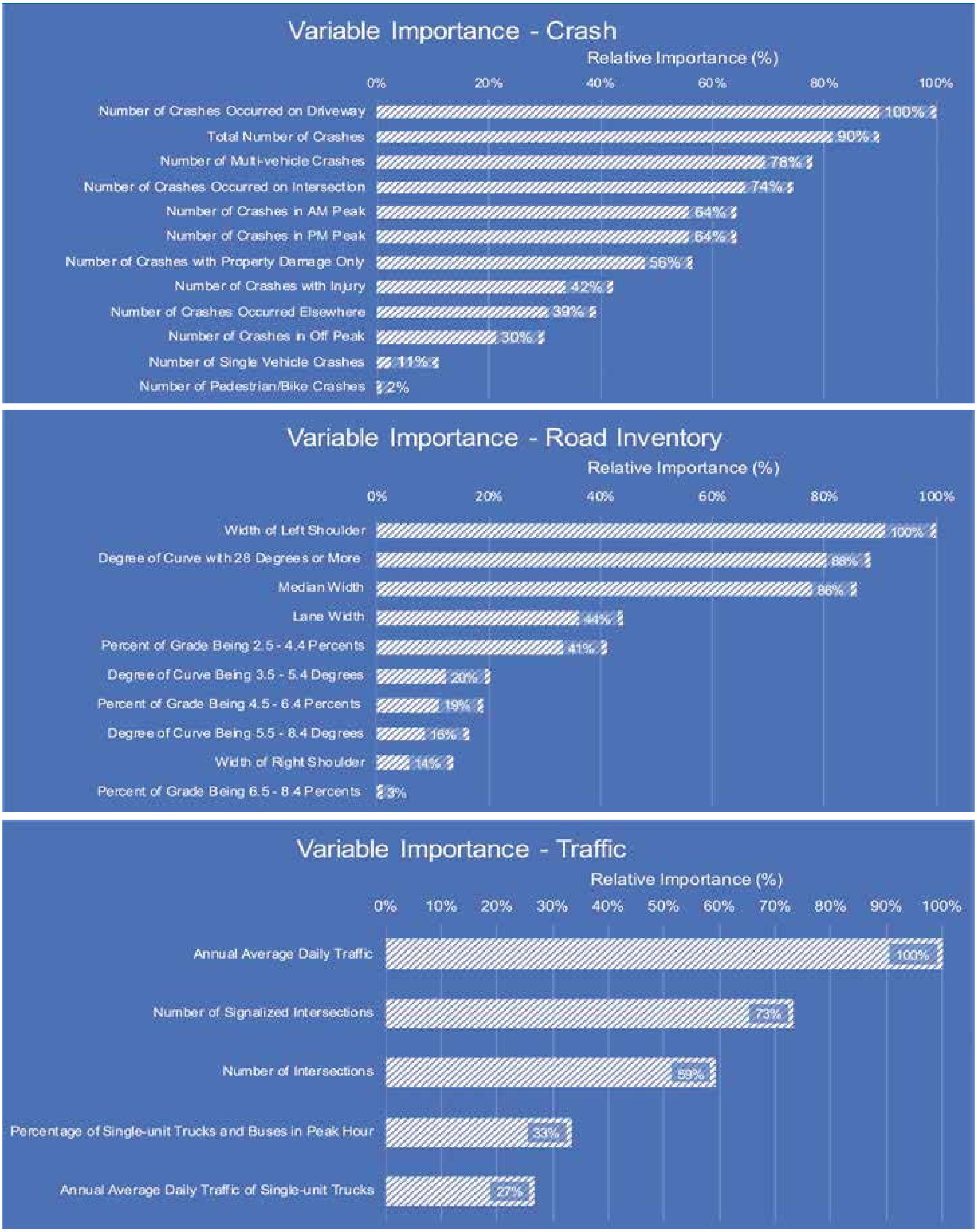

Figure 3. Variable Importance in Crash, Roadway Inventory and Traffic Related Aspect.

WA 522. The purpose is to study the similarities and differences between those predicted ones and the existing one on WA 522, and discuss the potentials of them as smart corridors.

Existing Smart Corridor on WA 522

Following the proposed Two-Step Criteria Selection in methodology, 13 safety criteria are selected out of 111 variables from HSIS and HPMS databases for the State of Washington:

- Crash related aspect: 1) Number of crashes occurred on driveway, 2) Total number of crashes, 3) Number of multi-vehicle crashes, 4) Number of crashes occurred on intersection, 5) Number of crashes in AM Peak, 6) Number of crashes in PM Peak, 7) Number of crashes with property damage only;
- Roadway inventory related aspect: 8) Width of left shoulder, 9) Degree of curve with 28 degrees or more, 10) Median width; and
- Traffic related aspect: 11) AADT, 12) Number of signalized intersections, and 13) Number of intersections.

The Top 1 and 2 criteria at each aspect are demonstrated in Figures 4-6. Those figures evaluate whether these safety criteria identified by RF machine learning are good representatives of a smart corridor.

a. Number of Crashes Occurred on Driveway *b. Total Number of Crashes*

Figure 4. Heat Maps to Demonstrate the Top Two Key Criteria in the Crash Related Aspect on the Smart Corridor, WA 522.

a. Width of Left Shoulder *b. Degree of Curve with 28 Degrees or More*

Figure 5. Heat Maps to Demonstrate the Top 2 Key Criteria in the Road Inventory Related Aspect on the Smart Corridor, WA 522.

a. Annual Average Daily Traffic *b. Number of Signalized Intersections*

Figure 6. Heat Maps to Demonstrate the Top Two Key Criteria in the Traffic Related Aspect on the Smart Corridor, WA 522.

Figures 4a and 4b illustrates the heat maps for the No. 1 and the No. 2 important criterion, from a crash-related aspect. Both criteria are representative as they are highlighted (i.e., with an orange/red color) in the existing smart corridor from WA 522 from NE 153rd Street to 83rd Place NE. The number of driveway crashes is relatively more important than the total number of crashes, because driveway crashes identify those segments under the smart corridor the most. While the total number of crashes is large on segments along the smart corridor, as well as some segments beside WA 522; the driveway crashes are mostly dense along the existing smart corridor. Therefore, the number of driveway crashes better describes the characteristic of the smart corridor. Overall, both are critical safety criteria to consider, because large crash volumes and/or at a specific location (i.e., near a driveway) on a signalized high-speed corridor demonstrate the room for the need of V2I applications. Similarly, the heat maps in Figure 5 and Figure 6 illustrate the No. 1 and the No. 2 important criteria from the roadway inventory and traffic related aspects. These criteria are highlighted along WA 522, and describe the characteristic of the smart corridor. Since poorly designed road inventory or heavy traffic over the capacity may lead to safety issues, the authors believe that these key factors align with the need for implementing smart technologies.

Potential Smart Corridors in Washington State Routes

More than identifying and verifying the key criteria through the characteristics of the existing corridor on WA 522, four potential smart corridors from three separate state routes (i.e., WA 161, WA 99, WA 202) are predicted. They are selected from a total of 221 state routes in Washington State using the 13 identified safety criteria. They are circled in the heat map on Figure 7. The red color represents a larger probability to be a smart corridor.

These four potential corridors are predicted by the RF algorithm using 13 identified safety criteria. However, they are with a lower selection priority than the existing smart corridor. Figure 7 maps the locations of those corridors along with the existing one. It is noticeable that although the potential smart corridor #2, #3 and

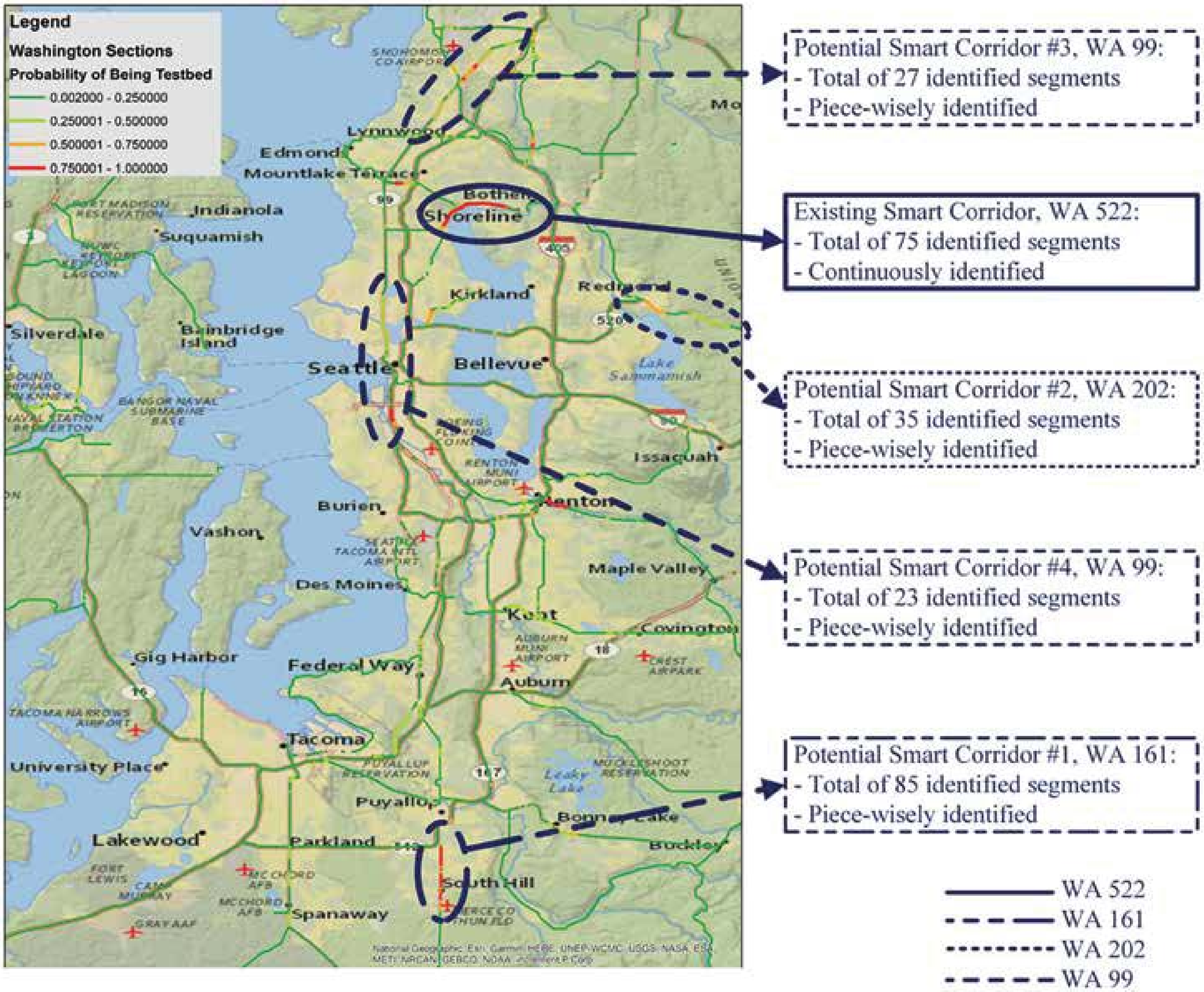

Figure 7. A Heat Map to Identify Potential Smart Corridors in Washington State.

#4 contain 35, 27, and 23 segments, these segments are identified separately by the criteria. That is, some segments on the corridor are around with safety concerns, while some are not. This leads to a lower potential to deploy smart technology than the existing corridor on WA 522. On the other hand, the potential smart corridor #1 on WA 161 has 85 continuously identified segments. It is almost identical to the existing smart corridor by considering those safety criteria. However, by examining the pre-selected variables, there is a difference brought by the truck percentage. The truck percentage on WA 522 varies from 2 percent to 8 percent, whereas it ranges from 2 percent to 13 percent on WA 161. For a smart corridor with signalized intersections, truck percentage is an additional factor to consider. It is because a higher truck percentage may minimize the benefit brought by the SPaT message and V2I applications. For example, a connected and autonomous vehicle receives signal timing message and wants to plan its trajectory accordingly to pass the intersection without a stop, but it is limited to speed up or change lanes because of trucks around intersection.

Summary and Future Study

This study demonstrated a use of the HSIS dataset to determine safety criteria for selecting a smart corridor using a machine learning approach, Random Forest. The HSIS contains a rich dataset and it well records data including various variables from many aspects of transportation. In this study, the authors implemented the Random Forest algorithm to finalize 13 safety criteria for selecting a smart corridor out of 111 variables in the HSIS and the HPMS from Washington State. Then, by evaluating those criteria with its existing SPaT enabled corridor, the authors believe that those criteria are critical to consider when selecting a smart corridor. These criteria also agree with the guidelines from FHWA and NOCoE for selecting a SPaT enabled corridor. Lastly, this study predicted potential smart corridors on WA 161, WA 99, and WA 202, and discussed their potentials in deploying ITS technologies. The safety criteria recommended in this study are generalized and ready to apply in other states. There are some limitations of this study that may lead to future improvements:

- Used limited data (i.e., data in 2015 only)
- Studied limited area (i.e., only in Washington State): The Two-Step Selection Method is adaptable to other states, a more comprehensive study is to use HSIS database in all eight states.

Nevertheless, as the selection process of a smart corridor is time-consuming and the costs of construction and maintenance are expensive, the 13 safety criteria recommended from this study are important. They are efficient and effective ways for state and local agencies to identify potential smart corridors in their state route network. Lastly, the authors believe that this study is a novel use of the HSIS data and demonstrates a diverse application of the HSIS data with the machine learning technology and the concept of ITS.

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Xiaoyu "Sky" Guo (S) *received her B.S. degree in mathematics with a minor in statistics from SUNY-Buffalo, and her M.S. degree from the Zachry Department of Civil and Environmental Engineering, Texas A&M University, where she is currently pursuing a Ph.D. degree. She is currently working as a research assistant for the Connected Infrastructure Group under the System Reliability Division at Texas A&M Transportation Institute (TTI). Her research interests include connected infrastructures and vehicles, traffic safety, and traffic operations.*

Yongxin Peng *received his M.Eng. degree from the Zachry Department of Civil and Environment Engineering, Texas A&M University. He is currently pursuing the Ph.D. degree at the Zachry Department of Civil and Environmental Engineering, Texas A&M University and he is a research assistant in Mobility Analysis Division, Texas A&M TTI. His research interests include traffic modeling, applications of machine learning in traffic operations, safety, and mobility analysis.*

Chaolun Ma *received his M.S. degree from the University of Illinois Urbana-Champaign. He is currently pursuing a Ph.D. degree at the Zachry Department of Civil and Environmental Engineering, Texas A&M University. His research interests include traffic modeling and simulation, applications of machine learning in traffic operations, safety, and freight transportation.*