Appl. Spatial Analysis
https://doi.org/10.1007/s12061-018-9265-7

A Risk-Based Systematic Method for Identifying Fog-Related Crash Prone Locations

Soyoung Jung[1] · Xiao Qin[2] · Cheol Oh[3]

Received: 9 August 2017 / Accepted: 9 July 2018

Abstract Fog is one of the most influential factors in fatal crashes because of reduced visibility. This study aims to propose a systematic safety analysis framework for selecting fog-crash-prone areas on freeways. To achieve these goals, the spatial analysis in ArcGIS was combined with the latent class cluster-based crash severity estimation models. Nine latent class cluster-based crash severity estimation models were built. Fog events led to a statistically significant increase in the likelihood of fatal crashes in two of the nine models. Comparing the ArcGIS spatial clusters of fog-related exposure with the fatal crash-prone freeway segments, 28 freeway segments were found to be fog-crash-prone areas where safety improvements are required, particularly in foggy weather. Based on the spatial patterns of the fog-crash-prone freeway segments, this study concludes that the current standard for fog-crash-prone area selection should be modified to apply spatially different standards over the Korean freeway network. This study is the first data-driven study to comprehensively examine the effects of fog visibility levels and frequencies on fatal crashes in the entire Korean freeway system. The findings provide meaningful insights to the policy decision making for fog-related policy changes, highway safety enhancement and active traffic management strategies.

✉ Soyoung Jung
jung2@dyu.ac.kr

Xiao Qin
qinx@uwm.edu

Cheol Oh
cheolo@hanyang.ac.kr

[1] School of Safety Engineering, Dongyang University, 2741 Pyeonghwa-ro, Dongducheon-si 11307, Republic of Korea

[2] Department of Civil and Environmental Engineering, University of Wisconsin-Milwaukee, NWQ4414, P.O. Box 784, Milwaukee, WI 53201, USA

[3] Department of Transportation and Logistics Engineering, Hanyang University Erica Campus, 55 Hanyangdaehak-ro, Sangnok-gu, Ansan 15588, Republic of Korea

Published online: 27 July 2018

Keywords Fog · Visibility · Safety analysis framework · Spatial analysis · Latent class cluster · Policy decision making

Introduction

The reduced visibility caused by fog can compromise the safety of traveling public (Abdel-Aty et al. 2011; Ahmed et al. 2014; Huang et al. 2010; Qin et al. 2009). In the US, from 2010 to 2014, the only weather condition associated with a statistically elevated rate of fatalities per crash was fog (Tefft 2016). During the same period, crashes that occurred in fog resulted in 155% more fatalities per crash than crashes that occurred in clear weather. In addition, US crashes that occurred in fog resulted in 17.3 fatalities per 1000 crashes, which is significantly more than the value in any other weather condition.

The roadways in the Republic of Korea (called Korea hereafter) have also suffered from severe crashes because of fog events. According to the records of the Korea Road Traffic Authority from 2013 to 2015, 11.2 fatalities per 100 crashes occurred in the entire Korean road network in foggy weather. This record is the highest of all weather conditions in the same period (Korea Road Traffic Authority 2016) and much greater than the aforementioned US record (17.3 fatalities per 1000 crashes). Particularly, in 2015, a disastrous rear-end freeway crash occurred in foggy weather, which caused 75 visible injuries with two fatalities, and 106 vehicles were involved in the crash. This crash ignited the necessity to identify fog-crash-prone areas in the Korean road system. Accordingly, the Korean Ministry of Land, Infrastructure, and Transport (KMLIT) has encouraged the identification of freeway segments prone to fog-related crashes where safety enhancement policies are preferentially required. Note that the fog-crash-prone freeway segments in this study refer to the freeway segments with comparatively high potentials of crash occurrences in foggy weather conditions.

Furthermore, the KMLIT has supported an evaluation of the current selection standard for fog-crash-prone areas, particularly in the freeway system because the freeway fatality rate in foggy weather conditions (20 fatalities per 100 crashes) has been the highest of all road function classes. The current selection standard for fog-crash-prone freeway areas in Korea is that "if fog with visibility of 250 m or less occurs on 30 or more days on average in a year or severe crashes occurred in a certain freeway segment, then the freeway segment is considered as the fog-crash-prone area (KMLIT 2015)." However, the 250-m visibility and 30-days thresholds in the current standard of fog-crash-prone area selection are not data-driven and have not been validated by comparing crash observations and fog occurrence records based on road surface visibility levels. To select fog-crash-prone areas, a risk analysis using reliable road surface visibility data is one of the most important tasks to address road safety issues that are associated with the reduced visibility caused by fog. In general, weather station data of airports are used to examine the increased hazard of limited-visibility for the adjacent roadways, but the road surface visibility is not widely detected in Korea because of the high system installation cost. In other words, the main obstacle for revising the fog-crash-prone area selection standards is the lack of a scientific and systematic safety analysis framework that incorporates fog-related crash risk and fog exposure analysis. Fog occurrence or fog-crash-prone hot spots have been identified in past studies (Huang et al. 2010; Srivastava et al. 2016). However, few studies have quantitatively and comprehensively proposed a systematic safety analysis framework to identify fog-crash-prone areas and evaluated the relevant selection standards based on fog occurrences and the relevant surface visibility data.

Hence, the goals of this study are to provide a systematic safety analysis method for the selection of fog-crash-prone areas, which is specified by the following: (1) identifying top-priority freeway segments where particularly fog-related safety improvements are required (namely, fog-crash-prone areas), and (2) quantitatively evaluating the current standards for fog-crash-prone area selection. To achieve these goals, this study combines spatial cluster analysis with latent class cluster-based crash severity estimation modeling.

Literature Review

Many studies have discussed the key contributing factors to crashes under foggy conditions. Ni et al. (2012) explained that the reduced visibility caused by fog decreased the driver's ability to detect impending collisions. Several studies further identified the degradation of driver's driving ability with speed (McCann and Fontaine 2016; Yan et al. 2014). More specifically, Yan et al. (2014) illustrated through a driving simulator experiment that a driver could not respond in time to impending changes in car-following speed and road geometries, although the driver intended to reduce the speed to compensate foggy conditions. Regarding road geometry and vehicle type, Peng et al. (2017) found that the reduced visibility due to fog would significantly increase the risk of rear-end crashes for truck drivers or drivers traveling on inner lanes. The authors concluded that these drivers should be more careful about speeding during the reduced visibility. A study by Wu et al. (2018) drew similar conclusions in regard to road geometry in fog based on a crash risk increase indicator. The authors stated that more attention should be paid to ramp vicinities when the visibility dramatically decreases due to fog. The authors also identified the innermost lanes with heavier traffic to be more dangerous under foggy conditions.

Appropriate safety improvement strategies have been proposed to reduce fog-related crashes. Typical ITS-based traffic control strategies such as dynamic message signs, variable speed limit signs, beacons, or ramp meter have been implemented to change traffic speed and/or flow in fog-prone areas (Balke et al. 2007; Peng et al. 2017; Wang et al. 2017). Wu et al. (2018) recommended an ITS-based safety management system in specific regions in foggy weather. Their study stated that ITS devices can be systematically employed near ramp areas or innermost lanes to notify drivers about the potential risk.

The use of overhead lighting in fog-prone locations is one of the most common measures to show the road direction in foggy conditions (Perry and Symons 2003). On the other hand, Buchner et al. (2006) considered vehicle backlight position. Vehicles are perceived to be further away in foggy conditions than in clear ones. The authors demonstrated that subjects perceived vehicles with higher-positioned rear lights that were closer together as further away. They stated that such vehicles may have a higher chance of being 'rear-ended' in fog. They also stated that rear lights that are positioned closer to the ground with greater separation may therefore help trailing motorists better estimate and maintain a safer following distance.

Past studies have focused on the effect of fog on various factors that contribute to the increase in crash risk. Some studies have developed indicators or index to measure the impact of fog on safety. Few studies have systematically and comprehensively evaluated the policy for selecting fog crash-prone areas, which is the purpose of this study.

Data

The study area is the entire freeway system in Korea. In connection with the study area, three data sources were used for data collection and successive data processing: fog frequency and visibility records, a crash dataset, and a freeway network log, which were provided by the Korea Expressway Corporation (KoEX). In this section, we will specify the data sources and relevant data processing as follows.

Fog Data

Surface visibility data in foggy weather are required to reliably analyze the association between foggy weather and surface vehicle crashes. Generally, a visibility meter is used to measure the road surface visibility in foggy weather. However, the visibility meters in Korean freeway system have been installed on only a few bridges, and their measurements suffer from considerable error. It is understood that visual observation by naked eyes is more consistent with how far a driver can see rather than equipment-based observations. Therefore, fog visibility in foggy weather conditions was observed by visual measurements in the Korean freeway system during periods of fog as follows.

The entire Korean freeway network has been managed by 396 KoEX regional offices. The weather event in each freeway segment was observed by CCTV and the assigned safety patrol of a specific regional office every 30 min. When a fog event was reported to the regional office, a team of two recorders was dispatched to the area where fog occurred to record the fog visibility distance. In the entire Korean freeway system, fog visibility signs are installed on the roadside at 50 m intervals, which were used by the recorders to visually measure the fog visibility. One recorder recorded the furthest distance that the 50 m-interval fog visibility signs came in sight under the effect of fog, and the other recorder verified the recorded fog visibility. The KoEX fog visibility sign is shown in Fig. 1.

For each freeway segment where a fog event occurred, the KoEX teams recorded the following fog-related data: the freeway route number, the segment starting/end post miles, the code for the lowest level of administrative district (called “dong” in Korea), the date of the fog event, and the level of fog visibility. The fog visibility was classified into four levels: less than 50 m (V1), 50–100 m (V2), 100–250 m (V3), and 250–1000 m (V4). A sample of the fog dataset reported by the KoEX is shown in Table 1.

Based on the KoEX fog visibility and frequency data, the monthly trends of foggy days are provided in Fig. 2.

Figure 2 shows the monthly trends of the sum of foggy days over all freeway segments from 2013 to 2015. The monthly trends are similar at each time point, where

Fig. 1 Fog visibility signs in Korean freeway system

fog events are comparatively frequent in spring and autumn. This result indicates that the study area had no annual disparity in the fog occurrence patterns during the 3 years. Throughout the entire Korean freeway network, fog events occurred in at least one area, on an average of 25 days in a month and 296 days in a year. Specifically, the foggy day counts in the study area for each visibility level in the 3 years were as follows: 18 days for the 50-m visibility, 60 days for the 50–100-m visibility, 393 days for the 100–250-m visibility, and 417 days for the 250–1000-m visibility.

Crash Data

All crashes occurred in the entire Korean freeway system from 2013 to 2015 were collected for the current study, which were provided by KoEX. The KoEX crash data contained 24,238 crash observations with three severity categories: 662 fatal crashes, 1894 crashes with injuries, and 21,682 crashes with property damage only. Fatalities were recorded based on the outcome 30 days after the crash. Multiple data fields were linked to each crash observation, including information related to roadway, environment, traffic, vehicle, human, and emergency medical service (EMS) at the crash location and moment.

In the KoEX crash data, most data fields were categorical. Categories with 30 cases or more were coded separately. Common category coding in each data field was

Table 1 A sample of fog dataset

Route No.	Segment post mile (km)		Administrative district code	Date of fog occurrence	Surface visibility (m)			
	Start	End			Less than 50	50~100	100~250	250~1000
1	282	293.1	2,505,061	2013-01-13	–	–	O	–
1	282	293.1	2,505,061	2013-08-25	–	O	–	–
1	293.1	296.6	3,331,035	2013-01-13	–	–	O	–
1	293.1	296.6	3,331,035	2013-08-25	–	O	–	–

- indicates "not applicable"

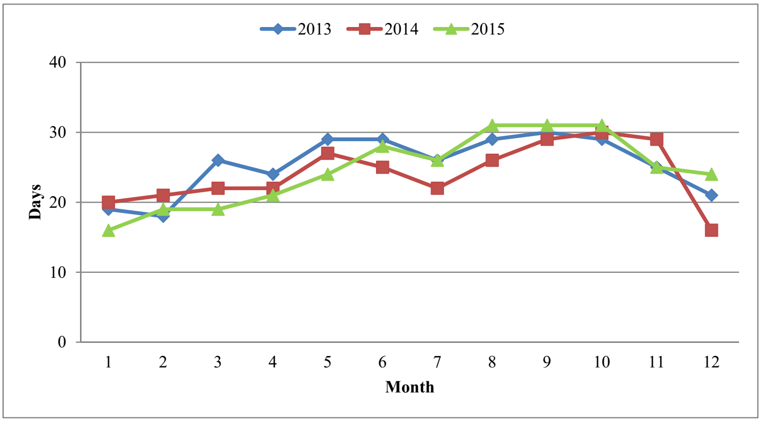

Fig. 2 Monthly trends of sum of foggy days over all freeway segments

employed in both the crash clustering and cluster-based crash severity estimation models. Based on the study aims, two categories of crash severity (fatal crashes vs. non-fatal crashes) were considered in the response variable to model cluster-based crash severity. The fields in the KoEX crash dataset are shown in Table 2.

Korean Freeway Network Log

The entire Korean freeway network is currently composed of 31 freeway routes with a total length of 3762 km (Korea Expressway Corportation 2013). The freeway network is divided into 508 freeway segments. A freeway segment is defined as the segment of freeway from one entry/exit ramp to the next ramp. For each freeway segment, the freeway network log provided by the KoEX included geometric and traffic information, such as the freeway route number, start/end post miles, segment length, number of travel lanes, heavy traffic percentage, and annual average daily traffic (AADT). The average freeway segment length is 7.4 km, with a range of 0.1 km to 31 km and an average of three travel lanes. By multiplying the AADT by the segment length, vehicle kilometers traveled (VKT) was computed for each freeway segment, and the average VKT for a freeway segment was approximately 367 thousand vehicles·km per day.

Methodology

This study aims to propose a systematic safety analysis framework to identify the top-priority fog-crash-prone areas in the Korean freeway system and evaluate the current standards of fog-crash-prone area selection. The framework includes two crucial elements: risk analysis and exposure analysis. The risk analysis was conducted by applying the latent class cluster (LCC)-based crash severity estimation model (binomial logit regression) to identify areas where fatal crashes are more susceptible to fog. For the exposure analysis, a local indicator of spatial autocorrelation (Getis-Ord G*) was applied to the spatially cluster size of fog exposure by the visibility levels (e.g., the number of foggy days by visibility levels). When a certain freeway segment with the potential for fog-affected fatal crashes and significant spatial cluster areas of fog-related

Table 2 Variable in crash dataset

Variable	Categories
Response	
Crash severity	Fatal crashes vs. non-fatal crashes
Temporal & Environmental	
Season of the year	Spring, summer, autumn, winter
Weekday	Weekend, weekdays
Weather	Adverse conditions (foggy, snowy, rainy, gusty), cloudy, clear
Driver	
Maneuvering	At-fault driver's maneuvering preceding crash: driving travel lanes, changing lanes, mistaking wheel operations, other violations
Physical status	At-fault driver's physical status: under the effects of alcohol/drugs, fatigue/drowsiness, sickness, distraction, normal
Sex	At fault driver's sex: female, male
Age group	Young (aged less than 25), elderly (aged 65 or greater), others (aged 25 to 64)
Vehicle	
At-fault vehicle type	Passenger car, van, truck, machine
Number of vehicles	Single vehicle involved, two vehicles involved, multiple vehicles involved
Roadway	
Crash location	Travel lane, ramp, acceleration/deceleration lane, shoulder, bridge/tunnel, rest area
No. of travel lanes	Number of travel lanes at the crash location
Province	Gangwon-do, Gyeonggi-do, Chungcheongbuk-do, Chungcheongnam-do, Jeonrabuk-do, Jeonranam-do, Gyeonsangbuk-do, Gyeongsangnam-do
Curve	Existence of a horizontal curve ($R < 1000$ m, $R \geq 1000$ m), tangent
Grade	Existence of a vertical curve (downgrade, upgrade), flat
Roadside protective facility	Existence of roadside facilities (guard rail/cable/fence/pipe, concrete wall), absence
Type of median	Fixed, moving, no median
Night light	Darkness at night, no need for light
Traffic	
Speed limit (km/h)	Traffic speed limit posted at crash location
AADT (vehs/day)	Average annual daily traffic volume for all travel lanes
Traffic limitation type	Traffic limitation (mainline occupied, shoulder occupied, work zone, traffic jam) at the moment of the crash, no traffic limitation
Crash	
Primary cause of crash	Driver factors (speeding, drowsiness, distraction, lane changing failure), vehicle factors (malfunction of equipment), roadway factors (animal or road surface interruption), others
Collision type	Head-on, rear-end, sideswipe, vehicle to road facilities, vehicle to animal or people
Emergency Medical Service (EMS) Time	
EMS unit response level	Time interval between EMS call received and EMS unit arrival: less than 5, 5~9, 10~14, 15~29, 30 or more minutes
On-scene time	Time interval between medical treatment by EMS unit and EMS unit leaving: less than 5, 5~9, 10~14, 15~29, 30 or more minutes

Binary coding is applied for categories of each variable; Each sub-category within parenthesis in each variable category is employed only for latent class cluster-based crash severity modeling exposure were common, the freeway segment was considered a top-priority fog-crash-prone area in this study. Combining the crash risk with the fog exposure, the areas with potential for improving safety were identified. The work flow for the study is shown in Fig. 3.

Theoretical concepts for the LCC-based crash estimation models and Getis-Ord G* for high fog occurrence locations and the reasons to use them are described as follows.

Latent Class Cluster-Based Crash Severity Estimation

Each element cluster membership in the LCC method can be computed from the estimated model parameters. The LCC was formulated as follows (Hosmer and Lemeshow 2000):

$$\mathrm{P}\left(Y_i|\theta\right) = \sum_{j=1}^{J} \mathrm{f}_j \ \mathrm{P}\left(Y_i\,|\mathrm{C}_j, \theta_j\right) \tag{1}$$

where P denotes the probability, Y_i represents the injury severity of a crash for the ith case (fatal crash or non-fatal crash), j ($j = 1$ to J) is a latent class number, f_j is the prior probability of data in latent class C_j, θ_j is the vector of cluster model parameters to be estimated, and P (Y_i | C_j, θ_j) is the mixture probability density. In the LCC method shown in Eq. (1), the posterior membership probabilities are directly estimated from the model parameters. Cases are assigned to the model class with the highest posterior probability.

Fog is one of the most significant environmental factors that cause severe crashes, but fog rarely occurs compared to other weather events such as clear, cloudy, snowy, or

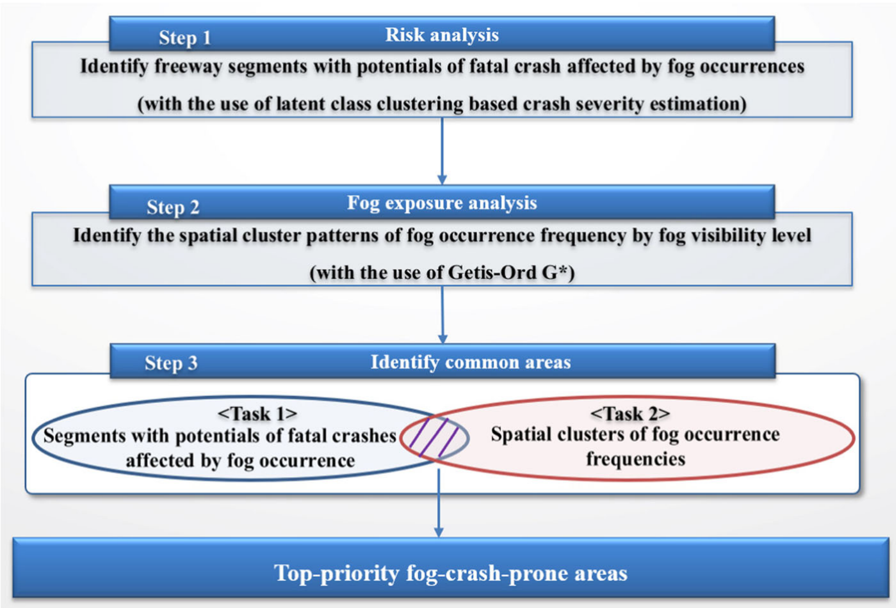

Fig. 3 Work flow for the study

rainy weather conditions. Moreover, the areas where fog frequently occurs are spatially specific. The number of crashes that occur in foggy weather is usually small. If we consider all crash observations that occur under all weather conditions, the effect of fog on crash occurrences may not be identified in the full data model because the effect of other factors with a large sample size on crashes is comparatively powerful. Therefore, this study did not rely on the full crash data-based model, so the clustering analysis was used to separate crashes that are mainly characterized by a few factors. The clustering approach enables us to identify crash groups where fog contributes to death, which mitigates the effect of confounding variables that may cause biased results (Jung et al. 2016).

The most common cluster analysis methods are partitioning-based (such as K-means), hierarchical-based (such as Ward's method), and density-based (such as latent class clustering) methods (Mohamed et al. 2013). Among these methods, the latent class clustering (LCC) method has several advantages. Several criteria to select the optimal number of clusters, such as Akaike information criterion (AIC), Bayesian information criterion (BIC), or consistent Akaike information criterion (CAIC), can be used in the LCC method (Depaire et al. 2008; Magidson and Vermunt 2002). Additionally, crashes are commonly associated with many contributing variables, and the crash dataset in the current study includes many data fields with various distributions. In this circumstance, the LCC method is advantageous to formulate a flexible model that does not imply any assumption regarding the nature of the variables, their underlying distributions, and the correlation patterns across observations and variables (Depaire et al. 2008; Magidson and Vermunt 2002). Therefore, the LCC method was used to separate homogenous crash groups in this study.

After separating each homogeneous crash cluster using the LCC, we conducted the LCC-based regression to quantify the effect of the explanatory variables in response to each crash cluster that is affected by fog events. For the LCC-based regression, Y is the crash severity, which is a binary response for fatal and non-fatal crashes. Because the "top-priority" fog-crash-prone areas are of interest in this study, the effect of the fog occurrence on fatal crashes in particular was emphasized instead of severe, moderate or minor injury crashes. Thus, the binary response (fatal crash vs. non-fatal crash) was considered in the LCC-based crash severity estimation. A standard binomial logit regression was combined with the LCC, as shown in Eq. 2 (Ni et al. 2012):

$$\text{logit P}(Y) = \log\left[\text{P}(Y)/(1-\text{P}(Y))\right] = \alpha + \beta X \tag{2}$$

where P is the probability of response Y (1 = fatal crash and 0 = non-fatal crash), α is the intercept, β is the vector of slope parameters, and $\boldsymbol{X}$ is a vector of crash-contributing variables.

Getis-Ord G* for High Fog Occurrence Locations

Freeway segments with a certain fog occurrence frequency are spatially distributed. Each freeway segment has a representative value of the number of foggy days in a year by visibility level, and each freeway segment is included in a single lowest administrative district. Comparing spatial clusters of the fog occurrence frequencies with freeway spots with potentials of fatal crashes discovered freeway segments where the number of foggy days and fatal crash potential were commonly high. The spatial cluster patterns in the number of foggy days by fog visibility level were identified by a local indicator of spatial autocorrelation (LISA). ArcGIS 10.1 was used for the LISA in this study.

For the LISA, the Getis-Ord G* statistic was employed to calculate the Z-score, which indicates whether features with high (hot) or low (cold) values are clustered at each location (Ord and Getis 1995). The Getis-Ord G* statistic begins with a null hypothesis that there is no spatial pattern among the studied features. The outcome is a Z-score and a p-value. If most values in the number of foggy days have higher positive Z-scores and lower p-values (such as a conventional value of 0.05), then, it is likely that this area is a fog-prone area. The Getis-Ord G* statistic is specified by:

$$G_i^* = \left[\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}\right] / \left[S\left\{\left(n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right) / (n-1)\right\}^{1/2}\right] \quad (3)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is the total number of features, $\overline{X} = 1/n\sum_{j=1}^{n} x_j$, and $S = [1/n\sum_{j=1}^{n} x_j^2 - \overline{X}^2]^{1/2}$.

For the spatial clusters in ArcGIS, a fixed distance band was used for the conceptualization of spatial relationships and Euclidian distance was used for the distance method. Because the distance band reflects the maximum spatial autocorrelation, this study used 31 km for the distance band based on the maximum value of the freeway segment length recorded in the Korean freeway network log.

Results and Discussion

LCC-Based Crash Severity Estimation

Based on the variables in Table 2, LCC was conducted to separate the homogeneous groups of crashes. To determine the number of clusters, several information criteria such as AIC, BIC, and CAIC were compared in the current study. For all three information criteria, a lower score indicates the more appropriate number of clusters. The three criteria values similarly and consistently decreased with the increase in the number of clusters. In particular, the BIC is more reliable than the other criteria because of its superior consistency and accuracy (Depaire et al. 2008; Magidson and Vermunt 2002; Nylund and Asparouhov 2007). Therefore, the BIC was preferentially considered to determine the number of clusters. The BIC values were almost constant after nine clusters. Therefore, nine was selected as the optimal number of crash clusters in the LCC, and Fig. 4 confirms the selection.

The R^2 value, which indicates how much of the variance of each explanatory variable is explained by a specific number of clusters, was used to measure the ability to discriminate the clusters. For each variable, its response attribute significantly contributes to the ability to discriminate the clusters. Among all variables in Tables 2, 10 variables had R^2 values greater than 0.1, whereas the other variables had notably small R^2 values (less than 0.05).

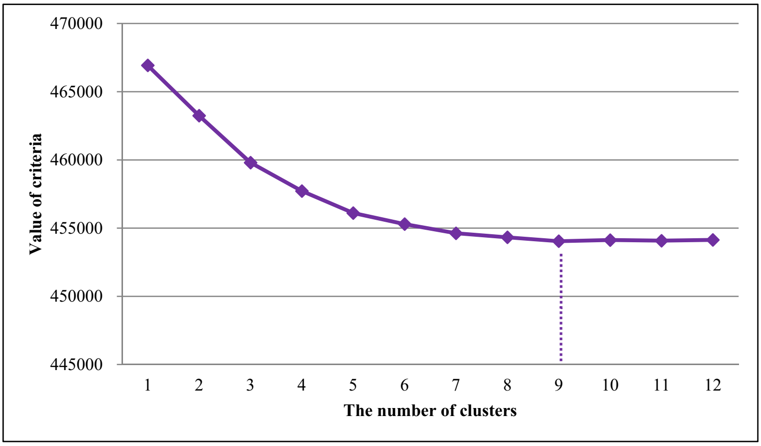

Fig. 4 Patterns of BIC values by the number of clusters

Various attributes associated with the road geometry, traffic, vehicle, EMS and environmental factors were included in the following 10 variables, which are listed in the order of their R^2 values: the existence of a vertical curve, the primary cause of crash, the at-fault vehicle size, the number of vehicles in a crash, the number of travel lanes, the weather, a high level of the administrative district, the roadside facility, the EMS unit response time, and the traffic limitation type. Using the 10 variables (called the clustering variable hereafter), Table 3 provides the resulting nine-cluster profile by conditional probabilities.

As shown in Table 3, all nine clusters included sizable crash samples of 2256 to 3098. Fatal crashes composed 0.7 to 16.8% of the total crash cases in each cluster. All crash cases in Cluster 1 (C1) occurred on vertical curves, and approximately 3.7% of the crash cases in Cluster 2 (C2) occurred on roadways with the installation of roadside protective facilities. For Clusters 7 (C7) and 9 (C9), 89 and 93.6% of the crash cases were primarily caused by vehicle malfunction and adverse weather conditions, respectively.

Clusters 3 (C3) and 8 (C8) were located in the areas characterized by high proportions of accidents occurring in particular administrative districts. For example, approximately 70% of the crash cases in C3 occurred in Jeonrabuk-do and Jeonranam-do, which are southwestern provinces of Korea. Approximately 20% of the crash cases in C8 occurred in Chungcheongnam-do, which is a central province of Korea.

The crash cases in Cluster 4 (C4) were characterized by two or more vehicles in the crash, crashes that occurred under traffic limitations such as an occupied mainline or shoulder, a work zone, or a traffic jam, and crashes with relatively long EMS unit response times. Truck and driver factors, such as speeding, drowsiness, distraction, or lane-changing failure, caused approximately 76 and 46%, respectively, of the crash cases in Cluster 5 (C5). In Cluster 6 (C6), most crash cases occurred on four-lane freeway sections in Gyeonggi-do province, which is the capital region of Korea.

Based on the contributing variables, the labels for the nine clusters are listed as follows:

Table 3 LCC profiles

Variables	C1	C2	C3	C4	C5	C6	C7	C8	C9	Full data
Crash sample	3098	2581	3006	2621	2286	2803	2843	2744	2256	24,238
Fatal crash (%)	1.4	0.7	1.0	16.8	2.1	1.4	1.0	1.0	0.7	2.8
Non-fatal crash (%)	98.6	99.3	99.0	83.2	97.9	98.6	99.9	99.0	99.3	97.2
Grade (%)	**100.0**	0.0	0.0	40.7	43.5	35.7	35.5	0.0	67.4	35.8
No. of lanes (mean)	2	3	2	3	2	**4**	2	3	2	3
Roadside protective facility (%)	73.9	**3.7**	59.4	63.3	66.2	61.0	56.7	38.3	75.0	55.3
Province (%)										
Gangwon-do	25.0	4.5	21.4	9.3	11.7	0.0	4.6	0.0	22.0	11.1
Gyeonggi-do	0.7	38.6	0.0	16.2	8.8	**92.5**	0.0	20.2	12.3	20.8
Chungcheongbuk-do	4.8	3.0	8.6	6.2	5.9	0.0	5.4	0.0	6.9	7.7
Chungcheongnam-do	5.5	7.4	0.0	9.8	11.0	7.4	2.2	**19.6**	7.1	4.5
Jeonrabuk-do	11.6	2.2	**32.9**	12.4	12.1	0.0	11.1	0.0	10.2	10.3
Jeonranam-do	14.8	2.4	**37.2**	8.1	12.1	0.0	10.4	0.0	14.6	11.1
Gyeonsangbuk-do	19.1	19.8	0.0	21.2	23.3	0.0	27.9	26.8	11.6	16.7
Gyeongsangnam-do	18.5	22.2	0.0	16.9	15.2	0.0	38.4	33.4	15.3	17.7
No. of vehicles (%)										
Single vehicle-involved	82.5	92.9	84.1	2.6	91.7	78.3	76.5	79.8	97.4	76.1
Two vehicle-involved	14.7	5.7	13.3	**65.5**	6.1	14.8	11.5	16.1	2.6	16.8
3 or more vehicle-involved	2.8	1.4	2.7	**31.9**	2.4	7.0	12.0	4.1	0.0	7.1
At-fault Vehicle type (%)										
Passenger car	96.4	35.5	92.4	40.6	14.0	76.5	78.3	96.6	57.2	65.6
Van	2.7	6.8	4.9	11.1	10.4	5.4	4.8	3.3	7.9	6.3
Truck	0.9	57.8	2.7	48.2	**75.6**	17.9	16.9	0.0	34.8	28.0
Machine	0.0	0.0	0.0	0.2	0.0	0.2	0.0	0.0	0.1	0.1
Traffic limitation (%)	1.4	0.0	0.9	**18.7**	1.9	0.7	0.3	0.4	0.1	2.7
Primary cause of crash										
Driver factor	7.8	7.5	7.7	1.1	**46.4**	3.7	0.0	3.7	1.8	73.9
Vehicle factor	11.4	6.6	8.9	2.5	6.7	22.9	**89.0**	6.9	0.0	9.0
Roadway factor	80.9	85.9	83.4	96.4	46.9	73.4	11.0	89.4	98.2	17.1
Level of EMS unit time (%)										
Less than 5 min (level 1)	88.2	97.9	86.4	47.8	87.4	95.5	99.7	91.4	93.6	87.5
5 to 9 min (level 2)	1.9	0.6	2.4	7.6	2.2	1.0	0.1	1.0	1.1	2.0
10 to 14 min (level 3)	4.0	0.7	4.1	12.3	4.1	0.8	0.0	2.6	1.3	3.4
15 to 29 min (level 4)	4.7	0.6	6.0	**27.0**	5.8	1.9	0.0	4.2	3.4	5.9
30+ min (level 5)	1.1	0.2	1.1	5.4	0.5	0.8	0.2	0.8	0.7	1.2
Weather conditions (%)										
Adverse weather (rain, snow, fog, gust)	24.4	30.3	23.5	14.0	3.8	13.3	6.2	26.8	**93.6**	25.0
Cloudy weather	17.0	13.0	16.6	14.3	15.8	15.5	13.8	14.1	6.2	14.2
Clear weather	58.6	56.7	60.0	71.8	80.5	71.2	80.1	59.0	0.2	60.8

Bold indicates % value of special feature that contributes to discriminating a certain cluster; Because the variable without sub-categories is based on binary coding, base category is not presented; C in title field of column indicates "cluster."

- C1: Crashes on freeway vertical curves (100%)
- C2: Few crashes on freeway sections with installed roadside protective facilities (3.7%)
- C3: Crashes on the southwest (70.1%) province freeway sections
- C4: Multiple vehicles involved in crashes (97.4%) with traffic limitations (18.7%) and long EMS unit response times (15 to 29 min)
- C5: Crashes caused by truck (75.6%) and driver factors (46.4%)
- C6: Crashes in the capital-area (92.5%) freeway sections with four travel lanes
- C7: Crashes caused by vehicle malfunction (89%)
- C8: Crashes in the central-area (19.6%) freeway sections
- C9: Crashes in adverse weather conditions (93.6%)

Only C9 was discriminated by adverse weather conditions such as rain, snow, fog, and gusts of wind. However, it is not guaranteed that fog, in particular, significantly affects the fatal crashes in C9 because other adverse weather conditions beside fog may affect the fatal crashes. This result implies that the effect of fog on fatal crashes in each cluster should be quantified and compared with those of other adverse weather conditions. Furthermore, weather-related factors were not selected as a clustering variable in the other eight clusters (C1 to C8). The LCC approach separates homogeneous groups of crash cases. The clustering variables in a certain cluster most strongly characterize the cluster. Thus, the effects of weather factors, particularly fog events, on the fatal crashes could be identified in the LCC-based crash severity estimation model, although the fog event was not selected as a clustering variable in the cluster that was not characterized by weather-related factors. Correspondingly, the effect of fog on fatal crashes in all nine crash clusters was examined using a LCC-based binomial logit regression as follows.

For the LCC-based binomial logit regression, the crash severity, which indicates a fatal or non-fatal crash, and all sub-categories of each variable in Table 2 were converted into dummy explanatory variables. A conventional significance level (0.05) for the parameter estimation was used. Comparative LCC-based binomial probit regression was also conducted. Based on the goodness of the model fit and the significance level of the parameter estimates, the binomial logit regression outperformed the binomial probit regression in estimating the crash severity. Table 4 provides the resultant LCC-based binomial logit regression models to estimate the crash severity.

Because the current study aims to identify locations with potential fatal crashes caused by fog, the discussion of the findings will focus on crash clusters where the effect of the fog indicator on fatal crashes is statistically significant.

The fog indicator was statistically significant in only C2 and C3 among the nine clusters. In both C2 and C3, the goodness-of-fit and all parameter effects were reasonable. In particular, fog was significantly identified as increasing the probability of fatal crashes in C2 and C3. In other words, the effects of other inclement weather conditions such as snow, rain or gusts were not statistically significant for the probability of fatal crashes in C2 and C3. The comparative full data model did not identify the effect of fog on fatal crashes but identified the effect of snow on fatal crashes. These findings imply that fog affects fatal crashes that occurred in spatially specific areas such as freeway sections without roadside protective facilities (C2) and the southwest region of Korea (C3). Additionally, the freeway network in the southwest region of Korea is near the sea, where comparatively thick fog events frequently occur, which likely affects the visibility during driving. The effect of fog on increasing fatal crashes in the C2- and C3-based crash severity regressions indicates that the LCC-based crash severity estimation models help to discover hidden fatal contributing factors. Furthermore, the interaction between fog and "freeway sections with roadside protective facilities installed" and the "southwest province" leads to more severe crashes, although the fatal percentage in clusters C2 and C3 is not high. Using Eq. (2) and the parameter estimates from C2 and C3 in Tables 4, 60 locations with the potential of fatal crashes were identified. These locations are freeway points where the potential of fatal crashes caused by fog is high, compared to the entire freeway network.

High Fog Occurrence Locations

For each fog visibility level, the product of the number of foggy days in a year and the traffic exposure (VKT) was defined as the fog-related exposure in this study. Using Getis-Ord G* statistic in ArcGIS, the spatial clusters for fog-related exposure were identified, as shown in Fig. 5. Based on the study goals, a large fog-related exposure for each visibility level is of interest. Therefore, areas with positive Z-scores of Getis-Ord G* statistics that are higher than 1.96 (p-value less than 0.05) were considered significant spatial clusters for each visibility level. The significant spatial clusters (simply called spatial clusters hereafter) have more recurrent fog events than the other areas, as highlighted in Fig. 5.

The spatial clusters for fog-related exposure were separately located by the fog-visibility level. The spatial clusters for each visibility level were mainly located in the following locations: the capital area and partial southwest coast freeway network for visibility level 1 (less than 50 m); the southwest coast and partial northeast freeway network for visibility level 2 (50–100 m); the central area and partial northeast freeway network for visibility level 3 (100–250 m); and the south and partial northeast freeway network for visibility level 4 (250–1000 m). These spatial clusters for all visibility levels covered 42 crash locations with the potential of fatal crashes in the total of 60 crash locations identified in C2 and C3. The 42 crash locations were distributed throughout the following 11 freeway routes: 1, 10, 15, 20, 25, 27, 30, 45, 50, 253, and 300. They were defined as the fog-crash-prone points in the current study.

The spatial cluster areas for visibility levels 1 (V1) and 2 (V2) overlapped in the southwest freeway network, as shown on the right side of Fig. 5. In the northeast freeway network, the spatial cluster areas for visibility levels 2 to 4 (V2, V3, and V4) were also common. These findings imply that multiple visibility standards for the fog-crash-prone area selection should be used in the southwest and northeast freeway networks. Generally, fog occurs throughout a certain area rather instead of a specific point. For future freeway management, accordingly, freeway segments that include the 42 fog-crash-prone freeway points were identified as shown in Table 5.

According to Tables 5, 28 segments in 11 freeway routes contained all 42 fog-crash-prone freeway points, which were nearly 323 km in total length. The 28 freeway segments are freeway stretches where fog-related safety improvement is preferentially required in the entire freeway network of Korea. As shown in Table 5 and Fig. 4, the spatial clusters for visibility levels 1 to 3 included 29 fog-crash-prone points of the total 42 freeway points, which is approximately three-fourths of the entire spatial cluster

Table 4 Cluster-based crash severity estimation models

	C1		**C2**		**C3**		C4		C5		C6		C7		C8		C9		Full	
Cluster characteristics	Vertical curve		Roadside protective facilities not installed		Southwest region of Korea		-Multiple vehicles involved -Many traffic limitations -Long EMS unit response time		- Caused by driver's factors - Truck at fault		- Four lanes - Capital region		- Caused by vehicle factors		- Central region of Korea		-Adverse weather conditions		Total crash observa-tions without clustering	
LR[1] p-val. > chisq.	<.0001		<.0001		<.0001		<.0001		<.0001		<.0001		0.0004		<.0001		<.0001		<.0001	
Parameter	Est.[2]	Sig.[3]	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.	Est.	Sig.
Constant	−0.57	0.05	2.28	0.02	1.31	0.06	−1.23	<.0001	−6.05	0.001	−1.70	0.001	0.0004	0.1	−2.47	0.01	−3.36	0.002	5.39	0.003
Fog			1.80	0.05	2.38	0.03														
Snow																			−1.11	0.005
EMS time level 1	−5.15	0.001	−6.04	0.001	−6.55	<.0001	−3.08	0.01			−4.80	0.001	−7.95	0.001	−5.13	0.001	−4.97	0.001	−4.13	0.001
EMS time level 2									4.16	0.001										
EMS time level 3									4.05	0.001										
EMS time level 4									4.32	0.001										
No traffic limited							−0.71	0.003											−1.94	0.001
Mainline occupied							0.96	0.002												
Shoulder occupied							1.17	0.003												
Traffic jam	3.81	0.04																	0.94	0.004
Drowsiness	0.76	0.04					0.46	0.004											0.71	0.001
Speeding					1.51	0.05									1.13	0.006			0.56	<.0001
Distraction					2.05	0.03														
Young driver							−0.70	0.001											−0.73	0.001

Table 4 (continued)

Elderly driver							0.75	0.005											0.63	0.002
Female driver	−1.32	0.005							3.38	0.01										
Moving median															4.60	0.001				
No median	0.90	0.03																		
Roadside facility											1.22	0.01								
No. of lanes							0.27	0.001									0.55	0.09	0.28	<.0001
Single vehicle			−3.37	0.002	−3.63	<.0001													−0.92	<.0001
Passenger car	−1.70	0.03																	−5.87	<.0001
Van					1.59	0.07													−5.43	0.003

Only significant explanatory variables are presented; [1] Log-likelihood ratio for goodness of fit; [2] Parameter estimate; [3] P-value for the significance of parameter coefficient

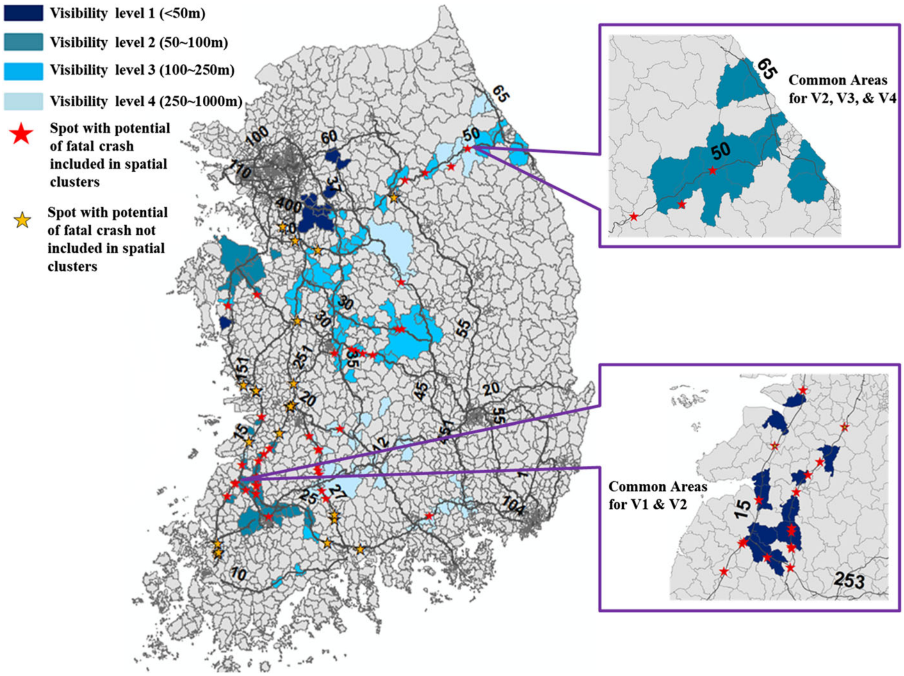

Fig. 5 Significant spatial clusters for fog-related exposure by visibility levels (V1 to V4 indicate visibility levels 1 to 4)

area. In other words, 13 fatal crash locations associated with fog occurrence were included in comparatively less dense (visibility level 4) fog-prone areas.

The current policy for the fog-crash-prone area selection in the Korean freeway system is "recurrent fog events for 30 or more days in a year with visibility of 250 meter or less". The fog-crash-prone areas based on the existing selection policy are displayed in Fig. 6.

The current fog-crash-prone areas in Fig. 6 are not data-driven results. Considerably fog-crash-prone areas in Fig. 5 were excluded in the areas in Fig. 6. Particularly, the southwest coast and southwest area freeway network (freeways No. 15, 25, and 27), where most fog-crash-prone freeway points in Fig. 5 were placed, was completely excluded from the fog-crash-prone areas in Fig. 6. In addition, the selected fog-crash-prone areas in the central, north, and southeast regions of Korea were spatially different between Figs. 5 and 6. In other words, segments in freeways No. 35 and 55 are the current fog-crash-prone areas as shown in Fig. 6, but they were not selected as the modified fog-crash-prone areas in Fig. 5 and Table 5. Furthermore, the current standard threshold of 30 days of fog in a year approaches the maximum value of the number of foggy days for visibility level 3, as shown in Table 5.

The spatial clusters in Table 5 were separately located according to the fog visibility levels. This finding indicates that a modified policy standard for the fog-crash-prone area selection should spatially vary for the freeway segments in terms of the fog frequency thresholds by visibility levels. Interestingly, the spatial cluster areas for certain visibility levels were located in the same places on the segments of freeways

Table 5 Involvements of freeway points with potential fatal crash occurrences affected by fog

Segment number	Freeway route number	Post mile (km, start~end)	The number of fatal crash locations involved	Visibility 1 (days/yr)	Visibility 2 (days/yr)	Visibility 3 (days/yr)	Visibility 4 (days/yr)
1	1	232.3~248.3	2	–	–	22	–
2	1	248.3~259.7	2	–	–	29	–
3	10	79.7~83.9	1	–	–	–	6
4	15	58.1~74.2	3	–	10	–	–
5	**15**	**84.9~94.7**	1	**3**	**9**	–	–
6	**15**	**124.8~137.4**	1	**3**	**9**	–	–
7	15	213.3~224.1	1	–	–	8	–
8	20	43.1~58.9	1	–	–	–	35
9	25	74.2~77	1	–	4	–	–
10	**25**	**99~111.1**	2	**1**	**8**	–	–
11	**25**	**111.1~120.3**	2	**1**	**2**	–	–
12	25	120.3~128.7	1	–	–	8	–
13	25	128.7~141.6	2	–	3	–	–
14	27	25~37.8	2	–	–	25	–
15	27	37.8~52.6	2	–	–	–	31
16	27	62.1~75.8	1	–	–	–	29
17	27	75.8~85.6	1	–	–	–	32
18	27	85.6~103.5	4	–	–	–	37
19	30	24.4~36.9	1	–	1	–	–
20	30	47.4~56.5	2	–	–	29	–
21	45	194.9~209.1	1	–	–	–	12
22	50	130.2~142.9	1	–	–	4	–
23	50	142.9~160	1	–	–	9	–
24	**50**	**160~177**	2	–	**2**	**12**	**10**
25	**50**	**191.9~199**	1	–	**1**	**6**	**8**
26	**253**	**2.5~12.6**	1	**1**	**4**	–	–
27	253	12.6~17.2	1	–	4	–	–
28	300	5.7~13.3	1	–	–	5	–
Average/Min./Max.		11.5/2.8/17.9	2/1/4	2/1/3	5/1/10	15/4/29	24/6/37
Sum		323.1	42	–	–	–	–

Value in each visibility column indicates the number of yearly foggy days in each freeway segment involved in significant spatial clusters; − indicates the cell that is not applicable; and Bold indicates that significant spatial cluster areas are concurrent across visibility levels

15, 25, 50 and 253. This result implies that multiple standards of fog visibility levels are required for the fog-crash-prone area selection.

Considering the average number of foggy days by visibility levels in Table 5, the current policy to select top-priority fog-crash-prone areas in the Korean freeway system should be modified as follows.

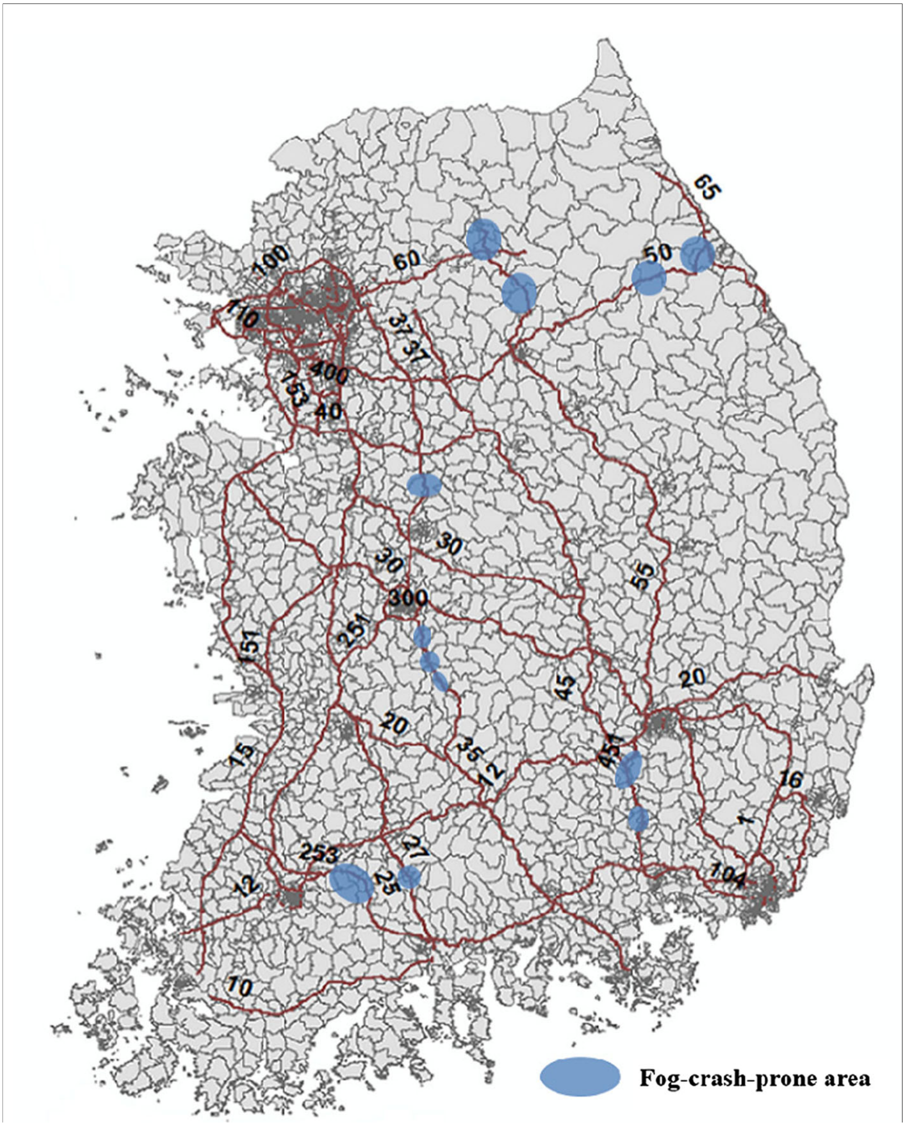

Fig. 6 Fog-crash-prone areas based on the current policy (KMLIT 2015)

- Freeway segments with multiple visibility standards (concurrent spatial cluster areas)

– Freeway 15, segments 84.9–94.7 km and 124.8–137.4 km (the southwest cost area): yearly two-days (average number of foggy days for visibility level 1) fog occurrence with visibility level 1 or five-days (average number of foggy days for visibility level 2) fog occurrence with visibility level 2

– Freeway 25, segment 99–120.3 km (the southwest area): yearly two-days fog occurrence with visibility 1 or five-days fog occurrence with visibility level 2

- Freeway 253, segment 2.5–12.6 km (the southwest area): yearly two-days fog occurrence with visibility level 1 or five-days fog occurrence with visibility level 2
- Freeway 50, segments 160–177 km and 191.9–199 km (the northeast area): yearly five-days fog occurrence with visibility level 2, 15-days (average number of foggy days for visibility level 3) fog occurrence with visibility level 3, or 24-days (average number of foggy days for visibility level 4) fog occurrence with visibility level 4

• Freeway segments with a single visibility standard

- Segments of the southwest and partial north area freeways 15, 25, 30, and 253: yearly five-days fog occurrence with visibility level 2
- Segments of the central and partial north area freeways 1, 15, 27, 30, 50, and 300: yearly 15-days fog occurrence with visibility level 3
- Segments of the south and partial north area freeways 10, 20, 27, and 45: yearly 24-days fog occurrences with visibility level 4.

The aforementioned results provide meaningful implications on decision making for fog-sensitive policy enforcement, active traffic management, and treatment strategies. According to Table 4, driver distractions such as the use of a mobile phone, eating or equipment operation significantly increase the likelihood of a fatal crash, which was only identified in C3. As supplemental safety improvement polices, enforcement and education against distracted driving will help to decrease crash severity, particularly in the southwest region of the freeway network. In this region, prohibiting driver distractions such as the use of cellular phones, eating or car equipment operation in foggy weather conditions should be reinforced through enforcement and driver behavior education.

In the southwest region, speeding was also found to significantly increase the likelihood of fatal crashes in the fog-crash-prone areas. An intelligent transportation system (ITS) for traffic speed control will be helpful to improve highway safety in fog-crash-prone areas, which was already recommended in several past studies (Peng et al. 2017; Wu et al. 2018; Yan et al. 2014). To decrease the freeway speed in foggy weather, dynamic message signs (DMS) or variable-speed-limit (VSL) signs will warn drivers in foggy weather. These traffic management strategies will be more effective in reducing severe crashes caused by fog if the system serves to alert the driver of the potentially hazardous areas ahead. Considering the ITS installment, the fog-crash-prone areas found in the current study have top priority for the ITS-based traffic control strategy implementation, which is cost-effective.

On the other hand, improved lighting or vehicle-based technologies may provide extra driver assistance under foggy conditions. Lee et al. (2012) proposed the Fog Detect and Warning System (FDWS) to inform drivers of safe speeds and distances between vehicles. According to their study, the FDWS includes visibility meters for measuring sight distance in fog, light bars for informing drivers the measured sight distance, and vehicle detectors. Especially, the light bars, which display red warning lights, inform a following vehicle of the position of the leading vehicle to keep a safe distance between the two. The high visibility of main LED lights can be recognized by drivers from far away. Their pilot study with the FDWS implementation on 1-km section of highway indicated that FDWS led to significant reduction in mean speed for both daytime and nighttime compared to the time when the system was turned off. Vehicle-based technologies such as lane departure warnings and forward collision warnings in electronic stability control are intended to help drivers maintain proper vehicle positioning and avoid rear-end crashes in fog- and smoke-related situations. However, according to a recent study by Mehler et al. (2014), these vehicle-based safety technologies received only 1 out of 5 stars in the user survey, which prompts the need for a thorough evaluation for the actual safety benefits versus perceived benefits.

As shown in Table 4, rapid EMS arrival and freeway segments without protective roadside facilities were found to decrease and increase the probabilities of fatal crashes in C2 and C3, respectively. Correspondingly, providing more resources such as exclusive freeway EMS stations or luminous protective roadside facilities should help to mitigate the effect of fog on freeway safety.

In several countries, such as the U.S., the U.K. and Japan, fog visibility levels have been classified and used to give warnings of low visibility and manage traffic speed based on their classifications (Balke et al. 2007; Perry and Symons 2003; Yamamoto 2002). However, few countries have provided both methodological process and resultant standards for the fog-crash-prone area selection. The current study provides a quantitative method of policy making to identify fog-crash-prone areas and modify the area selection standards, which can be applied in other countries to improve the fog-related highway safety.

Conclusions

The goal of reducing traffic-related fatalities has been made more challenging in Korea by the number of trips made under low visibility in foggy conditions. The study was inspired to identify the top-priority freeway segments where fog-related safety improvements are required and to modify the current standard for fog-crash-prone area selection. To achieve the goals, LCC-based crash severity estimation modeling was combined with Getis-Ord G* statistic-based hot spot analysis for high fog occurrence locations. This study is the first data-driven study to comprehensively examine fog recurrence- and visibility-related fatal crashes in the entire Korean freeway network. Accordingly, this study developed a systematic safety analysis framework for policy decision making of the selection of fog-crash-prone areas. These efforts produced following conclusions that would have useful implications on the applicability to fog-related freeway safety issues in other nations.

Among the resultant nine crash clusters that were identified using the LCC, fog caused a statistically significant increase in the probability of fatal crashes in two LCC-based crash severity estimation models. Two clusters (Clusters 2 and 3) were characterized by crash occurrences without roadside protective facilities and in the southwest provincial freeway network, which included 60 locations with the potential of fatal crashes in the entire freeway network. Spatial clusters for fog-related exposure in four visibility levels were also identified using the ArcGIS Getis-Ord G* statistics. As common areas between the spatial clusters and 60 fatal crash-prone locations, 28 freeway segments were identified as top-priority links where fog-related safety improvement is required. The top-priority freeway links were separately affected by significant spatial clusters with highly positive Z-scores of Getis-Ord G* statistics. This finding indicates that spatially different standards for the fog-crash-prone area selection are more appropriate than the current single global standard in the Korean freeway system. For example, Freeway 15 that stretches along the southwest coastline of South Korea where the area is relatively warm and humid may experience more fog events. In this study, some sections of Freeway 15 are ranked high as fog-crash-prone areas by more than two spatially different selection standards. Furthermore, speeding, driver distraction, and EMS time factors, which are significantly identified in Clusters 2 and 3, contribute meaningful implications to the decision making for fog-related advisory, ITS-based traffic control, treatment strategies and part of high-cost road- or vehicle-based technologies in fog-crash-prone areas.

The crash sample size in foggy weather conditions is relatively small. In this study, there are some limitations caused by data deficiency. Only two data fields associated with fog information (fog recurrence and visibility levels) were available. The duration of fog existence, roadway terrain, weather data such as temperature, humidity, wind speed, etc. should be used to define clustering variables. Temperature, humidity, and wind are closely associated with fog production, which varies by time of day or by topographic pattern. Between overnight and early morning hours, the temperature is generally the coolest and water vapors can condense into droplets, which is likely to form fog (Abdel-Aty et al. 2011). Additionally, fog occurs when the warmer airmass loses heat through conduction to the cooler surface, thus lowering temperature to its dew point. This phenomenon frequently occurs near coastal areas or upslope with natural wind (Ray et al. 2013). Therefore, safety studies will benefit from the use of long-term and extended crash- and fog-related data. Moreover, field survey for drivers can be helpful to identify relevant self-adjusting efforts under foggy conditions. Traffic counts on foggy days can provide more accurate measure of traffic exposure.

Acknowledgements This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education [NRF-2016R1D1A1B03930700].

Compliance with Ethical Standards

Conflict of Interest Author Soyoung Jung declares that she has no conflict of interest.
Author Xiao Qin declares that he has no conflict of interest.
Author Cheol Oh declares that he has no conflict of interest.

References

Abdel-Aty, M., Ekram, A., Huang, H., & Choi, K. (2011). A study on crashes related to visibility obstruction due to fog and smoke. *Accident Analysis & Prevention, 43*, 1730–1737.

Ahmed, M., Abdel-Aty, M., Lee, J., & Yu, R. (2014). Real-time assessment of fog-related crashes using airport weather data: A feasibility analysis. *Accident Analysis & Prevention, 72*, 309–317.

Balke, K., Songchitruksa, P., Liu, H., Brydia, R., Jasek, D., & Benz, R. (2007). *Concepts for managing freeway operations during weather events*. FHWA, report no. FHWA/TX-07/05278–1. (Available: https://static.tti.tamu.edu/tti.tamu.edu/documents/0-5278-1.pdf). Accessed 12 July 2018

Buchner, A., Brandt, M., Bell, R., & Weise, J. (2006). Car backlight position and fog density bias observer-car distance estimates and time-to-collision judgments. *Human Factors, 48*, 300–317.

Depaire, B., Wets, G., & Vanhoof, K. (2008). Traffic accident segmentation by means of latent class clustering. *Accident Analysis and Prevention, 40*, 1257–1266.

Hosmer, D., & Lemeshow, S. (2000). *Applied logistic regression*, (2nd edn). John Wiley & Sons, Inc.

Huang, H., Abdel-Aty, M., Ekram, A., Oloufa, A., Chen, Y., & Morrow, R. (2010). Fog- and smoke-related crashes in Florida: Identifying crash characteristics, spatial distribution, and injury severity. *Transportation Research Board 89th Annual Meeting*, Paper No. 10–1323.

Jung, S., Qin, X., & Oh, C. (2016). System-wide impacts of emergency medical service (EMS) resources on freeway crash severity. *Transportation Research Record, 2582*, 51–60.

Korea Expressway Corportation. (2013). *Expressway Construction*. (Available: http://www.ex.co.kr/site/com/pageProcess.do).

Korea Ministry of Land, Infrastructure, and Transport (KMLIT). (2015). *Road Safety Management Strategies in Fog-prone Areas*. (Available: http://www.molit.go.kr/USR/NEWS/m_71/dtl.jsp?id=95075431).

Korea Road Traffic Authority. (2016). *KoROAD Statistics* (Available: http://news.koroad.or.kr/articleview.php?idx=527).

Lee, S., Moon, J., & Jung, J. (2012). Implementing FDWS (fog Detect & Warning System) with LED module structure: Estimation of safety effects. *Journal of Korean Society of Hazard Mitigation, 12*(4), 101–106.

Magidson, J., & Vermunt, J. (2002). Latent class models for clustering: A comparison with K-means. *Canadian Journal of Marketing Research, 20*, 7–44.

McCann, K., & Fontaine, M. (2016). Examination of the safety impacts of varying fog densities: A case study of I-77 in Virginia. *Transportation Research Board 95th Annual Meeting*, Paper No. 16–1867.

Mehler, B., Reimer, B., Lavalliere, M., Dobres, J., & Coughlin, J. (2014). *Evaluating technologies relevant to the enhancement of driver safety*. Washington, DC: AAA Foundation for Traffic Safety.

Mohamed, M., Saunier, N., Miranda-Moreno, L., & Ukkusuri, S. (2013). A clustering regression approach: A comprehensive injury severity analysis of pedestrian-vehicle crashes in New York, U.S., and Montreal, Canada. *Safety Science, 54*, 37–44.

Ni, R., Bian, Z., Guindon, A., & Andersen, G. (2012). Aging and the detection of imminent collisions under simulated fog conditions. *Accident Analysis and Prevention, 49*, 525–531.

Nylund, K., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling, 14*, 535–569.

Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis, 27*, 286–306.

Peng, Y., Abdel-Aty, M., & Yu, S. (2017). Assessing the impact of reduced visibility on traffic crash risk using microscopic data and surrogate safety measures. *Transportation Research Part C: Emerging Technologies, 74*, 295–305.

Perry, A.H., & Symons, L.L. (2003). *Highway Meteorology*, Taylor & Francis Books, Inc.

Qin, X., Han, J., & Zhu, J. (2009). Spatial analysis of road weather safety data using a Bayesian hierarchical modeling approach. *Advances in Transportation Studies, 18*, 69–84.

Ray, P., Du, X., Rivard, J. (2013). Analysis of prospective systems for fog warning. Florida Department of Transportation, Report No. BDK82 977–10, 1–78. (Available: http://www.fdot.gov/research/completed_proj/summary_te/fdot-bdk83-977-19-rpt.pdf). Accessed 12 July 2018

Srivastava, S., Sharma, A., & Sachdeva, K. (2016). A ground observation based climatology of winter fog: Atudy over the indo-Gangetic plains, India. *International Journal of Environmental, Chemical, Ecological, Geological, and Geophysical Engineering, 10*(7), 678–689.

Tefft, B. (2016). Motor vehicle crashes, injuries, and deaths in relation to weather conditions, United States, 2010–2014, AAA Foundation for Traffic Safety. (Available: http://www.aaafoundation.org).

Wang, Y., Liang, L., & Evans, L. (2017). Fatal crashes involving large numbers of vehicles and weather. *Journal of Safety Research, 63*, 1–7.

Wu, Y., Abdel-Aty, M., & Lee, J. (2018). Crash risk analysis during fog conditions using real-time traffic data. *Accident Analysis and Prevention, 114*, 4–11.

Yamamoto, A. (2002). Climatology of the traffic accident in Japan on the expressway with dense fog and a case study, 11th International Road Weather Conference (Available: http://www.sirwec.org).

Yan, X., Li, X., Liu, Y., & Zhao, J. (2014). Effects of foggy conditions on drivers' speed control behaviors at different risk levels. *Safety Science, 68*, 275–287.