Assessing the Impact of Weather on Traffic Intensity

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Abstract

This paper focuses on the effect of weather conditions on daily traffic intensities (the number of cars passing a specific segment of a road). The main objective is a general examination of whether or not weather conditions uniformly alter daily traffic intensities in Belgium, or in other words whether or not the road usage on a particular location determines the size of the effects of various weather conditions. This general examination is a contribution which allows policy makers to assess the appropriateness of country-wide versus local traffic management strategies. In addition, a secondary goal of this paper is to validate findings in international literature within a Belgian context. To achieve these goals, the effects of weather conditions on both upstream (towards a specific location) and downstream (away from a specific location) traffic intensities of three traffic count locations, typified by a different road usage, are analyzed. The most interesting results of this study for policy makers are the heterogeneity of the weather effects between different traffic count locations, and the homogeneity of the weather effects on upstream and downstream traffic at a certain location. The results also indicated that snowfall, rainfall and wind speed clearly have a diminishing effect on traffic intensity, while maximum temperature has an increasing effect on traffic intensity. Further generalizations of the findings will be possible by studying weather effects on local roads and by shifting the scope towards travel behavior.

1. Introduction

a. Background

A clear insight into how weather conditions influence traffic is essential for policy makers. This is underlined by policy issues which are often related with adverse weather events such as increased fuel consumption, economic losses due to traffic delays, and higher traffic counts. Day-to-day weather conditions such as fog and precipitation can reduce travel demand, for instance when drivers postpone or cancel discretionary activities, but can also have an increasing effect when travel modes are shifted from slow modes (walking, cycling) towards motorized vehicles (Hranac et al., 2006). At the network level, adverse weather events increase the uncertainty in system performance, resulting for instance in a network capacity reduction ranging from 10% to 20% in heavy rain (De Palma and Rochat, 1999).

Figure 1 displays the conceptual framework of the interplay between weather conditions, traffic intensity (the number of cars crossing/passing a specific segment of a road, also referred to as traffic flow), traffic speed and road safety (Koetse and Rietveld, 2007). Take as an example heavy rain conditions during which drivers might reduce their travel speed, and as a consequence also have a reducing effect on road capacities and corresponding traffic intensities. There might be also a direct decrease in traffic intensity resulting from people cancelling their trips. The resulting reduction in traffic intensity and traffic speed could decrease the accident severity, but slippery roads on the other hand could increase the accident frequency. This example illustrates the long recognized proposition that road accidents and traffic intensities are the consequence of an interaction between behavioral, environmental and technological factors. A change in any of these factors could prevent an accident from occurring (Edwards, 1996; Levine et al., 1995).

<Insert Figure 1 about here>

The rise of advanced traffic management systems (ATMS) provides transportation agencies the opportunity to implement traffic management strategies that could limit weather-related side-effects on traffic operations (Zhang et al., 2005). A solid understanding of the impact of various weather conditions on roadside crash frequency and traffic intensity serves a good knowledge base for developing these strategies (Shankar et al., 2004; Smith et al., 2004).

The assessment of weather impacts on traffic intensity (the daily number of vehicles passing a specific location) is of significant value to travel demand modelers. Khattak and De Palma (1997) reported that adverse weather conditions cause important changes in travel decisions: mode changes, changes in departure time and diversions to alternate routes, were reported as the most prevalent behavioral adaptations.

The investigation of weather effects on traffic intensity is also important from a road safety point of view, because traffic intensity, commonly used as a proxy variable for exposure (the degree of participation in traffic) in traffic safety literature, is noted as the first and primary determinant of traffic safety (Van den Bossche et al., 2005). Injury accidents are nearly proportionally related with exposure (Fridstrøm et al., 1995), evidencing the strong relationship between traffic intensity conditions and the likelihood of traffic accidents (Golob et al., 2004).

Summarizing, weather events can affect two predominant traffic domains: traffic intensity or in a broader sense traffic demand (traffic intensities are the revealed traffic pattern on the road network, while traffic demand covers also the underlying demand for activity participation and demand for different transportation options) and traffic safety (Maze et al., 2006). This paper focuses on the impact of weather events on the first predominant traffic domain, namely traffic intensity. The main objective is a general examination of whether or not weather conditions uniformly alter daily traffic intensities in Belgium, or in other words whether or not the road usage (the main purpose why people are traveling on this road, i.e. commuting or leisure) on a particular location determines the size of the effects of various weather conditions. This general examination is a contribution which allows policy makers to assess the appropriateness of country-wide versus local traffic management strategies. In addition, a secondary goal of this paper is to validate findings in international literature within a Belgian context.

The remainder of this introductory section will address the specific weather variables that influence traffic intensities and traffic demand. Section 2 will address the data description, and the methodology is described in Section 3. Finally, this paper will present the results and elaborate on their transport policy relevant interpretation. Some general conclusions will be formulated and avenues for further research indicated.

b. Influence of weather on traffic intensities and traffic demand

Weather can affect traffic intensities and traffic demand in different ways, including diversions of trips to other modes or other paths, or even cancellations of trips (Maze et al., 2006). Bos (2001) indicated that in the Netherlands heavy rain is associated with a smaller number of cyclists, while mild winters and warm summers have an increasing effect on bicycle use. A similar relationship was found by Nankervis (1999) who examined the effect of both (short-term) weather conditions and (long-term) seasonal variation patterns on bicycle commuting patterns among students in the temperate climate of Melbourne, Australia. He found that cycle commuting was affected by long-term, climatic conditions as well as daily weather conditions. Guo et al. (2007) reported that temperature, rain, snow and wind all influence transit ridership of the Chicago Transit Authority: good weather increases ridership, while bad weather has a diminishing effect. Guo et al. (2007) also stress that not only the transit ridership is influenced by weather, but also vehicle running times (time it takes to complete the assigned route) and dwell times (time spent on allowing people to get on or off the public transit vehicle) are affected, as well as the cost of operation. In Brussels, Belgium, on the other hand, the transit agency reported higher levels of transit ridership during adverse weather (Khattak and de Palma, 1997).

From various studies on the effect of rain, snow and fog on traffic operations, it has become clear that adverse weather can significantly reduce not only capacity but also operating speeds on roadways, resulting in congestion and productivity loss (Agarwal et al., 2006; Datla and Sharma, 2008). When the effect of precipitation on traffic operations is explored, almost all studies indicate that speed and capacity are negatively influenced (Stern et al., 2003; Unrau and Andrey, 2006). Hanbali and Kuemmel (1993) found traffic volume reductions on highways away from the major urban centers in the United States ranging from 7% to 56% depending on the intensity of the snowfall. Maze et al. (2006) found comparable reductions in traffic volume on Interstate 35 in the northern rural Iowa ranging from 7% to 80% during snowstorms. In contrast, during rainstorms traffic volumes were reduced by less than 5%. According to Smith et al. (2004), who analyzed the effect of precipitation on traffic intensity in Hampton Roads, Virginia, highway capacity is reduced by a range from 4 to 10% during light rain (intensity of 0.01- 6.35 mm/h) and a range from 25 to 30% during heavy rain (intensity higher than 6.35 mm/h). When the focus in turned to highway speeds, Ibrahim and Hall (1994), found reductions in speed of respectively 2 and 3 km/h during light rain and light snow, and decreases in speed of 5 to 10 km/h during heavy rain, and 38 to 50 km/h during heavy snow. The reductions tend to be larger for larger precipitation amounts (Keay and Simmonds, 2005). Other factors influencing traffic intensity are visibility (fog), wind speed, sunshine hours and temperature, the latter two associated with slight increases in traffic activity (Hassan and Barker, 1999).

2. Data

To assess the impact of weather conditions on traffic intensity, and in particular to test the hypothesis that the road usage on a particular location determines the size of the effects of weather conditions on traffic intensities, the upstream (towards a specific location) and downstream (away from a specific location) traffic of three traffic count locations (represented by black squares in Figure 2) were considered. Weather conditions at these traffic count locations were approximated by weather conditions recorded in the closest weather stations (represented by grey circles in Figure 2).

<Insert Figure 2 about here>

a. Dependent variables: traffic intensity data

The traffic intensity data originate from minute-by-minute data coming from single inductive loop detectors, collected in 2003 and 2004 by the Vlaams Verkeerscentrum (Flemish Traffic Control Center). Every minute, the loop detectors generate four statistics: the number of cars driven by, the number of trucks driven by, the occupancy of the detector (the percentage of time that the detector is "occupied" by vehicles) and the time-mean speed of all vehicles (Maerivoet, 2006). Adding up the number of cars and trucks for all lanes in a specific direction, yields a total traffic count for each minute. The aggregation on a daily basis of all 1440 minutely total traffic counts then results in a single daily traffic intensity measure. Note that this aggregation on a daily level also filters away the noise caused by random fluctuations due to potential in accuracies of single loop detector counts. For a general discussion about the quality of traffic counts derived from single loop detectors the reader is referred to Chen et al. (2003) and Weijermars and Van Berkum (2006).

As indicated earlier, upstream and downstream traffic intensity of three traffic count locations (displayed as black numbered squares in Figure 2) are investigated in this study. The first location is a traffic count location measuring upstream and downstream highway traffic from Hasselt, a provincial city with a population of about 70 000 people. The highway were these upstream and downstream traffic counts are measured is characterized by 2 lanes in each direction, used both for commuting and leisure traffic. The second traffic count location is situated on one of the entranceways of Brussels, the capital of the European Union and thus an important location in terms of job opportunities. At the location of the traffic counts, the highway consists of 3 lanes in each direction, predominantly used by commuters. The third location is on one of the access highways (3 lanes in each direction) to the Belgian seashore, and thus more intensively used by leisure traffic. Note that the speed limit on all these locations was equal to 120 km/h.

b. Independent variables

1) WEATHER DATA

Data concerning weather events were recorded by the Royal Meteorological Institute of Belgium (KMI). These data originate from Automatic Weather Stations (AWS) equipped with a Present Weather Sensor (PWS). In addition to the PWS, these AWS are also equipped with a ceilometer, an anemometer, a temperature sensor, a hygrometer and rain gauges. Weather at the relevant traffic count locations was approximated by the conditions recorded at the nearest (available) weather stations. The following variables were included in the analysis: daily precipitation (expressed in 1/10 mm; all 24 hourly measurements from rain gauges are aggregated to a daily level), conditions of hail, snow and thunderstorm (a dummy variable indicating the presence of the weather event during the day under study was created for each of these weather events; the weather types were derived from the PWS, and enriched with data from the SAFIR lightning detection system), average and maximum cloudiness (expressed in eights; the average and maximum of all 24 hourly measurements was calculated; the degree of cloudiness was derived from the ceilometer), minimum, maximum and average temperature (expressed in °C; the minimum, maximum and average from all 24 hourly averages were tabulated), maximum hourly wind speed (expressed in m/s; the maximum of all 24 hourly averages was taken), sunshine duration (expressed in minutes; all 24 hourly durations were added up) and duration of diminished visibility due to fog (a dummy variables was created indicating that for the day under study for at least a few minutes the visibility was less than 200m).

In general, Belgium has a temperate maritime climate influenced by the North Sea and Atlantic Ocean, with cool summers and moderate winters. There is little variation in climate from region to region, although the marine influences are less inland. Rainfall is distributed throughout the year with a dryer period from April to September. Summary information about the meteorological conditions for the two years 2003 and 2004 are provided in Table 1.

<Insert Table 1 about here>

2) TEMPORAL EFFECTS

In addition to the different weather conditions that will be used to (partially) explain the variability in traffic counts, it is also necessary to incorporate temporal effects. Cools et al. (2007) found that day-of-week effects and holiday effects contribute significantly to differences in daily traffic intensity. A first holiday dummy variable was created for the following holidays: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints' Day and All Soul's Day), and finally Remembrance Day. It should be noted that for all these holidays, the adjacent weekends were considered to be a holiday. Similarly, for holidays occurring on a Tuesday or on a Thursday, respectively the Monday and weekend before and the Friday and weekend after were also defined as a holiday. A second holiday dummy variable was created for the summer holidays (excluding holidays considered for the first dummy variable). .Thus, for normal days both dummy variables were coded zero.

Next to these holiday effects, also day-of-week effects were taken into account in this study. As there are seven days in a week, the first six days (Monday until Saturday) were each represented by a dummy, equal to 1 for the days they represent and zero elsewhere. For the reference day (Sunday), all six dummies were coded zero.

3. Methodology

To develop an understanding of the effects of weather on traffic intensity, some basic descriptive statistics are provided. For the continuous variables the Spearman rank correlation between traffic intensity and the weather variables is calculated. Unlike the traditional Pearson product-moment correlation, the Spearman rank correlation is a non-parametric technique, robust for deviations from normality (Cohen and Cohen, 1983). For the categorical variables the group means are provided.

The main modeling approach implemented in this study is the classical linear regression approach. To accommodate for the risk of erroneous model interpretation, caused by autocorrelation (consecutive traffic counts being highly correlated) and heteroskedasticity (the variance of the residuals being dependent on the value of the dependent variable), Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrices are used for the estimation process [Eq. (A1)].

To ensure that all parameter estimates are stable and reliable, the models should be checked for multicollinearity. In the presence of multicollinearity (high correlation between explanatory variables) the effect of a single explanatory variable can not be isolated, as the regression coefficients are quite uninformative and confidence intervals very wide. Thus, the individual estimated coefficients should be interpreted with caution, since only imprecise information can be derived from the regression coefficients (Van den Bossche et al., 2004). Variance Inflation Factors (VIF) are used to assess the level of multicollinearity. VIFs measure how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related. The largest VIF value among all predictor variables is used as an indicator of the severity of multicollinearity. A maximum VIF value exceeding 10 indicates that the stability and reliability of the parameter estimates are questionable (Neter et al., 1996).

4. Results

a. Validation of findings in international literature within Belgian context

1) DIRECTION OF THE WEATHER EFFECTS

A first indication of the direction of the weather effects is given by the sign of the Spearman rank correlations (Table 2) and by the group means of the different categorical weather variables (Table 3). Bad weather conditions such as precipitation, cloudiness and wind speed are negatively correlated with traffic intensity, while good weather conditions such as temperature and sunshine duration are positively correlated. When the group means of the different categorical weather indicators are compared, ambiguity is found in the direction of hail, fog and thunderstorm effects: on some locations traffic intensity increases in the presence of these weather conditions, on other locations it decreases. In contrast, the impact of snow is univocal: snow decreases the traffic intensity on all traffic count locations.

<Insert Table 2 about here>

<Insert Table 3 about here>

A more thorough estimation of the direction of weather effects is obtained by the heteroskedasticity and autocorrelation consistent linear regression models. Estimates for the significant variables that were used in the final location-specific models, their corresponding standard errors and significance levels are displayed in Table 4. The VIFs (all smaller than 10) assure that the parameter estimates are stable and reliable. The temporal effects (day-of-week effects and holiday effects) are omitted from this table, since this paper focuses mainly on assessing the impact of weather conditions on traffic intensity and because Cools et al. (2007) already reported on the impact of temporal effects. The estimated weather effects are consistent with international literature addressing the impact of weather conditions on traffic intensity (Datla and Sharma, 2008; Kyte et al., 2001; Maze et al., 2006): rainfall, snowfall and wind speed significantly decrease traffic volumes, while temperature has a noticeable increasing effect.

<Insert Table 4 about here>

Summarizing one can conclude that snowfall, precipitation, cloudiness and wind speed clearly have a decreasing effect on traffic intensity, while temperature and hail increase traffic volumes. Note that while snowfall and rain have a decreasing effect on traffic intensity, hail has an increasing effect. The decreasing effect of snowfall and rain may be explained by the diminished capacity of the highway network, caused by a reduction in speed, while the increasing effect of hail might be attributed to the shift towards car as travel mode due to the unfavorable weather conditions. Finally, there is also some evidence that reduced visibility due to fog and longer sunshine duration increase traffic intensity.

2) MAGNITUDE OF THE WEATHER EFFECTS

Next to the direction it is also important to assess the magnitude of the weather effects. A first insight is obtained by looking at the Spearman rank correlations (Table 2). The highest correlations with traffic intensity are found for maximum temperature and maximum cloudiness and amount of precipitation. Most interesting are the considerably larger correlations of weather conditions at the seashore traffic count location. This indicates that weather conditions have a greater impact on leisure-related traffic than on commuting traffic.

An overall model was estimated to quantify the influence of weather conditions on traffic intensity. To accommodate for differences in magnitude of the traffic volume between the six traffic count locations (e.g. magnitude of the traffic volume of downstream traffic in Brussels is almost three times the magnitude of the traffic volume of downstream traffic in the seashore area), the percentage of the traffic volumes relative to their location specific mean were modeled instead of the absolute numbers. In order to obtain a parsimonious model, and based on the homogeneity observed in the location-specific models, upstream and downstream traffic locations were combined to estimate interaction effects between weather conditions and traffic count location. Estimates for the weather conditions and corresponding significance tests of this overall model are provided in Table 5. Note that only significant location dummy interactions were included in the final models to overcome the problem of multicollinearity. Since relative traffic intensity numbers were modeled instead of absolute numbers, the parameter estimates can be directly interpreted as the percentage of change in traffic intensity. When it snows for instance, traffic intensity will on average be 3.822 percent lower than during non-snow weather.

<Insert Table 5 about here>

b. Dependence of the effects of different weather conditions on the road usage

A first indication that the effects of various weather conditions differ among highways with a divergent road use are the clearly higher correlations (in absolute terms) between weather events and traffic intensity on the seashore highway when compared to the other locations. In contrast to these differences between locations, weather impacts are quite homogeneous when downstream and upstream (denoted as 'down' and 'up') intensities of the same locations are compared.

A similar conclusion can be drawn after investigation of the parameter estimates of the location-specific models: the impact of weather conditions is clearly more homogeneous (size of the effect and similar significant weather variables) between upstream and downstream traffic at a certain location, than between different locations. The heterogeneity (different effect sizes and different significant weather variables) between different locations can be (partially) explained by the underlying travel motives of the road users using these highways. Highways typified by their leisure traffic can be affected more easily than highways that are predominantly used by commuters. We suspect that the underlying reason is the relative high invariability of work activities (work activities are mandatory activities which can not be easily skipped) compared to the flexibility of adapting leisure activities (leisure activities are non-mandatory and thus be changed more freely).

The hypothesis of dependence of the effects of different weather conditions on the road usage is substantiated by the significant interaction terms in the overall model between location and temperature on the one hand, and between location and cloudiness on the other hand. This underlines the necessity for policy makers to formulate local traffic management strategies next to country-wide strategies.

5. Conclusions and further research

In this study the impact of various weather conditions on traffic intensity was investigated. Most important result for policy makers is the heterogeneity of the weather effects between different traffic count locations, and the homogeneity of the weather effects on upstream and downstream traffic at a certain location. Consequentially, traffic management strategies that minimize weather-related side-effects on traffic operations must adopt an approach that takes into account local usage and the flexibility of drivers to respond to weather conditions.

The results in this paper also indicated that precipitation, cloudiness, and wind speed have a clear diminishing effect on traffic intensity, while maximum temperature and hail have a significant increasing effect on traffic intensity. These significant impacts of weather conditions on traffic intensity underline the necessity of incorporating weather conditions in future traffic safety research not only in a direct way, but also indirectly by modeling the effects of weather conditions via traffic intensity. As suggested by the inherent relationship between traffic intensity, weather and traffic safety discussed in the introduction, the results support the recommendation to develop location specific traffic safety policies next to a country-wide strategy.

Further generalizations of the findings are possible by studying weather effects on local roads and by shifting the scope towards travel behavior. Moreover, further research should also include other potentially factors affecting traffic intensity next to weather conditions and temporal effects (day-of-week effects and holidays) in order to be able to isolate the effect of weather conditions and validate the findings reported in this study. Linking travel behavior research, traffic flow (traffic intensity) modeling, and safety research by simultaneously modeling of weather conditions, traffic intensity rates, collision risk and activity travel behavior is certainly a key challenge for further research.

Acknowledgments.

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APPENDIX

Newey-West heteroskedasticity and autocorrelation consistent covariance matrices

The Newey-West covariance matrix estimator is given by:

$$\hat{\Sigma}_{\mathbf{NW}} = \mathbf{X'X}^{-1}\,\hat{\mathbf{\Omega}}\;\mathbf{X'X}^{-1}, \tag{A1}$$

where the estimated error variance ($\hat{\Omega}$) is defined as:

$$\hat{\mathbf{\Omega}} = \frac{N}{N-k}\left\{\sum_{i=1}^{N} e_i^2 x_i x_i' + \sum_{v=1}^{q}\left(\left(1-\frac{v}{q+1}\right)\sum_{i=v+1}^{N} x_i e_i e_{i-v} x_{i-v}' + x_{i-v} e_{i-v} e_i x_i'\right)\right\} \tag{A2}$$

with N the number of observations, k the number of regressions, e_i the least square residual and q the number of truncation lags representing the number of autocorrelations used in evaluating the dynamics of the ordinary least squares residuals e_i (Newey and West, 1987) and v, an indicator variable for the truncation lag. Note that the use of HAC covariance matrices does not change the point estimates of the parameters, but only the estimated standard errors (Zeileis, 2004).

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List of Figures

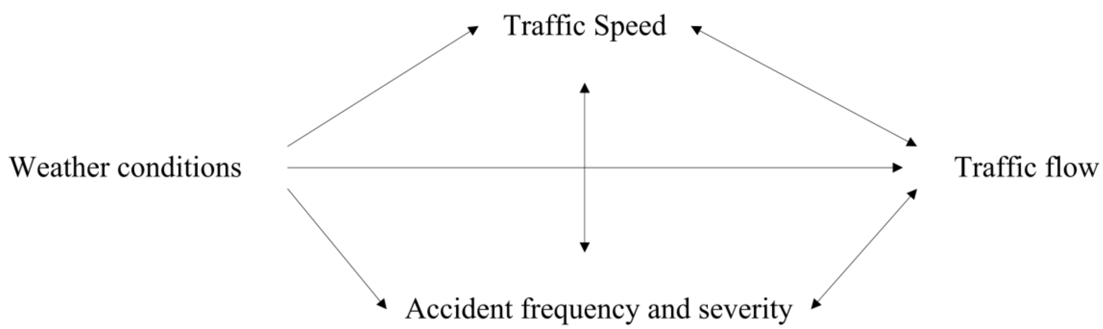

FIG. 1. Relationships between weather, road safety, traffic speed and traffic flow.

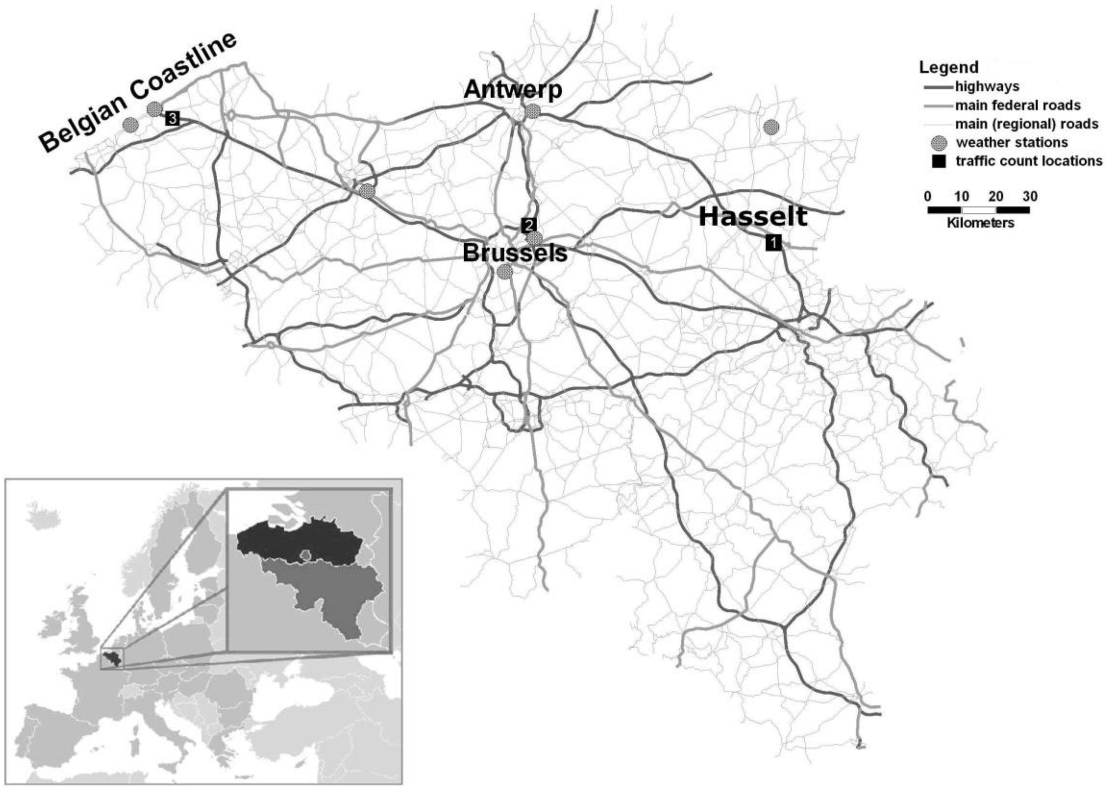

FIG. 2. Representation of the traffic count locations and weather stations under study.

TABLE 1. Meteorological conditions in 2003-2004 .

Parameter of the weather conditions	Mean	Std. Dev	Min	Max
Average maximum wind speed (m/s)	6.5	2.9	1	22
Average minimum temperature (°C)	6.7	5.9	-13.5	22.3
Average mean temperature (°C)	10.8	6.5	-8.3	27.8
Average maximum temperature (°C)	14.8	7.5	-4.0	37.1
Average sunshine duration (min/day)	307.2	262.1	0	935
Average cloudiness (eights)	4.7	2.0	0	8
Average precipitation (1/10 mm/day)	18.8	42.5	0	369
Parameter of the weather conditions	**2003**		**2004**	
Number of days with precipitation / year	149.3		195.7	
Number of days with hail / year	7.0		11.7	
Number of days with snow / year	14.3		22.0	
Number of days with thunderstorm / year	17.7		27.7	
Number of days with reduced visibility / year	9.7		14.7	

Values calculated over all 731 days and averaged over all locations (n = 4386).

TABLE 2. Spearman rank correlations between traffic intensity and continuous predictors.

Weather condition	Down Hasselt	Up Hasselt	Down Brussels	Up Brussels	Down Seashore	Up Seashore
Cloudiness (Mean)	-0.15 *	-0.18 *	-0.09 *	-0.10 *	-0.37 *	-0.33 *
Cloudiness (Max)	-0.17 *	-0.20 *	-0.09 *	-0.10 *	-0.34 *	-0.29 *
Precipitation	-0.10 *	-0.13 *	-0.14 *	-0.12 *	-0.26 *	-0.25 *
Temperature (Mean)	0.17 *	0.23 *	0.02	0.04	0.56 *	0.52 *
Temperature (Max)	0.20 *	0.27 *	0.05	0.07	0.61 *	0.57 *
Temperature (Min)	0.13 *	0,18 *	-0.01	0.01	0.45 *	0.42 *
Wind speed (Max)	-0.06	-0.09 *	-0.11 *	-0.09 *	-0.26 *	-0.25 *
Sunshine duration	0.15 *	0.20 *	0.11 *	0.13 *	0.45 *	0.42 *

* indicates p-value < 0.05, $n = 731$

TABLE 3. Average change in traffic intensity due to presence of weather condition (2003-2004).

Weather condition	Down Hasselt	Up Hasselt	Down Brussels	Up Brussels	Down Seashore	Up Seashore
Hail	2.58% (21)	1,61% (21)	6,91% (22)	6,72% (22)	-10,72% (13)	-11,38% (13)
Thunderstorm	3,61% (57)	2,81% (57)	-2,54% (51)	-1,64% (51)	3,73% (28)	4,53% (28)
Snow	-6,69% (48)	-7,26% (48)	-4,29% (39)	-5,83% (39)	-14,33% (22)	-15,54% (22)
Reduced visibility (Fog)	-3,99% (28)	-2,56% (28)	-6,17% (23)	-7,44% (23)	3,87% (22)	3,46% (22)

n = 731, changes are calculated relative to all other conditions, values between brackets indicate the occurrence of the weather condition

TABLE 4. Parameter estimates (HAC) for the location specific models.

Weather condition	Down Hasselt	Up Hasselt	Down Brussels	Up Brussels	Down Seashore	Up Seashore
Hail			2085.7**	2020.1**		
			(804.2)	(805.9)		
Snowfall			-2358.4**	-3049.8***		
			(1077.0)	(1025.2)		
Precipitation (in 0.1 mm)	-3.0**	-2.9**	-13.4***	-11.6***		
	(1.3)	(1.3)	(3.9)	(3.5)		
Precipitation (dummy variable)					-437.2***	-308.1***
					(89.1)	(105.9)
Cloudiness (Mean)	-57.3**	-55.4**			-152.1***	-217.2***
	(28.6)	(26.7)			(21.2)	(26.5)
Temperature (Max)	84.2***	84.0***	106.7***	93.3***	129.4***	148.5***
	(8.1)	(7.4)	(26.9)	(25.8)	(7.3)	(8.7)
Wind speed (Max)	-55.0**	-66.2***	-170.1***	-126.4**	-49.3***	-62.3***
	(23.1)	(21.3)	(59.7)	(54.6)	(13.9)	(17.0)
Sunshine duration			1.5**	1.9***		
			(0.7)	(0.7)		
Reduced Visibility (<200m)					615.0**	642.5***
					(278.6)	(220.3)
R-square	0.79	0.69	0.86	0.85	0.65	0.67

* indicates p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, n = 731

TABLE 5. Parameter estimates (HAC) for the overall model.

Weather condition	Estimate	Standard Error	P-value
Hail	2.734	0.831	***
Snowfall	-3.822	0.945	***
Precipitation	-0.019	0.004	***
Wind speed (Max)	-0.418	0.062	***
Cloudiness (Mean)	-1.639	0.160	***
Cloudiness (Mean) Hasselt	1.403	0.220	***
Cloudiness (Mean) Brussels	1.500	0.208	***
Cloudiness (Mean) Seashore	0.000	n.a.	n.a.
Temperature (Max)	1.034	0.071	***
Temperature (Max) Hasselt	-0.619	0.090	***
Temperature (Max) Brussels	-0.792	0.092	***
Temperature (Max) Seashore	0.000	n.a.	n.a.

n.a.: not applicable (Seashore location used as reference category),

* indicates p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, n = 4386