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Identifying crash-prone traffic conditions under different weather on freeways

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ABSTRACT

Introduction: Understanding the relationships between traffic flow characteristics and crash risk under adverse weather conditions will help highway agencies develop proactive safety management strategies to improve traffic safety in adverse weather conditions. *Method:* The primary objective is to develop separate crash risk prediction models for different weather conditions. The crash data, weather data, and traffic data used in this study were collected on the I-880N freeway in California in 2008 and 2010. This study considered three different weather conditions: clear weather, rainy weather, and reduced visibility weather. The preliminary analysis showed that there was some heterogeneity in the risk estimates for traffic flow characteristics by weather conditions, and that the crash risk prediction model for all weather conditions cannot capture the impacts of the traffic flow variables on crash risk under adverse weather conditions. The Bayesian random intercept logistic regression models were applied to link the likelihood of crash occurrence with various traffic flow characteristics under different weather conditions. The crash risk prediction models were compared to their corresponding logistic regression model. *Results:* It was found that the random intercept model improved the goodness-of-fit of the crash risk prediction models. The model estimation results showed that the traffic flow characteristics contributing to crash risk were different across different weather conditions. The speed difference between upstream and downstream stations was found to be significant in each crash risk prediction model. Speed difference between upstream and downstream stations had the largest impact on crash risk in reduced visibility weather, followed by that in rainy weather. The ROC curves were further developed to evaluate the predictive performance of the crash risk prediction models under different weather conditions. The predictive performance of the crash risk model for clear weather was better than those of the crash risk models for adverse weather conditions. *Impact on industry:* The research results could promote a better understanding of the impacts of traffic flow characteristics on crash risk under adverse weather conditions, which will help transportation professionals to develop better crash prevention strategies in adverse weather.

1. Introduction

Adverse weather conditions are known to contribute to the dangerous driving conditions and dramatically increase crash rates. Due to the reduced visibility and friction between pavement and tires, driving under adverse weather conditions increases the risk of being in a crash. As shown in Table 1, a number of existing studies have confirmed that crash rates and injury rates increased significantly under rainy weather conditions (Andrey & Yagar, 1993; Bertness, 1980; Brodsky & Hakkert, 1988; Fridstrom, Ifver, Ingebrigtsen, Kulmala, & Thomsen, 1995; Keay & Simmonds, 2005). Bertness (1980) compared the crash frequency and severity under rainy and clear weather conditions based on a matched-pair approach. The results showed that crash frequency increased by 100% and average injured persons involved in crashes increased by 70% under rainy weather conditions. Fridstrom et al. (1995) applied Poisson regression model to investigate the impact of rainfall on injury crash frequency based the crash data aggregated over months. It was found that the rainy weather increased the monthly injury crash counts. Keay and Simmonds (2005) conducted a matched-pair analysis to compare the crash risk of clear and rainy weather conditions, and found that the crash risk under rainy weather conditions was 0.7 times larger than that under clear weather conditions. The results also demonstrated that the length of time since the last rainfall tended to increase the crash risk under rainy weather conditions.

Several studies also evaluated the impact of snowy weather on crash risk (Andrey, Mills, Leahy, & Suggett, 2003; Brown & Baass, 1997; Eisenberg & Warner, 2005; Khattak & Knapp, 2001; Knapp, Smithson, & Khattak, 2000; Qiu & Nixon, 2008). Eisenberg and Warner (2005) developed a negative binomial regression model to investigate the impact of snowfall on crash rate. The finding showed that the snowfall increased the crash frequency but decreased the risk of fatal and serious injury crash. The nonfatal-injury crash rates and property damage only crash

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Table 1
Research results of previous studies regarding the impacts of adverse weather on traffic safety.

Authors	Country	Data and methods	Research findings
Bertness (1980)	United States	➢ Crash data aggregated over days ➢ Comparing crash frequency and severity in rainy and non-rainy days by a matched-pair analysis	➢ Crash frequency increased by 100% in rainy days ➢ Average injured persons involved in crashes increased by 70% in rainy days
Brodsky and Hakkert (1988)	United States	➢ Crash data aggregated over days ➢ Comparing injury crash frequency in rainy and non-rainy days by a matched-pair	➢ Injury crash frequency in rainy days was two to three times greater than that in dry weather conditions
Andrey and Yagar (1993)	Canada	➢ Crash data aggregated over the period between the beginning and end of rain events ➢ Comparing the relative risk ratio of crashes in rain and non-rain events by a matched-pair analysis	➢ Crash frequency increased by 70% during rainfall than normally ➢ Crash risk returned to normal as soon as the rain has ended
Brown and Baass (1997)	Canada	➢ Crash data aggregated over month ➢ Comparing crash frequency and crash rate among twelve months	➢ The numbers and rates of death and serious injure crashes were lowest in winter months ➢ The largest numbers of property damage only crashes occurred in winter months
Eisenberg (2004)	United States	➢ Crash data aggregated over days and months ➢ Negative binomial regression	➢ Monthly fatal crash counts decreased by 8.12% for each unit increase in snowfall ➢ Daily fatal crash counts increased by 2.74% for each unit increase in snowfall
Fridstrom et al. (1995)	Denmark, Finland, Norway, Sweden	➢ Crash data aggregated over months ➢ Poisson regression model	➢ The rainy weather increased the monthly injury crash counts ➢ The snowy weather decreased the monthly injury crash counts and fatal crash counts
Keay and Simmonds (2005)	Australia	➢ Crash data aggregated over 3 h ➢ Estimating relative risk of crashes in wet conditions by a matched-pair analysis	➢ Crash risk under wet conditions was 0.7 times larger than that under clear weather ➢ Length of time since the last rainfall increased the crash risk under wet conditions
Knapp et al. (2000)	United States	➢ Crash data aggregated over the period between the beginning and end of the snow events ➢ Poisson regression model	➢ Crash rates increased by 13 times during snow events ➢ Snowfall intensity significantly increased crash frequency during winter snow events.
Eisenberg and Warner (2005)	United States	➢ Crash data aggregated over days and states ➢ Negative binomial regression	➢ Fatal crash rates decreased by 7% in snow days ➢ Nonfatal-injury crash rates increased by 23% in snow days ➢ Property damage only crash rates increased by 45% in snow days
Khattak and Knapp (2001)	United States	➢ Crash data aggregated over the period between the beginning and end of the snow events ➢ Binary logit model	➢ Non-injury crash rates increased by 21 times during snow events ➢ Injury crash rates increased by 11 times during snow events ➢ The snow weather conditions decreased the risk of injury crash relative to non-injury crash conditional on crash occurrence
Qiu and Nixon (2008)	–	Meta-analysis	➢ The rainy weather could increase the crash rates by 71% and the injury crash rates by 49%. ➢ The snowy weather could increase the crash rates by 84% and the injury crash rates by 75%.
Andrey et al. (2003)	Canada	➢ Crash data aggregated over 6 h ➢ Comparing the crash risk between precipitation and clear weather	➢ Crash frequency increased by 75% under rainy or snowy weather ➢ Average injured persons involved in crashes increased by 45% under rainy or snowy weather ➢ The impact of snowfall on crash frequency was greater than that of rainfall

rates increased by 23% and 45%, respectively, under snowy weather conditions. However, the fatal crash rates were found to decrease by 7% under snowy weather conditions. Brown and Baass (1997) compared the crash frequency and crash rate among the 12 months. It was found that the risk of fatal and serious injury crash was lowest in winter months, and that the largest numbers of property damage only crashes occurred in winter months. Qiu and Nixon (2008) conducted a meta-analysis to evaluate the impacts of weather on traffic crashes by generalizing the research findings from previous studies between 1967 and 2005. The research results demonstrated that the snowy weather could increase the crash rate by 84% and the injury rate by 75%.

In recent years, attention has been given to developing real-time crash prediction models which estimate the likelihood of crash occurrence by traffic flow characteristics, such as traffic occupancy, vehicle speed and standard deviation of vehicle speed (Abdel-Aty, Uddin, & Pande, 2005; Ahmed, Abdel-Aty, & Yu, 2012; Christoforou, Cohen, & Karlaftis, 2010; Golob & Recker, 2003, 2004; Golob, Recker, & Pavlis, 2008; Hossain & Muromachi, 2011; Hourdos, Garg, Michalopoulos, & Davis, 2006; Li, Chung, Liu, Wang, & Ragland, 2012; Oh, Oh, Ritchie, & Chang, 2001, 2005; Qu, Wang, Liu, & Noyce, 2012; Xu, Liu, Wang, & Li, 2012; Xu, Wang, & Liu, 2013; Zheng, Ahna, & Monsere, 2010). Understanding these relationships will help transportation professionals to identify hazardous traffic conditions with high crash risk ahead of crash occurrence and to develop proactive traffic management strategies to remove the hazardous traffic conditions in dynamic traffic safety management systems. The first attempt to link the crash risk with traffic flow characteristics measured with loop detectors was conducted by Oh et al. (2001, 2005). They found that the standard deviation of vehicle speeds in 5-min time interval was a good indicator to identify hazardous traffic conditions with high crash potential. A non-parametric Bayesian classification approach was used to develop a real-time crash prediction model based on average occupancy and standard deviation of vehicle speeds.

Abdel-Aty et al. (2005) developed separate crash risk prediction models for high speed and low speed regime based on the conditional logistic regression model. The results showed that the crash risk in high speed regime was affected by the propagating shock wave towards the upstream, and that the queue formation and dissipation contributed to the high crash risk in low speed regime. Hourdos et al. (2006) applied the binary logistic regression model to identify crash-prone conditions on freeways using traffic data captured by video cameras. Several traffic flow variables contributing to crash likelihood were identified, such as large speed differences between lanes and compression waves leading to abrupt changes in traffic flow. Christoforou et al. (2010) applied the multivariate Probit model to examine the effects of various traffic characteristics on crash type. It was found that the traffic flow characteristics contributing to crash risk were quite different across different crash types. The rear-end crashes involving two vehicles were more likely to occur under traffic conditions with relatively low values of both speed and density, while the single-vehicle crashes appear to be largely geometry-dependent.