Accident Analysis and Prevention 43 (2011) 1730–1737

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

A study on crashes related to visibility obstruction due to fog and smoke

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ARTICLE INFO

Article history:
Received 21 September 2010
Received in revised form 31 March 2011
Accepted 2 April 2011

Keywords:
Fog and smoke
Visibility
Crash risk
Injury severity

ABSTRACT

Research on weather effects has focused on snow- or rain-related crashes. However, there is a lack of understanding of crashes that occur during fog or smoke (FS). This study presents a comprehensive examination of FS-related crashes using crash data from Florida between 2003 and 2007. A two-stage research strategy was implemented (1) to examine FS-related crash characteristics with respect to temporal distribution, influential factors and crash types and (2) to estimate the effects of various factors on injury severity given that a FS-related crash has occurred. The morning hours from December to February are the prevalent times for FS-related crashes. Compared to crashes under clear-visibility conditions, FS-related crashes tend to result in more severe injuries and involve more vehicles. Head-on and rear-end crashes are the two most common crash types in terms of crash risk and severity. These crashes were more prevalent on high-speed roads, undivided roads, roads with no sidewalks and two-lane rural roads. Moreover, FS-related crashes were more likely to occur at night without street lighting, leading to more severe injuries.

1. Introduction

The effect of weather events on the operations and safety of transportation is a key issue in today's transportation research. Previous studies have discussed this key issue from a rather generic viewpoint. Some studies have discussed climate change effects on the transportation sector as a whole (Koetse and Rietveld, 2009), while others (Maze et al., 2006) have shown the effect of different weather events on traffic operations, safety, demand, flow and intensity (Cools et al., 2008). Another study (Edwards, 1999) found a reduction in mean speed among motorists during wet and misty weather, although the reduction did not compensate for the hazards imposed by the inclement weather. The effects of weather and weather forecast on driver behavior have also been studied (Kilpelainen and Summala, 2007), and it has been concluded that drivers should be informed of specific local weather conditions rather than forecasts for an entire region.

In the United States, current records on crashes due to three major inclement weather events (rain, snow and fog/smoke; see Table 1) show that the fatal crashes under such weather conditions is certainly a major problem that needs to be addressed. These statistics show that snowy weather is a contributing factor in traffic crashes and, as expected, is more commonly associated with fatal crashes in the northern US states, whereas the top states in terms of rain- or Fog or Smoke (FS)-related fatal crashes are mostly located in the southern parts of the US, including Texas, Florida and California.

Previous studies (Qin et al., 2006; Khattak and Knapp, 2001; Oh et al., 2009) have heavily focused on snow- and rain-related crashes in certain northern states. However, there is a lack of comprehensive research on the crashes that occur under the influence of fog or smoke. One study (Qiu and Nixon, 2008) focused on vehicle crashes and the impact of weather on crash rates on highways; its main objective was to quantify the weather impact on traffic crashes. It used a meta-analysis approach to weather crashes, including fog-related crashes, with no conclusive result. Another study (Wanvik, 2009) focused on the effect of road lighting on crashes and implied that the effect of lighting during foggy conditions may be underestimated in safety studies. Still another study (Musk, 1991) mentioned that fog is the weather hazard that drivers fear most. Research on roadways in the UK (Moore and Cooper, 1972) concluded that despite a 20% decrease in the amount of traffic in dense fog, there was a 16% increase in personal injury crashes. Some studies (Codling, 1971; Summer et al., 1977) have shown that fog crashes tend to involve multiple vehicles, and one study (Perry, 1981) found that those crashes often occur in a few "black-spots" (locations where crashes are concentrated) and frequently on motorways. One study (Edwards, 1998) on crash severity on

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doi:10.1016/j.aap.2011.04.003

Table 1
Inclement weather-related fatal crashes in the US (2000–2007).

Rank	Rain		Snow		Fog/smoke	
	State	Fatal crashes	State	Fatal crashes	State	Fatal crashes
1	Texas	1927	Michigan	572	California	380
2	Florida	1403	Pennsylvania	429	Texas	356
3	California	1340	New York	380	Florida	299
4	Pennsylvania	1060	Ohio	316	North Carolina	168
5	North Carolina	1025	Wisconsin	304	Georgia	146
Mean*		447		97		73
S.D.*		428		121		82
Total*		22813		4972		3729

Data queried from Fatality Analysis Reporting System (FARS).
* Statistics based on all 50 states, the District of Columbia, and Puerto Rico.

British motorways concluded that speed is a major contributing factor in many of the pile-up crashes that occur in foggy conditions. The effects of fog on car following performance have been studied (Kang et al., 2008), and it was concluded that drivers tend to maintain an adequate distance headway under the most severe fog conditions. Another study (Cools et al., 2008) assessed the effect of weather on traffic intensity. This study had conclusive results for snowfall and rain, but the effect of reduced visibility due to fog and cloudiness remains inconclusive.

Previous results suggest that even though a significant amount of research has been conducted on the impact of weather on traffic crashes, conclusive findings are available only for rain and snow crashes. There is indeed a need to understand the crash characteristics and potential outcomes of FS-related crashes so that proper countermeasures could be proposed. As shown in Table 1, Florida is among the top states in the US in terms of fatal FS-related crashes. This study aims to provide a comprehensive analysis of FS-related crashes in Florida. The methods and the major results related to the two analyses undertaken in this study are as follows.

(1) A crash characteristics analysis examines the characteristics of FS-related crashes compared to crashes that occur under clear visibility conditions. Issues investigated include temporal distribution, crash types and the effects of various geometric, traffic, human and environmental factors.
(2) An injury severity analysis estimates the effects of various traffic and environmental factors on injury severity given that an FS-related crash has occurred. Results suggest several appropriate countermeasures that can be proactively proposed to reduce the risk of severe crashes at locations that are prone to FS-related crashes.

2. Data preparation

For the purpose of this study, all state roads in Florida were included. All crashes on these state roads were extracted from the Crash Analysis and Reporting (CAR) system database maintained by the Florida Department of Transportation. Data on roadway characteristics were collected from the Roadway Characteristics Inventory (RCI) database. Crash data from 2003 to 2007 were investigated, along with the corresponding RCI data pertaining to each crash location. These two databases were merged according to the unique roadway identifiers used in both. Hence, the final database contained various characteristics that can be associated with each specific crash, including (i) driver characteristics (e.g., age) (ii) roadway characteristics (e.g., posted speed and divided/undivided) and (iii) environmental characteristics (e.g., weather conditions and visibility conditions).

The FS-related crashes were specifically extracted based on several constraints to ensure that only those crashes that occurred in foggy or smoky conditions, without other weather conditions, were selected. Vision obstruction was used as the secondary filter variable, whereas "weather condition" was used as the primary filter variable. As such, FS-related crashes do not intertwine with other poor visibility conditions, such as heavy rain or glare from sun or headlights. As a result, a total of 994 FS-related crashes were identified during 2003–2007. Fig. 1 (plotted in ArcGIS) depicts the FS-related crashes on the state roads of Florida overlaid on a map of county boundaries. We merged fog- and smoke-related crashes together, given that the visibility obstructions they create are virtually the same. There is no information available on the level of visibility for fog or smoke in the CAR and RCI databases. So only information on fog or smoke (FS) versus clear visibility (CV) conditions was associated with crashes.

Furthermore, based on the spatial locations of these FS-related crashes, a total of 597 road segments were manually defined, which have largely uniform road characteristics. The length of these segments ranges from 2 to 5 miles. For the purpose of the comparison, a dataset that contains all CV crashes (120,053 crashes) occurring on these 597 road segments was created as a control group with respect to the FS-related crashes. Herein, the CV condition refers to an ambient environment with no prevalent vision obstruction.

3. Crash characteristics analysis

A detailed analysis of FS-related crashes that focuses on the temporal distribution of these crashes and compares FS-related crashes to CV crashes in terms of significant factors (i.e., driver, roadway and environmental factors) is provided here. Simple odds ratios are also introduced to compare the FS-related crashes to the CV crashes across various severity levels and/or collision types.

3.1. Temporal distribution

Vision obstruction due to FS occurs during different times of the day in different seasons. Therefore, the crash frequencies in these conditions vary with time of day and season. It is therefore worthwhile to examine the temporal distribution of FS-related crashes. As seen from Fig. 2, at the early dawn hours and subsequent hours when FS is prominent (especially from 5am to 8am), the number of crashes due to FS is relatively high. Moreover, looking at the monthly variations in these crashes, the period from December to February is associated with a high number of FS-related crashes. It is interesting to note that in the month of May, there is a sudden increase in the crash frequency trend. This can be explained by the increase in smoke-related crashes in particular; a dry season prevails at that time of the year, which probably increases the likelihood of wildfires or the propagation of fires. To summarize, the early morning hours from 5am to 8am from December to February are the most likely times for FS-related crashes.

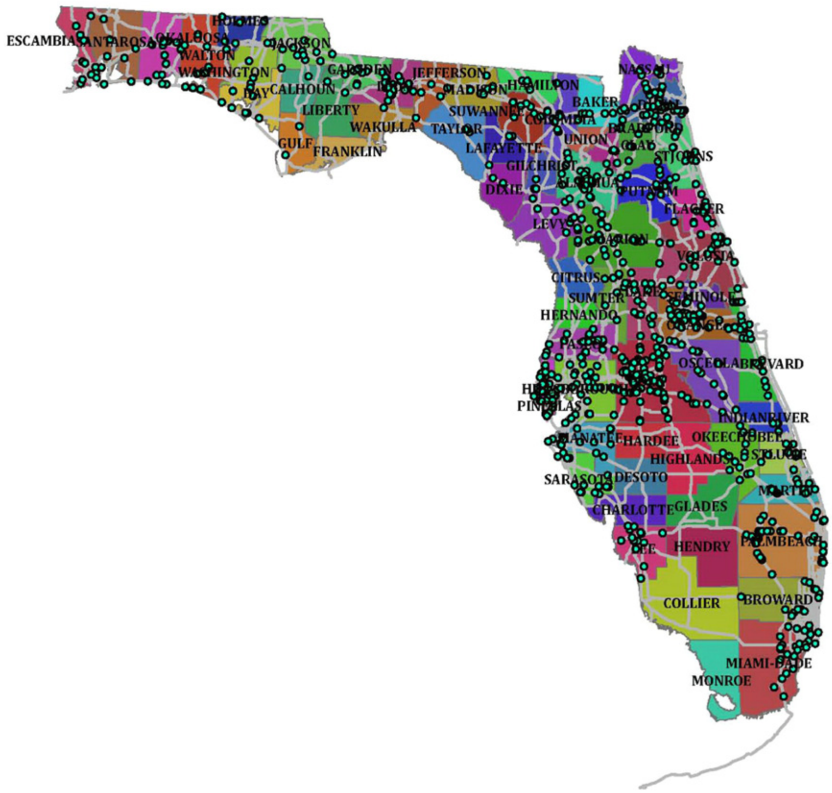

Fig. 1. Fog and smoke crashes in Florida (2003–2007).

3.2. Contributing factors

Different factors (i.e., roadway, driver and environmental factors) may have direct or indirect effects on the occurrence of FS-related crashes. In this analysis, the FS-related crash frequencies under different conditions are compared to corresponding CV crashes to indicate the significant factors that affect FS-related crashes. Fig. 3 shows the effects of different factors on FS-related crashes as compared to CV crashes.

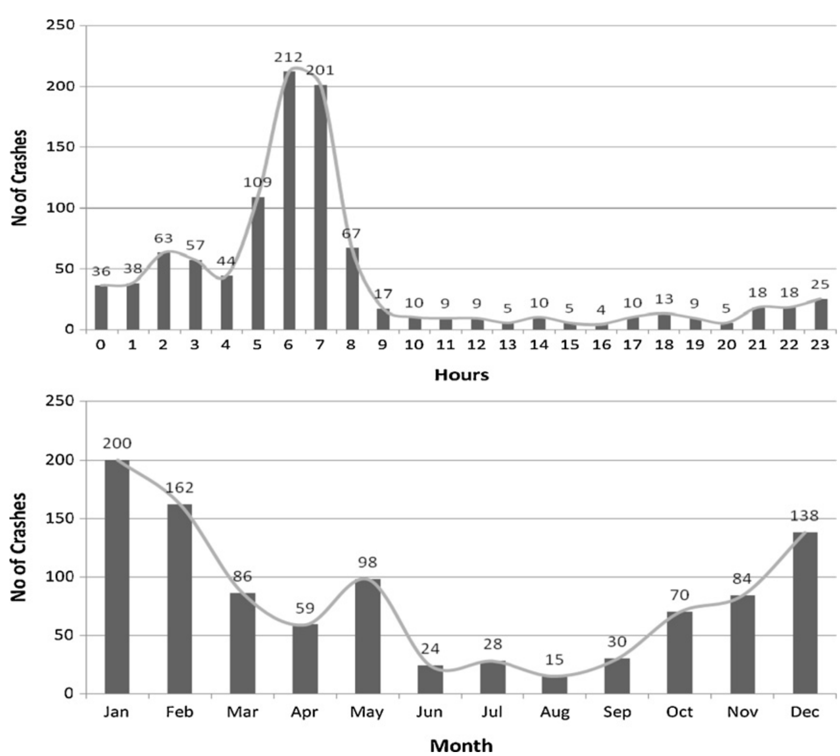

Fig. 2. Temporal distributions of fog and smoke crashes in Florida (2003–2007).

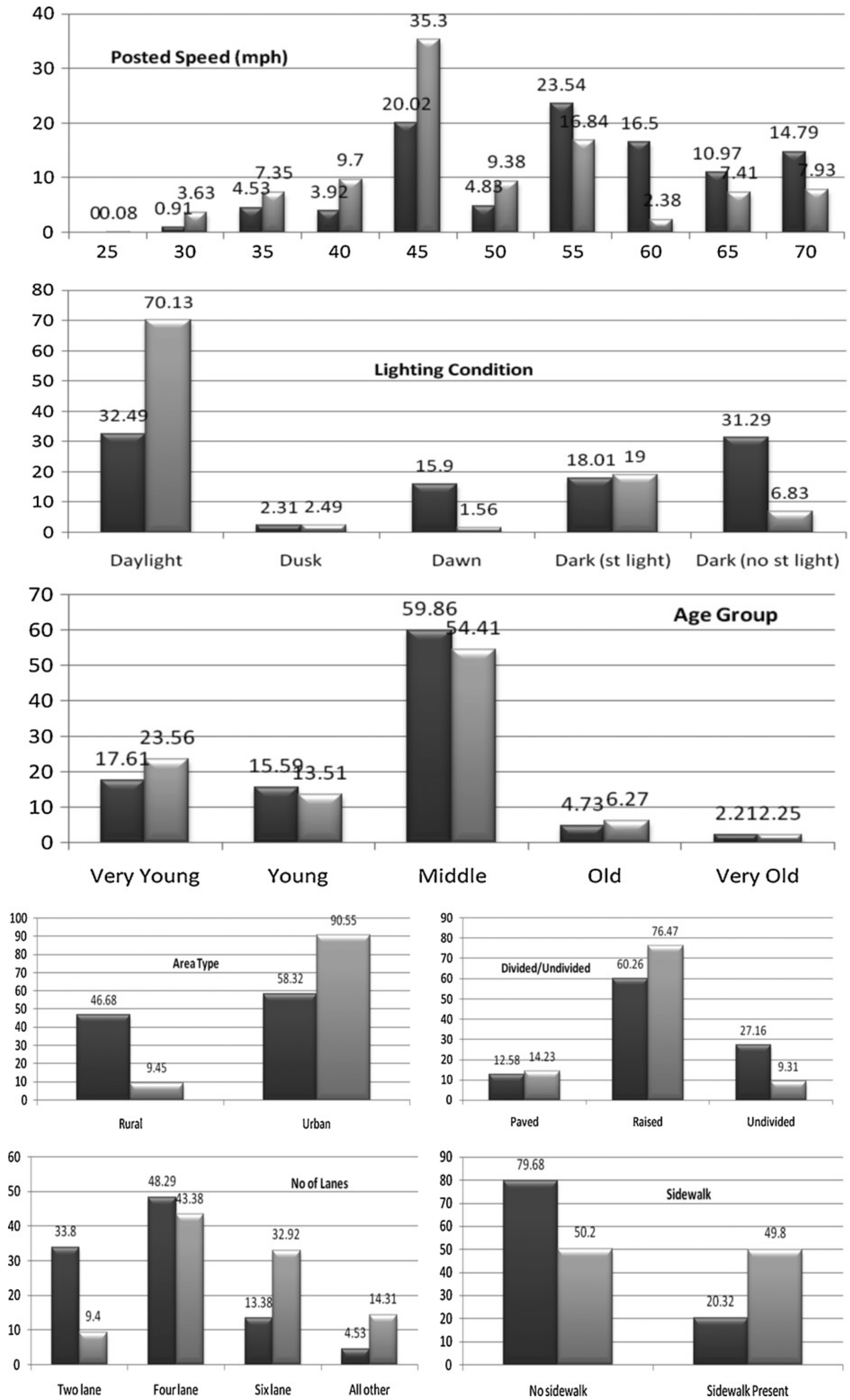

Fig. 3. Comparison of the effects of contributing factors on fog/smoke crashes versus clear-visibility crashes in Florida (2003–2007) (Black bar: % of fog/smoke crashes; Grey bar: % of clear-visibility crashes).

Several important and interesting inferences can be made from these comparisons of FS versus CV crash frequencies. At posted speeds of 55 mph or higher, the number of FS-related crashes is higher compared to corresponding CV crashes. Lighting conditions adversely affects FS-related crashes, as suggested in Fig. 3; at dawn and at night with no street lights, the crash frequencies are high in FS conditions (15.9% and 31.29% of FS-related crashes, respectively) compared to CV conditions, as only 1.56% of CV crashes occurred at dawn and 6.83% occurred at night with no street lights. These results also confirm the findings observed in Fig. 3 and are consistent with previous conclusions (Wanvik, 2009). Young and middle-aged drivers in particular are more prone to crashes under FS conditions. This might be due to the fact that during the night and the very early morning when fog prevail, young drivers have increased exposure. Moreover, young drivers drive to school in the early morning, and middle age drivers also drive to work at this time; thus, these drivers are more likely to be involved in FS-related crashes.

As shown in Fig. 3, FS is very prevalent in rural areas, as confirmed by the fact that 46.68% of FS-related crashes occurred in rural areas compared to only 9.45% of CV crashes. Looking at the roadway characteristics, 60.26% of FS-related crashes occurred on roadways with raised medians as compared to 76.47% of CV crashes. In addition, 9.31% of CV crashes occurred on undivided roadways as compared to 27.16% of FS-related crashes. Examining the surface width (i.e., the number of lanes), most (48.29%) FS-related crashes occurred on four-lane roadways compared to 43.38% for CV conditions. However, the key finding is the effect of two-lane roadways, where a substantial 33.8% of FS-related crashes occurred; only 9.4% of crashes occurred under CV conditions on these roadways. An absence of sidewalk also increased the number of FS-related crashes, as 79.68% of FS-related crashes occurred on roadways without sidewalks compared to 50.68% of CV crashes. This finding could indicate the increased frequency of FS-related crashes on rural highways.

3.3. Injury severity and collision type

The statistics shown in Table 1 reveal the startling fact that Florida is among the top three states for fatalities in crashes that occur in FS conditions. The injury severity of a traffic crash is a key issue. Therefore, in the absence of adequate studies of the severity of weather-related crashes and FS-related crashes in particular, it is important to examine the severity of crashes under FS conditions. In the crash database, injury severity is defined according to five levels; “no-injury/property damage only”, “possible injury” and “non-incapacitating injury” are considered non-severe crashes, and “incapacitating injury” and “fatal (within 30 days)” are considered severe crashes.

Moreover, in the event of a crash, the collision type may be unique to the FS conditions. Given that a driver’s vision is obstructed under FS conditions, FS collision types may be different from collision types under CV conditions. Therefore, some collision types may be prominent in FS-related crashes. Hence, odds ratios are introduced here to compare crashes in FS versus CV conditions across different collision types. The crash database record has a total of collision types based on the first harmful event. The major collision types that have an acceptable number of crash observations are investigated in this study; they include rear-end, head-on, angle, left turn and sideswipe collisions. Analysis is also applied to pile-up crashes in which more than two vehicles are involved; this collision type is referred to as a multiple vehicle crash in this study.

To address whether crashes under FS conditions lead to more severe injuries and which types of collisions are more commonly associated with FS-related crashes, odds ratios are calculated based on equation 1 as follows.

$$\text{O.R.(Type)} = \frac{\text{Type(FS)}/\text{Type(CV)}}{\text{All(FS)}/\text{All(CV)}} \quad (1)$$

where O.R. (Type) is the odds ratio of a particular type of crash (severe crash and/or collision types) under FS conditions versus CV conditions. Type(FS) is the crash number of a particular type under FS conditions. Type(CV) is the crash number of a particular type at the segments under CV conditions. All(FS) is the total number of all types of crashes under FS conditions. All(CV) is the total number of all types of crashes at the segments under CV conditions.

Furthermore, the interaction effects between crash severity and collision type and between multiple vehicle crash and collision types are introduced as well, and the odds ratios are calculated for these interactions. The important results from the analyses are summarized in Fig. 4. The top plot in Fig. 4 shows the odds of different crash types (including severe crashes) in FS conditions versus CV conditions, and the bottom plot shows the odds of different collision types in FS conditions versus CV conditions, given that the

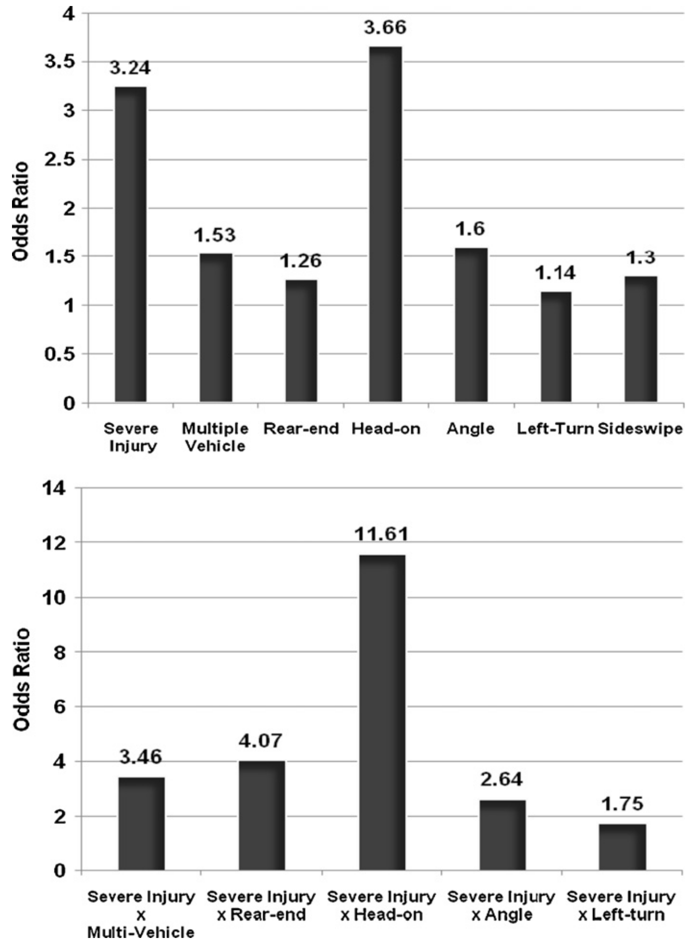

Fig. 4. Odds ratios for crash severity and collision type under FS conditions versus CV conditions in Florida (2003–2007).

crash is a severe crash. All Odds ratios shown in Fig. 4 for crash severity and collision type under FS conditions are significantly higher than 1 at the 95% confidence level using a Pearson Chi-square test, except the odds ratio for left-turn crashes.

It is quite revealing that compared to CV conditions, FS conditions pose a more deadly threat in terms of crash severity. The elevated odds ratios are as much as 3.24-times higher compared to CV conditions. Moreover, a higher probability (O.R. = 1.53) of a crash involving multiple vehicles is associated with FS conditions. As indicated in previous studies (Codling, 1971; Summer et al., 1977), pile-up crashes may predominate during FS conditions due to reduced visibility. Regarding collision type, the likelihoods of all typical collision types investigated are higher under FS conditions than under CV conditions. Notably, the highest odds are associated with head-on crashes (O.R. = 3.66). This result is interesting because a substantially greater proportion of FS-related crashes occurs on undivided roadways compared to CV crashes (i.e., 27.16% versus 9.31%), as noted above in Section 3.2. Crashes between vehicles travelling in opposite directions on undivided roads tend to be head-on collisions. Thus, this is consistent with the preliminary findings that most FS-related crashes occurred in rural areas and on undivided roadways. Regarding the dominance of FS-related crashes versus CV crashes in these rural conditions, it is also possible that high-speed roads might also be an important contributing factor to these high odds. It is possible that the reduction in visibility combined with high speed can contribute to FS-related crashes, and therefore, potential countermeasures should address preventing and reducing the severity of FS-related crashes.

Table 2
Crash severity model variables.

Variables	Description	mean	S.D.	Min	Max
Response variables					
Crash severity level	C1: no injury, property damage only (PDO) C2: possible injury C3: non-incapacitating injury C4: incapacitating injury C5: traffic fatality	2.22	1.22	1	5
Covariates					
Rural area	If road is in a rural area = 1, otherwise = 0	0.47	0.50	0	1
Principle arterial	If road is principle arterial = 1, otherwise = 0	0.47	0.50	0	1
No. of lanes	Continuous variable: number of lanes	3.67	1.46	2	10
ADT	Continuous variable: average daily traffic (k)	28.1	27.2	0.6	197
Speed limit	Maximum speed limit on the road segment	55.17	10.12	30	70
Shoulder width	Continuous variable (feet)	5.72	3.00	0	20
Truck factor	Average truck factor per day	13.12	8.63	0	47.3
No division	If road is undivided = 1, otherwise = 0	0.27	0.44	0	1
Skid	If skid coeff. ≤ 30, then = 1, otherwise = 0	0.06	0.23	0	1
Curve	If crash occurs at a curve = 1, otherwise = 0	0.08	0.26	0	1
Intersection	If crash occurs at an intersection = 1, otherwise = 0	0.36	0.48	0	1
Dusk or dawn	If crash occurs at dusk or dawn = 1, otherwise = 0	0.18	0.39	0	1
Dark with street light	If crash occurs at night with street light = 1, otherwise = 0	0.18	0.38	0	1
Dark w/o street light	If crash occurs at night w/o street light =1, otherwise =0	0.31	0.46	0	1
Vehicle type	If vehicle type is automobile = 0, otherwise = 1	0.53	0.50	0	1
Young driver	If driver's age < 25 then = 1, otherwise = 0	0.33	0.47	0	1
Old driver	If driver's age > 65 then = 1, otherwise = 0	0.07	0.25	0	1
Alcohol use	If crash occurs with alcohol use = 1, otherwise = 0	0.17	0.38	0	1

As suggested by the interaction effects, given a head-on, rear-end or multi-vehicle crash under FS conditions, there is a significantly higher probability of that crash being severe in contrast to other types of crashes. This implies that efforts to reduce injury severity in FS-related crashes will be most effective by reducing head-on, rear-end and multiple vehicle crashes. These preliminary results lead to a more in-depth analysis of the severity of FS-related crashes, which is described in the following section. The high and significant odds ratio (3.24) for severe crashes under FS conditions compared to the CV conditions motivate us to analyze injury severity under FS.

4. Injury severity analysis using a multilevel ordered logistic model

This section presents the results of an injury severity analysis for FS-related crashes based on a multilevel ordered logistic model.

4.1. Model description

According to the CAR database, the injury severity levels of the 994 FS-related crashes are defined into the following five ordered categories.

Category 1 (C1): no injury/property damage only (PDO)
Category 2 (C2): possible injury
Category 3 (C3): non-incapacitating injury
Category 4 (C4): incapacitating injury
Category 5 (C5): fatality

To examine ordinal severity outcomes, a multilevel ordered logistic model is specified to examine the effects of various risk factors. Suppose that y_{ij} is the severity level of the ith crash that occurred at the jth segment (i = 1,. . .,994; j = 1,. . .,597). In an ordinal response model, a series of latent thresholds are generally formulated. Specifically, a one-dimension space of real numbers is divided into five intervals according to four thresholds (γ_{kj}, k = 1, 2, 3, 4) that correspond to the five ordered categories C_1,. . .,C_5. In contrast to the ordinary ordered logistic model, the multilevel model accounts for cross-segment heterogeneities by specifying a set of variable thresholds for individual segments. The thresholds define the boundary between the intervals corresponding to observed severity outcomes. The latent response variable is denoted by y_{ij}^*, and the observed categorical variable y_{ij} is related to y_{ij}^* according to the threshold model defined as follows.

$$y_{ij} = \begin{cases} 1 & \text{if } -\infty < y_{ij}^* \le \gamma_{1j} \\ k & \text{if } \gamma_{(k-1)j} < y_{ij}^* \le \gamma_{kj}, \quad k = 2, 3, 4 \\ 5 & \text{if } \gamma_{4j} < y_{ij}^* < +\infty \end{cases}$$

The ordinal models can be written as follows.

$$y_{ij}^* = \theta_{ij} + \varepsilon_{ij}, \quad \text{and} \quad \theta_{ij} = \sum_{p=1}^{P} \beta_p x_{pij}$$

x_{pij} is the crash-level covariate, and ε_{ij} is the disturbance term, which is assumed to have a logistic distribution, with F as the cumulative density function. Thus, the cumulative response probabilities for the three categories of the ordinal outcome could be denoted as follows.

$$P_{ij(k)} = Pr(y_{ij} \le k) = F(\gamma_{kj} - \theta_{ij}) = \frac{\exp(\gamma_{kj} - \theta_{ij})}{1 + \exp(\gamma_{kj} - \theta_{ij})}, \quad k = 1, 2, 3, 4$$

The idea of cumulative probabilities leads naturally to the following cumulative logistic model.

$$\begin{aligned} \text{Logit}(P_{ij(k)}) = \log\left[\frac{P_{ij(k)}}{1 - P_{ij(k)}}\right] &= \log\left[\frac{\Pr(y_{ij} \le k)}{\Pr(y_{ij} > k)}\right] \\ &= \gamma_{kj} - \theta_{ij}, \quad k = 1, 2, 3, 4 \end{aligned}$$

At the segment level, γ_{kj} could be specified as random effects.

$$\gamma_{kj} = \gamma_k + \sum_{q=1}^{Q} \alpha_q z_{qj} + b_j, \quad k = 1, 2, 3, 4$$

Note that the intercept γ_k represents a constant threshold component for all segments. Given different segment-level covariates z_{qj}, the thresholds vary between segments. Furthermore, to accommodate cross-segment heterogeneities, a random effect

Table 3
Parameter estimation of the multilevel ordered logistic model.

Variable	Mean	S.D.	10%	Median	90%
Gamma1	−1.169	0.729	−2.116	−1.185	−0.273
Gamma2	−0.302	0.727	−1.243	−0.317	0.592
Gamma3	0.944	0.727	0.009	0.928	1.837
Gamma4	2.267	0.734	1.326	2.252	3.170
Ln(ADT)	−0.080	0.069	−0.170	−0.083	−0.005
Rural area	0.438	0.153	0.243	0.439	0.635
Dark w/o street light	0.216	0.135	0.039	0.218	0.389
Truck factor	−0.011	0.008	−0.021	−0.011	0.000
Young driver	−0.225	0.127	−0.390	−0.223	−0.064
Tau	65.82	63.15	10.06	40.83	145.9
Deviance	2824	13.79	2806	2827	2837
DIC	2844.7				

component b_j is formulated, which is normally distributed with a mean of zero and precision $tau \sim Gamma(0.01, 0.01)$. z_{qz} is a covariate parameter with different segment levels. The main motivation for introducing the residual term is that crashes within a segment are correlated. For the estimation of parameters (α, β), a positive coefficient indicates an increase in the likelihood of high severity given an increase in the corresponding covariate.

4.2. Model estimation and results

Eighteen covariates obtained from the CAR and RCI databases were used to explain the variations in FS-related crash severity. These variables are listed in Table 2 together with their descriptive statistics. The model was estimated using the MCMC technique under a Bayesian framework, which was implemented with WinBUGS software (Spiegelhalter et al., 2003).

In the model estimation, a backward procedure was employed for variable selection. Specifically, starting with all considered variables, each variable was tested for statistical significance, and insignificant variables were eliminated. Table 3 shows the final results from the parameter estimation; only statistically significant covariates are retained. The precision parameter *tau* is significant according to the Bayesian Credible Interval (10.06, 145.9). This justifies the specification of cross-segment heterogeneities. In other words, within-segment covariance exists among crashes that occurred in the same road segment.

The significant covariates include Ln(ADT), Rural area, Dark w/o street light, Truck factor and Young driver. As shown in Table 3, the increase in traffic volume (as reflected by the ADT) has a positive effect in reducing the injury severity level of FS-related crashes (−0.080). This result may be explained by the reduced speeds generally associated with heavy traffic roads. As reported in a previous study (Edwards, 1998), speeding is a major contributing factor leading to higher crash severity in pile-up crashes in foggy conditions. This result is further confirmed by the positive parameter for the variable Rural area (0.43). Specifically, results show that severe crashes are much more likely to occur in rural areas as compared to suburban and urban areas. This might be due to the fact that on rural roads, drivers tend to drive at high speeds with low levels of alertness due to the low traffic volume. Travelling at a high speed, especially in reduced visibility conditions due to fog or smoke, has been widely proven to be associated with a reduced capability of the driver to avoid crashes. Likewise, this problem becomes more serious at night without street lighting, as indicated by the corresponding variable (0.216). This is expected because drivers may have increased reaction time and better perception ability in environments with good street lighting (Huang et al., 2008). One previous study (Wanvik, 2009) calculated that the risk of a crash increases by 12% in foggy conditions on unlit roads. Combined with the results of the present study, it may be concluded that the installation of street lights at FS-prone locations will be helpful in reducing both FS crash risk and the injury severity. Furthermore, it is surprising to observe a negative effect for the Truck factor (−0.011), although the effect is very close to zero. There seems to be no clear explanation for a decrease in the severity level associated with a higher Truck factor. Perhaps overall speed is reduced when trucks are present in the traffic stream, resulting in less severe crashes. Finally, the results show that FS-related crashes that involve young drivers tend to be less severe (−0.225). This result may be presumably due to the better vision, reaction abilities and the stronger physical conditions of young drivers, which may help them detect road hazards and/or avoid severe injuries in a crash under reduced visibility conditions. Nevertheless, it is worth noting that young drivers were associated with a higher crash risk under FS conditions compared to CV conditions, as shown in Fig. 3.

5. Conclusions

Fatal crashes related to fog or smoke (FS) occur frequently in Florida, which ranks third among all states in the United States in terms of FS-related crash fatalities. Using five-year crash data records, this paper presents a comprehensive study of FS-related crashes in Florida. In terms of temporal distribution, the morning hours from December to February are the most likely times for FS-related crashes.

Moreover, comprehensive efforts have been made to examine the effects of various factors on FS-related crash risk, crash type and crash severity compared to CV crashes; in addition, variations in the severity level given that a FS-related crash has occurred were also investigated. The effects of significant factors on FS-related crash risk and injury severity are generally consistent. Compared to CV crashes, FS-related crashes tend to result in more severe injuries and involve more vehicles. Head-on and rear-end crashes are the two most prevalent crash types in terms of crash risk and crash severity. These crashes were more prevalent on high-speed roads, undivided roads, roads with no sidewalks and two-lane rural roads. Thus, a reduction in speed limits and the installation of road medians are expected to improve safety at FS-prone locations. Another suggestion is road lighting improvement at the identified hotspots because FS-related crashes tend to occur at night without street lights, which also leads to more severe injury.

The findings of this paper can also be used to develop engineering projects to increase road safety in FS conditions. The analyses found that most FS-related crashes occurred on undivided rural roads in dark conditions without lighting, and crash severity is also very high in these conditions. Hence, solar and battery-powered systems could be installed to detect fog or smoke conditions and provide warnings in these locations, and subsequent Variable Message Signs (VMS) could also be installed to warn drivers who are heading toward FS conditions.

There are several possible expansions of this study from both a methodological and application-based perspective. Because this paper contrasted FS and CV crashes using odds analysis, extending this comparison to a binary model of FS versus CV crashes could reveal the differences between these two crash conditions. An ordered logit model of CV crashes could be estimated to compare the results to the FS ordered model presented in this paper. Frequency models could also be estimated for both types of crash conditions, although results associated with FS conditions might suffer from excessive zero counts.

Acknowledgement

This research has been funded by District 5 of the Florida Department of Transportation. Part of the work was partially supported by the Korea Science and Engineering Foundation (KOSEF) grant funded by the Korea government(MEST) (No.2010-0029446).

References

Codling, J.P., 1971. Thick Fog and its Effect on Traffic Flow and Accidents. Transport and Road Research Laboratory, TRRL Report LR 397, TRRL, Crowthorne.

Cools, M., Moons, E., Wets, G., 2008. Assessing the impact of weather on traffic intensity. In: Proceedings of the 87th Annual Meeting of the Transportation Research Board. CD-ROM. Transportation Research Board of the National Academies, Washington, D.C.

Edwards, J.B., 1998. The relationship between road accident severity and recorded weather. Journal of Safety Research 29 (4), 249–262.

Edwards, J.B., 1999. Speed adjustment of motorway commuter traffic to inclement weather. Transportation Research Part F 2, 1–14.

Huang, H., Chin, H.C., Haque, M.M., 2008. Severity of driver injury and vehicle damage in traffic crashes at intersections: Bayesian hierarchical analysis. Accident Analysis & Prevention 40 (1), 45–54.

Kang, J.J., Ni, R., Anderson, G.J., 2008. The effects of reduced visibility from fog on car following performance. In: Proceedings of the 87th Annual Meeting of the Transportation Research Board. CD-ROM. Transportation Research Board of the National Academies, Washington, D.C.

Khattak, A.J., Knapp, K.K., 2001. Interstate highway crash injuries during winter snow and nonsnow events. Transportation Research Record 1746, 30–36.

Kilpelainen, M., Summala, H., 2007. Effects of weather and weather forecasts on driver behavior. Transportation Research Part F 10, 288–299.

Koetse, M.J., Rietveld, P., 2009. The impact of climate change and weather on transport: an overview of empirical findings. Transportation Research Part D 14, 205–221.

Maze, H.T., Agarwal, M., Burchett, G., 2006. Whether weather matters to traffic demand, traffic safety, and traffic operations and flow. Transportation Research Record 1948, 170–176.

Moore, R.L., Cooper, L., 1972. Fog and Road Traffic. Transport and Road Research Laboratory, TRRL Report LR 446, TRRL, Crowthorne.

Musk, L., 1991. Climate as a factor in the planning and design of new roads and motorways. In: Perry, A.H., Symons, L.J. (Eds.), Highway Meteorology. E&FN Spon, London.

Oh, S., Chung, K., Ragland, D.R., Chan, C., 2009. Analysis of wet weather related collision concentration locations: empirical assessment of continuous risk profile. In: Proceedings of the 88th Annual Meeting of the Transportation Research Board. CD-ROM. Transportation Research Board of the National Academies, Washington, D.C.

Perry, A.H., 1981. Environmental Hazards in the British Isles. George Allen & Unwin, London.

Qin, X., Noyce, D., Lee, C., Kinar, J.R., 2006. Snowstorm event-based crash analysis. Transportation Research Record 1948, 135–141.

Qiu, L., Nixon, W.A., 2008. Effects of adverse weather on traffic crashes: systematic review and meta-analysis. In: Proceedings of the 87th Annual Meeting of the Transportation Research Board. CDROM. Transportation Research Board of the National Academies, Washington, D.C.

Spiegelhalter, D.J., Thomas, A., Best, N.G., Lunn, D., 2003. WinBUGS version 1.4.1 User Manual. MRC Biostatistics Unit, Cambridge, UK.

Summer, R., Baguley, C., Burton J., 1977. Driving in Fog on the M4. Transport and Road Research Laboratory, TRRL Report LR 281, TRRL, Crowthorne.

Wanvik, P.O., 2009. Effects of road lighting: an analysis based on Dutch accident statistics 1987–2006. Accident Analysis and Prevention 41, 123–128.