

# Spatiotemporal Analysis of Pavement Roughness Using Connected Vehicle Data for Asset Management

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## Abstract

Pavement condition monitoring and its timely maintenance is necessary to ensure the safety and quality of the roadway infrastructure. The International Roughness Index (IRI) is a commonly used measure to quantify road surface roughness and is a critical input to asset management. In Indiana, the IRI statistic contributes to roughly half of the pavement quality index computation used for asset management. Most agencies inventory IRI once a year, however, pavement conditions vary much more frequently. The objective of this paper is to develop a framework using crowdsourced connected vehicle data to identify and detect temporal changes in IRI. Over 3 billion connected vehicle records in Indiana were analyzed across 30 months between 2022 and 2024 to understand the spatiotemporal variations in roughness. Annual comparisons across all major interstates in Indiana showed the miles of interstates classified as “Good” decreased from 1896 to 1661 miles between 2022 and 2024. The miles of interstate classified as “Needs Maintenance” increased from 82 to 120 miles. A detailed case study showing monthly and daily changes of estimated IRI on I-65 are presented along with supporting dashcam images. Although the crowdsourced IRI estimates are not as robust as traditional specialized pavement profilers, they can be obtained on a monthly, weekly, or even daily basis. The paper concludes by suggesting a combination of frequent crowdsourced IRI and commercially available dashcam imagery of roadway can provide an agile and responsive mechanism for agencies to implement pavement asset management programs that can complement existing annual programs.

## Keywords

Connected Vehicles, Pavement, Pavement Quality, Roughness, IRI, Dashcam

## 1. Introduction

Pavement asset management strategies play an important role in the maintenance of roadway systems. A classic pavement asset management system involves systematic processes and tools for optimizing pavement conditions by scheduling maintenance and repairs effectively within budgetary constraints [1]. In 2023, \$68.9 billion federal funding was allocated to modernize, repair and improve the safety and efficiency of roads and bridges in the United States [2]. With more than 3.2 million miles of highways in the United States [3], there is a need to have a data-driven and proactive approach to prioritize asset management strategies on roadway segments that need repair and improvement.

In the state of Indiana, the pavement asset management strategy is unique to pavement type and road category. Several factors impact the decision-making process including pavement roughness, rutting, surface distress, number of preventive measures, age of the pavement and age of the roadway surface. Deterioration curves are developed based on statistical quartiles and a pavement quality index (PQI) is computed for various components that normalize pavement condition across several road categories. An overall pavement condition is generated using a composite rating of component indices weighted most to roughness and least to rutting/faulting as shown in the below equation.

$$\begin{aligned}
 PQI_{overall} &= (0.5 * PQI_{IRI}) + (0.3 * PQI_{\%cracking}) + (0.2 * PQI_{RUT}) \text{ for HMA} \\
 PQI_{overall} &= (0.5 * PQI_{IRI}) + (0.3 * PQI_{\%cracking}) + (0.2 * PQI_{Faulting}) \text{ for Concrete}
 \end{aligned} \tag{1}$$

For both hot mix asphalt (HMA) and concrete, pavement roughness contributes to half of the overall pavement quality and is based upon the International Roughness Index (IRI) [4]. IRI is usually estimated using high quality inertial profilers or dedicated pavement data collection vehicles equipped with high-speed digital cameras, GPS, laser systems and accelerometers. Agencies typically inventory IRI once a year since these data collection efforts are expensive and labor intensive [5] [6]. However, pavement conditions change continually throughout the year, particularly during spring freeze thaw cycles or locations experiencing significant localized loading due to construction activities and/or detours. Consequently, there is a need to continuously monitor pavement quality on a system wide basis to implement efficient asset management strategies.

This research proposes a framework to analyze and monitor the pavement roughness using estimated IRI from crowdsourced connected vehicle (CV) data. The ubiquitous nature of this data allows continuous monitoring of pavement conditions both on a systemwide level as well as on selected roads and segments. This methodology also provides a data-driven and systematic approach to target timely mitigation strategies to manage the performance of the pavement and ensure their long-term functionality.

## 2. Literature Review

Traditional methods for characterizing pavement conditions involves the use of a

high-speed inertial profiler [7], a vehicle capable of collecting roughness data in terms of IRI. The measurement equipment is mounted on the front or rear of the vehicle and relevant data is collected at the posted speed limit. Several automated profilers are widely available and capable of collecting roughness including the Automated Road Analyzer (ARAN), Pathrunner, Multi-Functional Vehicle (MFV), Road Measurement Data Acquisition System (ROMDAS), and Laser Road Surface Test (Laser RST). Although this data is highly accurate, there are significant operating costs associated with these profilers and they require dedicated personnel to drive all the roadways in the system. Additionally, they are less reliable during low speeds and data extraction is labor intensive and time consuming [5] [6] [8].

Other studies have used image processing techniques [9]-[11], LiDAR [12]-[14] and Unmanned Aerial Vehicles (UAV) [15]-[17] to estimate pavement roughness. Maeda *et al.* used deep neural networks on images collected from smartphones to detect and classify pavement condition [18]. Results showed more than 70% accuracy in detecting and classifying road conditions with an inference time of roughly 1.5 s on a smartphone. In another image processing study, Obunguta *et al.* built a robust probabilistic pavement management model with a safety metric output based on the pavement condition [19].

Recently, researchers have also developed smartphone applications to calculate road roughness [20]-[22]. Results show that the accuracy of GPS and accelerometer sensors in the smartphones could affect the roughness calculations [23]. Another study developed a fully convolutional neural network architecture called IRI-Net that estimates IRI from vibration data collected using smartphones [24]. The study also outlines strategies for handling low resolution GPS data obtained from smartphones. Results showed that the developed model was able to accurately estimate IRI under real-world conditions irrespective of the vehicle type, driving speed, and smartphone used for data collection.

An early study conducted in 2014 explored the use of sensor data from crowdsourced CVs for effective pavement data collection and found that new metrics from this source could be implemented for transportation asset management practices within the near term of 3 - 5 years [25]. Bridgelall *et al.* used data from on-board accelerometers and speed sensors to estimate road roughness indices and found that the average margin of error between the measurements was less than 6% [26]. Researchers have also investigated the possibility of augmenting standard pavement survey data with spatiotemporally continuous sensor data crowdsourced from CVs. Kargah-Ostadi *et al.* leveraged a physics-integrated machine learning model and quarter-car simulation approach to predict standard IRI values using speed, acceleration and suspension data. The evaluation results yielded high accuracy, precision and generalization capability between the training and test datasets, especially on smoother road profiles [27].

A recent study exploring the potential uses of CV technologies found that

utilizing sensor data from CVs for pavement evaluation offers a cost-effective and efficient approach [28]. Few studies have used enhanced real-world CV data to evaluate pavement quality. A study compared IRI estimates from connected production vehicle data and inertial profilers, and found that there was a good correlation between the two with an  $R^2$  value of 0.79 [29]. Another study highlighted the scalability of this data by analyzing pavement roughness over 5800 miles of I-80 using CV data from 730,000 crowdsourced segments [30]. Other studies have applied machine learning techniques on data from inertial sensors to estimate roughness index [31] [32]. In general, the results suggest that estimated roughness from crowdsourced CV data is a viable tool for network level screening of pavement quality.

### 3. Study Objectives

The objectives of this study are the following:

- Develop a framework using crowdsourced CV data to identify and detect temporal changes in IRI
- Perform qualitative validation of the results from the crowdsourced data using dashcam imagery from commercial trucks
- Conduct analysis and comparisons at both systemwide levels and at individual interstates or road sections in Indiana
- Perform annual, monthly, and daily comparisons to understand how pavement conditions vary over time so agencies can adopt a systematic approach for the quantitative monitoring of pavement quality

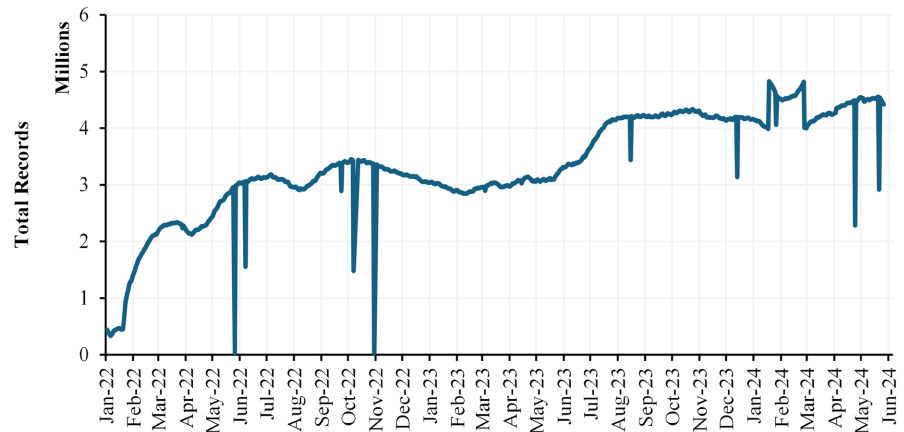
## 4. Data

### 4.1. Connected Vehicles

Enhanced CV data is currently available commercially through several third-party vendors. Data from on-board equipment such as accelerometers, pressure sensors, GPS and other vision/ultrasonic sensors are capable of extracting information on the current state of the pavement conditions. A new system in production vehicles can now provide pavement quality information by analyzing individual wheel speeds and drivetrain information [33]. This crowdsourced information from multiple vehicles is then analyzed over a moving window of 60 days to generate an estimated IRI value for a pavement segment.

**Figure 1** shows a count of the total daily CV records with pavement quality information available in Indiana between January 2022 and June 2024. On average, there are roughly 4.5 million records available per day which results in a sum of over 3 billion records during the study period of 30 months. The drops in the plot represent days with data outages (less than 1% of all the days). Data is refreshed every day and is available on spatial segments of 50 to 85 ft in length. The spatial segments are then mapped to 0.1-mile interstate segments using a methodology similar to the one highlighted by Mathew *et al.* [34] to follow a systematic linear referencing approach. Aggregation is performed using median values to

estimate the IRI for these 0.1-mile interstate segments. For CV segments spanning two adjacent interstate segments, only the first interstate segment in the direction of travel is included in the aggregation to avoid sampling bias. Although the analyses presented in this study are mostly over 0.1-mi and 1-mi segments, additional aggregations over different segments lengths and appropriate highway segmentations [35] can be easily performed.



**Figure 1.** Daily count of connected vehicle records.

## 4.2. Images

Dashcam images from Google street view, agency dashcams, and commercial truck dashcams are used to validate the results from the CV data. The commercial truck dashcam providers have capability to supply on-demand images from more than 64,000 trucks operating on U.S. roadways. The section of I-65 presented in this paper was traversed by approximately 230 trucks per day.

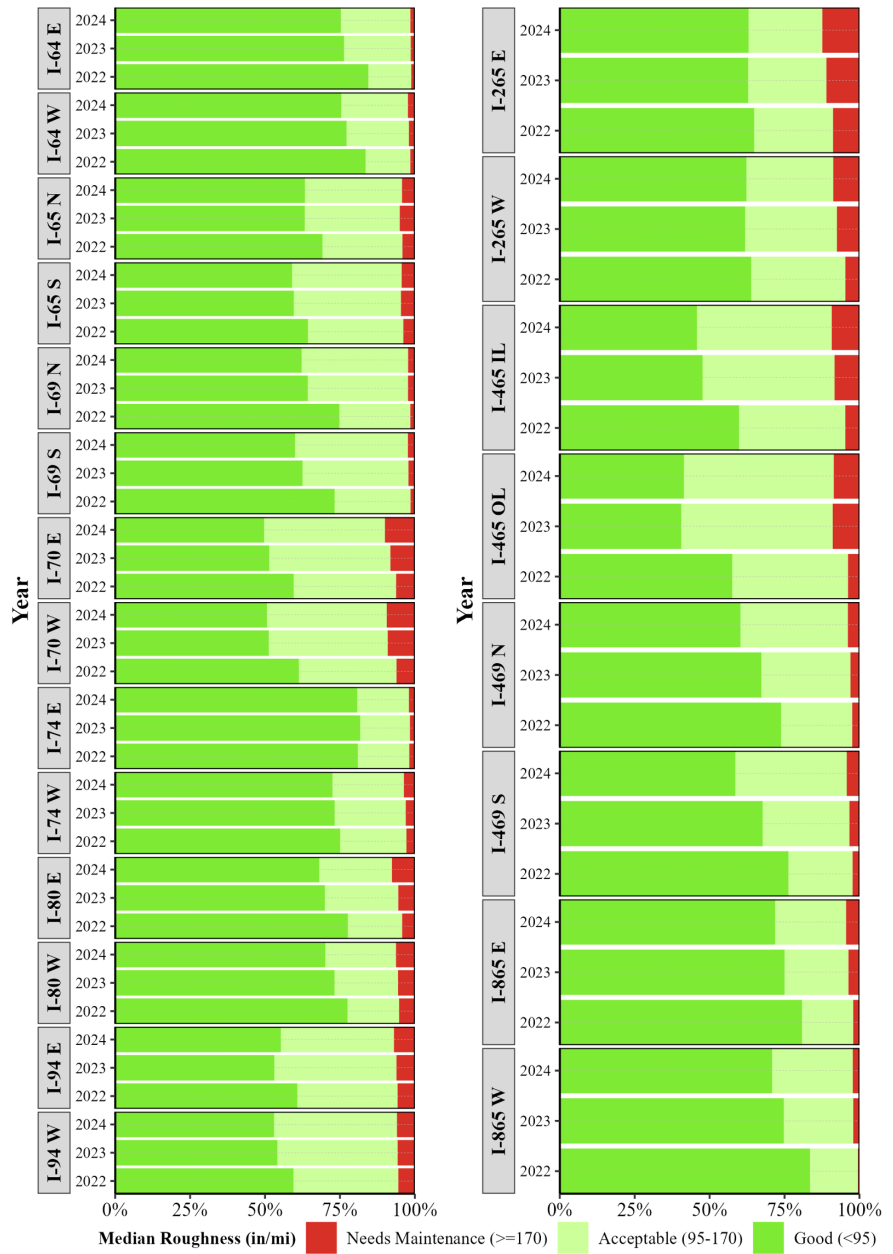
## 5. Systemwide Overview of Pavement Condition

**Figure 2** provides an annual comparison of the median roughness across all interstates (by direction) in Indiana during the study period. **Table 1** shows the total bi-directional miles of interstate roadways classified by pavement roughness condition between 2022 and 2024. The classification is performed using the IRI thresholds outlined by Federal Highway Administration (FHWA) [36]. In general,

- The miles of interstates classified as “Good” decreased from 1896.1 miles to 1661.2 miles between 2022 and 2024
- The miles of interstate classified as “Needs Maintenance” increased from 82.8 miles to 120.7

Changes in specific interstates are shown in **Figure 2**.

This systemwide overview of pavement roughness at both a system level and route level provides an important high-level status of pavement condition by year. The subsequent sections describe how this data can be further analyzed at more discrete spatial and temporal levels.



**Figure 2.** Annual IRI comparison across Indiana interstates.

**Table 1.** Pavement roughness by miles of interstates in Indiana and absolute change compared to 2022.

Median Roughness (in/mi)	2022		2023		2024*	
	Total miles (mi)	Total miles (mi)	Total miles (mi)	Absolute change (mi)	Total miles (mi)	Absolute change (mi)
Good (<95)	1896.1	1700.8	1661.2	-195.3	1661.2	-234.9
Acceptable (95 - 170)	641.8	812.7	838.8	170.9	838.8	197
Needs Maintenance (>=170)	82.8	107.2	120.7	24.4	120.7	37.9

\*6 months.

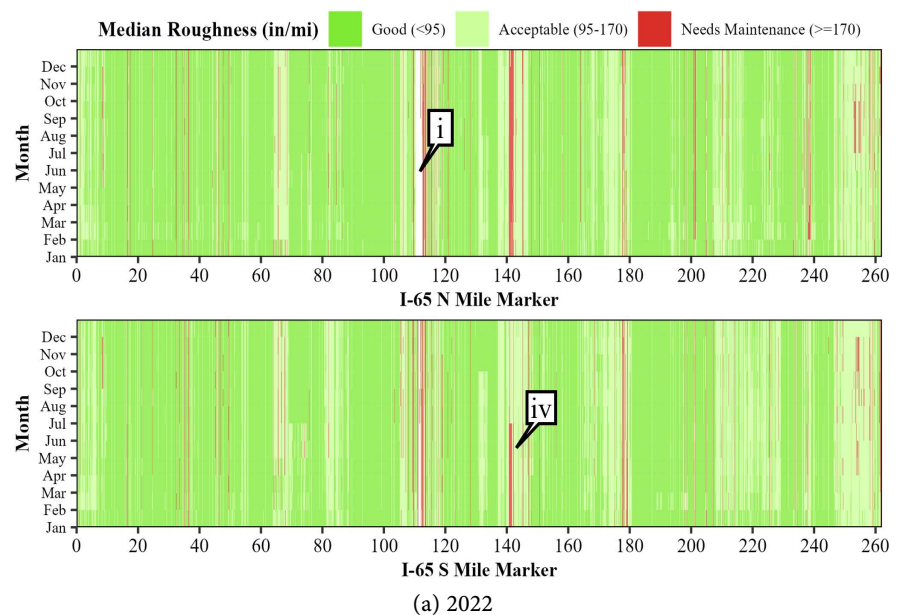
## 6. Case Study on I-65

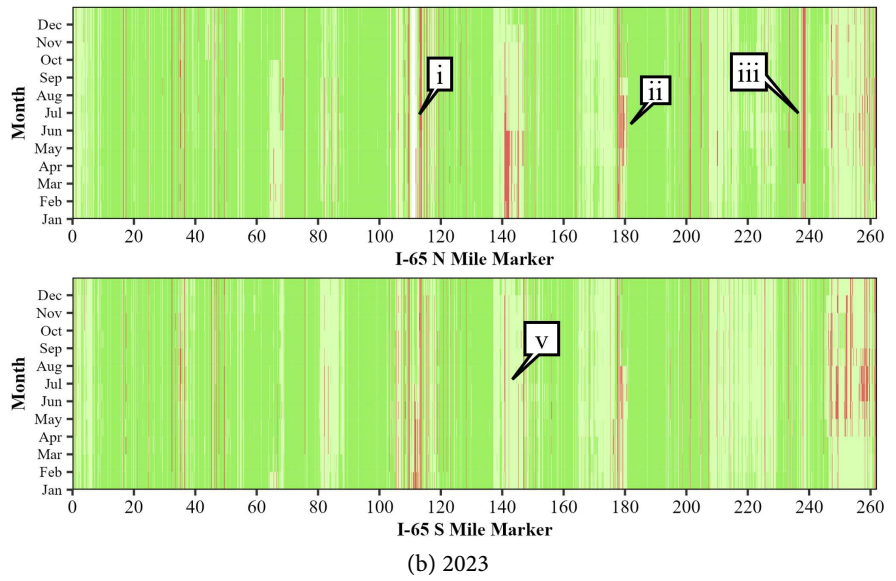
### 6.1. Annual Comparison by Mile Marker

**Figure 3** shows a spatiotemporal comparison of roughness on I-65 between 2022 and 2023. The top half of the plot in subfigures (a) and (b) represents the roughness in the northbound direction (I-65 N) and bottom half represents the southbound direction (I-65 S). The 0.1-mi segments along the route are shown on the horizontal axis and the months on the vertical axis. The plot is color coded by the median roughness aggregated by each month. The areas denoted in white highlight instances with data outage (callout i).

In general, the majority of I-65 is operating under acceptable roughness conditions with very few sections needing maintenance. In 2023 (**Figure 3(b)**), the area near mile marker (MM) 180 on I-65 N (callout ii) seems to have worsened further between the months of April and August, which was due to construction activities. It is common to have poor road conditions on work sites where construction activities can disrupt the smooth surface resulting in uneven surfaces, potholes, and construction debris. The area near MM 240 on I-65 N (callout iii) also worsened throughout the year.

The one area where the pavement condition improved was near MM 140 on I-65 S (callout iv and v). Construction activities in this area near Lebanon on I-65 wrapped up in June 2022 and this is highlighted by the stark improvement in pavement roughness (callout iv). Google Street View image obtained in May 2023 validate this smooth pavement after construction (**Figure 4(b)**), whereas GoPro images collected during May 2022 highlight some of the potholes and rough pavement conditions in this area during ongoing construction (callout i in **Figure 4(a)**). Callout ii shows the common tower in both **Figure 4(a)** and **Figure 4(b)** to highlight the same location.

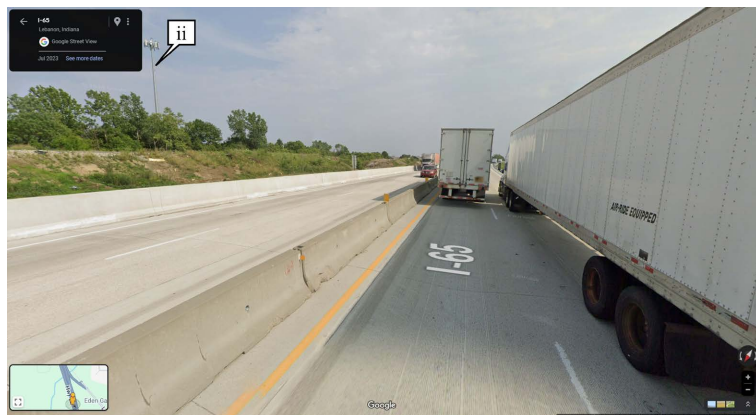




**Figure 3.** Monthly IRI comparison on I-65.



(a)



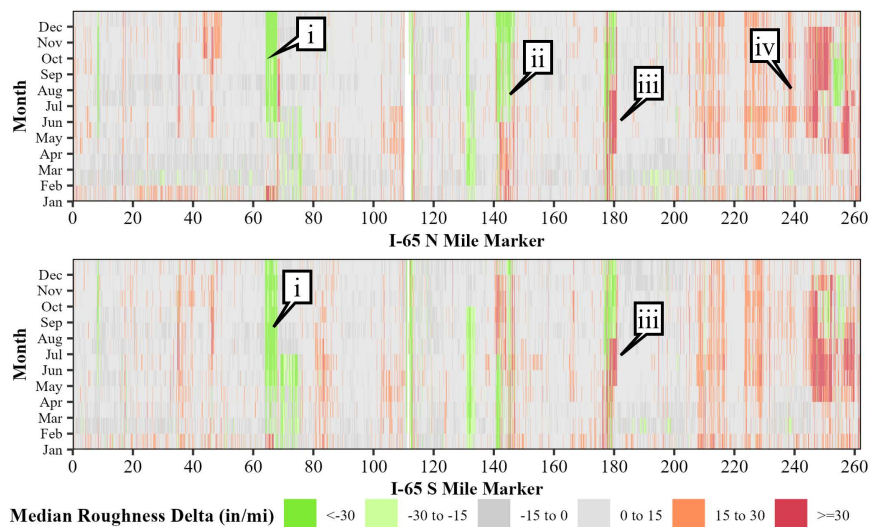
(b)

**Figure 4.** Pavement condition between 2022 and 2023. (a) GoPro image from May 2022 corresponding to callout iv in **Figure 3**; (b) Google Street View Image from July 2023 corresponding to callout v in **Figure 3**.

### 6.2. Variation in Pavement Conditions

In order to better understand the variations between the years, a delta plot showing the difference in median roughness between 2022 and 2023 is shown in **Figure 5**. Areas where median roughness decreased or pavement conditions improved are shown in green whereas areas with considerable degradations are shown in red. Areas with minor improvements or degradations are shown in light and dark grey, respectively.

This visualization helps to narrow down areas with considerable variation in roughness. This includes segments near MM 60 (callout i) and MM 140 (callout ii) where conditions improved as well as areas near MM 180 (callout iii) and MM 240 (callout iv) where conditions worsened. This performance measure will be an important tool for agencies to understand the time and location of when the pavement conditions are changing over time so that they can systematically allocate resources for asset management planning.

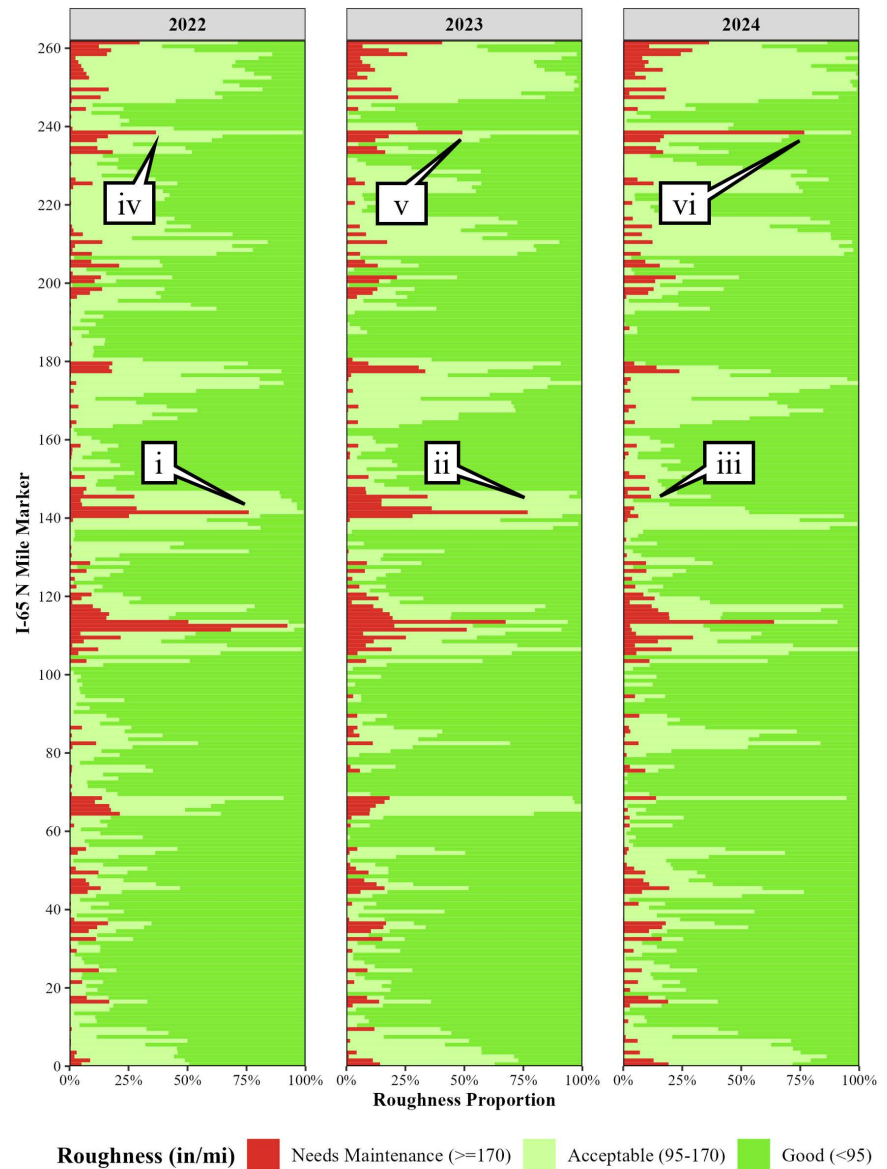


**Figure 5.** Delta IRI between 2022 and 2023.

### 6.3. Monthly Comparison

**Figure 6** shows a 100% stacked plot that compares the variation in median roughness values across I-65 N during the month of January between 2022, 2023 and 2024. Each bar on the vertical axis represents a one-mile segment on I-65 N and the values on horizontal axis show the percent of segments operating under various roughness conditions.

As seen earlier, more than 75% of the segment near MM 140 needs maintenance (callout i and ii) due to ongoing construction activities in January 2022 and 2023. When construction was completed in 2023, most of this segment operated under good conditions (callout iii). In contrast, the segments just before MM 240 seem to be degrading over time. In January 2022, roughly 40% of this segment needed maintenance (callout iv), whereas in 2023 this rose to 50% (callout v) and in 2024 to 80% (callout vi).

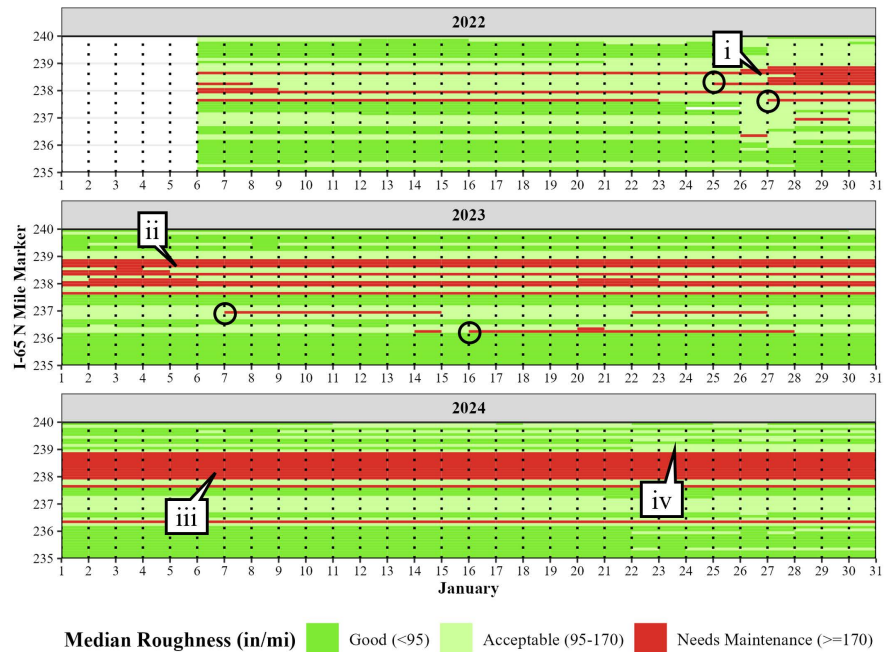


**Figure 6.** IRI comparison on I-65 N between 2022 and 2024.

#### 6.4. Daily Comparison

**Figure 7** shows a detailed comparison of the segments between MM 235 and MM 240 on I-65 N across January 2022, 2023, and 2024. The horizontal axis shows each day in January and vertical axis shows every 0.1-mi segment color coded by the pavement roughness condition. The first drop in pavement condition begins around January 27, 2022 (callout i) and worsens during January 2023 (callout ii). The conditions worsen and propagate across the entire one-mile stretch between MM 238 and 239 in January 2024 (callout iii). Dashcam images obtained from commercial trucks in February 2024 as shown in **Figure 8(a)** and **Figure(b)**, also validate the poor condition of the roadway between MM 238 and MM 239. The connected vehicle data also shows a stark improvement in conditions at the onset of MM 239 which is also validated using the dashcam image in **Figure 8(c)**.

Additionally, the black circles in **Figure 7** highlight the date when pavement conditions begin to degrade at several locations on the interstate. This information from crowdsourced data will be helpful for agencies to perform continuous monitoring of the pavement conditions and apply appropriate pavement management and rehabilitation techniques to ensure the safety of travelling motorists.



**Figure 7.** Daily variations in IRI across January 2022, 2023, and 2024.



(a)



(b)



(c)

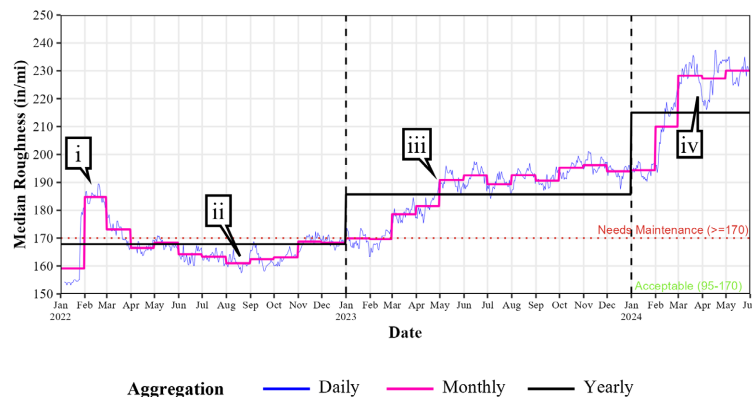
**Figure 8.** Connected truck dashcam images showing pavement condition on I-65 N. (a) I-65 N MM 238.4 on Feb 18, 2024 (callout iii on **Figure 7**); (b) I-65 N MM 238.5 on Feb 18, 2024 (callout iii on **Figure 7**); (c) I-65 N MM 239 on Feb 18, 2024 (callout iv on **Figure 7**).

### 6.5. Longitudinal Variation

**Figure 9** illustrates the longitudinal variation in IRI values for the highlighted section between MM 238 and MM 239 in **Figure 7**. The daily, monthly and yearly variation in pavement roughness over this section is illustrated by the blue, pink and black lines respectively. The monthly and yearly values are estimated by calculating the median of the daily estimates.

In early 2022, during the winter months of January and February, this section of the pavement deteriorated and required maintenance (callout i). After initial reactive patching and subsequent maintenance, pavement conditions improved to an acceptable level (callout ii). However, following completion of summer maintenance, subsequent pavement deterioration occurred over the winter (callout iii). In late 2023 and early 2024, conditions worsened through April 2024, when additional maintenance briefly improved conditions before they deteriorated again (callout iv).

These comparisons will be valuable for agencies to tailor their decision-making at various levels. For example, the daily or monthly variations can be used to understand the performance from a project or district level, whereas the yearly variations can be used for systemwide decisions. Additionally, as monthly estimates closely align with daily estimates, agencies could potentially opt for monthly results to reduce computational complexity and data storage requirements.



**Figure 9.** Daily, monthly and yearly roughness variation on I-65 N MM 238-239 section.

## 7. Conclusions

This study used crowdsourced connected vehicle data to develop spatiotemporal assessment of pavement roughness conditions for asset management planning. Over 3 billion connected vehicle records available between January 2022 and June 2024 (**Figure 1**) in the state of Indiana were linearly mapped to interstate roadways. Annual comparisons across all major interstates in Indiana showed the miles of interstates classified as “Good” decreased from 1896 to 1661 miles between 2022 and 2024. The miles of interstate classified as “Needs Maintenance” increased from 82 miles to 120 during that same period (**Figure 2** and **Table 1**). Annual (**Figure 3**), monthly (**Figure 6**) and daily (**Figure 7**) comparisons showing the variations in pavement conditions on I-65 were presented. Visualizations were also developed to easily identify segments along the interstate with considerable variations in pavement conditions over time (**Figure 5**). Dashcam images from commercial trucks (**Figure 8**) and Google Street View (**Figure 4**) were also used to validate the results generated using the crowdsourced data.

The methodology and framework presented in this study will help agencies understand the time and location when pavement conditions change so they can undertake a proactive approach to asset management planning. The real-time availability of this data will also provide additional opportunities for continuous pavement monitoring. Furthermore, the results from this methodology can be used for quantitative monitoring of pavement conditions and can be used to identify locations for additional targeted and enhanced data collection using advanced equipment. The visualizations and performance measures developed in this study could also aid in the systematic prioritization of pavement management strategies to ensure safety and long-term functionality of roadways.

Future research may be used to perform comprehensive assessments of pavement degradation rates. This will be particularly helpful for agencies to identify critical sections, optimize budget allocations, and prioritize maintenance tasks. By comparing daily, monthly, and yearly degradation rates, agencies can develop effective mitigation strategies at the system, network, or project level. Timely pavement maintenance can also significantly enhance user safety and reduce costs.

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## Conflicts of Interest

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

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