Toward the Development of an Impact-Based Decision Support Tool for Surface-Transportation Hazards. Part I: Tying Weather Variables to Road Hazards and Quantifying Impacts

DANA M. TOBIN,[a,b] JOSHUA S. KASTMAN,[b] JAMES A. NELSON,[b] AND HEATHER D. REEVES[c,d]

[a] Cooperative Institute for Research in Environmental Sciences, Boulder, Colorado
[b] Weather Prediction Center, College Park, Maryland
[c] Cooperative Institute for Severe and High-Impact Weather Research and Operations, University of Oklahoma, Norman, Oklahoma
[d] NOAA/OAR/National Severe Storms Laboratory, Norman, Oklahoma

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ABSTRACT: Development of an impact-based decision support forecasting tool for surface-transportation hazards requires consideration for what impacts the product is intended to capture and how to scale forecast information to impacts to then categorize impact severity. In this first part of the series, we discuss the motivation and intent of such a product, in addition to outlining the approach we take to leverage existing and new research to develop the product. Traffic disruptions (e.g., crashes, increased travel times, roadway restrictions, or closures) are the intended impacts, where impact severity levels are intended to scale to reflect the increasing severity of adverse driving conditions that can correlate with a need for enhanced mitigation efforts by motorists and/or transportation agencies (e.g., slowing down, avoiding travel, and imposing roadway restrictions or closures). Previous research on how weather and road conditions impact transportation and novel research herein to create a metric for crash impact based on precipitation type and local hour of the day are both intended to help scale weather forecasts to impacts. Impact severity classifications can ultimately be determined through consideration of any thresholds used by transportation agencies, in conjunction with the scaling metrics.

SIGNIFICANCE STATEMENT: Weather can profoundly impact surface transportation and motorist safety. Because of this and because there are no explicit tools available to forecasters to identify and communicate potential impacts to surface transportation, there is a desire for the development of such a forecast product. However, doing so requires careful consideration for what impacts are intended to be included, how weather corresponds to impacts, and how thresholds for impact severity should be defined. In this first part of the paper series, we outline each of these aspects and present novel research and approaches for the development of an impact-based forecast product specifically tailored to surface-transportation hazards. The product is ultimately intended to improve motorist safety and mobility on roads.

KEYWORDS: Winter/cool season; Operational forecasting; Decision support; Societal impacts; Transportation meteorology

1. Introduction

Slick roads, limited visibilities, and other dangerous driving conditions caused by winter weather can pose an extreme hazard to motorists. Each year, nearly 1000 winter-weather-related fatalities occur on U.S. roadways (Tobin et al. 2022), an order of magnitude larger than fatalities from all other weather-related hazards (Black and Mote 2015a). Of these fatalities, however, only one-third occurred within an official Winter Weather Warning, Watch, or Advisory (WSW) issued by the National Weather Service (NWS) (Tobin et al. 2022). In that study, it was found that the language used within WSWs does not clearly convey how much of an impact the winter weather is expected to have on surface transportation. For example, the use of language such as “hazardous driving conditions” versus “extremely hazardous driving conditions” is vague and does not objectively communicate impacts in an easily understandable manner. Further, the subjective use of “extreme” is, ostensibly, not used consistently and allows a variety of interpretations from motorists. In light of those findings, the authors recommended the development of a product complementary to official NWS WSWs that conveys tiered road-hazard impact levels consistently across the country, regardless of WSW status.

To properly develop an impact-based forecast product for surface transportation across the United States, it is important to first identify what the product would need to address in order to be useful and successful. Although surface transportation includes, but is not limited to, roadway transportation, properly accounting for impacts to roadway transportation is an important first step for an all-encompassing surface-transportation-based impact product that would include impacts to other surface-based transportation methods such as railways and even surface-based operations of airports. In the first part of this series outlining the development of such a product, we introduce a novel approach that leverages both preexisting and new research to pair weather information with nonmeteorological data in order to scale weather forecast data to potential transportation impacts and to categorize the severity of those impacts. In Tobin et al. (2024, hereafter Part II), we detail specifics about a new NWS forecast product in

Corresponding author: Dana M. Tobin, dana.tobin@noaa.gov

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development, including how the product performs for recent winter weather conditions that negatively impacted surface transportation.

2. Defining the impacts of weather and road conditions on surface transportation

a. Contextualizing the problem

Weather-related impacts to surface transportation can be separated into two categories: traffic disruptions and financial costs. Traffic disruptions include, but are not limited to, motor-vehicle crashes, increased travel times, and roadway restrictions or closures. Roadway restrictions (e.g., vehicle bans, lane restrictions, speed limit reductions, and chain controls) and closures are done either as a safety precaution (i.e., in response to or in anticipation of hazardous road conditions) or out of necessity (i.e., due to crashes or other road hazards that require traffic diversions to clear the roadway). Financial costs include those resulting from traffic disruptions (e.g., the financial cost of a motor-vehicle crash or delay; Blincoe et al. 2023) and the cost of winter road maintenance (e.g., plowing and applying spreading treatments such as salt, sand, and brine). To optimize cost spending and resource allocations, transportation agencies often develop and use metrics for assessing winter storm severity (e.g., a winter severity index) based on maintenance costs and resources used during a storm or winter season (e.g., Walker et al. 2019; Fay et al. 2020; Sturges et al. 2020; Villwock-Witte et al. 2021). However, these indices are inconsistent in their approaches due to varying service levels and data availability, meaning that an index developed for one agency often cannot be used for another agency (Sturges et al. 2020). Ultimately, the financial costs of winter road maintenance vary drastically across the United States owing to budgetary considerations, resources, and varying levels of service. This means that creating an impact-based forecast product based on financial costs related to winter weather would be a poor choice for a product intended to be consistently used across the United States. Instead, the focus should be on impacts related to traffic disruptions, which can easily be adapted and applied across the United States with knowledge of both how weather typically disrupts traffic flow and motorist safety and typical mitigation strategies employed by motorists and transportation agencies.

Weather can profoundly influence traffic flow and road safety. In response to adverse weather and driving conditions, motorists often make behavioral changes, such as lowering vehicle speeds, using alternate routes or modes of transportation, and adjusting their travel schedules or canceling trips altogether (e.g., Barjenbruch et al. 2016; Böcker et al. 2013; Maze et al. 2006). These driver adaptations can measurably affect traffic flow parameters of vehicle speeds and traffic volumes. Precipitation generally reduces both traffic volumes and vehicle speeds, with snow having a greater influence than rain. Higher precipitation rates and/or amounts also reduce traffic volumes and vehicle speeds. For example, rain reduces traffic volumes by 2%–3% (Codling 1974; Doherty et al. 1993; Keay and Simmonds 2005), while snow can reduce traffic volumes by nearly one-half, with reductions generally proportional to increasing snow amounts (e.g., Hanbali and Kuemmel 1993; Knapp and Smithson 2003). Similarly, Agarwal et al. (2005) found that heavy rain (>0.25 in. h^{-1}) results in urban freeway speed reductions of 4%–7% whereas heavy snow (>0.5 in. h^{-1}) results in speed reductions of 11%–15%. Other adverse weather conditions, such as visibility reductions, cold weather, and high wind speeds, can also reduce vehicle speeds (e.g., Maze et al. 2006).

In addition to limiting mobility, precipitation and adverse driving conditions negatively impact roadway safety. Nearly 25% of all collisions occur during precipitation, and precipitation increases the risk of both crash and injury (e.g., Andrey et al. 2003; Qiu and Nixon 2008). The risk of a crash is also a function of both precipitation type and intensity (e.g., Andrey et al. 2003; Qiu and Nixon 2008; Andrey 2010; Black and Mote 2015b; Black et al. 2017; Tobin et al. 2021). Several studies document that snow has a higher crash risk than rain, and Tobin et al. (2021) report that freezing precipitation has a higher crash risk than snow. Other studies generalize that higher precipitation intensities are typically associated with higher crash risk (e.g., Andrey et al. 2003; Qiu and Nixon 2008). Although diminished traffic volumes and reduced vehicle speeds can partially offset the increased risk of fatality or severe injury in snowfall, there is some debate on the net influence of snow on fatalities and injury severity (Andrey et al. 2003; Qiu and Nixon 2008). Nonprecipitation, vision-obscuring hazards such as dense fog or smoke can also profoundly impact transportation and result in injuries and fatalities yet are notoriously difficult to forecast (Ashley et al. 2015).

b. Outlining a solution

Translating the influences of winter weather on traffic flow and safety into an impact scaling is difficult and requires two things: 1) scaling weather information to its impact on surface transportation and 2) selecting appropriate thresholds for each impact severity level. Each will now be addressed.

1) Scaling weather information to impacts

Properly scaling weather data to transportation impacts involves addressing all aspects of potential impacts, including the increased travel times, the likelihood of crashes, and the severity of crashes that may occur. A single weather condition—such as 0.5 in. h^{-1} of snowfall—can result in different impacts based on a number of different factors, including what other ambient weather or road conditions there are (e.g., low vs high visibility and snowy vs wet roads) and what time of day or even day of week it is (e.g., overnight vs midday hours or weekend vs weekday). Here, we introduce how weather conditions can be scaled to impacts by combining the influences of how driving conditions affect travel times and how precipitation type affects motorist safety throughout the day.

The first tangible transportation-related impact of winter weather is often increased travel times, which can be partially attributed to reductions in vehicle speeds. The influence of weather and pavement conditions on vehicle free-flow speeds[1] has been documented by a number of studies (e.g., Kyte et al. 2001; Maze et al. 2006; Ye et al. 2009). For example, Maze et al. (2006) report that freeway speeds are reduced by 13% for snow rates > 0.5 in. h^{-1}, but only by 6% for rain rates > 0.25 in. h^{-1}. Similarly, Ye et al. (2009) suggest that travel speeds are 16% lower on snow-covered roads, but only 4% lower on wet roads. Maze et al. (2006) also report speed reductions for temperature, wind speed, and visibility conditions.

We suggest that these reductions in vehicle free-flow speeds under various weather and pavement conditions can be leveraged to approximate a combined disruption to traffic flow (i.e., in the form of increased travel times due to reduced vehicle speeds). For instance, a metric combining speed reductions based on the ambient weather conditions (precipitation, temperature, wind speed, and visibility individually) and pavement conditions (e.g., wet, snowy, slushy, and icy) can scale impacts based on how the overall driving conditions can influence vehicle speeds and thus travel times. Such a metric would help to, for example, increase impacts for snowfall that is concurrent with other poor driving conditions (e.g., low visibility, snowy roads) versus the same snowfall occurring with more manageable driving conditions (e.g., moderate visibility, wet roads).

Secondary impacts stemming from an increased crash risk may or may not materialize into an increased number of crashes during any single weather event. Further, any crashes that do occur can have widely varying impacts, ranging from single-vehicle slide-offs with no injuries or associated delays to large pileups with casualties that close interstates for an indefinite period of time. Chin et al. (2004) documented that the impact of crashes on delays, lane closures, and the time it takes to clear a crash and reopen lanes generally increases with the number of vehicles involved and the severity of the crash (e.g., property damage only, injury, or fatal). Ultimately, however, the same weather conditions that result in a pileup can just as easily result in no incidents.

To distill such a wide variety of potential crash-related impacts into a single metric, it becomes necessary to examine only the average observed outcome. For this, a targeted, yet comprehensive, research study is designed specifically to address the hourly time-of-day impacts of precipitation type. The goal of the study is to distill the following impact aspects into a single metric for each local hour of the day and for each precipitation type: 1) the likelihood of a crash occurring; 2) how many vehicles and casualties are typically involved with crashes that do occur; and 3) how many vehicles are usually traveling at that hour. This single metric is designed to capture the totality of impacts associated with precipitation type by accounting for crash risk, crash severity, and traffic volumes. This work is presented in detail in section 3.

2) IMPACT SEVERITY LEVEL THRESHOLDS

It is desired for increasing severity levels of an impact-based product to reflect the increasing severity of adverse driving conditions, which correspond to the need for enhanced mitigation efforts or strategies to maintain safety, if possible. Such mitigation efforts range from motorist behavior modifications (e.g., slowing down and avoiding travel) to transportation agencies imposing restrictions on roadways (e.g., lane or roadway closures, speed limit restrictions, vehicle bans, and chain controls). Because transportation agencies often only consider restrictions for weather conditions meeting or exceeding certain thresholds, knowledge of those thresholds is invaluable for developing a useful product. For example, weather conditions prompting the closure of an interstate should have a higher impact level than conditions that typically only trigger speed restrictions. Unfortunately, such thresholds are often not clearly defined, as agencies ultimately make decisions on restrictions through careful evaluation of not only weather and road conditions, but a number of other factors including resource availability, the status of restrictions in surrounding states, and any potential consequences—including economic impacts—of such restrictions [e.g., Commonwealth of Pennsylvania 2022; T. Greenfield, Iowa Department of Transportation (DOT), 2022, personal communication; S. Venegas, California DOT, 2022, personal communication]. Further, different states will likely have different thresholds owing to their own exposure to various weather hazards (e.g., the frequency and amount of snowfall) and availability of resources. Ultimately, threshold information from transportation agencies is crucial to ensure that the impact severity level thresholds chosen for the product are reasonable for locations across the United States.

Through the Pathfinder program—an initiative of enhanced collaboration between NWS offices, private weather providers, the Federal Highway Administration (FHWA), state Departments of Transportation, and other transportation agencies (FHWA 2018)—the Pennsylvania Turnpike has shared their "Weather Event Management Playbook," which includes specific thresholds for various weather event levels and the corresponding potential considerations for travel restrictions (Table 1). For example, the Pennsylvania Turnpike will consider imposing vehicle and/or speed restrictions or even closing the Turnpike with 3 in. h^{-1} of snowfall. These thresholds can thus be used to help inform the thresholds for each impact severity level, at least for the Pennsylvania area. Regionalization of thresholds—particularly for snow rate and ice accumulation—is necessary to appropriately define the impact for other areas of the United States. Whereas the thresholds for Pennsylvania serve as a proof of concept, the snow rate thresholds defined for Pennsylvania Turnpike are consistent with those outlined in the New York State (NYS) DOT Traffic Management Strategies (J. Thompson, NYS DOT, 2023, personal communication). This consistency suggests that those thresholds are likely representative of large regions. In

[1] The Highway Capacity Manual defines "free-flow speeds" as the "average speed of vehicles on a given segment, measured under low-volume conditions, when drivers are free to travel at their desired speed and are not constrained by the presence of other vehicles or downstream traffic control devices" (Transportation Research Board 2000).

TABLE 1. Criteria and potential restrictions detailed in the Pennsylvania Turnpike's Weather Event Management Playbook for each event level for the select weather events.

Weather event		Basic event	Medium event	Major event	Extreme event
Snow rate	Criteria	>0.5 in. h^{-1}	>1.0 in. h^{-1}	>2.0 in. h^{-1}	>3.0 in. h^{-1}
	Restrictions	None	Consider speed restrictions	Consider speed restrictions or imposing vehicle restrictions	Consider speed restrictions, imposing vehicle restrictions, or potential Turnpike closure
Rain rate	Criteria	>0.25 in. h^{-1}	>0.5 in. h^{-1}	>1.0 in. h^{-1}	>2.0 in. h^{-1}
	Restrictions	None	Consider speed restrictions	Consider speed restrictions	Consider speed restrictions
Ice accumulation	Criteria	–	<0.25 in.	>0.25 in.	>0.5 in.
	Restrictions	–	Consider speed restrictions	Consider speed restrictions or imposing vehicle restrictions	Consider speed restrictions, imposing vehicle restrictions, or potential Turnpike closure

the absence of knowledge of other thresholds across the United States, the Pennsylvania Turnpike thresholds will be used across the United States until regionalization can be introduced in the future. Such regionalization can be done through using climatological information to account for exposure, with resulting thresholds spot-checked against transportation-related criteria from other regions, if such information becomes known to the developers. Regionalization is necessary because regional or even local variations in preparedness, driver experience with and adaptation to hazardous winter weather, and traffic demands can also influence how impactful the weather conditions are.

3. Quantifying time-of-day impacts

Time-of-day factors are desired to scale the impact of active precipitation based on the local hour of the day and precipitation type. For example, the impact of precipitation during midday hours should be greater than that during overnight hours due to a higher number of motorists on the road. Additionally, the timing of the hazard in relation to peak traffic volumes is often of concern for the messaging of potential impacts (e.g., Barjenbruch et al. 2016; Tobin et al. 2022). Because of this, it is important to capture the influence of time of day on the product. Here, we present a novel research study that produces a single metric aggregating impacts associated with crash risk, crash severity, and typical traffic volumes. Precipitation-type data, crash data, and traffic volume data are all required for this analysis, which presents a unique challenge in terms of combining these separate datasets. Automated Surface Observing System (ASOS) data are often used to infer precipitation type at the time of motor-vehicle crashes that occur either within a set distance from the location (e.g., Tobin et al. 2019, 2022) or within a city or region close to the station (e.g., Black and Mote 2015b). However, accurate winter precipitation-type data are primarily only available from the select ASOS sites with human observers available to augment or correct automated observations (e.g., NOAA 1998; Reeves 2016; Landolt et al. 2019). Such routinely augmented ASOS sites are sparsely located and thus limit the areas within which analysis can be performed on crash and traffic data.

Crash and traffic volume data availability presents another limitation, as they are collected and managed by state or local agencies, with varying levels of availability. Unfortunately, this means that both crash and traffic datasets are not available for every state, which would be ideal for analysis across the United States. However, these datasets are available for several contiguous states in the Great Lakes region: Illinois, Indiana, Michigan, and Ohio. This region is appropriate for an initial analysis, though, as it has a high density of fatal winter-weather-related crashes (Tobin et al. 2022). Further, this region is contiguous with Pennsylvania, where we have information on thresholds used by the Turnpike to inform impact levels. These crash data include information such as the date, time, latitude, longitude, number of injuries and fatalities, and number of vehicles involved with each reported crash. Traffic volume data were obtained through the Midwest Software Solutions (MS2) Traffic Count Database System with accounts provided from each state. The traffic volume data obtained include vehicle counts for each hour at counting locations within the state.

The crash and traffic volume data for the years noted in Table 2 are first limited to cool-season months (October–April) to avoid warm season biases and further limited only to data points within 20 mi of routinely augmented ASOS sites (i.e., those in Reeves 2016). These sites are used to obtain accurate accounts of both precipitation type and respective beginning and ending times. Further, only data from the state where each ASOS is located are used, to avoid any biases resulting from state-specific crash reporting thresholds. For example, the reporting threshold in Indiana is any crash

TABLE 2. Periods of record for crash and volume data for each state.

State	Crash data years	Volume data (October–April only)
Illinois	2010–20	2011–21
Indiana	2007–20	2012–21
Michigan	2011–20	2010–21
Ohio	2016–20	2015–21

that results in a fatality, injury, or ≥\$1,000 in property damage, whereas in Illinois, the property damage thresholds are >\$1,500 if all drivers are insured or >\$500 if any driver is uninsured. The location of these ASOS sites, the corresponding 20-mi ranges, and locations of the traffic count sites within 20 mi of each ASOS site that are used for analysis are shown in Fig. 1. The traffic count sites are color coded by whether they are designated as urban or rural locations.

Using methods similar to those outlined in Tobin et al. (2021), event and control periods are identified for each ASOS location for rain (with no additional precipitation types), snow (with no additional precipitation types), and freezing precipitation (i.e., freezing rain and freezing drizzle, with the allowance of additional precipitation types) events. Ice pellet events are not examined because their infrequent occurrence is a significant limitation for such analysis (e.g., Tobin et al. 2021). Event periods are defined as the beginning and ending times of the precipitation type of interest, and control periods are the same period exactly 1 or 2 weeks before or after the event period in which no precipitation is

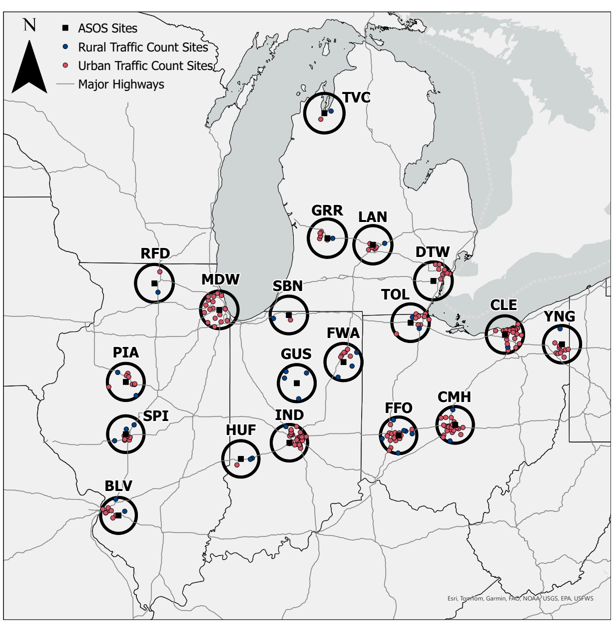

FIG. 1. A map of the locations of all routinely augmented ASOS sites (black squares) and the traffic count site locations (blue circles for rural locations and red circles for urban locations) used for analysis (black squares). Black circle outlines denote the 20-mi radius around each ASOS site, within which the crash and traffic volume data are used. Major highways are also displayed for reference.

reported. These event and control pairings are used to compare crash and vehicle count information during precipitation versus nonprecipitation, while also controlling for confounding variables such as time of day, day of week, and seasonality (e.g., Black and Mote 2015b). Control periods in May through September are discarded to avoid warm-season traffic biases (e.g., increased vehicle counts). Event periods that were not successfully matched to a control period are also discarded.

Viable event–control pairings are then broken into full-hour periods in local time. For example, rain between 1030 and 1315 LT is broken into two full-hour periods (1100–1200 LT and 1200–1300 LT). Subhourly event–control pairings (e.g., snow between 0950 and 1035 LT) are discarded. These full-hour event–control pairings are used to directly compare crash and vehicle count information during precipitation versus nonprecipitation for any local hour of the day. Because the total set of full-hour periods for any given hour comes from different storms, there is inherent variability owing to other factors that are outside the scope of this current work. These factors may include different road conditions or maintenance operations, the hour at which the storm is sampled at (e.g., the first hour vs later in the event), precipitation intensity (e.g., heavy snow vs light snow), and other weather conditions (e.g., visibility and varying light conditions). As a result, this study is meant to capture the general influence of precipitation during a local hour of the day.

To arrive at the final time of day factoring, the following calculations are performed: crash ratio, traffic volume ratio, crash factor, impact factor, traffic factor, and time-of-day factor. Each is discussed in detail below.

a. Crash ratio

The crash ratio addresses the question of how many crashes occur during precipitation relative to normal. It is calculated for each full-hour event–control pairing as

$$\text{crash ratio} = \frac{\text{crashes during the event hour} + 0.5}{\text{crashes during the control hour} + 0.5}. \quad (1)$$

The 0.5 constant ensures that the crash ratio does not become zero or undefined, while also minimizing bias (Black and Villarini 2019). Full-hour event–control pairs with no crashes during either the event or control period are omitted from analysis, consistent with suggestions in Black and Villarini (2019).

The mean, median, 25th percentile, and 75th percentile of hourly crash ratios for each precipitation type (rain, snow, and freezing precipitation) are shown in Fig. 2. Normalized frequency distribution of the 10th–90th percentile of the hourly data for each precipitation type is also plotted to further illustrate the distribution of the data. We perform light smoothing on the mean crash ratios by averaging the hourly crash ratio alongside half-weighted crash ratios of both the previous and following hour. These smoothed mean crash ratios are also plotted in Fig. 2.

A crash ratio of 1.0 indicates an equivalent number of crashes during both precipitation and nonprecipitation periods. A value of 2.0 indicates twice as many crashes during the

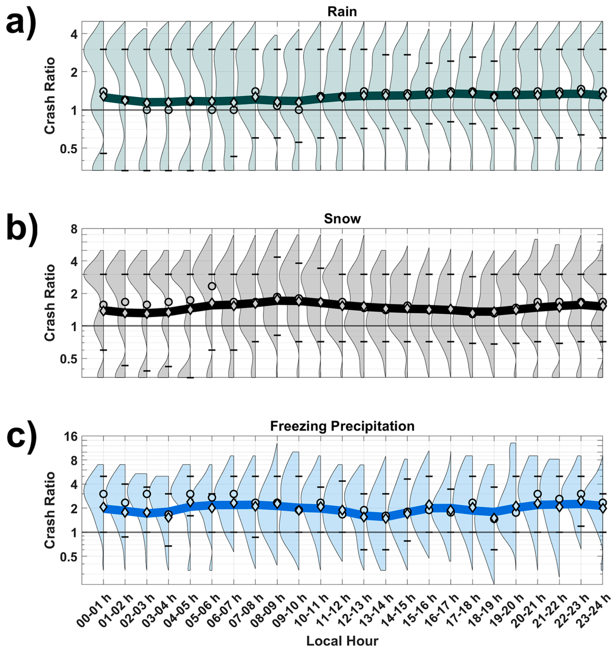

FIG. 2. Crash ratios for each local hour of the day for (a) rain, (b) snow, and (c) freezing precipitation. Circles indicate hourly mean crash ratios, and colored solid lines denote smoothed mean crash ratios. Colored distributions to the left of each hour marker are normalized distribution of the 10th through 90th percentile of crash ratio values. Horizontal ticks indicate the 25th and 75th percentiles, and diamonds indicate median values.

precipitation period than the nonprecipitation period. Similarly, a value of 0.5 indicates twice as many crashes during the nonprecipitation period than the precipitation period. All hourly mean crash ratio values for each precipitation type are >1.0, meaning that any precipitation type—on average—increases the number of crashes that occur at any hour of the day. Further, more crashes typically occur during snow than rain and even more occur during freezing precipitation than snow. This result is consistent with increased crash relative risk estimates reported in Tobin et al. (2021).

b. *Traffic volume ratio*

The traffic volume ratio addresses the question of how many vehicles are traveling on the roadway during precipitation relative to normal. The same approach that was done for computing crash ratios was done for computing volume ratios, but only after additional quality control was performed on the vehicle count data. Only traffic volume data from permanent traffic count sites were used, and only full-hour event–control pairings with an equivalent number of valid entries during both the event and control hour were used. For example, if there are two entries for a traffic count site during the control hour (e.g., a northbound count and a southbound count) but fewer than two entries during the event hour [e.g., a Not a Number (NaN) count or only a northbound count], the event–control pairing is discarded. Further, if both the event and control hour have zero vehicle counts, the event–control pairing is discarded. This is consistent with what was done for crash ratios following the suggestion in Black and Villarini (2019). One final scenario considered for quality controlling the traffic count data was for event–control pairings where 1 h had a zero count and the other had a nonzero count. If the nonzero count is >10, the data for the pairing are discarded. However, if the nonzero count is ≤10 vehicles, as may occur during low-volume periods such as early morning hours, the 0-vehicle count is increased to 1 to ensure that the volume ratio does not become zero or undefined.

The traffic volume ratio for each full-hour event–control pairing is computed as follows:

$$\text{volume ratio} = \frac{\text{sum of vehicle counts for all locations during the event hour}}{\text{sum of vehicle counts for all locations during the control hour}}. \quad (2)$$

The same statistics and visualizations done for crash ratios are performed for volume ratios and shown in Fig. 3. A value of 1.0 indicates equivalent vehicle counts during both precipitation and nonprecipitation periods. A value of 0.9 indicates 10% fewer vehicle counts during precipitation. All hourly smoothed mean volume ratios for each precipitation type are <1.0 (except rain for 1–2 h), meaning that there are fewer vehicle counts on average during precipitation. Further, there are typically fewer vehicle counts during snow than rain and even fewer vehicles during freezing precipitation. Further, precipitation during the afternoon and evening hours has a greater influence on reducing traffic volumes than the early morning hours, particularly for snow and freezing precipitation. This is likely attributed to a greater flexibility in traveler schedules in the afternoon relative to the morning, which may allow a shift in travel timing or avoiding travel altogether.

c. *Crash factor*

The crash factor is a proxy for a crash relative risk estimate and addresses the question of how likely a crash is to occur during precipitation relative to normal. Crash relative risk estimates are based on the odds of a crash occurring during precipitation compared to the odds of a crash occurring during normal, nonprecipitation conditions. The odds of a crash are simply the ratio between the number of crashes and noncrashes. Because the number of crashes is often much lower than the total number of vehicles on roadways, the number of noncrashes can be approximated with traffic volumes. As such, the crash relative risk estimate can be approximated with a crash ratio divided by a traffic volume ratio. For the purposes of this study, the smoothed mean crash and volume ratios computed in sections 3a and 3b, respectively, are chosen to estimate crash relative risk. This approach is chosen

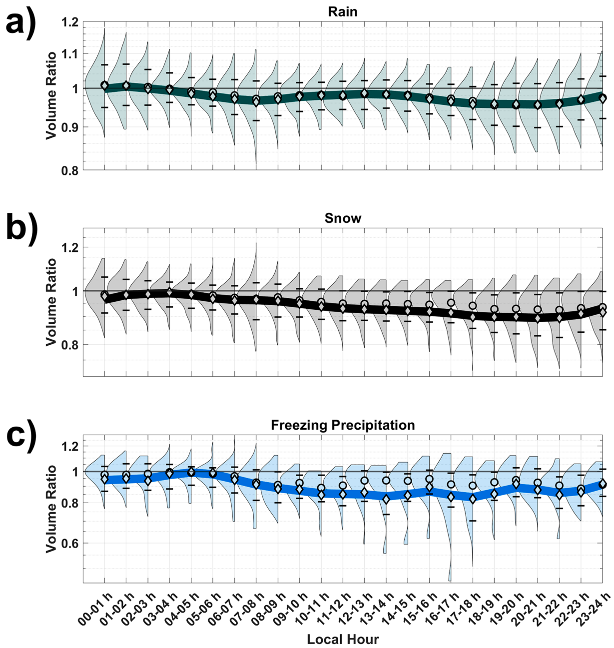

FIG. 3. As in Fig. 2, but for volume ratios.

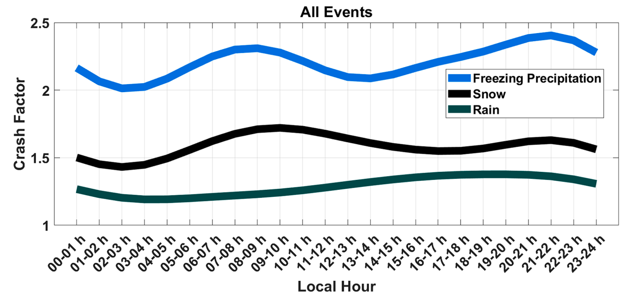

FIG. 4. Crash factors for each local hour of the day for rain, snow, and freezing precipitation, with a Gaussian-weighted moving filter with a window length of 10 h applied to the result.

instead of estimating crash risk directly for each full-hour event–control pairing because it increases the total number of data entries available for analysis. If crash relative risk were to be estimated directly, event–control pairings would need viable crash and traffic volume data. For example, a full-hour event–control pair with no crashes during either the event or control hour, but with reliable traffic volume data would need to be omitted, thus removing valuable information regarding traffic volumes. One limitation to this indirect approach is that statistics such as percentiles cannot be obtained; however, the mean value is sufficient for our needs of obtaining a single, mean metric for measuring crash risk.

The crash factor for each precipitation type at each local hour of the day is found by dividing the smoothed mean crash ratio by the smoothed mean traffic volume ratio. For visualization purposes, a Gaussian-weighted moving filter with a window length of 10 h is applied to the crash factors, as shown in Fig. 4 for rain, snow, and freezing precipitation. This smoothing filter is chosen to preserve the diurnal variation of crash factoring, while removing some variability from the individual hourly data. A value of 1.0 indicates that crashes on average are equally likely to occur during precipitation and nonprecipitation periods. A value of 2.0 indicates that crashes on average are twice as likely to occur during precipitation than normal. Any precipitation type increases the average crash risk at any hour of the day, yet crash risk is higher during snow than rain and highest during freezing precipitation. This is consistent with the findings in Tobin et al. (2021) of a hierarchy in crash relative risk with precipitation type. Further, there is evidence that crash risk is highest during the morning and overnight periods for snow and freezing precipitation, whereas crash relative risk is highest in the afternoon and evening periods for rain. This is also consistent with Tobin et al. (2021) where the highest crash relative risk is in the afternoon period for rain, but in the morning for snow. We speculate that warmer road surface conditions for the afternoon hours could account for the lower crash factor in the afternoon versus the morning hours.

d. Impact factor

The impact factor addresses the question of how severe and impactful a crash is during precipitation. A simple metric for the impact factor is defined for each local hour of the day as the average of the following per event-hour crash: the number of vehicles involved, plus one-half the number of injuries, plus the number of fatalities. This metric is proposed to give a sense of the gravity of the crashes that occur by combining the number of vehicles, injuries, and fatalities that occur, considering that increases in both the number of vehicles involved in a crash and the severity of a crash (i.e., property damage only, injury, or fatal) can lead to longer delays, more lane closures, and increased time to clear the crash and reopen lanes (Chin et al. 2004). The total number of crashes, vehicles involved, injuries, and fatalities that occurred during all full-hour event periods for each precipitation type (i.e., the set of data considered for this specific analysis of an impact factor) is presented in Table 3, in addition to an aggregate impact factor based on those values. Because the incidence of injury or fatality is much lower than the incidence of a crash involving more than one vehicle (i.e., an average of 0.19 injuries per crash, 0.0016 fatalities per crash, yet 1.8 vehicles involved per crash), the impact factor is primarily driven by how many vehicles are involved in each crash. The weighting factor of 1.0 for each vehicle was to ensure that no impact factoring was given if all crashes that occur involve only a single vehicle with no injuries or fatalities. Further, the weighting factors of 0.5 and 1.0 for injuries and fatalities, respectively, are assigned such that the impact factor is not strongly biased by these higher-severity outcomes.

The resulting impact factor data for each local hour and precipitation type are shown in Fig. 5, with mean values smoothed as was done for the crash and traffic volume ratios. Values of 1.0 indicate that crashes during precipitation involve only a single vehicle and no injuries or fatalities per crash. All precipitation types have mean impact factors > 1.0

TABLE 3. Total number of crashes, vehicles involved, injuries, and fatalities considered for the impact factor calculation. An aggregate impact factor for each precipitation type is also shown.

Precipitation type	Crashes	Vehicles involved	Injuries	Fatalities	Impact factor
Rain	134 386	254 885	28 493	251	2.00
Snow	130 548	233 734	22 592	157	1.89
Freezing precipitation	10 017	16 624	1898	20	1.76
Total	274 951	505 243	52 983	428	1.94

at all hours of the day, meaning that crashes during any precipitation type at any time typically involve either more than one vehicle or may also result in injuries and/or fatalities. Further, there is a pronounced diurnal pattern for all precipitation types where crash impact is higher during the afternoon and early evening hours and lower during the early morning hours. Very few full-hour event periods during daytime hours had all crashes involve just a single vehicle with no injuries or fatalities, as evidenced by elevated 10th and 25th percentile values, particularly between 0900 and 1700 LT. Overnight and early morning hours, particularly between 0100 and 06:00 LT, have 25th percentile values of 1.0 for all precipitation types, meaning that one-quarter of those full-hour event periods have crashes involving only a single vehicle with no injuries or fatalities. The diurnal shape of these curves is consistent with expectations based on traffic volume patterns (see next subsection below) where crash impacts are higher during hours with more vehicles on the roadway and lower during hours with fewer vehicles. This follows logical reasoning: the higher the number of vehicles on the roadway is, the more likely crashes are to involve additional vehicles (Tobin et al. 2022).

In comparing the smoothed mean impact factors among the precipitation types (and the aggregate impact factors in Table 3), a hierarchy is evident such that the impact factor for rain is higher than that for snow, which is higher than freezing precipitation. This means that for each crash that occurs, crashes during rain are typically more impactful—strictly speaking with the metric outlined here—than snow, and crashes during freezing precipitation are the least impactful. Although this result may seem counterintuitive, owing to the enhanced overall impacts associated with freezing rain and snow, it is important to note that crashes during rain typically occur at higher speeds and with higher traffic volumes than during snow or freezing rain, which can lead to crashes involved more vehicles, and/or more severe crashes as a result. These influences translate to a higher impact factor using the formulation defined here. Further, these impact factors are an estimate per crash. It is important to keep this factoring in context with the crash factor, which paints a clearer picture that although there are more crashes during snow and freezing rain, they tend to involve fewer vehicles and/or casualties.

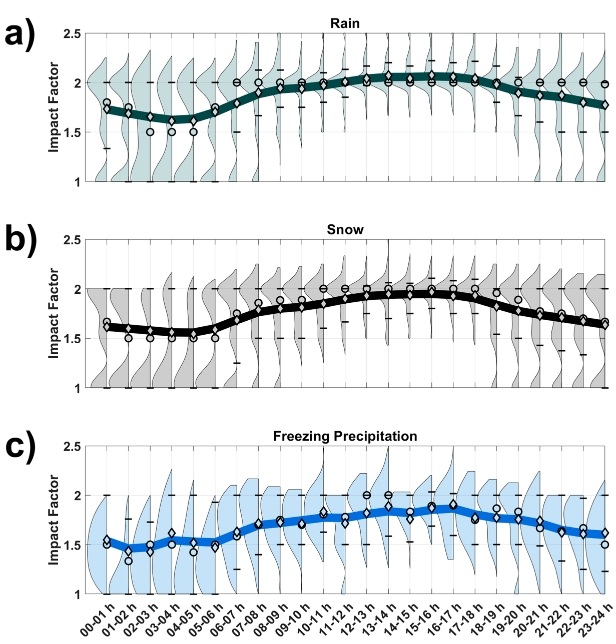

FIG. 5. As in Fig. 2, but for impact factors.

e. Traffic factor

The traffic factor accounts for how many vehicles are typically on the roadway at a given local time of day during a weekday, weekend, or holiday (Thanksgiving, Christmas Eve, Christmas, New Year's Eve, and New Year's Day). Whereas the crash and impact factors are not disaggregated by day of week or holidays due to limited data availability to cover all 24 h of each day classification, the traffic factor aims to address these differences. It is taken as the local hourly average of all vehicle counts from the entire period of record within each state for weekdays, weekends, and holidays, separately, and then averaged for the analysis region. These average counts for the three categories are then normalized by the maximum average combined count (i.e., any day category). The traffic factor is then defined to give a 25% increase if the normalized vehicle count is equivalent to the maximum average hourly overall count. These resulting traffic factors for weekdays, weekends, and holidays are shown in Fig. 6. Weekdays feature distinct morning and afternoon peaks for rush hour traffic periods, whereas weekends feature a broad increase in traffic throughout the late morning through evening period. Holidays have similar patterns to weekends, yet with slightly lower total traffic volumes.

f. Time-of-day factor

The time-of-day factors are the final factoring values for each precipitation type that can then be integrated into an impact-based product. Specifically, our intended use for these factors is to use them to adjust the forecasted precipitation rates based on the local time of day, to account for diurnal influences of precipitation type on motorist safety and transportation-

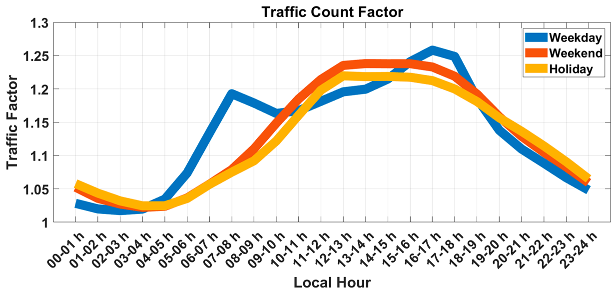

FIG. 6. Traffic factors for each local hour of the day for weekdays, weekends, and holidays.

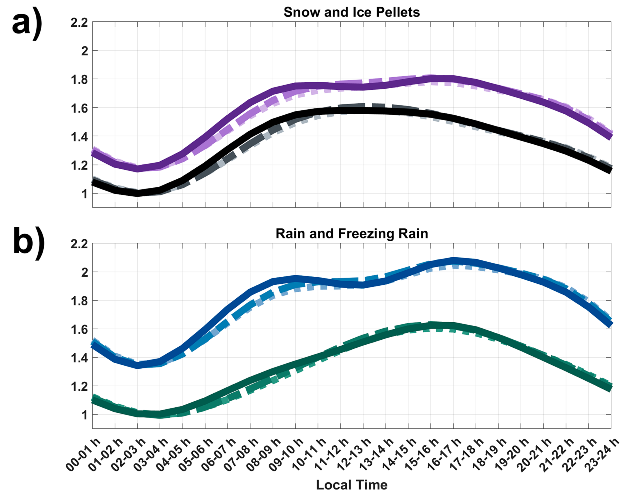

FIG. 7. Final time-of-day factors for each local hour of the day for (a) snow (black lines) and ice pellet (purple lines) precipitation types and (b) rain (green lines) and freezing rain (blue lines) precipitation types. Dark solid lines of each color denote the factoring for weekdays, medium-shaded dash–dotted lines denote those for weekends, and light-shaded dotted lines denote those for holidays.

related impacts. For example, 0.5 in. h^{-1} of snowfall should have a higher impact during hours where the crash ratio, impact factor, and traffic factor are all high. These higher-impact hours indicate that crash risk is higher, crashes are more impactful (i.e., involve more vehicles and/or fatalities), and traffic volumes are typically higher (e.g., during midday hours).

Time-of-day factors are based on the product of the smoothed crash and impact factors for each precipitation type and the appropriate traffic factor (weekday, weekend, or holiday) corresponding to the local hour of the day. These values are then smoothed with a Gaussian-weighted moving filter with a window length of 10 h to provide a smoother accounting of diurnal variations. Although this smoothing does reduce the more pronounced influences of the morning and evening weekday peaks evident in Fig. 6, it preserves the differences between daytime and overnight traffic patterns. Rush hours can be extremely localized, with different cities or roadways experiencing different peak travel hours. For example (not shown), the weekday traffic patterns from the traffic count sites located within 20 mi of GUS (Peru, IN)—all of which were designated as rural and away from a major highway (Fig. 1)—did not feature the same "peakiness" of a morning rush hour as for the all-urban traffic count sites within 20 mi of MDW (Chicago, IL). Further, traffic patterns in the wake of the COVID-19 pandemic have changed such that the peak travel hours may be shifted or spread out (e.g., Javadinasr et al. 2022; Bhagat-Conway and Zhang 2023). These changes are not well reflected in the data here, which is dominated by pre-COVID-19 traffic patterns, so accounting of localized and current traffic patterns should be considered in future studies.

Finally, the resulting time-of-day values for snow are divided by the minimum value of snow, and the values for rain and freezing precipitation are divided by the minimum value of rain. This division is done to help scale snow and liquid precipitation types independently, because snow and liquid precipitation have separate impact-based thresholds (see Table 1; snow has a higher impact than rain of the same rate due to thresholding, not the time-of-day factors). For simplicity, ice pellets are given time-of-day factors that are the average of snow and freezing precipitation for each hour, which is in line with results from Tobin et al. (2021) where the crash relative risk estimates of ice pellets are between those for snow and freezing precipitation. These final time-of-day factors are shown in Fig. 7. These factors mean that ice pellets will have a greater impact on surface transportation than snow at any given hour. Similarly, freezing rain will have a greater impact on surface transportation than rain at any given hour of the day. Further, the impact of each precipitation type is lower during overnight hours and higher throughout the day. The influences of day of the week are subtle, yet weekday mornings have a distinct increase in factoring relative to weekends or holidays.

One way in which these factors can be used for a surface-transportation-related impact-based forecast product is by combining precipitation rate, the metric for driving conditions [discussed in section 2b(1)], and the time-of-day factor assigned to the precipitation type for the forecast hour. In this way, precipitation type, precipitation rate, local time of day, and driving conditions are all accounted for when determining impacts. Whereas the time-of-day factors address transportation disruptions stemming from motorist safety (i.e., crash risk, severity, and exposure), the metric for driving conditions—which is based on reductions to vehicle free-flow speeds—addresses transportation disruptions owing to reduced vehicle speeds, such as increased travel times. By combining these influences, the weather conditions can be scaled appropriately to impacts. However, because the guidelines provided by the Pennsylvania Turnpike are only based on precipitation type and rate, it is important to ensure that the additional factoring from driving conditions and time of day does not completely overwhelm the raw precipitation rates. For example, 0.5 in. h^{-1} of snowfall should never have impacts on par with 3.0 in. h^{-1} of snowfall.

4. Conclusions

This article outlines a novel approach for the development of an impact-based forecast product for surface transportation.

Such a product would be invaluable to communicating the potential severity of impacts from weather—particularly winter precipitation—on surface transportation and motorist safety. This development involves careful consideration for what impacts are intended to be captured, how to scale weather and road conditions to impacts, and how to categorize impact severity. Tying impacts to traffic disruptions are ideal, as these can range from increased travel times and delays, to road closures due to impassable road conditions. In this way, impact severity can scale with increasingly poor driving conditions, which can necessitate enhanced mitigation efforts or strategies by motorists or transportation agencies to maintain safety on roads, if possible.

To scale hourly weather forecast data to transportation impacts, we propose the following: 1) Incorporate a metric representative of driving conditions and 2) introduce time-of-day factoring for active precipitation to address the increase in crash risk and the impact of crashes that may occur. The former leverages existing research to address disruptions to vehicle free-flow speeds to ensure that, for example, 0.5 in. h^{-1} of snow on snow-covered roads with low visibility will have higher impacts than on wet roads with higher visibility. The time-of-day factors introduced here were based on research methods that combine crash and traffic volume data during rain, snow, and freezing precipitation types to assess the crash risk and the impact of crashes at each local hour of the day for each precipitation type. These factors also address potential impact variations during weekdays, weekends, and holidays. Time-of-day factors are used to ensure that, for example, snow during overnight hours has a lower impact than snow during midday hours and that weekday rush hours are handled appropriately versus weekend traffic patterns. Owing to data availability limitations, the analysis performed to obtain the time-of-day factors was limited to a single region of the United States, which may not adequately reflect the diurnal influences of precipitation type on motorist safety and transportation impacts in other areas. However, the methods used to create the time-of-day factor values can be applied to additional regions or states in the future to improve regionalized utility of the product.

Although the time-of-day factors defined here were developed for a specific intended use case (i.e., Part II of this series), the research done on crash ratios, volume ratios, and impact factors also has important implications for understanding how motorist safety changes throughout the day and with different precipitation types. This work also helps to further our understanding of crash risk by separately interrogating the influences of precipitation type on crash rate and traffic volume reduction. We document higher crash ratios in the morning hours for snow and freezing precipitation types yet slightly higher crash ratios in the evening hours for rain. There also exists a hierarchy where crash ratios are highest for freezing precipitation and lowest for rain. For traffic volume ratios, there is a pronounced diurnal cycle for all precipitation types where traffic volume reductions are minimal in the morning hours but increase throughout the day. Traffic volume reductions are also highest for freezing precipitation and lowest for rain. We also introduce a unique method for quantifying the impact of a crash by combining vehicle counts, injuries, and fatalities into a single metric. This metric is lowest overnight and increases throughout the day, indicating that crashes overnight involve fewer vehicles, injuries, and/or fatalities, yet crashes involve more vehicles, injuries, and/or fatalities during the day. This metric is also highest for rain and lowest for freezing rain, which is a reflection of the combined influence of vehicle speeds and traffic volumes on the severity of crashes and number of vehicles involved in crashes.

Identifying appropriate thresholds for impact severity levels involves awareness of what thresholds may exist for transportation agencies to potentially impose travel restrictions. However, such thresholds or guidelines are difficult to obtain due to either the inexistence of specific guidelines or the need to leverage specific partnerships between NWS offices and transportation agencies. Thresholds from the Pennsylvania Turnpike, in addition to the scaling metrics of both driving conditions and time-of-day factors, can be used to help inform impact levels. Ideally, however, thresholds from other areas are desired to ensure that impact levels are appropriately scaled to all regions of the United States. In the absence of specific knowledge of these thresholds, climatology may be used as a proxy.

Now that the development of a new NWS impact-based forecast product for surface transportation has been framed in the context of its motivation, intent, and considerations for impacts, Part II of this series will describe more specifics about the product in development and highlight its performance for the select case studies where surface transportation was negatively impacted by winter weather.

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Data availability statement. ASOS data are openly available through the Iowa State University's Iowa Environmental Mesonet archive (https://mesonet.agron.iastate.edu/request/download.phtml). Crash data are available from each state as follows: Ohio (https://ohtrafficdata.dps.ohio.gov/crashstatistics/home), Michigan (https://www.michigantrafficcrashfacts.org/querytool), Indiana (https://hub.mph.in.gov/dataset/aries-crash-data-2007-2017), and Illinois (the request for data was submitted to DOT.DTS.DataRequests@illinois.gov). Traffic volume data are available through Midwest Software Solutions (MS2; https://www.ms2soft.com/) data portals for each state as follows: Ohio (https://odot.ms2soft.com/tcds), Michigan (https://mdot.ms2soft.com/tcds), Indiana (https://indot.ms2soft.com/tcds), and Illinois (https://idot.ms2soft.com/tcds). MS2Soft account logins for each state were requested for access to the ability to download bulk data.

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