Developing Safety Performance Functions for Freeways at Different Aggregation Levels Using Multi-State Microscopic Traffic Detector Data

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ABSTRACT

Safety Performance Functions (SPFs) have been widely used by researchers and practitioners to conduct roadway safety evaluation. Traditional SPFs are usually developed by using annual average daily traffic (AADT) along with geometric characteristics. However, the high level of aggregation may lead to a failure to capture the temporal variation in traffic characteristics (e.g., traffic volume and speed) and crash frequencies. In this study, SPFs at different aggregation levels were developed based on microscopic traffic detector data from California, Florida, and Virginia. More specifically, five aggregation levels were considered: (1) annual average weekday hourly traffic (AAWDHT), (2) annual average weekend hourly traffic (AAWEHT), (3) annual average weekday peak/off-peak traffic (AAWDPT), (4) annual average day of the week traffic (AADOWT), and (5) annual average daily traffic (AADT). Model estimation results showed that the segment length and volume, as exposure variables, are significant across all the aggregation levels. Average speed is significant with a negative coefficient, and the standard deviation of speed was found to be positively associated with the crash frequency. It is noteworthy that the operation of the high occupancy vehicle (HOV) lanes was found to have a positive effect on crash frequency across all the aggregation levels. The model results also showed that the AAWDPT and AADOWT models consistently performed better (the improvements range from 3.14% to 16.20%) than the AADT-based SPF, which implies that the differences between the day of the week and peak/off-peak periods should be considered in the development of crash prediction models. The model transferability results indicated that the SPFs between Florida and Virginia are transferrable, while the models between California and the other two states are not transferrable.

Keywords: Safety Performance Function, Freeway, Aggregation Level, High Occupancy Vehicle Lane**,** Microscopic Traffic Detector Data

INTRODUCTION

Traffic safety researchers usually deal with highly aggregated data when analyzing traffic crashes. Data aggregation is essential due to the rare nature of traffic crashes and to account for the regression-to-the-mean bias. Nevertheless, a high level of aggregation may lead to a failure to capture the temporal variation in traffic characteristics (e.g., traffic volume and speed) and crash frequencies. The state-of-the-practice crash prediction models, Safety Performance Functions (SPFs), employ annual average daily traffic (AADT), roadway geometrics, and limited operational characteristics to predict the annual average crash frequency on transportation facilities. SPFs provide transportation agencies a representation of the roadway crash risk for longer time horizons (such as annually or multi-year), which are less suitable to address crash risk for shorter time intervals (such as peak periods) or during the operation of specific traffic demand or capacity management strategies (e.g., high occupancy vehicle (HOV) lanes and ramp metering). The limitations of the current approach in crash prediction are accentuated by the data explosion in the transportation field.

Automatic traffic detection systems can continuously monitor the traffic flow at the location or on a specific segment and archive the information at short time intervals (usually 30 seconds or 1 minute). Traffic volume, speed, density in terms of occupancy, and simple vehicle classification are the most common parameters collected by these detection systems. With these types of microscopic traffic information, traffic operators can effectively monitor the transportation system and make informed decisions. At the same time, the availability of microscopic traffic detector data has also opened a new frontier for traffic safety researchers. In this context, real-time crash risk prediction has been widely conducted by investigating the differences between the traffic conditions before crashes and non-crashes (Abdel-Aty and Pande, 2005; Abdel-Aty et al., 2004; Oh et al., 2001; Shi and Abdel-Aty, 2015; Xu et al., 2013; Yu and Abdel-Aty, 2013b; Yuan and Abdel-Aty, 2018; Yuan et al., 2018). However, real-time crash risk prediction models are mainly designed for real-time traffic management, which requires quick responses and frequent interventions. The real-time models might not be as stable as the SPFs due to the potential randomness within short periods. Due to the instability, it is hard to make long-term decisions based on real-time crash risk predictions. Therefore, this study aims to develop safety performance functions (SPFs) at more disaggregated levels (e.g., peak/off-peak periods), which lies between real-time crash risk prediction and AADT-based SPFs, by using microscopic traffic detector data. It is expected that these disaggregated SPFs will enable practitioners and policymakers to better understand the temporal variation in safety assessment and to provide effective countermeasures, including the implementation of active traffic management technologies (e.g., variable speed limits, ramp metering, and queue warning).

Several previous studies tried to develop hourly traffic based SPFs. Martin (2002) investigated the relationship between crash rates and hourly traffic volume based on 2,000 km of French interurban motorways over two years. Lord et al. (2005) developed crash prediction models based on hourly traffic flow characteristics, including traffic volume, density, and V/C ratio. They found that the model with hourly traffic density and V/C ratio performs better than the model with hourly traffic volume only. Kononov et al. (2012) calibrated SPFs to relate crash rates to hourly volume-density and speed. They found that the increase in flow and density without a notable reduction in speed has a significant influence on safety. Wang et al. (2018) developed and compared three types of models: daily crash frequency estimation using average daily traffic (ADT), hourly crash frequency estimation using average hourly traffic (AHT), and real-time crash risk prediction using microscopic traffic data. They found that the crash contributing factors found by different models are comparable, and the ADT- and AHT-based models have similar performance in predicting daily and hourly crash frequencies. Al Amili (2018) utilized disaggregated microwave traffic detector data to develop SPFs for weekdays and weekends. He considered four time periods for weekdays and two time periods for weekends at four aggregation levels (i.e., 5, 15, 30, and 60 minutes). The comparison results between AADT-based SPFs and disaggregated SPFs showed that the disaggregated SPFs perform better. Dutta and Fontaine (2019) evaluated the relationship between crashes and traffic flow at different levels of temporal aggregation (i.e., 15-minute, hourly, and annual) using continuous count station data and probe data in Virginia. They found that the model with hourly volume along with average speed and geometric variables achieved better prediction performance than the AADT-based model.

In summary, none of the previous studies have systematically investigated the impact of various types of aggregation strategies in the development of SPFs. Considering that the traffic and crash characteristics during weekdays and weekends are quite different (Yu and Abdel-Aty, 2013a), weekdays and weekends should be differentiated during the data aggregation. In addition, the difference between peak and off-peak periods should also be considered as the safety impact of different traffic states are quite different (Xu et al., 2012). In addition, with the help of microscopic traffic detector data, more time-varying variables (i.e., average speed and speed variation) could be introduced into the development of SPFs. Meanwhile, the effects of average speed and speed variation on crash frequency could be quantified. Considering the speed characteristics are quite different between weekdays and weekends, and peak period and non-peak period, various aggregation levels would be required to better reveal the safety effects of speed characteristics and improve the model performance. Moreover, the SPFs at different aggregation levels could be integrated with different time-of-day operated active traffic management (ATM) systems. For example, the aggregation level of annual average weekday peak/off-peak can be utilized to evaluate the safety impact of those peak-period-operated ATM systems, e.g., HOV, dynamic lane control, and ramp metering.

Above all, this study aims to develop SPFs at different aggregation levels (i.e., annual average weekday hourly traffic (AAWDHT), annual average weekend hourly traffic (AAWEHT), annual average weekday peak/off-peak traffic (AAWDPT), annual average day of the week traffic (AADOWT), and annual average daily traffic (AADT)) for freeways by using microscopic traffic detector data from Florida, Virginia, and California. Meanwhile, the time-of-day operation status of HOV lanes in California is integrated into different aggregation levels to systematically evaluate the safety performance of HOV. In addition, the transferability of SPFs at different aggregation levels between the three states is investigated. To summarize, the main contributions of this study include the following aspects:

(1) This paper systematically develops and compares SPFs at different aggregation levels (i.e., AAWDHT, AAWEHT, AAWDPT, AADOWT, and AADT) for freeways by using microscopic traffic detector data from Florida, Virginia, and California.
(2) The effects of average speed and speed variation on crash frequencies are revealed at different aggregation levels.
(3) The time-of-day operation status of HOV lanes is introduced to the disaggregated SPFs, and the safety performance of HOV lanes at different aggregation levels are evaluated and compared.
(4) The transferability of SPFs at different aggregation levels between Florida, Virginia, and California is evaluated.

DATA PREPARATION

In total, 11 freeways/expressways from California, Florida, and Virginia were chosen. Figure 1 shows the location of all the selected freeways/expressways and the corresponding microscopic traffic detectors. The total mileage of the selected roadways is 2,338 miles, and there are 4308 microscopic traffic detectors on the selected roadways.

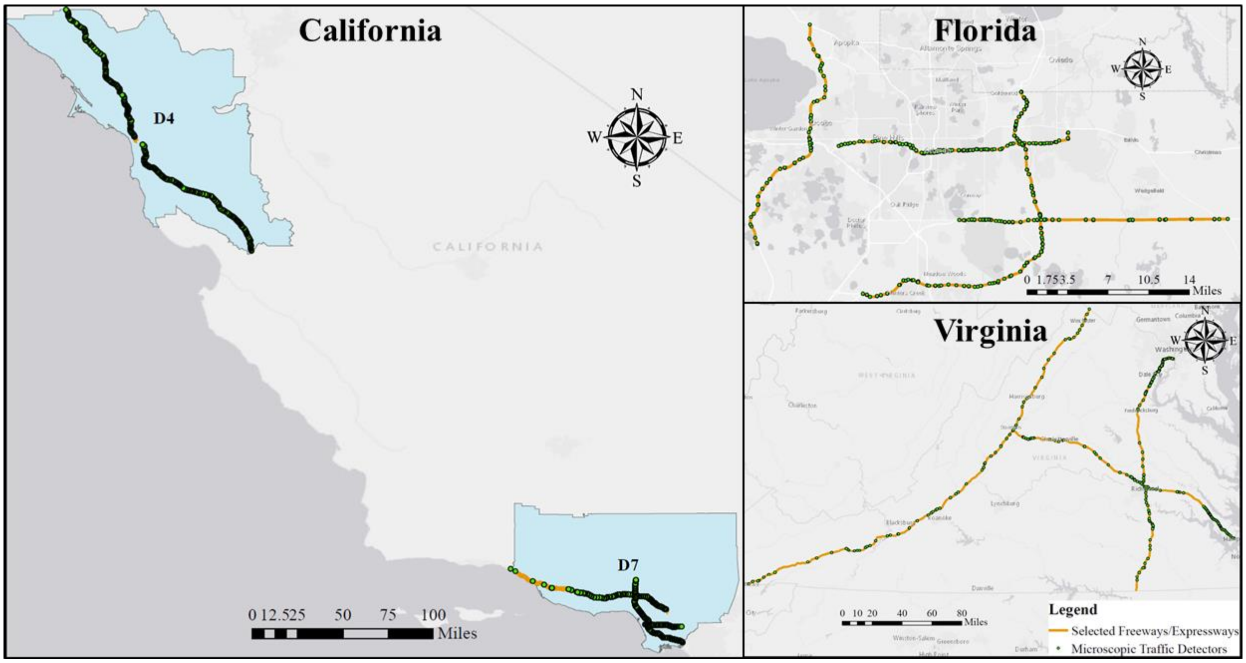

Figure 1 Selected freeways/expressways and the microscopic traffic detectors in California, Florida, and Virginia

Three main datasets were collected for every state, including crash, traffic detector, and geometric data. The crash and traffic detector data were collected for 2018 and 2019 for the three states. TABLE 1 shows the data sources and data elements for the three types of datasets from the three states. In general, the crash and traffic detector data were collected from state-specific databases, and the roadway geometry data were mainly collected from federal-level databases (i.e., National Performance Management Research Data Set (NPMRDS) and Highway Performance Monitoring System (HPMS)).

TABLE 1 Summarization of data sources

State	Data Type	Data Source	Data Elements
California	Crash	Transportation Injury Mapping System (TIMS)	Crash time, location, type, and severity
	Traffic Detector	Caltrans Performance Measurement System (PeMS)	Speed, volume, and occupancy at every 30 seconds
	Roadway Geometry	National Performance Management Research Data Set (NPMRDS), Highway Performance Monitoring System (HPMS), and California State Geoportal	Number of lanes, urban code, speed limit, International Roughness Index (IRI), and High-Occupancy Vehicle (HOV) lane
Florida	Crash	Signal Four Analytics	Crash time, location, type, and severity
	Traffic Detector	Central Florida Expressway Authority (CFX)	Speed, volume, and occupancy at every 1 minute
	Roadway Geometry	Roadway Characteristics Inventory (RCI) and HPMS	Number of lanes, urban code, speed limit, and IRI
Virginia	Crash	VDOT's open data portal (SmarterRoads)	Crash time, location, type, and severity
	Traffic Detector		Speed, volume, and occupancy at every 1 minute
	Roadway Geometry	NPMRDS and HPMS	Number of lanes, urban code, speed limit, and IRI

Figure 2 shows the data processing pipeline for every state. The left side of the figure illustrates the procedures of base map processing, including roadway segmentation, geometric data collection, and traffic detector matching. It is worth noting that the roadway segmentation in this study is based on the location of traffic detectors, as this study is trying to maximize the ability of the data from every detector and also capture the data variability between different detectors. Specifically, the segment between two adjacent detectors is treated as a segment, which is in line with previous real-time safety studies (Abdel-Aty and Pande, 2005; Abdel-Aty et al., 2004; Oh et al., 2001; Shi and Abdel-Aty, 2015; Xu et al., 2013; Yu and Abdel-Aty, 2013b). In addition, all segments that are shorter than 0.1 miles were combined with the adjacent segment. The right side of the figure presents the aggregation procedure of crash and traffic data for every segment. (1) For the AAWDHT data aggregation, the high-resolution traffic detector data were first aggregated to the hourly level, which results in 17,520 (24 hours × 730 days) observations for every segment. Then, the AAWDHT dataset can be generated by averaging the hourly data over all the weekdays during 2018-2019, which results in 24 (24 hours) observations for every segment. Similarly, the corresponding crash data were also aggregated to be 24 observations for every segment. (2) The AAWEHT data aggregation is similar to the AAWDHT data aggregation, where the only difference is that the AAWEHT dataset was averaged over all the weekends. (3) For the AAWDPT aggregation, the high-resolution traffic data were first aggregated to four time periods for every weekday (4 periods × 522 days), that is, morning peak (6 am to 9 am), daytime off-peak (9 am to 4 pm), afternoon peak (4 pm to 7 pm), and nighttime (7 pm to 6 am). Then, the time period data were averaged over all the weekdays to generate the AAWDPT dataset (4-period observations for every segment). (4) The AADOWT dataset was generated by averaging the daily data for every day of the week, which results in 7 day-of-week observations for every segment. (5) The AADT aggregation is the highest aggregation level, where the daily data were averaged over the years (1 observation for every segment). This is the most widely used aggregation strategy in highway safety studies, and the annual average daily traffic (AADT) is the most important factor in developing SPFs. To the end, five aggregation datasets (i.e., AAWDHT, AAWEHT, AAWDPT, AADOWT, and AADT) were generated for every state.

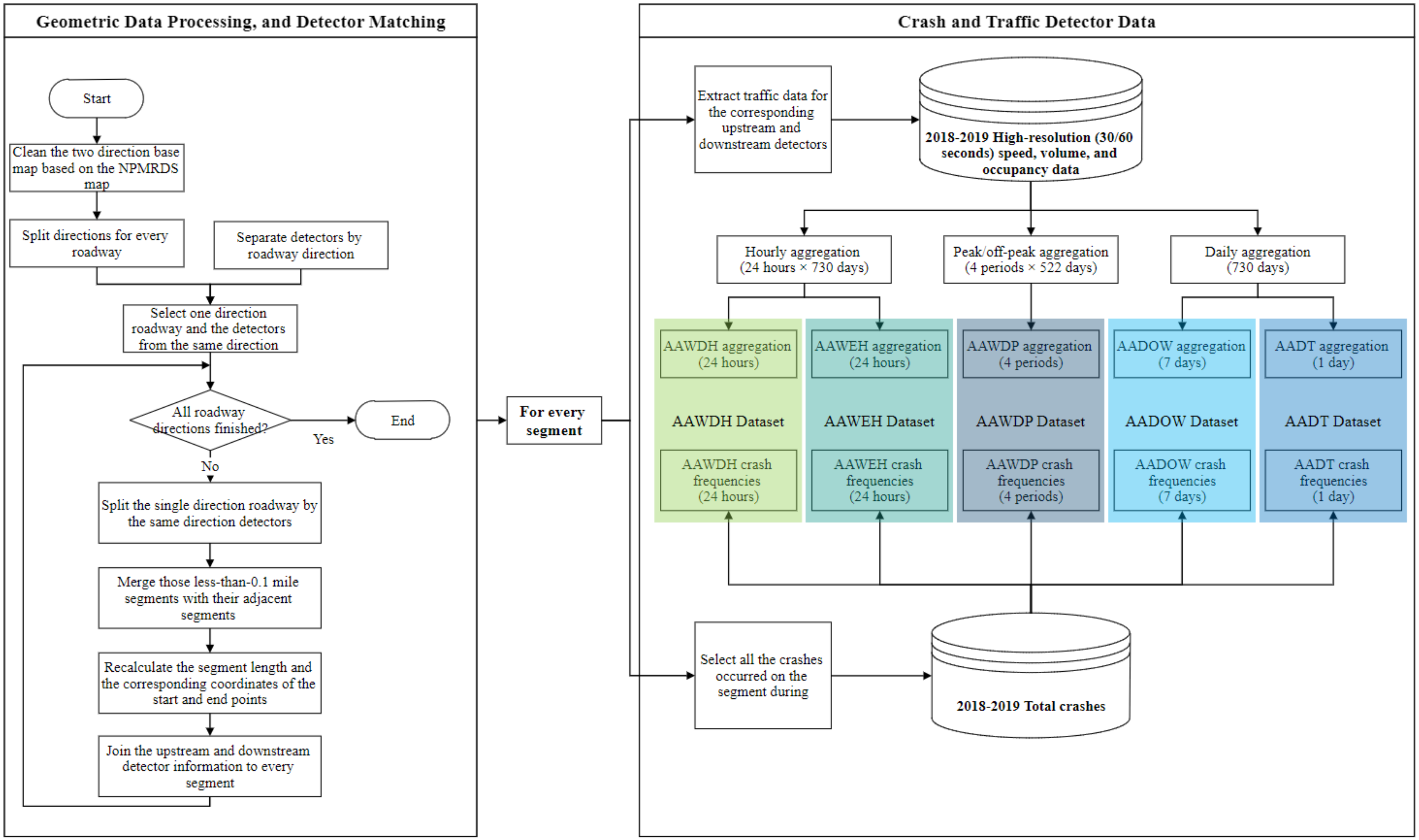

Figure 2 The flowchart for data processing

TABLE 2, TABLE 3, and TABLE 4 summarize the descriptive statistics of all the collected variables for the three selected states, respectively. Among all the selected roadways, there are 365 miles of roadway segments in California that have High Occupancy Vehicle (HOV) lanes operated. Therefore, the variables of HOV and HOV hours are only included in TABLE 2. It is noteworthy that both the HOV and HOV hours were collected by integrating the HOV location and their corresponding operating-hour plan. For example, most of the HOV lanes are operating during 05:00-09:00 & 15:00-19:00 (Monday to Friday); therefore, in the AAWDHT dataset, only those segments that have HOV lanes and the corresponding hour is within the operating hours will be labeled as HOV operated. Due to detector failure, some of the segments without complete traffic data (i.e., volume, speed, and occupancy) were removed from the final dataset. Therefore, the final datasets included 2050 miles of roadway segments from the three states.

TABLE 2 Summary statistics of collected variables (California: 1466 segments, 518 miles, 8,434 crashes)

Aggregation Level	Variable	Description	Mean	SD	Min	Max
AAWDHT (N=23404)	Crash Frequency	Annual weekday hourly crash frequency	0.075	0.231	0.000	4.000
	Volume	Annual average weekday hourly volume (veh)	3258.973	2246.423	1.150	14777.678
	Avg Speed	Annual average weekday hourly speed (mph)	60.908	14.739	8.638	99.957
	SD Speed	Annual average weekday hourly standard deviation of speed (mph)	6.226	4.870	0.000	87.865
	Avg Occupancy	Annual average weekday hourly occupancy (%)	0.095	0.087	0.002	0.666
	SD Occupancy	Annual average weekday hourly standard deviation of occupancy (%)	0.022	0.017	0.001	0.192
	HOV	HOV operation (0: not operation/no HOV; 1: HOV operated)	0.391	0.488	0.000	1.000
	HOV Hours	Number of hours for HOV operation	0.387	0.485	0.000	1.000
AAWEHT (N=24315)	Crash Frequency	Annual weekend hourly crash frequency	0.026	0.127	0.000	3.000
	Volume	Annual average weekend hourly volume (veh)	3066.095	2175.945	1.885	13072.278
	Avg Speed	Annual average weekend hourly speed (mph)	65.894	12.277	11.320	99.841
	SD Speed	Annual average weekend hourly standard deviation of speed (mph)	5.388	4.156	0.000	77.148
	Avg Occupancy	Annual average weekend hourly occupancy (%)	0.076	0.073	0.002	0.595
	SD Occupancy	Annual average weekend hourly standard deviation of occupancy (%)	0.017	0.014	0.000	0.192
	HOV	HOV operation (0: not operation/no HOV; 1: HOV operated)	0.287	0.452	0.000	1.000
	HOV Hours	Number of hours for HOV operation	0.287	0.452	0.000	1.000
AAWDPT (N=3921)	Crash Frequency	Annual weekday period crash frequency	0.450	0.750	0.000	8.000
	Volume	Annual average weekday period volume (veh)	19300.217	12252.874	174.889	106527.002
	Avg Speed	Annual average weekday period speed (mph)	58.073	14.990	9.699	96.037
	SD Speed	Annual average weekday period standard deviation of speed (mph)	8.642	4.682	0.834	54.895
	Avg Occupancy	Annual average weekday period occupancy (%)	0.113	0.087	0.008	0.645
	SD Occupancy	Annual average weekday period standard deviation of occupancy (%)	0.039	0.024	0.003	0.194
	HOV	HOV operation (0: not operation/no HOV; 1: HOV operated)	0.590	0.492	0.000	1.000
	HOV Hours	Number of hours for HOV operation	2.334	3.108	0.000	11.000
AADOWT (N=7343)	Crash Frequency	Annual day of week crash frequency	0.350	0.580	0.000	8.500
	Volume	Annual average day of week volume (veh)	74995.331	35115.844	1336.252	280367.575
	Avg Speed	Annual average day of week speed (mph)	62.421	11.676	16.000	99.932
	SD Speed	Annual average day of week standard deviation of speed (mph)	11.367	5.297	0.000	38.282
	Avg Occupancy	Annual average day of week occupancy (%)	0.089	0.067	0.014	0.631
	SD Occupancy	Annual average day of week standard deviation of occupancy (%)	0.056	0.029	0.003	0.192
	HOV	HOV operation (0: not operation/no HOV; 1: HOV operated)	0.536	0.499	0.000	1.000
	HOV Hours	Number of hours for HOV operation	6.241	9.183	0.000	24.000
AADT (N=1466)	Crash Frequency	Annual crash frequency	2.877	3.229	0.000	38.500
	Volume	Annual average daily volume (veh)	78332.065	33286.787	1873.215	270079.190
	Avg Speed	Annual average daily speed (mph)	63.283	13.271	11.333	99.579
	SD Speed	Annual average daily standard deviation of speed (mph)	9.901	4.962	2.070	31.390
	Avg Occupancy	Annual average daily occupancy (%)	0.095	0.070	0.016	0.648
	SD Occupancy	Annual average daily standard deviation of occupancy (%)	0.059	0.026	0.005	0.190

Aggregation Level	Variable	Description	Mean	SD	Min	Max
	HOV	HOV operation (0: not operation/no HOV; 1: HOV operated)	0.527	0.499	0.000	1.000
	HOV Hours	Number of hours for HOV operation	8.265	10.169	0.000	24.000
Geometry	Segment Length	Segment length (mile)	0.354	0.380	0.100	7.879
	Lane Number	Number of lanes in both travel directions (0: <=4 lanes; 1: 5-7 lanes; 2: >=8 lanes)	1.658	0.576	0.000	2.000
	Rural or Urban	Rural area (0) or urban area (1)	0.997	0.058	0.000	1.000
	Speed Limit	Posted speed limit (mph)	65.000	0.000	65.000	65.000
	IRI	International Roughness Index (inch per mile)	107.621	74.788	0.000	400.000

TABLE 3 Summary statistics of collected variables (Florida: 338 segments, 197 miles, 4,699 crashes)

Aggregation Level	Variable	Description	Mean	SD	Min	Max
AAWDHT (N=8112)	Crash Frequency	Annual weekday hourly crash frequency	0.237	0.564	0.000	9.500
	Volume	Annual average weekday hourly volume (veh)	1796.559	1363.432	45.365	8800.325
	Avg Speed	Annual average weekday hourly speed (mph)	67.060	5.739	24.910	103.492
	SD Speed	Annual average weekday hourly standard deviation of speed (mph)	3.744	1.611	1.565	14.719
	Avg Occupancy	Annual average weekday hourly occupancy (%)	3.920	3.185	0.093	28.359
	SD Occupancy	Annual average weekday hourly standard deviation of occupancy (%)	1.295	0.846	0.210	10.395
AAWEHT (N=8112)	Crash Frequency	Annual weekend hourly crash frequency	0.052	0.173	0.000	2.000
	Volume	Annual average weekend hourly volume (veh)	1385.006	920.057	43.330	4953.786
	Avg Speed	Annual average weekend hourly speed (mph)	68.965	4.842	52.597	104.349
	SD Speed	Annual average weekend hourly standard deviation of speed (mph)	3.504	1.361	1.535	10.648
	Avg Occupancy	Annual average weekend hourly occupancy (%)	2.546	1.676	0.086	10.435
	SD Occupancy	Annual average weekend hourly standard deviation of occupancy (%)	0.887	0.364	0.199	2.970
AAWDPT (N=1352)	Crash Frequency	Annual weekday period crash frequency	1.423	1.851	0.000	15.500
	Volume	Annual average weekday period volume (veh)	10709.026	5451.305	1256.267	37245.946
	Avg Speed	Annual average weekday period speed (mph)	66.391	6.169	33.423	101.374
	SD Speed	Annual average weekday period standard deviation of speed (mph)	4.318	2.149	1.861	16.215
	Avg Occupancy	Annual average weekday period occupancy (%)	5.171	3.280	0.228	20.111
	SD Occupancy	Annual average weekday period standard deviation of occupancy (%)	2.119	1.366	0.399	11.871
AADOWT (N=2366)	Crash Frequency	Annual day of week crash frequency	0.993	1.181	0.000	9.000
	Volume	Annual average day of week volume (veh)	39287.722	15143.783	5398.944	101121.570
	Avg Speed	Annual average day of week speed (mph)	67.615	5.041	52.103	102.733
	SD Speed	Annual average day of week standard deviation of speed (mph)	5.041	1.560	2.788	13.594
	Avg Occupancy	Annual average day of week occupancy (%)	3.532	1.289	0.279	8.989
	SD Occupancy	Annual average day of week standard deviation of occupancy (%)	2.878	1.316	0.405	8.634
AADT (N=338)	Crash Frequency	Annual crash frequency	6.951	6.408	0.000	44.000
	Volume	Annual average daily volume (veh)	39347.625	13964.178	7273.319	90301.369
	Avg Speed	Annual average daily speed (mph)	67.603	4.950	53.232	101.414
	SD Speed	Annual average daily standard deviation of speed (mph)	5.052	1.232	3.152	10.851
	Avg Occupancy	Annual average daily occupancy (%)	3.540	1.063	0.404	7.826
	SD Occupancy	Annual average daily standard deviation of occupancy (%)	2.894	1.000	0.538	6.562
Geometry	Segment Length	Segment length (mile)	0.582	0.428	0.107	3.161
	Lane Number	Number of lanes in both travel directions (0: <=4 lanes; 1: 5-7 lanes; 2: >=8 lanes)	0.479	0.622	0.000	2.000
	Rural or Urban	Rural area (0) or urban area (1)	0.932	0.252	0.000	1.000
	Speed Limit	Posted speed limit (mph)	66.893	5.048	55.000	70.000
	IRI	International Roughness Index (inch per mile)	57.607	36.980	0.000	182.000

TABLE 4 Summary statistics of collected variables (Virginia: 1170 segments, 1335 miles, 21,001 crashes)

Aggregation Level	Variable	Description	Mean	SD	Min	Max
AAWDHT (N=27806)	Crash Frequency	Annual weekday hourly crash frequency	0.264	0.615	0.000	15.500
	Volume	Annual average weekday hourly volume (veh)	1313.976	1217.376	1.032	20235.042
	Avg Speed	Annual average weekday hourly speed (mph)	66.718	6.947	7.911	76.872
	SD Speed	Annual average weekday hourly standard deviation of speed (mph)	2.126	1.737	0.000	21.956
	Avg Occupancy	Annual average weekday hourly occupancy (%)	5.069	3.623	0.001	34.612
	SD Occupancy	Annual average weekday hourly standard deviation of occupancy (%)	1.101	0.888	0.000	19.991
AAWEHT (N=27806)	Crash Frequency	Annual weekend hourly crash frequency	0.110	0.320	0.000	11.000
	Volume	Annual average weekend hourly volume (veh)	1223.438	1108.140	1.207	15027.513
	Avg Speed	Annual average weekend hourly speed (mph)	67.640	6.287	8.806	76.735
	SD Speed	Annual average weekend hourly standard deviation of speed (mph)	2.102	1.642	0.493	19.791
	Avg Occupancy	Annual average weekend hourly occupancy (%)	4.151	3.130	0.000	35.306
	SD Occupancy	Annual average weekend hourly standard deviation of occupancy (%)	0.896	0.682	0.000	8.587
AAWDPT (N=4650)	Crash Frequency	Annual weekday period crash frequency	1.582	2.471	0.000	31.000
	Volume	Annual average weekday period volume (veh)	7716.436	6206.780	19.827	95219.536
	Avg Speed	Annual average weekday period speed (mph)	66.600	6.837	14.473	75.921
	SD Speed	Annual average weekday period standard deviation of speed (mph)	2.965	2.759	0.000	28.741
	Avg Occupancy	Annual average weekday period occupancy (%)	6.014	3.584	0.047	34.422
	SD Occupancy	Annual average weekday period standard deviation of occupancy (%)	1.893	1.352	0.000	11.421
AADOWT (N=8141)	Crash Frequency	Annual day of week crash frequency	1.282	1.942	0.000	37.000
	Volume	Annual average day of week volume (veh)	29564.963	19543.480	8.000	236056.574
	Avg Speed	Annual average day of week speed (mph)	67.050	5.766	32.369	75.950
	SD Speed	Annual average day of week standard deviation of speed (mph)	3.902	3.306	0.000	25.671
	Avg Occupancy	Annual average day of week occupancy (%)	4.801	2.097	0.016	16.287
	SD Occupancy	Annual average day of week standard deviation of occupancy (%)	3.069	1.595	0.000	14.276
AADT (N=1170)	Crash Frequency	Annual crash frequency	8.975	11.630	0.000	120.000
	Volume	Annual average daily volume (veh)	29413.536	19001.354	16.000	211904.582
	Avg Speed	Annual average daily speed (mph)	67.016	5.693	35.430	75.257
	SD Speed	Annual average daily standard deviation of speed (mph)	3.878	3.159	0.000	23.967
	Avg Occupancy	Annual average daily occupancy (%)	4.802	1.975	0.398	14.302
	SD Occupancy	Annual average daily standard deviation of occupancy (%)	3.050	1.466	0.000	13.655
Geometry	Segment Length	Segment length (mile)	1.141	1.325	0.100	7.725
	Lane Number	Number of lanes in both travel directions (0: <=4 lanes; 1: 5-7 lanes; 2: >=8 lanes)	0.521	0.715	0.000	2.000
	Rural or Urban	Rural area (0) or urban area (1)	0.579	0.494	0.000	1.000
	Speed Limit	Posted speed limit (mph)	65.585	5.423	55.000	70.000
	IRI	International Roughness Index (inch per mile)	67.575	49.071	0.000	239.000

METHODOLOGIS

In terms of the development of SPFs, there are a variety of statistical methods that have been used in previous studies, including Poisson, negative binomial, Poisson log-normal, zero-inflated Poisson, etc. Since the main objective of this study is to verify the feasibility of developing SPFs at different aggregation levels based on microscopic traffic detector data, only the basic negative binomial (NB) model was employed in this study. Also, NB model is the recommended modeling approach in the Highway Safety Manual (AASHTO, 2010), and it is the most frequently used model in previous crash frequency modeling research (Lord and Mannering, 2010). The NB model can be expressed as:

$$\lambda_i = \exp\,(\boldsymbol{\beta X_i} + \varepsilon) \tag{1}$$

where $\boldsymbol{\lambda_i}$ represents the expected number of crashes at the designated site during a specific period; $\boldsymbol{X_i}$ is the vector of explanatory variables; β is the vector of coefficients; $\mathbf{exp}\,(\boldsymbol{\varepsilon})$ is a gamma-distributed error term with mean 1 and variance $\mathbf{1}/\boldsymbol{k}$, where $\boldsymbol{k}$ denotes the over-dispersion parameter in the NB model.

Model Estimation and Comparison

For model comparison, the Akaike information criterion (AIC) (Akaike, 1974) was chosen to conduct model selection. AIC is a mathematical method for evaluating how well a model fits the data from it was generated. In this study, AIC is used to compare different possible models and determine which one is the best fit for the data. Especially when two variables are highly correlated (i.e., the Pearson correlation coefficient is greater than 0.4), only the variable that achieves lower AIC value will be kept in the model.

$$AIC = -2LL + 2p \tag{2}$$

Where LL is the log-likelihood estimate; p is the number of independent variables used. It is worth noting that the AIC value is only used for the model comparison with the same dataset. For the model comparison between different datasets, the mean absolute deviation (MAD) was employed in this study.

$$MAD = \frac{\sum_{i=1}^{n} \left| y_{predict} - y_{observed} \right|}{n} \tag{3}$$

Where $y_{predict}$ is the predicted crash frequency, $y_{observed}$ is the observed crash frequency, n is the sample size. For every state, all the roadway segments were randomly split into training and test segments with a ratio of 70:30. Then, training and test datasets for different aggregation levels were generated. All the model evaluation results reported in this study were based on the corresponding test dataset.

Transferability Evaluation

Transfer index (TI) was chosen to evaluate the model transferability between different states. TI has been widely used in previous studies to evaluate the spatial transferability of SPFs (Farid et al., 2018; Farid et al., 2016; Sikder et al., 2014). TI is able to provide an indication of the performance of the transferred model (i) on the state of interest (j), which is defined as follows:

$$TI_j(\beta_i) = \frac{LL_j(\beta_i) - LL_j\left(\beta_{reference,j}\right)}{LL_j\left(\beta_j\right) - LL_j\left(\beta_{reference,j}\right)} \tag{4}$$

where the $LL_j(\beta_i)$ indicates the log-likelihood of applying the SPF developed on state i to estimate the safety performance of state j. $LL_j\left(\beta_{reference,j}\right)$ represents the log-likelihood of the constant only SPF developed on state j. $LL_j\left(\beta_j\right)$ is the log-likelihood of the full SPF developed on state j. The closer the value of TI is to 1 indicates that the performance of the transferred model is closer to the locally estimated model.

RESULTS

Model Estimation Results

TABLE 5 shows the estimation results of the developed SPFs at different aggregation levels based on California data. Six variables were found to be significant at the 95% level. The segment length and volume, as exposure variables, are significant across all the aggregation levels. For the operating speed, the average speed is significant with a negative coefficient, which indicates that higher operating speed can significantly reduce crash frequency. This finding is consistent with a previous study (Dutta and Fontaine, 2019; Garach et al., 2016; Hauer et al., 2004; Imprialou et al., 2016; Jonsson, 2005; Pei et al., 2012; Yu et al., 2013; Yu et al., 2018). The standard deviation of speed was found to be positively associated with the crash frequency at the AAWDPT, AADOWT, and AADT aggregation levels, which means that a higher standard deviation of speed can significantly increase the crash frequency. This finding implies that traffic safety could be significantly improved through appropriate speed management strategies, e.g., speed harmonization or variable speed limit.

In estimating these disaggregated SPFs, the short-term safety effect of active traffic management strategies can also be evaluated. Specifically, the HOV location and operating hours were integrated into the five aggregation levels, which enable us to capture the short-term impact of the actual HOV operation. This type of short-term quantitative safety impact analysis should be preferable to traditional aggregated analyses. The model estimation results identified that the more disaggregated model (AAWDHT) generates higher values of the coefficient of HOV than the aggregated model (AADT). For example, the AAWDHT model reveals that the operation of HOV would increase the weekday hourly crash frequency by 42.33%, while the AADT model indicates that the operation of HOV would increase the total crash frequency by 21.29%. This can be explained in that the more disaggregated SPF can better capture the safety impacts of the actual operating hours of HOV lanes rather than blend the operating and non-operating hours of HOV lanes. The increase in crash frequency might be caused by the increased lane-change maneuvers during the operation of the HOV lanes.

TABLE 5 Model estimation results of different aggregation level SPFs (California)

Variable	Aggregation Level				
	AAWDHT	**AAWEHT**	**AAWDPT**	**AADOWT**	**AADT**
Intercept	-0.531* (0.025)	-1.14 (0.002)	-5.254 (<0.0001)	-5.986 (<0.0001)	-3.775 (0.001)
Log (Segment Length)	0.876 (<0.0001)	0.867 (<0.0001)	0.878 (<0.0001)	0.86 (<0.0001)	0.866 (<0.0001)
Log (Volume)	-	-	0.642 (<0.0001)	0.587 (<0.0001)	0.557 (<0.0001)
Avg Speed	-0.04 (<0.0001)	-0.04 (<0.0001)	-0.023 (<0.0001)	-0.019 (<0.0001)	-0.019 (<0.0001)
SD Speed	-	-	0.036 (<0.0001)	0.036 (<0.0001)	0.042 (<0.0001)
HOV	0.353 (<0.0001)	0.308 (0.012)	0.254 (0.001)	0.198 (0.002)	0.193 (0.064)
Lane Number in both direction (reference: <=4 lanes)					
Lane Number (5-7 lanes)	0.864 (<0.0001)	0.429 (0.157)	-	-	-
Lane Number (>=8 lanes)	1.044 (<0.0001)	0.853 (0.002)	-	-	-
IRI	0.001 (0.062)	0.001 (0.099)	-	-	-
AIC	8159.562	3665.147	4502.610	6875.299	2662.154

Note: *regression coefficient with P-value in parenthesis.

TABLE 6 presents the estimation results of different aggregation level SPFs based on Florida data. In general, the significant variables and the corresponding signs are consistent with the California models. The speed limit was found to have a significant negative effect on the crash frequency at the AAWDPT aggregation level, which means that a higher speed limit can significantly decrease the crash frequency. The possible reason is that the average operating speed on these roadway segments is higher than 66 mph at any aggregation level; therefore, the value of the posted speed limit also represents the average operating speed. A higher speed limit was found to be significantly associated with lower crash frequency, which is consistent with previous studies (Hauer et al., 2004; Wang et al., 2017).

TABLE 6 Model estimation results of different aggregation level SPFs (Florida)

Variable	Aggregation Level				
	AAWDHT	**AAWEHT**	**AAWDPT**	**AADOWT**	**AADT**
Intercept	-1.632* (0.007)	-0.195 (0.879)	-6.896 (<0.0001)	-5.836 (<0.0001)	-5.46 (0.07)
Log (Segment Length)	0.943 (<0.0001)	0.927 (<0.0001)	0.821 (<0.0001)	0.844 (<0.0001)	0.849 (<0.0001)
Log (Volume)	0.801 (<0.0001)	0.308 (<0.0001)	0.789 (<0.0001)	0.828 (<0.0001)	0.96 (<0.0001)
Avg Speed	-0.08 (<0.0001)	-0.066 (<0.0001)	-	-0.047 (<0.0001)	-0.045 (0.014)
SD Speed	-	-	0.176 (<0.0001)	0.129 (<0.0001)	0.151 (0.013)
Lane Number in both direction (reference: <=4 lanes)					
Lane Number (5-7 lanes)	-	0.305 (0.039)	-	-	-
Lane Number (>=8 lanes)	-	0.754 (0.002)	-	-	-
Speed Limit (reference: 55 mph)					
Speed Limit (65)	-	-	-0.223 (0.138)	-	-
Speed Limit (70)	-	-	-0.502 (0.001)	-	-
IRI	-	-	-	0.002 (0.082)	-
AIC	5779.459	2308.504	2836.774	4251.995	1359.415

Note: *regression coefficient with P-value in parenthesis.

TABLE 7 shows the estimation results of different aggregation levels SPFs based on Virginia data. Also, the general significant variables and their corresponding signs are consistent with the California and Florida models.

TABLE 7 Model estimation results of different aggregation level SPFs (Virginia)

Variable	Aggregation Level				
	AAWDHT	**AAWEHT**	**AAWDPT**	**AADOWT**	**AADT**
Intercept	-5.717* (<0.0001)	-6.322 (<0.0001)	-3.479 (<0.0001)	-4.049 (<0.0001)	5.297 (<0.0001)
Log (Segment Length)	0.744 (<0.0001)	0.805 (<0.0001)	0.731 (<0.0001)	0.733 (<0.0001)	0.736 (<0.0001)
Log (Volume)	0.653 (<0.0001)	0.595 (<0.0001)	0.479 (<0.0001)	0.436 (<0.0001)	0.142 (0.014)
Avg Speed	-	-	-	-	-0.073 (<0.0001)
SD Speed	0.227 (<0.0001)	0.243 (<0.0001)	0.149 (<0.0001)	0.125 (<0.0001)	-
Lane Number in both direction (reference: <=4 lanes)					
Lane Number (5-7 lanes)	-	-	-	-	0.652 (<0.0001)
Lane Number (>=8 lanes)	-	-	-	-	1.154 (<0.0001)
Speed Limit (reference: 55 mph)					
Speed Limit (60)	-0.472 (<0.0001)	-0.536 (<0.0001)	-0.491 (<0.0001)	-0.468 (<0.0001)	-
Speed Limit (65)	-0.559 (<0.0001)	-0.368 (<0.0001)	-0.591 (<0.0001)	-0.532 (<0.0001)	-
Speed Limit (70)	-1.005 (<0.0001)	-0.765 (<0.0001)	-1.104 (<0.0001)	-0.976 (<0.0001)	-
AIC	21849.156	12241.031	9868.007	15745.637	4888.955

Note: *regression coefficient with P-value in parenthesis.

TABLE 8 shows the model estimation results of the disaggregated SPFs based on the state-combined datasets. The significant variables are slightly different from the abovementioned state-specific models. In the combined model, the logarithm of volume is not included in the model due to that they are highly correlated with the variables of lane number and HOV operation. Also, the variable of HOV operating hours was found to be positively associated with the crash frequency, which indicates that the longer HOV operation may significantly increase the crash frequency. Virginia and Florida were found to have significantly higher crash frequencies than California. The roadway segments in urban areas were found to have significantly higher crash frequency than the segments in rural areas.

TABLE 8 Model estimation results of different aggregation level SPFs (California, Florida, and Virginia)

Variable	Aggregation Level				
	AAWDH	**AAWEH**	**AAWDP**	**AADOW**	**AAD**
Intercept	-4.045* (<0.0001)	-4.515 (<0.0001)	-2.42 (<0.0001)	-2.602 (<0.0001)	-0.598 (<0.0001)
Log (Segment Length)	0.71 (<0.0001)	0.811 (<0.0001)	0.724 (<0.0001)	0.724 (<0.0001)	0.73 (<0.0001)
SD Speed	0.035 (<0.0001)	0.027 (<0.0001)	0.1 (<0.0001)	0.087 (<0.0001)	0.081 (<0.0001)
HOV	0.876 (<0.0001)	0.706 (<0.0001)			-0.368 (0.009)
HOV Hours			0.077 (<0.0001)	0.016 (<0.0001)	0.034 (<0.0001)
Lane Number in both direction (reference: <=4 lanes)					
Lane Number (5-7 lanes)	0.923 (<0.0001)	0.8 (<0.0001)	0.807 (<0.0001)	0.746 (<0.0001)	0.77 (<0.0001)
Lane Number (>=8 lanes)	1.333 (<0.0001)	1.441 (<0.0001)	1.064 (<0.0001)	0.988 (<0.0001)	0.978 (<0.0001)
State (reference: California)					
Florida	2.052 (<0.0001)	1.496 (<0.0001)	1.978 (<0.0001)	1.951 (<0.0001)	1.852 (<0.0001)
Virginia	1.995 (<0.0001)	1.797 (<0.0001)	1.989 (<0.0001)	1.994 (<0.0001)	1.93 (<0.0001)
Rural or Urban	0.395 (<0.0001)	0.097 (0.072)	0.407 (<0.0001)	0.302 (<0.0001)	0.377 (<0.0001)
IRI	0.001 (0.043)				
AIC	38706.532	18918.712	17726.523	27352.497	8958.940

Note: *regression coefficient with P-value in parenthesis.

Model Comparison

To compare the model prediction performance between different aggregation levels, six predictors were employed to calculate the MAD: (1) annual weekday hourly crash frequency; (2) annual weekend hourly crash frequency; (3) annual weekday peak/off-peak crash frequency; (4) annual weekday crash frequency; (5) annual weekend crash frequency; (6) annual crash frequency. For some models, the predictors were calculated by summing the corresponding disaggregated predictions. For example, the initial predicted values of the AAWDHT model are the annual weekday hourly crash frequency for every segment; this can be aggregated to be annual weekday peak/off-peak crash frequency by summing all the corresponding hourly predictions during peak/off-peak periods. TABLE 9 presents the MAD for every predictor by using different aggregation level SPFs. In general, the MADs of the California models are much smaller than the Florida and Virginia models, and the performance of Florida and Virginia models are quite close. In terms of the comparison between different aggregation levels, the differences between the MADs are small, which indicates that the prediction performance of the disaggregated models is as good as the aggregated model. This conclusion is consistent with the previous study, which compared the AHT-based model and the ADT-based model (Wang et al., 2017). However, the AADOWT and AAWDPT models consistently perform better (the improvements range from 3.14% to 16.20%) than the other models over the three states, which implies that the difference between the day of the week and peak/off-peak periods should be considered in the development of crash prediction models.

TABLE 9 Model comparison results of SPFs for California, Florida, Virginia, and the Combined States

SPF		MAD for Predicted Crash Frequencies					
Estimation State	**Aggregation Level**	**Annual Hourly Crash Frequency (weekday)**	**Annual Hourly Crash Frequency (weekend)**	**Annual Period Crash Frequency (weekday)**	**Annual Crash Frequency (weekday)**	**Annual Crash Frequency (weekend)**	**Annual Crash Frequency**
California	AAWDHT	0.109	NA	0.399	1.039	NA	1.371 (1+2)* 1.352 (1+4)
	AAWEHT	NA	0.045	NA	NA	0.539	1.371 (1+2) 1.346 (2+3) 1.364 (2+4)
	AAWDPT	NA	NA	0.393	1.031	NA	1.346 (2+3) 1.346 (3+4)
	AADOWT	NA	NA	NA	1.051	0.528	1.363
	AADT	NA	NA	NA	NA	NA	1.411
Florida	AAWDHT	0.279	NA	1.050	3.331	NA	3.853 (1+2) 3.940 (1+4)
	AAWEHT	NA	0.095	NA	NA	0.845	3.853 (1+2) 3.801 (2+3) 3.700 (2+4)
	AAWDPT	NA	NA	1.047	3.320	NA	3.801 (2+3) 3.829 (3+4)
	AADOWT	NA	NA	NA	3.211	0.887	3.792
	AADT	NA	NA	NA	NA	NA	3.820
Virginia	AAWDHT	0.298	NA	1.051	3.173	NA	4.348 (1+2) 4.195 (1+4)
	AAWEHT	NA	0.164	NA	NA	1.527	4.348 (1+2) 4.097 (2+3) 4.067 (2+4)
	AAWDPT	NA	NA	1.025	2.966	NA	4.097 (2+3) 4.017 (3+4)
	AADOWT	NA	NA	NA	2.924	1.437	3.982
	AADT	NA	NA	NA	NA	NA	4.752
California, Florida, and Virginia	AAWDHT	0.252	NA	0.913	2.419	NA	3.242 (1+2) 3.175 (1+4)
	AAWEHT	NA	0.113	NA	NA	1.123	3.242 (1+2) 3.126 (2+3) 3.071 (2+4)
	AAWDPT	NA	NA	0.872	2.329	NA	3.126 (2+3) 3.120 (3+4)
	AADOWT	NA	NA	NA	2.285	1.108	3.071
	AADT	NA	NA	NA	NA	NA	3.278

Note: NA = not applicable; * the value in parentheses represents the integrated models that the predictor is based on (1: AAWDHT; 2: AAWEHT; 3: AAWDPT; 4: AADOWT; 5: AADT).

Model Transferability

TABLE 10 shows the transfer indices of SPFs between California, Florida, Virginia, and the combined states. As discussed in the previous section, the model estimation results between Florida and Virginia are quite similar. The transfer indices between Florida and Virginia also verified this finding. The Florida SPFs (AAWDHT, AAWEHT, AAWDPT, and AADOWT) can successfully be transferred to Virginia with an average transfer index of 0.84. This can be potentially explained from the following aspects: (1) both Virginia and Florida represent the southeast region of the U.S., which have similar features in geography, traffic management strategies, safety culture, and climate; (2) Virginia and Florida share similar demographics and macro-level traffic characteristics. For example, the population of both states are among the top 25% states in the U.S., their percentages of adults age 25+ with at least a high school education are very close (Sarte et al., 2018), and the highway vehicle-miles traveled per vehicle between Virginia (11,222 miles) and Florida (12,678 miles in) are close (USDOT, 2018); (3) The characteristics of freeways between Virginia and Florida are similar, including the number of lanes, speed limit, and IRI. On the other hand, the Virginia SPFs can also be transferred to Florida except for the AAWEHT model. A possible reason might be that the AAWEHT is specially developed for weekend crashes, while the weekend traffic between Virginia and Florida are very different due to the tourism traffic. California SPFs at all aggregation levels are not transferable to Virginia and Florida. The most critical reason might be that California represents the west region of the U.S. while Virginia and Florida represent the southeast region, where they have different topography, weather, traffic management strategies, safety culture, and demographics.

It should be noted that even though the combination of multi-state data has significantly improved the model transferability for California, where the transfer indices of the combined models are much higher than the Florida and Virginia models. The transfer indices for California are still lower than 0 (except for the AADT-based SPF), which implies that combined models are still not transferable to California. On the other hand, the transfer indices from combined models to Florida and Virginia are relatively lower than the indices of the separated Florida and Virginia models, which implies that the combination of the three-state data deteriorated the model transferability for Florida and Virginia.

TABLE 10 Transfer indices of SPFs between California, Florida, and Virginia

SPF		Application State		
Estimation State	**Aggregation Level**	**California**	**Florida**	**Virginia**
California	AAWDHT	1.000	-1.654	-0.683
	AAWEHT	1.000	-1.790	-0.412
	AAWDPT	1.000	-3.254	-1.806
	AADOWT	1.000	-3.645	-1.817
	AADT	1.000	-6.540	-3.950
Florida	AAWDHT	-7.983	1.000	**0.855**
	AAWEHT	-5.321	1.000	**0.899**
	AAWDPT	-6.646	1.000	**0.775**
	AADOWT	-12.734	1.000	**0.844**
	AADT	-7.615	1.000	**0.033**
Virginia	AAWDHT	-16.565	**0.695**	1.000
	AAWEHT	-30.036	-1.131	1.000
	AAWDPT	-9.062	**0.707**	1.000
	AADOWT	-13.952	**0.610**	1.000
	AADT	-4.065	**0.546**	1.000
California, Florida, and Virginia	AAWDHT	-0.429	**0.068**	**0.407**
	AAWEHT	-0.562	**0.597**	**0.518**
	AAWDPT	-0.584	**0.376**	**0.591**
	AADOWT	-0.678	**0.406**	**0.617**
	AADT	**0.063**	**0.490**	**0.655**

In summary, the SPFs estimated based on California, Florida, and Virginia datasets are generally consistent in the significant variables and their corresponding signs. However, the specific values for most of the coefficients are quite different. The model transferability results indicate that the SPFs between Florida and Virginia are transferrable, while the models between California and the other two states are not transferrable. In terms of the SPFs between the five aggregation levels, the model estimation and comparison results indicate that the more disaggregated SPFs are able to provide more dynamic predictions, and at the same time, the summation of the dynamic predictions is even slightly better than the predictions from the aggregated model. These SPFs can be used for dynamic hotspot identification to screen not only the high-risk segments but also the high-risk hour or time periods. In addition, these SPFs can be developed to accurately quantify the short-term safety impact of the routinely operated ATM strategies, e.g., HOV lanes, dynamic shoulder use, and ramp metering.

CONCLUSIONS AND DISCUSSION

Safety Performance Functions (SPFs) have been widely used by researchers and practitioners to conduct roadway safety evaluation. Traditional SPFs are usually developed by using annual average daily traffic (AADT) along with geometric and operational characteristics. However, the high level of aggregation may lead to a failure of capturing the temporal variation in traffic characteristics (e.g., traffic volume and speed), as well as crash frequencies. In this study, five SPFs at different aggregation levels were developed based on microscopic traffic detector data from California, Florida, and Virginia, separately. The five aggregation levels are (1) annual average weekday hourly traffic (AAWDHT), (2) annual average weekend hourly traffic (AAWEHT), (3) annual average weekday peak/off-peak traffic (AAWDPT), (4) annual average day of the week traffic (AADOWT), and (5) annual average daily traffic

(AADT). The AADT aggregation-based model is the same as the traditional AADT-based SPF, which was developed for comparing the different aggregation level SPFs with the traditional SPFs. In terms of the explanatory variables, both short-term dynamic and long-term static variables were considered. Among them, volume, average speed, the standard deviation of speed, average occupancy, standard deviation of occupancy are short-term variables, which were collected for different aggregation levels. The segment length, lane number, rural/urban, speed limit, and International Roughness Index (IRI) were collected as long-term static variables. It should be noted that the HOV location and the corresponding operating hours were integrated into the California dataset to generate two extra short-term variables: HOV operation status and HOV operating hours. In addition, the transferability of SPFs between three states were also investigated.

Model estimation results showed that all the significant variables across different states are consistent. Segment length and volume, as exposure variables, are significant across all the aggregation levels. For the operating speed, the average speed is significant with a negative coefficient, which indicates that higher operating speed can significantly reduce crash frequency. This finding is consistent with a previous study (Dutta and Fontaine, 2019; Garach et al., 2016; Hauer et al., 2004; Imprialou et al., 2016; Jonsson, 2005; Pei et al., 2012; Yu et al., 2013; Yu et al., 2018). The standard deviation of speed was found to be positively associated with the crash frequency, which means that a higher standard deviation of speed can significantly increase the crash frequency. This finding implies that traffic safety could be significantly improved through appropriate speed management strategies, e.g., speed harmonization or variable speed limit. One of the key advantages of these disaggregated SPFs is the ability to include more time-varying traffic and operational factors (e.g., speed and speed standard deviation) that are important to crash frequency prediction.

In California models, the HOV operation status was found to have a positive effect on crash frequency across all the aggregation levels, which reveals that the HOV operation can significantly increase the crash frequency. It should be emphasized that the coefficients of HOV in the disaggregated SPFs are higher than the aggregated model (AADT). For example, the AAWDHT model reveals that the operation of HOV would increase the weekday hourly crash frequency by 42.33%, while the AADT model indicates that the operation of HOV would increase the total crash frequency by 21.29%. This can be explained in that the more disaggregated SPF can better capture the safety impacts of the actual operating hours of HOV lanes rather than blend the operating and non-operating hours of HOV lanes. The increase in crash frequency might be caused by the increased lane-change maneuvers during the operation of the HOV lanes. These results also imply that the disaggregated SPFs might provide a more accurate quantitative assessment of the short-term safety effects of active traffic management (ATM) strategies, which should be further investigated by including more ATM strategies (e.g., dynamic lane control, variable speed limit, and ramp metering).

The model comparison results in MAD values indicated that the MADs of the California models are much smaller than the Florida and Virginia models, and the performance of Florida and Virginia models are very close. In terms of the comparison between different aggregation levels, the differences of the MADs are relatively small, which indicates that the prediction performance of the disaggregated models is as good as the aggregated model. This conclusion is consistent with the previous study, which compared the AHT-based model and the ADT-based model (Wang et al., 2017). However, the AADOWT and AAWDPT models consistently performed better (the improvements range from 3.14% to 16.20%) than the other models over the three states, which implies that the difference between the day of the week and peak/off-peak periods should be considered in the development of crash prediction models.

The model transferability results indicated that the disaggregated SPFs between Florida and Virginia are mutually transferrable, while the models are not transferrable between California and the other two states. This might be explained in that Virginia and Florida represent the southeast region of the U.S., and they have many similar features in geography, traffic management strategies, safety culture, climate, and demographics, while California represents the western region of the U.S. These findings imply that those states from the same region with similar geography, culture, climate, and demographics are more likely to have mutually transferable SPFs. Therefore, local jurisdictions that are willing to adopt existing

SPFs rather than developing their own SPFs would be recommended to choose those SPFs which were developed based on the data from neighboring states or the states from the same region of the U.S. with similar geography, traffic management strategies, safety culture, climate, and demographics. But even so, the successful transferability is not guaranteed unless demonstrated by the results of a solid SPF transferability study.

To the best of the authors' knowledge, this is the first attempt to systematically develop disaggregated SPFs at different aggregation levels by using multi-state microscopic traffic detector data. Meanwhile, the safety effects of speed characteristics and HOV operation status have been quantified. Also, the transferability of SPFs at different aggregation levels have been evaluated. The results are promising but have some limitations for which possible improvements could be made in future research: (1) crash severity was not considered in the present study, which should be included in future research to investigate the interactions between the time-varying factors, aggregation levels, and crash severities; (2) Human factors (e.g., drivers' familiarity) are another type of critical factors that may significantly affect the roadway safety performance (Intini et al., 2019a; Intini et al., 2018; Intini et al., 2019b), which should be considered in future research; (3) More ATM strategies should be integrated to maximize the benefits of disaggregated SPFs; (4) Given the microscopic traffic detector data, integrating real-time crash prediction models into the disaggregated SPFs might achieve better prediction performance; (5) This study only employed the basic NB model. More advanced spatial and temporal statistical models should be considered in future research.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Jinghui Yuan: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Mohamed Abdel-Aty**: Conceptualization, Investigation, Writing - review & editing, Supervision. **Jingwan Fu**: Data Curation. **Yina Wu**: Conceptualization, Methodology. **Lishengsa Yue**: Methodology, Formal analysis. **Naveen Eluru**: Conceptualization, Methodology, Writing - review & editing.

DECLARATION OF COMPETING INTEREST

The authors report no declarations of interest.

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