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Correlating Connected Vehicle Estimated Deceleration Events with Crash Incidents near Interstate Interchanges

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Abstract

Historical roadway safety analyses have used labor and time-intensive crash data collection procedures. However, crash reporting is often delayed and crash locations are reported with varying levels of spatial accuracy and detail. Recent advances in connected vehicle (CV) data provide an opportunity for stakeholders to proactively identify areas of safety concerns in near-real time with high spatial precision. Public and private sector stakeholders including automotive original equipment manufacturers (OEM) and insurance providers may independently define acceleration thresholds for reporting unsafe driver behavior. Although some OEMs have provided fixed threshold hard-braking event data for a number of years, this varies by OEM and there is no published literature on the best thresholds to use for identifying emerging safety issues. This research proposes a methodology to estimate deceleration events from raw CV trajectory data at varying thresholds that can be scaled to any CV. The estimated deceleration events and crash incident records around 629 interstate exits in Indiana were analyzed for a three-month period from March 1-May 31, 2023. Nearly 20 million estimated deceleration events and 4800 crash records were spatially joined to a 2-mile search radius around each exit ramp. Results showed that deceleration events between −0.5 g and −0.4 g had the highest correlation with an R^2 of 0.69. This study also identifies the top 20 interstate exit locations with highest deceleration events. The framework presented in this study enables agencies and transportation professionals to perform safety evaluations on raw trajectory data without the need to integrate external data sources.

Keywords

Connected Vehicles, Hard-Braking, Crashes, Safety, Deceleration

1. Introduction

An important goal for most states' highway safety improvement programs is the reduction of serious injuries and fatalities from traffic incidents, bolstered in part by continued funding apportioned by the Fixing America's Surface Transportation Act (FAST). In the year 2020, the Federal Highway Administration's (FHWA) Roadway Safety Data Dashboards reported approximately 4908 of the 38,824 fatalities nationwide occurred on Interstates [1]. This represents approximately 13% of roadway fatalities. The State Highway Safety Report for the state of Indiana alone observed 897 and 932 fatalities for the years 2020 and 2021 respectively, with 11.25% occurring on Interstate routes in 2020 [1] [2].

Traditional roadway safety analyses conducted by stakeholders at the national, state and local level have relied on crash incident histories which often take weeks, months or years at a time to collect. Additionally, crash data reporting is often associated with geolocation uncertainties and inconsistencies depending on the responding agency, the severity of the crash, the functional class of the roadway and resulting traffic queues in addition to reporting delays. This makes it challenging to identify emerging safety issues in areas with high growth in traffic as well as short term work zones. Emerging advances in the availability of connected vehicle (CV) event and trajectory data have shown promise in near real-time analysis of driver behavior for conducting proactive road safety assessments. The insurance industry has been quick to adopt the use of CV data for rating drivers [3] [4] [5], but transportation agencies have only just begun to use this data [6] [7] [8] [9].

2. Historical Crash Data

Crash incidents have historically suffered from underreporting issues [10] [11], especially for events of lower severity, and delayed reporting often due to changing injury severities. A 2013 study on Indiana's crash datasets observed a typical time frame of 2 - 3 days for crash records to appear in a centralized repository from the time of occurrence, and recommended continuous quality control for crash datasets to ensure standardized data collection procedures for effective use in monitoring road safety [12]. A 2019 study into the quality of crash data for use in road safety research identified multiple potential issues and limitations in crash data collection techniques with the location, severity and time of a crash being the attributes most often erroneously reported [13]. These underlying issues may often tend to impact any potential crash-based road safety analysis by biasing the results and incorrectly estimating the impacts of safety countermeasures [14] [15]. This has led to researchers having to anticipate for underreporting in crash-frequency based analysis to account for these biases [16].

In order to ensure consistency and standardization in crash reporting, the Model Minimum Uniform Crash Criteria (MMUCC) guideline was developed in 1998 by the National Highway Traffic Safety Administration (NHTSA) and has been periodically updated to provide a framework to responding agencies on what crash data variables to document. Studies have since looked at the level of MMUCC compliance across multiple states [17] [18] [19]. However, the inherent manual component of crash data collection and issues with underreporting, inconsistency and delayed reporting severely limit the ability of stakeholders to effectively use this data for tactical real-time decision making until higher levels of MMUCC compliance are achieved nationwide.

3. Emerging Connected Vehicle Event Data Opportunities

Emerging CV event data have shown valuable potential in reducing the data collection time period for roadway safety analysis by providing driver event data including hard-braking and hard-acceleration in near real-time at a widely available geographic footprint without the need for any intelligent transportation system infrastructure. This data has already been used to show strong correlations with crash incidents in interstate construction work zones [7], evaluating intersection safety [6], evaluating safety performance of low volume rural highways [20], predicting real-time crash potential [21], identifying roadway hazards [22], evaluating the safety of rolling slowdowns compared to road closures [23], as well as evaluating the effectiveness of work zone safety equipment such as queue warning trucks [24] to name a few. These event data are widely available and can be scalably used for systematic and consistent local, state, multi-state or even national level safety analyses.

4. Limitations of CV Event Data and Need for Transparent Thresholds

However, such event datasets often have pre-defined deceleration thresholds assigned by the Original Equipment Manufacturer (OEM) with limited transparency on exact threshold values associated with a hard-braking event. This presents challenges of integrating data from multiple CV OEMs. Furthermore, a hard-braking threshold that shows strong correlations with crash incidents for one location or one functional class of roadway may not present similar results in another location for a different class of roadway due to varying driver behavior, differing speed limits and changing road geometry and configuration in each case. Such datasets, while effective in conveying aggregated safety performance insights, do not provide visibility on deceleration thresholds and may potentially be masking or underrepresenting the impacts of severe deceleration events due to broad thresholds.

Thus, access to near real-time CV trajectory data with individual vehicle waypoints at 60-second latencies will present practitioners, researchers and stakeholders with an opportunity to define their own acceleration or deceleration thresholds for generating system level safety performance metrics that include a diverse set of data from multiple OEMs. While previous studies have focused on localized analysis of safety upstream, downstream or within construction work zones or at selected corridors of signalized intersections, this study aims to present a systemwide analysis of estimated deceleration events computed using CV trajectory data for conducting road safety assessments.

5. Objectives and Scope

The scope of this study is to evaluate the correlation between various thresholds of estimated deceleration events and crash incident counts recorded around exit ramps on Indiana's Interstate System. The objectives of this study are:

1) To evaluate the correlation between various deceleration thresholds and crash incidents around Indiana Interstate exit ramps and provide a recommendation on what threshold should be used on interstates.

2) To demonstrate how this data can be used to identify exit ramp locations around the state showing the highest deceleration events per mile values as a framework for filtering locations for safety assessments.

These techniques can be scaled to other highway use cases such as merge areas, signalized intersections, toll booths and border crossings.

6. Study Location

The study identified 629 unique exit locations on Indiana's Interstate System for this analysis. For each exit location, the mile marker at which the exit ramp departs from the mainline interstate was recorded. This mile marker was then used as the center point for various search radii (0.5 miles, 1 mile and 2 miles) extending both upstream and downstream for aggregating crash incident counts as well as estimated deceleration event counts for analysis. Figure 1 shows an overview of these exit ramp locations in a statewide context showing near ubiquitous coverage along the entire Interstate system. A significant concentration of exits is seen near the metropolitan areas of Gary (callout i), Indianapolis (callout ii), Louisville (callout iii), Evansville (callout iv) and Fort Wayne (callout v) as a result of the need to service the high population density and corresponding vehicle volumes in the area.

7. Data Description

7.1. Estimated and OEM Provided CV Deceleration Events

CV trajectory data were provided by a third-party commercial data aggregator. Each CV trajectory consists of waypoints available at 1 - 3 second frequency with a 3-meter geolocation accuracy. Each waypoint also had an associated anonymized trajectory identifier, geolocation, timestamp, heading and speed attribute. This dataset represents an average penetration of about 4% on interstates in Indiana [25] [26]. These attributes were used to compute acceleration or deceleration between consecutive CV waypoints for all such events with an absolute acceleration value greater than or equal to 0.1 g (0.98 m/s^2). In the interest of consistency, only pairs of waypoints 3-seconds apart were utilized to compute estimated deceleration to avoid any bias caused by waypoint reporting frequency.

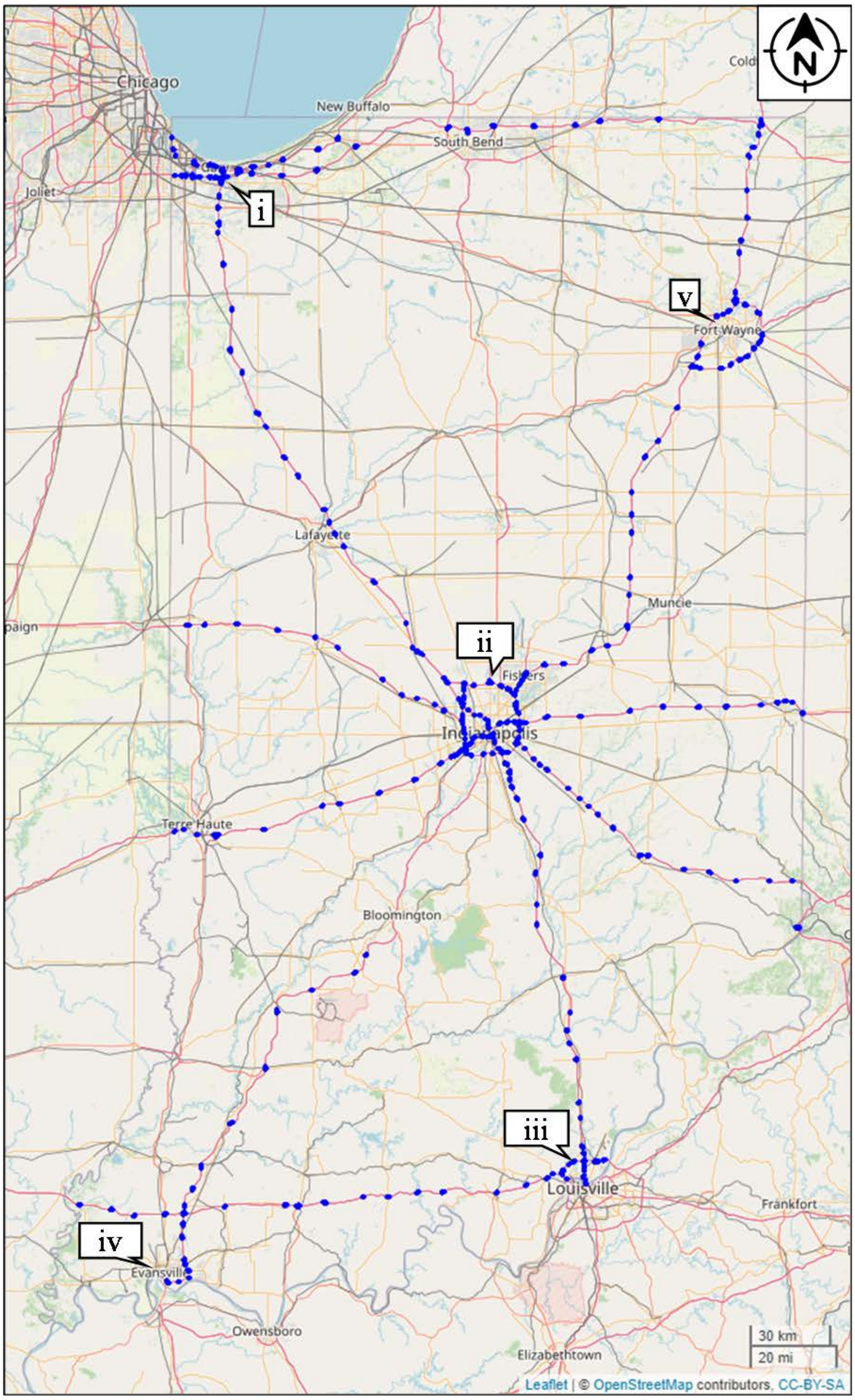

Figure 1. 629 exit ramp locations on Indiana interstates.

Prior research using three-axis smart phone accelerometer data has suggested that on average an absolute g-force of less than 0.1 g is experienced by drivers when changing lanes [27]. Assuming that a driver would at least experience this g-force value on unsafe braking, a maximum deceleration threshold of −0.1 g was considered when filtering estimated deceleration events for analysis. Each such estimated deceleration event was then spatially joined and linear referenced to Indiana's interstate route network using common geographic information system (GIS) techniques [28] [29] to reference data to the interstate route, direction of travel and mile marker location. For comparison, CV hard-braking event data provided directly by the same third-party commercial data provider have also been included in the analysis. These events are henceforth referred to as CV Events to distinguish them clearly from estimated deceleration events.

Table 1 represents a summary count of estimated deceleration events found along the study location categorized by the search radius as well as the range of deceleration in equal sized intervals of 0.1 g with a final interval accounting for all events with deceleration lower than −0.5 g. The widest search radius of 2 miles both upstream and downstream of all exit ramps quite expectedly captures the highest number of estimated deceleration events. For comparison, CV Event counts captured within each search radius are also shown.

7.2. Crash Dataset

Table 2 correspondingly shows a count of the total number of crash incidents, generated as a curated selection of interstate crashes from Indiana's centralized crash repository, detected within a 0.5, 1 and 2 mile search radius of the study

Table 1. Estimated deceleration event counts categorized by deceleration range and search radius around interstate exit ramps (March 1-May 31, 2023).

Deceleration	Number of deceleration events by search radius		
	±0.5 mile	±1 mile	±2 mile
(−∞, −0.5 g)	1,578	2,259	2,831
[−0.5 g, −0.4 g)	9,707	13,204	15,744
[−0.4 g, −0.3 g)	89,634	120,129	141,143
[−0.3 g, −0.2 g)	992,348	1,281,204	1,470,332
[−0.2 g, −0.1 g)	11,199,328	14,399,718	16,461,699
CV Events	439,159	598,554	699,171

Table 2. Crash counts categorized by search radius around interstate exit ramps and date range.

Date Range	Number of crashes by search radius		
	±0.5 mile	±1 mile	±2 mile
01/01/19-05/31/23	33,636	49,179	61,041
01/01/20-05/31/23	24,488	35,644	44,225
01/01/21-05/31/23	18,797	27,274	33,799
01/01/22-05/31/23	11,936	17,244	21,264
01/01/23-05/31/23	3,444	5,060	6,122
03/01/23-05/31/23	2,244	3,325	4,033

location. The crash counts are also categorized by six different time periods beginning January 1, 2019 and ending with the final analysis period of March 1-May 31, 2023.

For a geographical context on crash frequency, **Table 3** shows crash counts aggregated by the interstate route they were recorded on for the period of March 1-May 31, 2023. I-465, a major beltway around the city of Indianapolis in central Indiana observing heavy daily commuter traffic shows the highest number of crashes.

8. Statistical Analysis of Crash and CV Data

Using these estimated deceleration events and crash incident counts defined in **Table 1** and **Table 2**, simple linear regression analysis was conducted to evaluate the correlation between each set of datapoints for the 629 locations in the study area. The coefficient of determination (R^2) for each such comparison is reported in the tables that follow as a measure of how close the correlation aligns to the fitted line.

Tables 4-6 show the coefficient of determination or goodness-of-fit measure exhibited by linear regression models relating estimated deceleration events with crash incidents in search radii varying from 0.5, 1 and 2 miles around the study location respectively. In case of a 1 or 2 mile search radius, the highest correlation is exhibited by estimated deceleration events greater than or equal to −0.5 g and lower than −0.4 g. Crash locations are often reported with considerable inaccuracies. GPS units, offset from nearest junction or intersection, mile marker location and address are some of the various location reporting methods used which may cause significant errors [13]. This may point to the potential low correlation levels observed when using a search radius of 0.5 miles as errors in reported crash locations may exceed the 0.5 mile search radius, while the estimated deceleration events are accurate to within a 3-meter radius.

Table 3. Crashes categorized by interstate route for a 2-mile search radius around interstate exit ramps (March 1-May 31, 2023).

Interstate Route	Number of crashes
I-265	55
I-465	1,014
I-469	68
I-64	111
I-65	998
I-69	506
I-70	434
I-74	123
I-90	133
I-94	591

Table 4. Estimated deceleration events (March 1-May 31, 2023) and crash correlations for a 0.5-mile search radius around interstate exit ramps.

Crash Date Range	Deceleration Range/R^2				
	(−∞, −0.5 g)	[−0.5 g, −0.4 g)	[−0.4 g, −0.3 g)	[−0.3 g, −0.2 g)	[−0.2 g, −0.1 g)
01/01/19-05/31/23	0.47	0.55	0.54	0.46	**0.58**
01/01/20-05/31/23	0.47	0.53	0.53	0.45	0.57
01/01/21-05/31/23	0.49	0.55	0.54	0.45	0.57
01/01/22-05/31/23	0.49	0.56	0.55	0.46	0.57
01/01/23-05/31/23	0.52	0.56	0.53	0.44	0.53
03/01/23-05/31/23	0.54	0.55	0.52	0.42	0.50

Table 5. Estimated deceleration events (March 1-May 31, 2023) and crash correlations for a 1-mile search radius around interstate exit ramps.

Crash Date Range	Deceleration Range/R^2				
	(−∞, −0.5 g)	[−0.5 g, −0.4 g)	[−0.4 g, −0.3 g)	[−0.3 g, −0.2 g)	[−0.2 g, −0.1 g)
01/01/19-05/31/23	0.53	0.63	0.63	0.56	0.67
01/01/20-05/31/23	0.53	0.62	0.62	0.55	0.67
01/01/21-05/31/23	0.54	0.64	0.63	0.57	0.67
01/01/22-05/31/23	0.56	0.67	0.66	0.59	0.68
01/01/23-05/31/23	0.59	0.66	0.63	0.54	0.62
03/01/23-05/31/23	0.62	**0.69**	0.65	0.55	0.62

Table 6. Estimated deceleration events (March 1-May 31, 2023) and crash correlations for a 2-mile search radius around interstate exit ramps.

Crash Date Range	Deceleration Range/R^2				
	(−∞, −0.5 g)	[−0.5 g, −0.4 g)	[−0.4 g, −0.3 g)	[−0.3 g, −0.2 g)	[−0.2 g, −0.1 g)
01/01/19-05/31/23	0.55	0.64	0.63	0.56	0.65
01/01/20-05/31/23	0.55	0.63	0.61	0.55	0.65
01/01/21-05/31/23	0.56	0.65	0.63	0.56	0.66
01/01/22-05/31/23	0.57	0.67	0.65	0.59	0.68
01/01/23-05/31/23	0.60	**0.70**	0.65	0.56	0.63
03/01/23-05/31/23	0.61	0.69	0.63	0.54	0.60

In each case with a wide enough search radius (**Table 5** and **Table 6**), the highest or near highest coefficient of determination is observed when the crash date range aligns exactly with the estimated deceleration event date range of

March 1-May 31, 2023. This potentially points to how estimated deceleration events could be easily leveraged as near real-time indicators as well as historical indicators of safety performance without having to wait for a crash history to develop over a period of time.

9. Recommended Deceleration Rate Thresholds

Table 7 shows a summary comparison of the coefficient of determination between estimated deceleration events and crash incidents for the study period of March 1-May 31, 2023. In each choice of search radius, the highest correlation observed between deceleration events and crash counts were for those estimated deceleration events in the range of −0.5 g to −0.4 g. CV Events on the other hand display very similar correlation statistics. Based upon this close agreement between estimated deceleration and OEM provided events, we believe agencies are best served by calculating deceleration from trajectory data in a systematic manner across all OEMs and establishing their own threshold for the type of facility being analyzed. This provides tremendous flexibility to look at different facilities such as freeways, interchanges, merge areas, traffic signals, roundabouts, driveways, trails, toll booths and border crossings. Not only does this provide transparency to the agency, but also ensures the data set is not biased by the type of driver that may drive a particular type of vehicle.

Figure 2 shows a scatter plot of the crashes per mile recorded at the 629 exits in the study area compared with the estimated deceleration events per mile at the same locations on the horizontal axis for a 2 mile search radius and deceleration events in the range of −0.5 g to −0.4 g. The correlation shows a fairly high coefficient of determination value of 0.69 for the limited study period. The 20 locations with the highest deceleration events per mile values have been highlighted in red. As crash incident counts only for the state of Indiana were utilized, any search radius extending beyond the state border was limited to the state's last mile marker. This resulted in the need for normalizing deceleration events and crash incidents counts per mile for each of the study locations to ensure systematic assessment. Hence a per mile value is used in **Figure 2** even though a consistent search radius upstream and downstream was used for the entire study location.

Table 7. Estimated deceleration events and crash correlations for varying search radii around interstate exit ramps (March 1-May 31, 2023).

Search Radius	Deceleration Range/R^2					CV Events
	(−∞, −0.5 g)	[−0.5 g, −0.4 g)	[−0.4 g, −0.3 g)	[−0.3 g, −0.2 g)	[−0.2 g, −0.1 g)	
±0.5 mile	0.54	**0.55**	0.52	0.42	0.50	0.59
±1 mile	0.62	**0.69**	0.65	0.55	0.62	0.71
±2 mile	0.61	**0.69**	0.63	0.54	0.60	0.69

A tabular summary of these 20 locations ranked by the highest deceleration events per mile values is shown by Table 8. The exit ramp location at I-94 W MM 10.2 shows the highest deceleration events per mile value for the analysis period of March 1-May 31, 2023. For each location, the search area upstream and downstream is shown by their respective columns to demonstrate the near 4-mile coverage used for capturing deceleration event and crash counts.

Figure 3 shows a spatial representation of these 20 ramp locations (Table 8) with the highest deceleration events per mile values across the state of Indiana. The "Route" column denotes the interstate route as well as direction of travel for each such location (E/W representing East/West, N/S representing North/South and IL/OL representing Inner Loop/Outer Loop respectively). A number of these locations were found to be on I-465 (callout i), the beltway around the city of Indianapolis with 4 - 5 lanes in each direction that has heavy weekday commuter traffic as well as substantial commercial vehicles. Similar trends are seen

Table 8. 20 Interstate Exit Ramp Locations with highest estimated deceleration events per mile values for deceleration in the range of [−0.5 g, −0.4 g) (March 1-May 31, 2023).

Route	Search Radius Start MM	Exit Ramp MM	Search Radius End MM	Deceleration Events Per Mile
I-94 W	8.2	10.2	12.2	80.5
I-465 IL	34.2	36.2	38.2	80.3
I-94 W	4.7	6.7	8.7	79.0
I-465 OL	35.3	37.3	39.3	74.5
I-465 IL	2.0	4.0	6.0	62.0
I-90 W	0.0	0.6	2.6	61.9
I-69 S	199.4	201.4	203.4	61.8
I-94 E	4.0	6.0	8.0	61.8
I-465 OL	39.8	41.8	43.8	58.8
I-465 IL	24.1	26.1	28.1	58.3
I-69 S	202.3	204.3	206.3	57.3
I-465 OL	25.1	27.1	29.1	54.5
I-94 W	7.2	9.2	11.2	54.5
I-94 W	10.6	12.6	14.6	53.5
I-465 OL	29.3	31.3	33.3	52.0
I-465 IL	22.3	24.3	26.3	48.0
I-469 N	28.4	30.4	30.4	48.0
I-69 S	201.2	203.2	205.2	47.8
I-70 W	78.4	80.4	82.4	47.8
I-70 E	78.5	80.5	82.5	47.5

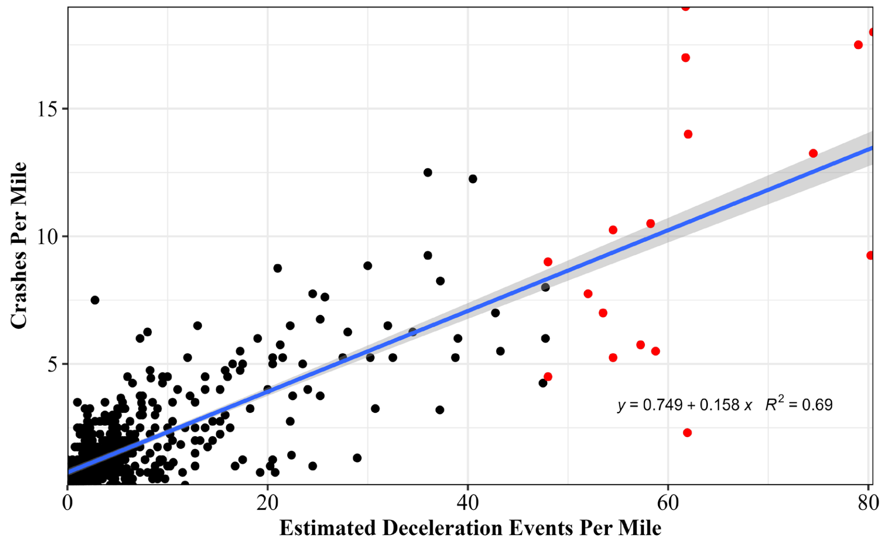

Figure 2. Scatter plot showing crashes per mile versus estimated deceleration events per mile in a 2-mile radius around Indiana's interstate exit ramps for deceleration in the range of [−0.5 g, −0.4 g) (March 1-May 31, 2023).

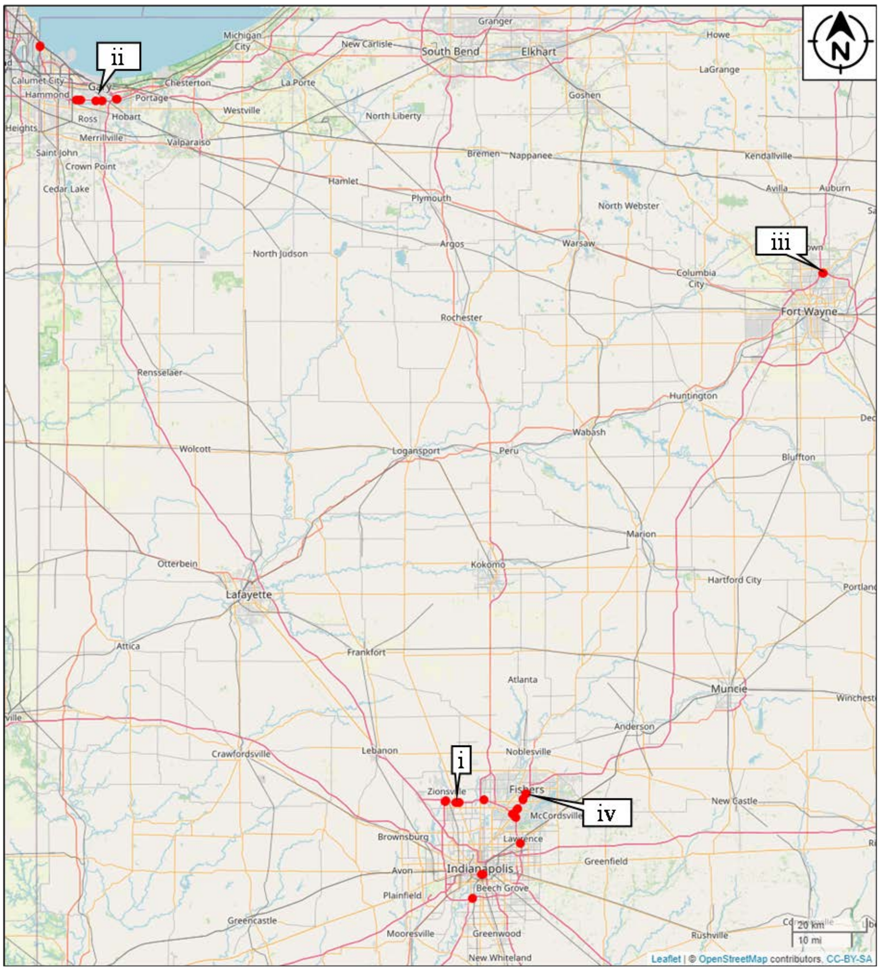

Figure 3. 20 Interstate exit ramp locations with highest estimated deceleration events per mile values for deceleration in the range of [−0.5 g, −0.4 g) (March 1-May 31, 2023).

in the high number of locations observed on I-94 (callout ii), a heavily used route for commutes into or out of the Chicago metropolitan area. The I-469 N location (callout iii) highlighted by the analysis is another example of a commuter beltway around the city of Fort Wayne which sees heavy traffic for vehicles looking to either join or exit from the primary north-south interstate I-69 (callout iv).

The techniques and analysis presented thus demonstrate the applicability of CV trajectory data and estimated deceleration events to conduct systemwide assessment of safety performance near interstate exits and how well these assessments correlate to historical crash trends.

10. Conclusions

This study analyzed nearly 20 million estimated CV deceleration events and more than 4800 crashes near 629 exits along Indiana's Interstate system to present the relationship between estimated CV deceleration events and crashes for a three-month period from March 1-May 31, 2023. Results showed that:

1) The highest coefficient of determination among these datasets was 0.69 for deceleration events in the range of −0.5 g to −0.4 g. Since these values can be computed in real time, this provides the opportunity for not only long-term safety studies, but real time monitoring of trends, particularly in construction zones.

2) Based upon this close agreement between estimated acceleration and OEM provided events, we believe agencies are best served by calculating deceleration from trajectory data in a systematic manner across all OEMs and establishing their own threshold for the type of facility being analyzed (freeways, signals, roundabouts, driveways, trails, toll booths or border crossings).

The methodologies shown enable practitioners and state agencies to utilize a single CV trajectory dataset to conduct both mobility and safety evaluations on their road network without the need for integrating any external data sources. Access to estimated deceleration values from raw CV data additionally presents stakeholders with valuable insights into the true quantified severity of these braking events and enables comparative assessments across locations and allows for safety improvement solutions tailored to the driving profile at a location rather than based on a universal non-transparent threshold. Additionally, the analyzed dataset and associated methodologies are highly scalable at the local, state, multi-state or even national level due to the consistency and widespread availability of the data as well as users of this data not being hamstrung by underreporting, inconsistency or delayed reporting issues.

Future research in this domain will look at incorporating estimated acceleration across a much broader set of transportation facilities including rural freeway sections, merge areas, traffic signals, roundabouts, driveways, trails, toll booths and border crossings. Additional evaluations and modeling of combined correlations between acceleration events, deceleration events and crashes may reveal insights into driver behavior at short merge and exit ramps.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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