TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
1–15

DOI: 10.1177/03611981231165516
journals.sagepub.com/home/trr
SAGE

Using Crowdsourced Data to Reduce Traffic Congestion by Improving Detection of and Response to Disabled or Abandoned Vehicles on Florida Limited-Access Facilities

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Abstract

Disabled or abandoned vehicles (DAVs) cause a significant proportion of non-recurring traffic congestion. Waze data has the potential to help traffic management center (TMC) operators detect and respond to DAVs more quickly, reducing congestion. Previous studies have examined Waze data on a small scale, but not at a statewide level. This paper analyzes over 2 years of DAV Waze data on Florida Department of Transportation (FDOT) limited-access roadways (with more than 10 million alerts) and compares them with reported DAV events (crashes and non-crash TMC reports). Over 46% of the DAV events had an associated Waze alert before the DAV event occurred, indicating significant potential for earlier detection. These Waze alerts typically happened about 16 min before the DAV event and were most common during daytime hours and in urban areas. Two roadway segments, I-4 in FDOT District 5 and State Road 91 (SR-91) in FDOT District 4, were examined in more detail. A methodology was developed to estimate the delay reduction and congestion savings achieved by the earlier detection provided by the Waze alerts for lane-blocking and shoulder-blocking disabled vehicle events. The estimated congestion savings for the second half of 2019 were \$4.3 million (I-4) and \$2.5 million (SR-91), with benefit-cost ratios of 61 and 27, respectively. An additional \$4.3 million could potentially have been saved as a result of Waze alerts allowing responders to reach DAVs before a crash occurred. These results can help agencies understand how crowdsourced data can be effectively utilized to best improve freeway operations.

Keywords

operations, freeway management, incident management

Minimizing traffic congestion is a major goal for transportation agencies. According to the Federal Highway Administration (FHWA), about 50% of traffic congestion is caused by non-recurring congestion, with about half of this non-recurring congestion caused by traffic incidents (*1*). A large portion of these incidents are a result of disabled or abandoned vehicles (DAVs). Researchers in Tennessee, U.S., found that approximately 78% of freeway incidents involved a DAV, with these incidents lasting 57 min on average (*2*). Identifying ways to quickly detect and respond to DAVs could help substantially reduce traffic congestion. Many U.S. states have implemented safety service patrol (SSP) programs to help respond to and clear DAVs. While these programs are highly effective, there remains potential for earlier detection of DAVs through the use of crowdsourced data.

Crowdsourced data are traffic data collected from ordinary road users, either passively or actively when

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interfacing with applications like Waze. Waze allows users to report traffic events (crashes, vehicles on shoulder, roadway obstructions, etc.) while also being alerted to other reports via mapping and navigation functionality. Waze has also partnered with over 3,000 public and private entities worldwide through the Waze for Cities Program to enrich their collected data with other datasets (*3*). Many state and local transportation agencies use Waze data for incident management purposes, including the Florida Department of Transportation (FDOT), which has integrated a Waze feed into SunGuide (FDOT's advanced traffic management system [ATMS]) (*4*). FDOT was the first U.S. Waze partner and one of the first to integrate a Waze feed into their ATMS (*5*). Because of the high volume of Waze alerts, only crash and road blockage alerts are currently reported to traffic management center (TMC) operators, reducing response times for these events (*4*). Integrating DAV Waze alerts into SunGuide could help reduce DAV durations and associated congestion if properly filtered to avoid operator overload. This paper will examine and analyze the potential for Waze alerts to provide earlier DAV detection for different times of day and locations. Potential congestion and crash savings will be quantified to illustrate the benefits and costs of this integration. These results will help agencies understand how Waze data can best be used to help reduce the impacts of DAV events.

Literature Review

Waze data are typically used for incident detection, but Maryland and Nevada have used machine learning to predict incidents based on Waze data (*4*). Waze data are also used for other purposes, including traveler information systems, weather conditions, work zone management, and detection of maintenance needs (*4*). These data can also be used to improve the accuracy of traffic performance measurements. Researchers from the University of Tennessee used raw speed data to supplement the existing Highway Capacity Manual (HCM) level of service calculations, resulting in an approximately 10% improvement in estimation accuracy (*6*). Waze data have also been used for planning purposes to improve traffic conditions in Ghent, Belgium, (resulting in 30% fewer crashes and more cyclists and public transit users) and to develop traffic control plans for the Olympic Games in Rio de Janeiro, Brazil (*7, 8*).

A significant benefit of crowdsourced data is its ability to fill gaps in geographic coverage of intelligent transportation system (ITS) infrastructure. Comparing Waze data with existing ITS data sources can be helpful. In Knoxville, Tennessee, the use of Waze data to detect end-of-queue was compared with existing roadside sensors, with the results suggesting that the Waze feed would be a valuable supplement for areas with no sensors (*9*). A study in Kentucky used four different data sources (including Waze) to determine roadway clearance time, incident clearance time, and secondary crashes. Even though crash reports ended up being the primary data source, Waze data was an important supplementary source because of its speed data helping to quickly identify potential incidents (*10*). A case study in Norfolk, Virginia, for road flooding identification found Waze data to be 71.7% trustworthy, showing its potential for rapid situation response (*11*). Another case study in Virginia validated Waze-reported crashes and disabled vehicles against traffic camera footage and found a 23% false reporting rate for disabled vehicles, with 4% of the disabled vehicles being reported by Waze before being detected by operators (*12*). However, it was noted that this study took place in an urban area with extensive video surveillance and Waze data could be more useful in rural areas with limited video coverage (*12*). In addition to providing early detection, Waze alerts might also identify incidents that otherwise would have been unnoticed. A study in Iowa determined that 34.1% of Waze crash, congestion, and stalled vehicle alerts might have been otherwise unrecorded because of sensing difficulties in rural areas (*13*). This study also found that Waze detected incidents almost 10 min earlier than INRIX data (*13*).

This literature review shows that agencies throughout the U.S. are using Waze data to assist in incident management, among other applications. However, very limited research has quantified the benefits of using Waze data to detect DAVs earlier. Some studies have compared Waze data with existing data sources, but these were typically for small roadway segments and a short period of time. Analyses using multiple years of statewide data will help show the variation of Waze alerts for different times of day and locations. This paper will compare and analyze multiple years of DAV crash, SunGuide, and Waze data on Florida limited-access roadways. Benefit-cost evaluations will also be conducted for selected roadways to identify the delay reductions (with associated congestion savings) and potential DAV crash prevention that could have been realized by the use of Waze data.

Research Goal and Objectives

The goal of this paper is to analyze and identify how crowdsourced Waze data can be best used to improve DAV detection and response. This earlier detection can help TMC operators more quickly recognize DAVs and notify responding agencies, reducing incident durations and their associated congestion. To achieve this goal, the following objectives are accomplished:

1. Develop a multi-year database of DAV crashes, non-crash DAV SunGuide reports, and DAV Waze alerts on Florida limited-access facilities to help compare these data sets.
2. Analyze the collected data to understand the spatiotemporal variance of DAV events (crashes and SunGuide reports) and identify which Waze alerts overlap with and/or occur before DAV events.
3. Conduct benefit-cost evaluations for select locations to determine the potential congestion reduction and crash prevention benefits of incorporating DAV Waze alerts into SunGuide.

Achieving these objectives will show the potential benefits of using Waze or similar crowdsourced data to detect DAVs on freeways. This paper will quantify these benefits more thoroughly than previous research, providing agencies with a comprehensive understanding of crowdsourced data. The methodology and results from this paper can help transportation agencies throughout the U.S. utilize crowdsourced data effectively and efficiently.

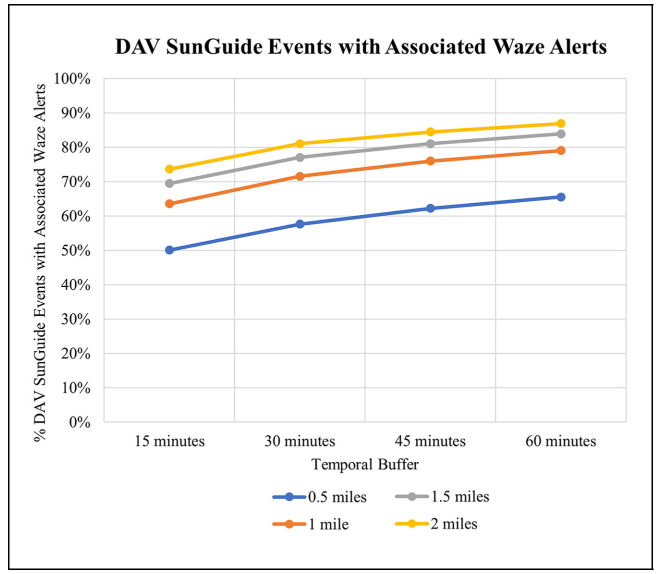

Figure 1. Disabled or abandoned vehicle (DAV) SunGuide events with associated Waze alerts for each spatial buffer.

Description of Florida DAV Database and Queries

The developed Florida DAV database contains three datasets: DAV crash reports, DAV SunGuide non-crash reports, and DAV Waze alerts. The term "DAV event" is used when referring to combined DAV crash reports and SunGuide non-crash reports in this paper. DAV crash reports on Florida limited-access facilities from 2015 through 2020 were obtained through Signal 4 Analytics, a statewide crash database maintained by the University of Florida (*14*). Multiple queries and manual reviews were used to obtain reports for 1,256 DAV crashes (1,051 disabled vehicle crashes and 205 abandoned vehicle crashes). DAV SunGuide data for Florida limited-access facilities from 2018 through 2021 were obtained from Florida TMCs. This dataset contained 1,591,508 reports with a type of "Disabled Vehicle" (90%) or "Abandoned Vehicle" (10%). Since crashes are classified separately in SunGuide, these SunGuide data are only non-crash reports. DAV Waze alerts on Florida limited-access facilities from April 22, 2019, through December 31, 2021, were obtained from FDOT (through their partnership with Waze). After filtering, this dataset contained 10,319,417 DAV Waze alerts with type = WEATHERHAZARD and subtype = HAZARD_ON_SHOULDER_CAR_STOPPED.

To store the aforementioned data, a MySQL (structured query language) database was developed. Formatting changes were made to ensure compatibility between the three datasets. Queries were then developed to identify overlap between the Waze and DAV event data (i.e., match DAV events with associated Waze alerts based on location, date, and time). Since the location information in the Waze data is not as precise as the location information in the event data (because of user errors when reporting in Waze), temporal and spatial buffers were used when matching SunGuide events to associated Waze alerts. With these buffers, Waze alerts that occur within a certain spatial distance around a SunGuide event and a certain time before a SunGuide event will be matched with the SunGuide event (in addition to Waze alerts at the same location and time as the SunGuide event).

To determine the optimal buffers, various buffers were tested on a one-week sample of data from February 9, 2020, through February 15, 2020, which contained over 72,000 DAV Waze alerts and 7,800 DAV SunGuide reports. Four different spatial buffers (0.5 mi, 1 mi, 1.5 mi, and 2 mi) and four different temporal buffers (15 min, 30 min, 45 min, and 60 min) were tested, resulting in 16 buffer combinations. For each buffer combination, the percentage of SunGuide events with at least one associated Waze alert was determined. Figures 1 and 2 show how these percentages differ for the various buffer combinations. Figure 1 shows lines for each spatial buffer and how the percentages change as the temporal buffers change, while Figure 2 shows lines for each temporal buffer and how the percentages change as the spatial buffers change. As the buffers get larger, it becomes more likely for unrelated data points to be matched with each other. Therefore, an increase in a specific buffer should not be made if the larger buffer only provides slightly more overlap between the data sets. Figure 1 shows a large increase between the 0.5 mi and 1 mi buffers for all

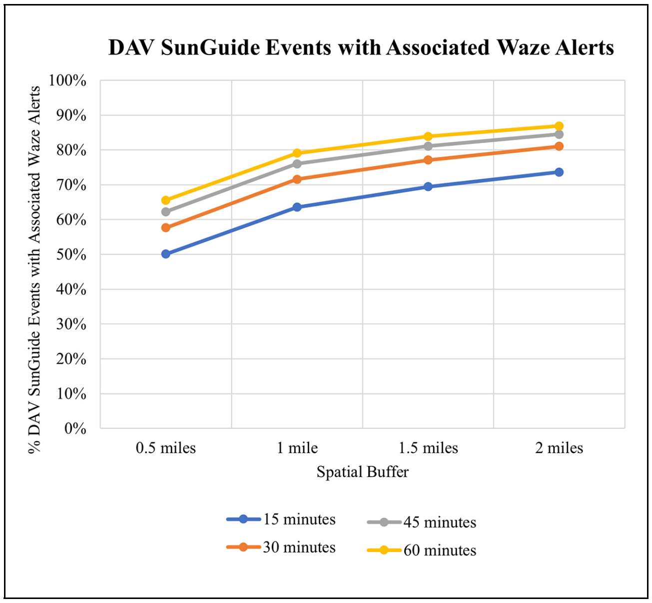

Figure 2. Disabled or abandoned vehicle (DAV) SunGuide events with associated Waze alerts for each temporal buffer.

temporal buffers, with small increases from 1 mi to 1.5 mi and from 1.5 mi to 2 mi. This suggests that a 1 mi buffer would be the best. Figure 2 shows a similar behavior for the temporal buffers, with the largest gap being between the 15 min and 30 min buffers. This suggests that a 30 min buffer would be the best. Therefore, a 1 mi spatial buffer in each direction from each DAV event was used to identify associated Waze alerts. Additionally, a temporal buffer of 30 min before each DAV event occurred was used.

After incorporating these buffers into the developed queries, the following output data sets were obtained, with the names used to identify these data sets throughout this paper shown in parentheses:

- DAV SunGuide reports with at least one associated Waze alert ("SunGuide with associated Waze alert")
- DAV SunGuide reports with at least one associated Waze alert before the SunGuide report was created ("SunGuide with preceding Waze alert")
- DAV crashes with at least one associated Waze alert ("crash with associated Waze alert")
- DAV crashes with at least one associated Waze alert before the crash occurred ("crash with preceding Waze alert")

Analyses of these data sets are discussed in the next section. Additional queries were then used to obtain DAV events and Waze alerts for benefit-cost evaluations on selected roadways. These benefit-cost evaluations, including their methodology and results, are detailed after the data analysis discussion.

DAV Event Data Analysis and Findings

Since the three DAV datasets contained data for different time periods, only the common period from April 22, 2019, through December 31, 2021, was analyzed. During this time period, there were 360 DAV crashes, 1,036,775 DAV SunGuide reports, and 10,319,417 DAV Waze alerts. The "crash with associated Waze alert" output data set contained 238 DAV crashes (66.1% of studied crashes) and the "crash with preceding Waze alert" output data set contained 134 DAV crashes (37.2% of studied crashes). DAV Waze alerts which precede crashes are not passed to SunGuide, but associated Waze alerts after a crash occurs are passed to SunGuide. For the SunGuide data, the "SunGuide with associated Waze alert" output data set contained 721,728 SunGuide reports and the "SunGuide with preceding Waze alert" output data set contained 481,839 SunGuide reports (69.6% and 46.5% of the studied SunGuide reports, respectively). These results show that non-crash DAVs were more likely to have associated Waze alerts than DAV crashes. The overlap also suggests that, while most DAVs are detected by TMC operators or SSPs, there might be some that are only reported in Waze. Additionally, there is significant potential for Waze alerts to provide earlier detection, as almost one-half of the SunGuide reports had a preceding Waze alert. Because of the significantly greater number of DAV SunGuide reports compared with crashes, only the SunGuide reports are analyzed in the remainder of this section, but both SunGuide and crash data will be considered in the benefit-cost evaluations later. This paper is mainly focused on the benefits Waze data can provide for non-crash DAVs, but a detailed analysis of the benefits for DAV crashes is a topic for future study.

The first analysis examined the relationship between DAV SunGuide reports and Waze alerts for each hour of the day. Figure 3 shows the number of studied DAV SunGuide reports per hour, along with the percentage of these SunGuide reports in the "SunGuide with associated Waze alert" and "SunGuide with preceding Waze alert" data sets. There were over 50,000 DAV SunGuide reports per hour from 7 a.m. to 6 p.m, with a peak of 74,517 events at 3 p.m.. Nighttime hours had lower counts, with a minimum of 14,362 DAV reports at 4 a.m. The "SunGuide with associated Waze alert" and "SunGuide with preceding Waze alert" percentages agree with this trend, with these percentages highest during daytime hours and lowest during nighttime hours. From 7 a.m. to 7 p.m., over 70% of SunGuide reports had an associated Waze alert and over 45% of SunGuide reports had a preceding Waze alert. During nighttime

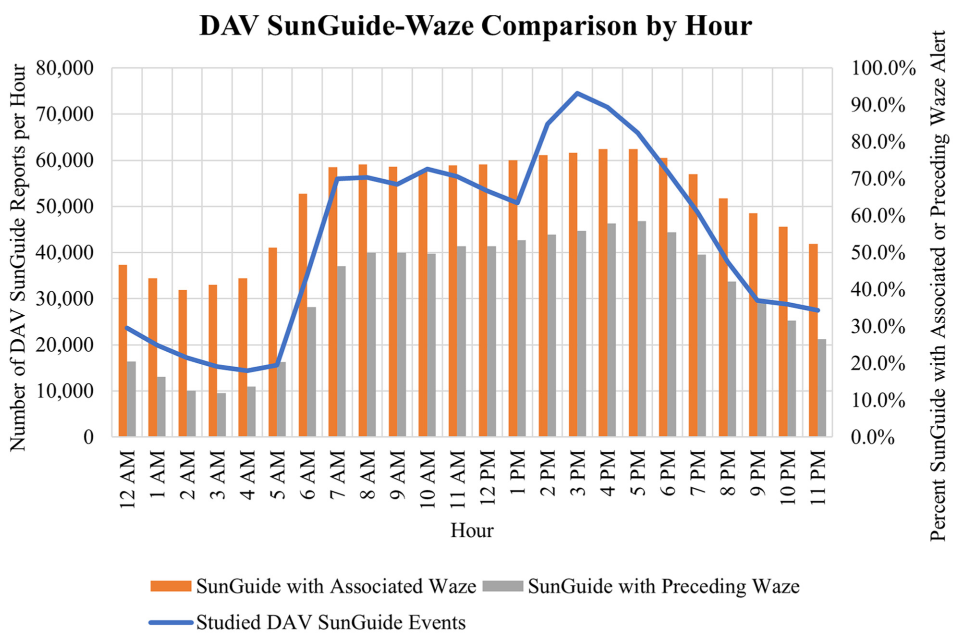

Figure 3. Disabled or abandoned vehicle (DAV) SunGuide reports and SunGuide-Waze comparison by hour of day.

hours, these percentages drop down to lows of 40% and 12%, respectively. This suggests that Waze alerts are more likely to be accurate and provide earlier DAV detection during daytime hours. Focusing on hours with the highest "SunGuide with preceding Waze alert" percentages (2 p.m. through 6 p.m.) would likely provide the most congestion reduction benefits. However, these are the hours when TMCs are usually busiest, because of higher traffic and incident volumes compared with nighttime hours. Reporting additional DAV Waze alerts to TMC operators during these hours could easily be overwhelming. Finding the right balance between the benefits provided by the Waze data and the additional resources required to properly utilize these data is important for agencies to use these data most effectively.

For the "SunGuide with preceding Waze alert" events, the time differences between each SunGuide report and its first preceding Waze alert were also analyzed. This is a valuable analysis since DAV Waze alerts do not currently pass to SunGuide, but often detect DAVs before TMCs become aware of them. Figure 4 shows how these average time differences (in minutes) vary by hour of the day. Larger time differences indicate that Waze alerts will provide more benefits, since they are detecting DAVs earlier than cases with smaller time differences. The largest time differences occurred during daytime hours, further emphasizing that Waze alerts can provide more benefits in daytime compared with nighttime. The average time differences range from 13.8 min at 5 a.m. to 16.5 min at 6 p.m., with an overall average of 16.0 min.

Next, the "SunGuide with associated Waze alert" and "SunGuide with preceding Waze alert" data were analyzed with respect to FDOT district (map shown in Figure 5, with major limited-access roadways highlighted and other limited-access roadways shown in black). FDOT splits the state into seven districts based on county lines, with the Florida's Turnpike Enterprise (FTE) toll road network being an eighth district. Table 1 shows the percentage of the studied DAV SunGuide reports in the "SunGuide with associated Waze alert" and "SunGuide with preceding Waze alert," along with the average time differences between the DAV SunGuide report and earliest preceding Waze alert (in minutes) for each FDOT district. Districts with more urban areas (D4, D5, and D7) tended to have more SunGuide reports, higher percentages of events in the "SunGuide with associated Waze alert" and "SunGuide with preceding Waze alert" data sets, and higher time differences between the SunGuide report and preceding Waze alert, indicating that Waze data could provide more benefits in urban areas. D3 is of particular note, as it had very low association between the DAV SunGuide and Waze data compared with the other districts, suggesting a low volume of DAV Waze alerts.

Similar analyses were also conducted for each Florida limited-access roadway, with the results shown in Table 2, and Figures 6 and 7. The "Other" category contains all roadways which had less than 0.1% of all studied DAV SunGuide reports. Like the district analysis, roadways in urban areas tended to have more SunGuide events with

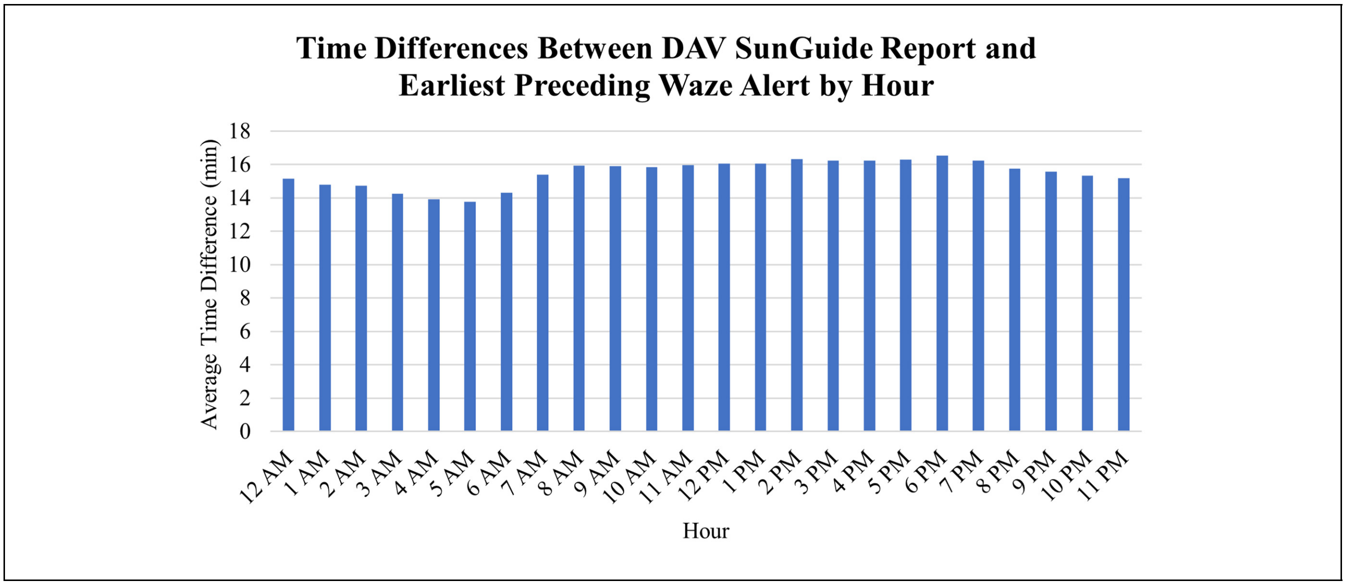

Figure 4. Average time differences between disabled or abandoned vehicle (DAV) SunGuide report and earliest preceding Waze alert by hour of day.

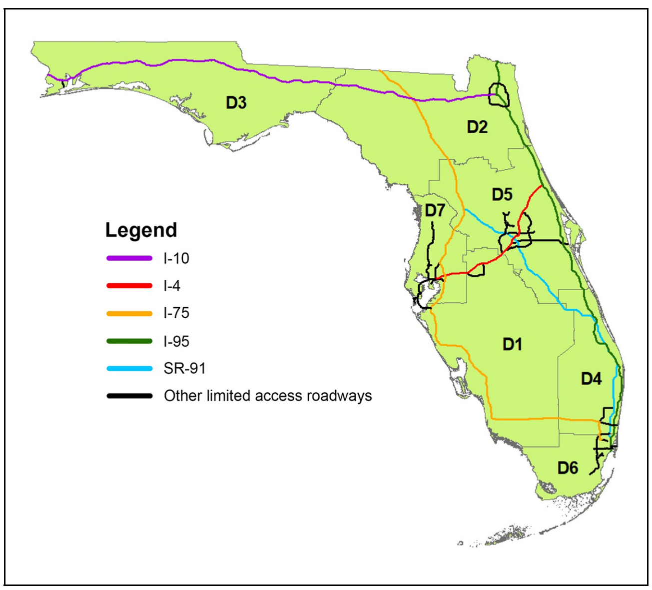

Figure 5. Florida Department of Transportation (FDOT) district and limited-access roadway map.

associated and preceding Waze alerts compared with roadways in rural areas. I-4 was the roadway with the highest percentage of SunGuide events in the "SunGuide with associated Waze alert" (82.1%) and "SunGuide with preceding Waze alert" (62.5%) data sets. It also had the highest average time difference between the SunGuide report and the earliest preceding Waze alert (16.85 min), while SR-91/SR-821 (Florida's Turnpike) was the toll road with the most DAV SunGuide reports and the highest average time difference. Two of the roadways with the lowest percentages were I-10 and I-110. These roadways are mainly located in D3, which agrees with the results of the district analysis.

These analyses show that incorporating DAV Waze alerts would likely provide the most benefits during daytime hours in urban areas. Since these are the times and locations where TMC operators are typically busiest, care is needed to ensure that the additional data do not excessively overwhelm the operators. The best use of these data will likely vary by location and time of day. To understand the potential benefits and costs of utilizing these Waze data, sample benefit-cost evaluations were conducted for two roadway segments: I-4 in D5 and SR-91 in D4 (shown in Figure 8 with I-4 segment in red and SR-91 segment in blue). I-4 in D5 was chosen because I-4 is the roadway with the highest percentage of SunGuide reports with associated and preceding Waze alerts, the largest time difference between SunGuide reports and their earliest preceding Waze alert, and over half of I-4 is in D5. SR-91 in D4 was chosen since SR-91 is the toll road with the most DAV SunGuide reports and the largest time difference between SunGuide reports and their earliest preceding Waze alert, with D4 being the FDOT district with the most DAV SunGuide reports and the largest time difference.

Sample Benefit-Cost Evaluations

To evaluate the use of Waze alerts in detecting DAVs, congestion savings benefits attributed to the earlier detection provided by Waze alerts and costs were estimated for the two roadway segments shown in Figure 8. The methodology used to calculate the congestion savings is discussed first, followed by the results of these

Table 1. Analysis of Disabled or Abandoned Vehicle (DAV) SunGuide Reports and Waze Alerts by Florida Department of Transportation (FDOT) District

District	Number of studied DAV SunGuide reports	Percent of DAV SunGuide reports with associated Waze alert	Percent of DAV SunGuide reports with preceding Waze alert	Average time difference between SunGuide report and earliest preceding Waze alert (minutes)
FTE	193,470	73.7%	49.1%	15.96
D4	159,897	80.2%	54.3%	16.36
D5	153,676	77.8%	55.5%	16.20
D3	135,116	39.3%	13.2%	15.03
D7	123,726	77.5%	57.0%	16.34
D1	116,103	67.2%	44.3%	14.88
D2	84,181	66.0%	50.4%	15.61
D6	70,606	69.0%	46.2%	15.93
Total	**1,036,775**	**69.6%**	**46.5%**	**15.95**

Note: FTE = Florida's Turnpike Enterprise.

Table 2. Analysis of Disabled or Abandoned Vehicle (DAV) SunGuide Events and Waze Alerts by Roadway

Roadway	Number of studied DAV SunGuide reports	Percent of DAV SunGuide reports with associated Waze alert	Percent of DAV SunGuide reports with preceding Waze alert	Average time difference between SunGuide report and earliest preceding Waze alert (minutes)
I-95	219,434	78.8%	53.9%	16.21
I-75	224,222	71.5%	49.7%	15.53
SR-91/SR-821	144,604	77.7%	52.1%	16.21
I-4	89,672	82.1%	62.5%	16.85
I-10	144,723	41.1%	15.9%	15.05
I-275	43,546	74.6%	54.4%	16.14
SR-826	28,130	69.0%	46.2%	15.87
SR-417	22,326	71.2%	46.7%	15.31
I-295	21,435	62.1%	46.2%	15.26
SR-528	18,866	69.4%	46.2%	15.34
SR-408	15,907	72.8%	52.7%	15.87
SR-589/SR-568	19,384	53.4%	34.0%	14.00
SR-429	15,349	67.4%	44.0%	15.57
SR-869	5,694	78.3%	53.1%	15.93
SR-202	3,659	60.8%	45.3%	15.01
I-595	2,547	75.3%	47.7%	16.51
I-110	3,842	39.8%	14.2%	14.79
SR-570	3,508	42.0%	22.9%	14.39
I-195	1,793	58.3%	32.5%	15.35
SR-414	1,607	58.1%	33.4%	14.87
Other	6,527	45.0%	27.9%	15.95
Total	**1,036,775**	**69.6%**	**46.5%**	**15.95**

benefit-cost evaluations. This methodology required various assumptions and did not consider certain aspects (e.g., fuel consumption). Therefore, the results discussed in this paper represent theoretical conditions and will not necessarily match real-world conditions. However, these results can provide a general understanding of the potential benefits of utilizing DAV Waze alerts.

Congestion Savings Methodology

The estimated congestion savings were based on the total vehicle delay in vehicle-hours (shaded area in Figure 9), which was calculated using Equation 1, with Equation 2 used to calculate the duration of congestion after the incident has been cleared. This methodology assumes constant flow rates and capacities during the entire analysis period. More complicated equations could be derived for cases with varying arrival and departure rates, but these equations would require additional data which are currently unavailable. Depending on the situation, this assumption could result in the estimated congestion being either higher or lower than actual.

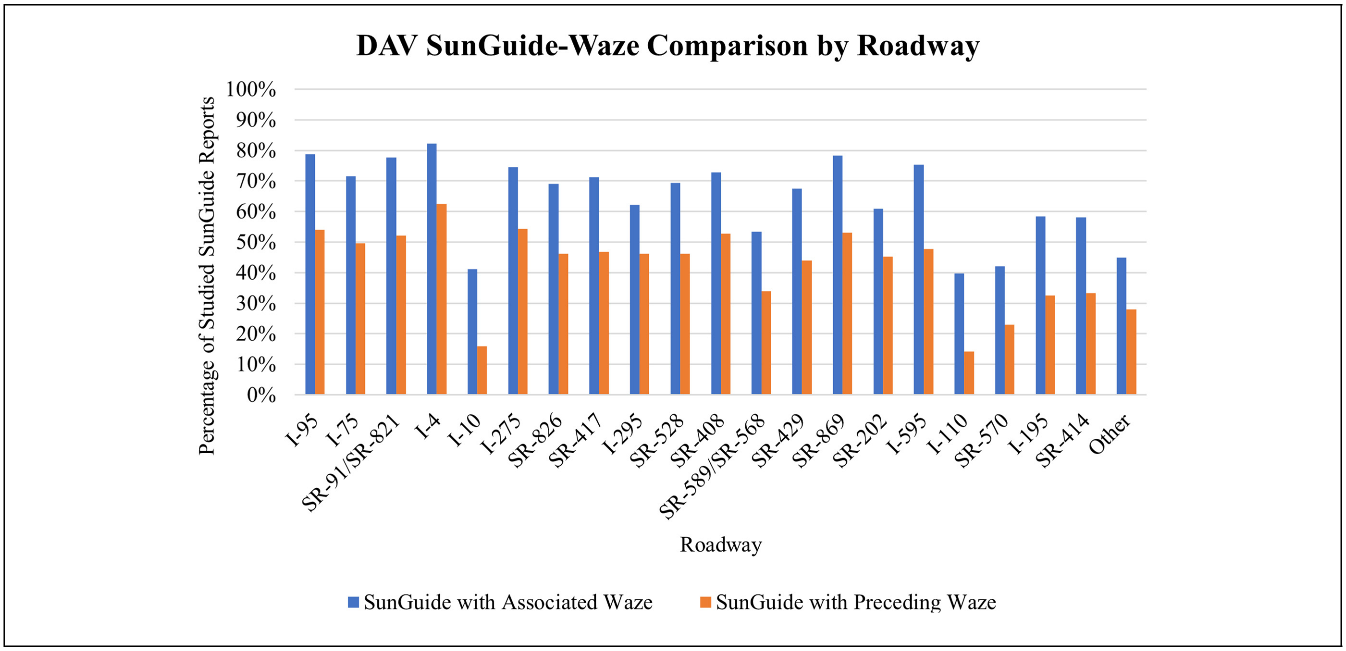

Figure 6. SunGuide-Waze comparison by roadway.
Note: DAV = disabled or abandoned vehicle.

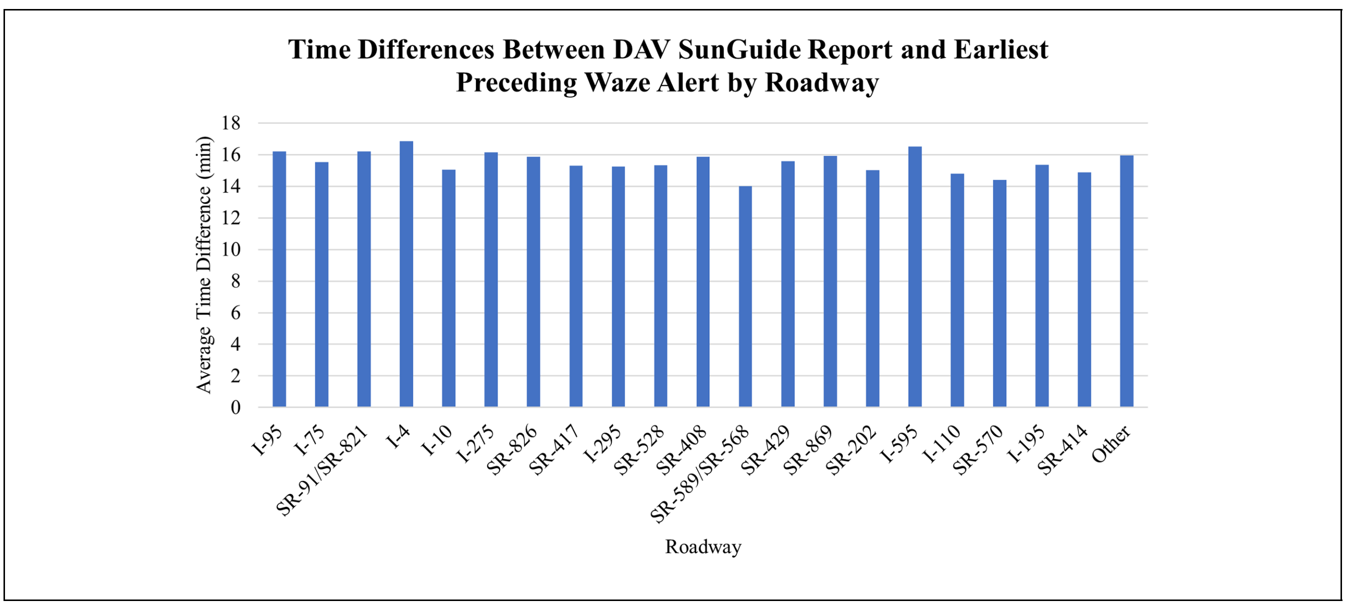

Figure 7. Average time differences between disabled or abandoned vehicle (DAV) SunGuide report and earliest preceding Waze alert by roadway.

$$Total\ Vehicle\ Delay = \frac{\lambda T^2}{2}\left(\frac{\mu-\mu^*}{\mu-\lambda}\right)^2 - \frac{\mu^* T^2}{2} - T^2\left(\frac{\lambda-\mu^*}{\mu-\lambda}\right)\left[\frac{\mu}{2}\left(\frac{\lambda-\mu^*}{\mu-\lambda}\right)+\mu^*\right] \quad (1)$$

$$X = T\left(\frac{\lambda-\mu^*}{\mu-\lambda}\right) \quad (2)$$

where

λ = flow rate for all lanes (vehicles per hour [vph]),
μ = capacity for all lanes (vph),
μ^* = remaining capacity for all lanes because of the capacity-reducing incident (vph),
T = incident duration (h), and
X = congestion duration after the incident has been cleared (h).

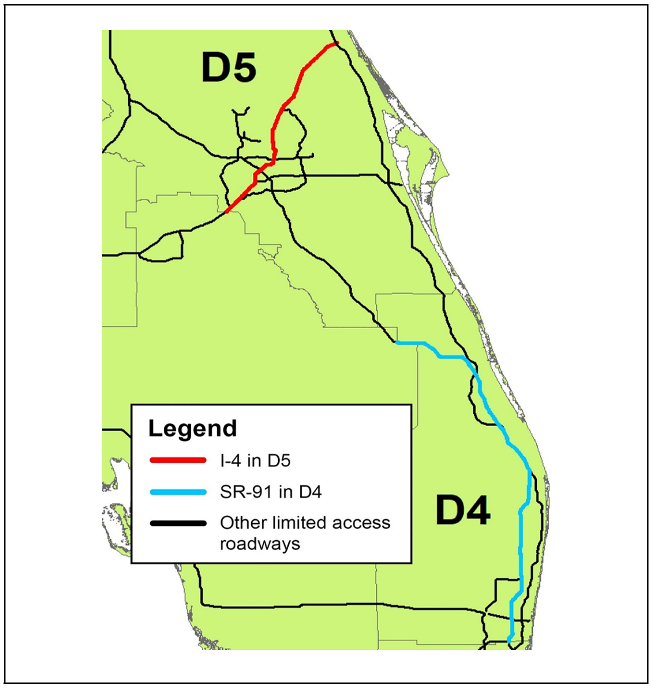

Figure 8. Selected roadway segments for benefit-cost evaluations.

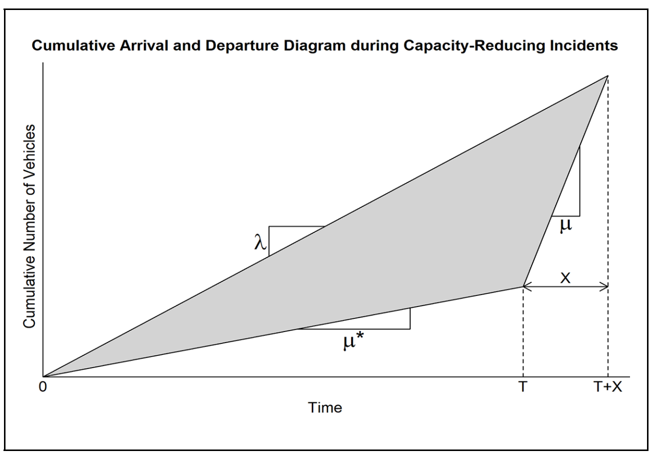

Figure 9. Cumulative traffic arrival and departure diagram during capacity-reducing incidents.
Note: shaded area = the total vehicle delay in vehicle-hours.

Since the DAV datasets did not contain any information on flow rates or capacities, these were estimated for each event using additional data obtained from FDOT geographic information system (GIS) shapefiles (*15*). Flow rates were estimated by multiplying the annual average daily traffic (AADT) at the incident location by the appropriate peak hour proportion (K) and the directional peak hour proportion (D). Estimating the flow rates in this manner would likely overestimate congestion for off-peak incidents. Capacities were estimated using the methodologies and recommendations in the seventh edition of the Highway Capacity Manual (HCM7) (*16*). These resulted in a base capacity (μ) and a capacity adjustment factor (which adjusts for peak hour, heavy vehicles, number of lanes, and number of lanes blocked). Multiplying these together results in μ^*.

Using these flow rates and capacities, delay was calculated for all DAV events in the "crash with preceding Waze alert" and "SunGuide with preceding Waze alert" datasets which met the following three criteria. First, the DAV must be lane-blocking or shoulder-blocking, but not result in a full road closure, as the HCM7 methodologies do not apply to full road closures. The SunGuide data contained information on the worst blockage, which was used to determine whether a DAV was lane-blocking (blocked at least one travel lane), shoulder-blocking (blocked no travel lanes, but at least one shoulder), or neither. For crashes, the crash reports were manually reviewed to determine if the crash was lane-blocking or shoulder-blocking. Next, the DAV must be located on a basic freeway segment and not in a merge, diverge, or weaving segment. Therefore, all DAVs on exit or entrance ramps were not considered. Finally, it is necessary that $\mu^* < \lambda \ll \mu$, otherwise Equations 1 and 2 will result in unrealistic values. The diagram in Figure 9 assumes that there is no congestion before the incident and that congestion occurs after the incident and because of it. This means that delay cannot be estimated using this methodology for cases where the incident does not cause any congestion ($\lambda < \mu^*$) and cases where congestion exists before the incident ($\lambda > \mu$). If λ is only slightly smaller than μ, free-flow conditions likely do not exist, also producing unrealistic values. To ensure all included events met this last criterion, the value of λ/μ was calculated for each event, and events with λ/μ values over a certain threshold were excluded (this threshold varied by roadway). All three of these criteria cause some congestion-causing incidents to be excluded from the congestion savings estimates, meaning that the estimated congestion savings will be lower than the actual savings.

In addition to these criteria, a few assumptions were needed because of limitations in the available data. The DAV event data contained information on the overall incident duration and worst blockage, but they did not indicate for how long these blockages occurred. Therefore, it was assumed that the reported blockage occurred for the entire incident duration. This assumption is reasonable, since most lane-blocking DAVs require the dispatch of a tow truck, causing the roadway clearance and incident clearance to occur around the same time. However, it could result in congestion being overestimated for some events. Because of this assumption, all abandoned vehicle events were excluded, since it is likely that abandoned vehicles would have been removed from the travel lanes before the incident was closed (as abandoned vehicle events can take 24 h or more to close). Additionally, any disabled vehicle events with T greater than a certain threshold (which will vary by roadway based on the event data) were excluded, since the benefits would probably be overestimated (as the worst blockage likely did not last the whole incident duration). Excluding these events means that the estimated savings will be lower than the actual savings.

The next assumptions involved the determination of the incident duration with and without the integration of DAV Waze alerts into SunGuide. This duration consists of two components which result in T when added together: the reported event duration (T_R) and the time difference between the earliest preceding Waze alert and the DAV event (T_W). First, it was assumed that the time of the first preceding Waze alert corresponds to $Time = 0$ in Figure 9. The DAV could have been on the roadway before this first Waze alert was received, but this is unknown based on the available data. Next, it was assumed that integration of DAV Waze alerts into SunGuide would have caused the DAV event to start when the first preceding Waze alert was received. This assumption means that T_W would be equal to zero. Since only DAV events with a Waze alert before the event start time (i.e., $T_W > 0$), are considered, this means that T with DAV Waze integration would be less than T without this integration. In reality, the operators would have to spend some time validating the DAV before creating an event, so T_W would be slightly greater than zero. This validation time is unknown and would likely vary by event, so it was decided to not consider validation time in this paper's calculations. Because of this limitation, the actual congestion savings for each event will be lower than calculated. If accurate and reliable filtering protocols were developed in the future which allowed for automatic creation of SunGuide events without the need for operator validation, the actual savings would approach the savings calculated in this paper. Lastly, it was assumed that T_R would not have changed if the TMC was notified of the DAV event earlier because of the Waze alert. It is likely that the reported event duration would not change much, so this assumption is reasonable and likely would not cause any significant differences between the estimated and actual congestion savings.

Based on these assumptions, the integration of DAV Waze alerts into SunGuide would have reduced the incident duration for each studied DAV event by an amount equal to T_W. Therefore, the delay reduction provided by the Waze alerts was calculated for each DAV event by taking the difference between the delay when $T = T_R + T_W$ and the delay when $T = T_R$. While more complicated methodologies could be used to calculate the delay reduction, these would require additional data parameters which are not available, leading to additional assumptions without any support which could significantly affect the results. The authors believe it is preferable to use a simple method with few supported assumptions rather than a complex method with many unsupported assumptions.

Once the estimated delay reduction was determined for each applicable DAV event, the cost of this delay was calculated. Congestion costs of \$28.71 per hour per passenger vehicle and \$49.49 per hour per commercial truck were used; these values were obtained from the *2021 Urban Mobility Report* (*17*). Multiplying these congestion costs by the delay reductions and appropriate truck proportions resulted in the estimated congestion savings benefits achieved by the Waze alerts. For the costs of utilizing DAV Waze alerts, the additional time spent by TMC operators responding to the DAV Waze alerts was considered. These include DAV Waze alerts associated with reported DAV events, as well as alerts not associated with any reported DAV event. Some of these non-associated DAV Waze alerts could have been for actual DAVs which were not reported otherwise (thereby providing additional benefits by notifying operators of these otherwise unreported DAVs), but the frequency of these unreported DAV events is unknown. It was assumed that it would take 2 min for a TMC operator to check and verify each DAV Waze alert, based on the target time of 2 min for TMC operators in D6 to confirm an event (*18*). Multiplying the total time spent by TMC operators verifying Waze alerts with the average TMC operator salary of \$20.60 per hour provided by FDOT results in the estimated costs. Another potential benefit of utilizing Waze alerts is the ability for responders to get to a DAV before a crash occurs. This benefit will be examined but will not be included when calculating benefit-cost ratios since it is unknown if earlier arrival of responders to the DAV would have actually prevented the crash or not.

Benefit-Cost Evaluation Results

Both evaluations (I-4 in D5 and SR-91 in D4) used 6 months of data from July 2019 through December 2019, as this period included data from all three DAV data sources (crashes, SunGuide reports, and Waze alerts) while avoiding potential impacts of the COVID-19 pandemic which started in early 2020. For each evaluation, MySQL queries were used to obtain the following 11 output data sets from the developed Florida DAV database (filtered to only include data from July 2019 through December 2019 and on the studied roadway segments):

- All DAV Waze alerts
- All DAV SunGuide reports

- All DAV crashes
- All DAV SunGuide reports in the “SunGuide with associated Waze alert” dataset
- All DAV crashes in the “crash with associated Waze alert” dataset
- All DAV SunGuide reports in the “SunGuide with preceding Waze alert” dataset
- All DAV crashes in the “crash with preceding Waze alert” dataset
- All lane-blocking DAV SunGuide reports in the “SunGuide with preceding Waze alert” dataset
- All shoulder-blocking DAV SunGuide reports in the “SunGuide with preceding Waze alert” dataset
- All lane-blocking DAV crashes in the “crash with preceding Waze alert” dataset
- All shoulder-blocking DAV crashes in the “crash with preceding Waze alert” dataset

The first three queries identified the DAV event and Waze data for the evaluated dates and locations, the next two queries identified the DAV events with associated Waze alerts, the next two queries identified the DAV events with one or more preceding Waze alerts, and the last four queries identified the lane-blocking and shoulder-blocking DAV events from the previous two queries. The results from these last four queries were then filtered further to remove all abandoned vehicle events and any events which did not meet the criteria of the congestion cost methodology previously defined. Additionally, λ/μ and T thresholds were determined for each roadway segment after examining the event data for each roadway. and events were excluded accordingly. These thresholds were $\lambda/\mu>0.92$ and $T>2$ h for I-4 and $\lambda/\mu>0.9$ and $T>5$ h for SR-91. The differences in these thresholds were because of I-4 having higher traffic volumes and shorter incident durations than SR-91. With these thresholds, any incidents on I-4 where the volume was greater than 92% of capacity or the incident lasted longer than 2 h were excluded, as were any incidents on SR-91 where the volume was greater than 90% of capacity or the incident lasted longer than 5 h. Congestion savings were then estimated for all remaining events, with the costs estimated based on the number of DAV Waze alerts obtained from the first query listed above.

Table 3 shows the results of the 11 queries mentioned above, along with the number of events included based on the criteria and assumptions of the congestion savings methodology, estimated delay reduction and associated congestion savings, costs (number of hours and personnel cost to verify DAV Waze alerts), and benefit-cost ratios for both evaluated roadway segments. Where appropriate, results are reported for lane-blocking and shoulder-blocking events separately and combined, with LB indicating lane-blocking events and SB indicating shoulder-blocking events. Additionally, benefit-cost ratios are provided for lane-blocking events only and combined lane-blocking and shoulder-blocking events, as agencies would typically not use Waze alerts for only shoulder-blocking events. This table shows that there were only three shoulder-blocking crashes and no lane-blocking crashes with preceding Waze alerts. However, the methodology was not applicable for any of these three crashes (as one had pre-existing congestion and the other two did not result in congestion), so only non-crash events were used to calculate the congestion savings.

Utilizing DAV Waze data for I-4 in D5 from July 2019 through December 2019 would have provided an estimated $4,344,367 in congestion savings for a cost of $71,010 (benefit-cost ratio of 61), while utilizing Waze alerts for SR-91 in D4 during the same time period would have provided an estimated $2,578,437 in congestion savings for a cost of $95,652 (benefit-cost ratio of 27). Both of these benefit-cost ratios are much larger than 1.00, indicating that utilizing DAV Waze alerts for these two locations would be cost-effective. Comparing the benefits for lane-blocking events with the benefits for shoulder-blocking events shows that the benefits for lane-blocking events were higher for both roadways. However, the shoulder-blocking benefits were 46.6% of the lane-blocking benefits for SR-91, compared with only 2.6% for I-4. This shows that the benefits for shoulder-blocking events can vary substantially among roadways. For I-4, 63,583 of the 103,413 DAV Waze alerts (61.5%) were not associated with any DAV SunGuide report or crash, while 102,260 of the 139,299 DAV Waze alerts on SR-91 (73.4%) were not associated with any DAV SunGuide report or crash. These high false positive counts indicate the need for filtering protocols which could help reduce these false positives without significantly reducing the number of beneficial alerts. The calculated benefit-cost ratios do not consider the potential for Waze alerts to identify previously unreported DAVs or congestion arising from DAV events which did not meet the methodology’s criteria, all of which could increase the benefits. The costs of training new TMC operators to handle the massive influx of Waze data were also not considered, nor were the potential impacts that the increased burden of these data could have on operators’ responses to other incidents. Detailed investigations into benefits and costs for different locations and times of day could provide additional insights into the best ways to effectively manage DAV Waze data and obtain the most benefits without overburdening operators.

In addition to the congestion savings shown in Table 3, it is possible that the earlier detection provided by non-crash DAV Waze alerts could have allowed responders to get to some DAVs before a crash occurred,

Table 3. Benefit-Cost Evaluations of Incorporating Disabled or Abandoned Vehicle (DAV) Waze Data into Traffic Management Centers (TMCs) for Select Florida Limited-Access Roadway Segments (July, 2019, through December, 2019)

Parameter	I-4 in FDOT District 5	SR-91 in FDOT District 4
Number of DAV Waze alerts	103,413	139,299
Number of DAV SunGuide reports	9,867	12,975
Number of DAV crashes	8	4
Number of SunGuide reports with associated Waze alerts	7,316	9,960
Number of SunGuide reports with preceding Waze alerts	5,598	6,593
Number of lane-blocking SunGuide reports with preceding Waze alerts	340	54
Number of shoulder-blocking SunGuide reports with preceding Waze alerts	391	3,109
Number of crashes with associated waze alerts	4	3
Number of crashes with preceding Waze alerts	3	1
Number of lane-blocking crashes with preceding Waze alerts	0	0
Number of shoulder-blocking crashes with preceding Waze alerts	2	1
Events included for congestion savings methodology	186 (133 LB + 53 SB)	259 (26 LB + 233 SB)
Total estimated delay reduction (vehicle-hours)	144,184 (140,573 LB + 3,611 SB)	83,822 (57,237 LB + 26,585 SB)
Estimated congestion savings	$4,344,367 ($4,235,759 LB + $108,608 SB)	$2,578,437 ($1,759,201 LB + $819,236 SB)
Estimated time spent by TMC operators verifying DAV Waze alerts (hours)	3,447	4,643
Estimated cost of verifying DAV Waze alerts	$71,010	$95,652
Benefit-cost ratio	60 (LB only); 61 (LB and SB)	18 (LB only); 27 (LB and SB)

Note: FDOT = Florida Department of Transportation; LB = lane-blocking; SB = shoulder-blocking.

Table 4. Details of Disabled or Abandoned Vehicle (DAV) Crashes with a Waze Alert Before the Crash Occurred for Select Florida Limited-Access Roadway Segments (July 2019 through December 2019)

Roadway	Crash date and time	Time difference between crash and earliest preceding non-crash DAV Waze alert (minutes)	Response time (minutes)	Resulting injuries	Estimated comprehensive injury costs	Reported vehicle and property damages
I-4	Aug 1, 2019 12:13 a.m.	29.4	0	None	$ 0	$2,500
I-4	Sep 14, 2019 12:10 a.m.	28.7	12	3 incapacitating injuries, 1 non-incapacitating injury, 1 possible injury	$4,148,000	$12,000
I-4	Dec 17, 2019 10:34 a.m.	6.7	42	None	$ 0	$1,000
SR-91	Dec 4, 2019 12:03 p.m.	24.2	17	1 possible injury	$155,000	$9,500

thereby potentially preventing the crash. These potential crash prevention benefits will depend on the specific nature of each crash (including the number of fatalities and injuries and the time it takes responders to reach the crash once it is reported). To identify the potential crash prevention benefits for the studied roadways, the four crashes with preceding non-crash DAV Waze alerts (three on I-4 and one on SR-91) were examined in more detail. Table 4 shows various details of these crashes. The response time was taken from the crash reports as the difference between the time when responders were dispatched and the time they arrived on scene. The estimated comprehensive injury costs used costs per injury severity level from the National Safety Council, while the vehicle and property damages were taken from the crash reports (*19*). The comprehensive injury costs used (in 2019 dollars) were $11,148,000 per fatality, $1,219,000 per incapacitating injury, $336,000 per non-incapacitating injury, and $155,000 per possible injury (*19*). Comparing the time differences between the crash and the earliest preceding non-crash DAV Waze alert to the response times shows that if responders had received the DAV Waze alerts, they could have reached the DAV before a crash occurred for the crashes on Sep 14, 2019, and Dec 4, 2019, but would have not reached the DAV on Dec 17, 2019, before a crash occurred. The crash on Aug 1, 2019, had a reported response time of zero (suggesting that the crash was first noticed by law enforcement approaching and then stopping at the crash scene), so it is unknown how long the response time would have been if responders were notified by the Waze alert. Therefore, this crash was not considered to have potentially been prevented. By potentially preventing the DAV crashes on Sep 14, 2019, and Dec 4, 2019, the non-crash DAV Waze alerts could have provided savings of $4,324,500.

Summary and Conclusions

Effective incident detection and response is important to reduce congestion on freeways. The use of Waze or other crowdsourced data could help improve incident detection and reduce congestion. This paper examined the potential for Waze alerts to reduce congestion caused by DAVs, which are a major source of non-recurring congestion. Many agencies use Waze data for incident management, but no previous studies have analyzed these data on a statewide level with a focus on DAVs. Comparing multiple years of DAV Waze alerts with verified DAV crashes and non-crash SunGuide reports provides a better understanding of these Waze data and how to best integrate them into TMC data streams.

To accurately compare between the datasets, a Florida DAV database was developed consisting of 1,256 DAV crashes, 1,591,508 non-crash DAV SunGuide reports, and 10,319,417 DAV Waze alerts. Analyses of these datasets during the common time period of April 22, 2019, through December 31, 2021, showed that 66% of DAV crashes had associated Waze alerts, with 37% having a Waze alert preceding the crash. These values were 70% and 47%, respectively, for DAV SunGuide reports. Further analyses of the DAV SunGuide reports showed that most occurred during daytime hours, with the percentages of reports with associated Waze alerts and preceding Waze alerts also highest during these hours. Therefore, Waze alerts are most likely to provide earlier detection of DAVs during the daytime, with over 50% of DAV SunGuide reports having preceding Waze alerts between 11 a.m. and 6 p.m. The time difference between the SunGuide reports and earliest preceding Waze alert was also largest during daytime hours (maximum of 16.5 min at 6 p.m.), further suggesting more benefits during these times. Location analyses showed that FDOT districts with more urban areas tended to have more SunGuide reports with associated and preceding Waze alerts, as did high-volume roadways in urban areas. Further research is needed on a roadway-by-roadway basis to better identify the most effective use of DAV Waze data without overloading TMC operators with excessive Waze alerts during their busiest hours.

Two roadway segments (I-4 in FDOT D5 and SR-91 in FDOT D4) were studied in more detail to evaluate the potential benefits and costs of utilizing DAV Waze alerts. Congestion reductions for lane-blocking and shoulder-blocking DAV events on these roadway segments were estimated for the last 6 months of 2019. Capacities, flow rates, reported incident durations, blockage information, and time differences between DAV events and preceding Waze alerts were used to estimate the delay reductions which could have been provided by Waze alerts. Overall, the earlier detection provided by Waze resulted in estimated congestion savings of over $4.3 million for the I-4 segment and $2.5 million for the SR-91 segment. When considering the cost of time spent by TMC operators verifying DAV Waze alerts, the benefit-cost ratios were 61 and 27 for I-4 and SR-91, respectively. Additionally, responders could have potentially reached two DAVs which ended up causing a crash before the crash occurred, possibly preventing over $4.3 million in comprehensive injury costs, vehicle damages, and property damages.

The results of this paper show the significant benefits that could be achieved by integrating DAV alerts into SunGuide. Because of the various assumptions of the methodology and data limitations, the actual benefits will likely differ from the estimated benefits in this paper. It is unknown whether the actual benefits will be higher or lower than the estimated benefits, as some assumptions resulted in underestimation of congestion (e.g., the exclusion of cases where pre-existing congestion was present, or not accounting for the potential of Waze alerts to identify otherwise unreported DAVs) and some assumptions resulted in overestimation of congestion (e.g., not considering operator validation time, and assuming that the worst blockage occurred for the entire incident duration). However, because of the high benefit-cost ratios obtained in this paper, it is likely that the incorporation of Waze alerts into SunGuide would provide higher benefits and costs. Transportation agencies with access to Waze data can use the methodology in this paper to analyze and understand these data for their roadways. Future research could expand on this study by developing filtering protocols for cost-effective integration of Waze data into TMCs. With these protocols, which could vary for different locations or times of data, agencies could reduce the incoming Waze data to a manageable level while still obtaining benefits from the earlier detection which can be provided by Waze alerts. To develop these filters, a more detailed investigation of the Waze data, including a thorough analysis of Waze alerts with no matched SunGuide events, is needed to identify the best locations and times for reporting of DAV Waze alerts to TMCs. Additionally, further investigation of the Waze data, including Waze user reliability scores, could be used to help develop automated filtering protocols and ensure that only the most accurate alerts are reported to the TMC operators. If more detailed data about DAV timelines and blockages are available, more complex methodologies could also be used to estimate congestion savings more accurately. With proper management, crowdsourced data has significant potential to improve traffic operations and safety on limited-access roadways.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: A. Sandt, J. McCombs, H. Al-Deek, G. Carrick; data collection: A. Sandt, J. McCombs, E. Cornelison, H. Al-Deek, G. Carrick; analysis and interpretation of results: A. Sandt, J. McCombs, E. Cornelison, H. Al-Deek, G. Carrick; draft manuscript preparation: A. Sandt, J. McCombs, E. Cornelison, H. Al-Deek, G. Carrick. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The research discussed in this paper was funded by the Florida Department of Transportation. The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the Florida Department of Transportation or the U.S. Department of Transportation. Award Number is AWD00000841.

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The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the Florida Department of Transportation or the U.S. Department of Transportation.