# CHARACTERISING MAJOR STORM EVENT IMPACTS ON RURAL ROUTES

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ABSTRACT
Probe vehicle data is playing a critical role in the evaluation and creation of infrastructure performance measures across diverse driving conditions. This is particularly important at bridge-crossings during storm events, where bridges may become impassable, thus providing a measurable means to stress-evaluate the network. During a major storm, many bridges can be flooded, an attribute assessed and documented by the United States National Bridge Inventory. When a major storm event occurs, the intensity and location of the event can impact the transportation system across a route or region. The objective of this research is to define rural roadway performance metrics based on the absence of normally available probe vehicle data. The research employs a dual approach – leveraging a defined congestion metric against a data availability metric for rural bridges affected by a storm event. Three counties in New Jersey were assessed during the Tropical Storm Ida, which made landfall in New Jersey, US on 1 September 2019. The project analysed 107 rural bridges, their spatially defined traffic message channels and associated anonymous probe vehicle speed data over 29 days. The results indicate that both congestion and null data can be used to assess and rank the reliability of rural bridge performance during major storms. The metric models can be deployed to evaluate infrastructure performance in near real-time during storm events and to evaluate where capital investments may improve infrastructure reliability and sustainability.
*Keywords: sustainable transportation, bridges, reliability, probe vehicle, capital investment.*

## 1 INTRODUCTION

Anonymous probe vehicles (APVs) provide large speed datasets with high spatial and temporal resolution over a large portion of the United States (US). Under the Operations Performance Measurement Program [1] of the United States Department of Transportation (USDOT), federal, state and local agencies have been increasingly using the National Performance Management Research Data Set. The main focus has been defining evaluation metrics for larger roadways [2], along with other national reports [3], [4]. These performance measures are generally applied to roadways which have consistent traffic and therefore a reliable and consistent data signal. This research explores the application of speed datasets to smaller, more rural routes which may be less frequently travelled by APVs, thus providing a less reliable data signal. Speed data was used to evaluate the performance of rural roads during a major storm event where heavy rains made some roadways temporarily or permanently unusable, while restricting passage on other roadways and increasing traffic flow on viable roads.

Monitoring changes in speed conditions and fluctuations in data availability is crucial as a measure of the near-term reliability of a roadway system, and longer-term sustainability of the network. This type of monitoring has been applied to major natural disasters in Japan [5], as well as the US [6]. While a bridge might not be the primary reason for a route's inaccessibility, the research group is examining where roadways become problematic at stream crossings, which are easily identified in the US National Bridge Inventory (NBI). NBI bridges are structurally rated based on waterway adequacy, where a rating of 5 for minor collectors in New Jersey indicates some overtopping, and a rating of 2 indicates frequent

 
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overtopping. When a bridge overtops, the effects can be reasonably determined by analysing the traffic patterns. However, in the case of rural roadways, the lack of data can be more of an indication of an impact on the network. This investigation aims to explore how congestion patterns, coupled with data availability, might identify rural infrastructure in need of improvement at a county-wide level using APV data. Observing congestion fluctuations on a regional scale allows for closer scrutiny of the data, revealing where, when, and how capital investments might improve local transportation system storm reliability and long-term sustainability.

## 2 BACKGROUND ON STORM EVENT

Even minor storms can have long-term impacts on infrastructure and near-term impacts on first responders and the motoring public, however a major storm provides researchers with a means to evaluate how the system performs under extreme conditions. On 1 September 2021, Tropical Storm Ida dropped 3.24 inches of rain in 1 hour, setting a state record for the state of New Jersey in a 1-hour period [7]. New Jersey experienced the highest death toll among all states affected by the storm, with flood damage costs estimated at approximately $3.84 billion [8]. The storm led to numerous fatalities and instances of people being trapped in vehicles; in one county, six people died when they became trapped in flooded vehicles [9]. The ability to pinpoint problematic locations provides a more quantitative approach to planning financial and operational capital improvement decisions.

## 3 TEST BED

The evaluation of APV speed data requires a cross reference between spatially defined traffic message channels (TMC) and temporal speed data sets [10]. Each speed record includes a timestamp, c-value and confidence score as its attributes associate with each probe speed records. A confidence score of 30, along with a c-value of 100, indicates that the speed is not calculated and reflects actual roadway conditions. For this research, only records with a score of 30 and c-value of 85 or greater were included.

The study region included three counties in New Jersey, with a focus on rural routes (Fig. 1). To identify TMC's which cross waterways on rural routes, the National Bridge Inventory (NBI) was used. The NBI contains longitude and latitude coordinates tied to route types that can be used to identify TMC's crossing water ways. 327 rural bridges were identified using the NBI, but only 107 of the bridges had APV data available. The 107 test bed bridges (Fig. 1) are associated with 224 TMCs, or about 1.3% of the 16,256 TMCs available state-wide. The data was collected between 17 August and 16 September 2021. The study period was kept small to focus on the specific storm event.

## 4 MEASURES OF RELIABILITY

The base free-flow speed (BFFS) used in this research is similar to the Highway Capacity Manual's definition of BFFS [11], but with an alternative calculation. BFFS for each TMC was determined by calculating the minute-by-minute average segment speed for the entire study period between 02:00–10:00 hours when congestion due to volume is unlikely. However, because these are rural routes, there is already a low probability of congestion, and during the early morning hours speed records may be difficult to obtain. To get the BFFS, the sample time was extended to 10:00, instead of 06:00 which had been done in previous research [12]. The BFFS is calculated using the following:

$$BFFS_i = \frac{1}{n_j}\sum_{j\in F} v_{ij}\,, \tag{1}$$

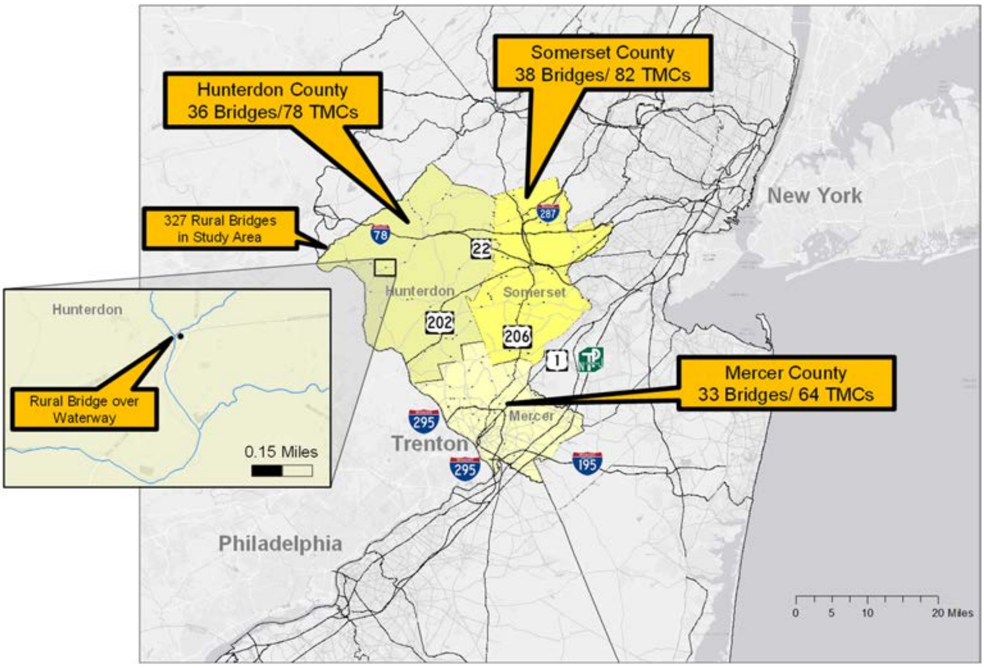


Figure 1: Three county study areas in New Jersey, consisting of 107 rural bridges.

where:

- *BFFS* is the variable speed threshold for TMC *i* (each TMC is assigned a BFFS);
- $v_{ij}$ are speed records for TMC *i* for the 15-minute interval *j*;
- $n_j$ is the total count of 15-minute intervals within the free-flow time *F*, which is defined as all of the minutes between 02:00 and 10:00 during the entire 29-day study period.

Both the analysis timeframe and the percent speed threshold can be adjusted to better understand how the transportation system reacts and recovers under recurring conditions as well as extreme events. The base free flow speed for each TMC was used to calculate the percentage of base congestion (PBC), which basically the number of 15-minute bins considered to be congested, divided by the number of total 15-minute bin with data as reflected in eqn (3):

$$PBC_{ij} = \frac{\Sigma\begin{cases} 1 & (v_{ij} < 0.7 \times BFFS_i) \\ 0, & (v_{ij} \geq 0.7 \times BFFS_i) \end{cases}}{\Sigma\, v_{ij} \neq null}, \qquad (2)$$

where:

- $PBC_{ij}$ is percent base congestion, which is the number of 15-minute bins considered to be congested for $TMC_i$ at time period *j* divided by the total number of speed data available;
- The time period (*j*) is a 15-minute bin that can be aggregated by hour, day, month as needed;

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- The 0.7 value can be adjusted, but for this equation it is used to establish a threshold congestion, meaning that any speed below 70% of the base free flow speed is counted as congested.

Conversely, when data are not available on a rural route, the lack of data itself can be used as a means to evaluate reliability of the system. A null-performance metric (NPM) is applied to each $TMC_i$ associated with a rural bridge. This equation is:

$$NPM_{ij} = \frac{\left[\sum v_{ij} \;= null\right]}{\sum x_j}, \tag{3}$$

where:

- $NPM_{ij}$ is the percentage of the NPM representing the number of 15-minute bins where no data was reported for $TMC_i$, divided by the total number of 15-minute time periods $x_j$ within the study window (e.g., if one day is being shown, then there are a total of 96, 15-minute bins available for that period);
- The time period ($j$) can be aggregated by hour, day, month as needed.

NPM is a direct measure of the data massing within a time-period. To better compare the number of time periods without data, an additional performance metric is being proposed to document the deviation from the null data. This can be helpful in two ways; congestion can be evaluated as a deviation from the free-flow speed, and NPM can also be evaluated as deviation from base daily null period (BDNP). Furthermore, when more data sets are observed at a location that normally does not incur APVs, it can be an indication of changing traffic patterns due to decreased capacity on alternative routes, or even long-term changes in development in a region. The equation for BDNP is as follows:

$$BDNP_i = \frac{\left[\sum v_{ij} \;= null\right]}{\sum d}, \tag{4}$$

where:

- $BDNP_i$ is the ratio of the null performance metric representing the number of 15-minute bins ($v_i$) where no data was reported for $TMC_i$, divided by the total number of days ($d$) within the study window (e.g., if one week is being studied, then there is a total of 672, 15-minute bins available for that period. If this particular location is never used BDNP = 96). This allows a comparison bench mark for the average number of nulls.

With a baseline number of null values determined, deviation from this baseline can be evaluated in the following equation:

$$NDM_i = \frac{\left[\sum v_{ij} \;= null\right] - BDNP_i}{BDNP_i}, \tag{5}$$

where:

- $NDM_i$ is daily percentage-based metric compared to its shift from $BDNP_i$ and the number of 15-minute bins where no data was reported;
- $NDM_i$ can be both positive or negative. Positive values indicate a reduction in use by APV's (increased NULL values) and negative values represent an increase.


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This baseline establishes the typical number of null values expected from a TMC to allow a comparison between the observed null values and the expected number of null values.

## 5 COUNTY CONGESTION AND NULL VALUE ANALYSIS

The county-wide percentage of null points, along with the percentage of congestion, is shown in Fig. 2. From the initial analysis, there are a limited number of data points available during the study period for rural routes with bridges. As reflected in the graph, Somerset County, which is flanked by two interstate highways, had a higher amount of congestion and a lower amount of missing data. However, overall, there is a limited amount of congestion observed. Additionally, across each county, there is a limited amount of data available for analysis.

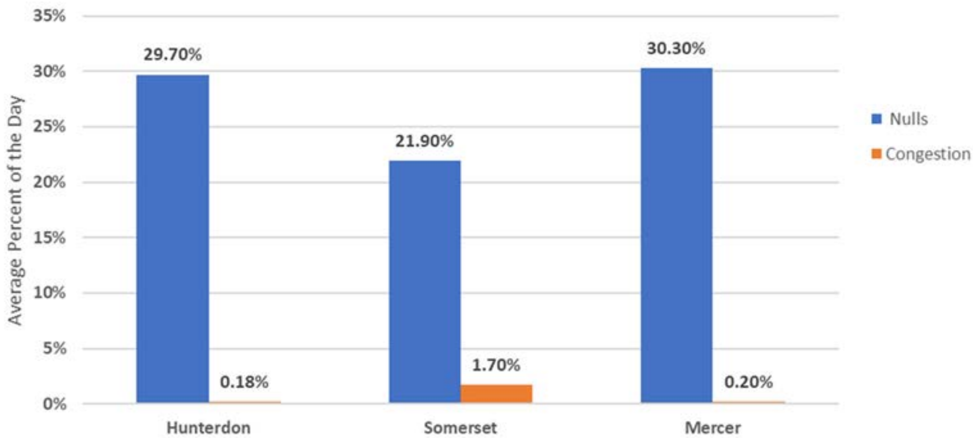
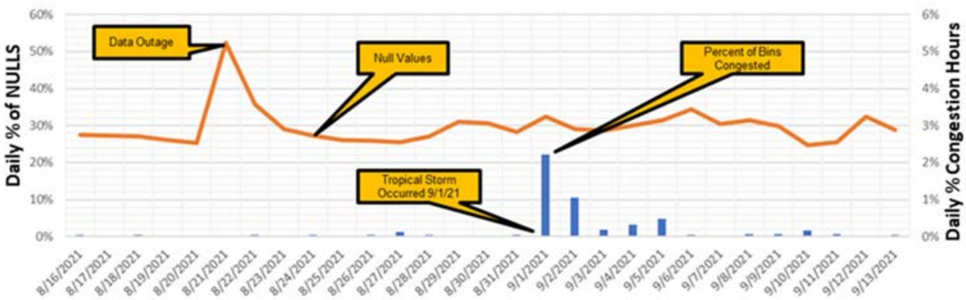


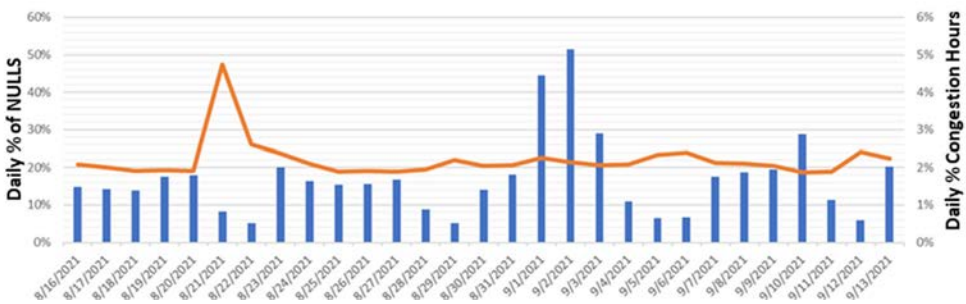

Figure 2: Study area NPM and PBC for 16 August–13 September 2021.

The figure demonstrates the issue with the lack of data and lack of congestion. The next step of the research process was to look at the daily fluctuations. This step was conducted to determine if the storm would register an impact at the county level. This step is also being done prior to determining which bridges might have been most impacted. As shown in Fig. 3, there are a few items that stand out. On 21 August, there was a state-wide data outage that affected each county. Also seen in the figure is a clear increase in congestion on 1 September 2021 for each county, which indicates that the storm did increase the frequency of congestion along the county's rural routes that have a bridge associated with them. It is noteworthy that it does not appear that there is a reduction in data availability during the storm, potentially an indication that on the whole the system performed close to normal during the storm event, but there still may remain some underlying issues in the system on a TMC to TMC basis.

A cumulative frequency analysis for the TMCs was conducted to see if there was a shift before and after the storm. Shown in Fig. 4 are the frequencies of data outages for the TMCs 7 days before and after the storm, excluding the day of the storm. In all cases there appears to be an increase in the number of null values above the 50% margin, indicating that there are routes receiving less data after the storm. What is not known is where this is occurring and if only a few TMCs are impacting the system. What can be seen is that there was a minimum increase in data availability, indicating again that overall, the system is performing well after the storm, albeit with some minor issues.




(a)

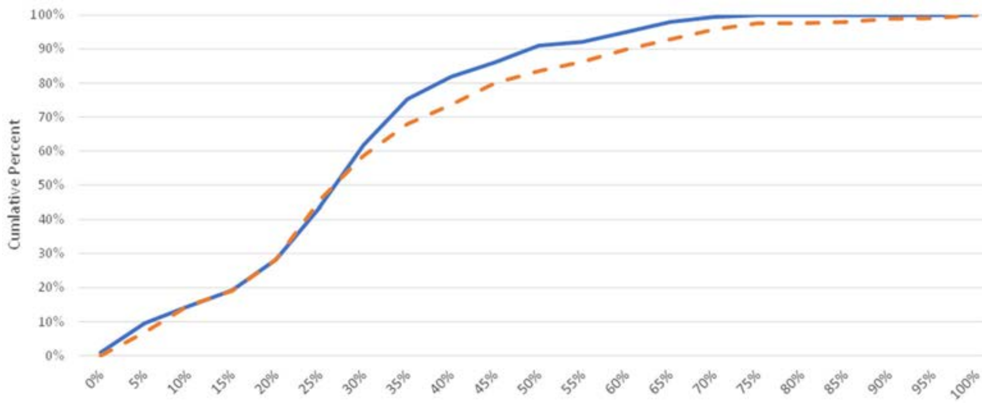



(b)

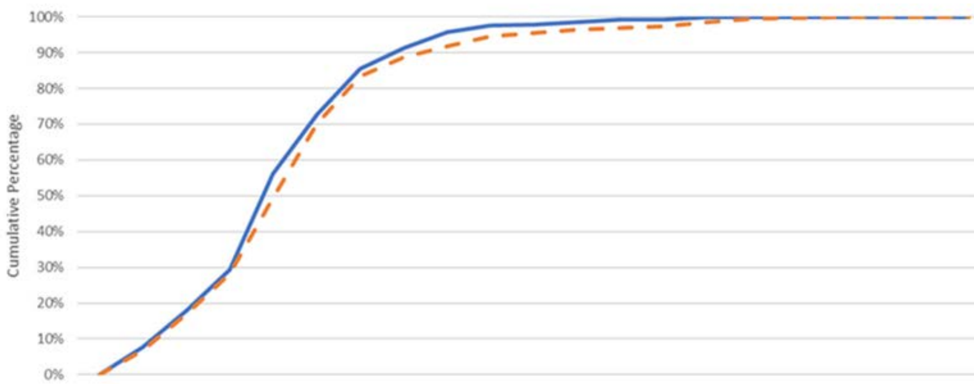

(c)

Figure 3: Daily NPM (1st axis) and PBC (2nd axis) for 96 15-minute bins. (a) Hunterdon County; (b) Somerset County; and (c) Mercer County.

The deviation from the NDM (daily percentage-based metric) provides another means to observe the changes between the null values as compared to the percentage of congestion hours. An example of this metric is shown in Fig. 5 where, on 1 September, there was an increase in congestion for the normally non-congested 78 TMCs in Hunterdon County. This graph illustrates the potential impact of the storm as it relates to data availability. The slight change reflects a minor disparity that is county wide but looking at the same information on a daily level might provide more insight on long term fluctuations in the data availability as compared to congestion.




(a)

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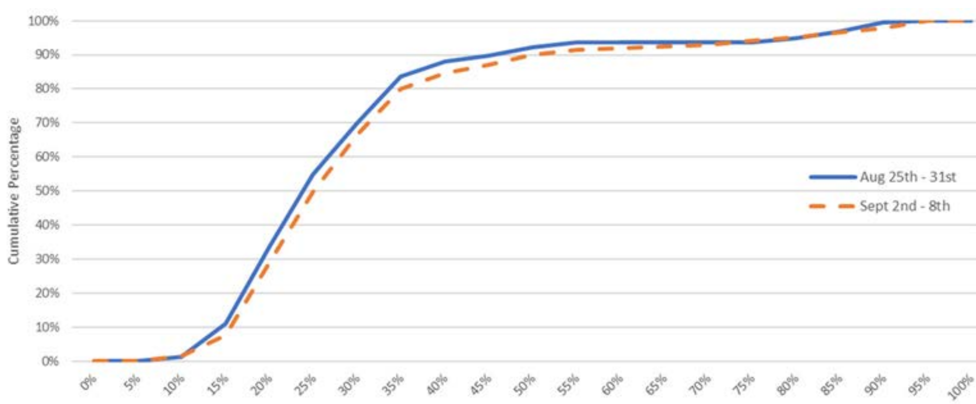


(c)

Figure 4: Cumulative NPM for 7 days before and after Tropical Storm Ida in 2021. (a) Hunterdon County; (b) Somerset County; and (c) Mercer County.

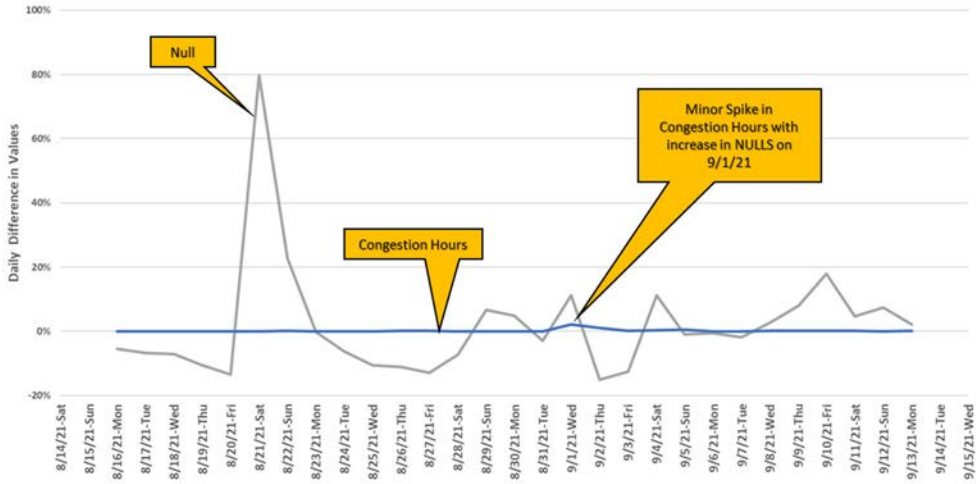


Figure 5: Hunterdon daily deviation from normal percentage of null values.

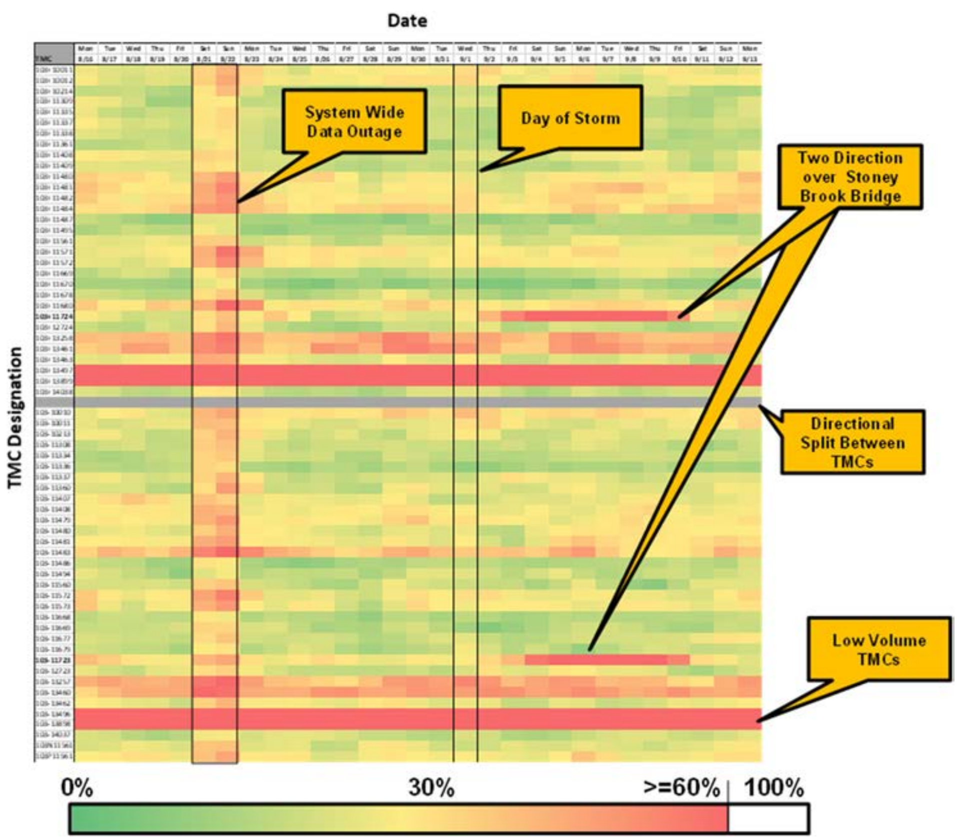


Figure 6: Two day moving average map for each TMC associated with a rural bridge.

A final analysis was conducted to determine which TMCs, which are also associated with an NBI bridge, were most impacted by the storm. To accomplish this a heat map of the moving 2-day average of the percent null was conducted. This analysis only considered the lack of data to determine impact. In Fig. 6, all the TMCs for Mercer County are shown along the *y*-axis with respect to the day of the week. On the day of the storm there is limited changes, however starting the day after the storm there is a clear change in data availability, where one location stands out: a bridge that crosses Stoney Brook. There was documented flooding in this area, where a police officer survived the flooding by clinging to a tree [13]. Other locations are also shown, but if a location does not show data the storm's impact cannot be assessed. However, at no point was data completely absent from the 2-day average. This does not necessarily mean a bridge was passable, because dependent on the length of the TMC vehicles could register a data point, but not be able to traverse the entire length. This is an issue with rural routes that needs to be addressed, where more granular TMC information might be obtained. Another item to address is how the data is perceived visually. The same data is viewed in Fig. 7, where the heat map scale was adjusted. Once adjusted, the Stoney Brook TMCs become more apparent, while other locations can start to show their fluctuations in weekend traffic.

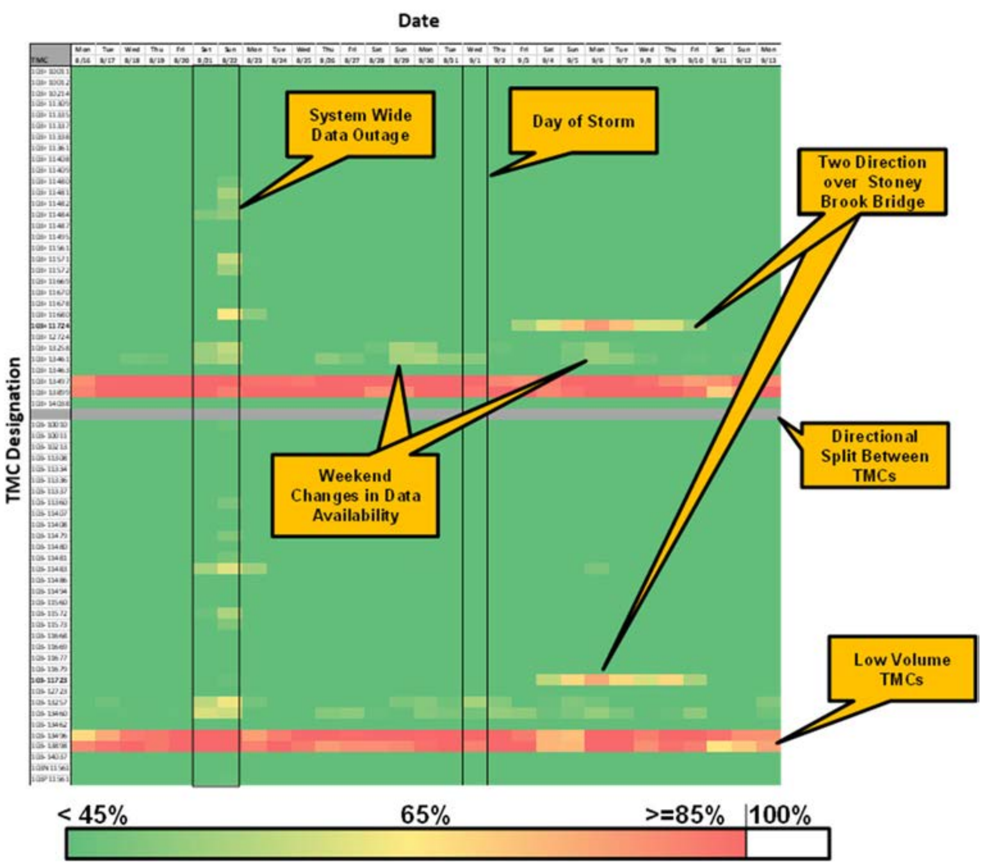


Figure 7: Alternative scale for 2 day moving average for each TMC associated with a rural bridge.

## 6 CONCLUSIONS

This research addresses whether probe vehicle data could be used to assess rural bridge performance during a major storm event using a high-level analysis of rural bridge performance in the state of New Jersey during the Tropical Storm Ida. Because rural routes have limited traffic volume, there is generally a low percentage of congestion, making it difficult to assess a bridge's performance. The methodology included a step to determine if the lack of probe vehicle data (null data) and the amount of time a TMC is congested might serve as performance indicators for rural routes with bridges. It was noted that only 107 of the 327 rural bridges in the study area had available data, indicating that more TMCs should be created. Additionally, TMCs can be made more granular, with lengths defined for specific bridge monitoring. The results showed that by measuring the change in data availability, a basic performance metric could be developed. Ultimately, this study aims to identify areas where more probe vehicle data should be collected to determine roadway reliability during disaster events.

The preliminary results can be used in two ways. First, the data can inform capital improvement assessments and decision-making. Better data can lead to better decisions on capital improvements along rural routes, based on where network improvement is most needed. The methods and metrics outlined in this research set the foundation for creating a more state-wide understanding of rural bridge performance during a natural disaster and the long-term sustainability of these structures. Although this research explores only historical speed data, the methodologies can be applied to real-time speed data sets. The authors are currently advancing this research towards developing additional real-time visualisation tools and machine learning algorithms to identify congestion performance specific to rural routes. By mining historical probe vehicle data through machine learning and other data analytics, predictive models can be developed to help evaluate a region not only for improvement under emergency situations, but long-term development of both residential and commercial areas. These models can evaluate the impacts of regional policy, economic changes, responses to natural disasters, and other factors affecting roadway congestion. This methodology can be applied in both real-time for first responders and to determine long-term capital investments.

Although not fully analysed, the study noted that some non-rural bridges flooded along the same waterway, indicating that the waterway might need improvement instead of the bridge structures that flooded. Previous work using probe speed data to assess the functional obsolescence (FO) of bridges found that congestion did not necessarily correlate with bridge FO based on geometry. This study aimed to see if waterway adequacy reflected bridge performance during a storm, but initial results suggest further research is needed. Second, near real-time data can help make better operational decisions for first responders and travellers. With better data, decisions on when and where to divert or delay trips can be made to avoid catastrophic situations. News reports indicated that injuries, fatalities, and people being stranded occurred in New Jersey. A better system to quickly notify drivers of potential hazards could have minimised these issues. Further granularisation of TMC data to specific bridges would enhance this process by providing specific bridge conditions related to APV data.

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obtained through INRIX Inc. All authors reviewed the results and approved the final version of the manuscript.

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