Impact of Adverse Weather on Freeway Bottleneck Performance

Joshua Seeherman, Ph.D., P.E.[1]; and Alexander Skabardonis, Ph.D.[2]

Abstract: Congestion on freeways occurs when demand exceeds the available capacity. Common causes of recurring congestion, also known as freeway bottlenecks, include lane drops, on-ramp merges, and weaving sections. Adverse weather can reduce the maximum queue discharge flow, but this effect has not been systematically investigated. This research examined the relationship between discharge flow and weather characteristics including rainfall intensity, wind speed, and visibility. Queue discharge rates at four isolated merge bottlenecks were measured using an established methodology of cumulative count and occupancy curves. An analysis of discharge variation by rainfall intensity revealed reduced discharge ranging from 5% in drizzle (rainfall <0 in./h) to 27% in heavy rainfall [rainfall >2.54 mm/h (>0.1 in./h)]. However, rain intensity accounts for only a portion of the variability in discharge flow. Two hypotheses were tested using the additional variables of wind speed and visibility as well as dividing the periods of discharge flow into multiple groupings. Analyses based on these hypotheses described the variation in queue discharge flow better than the analysis with a single independent variable. This research showed that weather characteristics are an important predictor of bottleneck queue discharge rates. **DOI: 10.1061/JTEPBS.0000434.** © *2020 American Society of Civil Engineers.*

Author keywords: Weather; Freeway congestion; Bottleneck capacity; Congestion; Queue discharge; Rainfall.

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

Introduction

It has long been understood anecdotally by motorists that adverse weather is likely to lengthen one's driving time, particularly during a commute in the peak hour. Micro effects of increased braking distance caused by slippery roads, slower speeds, and cautious drivers can combine to create reduced performance on the freeway. In locations of light volume, such as rural areas, this can be a simple nuisance; in areas of congestion, particularly during the peak period, weather can create a commuting nightmare. Freeway bottlenecks, defined as points of recurring congestion where demand exceeds capacity forming a queue, are locations likely to have decreased discharge flow during weather, resulting in increased travel times for daily commuters. These bottlenecks can often define a commute, and the ability to move through them controls overall trip time.

There has been extensive work on the general effects of weather on corridor characteristics such as speed and flow; examples include Ibrahim and Hall (1994) and Kyte et al. (2001). Additionally, initial work by Dehman (2012) described discharge flow from an active bottleneck during adverse weather. However, these studies only addressed weather with a discrete function: the effect of rain on speeds categorized as light, moderate, and heavy. None of them examined the complexities of changes in discharge flow from an active bottleneck due to weather as a continuous function, nor did they address the variability in discharge flow. As more emphasis is placed on managing freeway capacity as opposed to adding to it, understanding how bottleneck discharge flow changes during weather will be increasingly important for agencies as they incorporate strategies to reduce congestion within the existing footprint. This is especially the case in terms of climate change mitigation, where in many places storms will be more severe. For example, the European Union has already begun to calculate climate change in its risk planning, as documented by Snelder and Calvert (2016).

By examining changes in discharge flow during different weather conditions, this research will quantify the effect of variables related to adverse weather, including rainfall intensity, wind speed, and visibility, on discharge flow from active freeway bottlenecks. The findings have the potential not only to more accurately represent the relationship between weather effects and bottleneck performance with a continuous function, but also to be generic across multiple bottlenecks. While this research examines bottlenecks in only one geographic area, this work could be a first step in predicting commute times in different regions. Many metropolitan areas that have travel information systems in place may benefit from results generated by this research.

The bottleneck sites were located in Southern California. While one may question why test sites were chosen in a place that receives only 30 days of rain per year, the authors hypothesized that the effect of rain would be magnified and easier to detect. Furthermore, as climate change creates larger areas of desertification, rain may become more infrequent in many metropolitan areas and climates may become increasingly similar to those where the analyses in this report were carried out. Fig. 1 is a sample diagram of a recurring freeway bottleneck and a summary of the proposed research.

The organization for this paper is as follows. First, a brief background, the data collection process, and a summary of the methodology will be presented, which in turn will create a set of basic results. Next, three hypotheses will be offered that will attempt to improve the predictions beyond what is already in the

[1]Postdoctoral Researcher, Dept. of Civil and Environmental Engineering, Univ. of California, Berkeley, CA 94720-1720 (corresponding author). ORCID: https://orcid.org/0000-0001-5167-1638. Email: jseeher@yahoo.com

[2]Professor-In-Residence, Dept. of Civil and Environmental Engineering, Univ. of California, Berkeley, CA 94720-1720. Email: skabardonis@ce.berkeley.edu

Note. This manuscript was submitted on August 14, 2019; approved on May 19, 2020; published online on August 5, 2020. Discussion period open until January 5, 2021; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering, Part A: Systems***, © ASCE, ISSN 2473-2907.

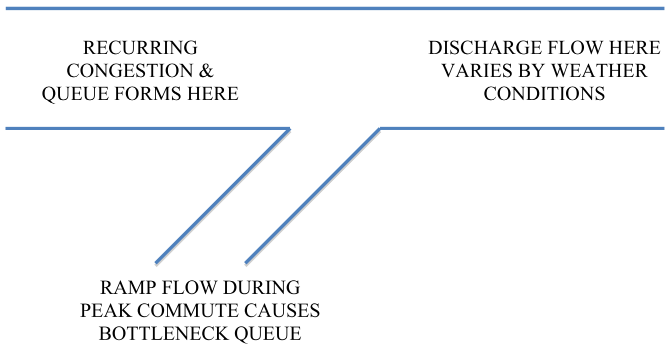

Fig. 1. Recurring bottleneck.

basic results. Last, the hypotheses will be compared and a discussion of their performance will conclude the paper.

Background

Although it is well understood that adverse weather will affect one's commute, the study of this effect is a fairly small field within congestion management. For many years, editions of the *Highway Capacity Manual* (*HCM*) continued to address the effect of weather in a simple figure largely based on foreign studies by Ibrahim and Hall (1994) and Brilon and Ponzlet (1996). Ibrahim and Hall found a 10%–20% reduction in maximum capacity with rain, with snow producing dramatic capacity decreases ranging from 30% to 48%. Brilon and Ponzlet expressed maximum capacity reduction in the context of vehicles per freeway lane, with rain creating a flow drop of 175 vehicles per hour per lane (ph-pl) on a two-lane freeway, representing a 10% drop. Darkness and rain resulted in a capacity drop that exceeded 250 vehicles per hour per lane, or over 15%.

This approach employed by the HCM has been criticized by many researchers, such as Kyte et al. (2001), as a simplistic view. This criticism served as the primary rationale for a significant amount of weather-related traffic research in the past two decades. For example, Agarwal et al. (2005) examined conditions on an urban freeway in Minneapolis, where they found that light rain impacts capacity 5%–10%, in contrast to the 2000 edition of the *HCM*, which did not regard light rain as significant. Agrawal et al.'s speed reductions were similar. However, recent editions of the *HCM* have included more information, shown in Fig. 2, which is more precise and an important step toward properly representing the effect of weather on capacity and speed.

In the United States, a number of studies have sought to increase understanding of the influence of bad weather on freeway capacity. Saberi and Bertini (2010) looked at three years of data

Weather Type	Weather Event Definition	Speed Adjustment Factors 55 mi/h	60 mi/h	65 mi/h	70 mi/h	75 mi/h
Medium rain	>0.10–0.25 in./h	0.96	0.95	0.94	0.93	0.93
Heavy rain	>0.25 in./h	0.94	0.93	0.93	0.92	0.91
Light snow	>0.00–0.05 in./h	0.94	0.92	0.89	0.87	0.84
Light–medium snow	>0.05–0.10 in./h	0.92	0.90	0.88	0.86	0.83
Medium–heavy snow	>0.10–0.50 in./h	0.90	0.88	0.86	0.84	0.82
Heavy snow	>0.50 in./h	0.88	0.86	0.85	0.83	0.81
Severe cold	<–4°F	0.95	0.95	0.94	0.93	0.92
Low visibility	0.50–0.99 mi	0.96	0.95	0.94	0.94	0.93
Very low visibility	0.25–0.49 mi	0.95	0.94	0.93	0.92	0.91
Minimal visibility	<0.25 mi	0.95	0.94	0.93	0.92	0.91
Non–severe weather	All conditions not listed above	1.00	1.00	1.00	1.00	1.00

Fig. 2. Adjustments by weather type (*Highway Capacity Manual 2010*, published by the Transportation Research Board of the National Academies of Sciences, Engineering, and Medicine.).

on Interstate 5 in Portland, Oregon, and found reductions starting at 0–110 vehicles ph-pl for drizzle, slowly rising to 190 vehicles ph-pl during heavy rain (approximately 10%), consistent with Ibrahim and Hall (1994). Saberi and Bertini's study also noted that crash rates were higher after 3 h of continuous rain, a common occurrence during Portland rainy season. Smith et al. (2004) found that the *HCM* significantly underestimated the capacity reduction effect of rain in urban Virginia but that its assumptions regarding speed reductions were valid. They reported capacity reduction ranging from 3% to 10% in light rain to up to 30% in heavy rain. Maze et al. (2006) and Cools et al. (2010) followed up on Smith et al. and, using different sites (in Minneapolis and Belgium), were able to look at snow in addition to rain, wind, and visibility (fog). Results from Maze et al. were similar in light rain (2%–7%) but much different in heavy rain (14%), which the authors attributed to fewer data points. Heavy snow conditions caused the largest reductions in freeway capacity (22%). Cools et al. found similar rates in Belgium in rain but fewer effects in snow. Goodwin (2002) performed a review of capacity but on arterial streets. Not surprisingly, arterials performed worse than freeways (10%–25% in rain; 30%–40% in snow) because of reductions in the quality of timing coordination during bad weather.

Byun et al. (2010) developed an empirical model of rainy conditions on six New Jersey freeways. This was an attempt to provide a model based on local driver behavior. Although the model did not address bottlenecks, it provided some insight as an early effort to predict travel times during weather events. The model estimated speed based on existing traffic flow and rainfall intensity, which had a fairly large range of data points including reductions of 1%–20% in capacity. Byun et al. were able to verify their macroscopic model with data from other New Jersey freeways, but did not analyze specific bottlenecks or areas of congestion. Snelder and Calvert (2016) created a more comprehensive network performance model of the potential effects of weather events on a major city (Rotterdam). Different weather scenarios—for example, short heavy downpour and long-duration snowstorm—caused different delays at strategic locations. Government officials could use the results of this model when creating response plans for differing weather conditions.

Recent studies by the Federal Highway Administration (FHWA 2006) and Rahka et al. (2008) investigated rain and snow effects in Minneapolis, Seattle, and Baltimore, and sought to create weather adjustment factors (WAFs) based upon multiple weather characteristics such as wind speed, precipitation intensity, and visibility for both rainy and snowy weather. The findings again confirmed those of Ibrahim and Hall (1994). The main difference is that in Rahka's work the capacity reduction drops more at the onset of precipitation but does not continue to decrease as dramatically as quantity increases. In contrast, the *HCM* factors continue to decrease in a more linear fashion with the increase in precipitation. One interesting additional finding of the FHWA work is that the speed drop during snow conditions for Baltimore drivers was less than that for Minneapolis drivers, which the authors theorized as reflecting Minnesota drivers' greater awareness of the dangers of driving in adverse weather compared with Maryland drivers. This finding indicates that weather impacts can vary by location due to driver behavior.

Three studies have focused on the effect of weather on bottlenecks, albeit only at the discrete level by aggregating flows into qualitative categories. Kim et al. (2010) primarily examined characteristics of flow breakdown and congestion duration in California, concluding that duration of congestion did not change if the rain began prior to its onset, but increased if rain occurred when congestion started. Additionally, the drop from maximum pre-breakdown discharge flow to post-breakdown queue discharge flow did not appear to change if rain occurred. However, many of

J. Transp. Eng., Part A: Systems, 2020, 146(10): 04020120

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

Table 1. Summary of weather effects on freeway capacity

Source	Location	Rain	Snow
Ibrahim and Hall (1994)	Toronto	10%–20% capacity drop	30%–50% capacity drop
Brilon and Ponzlet (1996)	Germany	10% capacity drop with rain up to 15% at night	—
Smith et al. (2004)	Norfolk (Virginia)	3%–10% drop in light rain, up to 30% in heavy rain	—
Maze et al. (2006)	Minneapolis (Minnesota)	2%–7% drop in light rain, up to 14% in heavy rain	4%–22% capacity drop
Rahka et al. (2008)	Multiple states	Light rain 10%–12% capacity drop	12%–20% capacity drop
Saberi and Bertini (2010)	Portland (Oregon)	0%–10% capacity drop depending on intensity of rainfall	—
Byun et al. (2010)	New Jersey	I-80 average flow drop of 25% with rain	—
Kim et al. (2010)	California	7.7%–11.7% capacity drop	—
Dehman (2012)	Milwaukee (Wisconsin)	10.9%–13.4% capacity drop	9.9%–10.7% capacity drop

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

the discharge flow quantities were quite low even without rain (1,100–1,900 vehicles/ph-pl), which might indicate a possible error in bottleneck identification and did not address intensity of weather. Dehman (2012) addressed this issue at four urban sites in Milwaukee and created discrete correction values for discharge flow based on the severity of the weather. For example, light rain affected discharge flow between 11% and 12% depending on the site, while fog reduced discharge flow between 4% and 7%. Finally, Van Stralen et al. (2014) looked at the probability of breakdown under the influence of rain and found the probability higher in light rain than in heavy rain, which indicates the effect of travel behavior given that drivers may wait for the heavy rain to end before heading out to the freeway.

Table 1 summarizes the literature on the effect of weather on freeway corridors, and it can be seen that a majority of the results fall within the recent guidelines shown in Fig. 2. The research in this paper will be a synergy between research on continuous effects of weather on basic freeway segments (Rahka et al. 2008; Byun et al. 2010) and that focused on bottlenecks but only produce discrete relationships (Kim et al. 2010; Dehman 2012). Although there is no significant research comparing discrete versus continuous analysis in the transportation sector, notable work can be found in the field of medicine, such as Royston et al. (2006) and Sauerbrei and Royston (2010). In an analysis where independent variables are continuous, Sauerbrei and Royston concluded that artificial discrete categories can lead to overestimating the differences between the bins with smaller confidence intervals for the results. Additionally, the selection of the cut-points between categories can be arbitrary and affect outcomes. This is particularly the case when selecting the cutoff for a light rain category. This research will try to explore continuous relationships of weather, but will focus on the performance of active bottlenecks as opposed to simple freeway segments or weather in specific categories.

Data Collection and Methodology

Data Collection and Site Selection

The major objective of this paper is to quantify the effect of adverse weather on discharge flow from an active freeway bottleneck using archived traffic data and weather data. With enough samples, conclusions can be drawn about discharge flow changes based on specific weather conditions such as rainfall intensity, wind, and visibility.

Traffic detector data in California are readily available via the Performance Measurement System, or PeMS (pems.dot.ca.gov). In most urban areas, PeMS detectors are placed every 0.4–0.8 km (0.25–0.5 mi) for each lane, including carpool lanes, and provides over 10 years of data depending on the age of the detector, in addition to contour plots documenting areas of congestion and bottlenecks. PeMS also provides information on other sources of nonrecurrent delay, including incidents and work zones, enabling researchers to exclude those data. Since the analysis here was performed for weekday peak periods, there was no interference from work zones or special events. Sites were selected to be far away from sporting venues. It is important to note that PeMS does not operate at 100% functionality; at any given time, 20%–30% of the detectors are not working. Data with loop detector failures were removed during the data cleaning process. Some potential bottleneck sites could not be examined due to persistent loop detector failure.

In terms of weather data, the electronic public archive of the National Weather Service (mesowest.utah.edu) provides up-to-date data at all airport weather stations. In this study, it was very important to have weather stations as close to the bottleneck sites as possible. Small microclimates do occur, and the weather can be quite different within a distance of a few miles.

In summary, the data collection should occur in an area where the freeway network is dense enough to have multiple merge bottlenecks in close proximity to weather stations, and those bottlenecks should be freestanding so as not to be typically engulfed by other larger downstream bottlenecks.

Site Selection

With the guidelines for site selection just described, an exhaustive process was undertaken to identify bottlenecks suitable for analysis by finding recurring bottlenecks and weather station proximity. With all preferences considered, four recurring merge bottlenecks were selected in Orange County in Southern California, where there are approximately 30 rain days per year, as shown in Table 2.

Table 2. Test sites

Bottleneck location	Freeway	Secondary road	Direction	Time of day	Weather station
Irvine (1)	I-405 San Diego Freeway	University Drive and Jeffrey Road	Northbound Postmile 4	AM	John Wayne Airport
Irvine (2)	I-405 San Diego Freeway	University Drive and Jeffrey Road	Southbound Postmile 4	PM	John Wayne Airport
La Palma (3) (Buena Park)	SR 91 Artesia Freeway	Valley View Street	Eastbound Postmile 15	PM	Fullerton Airport
Fullerton (4)	SR 57 Orange Freeway	Chapman Avenue	Southbound Postmile 6	PM	Fullerton Airport

J. Transp. Eng., Part A: Systems, 2020, 146(10): 04020120

In all four cases, the on-ramps that create the merge bottlenecks are metered. The process of finding proper bottlenecks with functional detectors both upstream and downstream in addition to being clear of any larger downstream bottlenecks was quite time-consuming.

Methodology

For the identification of bottlenecks, this research used cumulative curves, an approach outlined by Cassidy and Bertini (1999). This approach employs an established procedure to recognize an active bottleneck, allowing measurement of discharge flow from it. Weather data are mapped to the congested period in 30–60-min segments depending on the duration of the discharge. The objective is threefold: time of bottleneck activation, proof that the bottleneck has remained active further along in time, and measurement of queue discharge flow.

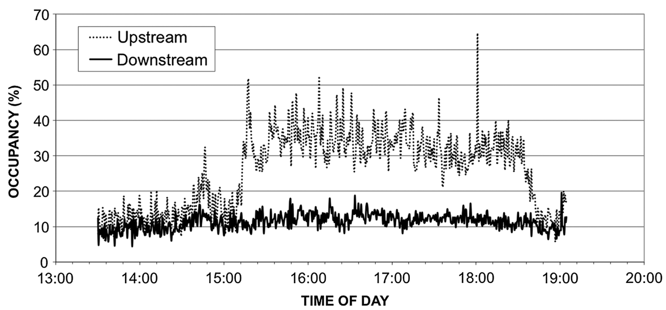

Fig. 3. Detector occupancy, SR 57 SB at Chapman Avenue, Fullerton.

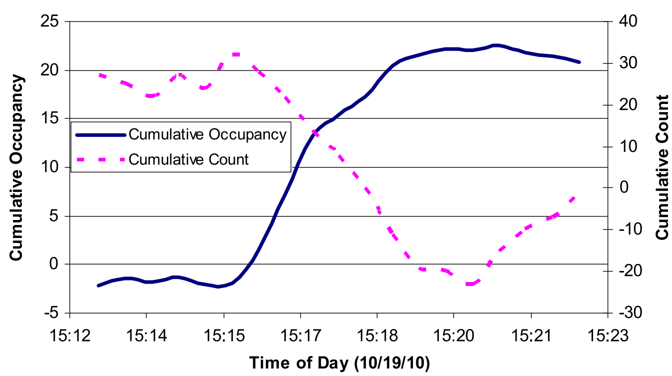

Fig. 4. Upstream detector cumulative curves.

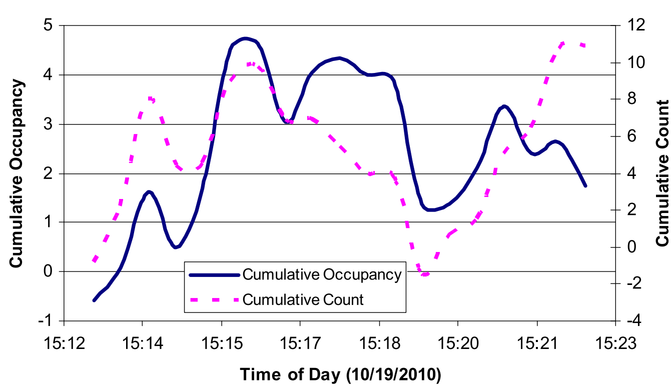

Fig. 5. Downstream detector cumulative curves.

The main theory behind cumulative curves is that during free-flow (uncongested) conditions the accumulation of vehicle count and occupancy will track each other on a graph visible to the naked eye once a significant amount of volume background is removed. If the occupancy increases, one should see more vehicles being counted. Similarly, if the occupancy decreases, one should see the count of vehicles across the detector decrease; with enough cumulative occupancy background removed, this decline will appear as a negative slope. In congestion the opposite will occur. If cumulative occupancy increases and the cumulative count decreases, this indicates that vehicles are in a congested state. Changes from the uncongested regime (where cumulative count and cumulative occupancy track each other) to the congested regime (where the two curves oppose each other) are a reliable indicator that a backward-forming shockwave from an unknown cause of congestion has reached the detector in question. This can also be shown with oblique cumulative curves, which will verify the beginning of the congestion.

Examples of cumulative curves are shown in Figs. 3–5. Fig. 3 is a graph of occupancy in 30-s intervals at detectors upstream and downstream of Bottleneck 4 on SR 57 in Fullerton on October 19, 2010. Note the jump in instantaneous occupancy around 15:15 for the upstream detector. Figs. 4 and 5 show the cumulative curves for the Fullerton Bottleneck for 10 min surrounding 15:15 at the upstream and downstream detector. As a reminder, a significant amount of background flow and occupancy has been removed.

As shown in Figs. 4 and 5, the characteristics of the traffic streams at the upstream and downstream detector differ. In Fig. 4, upstream of the merge bottleneck, there is an abrupt climb in cumulative occupancy at 15:15, which corresponds with a drop in the cumulative count, an indication of the detector being hit with a backward-forming shockwave. However, as shown in Fig. 5, the downstream detector does not show any ill effects of congestion. Increases in cumulative occupancy are equaled by an increase in cumulative count, showing that the traffic stream at this location is free-flowing and not congested. By creating cumulative curves at multiple time points, one can reliably state that the Fullerton bottleneck was active on October 19, 2010, and therefore queue discharge measurements on that day were appropriate. An oblique cumulative curve can be used to verify the onset of congestion at 15:15, as shown in Fig. 6. Finally, speed curves confirm the duration of congestion, shown in Fig. 7.

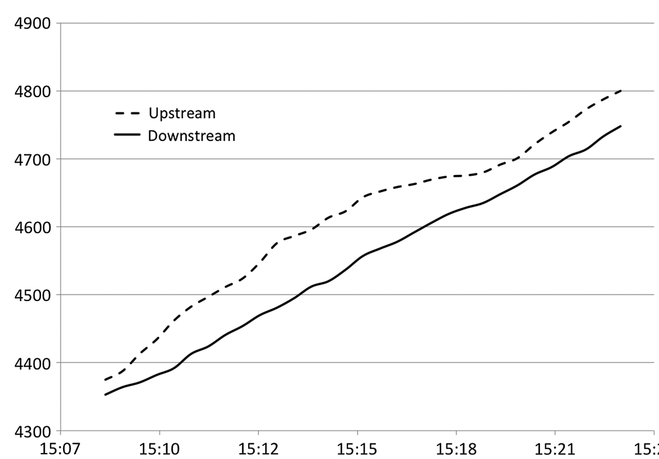

Fig. 6. Oblique cumulative curves.

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

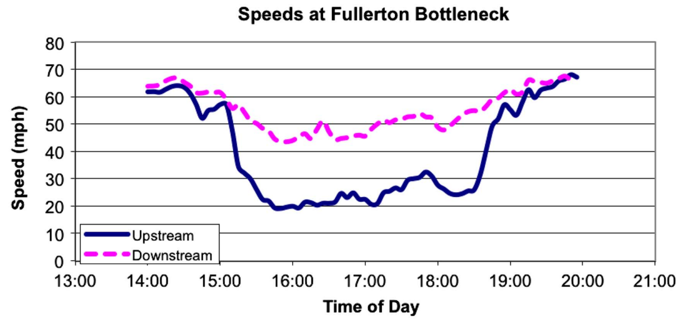

Fig. 7. Speed curves.

Fig. 3 shows instantaneous occupancy and describes the procedure for mapping weather data onto discharge flow. The weather data are most reliably given per hour ending on the hour. Therefore, weather data from the hour at the onset of congestion is mapped to that hour, with all subsequent full hours mapped to their corresponding weather data. Here, if the final period before the end of congestion was more than half of the hour, it was also included. Thirty minutes of sustained congestion was set as the minimum amount of congestion required. The three weather variables used in this experiment were total rainfall [from 0 (dry) to 25 mm per hour (1 in./h) (downpour)], maximum sustained wind [from 0 mi/h (calm) to 48 km per hour (30 mi/h) (gale)], and lowest sustained visibility [from 16 km (10 mi) (clear) to 400 m (0.25 mi) (heavy fog)]. Fig. 8 shows how the weather data map to the respective hours of congestion for the Fullerton Bottleneck on October 19, 2010. There are three data slices for this day, with each slice corresponding to the three weather variables and the average discharge flow as measured by the downstream detector at that time. This process was repeated for every site and for every day on which there was rain during or near the peak period, creating a large data bank of discharge flows (Table 3 and Fig. 9).

The report controlled for time of day beyond the descriptive statistics section by separating the AM site, as it was possible that the AM discharge flow was different from that of the three PM sites. However, in terms of day of week and month of year, drivers in this region were highly familiar with the roadway design; also, rain only falls during a three-month period. Since the dependent variable was discharge flow and the duration of congestion was not considered, the analysis did not control for these time-based variables.

Descriptive Statistics

Table 4 shows the average queue discharge reductions for different rainfall events based on the analysis; these reductions are compared to those in Dehman (2012) and the HCM (Transportation Research Board 2010). The percentages are generally within the range of the earlier results. One would expect that the decrease in discharge flow in Dehman would be smaller than in the current research, as Milwaukee enjoys over 125 days of precipitation (35 being snow) and so drivers there are more familiar with bad weather. This appears to be the case for heavy rainfall but not for light or moderate rainfall.

The queue discharge rates are plotted against rain intensity in Fig. 10. There is wide scatter in the data, especially under light rain conditions. A linear regression [Eq. (1)] shows a fairly poor fit.

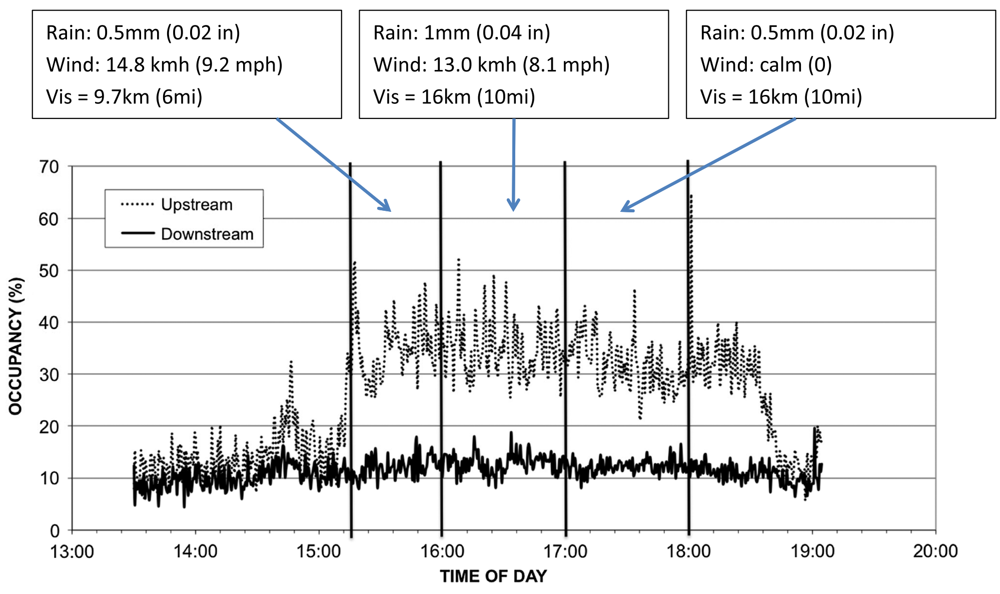

Fig. 8. Bottleneck 4 (Fullerton) weather data mapping.

Table 3. Summary of data processing

Bottleneck site	Range of discharge flow (vehicle/lane/h)	Range of rainfall (in./h)	Range of sustained wind (mi/h)	Range of sustained visibility (mi)	No. of samples
Irvine NB I-405 AM	1,612–2,291	0–0.17	0–11.5	1.75–10	29
Irvine SB I-405 PM	1,316–2,129	0–0.40	0–24.2	0.75–10	52
La Palma SR 91 PM	1,442–2,283	0–0.31	0–12.7	0.5–10	48
Fullerton SR 57 PM	1,247–1,991	0–0.95	0–13.8	0.5–10	48

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

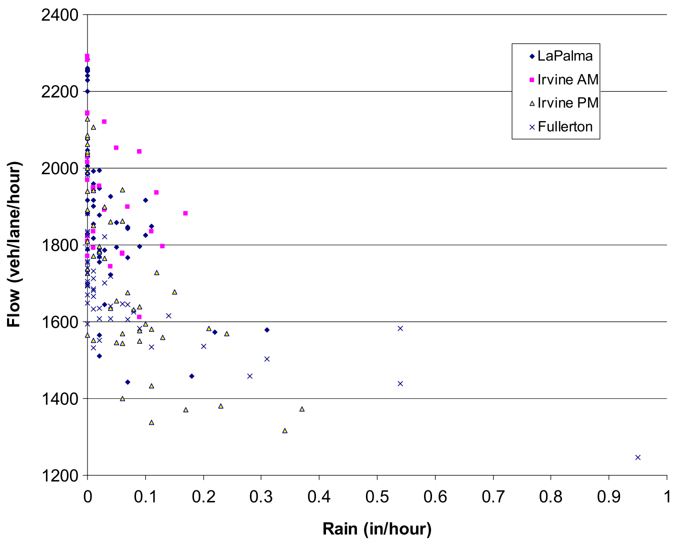

Fig. 9. Raw values of discharge flow for the four sites.

Table 4. Percentage reduction in average discharge flow versus rain

		Rainfall (in./h)		
Bottleneck location	Average discharge flow no rain (vehicle/lane/h)	Drizzle (0.01–0.02) (%)	Moderate (0.03–0.1) (%)	Heavy (≥0.1) (%)
Irvine NB I-405 AM	2,007	5.5	6.3	7.7
Irvine SB I-405 PM	1,942	6.1	14.1	25.6
La Palma SR 91 PM	2,115	12.8	16.5	27.1
Fullerton SR 57 PM	1,768	5.7	6.1	16.7
Average of all sites	1,958	7.5	10.8	19.3
Dehman (2012)		5.4–12.5	11.5–18.3	
HCM (Transportation Research Board 2010) (Chap. 11)		—	8	14

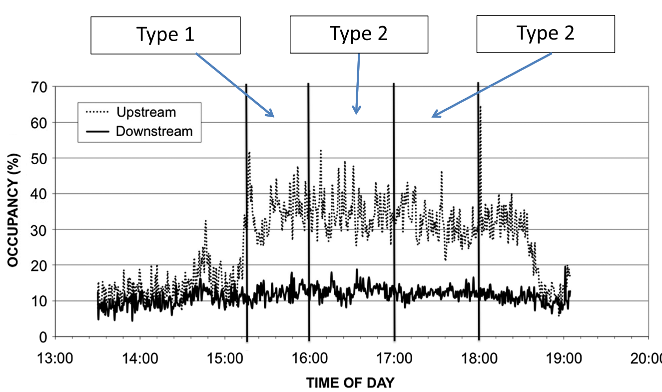

Fig. 10. Division of periods into two types, Fullerton bottleneck.

The R^2 associated with Eq. (1) is only 0.27. A quadratic expression [Eq. (2)] does not significantly improve the fit (R^2 of 0.33). The removal of the Irvine AM data also does not change the fit in any meaningful way with the simple regressions

$$Q_d = 1{,}854 - 1{,}037.7r \tag{1}$$

$$Q_d = 1{,}885 + 1{,}561.2r^2 - 1{,}981r \tag{2}$$

where Q_d = queue discharge flow; and r = rainfall intensity.

Additional Analyses

Regression based on a single variable, rain, did not create a continuous solution with a good fit. Therefore, additional analyses were performed to explore the relationship between discharge flow from an active bottleneck and adverse weather through the use of multiple weather variables (rainfall, sustained wind, visibility). These analyses were conducted to determine if additional weather variables could significantly improve the one-variable relationship shown in Eq. (1) and to help to explain the variability in discharge flow during light rain. These analyses and their results are discussed next.

Simple Hypothesis

The first simple hypothesis is a regression with three regressors of rainfall, wind speed, and visibility. The early regression runs showed that the wind variable was generally not significant unless it was raining. However, visibility could affect driver behavior in the absence of rain, such as in dense fog. Hypothesis 1 is as follows:

$$Q_d = \alpha + \beta r + \gamma w d_0 + \theta v + \varepsilon \tag{3}$$

where Q_d = queue discharge flow; r = rainfall intensity; w = wind speed; v = visibility; and d_0 = dummy for the presence of rain: 0 if no rain, 1 if raining.

The findings of the simple hypothesis, including all three weather variables as regressors [Eq. (3)] are provided in Table 5. For this table and for all subsequent tables, significant independent variables (p-value <0.05) are shown in bold. Additionally, in all tables values are shown with their p-values in parentheses. They are also compared in the table to regression with just one independent variable (rain).

For three out of the four sites, the regression showed a value of rainfall intensity that was significant, with a p-value less than 0.05. With the same three out of four sites, the new analysis improved on the regression with rain only. Although wind and visibility were significant at fewer sites, in every case when wind or visibility was significant, the sign of the independent variable was correct. In the case of wind, at the sites with significant findings the driving

Table 5. Findings from the simple hypothesis

Bottleneck site	Intercept	Rainfall (in./h)	Wind (mi/h)	Visibility (mi)	Adjusted R^2
Irvine NB	2,119	−1,154.2 (0.21)	−14.7 (0.42)	−12.3 (0.32)	0.04
I-405 AM	1,970	−1,094.5	—	—	0.07
Irvine SB	1,845	**−894.8** (0.02)	**−15.9** (0.002)	7.4 (0.65)	0.60
I-405 PM	1,853	−1,875.6	—	—	0.48
La Palma	2,096	**−1,174.6** (0.01)	**−30.9** (0.0001)	−2.1 (0.83)	0.54
SR 91 PM	1,982	−2,057.9	—	—	0.31
Fullerton	1,613	**−244.0** (0.007)	−7.5 (0.06)	**16.1** (0.0005)	0.65
SR 57 PM	1,714	−518.9	—	—	0.46

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

direction of vehicles in the bottleneck (to the southeast) was directly into the wind. One would expect that an increase in wind would result in a decrease in discharge flow (e.g., harder to see) while an increase in visibility would result in an increase in discharge (e.g., easier to see). At the Fullerton site, the site with the highest R^2, two out of the three variables were highly significant (p-value < 0.01) and the third one was significant to the 90th percentile. This was the only site where visibility was both significant and had a proper sign (the greater the visibility, the greater the discharge). As a result, the effect of rainfall alone was much lower than at the other three sites. The adjusted R^2 terms were all above 0.50 with the exception of the first site, I-405 at Irvine, in the morning. This was the only site in the AM hour and had the fewest samples. Nevertheless, the other three sites in the PM hour were moderately better at describing the queue discharge flow than Eq. (1). The same four regressions were also run with an added quadratic term for rain ($r^2 + r$), but did not improve on the previous results.

Referring to the graph in Fig. 7, it was observed during the analysis runs of the simple hypothesis that as the rain became steadier the predictions became more accurate. This led to the theory behind the complex second hypothesis: by breaking periods of congestion into different groups, the improved specificity would lead to a better predictive model than the moderate improvement found by testing the simple hypothesis and adding additional independent variables.

Complex Hypothesis

The complex hypothesis attempts to be more fine-tuned than the simple hypothesis, which along with prior work relied on the premise that all periods of discharge flow from an active bottleneck are affected by the same weather variables. However, it is possible that certain periods of queue discharge are more likely to be affected by different variables when compared with other periods.

For the Fullerton Bottleneck (Fig. 3), there were three periods of congestion in which queue discharge was measured. The complex hypothesis breaks up these three periods into Type 1, the first period after congestion starts; and Type 2, all subsequent periods. This is shown in Fig. 10. The complex hypothesis assigns a group of independent variables to each type as shown in Table 6.

The rationale for the choice of variables is fairly intuitive. For Type 1A, consider a situation where heavier rain is ending but there is still mist or drizzle and the pavement is wet. If the daily start of congestion occurs during this time, current weather characteristics will be important, but clearly the wetness of the pavement from the heavy rain may be equally important. Based on their prior experience driving in rain, drivers seeing the wet pavement while in free flow may be more apprehensive as they move through the congestion. However, for Type 1B, if there is medium or heavy rain, the current weather characteristics are far more important than whatever weather might have occurred in the prior few hours.

For Type-2 conditions, the queue is already formed when drivers arrive at the bottleneck proper. In this case, the complex hypothesis calls for a first-differences analysis, which regresses the change in discharge flow on the change in weather conditions. While there are many reasons to use (or not to use) first-differences, in this situation the advantage over conventional regression techniques associated with the first two hypotheses is that first-differences can eliminate issues of omitted variables such as geometry and potential for serial correlation, as these biases fall out during subtraction of the differences.

Table 6. Independent variables by period type for the complex hypothesis

Type	Variables
1A—first period of congestion Light rain (<0.05 per hour)	Current weather + prior rain
1B—first period of congestion Steady rain (≥0.05 per hour)	Current weather
2—all subsequent periods of congestion	Differences in weather variables from previous period only

Complex Hypothesis Findings

Type-1A Periods

The findings of Hypothesis 2 (the complex hypothesis) are divided into Type-1A, Type-1B, and Type-2 periods. In the Type-1A periods, which occurred at the onset of congestion with light rain, only two sites (Fullerton and La Palma) had sufficient sample size. Table 7 shows the comparison between Hypothesis 1 (the simple hypothesis) and Hypothesis 2, which adds the effect of prior rain for these periods.

It is important to note that Table 7 only compares periods where less than 1.27 mm (0.05 in.) of rain fell during the onset of congestion. Values in Table 7 for Hypothesis 1 differ from those in Table 5 because in the previous table all data points for all types of rainfall are included.

The addition of prior rain to the regression in Hypothesis 2 did not substantially improve predictions for queue discharge flow during the first period of congestion with light rainfall. There was modest improvement at the Fullerton site, with a higher adjusted R^2, but none of the variables were significant even to a p-value of 0.1. The theory of prior rainfall and wet pavement was not proven with this data set. It is possible that a larger sample will verify this hypothesis in the future.

Type-1B Periods

Findings for the second part of the complex hypothesis that examines the first period of queue discharge during steady rain (Type 1B) show that the advantage of segregating the discharge periods is the ability to combine multiple study sites. Since these periods are dominated by steady rain, one can perform a log-likelihood ratio test to combine data to create a generic effect. To pass the log-likelihood ratio test for restricting dependent variables, the Irvine I-405 site in the AM was omitted because there were very few AM first periods with moderate or heavy rain. The findings for Type 1B based on combining the three PM sites are provided in Table 8.

Table 8 presents a noteworthy finding. Discharge flows from three different sites with geometric differences could be combined,

Table 7. Findings for Hypothesis 2, Type-1A periods

Bottleneck site	Hypothesis	Intercept	Rainfall (in./h)	Wind (mi/h)	Visibility (mi)	Prior rainfall (in./h)	Adjusted R^2
La Palma SR 91 PM	Simple	2,071	−7,207.1 (0.07)	−20.9 (0.23)	7.7 (0.59)	N/A	0.65
La Palma SR 91 PM	Complex	2,058	−7,283.9 (0.08)	−20.5 (0.26)	8.6 (0.57)	173.8 (0.77)	0.63
Fullerton SR 57 PM	Simple	1,621	−2,119.9 (0.63)	−6.7 (0.60)	18.6 (0.21)	N/A	0.32
Fullerton SR 57 PM	Complex	1,652	−3,538.4 (0.42)	−5.4 (0.66)	19.5 (0.17)	−1,487.8 (0.14)	0.39

J. Transp. Eng., Part A: Systems, 2020, 146(10): 04020120

Table 8. Findings for Hypothesis 2, Type-1B periods

Intercept	Rainfall	Wind	Visibility	Adjusted R^2
1,754	−283.3 (0.07)	−**16.7** (0.008)	4.3 (0.79)	0.54

passing the log-likelihood ratio test for accepting restrictions. This union produced a fairly strong regression result with an adjusted R^2 exceeding 0.50. All three variables were of the correct sign, with the wind variable highly significant (p-value <0.01) and the rain variable modestly significant (p-value <0.1). This supports the argument that during moderate or high rainfall current weather conditions strongly influence the queue discharge from an active bottleneck. One can imagine wind and significant rain adversely affecting the traffic stream in this case.

Type-2 Periods

The last set of findings in the complex hypothesis concerns the Type-2 periods. To recap, these periods always follow the initial period of congestion and therefore are blind in the sense that they depend only on the change in weather at that moment. As such, they require a differences analysis as opposed to a traditional regression to exploit the ability to eliminate the effects of unobserved variables. The comparison between predicted and observed conditions is based not on the absolute discharge flow from weather characteristics but on the change in discharge flow from the change in weather characteristics. Additional power was again obtained by combining sites into a generic form using the log-likelihood ratio test. In this instance, restrictions were allowed for geometry, rainfall, and visibility. The findings are shown in Table 9, with the values now expressed in percentage change rather than absolute change. For example, for every inch of increased rain, discharge flow from the bottleneck decreases by 18%.

Both the rainfall and the visibility measurements were not only generic but significant (p-value <0.05) and, in the case of visibility, highly significant (p-value <0.01). In the case of wind, the only significant variable was at the La Palma site. This makes sense as the angle of the freeway in the area of congestion faces directly into the primary wind direction during rainfall, a topic to be discussed further. The intercept also reflects an important finding revealed during data collection: if there are no changes in the weather, the discharge will naturally improve by a small margin of approximately 0.7%. In contrast, previous research found changes in weather conditions to be reflected only in the coefficients of the independent variables.

A good check of whether the differences technique is effective is to compare the two hypotheses for predicting the flow for these Type-2 periods. If the value from the differences technique in the complex hypothesis equals or improves on the standard predictions from the simple hypothesis, then the generic power of the differences analysis proves to be a superior method. Certainly a tool for examining all four sites is more powerful than one that examines each site individually. The results of the comparison are shown in Table 10, which compares differences for Type-2 periods only.

Table 10. Comparison of hypotheses for Type-2 periods

	Average error from prediction to observed	
Bottleneck site	Complex (%)	Simple (%)
Irvine NB I-405 AM	−1.15	−1.64
Irvine SB I-405 PM	0.84	−1.44
La Palma SR 91 PM	−1.48	−9.41
Fullerton SR 57 PM	0.27	−2.59
Average for all data points combined	0.01	−3.50

For all sites, the differences technique used in the complex hypothesis performed better than the simple regression in the simple hypothesis in predicting changes in queue discharge flow after the initial period of congestion. The improvement reveals that separating the two period types improved prediction, as the difference from the simple hypothesis was based on regression of all time periods. This separation allows the power of the generic descriptions to be used. For the La Palma site, where all three variables were significant in Hypothesis 2 (p-value <0.05), the improvement over Hypothesis 1 exceeded 7%.

Discussion and Findings

This paper describes the performance of freeway bottlenecks during adverse weather using three weather variables (rainfall, wind, and visibility) which are commonly measured at local airport-based weather stations. Performance is defined by measuring the queue discharge flow from each bottleneck. Four bottleneck sites in Orange County, California, on I-405, SR 57, and SR 91, were examined.

By aggregating rainfall into qualitative bins for light, moderate, and heavy rain, the performance of the four bottlenecks in Orange County generally agreed with prior work in Milwaukee, Wisconsin, and values reported in the *HCM*. The decrease in bottleneck performance ranged from 5% in drizzle to 27% in heavy rain. The variability of queue discharge was very high in periods of light rain.

Hypotheses were proposed to describe the bottleneck discharge based on differing numbers of independent variables. A simple hypothesis was undertaken to predict queue discharge from an active bottleneck using three weather variables (rainfall, sustained wind, visibility) as regressors. This regression produced results with adjusted R^2 values greater than 0.60, but did not accurately depict discharge flow with light rain [i.e., <1.27 mm/h (<0.05 in./h)]. However, at a majority of the sites at least two if not all three weather variables had p-values less than 0.05.

A second more complex hypothesis for predicting queue discharge flow revealed that generic summations could be constructed for different periods of rain. The periods of congestion were divided into three categories: onset of congestion with light rain, onset of congestion with steady rain, and all subsequent periods. The first group was regressed on both current and prior weather conditions, while the second group was regressed only on current conditions.

Table 9. Discharge flow prediction for Hypothesis 2, Type-2 periods

Bottleneck site	Intercept	Change in rainfall (in./h)	Δ wind (mi/h)	Δ visibility (mi)	Adjusted R^2
Irvine NB I-405 AM	0.69%	−**17.99**% (0.03)	0.34% (0.34)	**0.95**% (0.0001)	0.55
Irvine SB I-405 PM			0.39% (0.11)		
La Palma SR 91 PM			−**0.73**% (0.04)		
Fullerton SR 57 PM			−0.02% (0.94)		

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

J. Transp. Eng., Part A: Systems, 2020, 146(10): 04020120

The third group of periods used only the change in weather from the previous period in making the prediction.

The first group of queue discharge observations (Type 1A), those at the onset of congestion with light rain, did not improve with the addition of prior rainfall for the two sites that had more than twenty samples. It was hypothesized that wet pavement would be a significant regressor, but this was not the case for this small sample. Conversely, predictions for the second and third groupings of queue discharge observations were equal to or better than predictions with rainfall only or with the simple hypothesis. However, by isolating these groups, the data points could be combined from multiple sites with restrictions on certain variables passing the log-likelihood ratio test. This led to a powerful generic description of bottleneck discharge flow for these two groupings.

The work discussed here replicated prior work but in Southern California, an area not known for rainfall. It validated *HCM* reduction factors and provided additional analyses involving the effect of different weather variables and how that changed over the course of the daily commute. However, there are several ways to improve on the findings. These include adding more sites, additional variables, and different types of weather conditions. In the first-differences analysis, it was discovered that restrictions on rainfall and visibility (e.g., the rainfall effect being the same at all four sites) passed the log-likelihood ratio test, while the restriction on wind did not. At this time, a brief investigation was undertaken of wind direction during rainfall. At the Fullerton Airport, the average direction of wind during rain was 146°(i.e., from the southeast). This direction blows straight into the front windshields of vehicles at one particular site, La Palma, which was where wind was significant p-value <0.05. The addition of wind direction may benefit future analyses.

Similarly, going back to 2005 there were only two periods of weather in the study area that had rainy conditions for more than two days in a row, January 19–22, 2010, and December 20–22, 2010. However, north of California, in Washington and Oregon, periods of rain can last for many days and sometimes weeks during wet periods. By studying bottlenecks in locations such as Seattle and Portland, one might determine whether performance changes day to day as rain continues. It is possible that performance may improve slowly as drivers in the Northwest become used to the wet roadway, indicating historical familiarity with wet weather.

The most significant step for future work will be investigating changes in travel demand and whether trip start times might change if inclement weather is forecast. This will affect both affect queue length and overall delay. Some research has concluded that there is no significant change in start time (Cools and Creemers 2013; Khattak and de Palma 1997), but others have seen a statistically significant change in travel plans (Kilpelainen and Summala 2007). While this research has relied on European data, there has been little work on this topic in the United States. With the ultimate goal of being able to forecast trip time on the basis of weather (e.g., to allow an extra 20 min for rain forecast on Wednesday), one will need to investigate queue length and queue duration during different intensities of adverse weather. It may be that, while bottleneck performance does not vary by region, travel demand may vary substantially. For example, snow may drastically change freeway performance where it snows 1–3 times per year while commuters may be less likely to change their behavior in a place where it snows 20 times per year.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available in a repository online in accordance with funder data retention policies. Traffic data are available from the California PeMS database, while eather information is available from the National Weather Service archive hosted by the University of Utah (mesowest.utah.edu). Full citations for traffic data (CALTRANS 2019) and weather data (University of Utah 2019) can be found in the reference list.

References

Agarwal, M., T. Maze, and R. Souleyrette. 2005. "Impacts of weather on urban freeway traffic flow characteristics and facility capacity." In *Proc., Mid-Continent Transportation Research Symp.*, 18–19. Ames, IA: Center for Transportation Research and Education, Iowa State Univ.

Brilon, W., and M. Ponzlet. 1996. "Variability of speed-flow relationships on German autobahns." *Transp. Res. Rec.* 1555 (1): 91–98. https://doi.org/10.1177/0361198196155500112.

Byun, J., J. Daniel, and S. Chien. 2010. "Speed-flow relationships under adverse weather conditions." In *Proc., 89th Annual Meeting of the Transportation Research Board*. Washington, DC: Transportation Research Board.

CALTRANS (California DOT). 2019. "Performance Measurement System (PeMS)." Accessed September 3, 2013. http://pems.dot.ca.gov.

Cassidy, M., and R. Bertini. 1999. "Some traffic features at freeway bottlenecks." *Transp. Res. Part B: Methodol.* 33 (1): 25–42. https://doi.org/10.1016/S0191-2615(98)00023-X.

Cools, M., and L. Creemers. 2013. "The dual role of weather forecasts on changes in activity level behavior." *J. Transp. Geogr.* 28 (Apr): 167–175. https://doi.org/10.1016/j.jtrangeo.2012.11.002.

Cools, M., E. Moons, and G. Wets. 2010. "Assessing the impact of weather on traffic intensity." *Weather Clim. Soc.* 2 (1): 60–68. https://doi.org/10.1175/2009WCAS1014.1.

Dehman, A. 2012. "Effect of inclement weather on two capacity flows at recurring freeway Bottlenecks." *Transp. Res. Rec.* 2286 (1): 84–93. https://doi.org/10.3141/2286-10.

FHWA (Federal Highway Administration). 2006. *Empirical studies on traffic flow in inclement weather*. Publication FHWA-HOP-07-073. Washington, DC: FHWA.

Goodwin, L. 2002. *Weather impacts on arterial flow*, 4–8. Falls Church, VA: Mitretek Systems.

Ibrahim, A. T., and F. Hall. 1994. "Effect of adverse weather conditions on speed-flow occupancy relationships." *Transp. Res. Rec.* 1457: 184–191.

Khattak, A., and A. de Palma. 1997. "The impact of adverse weather conditions on the propensity to change travel decisions: A survey of Brussels commuters." *Transp. Res. Part A: Policy Pract.* 31 (3): 181–203. https://doi.org/10.1016/S0965-8564(96)00025-0.

Kilpelainen, M., and H. Summala. 2007. "Effects of weather and weather forecasts on driver behaviour." *Transp. Res. Part F: Traffic Psychol. Behav.* 10 (4): 288–299. https://doi.org/10.1016/j.trf.2006.11.002.

Kim, J., H. Mahmassani, and J. Dong. 2010. "Likelihood and duration of flow breakdown: Modeling the effect of weather." *Transp. Res. Rec.* 2188: 19–28. https://doi.org/10.3141/2188-03.

Kyte, M., Z. Khatib, P. Shannon, and F. Kitchener. 2001. "Effect of weather on free-flow speed." *Transp. Res. Rec.* 1776 (1): 60–68. https://doi.org/10.3141/1776-08.

Maze, T., M. Agrawal, and G. Burchett. 2006. "Whether weather matters to traffic demand, traffic safety and traffic operations and flow." *Transp. Res. Rec.* 1948 (1): 170–176. https://doi.org/10.1177/0361198106194800119.

Rahka, H., M. Farzaneh, M. Arafeh, and E. Sterzin. 2008. "Inclement weather impacts on freeway traffic stream behavior." *Transp. Res. Rec.* 2071 (1): 8–18.

Royston, P., D. Altman, and W. Sauerbrei. 2006. "Dichotomizing continuous predictors in multiple regression: A bad idea." *Stat. Med.* 25 (1): 127–141. https://doi.org/10.1002/sim.2331.

Saberi, M., and R. Bertini. 2010. "Empirical analysis of the effects of rain on measured freeway traffic parameters." In *Proc., 89th Annual Meeting of the Transportation Research Board.* Washington, DC: Transportation Research Board.

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

Sauerbrei, W., and P. Royston. 2010. "Continuous variables: To categorize or to model?" In *Proc., 8th Annual Conf. on Teaching Statistics (ICOTS).* Voorburg, Netherlands: International Statistical Institute.

Smith, B., K. Byrne, R. Copperman, S. Hennessey, and N. Goodall. 2004. "An investigation into the impact of rainfall on freeway traffic flow." In *Proc., 83rd Annual Meeting of the Transportation Research Board.* Washington, DC: Transportation Research Board.

Snelder, M., and S. Calvert. 2016. "Quantifying the impact of adverse weather conditions on road network performance." *Eur. J. Transp. Infrastruct. Res.* 16 (1): 128–149. https://doi.org/10.18757/ejtir.2016.16.1.3118.

Transportation Research Board. 2010. *Highway capacity manual*. Washington, DC: Transportation Research Board.

University of Utah. 2019. "MesoWest." Accessed September 3, 2013. http://mesowest.utah.edu.

Van Stralen, W., S. Calvert, and E. Molin. 2014. "The influence of adverse weather conditions on the probability of congestion on Dutch motorways." In *Proc., 93rd Annual Meeting of the Transportation Research Board.* Washington, DC: Transportation Research Board.

Downloaded from ascelibrary.org by SUNY at Stony Brook on 08/11/20. Copyright ASCE. For personal use only; all rights reserved.

J. Transp. Eng., Part A: Systems, 2020, 146(10): 04020120