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Analyzing Driving Risks of Roadway Traffic under Adverse Weather Conditions: In Case of Rain Day

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Abstract

Among adverse weather conditions, rainy weather may be one of the conditions which cause significant negative impacts on traffic safety. This paper develops a quantitative model that is used to analyze driving risks under rainy weather conditions. The data is derived from an extensive questionnaire survey in shanghai. And the questionnaire includes those factors related to roadway, drivers, vehicles, and traffic that may have significant impacts on traffic safety under rainy weather conditions. The study makes correlation test on 286 samples selected randomly from the population and builds a multi-ordered discrete choice model (MDCM) to analyze those risk factors and their influence degree. And this kind of procedure and method is also useful and appropriate for other adverse weather conditions.

Keywords: Adverse Weather Conditions; Rain Day; Discrete Choice Model; Risk Analysis;

1. Introduction

1.1. Background

Adverse weather conditions, such as strong wind, heavy rain or snow, heavy fog and so on, have obvious impacts on roadway traffic operations, especially traffic safety. When it is raining, drivers' visibility could be affected, meaning safety performance of the roadway may be discounted. In addition, rainy weather would result in reduction in pavement skid resistance and vehicular stability (such as braking stability and steering operation), which may cause the reduction in traffic operational speed (Maze, Agarwal & Burchett, 2005). The combined impacts from roadway, vehicle, traffic control, and driver behavior conditions under rainy weather conditions could increase the potential for safety problems and traffic crashes. In recent years, some research studies have concluded that impacts from rainy weather conditions on traffic operations and safety cannot be ignored (FHWA, 2008, Billot, El Faouzi, Sau & De Vuyst, 2008, Jung, 2010). TABLE 1 presents some traffic crash data under different weather conditions with the original crash data provided from a previous study (Qin & Shao, 2003). In the table, 1085 traffic crashes during 1998-1999 on Ji-Qing Freeway in Shandong Province are analyzed to reflect traffic safety risk for different weather conditions. Risk index (which is equal to the percentage of accidents divided by the

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percentage of days in corresponding weather category) is used to indicate the diving safety risk under each weather condition. It is found from the table that snowy and rainy conditions (with a risk index of 1.75 and 1.57, respectively) are ranked top one and top two, meaning driving under snowy or rainy conditions could be much more risky as compared with other weather conditions. If average daily accident (crash) rate is used, it is found that Ji-Qing Freeway had an average daily accident rate of 5.20 and 4.68 for snowy and rainy conditions, respectively, which results in the same conclusions as concluded by risk indices.

Table 1. Risk index analysis for Ji-Qing Freeway under different weather conditions

Weather conditions		Sun	Rain	Fog	Cloud	Snow	Strong Wind
Annual accident distribution	Numbers of accidents	794	117	111	32	26	5
	Percentage (%) of accidents	73.18	10.78	10.23	2.95	2.40	0.46
Annual weather distribution	Number of days	273	25	42	16	5	4
	Percentage (%) of days	74.79	6.85	11.51	4.38	1.37	1.09
Average daily Accident rate		2.91	4.68	2.64	2.00	5.20	1.25
Risk index		0.98	1.57	0.89	0.67	1.75	0.42

Another similar analysis was performed to analyze risk indices under different weather conditions with crash data provided from another study (Wang, Xie & An, 2004). In the analysis, 50,000 traffic accidents from 1999 to 2002 in Changchun City in Liaoning Province were analyzed to calculate risk indices and average daily accident (crash) rate under different weather conditions. TABLE 2 summarizes the analysis results. It can be concluded that fog and rainy weather conditions have higher risk indices as compared with other weather conditions and similar conclusion can be obtained if average daily crash rates are used.

Table 2. Risk index analysis for roadways in Changchun City under different weather conditions

Weather Conditions	Rain	Snow	Mist	Fog	Strong Wind	Cloud	Sleet	Sun	Ave.
Percentage (%) of Days	4.63	3.93	1.18	0.27	3.18	26.3	0.21	60.3	12.5
Percentage (%) of Accidents	4.86	3.83	1.05	0.31	2.87	26.59	0.19	60.8	12.5
Average Daily Accidents	40.24	37.34	34.43	44.97	28.75	38.79	33.65	38.69	38.64
Risk Index	1.05	0.97	0.89	1.15	0.90	1.01	0.90	1.01	1

In summary, whether it is average daily crash rate or risk index, rainy weather may have significant impacts on safe operations of road traffic. However, such an impact could involve the combined effects from driver, vehicle, roadway, and traffic conditions. It is meaningful to study and analyze the combined effects of these factors under rainy weather conditions. And results from such studies could enhance traffic emergency management and optimize emergency sources allocation.

1.2. Literature review

Many research studies have been performed to analyze traffic operations and safety under rainy weather conditions. In 1991, Palutikof (1991)found that rainy weather was the most significant one among all weather factors which resulted in traffic fatalities. In a study by Sherretz and Farhar (1978) to analyze traffic weather data from seven cities in south Illinois, USA, it was found that there existed a linear positive correlation between rainfall and traffic crash frequency. Some research studies found that geographical differences could play an important role in determining impacts of rainy weather on traffic safety. Brotsky and Hakkert (1988), Smith (1982), Codling (1974), and Andrey and Yagar (1993) compared the impact differences of sunny weather and rainy weather on traffic safety and found that rainy weather resulted in 6%, 22%, 52%, and 70% more crash rates, respectively, as compared to sunny weather conditions. More detailed finding about rainy weather impacts on traffic safety are summarized by Andrey, Mills & Vandemolen (2001) and Eisenberg (2004).

In addition, many statistical modeling approaches have been used to develop statistical models to analyze impacts of various factors in the groups of users, vehicles, roadways, and control on traffic safety. Hill and Boyle (2006) used a logistic regression model to predict traffic fatality and incapacitating injury, and they concluded that female drivers older than 54 could have more severe injuries under adverse weather conditions as compared to male drivers in the same age group. Khorashadi, Niemerier, Shankar & Mannering, (2005) used a multinomial Logit model to analyze the severity of truck drivers involved in crashes, and his research found that rainy weather was the key factor resulting in the increase in traffic crash injuries. An Ordered Probit model was used by Abdel-Aty (2003) to predict drivers' injury severity, and results showed that drivers at signalized intersections could suffer more serious injuries under adverse weather and dark environmental conditions as compared with under other conditions. In a similar study, ordinal logistic regression model and sequential logistic regression model were used to evaluate impacts of rainfall on single-vehicle crashes with the considerations of weather conditions and non-weather conditions (Jung, 2010), and it was concluded that the backward sequential logistic regression model might be the best fit to predict crash severity under rainy weather conditions.

1.3. Problem statement

Many research projects have studied the impacts of rainy weather conditions on traffic safety, and most of them have concluded that rainy weather could negatively impact traffic operations and safety. However, there are three basic issues that have not been well understood: (1) most of past studies have been based on historical crash data. But many places, like areas in China, may not have the capabilities to accumulate traffic crash data for modeling purposes. Thus, sometimes the incomplete data is not enough to conduct crash analysis; (2) since the impact of rainy weather conditions has obvious geographical differences, a lot of research is not universal; (3) traffic risk and traffic accident are two different concepts. Most of past studies use historical accident data to analyze traffic operations under rainy weather conditions, which describe a kind of results. But less accidents and low risk level are different. The relation also depends on driver's perception. For example, if a driver is on the alert, the number of accidents may not be increase obviously, even decrease. With the considerations mentioned above, data derived from drivers' questionnaires is a good choice.

In addition, it can't be denied that the data from questionnaires exists certain limitations. There are two reasons: (1) the content of drivers' questionnaires can't include any data that the study needs; (2) the data is easy to influence by subjective consciousness. However, discrete choice model can compensate for these shortcomings to some extent. The paper calls uncontrollable factors as non-observable variables. Based on the structure of a multi-ordered choice model (MDCM), if the probability distribution of non-observable variables is assumed reasonably, to some extent, impacts mentioned can be weakened.

In conclusion, the paper uses data from drivers' questionnaires to build a multi-ordered discrete choice model, in order to analyze the combined impacts from roadway, vehicle, traffic conditions and drivers' characteristics under rainy weather conditions, which is helpful and useful to optimize emergency resource allocation and make reasonable emergency measures.

2. Approach

2.1. Procedure and participants

As stated above, past crash analysis studies have certain limitations and traffic risk and accident are different concepts. So questionnaire surveys to drivers were conducted in order to analyze and evaluate impacts of rainy weather condition. Survey sites are parking lots and shopping malls. The total number of questionnaires received is 1080. The study selects 286 samples randomly among them. Comparing with the population, the ratio of large vehicle and female drivers in the sample is slightly smaller. But the consistency between the sample and the population can be accepted. The factual statistics were shown in TABLE 4: drivers' age was distributed from 21 to 55 with a mean of 34 (S.D. =9.585 years); driving age ranged from 1 to 20 years with a mean of 8 years (S.D. =5.894 years); the ratio of male to female was 1.47:1; the ratio of passenger cars to large vehicle was 1.4:1. Note that, based on the national specifications JTG B01-2003 (2004), the research group combine middle size vehicles, two-axle large trucks, and multi-axle large tracks to form one type (large vehicle type).

2.2. Questionnaire

The questionnaire survey should not only consider multiple characteristics related to drivers and vehicle, but also roadways, traffic volume, and severity of rainy situation. Roadway segment types are divided into type A (level and straight road segments), type B (level segments with some obstructions on road sides), and type C (segments with horizontal and vertical curves). Because a driver is difficult to estimate the volume on the road correctly, traffic volume is processed indefinitely. And there are only descriptions of low volume or high volume. The rain levels include light rain, moderate rain, heavy rain and rainstorm. The risk levels are defined considering accident severity and vehicle speed. The rain levels and risk levels are shown in TABLE 3.

Table 3. Descriptions of rain levels and risk levels

Rain severity levels	
Light Rain	Visibility of 200-500 Meters, Daily Rainfall Less Than 10 Millimeters
Moderate Rain	Visibility of 100-200 Meters, Daily Rainfall between 10 and 25 Millimeters
Heavy Rain	Visibility of 50-100 Meters, Daily Rainfall between 25 and 50 Millimeters
Rainstorm	Visibility Less Than 50 Meters, Daily Rainfall More Than 50 Millimeters
Driving risk levels	
Slight	may cause slight traffic congestion, about 65 km/h driving speed, and surrounded by cars or cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB.
General	may cause normal traffic congestion, and about 50 km/h driving speed or cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB.
Serious	may cause serious traffic congestion, less than 35 km/h driving speed or cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB.
Catastrophic	may cause extreme traffic congestion, less than 20 km/h driving speed or cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB.

2.3. Survey data Collection

For the modeling purpose, all variables about the questionnaire should be quantified and analyzed. TABLE 4 presents all variables used in modeling process and their statistical indicators. The variables of derivers' age and driving age are defined based on the actual age (years) and years with driving experience, respectively. However, in order to avoid variables producing heteroscedasticities, roadway segment types are divided into two categories with two dummy variables in each category as shown in TABLE 4.

Table 4. Definitions of all variables

Quantitative variables				
Variables name	Definition of variables	Mean	Standard deviation	Min~Max
Age	Actual Years	34	9.585	21~55
Driving Age	Actual Years	8	5.894	1~20
Qualitative variables				
Variables name	Definition of variables	Frequency	Percent %	Cumulative percent %
Gender	Male=1	238	59.50	59.50
	Female=0	162	40.50	100.00
Vehicle Type	Large Vehicle=1	167	41.75	41.75
	Small Vehicle=0	233	58.25	100.00
Rain Level	Rainstorm=4	100	25.00	25.00
	Heavy=3	97	24.25	49.25
	Moderate=2	103	25.75	75.00

	Light=1	100	25.00	100.00
Segment Category 1	Type B=1	129	32.25	32.35
	Others=0	271	67.75	100.00
Segment Category 2	Type C=1	141	35.25	32.25
	Others=0	259	64.75	100.00
Traffic Volume	High Traffic Demand=1	192	48.00	48.00
	Low Traffic Demand=0	208	52.00	100.00
Risk Level	Catastrophic=4	76	19.00	19.00
	Serious=3	113	28.25	47.25
	General=2	122	30.50	77.75
	Slight=1	89	22.25	100.00

3. Model development

Multi-ordered discrete choice models originally started from economics have been widely used in modeling choice of individual behavior. Such models have the following characteristics: (1) Depend variables are discrete, and independent variables could be observable or non-observable, (2) The main difference between multi-ordered discrete choice models and other discrete choice models is that the former should have a dependent variable with at least three discrete levels, and these levels are ordered, (3) non-observable variables are assumed to fit some probability distributions, and different distributions could have certain impacts on modeling qualities. Actually, the data from questionnaire can't include all variables. A random error term must be assumed to correct impacts of non-observable factors. And the driving risk levels in the study are discrete and ordered. So multi-ordered discrete choice models could be an adequate choice for the modeling purpose.

3.1. Variable associations

Prior to building the model, the associations of the variables discussed in TABLE 4, including the response variable, were investigated by determining the correlation among the variable pairs. For comparison of continuous variables the Pearson r was calculated. For continuous–discrete pairs the Spearman correlation was calculated. And finally, for discrete variable pairs the Phi coefficient was calculated. The correlation for all variable pairs is reported in TABLE 5.

At the 0.05 significance level, the response variable Risk Level is associated with Gender, Vehicle Type, Rain Level, Segment Category 2, and Traffic Volume. And relationships between Risk Level and these variables except Gender are positive. At the same time, the table has shown that Age, Driving Age and Gender are all relative, but Age and Driving Age are not associated with Risk Level. This isn't a mistake. The relationship between Age and Driving Age isn't linear completely.

For the modeling purpose, it is very important to select independent variables scientifically. In general the relationship of independent variables should be linear independently. In contrast, there is a strong correlation between independent variables and dependent variables. Under these considerations, driver's gender, vehicle type, rain level, segment category 2 and traffic volume are selected as the independent variables of the model.

Table 5. Correlation tests of all variables from the questionnaire survey

	Age	Driving Age	Gender	Vehicle Type	Rain Level	Segment Category 1	Segment Category 2	Traffic Volume	Risk Level
Age	—								
Driving Age	**0.751**	—							
Gender	**0.475**	**0.478**	—						
Vehicle Type	**0.236**	**0.378**	**0.335**	—					
Rain Level	0.003	0.044	0.054	0.050	—				

Segment Category 1	0.023	-0.041	-0.042	-0.029	0.023	—			
Segment Category 2	0.011	-0.021	-0.027	0.011	0.054	-0.509	—		
Traffic Volume	0.032	0.040	0.038	0.022	0.088	-0.031	0.014	—	
Risk Level	0.036	-0.019	**-0.198**	**0.184**	**0.604**	0.071	**0.259**	**0.125**	—

Note: In each cell, the numbers give the correlations respectively. And those boldfaced numbers represent significant correlations when the significant level is 0.05.

3.2. The model structure

As mentioned before, driver safety risk level (y_i) as dependent variable is considered discrete in the modeling with y_i ranged from slight risk, general risk, serious risk, and catastrophic risk, and i representing a risk level that a driver selects. Observable independent variables include driver's age, driving age, gender, vehicle type, roadway segment type, traffic demand, and rainy weather severity level. As a general practice, a non-observable ε_i is assumed in order to calculate a continuous latent variable y_i^*:

$$y_i^* = \sum_{j}^{J} x_{ij}\beta_{ij} + \varepsilon_i, \qquad y_i = 1,2,...,M \tag{1}$$

where, ε_i is assumed to be independently distributed and to fit a Gumbel distribution in this study, J is the number of observable independent variables, M is the number of dependent levels (M=4 in this study), β_{ij} is the parameter for the j^{th} variable, and the dependent variable y_i has the following relationship with the latent variable y_i^*:

$$y_i = \begin{cases} 1 & if \;\; y_i^* \le c_1 \\ 2 & if \;\; c_1 < y_i^* \le c_2 \\ 3 & if \;\; c_2 < y_i^* \le c_3 \\ \vdots & \quad \vdots \\ M & if \;\; c_{M-1} < y_i^* \end{cases} \tag{2}$$

Where, c_k (k = 1, 2, …, M-1) are threshold values to satisfy: $c_1 < c_2 < ... < c_{M-1}$.

The paper assumes non-observable variables to fit a Gumbel distribution in order to calculate corresponding probability of a certain risk level. And the method of calculation is as follow:

$$P(y_1 = 1) = \frac{e^{c_1-(\sum x_{1j}\beta_{1j})}}{1+e^{c_1-(\sum x_{1j}\beta_{1j})}} \tag{3}$$

$$P(y_2 = 2) = \frac{e^{c_2-(\sum x_{2j}\beta_{2j})}}{1+e^{c_2-(\sum x_{2j}\beta_{2j})}} - \frac{e^{c_1-(\sum x_{1j}\beta_{1j})}}{1+e^{c_1-(\sum x_{1j}\beta_{1j})}} \tag{4}$$

……

$$P(y_M = M) = 1 - \frac{e^{c_{M-1}-(\sum x_{M-1,j}\beta_{M-1,j})}}{1+e^{c_{M-1}-(\sum x_{M-1,j}\beta_{M-1,j})}} \tag{5}$$

Then their Log Likelihood is

$$\ln L = \sum_{i=1}^{n}\sum_{m=0}^{M} d_{im} \ln\left[\frac{e^{c_m-(\sum x_{mj}\beta_{mj})}}{1+e^{c_m-(\sum x_{mj}\beta_{mj})}} - \frac{e^{c_{m-1}-(\sum x_{m-1,j}\beta_{m-1,j})}}{1+e^{c_{m-1}-(\sum x_{m-1,j}\beta_{m-1,j})}}\right] \tag{6}$$

where d_{im} = 1, meaning the i^{th} individual selects the m^{th} risk level, and d_{im} = 0, meaning the i^{th} individual does not select the m^{th} risk level. If partial derivative is taken for Equation (6) and let

$$\frac{\partial \ln L}{\partial \beta} = 0$$

then, the maximum likelihood of all parameters can be obtained. And corresponding probability of a certain risk level can also be calculated.

3.3. Risk analysis

As mentioned previously, the model was developed by putting the five variables discussed into the model at the beginning of the analysis. Then relevant parameters were estimated using maximum likelihood value. The modeling results based on Multi-ordered Logit Model approach are presented in TABLE 6. The model output included the coefficients of the five variables, standard error, z-statistic value， pseudo R-squared and the associated p-value. And the coefficients of variables and the associated p-value are important parameters. The relationship between dependent variables and independent variables is decided by the coefficients of variables and tested by the p-value.

In TABLE 6, the p-value means good correlation between dependent variables and independent variables. The pseudo R-squared value isn't very close to 1 because of impacts of non-observable variables. But it can be accepted in general. Besides, there is only driver's gender that has a negative impact on driving risk levels considering the coefficients of variables. Yet other variables all have positive impacts.

TABLE 6 Parameter Estimation of the Multi-ordered Logit Model

Variable	Coefficient	Std. Error	z-Statistic	*p*-Value
Gender	-1.296516	0.244768	-5.296927	0.0000
Vehicle Type	1.387561	0.251217	5.523355	0.0000
Rain Level	1.473376	0.115059	12.80542	0.0000
Segment Category 2	1.179286	0.210046	5.614406	0.0000
Traffic Volume	0.888443	0.200028	4.441587	0.0000
Pseudo R-squared	0.352546	*p*-Value (LR statistic)		0.0000

The influence degree of the five independent variables can be determined by calculating their marginal effects. In the model of risk analysis, independent variables include driver gender, vehicle type, rain level, segment category 2 and traffic volume. All five variables are qualitative and categorical, for example, the appropriate marginal effect for an independent variable, Gender, would be

$$\textit{Marginal Effect} = P\left(y = i \,\middle|\, \bar{x}(Gender), Gender = 1\right) - P\left(y = i \,\middle|\, \bar{x}(Gender), Gender = 0\right) \tag{7}$$

Where, $\bar{x}(Gender)$ denotes the means of four other variables and *i* represents i^{th} risk level in the model. Similarly, other variables also adopt the formula (7) to calculate their own marginal effects. Marginal effects of five independent variables are shown in TABLE 7.

TABLE 7 Marginal Effects of All Independent Variables in Risk Analysis

Variable	Value	Slight risk (y=1)	General risk (y=2)	Serious risk (y=3)	Catastrophic risk (y=4)
Gender	0→1	3.5742%	17.515%	6.0239%	-27.114%
Vehicle Type	0→1	-3.8881%	-18.789%	-6.1701%	28.847%
Rain Level	1→2	-15.850%	-19.014%	23.03%	11.834%
	2→3	-4.5821%	-20.828%	-4.0006%	29.411%
	3→4	-1.1136%	-7.9177%	-23.953%	32.985%
Segment Category 2	0→1	-7.4008%	-20.042%	12.188%	15.255%
Traffic Volume	0→1	-2.6231%	-12.697%	-2.6999%	18.020%

The probabilities of different risk levels vary with different values of independent variables. The following discusses the implication of these variables.

(1) A male driver is more likely to face slight, general and serious risk than a female one, when driving under rainy weather conditions. And among them the probability of general risk is highest. But he has less probability to be involved in catastrophic risk as compared to a female driver.

(2) Small vehicle is easier to be involved in slight, general and serious risk than large vehicle under rainy weather. Yet catastrophic risk is more likely to occur in large vehicle.

(3) The impact of rain levels on risk levels is very complex. As rain gets severer, different risk levels don't have the same tendency. But considering catastrophic risk, it results in more potential in traffic crashes with rain level getting higher. While, slight risk has an opposite change.

(4) When roadway geometric and other conditions get worse, driving under rainy conditions could have more probability to be involved in serious and catastrophic risk, which agrees with our common sense.

(5) The impact of traffic volume and vehicle type on risk level is similar. Low traffic demand means that slight, general, and serious risk occur more possibly. While traffic demand is high, it is more likely to be involved in catastrophic risk.

3.4. Discussion

The marginal effects of independent variables are very useful to make effective and reasonable measures to reduce driving risks. Because managers know which variable may be more important and have higher cost-benefits in different situations. So they can spend less money and less time gaining better improving effect. Furthermore, this kind of procedure and method is also used to forecast possible risk levels and corresponding probability when different conditions occurring in rain days.

4. Conclusion

In the study, the data is derived from driver's questionnaires, because of lack of historical data and the concept difference of risk and accident. And considering limitations of questionnaire survey method, the paper develops a multi-ordered discrete choice model to analyze driving risks of roadway traffic under rainy weather conditions. The model assumes non-observable variables to fit a Gumbel distribution. And maximum likelihood method is adopted to estimate relevant parameters of the model. Considering p-value and pseudo R-squared, the model is accepted in general. So impacts of different risk factors on driving risk levels under rainy weather conditions are analyzed, and their marginal effects are calculated, which is helpful to optimize emergency resource allocation and help managers make reasonable emergency measures. More importantly, this kind of method is also appropriate for other adverse weather conditions, such as snow, fog, wind and so on.

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