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# *The Impact of Weather Conditions on Road Safety Investigated on an Hourly Basis*

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## ABSTRACT

In this paper we investigate the impact of several weather conditions on the hourly number of crashes in the Netherlands during 2002. The impact of 17 climatic factors, belonging to the categories wind, temperature, sunshine, precipitation, weather image and visibility is quantified and compared with results from other research. The following could be concluded: an increase in maximum wind gust causes an increase in the number of crashes. Global radiation and sunshine duration both have a significant negative impact on road safety. Of all categorical weather indicators, presence of precipitation had the most significant impact. Moreover, the impact of precipitation duration seemed higher than the amount of precipitation. Finally, the direction of the effect of cloudiness on the number of crashes was also found positive. We applied a regression methodology making use of several distributions of the Poisson family. We tested which distribution fitted the actual observations best and found that, on average, the Negative binomial model performed better than the Poisson model, the Zero-inflated Poisson model and the Zero-inflated negative binomial model.

## 1. INTRODUCTION

Worldwide, an estimated 1.2 million people are killed in road crashes each year and as many as 50 million are injured (*1*). The human as well as material damage caused by road accidents is estimated on 1 to 2% of the gross national product. Consequently, there is a lot of interest in the way road safety can be enhanced. Research on specific aspects has been done in order to gain insights in the processes affecting accident risk. Knowledge about which factors affect road safety and what their influence is can be helpful to reduce the accident toll. The impact of factors influencing road safety is, however, a complex theme. Looking at the causes of crashes a distinction can be made into three categories: human, vehicle and infrastructure (*2*).

Of all the groups of explanatory factors worth investigating, in this research we will focus on the impact of weather conditions on crashes. The relationship between weather conditions and crashes has been the subject of a number of studies. It is estimated that weather conditions can explain 5% of the variation in injury crashes. This may seem small but one has to take into account that traffic intensity explains over 70% of the variation and another 5% is determined by randomness (*3*). In this study, we will look at the number of crashes on an hourly basis using regression techniques on distributions of the Poisson family. The analyses have the objective to investigate whether the examined weather phenomenon has a significant impact on road safety and in case it does, which effect this is. Besides quantifying to what extent a change in the weather produces a change in road safety we investigate which statistical model is most appropriate for the analyses.

The paper is organized as follows: in the background section we give an overview of the most relevant literature concerning weather impact studies. Second, the methodology will be amplified, followed by the presentation of the data and an elucidation of the data processing. After that, the results will be presented and discussed. Finally, this report is completed by a summary of the conclusions and topics for further research.

## 2. BACKGROUND

In the literature a considerable amount of information concerning the impact of weather conditions on road safety can be found. Research on this subject began in the fifties. Although these studies are clearly on the rise since the seventies, gaps are still noticeable and knowledge on this subject is far from complete. Certain sub domains received much attention from the academic world, while others barely.

Research on this subject can be classified in several ways, depending on the statistical methods being used, the level of aggregation, considered time period, choice of road system, the dependent variables being studied and the explanatory variables included in the models. Concerning the level of aggregation or size of the studied observation periods three levels are usually distinguished: the macro level with one observation each year, the meso level with one observation each day and the micro level, which covers only one observation each fraction of a day. Furthermore, there exist intermediate forms which study road safety for example season per season or on a monthly or weekly basis. The oldest studies concentrated especially on the macro level. Later on, the meso level received more attention. Nowadays, most information is available on the macro and meso level. Research on an hourly basis (the so-called micro level) is rarely done. Yet, all levels of aggregation have their advantages and disadvantages. Traffic studies on the macro level can be used to detect structural influences like car design or road policy but have difficulties distinguishing weather or seasonal effects

(*4*). Monthly studies can take seasonal influences into account while retaining the advantages of studies on a yearly basis. However, they are also less appropriate for measuring weather influences due to oversimplification. Next, they can not take into account traffic volume patterns, which are mostly daily or hourly related. Researchers have therefore warned against the modelling of accidents with a high level of aggregation (*5*). Studies on the meso or micro level succeed much more in linking accidents to weather conditions. However, as the number of crashes per observation is on average lower (which is obviously the case since the periods are shorter) a larger part of the variation in the number of crashes will be attributable to randomness. The systematic causal factors however still determine the expected crash count around which the observed variation in crash data will be centred (*3*). Furthermore, we remark that not all studies work with constant observation periods. For example, in the study of Knapp (*6*) one observation period coincides with one winter storm. The level of aggregation also has an impact on the duration of the time period and the size of the territory. Macro studies need much longer periods to obtain a sufficient number of observations and have the objective to study general tendencies in a large territory of one or several countries (*4*). In case a large number of variables, which are generally only measured in densely populated areas, like traffic counts, are necessary one may opt to geographically restrict the research to a metropolis (*4*) or a certain road section (*6*).

Although all traffic studies describe road safety, the dependent variable can differ. Concerning road crashes, one can study the total number of crashes, the number of crashes with injured persons or the number of fatal crashes. It may however be practical to use all three crash series (*7, 3*). Then it is possible to detect which weather variables have a different effect on the frequency and severity of accidents. Additionally, crash figures can be split up according to other crash types, like single-vehicle crashes, frontal crashes, involvement of vulnerable road users, etc. in order to get an idea about the influence of weather on certain crash types (*8*). The number or severity of victims as the central variable is less appropriate since they result from probabilistic dependent events.

Furthermore, some studies only take one weather aspect into account, whereas other aim at describing a weather image as completely as possible. In the next paragraphs, we present some general conclusions per weather variable as reported by earlier studies.

<u>Snow</u> seems to have a positive effect on material-damage-only-crashes as well as non-fatal injury crashes while the impact on fatal crashes is favourable (*7*). Fridstrøm (*3*) found negative coefficients when he tested the monthly number of days with snow for different crash severities. Possible explanations are reduced exposure during winter, increased visibility at night and adaptation of driving habits (driving more slowly) in case of high-risk situations. Research on a daily basis showed some other insights. Snowfall shows an inverted U-relationship with respect to crash rates (*7*). Crash rates appear to peak around the medium level of snow and actually decrease during very heavy snowfall. This is not surprising considering the reduced traffic volumes and driving speeds during snowstorms. Knapp (*6*) found that winter storms – defined as lasting for at least four hours with 2.5 centimeters each hour – increases the relative risk with 1303%. Zhang et al. (*9*) concluded that crash risk is highest under snow conditions with the overall relative risk ratio 53.12% higher than under non-precipitation conditions.

The impact of <u>black ice</u> has been studied for the Scandinavian countries. Each time significant decreases for an extra day of frost were found. Here the same reasoning goes as for snow.

The next weather element that will be discussed is precipitation. Slight rainfall did not significantly effect the total number of highway accidents in California, contrary to 29% more crashes on very wet days and an increase of 123% in case of extremely wet days (*8*). Strong and extreme rainfall specifically effected single-vehicle and frontal crashes. Due to reduced friction on the road surface, braking distances are longer. Furthermore, visibility diminishes because of the reflection on wet surfaces. Zhang et al. (*9*) concluded that the overall relative risk ratio under rain conditions is 39.79% higher than under non-precipitation conditions. This positive relationship between precipitation and crashes was also found in (*3*). Keay and Simmonds (*10*) studied the relative impact of precipitation during night and daytime. Generally, an increase in precipitation causes an increase in the number of crashes. Moreover, if it concerns the first day after a dry period this number is even higher. An often suggested explanation is that during dry periods, oil and fuel end up on the road which mixed with rainwater forms slippery spots that disappear in time (*4, 7, 11*). These conclusions are in line with the study of Eisenberg (*7*) on a monthly and daily basis.

Concerning thunderstorm Laaidi (*11*) noticed that crashes happen just before a thunderstorm bursting instead of during. Once lightning and rainfall begin, the risk decreases. Limited research has been done concerning the effects of wind on road safety. One study (*11*) found a positive relationship between wind variation and the total number of crashes. It is assumable that wind has an impact because a side wind of 13m/s is sufficient to cause a considerable change of route for a standard bus and a gust of 20m/s can results in overturning of vehicles (*12*).

Subsequently, the impact of sunlight on road safety will be discussed. In areas closer to the poles the difference in duration between night and day are larger, which makes these areas suitable for this kind of research. Extra daylight has a favourable effect on the expected number of crashes in the Scandinavian countries (*3*). Laaidi and Laaidi (*11*) reported that sudden variations in the strength of sunlight reaching the earth cause an increase in the number of crashes. Drivers have probably difficulties to adjust. Van den Bossche et al. (*13*) found that the monthly number of sunny hours decreased road safety. It is plausible to assume a higher exposure on sunny days or crashes caused by the dazzling sun. Satterthwaite (*8*) concluded that fewer crashes occurred during cloudy and very cloudy days.

Concerning temperature, researchers (*11*) found that in France heat waves have strongly positive effects on injury crashes. Possible reasons are that drivers prefer to shift their planned trips to the late evening or early morning. Furthermore, heat waves disturb the sleeping pattern of persons, which could cause a higher degree of tiredness amongst drivers.

A final point of difference between studies is the inclusion of a measure for intensity as explanatory variable in the model. This determines if the absolute or relative effect of weather on road safety is investigated. To be able to estimate the relative risk one has to find a way of including exposure in the model. The problem is that such data are rarely on hand and when they are it often is an average for a very large area or counted solely on a few points of the road system. The scope of the research can be restricted or surrogate variables like fuel sales (*3*) can be used. This is, however, no option in case of a low level of aggregation.

The two mostly applied statistical methods in earlier studies are the ‘matched pair approach’ and ‘regression analysis’. The basic idea of the matched pair approach is to compare crash figures of time periods in which the studied weather phenomenon happened with a similar period (for example the same day and same hour but one week later) in which the phenomenon was absent. In case of regression analysis the dependent variable is regressed on a selection of explanatory variables. Several types of regressions are possible. For count data, like crash data, the Poisson regression is generally the most adopted and well known (*6*). Various researchers, however, recommend the use of generalized Poisson regression models like the negative binomial regression model, which takes possible overdispersion into account (*3, 7*). In this study, we will apply regression techniques, further discussed in the following section.

## 3. METHODOLOGY

Crashes on the road seem to occur randomly in time and space. In addition, the probability of a crash occurring during a short period of time is constant within this period of time. Since crashes are assumed to be Poisson distributed, this distribution has been used in earlier research. From the study of Lord, Washington and Ivan (*14*) discussing the range of statistical count models commonly applied, the following is derived:

A crash is in theory the result of a Bernoulli trial with $p$ the probability of success (a crash) and $q$ = 1-$p$ the probability of failure (no crash). The random variable $Z$ records the number of successes out of $N$ independent trials. The binomial distribution is given as:

$$P(Z = n) = \binom{N}{n} p^n (1-p)^{N-n} \quad \text{where } n = 0,1,2,\ldots,N.$$

For typical motor vehicle crashes where the event has a very low probability of occurrence but a large number of trials exist (e.g. million driving vehicles simultaneously on the road) it can be shown that the binomial distribution is approximated by a Poisson distribution

$$P(Z = n) = \binom{N}{n} p^n (1-p)^{N-n} \cong \frac{e^{-\lambda}\lambda^n}{n!}$$

This approximation works well when the mean $\lambda$ and $p$ are assumed to be constant. Properties of a hypothetical population of identical drivers all having the same crash risk can be computed using the Poisson distribution (*15*). In practice however, it is reasonable to assume that crash probabilities differ across drivers and road segments due to driving experience, risk adversity, reaction times and vehicle characteristics.

The Poisson is a one-parameter distribution, with the property that the variance equals the mean, both being equal to the Poisson parameter $\lambda_i$. To identify and estimate the effects of systematic factors on the crash counts, we specify $\log(\lambda_i) = \beta x_i$ where $\beta$ is a vector of regression coefficients and $x_i$ a vector of independent variables. Then, the Poisson regression model has the following algebraic form:

$$P(Y_i = y) = \frac{e^{-\exp(\beta x_i)} \exp(\beta x_i)^y}{y!} \quad \text{with } y \text{ the actual number of crashes (16).}$$

In a number of studies (*3, 7, 17*) crash data were found to be significantly overdispersed. Strong overdispersion means presence of extra variation in the data, not explained by the model. Overdispersion arises from crash data as a result of Bernoulli trials with non-equal zeros (more zeros than expected under a Poisson process), excess large outcomes (large values of $Z$) or both (*14*). In that case, the Poisson approximation is unlikely to be appropriate. One solution is to use the Negative binomial distribution, a generalization of the Poisson distribution, which does no longer assume the expected value of the distribution to be equal to the variation. Instead a parameter $\theta$ is used for the over- or underdispersion compared to the Poisson distribution. In the special case that this parameter is zero, the negative binomial distribution equals the Poisson distribution. The negative binomial regression model is given by:

$$P(Y_i = y) = \frac{\Gamma(r+y)}{\Gamma(r)y!}\left(\frac{\alpha}{\alpha + \exp(\beta x_i)}\right)^r \left(\frac{\exp(\beta x_i)}{\alpha + \exp(\beta x_i)}\right)^y$$

with $r$ and $\alpha$ the shape respectively scale parameter of a gamma distribution with mean $\frac{r}{\alpha}$ and variance $\frac{r}{\alpha} + \frac{r}{\alpha^2}$.

Especially for the modelling of data containing a preponderance of zeros, like crash data, two new variants of the Poisson distribution were drawn up, more specifically the Hurdle model (*18*) and the Zero-inflated model (*19*). Both assume a so-called dual-state data generation process. An observation passes a first step in which it is determined if its value is zero or the observation has to go through the second step. In this possible second step the final value will be assigned. In that case a Poisson or other family related distribution is applicable. The difference between the two models is that the Hurdle model does not generate zeros in the second stadium while the Zero-inflated model does. Taking this difference into account, we opt here for the Zero-inflated model. Even in case of the most dangerous weather conditions there still exists a probability that no crash will take place. It has to be noticed, however, that the difference between the finally obtained models of both methods is usually very small (*20*). The Zero-inflated model will be applied with a Poisson model as well as a negative binomial model for the second stage. The Zero-inflated Poisson and negative binomial regression model are algebraically shown below:

$$P(Y_i = y) = \delta_{y=0}\pi + (1-\pi) \times \frac{e^{-\exp(\beta x_i)}\left[\exp(\beta x_i)\right]^y}{y!}$$

respectively

$$P(Y_i = y) = \delta_{y=0}\pi + (1-\pi) \times \frac{\Gamma(r+y)}{\Gamma(r)y!}\left(\frac{\alpha}{\alpha + \exp(\beta x_i)}\right)^r \left(\frac{\exp(\beta x_i)}{\alpha + \exp(\beta x_i)}\right)^y$$

with $\pi$ the probability for the observed count to be located in a perfect state, or $(1-\pi)$ to be located in the Poisson respectively negative binomial distribution with unknown mean. Now that all four regression models have been presented, the data will be discussed.

## 4. DATA

Two types of data will be used in this study, namely the hourly number of crashes taken place in 2002 on the primary Dutch road system and measurement data of 37 weather stations of the Dutch Meteorological Institute KNMI spread across the Netherlands (see figure 1). The crash data were obtained from the Transport Research Centre AVV of the Dutch Ministry of Transport and Public Works. In total 26,940 crashes with material and/or physical damage occurred, most of them between 6-10 am and 3-6 pm. This indicates that part of the variation in the data can be attributed to traffic intensity.


**FIGURE 1 Location of the Weather Stations in the Netherlands.**

Additional to the dependent variable, we distinguish six groups of weather variables: wind, temperature, sunshine, precipitation, weather indicators and visibility. However, not all weather stations measure the same data. Since the measurements took place each hour during one year, each station disposes of 8,760 observations per variable.

In a first phase, the data were processed in order to obtain useful variables. Certain factors were removed, other transformed to a more usable form. Furthermore, in case it was possible, missing values were filled in and certain samples were split . After these operations, we disposed of 41 samples with at most 17 explanatory factors describing several aspects of the weather. The data pre-processing will be discussed in the remainder of this section.

Based on its location, each individual crash was assigned to the closest and thus most relevant weather station. Next, all crashes were counted per weather station, date and hour in time. This information formed the key in combining the crash and the climatologic dataset. Three weather stations that registered, as result of the absence of neighbouring primary roads, no crashes during 2002 were eliminated. Next, the explanatory variables will be described.

The wind direction (DD) represents the direction the wind comes from and is expressed in degrees. In case of no wind this variables takes value ‘0’, in case of a strongly varying wind direction it takes the value ‘990’. The remaining wind variables are expressed in meter per second and measure the maximum wind gust (FX), the average hourly wind speed (FH) and the average wind speed during the latest ten minutes (FF) at the weather station. To the group of temperature variables belong four variables, all expressed in centigrade Celsius. T stands for the temperature during the observation on a 1.5 meters height, TX6 respectively TN6 for the maximum and minimum temperature during the last six hours while T10 represents the minimum temperature during the last six hours at 10 centimeters above the surface. The next three variables are related to sunshine. The global hourly radiation (Q) measures how much sun energy reaches the earth surface in one hour, expressed in Joule per square centimeter. The variable SQ describes, in tenths of an hour, how long the sun was shining during an hour. The variable N is an indicator of the total sky surface coverage. Value ‘0’ represents an open sky while value ‘8’ points at an entirely clouded sky. Another group of weather conditions that will be examined is linked to precipitation. The variable U stands for the percentage relative humidity, RD for the hourly precipitation duration in tenths of an hour and RD represents the precipitation amount during the previous hour in millimeters.

The largest group of independent variables is formed by the overall weather indicators. These are six Boolean (0-1) variables indicating if a certain weather type has occurred during the last hour. More specifically, it concerns precipitation (WW-R), fog (WW-M), snow (WW-S), hail (WW-H), thunderstorm (WW-O) and black ice (WW-Y). The final group contains visibility variables. VV represents the horizontal sight on a scale of ‘0’ to ‘100’. This scale is however not entirely linear. Until a value of ‘50’ one unity corresponds to 100 meters. In case of higher values one unity resembles more meters. We use the additional variable V if VV is equal to ‘0’ (or a visibility less than 100 meters) to give a more precise indication (in decameters). We believe that the described variables create a rather complete weather image. Nevertheless, information concerning extra variables, like the quantity or duration of snowfall, would have been desirable.

Since in this study the effect of several weather related variables will be tested one may assume that multicollinearity is present. Several heuristics are available to assess the degree of multicollinearity (*21*). A first technique makes use of scatter diagrams. For each observation the values of two variables will be plotted against each other. From the pattern in the diagram the relationship between the two variables is deduced (*22*). However, because of the large number of variables this graphical method is not very efficient. The second technique looks at the pair wise correlations between the variables. Too large values indicate danger for multicollinearity. As could be expected intuitively high correlations are found between the wind related variables FF, FX and FH. Correlation coefficients close to one and significant at the 0.001 level ask for a solution. Less extreme, but still high correlation was found between the duration and the quantity of precipitation. Both factors are related to the presence of precipitation. The radiation and duration of sunshine and relative humidity also have a strong relationship, even as the presence of fog and visibility (negatively correlated). Because we may conclude that there is a certain significant level of multicollinearity present, which influences the regression results, attention has been paid to reduce the amount of multicollinearity to an acceptable level. In order to obtain an as extensive as possible description of the impact of weather on road safety, we try not to eliminate too much variables. Some removal is however inevitable. Available techniques are the exclusion of certain highly correlated variables which are less justified, factor analysis and principal component analysis. Use of these last two methods is however hampered here because for the weather stations different variables are available. Beside the removal technique we opt for post-regression techniques such as stepwise selection.

The temperature variables measuring over six hours (TX6, TN6, T10) do not fit the research intention. Although previous studies showed a relationship between so-called history variables for precipitation and road safety, nothing seems to indicate that this will also be the case with history variables concerning temperature. These two reasons justify the exclusion of these three variables. As mentioned before, a high correlation was also found between the wind variables. Since FF and FH both measure average wind speed with the distinction of FF measuring the speed ten minutes before the observation, the use of FF is less justified and will be deleted in favour of FH. DD, the wind direction variable, has the problem of many possible values. However, this variable is still useful because DD can take value ‘990’ to indicate a strongly varying wind direction. DD will be replaced by a Boolean variable WIS, which takes value ‘1’ if DD has value ‘990’ and zero otherwise. The additional visibility variable V will also be eliminated from the dataset because this variable is only used when the original variable VV indicates a horizontal sight of less than hundred meters, which only occurs in 0.2% of the observations.

A last point in the data pre-processing relates to missing values. Due to technical failure in the equipment, organizational problems, etc. not every measurement of all variables the specific station should have measured is available. For certain missing values, a value can be proposed based on known measurements. For other variables the group of missing values was too large so the variable was deleted from the dataset. For 7 weather stations a considerable number of weather image observations are missing. Since several thousands of observations per weather station are still sufficient, the data of these weather stations are divided. Each of these stations contains an A part including the weather indicators and a B part without these variables. As indicated above, all these data operations finally resulted in 41 different samples of data, each with at most 17 explanatory variables describing several weather aspects.

## 5. RESULTS AND DISCUSSION

The dependent variable in this research – the hourly number of accidents per weather station – is a count variable. As discussed earlier, a Poisson distribution is therefore assumed. The expected value and the variance of a Poisson distribution are both equal to the expected incidence of an accident during the observation period. As a consequence, the dispersion – defined as the ratio of variance and expected value – equals one. Calculating the dispersion for each weather station separately and the Netherlands as a whole learn us that most stations have values close to one but for a number of areas, more specifically around large cities, overdispersion in the crash counts occurs. For this reason, the second model assumes the accident data to follow a negative binomial distribution. Furthermore, the exploratory analysis revealed in addition to overdispersion the presence of a large proportion of zeros in the data. In fact, as a result of the high number of zeros, the average crash count per hour per weather station lies at 0.09. Therefore, the Zero-inflated Poisson and Zero-inflated negative binomial model will also be tested.

The frequency of the hourly area crashes is presented in Figure 1. The graph also shows the division into the eight categories for the four models. As can be seen, the actual proportion of zeros is slightly higher than is assumed for a Poisson distributed variable with parameter 0.09. This distribution overestimates the frequency of 1 crash while the occurrence of 2 and 3 crashes is too low compared to the observed number. Values higher than three are almost impossible according to the Poisson distribution whereas in our dataset this was 200 times the case. Furthermore, the figure indicates that the negative binomial distribution approaches the observed counts better than the Poisson distribution does. Especially for the categories with large crash figures the negative binomial distribution is superior. The Zero-inflated Poisson distribution seems to fit reality better than the Poisson distribution while the Zero-inflated negative binomial seems to yield a worse fit than the negative binomial distribution.

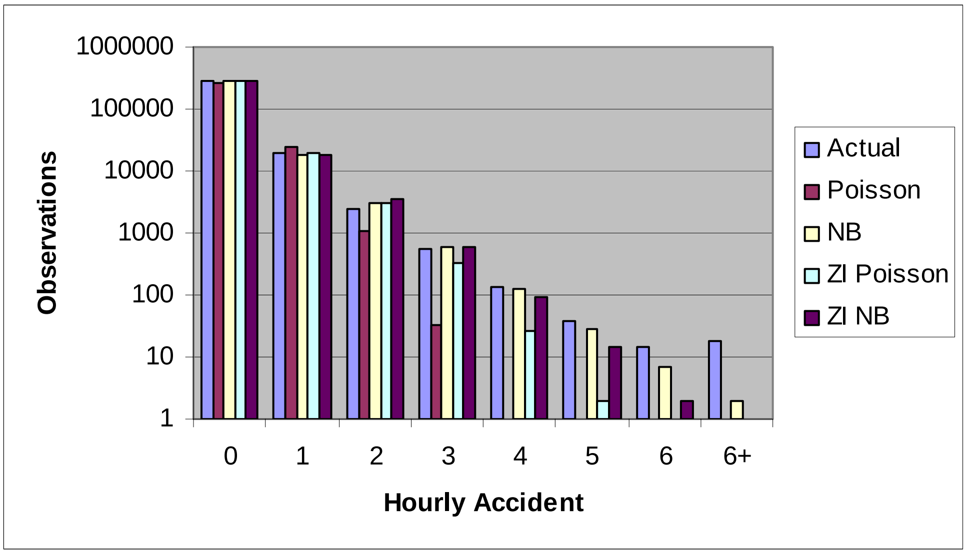


**FIGURE 2 Frequency of the actual hourly area crashes together with the expected numbers from the Poisson, Negative binomial, Zero-inflated Poisson and Zero-inflated negative binomial distribution.**

As mentioned before a large degree of multicollinearity is suspected. Although some measures have already been taken, the most important one – stepwise regression – will now take place. After the execution of the original regression, a number of variants will be elaborated. Each time, one of the explanatory variables will be removed. For all models (the original one plus the models which contain one variable less) the Akaike Information Criterion (AIC) (*23*) will be calculated, defined as $AIC = -2LL + 2d$ with $LL$ the value of the log likelihood function and $d$ the number of parameter estimates. The model with the lowest AIC offers the best balance between fit and complexity and is temporarily the optimal model. This process of removing one variable at the time repeats itself until the more complete model yields a lower AIC than each of the variants. Then the final solution is found.

All four regression models are fitted. A stepwise regression is, however, not possible for the Zero-inflated models. For these models, the complete model will be fitted and the explanatory factor with the least significant coefficient will be eliminated. This process is repeated as long as AIC decreases.

In the output, we find the coefficients of the regressors, their standard error, *t*- and *p*-value, the AIC and information concerning the disturbances. The estimated regression parameters represent the expected relative change in the number of accidents due to a change in the explanatory variable. The significance of a variable can be deduced from the *t*- and *p*-value. In general it is assumed that 0.05 is the minimum level on which a result has to be significant. However, there are cases in which the 0.05 rule can be relaxed and findings with a slightly lower significance are acceptable (*24*). The use of stepwise regression made the coefficients retained from this research to a large extent significant on the 0.05 level.

So far, for each weather station, four regression models have been estimated. Obviously, we want to determine the optimal model. The results of the four models are generally quite similar. Furthermore, the explanatory variables included in the models are equal in 28 of the 41 cases. For the comparison of nested models we use the Likelihood Ratio Test that calculates the difference in Log Likelihood of two models. If this difference exceeds a certain critical value, the more complex model (requiring more estimates) is accepted in favour of the more parsimonious model. In case of non-nested models like the negative binomial and the Zero-inflated Poisson model the comparison is made based on the Bayesian Information Criterion (BIC) which also balances fit against complexity. Executing these procedures gives the following results: 5 weather stations are best fitted by the Poisson model, 31 by the negative binomial model, 1 by the Zero-inflated Poisson model, 3 by the negative binomial model as well as the Zero-inflated Poisson model and 1 by the Zero-inflated negative binomial model.

Table 1 gives an overview of the results of the negative binomial regression models for each explanatory variable. Columns 3, 4 and 5 represent respectively the minimum, median and maximum of the coefficients obtained for each weather variable. Columns 6 and 7 give the number of times a positive coefficient, significant on the 0.05 level and only on the 0.10 level appeared. Columns 8 and 9 report this for the negative coefficients. The last column shows in how many cases e.g. weather stations the variable was available for a model.

**TABLE 1 Explanatory Results of the Negative Binomial Regression Models**

| | VAR | MIN | MED | MAX | $P_{0.05}$ | $P_{0.05-0.10}$ | $N_{0.05-0.10}$ | $N_{0.05}$ | Cases |
|---|---|---|---|---|---|---|---|---|---|
| Maximum wind gust | FX | -0.0061 | 0.0040 | 0.0196 | 18 | 1 | 1 | 1 | 40 |
| Average wind speed | FH | -0.0347 | -0.0089 | 0.0108 | 3 | 2 | 4 | 6 | 40 |
| Varying wind direction | WIS | -0.7420 | 0.3830 | 2.7820 | 5 | 0 | 0 | 1 | 40 |
| Temperature | T | -0.0031 | -0.0018 | 0.0178 | 3 | 1 | 1 | 7 | 39 |
| Global radiation | Q | 0.0014 | 0.0029 | 0.0168 | 26 | 4 | 0 | 0 | 38 |
| Sunshine duration | SQ | -0.2530 | 0.0552 | 0.1140 | 15 | 6 | 0 | 1 | 38 |
| Cloudiness | N | -0.0626 | 0.0493 | 0.0812 | 8 | 0 | 1 | 1 | 16 |
| Precipitation duration | RD | 0.0322 | 0.0629 | 0.1380 | 26 | 2 | 0 | 0 | 38 |
| Precipitation amount | RH | 0.0100 | 0.0178 | 0.0405 | 8 | 1 | 0 | 0 | 38 |
| Relative humidity | U | -0.0193 | 0.0011 | 0.0221 | 2 | 2 | 1 | 3 | 39 |
| Presence of precipitation | WW_R | 0.3160 | 0.4050 | 0.8320 | 11 | 0 | 0 | 0 | 16 |
| Presence of fog | WW_M | -1.2800 | 0.0288 | 0.7170 | 2 | 1 | 0 | 1 | 16 |
| Presence of snow | WW_S | 1.0700 | 1.2500 | 1.4300 | 1 | 1 | 0 | 0 | 16 |
| Presence of thunderstorm | WW_O | 0.7950 | 0.7950 | 0.7950 | 1 | 0 | 0 | 0 | 16 |
| Presence of black ice | WW_Y | 0.6800 | 0.8680 | 1.2000 | 3 | 0 | 0 | 0 | 12 |
| Presence of hail | WW_H | / | / | / | 0 | 0 | 0 | 0 | 14 |
| Horizontal visibility | VV | -0.0091 | 0.0044 | 0.0123 | 2 | 2 | 0 | 2 | 28 |

The maximum wind gust seemed significant in half of the cases, almost always on the 5% level. The obtained parameters vary between -0.006 and 0.020, on average around 0.004. The impact is unambiguous since almost all significant relationships are positive. The hourly mean wind speed has a less clear impact. The effect was significant in 15 of the 40 models of which 10 times negative. A closer inspection shows that the coefficients were nearly always negative when FX was included in the model and positive otherwise. Strong variation in wind direction proved little significant.

In 12 of the 39 cases for which temperature was available this variable was retained and found significant. Although the results for temperature vary, the negative influence on the number of accidents seems to dominate.

A link between sun(light) related variables and traffic intensity must be kept in mind. The radiation seems to have a significant impact in 30 out of 38 cases.

An increase in radiation causes more crashes. Additionally, SQ has a significant positive impact in 21 cases, nearly always positive meaning that extra sunshine increases the number of accidents.

Cloudiness (N) has a significant impact in 10 of 16 cases, 8 times with a positive significance between exp(-0.063) and exp(0.081).

Of all the 38 cases for which precipitation data were available, RD had 28 times a significant positive effect while this was only 9 times the case for RH. It often happened that only one of these variables was selected to be retained in the model. Precipitation is unfavourable for road safety, especially the impact of precipitation duration.

The impact of relative humidity however is harder to quantify. First, the variable is only retained in a restricted number of cases. Second, the division between positive and negative impact is equal.

For most of the overall weather variables the number of significant results are small. WW_R however is an exception: 11 times out of 16 a significant positive impact was found. The presence of precipitation during the observation period reduces road safety by 37 to 130%. The presence of fog was significant in 4 cases, the presence of snow had 2 times a positive significant effect. For the presence of thunderstorm only one significant result was found. Also for black ice very few significant combinations proved significant. In case significant results were found, these showed that black ice causes an increase in the number of accidents with factor 2 to 3 and snow with factor 3 to 4. The presence of hail is the only tested variable for which none significant effect could be detected.

Of all the 28 cases where visibility VV was measured this factor did mostly not have a significant effect on the number of crashes. The six significant coefficients showed 4 times positive and 2 times negative significance resulting in an unclear impact.

## 6. CONCLUSIONS AND FURTHER RESEARCH

In this study we investigated the relationship between the hourly number of crashes on the main roads in the Netherlands during the year 2002 and the corresponding hourly weather variables.

The methodological analysis concluded that the data in most areas (defined by nearest weather station) could best be described by the Negative binomial distribution instead of the Poisson, Zero-inflated Poisson and Zero-inflated negative binomial distribution although the results of the four models did not differ strongly.

After data pre-processing the impact was tested of 17 climatic factors belonging to the categories wind, temperature, sunlight, precipitation, weather image and visibility. Because multicollinearity was present, a stepwise variable selection was performed and applied. This selection excluded variables that made the model more complex without significantly contributing to the explanatory power of the model.

The significances that are found in this study are:

- An increase in maximum wind gust causes an increase in the number of crashes.
- Global radiation and sunshine duration both had a significant negative impact on road safety.
- Ten extra minutes of precipitation increases the number of crashes by 6.5% on average while a higher amount of precipitation has a smaller impact.
- Of all overall categorical weather indicators, presence of precipitation has the most significant impact.
- The direction of the effect of cloudiness on the number of crashes was also found positive.
- For the other variables less significant or unambiguous relationships were found.

Most of these results are in line with other research.

In general, we believe that the quantified weather effects found in this study serve as an enhancement to the overall statistics on road safety intended for policy makers. At this moment, the weather effects are often captured by the police accident reports, which are usually based on subjective and qualitative weather indicators.

More specifically, these results can be used in dynamic traffic management, information campaigns, … In case of 'dangerous' weather, measures can be taken temporarily – by means of dynamic overhead traffic signs for example indicating a lower maximum speed – or geographically – for certain regions with a significantly higher impact of a weather element – structural measures can be taken.

A topic for further research is to include an exposure measure. Weather conditions are assumed to have a direct impact on road safety as well as an indirect impact through traffic intensity. In order to make a distinction between these two effects a measure for traffic intensity must be included in the model. Currently, the effect of exposure was 'artificially' filtered out by including a region-specific offset ($\beta_0$) into the regression part of the model, hereby preventing the weather effects to be overestimated. It is also worth investigating whether there are regional differences in the effect of the weather variables on crashes. It is reasonable to believe that weather effects are different in a coastal area compared to the centre of the country. In fact, a preliminary analysis revealed such kind of effects. For instance, the effect of the variable 'maximum wind gust' on crashes turns out to be larger and positive for weather stations close to the coast, which is not surprising since wind plays a more dominant role in coastal regions. Further research should reveal the exact differences. Finally, it is our objective to include information from RWIS sites and weather forecasts as these are highly relevant for this type of research. However, at the time this study was carried out, these data were not yet easily accessible, but they will be in the near future.

Finally, we aim to generalize the results of individual weather stations to the country level using the statistical technique of meta-analysis (*25*).

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