Incorporating Weather Into Region-Wide Safety Planning Prediction Models

Ida van Schalkwyk, Assistant Research Professional, Arizona State University, P O Box 875306, Tempe, AZ 85287-5306, Tel. (480) 965-3001, idavan@asu.edu.

Sudeshna Mitra, Graduate Assistant, Arizona State University, P O Box 875306, Tempe, AZ 85287-5306, sudeshna.mitra@asu.edu.

Simon Washington, Professor, Arizona State University, P O Box 875306, Tempe, AZ 85287-5306, simon.washington@asu.edu.

ABSTRACT

Predicting safety on roadways is standard practice for road safety professionals and has a corresponding extensive literature. The majority of safety prediction models are estimated using roadway segment and intersection (microscale) data, while more recently efforts have been undertaken to predict safety at the planning level (macroscale). Safety prediction models typically include roadway, operations, and exposure variables—factors known to affect safety in fundamental ways. Environmental variables, in particular variables attempting to capture the effect of rain on road safety, are difficult to obtain and have rarely been considered. In the few cases weather variables have been included, historical averages rather than actual weather conditions during which crashes are observed have been used. Without the inclusion of weather related variables, researchers have had difficulty explaining regional differences in the safety performance of various entities (e.g. intersections, road segments, highways, etc.)

As part of the NCHRP 8-44 research effort, researchers developed PLANSAFE, or *plan*ning level *safe*ty prediction models. These models make use of socio-economic, demographic, and roadway variables for predicting planning level safety. Accounting for regional differences - similar to the experience for microscale safety models - has been problematic during the development of planning level safety prediction models. More specifically, without weather related variables there is an insufficient set of variables for explaining safety differences across regions and states. Furthermore, omitted variable bias resulting from excluding these important variables may adversely impact the coefficients of included variables, thus contributing to difficulty in model interpretation and accuracy.

This paper summarizes the results of an effort to include weather related variables, particularly various measures of rainfall, into accident frequency prediction and the prediction of the frequency of fatal and/or injury degree of severity crash models. The purpose of the study was to determine whether these variables do in fact improve overall goodness of fit of the models, whether these variables may explain some or all of observed regional differences, and identifying the estimated effects of rainfall on safety. The models are based on Traffic Analysis Zone level datasets from Michigan, and Pima and Maricopa Counties in Arizona. Numerous rain-related variables were found to be statistically significant, selected rain related variables improved the overall goodness of fit, and inclusion of these variables reduced the portion of the model explained by the constant in the base models without weather variables. Rain tends to affect and diminish safety, as expected, in fairly complex ways, depending on rain frequency and intensity.

BACKGROUND

The literature on safety prediction is extensive, as road safety professionals routinely use predicted safety to aid in the identification of sites with promise and to gain insights into the role of various factors on safety. As a small sampling of the extent of this literature, two-lane rural roads has been examined by Harwood et al (1), Council and Stewart (2); rural intersections by Maze, Henderson and Sankar (3), Vogt (4), Gibby et al (5), Poch and Mannering (6); suburban roads has been examined by Harwood (7); and low volume roads by Zegeer et al (8).

This section describes recent developments in the field of planning level safety prediction models, provides a discussion of the effect of weather on safety, and background on how weather data has been included in previous safety related research.

Planning Level Safety Prediction Models

Recent developments in planning level safety prediction models now enable professionals to predict safety at a planning level. However, during the development of these models, also known as PLANSAFE, the researchers found substantial differences between models for different regions. These models have included roadway and population based variables. This paper explores the inclusion of weather related variables, rain in particular, into planning level safety prediction models. It is hypothesized that these weather related variables may provide explanatory power in terms of regional differences found in these models and that the inclusion of weather variables will improve the prediction power of planning level safety prediction models.

Weather and Safety Prediction

It is recognized that weather can be a contributing factor to crash occurrence, in particular rain. Rain can reduce visibility, reduces friction between tires and the road, changes the perception of risk of the driver, and may turn to ice or sleet further impacting the friction coefficient. Rain may also induce a subset of motorists to drive at different times, thus altering demand during the rain event. For these reasons and others, rain is thought to impact safety in sometimes difficult to quantify ways and is thought to be critical for inclusion in predictive models of safety.

Rain-related weather influences, among others:

- wet pavement and friction
- combined conditions of wet pavement and lower visibility resulting from cloudiness
- rain and visibility
- vehicle stability during rainy and windy conditions
- risk perception and driver demand during different levels of rain intensity.

When rain makes contact with the pavement, a water film starts building up on the macro and microstructure of the pavement. When a vehicle wheel traverses the pavement, water on the pavement surface is displaced. The remaining film of water, if it exists, is what reduces skid resistance of the pavement (9). Stopping distance, for example, is much larger at lower skid resistance levels while oil and fine debris on the pavement surface can further interact with the water to further reduce skid resistance.

It is hypothesized that rainy weather doesn’t only affect safety as a result of skid reduction but that periods prior, and after rain also affects safety and travel behavior. Cloudiness can reduce visibility and reduce contrast in the road environment. During rainy conditions, heavy rain can reduce visibility of the driver through the interaction between the rain and the windshield. Wet pavement surfaces can become reflective, reducing the visibility of road markings and roadway features such as speed humps. When windy conditions accompany the rain, the wind can affect vehicle stability.

A possible effect of rain that is much more difficult to quantify is driver behavior resulting from decisions whether or not to make a trip, decisions regarding route of travel, and decisions made during the driving task. It is generally accepted that older drivers, for example, reduces their travel during rainy conditions. In a similar manner, a driver may decide not to make a trip or to use a different route to avoid adverse weather; rain could therefore potentially affect trip generation and/or trip distribution. During rainy conditions drivers are advised to reduce vehicular speed to accommodate the longer stopping distances resulting from the reduced skid resistance levels. However, driver behavior may be more complex as hypothesized by risk compensation theory. According to this theory the driver maximizes benefits by balancing perceived risk. It may be reasoned that a driver will only reduce speed voluntarily if the risk is perceived to be high enough to warrant increased travel time due to the higher perceived risk.

Boyle and Mannering (10) studied travel advisory speed systems for adverse weather, among others. They found localized speed reduction in the area of adverse conditions but higher speeds downstream, possibly suggesting driver compensation. One may then reason that rainy conditions at one location may affect the safety of downstream facilities not physically affected by the wet pavement conditions.

Approaches to Include Weather Variables

While many papers have discussed and analyzed weather as part of their research (11), few studies have used weather as part of safety prediction modeling research. In the cases where these studies included weather as a variable, one of the following approaches was followed:

1. Analysis of accidents and the weather conditions during the accident as reported in the accident report. In other words, only weather at the time of the accident are considered and not an annual weather.
2. Inclusion of average annual weather characteristics, i.e. historical averages rather than weather characteristics for the period over which crashes are observed.

Several studies focused on estimating microscopic safety prediction models have revealed evidence supporting relationships between crashes and weather. These include a recent study by Shankar and Chayanan (12), which evaluated segments using average annual precipitation rather than the actual weather for the analysis period. Multivariate models developed for Washington State by Milton and Mannering (13) clearly showed regional differences between models for Eastern and Western Washington. These two regions have very different associated weather, with heavier and longer duration of rainfall in the east and dryer weather in the west. Satterthwatte (14) evaluated seasonal and weather effects on crash frequency in California and found that once extreme weather events were removed, the highest accident frequencies occurred during sunny days and on wet days during the winter season. He hypothesized that the low frequencies observed on cloudy but dry days were the result of drivers reducing travel (and therefore exposure) while the absence of wet pavement provided higher levels of pavement friction compared to wet conditions.

Other studies have observed differences between regions in the absence of weather variables to explain them. A study by Oh et al. (15) found that variables were not available to explain differences across states for various rural intersection crash models. A more complete accounting of statewide differences can be found in Washington et al. (16). Other studies conducted at the regional level have included indicator variables for state-level effects (e.g. (17)), which are likely to capture, at least at some level, the effects of weather related variables. Other studies that have failed to account fully for regional or state-level difference in safety performance are likely to suffer from the omission of weather related variables.

This paper presents the results of an evaluation that incorporates weather related variables to account for regional differences in PLANSAFE models. The work constitutes a continuation of work on PLANSAFE, planning level safety prediction models that were developed as part of NCHRP 8-44: Incorporating Safety Into Long-Range Transportation Planning.

DATASET DEVELOPMENT

Researchers developed planning level datasets by Traffic Analysis Zone (TAZ) for Michigan, Pima County (AZ), and Maricopa County (AZ) for 2001 and 2002. These datasets include crash statistics, various population based variables using block group level data from the Summary File 1 and Summary File 3 datasets from the 2000 US Census, road network summary statistics, and weather using Geographic Information System (GIS) geoprocessing.

Road network related summary statistics that include miles of different functional classes of roads, vehicle miles traveled, and bicycle facilities were calculated by intersecting the TAZ boundaries for these various layers of information in the GIS environment. Data by census block group were assumed to be homogeneous and were assigned proportionally to the TAZs. Daily weather was downloaded from the National Oceanic and Atmospheric Administration (NOAA) National Weather Service for the analysis period and assigned using the near analysis method.

Although hours of sunlight, cloudiness, temperature, precipitation and snow fall for various weather stations are included in the data that NOAA provides, some factors such as sunlight hours, cloudiness hours, were recorded for about 50% of the weather stations. Snowfall and sunlight hour variables therefore can be expected to be less accurate but nevertheless may provide information indicative of variation between TAZs.

Rainfall

It is generally accepted that the major contributing factor of rainy conditions to crashes is the reduction in pavement friction resulting from a water film on the pavement, as discussed previously. It was therefore necessary to develop a variable that would be indicate the likely presence of this water film – whether it exists and its' extent.

A detailed literature review of pavement friction and wet weather indicated that a precipitation of 0.1 mm over a one hour period will cause wet pavement (9). Andrey and Knapper (11) also used this threshold as criteria in the comparison of risks during precipitation relative to normal seasonal weather. If the average intensity of rainfall (calculated as an average per hour) on a particular day was equal to or higher than this value, it was classified as a wet pavement day with wet pavement hours. It is recognized that this assumption does not account for the effect of sunshine or wind on pavement wetness, two factors that can reduce the wetness of the pavement.

Given the knowledge of rain and its expected impact on safety, the possible complex relationships between pavement surface and safety, and the nature of the available weather data, five rain related variables were developed for use in this study:

- Total precipitation for 2001 and 2002 in inches,
- Number of rainy days in 2001 and 2002,
- Number of wet pavement days in 2001 and 2002 (as defined above),
- Hours of wet pavement in 2001 and 2002 (as defined above), and
- Average rainfall intensity defined as the total precipitation (as defined previously) divided by the number of rainy days (as defined previously).

Total Precipitation

The total precipitation variable indicates differences between low precipitation and high precipitation areas. However, it is reasoned that this variable is not sufficient to account for the amount of exposure to wet conditions because it does not provide information regarding intensities or frequencies of rainfall events. It may, however, capture to some extent how familiar or 'experiened' local drivers are when it comes to wet weather driving.

Number of Rainy Days

While total precipitation is likely to indicate wet and dry regions, the number of rainy days provides a measure of the frequency of days in which the driver is exposed to rainy weather. This variable may capture the effect of the driver experience with rainy conditions, perhaps even better than Total Precipitation.

Number of Wet Pavement Days

This variable is distinctly different from the number of rainy days as it only captures the number of days in which the hourly rainfall intensity exceeded a threshold that would indicate reduction in skid resistance. It is hypothesized that this variable may capture the frequency of days in which a driver is exposed to lower skid resistance conditions.

Hours of Wet Pavement

The hours of wet pavement represents the average number of hours in which a driver is exposed to lower skid resistance conditions, i.e. the average rainfall intensity measured during one day is sufficient to reduce skid resistance of the pavement. This variable is reasoned to be an exposure measure that is indicative of the number of hours in a day that a driver is exposed to lower skid resistance levels.

Average Rainfall Intensity

While the exposure measures listed previously indicate the frequency of rainfall events, this measure captures the average intensity of rainfall events. For example, if two regions are compared and they share similar annual rainfall, higher average rainfall intensity in one region would be indicative of more infrequent and intense events. Following the work by Satterthwatte (14) these event types would be more influential on safety than the frequent and less intense events. It may also be indicative of the likelihood that a driver would avoid driving in such conditions due to the perceived risk associated with the planned trip. Also, high intensity may be associated with flooding, high winds, and more hazardous driving conditions.

Assignment of Weather Variables to TAZs

Values of the weather variables were assigned to the centroids of the TAZs using the weather of the nearest weather station (known as the near station method). It is recognized that this approach has limitations, mainly because weather may not be homogeneous across an area. It was expected, however, that this method would provide an indication of inter-TAZ differences, especially between TAZs that are sufficiently far apart (e.g. different states). Alternative geoprocessing methods include methods in which surfaces are developed using the weather station observations as point values, interpolating between stations, and incorporating elevation differences into estimates.

It was decided that these more sophisticated methods would be too labor intensive to justify exploratory analysis on a planning level.

PLANNING LEVEL SAFETY PREDICTION MODELS (PLANSAFE)

Researchers involved in NCHRP 8-44 developed a planning level safety prediction model, dubbed PLANSAFE. This model is intended to facilitate regional safety planning. The approach uses socio-economic, demographic, and transportation related data to predict the safety of TAZs or larger sub-areas of a jurisdiction. The intent of the approach is to facilitate the use of travel demand model output and planning level data to allow for the incorporation of safety into planning level decision-making. The intended uses of the model include:

1. Setting Safety Targets: Safety targets serve as milestones for accomplishment. For example, a region may want to achieve a measurable decrease in pedestrian involved crashes. The PLANSAF models are suitable for establishing the expected number of crashes in some future time period in the absence of targeted safety countermeasures. PLANSAF is useful because crashes in the future are expected to change as a result of population growth, new road mileage, new schools, changing of the driving population, etc.
2. Understand the safety impacts of large scale projects (corridor level or higher): Large scale projects that may affect VMT, future growth, and other planning related factors will impact safety. The PLANSAF model is appropriate for forecasting the future expected safety performance of these projects in the absence of targeted safety countermeasures.
3. Compare and contrast growth scenarios: Growth scenarios are often compared looking 5, 10, and 20 years into the future. PLANSAF is suitable for predicting the safety performance of the region under different growth scenarios (e.g. infill development, sprawl, interstate vs. highway, population and demographic shifts, etc.) in the absence of targeted safety countermeasures.

Planning level models, in contrast, are not suitable for selecting land/use transportation investments (as say the sole criterion), for evaluating the impact of safety countermeasures, or for selecting safety countermeasures.

The PLANSAFE models are fundamentally different in nature to corridor or site specific safety prediction models that dominate the literature because the input data are aggregate and not site or project specific. Predictions are not location specific, as would be obtained from microscopic models of safety. Instead, predictions of safety are at the TAZ level. Macroscopic or planning level models are justified using the following three principles:

1. *Crashes are largely random events*. Much research has shown that crashes are largely caused by human errors, with estimates ranging between 60% and 90% of crashes being caused by human errors. Thus, many crashes are more a function of human related factors rather than roadway related factors. As simple examples, crashes that result from of a driver tuning a radio, answering a cell phone, following another vehicle too closely, speeding, and running a red light are events that occur somewhat randomly on a network. It is easy to understand, then, that modelling crashes at the segment or intersection level is challenging, because there is a large random component to crashes that is not explained by local road characteristics. At a more aggregate level, in contrast, crashes are related to aggregate predictors, such as population demographics, 'high risk' driving populations, the general classes of road facilities, etc., and assigning crashes to specific links or segments is not necessary. Thus, by aggregating the transportation system at the TAZ level, some of the difficulties caused by 'lumpiness' of random events that we see across intersections or across road segments are reduced.
2. *Aggregate safety differences are substantiated by research*. Much research supports 'aggregate' or average safety differences across groups. Older drivers suffer from reduced reaction and perception times, as well as reduced vision and flexibility. Younger drivers suffer from inexperience and aggressiveness. Minorities have been shown to wear safety restraints less than whites, and restraint use in rural areas is less than in urban areas. Interstates are associated with relatively low crash rates, while rural roads with high speeds are associated with more serious injury crashes. Crashes in urban areas are attended by emergency medical services more quickly than crashes in rural areas. Intersections are locations of complex traffic movements and thus are associated with greater numbers of crashes than road segments. Increasing traffic congestion tends to reduce crash severity. School zones are associated with bicycle and pedestrian crashes. These well supported aggregate relationships, and others not listed here, are the relationships captured in aggregate level prediction models. The aggregate relationships described above form the basis for the statistical modelling at the TAZ level. It is the reliance on these 'average' relationships, and characteristics measured at the TAZ level, on which model predictions are based.

3. *Models for predicting have fewer restrictions than models for explaining.* Intersection and road-segment level accident prediction models are usually held to a high standard, as they are often used both to predict the expected performance of such facilities but also to explain relationships between variables. Often, and sometimes wrongly, these microscopic models are used to infer the effects of countermeasures, such as the safety effect of the presence of a left-turn lane on angle crashes. When a model is used simply for prediction, however, and not inference, there is greater flexibility in model estimation and variable selection choices. The PLANSAF model is intended only for prediction, and not explanation. Thus, for example, if a population variable is used to predict fatal crashes per TAZ, its estimated coefficient is used solely in the prediction equation but is not interpreted to have specific explanatory marginal effects.

These three arguments, or justifications, form the basis for the development of aggregate level accident prediction models. A consequence of these arguments, however, is that the models cannot be used for explanation of crash causation or for the assessment of roadway-specific countermeasures. The aggregate relationships modeled are suitable for predicting a hypothetical or future outcome should the set of predictors be changed. This restriction is not too dissimilar from the restriction placed on travel demand models, whose primary purpose is to predict demand for roadway space of motor vehicles in hypothetical or future scenarios.

MODELLING METHODOLOGY

Linear regression models with a logarithmic transformation of the dependent variable were developed in the study. This modelling framework was chosen because the log transform of crashes at the TAZ level are approximately normally distributed and because the linear regression framework is quite flexible with respect to functional forms.

A common dataset was developed for three regions by TAZ: Michigan State, Pima County (from hereon referred to as PAG), Arizona, and Maricopa County (from hereon referred to as MAG), Arizona. Indicator variables were created for each region and LIMDEP was used to perform the modeling. The base model variables for the accident frequency prediction model were:

- POP_PAC: the total population in the TAZ per acre. It was calculated using the population frequency as provided as variable P001001 in the US Census Summary File 1 dataset.
- POP16_64: the total population ages 16 to 64. It was calculated by adding the following variables the US Census Summary File 1 dataset together: P012007…P012019 + P012031..P012043 + P014019 + P014020 + P014040+ P014041.
- TOT_MILE: the total miles of roadway in the TAZ. This includes the total mileage of roadways as contained in the GIS layers and also those provided by the respective roadway agencies. These include all the different functional classes of roads.

This set of variables surfaced as a ‘common set’ of explanatory variables that were found to be significant in accident frequency models across regions. While other variables were available, such as lane miles of specific functional classes and other age categories, these variables did not offer improved fit across the three regions. Although PLANSAFE models are not meant to be explanatory in nature, the abovelisted variables do represent reasonable variables affecting safety. While the total miles of roadway in the area (TOT_MILE) provides information regarding the exposure of individuals to accident risk, the portion of the population ages 16 to 64 represents the number of individuals that experiences the largest exposure to accident risk because it represents a group of individuals that are generally economic active, engages in increased travel resulting from trips in addition to work and retail related travel such as taking children to school etc. The population density variable (POP_PAC) is thought to represent the frequency of expected conflicts as larger densities is likely to increase the number of conflicts resulting from increased levels in travel compared to lower density areas. It may also be indicative of residential areas that generate relatively consistent daily work related travel patterns.

The base models for the prediction of crashes with a fatal and/or injury severity is more complex as the base models varies substantially between regions. An example of the variables included in such a model was included in Table 6.

Correlation between variables and the rain-related weather variables under consideration were evaluated. The following rain-related variables were considered for inclusion in the base accident frequency and the base injury + fatality accident frequency models:

- TOTPREC: Total precipitation for 2001 and 2002

- RAINDAYS: Number of rainy days in 2001 and 2002
- WETPVDAY: Number of wet pavement days in 2001 and 2002 (as defined above)
- HRWETPAV: Hours of wet pavement in 2001 and 2002 (as defined above).
- AVERINT: Average rainfall intensity = Total Precipitation (as defined above)/ Number of rainy days (as defined above).

It is hypothesized that the variation in weather is relatively large between TAZs in Michigan and those in the two regions in Arizona (PAG, and MAG). It is also hypothesized that the effect of rain or weather in general is relatively more influential for the TAZs in Michigan compared to the two regions in Arizona (PAG, and MAG).

FINDINGS

The study evaluated the inclusion of weather related variables into existing PLANSAFE (planning level safety prediction) models for overall crash frequency and frequency of crashes with a degree of severity of injury and higher. The evaluation also included the consideration of regional indicators instead of or in combination with the weather variables. This section first describes the findings related to models predicting crash frequency, then models predicting the frequency of injury + fatal degree crashes, and lastly discusses the findings related to the consideration of inclusion of regional variables into PLANSAFE models.

In both model types models were valuated for different regions. These regions include one or a combination of the following regions: Michigan State, PAG, and MAG.

Predicting Crash Frequency

Planning level models for predicting crash frequency per TAZ were developed for the combined dataset, i.e. the dataset consisting of Michigan, MAG, and PAG; and also for the individual regions. The model form is shown below.

$$\text{Log(Accident Frequency +1)} = \text{constant} + b_1\text{*POP\_PAC} + b_2 * \text{POP16\_64} + b_3 * \text{TOT\_MILE}$$

Table 1 summarizes the variable statistics for a region that consists of a combination of Michigan State; Michigan State only; MAG only; PAG only; and a combination the MAG and PAG regions. Table 2 summarizes the coefficients and t values for the base accident frequency models by region.

The base model for accident frequency performs relatively well for the combination of all the regions in the dataset. However, the model performance for the two regions in Arizona are poorer with a lower goodness of fit than that associated with the model for Michigan State and the combination of all the regions used for the evaluation. It is indicative of omitted variables and the necessity to introduce variables that vary sufficiently between the regions and that would improve overall model performance.

Table 3 summarizes the characteristics of the rain related variables that were developed to evaluate the value of rain related variables in planning level accident frequency prediction models. Table 4 summarizes the t-values for the base accident frequency model for each region and then also the significance of the variables and overall goodness of fit of the models when adding rain-related variables.

In all cases shown in Table 4 the rain-related variables were statistically significant and improved overall goodness of fit. The t values and coefficients associated with the weather variables, suggest that these variables provide better explanatory power than models without the weather variables.

The largest improvements were found for two regions: the models developed for the combination of the three regions and also for Michigan State alone. It is hypothesized that these regions provide adequate levels of variation in the weather variables while regions such as PAG and MAG shows relatively low variation and thereby reducing the effect of the variables in the model.

Interaction between the weather variables and the variables in the base model differed between models for different regions. This may indicate that the effect of the rain-related variables is not likely to be consistent between regions.

Another possible explanation may be that the combination of rain-related variables may be indicative as a group of regional differences.

An interesting observation is the observed effect of average intensity (AVERINT). This variable generally performed well in the models and consistently acted as a variable that reduces the baseline accident frequency estimated. While this seem to be contradicting the general hypothesis that rain reduces safety, it can be argued that this variable in fact provides information beyond skid resistance reduction but provides information related to driver behavior and travel choices. For example, if driver A lives in Phoenix, Arizona, rainfall events are relatively scarce but the average intensity of these events are high. Driver A who lives in a wetter region in Michigan may experience more frequent but less intense rainfall events. It can be reasoned that driver A would be more likely to postpone the trip to a later time to avoid the wet pavement (reduced skid resistance) conditions and therefore reduce exposure rates and therefore reduce the expected accident frequency. In other words, interpretation of rain intensity may be indicative of risk compensation whereby a driver perceives light rain as slightly more risky compared to intense rain where significantly greater risk is perceived and where the driver then compensates accordingly. This risk compensation interpretation is a post-hoc observation that warrants further investigation. It may be indicative of more complex phenomenon not captured by the total precipitation variables that are most often used in studies that incorporates weather into the analysis.

When comparing the modelling results for Michigan State, only with accident frequency models for the other regions and combinations of Michigan State with these regions, another interesting aspect is noted. Coefficients for the wet pavement hours (HRWETPAV) and wet pavement days (WETPVDAY) were consistently negative, in other words, these variables consistently reduced accident frequency in the Michigan state but increased accident frequency for models for the other regions and for combinations of regions that included Michigan State. It is hypothesized that these two variables are indicative of exposure to actual lower skid resistance conditions, i.e conditions where stopping distances are increased and where the driver is required to reduce travel speed to achieve the same level of risk. It is hypothesized that this may be indicative of differences in driver behavior between regions where rainfall is a common event, such as Michigan State, and those in which rainfall is a relatively rare event, such as in Pima or Maricopa county in Arizona. The expected reduction in accident frequency suggested by these variables for Michigan State may indicate that drivers that are more used to rainy conditions may be more likely to adjust travel speeds to allow for adequate stopping distances while drivers in areas where rainfall is relatively rare are less likely to reduce their travel speed and therefore increase crash risk.

The total precipitation variable (TOTPREC) also behaved differently between models for Michigan State and those for PAG and MAG. In the case of Michigan it increased the baseline crash frequency while in PAG and MAG it was more likely to reduce the baseline frequency levels. This seems to support the theory that rain events would be more likely to affect travel behavior in areas where rainfall are less common events.

Table 5 summarizes modelling efforts to evaluate the effect of using regional indicators rather than weather related variables, using regional indicator variables compared to selected rain-related variables, and models with rain-related variables but without regional indicators. This analysis was completed as part of the study to allow the researchers to compare benefits achieved through the use of a regional indicator rather than using a combination of rain-related variables that would be more labor intensive and complex. The regional variable for the models using the combined dataset (Michigan State, MAG, and PAG) did improve the overall model fit and in some cases reduced the significance of rain-related variables that were quite significant in previous modelling efforts. This improvement may indicate that the rain related variables do not provide sufficient information to explain the regional differences. However, in the cases where models were developed for a particular region, i.e. only Michigan State, or MAG, or PAG, the use of a regional indicator is not available alternative modeling approach and in those cases the rain-related variables improved model fit (as shown in Table 4), thereby providing opportunity for the development of models that has improved explanatory power. However, the fact that the regional indicator do offer model improvement for models across regions suggests that further investigation of other weather variables and other variables for the PLANSAFE models are warranted.

Predicting Frequency of Fatal and Injury Crashes

Generally authorities are more concerned about crashes with injuries and/or fatalities. It is also generally accepted that property damage only crashes are more likely to be underreported than those with injuries and/or fatalities.

Researchers therefore decided to evaluate models for crashes that would be more stable, i.e. would be more suitable for safety prediction, and would meet a particular need of expected users of the models.

The PLANSAFE models for the prediction of crashes with a fatal and/or injury severity is more complex because the base models varies substantially between regions, i.e. there wasn't a common base model that performed adequately across regions and for each of the regions separately. Weather variables were found to be statistically significant in most cases, and the inclusion of one or more of these rain-related variables models improved overall goodness of fit. Table 6 provides a summary of one base model, with associated variables, for the combined dataset (combination of Michigan State, MAG, and PAG) and the subsequent improved model when incorporating one or more rain-related variables. The total precipitation (TOTPREC) and average intensity (AVERINT) variables behaved consistent with the behavior found for the accident frequency models, i.e. base line accident frequency were increased with an increase in total precipitation and reduced for an increase in average intensity.

When evaluating the extent of improvement of goodness of fit between models across regions, researchers found that the extent of this improvement is the largest for regions that includes all the regions (combination of Michigan State, MAG, and PAG) and models for Michigan State only. This seem to indicate that regions with higher degrees of variation in weather would benefit more from the inclusion of weather related variables to account for the portion of unexplained phenomenon in the base model.

CONCLUSIONS AND RECOMMENDATIONS

Based on the results of this study, the following conclusions are drawn:

1. The inclusion of rain related variables in general improves the overall fit of planning level safety prediction models (PLANSAFE models) for both the models that predict total accident frequency and the frequency of crashes with a fatal and/or injury.
2. Weather variables in PLANSAFE models are generally statistically significant.
3. Combinations of rain-related variables in accident frequency and frequencies of accidents with injury + fatal injury models are generally more efficient than models that incorporates only one of the rain-related variables. This seem to suggest that the different rain-related variables that were evaluated in this study explains different aspects of factors accounting for differences between regions.
4. The difference found in the behavior of the total precipitation, average rainfall intensity, and wet pavement related variables between models seem to be indicative of different driver behavior and warrants further investigation.
5. The effect and behavior of the various rain-related variables evaluated in this study suggest that the variables explain different phenomenon related to weather and the safety in a region. For example, the number of rainy days may allow for an adjustment of the baseline accident frequency while rainfall intensity may be indicative of different driving behavior.
6. The significance of the region level indicator variables suggest that regional differences are not completely explained by the included weather variables. It is possible that additional weather related variables are needed, or non weather variables are needed to explain the inter-regional differences as yet unexplained. However, in cases where the use of a regional indicator is not possible, i.e. there isn't sufficient regional differences that can be captured by a regional indicator only, inclusion of rain-related variables is warranted.

The following recommendations are made based on the results of the study:

1. Weather, in particular rain, plays a significant role in driving risk. Rain-related variables are needed to help explain differences between crash experience across regions and the results seem to indicate sufficient improvement of the models to warrant the additional effort required to include these variables into datasets.
2. Additional weather related variables, such as ice, snow, and fog, should be examined.
3. Risk compensation needs to be examined. Because rain has a theoretically complex influence on roadway safety, the way in which different drivers respond to rain is of extreme interest. Risk compensation—a driver's response to perceived risk—is likely to play a critical role in sorting out the exact impacts of rain on roadway safety.

ACKNOWLEDGEMENTS
The research team ackowledges the Arizona Department of Transportation, Pima County, Maricopa County, and Michigan Department of Transportation for providing roadway and accident related datasets for the study and for the National Oceanic and Atmospheric Administration (NOAA) National Weather Service for making daily weather available online. The National Academies of Science deserve recognition for funding the initial research for NCHRP 8-44 on which this study rests.

REFERENCES

1. Harwood, D. W., Council, F. M., Hauer, E., Hughes, W. E., and Vogt, A. Prediction of the Expected Safety Performance of Rural Two-Lane Highways. Publication No. FHWA-RD-99-207, 2000, U.S. Department of Transportation, Turner-Fairbank Highway Research Center, McLean, VA 22101-2298.
2. Council, F. and Stewart, J. R. Safety effects of the conversion of two-lane rural to four-lane rural roadways based on cross-sectional models, 2000, Transportation Research Board Annual Meeting, Washington D.C.
3. Maze, T. H., J. L. Henderson, and S. Sankar. Impacts on Safety of Left-Turn Treatment at High-Speed Signalized Intersections, Iowa Highway Research Board Project HR-347, January 1994, Iowa State University.
4. Vogt, A., Crash Models for Rural Intersections: 4-Lane by 2-Lane Stop-Controlled and 2-Lane by 2-Lane Signalized, Report No. FHWA-RD-99-128, Federal Highway Administration, October 1999.
5. Gibby, A., Reed, A., Washington, S.P., and Ferrara, T.C. Evaluation of High-Speed Isolated Signalized Intersections in California, Transportation Research Record 1376, 1993, Publication No. UCD-ITS-RP-93-3.
6. Poch, M., and F. L. Mannering. Negative Binomial Analysis of Intersection Accident Frequencies, January 1996, Annual meeting of the Transportation Research Board, Washington, D.C.
7. Harwood, D.W..Multilane Design Alternatives for Improving Suburban Highways, NCHRP Report 282, 1986, Transportation Research Board, Washington, D.C.
8. Zegeer, C. V., R. Stewart, F. Council, and T. R. Neuman, "Accident Relationships of Roadway Width on Low-Volume Roads," Transportation Research Record 1445, Transportation Research Board, 1994.
9. Kokkalis, A.G., and Panagouli, O.K. Factual Evaluation of Pavement Skid Resistance Variation. I: Surface Wetting from Chaos, Solitions & Fractals, Vol. 9, No. 11, 1998, pp.1875-1890.
10. Boyle, L.N., and Mannering, F. Impact of traveler advisory systems on driving speed: some new evidence, Transportation Research Part C: Emerging Technologies, Vol.2, Issue 1 , February 2004, pp. 57-72.
11. Andrey, J., and Knapper, C. (edited by). Weather and Transportation in Canada, Department of Geography Publication Series, 2003, Department of Geography, University of Waterloo.
12. Shankar, V.N and Chayanan, S. The Marginal Impacts of Design, Traffic, Weather, and Related Interactions on Roadside Crashes, presented at the 82nd Annual Meeting of the Transportation Research Board, 2004, Washington D.C.
13. Milton, J. and F. Mannering (1998) The relationship among highway geometrics, traffic related elements and motor vehicle accident frequencies, Transportation, Vol. 25, No. 4, pp.395-413.
14. Satterthwatte, S.P. An Assessment of Seasonal and Weather Effects on the Frequency of Road Accidents in California, Accident Analysis and Prevention, Vol.8, pp.87-96, 1976, Pergamon Press.
15. Oh, J., Lyon, C., Washington S.P., Persaud B., and Bared J. Validation of the FHWA Crash Models for Rural Intersections: Lessons Learned. Journal of the Transportation Research Board. National Academy Press, Washington D.C., No 1840, 2003, pp 41-49.
16. Washington, S.P., Persaud B., Oh, J., and Lyon, C. Validation and Recalibration of Accident Prediction Models for Rural Intersections. Final Report, 2005, Department of Transportation, Federal Highway Administration, Office of Acquisition Management, Washington D.C.
17. Lyon, C., Oh, J., Persaud, B., Washington S.P., and Bared, J. Empirical Investigation of the IHSDM Accident Prediction Algorithm for Rural Intersections. Journal of the Transportation Research Board, 2003, National Academy Press, Washington D.C., No 1840. pp 78-86.

Table 1: Variable Statistics for Planning Level Accident Frequency Model

VARIABLE	Statistic	MICHIGAN STATE, MAG, PAG	MICHIGAN STATE	MAG	PAG	MAG, PAG
POP_PAC (population per acre)	Mean	1.87387	2.21634	0.386094	3.90137	1.55454
	Std.Dev.	3.22845	3.51992	0.438722	4.0731	2.89511
	Skewness	2.621	2.34367	1.63245	1.32129	2.93912
	Kurtosis	11.6255	10.0868	7.64235	5.16343	13.4456
	Minimum	2.51E-06	0.001083	4.12E-06	2.51E-06	2.51E-06
	Maximum	30.8821	30.8821	3.75561	24.4839	24.4839
	NumCases	4779	2306	1651	822	2473
POP16_64 (population age 16 to 64)	Mean	0.641392	0.637632	0.647475	0.639722	0.644898
	Std.Dev.	0.078925	0.047601	0.100471	0.0974	0.099508
	Skewness	-1.11009	2.49446	-1.5285	-1.15505	-1.40671
	Kurtosis	13.8933	17.0196	10.4846	9.10921	10.024
	Minimum	0.117531	0.510894	0.117531	0.178771	0.117531
	Maximum	0.999809	0.999809	0.99673	0.998213	0.998213
	NumCases	4779	2306	1651	822	2473
TOT_MILE (total mileage – includes all functional classes)	Mean	33.0001	58.9728	12.2203	1.87406	8.78135
	Std.Dev.	38.1929	37.5681	19.787	2.60765	16.9516
	Skewness	2.11378	1.16997	16.1242	5.52901	17.6505
	Kurtosis	13.9249	6.39375	385.459	47.376	491.763
	Minimum	0	2.167	0	0.003176	0
	Maximum	556.749	323.448	556.749	32.036	556.749
	NumCases	4779	2306	1651	822	2473

Table 2: PLANSAFE Accident Frequency Base Model

VAR	MAG, PAG, MI	MICHIGAN ONLY	MAG and PAG	MAG ONLY	PAG ONLY
	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)
Constant	3.5 (139.758)	4.59 (143.907)	2.98 (81.765)	2.96 (67.113)	2.51 (34.166)
POP_PAC	7.34×10^{-2} (12.533)	4.53×10^{-2} (8.537)	5.56×10^{-2} (6.197)	1.39 (13.806)	0.118 (8.795)
POP16_64	2.72×10^{-4} (34.342)	1.98×10^{-4} (36.217)	6.15×10^{-4} (28.952)	2.79×10^{-4} (8.883)	4.37×10^{-4} (4.528)
TOT_MILE	1.14×10^{-2} (23.390)	1.51×10^{-3} (3.45)	8.4×10^{-3} (5.312)	9.85×10^{-3} (6.220)	6.84×10^{-2} (3.998)
Adjusted R-squared	0.43394	0.54526	0.30335	0.39197	0.22752

Table 3: Variable Statistics for PLANSAFE Accident Frequency Model

VARIABLE	Statistic	MICHIGAN STATE, MAG, PAG	MICHIGAN STATE	MAG	PAG	MAG, PAG
TOTPREC (total precipitation for 2001 to 2002)	Mean	36.172	59.6457	11.5225	19.8289	14.2834
	Std.Dev.	24.761	13.2787	1.96443	5.32739	5.22673
	Skewness	0.3061	-1.23279	0.579336	2.65735	2.20257
	Kurtosis	1.4145	5.67529	3.22417	12.3601	11.3578
	Minimum	1.39E+00	7.69	1.39E+00	15.62	1.39
	Maximum	91.14	91.14	16.88	49.3	49.3
	NumCases	4779	2306	1651	822	2473
RAINDAYS (total days with any rain for 2001 and 2002)	Mean	148.377	233.585	50.1981	106.53	68.9224
	Std.Dev.	94.3777	59.2249	12.3697	12.3225	29.2751
	Skewness	0.378295	-0.54534	0.04639	-0.16326	0.526633
	Kurtosis	1.74476	3.68843	3.40444	4.42671	1.9844
	Minimum	2	36	2	64	2
	Maximum	380	380	84	152	152
	NumCases	4779	2306	1651	822	2473
HRWET PAV (total hours that average rainfall exceeded 0.1mm per hour)	Mean	1298.24	2010.83	519.081	864.101	633.762
	Std.Dev.	947.77	908.121	120.075	218.093	227.699
	Skewness	1.1827	0.501749	-0.57796	0.349052	0.948391
	Kurtosis	3.36143	2.12321	3.15216	3.41521	4.18794
	Minimum	14	256	14	528	14
	Maximum	4369	4369	752	1717	1717
	NumCases	4779	2306	1651	822	2473
WETPV DAY (number of days in which one or more wet pavement hours occurred)	Mean	99.9789	163.961	33.6045	53.8017	40.3178
	Std.Dev.	69.0768	42.2482	6.8394	13.1066	13.3729
	Skewness	0.47897	-0.24983	0.856175	1.20195	1.41073
	Kurtosis	1.82937	4.25273	3.19278	3.73959	5.25022
	Minimum	2	15	2	42	2
	Maximum	327	327	55	101	101
	NumCases	4779	2306	1651	822	2473
AVERINT (average intensity as calculated: TOTPREC/ RAINDAYS	Mean	0.224888	0.224888	0.242865	0.188781	0.224888
	Std.Dev.	0.071088	0.071088	0.071698	0.054122	0.071088
	Skewness	1.39912	1.39912	1.43988	1.52876	1.39912
	Kurtosis	5.24108	5.24108	5.14685	5.02344	5.24108
	Minimum	0.142	0.142	0.16375	0.142	0.142
	Maximum	0.695	0.695	0.695	0.410833	0.695
	NumCases	2473	2473	1651	822	2473

Table 4: Estimated t-values for planning level models developed with rain-related variables: accident frequency models

REGION/ *MODEL*	VARIABLE t VALUES									
MI, PAG, MAG	**Constant**	**POP_PAC**	**POP16_64**	**TOT_ MILE**	**TOTPREC**	**RAINDAYS**	**HRWETPAV**	**WETPVDAY**	**AVERINT**	**Adjusted R squared**
BASE MODEL	3.5	-139.758	7.34 x 10^{-2}	-12.533						0.43394
BASE MODEL WITH WEATHER	59.183	6.262	36.959	10.433	17.43				-9.720	0.47115
	110.423	8.391	36.212	10.090	15.453					0.43394
	50.690	6.552	36.688	11.466		14.902			-4.443	0.46249
	53.746	7.393	35.361	16.111			13.938		-5.189	0.45949
	54.361	6.364	36.709	9.964			5.986	9.929	-6.911	0.47032
	56.755	7.47	37.076	10.309				16.097	-7.755	0.46645
	106.399	7.437	36.240	9.324			6.941	8.806		0.46513
MI STATE	**Constant**	**POP_PAC**	**POP16_64**	**TOT_ MILE**	**TOTPREC**	**RAINDAYS**	**HRWETPAV**	**WETPVDAY**	**AVERINT**	**Adjusted R squared**
BASE MODEL	143.907	8.537	36.217	3.45						0.54526
BASE MODEL WITH WEATHER	42.126	8.479	34.08	4.575	3.757		-2.797	-4.973	-4.493	0.55135
	63.998	8.408	36.113	3.549					-2.531	0.54636
	74.505	8.49	34.423	3.81				-3.494		0.54746
	40.677	8.493	34.809	3.65		-2.294			-3.337	0.54719
	51.857	8.343	34.234	3.944				-3.717	-2.857	0.54887

MAG	**Constant**	**POP_PAC**	**POP16_64**	**TOT_ MILE**	**TOTPREC**	**RAINDAYS**	**HRWETPAV**	**WETPVDAY**	**AVERINT**	**Adjusted R squared**
BASE MODEL	67.113	13.806	8.883	6.22						0.39197
BASE MODEL WITH WEATHER	3.937	10.869	8.543	8.554	-7.995	-4.441	11.889	9.749		0.45101
	2.249	10.736	8.876	8.053	-6.81		10.222	7.737	2.077	0.44588
	31.918	12.15	9.24	7.157					-7.389	0.41113
	13.213	11.347	9.645	8.13			6.677		-5.397	0.42632
PAG	**Constant**	**POP_PAC**	**POP16_64**	**TOT_ MILE**	**TOTPREC**	**RAINDAYS**	**HRWETPAV**	**WETPVDAY**	**AVERINT**	**Adjusted R squared**
BASE MODEL	34.166	8.795	4.528	3.998						0.22752
BASE MODEL WITH WEATHER	59.183	6.262	36.959	10.433	17.43				-9.72	0.43394
	50.69	6.552	36.688	11.466		14.902			-4.443	0.46249
	53.746	7.393	35.361	16.111			13.938		-5.189	0.45949
	54.31	6.364	36.709	9.964			5.986	9.929	-6.911	0.47032
	56.755	7.47	37.076	10.309				16.097	-7.755	0.46645
	58.089	11.577	34.591	24.123					-5.667	0.4376
MAG & PAG	**Constant**	**POP_PAC**	**POP16_64**	**TOT_ MILE**	**TOTPREC**	**RAINDAYS**	**HRWETPAV**	**WETPVDAY**	**AVERINT**	**Adjusted R squared**
BASE MODEL	81.765	6.197	28.952	5.312						0.30335
BASE MODEL WITH WEATHER	32.139	2.776	28.496	5.3	-14.089		9.698			0.36078
	33.08	7.68	25.466	6.079		-11.123			-14.54	0.36239
	28.965	3.198	29.278	5.156				-10.093	6.771	0.33674
	39.864	5.606	27.207	5.581	-10.093				-8.882	0.35697

Table 5: Accident Frequency Models with Regional Indicators and Combinations of Rain-Related and Regional Indicators

MODELS	**VARIABLES WITH ASSOCIATED COEFFICIENT (t-values)**										
	Constant	**POP_PAC**	**POP16_64**	**TOT_ MILE**	**TOTPREC**	**RAINDAYS**	**HRWET PAV**	**WETPV DAY**	**AVER INT**	**AZ_IND**	**Adjus-ted R Square Value**
BASE 1	3.500 (139.758)	7.339 (12.533	2.720 x 10^{-4} (34.342)	1.141 x10^{-2} (23.390							0.43394
MOD 1	4.328 (94.321)	4.149x10^{-2} (7.155)	2.634 x 10^{-4} (34.722)	3.115 x10^{-3} (5.110)						-0.925 (-21.154)	0.48234
BASE 2	3.804 (59.183)	3.752x 10^{-2} (6.262)	2.840 x 10^{-4} (36.959)	6.120 x10^{-3} (10.433)	1.462 x10^{-2} (17.430)				-2.531 (-9.720)		0.47115
MOD 2	5.413 (44.198)	3.111x 10^{-2} (5.305)	2.573 x 10^{-4} (33.420)	3.300 x10^{-3} (5.474)	-6.426 x10^{-3} (-4.013)				-2.575 (-10.128)	-1.318 (-15.296)	0.49576
BASE 2	3.247 (110.423)	4.965x10-2 (8.391)	2.807 x10-4 (36.212)	5.975 x10^{-3} (10.090)	1.273 x10^{-2} (15.453)						0.46079
MOD 2	4.834 (44.161)	4.351x10^{-2} (7.505)	2.542 x10^{-4} (32.691)	3.168 x10^{-3} (5.210)	-8.189 x10^{-3} (-5.090)					-1.308 (-15.023)	0.48503
BASE 4	3.495 (50.690)	3.984x10^{-2} (6.552)	2.845 x10^{-4} (36.688)	6.826 x10^{-3} (11.466)		3.181 x10^{-3} (14.902)			-1.139 (-4.443)		0.46249
MOD 4	6.008 (40.693)	3.508 x10^{-2} (40.693	2.493 x10^{-4} (32.348)	3.504x10^{-3} (5.842)		-2.987 x10^{-3} (-7.791)			-3.641 (-13.010)	-1.559 (-19.059)	0.50041
BASE 5	3.610 (53.746)	4.460x10^{-2} (7.393)	2.738 x10^{-4} (35.361)	8.700 x10^{-3} (16.111)			2.722 x10^{-4} (13.938)		-1.330 (-5.189)		0.45949
MOD 5	5.097 (48.664)	2.957x10^{-2} (5.016)	2.643 x10^{-4} (35.203)	3.241x10^{-3} (5.373)			-1.925 x10^{-5} (-0.776)		-2.731 (-10.514)	-1.050 (-18.105)	0.49412
BASE 6	3.614 (54.361)	3.822x10^{-2} (6.364)	2.838 x10^{-4} (36.709)	5.984x10^{-3} (9.964)			1.404 x10^{-4} (5.986)	3.590 x10^{-3} (9.929)	-1.781 (-6.911)		0.47032
MOD 6	5.523 (40.272)	2.967 x10^{-2} (5.044)	2.547 x10^{-4} (32.812)	3.557x10^{-3} (5.875)			-1.116 x10^{-5} (-0.467)	-2.501 x10^{-3} (-4.780)	-2.821 (-10.858)	-1.353 (-15.762)	0.49643
BASE 7	3.699 (56.755)	4.437 x10^{-2} (7.470)	2.870 x10^{-4} (37.076)	6.202x10^{-3} (10.309)				4.816 x10^{-3} (16.097)	-1.988 (-7.755)		0.46645
MOD 7	5.495 (44.446)	2.933 x10^{-2} (5.025)	2.548 x10^{-4} (32.844)	3.570x10^{-3} (5.902)				-0.252 x10^{-3} (-4.821)	-2.795 (-11.022)	-1.338 (-16.910)	0.49651
BASE 8	3.204 (106.399)	4.439 x10^{-2} (7.437)	2.812 x10^{-4} (36.240)	5.603 x10^{-3} (9.324)			1.620 x10^{-3} (6.941)	3.150 x10^{-3} (8.806)			0.46513
MOD 8	4.581 (42.490)	4.030 x10^{-2} (6.865)	2.560 x10^{-4} (32.582)	3.418 x10^{-3} (5.578)			4.715 x10^{-5} (1.924)	-2.088 x10^{-3} (-3.954)		-1.117 (-13.284)	0.48409

Table 6: Example of Planning Level Safety Prediction Models for the Prediction of Frequency of Crashes with a Fatal and/or Injury Level of Severity for the region that includes the entire Michigan State, Pima County (AZ), and Maricopa County (AZ)

VARIABLE NAME	**VARIABLE DESCRIPTION**	**BASE MODEL WITHOUT RAIN-RELATED VARIABLES: Coefficients (t-value)**	**BASE MODEL WITH SELECTED RAIN-RELATED VARIABLES Coefficients (t-value)**
Constant		1.363 (62.117)	1.374 (26.916)
TOT_MILE	Total number of miles in the TAZ (includes all different functional classes) (US Census 2000)	1.580×10^{-2} (38.512)	6.344×10^{-3} (14.139)
POP00_15	Number of individuals age 0 to 15 in the TAZ (US Census 2000)	6.590 x 10-4 (40.102)	6.663×10^{-4} (46.239)
NF0214PA	Total miles of Other Principal Arterial (excludes principal arterials that are interstate) as a portion of the total size of the TAZ in acres	170.69 (18.376)	135.358 (16.465)
NF0616PA	Total miles of Minor Arterial roads (excludes principal arterials that are interstate) as a portion of the total size of the TAZ in acres	193.933 (20.373)	114.260 (13.251)
TOTPREC	Total precipitation in the area measured over two years (2001 and 2002)		2.547×10^{-2} (37.850)
AVERINT	Average Intensity of Rainfall (calculated by dividing TOTPREC and number of days with any rainfall)		-2.225 (-10.710)
Adjusted R-squared value		0.55536	0.65819