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INDIANA DEPARTMENT OF TRANSPORTATION
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Connected Vehicle Trajectory Data to Screen Network for Hard-Braking and Hard-Acceleration Events



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16. Abstract Hard-braking and hard-acceleration data have been demonstrated as an important emerging data source that provides quicker feedback than crash data. In fact, a strong correlation between hard braking on the interstate and crash rates has been reported in previous studies. A previous study has shown that there are approximately 147 hard braking events in a work zone for every crash. However, there have been subtle changes in acceleration thresholds as well as techniques automotive companies and third-party vendors use to compute hard braking. The motivation of this study is to define scalable and sustainable procedures for obtaining consistent hard braking data. That data can then be used to develop a statewide system for longitudinal monitoring of hard braking trends to assist in identifying and prioritizing roadways for more detailed safety studies. This study developed 0.1-mi "smart polygons" (linear-referenced geofencing features) that provide a directional base map for the entire system of Interstates, U.S. routes, and state routes across the state of Indiana. Approximately 100 billion connected vehicle records were analyzed to derive hard braking statistics for the smart polygons.			
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EXECUTIVE SUMMARY

Motivation

Hard-braking (HB) and hard-acceleration (HA) data have been demonstrated as an important emerging data source that provides quicker feedback than crash data. In fact, a strong correlation between hard braking on the interstate and crash rates has been reported in previous studies. Desai, Li, et al. (2021) showed that there are approximately 147 HB events in a work zone for every crash. However, there have been subtle changes in acceleration thresholds as well as techniques automotive companies and third-party vendors use to compute hard braking. The motivation of this study is to define scalable and sustainable procedures for obtaining consistent HB data. That data can then be used to develop a statewide system for longitudinal monitoring of HB trends to assist in identifying and prioritizing roadways for more detailed safety studies.

Study

This study developed 0.1-mi *smart polygons* (linear-referenced geofencing features) that provide a directional base map for the entire system of interstates, U.S. routes, and state routes across the state of Indiana. Approximately 100 billion connected vehicle records were analyzed to derive HB statistics for the smart polygons.

Results and Impact

- A system assessment dataset was developed for more than 24,831 directional miles of interstates, U.S. routes, and state routes in

Indiana. The spatial resolution of the directional segments was 0.1 mile.

- Each of those segments was assigned 317 attributes focused on speeds, travel time indexes, and reliability, as well as 250 attributes focused on HB and HA events at different severity thresholds for connected vehicle (CV) data from June 1 to December 31, 2024.
- This curated dataset has been provided to the Indiana Department of Transportation (INDOT) as well as published in an open access repository available through the Purdue University Research Repository (Sakhare et al., 2025).
- Web portal geographic information system (GIS) links have been developed and shared with INDOT to provide easy visualization of these data.
- Although there are dozens of use cases for this HB dataset, one recent use case found that 7% of CVs approaching the back of the queue exhibited an HB event with R-squared value of 0.74. The percentage of vehicles experiencing HB at the back of the queue was approximately 53 times higher than the control group.

Recommendations

The main recommendations from this study include, but are not limited to the following:

- HB events continue to be strongly correlated with crashes and secondary crashes and are a key surrogate measure for safety.
- Systemwide assessment dataset can be easily imported into preferred GIS layers to use relevant measures for data-driven decision making.
- Integrating the speed and HB data with other GIS data layers that define intersections, geometrics, shoulders, speed limits, and volumes will further increase the utility of this data for identifying and prioritizing future capital projects.

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1. INTRODUCTION

Traffic safety is important to all transportation agencies. Historically, that has been monitored via crash reports. In 2023, 198,247 traffic collisions occurred in Indiana, a 4% decrease from 2022; fatal collisions decreased 5%, from 914 in 2022 to 871 in 2023 (Palmer et al., 2023). However, collecting a statistically significant number of crash records over a corridor takes a long time. As an alternative safety surrogate measure in the past few years, hard-braking (HB) data have been documented as an important emerging data source that provides quicker feedback than crash data. In fact, a strong correlation between hard braking on the interstate and crash rates has been reported by Desai, Li, et al. (2021). This study has also shown there are approximately 147 HB events in a work zone for every crash (Desai, Li, et al., 2021).

With different original equipment manufacturers (OEM) using different techniques to collect HB/hard-acceleration (HA) events, it is important to have a precise definition of how these data are derived and document variations in how it is collected between OEMs to have a consistent methodology to have high confidence in the quality and implications of derives performance measures. For example, some OEMs use a fixed, instantaneous trigger. Other OEMs derive acceleration/deceleration over a fixed threshold of 2–3 s. However, during the early stages of this study, the OEM provided “instantaneous” HB event data was discontinued. This unexpected challenge also presented an opportunity to develop procedures to estimate deceleration (and acceleration) in a consistent and scalable manner. Estimating these directly from the raw trajectory data also provides the severity of the braking, an additional dimension that is useful for agencies during evaluations.

1.1 Motivation

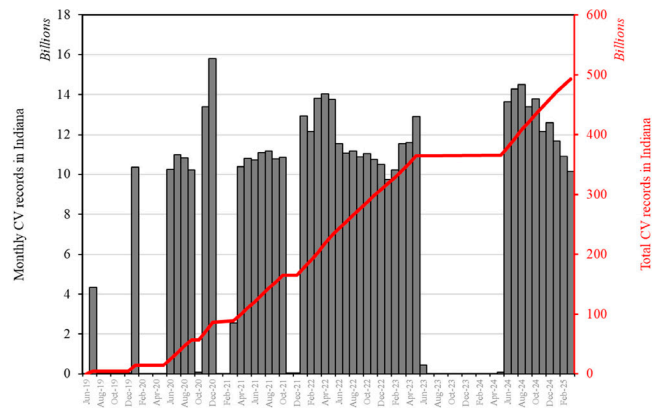
The motivation of this study is to define scalable and sustainable procedures for obtaining consistent HB and HA data. That data can then be used to develop a statewide system for longitudinal monitoring of HB trends to assist in identifying and prioritizing sections of roadway for more detailed safety studies.

2. DATA DESCRIPTION

2.1 Connected Vehicle Data

Previous studies and reports have highlighted the extent of connected vehicle (CV) data and several use cases, including:

- “Big Data Applications for Managing Roadways” from Mathew et al. (2021)
- “Integrating Connected Vehicle Data for Operational Decision Making” from Sakhare (2023)
- “Evaluation of the Impact of Queue Trucks With Navigation Alerts Using Connected Vehicle Data” from Sakhare et al. (2021)
- “Using Connected Vehicle Data to Evaluate Impact of Secondary Crashes on Indiana Interstates” from Desai, Sakhare et al. (2021)
- “National Mobility Analysis for All Interstate Routes in the United States: August 2022” and “National Mobility Analysis for



future. To overcome this challenge, this study developed a consistent derivation of HB or HA events using the raw CV data on a scale and was able to perform longitudinal analysis.

2.2 Redacted Crash Reports

Public safety agencies around the state of Indiana utilize a centralized online crash repository called the Automated Reporting Information Exchange System (ARIES). The crash reports housed herein contain detailed information on the circumstances of a crash incident along with key timeframes as well as geo-locations recorded by the first responders on scene who aid in recovery efforts. They provide valuable input and much-needed context for establishing an event sequence in which the traffic incident was managed. Any personal or identifying information is redacted from these crash reports to ensure confidentiality.

Figure 2.2 shows cumulative weekly crashes by year across the Indiana interstate system as reported by law enforcement

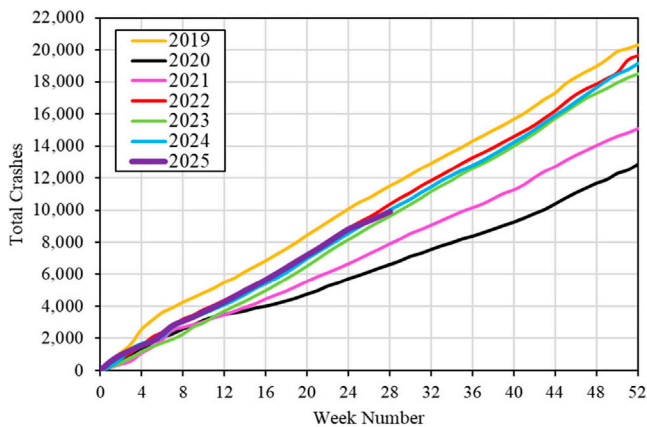


Figure 2.2 Cumulative Weekly Crashes on the Indiana Interstate System by Year From 2019 to 2025.

agencies through ARIES, curated to remove crashes that occurred on entry ramps and crashes where a location could not be determined.

3. EVOLUTION OF HB EVENTS

Traditionally, crash report data are used to identify opportunities to improve the design of future work zones or safety corridors. Due to the infrequency of crashes, it takes a long time to collect a statistically significant number of them for a corridor. This resulted in a need for a safety surrogate measure. One of these measures identified in the past is HB events.

3.1 Correlation of HB Events and Crashes

A previous study from Desai, Li, et al. (2021) reported that approximately one crash occurred for every 147 HB events per mile. This section summarizes the study titled “Correlating Hard-Braking Activity with Crash Occurrences on Interstate Construction Projects in Indiana” (Desai, Li, et al., 2021). Figure 3.1 shows a scatterplot of crashes per mile against HB events per mile for each of the 23 work zones, calculated separately for each direction of travel, for data totaled over the months of July and August in 2019. The plot showed that one crash per mile is to be expected for approximately every 147 HB events per mile within a work zone. This was one of the foundational works in strengthening the use of HB events as a safety surrogate measure for crashes.

3.2 Changes in HB Thresholds From Data Providers

During the early years of tracking HB events (2019 to 2023) there was little to no visibility of the data models or HB values that were directly provided by the data providers. During this period, data providers also changed the threshold values

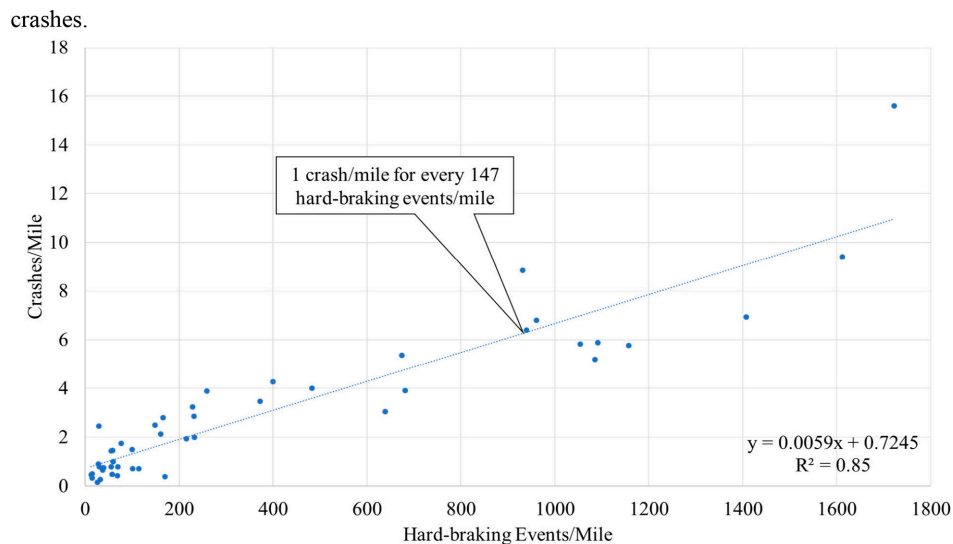


Figure 3.1 Scatterplot Showing Crashes and HB Events Per Mile Across 23 Work Zones From July 1 Through August 31, 2019 With a Linear Trendline.

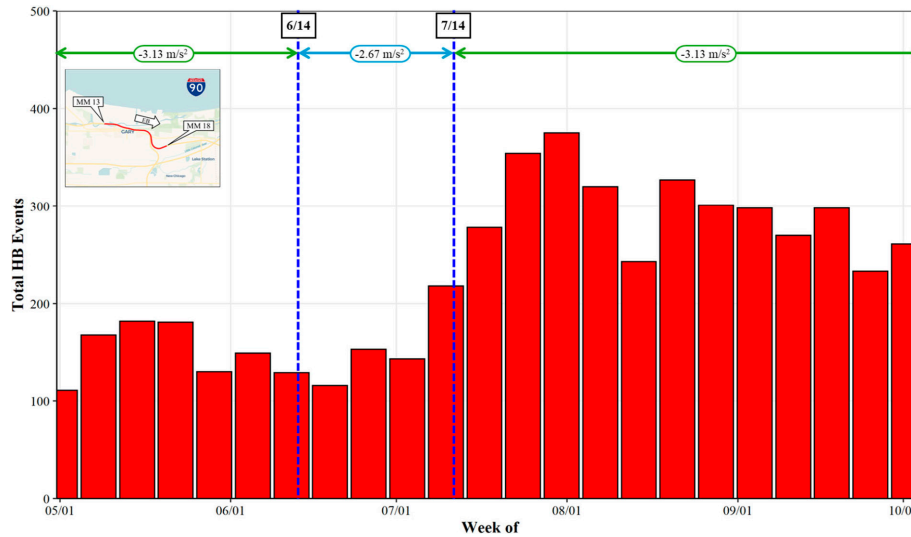


Figure 3.2 Total Count of HB Events in Indiana on I-90 EB MM 13–18 by Week in 2022.

that were used to trigger HB events. One such example from 2022 is shown in Figure 3.2 that presents a weekly count of HB events within a section Interstate 90 (I-90) in the eastbound (EB) direction from mile marker (MM) 13 to 18. Vertical blue dashed lines point to the period from June 14 to July 14 when the HB threshold dropped from the usual 3.13 m/s² to 2.67 m/s². This also highlights the risk of using varying thresholds across different data providers and OEMs.

To derisk efforts in this space, the research team began systematically estimating HB and HA events directly from CV trajectory waypoints by computing the difference in speeds over consecutive waypoints that were 3 s apart. This ensures consistency in estimating HB and HA events and ensures before and after comparisons are not biased by estimation methodologies varying across OEMs and data providers.

3.3 Correlation of Estimated HB With Crashes

Another study from Desai et al. (2023) has also shown that estimated HB events at different severity thresholds were correlated with crashes at interchanges. This section is a summary of the detailed study from Desai et al. (2023) titled “Correlating Connected Vehicle Estimated Deceleration Events with Crash Incidents near Interstate Interchanges.” Each CV trajectory consists of waypoints available at approximately 3-s frequency with a 3-m geolocation accuracy. Each waypoint also had an associated anonymized trajectory identifier, geolocation, timestamp, heading, and speed attribute. 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/s²). In the interest of consistency, only pairs of waypoints 3 s apart were utilized to compute estimated deceleration to avoid any bias caused by the waypoint reporting frequency.

Table 3.1 represents a summary count of estimated deceleration events found along with the study location, categorized by

TABLE 3.1
Estimated Deceleration Event Counts Categorized by Deceleration Range and Search Radius Around Interstate Exit Ramps From March 1 to May 31, 2023.

Deceleration Range	Number of Deceleration Events by Search Radius		
	+/- 0.5 mi	+/- 1 mi	+/- 2 mi
(∞, -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

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 mi, both upstream and downstream of all exit ramps, quite expectedly captures the highest number of estimated deceleration events.

Figure 3.3 shows a scatterplot 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-mi search radius and deceleration events in the range of -0.5 g to -0.4 g. 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.

3.4 Correlation of Estimated HB with Secondary Crashes

Secondary crashes are a nationally recognized problem and are defined as crashes that occur as a result of traffic disruptions caused by a primary crash. The content of this section was

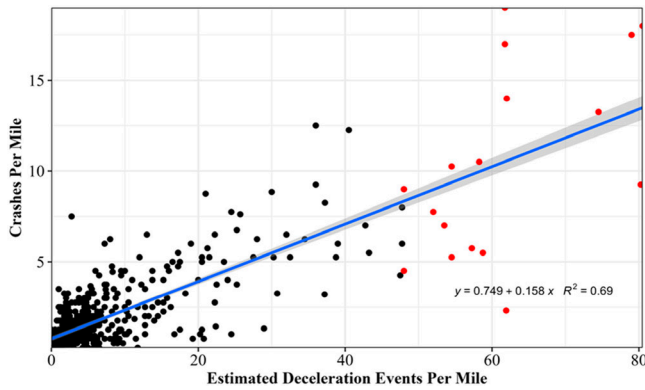


Figure 3.3 Scatterplot Showing Crashes Per Mile Versus Estimated Deceleration Events Per Mile in a 2-mi Radius Around Indiana’s Interstate Exit Ramps for Deceleration in the Range of 0.5 g to 0.4 g From March 1 to May 31, 2023 With Top 20 Locations With Highest Decelerations Per Mile Highlighted in Red.

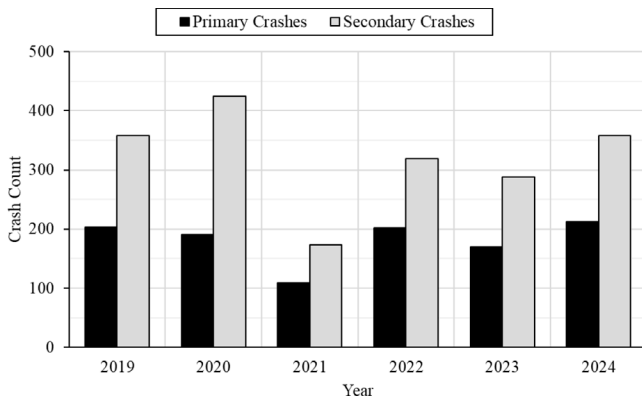


Figure 3.4 Primary and Secondary Crashes on Indiana Interstates from 2019 to 2024.

recently published under the title “Quantifying Hard Braking Activity Occurring Prior to Secondary Crashes on Indiana Interstates” (Mukai et al., 2026). Raub (1997) estimated that more than 15% of all crashes were caused by an earlier incident. Secondary crashes on interstates are often severe when vehicles impact stopped or slow-moving traffic while traveling at interstate speeds (70 mph). Secondary crashes are particularly severe when they involve trucks or large vehicles impacting the back of the queue (BOQ). Although secondary crashes are a well-known phenomenon (Wang et al., 2019; Yang et al., 2018; Zhan et al., 2009), there has been very little literature reporting quantitative methods to assess factors that influence BOQ crash rate.

Interstate crash data are collected weekly from the ARIES portal. The ARIES portal is a central database run by the Indiana State Police (ISP), which hosts all submitted crash reports in the state of Indiana (ISP, n.d.). The research team has developed a database that is referenced by route, direction, MM, date, and time for all interstate crashes that have occurred over the past 6 years in Indiana. That database currently has approximately 115,000 records. Figure 3.4 quantifies the total amount of primary and secondary crashes that have been recorded since 2019.

To be included in the secondary crash inventory, a primary crash must have had at least one secondary crash confirmed and impacted duration greater than 2 hr. The 2-hr duration was used to ensure sufficient sampling window for HB data. All crash reports associated with a primary and secondary crash are read to verify the primary-secondary relationship.

As with any human data entry, there are some discrepancies. Some secondary crash reports refer to a prior crash that has no known crash report associated with it. For example, in 2024, there were 227 primary crashes that were recorded; however, there were only 212 primary crashes that had a crash report associated with them and reflected in Figure 3.4. Additionally, some primary crashes have more than one secondary crash associated with them and are referred to as tertiary crashes in this study. A tertiary crash is defined as a secondary crash that occurs as a result of the queue created by a prior secondary crash. For this study, the research team focused on primary, secondary, and tertiary crashes in 2024.

Figure 3.5 shows a traffic speed heatmap for a primary crash and a secondary crash on I-70 EB. Callouts i and ii show the location and time of the primary and secondary crash, respectively. The primary crash occurred at 1:50 p.m. on June 03, 2024, near MM 34, and the secondary crash occurred at 4:00 p.m. near MM 28. The details for each crash were initially extracted from crash reports and were further verified using CV data plots similar to those shown in Figure 3.5. When CV data are displayed visually with the crash location and time, the corresponding slowdown in traffic can be identified just before 2:00 p.m. on the x-axis and a little after MM 32 on the y-axis. The secondary crash can be confirmed in the same way by visually confirming where the start of the secondary queue begins.

CV data can also be used to identify crash times and locations when a crash report is missing. Additionally, the CV data confirms the date and direction; the date is verified with the time stamp, and the direction is verified using the heading. Beyond verifying crash details, CV data can be used to identify external factors impacting traffic, such as when adverse weather conditions are impacting speeds (Sakhare, Desai, et al., 2023), where recurring congestion occurs, and where construction is occurring (Sakhare et al., 2022).

The HB counts for the curated dataset of 54 secondary crashes were plotted against the trajectory counts for both the week of the crash and the corresponding control week in Figure 3.6. A control week was defined as the week before or after with the same temporal and spatial window. The slope of the linear trendline, with the intercept forced through zero, is 0.0686. In general terms, this indicates approximately 7% of all trajectories experiencing a HB event when approaching the queue associated with a primary crash. The R-squared value for this was 0.74. In comparison, the control week had approximately 0.1% of all trajectories with a HB event. The R-squared value for the control week was 0.23. Another way of looking at this analysis is that HB events increase by a factor of approximately 53 when traffic encounters unexpected queues on the interstate system. The trendlines clearly indicate a discernible relationship between HB and trajectory counts compared to the control week and may be used as a framework

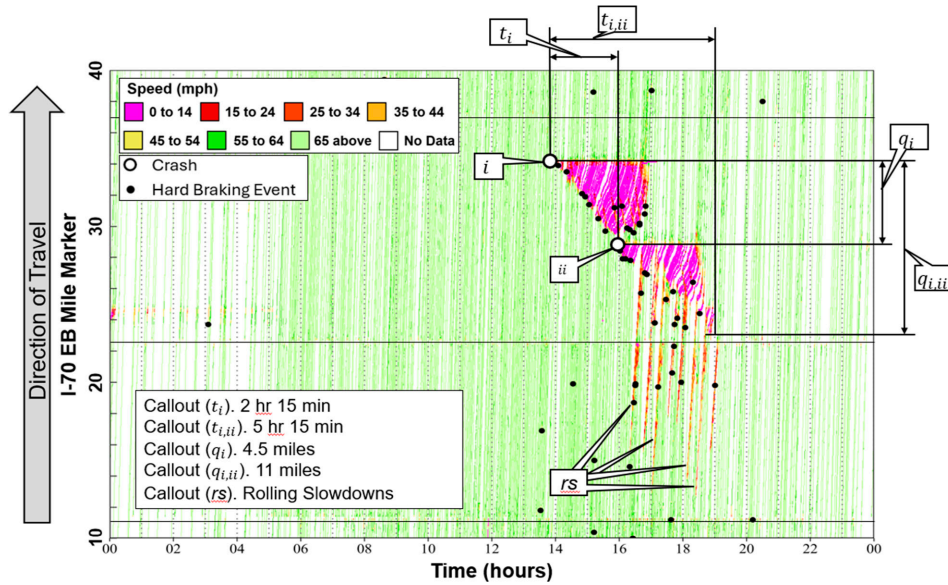


Figure 3.5 Traffic Speed Heatmap Along I-70 EB From MM 10–40 on June 3, 2024, Showcasing a Primary and a Secondary Crash With HB Events.

by agencies tracking freeway incidents in near real-time for flagging emerging safety issues on active incidents.

A quantitative analysis on the relationship between HB events and secondary crashes was conducted. It analyzed 47 different primary crashes and 54 total secondary and tertiary crashes across the state of Indiana over a 7-month period in 2024. The rate of HB events when a secondary crash occurred was found from the relationship between HB count and trajectory count. For this study, a HB threshold of 0.25 g was used.

- Approximately 7% of vehicle trajectories experienced a HB event when approaching the queue associated with a primary crash and before the occurrence of a secondary crash.
- For the control dataset corresponding to the same location either a week prior or after the primary and secondary crash, approximately only 0.1% of all trajectories experienced an HB event.

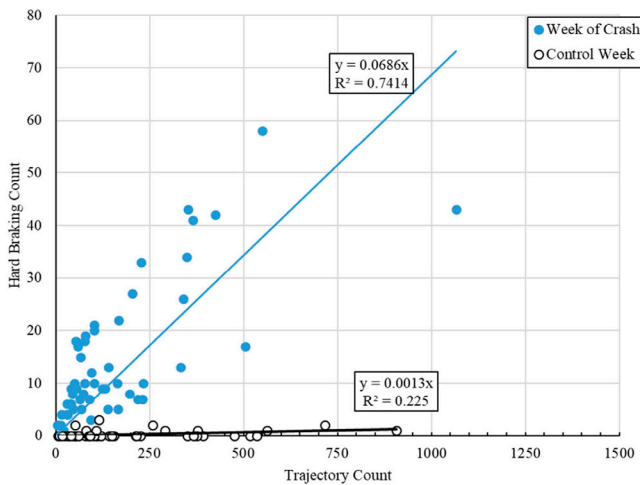


Figure 3.6 Graph of HB Count Against Trajectory Count.

This analysis provides quantitative data on the increased crash risk associated with freeway queuing using HB data. The literature is still maturing on the best HB threshold for conducting “near-miss” evaluation and varying values from 0.2–0.5 g have been proposed.

3.5 Correlation of Estimated HB With Land Use Change

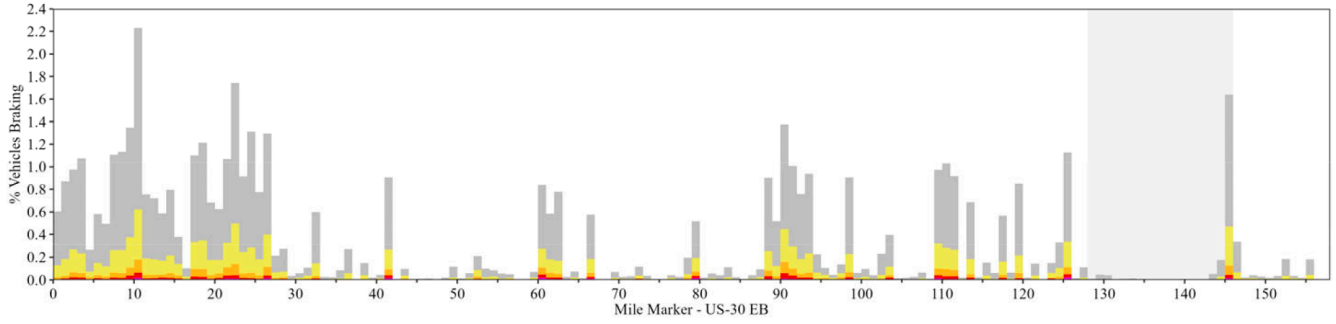
This case study demonstrates how systemwide tracking of HB events can be used to identify anomalies that relate to key land use changes. Figure 3.7 shows monthly normalized HB events categorized into different deceleration bins by mile along US 30 EB. Some of the areas that show up consistently month over month relate to major cities along the route. However, callout a in Figure 3.7c points to MM 124 that had shown significant increase in HB events from March to April 2023.

To emphasize the change further, Figure 3.8 shows the percentage change in the normalized hard braking from March to April in 2023. A clear spike was observed at MM 124 compared to any other location along US 30 EB.

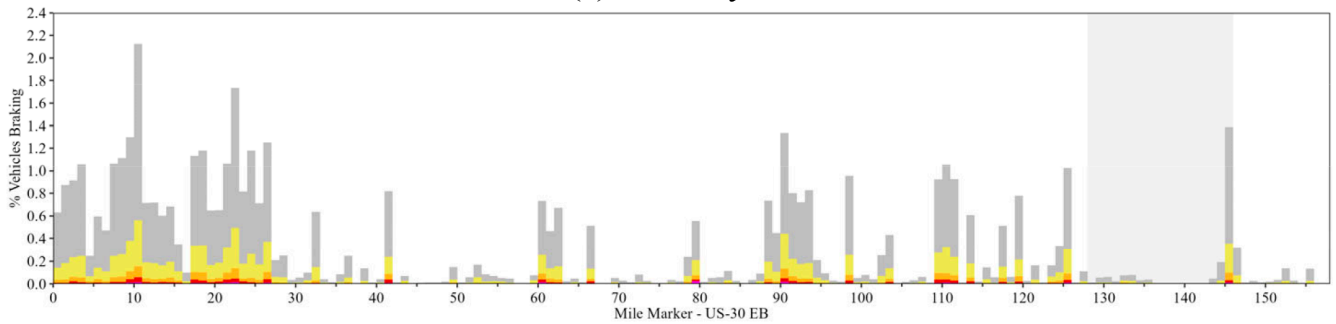
This location was further evaluated using Google Earth imagery that showed the development of an Amazon fulfillment center near Fort Wayne. Figure 3.9 shows satellite imagery and Street View imagery before the fulfillment center (Figure 3.9a), after the center was built shown by Figure 3.9b, Callout i, and after the conversion to a signalized intersection (Figure 11c, Callout ii).

Figure 3.10 shows HB count, trajectory count, and normalized HB count for only the 0.1-mi section of US 30 next to the new facility. It can be observed from Figure 3.10b that trajectory counts, that is, the number of CVs going through this section of the U.S. route, did not significantly change over time. However, Figure 3.10b, Callout i points that after April 1, that both the

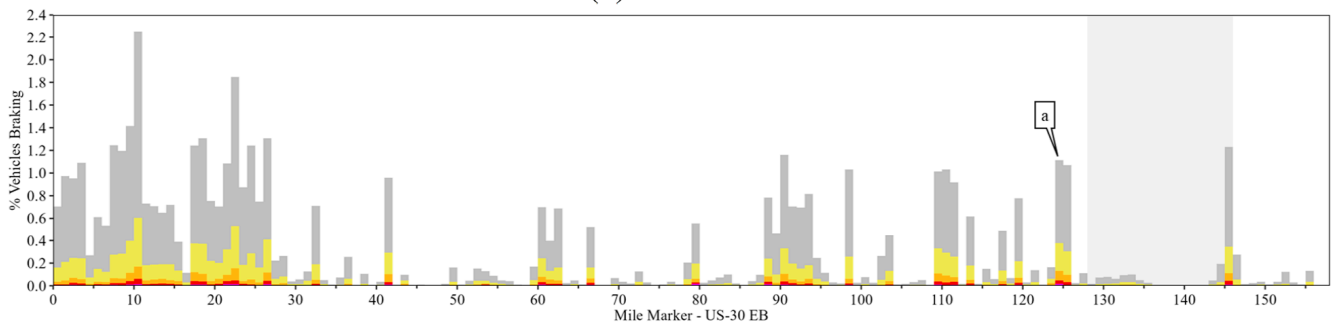
Estimated deceleration (g) 0.25-0.3 0.3-0.35 0.35-0.4 0.4-0.45 >0.45



(a) February 2023



(b) March 2023



(c) April 2023

Figure 3.7 Normalized Estimated HB Events Along US 30 EB.

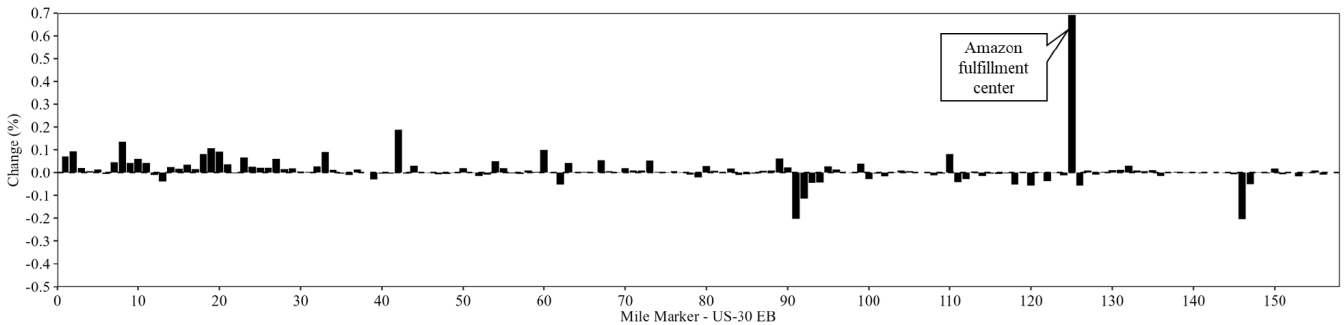


Figure 3.8 Percentage Change in Normalized Hard Braking Along US 30 EB From March to April 2023.

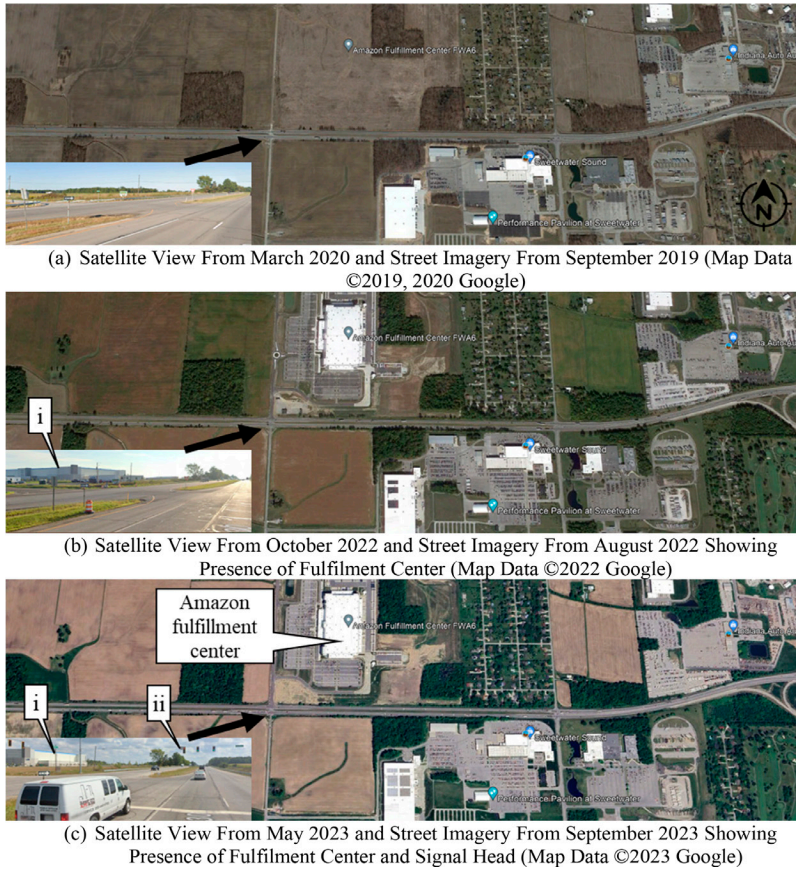


Figure 3.9 Changes Seen Over Time From the Satellite and Street Imagery (Map Data ©Google).

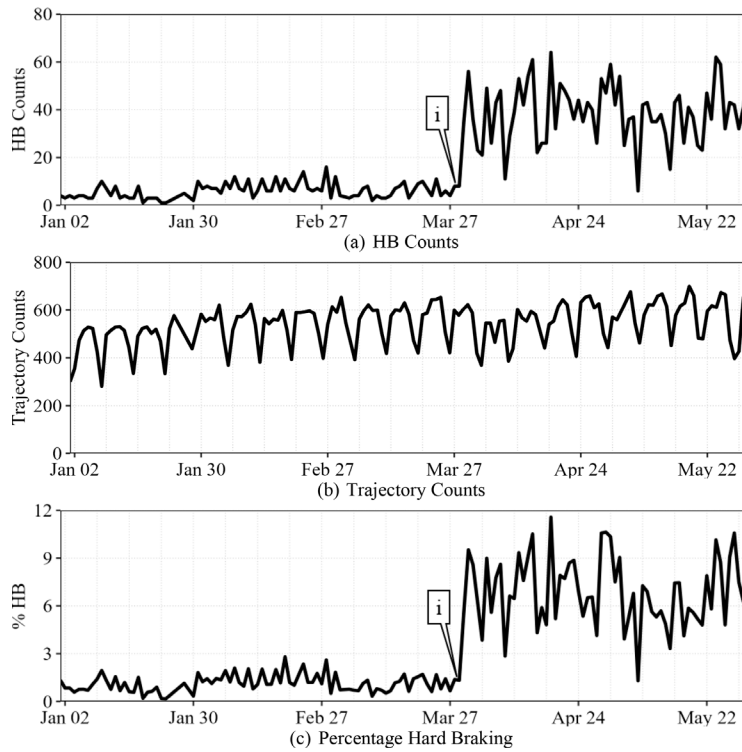


Figure 3.10 HB Events and Trajectory Counts Before and After the Opening of the Amazon Fulfillment Center.

absolute count and normalized count of HB events increased significantly. A local news article confirms the opening of the Amazon fulfillment center near Fort Wayne posted around the same date (Carroll, 2023).

4. NETWORK-WIDE SCREENING

The content of this chapter was recently published under the title “Deriving Systemwide Granular Segment Level Traffic Mobility Performance Metrics using Connected Vehicle Data to Identify Safety and Mobility Improvement Opportunities” (Sakhare et al., 2026). Many state and local agencies’ mobility metrics are based upon selected spot speed studies, modeled segment speeds and modeled intersection delays. Field visits to collect speed and mobility data are expensive, time consuming and do not scale. CV data are an emerging data source that provides richer, higher fidelity, scalable, and timelier information. However, the sheer volume of CV data requires additional skills in processing big data. As a point of reference, data from vehicles traveling in the United States, from one original equipment manufacturer, are on the order of 500 billion records per month. In its raw form, these data can be challenging for many state and local agencies to efficiently process and extract insightful information.

This section proposes a novel framework to derive mobility and safety related attributes at 0.1-mi segment resolution. These attributes characterize speeds, travel time indexes and reliability with temporal variations. These techniques are applied to more than 24,831 directional miles of interstates, U.S. routes, and state routes in Indiana. Approximately 108 billion CV records over a 7-month period from June 1 to December 31, 2024, were used to distill down to a system assessment database comprised of 248,314 rows and 317 parameters. The derived mobility metric dataset is also available through an open access data repository that can be easily ingested into any geographic information system (GIS) platform. A discussion on agency use cases is also provided.

The motivation was to develop techniques that can use CV data to derive mobility and safety related attributes at a 0.1-mi segment resolution. To address that, this study focused on all the interstates and U.S. and state routes in Indiana. Figure 4.1 shows 24,831 directional miles of roadways colored by road class in Indiana. Some of the routes do overlap partly for continuity. Of the 24,831 directional miles, 12% are interstates, 25.7% are U.S. routes and 62.3% are state routes. There are 13, 20, and 172 unique interstates, U.S. routes, and state routes, respectively. The Indiana Department of Transportation (INDOT) has also divided the state into six districts: Crawfordsville, Fort Wayne, Greenfield, La Porte, Seymour, and Vincennes as shown by the six callouts in Figure 4.1.

Figure 4.2 shows the flow diagram for the methodological overview. The methodology is categorized into four different steps: (A) Base Map, (B) Smart Polygons, (C) CV data, and (D) Output.

4.1 Base Map

The first task was to develop a base map layer, beginning with route identification (Figure 4.2, A.I). For this study, a base map for the entire network of Interstates, U.S. routes, and state

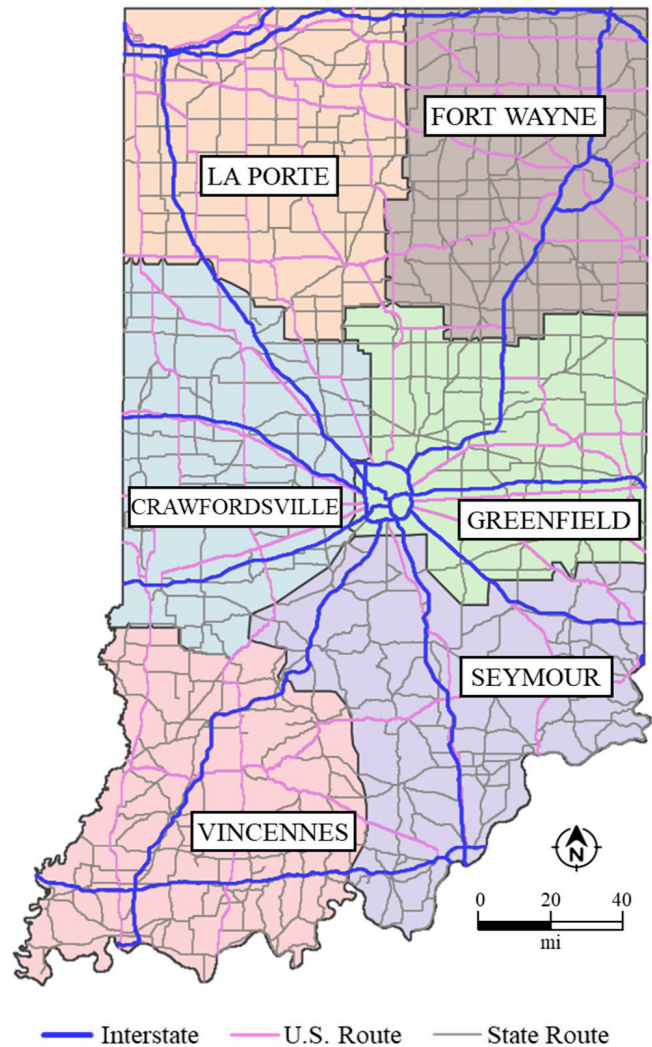


Figure 4.1 Indiana Roads Covering 24,831 Directional Miles.

routes were systematically defined. The same exercise can be carried out for any other local road; however, it will require additional effort. Following route identification (Figure 4.2, A.I), the latitude and longitude of start and end locations for each of the routes are compiled (Figure 4.2, A.II). This step is performed manually with help from publicly available maps and agency defined route names. The next task was to map an entire directional path using a routing API (Figure 4.2, A.III). Each generated route is visually inspected for quality assurance (Figure 4.2, A.IV). In many cases, the generated route may not exactly follow the desired route number of interest due to alternative shortest paths or temporary road closures influencing routing. To address this, intermediate waypoints are iteratively added along the route until the desired route is properly mapped and inspected.

Once all the routes are mapped, the resulting directional route paths are further segmented into structured segments, called Smart Polygons (Figure 4.2, B), that serve as the foundation for a high-quality base map. Developing this high-quality

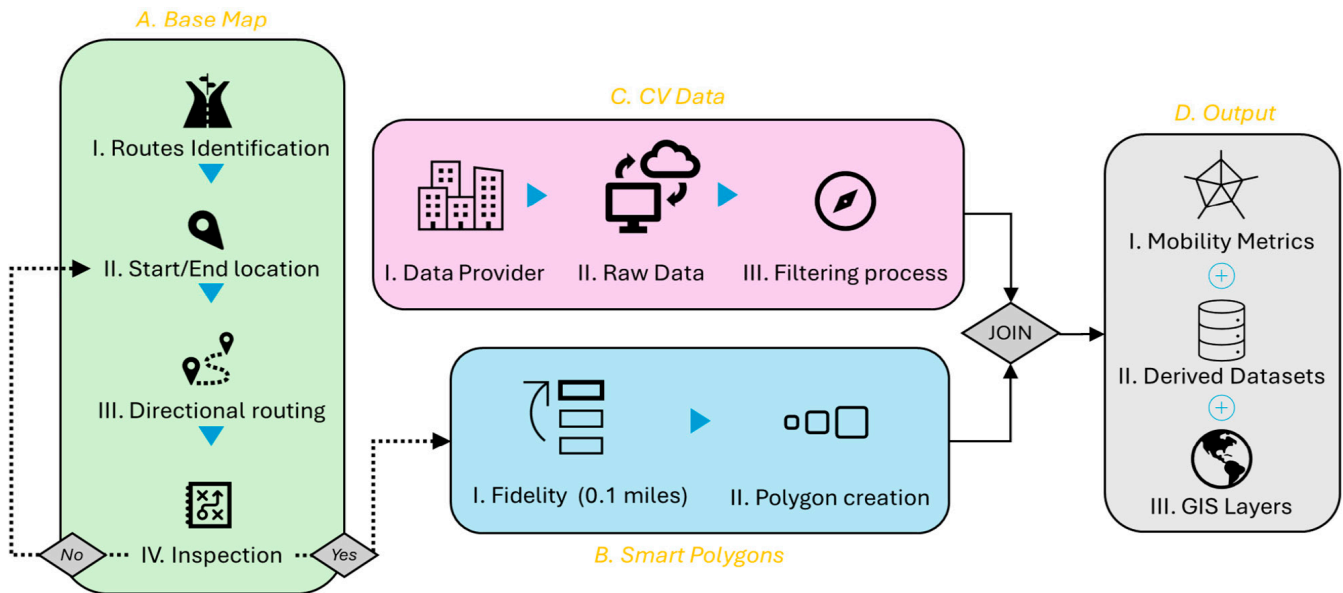


Figure 4.2 Flow Diagram for Methodology.

base map is a very important step for the agency to ensure there is a well-defined structure for subsequent processing of CV data (Figure 4.2, C) and creating the desired outputs (Figure 4.2, D).

4.2 Smart Polygons

Each directional route path is then split into equal segments of required precision (Figure 4.2, B). This choice of spatial precision of segments depends on a combination of factors such as the temporal frequency of CV data, road geometry, and practical usability. This study used 0.1 mi as the fidelity of the segments after testing for 0.02-, 0.1-, 0.5- and 1-mi sections (Figure 4.2, B.I). The route is then divided into segments of 0.1 mi in both travel directions. A transverse buffer of 60 ft is added on either side of the route then polygons are created in both directions of travel to facilitate matching of the CV data to directional segments (Figure 4.2, B.II). The segments are also assigned a linear reference (mile marker) value, incrementally in the primary direction of travel and decremental in the opposing direction. For example, north and east is assumed to be primary direction of travel in Indiana.

4.3 CV Data Ingestion

In parallel, data pipelines must be identified to provide CV data that must be mapped to the smart polygons. Raw CV data are stored on a cloud platform due to large volumes and efficiencies in analytics (Figure 4.2, C.II). The raw data are passed through filtering techniques to remove duplicate records, any missing data and truncated waypoints (Figure 4.2, C.III). The raw CV data are also associated with a corresponding geohash (spatial cluster) during preprocessing of the data and stored in a time partitioned tables. This helps with time as well as cost-effective analytics on data.

4.4 Output

The CV data are spatially joined to the generated smart polygons to associate each CV waypoint with segments along a route by direction of travel. A list of mobility and safety metrics are formulated as detailed in the following sections. A set of outputs are also compiled as derived metric dataset and visualization layers using GIS platforms.

5. MOBILITY METRICS

Using high-fidelity CV data points that are generated at approximately 3-s intervals, mobility and safety metrics are computed. Figure 5.1 presents an overview of the metrics in the derived dataset that are commonly used by agency stakeholders for various decision making. Although this is a relatively comprehensive list, different agencies could easily derive variations from this list.

These metrics are derived for each 0.1-mi roadway section by direction, or a segment. A total of 248,314 directional segments were constructed for the statewide system. Each record in the derived dataset corresponds to a segment. For each segment, there are also ten identifier attributes added that cover the name of the route including direction, mile marker, latitude, longitude, analysis period, and more. (Figure 5.1, B).

5.1 Trajectory Count

The number of trajectories or journeys that pass through a segment provides a relative comparison of traffic volumes across the region. It is important to note that these are CVs sourced from one of the data providers and might have some biases depending on the source's make and model. There is no direct correlation between trajectory count and Annual Average Daily

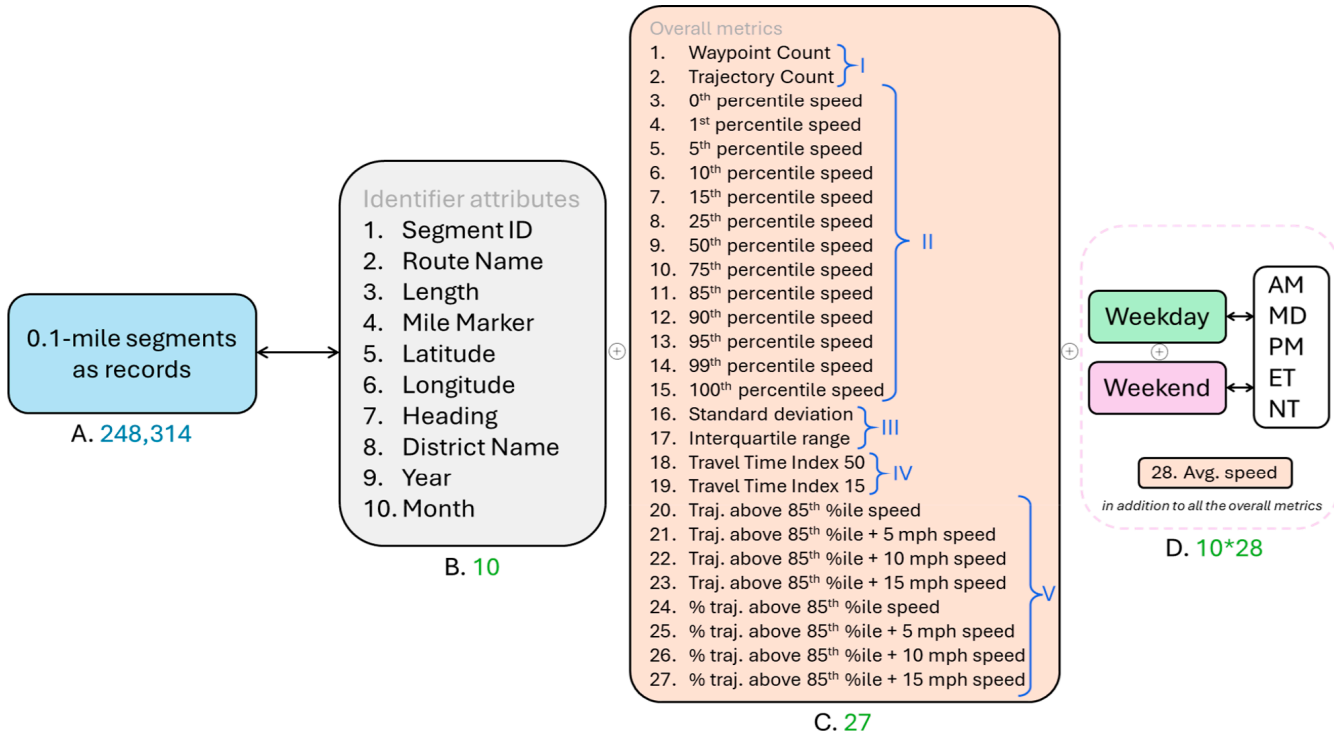


Figure 5.1 Schematic of the Derived Metric Dataset.

Traffic (AADT) due to changes in sampling rates. However, for all high-level purposes, the count of trajectories provides an acceptable quantitative measure for analysis. Trajectory count through a segment is calculated as the number of unique journey identifiers within the smart polygon over the entire analysis period. It is not the number of unique vehicles itself. The total number of waypoints is also reported (Figure 5.1, C.I).

5.2 Speed

Traffic speed is one of the most used and widely recognized mobility metrics. It refers to the speed at which drivers pass through a section of roadway. CV data provides instantaneous vehicle speed at a time a ping is transmitted for each vehicle. A sample journey moving through one of the 0.1-mi segments in northwest Indiana is shown in Figure 5.2. Any journey is denoted by j and there is a total number of m trajectories or trips going through a segment. For each journey, j , the waypoints are denoted by i . For any journey, j , there are n waypoints within a segment, that is, i increments from 1 to n . For a sample shown in Figure 5.2, there is one journey with ten waypoints, that is, $m=1$ and $n=10$. Time and instantaneous speed of a waypoint are denoted by t and S , respectively. It can be observed from the speed that the vehicle slowed down and came to a complete stop at the intersection before speeding back up within this 0.1-mi segment. The waypoints are color-coded by the speed bins, as indicated.

Time Mean Speed (S_j) for journey, j , within a 0.1-mi segment is given by Equation 5.1, which averages instantaneous speeds for waypoints (i) of this journey within that segment.

$$S_j = \frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \quad \text{Equation 5.1}$$

where j is a journey identifier associated with one particular CV trip, i is the waypoint or ping along the journey j , S_j^i is the instantaneous speed of i^{th} waypoint of j^{th} journey, and n_j is the total number of waypoints available for j^{th} journey within this segment. For a sample journey shown in Figure 5.2, the Time Mean Speed (S_j) is calculated as 14.2 mph.

5.3 Speed Quantiles

After calculating speed (S_j) for each journey within a segment, aggregate-level analytics are computed for all journeys passing through a segment during an analysis period. To understand this distribution of speeds as well as prevailing or operational speeds, various continuous percentiles were computed per segment. $P_n[S_j]$ denotes n^{th} percentile for all journey speeds per segment. $P_0, P_1, P_5, P_{10}, P_{15}, P_{25}, P_{50}, P_{75}, P_{85}, P_{90}, P_{95}, P_{99}$, and P_{100} were computed and reported for each segment (Figure 5.1, C.II). These different percentile speeds provide information about the minimum, maximum, median, operational, and three quantile speeds for a segment. The absolute minimum (P_0) and maximum (P_{100}) might sometimes be erroneous with speedometer or communication issues resulting in faulty speeds within the data. With an assumption that a maximum of 1% of journeys have such issues, the 1st percentile (P_1) and 99th percentile (P_{99}) should be used as a minimum and maximum speed values through a segment.



Speed (mph): ■ 0 to 5 ■ 5 to 10 ■ 10 to 20 ■ 20 to 30 ■ 30 to 40 ■ 40 to 50 ■ > 50

Figure 5.2 A Sample of One CV Trajectory/Journey Through a Segment With Ten Waypoints.

5.4 Reliability

Reliability is a concern when using speeds for analysis or decision making. If a median speed is utilized for analysis, how reliable are results, that is, spread of speeds within a segment. One of the measures for assessing reliability is the interquartile range (*IQR*) given by Equation 5.2.

$$IQR = P_{75} \left[\frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \right] - P_{25} \left[\frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \right] \quad \text{Equation 5.2}$$

If the *IQR* value is higher in a segment or series of segments, it means that the speeds or travel times are less reliable, that is, the variation in speeds is high. If the *IQR* value is small, all motorists travel through the segment at a similar speed or similar travel time. The standard deviation of speeds for each segment over the analysis period was also computed and reported (Figure 5.1, C.III).

5.5 Travel Time Index

Travel Time Index (*TTI*) is another commonly used metric (Schrank et al., 2023; U.S. Department of Transportation, 2021) The *TTI* is a ratio of travel time during the peak period to travel time at free-flow speeds. For a constant segment length of 0.1 mi, travel time in hours can simply be computed as 0.1 times the inverse of speed in miles per hour. Therefore, travel times are not reported as separate metrics in the derived dataset.

Peak periods are traditionally assumed to be morning or evening work-related trip hours, when most motorists are out on the roadways. On the other hand, free-flow conditions are assumed to be late-night hours or early-morning hours when there is minimal traffic, and vehicles can travel freely without interruptions. While these are reasonable assumptions in most cases, granular CV data equip us with an ability to constantly measure speeds and estimate conditions instead of at fixed hours.

Speed at free-flow condition is assumed to be the 85th percentile speed, being the same as the operational or design speed.

The top 15% of speeds are excluded to account for high-speed drivers. Peak period conditions are defined as two conditions: (a) 15th percentile speed—slow traffic conditions without the lower 15% for extreme conditions, complete stop, or more and (b) 50th percentile speed—median traffic conditions. Two different TTI values, TTI_{15} and TTI_{50} were computed using Equation 5.3 and Equation 5.4, respectively, corresponding to the two assumed conditions. TTI_{15} is an aggressive estimate and will always be greater than or equal to TTI_{50} (Figure 5.1, C.IV). Practitioners can also compute TTI by defining preferred peak period conditions and using reported speed percentiles.

$$TTI_{15} = \frac{P_{85} \left[\frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \right]}{P_{15} \left[\frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \right]} \quad \text{Equation 5.3}$$

$$TTI_{50} = \frac{P_{85} \left[\frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \right]}{P_{50} \left[\frac{\sum_{i=1}^{n_j} S_j^i}{n_j} \right]} \quad \text{Equation 5.4}$$

Figure 5.3 shows four selected locations of 0.1-mi segments under different conditions with computed metrics for August 2024. All waypoints are shown as circular dots color-coded by speed bins. Figure 5.3a shows a segment within a city hub that is part of a corridor of intersections. It is the same segment as shown in Figure 5.2. Figure 5.3b shows a segment in a rural area with no interruption to traffic. Figure 5.3c shows a minor moment turning into the segment without any active interruptions to the major movement along the segment. Figure 5.3d shows a signalized intersection on a major roadway in a city area.

5.6 Contextualizing Metrics

Total unique trajectory counts, or number of trips, are denoted by m . It shows CV trips and comparative measures of actual traffic volumes on each of the segments. Figure 5.3b has the least traffic volume compared to other segments expected in rural areas. Figure 5.3a and Figure 5.3c have moderate traffic volumes, and the highest in Figure 5.3d by almost 3 times the other two segments (a and c) and 9 times the segment in rural area (d). $\sum n$ denotes the total number of waypoints from all journeys, that is, the number of points shown in Figure 5.3.

The median speed, that is, 50th percentile speed, is denoted by $P_{50}[S_j]$. The segment from rural area (Figure 5.3b) had the highest median speed of 59 mph. Segments with signalized intersection (Figure 5.3d) and minor turning movement (Figure 5.3c) had median speeds of 31.8 mph and 35.4 mph, respectively. The segment along the corridor of intersections with multiple stops (Figure 5.3a) had the lowest median speed of 14.4 mph.

Even though the speeds were at extreme ends for Figure 5.3a and Figure 5.3b, the interquartile range given by IQR was least at around 5 mph, meaning they were the most reliable. The speeds

are always low and always high, respectively. For the segment with the minor turning movement, the IQR increases to 9.3 mph. It is because of the variations in volume of minor movement throughout the day impacting the speeds on major movement. The IQR was highest for the signalized intersection with high volumes at 19.2 mph, as some vehicles can get through on green with high speeds and others stopped at red light impacting the speed through the segment.

The last measure shown is the aggressive travel time index (TTI_{15}). TTI_{15} was lowest for the uninterrupted rural segment at 1.3 followed by the minor turning moment at 1.7. As expected, the TTI_{15} was high for segments with signalized intersections around 2.6. Typical interpretations of TTI values from some agency recommendations are as follows:

- Strategic Highway Research Program (SHRP2) report on analytical procedures for determining the impacts of reliability mitigation strategies states that, in the case of highways, TTI less than 1.1 represents relatively uncongested sections whereas TTI greater than 1.4 represents congested conditions (Cambridge Systematics et al., 2013).
- Another report on travel time reliability as a service measure for urban freeways in Florida uses a TTI threshold of 1.33 for freeways and 2.50 for urban streets (Margiotta et al., 2013).

5.7 Quantifying Segments with High-Speed Outliers

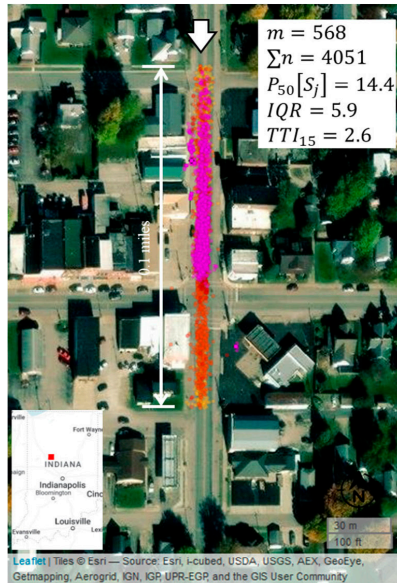
One of the other concerns for the agency from a safety perspective is what proportion of trips are going through a segment at high speeds. As a measure for this, the number as well as the percentage of trips greater than the 85th percentile speed, plus 5 mph, plus 10 mph, and plus 15 mph through a segment are reported at an aggregate level (Figure 5.1C.V). Practitioners can customize these thresholds depending on factors such as area, traffic volume, and posted speed limit.

5.8 Temporal Variation Characteristics

Mobility and safety metrics have temporal variations. For applications such as signal optimization, practitioners desire metrics during a specific time of day. Traffic patterns also vary on weekends compared to weekdays due to differences in the type of travel and trips. The Federal Highway Administration (FHWA, n.d.) identified different categories for hours of the day. Taking this into account, the mobility metrics are developed in this study using the following categories:

- Overall, indicating all days and all hours of the day combined
- Morning peak (AM) period is from 6 a.m. to 9 a.m.
- Midday (MD) period is from 9 a.m. to 4 p.m.
- Afternoon peak (PM) period is from 4 p.m. to 7 p.m.
- Evening time (ET) is from 7 p.m. to 10 PM
- Nighttime (NT) is from 10 p.m. to 6 a.m.
- Weekday and weekend separately

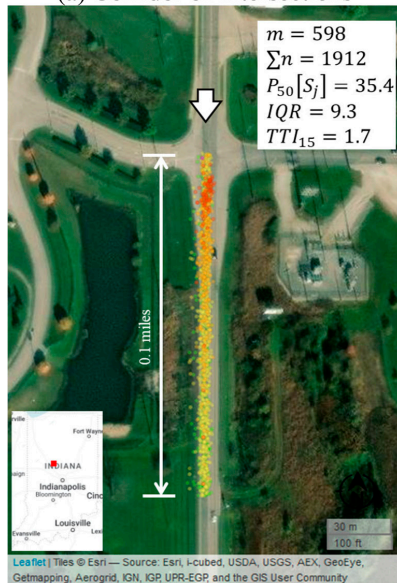
Hence, all the mobility metrics discussed above are reported both as an overall metric, that is, all hours inclusive, as well as separately for weekdays and weekends by the five time-of-day categories (Figure 5.1D). The above periods



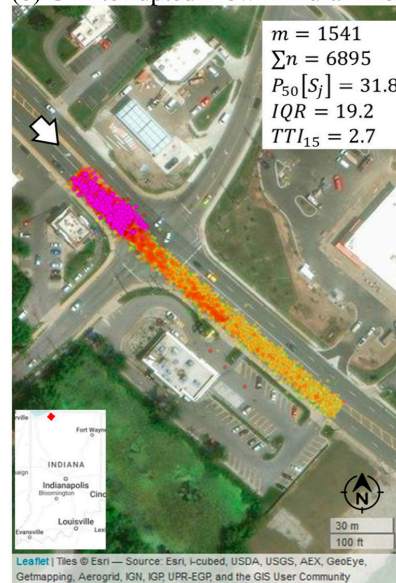
(a) Corridor of Intersections



(b) Uninterrupted Flow in Rural Area



(c) Minor Stop



(d) Major Signalized Intersection

Speed (mph): ■ 0 to 5 ■ 5 to 10 ■ 10 to 20 ■ 20 to 30 ■ 30 to 40 ■ 40 to 50 ■ > 50

Figure 5.3 Four Segment Locations With Varying Conditions Showing Derived Metrics for August 2024.

represent a combination of typical design periods and subjective decisions on how to group them. Other agencies may determine different time periods and number of time periods that better meet their needs.

6. DATA VISUALIZATION

All the metrics mentioned in Figure 5.1 are derived for every 0.1-mi segment along all of Indiana’s interstates, U.S. routes, and state routes for a 7-month period from June 1 to December 31, 2024. Table 6.1 presents the number of records and attributes per record in the derived output dataset.

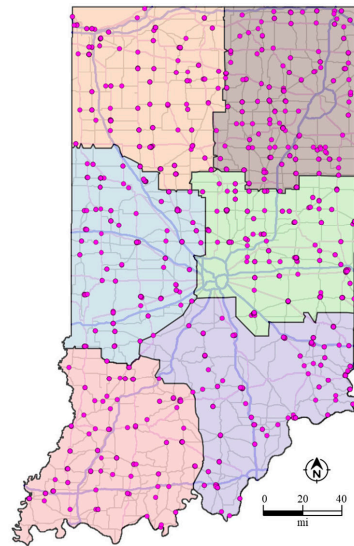
TABLE 6.1
Summary of the Derived Metric Dataset.

Description	Calculation	Value
a Total directional miles analyzed		24,831
b Total number of 0.1-mi segments (records)	$\sim 10 * a$	248,314
c Segment identifying attributes		10
d Overall mobility and safety metrics		27
e Day of week categories		2
f Time of day categories		5
g Metrics per time category	$d+1$	28
h Total number of attributes (attributes)	$c + d + e*f*g$	317
i Total cells in the derived metric dataset	$b * h$	78,715,538

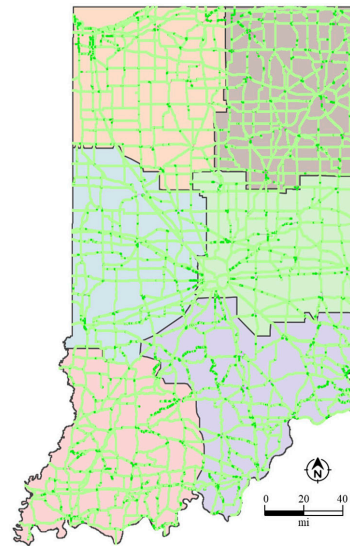
For 24,831 directional miles of the roadways (Figure 4.1), there are a total of 248,314 rows, one for each 0.1-mi segment. Each row has 317 attributes computed, as shown in Table 6.1. This derived output dataset condensed information by a factor of 430,000 from 108 billion waypoints resulting in a comprehensive statewide assessment dataset. Agency stakeholders without expertise in big data analytics or cloud services can explore the dataset with any common tools, such as Microsoft Excel. This dataset is also made publicly available (Sakhare et al., 2025) so it can be easily accessible and usable by agencies, the consulting community, and the wider research community to further enhance these metrics.

Esri's ArcGIS is one of the common platforms used by agency to visualize traffic related data. The derived metric dataset was incorporated and hosted on this visualization platform. The map shows the color-coded 85th percentile speed for segments (Sakhare et al., 2025). Clicking at any point displays all 317 attributes for a particular segment. Some possibilities for visualization and identification of critical areas at scale are explored.

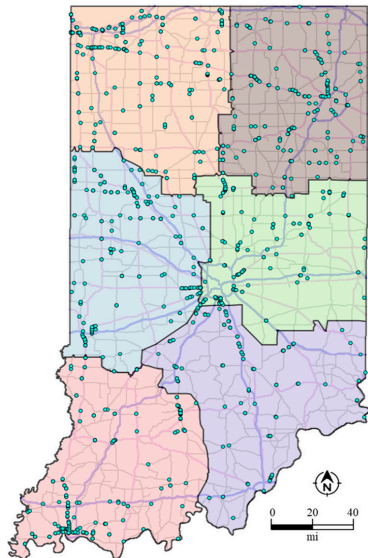
Figure 6.1 shows a summarized visualization of a few derived metrics. Segments with overall (i.e., all days and hours included) 85th percentile speeds less than 25 mph and greater than 45 mph are shown in Figure 6.1a and Figure 6.1b,



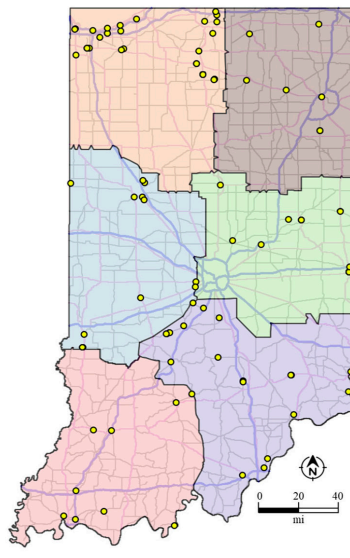
(a) 85th percentile speed < 25 mph (n = 1,024)



(b) 85th percentile speed > 45 mph (n = 23,622)



(c) IQR for speed > 30 mph (n = 1,035)



(d) $TTI_{15} > 12.15$ (n = 100)

Figure 6.1 Systemwide Visualization of Derived Metrics.

respectively. Each of the points represents a 0.1-mi segment. Most of the segments shown in Figure 6.1a may pertain to major signalized intersections in cities. However, some of these that are present in rural or unexpected areas will help agencies narrow down the focus to segments that are having significant operational challenges. Figure 6.1b covers almost the entire interstate system in Indiana as the speeds are usually higher on freeways. A string of continuous and consecutive segments with lower speeds can lead to identifying operational challenges related to long corridors. These can be potential areas of mobility improvements with maximum benefits. Figure 6.1c shows segments with an *IQR* of speed greater than 30 mph. These are the segments where the reliability is lower. Clusters of these segments are observed in Gary, in the northwest corner of the state, and Evansville, in the southwest corner of the state. Figure 6.1d shows the top 100 segments with the highest overall TTI_{15} values across the state. Of the 100 segments, four are on interstates, 33 are on U.S. routes, and the remaining 63 are on state routes. A combination of these metrics reveals key insights and leads agencies into making informed data-driven decisions.

7. AGENCY USE CASES

The derived metrics provide speed and mobility data for the entire statewide system without requiring field visits. This eliminates the need for agencies to physically send out personnel to one location at a time to collect data manually. The derived metrics dataset provides high-quality, more complete data at a lower cost for the entire system, saving time and money on data collection. Key stakeholders at INDOT are using this dataset and evaluating its potential in daily operations and decision making.

7.1 Network-Wide Screening

The dataset is used for efficiently and effectively identifying areas or corridors with operational concerns (Figure 6.1). The dataset saves the agency efforts and time by reducing the number of field studies required. Insights are made available at a scale, allowing for network-wide screening and enabling data-driven decision making. The derived statewide mobility and safety metrics dataset could easily be adapted for project identification proposed by the U.S. Department of Transportation (Duffy, 2025) for mobility and safety improvements or for any other related national initiatives.

7.2 Capital Investment Program Needs

The dataset is used during capital investment program discussions and assessments by the agency in 2025. The statewide scale, holistic view, granularity (every 0.1-mile), and in-depth performance measures are key features for efficient resource allocation of statewide capital investment programs. In the long run, such data can also help in estimating returns on capital investments.

7.3 Stakeholder Engagements

The dataset is detailed yet easily visualized in GIS layers. Such visualizations are used for district-level meetings and discussions tying together real-world, data-driven insights with anecdotal evidence from stakeholders. The dataset is also accessible in native spreadsheet software for all stakeholders looking for statewide insights without requiring specialized tools or skillsets.

7.4 Safety Evaluations

The agency is investigating the effectiveness of the dataset for speed limit evaluations. Operational speeds from the dataset can be compared against the posted speed limits or advisory speeds to identify areas where motorists drive well below the limits. Roadways in rural areas with steep vertical or horizontal curves that stand out through this evaluation are of interest in reducing advisory speeds. Furthermore, segments with higher proportions of high-speed outliers are candidates to implement safety countermeasures to reduce operational speeds.

7.5 Quantifying Longitudinal Impact

The dataset can quantify the impact of infrastructure upgrades in before and after studies for projects like capacity improvement, signal retiming, roundabout construction, and more.

7.6 Day-to-Day Decision Making

The dataset helps in addressing public comments, customer requests, and investigations on regional speeds. While speeds are perceived as lower or higher during certain hours of the day, the dataset provides a fair, quantifiable means and temporal variation visibility to verify the claim in a timely manner. It also helps in conveying data-backed messaging of prevailing conditions to the public by enhancing the ability to communicate information for the entire state at the time of inquiry. The data also helps with permits for new developments on a day-to-day basis.

Overall, the agency has quickly adopted this dataset and started to incorporate its use in their processes and help with critical data-driven decision making. It saves the agency critical efforts and time.

8. HB AND HA SCREENING

Similar to the speed focused performance measures detailed in the previous chapter, statewide HB and HA measures were developed for the entire state. Table 8.1 presents an overview of the safety measures that were included as part of this dataset. Similar to Figure 5.1d, these were also separately estimated for each time of day by weekday and weekend, as well as an overall value for all days included.

GIS layers for both the statewide absolute HB events and normalized HB events are provided in Appendix A, Sections A.4 and A.5.

TABLE 8.1
Data Attribute Description for HB and HA Dataset.

Sr	Attribute	Description
1	wp_cnt	Total number of waypoints/records
2	traj_cnt	Total number of journeys/trajectories
3	decel_b1	Count of HB events (0.1–0.2 g)
4	decel_b2	Count of HB events (0.2–0.3 g)
5	decel_b3	Count of HB events (0.3–0.4 g)
6	decel_b4	Count of HB events (> 0.4 g)
7	decel_total	Total count of HB events (> 0.1 g)
8	accel_a1	Count of HA events (0.1–0.2 g)
9	accel_a2	Count of HA events (0.2–0.3 g)
10	accel_a3	Count of HA events (0.3–0.4 g)
11	accel_a4	Count of HA events (> 0.4 g)
12	accel_total	Total count of HA events (> 0.1 g)
13	per_decel_b1	Percent of HB events (0.1–0.2 g)
14	per_decel_b2	Percent of HB events (0.2–0.3 g)
15	per_decel_b3	Percent of HB events (0.3–0.4 g)
16	per_decel_b4	Percent of HB events (> 0.4 g)
17	per_decel_total	Percent of total HB events (> 0.1 g)
18	per_accel_a1	Percent of HA events (0.1–0.2 g)
19	per_accel_a2	Percent of HA events (0.2–0.3 g)
20	per_accel_a3	Percent of HA events (0.3–0.4 g)
21	per_accel_a4	Percent of HA events (> 0.4 g)
22	per_accel_total	Percent of total HA events (> 0.1 g)

9. DATA MODEL FOR SCALING SYSTEMWIDE

This chapter discusses a data model that proposes how the performance measures (PMs) derived in earlier sections for systemwide assessment can actually be integrated into agency processes and maximize their utilization. The content of this chapter was recently published under the title “A Scalable Data Model for Signalized Intersection Performance Measures” (Gartner et al., 2025).

The proposed data model addresses two critical points in big data analysis in the transportation industry:

1. Combining multiple sources/vendors/tools used to generate PMs (e.g., high-resolution systems and CV data vendors), and
2. Defining a scalable architecture facilitating analyses at different spatial levels (e.g., a movement, intersection, corridor, or system), across levels of temporal aggregation (e.g., 1-day, 1-month, 1-year).

Figure 9.1 defines a conceptual flow for deriving, combining, and using intersection PMs in day-to-day operations. The domain knowledge of the system (Callout i) and data source (Callout ii) are combined using big data analysis techniques, resulting in a database. This dataset, using the proposed data model, can then be reported in different formats (reports, visualizations, and geospatial layers) to address business questions where intermediate scripts and queries (Callout iv) can be used to quickly generate uniform, insightful derived datasets.

Although not directly presented, this model can be applied to PMs generated from high-resolution data, LiDAR data, camera-based data, field data, and other sources. In the era of big data and vast historical datasets, a model, such as the

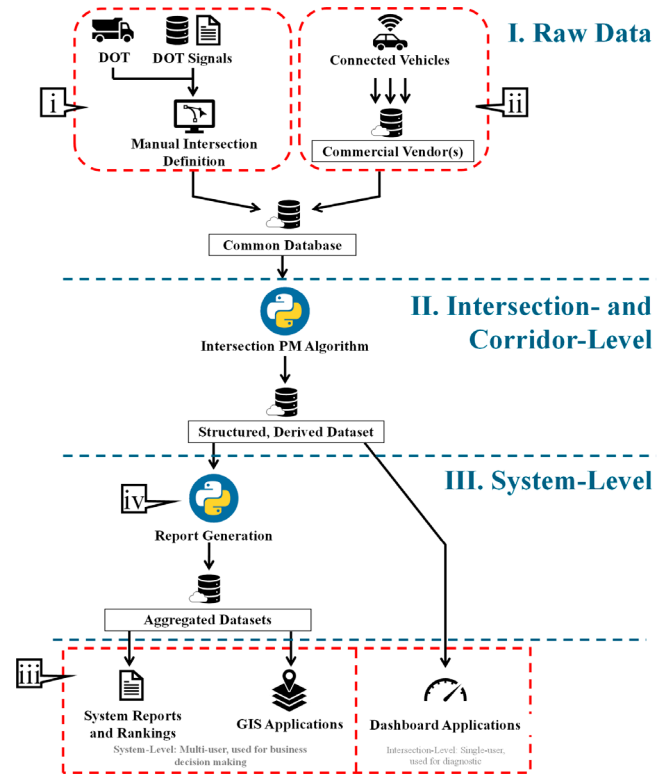


Figure 9.1 Complete Flow Diagram for Using Intersection PMs Under the Proposed Data Model.

one proposed, is necessary for agencies to operate and maintain their signalized intersection networks at a high capability maturity.

The proposed data model is given as an example set of performance measures for connected vehicle data in Figure 9.2. The crucial aspect of this schema is indexing on the unique combination of time, date, movement, approach, and intersection ID (Callout i).

Finally, this model enables proactive (and reactive) decision-making at all levels of analysis. Figure 9.3 is a conceptual diagram that captures the reactive (bottom-up) model widely utilized, as well as the proactive (top-down) model, which this data model enables across various datasets.

Making proactive decisions involves making the decision before public comments are made. To do this, agencies must constantly assess the performance of all intersections at all times for emerging issues. Under traditional approaches, this is not feasible. Using a top-down approach (with the proposed data model), agencies can screen their entire signalized network on a routine basis (e.g., every month; Gayen et al., 2024; Grover et al., 2018; Xiang et al., 2007)

Because not all decisions can be proactive, this model should ideally be able to verify and aid reactive decisions as well, which it does. Having processed data on a routine basis for an entire network, public comments can be addressed without the need for lengthy field studies to verify perceived concerns.

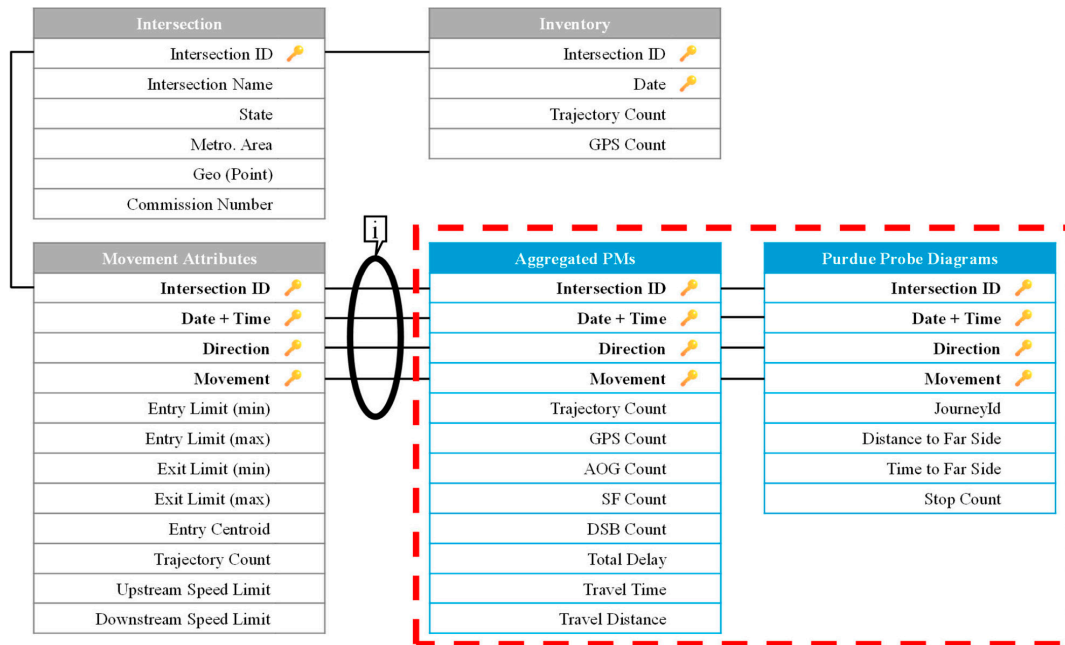


Figure 9.2 Joint Transportation Research Program Connected Vehicle Performance Measure Database Structure.

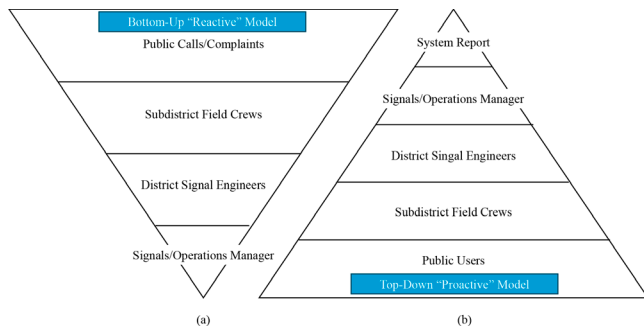


Figure 9.3 Traditional and Proposed Hierarchical CV Data Practices for Signalized Intersections.

10. SUMMARY OF ENGAGEMENTS AND DISSEMINATION

A summary of engagements including presentations are included below as dissemination of research materials:

- Estimated HB events are being computed in near real-time since the resumption of CV data in June of 2024. These were first incorporated into weekly interstate heatmaps with 10-mi visibility across all of Indiana’s borders and such weekly heatmaps for 13 Indiana interstates for 62 weeks, as of this writing, have been delivered to INDOT stakeholders on a weekly basis.
- Following this, the estimated HB events were also incorporated into the weekly work zone reports for the 2025 construction season, shared every Monday with key agency stakeholders. More than 21 such reports have been distributed since the incorporation of the estimated HB events into the weekly summaries.
- The following research articles that map into the study objectives have been submitted to the Transportation Research Board (TRB)

annual meeting 2026 for presentations and will subsequently be published in relevant journals:

- “Deriving Systemwide Granular Segment Level Traffic Mobility Performance Metrics using Connected Vehicle Data to Identify Safety and Mobility Improvement Opportunities” from Sakhare et al. (2026)
- “Quantifying Hard Braking Activity Occurring Prior to Secondary Crashes on Indiana Interstates” from Mukai et al. (2026)
- “A Scalable Data Model for Signalized Intersection Performance Measures” from Gartner et al. (2025)
- Other relevant journal publications:
 - “Correlating Hard-Braking Activity with Crash Occurrences on Interstate Construction Projects in Indiana” from Desai, Li, et al. (2021)
 - “Correlating Connected Vehicle Estimated Deceleration Events with Crash Incidents near Interstate Interchanges” from Desai et al. (2023)
 - “Large Scale Evaluation of Normalized Hard-Braking Events Derived from Connected Vehicle Trajectory Data at Signalized Intersections, Roundabouts, and All-Way Stops” from Vajpayee et al. (2024)

11. CONCLUSIONS

This study defined scalable and sustainable procedures for obtaining consistent HB and HA data even after disruptions in the data provider landscape. That data can then be used to develop a statewide system for longitudinal monitoring of HB trends to assist in identifying and prioritizing roadways for more detailed safety studies. The key developments from this study are summarized below:

- A system assessment dataset was developed for over 24,831 directional miles of interstates, U.S. routes, and state routes in Indiana. The spatial resolution of the directional segments was 0.1 mi.

- Each of those segments were assigned 317 parameters focused on speeds, travel time indexes, and reliability, as well as 250 parameters focused on HB and HA events at different severity thresholds.
- This curated dataset has been provided to INDOT as well as published in an open access repository (Sakhare et al., 2025).
- Web portal GIS links have been developed to provide easy visualization of this data.
- One of the case studies has shown that 7% of CVs approaching the back of the queue exhibited an HB event with R-squared value of 0.74. The percentage of vehicles experiencing HB at the back of the queue was approximately 53 times higher than the control group.

11.1 Limitations

One of the key limitations of CV data is its penetration rates. In remote areas, lack of market penetration of CVs can influence the ability to calculate the metrics on local roads. This also becomes a key criterion for evaluating newer data providers in this field. One way to overcome this is by collecting and aggregating data over a longer period in certain areas. Market forces can dictate the availability and reliability of CV data and its providers. The mobility and safety metrics derived in this study are at a spatial fidelity of 0.1-mile. Any microscopic changes or behaviors within this distance of 0.1-mi are not captured in this dataset.

11.2 Future Scope

The presented mobility metrics use CV data from passenger cars only. Future developments can look at combining data from passenger cars and commercial trucks. Advanced datasets such as lateral movements or collision alerts can further enhance the safety metrics. The changes in road geometry or in road alignment will need to be accounted for to maintain a temporally accurate base map of an agency's road network.

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APPENDICES

Appendix A. List of Acronyms

Appendix B. GIS Links

Appendix A. List of Acronyms

AADT	Annual Average Daily Traffic
ARIES	Automated Reporting Information Exchange System
AVL	Automatic Vehicle Location
BOQ	Back-of-queue
CV	Connected Vehicle
DOT	Department of Transportation
EB	Eastbound
EST	Eastern Standard Time
FHWA	Federal Highway Administration
GIS	Geographic Information System
GPS	Global Positioning System
HRRR	High-Resolution Rapid Refresh
HB	Hard braking
INDOT	Indiana Department of Transportation
ISP	Indiana State Police
IQR	Interquartile range
MM	Mile Marker
OEM	Original Equipment Manufacturer
PMs	Performance Measures
TRB	Transportation Research Board
TTI	Travel Time Index

Appendix B. GIS Links

GIS links that visualize the key metric from the statewide performance measures. Clicking each dot shows all the metrics for the segment.

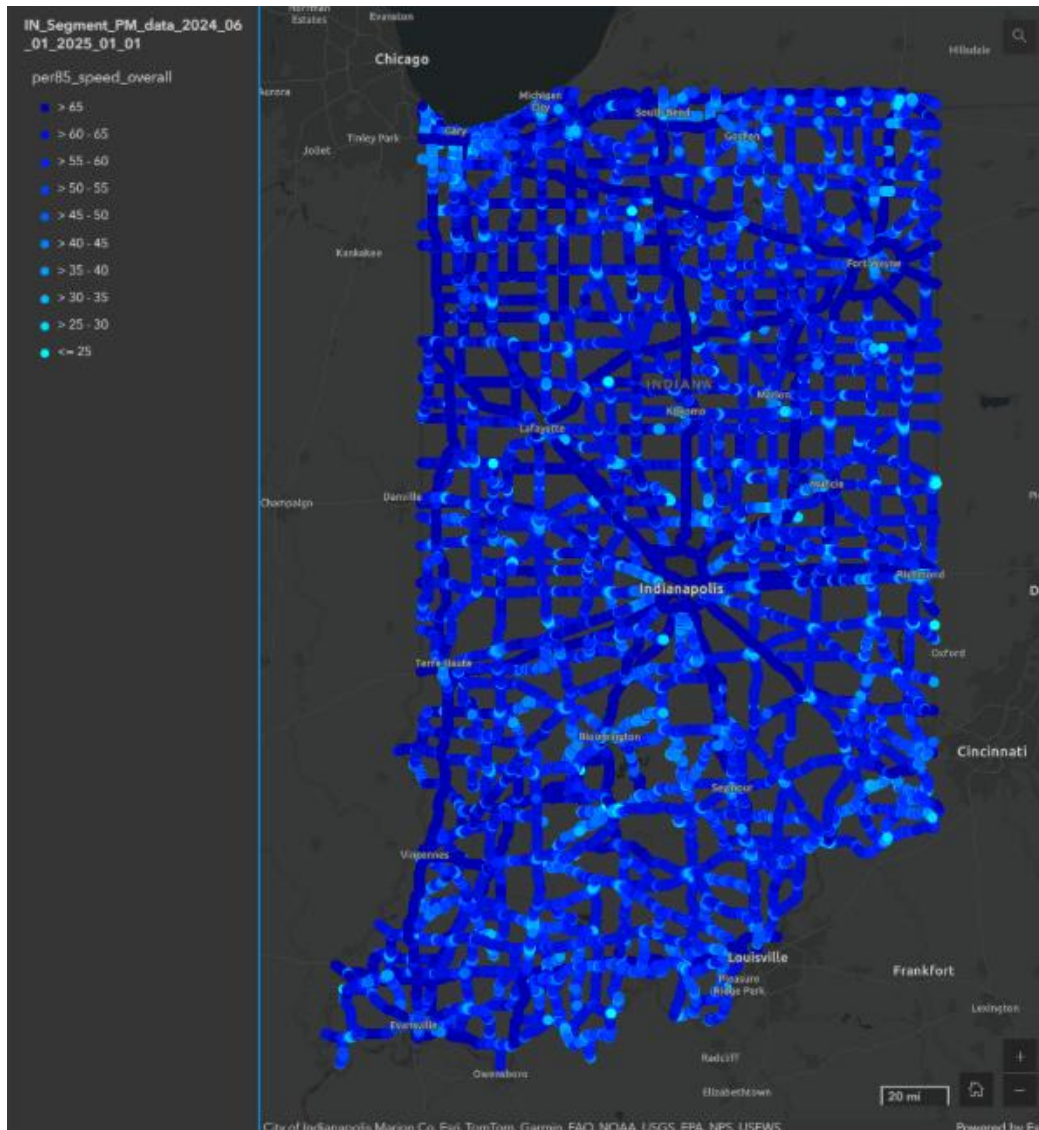


Figure B.1 2024 Annual Segment PMs – 85th Percentile Overall Speeds Color Coded by Speed Bins.

<https://purdueuniversity.maps.arcgis.com/apps/instant/sidebar/index.html?appid=3361048f015e4176b75522e8588e108b>



Figure B.2 2024 Annual Segment PMs – 85th Percentile Overall Speeds Color Coded by Speed Bins.
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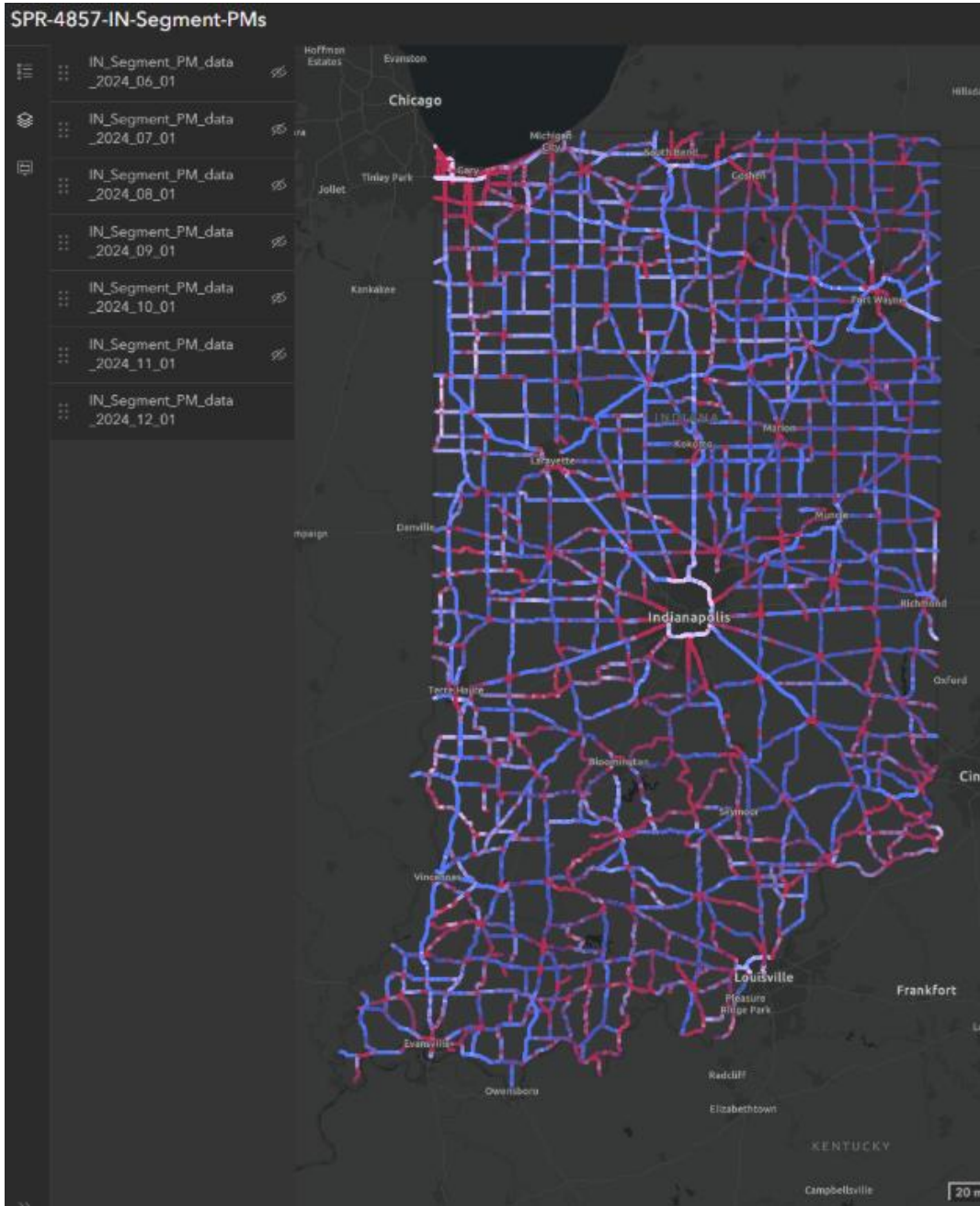


Figure B.3 2024 Monthly Segment PMs – Combination of Speed and TTl.
<https://purdueuniversity.maps.arcgis.com/apps/instant/sidebar/index.html?appid=fb14e481875547e8a4d3e63f576ce4a6>

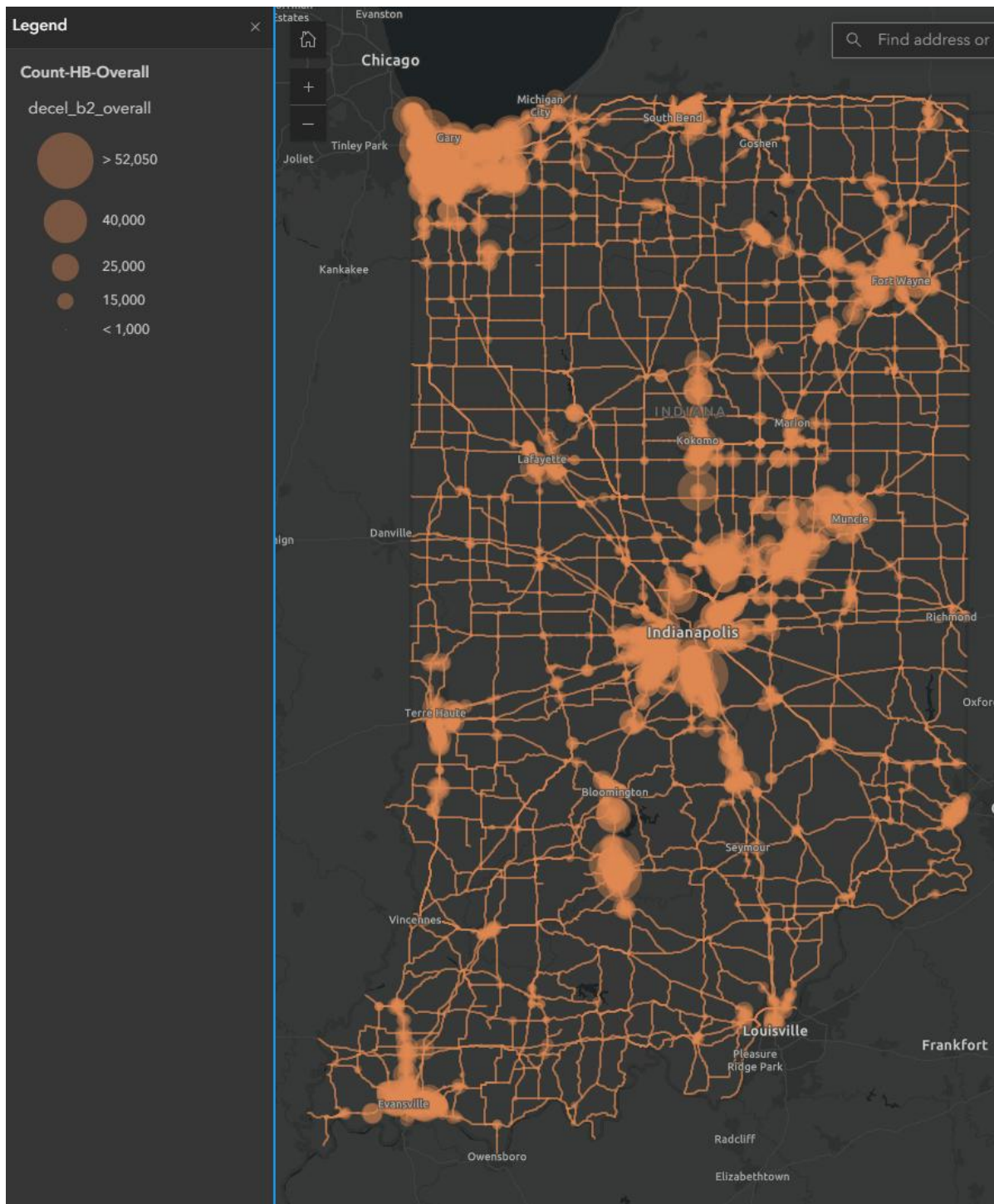


Figure B.4 2024 Annual Hard-Braking Events (Layer 1).

<https://purdueuniversity.maps.arcgis.com/apps/instant/sidebar/index.html?appid=316271ede5bd47d6aa05fd3f3eaf883>

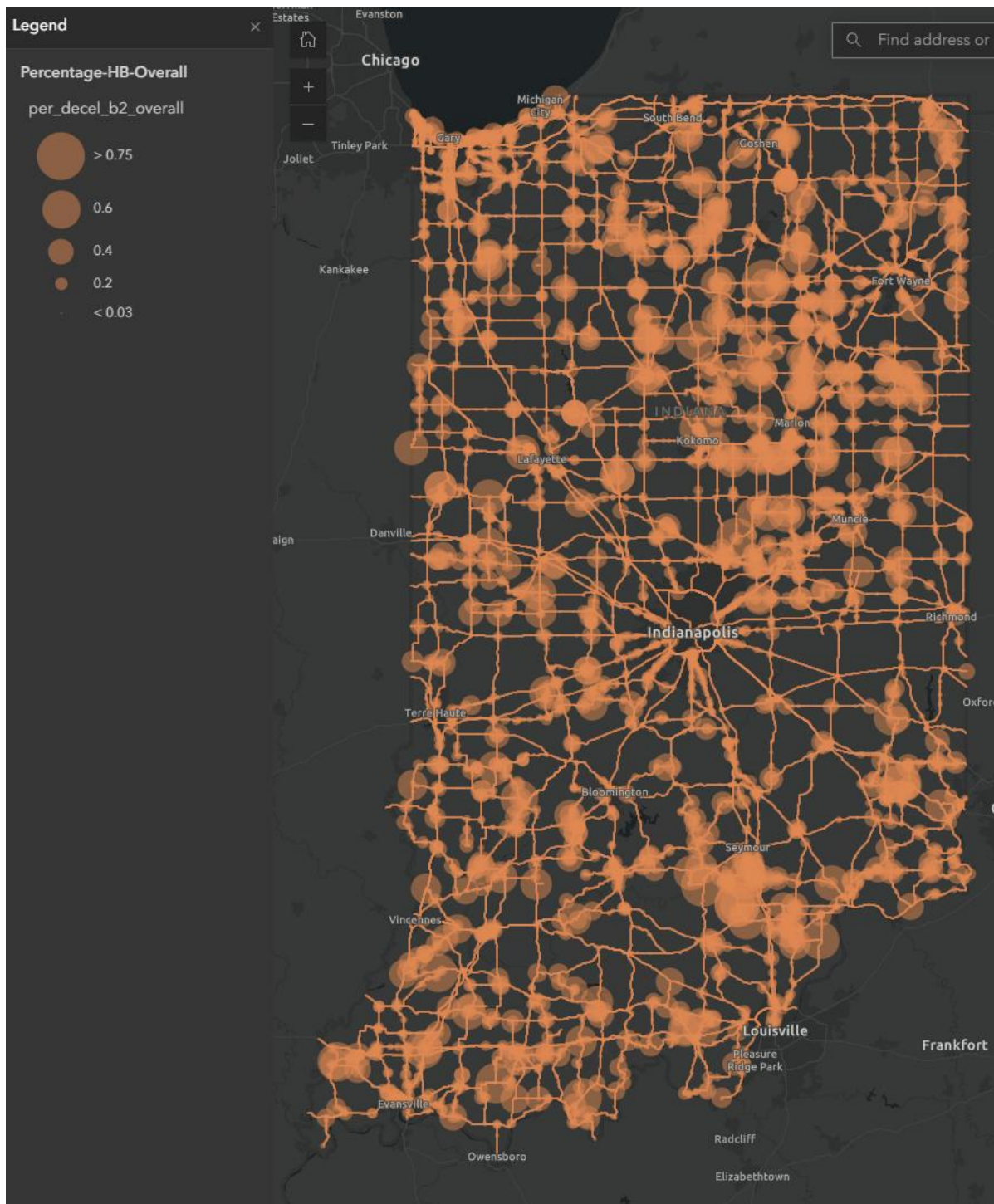


Figure B.5 2024 Annual Normalized Hard-Braking Events (Layer 2).
<https://purdueuniversity.maps.arcgis.com/apps/instant/sidebar/index.html?appid=316271ede5bd47d6aa05fd3f3eaf8835>

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1 — evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at docs.lib.purdue.edu/jtrp/.

Further information about JTRP and its current research program is available at engineering.purdue.edu/JTRP.

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