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Quantifying the impact of adverse weather conditions on road network performance

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Adverse weather conditions regularly lead to severe congestion and large travel time delays on road networks all over the world. Different climate scenarios indicate that in the future adverse weather conditions are likely to become more frequent, last longer and will be more extreme. Although climate mitigation measures are being taken, it remains important to investigate how adverse weather events will affect the performance of the road network in the future. The main objective of this paper is to give an overview of how the impact of adverse weather conditions and adaptation measures on road network performance can be quantified. A literature review has been performed to show what is empirically known about the impact of adverse weather conditions on the road network performance. Furthermore, available methods to quantify the impact of adverse weather conditions and adaptation measures on the road network performance for future situations are reviewed. As an example, a case study for the municipality of Rotterdam has been carried out that shows how a combination of models can be used to analyse which links in the road network are most vulnerable for increasingly severe local weather related disturbances. The results of the case study allow local authorities to decide whether or not they need to take adaptation measures.

Keywords: *weather disturbances, extreme weather, climate change, road network, vulnerable locations.*

1. Introduction

Adverse weather conditions regularly lead to severe congestion and large travel time delays on road networks all over the world. For example, in the United States it is estimated that 18% of the total delay on roads is caused by weather events such as fog, snow, and heavy rain (SHRP2, 2013). Different climate scenarios (KNMI, 2014) indicate that in the future adverse weather conditions are likely to become more frequent, last longer and will be more extreme (e.g. Lenderink et al., 2011). And although climate mitigation measures are being taken, it is necessary to investigate how adverse weather events will affect the performance of road networks in the future. While weather events also affect other transport systems, the focus in this paper is on road networks.

The main contribution of this paper is to demonstrate how the impact of adverse weather conditions and adaptation measures influence road network performance and how this can be quantified. To do this a number of components are required to allow such a process to be carried out. The main components and their relationships are shown in figure 1, in which the

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relationship between weather events and network performance are also presented. Weather events such as snow, rain, extreme high and low temperatures all have a probability of occurrence and duration. Within these categories different levels of intensity can be distinguished, such as the precipitation intensity or visibility distance. A direct effect of these weather events is a local reduction of the capacity of the road network, such as localised flooding, or in a large part of the network, for example due to widespread snowfall. Besides these capacity or supply effects, behavioural effects can also be expected. Travellers might respond to adverse weather conditions by cancelling their trip, by shifting to another mode, by changing their departure time or by changing their destination leading to changes in travel demand. Furthermore, indirect and cascading effects can also cause capacity reductions and demand changes. Examples of these are incidents caused by heavy rain, tunnels closures, electrical malfunctions due to lighting strikes and disturbances in other transport networks (i.e. public transport, bike). The combined effect on the capacity of a network and the demand determine how a road network performs in terms of congestion levels, congestion locations, travel times and network delay. In this contribution the effects of adverse weather conditions are adopted from existing literature. Negative demand and capacity effects can be reduced by taking measures, such as creating route alternatives, increasing spare capacity, giving travel time information, mobility management and intelligent transport systems, and should therefore increase the performance of the network, or at least prevent deterioration. The effects from adverse weather and of such measures can be quantified to give insight into the overall effects on the traffic performance in a network. This process, as described in figure 1, is the main premise of the contribution.

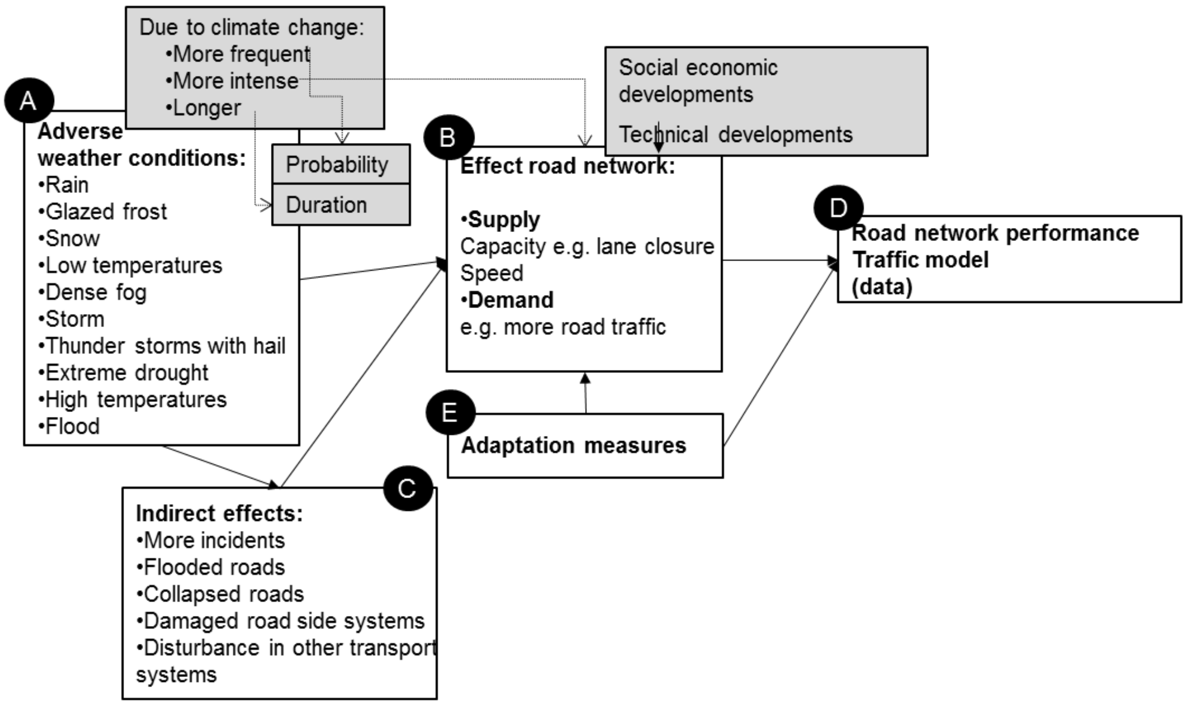

Figure 1. Relationship between adverse weather conditions and the performance of the road network

As will be shown in section 2, much literature is available about specific elements shown in figure 1. However, a consistent overview on all the elements and interactions shown in figure 1 does not exist. Furthermore, as will be shown in section 3, there is limited literature available on the use of traffic and transport models for quantifying the effects of adverse weather conditions and adaptation methods towards the future. This paper contributes to the existing literature by giving a concise and consistent overview of what is empirically known about all the elements in figure 1.

It furthermore gives an overview of which models can be used and how they can be used to quantify the impact of adverse weather conditions and adaptation measures on road network performance for future situations. Furthermore, a first example is presented for the municipality of Rotterdam of how a combination of these models can be used to identify the most vulnerable links in a network in case of adverse weather events. This is given in section 4. Finally, in section 5 the conclusions are presented as well as a discussion about how the results can be used to derive adaptation measures.

2. Empirical data about the effect of adverse weather conditions on the capacity of the road network and the demand effects

In this section an overview is given of a selection of empirical analyses found in literature for the separate elements indicated in figure 1. This overview is merely given as an indication of effects on traffic and is not by any means exhausted.

A. Estimation of adverse weather conditions

Climate change research in past decades has offered a wide range of sources estimating how different weather conditions may develop in the future. While some make general estimations of future trends, others make predictions of the probabilities of certain weather conditions occurring and of their duration and intensity. It is obvious that climate change and the corresponding weather conditions are geographically dependant. As the analysis presented here focusses on The Netherlands, we will focus mainly on climate change and forecasting predictions for this region, while recognising that each region in the world has its own specific climate developments. Nevertheless the presented approach remains generic. Recent climate scenarios developed by the The Netherlands meteorological institute (KNMI), show extensive climate change on a seasonal scale for the coming half century. An overview of the analysis is shown in table 4 in Appendix A.

Table 4 contains indicators for the period 1951-2010, the period 1981-2010 and for four different scenarios for 2050. The scenarios differ depending on increases to the global temperature ('Moderate(G)' and 'Warm(W)') and the possibility of a change to the global atmospheric circulation ('Low (L)' and 'High (H)'). Further indicators for 2085 can be found in (KNMI, 2014). The following is indicated with respect to road transport for the Netherlands:

Winter: In the winter, temperatures may increase between 1°C to 2.8°C by the year 2050 and the number of frost days may decrease by 30% to 60% which implies that snow, low temperatures and frost may occur less frequently. The number of wet days (>0.1 mm per day) is not predicted to change much. However, the number of wet days with more than 10 mm precipitation per day and the possibly of thunder storms with hail is forecasted to increase by 9.5% - 35%. As a consequence, the flood risk from rivers may increase. The effect of wind is not forecasted to significantly change.

Summer: In the summer the average temperature is forecasted to increase slightly, while the number of days with a temperature higher than 25°C may increase by 22%-70%. The number of wet days with more than 0.1 mm and with more than 20mm of rain decreases or increases depending on the scenario. Rainfall is due to be more intense with a maximum hourly intensity increase of 5.5% to 25%.

B. Quantitative effect on road networks

Climate change is expected to have the largest impact on traffic under heavy rain, snow and frosty conditions for The Netherlands and countries with a similar climate. This expectation is due to either a high probability of occurrence or a relatively high impact that these conditions can have on traffic. In other countries other weather conditions, such as high temperatures and dryness, may lead to a higher impact.

As precipitation is expected to be a main threat to The Netherlands, a summary of the quantitative relations that can be found of both snow and rain is given in table 1. Table 1 is based on international literature. Although table 1 does not give an exhaustive overview of all available literature it does give a clear indication of the range in which speed reductions, capacity reductions and demand effects due to rain and snow lie. In general the influence on these three quantities can be summarised as follows:

Capacity reduction: table 1 shows that the capacity decreases by 4% to 30% depending on the rain intensity and the location. The majority of capacity reduction observations were found to be in the range 5-15% Only in (Smith et al, 2004) for Virginia was there a capacity reduction reported of up to 30% for rain intensities that exceeded 6.35 mm/hour. For the other locations the maximum reduction does not exceed 17%. For snow, capacity reductions between 3%-27% have been reported, while other literature reports reductions without stating clear quantitative values (Call, 2011).

Speed reductions: in general the free flow speed on a freeway has been shown to drop due to rain. Values between 2%-10% or by 9.5-12 km/hour have been reported also depending on the rain intensity and the location. However Vukovic et al. (2012) also report that incidental speed reductions may be higher than 40% for short intense rainfall. The speed at capacity was shown to drop by 8%-14% according to Hranac et al. (2006). For snowfall greater free flow speed reductions were found of 3%-16% and for the speed at capacity of 5%-16%.

Demand effects: Much research has been performed on determining factors that influence traffic, however most focus on determining explained variables. However there remains literature in which estimates of demand under adverse weather conditions are given, especially for precipitation. In table 1 some of these findings are summarised. Most sources report a decrease in demand of 2% - 14% for rainfall. While Chung et al. (2005) find a reduction of 14% in the weekends, the majority of literature finds values between 2-5%. Incidentally it was reported by Van Stralen et al. (2014) that an increase in demand was found for light rain (+2%). Furthermore, Vukovic et al. (2013) indicate that although there may be an average decrease in demand for rain, on some specific on- and off ramps and at specific moments in time the demand may increase. For snow, a wide range of demand reductions were found in literature varying between 7%-53%.

Speed reductions reflect changes in driving behaviour and demand effects reflect the changes in destination, mode and departure time choice. While amp literature exists on the influence of precipitation on traffic, there is limited literature available that gives a quantification of the effects on supply (capacity and speed) and demand of other weather conditions. This was also the case for the combined effects of other adverse weather conditions on both traffic flow and demand. Some additional quantitative literature was found in relation to cold, mist weather conditions. Hoogendoorn et al (2010) found that dense mist can lead to speed reductions of up to 30% on freeways. Agarwal et al (2006) indicate that extreme cold weather with temperatures down to -20 degrees Celsius can result in a capacity reduction of 6-10%.

While the influence of many other effects on travel behaviour have been considered, few give a quantitative value and are therefore not further considered here. Therefore, in addition to literature a set of hypotheses on the qualitative relationship between weather conditions and supply and demand effects are constructed and shown in table 2. These hypotheses are based on a wide range of literature, including Mannering et al. (1995), Khattak and de Palma (1997), de Palma and Rochat (1999), Maze et al. (2006), Kilpelainen and Summala (2007), NRC (2008), Mahmassani et al. (2009), Koetse and Rietveld (2009), Cool et al. (2010), Call (2011), Sabir (2011), Saneinejad et al. (2012) and Böcker et al. (2013a; 2013b); and are extended based on expert judgement. The combination of this expert judgement with the resourced literature gives a complete basis for the further analysis.

Table 1. Expected road supply and demand effect of adverse weather conditions

Weather condition	Source and location	Intensity	Capacity reduction	Free Speed reduction	Speed at capacity reduction	Demand effect road
Rain	Agarwal et al (2006), Minneapolis & St. Paul	0.25-6.35 >6.35 mm/h	5%-10% 10%-17%	5%-6.5%	-	-
	Al Hassan and Barker (1999), Scotland	Heavy rain	-	-	-	-4.6%
	Brilon and Ponzlet (1996), Germany	Rainy weather	-	9.5 km/hour (2 lanes) 12 km/hour (3 lanes)	-	-
	Calvert and Snelder (2013), Netherlands	For every 1 mm/h up to max 5 mm/h	1.9% per mm/h	-	-	-
	Chung et al. (2005), Tokyo Metropolitan expressway	0-1 mm/h 1-10 mm/h	4%-7% 8%-14%	4.5% 8.2%	-	-2% - -4% weekdays -4 - -14% weekend
	Hogema (1996), Dutch A16 motorway	Rainy weather	-	11 km/hour	-	No increase in demand
	Hranac et al. (2006), Seatle, Baltimore, Minneapolis & St. Paul	<0.1 mm/h 0.1-17 mm/h	 10%-11%	2%-3.6% 6%-9%	8%-10% 8%-14%	-
	Keay and Simmonds (2005), Melbourne	-	-	-	-	-2% - -3%
	Martin et al (2000)	-	-	10%	-	-
	Maze et al. (2006), Minneapolis/St. Paul	-	-	6%	-	-
	Smith et al. (2004), Virginia	0.25-6.35 >6.35 mm/h	4%-10% 25%-30%	5%-6.5%	-	-
	Van Stralen et al. (2014), Netherlands	Light rain (0.01-1 mm) Heavy rain (>1 mm)	4% - 9% (ave 6%) 4% - 11% (ave 8%)	-	-	+2.3% -7.7%
	Vukovic et al. (2013)	> 2 mm/h	4.5 x more incidents	5%-10%	-	-1.5%- -5%
Snow	Agarwal et al. (2006)	0 – 1.3 1.5-12.7 12.7 mm/h	3%-5% 6%-13% 19%-27%	3%-5% 7%-10% 11%-15%	-	-
	Al Hassan and Barker (1999)	-	-	-	-	-15%
	Cools et al. (2009)	-	-	-	-	-3.8%
	Hanbali and Kuemmel (1993)	<25 mm/day 25–75 75–150 150–225 225–375	-	-	-	-7%– -17% -11%– -25% -18%– -43% -35%– -49% -41%– -53%
	Hranac et al. (2006)	Light Snow	-	5%-16%	5%-16%	-
	Martin et al. (2000)	-	-	13%	-	-
	Maze (2006)	-	-	13%	-	-
	Van Stralen et al. (2014)	-	-	-	-	-22% - -29%

Table 2. Expected supply and demand effect of adverse weather conditions

Weather condition	Primary effect	External conditions	Supply effect	Demand effect
Rain	- Water on the roads and in tunnels → slippery roads - Rain in the air → reduced visibility	- A limited sewer capacity can cause water on the roads and in tunnels - Road surface is important (asphalt type and quality) for the amount of water on the roads	- Reduced capacity: reduced speeds and increased time gaps - Closure of tunnels - Incidents due to aquaplaning	- Light rain: small changes - Heavy rain: decrease in demand
Frost	- Slippery roads	- Steel bridges: water freezes faster on the roads - Black ice is difficult to see for drivers → higher incident risk	- Reduced capacity: reduced speeds and increased time gaps - More incidents, especially on on- and off-ramps, motorways and bridges	- No effect
Snow	- Snow on the roads → slippery roads - Snow in the air → reduced visibility - more frequent maintenance, repairs, and rebuilding	- Sometimes snow clearing vehicles cannot access the motorways or other roads due to steep onramps and barriers - Sometimes the snow cannot be removed from the road because there is no space next to the road - Melt water can be a problem if the sewer capacity is insufficient	-Reduced road capacity , on- and off-ramps - Reduced capacity: reduced speeds and increased time gaps -Extra incidents	- Reduced demand
Low tempera-ures	- Possibly slippery roads	- Steel bridges: water freezes faster on the roads - Possible leakages in tunnels in combination with precipitation	- No effect in case of low temperatures (only effect in combination with precipitation)	- Increased demand
Dense fog	Reduced visibility More incidents		- Reduced capacity: reduced speeds and increased time gaps - Extra incidents	- Reduced demand
Storm	-Difficult to keep lanes (especially for trucks) - Risk of overturning especially for trucks, trailers and caravans		- Closure of bridges and fly-overs in case of storm - Reduced speeds on bridges and fly-overs (which are not closed) - No ferries - Extra incidents	- Reduced demand
Lightning	-Electricity problems which may cause failures in tunnel pumps or dynamic traffic management systems		- No significant effect expected (due to very low probabilities)	-No effect
Extreme drought	- Increased likelihood of wildfires	- Reduced visibility	- (Partial) road closures and speed reduction	-No effect
High tempera-tures	- More incidents - Reduced visibility due to roadside fires - Problems with the pavement	- Steel bridges need to be cooled - Sand on the road can strengthen the asphalt	- No significant effect expected	-Mode choice
Flooding	- Roads under water - Danger of sinkhole occurrence	- Electricity supply for dynamic traffic management - Road closures for emergency services and evacuations	-First reduced speeds -Then roads closed for regular traffic	-Evacuation traffic - Reduced regular demand

C. Indirect effects on road networks

The occurrence of incidents, such as accidents, is the most studied area of indirect effects on road networks. Koetse and Rietveld (2009) conclude, based on a literature review, that on average, precipitation increases the number of accidents by 75% and the number of related injuries by 45%, with snowfall having a more substantial effect than rainfall. They also mention the lagged precipitation effect implying that rainfall leads to a stronger increase in the number of accidents after a dry spell. Vukovic et al. (2013) report an even larger increase of the incident risk. They concluded that the incident risk is 4.5 times higher for rain compared to dry weather conditions. With respect to other weather conditions Koetse and Rietveld (2009) conclude that the risk of an accident increases with increasing heat. Also fog and wind may have an increasing effect on the number of accidents. Brijs et al (2008) found that there is an increased number of accidents in The Netherlands under wet conditions and also for low temperatures mainly below or near to freezing point.

D. Road network performance measures

In (SHRP2, 2013) it is estimated that for the United States 18% of the total delay on roads is caused by weather events such as fog, snow, and heavy rain. However, it is not explained what the share is of the different weather events and how much higher (or lower) the network delay is for adverse weather conditions compared to dry weather conditions. In this regard Vukovic et al. (2013) found that the average total extra travel time per minute of rain in the Netherlands is 14 to 19 seconds depending on the rain intensity. On a yearly basis, they found that the total network delays vary between 50 to 80 million hours which corresponds to an economic damage of about 0.5 to 0.75 billion euro. However, they state that this is an upper bound as this was not corrected for other causes of delay. Van Stralen et al. (2014) found that the congestion probability (or probability of break down) is 86.7% higher for light rain (<1 mm) compared to dry conditions. For heavy rain (>1 mm) this is 77.4%, which remarkably is lower compared to light rain. The explanation given can be found in the increase in demand that they found for light rain. In relation to flooding, The Netherlands Centre for Transport and Navigation (2006) estimated the economic costs associated with changes in traffic and transport due to a single flooding incident. This was performed using a transport model for four economic scenarios in which the behavioural assumptions and the value of time where varied. They estimated the costs to be between €414 million and €1.1 billion. Furthermore, Suarez et al. (2005) investigated the impact of coastal flooding due to sea level rises, and of river flooding due to heavy rainfall. In this they focussed on urban transportation in the Boston Metropolitan Area in terms of cancellations of trips and in terms of delays due to rerouting and changes in congestion. Assuming a sea level rise of 0.3 cm per year, and an increase in the magnitude of heavy rainfall of 0.31% per year, the results showed an increase in delays and lost trips of around 80% in 2100 compared to 2000.

E. Adaption measures

Finally, with respect to the effect of measures (element E in figure 1), Kim et al. (2013) show for several weather scenarios with respect to rain, snow and visibility what the impact of advisory and control strategies, demand management and incident management can be. This is however not based on empirical data, but on simulation. Furthermore, Snelder et al (2008) give an overview of adaptation measures that may be taken. Besides the above mentioned measures they also mention structure and surface related infrastructure measures. They present a pure qualitative overview, without giving an indication of the quantitative effects of the measures.

3. Method for modelling the effects of adverse weather conditions on road network performance

In order to determine the extent to which climate change may affect the long term road network performance (element D in figure 1) and in order to determine what the benefits of adaptation measures could be (element E in figure 1), a large range of weather related disturbances needs to be modelled on different locations and different times of the day which might require hundreds or thousands of simulation runs representing the different weather scenarios that can occur in the future. This section explains which modelling techniques are available for this purpose and how they can be used. Section 3.1 discusses indicators. Section 3.2 shows what is required to model a single disturbance and adaptation measure. In section 3.3 it is explained what is required if the yearly impact of all weather related disturbances is to be modelled.

3.1 Indicators

In order to express the effect of weather related disturbances on network performance, many indicators or even a combination of indicators can be used. In general the indicators can be classified into robustness and reliability indicators. Robustness indicators relate to trips that are affected by a single disturbance or combination of disturbances that occur in the same period of time. Examples of robustness indicator can be found in (Snelder et al., 2012). Reliability indicators relate to a series of trips that are made over time of which some might be affected by weather related disturbances. Examples of these can be found in (Lomax et al., 2003; Van Lint et al., 2008).

All these indicators can offer valuable insights. For each model application one or more robustness or reliability indicators can be selected that best fit the purpose of the analysis.

In this paper we choose the total extra travel time (or network delay) caused by the weather event(s). In the case study (section 4) this choice is explained in more detail.

3.2 Modelling a single weather related disturbance or adaptation measure

In order to simulate the effect of a single weather related disturbance on a road network, a reference scenario should first be modelled (without adverse weather conditions). This could for instance be an average morning or evening peak hour or even an entire average day under normal weather conditions (average and normal need to be clearly defined). There are all kinds of traffic and transport models available for doing this, either static/dynamic or microscopic/mesoscopic/macroscopic. The models differ in the way in which location choices, destination choices, mode choices, departure time choices, routes choice and driving behaviour are modelled. In most cases the choice models are only applied to passenger transport. The resulting demand is often combined with a fixed demand matrix for trucks. However, more detailed freight models are available that also consider choices like shipment size, load factor, tour formation, use of consolidation and distribution centres or even their number and location.

Consequentially, also the level of accuracy and the computation time differs between the different model types. If all these choices and congestion phenomena are modelled accurately for a large realistic network the computation time of the models can easily add up to several hours on a normal desktop computer.

Based on this reference situation the effects of weather related disturbances and adaptation measures can be modelled. As explained in figure 1 (element A→C→B) the models require quantitative input on how adverse weather conditions directly and indirectly affect the supply and demand. This is input with respect to location, duration, time of day and impact on road supply and demand. The location, duration and time of day will have to be chosen by the modeller. In the previous section an indication is given of input values that can be obtained from empirical data with respect to the impact of different disturbances on the road supply and demand.

As far as the authors of this paper are aware, Mahmassani et al. (2009) and Kim et al. (2013) are the first to propose a model approach that is especially suited for adverse weather conditions. They propose a Traffic Estimation and Prediction System for weather responsive traffic management in which a mesoscopic dynamic traffic assignment model DYNASMART is used and calibrated for different rain, snow and visibility conditions. In fact, they estimated a weather adjustment factor for all the important model parameters with respect to the supply side. Furthermore, the changes in dynamic OD patterns are estimated by real time estimation of the OD-matrix, by making assumptions on user responses to information and control measures and by adding a new attribute associated with weather-related risk in the generalised cost (affects route choice). By using this estimation and calibration approach they did not have to make assumptions about the effect of adverse weather conditions on the supply and demand (element B of figure 1). If the impacts of adverse weather conditions in the future are to be modelled, assumptions will still need to be made on how climate changes, socio-economic changes and technological changes affect the demand and the supply. Kim et al. (2013) applied the model to different advisory and control strategies, incident management strategies and demand management strategies.

3.3 *Modelling the impact of 'all' yearly weather related disturbances*

As stated in the introduction of section 3, in order to determine the extent to which climate change may affect the long term road network performance (element D in figure 1) and in order to determine what the benefits of adaptation measures could be (element E in figure 1), a large range of weather related disturbances needs to be modelled on different locations and different times of the day which might require hundreds or thousands of simulation runs.

A method like the method of Mahmassani et al. (2009) can be used to explore different weather scenarios. However as stated above the computation time can increase rapidly if many scenarios or combinations of input factors have to be modelled. The computational load can either be reduced by using advanced sampling techniques (e.g. Calvert et al., 2014) or by using advanced modelling techniques. An example of the latter are marginal models in which a significant overlap between traffic flow in successive simulation iterations is presumed. By only simulating the marginal difference in traffic flow, repetitive network loading with a full dynamic micro-, meso- or macroscopic model is not required. Therefore the marginal simulation method only requires a single full initial model simulation. Thereafter, only the marginal differences are modelled which results in computation times of seconds instead of hours. Examples can be found in (e.g. Corthout et al. 2009, Corthout et al. 2011; Himpe et al. 2013, Corthout et al. 2014).

With respect to advanced sampling techniques we refer to literature about uncertainty or sensitivity analysis (e.g. Punzo, 2014). These methods vary the input factors of a traffic model in such a way that the empirical probability density function and the confidence bounds of the model output can be obtained. The input factors are in this case the independent variables and coefficients with respect to supply (e.g speed, capacity reduction and duration and location of capacity reductions caused by weather related disturbances) and demand (e.g. total trips and behavioural responses to weather related disturbances). It must be noted that the input factors can be correlated because certain weather events (e.g. snowfall) affect both the capacity and the demand. In this case it can easily be understood that the bandwidth of possible outcomes with respect to the network performance in the future will be very large. This may be the case for the uncertainties in climate scenarios, and for the weather events effect on capacity and demand. This makes it difficult to determine whether or not adaptation measures will have a net benefit to society.

A suggested solution is to identify which factors or groups of factors are mostly responsible for the uncertainty in the prediction. This is called sensitivity analysis (Saltelli et al., 2010). If for instance, it is known that disturbances on a certain location in the network have the largest impact on the network performance, the adaptation measures could focus on that location. Different methods are available to sample the input space which can be classified in local sensitivity analysis, global sensitivity analysis (e.g. Saltelli et al., 2008) and one-at-a-time variation of a single input factor while keeping the others fixed. Saltelli and Annoni (2010) explain that the latter is inferior to global sensitivity analysis in which the full range of uncertainty in the input space is considered. Quaglietta and Punzo (2013) briefly describe a few methods for global sensitivity analysis: input/output scatter-plots, sigma-normalized derivatives, standardized regression coefficients, elementary effects, and variance-based techniques.

Related to this, one could also try to identify for which combinations or levels of an input factor a threshold value for a selected indicator is exceeded. A possible outcome might be that the indicator exceeds the threshold if the capacity of one link or a set of links in the network is reduced by more than a certain percentage and/or demand increases by more than a certain percentage. A decrease in demand in combination with a decrease in supply could also result in a total network delay that exceeds the threshold. This allows for adaptive policy making which one could monitor over the years. This may be for instance at which levels of demand a threshold value is exceeded for certain weather related disturbances or at which expected weather conditions additional traffic management, mobility management or incident management measures should be taken.

Although the above mentioned methods appear to be promising they have not yet been applied for analysing the effects of weather related disturbances as far as the authors are aware of. As an example, a case study in which one of these methods is used is presented in the next section.

4. Case study for Rotterdam

In this section a case study for the municipality of Rotterdam is presented that shows how a combination of models can be used to analyse which links in the road network are most vulnerable for increasingly severe local weather related disturbances. As an indicator for the network performance we choose the total extra travel time (or network delay) caused by the disturbances. This indicator can be valued economically and is therefore relatively easy to explain. Furthermore policy and decision makers are used to thinking in terms of travel time losses, which also adds to the indicators clarity. Of course other indicators are also valid, but are not applied here. By local disturbances we refer to weather related disturbances that affect a single link or a part of the network and not the entire network. For these local disturbances Snelder et al. (2012) propose a method for identifying links that are vulnerable in case of incidents. In this paper the method is generalised in such a way that it can also be used for adverse weather conditions. The method can briefly be summarised as:

- Step 1: An equilibrium assignment is performed with the macroscopic dynamic traffic assignment model Indy (Bliemer, 2007). This model has an accurate network loading model that models spillback effects according to the simplified kinematic wave theory of Newell (Yperman, 2007). Furthermore, the model can compute an equilibrium route choice and can deal with fixed route choice. Indy is a dynamic model, which makes the modelling of time dynamics possible. Among others, this results in the cumulative inflows and outflows per link to all other connecting links. This is used as an input for step 2.
- Step 2: In order to model the effects of adverse weather conditions, a marginal incident computation model (MIC) (Corthout et al., 2009) has been attached to Indy. The MIC-module is able to generate an estimate of the impact of local capacity reductions very quickly based on an analytical approximation of the queues that build up upstream of the bottleneck. Figure 2 briefly explains the method. From the base simulation run with Indy, the cumulative vehicle numbers for all link boundaries are derived for the situation

without a disturbance. The dashed lines in figure 2 represent the upstream (X_j^0) and downstream (X_j^L) cumulative vehicle numbers *N(X, t)* for link *j* over time *t*. Upstream refers to vehicles that enter the link and downstream refers to vehicles that leave the link. The MIC-module alters the cumulative vehicle numbers of the base simulation given the capacity reduction that is imposed by a disturbance downstream of the link, reducing them to fit the constraints of the spillback wave on the affected link. First the downstream cumulative numbers are changed, then the changes in the downstream curve are copied to the upstream boundary according to Newell's theory (Newell, 1993): shifted $L/-w$ in time and k_jL in cumulative vehicle numbers (*L* being the length of the link, w the negative spillback wave speed and k_j the jam density). If a spillback wave moving on an affected link *j* reaches the upstream node, congestion spills back onto some or all of the incoming links. When the disturbance ends, the capacity at the location of the disturbance is restored. The acceleration wave proceeds through the affected links in a way similar to the spillback wave and finally catches up with the spillback wave. The total extra travel that is caused by the disturbance can now be computed based on the differences between the cumulative curves (grey area minus black area).

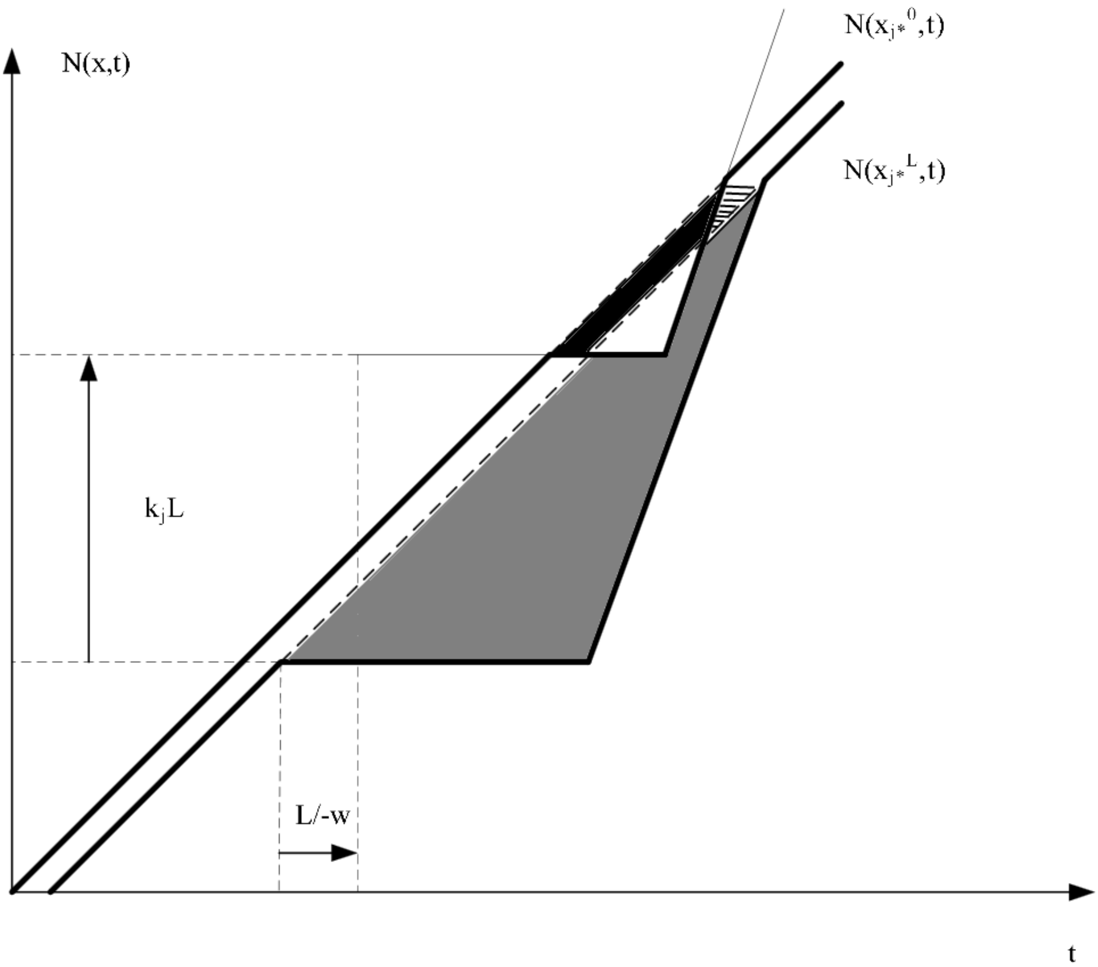

Figure 2. Approximation of the effects of disturbances (Corthout et al.,2009)

The MIC module assumes that vehicles do not change their behaviour during disturbances. This is a simplification because in practice some people will change their route, departure time, mode or even destination in case of severe disturbances. Therefore, the modelled situation represents a worst case situation.

- Step 3: The MIC model is used to model the extra travel time that is caused by local weather related disturbance. This may be incidents that are caused by frost or snow, blocked on- and off ramps due to snow, closed bridges due to storm or closed roads due to water on the road etc. From the literature review it can be concluded that the direct capacity reductions caused by rain and snow may very between 3% to 30% depending on the rain and snow intensity. Indirect effects like water on the roads, incidents etc. may however cause larger capacity reductions due to closure of one or more lanes (e.g. 50% or 95%). Also the duration of these disturbances may vary. Because of the high uncertainty a sensitivity analysis based approach is used for five types of increasingly severe local weather related disturbances:
    - Type 1: capacity reduction: 30%; duration 24 minutes. (e.g. extremely heavy rainfall during a short time interval)
    - Type 2: capacity reduction: 50%; duration 30 minutes. (e.g. lane closure due to an incident caused by a slippery road)
    - Type 3: capacity reduction: 50%; duration 60 minutes. (e.g. reduced capacity due to water on the road)
    - Type 4: capacity reduction: 95%; duration 45 minutes. (e.g. localised road closure, for example due to flooding, for a short time interval)
    - Type 5: capacity reduction: 95%; duration 90 minutes. (Localised road closure, for example due to flooding, for a longer time interval)

  The MIC module is run for weather related disturbances on each link. In every simulation run the capacity of a single link is reduced. This is performed five times (for the five types) for every link. The output of the method is the total extra travel time of all vehicles per disturbance type and per link.

The method is applied to the network of the city of Rotterdam in the Netherlands. The model contains 6669 unidirectional links (motorways and lower level roads), 3053 nodes and 233 zones. The model is calibrated for regular conditions for the base year 2012 based on traffic counts for 116 locations. The model is validated based on travel time data for 7 routes from the motorway ring road to the city centre.

For the five types, table 3 shows the percentage of all links in the network of which the extra travel time that is caused by disturbances on that link exceeds a threshold value.

Table 3. Percentage of links of which the extra travel time that is caused by disturbances of type 1, 2, 3, 4 and 5 exceeds a threshold value

Threshold value extra travel time (hours)	type 1	type 2	type 3	type 4	type 5
2500	0.2%	0.8%	2.0%	24.5%	44.1%
5000	0.2%	0.6%	1.7%	22.1%	42.3%
7500	0.2%	0.6%	1.6%	21.0%	41.1%

In figure 3 the results are shown on a map. Similar figures can be made for an increasing or decreasing demand level. For the sake of readability, the results are only visualised for motorway links and the most important routes in the city centre. The colour of the links indicates the delay that a specific link causes upstream in the network for the simulated weather event. The links that are coloured black in the first incident type are the links that are most vulnerable if the frequency of occurrence is not considered. The links that are coloured black for the other incident types become vulnerable if the severity and duration of the weather events increase. This can be monitored over a longer period of years and threshold values can be specified.

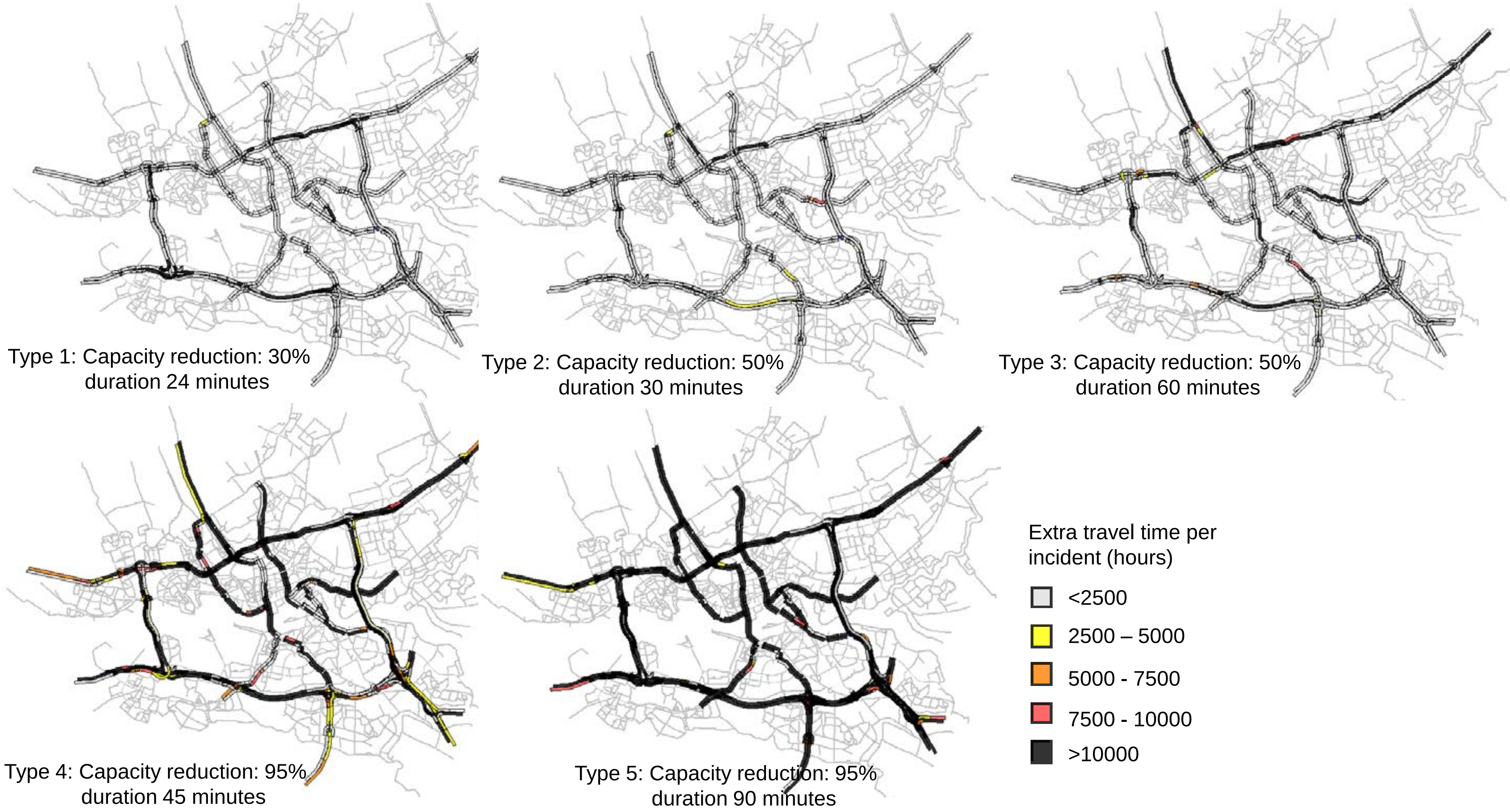

Figure 3. Extra travel time per local weather related disturbance

The results of the case study allow the municipally of Rotterdam to decide whether or not they need to take adaptation measures. For locations that are already vulnerable in the existing situation adaptation measures might already have a net benefit to society. Especially since measures that reduce the vulnerability of the road network for weather related events are also likely to have a net benefit to society in case of non-weather related disturbances such as incidents. For example, information provision about alternative routes can have a net benefit to society in case of a road closure due to water on the road and also in case of a road closure due to an incident.

Of course, the model results should be combined with the frequency of the different types of local weather related disturbances in order to be able to perform a cost-benefit analysis. This frequency might be different for all links, because this depends on the traffic volumes, the type of asphalt, the gradient of the roads, the sewer capacity etc. It is outside the scope of our paper to make extensive estimates of the likelihood that different rain intensities or other weather conditions cause certain capacity reductions. For illustrative purposes, figure 4 does show the results of a workshop in which experts from the municipality of Rotterdam, the snow clearing vehicles, the police and the national road authority gave their expert opinion about the locations where different weather conditions most frequently caused capacity reductions in the previous years. In this figure the coloured ovals indicate locations where rain, frost, high water or a combination of bad weather conditions most frequently caused capacity reductions. The purple/green line marks an entire route with multiple tunnels where rain and frost are likely to cause capacity reductions. The locations that are both marked in figure 3 and in figure 4 are the locations that are most vulnerable for weather related disturbances.

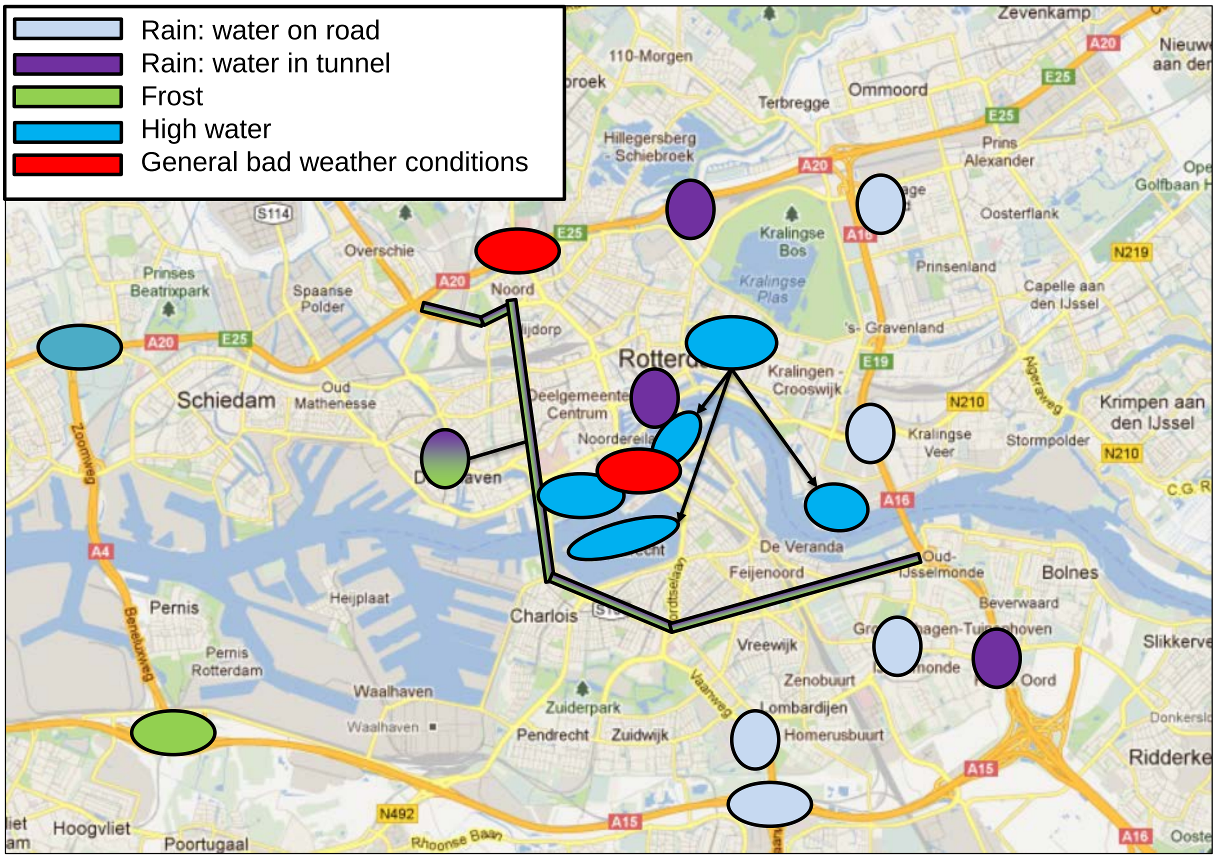

Figure 4. Locations where weather events are likely to cause capacity reductions.

5. Conclusions

The main objective of this paper is to give an overview of how the impact of adverse weather conditions and adaptation measures on road network performance can be quantified. Based on that overview we conclude the following:

Conclusion 1: more empirical analysis is required in order to gain a thorough understanding of the way different weather conditions affect the road network performance now and in the future. Different weather statistics and climate scenarios are available for the Netherlands and some other countries that indicate how often different adverse weather conditions occur now and in the future. For rain and snow, quantitative relations can be found in literature that indicate how these weather conditions affect the road capacity, the speed and the level of demand. For most other adverse weather conditions there is very limited quantitative evidence. Indirect effects such as incidents caused by heavy rain, tunnel closures, electrical malfunctions, lighting strikes and disturbances in other transport networks (e.g public transport, bike) seem to be understudied as well. Finally, limited empirical evidence was found on the extent to which weather conditions affect the total network delay.

Conclusion 2: traffic and transport models in combination with marginal simulation and/or advanced sampling techniques appear to be promising methods for analysing the impact of adverse weather conditions and adaptation measures on the future road network performance. However, they have not been widely applied for this purpose yet. A first case study that was presented in this paper for the municipality of Rotterdam showed that it is possible to use a combination of models (macroscopic dynamic traffic assignment model in combination with a marginal model) in order to identify which links in the road network are most vulnerable for increasingly severe local weather related disturbances. Since behavioural responses are not included in the model, the results represent an upper bound. Future research is required, in order to investigate how behavioural responses can be added in such a way that the computation time stays within acceptable ranges. Furthermore, future research is required in order to investigate how, depending on the objective of the analysis, other combinations of traffic and transport models, marginal simulation and/or advanced sampling techniques can be used.

Conclusion 3: given the uncertainties in climate scenarios and the extent to which weather events affect the capacity and the demand directly or through indirect or cascading effects, the range in which the network delays that are caused by adverse weather conditions lie in the future could be very large which makes it difficult to determine whether or not adaptation measures have a net benefit to society.

Given the above, the question is posed how the above mentioned empirical analyses and models can be used in such a way that they give relevant input to transport planners and operators and policy makers. A possible way forward could be found in empirical analysis and in analysing the effects of measures in the current situation. Several authors showed that it is possible to analyse the extent of large network delays caused by weather related disturbances. This already shows the maximum potential of adaptation measures in terms of travel time gains. A value of time for unexpected delays is required to express this potential in monetary units. A next step would be an economic analysis of how different measures can contribute to achieving this potential. Furthermore, Mahmassani et al. (2009) showed that it is possible to calibrate a model for weather related disturbances for the current road network which makes it possible to estimate the effects of adaptation measures. These type of analyses are especially suited for tactical and operational measures with an effect on the short term in case it is known which weather related disturbance are expected in the short term through weather forecasts.

For more strategic measures, long term effects should also be considered. This is more difficult because many different weather conditions on different locations in the network will have to be considered and because of the many uncertainties that are mentioned above. In order to overcome this problem, one could investigate whether strategic measures already have a net benefit to society in the current road network conditions. Because different climate scenarios indicate that in the future adverse weather conditions are likely to become more frequent, last longer and will be more extreme, it can be expected that if these measures already have a net benefit to society in the current conditions, they will have an even larger net benefit in the future (even more so if the demand will increase). Finally, sensitivity analysis could provide insight in which weather conditions have the largest negative impact on road network performance and on which locations in a network they have the largest negative impact, as was shown in the case study for the municipality of Rotterdam.

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Appendix A

Table 4. Climate scenarios (KNMI, 2014)

Season	Variable	Indicator	Climate 1951-1980	Climate 1981-2010[a]	Scenario change values for 2050 (2036-2056)				Natural change[b]	Unit change
					G_L	G_H	W_L	W_H		
Global temperature rise					+1	+1	+2	+2		°C
Change in air circulation pattern					low	high	low	high		
Year	Sea level at North sea coast	absolute level	4 cm below NAP	3 cm above NAP	+15to +30	+15 to +30	+20 to +40	+20 to +40	± 1.4	cm
		rate of change	1.2 mm/year	2.0 mm/year	+1 to +5.5	+1 to +5.5	+3.5 to +7.5	+3.5 to +7.5	± 1.4	mm/year
	Temperature	mean	9.2°C	10.1°C	+1	+1.4	+2	+2.3	±0.16	°C
	Precipitation	mean amount	774 mm	851 mm	+4.0	+2.5	+5.5	+5.0	±4.2	%
	Solar radiation	solar radiation	346k J/cm2	354 kJ/cm2	+0.6	+1.6	-0.8	+1.2	±1.6	%
	Evaporation	potential evaporation (Makkink)	534 mm	559 mm	+3.0	+5.0	+4.0	+7.0	±1.9	%
	Fog	number of hous with visibility <1 km	412 hours	300 hours	-110	-110	-110	-110	±39	hours
Winter	Temperature	mean	2.4 °C	3.4 °C	+1.1	+1.6	+2.1	+2.7	±0.48	°C
		year-to-year variation	-	± 2.6 °C	-8.0	-16.0	-13.0	-20.0	-	%
		daily maximum	5.1 °C	6.1 °C	+1	+1.6	+2	+2.5	±0.46	°C
		daily minimum	-0.3 °C	0.5 °C	+1.1	+1.7	+2.2	+2.8	±0.51	°C
		coldest winter day per year	-7.5 °C	-5.9 °C	+2	+3.6	+3.9	+5.1	±0.91	°C
		mildest winter day per year	10.3 °C	11.1 °C	+0.6	+0.9	+1.7	+1.7	±0.42	°C
		number of frost days (min temp < 0°C)	42 days	38 days	-30.0	-45.0	-50.0	-60.0	±9.5	%
		number of ice days (max temp < 0°C)	11 days	7.2 days	-50.0	-70.0	-70.0	-90.0	±31	%
	Precipitation	mean amount	188 mm	211 mm	+3.0	+8.0	+8.0	+17.0	±8.3	%
		year-to-year variation	-	± 96 mm	+4.5	+9.0	+10.0	+17.0	-	%
		10-day amount exceeded once in 10 years	80 mm	89 mm	+6.0	+10.0	+12.0	+17.0	±11	%

		number of wet days (≥ 0.1 mm)	56 days	55 days	-0.3	+1.4	-0.4	+2.4	±4.7	%
		number of days ≥ 10 mm	4.1 days	5.3 days	+9.5	+19.0	+20.0	+35.0	±14	%
	Wind	mean wind speed	-	6.9 m/s	-1.1	+0.5	-2.5	+0.9	±3.6	%
		highest daily mean wind speed per year	-	15 m/s	-3.0	-1.4	-3.0	+0.0	±3.9	%
		number of days between south and west	44 days	49 days	-1.4	+3.0	-1.7	+4.5	±6.4	%
Spring	Temperature	mean	8.3 °C	9.5 °C	+0.9	+1.1	+1.8	+2.1	±0.24	°C
	Precipitation	mean amount	148 mm	173 mm	+4.5	+2.3	+11.0	+9.0	±8.0	%
Summer	Temperature	mean	16.1 °C	17.0 °C	+1	+1.4	+1.7	+2.3	±0.25	°C
		year-to-year variation	-	± 1.4 °C	+3.,5	+7.5	+4.0	+9.5	--	%
		daily maximum	20.7 °C	21.9 °C	+0.9	+1.4	+1.5	+2.3	±0.35	°C
		daily minimum	11.2 °C	11.9 °C	+1.1	+1.3	+1.9	+2.2	±0.18	°C
		coolest summer day per year	10.3 °C	11.1 °C	+0.9	+1.1	+1.6	+2	±0.43	°C
		warmest summer day per year	23.2 °C	24.7 °C	+1.4	+1.9	+2.3	+3.3	±0.52	°C
		number of summer days (max temp ≥ 25°C)	13 days	21 days	+22.0	+35.0	+40.0	+70.0	±13	%
		number of tropical nights (min temp ≥ 20°C)	< 0.1 days	0.1 days	+0.5	+0.6	+1.4	2.2	-	%
	Precipitation	mean amount	224 mm	224 mm	+1.2	-8.0	1.4	-13.0	±9.2	%
		year-to-year variation	-	± 113 mm	+2.1 to +5	-2.5 to +1.0	+1.4 to +7	-4 to +2.2	-	%
		daily amount exceeded once in 10 years	44 mm	44 mm	+1.7 to +10	+2.0 to +13	+3 to +21	+2.5 to +22	±15	%
		maximum hourly intensity per year	14.9 mm/hour	15.1 mm/hour	+5.5 to +11	+7 to +14	+12 to +23	+13 to +25	±14	%
		number of wet days (≥ 0.1mm)	45 days	43 days	+0.5	-5.5	+0.7	-10.0	±6.4	%
		number of days ≥ 20 mm	1.6 days	1.7 days	+4.5 to +18	-4.5 to +10	+6 to +30	-8.5 to +14	-	%
	Solar radiation	solar radiation	149 kJ/cm2	153 kJ/cm	2.1	5.0	1.0	6.5	±2.4	%
	Humidity	relative humidity	78%	77%	-0.6	-2.0	0.1	-2.5	±0.86	%
	Evaporation	potential evaporation (Makkink)	253 mm	266 mm	4.0	7.0	4.0	11.0	±2.8	%
	Drought	mean highest precipitation deficit during growing season	140 mm	144 mm	4.5	20.0	0.7	30.0	±13	%

		highest precipitation deficit exceeded once in 10 years	-	230 mm	5.0	17.0	4.5	25.0	-	%
Autumn	Temperature	Mean	10.0 °C	10.6 °C	1.1	1.3	2.2	2.3	±0.27	°C
	Precipitation	mean amount	214 mm	245 mm	7.0	8.0	3.0	7.5	±9.0	%

a = reference period

b = averaged over 30 years