Weather Codes and Travel Behavior

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Analysis of the Impacts of Weather Codes on Travel Behavior of Road Users in the Netherlands

by

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1 Preface

This report is the summary of six months of graduation research. The research marks the final stage of the MSc. Transport, Infrastructure and Logistics at the faculty of Civil Engineering and Geosciences at the TU Delft. As the master itself, the research presented in this report is multidisciplinary, as it is supported by knowledge from both the faculty of Civil Engineering and Geosciences and the faculty of Technology, Policy and Management. Therefore, the research contains a mixture of analysis that touches upon the field of transport modeling as well as the field of travel behavior.

The theme of this research has been subject of societal discussions. Several news articles have been, and probably will be, dedicated to the theme of weather codes every time a weather code is issued. It is exactly this debate, in which the reliability and the effectiveness of weather codes are discussed, that triggered my interests for the matter. Furthermore, this theme was enabling me to do a research project with large amounts of data, as previous master projects had drawn my interests into the methods of doing so.

Societal debates on the matter of weather codes will certainly not end with this research. However, I hope that the insights provided in this report can contribute to the understanding on how travelers cope with weather codes, and more generally with weather related travel advices.

2 Acknowledgements

I would like to thank all people that helped me with the research that led to this report. Firstly, I would like to thank my graduation committee for guiding me in the process that led to this research. Caspar Chorus, chair of the committee, inspired me on the topic of travel behavior modeling. Adam Pel always made time to guide me into the right direction. Sander van Cranenburgh always questioned my methods in order to increase the quality of the research.

Furthermore, I would like to thank the Emerging Technologies unit of CGI for hosting me and sharing their extensive knowledge in the field of data analytics. A special thanks to Thim van der Weijden, who always took the time to take a critical look at my work.

Lastly, I would like to thank the NDW and the KNMI for providing the data that was used in this report.

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3 Introduction

This chapter will describe the outline of this research, without going into detail. First, the goal of the research will be described. After the goal of the research is defined, the relevance of this research for various stakeholders and science will be explained. Lastly, the research questions will be defined and the methods to answer these questions will be briefly explained.

3.1. Research Goal

In the case of adverse weather conditions, the KNMI can decide to activate a weather code. Weather codes are accompanied with advices, aimed at impacting travelers choice to make a trip during the duration of this weather code. For example, when a code red for wind gusts is activated, the advice 'Do not travel if not strictly necessary' will be communicated (KNMI & Ministry of I&E, 2015). However, no literature has been found where these impacts are assessed through analyzing revealed preference data (see Chapter 4 for more information). The first goal of this research is to **reveal the impacts of weather codes on travel behavior**. It is hypothesized that weather codes have a negative impact on travel demand. Furthermore, it is hypothesized that codes red have a higher impact than codes orange, as advices for codes red are more explicitly advising people not to travel. For the departure time choice, it is expected that travelers are planning their trip outside the period for which a weather code is active, which will lead to a change in demand patterns over the days for which a weather code was present.

Furthermore, this research aims to **assess the impacts of a travelers' perception of a weather code on travel behavior**. In this research, it is hypothesized that perceived unreliability of a weather code will reduce the impact of the next weather code. By analyzing the sentiment of travelers during it is aimed to explain why people do tend to travel, while the KNMI advises not to do so.

3.2. Relevance

If the first reserach goal is reached, the impacts of weather codes on travel behavior will be known. Outcomes of such an analysis could provide insights for the KNMI on the impacts of their weather codes. As the KNMI hopes that their advices will be taken seriously (see Chapter 4), which would result in visible impacts in travel behavior, this research is relevant for the KNMI. Insights into the perception of weather codes will also be relevant for the KNMI. These insights might be useful when reconsidering the phrasing of advices which are communicated together with the activation of weather codes.

If impacts of weather codes are observed, this means that there are changes observed in traffic volumes on different road segments in the Netherlands. A vast amount of literature can be tied to the domain of traffic forecasting, which is stated to be interesting for multiple stakeholders. Short-term traffic forecasting [1] has its applications in Intelligent Transportation Systems, which, in the Netherlands, are of interest for the Road Authority, Rijkswaterstaat (RWS). When impacts of weather codes are found to be having a significant impact on traffic volumes, weather code information will be a valuable input variable for short-term traffic forecasting models. RWS indicates that the organization indeed is interested in outcomes of the research, as they would like to know how travelers react in adverse weather conditions (H. Taale, personal communication, 23-07-2018).

The methods used to assess the impacts of weather codes on travel behavior, will yield insights into the ability of a certain method to cope with the included variables. As a time-series will be modeled, this research will more specifically contribute to insights into time-series modeling applications. Recommendations on the use of time-series models in traffic volume analysis will be useful for future research in the field of similar themes.

To assess the impacts of weather codes, the data should be corrected for the weather conditions. Although this research does not aim to assess the impacts of weather on travel behavior, as the aim is to determine

[1] For an overview of existing literature related to short-term traffic forecasting, see Vlahogianni et al. (2014)

the effects of weather codes, this analysis will be a byproduct of the total research. Results of this analysis might provide insight on the impacts of different weather characteristics on travel behavior from a revealed preference point of view. This knowledge can verify hypotheses in this field that follow from stated preference work and will add knowledge to the revealed preference domain.

Besides its relevance for earlier mentioned parties and science, this research is relevant in societal discussions. The use and effectivity of weather codes are regularly debated. In news and opinion articles the reliability of weather codes are questioned (Kersten, 2018), people are said to be 'warning-tired' (Pel, 2016), the messages of the KNMI are ridiculed as being exorbitant (Bouma, 2017) and the suitability of one advice for every traveler is questioned (Chorus, 2010). The latter states that the government (KNMI) is deciding for citizens what is best for them, by advising on how to travel with a weather code, while the responsibility for traveling or not lies with the traveler himself. As the government takes away this responsibility, complaints of travelers can be expected if the weather situation turns out to have other effects than expected. The research of this report provides quantitative analyses on how travelers responded during weather codes, which contributes to the factual basis of societal discussions that surround the theme of weather codes and weather related travel advices.

3.3. Research Questions

The goal of this research will be reached by systematically answering a set of research questions. The main question, which will be answered in the conclusion of this report, is:

What are the Impacts of Weather Codes and Travelers' Perception of Weather Codes on Travel Behavior?

Answers on this question can be found by following a set of steps that will provide more insights into the theme of weather codes and travel behavior.

In this research, detection loop data will be used as the source for measuring travel behavior in a revealed preference approach. Travel behavior will be influenced both by the weather codes and by the weather itself (see Chapter 4). Two indicators for travel behavior can be researched with revealed preference data. The first indicator is the total travel demand, which says something about the travel choice to make a trip, or not. This frequency choice is researched with the following research question:

1. What are the effects of weather and weather codes on frequency choice?

The second indicator for travel behavior is the spread of demand throughout the day. This indicator says something about the departure time choice that travelers make. Throughout the day, a demand pattern can be observed, in which for example the morning and afternoon peak can be observed. This departure time choice is researched with the following research question:

2. What are the effects of weather codes on departure time choice?

The last part of the research tries to explain a part of the variation in the impacts of weather codes on travel behavior. From the theoretical framework as presented in Chapter 4, it is expected that this variation is produced by the compliance of travelers towards advices. Firstly, the reliability of previous weather codes is assessed, by comparing the forecast in the weather code with the corresponding weather measurements. Secondly, the sentiment of travelers during weather codes is measured with the use of web scraping techniques. These two factors are assumed to be a proxy for the *'unreliability of information'*, which is further explained in Section 4.2.5. Both the sentiment of travelers, as well as the impact of (the reliability of) previous weather codes on the next weather code are part of, what we call in this research, the perception of information. Insights in how this perception works on compliance towards advices are answering the following research question:

3. How does traveler perception of weather codes influence the compliance towards weather code advices?

3.4. Report Outline

The report will start with background information on the themes related to the research as presented in this Chapter, in Chapter 4. This Chapter will introduce the reader to weather codes and their meaning, goal, related decision process and historical occurrences. After this, related existing literature will be summarized. Literature on the impacts of weather on travel behavior, the impacts of weather forecasts, the impacts of travel advices and the impacts of weather codes is explained and used to sketch the knowns and the unknowns related to the theme of this research. After this, a theoretical framework will be introduced which will be used to derive hypotheses and to structure the research. Lastly, the research approach that follows from the theoretical framework will be introduced. In this Section, both the data as well as the methods that will be worked with in the rest of the report are explained.

Chapter 5 will explain the steps that are undertaken to go from raw data towards interpretable data for the analyses in the next Chapters. In this Chapter, the measurement locations for both traffic as well as weather observations are chosen, as well as the aggregation level of the data. Furthermore, traffic data is inspected to identify any anomalies, after which the traffic data will be deseasonalized. The work in this Chapter is supported by Appendix B, Appendix C and Appendix D.

Chapter 6 will find an answer to the first research question. In this chapter, linear regression models as well as regression models with autoregressive errors are used to assess the significance and coefficients of different weather and weather code variables that affect traffic volumes. The work in this Chapter is supported by Appendix E, Appendix F and Appendix G.

Chapter 7 will answer the second research question, related to the effects of weather codes on trip scheduling. Six case studies are undertaken for all chosen road segments, for which demand patterns are assessed. The work in this Chapter is supported by Appendix H.

Chapter 8 will answer the third and last research question, by assessing the relation between the perception of weather codes, and traveler compliance towards advices. Firstly, the reliability of the previous weather code is introduced as a variable that might be influencing the impact on travel behavior of the next weather code. After this, Twitter data will be analyzed to see whether sentiment can explain compliance with weather code related advices. The work in this Chapter is supported by Appendix I.

In Chapter 9, the answers on the three subquestions are combined to give an answer on the main research question. Finally, Chapter 10 will critically discuss the process that led to the results and the results themselves. At the end of this Chapter, recommendations are presented for further research on related themes.

4 Theoretical Background

4.1. Introduction to Weather Codes

Since 1998 the KNMI gives out warnings in case of expected adverse weather conditions (Koek & Kok, 2016). Several iterations led to the currently used systematics, which have been in place since 2015. Weather codes in the Netherlands are coherent with international standards, but weather types and thresholds for codes can differ per country. This Section will introduce the different weather codes, their goal and the decision process leading to a weather code.

4.1.1. Different Codes and their Meaning

Weather codes come in four levels, or colors. Per province (plus the Wadden Islands and the Ijsselmeer area) a code is issued, indicating the weather status. Each code has its own meaning. Code **Green** is active when no anomalies are occurring. Code **Yellow** indicates a chance on dangerous weather conditions. Citizens are asked to be alert, especially when in traffic. Code **Orange** is issued when chances are high that dangerous or extreme weather conditions will occur. In this case, citizens are asked to be prepared. Code **Red** is also called a **Weather Alarm**, indicating that citizens should take action. Weather conditions under code red can cause damage and injury such that it can be disruptive for the society.

Codes can be issued for different types of weather. In the Netherlands these weather types are wind, snow/ice, thunderstorms, fog, extreme high temperature, extreme low temperature, coastal events, rain and flood. For some other countries, this list is completed with the types forest fire, avalanches and rain-flood, as depicted in Figure 4.1. Avalanches are not prevailing in the Netherlands, due to the absence of mountains. Events of rain-flood are captured with the type rain. Codes due to forest fires are issued by the fire department in the Netherlands.

Figure 4.1: Weather types for which codes can be issued (Meteoalarm, 2018)

4.1.2. Goal of Weather Codes

Official documents of the KNMI state that the KNMI warns to contribute to the safety and accessibility of the Netherlands. Warned people can prepare for the weather, which will limit the chances on damage and injury (KNMI, 2015). How people should prepare depends on the weather type. Per weather type, different advices will be issued. Appendix 3 of KNMI & Ministry of I&E (2015) gives general advices per weather type and per warning level. For most of the advices it stays unclear what the exact action should be, or to what extent a certain advice should be followed. The more concrete advices, proposing a direct action for citizens, are listed in Table 4.1. Although these advices are quite concrete, there are no documents stating that the KNMI has the goal that these advices are followed up. In contacts with the KNMI, it is stated that the KNMI has the legal task to warn publicly for dangerous weather. Generic statements on how to act are put together by a taskforce of (communication-) experts. However, in this contact, the KNMI also emphasizes that the choice to act according to the statements is up to the user, although the KNMI hopes that the user takes the statements seriously (R. Sluijter, personal communication, 12-06-2018). The road authority, RWS, does state that they hope that warnings for adverse weather influences travel behavior, and that less people choose to make a trip during such warnings (H. Taale, personal communication, 23-07-2018).

4.1.3. Decision Process

Although KNMI is the organization publishing the weather codes, the decision leading to this code is not made solely by the KNMI. Figure 4.2 depicts a flowchart with the steps that are undertaken to come to a deci-

Table 4.1: Advices per weather type (KNMI & Ministry of I&E, 2015)

Weather type	Code	Action
Wind gusts	Red	Don't go onto the water Don't travel if not strictly necessary
Snow and slipperiness	Red	Don't travel if not strictly necessary
Thunderstorms	Orange	Avoid open water Do not take shelter under trees
Thunderstorms	Red	Avoid open water Do not take shelter under trees Stay inside if possible

sion on which code should be activated. If there is a chance higher than 60% on extreme weather events, the weather events will be evaluated to see whether the conditions will surpass the thresholds for code orange. If this is not the case, code yellow will be activated. If this is the case, a team of experts (Departementale Coördinatiecentra, National Crisis Centre, Verkeerscentrum Nederland, police and fire department and Prorail) will get together to assess the risks of the weather. This weather impact team will give an advice, which will be used by the KNMI to issue either code orange or code red. Code red is only issued when the impacts of the weather can be disruptive for society. This can also mean that there is a low chance on an event with very high risks. If there is a relatively high density of citizens in an area that has a chance of being hit by extreme weather, chances are relatively high that a code red will be issued, in comparison to low density areas.

The threshold values, listed in Table 4.2 are the guidelines for the different decisions. These guidelines have been developed in collaborations with parties that understand the impacts of certain weather conditions (KNMI, 2018a)

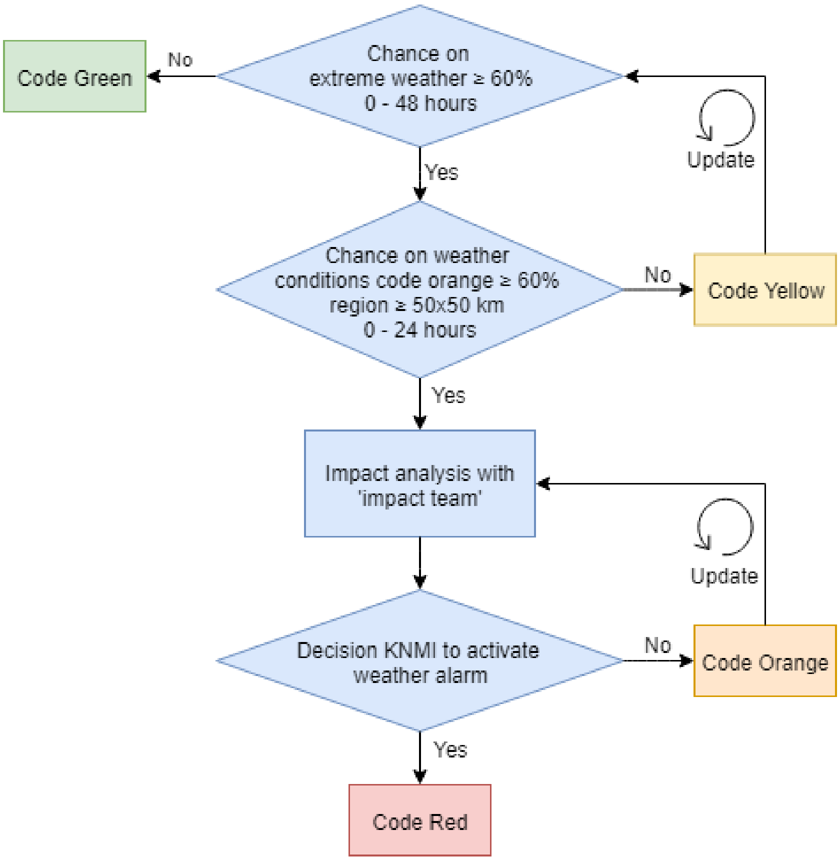


Figure 4.2: Decision tree for the activation of weather codes (Koek & Kok, 2016; KNMI, 2018a)

Table 4.2: Weather characteristic threshold values for weather codes (KNMI & Ministry of I&E, 2015)

Weather type	Code yellow	Code orange	Code red
Heavy rain	Traffic disruption due to aqua-planing, or >50mm in 24h	>75mm in 24h	>100mm in 24h
Snow and slipperiness	Local slipperiness due to frozen road surfaces, hail, snow rests or black ice or: up till 5cm of snow in 6h and/or: up till 3cm of snow in 1h	Slipperiness on an extensive scale due to black ice or freezing or: 5-15cm of snow in 6h and/or: 3-5cm of snow in 1h and/or: snowfall and/or ground blizzard (>40km/h), leading to snow dunes	Slipperiness on a large scale due to black ice or freezing or: >15cm of snow in 6h or: >5cm of snow in 1h and/or: snowfall and/or ground blizzard (>50km/h), leading to snow dunes
Thunder-storms	Local thunderstorms with locally one or more of the following phenomena: - wind gusts >60km/h - heavy rain >30mm/h - hail up to 2cm diameter	Organized thunderstorms with locally one or more of the following phenomena: - heavy wind gusts >75km/h - heavy rain >50mm/h - large hail 2-4cm diameter	Very well organized thunder-storms with locally one or more of the following phenomena: - heavy wind gusts >100km/h - heavy rain >75mm/h - large hail >4cm diameter
Wind gusts	>75km/h Coast, winter: 90km/h	>100km/h Coast, winter: 120km/h	>110km/h Coast, winter: 130km/h
Temperature (high) Temperature (low)	4 days with day temperature >27°C Or temperature >35°C Wind chill <-15°C	3 days in a row with a day temperature >30°C and a night temperature >18°C Wind chill <-20°C	3 days in a row with a day temperature >32°C and a night temperature >20°C Wind chill <-25°C
Sight	<200m	<10m	no sight (due to firework)
Spouts	At observation		

4.1.4. Overview of Weather Codes

Appendix A shows a list of weather codes issued between the beginning of 2015 to 2018. During 28 days there was a code orange active, of which 7 days involved a code red for some provinces as well. Amongst these 28 codes, 12 were issued due to slipperiness, 9 due to wind gusts and 7 due to thunderstorms. It should be noted that only days were logged which had a code orange or red. Days on which only a code yellow was issued are not logged in the KNMI archive, as found on KNMI (2018b). Codes red and orange were not issued for sight, high or low temperatures, heavy rain or spouts in the period between 2015 and 2018.

4.2. Introduction to Existing Literature

Although some of the advices of Table 4.1 clearly state that it is better to avoid traveling, no literature can be found on the connection between weather codes and travel behavior. Related connections are assessed, including the impacts of weather conditions, weather forecast and travel advices on travel behavior or traffic volumes. This Section will describe the available literature and their findings.

4.2.1. Impacts of Weather

The effects of weather conditions on travel behavior have been researched by Cools et al. (2010). Here it was surveyed whether travelers are likely to change their behavior under certain weather conditions. Relations between weather conditions and travel behavior were found to be significant, indicating that weather indeed alters travel behavior. Madre et al. (2007), a study less specifically aimed at the link between weather and travel behavior, finds that bad weather is seldom a reason for canceling trips. Only snow and rain have an impact on trip cancellation. This is the case for 1% of the stated preference respondents. The impact of snow and cold in Alberta, Canada, were analyzed from a revealed preference perspective by Datla & Sharma (2008). Here, the impacts of certain weather conditions was found to be impacting traffic volumes to a greater extend than expected from earlier mentioned stated preference research, with snow resulting in a -7% to -17% change in traffic volume per cm of snow. Cools & Moons (2010) assessed the impacts of weather on traffic intensity in Belgium. The major conclusions of this assessment were that weather effects are heterogeneous between different traffic count locations. Furthermore, precipitation, cloudiness and wind speed reduces, while high temperatures and hail increases traffic intensity. Other revealed preference research into adaptation of travel behavior in case of adverse weather conditions is performed by Sabir et al. (2008). This research focuses on the choice between traveling by bicycle, public transport or car. Results are yielding higher mode shares for road traffic in the case of adverse weather conditions. Empirically measured effects of weather conditions on other travel choices (i.e. trip frequency choice, departure time choice, destination choice and route choice) were stated to be key for further research by Cools et al. (2010).

4.2.2. Impacts of Weather Forecast

Cools & Creemers (2013) researched the influence of weather predictions. This research concluded that changes in travel behavior are significantly related to the weather type as forecast. A second conclusion is that the kind of method for retrieving weather forecast information does not influence the likelihood of changes in travel behavior. This research distinguishes utilitarian and recreational trips. The results show that trips for recreational purposes are more often canceled than utilitarian trips. Travelers are also more likely to reschedule their trip outside morning peak hours when traveling for recreational purposes. For utilitarian trips, weather alarms were found to be significantly influencing the choice to travel by motorway in peak hours (negatively), to avoid the motorway (positively in case of rain, negatively in case of snow) and to travel by bike (negatively). These effects are the same for recreational trips, except for avoiding the motorway, which is not significantly influenced by a weather alarm for rain.

4.2.3. Impacts of Travel Advices

In several papers, the impacts of travel advices on travel behavior are assessed. Some papers are aiming to assess policies intended to change travel habits (Gärling & Fujii, 2009; Fujii & Taniguchi, 2005), where others are aiming to assess adaptation effects towards advices on shorter terms. Within the latter researches, several papers assess impacts of travel advices on which Chorus et al. (2006) gives an overview. An observation in this paper is that information about delays caused by bad weather conditions are impacting travel behavior, or more specific route choice, to a lesser extend than delays due to incident congestion. Nonetheless, providing travel advice is considered to be a powerful tool for travel demand management. It must be noted that the advices and information meant here are related to network performance (i.e. disruptions and congestion), while information and advices from weather codes concern information purely about the weather and it's consequences.

4.2.4. Impacts of Weather Codes

Van Stralen et al. (2015) researches the influences of weather and weather alarms (i.e. codes red) by means of a stated choice experiment. Respondents are asked to make a travel choice under a described scenario. These scenarios include information on the current temperature, the current weather described in words and with an image, the weather forecast and the weather alarm status. The respondent can choose to travel by car on the motorway in the morning peek, to reschedule his trip outside the morning peak, to change route by avoiding the motorway, to change mode towards bicycle or public transport, or to cancel his trip. The results show that current weather conditions impact choices to a larger extend than a weather forecast or alarm does. However, the weather alarm does influence travelers to opt more often for the option to cancel a trip. The weather alarm led to a reduction in traffic demand during the morning peak of 20.3% in case of an alarm due to heavy rain, 27.9% in case of an heavy snow alarm and 30.7% in case of an alarm due to icy roads.

4.2.5. Synthesis of Literature

When the advice of the KNMI is seen as one of the methods of acquiring weather information as described in Cools & Creemers (2013), one could doubt about the influence of this advice. In this case a weather code acts as a weather forecast. If a weather code is assumed to be a travel advice, the poor performance (caused by adverse weather) of the currently chosen travel alternative can lead to a relatively high change to other alternatives (Chorus et al., 2006). Additionally, Chorus et al. (2009) derives that higher compliance towards an advice is to be expected if the reliability of a travel advice increases. The reliability of a weather code can therefore assumed to be influencing its own impact.

The subject of the research in this report differs from related research on a couple of points. Firstly, weather codes are issued in the case of extreme weather. Other research focuses more on the full range of weather conditions. Focusing on extreme weather could provide specific insights, as extreme weather characteristics might not be linearly related with travel demand characteristics, where non-extreme weather conditions might do. The difference in impacts between light rain and heavy rain in van Stralen et al. (2015) are supporting this claim. Secondly, if we see weather codes as a travel advice, this travel advice might be different in its impacts in comparison to non-weather related travel advices. Thirdly, travel behavior in the case of weather codes might be influenced by weather, as well as the code itself. These interrelated variables might present unique characteristics in comparison to cases where the impacts of only weather or only travel advises are assessed. The stated preference experiment in van Stralen et al. (2015) support this, by showing that weather alarms are in some cases significantly influencing choice behavior among respondents.

Table 4.3 gives an overview of scientific work per theme and method. Summarizing, scientific gaps related to the effects of travel advises in adverse weather conditions and empirical research on changes in travel behavior during adverse weather conditions are generating uncertainty about the impacts of the advices given by the KNMI.

Table 4.3: Overview of scientific material per theme and method

Method \ Theme	Effects weather on driving behavior	Effects weather on travel behavior	Effects weather forecast on travel behavior	Effects travel advice on travel behavior	Effects weather related travel advice on travel behavior
Stated Preference	Hassan & Abdel-Aty (2011)	Cools et al. (2010); Madre et al. (2007)	Cools & Creemers (2013)	Wardman et al. (1997); Khattak et al. (1996)	(van Stralen et al., 2015)
Revealed Preference	Hoogendoorn (2012)	Sabir et al. (2008); Cools & Moons (2010)		Khattak et al. (1996); Bogers et al. (2005)	**Research as proposed in this document**

4.3. Introduction to Theoretical Framework

When effects of weather codes on travel behavior are assessed, all other factors that effect travel behavior should be corrected for. To do this, it is necessary to get a full understanding of all relevant factors. Besides correcting for other factors, the way that people cope with an advice is also influencing the impact of weather codes. A third part necessary to assess the impact of weather codes on travel behavior is a variable with which travel behavior is measured. This Section introduces a theoretical framework, based on available literature related to travel behavior. The theoretical framework will provide insight in which factors should be corrected for and how travelers will cope with advices, when interpreting revealed preference data.

Since the research in this report tries to unravel impacts of weather codes on travel behavior with revealed preference data, the theoretical framework must be able to cope with this. This means that the measured variables, needed to estimate latent variables, must be measured on the basis of revealed preference data.

4.3.1. Factors Influencing Travel Behavior

In Section 4.2 impacts of weather, weather forecast, travel advices and weather codes were explained. Weather significantly influences travel behavior in both stated- as revealed preference researches. Historical data of weather circumstances are available, which enables incorporation of this data in a revealed preference approach. Examples of weather characteristics that can be taken into account are rain, wind, thunderstorms, snow, sight, temperature and ice formation.

Weather forecast was also found to be influencing travel behavior, when this was tested with a stated preference approach. However, two problems arrive when weather forecast is taken into account in a revealed preference research. Firstly, no historical data of weather forecast is found. Secondly, it is hard to determine which forecast is influencing travel behavior. Some travelers will consult the weather forecast just before making a trip, while others might do this several hours earlier. Therefore, weather forecast cannot be taken into account as a measured variable. In this research the weather and weather forecast will be taken into account as one variable. This can be done as it is assumed that weather and its forecast are strongly correlated. An error term must be introduced to take into account any discrepancies between the weather and the weather forecast.

The third influence is the presence of a weather code and its complementary travel advice. Weather codes (orange and red) are logged by the KNMI, which enables incorporation of this factor in a revealed preference research. Codes yellow are not logged, except for instances where there was a code yellow in a province, while a code orange or red occurred in another province.

4.3.2. Traveler Compliance to Travel Advices

In Section 4.2.3 two types of advices were presented: advices to change travel habits and advices that aim to change travel behavior on shorter terms. A weather code and its cohesive advices are of the second type, as these are advises are aimed at travel behavior during the period of extreme weather events only.

Literature covering the influences of weather related travel advises is absent. To set up a theoretical framework for the working of these weather related travel advises, knowledge on travel advises related to network performance are used. Although parallels can be drawn between the two advises, it cannot be stated that all aspects of the compliance to weather related travel advises will be covered. In this report, the hypothesis that compliance towards weather related travel advises is similar to compliance towards network performance related travel advises, will be tested.

Chorus et al. (2009) presents a formal model to describe traveler compliance towards travel advice. In this work, a measure of unreliability is used as one of the factors that explains the propensity to comply with an advice. Furthermore, preferences for travel alternatives, relative importance for travel times and travel time uncertainty are included in this model, as shown in Figure 4.3. Advises in Chorus et al. (2009) are related to route choice, which explains the relevance of travel time attributes.

However, when looking at advises from weather codes, the main choice involved is the choice to make a trip. The factors mentioned in Chorus et al. (2009) cannot all be used directly for this choice. The unreliability of information might be influencing compliance towards weather codes as well. Logically, when a weather

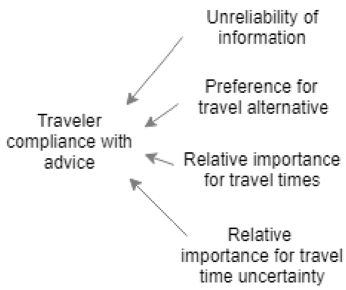


Figure 4.3: Factors influencing compliance with advice (Chorus et al., 2009)

code is perceived as being unreliable, travelers are less inclined to follow its accessory advices. The travel alternative provided by a weather code is to not travel during the activation of the weather code. This results in the choice to either cancel a trip, or to change the departure time towards a time frame outside the activation time of the weather code. How open travelers are towards these alternatives will depend on their flexibility to avoid traveling, or reschedule a trip. The relative importance for travel times might be affecting compliance towards weather related advices as well. If travelers use a weather code to conclude that travel times will rise, in accordance to the advice for wind gusts and slipperiness at code orange (KNMI & Ministry of I&E, 2015, p.32-33), travelers might opt for the choice to cancel or reschedule their trip. The same accounts for travel time uncertainty, as risks for road users prevail (KNMI & Ministry of I&E, 2015, p.33), inducing the risks on disruptions.

The focus of this research lies in travelers' perception of weather codes. Sentiment of travelers and the effect of the reliability of the previous code on the subsequent measurement are assessed. This perception can be seen as a proxy for the unreliability of information. When travelers perceive a weather code in such a way that they think that the weather will indeed be causing disruptions that may lead to injury and damage, they will be more likely to comply with the advice. To focus on this perception, only the 'unreliability of information' factor will be taken into account. The other factors, seen in Figure 4.3 will be taken into account as unobserved variability, or as error term.

Traveler compliance is included in the framework as a measured variable. One could say that, in the case of a code red, no trips will be made if all travelers would comply with the given advice. Here, we can measure the difference between the expected counts during a day without codes, and the measured counts. If 25% of the expected counts are measured, we can say that the compliance rate is 75%. Note that compliance cannot be measured in cases of weather codes where the advice is not to avoid to travel. In these cases the compliance rate will be a latent variable.

All factors are combined in the diagram depicted in Figure 4.4. This theoretical framework will be used when explaining the impacts that will be measured in Chapter 6, Chapter 7 and Chapter 8. Hypotheses that will be tested in this research can be derived from this framework. The 'E' going to 'traveler compliance with advice' represents the variables of Figure 4.3 other than 'unreliability of information', which are included as an error term.

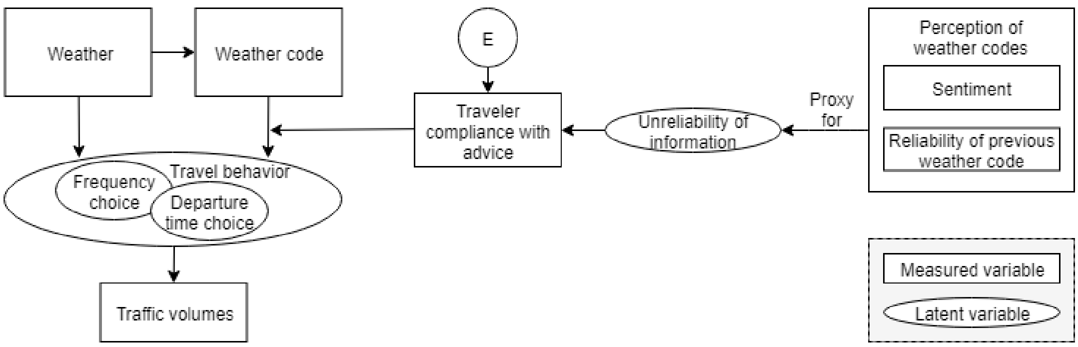


Figure 4.4: Theoretical Framework

4.4. Introduction to the Research Approach

Now the theoretical framework has been explained, we can search for data and methods which allow for working towards the goal of this research. This Section will sketch the data and methods that will be used. More specific information on the methods can be found in the Chapters in which the subquestions of this research will be answered.

4.4.1. Data

In order to choose methods, it is first necessary to know which data can be used for the analyses that will give answers to the research questions. The following Subsections will give insight into the format of different data sources that will be used in this research.

Travel Behavior Data

When assessing travel behavior changes in a revealed preference research, a couple of data sources can be consulted. Some researches use GPS data, which can give information on for example route choice (Vacca et al., 2017), while others use traffic counts in order to recognize demand patterns (Cools et al., 2009). Whereas weather codes occur with exception, there is a need for a dataset which gives as much samples as possible. Traffic counts are providing large sets of data, as detection loop data is widely available on Dutch primary roads. This makes this data source applicable for recognizing demand patterns for the purpose of this research as well.

As the advices during weather codes are related to the choice to travel during a weather code, we are most interested in travel behavior related to this choice. When modeling travelers choices, generally five choices are taken into account: frequency choice, destination choice, mode choice, departure time choice and route choice (de Dios Ortúzar & Willumsen, 2011). The choices related to the advices of weather codes are frequency and departure time choice. Travelers can either choose to cancel a trip, reschedule their trip to a time frame outside the activation period of a weather code, or to not let a weather code influence their trip. Other choices can be influenced by the weather itself, but are not expected to change purely due to the weather codes. For example, travelers who are able to choose between traveling by bicycle or by car might opt for a car (i.e. mode choice) during rainy conditions (Sabir et al., 2008), or might travel via other roads (i.e. route choice), or to an alternative destination (i.e. destination choice) during snowfall (Cools et al., 2010).

Changes in frequency choice and departure time choice can be observed within traffic count data, as total counts are decreasing in the case of trip cancellations, and daily count patterns will change in the case of trip rescheduling. It must be stated that choices are analyzed on a macroscopic level. Individual changes will not be seen in this analysis, but changes in average behavior will be visible.

Weather Data

As seen in this Chapter, multiple researches have been conducted to look at the impacts of weather on travel behavior (Cools & Moons, 2010; Datla & Sharma, 2008; Keay & Simmonds, 2005; Sabir et al., 2008). From these researches a list of important weather characteristics can be identified, for which the data should be corrected in order to assess the impacts of weather codes. The weather characteristics that were found to be relevant in literature are listed in Table 4.4. Except for hail and cloudiness, all these weather characteristics are available in the KNMI archive (KNMI).

Weather Code Data

The KNMI provides an overview of weather codes per year, with factsheets. These factsheets contain more detailed information on the weather conditions and the activation period of the weather code. The activation period is of importance for this research, since it is the goal to assess whether travel behavior altered during these activation periods.

A table can be derived from manually going through these factsheets. The result is attached in Appendix A. It should be noted that the activation time is not always accurately archived. Sometimes the factsheet denotes the time of communication about a weather code. In other factsheets the KNMI specifically denotes the time

Table 4.4: Weather characteristics in literature and their measurement unit as logged by the KNMI (KNMI)

Weather Characteristic	Measurement Unit
Hail	N.A.
Snow	Dummy to indicate whether snow occurred
Rain	Hour sum (mm/h)
Cloudiness	N.A.
Temperature	0.1 °C
Wind speed	Hourly average (m/s) and highest wind gust (m/s)
Sunshine	Duration of sunshine in 0.1 hours
Fog/sight conditions	Horizontal sight, binned in km's
Slipperiness	Dummy to indicate whether slipperiness occurred

of activation. This will limit the accuracy with which the impacts of weather codes can be analyzed.

Sentiment Data

Multiple online platforms provide room for people to discuss on weather related topics. The archive of Twitter provides a lot of data which might include insights into sentiment, prevailing during a weather code. This data is accompanied by a location and a time stamp, which makes it possible to link the sentiment to a specific weather code. Forums, more specifically aimed at discussing about weather topics, are available as well. The Association for Meteorology and Climatology hosts such a forum. However, no specific forums are found on which weather codes were discussed. Therefore, the data source for sentiment data will be Twitter.

Twitter allows to search a certain query, for a certain time period. The chosen time period corresponds with the days for which a weather code was issued. For the query, it is important that all tweets in the dataset are about the weather code. Since 'code red' or 'code orange' is not only used for indicating the weather situation, but also for other situations that people are trying to get attention for, 'KNMI' is added. With this, chances are high that the resulting tweets are actually saying something about the weather code issued by the KNMI. When this query and time period are specified, a list of tweets is shown. When we then sort the tweets to 'most recent', a list of all tweets in the specified time period, that confirm to the set query, can be called. However, the Twitter website loads only the first 40 tweets. When scrolling down, the Twitter 'feed' extends, and shows more tweets. When accessing tweets through a web scrape script, using the URL to access Twitter including a query, no more then the first 40 tweets can be loaded. The same accounts for using the Twitter API. No method has been found to automatically acquire all tweets for a certain query. To overcome this problem, tweets are acquired manually. By scrolling down the Twitter feed until there are no more tweets to be shown, a full list of tweets can be acquired. Subsequently, the resulting web page can be saved as a *.txt* file, which can be made ready to interpret.

When analyzing sentiment, we can look at the occurrence of certain words, which are often found for a certain sentiment. Combinations of words, part of speech, punctuation or lengths or locations of words are also found to be features that can say something about the sentiment of a text (Bollegala, 2017). When we want to take into account combinations of words, there is a need for analyzing tweets individually. As the Twitter data is acquired in a *.txt* file, tweets can not be interpreted individually. Therefore, the structure of the text file is analyzed in order to be able to split the data into tweets.

Although we now have separate tweets which can be analyzed, a lot of text is present that does not contribute to the textual content of the tweet. Examples of this are URL's, or the word *'retweet'*, indicating that the tweet is a forwarded tweet, or a reaction on a forwarded tweet. If these parts of the text are removed from the tweets, a relatively clean and interpretable piece of text is left.

4.4.2. Methods

Now the research questions and the data which will be used are known, methods can be chosen that best lead to the conclusions that this research is aiming to draw. The following Subsections will explain the used methods per research question.

Method for Assessing Impacts on Traffic Volumes

When looking at traffic counts, it can be seen that the time of day and the day of the week are the largest influences of the amount of counts. Logically, relatively many people travel during peak hours on weekdays. Furthermore, holidays are resulting in different travel demand patterns than non-holidays Cools et al. (2009). In order to assess the effects of weather characteristics, these cyclic patterns should firstly be corrected for. This step will be undertaken before analyzing weather and weather code impact, in Chapter 5.

The deseasonalized counts can be analyzed with regression analyses. Linear regression is used, which results in significant coefficients for a large share of the weather and weather code variables. However, the Durbin-Watson statistic yields an indication for autocorrelation amongst observations, which tells us that there is a significant chance on overestimation of the significance of the regression outcomes. Therefore, regression with autoregressive errors is applied, which yields non-autocorrelated results and interpretable coefficients. Since multicollinearity between weather codes and weather characteristics might be problematic for the regression model, a sequential modeling approach will be conducted as well. Here, first the weather characteristics serve as an input for the regression model with autoregressive errors. Subsequently, weather code variables are regressed on the residuals of the autoregressive model. This will yield the minimum impact of weather codes on travel demand.

Regression techniques are well suited for this research, since these models allows to assess the impact (coefficients) and significance of different weather and weather code characteristics. The model allows to quickly remove any insignificant parameters and allows for all the measurement units (categorical, ordinal and continuous data), as listed in Table 4.4. Therefore this method is suitable for testing hypotheses.

Method for Assessing Impacts on Departure Time Choice

When assessing the departure time choice, the demand pattern throughout a day is of interest. When a weather code is issued during the day, people might choose to make their trip outside this period. If travelers indeed reschedule their trip, this will be visible in the demand pattern during a day. Above average counts will be visible for hours for which no weather code was active, while counts during the weather code are below average.

A set of case studies will be selected, for which the observed counts are plotted and compared to the expected counts based on the average counts throughout all weeks (i.e. the seasonal trend). The begin and end of the weather code period will be plotted as well. Any deviations from the expected counts will be analyzed.

Method for Analyzing the Impacts of the Perception of Weather Codes

As seen in the theoretical framework in Figure 4.4, two variables are stated to contribute to the perception of weather codes, being the reliability of information and sentiment.

Reliability

By comparing the thresholds of a certain weather code with the actual measured weather conditions, a reliability score can be assigned to each weather code. Subsequently, it can be assessed whether a low reliability of a weather code negatively influences the impact of the next weather code. If the reliability of the previous weather code correlates with the impact of the weather code on traffic counts, chances are high that the reliability of the previous weather code indeed changes the compliance rate of travelers towards the travel advice of a weather code.

Sentiment

Sentiment can be seen as a proxy for the unreliability of information (see Section 4.3). By performing web scrapes on Twitter, and relating tweets to a certain sentiment, a general picture can be sketched on the prevailing sentiment during a certain time frame.

Several methods will be used to analyze this sentiment. Firstly, counts of words that are often paired with negative sentiment are counted. The occurrence of these ’negative words’ can indicate the amount of tweets with a negative sentiment during a day with a weather code. Secondly, a sample set of tweets will be manually assessed on their sentiment. Subsequently, the prevailing words in the tweets of both neutral and negative sentiment can be compared. These words can then be used as input to determine the sentiment of tweets outside the sample set. Thirdly, a manual inspection of all the tweets can be done if the first two methods do not provide any outcomes. In this method all tweets will be reviewed and labeled with a sentiment by the author of this report.

For the analysis, three classes are distinguished. A tweet is either positive, negative, or neutral towards the weather code as issued by the KNMI. A positive tweet might for example state that it was a good choice that the KNMI issued a weather code. A negative tweet might for example state that the weather code was not necessary. A neutral tweet does not hold an opinion towards the weather code. An example of this is the statement that the KNMI issued or a code, or a description of the weather circumstances for the day.

Since this sentiment analysis of Twitter data on this theme is the first of its kind, it is not guaranteed that it results in usable findings. This is also the reason why three methods are tested. When a method does provide results, the analysis can give insight into the perception of weather codes, which might explain observed variabilities.

5 Data Preparation

To be able to process data in such a way that conclusions can be drawn with respect to the research questions, data must be acquired and prepared. This Chapter explains which data is acquired and how, followed by how the data is prepared. First the measurement locations are determined, after which the aggregation level of the traffic data is determined. Subsequently, the weather and weather code data is aggregated on the same level as the traffic data. Furthermore, any anomalies in the counts are manually checked. Lastly, the data is corrected for seasonality, which will be an important step in order to be able to find the effects of weather and weather codes on traffic volumes and traffic demand patterns.

5.1. Measurement Locations

For this research, a set of locations are selected on which analyses are performed. Before selecting these locations, the requirements for these locations must be defined:

- The measurement locations must have measurement data in the period between 2015 and now. This period is aligned with the period for which detailed weather code data is available.
- The measurement locations must be in different provinces. This will make sure that the variety of weather codes is as big as possible, since weather codes are issued per province.
- The traffic flow on the measurement locations have to be as least as possible influenced by factors other than weather. Roads were congestion and disruptions occur regularly are to a lesser extent suitable for analyzing weather effects on traffic volumes.
- The measurement location of the traffic flow and the weather characteristics must be in the same region, such that it can be assumed that the weather at a measurement location was similar to the weather at the measurement location for measuring traffic volumes.

As a starting point, the NDW was consulted on road segments that are to a low degree subject to congestion. The points that were stated to be relatively calm were the A30, the A67 near Eersel, the A37 near intersection Hoogeveen, the A7 near Winschoten, the A31 near Franeker, the A58 in Zeeland, the A6 near Emmeloord and the A79. Speed diagrams for these road segments can be found in Appendix B. Only the segment on the A67 towards Eindhoven seems to be suffering from congestion, which is the reason for not including this road segment in the dataset. All other segments yield relatively high speeds, with minimum speeds measured to be around 70 km/h. Note that the segment on the A37 towards Hoogeveen misses a substantial amount of measurement data, which needs to be taken into account in further analysis.

No segments were included in South-Holland, although this is an interesting case due to the fact that three codes red were issued in this province. Therefore some extra segments, the A20 and A29, were analyzed in order to find a segment in South-Holland that meets the criteria. Appendix B shows that the A20 at exit 7 yields congestion in only four occasions in the time span of a month. The A29 at exit 22 yields more frequent occurrences of congestion, making this segment less fit for the proposed analysis.

No codes red were issued in the period from 2015 untill 2018 for the province of Limburg. This makes the segment on the A79 not useful for the next steps of the research in this report. For this reason, this segment will not be assessed.

A list of seven road segments that fit the requirements is deducted. Table 5.1 and Figure 5.1 specify these points that will be used for the analysis of this research. In Figure 5.1 the red dots indicate the locations of the nearest weather stations. The measurement locations for weather and traffic are furthest away in the case of the A30, where the distance is 20km.

Figure 5.1: Traffic (brown) and weather (red) measurement locations

Road	Province	Location
A20	Zuid-Holland	Exit 7
A6	Flevoland	Exit 14
A37	Drenthe	Exit 1
A58	Zeeland	Exit 37
A30	Gelderland	Exit 3
A31	Friesland	Exit 20
A7	Groningen	Exit 46

Table 5.1: Traffic measurement locations

5.2. Aggregation level

The loop detector data from the NDW can be obtained per minute. However, it can be doubted whether data on this aggregation level is needed for the research of this report. When plotting traffic counts at a 15 minute aggregation level, as done in the top row of Figure 5.2, shocks can be observed. As travelers do not evenly distribute along a road stretch, and might even clump since the desired speed varies over travelers and overtaking is not always possible, these shocks do not tell us something about the travel behavior, i.e. frequency choice or departure time choice. When aggregating the data on a 30 minute or 1 hour interval, we see that these shocks disappear, and a more stable demand pattern can be observed. Figure 5.2 still shows some shocks at a 30 minute aggregation level. This is why the dataset will be aggregated to 1 hour. With this, it becomes more likely that changes in observed patterns are due to the exogenous variables taken into account in this report.

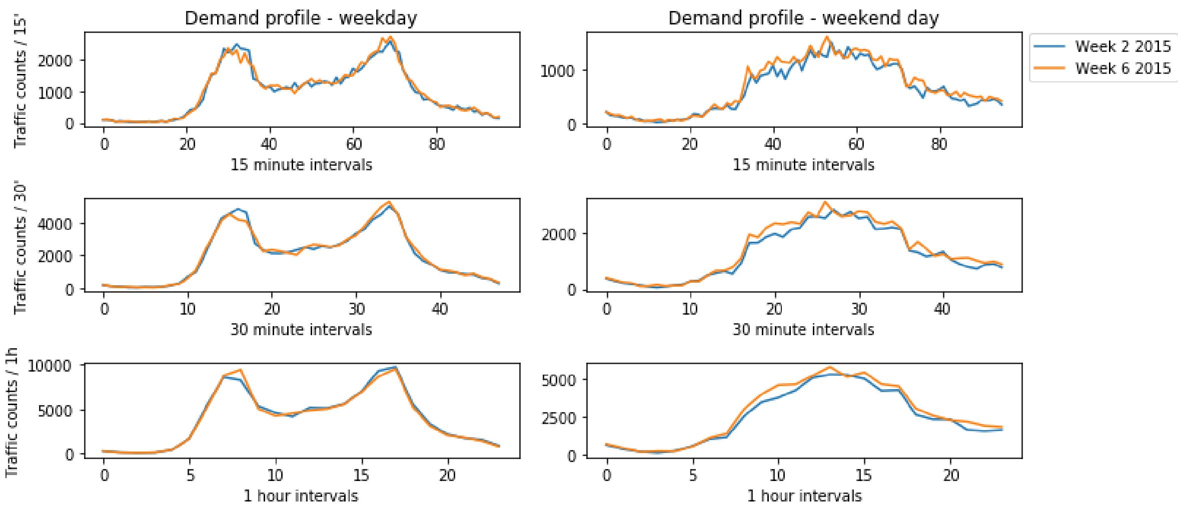


Figure 5.2: Traffic demand plots for different aggregation levels, on weekdays and weekend days for the A20 Westbound

When aggregating the traffic data, the weather data should be aggregated as well. Table 5.2 gives the aggregated weather characteristics. Note that average wind is available (see Table 4.4) but is not taken into account since it is highly correlated with the maximum wind. Additionally, the snow height is calculated. This is done by multiplying the precipitation with a factor, dependent on the temperature. This factor is estimated per temperature bin. The temperatures bins run from -20 to -7°C, -7 to -3°C, -3 to -1.11°C and 1.11 to 40°C, and the corresponding factors are 20, 15, 10 and 0 (Richard Graham, 2018). For example, when it is -6°C, it has been snowing, and the precipitation was 3mm, the corresponding snow height is $15*3 = 45mm$.

Table 5.2: Hourly aggregated weather characteristics

Weather Characteristic	Measurement Unit per hour
Snow	Dummy to indicate whether snow occurred
Rain	Hour sum (mm/h)
Temperature	Average temperature in °C
Wind speed	Average of the maximum wind speed (m/s)
Sunshine	Duration of sunshine in 0.1 hours
Fog/sight conditions	Horizontal sight, binned in km's
Slipperiness	Dummy to indicate whether slipperiness occurred
Snow height	Snow height in mm

5.3. Visual Inspection

The next step in preparing the data is a visual inspection of the data. With this we can spot any irregularities in the dataset that might not be explained by either the weekly or yearly cycle, weather influences, or weather code influences. If irregularities are significant, but cannot be explained, the dataset is unfit to analyze for the purpose of this research. All graphs that are inspected can be found in Appendix C.

For the A20, measurements for 2015 result in higher counts in comparison to the next years, as can be seen in Figure 5.3. This can be explained by the completion of the A4 in December 2015, which serves as an alternative route to the A20. A correction factor has been applied to correct for this alternative route. For the westbound direction of the A37, a lot of variation can be seen, compared to the eastbound direction. As no corresponding events can be identified with which a correction can be done, this segment will not be analyzed further. For the westbound direction of the A31, a dip in traffic can be observed between November 2015 and June 2016. A correction factor has been applied to correct for this dip. Furthermore, the A31 yields a significantly more (positive) outliers than other segments. This might cause problems when analyzing the data. All other segments yield a relatively stable demand.

Furthermore it can be seen that counts are heavily influenced by holidays. This observations supports the findings of Cools et al. (2007), in which this 'holiday effect' is researched through autoregressive methods. As counts during holidays are harder to predict, since the sample set is much lower than for 'normal' days, holidays are left out of the scope of this research.

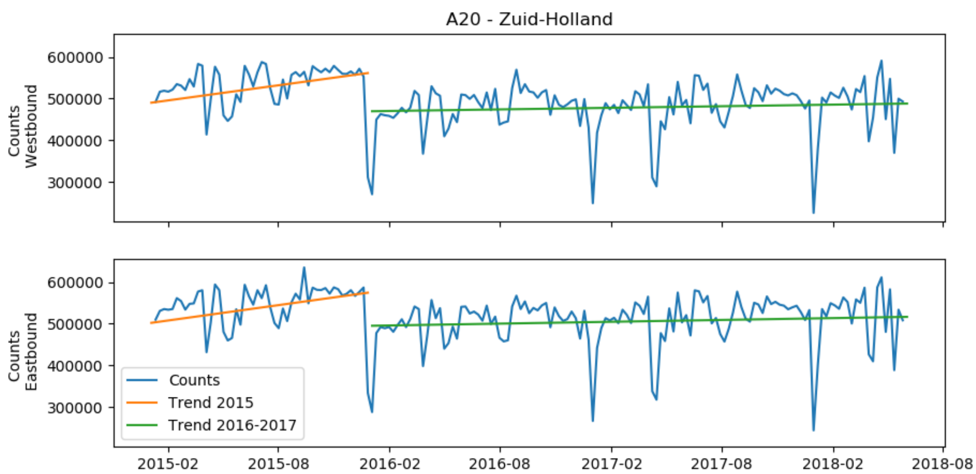


Figure 5.3: Weekly counts on the A20 with trend lines before and after the opening of the A4

5.4. Deseasonalization

When looking at data on a 1 hour aggregation level, some difficulties arise when weather characteristics are regressed. For example, temperatures are relatively low during the night, and there is no sun during night hours. At the same time, traffic volumes during night time are significantly lower than during the day. A regression model will interpret that these low temperatures and low sunshine are causing low counts, while actually people are not traveling because of the time of day.

For each road segment, an 'average week' was composed. This was done by taking the average of counts over every hour of each day of the week. When the resulting 'average week' is subtracted from the observed counts, the variability of counts, not explained by the weekly trend, is observed. Figure 5.4 shows a graph with the observed and expected count, and the difference between the observed and expected counts. The empirical 95% confidence interval is also plotted, indicating the variability of counts between weeks.

As described in the previous Section, holidays are left out of the scope for the analysis, and are not taken into account when deriving the deseasonalized pattern.

Mathematically we can write the deseasonalization process as follows:

$$C_t = \frac{1}{N}\sum_{i=1}^{N} c_{i,t}, \quad \text{with} \quad i = 0, 1..., 168 \tag{5.1}$$

$$D_t = c_t - C_t \tag{5.2}$$

With C_t the average count at time t for each hour of the week, N the amount of observations, $c_{i,t}$ the i^{th} observation of counts at time t and D_t the deseasonalized counts at time t.

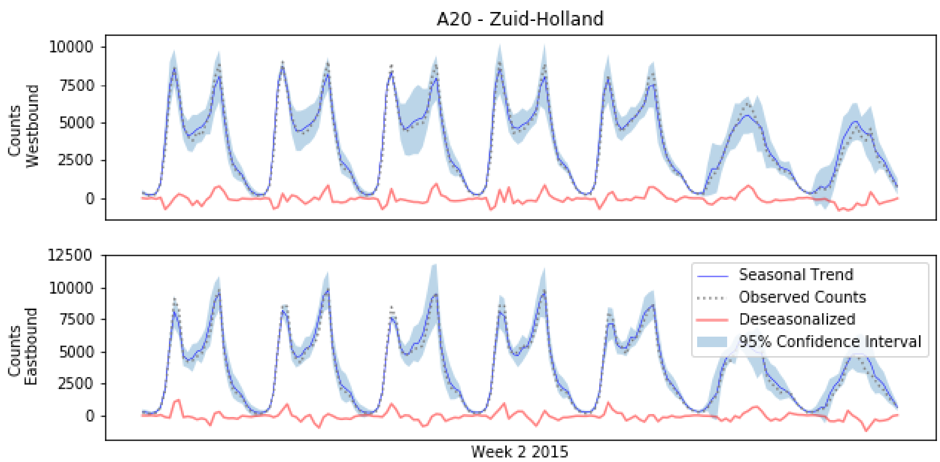


Figure 5.4: Two Weeks with the Expected Counts Based on the Weekly Trend

6 Influences of Weather Codes on Travel Demand

This Chapter will present the steps that are undertaken to estimate the influences of weather and weather codes on the total travel demand. The total travel demand is the first of two travel behavior components that will be researched in this report. At the end of this Chapter, an answer will be given on the following research question:

1. What are the effects of weather and weather codes on frequency choice?

Looking at the theoretical framework, this Chapter researches the hypotheses that bad weather leads to less traffic counts and that weather codes have a similar effect. The place of the research of this Chapter is depicted in the theoretical framework in Figure 6.1, with the unshaded boxes.

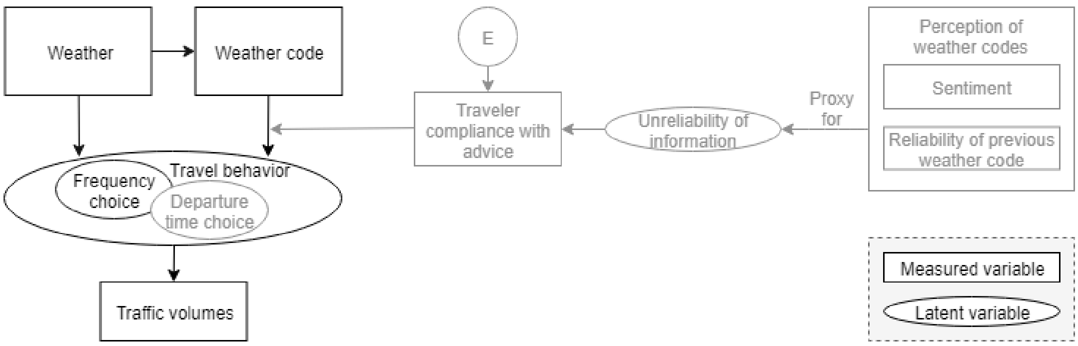


Figure 6.1: Theoretical framework for Chapter 6

6.1. Least Squares Regression

As explained in Chapter 4 it is hypothesized that both weather and weather codes have an effect on travel demand. To test the significance of these variables, regression models are set up with all the weather characteristics as found in Section 4.4 and all weather codes (unique combinations of color and type).

To see what is the best way to include weather characteristics in this regression model, the characteristics are plotted against the deseasonalized counts. An example of these plots can be seen in Figure 6.2. For some of the road segments, a positive trend between deseasonalized counts and temperature can be observed, which implies that warmer weather coincides with relatively high traffic counts. Furthermore, on the A31 in Friesland, a positive correlation can be observed between wind and counts, implying that more people travel at higher wind speed. However, other weather characteristics do not provide such insights. Although it is hypothesized that bad weather conditions coincide with low traffic volumes, this hypothesis cannot be drawn from these plots. This being said, it is hard to determine whether there is a linear or any other non-linear trend which should be included in the regression model. For this reason, the most simple model, a linear model, is chosen for modeling weather characteristics. An alternative model, in which weather characteristics were grouped, was set up as well, but did not yield significant results.

All plots of weather characteristics and deseasonalized counts can be found in Appendix E

The full results of the Least Squares Linear Regression models for all segments can be found in Appendix F. Here it can be observed that most of the weather characteristics are significantly impacting traffic demand, with a recurring exception for thunder. For the weather codes applies that the expected pattern can be observed with respect to the code color, as codes red are most significant, followed by codes orange. Codes for snow and slipperiness were the most significant, followed by wind. Codes for thunderstorms were least often found to impact travel demand significantly.

Even though the endogenous variable in the regression model is the deseasonalized traffic count, the dataset is still a time-series. Therefore, an underlying assumption of the regression model might not be satisfied. For the case of a regression model, it is assumed that observations are independent amongst themselves

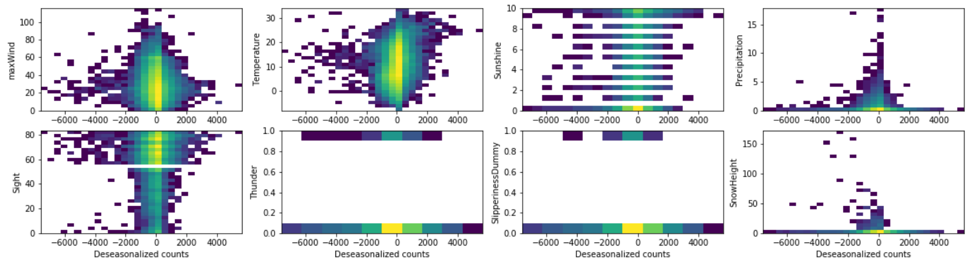


Figure 6.2: Deseasonalized counts and weather characteristics for the A20 - Westbound

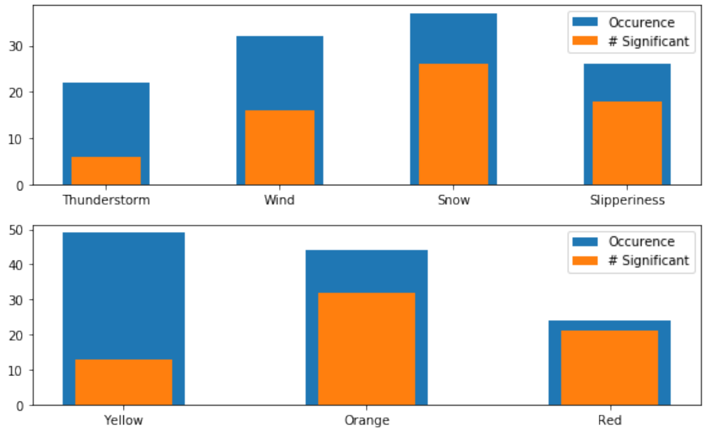


Figure 6.3: Significance of weather codes and weather for the regression model

Code	Occurence	# Significant	% Significant
Slipperiness Yellow	10	3	30
Slipperiness Orange	11	10	91
Slipperiness Red	5	5	100
Snow Yellow	13	5	38
Snow Orange	11	11	100
Snow Red	13	10	77
Thunderstorm Yellow	13	2	15
Thunderstorm Orange	9	4	44
Thunderstorm Red	0	0	
Wind Yellow	13	3	23
Wind Orange	13	7	54
Wind Red	6	6	100

and with this, the successive errors are independently distributed. This leads to pitfalls for a regression model, as the confidence interval for coefficients can be overestimated. (Durbin & Watson, 1950).

In the regression results in Appendix F the Durbin-Watson statistic is printed. A value of approximately 2 implies that there is no autocorrelation between subsequent observations. A value between 0 and 2 implies positive autocorrelation, and a value between 2 and 4 implies negative autocorrelation. The regression models yield Durbin-Watson values between 0.3 and 0.8, which confirms the doubt about the independence of successive observations. Savin & White (1977) gives the upper and lower bounds of the Durbin-Watson statistic with which it can be determined if the assumption of independence amongst observations holds. Although the tables of Savin & White (1977) do not reach the sample size as big as the one presented in this research, it is clear that for the datasets of the seven road segments, serial observations are interdependent.

6.2. Regression with Autoregressive Errors

The conclusion that observations are interdependent leads to the need to correct for this. Box et al. (2015) presents an approach to cope with time-series modeling. As it is the goal of this research to unravel effects of weather and weather codes on travel behavior, and not to find the best modeling method for handling these variables in a time-series environment, it is chosen to work with the most basic autoregressive model. This model needs to overcome the assumption of a least squares regression model, in which the error term is independent, and needs to take into account the previous lags that are significantly influencing the current lag.

Model Specification

To see which lags are significantly autocorrelated, the autocorrelation function (ACF) or correlogram is plotted in Figure 6.4. The blue shaded region is the 95% confidence interval for significance of the correlation.

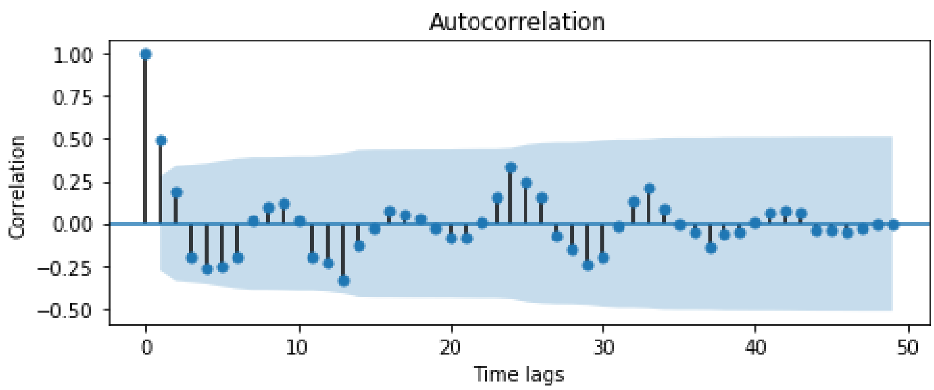


Figure 6.4: ACF for random time interval on the A20 - Westbound

A significant correlation can be observed at time lag 1. This means that an observation at time t is significantly autocorrelated with the observation at time $t-1$. To correct the error term for this, a regression model with autoregressive errors is proposed:

$$y_t = \sum_{i=1}^{n} \beta_i x_{it} + u_t \tag{6.1}$$

$$u_t = \phi_1 u_{t-1} + \epsilon_t, \quad \text{with} \quad \epsilon_t \sim N(0, \sigma^2) \tag{6.2}$$

With y_t the observation at time t, β_i the coefficient for exogenous variable i, x_{it} the value for the exogenous variable i at time t, and u_t the autoregressive error term at time t. This error term consists of the error at the previous time lag u_{t-1}, multiplied by coefficient ϕ_1, and a error term ϵ_t which is normally distributed with a zero mean (Penn State University, 2018). For the case presented in this report, this can be interpreted as follows: the observed deseasonalized counts are the sum of the weighed influence of all weather and weather code variables and an error term. The error term is influenced by the error term in the previous observation, meaning that the amount of unexplained variability at time $t-1$ will serve as part of the unexplained variability at time t.

There is some multicollinearity between weather characteristics and weather codes, which can be expected as weather codes are activated on the base of expected weather characteristics. Although counterfactuals (i.e. cases in which you would expect a weather code, but none was activated, or cases where a weather code was activated, but weather characteristics did not pass weather code thresholds) can be found in the data, chances are that weather effects are attributed to weather code variables, or the other way around. To find the minimum effect of the weather codes, an additional modeling approach is proposed. Here, firstly the weather variables are regressed following the model as mathematically described in Equation (6.1). Secondly, the residuals of this models are regressed with a linear regression model to test the significance of the weather code variables. This model will be referred to as the *'Sequential model'*, where the first model will be referred to as the *'Simultaneous model'*.

Mathematically we can write this sequential model as follows:

$$\hat{y}_t = \sum_{w=1}^{N} \beta_w x_{wt} + u_t \tag{6.3}$$

$$y_t - \hat{y}_t = \sum_{c=1}^{M} \beta_c x_{ct} + \epsilon_t, \quad \text{with} \quad \epsilon_t \sim N(0, \sigma^2) \tag{6.4}$$

Where for Equation (6.3) applies that $\hat{y}_t$ is the estimated value for y at time t, based on the regression model with AR(1) errors, β_w the coefficients for the weather variables, x_{wt} the weather variable values at time t, and u_t the AR(1) error term as described in Equation (6.2). Equation (6.4) accounts for the regression over the residuals, with the difference between the obtained and the predicted value $y_t - \hat{y}_t$ being the residuals of Equation (6.3), β_c the coefficients for the weather code variables, x_{ct} the weather code values at time t and ϵ_t the normally distributed error term with a zero mean.

Model Results

The full results of the specified model can be found in Appendix G. The Durbin-Watson is derived and yields values close to 2, implying that the model handled the autoregressive character of the dataset well and the significance of the estimated coefficients is not overestimated. Overall we can see a significant increase in model fit, as the log-likelihood of the autoregressive model is closer to zero than the regression model. This means that, while correcting for autocorrelated errors, we were also capable of creating a model with better predictive capabilities.

The A58 segments show a Durbin-Watson for which it could be doubted whether problems with autocorrelation are removed. ACF plots for this segment show some autocorrelation at and around 24 legs. This means that the deseasonalization, as performed in Chapter 5 did not filter out weekly demand patterns, as the counts are correlated with the counts from the previous day. Although models exist that are theoretically capable of dealing with seasonal autoregression, the amount of regressors in combination with a relatively high seasonal leg (i.e. 24), make this model impracticable. Therefore, the results for these segments cannot be assigned the same value as the other results.

Impacts of Weather

Figure 6.5 shows the significance of the weather variables for both the simultaneous and the subsequent model. Over all the segments we can see that, for the simultaneous model, temperature, followed by wind, is in the most cases significantly influencing traffic volumes. Snow and sunshine are significant for 9 out of 13 segments. Precipitation and sight are significant for 8 out of 13 segments. Thunder (6 out of 13) and slipperiness (4 out of 13) are the weather characteristics that are significant on the least segments.

Comparing these results with the sequential model, it can be observed that wind and snow are yielding significant results on more segments (13/13 and 12/13 respectively). Temperature, precipitation, slipperiness and thunder become less often significant (11/13, 7/13, 2/13 and 2/13 respectively). Sight and sunshine stay significant for as much segments as for the simultaneous model. This last two characteristics are less related to weather codes than the other variables, whereas the other characteristics are part of the characteristics that are taken into account when weather codes are activated.

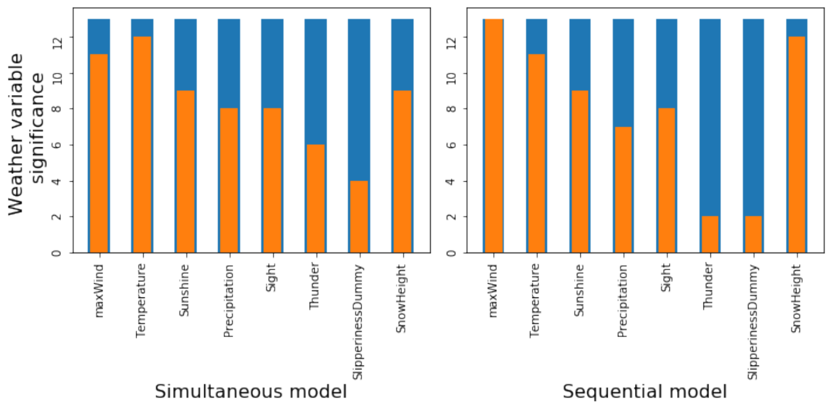


Figure 6.5: Significance of weather variables

From previous studies, some hypotheses can be derived (van Stralen et al., 2015; Datla & Sharma, 2008), on the impacts of weather on traffic volumes. An overview of these hypotheses, and the results from the models for the different road segments can be found in Table 6.1. From this table we can see that sunshine and thunder show in the majority of the segments an unexpected sign, which gives reason to doubt the impact of these variables. Furthermore we see that the A31 shows unexpected signs on variables that have the expected signs on other segments. As described in Section 5.3, the A31 yields a lot of positive outliers when manually inspecting the counts. This is possibly a reason for doubtful outcomes when interpreting the impacts of weather conditions on traffic volumes for this segment. Wind, temperature, precipitation, sight, slipperiness and snow all yield the expected signs on segments other than the A31. This leads to the conclusion that these variables are significantly contributing to travel demand.

Table 6.1: Hypotheses and model results

Hypothesis	**Expected sign**	**A20**	**A6**	**A37**	**A58**	**A30**	**A31**	**A7**
Wind leads to less traffic	-	-	-	-	-	-	+	-
Lower temperature leads to less traffic	+	+	+	+	+	+	-	+
Sunshine leads to more traffic	+		+	-	-	-	+	-
Precipitation leads to less traffic	-	-		-		-	-	
Less sight leads to less traffic	+	-	-	-	-		-	
Thunder leads to less traffic	-	-	+	+	+		-	+
Slipperiness leads to less traffic	-		-	-	-		-	
Snow leads to less traffic	-	-	-	-	-	-	+	-

As weather characteristics have different measure scales, it is hard to say that one characteristic has more impact on traffic volumes than the other. To give an indication of the impacts, density plots are derived and shown in Figure 6.6. The density of coefficients over all segments is described with a kernel density estimator (KDE). Each plot represents a variable. For both the simultaneous and the sequential model a density plot is shown.

From these density plots, we can see for example that the coefficient for snow for the majority of the segments is around -3, which means that per centimeter of snow, approximately 3 cars per hour less are registered than can be expected at similar day and time combinations with no snow. For example for temperature, we see less of a peak at a certain value, meaning that there is more difference in the coefficients between segments.

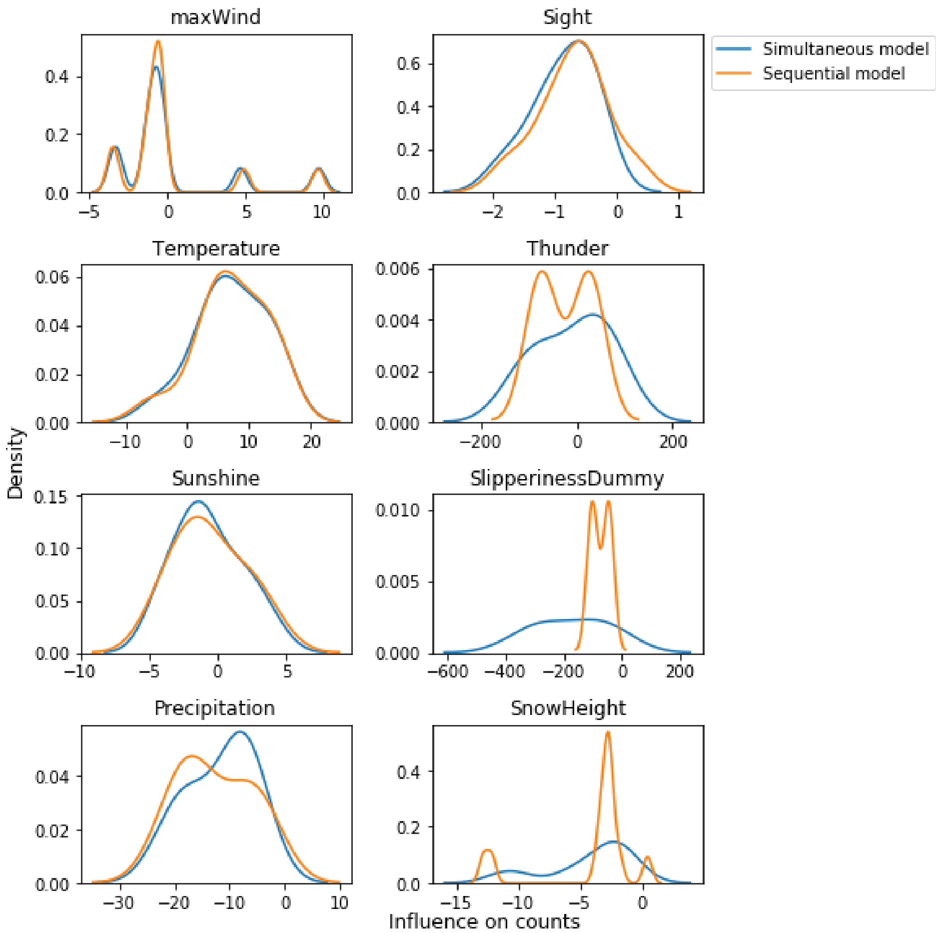


Figure 6.6: KDE for weather variables

Impacts of Weather Codes

With the approach as described in this Chapter, a *'best fit influence'*, and a *'minimum influence'* is yielded for weather codes. In Figure 6.7, bar plots are given to indicate how often a code yielded significant results. On the first row of plots, the weather codes are split per code type. For the simultaneous model, we can see that a code for weather type slipperiness yields significant results 16 out of the 26 occurrences. Snow is also resulting significant coefficients for the majority of occurrences (21/37). Thunderstorm and wind codes are less often significantly influencing traffic volumes, with 6/22 and 13/32 occurrences respectively. When grouping the codes per code color, we can see that yellow codes are the least significant, followed by orange codes. Codes red have an impact on traffic volumes most of the occurrences.

For the sequential model, weather codes are yielding less significant results, as can be expected from the modeling approach. However, the same patterns can be observed, as slipperiness is still the most often significant, followed by snow. Thunder is the least often significant again. For the colors, yellow is the least often influencing traffic volumes, whereas codes red are most of the time influencing traffic volumes.

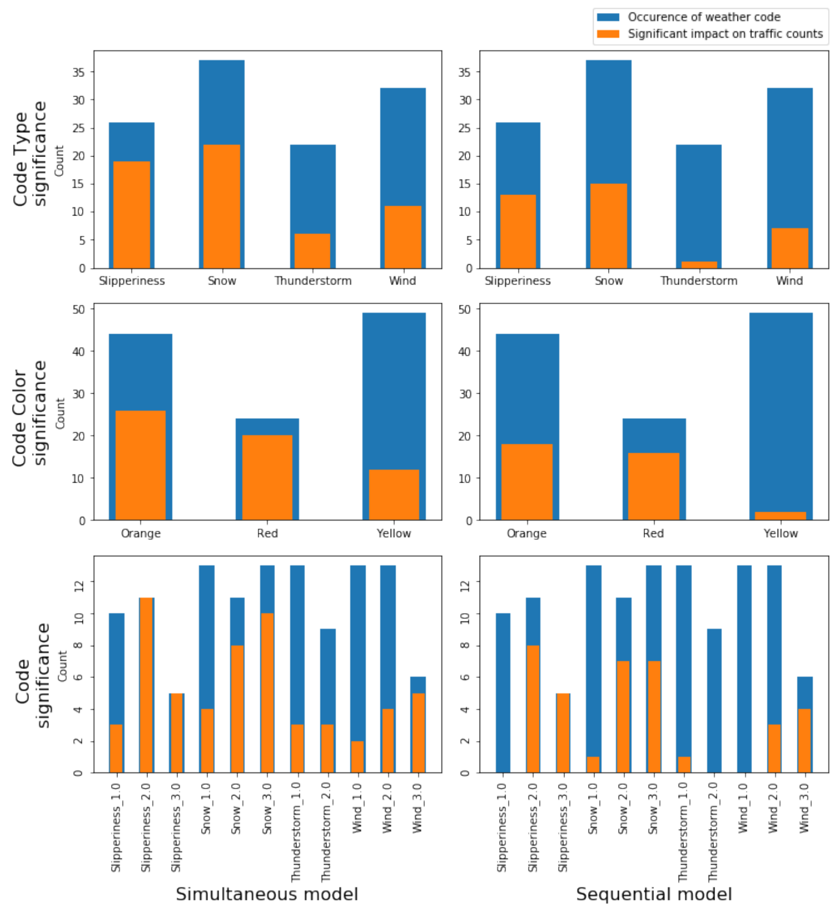


Figure 6.7: Significance of weather code variables

For weather codes, all the hypotheses are that a weather code will result in less travel demand. However, when looking at Table 6.2 we can see that this is not always the case. Code yellow for snow, orange for thunderstorms, and code yellow, orange and red for wind are yielding unexpected signs. All codes for slipperiness yield the expected sign. Furthermore, the codes orange and red for snow, and codes yellow for thunderstorms yield the expected sign as well. For these codes we can conclude that they have a clearly measurable effect on the traffic volumes.

When looking at the KDE plots as depicted in Figure 6.8, we can see that for the most weather types, the impacts of codes red are higher than codes orange and yellow. A more surprising result can be observed when looking at the differences in densities between the simultaneous and the sequential model. For all the

Table 6.2: Signs for weather code results

Weather code	A20	A6	A37	A58	A30	A31	A7
Slipperiness yellow				-			
Slipperiness orange		-	-		-	-	-
Slipperiness red						-	-
Snow yellow		-	+	-		+/-	
Snow orange		-	-		-	-	-
Snow red	-		-	-	-		-
Thunderstorm yellow		-	-			-	
Thunderstorm orange	+			+			
Wind yellow		+				-	
Wind orange	-	-				+	
Wind red	-	+		-	-		

weather codes the sequential model has coefficients that are closer to zero than the coefficients of the simultaneous model, which is logical, since the model specification allows the assignment of measured impacts to the weather variables first. In most of the plots, it can be observed that the sequential model has a more concentrated density, meaning that over the segments, there is more consensus on the impacts of the weather codes.

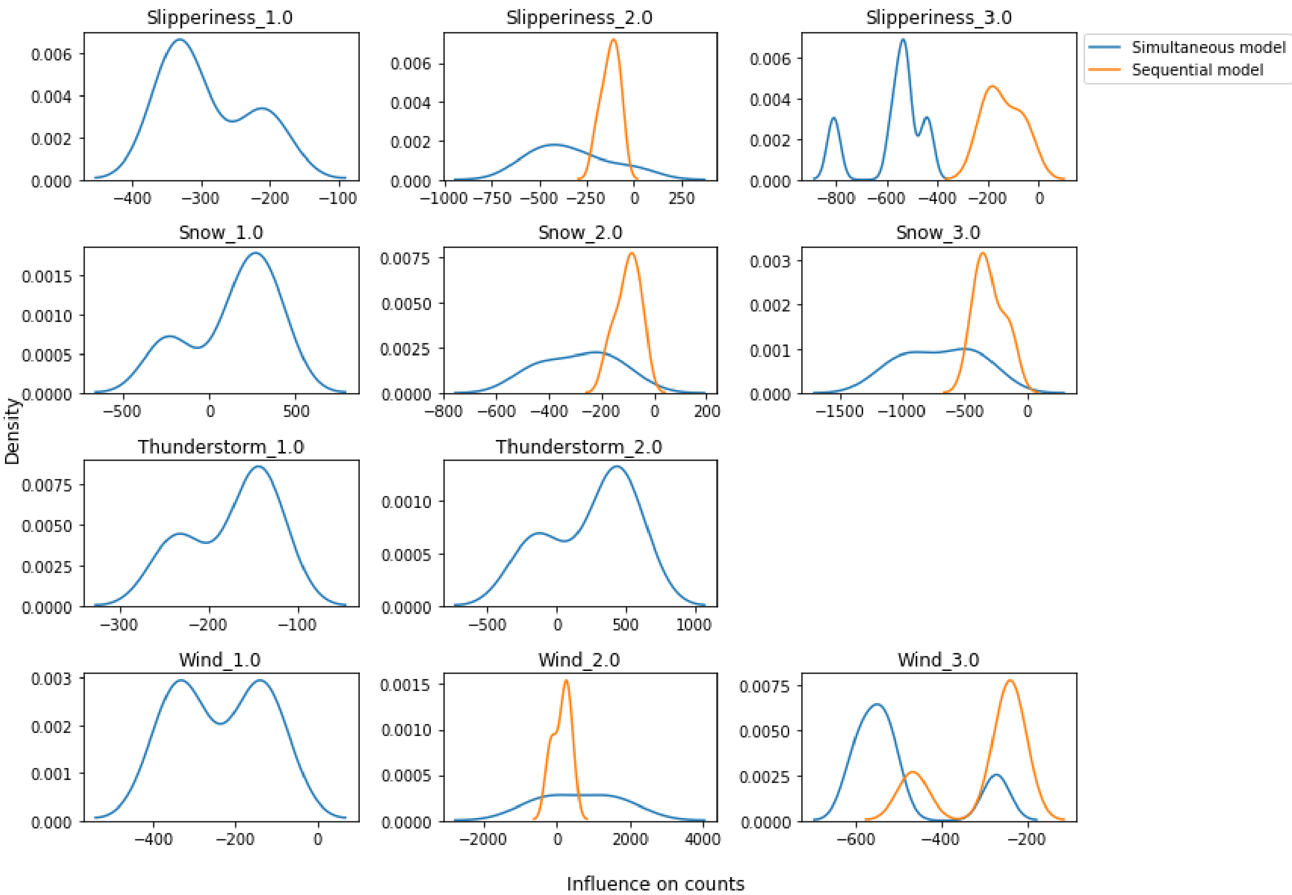


Figure 6.8: KDE for weather code variables

6.3. Conclusion

This Chapter tries to answer the following research question:

1. What are the effects of weather and weather codes on frequency choice?

Several model setups were tried in order to reach significant and reliable results. Linear regression did not yield reliable results, as observations were autocorrelated, which results in overestimation of the significance of coefficients.

A regression model with autoregressive errors, in which weather and weather code variables were included simultaneously, yields significant and interpretable results. This model yields that wind, temperature, precipitation, sight and snow are on the majority of the segments significantly influencing traffic counts. Weather code variables of the types slipperiness and snow are significant for most of the segments as well, whereas weather codes for thunderstorms and wind are significant on a relatively low amount of road segments. Furthermore, it is observed that weather codes are more often significant when the code color intensifies towards red.

A regression model with autoregressive errors, in which weather and weather code variables respectively were included sequentially, yields significant and interpretable results as well. This model describes the statistical minimum effect for weather codes on traffic volumes, and the statistical maximum effect for weather variables. This model yields a higher significance for wind and snow, in comparison to the simultaneous model specification. Thunder, precipitation and slipperiness are less significant than in the simultaneous model. For weather code variables, it can be observed that codes for snow still has the most occurrences of significant coefficients, but that only codes for slipperiness are significant on the majority of road segments. When codes are grouped per color, codes red are significant most of the occurrences. Orange codes are slightly less significant, and yellow codes only 2 out of the 49 occurrences.

These results are in line with expectations when looking at the advices that are accompanying the weather codes. For codes red for slipperiness, snow and wind, the advice is to avoid traveling (KNMI & Ministry of I&E, 2015)

With the result we can simulate the traffic counts with and without a weather code. An example of this can be seen in Figure 6.9. Here, 24-01-2015 is plotted. Between 4AM and 10AM, snow occurred. However, the KNMI did not issued a code orange or code red. The plot in Figure 6.9 shows

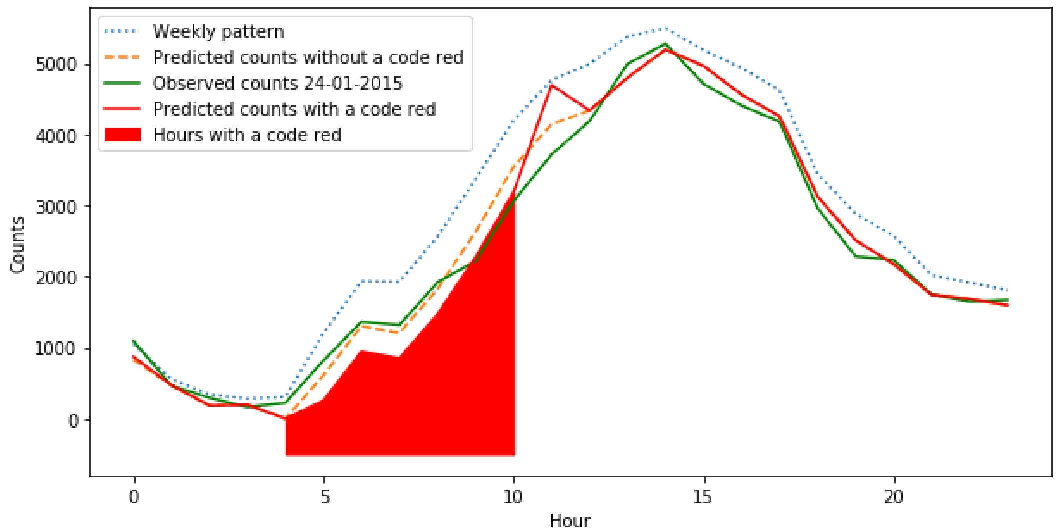


Figure 6.9: Example of the predicted counts with and without a code red for snow

A comprehensive overview of the model results is shown in Table 6.3. The full results of the linear regression models are found in Appendix F. The full results of the regression models with autoregressive errors are found in Appendix G. These weather codes are found to be significant on the large share of road segments. The relatively high impacts for slipperiness and snow, code orange, are less expected when looking at the advices, since there is no advice to avoid traveling. This might imply that people acknowledge the risks that the KNMI informs on, and do not value their trip over the safety of not making a trip. Another explanation may be that not all people are aware of the meaning of a code orange, and that some travelers might see this code as an advice to not make a trip.

Table 6.3: Overview of model results, with the average, minimum and maximum coefficient value

Code	Model	Significance [%]	Average	Minimum	Maximum
Slipperiness_1.0	Simultaneous	30	-291,1	-209,3	-334,8
	Sequential	0			
Slipperiness_2.0	Simultaneous	100	-331,1	0	-572,4
	Sequential	72,7	-124,5	-74,3	-199,7
Slipperiness_3.0	Simultaneous	100	-575,4	-440,9	-808,4
	Sequential	100	-139,3	-60,2	-206,5
Snow_1.0	Simultaneous	30,8	141,4	368,8	-236,1
	Sequential	7,7	102,1	102,1	102,1
Snow_2.0	Simultaneous	72,7	-286,5	-96,2	-469,1
	Sequential	63,6	-99,2	-44,3	-173,8
Snow_3.0	Simultaneous	76,9	-701,5	-303,8	-1109,9
	Sequential	53,8	-301,4	-144,1	-438,8
Thunderstorm_1.0	Simultaneous	23,1	-173,7	-137,9	-234,8
	Sequential	7,7	-123	-123	-123
Thunderstorm_2.0	Simultaneous	33,3	246	480,2	-144,2
	Sequential	0			
Wind_1.0	Simultaneous	15,4	-236,2	-136,3	-336,1
	Sequential	0			
Wind_2.0	Simultaneous	30,8	621,5	1585,6	-328,4
	Sequential	23,1	134,5	348	-150,9
Wind_3.0	Simultaneous	83,3	-499,7	-271,5	-603
	Sequential	66,7	-295,8	-224,8	-466

7 Influences of Weather Codes on Departure Time Choice

This Chapter will present the steps that are undertaken to estimate the influences of weather codes on the daily demand pattern. The daily demand pattern is the second of two travel behavior components that will be researched in this report. At the end of this Chapter, an answer will be given on the following research question:

2. What are the effects of weather codes on departure time choice?

Looking at the theoretical framework, this Chapter researches the hypotheses that weather codes lead to less traffic counts within the period of the activation of this code. The place of the research of this Chapter is depicted in the theoretical framework in Figure 7.1, with the unshaded boxes.

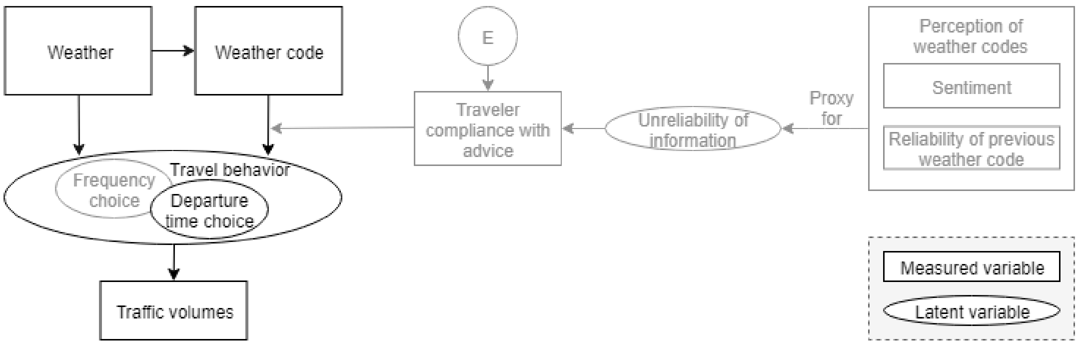


Figure 7.1: Theoretical framework for Chapter 7

From Chapter 6 follows that both weather and weather codes have impacts on traffic volumes. However, we do not know if travelers have rescheduled their trip towards a time outside the activation time of a weather code. With this, we do not know whether people actually canceled their trips due to the weather code. To assess this, this Chapter will study the daily demand pattern of some cases in which a weather code was issued.

7.1. Case Study Selection

From the results of Chapter 6 we can observe that codes orange for slipperiness and snow, and code red for wind have significant effects on traffic volumes during an hour in which these codes are active. Therefore, these codes are most usable for the case studies in this Chapter. Since not all segments yielded significant results, or had observations for these codes, a list can be derived for combinations of weather codes and road segments which are interesting case studies. This list can be found in Table 7.1

Table 7.1: Case study selection

Weather Code	Date	A20	A6	A37	A58	A30	A31	A7
Slipperiness Orange	04-01-2016		x	x			x	x
Slipperiness Orange/Red	05-01-2016		x	x			x	x
Slipperiness Orange/Red	07-01-2016		x	x		x	x	x
Snow Orange	10-12-2016	x	x	x		x	x	x
Snow Orange/Red	11-12-2016	x	x	x	x	x	x	x
Wind Orange/Red	18-01-2016	x	x	x	x	x	x	x

7.2. Hypotheses

Before the case studies are plotted and assessed, hypotheses are determined. With these hypotheses assess all 60 cases over 7 segments with a more dedicated focus.

The hypotheses for Chapter 6 were confirmed, from which we know that some weather codes are significantly influencing travel demand. Furthermore, the selected cases look specifically at days that have a code which yields significant coefficients from the statistical tests in Chapter 6. Therefore the first hypothesis is that we can visibly observe less than average traffic volumes on periods for which a weather code, when looking at travel demand patterns for the corresponding days.

The second hypothesis is that travelers reschedule their trip outside the period in which a weather code is active. This will result in above average counts on the edges of the period in which the weather code is active. Figure 7.2 reflects this hypothesis, as peaks are seen before and after the period in which a code red was issued.

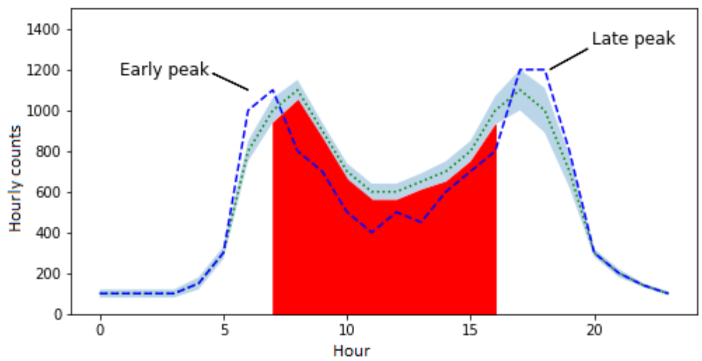


Figure 7.2: Graphical representation of the second hypothesis

7.3. Results

The full overview of the plots can be found in Appendix H.

For most of the plots, the first hypothesis can be verified, as the majority of the counts during codes orange and red for slipperiness and snow, and codes red for wind are under the expected counts. Exceptions for this are the cases for code red for snow on 11-12-2017 on the eastbound direction of the A6 and the eastbound direction of the A37. Furthermore, for both directions on the A31 on 7-1-2017, and the westbound direction on the A31 on 11-12-2017 accounts that counts are above average in the evening hours.

The second hypothesis is not verified by the majority of the plots in Appendix H. A few cases can be found in which peaks are slightly moved towards hours in which no code was active. For the A20 in the eastbound direction and the A30 in southbound direction on 11-12-2017, a small peak can be observed at around midday, just before the code red is active. A similar effect can be seen for the same date on the A6 in the eastbound direction. However, here the peak is located just inside the period of the code red. It seems that here, travelers decided to travel before the usual evening peak to avoid traffic, instead of avoiding traveling during code red. The A37 yields a similar pattern for 11-12-2017. Here, some travelers chose to travel before the afternoon peak, during code orange. Hereby, these travelers avoided the evening peak as well as traveling in code red. For the code red for wind on 18-01-2018, it can be observed for the A6 in eastbound direction that travelers postponed their trip towards the hours after the weather code was terminated. This effect is to a lesser extend visible for the A30 in northbound direction.

Generally we can see that rescheduling only can be observed in cases of codes red. this is also the case when a code orange is preceding or succeeding the code red. Codes orange themselves do not lead to rescheduling behavior amongst travelers.

7.4. Conclusion

This Chapter assessed the influence of weather codes on departure time choice. This was done by inspecting demand patterns on days with a weather code, and comparing these patterns with the pattern that is expected under normal weather conditions.

The analysis of this Chapter is done to find an answer on the following research question:

2. What are the effects of weather codes on departure time choice?

First of all, it can be observed that less people than usual are making their trip during weather codes. The majority of these people are canceling their trips, as no peaks outside the code periods are making up for the dip during the codes.

For some segments, small peaks can be observed just before or after the period in which a weather code is active. This might indicate that some people are rescheduling their trip from a time for which the KNMI advises people not to travel, towards a time for which no weather code has been issued.

8 Travelers Perception and Compliance

This Chapter will present the steps that are undertaken to estimate the influences of perception of weather codes, on the impacts of weather codes on travel demand. As seen in Chapter 4, it is expected that perception of information influences traveler compliance towards certain advices. In the case of this research, this leads to the hypothesis that the perception of travelers on weather codes impacts the compliance towards the advices that are given along with the activation of a weather code. At the end of this Chapter, an answer will be given on the following research question:

3. How does traveler perception of weather codes influence the compliance towards weather code advices?

The place of the research of this Chapter is depicted in the theoretical framework in Figure 8.1, with the unshaded boxes.

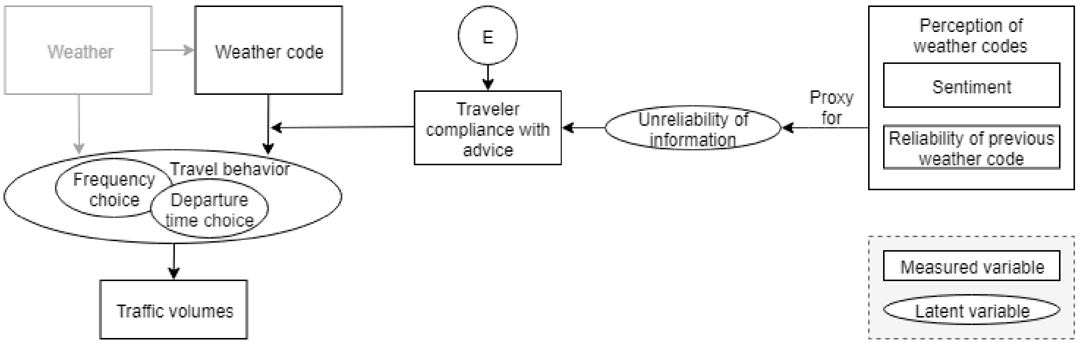


Figure 8.1: Theoretical framework for Chapter 8

From Figure 8.1 follows the hypothesis that sentiment and the reliability of a previous weather code are a proxy for the unreliability of information. This subsequently influences the traveler compliance with advices, which has a negative effect on the impacts of weather codes on travel behavior.

8.1. Reliability

The first part of the research on the impacts on perception on the working of the weather codes looks at the reliability of codes. It is hypothesized that when a weather code at time t is unreliable, the impacts of a weather code at time $t+1$ is relatively low. On the other side, it is expected that a reliable code will lead to more impact the next time a weather code is issued. Note that the reliability of a code at time t has already been found to be significantly influencing travel behavior at time t, as the influences for several weather characteristics were found to be significant in Chapter 6

Measuring Reliability

If we want to find the relationship between the reliability of a weather code, and the impact, we first must define reliability.

(KNMI & Ministry of I&E, 2015, Appendix 1) gives an overview of the threshold values for weather codes, which are explained in Section 4.1. Although for some codes multiple weather characteristics can determine the code color, the thresholds for the weather characteristics are very clearly defined. This means that, for historical data, we can accurately determine whether a weather code met the threshold values. Note however, that a weather code is issued for a province, while weather data is measured at one geographical location in this province. Therefore, a code might be justified by the weather in other parts in the province. As the chosen traffic measurement locations and weather measurement locations are chosen as close together as possible, we assume that the perceived reliability of the code by travelers on the measured segment can be approximated by the comparison of the weather at this location and the threshold values for the weather code issued.

As the data used in this research is aggregated per hour, the reliability of the weather code can be assessed per hour. If the conditions for the issued weather code are met at hour h, the reliability at hour h is 1. If the threshold values for weather characteristics related to the weather code are not exceeded, the reliability is 0. Subsequently, the reliability for the code on day d is determined as the mean of the reliability over all the hours in which the weather code was active.

Mathematically we can write this down as:

$$R = \frac{1}{H}\sum_{h}^{H} R_h, \quad \text{with} \quad h \in H \tag{8.1}$$

Where R is the reliability, R_h the reliability at hour h, and H being the collection of hours at day d for which a code was active.

Results

The correlation between the reliability of the previous code and the impact on counts for the next code are checked by plotting the measurements with the reliability and the deviation from the expected counts [1] on the x-axis and y-axis respectively. A full overview of these plots can be found in Appendix I, and an example is shown in Figure 8.2.

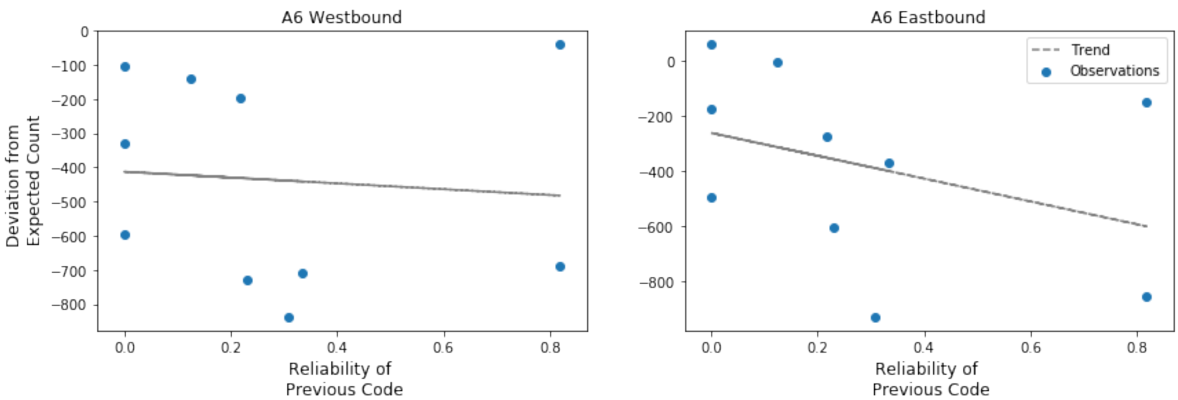


Figure 8.2: Reliability of previous code in relation to deviation from expected counts for the A6

It can easily observed that, for the plots per segment, the two variables are not correlated. However, this can be due to the lack of observations. Therefore, all datasets are combined to plot all observations for all segments in one figure. The result is depicted in Figure 8.3. Here we can see a relatively high amount of positive deviations at for reliability values between 0 and 0.2. The trend line fits the data better than the individual segments. When we statistically test this trend line, this better fit is confirmed with a p-value of 0.034.

To confirm the findings, reliability was added in the autoregressive regression model as presented in Chapter 6. Reliability of the previous weather code affected the counts significantly for the A20, A37 and A31 in eastbound direction, and the A6 and A58 in both directions. However, both increases and decreases of counts are observed, from which we can conclude that the effect of reliability of the previous weather code on travel behavior is dubious.

8.2. Sentiment

The second part of this Chapter looks into the prevailing sentiment during weather codes. As mentioned in Section 4.4.1, the data used for this analysis is data from Twitter. With this sentiment analysis, it is tried to

[1] Counts as expected based on the weekly pattern as described in Section 5.4

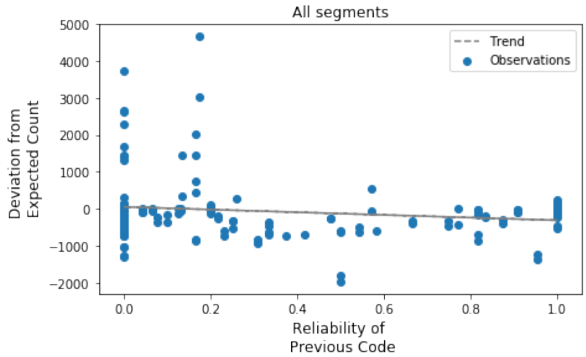


Figure 8.3: Reliability of previous code in relation to deviation from expected counts for all road segments

reveal what people think about the weather code as issued by the KNMI. The outcomes might give insight into the reasons why people do or do not travel during a weather code.

Hypotheses

A theory driven approach is used to research the sentiment, prevailing during a weather code. This is done at the hand of hypotheses. For this Section, it is hypothesized that a negative sentiment is correlated with a lower impact of a weather code on travel behavior. This follows from the hypothesis that people are less likely to follow up advices which they don't believe, or perceive as unreliable. Furthermore, it is hypothesized that the reliability of previous weather codes plays a part in the sentiment of people. When a previous weather code was unreliable, people will question the next weather code. It is hypothesized that this pattern can be observed in Twitter data as well.

Note that the focus lies on negative sentiment. Experience with the analysis of Twitter data at CGI resulted in the conclusion that Twitter is hardly used to express positive sentiment on subject matters. It is not expected that the case presented in this research yields different results.

Results of Used Methods

As explained in Section 4.4.2, three methods were used for the sentiment analysis. The suitability of the three methods was tested on a small dataset, to see which methods can provide information on the sentiment of a list of tweets.

The first method first uses a list of words and combinations of words which are related to a certain sentiment, and then searches the tweets for these words. The python package of *pattern-nl* is used, which uses a lexicon of adjectives to determine sentiment. The package has been tested to analyze book reviews. For this case, the package was able to predict the correct sentiment for 82%. However, the package was not able to cope with the case of this research. This can be explained by the fact that not all negative tweets are negative with respect to the weather code itself. Examples of codes which were considered to be negative are:

"vandaag is draaien in de torenkraan echt onmogelijk wind boven 100 km per uur.", translated as *"Today, working in the tower crane really is impossible, winds above 100 km/h."*

"het is weer code rood! en dat betekent in nederland dat treinen niet rijden en dat thuis komen dus erg lastig is. heb jij een plekje over in de auto voor iemand die graag naar huis wil? tweet ons met hashtag #carpoolcoderood", translated as *"It's code red again! This means for the Netherlands that trains are not running and that traveling home is very hard. Do you have a spot left in the car for someone who wants to go home? Tweet us with the hashtag #carpoolcoderood"*

As the *pattern-nl* package was not usable in this case, a list of words that would indicate a negative sentiment with respect to weather codes was put together. In order to be able to confirm or deny our hypothesis, these words were specifically targeting opinions with regard to the reliability of a weather code. However, searching the list of tweets for the words in this list did not result in a useful dataset as well. Tweets with a negative sentiment were not filtered with this approach.

With the second method, a subset of the total set of tweets is assessed. For the tweets in this subset, it is per tweet manually determined what sentiment is prevailing. Based on the sentiment classification of this subset, we determine characteristics of each sentiment class. Subsequently, the full list of tweets can be tested for these characteristics, and a class can be assigned. However, the large share of words in both sentiment groups were overlapping, which made it not feasible to recognize features of a sentiment class.

The last method is a manual inspection of all tweets, to filter out the negative tweets. While being a very labor-intensive method, this is the only method found by the author to accurately compile a list of tweets that expressed a negative sentiment.

Data Selection

Since only the third method was usable for the sentiment analysis, it was not feasible for this research to assess all the days for which a weather code was issued, since this method is very labor intensive. Therefore, a selection of the days with a weather code was made. The results of the analysis on reliability of the weather codes in Section 8.1 are used to make this selection. The selection of days is presented in Table 8.1. They were chosen in such a way that the characteristics of the codes, reliability and impact varied over the selection. With this, it is hoped that the sentiment is varying over the selection as well, which could provide insights on the link between code characteristics and the prevailing sentiment.

Table 8.1: Selected days for the sentiment analysis

Date	Reliability previous code	Reliability code	Impact	Weather code
09-12-2017	low	medium	medium	Snow/slipperiness orange
11-12-2017	medium	high	high	Snow/slipperiness orange/red
18-01-2017	low	low	low	Wind orange/red

Results

For the days as presented in Table 8.1, respectively 206, 725 and 507 tweets were available. The tweets that were assessed to be negative with regards to the weather code are presented in Table 8.2. for 09-12-2017 only two negative tweets were found that had both the words 'code' and 'knmi' in them. For 11-12-2017 this number was 10, while 18-01-2018 yields 6 negative tweets. Some tweets are about the unreliability of weather codes. In other tweets, people express that they don't agree with the danger that the KNMI warns for. Besides this, several tweets express their dissatisfaction on the timing of the code red.

With a dataset as small as Table 8.2 it is difficult to confirm or deny the hypotheses. It can be seen that for 18-01-2018 half of the negative tweets were complaints about the timing of the code. For this day, we see a low reliability, although there was in fact a very heavy storm. This can be explained by the used method for measuring reliability, which takes into the average reliability over all hours that the code was active. If a code is active longer than necessary, reliability is going down.

The most negative tweets are found for 11-12-2017. This contradicts the hypothesis that more negative tweets will be observed at weather codes with a low reliability, since the reliability for the code on 11-12-2017 was high. Since the total amount of tweets were highest for this day, the amount of negative sentiment might be more related to the total attention that is given to the weather code.

8.3. Conclusion

This Chapter tried to explain the relation between the perception of travelers towards weather codes, and the compliance rate of travelers towards travel advices that were given along with the activation of a weather code. With this, it was tried to answer the following research question:

3. How does traveler perception of weather codes influence the compliance towards weather code advices?

Table 8.2: List of negative tweets during the selected dates with the words 'code' and 'knmi'

Date	Negative Tweet
09-12-2017	code oranje. dan weet je dus dat niets maar dan ook niets gebeurd meestal.
	geen paniek. het komt geregeld voor dat een code oranje voorbarig is gebleken en dat het toch nog een prachtige, zonnige dag werd.
11-12-2017	anno 2017. zoek "winter 1963". we zijn volgens mij de weg kwijt. code rood = zoveel overlast dat de maatschappij ontwrichtend kan zijn.
	overal is er chaos met sneeuw en hier ligt het alweer te smelten. gisteren code oranje en gladde wegen, maar ik heb helemaal niks gemerkt.
	code rood afgegeven door knmi... nou hier in fryslan ligt niets hoor...
	code rood. code rood! code rood!!! code roooooooood!!!!!! serieuze vraag aan het knmi: is er ook nog een code zwart, voor "nu zijn jullie allemaal serieus fucked"? want code rood voor een paar sneeuwvlokken maak je je wereldwijd toch een piepklein beetje belachelijk mee...
	okay. code rood knmi. klinkt alsof nederland vergaat. wat nu? wat betekent code rood in landen waar dagelijks zo'n dik pak sneeuw ligt? zoveel vragen!
	komt het knmi even aanzetten met code rood. hele dag nog heen sneeuwvlok gevallen
	typisch nederlands: mensen afraden de weg op te gaan, aanraden thuis te werken. maar dan niet de code rood afkondigen die dit rechtvaardigt, knmi
	het knmi maakt de mensen weer is gek met hun code oranje! de meeste wegen zijn heel goed begaanbaar! maar natuurlijk zullen collega's die ver af wonen er weer zijn en diegene die relatief dichtbij wonen zeggen dat ze er niet doorkomen...
	ohh.. ahhh...men waar blijft de voorspelde code rood?!?!?!?
	knmi geeft opnieuw code oranje af wegens verwachte sneeuwval. een instantie die opgedoekt kan worden. steeds weer code oranje of rood en gebeurt er niets. dus opdoeken met de instantie die verkeerde info verstrekt en mensen op het verkeerde been zet
18-01-2018	de volgende keer moet er bij deze extreme weersomstandigheden eerder code rood worden afgegeven. daarnaast moet de overheid de scholen verplicht gesloten houden, en een verbod van vrachtwagens om te rijden! alleen waarschuwen werkt niet!
	het is hier nu bijna windstil. gaan we die code ook nog even publiekelijk intrekken a.u.b.?
	knmi, zijn jullie vergeten code rood in te trekken?
	trekt maar in weer in die code rood voor vleuten/de meern/utrecht het valt hier nu reuze mee
	hee, knmi, eerst code oranje afkondigen, waarmee velen naar school/werk moeten, en dan code rood waardoor iedereen thuis moet blijven? beetje moeilijk als je al op werk/school bent!
	knmi met die weeralarmen geloof ik niet meer. paniekzaaierij. wat vroeger winter was met een dagje sneeuw is vandaag de dag ineens een code rood waard...

Two themes were researched, which were hypothesized to be a proxy for this compliance. First, the reliability of weather codes is assessed to see whether a correlation exist between the reliability of the previous weather code with impacts on travel behavior during the next weather code. When assessing road segments for this correlation separately, no correlation can be found. However, when combining the data sets, a correlation was found, indicating that a low reliability of a previous code will lead to less impact for the next weather code. However, this conclusion was not confirmed when reliability of the previous weather code was added to the variables of the autoregressive regression model of Chapter 6, which casts doubts on the certainty with which conclusions can be drawn with respect to this variable.

The second theme that was researched was sentiment. Efforts have been made to compute the characteristics of tweets with a negative sentiment, and to classify tweets based on a predefined list of words which would be correlated with a negative sentiment. However, only a manual inspection of all tweets proved sufficient to filter out tweets with a negative sentiment. The resulting list of tweets was 18 tweets long, which makes it hard to confirm any hypotheses. Although the findings have their limitations, the hypothesis that more negative sentiment will prevail amongst tweets if the reliability of a weather code is low, could not be verified. On the other hand, the used method for measuring reliability of a code gave the insight that a low reliability can coincide with complaints about the timing of a weather code.

9 Conclusion

In this chapter, the answer on the main research question will be provided. In the previous Chapters, the influence of all components in the theoretical framework of Figure 4.4 is estimated. Three subquestions are answered, which have given insights into the effects of weather codes on travel behavior from different perspectives. Answers to the three subquestions therefore give an answer to the main question:

What are the Impacts of Weather Codes and Travelers' Perception of Weather Codes on Travel Behavior?

9.1. Impacts on Travel Demand

The first part of travel behavior that is analyzed is the travel demand per hour. Both weather and weather code variables were taken into account.

First, a linear regression model was used to unravel the effects of these variables. However, a low Durbin-Watson statistic pointed out that there was a high chance of correlation between observations, which is a common risk when dealing with time-series. As regression models assume independence between observations, normal regression models are not fit for this dataset, as significance of variables will be overestimated. Therefore, a regression model with autoregressive errors is used to assess the impacts of weather characteristics and weather codes. This model, which takes into account the previous observation in the error term of the current observation, was able to model the variables while dealing with autocorrelation.

A regression model with autoregressive errors was run with both weather and weather code variables. This simultaneous model resulted in significant parameters for the weather variables wind, temperature, sunshine, precipitation, sight and snow height for the majority of the road segments that were analyzed. These parameters yielded the expected sign, except for sunshine, which yielded a negative coefficient, implying that more sunshine leads to less traffic. Thunder also yielded unexpected coefficients, for four cases, implying that thunderstorms increase the travel demand. The findings are confirming part of the results of Cools & Moons (2010), except for the results on the sunshine variable, which yields positive coefficients for the work of Cools. Weather codes for slipperiness and snow yield significant results for most of the road segments. Codes for thunderstorms and wind are less often of influence on travel demand. Furthermore, the expected pattern is confirmed with respect to the color of a code. Codes red are most often significant, followed by orange. Codes yellow are the least often significant. The vast majority of the weather codes yields the expected sign, implying that travel demand reduces when a weather code is active. The highest impact is measured for snow code red, which in some cases resulted in 1000 counts less than expected in an hour.

Besides the simultaneous model, a subsequent model is run that first includes the weather variables in a regression model with autoregressive errors, and subsequently runs a linear regression model on the residuals of the autoregressive model. This is done to determine the minimum of the impacts of weather codes. This follows from the hypothesis that travelers are primarily influenced by weather. The subsequent model is able to provide significant result as well. The results differ from the simultaneous model on a couple of points. Wind, temperature and snow height were more often significantly influencing traffic volumes in comparison to the subsequent model. Precipitation, thunder and slipperiness were less often yielding significant results. Furthermore, as expected, weather codes are less often significant. The same patterns as for the simultaneous model can be observed, as codes for snow and slipperiness are the types with the most significant impact. Codes red, followed by codes orange, are most often influencing travel demand when looking at code color. Code yellow for slipperiness, code orange for thunderstorms and code yellow for wind yield no significant results.

9.2. Impacts on Departure Time Choice

Besides the effect of weather codes on travel demand, this research also looked at effects on departure time choice. The hypothesis that the travel demand outside the period of a weather code will be above average is tested. If this can be observed, this means that some travelers have rescheduled their trip in order to avoid traveling during a weather code. The codes for 04-01-2016, 05-01-2016, 07-01-2016, 10-12-2016, 11-12-2016 and 18-01-2016 are studied, covering all weather codes for which Chapter 6 proved that they have a significant influence on travel demand. The demand pattern for these days was plotted for all road segments. In the same plots the expected counts, and the period in which a weather code was active was shown. The demand pattern was compared to the expected counts, and deviations were interpreted. For most of the studies, it was clearly visible that the demand during hours for which a code was active was lower than we would expect on a day without a weather code. However, peaks just before or after the code period were less clearly visible. For some segments, small peaks can be observed just outside the weather code period, indicating a shift in demand and rescheduling of trips by travelers. However, far more travelers tend not to travel, instead of rescheduling a trip.

9.3. Perception and Compliance

From the theoretical framework follows that the impact of weather codes on travel behavior is influenced by the compliance of travelers towards advice. More specifically in this case, the advice refers to the advice that accompanies a weather code. It is hypothesized that reliability of weather codes and the prevailing sentiment during the activation period of a weather code are a proxy for the unreliability of information, which influences the compliance of travelers towards advice.

First, it is analyzed whether the reliability of the previous weather code correlates with the impact of the next weather code. Per hour for which a weather code was active it is checked whether the weather characteristics exceed the threshold values that are determined for the activated weather code. If so, the reliability is 1, while it is 0 if the threshold values are not met. The reliability of a code is then determined per day by taking the mean of all hourly reliability scores for the hours for which a code was active. When we plot these reliability scores against the deviations from the expected counts of the next code day, we can see that they are significantly correlated on a 95% confidence interval. It is observed that a low reliability for the previous weather code is often paired with a lower impact for the next weather code.

Secondly, Tweets are analyzed during three days for which a code was active, to see whether reliability of a weather code, or previous weather codes are affecting the sentiment with respect to weather codes. 1438 tweets were manually assessed on their sentiment. 18 of these tweets were defined to be negative regarding the weather code. With this small dataset left, drawing conclusions is hard. It could however be observed that a low reliability does not always lead to more negative sentiment.

10 Discussion and Further Research

This last Chapter will end the research with a discussion on the methods that are used to come to results, and the results themselves. Furthermore, recommendations are done for further research

10.1. Discussion

This research adds new insights into the field responses of travelers towards weather and, more specifically, towards weather codes. Besides this work, the author of this report found one other work on this theme, found in van Stralen et al. (2015). However, as this concerned a stated choice research, this report is the first revealed preference research on the effects of weather codes and weather related travel advices on travel behavior.

The results for the influences of weather codes can only be compared to the work of van Stralen et al. (2015). This paper includes not only trip frequency choice and departure time choice, but route choice and mode choice as well. However, departure time choice was included here as the choice to not travel during the morning peak. The stated choice results for trip frequency choice were confirmed by the research in this report, as travel demand decreased for hours with a weather code. The work of van Stralen et al. (2015) includes only code red (weather alarm), whereas this report also included codes yellow and codes orange. The inclusion of codes orange resulted in interesting results, whereas codes orange for slipperiness and snow were significant on multiple road segments.

Thunderstorms and slipperiness were included in the weather variables as dummies. Historical data from the KNMI did not allow us to differentiate between 'some thunder' and 'heavy thunder'. First of all, this might have reduced the significance of the results for these weather variables. Secondly, this has implications for the way we can measure the reliability of weather codes for these weather types.

Information on weather codes has been retrieved from fact sheets that are published by the KNMI. These fact sheets do not always provide information on the exact timing of a weather code. Furthermore, no information is known on the timing of the communication of these weather codes towards the public. When a weather code is communicated far before the activation, this might lead to different travel behavior than when a weather code is activated on relatively short notice.

Although the manual corrections and deseasonalization process in Chapter 5 and, to a lesser extend, the weather and weather code regression in Chapter 6 take a way a lot of variability, there are still some unexplained trends and peaks in travel demand. Although road segments are analyzed that are relatively low on congestion, this variability can probably be explained to some extend by the traffic intensity. Furthermore, incidents can have big impacts on traffic volumes, as road capacity can be severely decreased in case of closed lanes.

The results in Chapter 6 yield information on the coefficients and significance of weather variables. However, the research methods as proposed were not aimed at optimally modeling the effects of weather on travel behavior. Interaction effects between time and weather, or collinearity between weather characteristics themselves are not taken into account. Therefore, improvements are possible for measuring the effect of weather on travel demand.

Societal Relevance

As mentioned in Chapter 3, the theme of weather codes is often part of the societal debate. As the use and effectiveness of weather codes are criticized in opinion articles, this report shows what the empirically measurable effects were of the weather codes in the last three and a half year. As weather codes do clearly affect travel demand, we can state that some citizens take the advices of the KNMI into account. Note that this is an additional effect, besides weather effects themselves. So even though travelers are able to assess safety risks while traveling themselves, as stated in Chorus (2010), people are influenced by the risk assessment of the government, or the KNMI. Although the meaning of different codes is not always clear for travelers, the regression results show that codes red are more often taken seriously than codes orange. Codes orange are in turn more often taken seriously than codes yellow. From this we might conclude that, although unclarities might exist, the average traveler is more likely to adjust his travel behavior during a more serious warning.

For the road authority (RWS), who is guarding the safety of roads, this change in travel behavior is positive. Safety is decreasing if cars are closer to each other, which happens more in the case of high traffic intensity. The decrease in travel demand during weather codes might provide safer infrastructure in comparison to a situation without weather codes.

During the analysis of Twitter data, and while assessing the reliability of weather codes, it was observed that the timing of weather codes is often not accurate. As the reliability of weather codes was slightly correlated with the impact on travel demand for the next weather code, it is a risk to issue a weather code unnecessarily. A surplus of weather codes might lead to less travelers changing behavior, which might have consequences for instances where extreme weather does indeed disrupt the society.

Although changes in travel behavior can be observed during weather codes, we can also observe that the large share of travelers is making a trip even during codes red. It is the belief of the author of this report that this is the consequence of the attitude of travelers towards weather related warnings from the KNMI. This is consistent with the statements in Chorus (2010), saying that one advice or weather code is to generic for individual travelers.

The conclusion that weather codes in the current state have impacts on travel behavior, do not imply that abolishment of weather codes would lead to more travel demand. As the KNMI takes some of the responsibility of travelers away to determine weather it is safe to travel, travelers might be less regardful towards the weather itself. As predictions on weather are likely to become more accurate and information is becoming more accessible for travelers with an increase in internet connectivity, travelers might be more capable of assessing risks for themselves than in the past.

10.2. Recommendations for Further Research

The approach taken in this research provided new insights, but also had its limitations. The wish to include data for different provinces, which allowed us to assess more weather codes, led to the choice to only include highway segments. As demand patterns can be different for secondary roads, it would be interesting to do similar analyses for these secondary roads. This statement is supported by van Stralen et al. (2015), who found that a weather alarm was of significant influence for the choice of avoiding the motorway.

Autoregression played a part in the models with which the impacts of weather codes on travel demand were calculated. However, it is likely that the variable time plays a bigger role in the composition of travel demand. For example, the combination of weather characteristics with time might have a specific effect on travel demand. Besides this, combinations of different weather characteristics might alter travel demand. We could for example hypothesize that the combination of warm weather and sunshine leads to more people traveling towards for example beaches. Future research can be conducted, including such interaction effects.

The research in this report does not differentiate on travel purpose. Stated preference work points out that differences can be measured between changes in travel behavior for utilitarian and recreational trips, when varying the weather circumstances (van Stralen et al., 2015). We can imagine that people who feel less obligated to make a trip are more likely to be influenced by weather codes as well. The research in this report does not touch upon such hypotheses. Future research could model the share of travelers with a certain travel purpose, for example by looking at the functions of the urban areas in the origin and destination location. For example, more recreational trips are expected to and from shopping malls, while more utilitarian trips are expected to and from business districts. Differences in changes in travel demand between these two types of locations can be a proxy for the compliance rate of travelers of different travel purposes.

The research in this report assumes that travelers are primarily influenced by weather, and subsequently can be additionally influenced by weather codes. However, no research has been found that confirms this assumption by means of a stated choice experiment. It's recommended for future research to look into the causal relationships into the field of weather, weather codes and their impacts on travel behavior. This can be done by means of a stated choice experiment in which travelers prioritize the variables that influence their travel behavior.

Although substantial efforts were made, the research in this report yielded summary conclusions with respect to the relation between sentiment and compliances rates. It proved to be hard to use Twitter data for this purpose. However, the insights that the research aimed to give might be valuable for insights into the best way of communicating about the weather codes. Furthermore, insights into the motivations for the choice of travelers to (not) make a trip during the active period of a weather code might be revealed if the sentiment amongst travelers can be analyzed. Future research might be conducted with the help of surveys, that collect data during, or just after the occurrence of a weather code. This survey should be aimed at revealing travelers opinions with regards to the KNMI issuing the code. Besides this, questions should be asked on the motivations of travelers to stay home, or to make a trip and disregarding the travel advices. Furthermore, artificial intelligence (AI) is increasingly powerful in analyzing text. New tools might be able to decide whether a Tweet or a news article is about a weather code. With this, larger amounts of tweets might be harvested than was done with the query in this research. From this larger data set, AI might also be capable of determining some form of average sentiment. One of the limitations of the sentiment analysis in this research was that the tweets were in Dutch. As new developments in natural language processing (NLP) are mainly done in the English language, research on sentiment with regards to weather codes might prove to be easier for an English speaking country. Another limitation of this research was that a large share of the tweets were (re-)tweets of news articles that were neutrally stating the conditions of the weather or the weather code. If researchers are able to filter out this type of tweets, the resulting list of tweets contains a higher share of tweets with opinions on the weather code.

10.3. Recommendations for Stakeholders

As discussed in Section 3.2, the results of this research might be interesting for the KNMI and RWS. From the results, some recommendations can be drawn up.

The KNMI states that it hopes that advices that are given with weather codes are taken seriously by travelers. As seen in the analyses of this report, low reliability of the previous weather code is often paired with a low compliance rate towards travel advices. As the compliance rate is seen as a proxy for how serious travelers take the advice of the KNMI, this means that it is important for the KNMI that weather codes are reliable. Making the weather code more location specific and more time specific might be helpful for this reliability. Nowadays, weather codes are issued per province, while extreme weather can occur very local. Furthermore, the timing of a weather code is often unclear. Even the official documentation of the KNMI does not always provide an answer on the precise activation time of a weather code. This makes it harder for travelers to reschedule their trip towards a time outside the activation period. Furthermore, when a code red is issued while the extreme weather is not occurring yet, travelers might think that the weather code is unnecessary.

For the RWS, we can conclude that, as some weather codes influence travel behavior, weather codes are a valuable variable to include in traffic forecasting models. The RWS can expect less traffic in the case of weather codes red for slipperiness, snow and wind, and for codes orange for slipperiness and snow. If this updated traffic forecasting model is combined with models that can predict congestion or chances on accidents, the chances on congestion and accidents during weather codes can be more accurately predicted.

As the RWS is aiming to reduce the amount of trips during the active period of weather codes, it might be useful to search for other ways to reduce the amount of trips during extreme weather. The weather code and its advices are reducing the amount of trips, but still the larger share of trips is undertaken. Apparently, the majority of travelers is not willing to change travel behavior due to advises from the KNMI.

A Weather Codes Overview

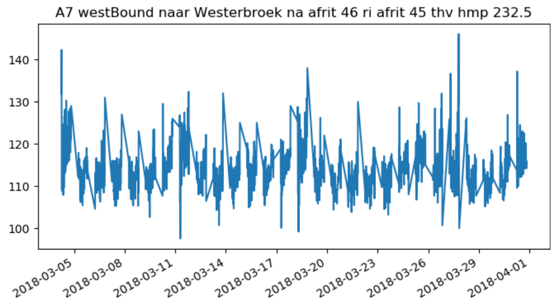
This Appendix gives an overview of all the days on which there was a code orange or code red issued. Although codes yellow are included for the days that yielded a code orange or red as well, days that yield only code yellow are not logged. The columns represent the provinces and regions for which the KNMI separately issues weather codes: Drenthe (Dr), Flevoland (Fl), Friesland (Fr), Gelderland (GD), Gronignen (Gr), Limburg (LB), Noord-Brabant (NB), Noord-Holland (NH), Overijssel (Ov), Utrecht (Ut), Wadden Islands (Wa), Zeeland (ZL) and Zuid-Holland (ZH).

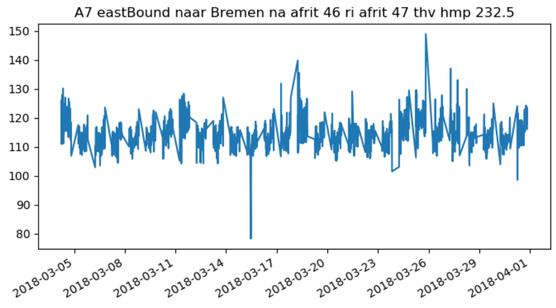
Table A.1: Weather codes per day per province between 2015 and 2018 (KNMI, 2018b)

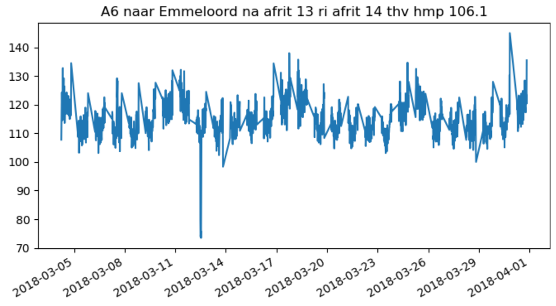
Reason	Date	Dr	Fl	Fr	GD	Gr	LB	NB	NH	Ov	Ut	Wa	ZL	ZH
Wind gusts	25-07-15													
Thunderstorm	31-08-15													
Wind gusts	17-11-15													
Wind gusts	29-11-15													
Slipperiness	3-01-16													
Slipperiness	4-01-16													
Slipperiness	5-01-16													
Slipperiness	6-01-16													
Slipperiness	8-01-16													
Thunderstorm	30-05-16													
Thunderstorm	7-06-16													
Thunderstorm	20-07-16													
Slipperiness	1-01-17													
Slipperiness	6-01-17													
Slipperiness	12-01-17													
Wind gusts	23-02-17													
Thunderstorm	19-07-17													
Wind gusts	13-09-17													
Wind gusts	5-10-17													
Slipperiness	9-12-17													
Slipperiness	10-12-17													
Slipperiness	11-12-17													
Slipperiness	17-12-17													
Wind gusts	3-01-18													
Wind gusts	17-01-18													
Wind gusts	18-01-18													
Thunderstorm	27-05-18													
Thunderstorm	29-05-18													
Count code orange		9	9	13	12	14	11	12	9	13	11	10	7	10
Count code red		4	2	4	2	4	0	2	3	2	2	0	2	3

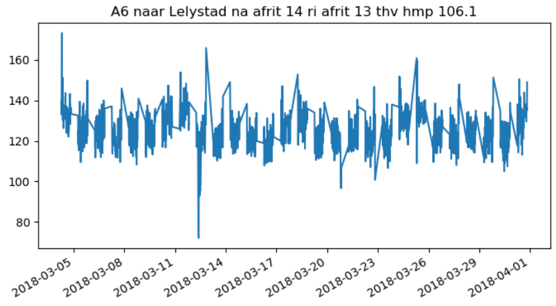
B Speed Diagrams

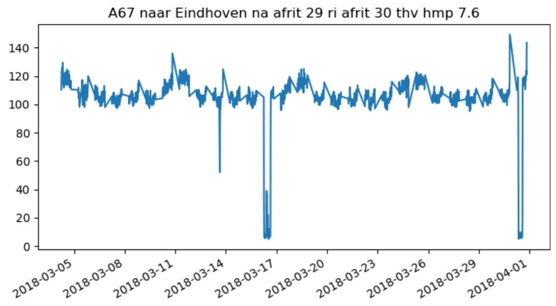
The following diagrams show the average speeds on road segments, driven between the 4th and 31st of March 2018, between 6AM and 8PM. All data is gathered from the NDW database. All counts are aggregated on 15 minute intervals.

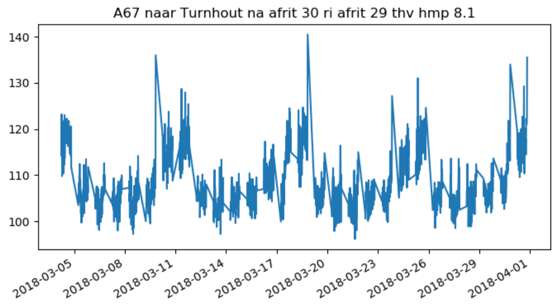

A7 westBound naar Westerbroek na afrit 46 ri afrit 45 thv hmp 232.5

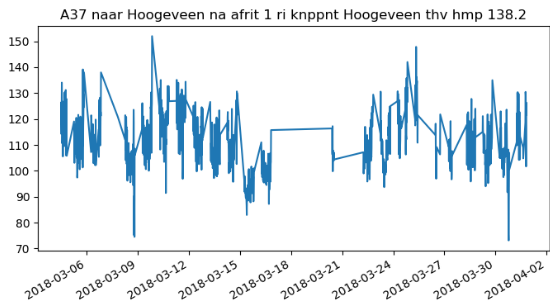

A7 eastBound naar Bremen na afrit 46 ri afrit 47 thv hmp 232.5

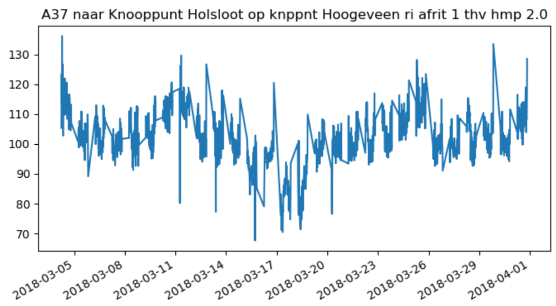

A6 naar Emmeloord na afrit 13 ri afrit 14 thv hmp 106.1

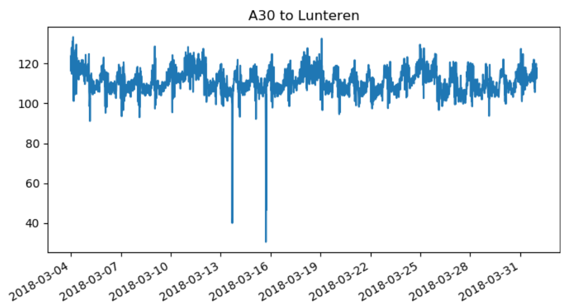

A6 naar Lelystad na afrit 14 ri afrit 13 thv hmp 106.1

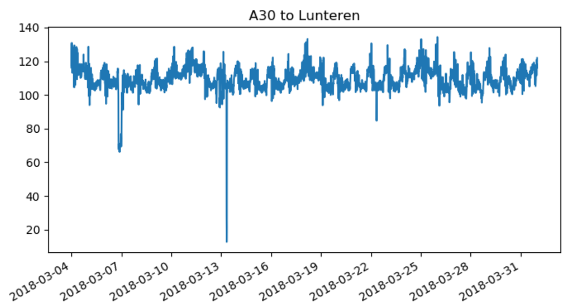

A67 naar Eindhoven na afrit 29 ri afrit 30 thv hmp 7.6

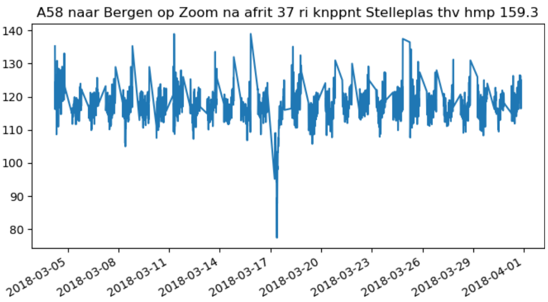

A67 naar Turnhout na afrit 30 ri afrit 29 thv hmp 8.1

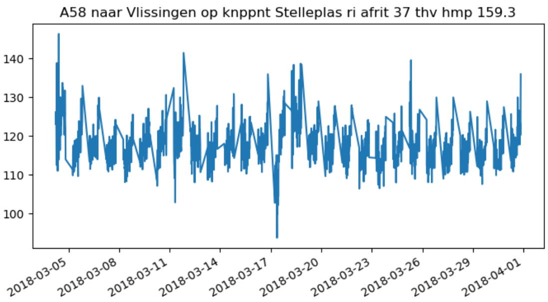

A37 naar Hoogeveen na afrit 1 ri knppnt Hoogeveen thv hmp 138.2

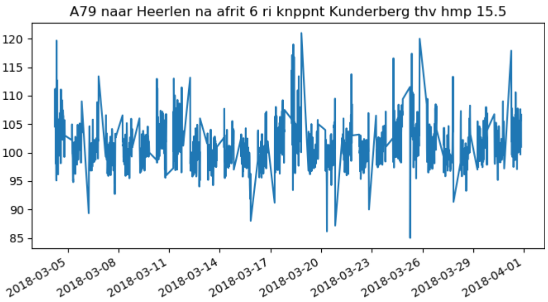

A37 naar Knooppunt Holsloot op knppnt Hoogeveen ri afrit 1 thv hmp 2.0

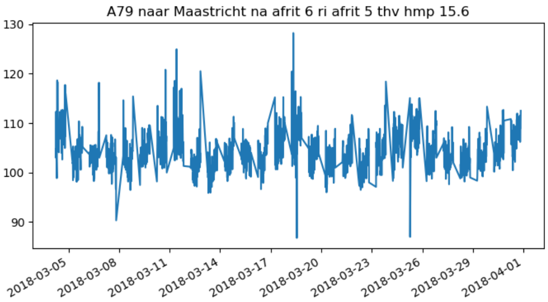

A30 to Lunteren

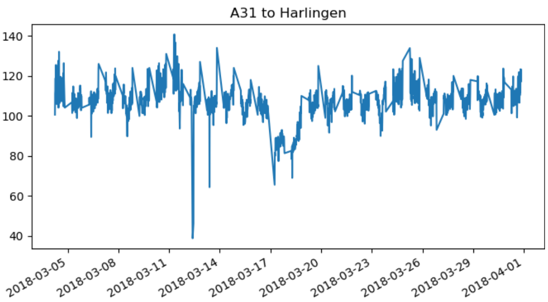

A30 to Lunteren

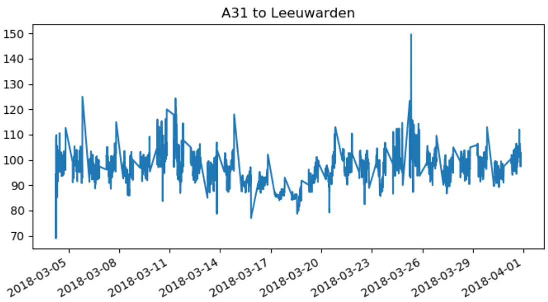

A58 naar Bergen op Zoom na afrit 37 ri knppnt Stelleplas thv hmp 159.3

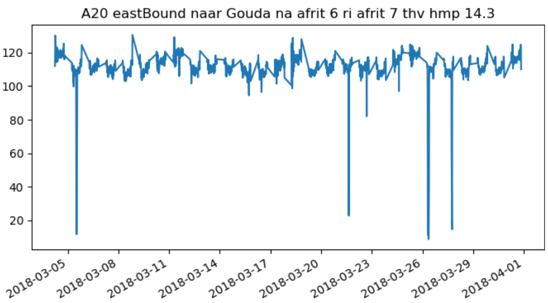

A58 naar Vlissingen op knppnt Stelleplas ri afrit 37 thv hmp 159.3

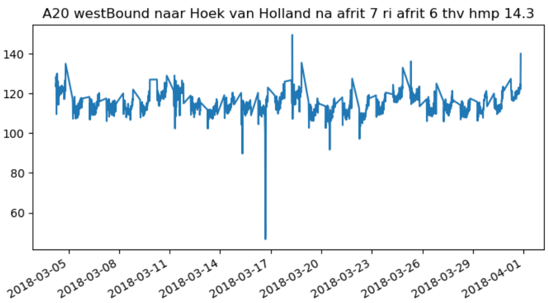

A79 naar Heerlen na afrit 6 ri knppnt Kunderberg thv hmp 15.5

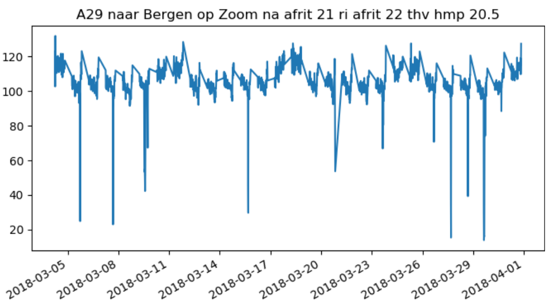

A79 naar Maastricht na afrit 6 ri afrit 5 thv hmp 15.6

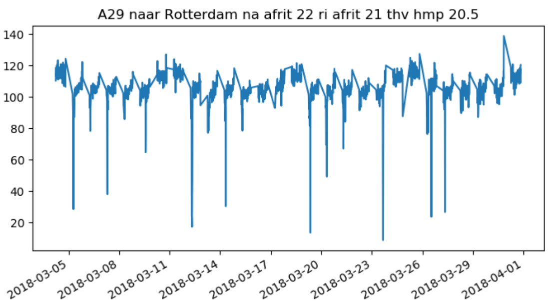

A31 to Harlingen


A31 to Leeuwarden


A20 eastBound naar Gouda na afrit 6 ri afrit 7 thv hmp 14.3


A20 westBound naar Hoek van Holland na afrit 7 ri afrit 6 thv hmp 14.3


A29 naar Bergen op Zoom na afrit 21 ri afrit 22 thv hmp 20.5


A29 naar Rotterdam na afrit 22 ri afrit 21 thv hmp 20.5

C Manual Inspection

A20 Zuid-Holland

For the A20 segment, a drop in counts can be seen in December 2015. This drop can be explained by the opening of the A4, which serves as an alternative route for routes that use the A20.

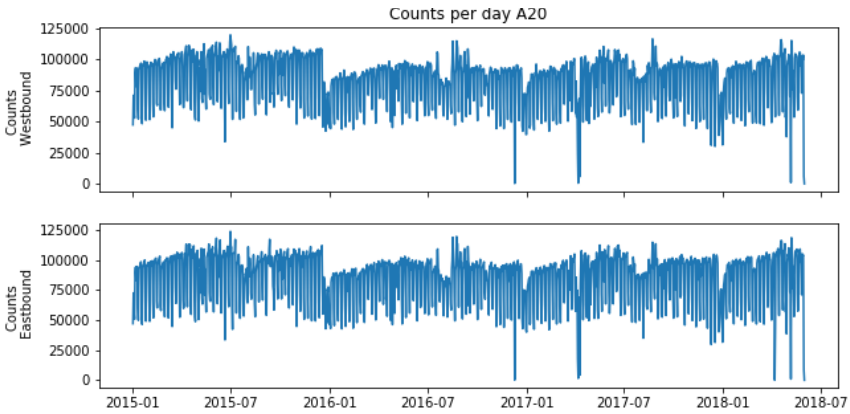


Figure C.1: Daily counts on the A20

A6 Flevoland

For the eastbound direction, a drop in counts can be observed in May 2017. Furthermore, the dataset for the westbound direction misses records from May 2018 onwards. The eastbound direction dataset misses data from April 2018 onwards.

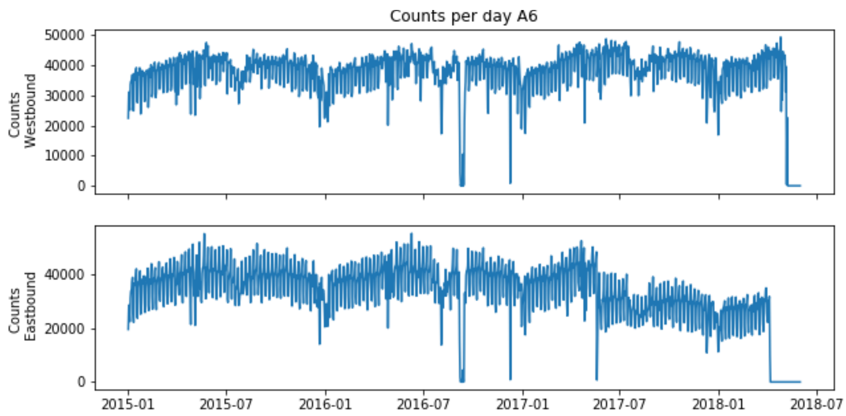


Figure C.2: Daily counts on the A6

A37 Drenthe

The counts for the westbound direction of the A37 follow a relatively unstable trend in comparison to other trends. As the variability that cannot be explained by weather circumstances is relatively high, estimation of the impacts of these weather circumstances will be tough. For this reason, the westbound direction of the A37 will be left out of the scope of this research.

The data for the eastbound direction runs until March 2018.

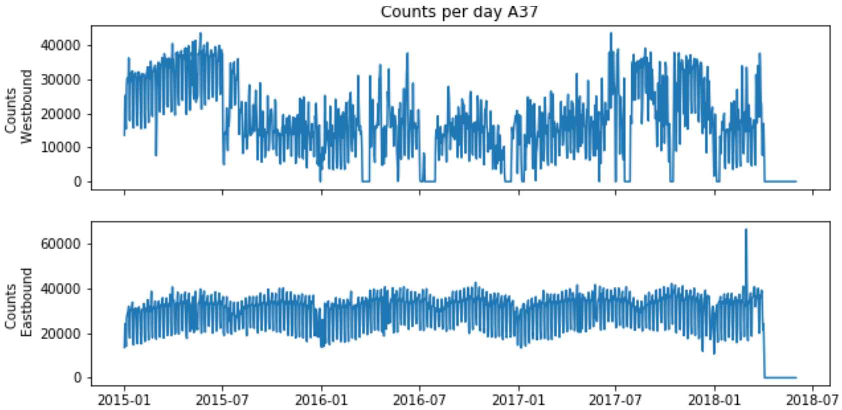


Figure C.3: Daily counts on the A37

A58 Zeeland

For the A58, no break in the trend is observed. Both directions have records until March 2018.

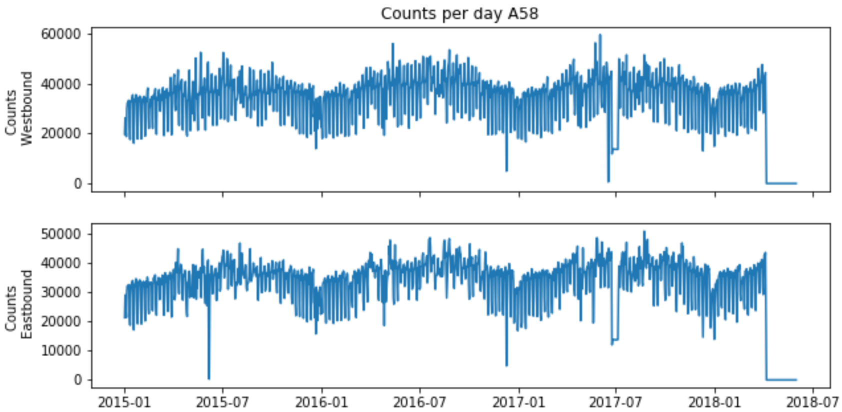


Figure C.4: Daily counts on the A58

A30 Gelderland

For the A30, no break in the trend is observed.

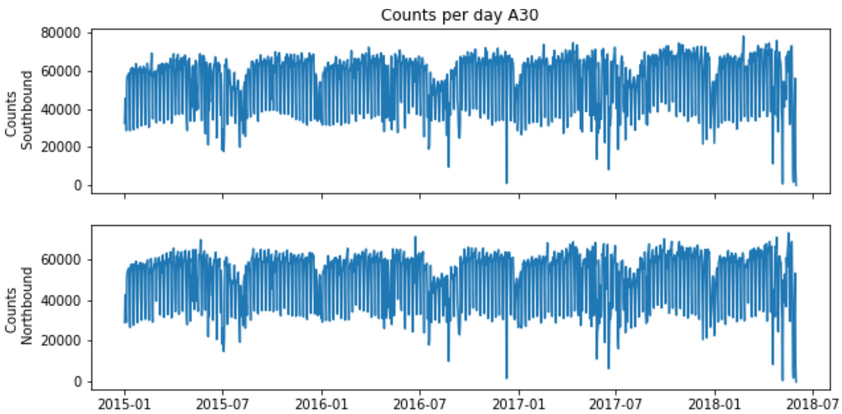


Figure C.5: Daily counts on the A30

A31 Friesland

For the westbound direction of the A31, a dip in traffic can be observed between November 2015 and June 2016. The rest of the year, and the full dataset for the eastbound direction yield a steady trend. However, relatively many peaks can be observed in comparison to other trends.

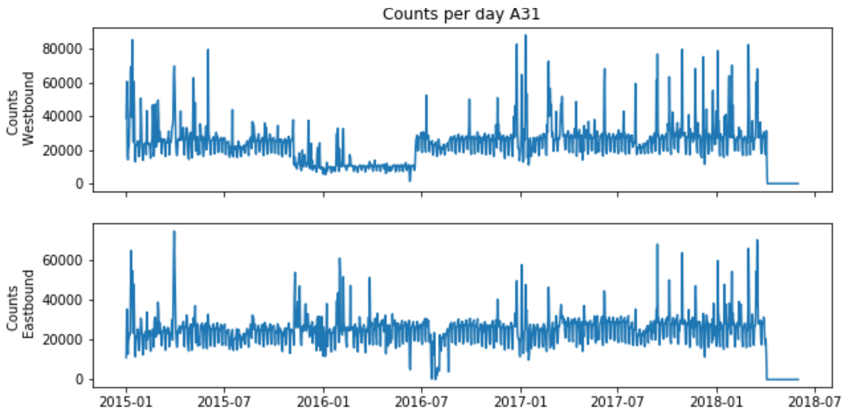


Figure C.6: Daily counts on the A31

A7 Groningen

No breaks in the trend can be observed for the A7. The eastbound direction has records from May 2015 onwards.

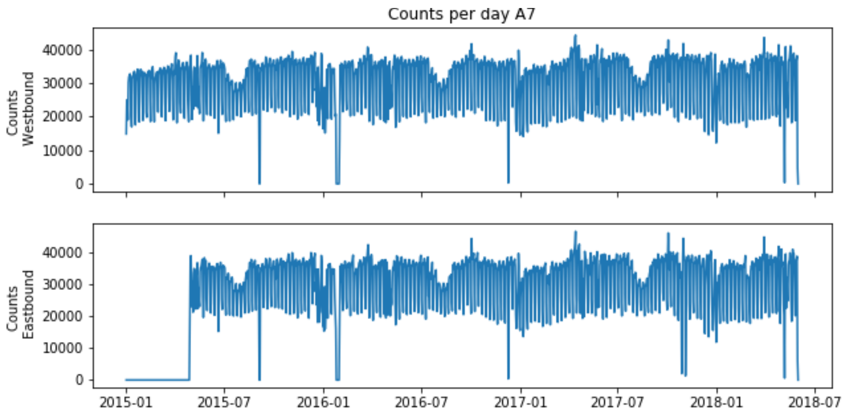


Figure C.7: Daily counts on the A7

D Deseasonalization

A20 Zuid-Holland

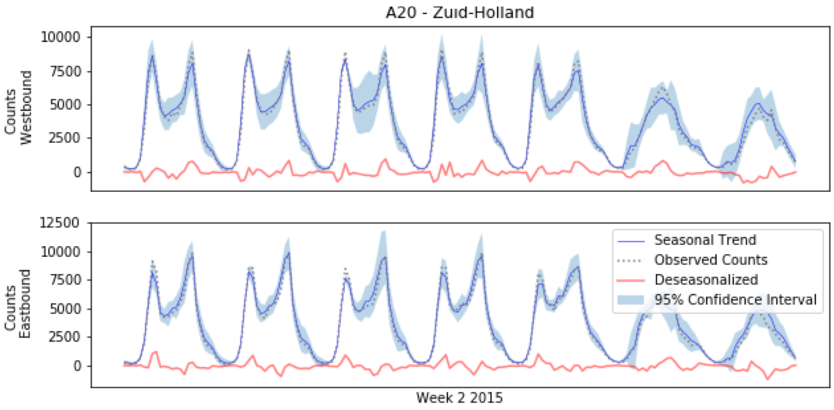


Figure D.1: Random week with the Expected Counts Based on the Weekly Trend

A6 Flevoland

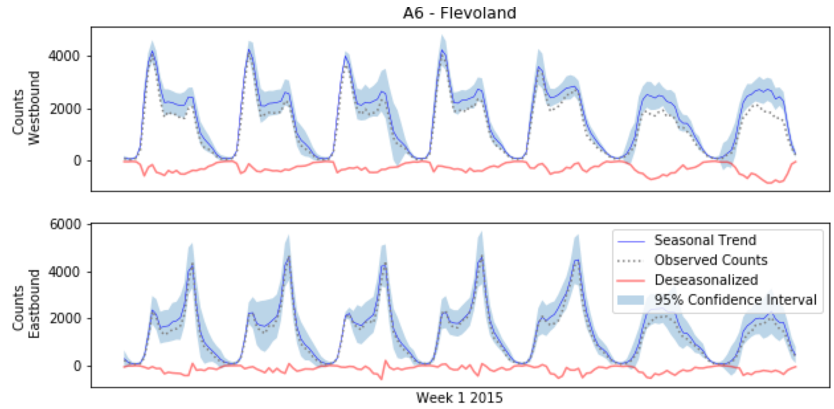


Figure D.2: Random week with the Expected Counts Based on the Weekly Trend

A37 Drenthe

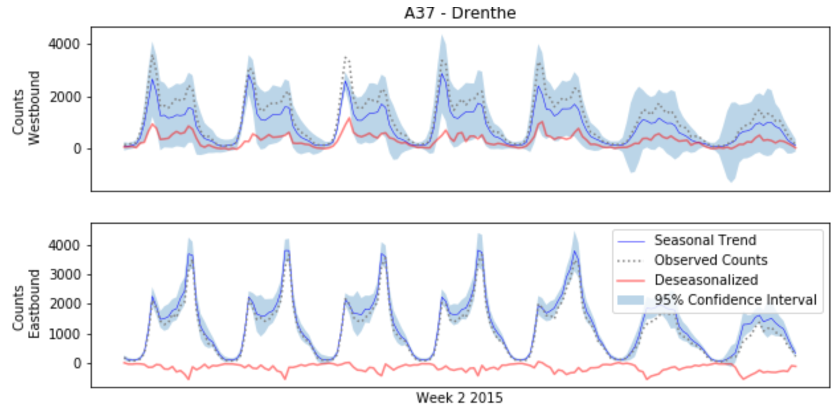


Figure D.3: Random week with the Expected Counts Based on the Weekly Trend

A58 Zeeland

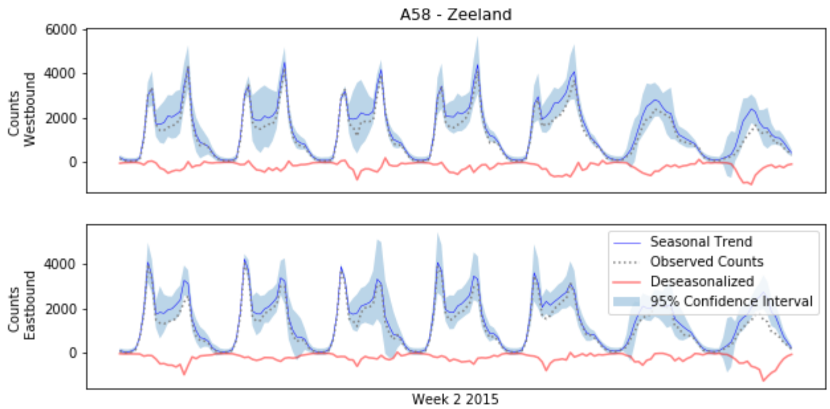


Figure D.4: Random week with the Expected Counts Based on the Weekly Trend

A30 Gelderland

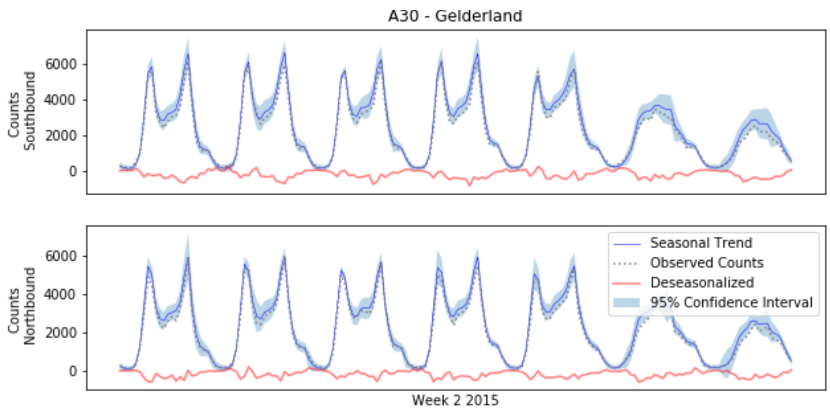


Figure D.5: Random week with the Expected Counts Based on the Weekly Trend

A31 Friesland

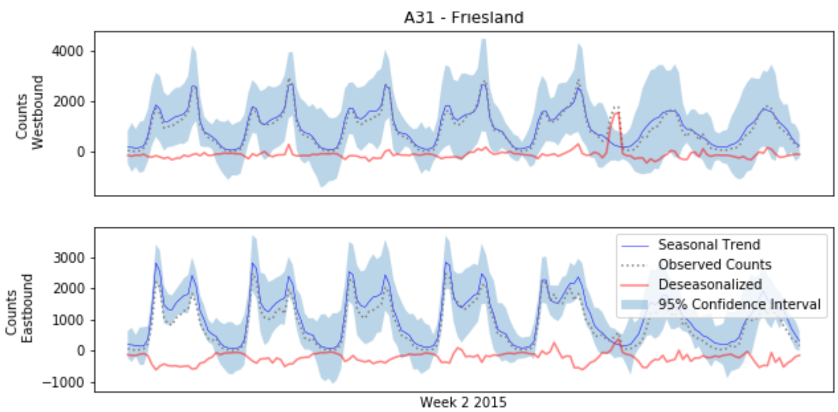


Figure D.6: Random week with the Expected Counts Based on the Weekly Trend

A7 Groningen

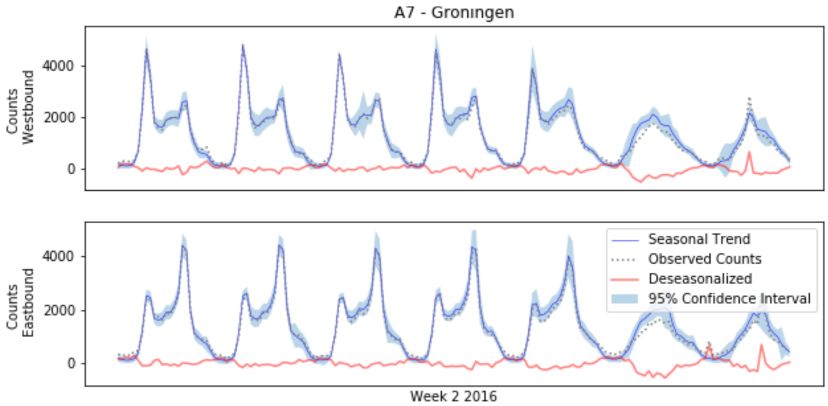


Figure D.7: Random week with the Expected Counts Based on the Weekly Trend

E Weather Characteristics

A20 Zuid-Holland

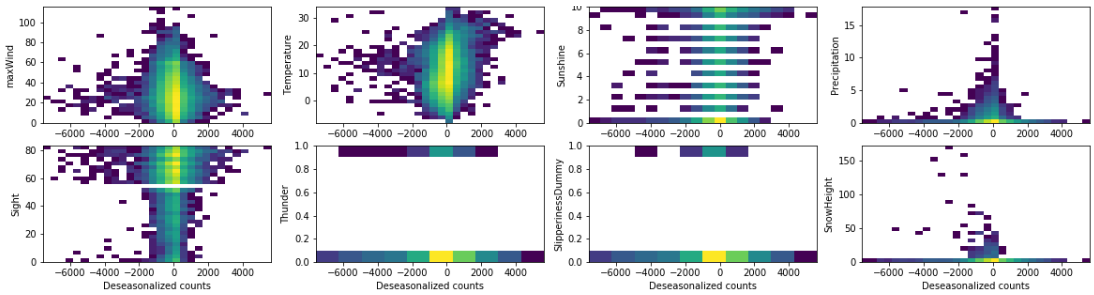


Figure E.1: Deseasonalized counts and weather characteristics for the A20

A6 Flevoland

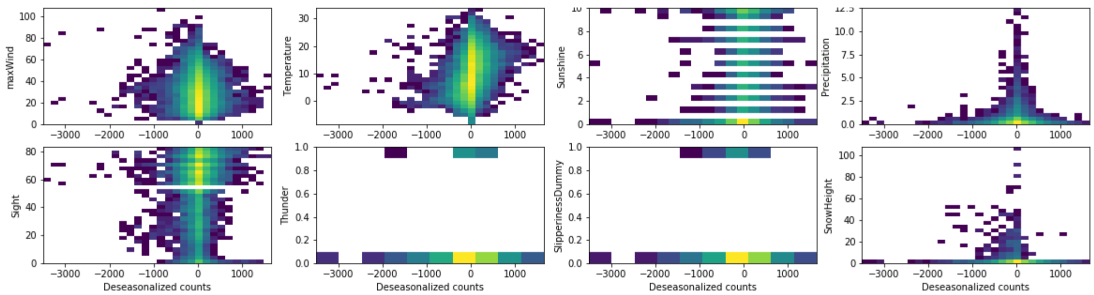


Figure E.2: Deseasonalized counts and weather characteristics for the A6

A37 Drenthe

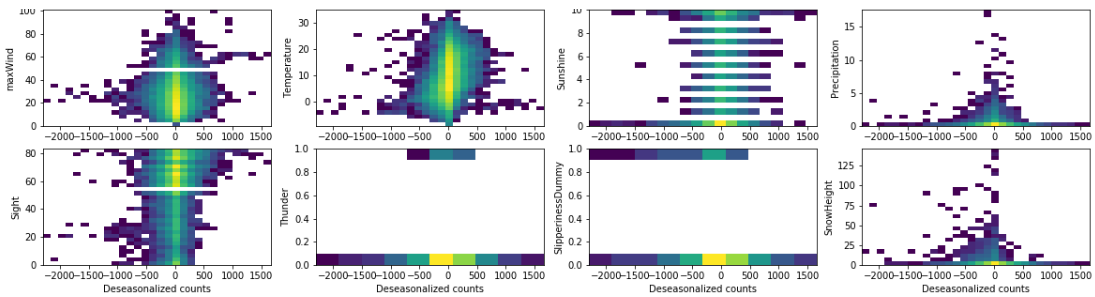


Figure E.3: Deseasonalized counts and weather characteristics for the A37

A58 Zeeland

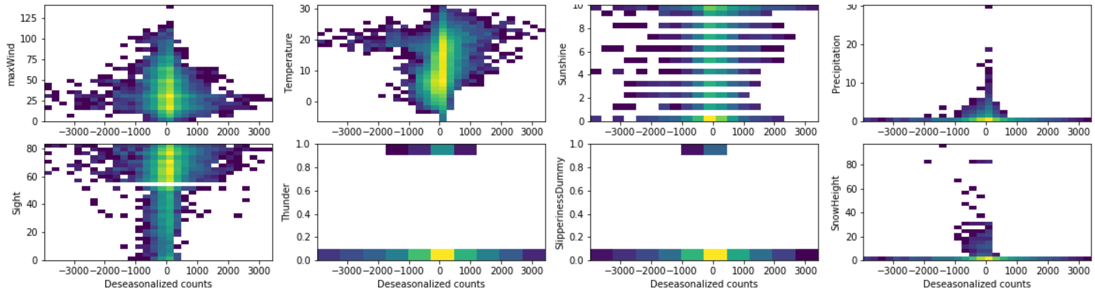


Figure E.4: Deseasonalized counts and weather characteristics for the A58

A30 Gelderland

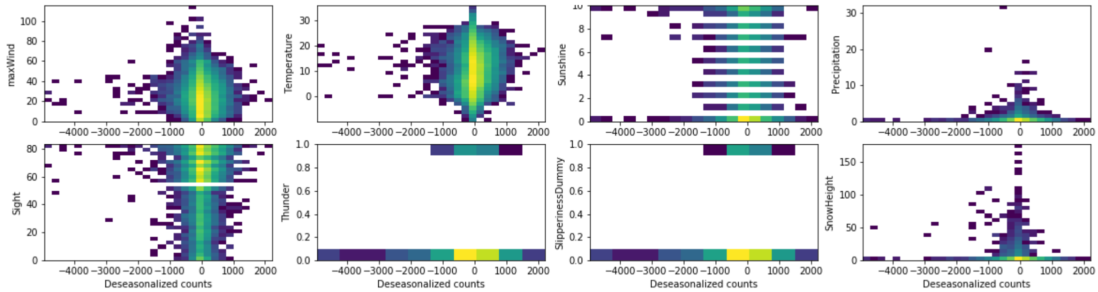


Figure E.5: Deseasonalized counts and weather characteristics for the A30

A31 Friesland

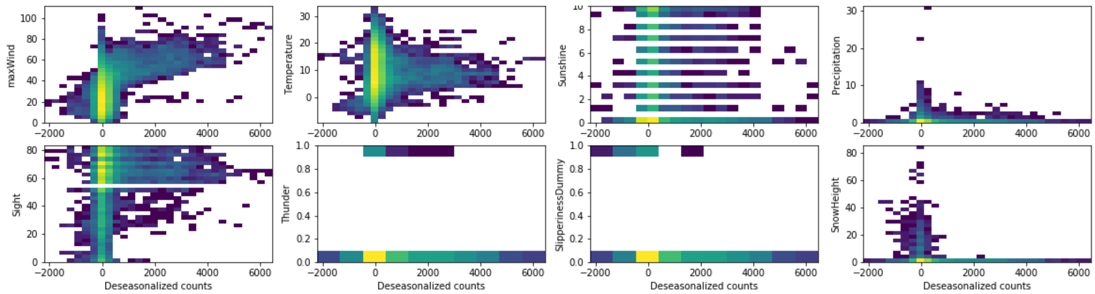


Figure E.6: Deseasonalized counts and weather characteristics for the A31

A7 Groningen

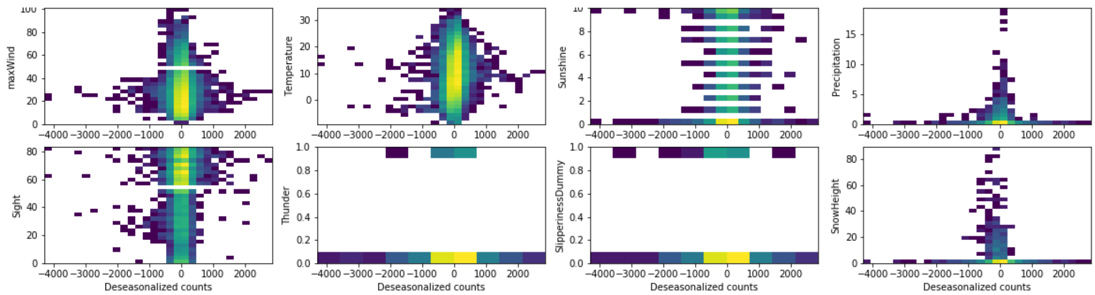


Figure E.7: Deseasonalized counts and weather characteristics for the A7

F Model Results - Linear Regression

In this Appendix, the linear regression results can be found for all seven road segments.

A20 Zuid-Holland

	Model: A20 Westbound
No. Observations	22874
Deg. of freedom	17
Log-Likelihood	-175394
R-squared	0,081
Durbin-Watson	0,843

	Model: A20 Eastbound
No. Observations	22786
Deg. of freedom	17
Log-Likelihood	-175106
R-squared	0,067
Durbin-Watson	0,809

	Coeff	Std error	p-value
maxWind	-3,905	0,250	0,000
Temperature	16,185	0,622	0,000
Sunshine	9,589	1,055	0,000
Precipitation	-45,854	6,958	0,000
Sight	-2,052	0,148	0,000
Thunder	-64,939	40,325	0,107
SlipperinessDummy	-112,246	42,058	0,008
SnowHeight	-10,717	1,228	0,000
Slipperiness_1.0	-207,837	231,696	0,370
Snow_1.0	216,844	164,934	0,189
Snow_2.0	-249,424	107,658	0,021
Snow_3.0	-947,853	157,446	0,000
Thunderstorm_1.0	-18,238	134,654	0,892
Thunderstorm_2.0	-94,300	127,815	0,461
Wind_1.0	-251,478	134,220	0,061
Wind_2.0	-186,276	85,682	0,030
Wind_3.0	-780,811	211,827	0,000

	Coeff	Std error	p-value
maxWind	-4,227	0,255	0,000
Temperature	16,348	0,633	0,000
Sunshine	2,704	1,075	0,012
Precipitation	-48,677	7,079	0,000
Sight	-1,249	0,151	0,000
Thunder	-13,803	41,015	0,736
SlipperinessDummy	-17,521	42,777	0,682
SnowHeight	-10,512	1,249	0,000
Slipperiness_1.0	256,330	235,659	0,277
Snow_1.0	250,189	167,754	0,136
Snow_2.0	-280,537	109,500	0,010
Snow_3.0	-1124,320	160,139	0,000
Thunderstorm_1.0	83,080	136,957	0,544
Thunderstorm_2.0	494,528	130,001	0,000
Wind_1.0	-254,284	136,517	0,063
Wind_2.0	-331,740	87,149	0,000
Wind_3.0	-571,339	235,824	0,015

A6 Flevoland

	Model: A6 Westbound
No. Observations	22204
Deg. of freedom	17
Log-Likelihood	-149206
R-squared	0,157
Durbin-Watson	0,692

	Model: A6 Eastbound
No. Observations	21632
Deg. of freedom	17
Log-Likelihood	-150841
R-squared	0,306
Durbin-Watson	0,838

	Coeff	Std error	p-value
maxWind	-1,978	0,107	0,000
Temperature	10,341	0,261	0,000
Sunshine	0,713	0,426	0,094
Precipitation	-7,320	3,159	0,020
Sight	-0,637	0,061	0,000
Thunder	15,114	16,795	0,368
SlipperinessDummy	-27,388	14,198	0,054
SnowHeight	-2,080	0,460	0,000
Slipperiness_1.0	-49,638	17,238	0,004
Slipperiness_2.0	-258,818	15,039	0,000
Snow_1.0	-57,657	7,233	0,000
Snow_2.0	-385,348	38,534	0,000
Snow_3.0	-1,045	17,237	0,952
Thunderstorm_1.0	-31,541	3,584	0,000
Wind_1.0	52,602	3,436	0,000
Wind_2.0	-25,861	12,411	0,037
Wind_3.0	51,283	4,817	0,000

	Coeff	Std error	p-value
maxWind	-0,477	0,140	0,001
Temperature	12,248	0,347	0,000
Sunshine	7,849	0,559	0,000
Precipitation	-8,048	4,092	0,049
Sight	0,313	0,079	0,000
Thunder	43,230	22,139	0,051
SlipperinessDummy	27,045	18,291	0,139
SnowHeight	-2,717	0,593	0,000
Slipperiness_1.0	5,280	22,206	0,812
Slipperiness_2.0	-209,979	19,378	0,000
Snow_1.0	-2,558	9,329	0,784
Snow_2.0	-408,803	49,644	0,000
Snow_3.0	-64,722	22,211	0,004
Thunderstorm_1.0	-7,602	4,625	0,100
Wind_1.0	32,528	4,433	0,000
Wind_2.0	-65,101	15,996	0,000
Wind_3.0	-3,533	7,197	0,624

A37 Drenthe

	Model: A37 Eastbound
No. Observations	21872
Deg. of freedom	17
Log-Likelihood	-140940
R-squared	0,13
Durbin-Watson	0,745

	Coeff	Std error	p-value
maxWind	-0,480	0,085	0,000
Temperature	5,736	0,179	0,000
Sunshine	-0,888	0,330	0,007
Precipitation	-14,544	2,273	0,000
Sight	-0,348	0,044	0,000
Thunder	11,959	13,546	0,377
SlipperinessDummy	-67,994	8,827	0,000
SnowHeight	-2,142	0,290	0,000
Slipperiness_2.0	-354,476	21,450	0,000
Slipperiness_3.0	-573,236	19,911	0,000
Snow_1.0	161,774	59,128	0,006
Snow_2.0	-162,108	27,111	0,000
Snow_3.0	-481,553	55,418	0,000
Thunderstorm_1.0	-139,501	40,797	0,001
Thunderstorm_2.0	-41,723	68,635	0,543
Wind_1.0	9,084	21,337	0,670
Wind_2.0	-62,992	62,419	0,313

A58 Zeeland

	Model: A58 Westbound
No. Observations	21841
Deg. of freedom	15
Log-Likelihood	-156433
R-squared	0,083
Durbin-Watson	0,357

	Model: A58 Eastbound
No. Observations	21842
Deg. of freedom	15
Log-Likelihood	-156362
R-squared	0,065
Durbin-Watson	0,326

	Coeff	Std error	p-value
maxWind	-2,221	0,132	0,000
Temperature	11,962	0,408	0,000
Sunshine	8,849	0,621	0,000
Precipitation	-6,679	4,582	0,145
Sight	-0,763	0,097	0,000
Thunder	3,085	27,017	0,909
SlipperinessDummy	-69,043	42,957	0,108
SnowHeight	-2,376	1,135	0,036
Slipperiness_1.0	-334,033	139,696	0,017
Slipperiness_2.0	0,000	0,000	0,003
Snow_1.0	-129,810	52,401	0,013
Snow_3.0	-403,046	103,961	0,000
Thunderstorm_1.0	-23,626	86,746	0,785
Thunderstorm_2.0	-184,234	127,579	0,149
Wind_1.0	28,249	64,361	0,661
Wind_2.0	14,453	53,899	0,789

	Coeff	Std error	p-value
maxWind	-1,748	0,132	0,000
Temperature	12,197	0,407	0,000
Sunshine	2,832	0,618	0,000
Precipitation	1,544	4,564	0,735
Sight	-0,920	0,097	0,000
Thunder	69,593	26,920	0,010
SlipperinessDummy	-41,506	42,804	0,332
SnowHeight	-2,450	1,131	0,030
Slipperiness_1.0	-83,936	139,197	0,547
Slipperiness_2.0	0,000	0,000	0,136
Snow_1.0	-208,926	52,214	0,000
Snow_3.0	-449,809	103,589	0,000
Thunderstorm_1.0	-112,390	86,436	0,194
Thunderstorm_2.0	412,544	127,123	0,001
Wind_1.0	-91,113	64,131	0,155
Wind_2.0	40,260	53,707	0,453

A30 Gelderland

	Model: A30 Westbound
No. Observations	22459
Deg. of freedom	17
Log-Likelihood	-158667
R-squared	0,049
Durbin-Watson	0,703

	Model: A30 Eastbound
No. Observations	22460
Deg. of freedom	17
Log-Likelihood	-155986
R-squared	0,05
Durbin-Watson	0,733

	Coeff	Std error	p-value
maxWind	-1,748	0,157	0,000
Temperature	6,036	0,332	0,000
Sunshine	-5,490	0,618	0,000
Precipitation	-6,884	3,787	0,069
Sight	0,389	0,078	0,000
Thunder	22,667	23,343	0,332
SlipperinessDummy	7,986	16,604	0,631
SnowHeight	-2,234	0,436	0,000
Slipperiness_1.0	0,000	0,000	0,000
Slipperiness_2.0	-236,247	37,611	0,000
Snow_1.0	-216,831	200,330	0,279
Snow_2.0	-215,653	52,832	0,000
Snow_3.0	-1101,713	83,752	0,000
Thunderstorm_1.0	-106,889	94,531	0,258
Thunderstorm_2.0	-152,653	67,899	0,025
Wind_1.0	48,058	49,779	0,334
Wind_2.0	25,841	65,125	0,692
Wind_3.0	-492,127	115,993	0,000

	Coeff	Std error	p-value
maxWind	-0,900	0,139	0,000
Temperature	5,372	0,294	0,000
Sunshine	-3,116	0,549	0,000
Precipitation	-13,782	3,359	0,000
Sight	0,111	0,069	0,106
Thunder	9,353	20,709	0,652
SlipperinessDummy	-6,272	14,756	0,671
SnowHeight	-3,466	0,387	0,000
Slipperiness_1.0	0,000	0,000	0,330
Slipperiness_2.0	-217,098	33,367	0,000
Snow_1.0	-222,277	177,726	0,211
Snow_2.0	-110,640	46,871	0,018
Snow_3.0	-940,184	74,302	0,000
Thunderstorm_1.0	-139,054	83,865	0,097
Thunderstorm_2.0	2,192	60,238	0,971
Wind_1.0	20,565	44,162	0,641
Wind_2.0	0,418	57,777	0,994
Wind_3.0	-266,367	102,905	0,010

A31 Friesland

	Model: A31 Westbound
No. Observations	21856
Deg. of freedom	16
Log-Likelihood	-166268
R-squared	0,37
Durbin-Watson	0,342

	Model: A31 Eastbound
No. Observations	21831
Deg. of freedom	16
Log-Likelihood	-157852
R-squared	0,228
Durbin-Watson	0,403

	Coeff	Std error	p-value
maxWind	22,208	0,238	0,000
Temperature	-1,940	0,605	0,001
Sunshine	4,448	1,023	0,000
Precipitation	-33,812	7,387	0,000
Sight	-6,610	0,140	0,000
Thunder	-99,088	53,626	0,065
SlipperinessDummy	-329,465	33,839	0,000
SnowHeight	-14,973	1,478	0,000
Slipperiness_2.0	-587,073	73,443	0,000
Slipperiness_3.0	-822,166	64,422	0,000
Snow_1.0	269,464	164,370	0,101
Snow_2.0	-481,218	86,719	0,000
Snow_3.0	-109,453	188,900	0,562
Thunderstorm_1.0	1,523	113,641	0,989
Wind_1.0	-349,620	112,033	0,002
Wind_2.0	1402,670	78,976	0,000

	Coeff	Std error	p-value
maxWind	10,892	0,163	0,000
Temperature	-0,971	0,415	0,019
Sunshine	5,026	0,702	0,000
Precipitation	-45,440	5,084	0,000
Sight	-4,476	0,096	0,000
Thunder	-3,096	37,200	0,934
SlipperinessDummy	-262,063	23,220	0,000
SnowHeight	-12,080	1,019	0,000
Slipperiness_2.0	-455,826	50,387	0,000
Slipperiness_3.0	-441,832	44,198	0,000
Snow_1.0	354,526	112,832	0,002
Snow_2.0	-293,777	59,506	0,000
Snow_3.0	-222,096	129,627	0,087
Thunderstorm_1.0	36,301	77,985	0,642
Wind_1.0	-137,370	76,862	0,074
Wind_2.0	1584,901	54,183	0,000

A7 Groningen

	Model: A7 Westbound
No. Observations	22739
Deg. of freedom	17
Log-Likelihood	-149734
R-squared	0,062
Durbin-Watson	0,72

	Model: A7 Eastbound
No. Observations	19069
Deg. of freedom	17
Log-Likelihood	-125359
R-squared	0,066
Durbin-Watson	0,738

	Coeff	Std error	p-value
maxWind	-0,516	0,092	0,000
Temperature	3,269	0,204	0,000
Sunshine	-1,788	0,370	0,000
Precipitation	-1,250	2,785	0,653
Sight	0,001	0,049	0,981
Thunder	-18,894	16,630	0,256
SlipperinessDummy	-15,072	9,396	0,109
SnowHeight	-3,383	0,426	0,000
Slipperiness_2.0	-356,898	23,800	0,000
Slipperiness_3.0	-523,636	21,841	0,000
Snow_1.0	97,335	65,149	0,135
Snow_2.0	-98,847	29,890	0,001
Snow_3.0	-90,816	71,912	0,207
Thunderstorm_1.0	-82,604	47,104	0,080
Thunderstorm_2.0	-27,294	49,818	0,584
Wind_1.0	-59,004	40,313	0,143
Wind_2.0	6,936	28,447	0,807

	Coeff	Std error	p-value
maxWind	-0,314	0,102	0,002
Temperature	2,268	0,218	0,000
Sunshine	-1,149	0,406	0,005
Precipitation	-2,374	2,936	0,419
Sight	0,046	0,053	0,384
Thunder	-24,490	17,616	0,164
SlipperinessDummy	-16,035	10,430	0,124
SnowHeight	-2,579	0,485	0,000
Slipperiness_2.0	-390,404	23,653	0,000
Slipperiness_3.0	-518,095	21,634	0,000
Snow_1.0	78,539	65,418	0,230
Snow_2.0	-203,222	29,646	0,000
Snow_3.0	-295,905	72,855	0,000
Thunderstorm_1.0	-86,779	46,633	0,063
Thunderstorm_2.0	-27,909	77,839	0,720
Wind_1.0	-37,242	39,902	0,351
Wind_2.0	26,901	28,242	0,341

G Model Results - Regression with Autoregressive Errors

In this Appendix, the results of all models that are used to determine the significance of weather and weather code influences are shown. The Sections of this appendix represent each of the measurement locations. Within these Sections, first the results of the full AR(1) model is presented, that includes both weather and code variables. The second table represents the outcomes same model, but rerun with parameters that are significant on a 95% confidence interval. The third table represents the model results for the AR(1) model with only weather variables included, after which the fourth table shows the same model with parameters that are significant on a 95% confidence interval. The last table shows the least squares regression model with weather codes only, with the residuals of the AR(1) model with only weather variables as the dependent variable. Note that per model there are two tables, for each road direction, with an exception for the A37.

A20 Zuid-Holland

Table G.1: AR(1) model results with weather and weather code variables

	Model: A20 Westbound
No. Observations	29927
Log-Likelihood	-170497
Durbin-Watson	2,063

	Coeff	Std error	p-value
maxWind	-3,450	0,356	0,000
Temperature	13,861	1,069	0,000
Sunshine	0,797	1,176	0,498
Precipitation	-33,754	4,483	0,000
Sight	-1,602	0,250	0,000
Thunder	-64,263	22,753	0,005
SlipperinessDummy	-111,976	66,528	0,092
SnowHeight	-9,255	2,134	0,000
Slipperiness_1.0	-207,797	465,168	0,655
Slipperiness_2.0	0,000		
Snow_1.0	216,769	296,902	0,465
Snow_2.0	-249,435	318,158	0,433
Snow_3.0	-947,740	121,897	0,000
Thunderstorm_1.0	-18,197	205,452	0,929
Thunderstorm_2.0	-94,266	214,421	0,660
Wind_1.0	-251,338	185,415	0,175
Wind_2.0	-185,877	48,179	0,000
Wind_3.0	-780,813	449,963	0,083
ar.L1	0,609	0,002	0,000

	Model: A20 Eastbound
No. Observations	29927
Log-Likelihood	-169848
Durbin-Watson	2,095

	Coeff	Std error	p-value
maxWind	-3,689	0,381	0,000
Temperature	14,135	1,188	0,000
Sunshine	-0,974	1,120	0,384
Precipitation	-17,096	5,143	0,001
Sight	-1,054	0,281	0,000
Thunder	-12,087	20,475	0,555
SlipperinessDummy	-17,799	104,139	0,864
SnowHeight	-9,041	2,321	0,000
Slipperiness_1.0	256,225	317,290	0,419
Slipperiness_2.0	0,000		
Snow_1.0	250,037	296,736	0,399
Snow_2.0	-280,489	340,277	0,410
Snow_3.0	-1124,110	130,502	0,000
Thunderstorm_1.0	83,201	278,547	0,765
Thunderstorm_2.0	494,201	144,795	0,001
Wind_1.0	-253,886	164,956	0,124
Wind_2.0	-330,980	38,193	0,000
Wind_3.0	-571,197	168,200	0,001
ar.L1	0,632	0,002	0,000

Table G.2: AR(1) model results with significant weather and weather code variables

	Model: A20 Westbound
No. Observations	29927
Log-Likelihood	-170497
Durbin-Watson	2,062

	Coeff	Std error	p-value
maxWind	-3,364	0,355	0,000
Temperature	14,550	1,028	0,000
Precipitation	-20,894	4,608	0,000
Sight	-1,748	0,251	0,000
Thunder	-74,676	22,865	0,001
SnowHeight	-11,353	1,675	0,000
Snow_3.0	-908,951	111,194	0,000
Wind_2.0	-178,482	47,893	0,000
ar.L1	0,610	0,002	0,000

	Model: A20 Eastbound
No. Observations	29927
Log-Likelihood	-169847
Durbin-Watson	2,093

	Coeff	Std error	p-value
maxWind	-3,468	0,382	0,000
Temperature	13,814	1,159	0,000
Precipitation	-17,448	4,806	0,000
Sight	-1,196	0,280	0,000
SnowHeight	-10,502	2,074	0,000
Snow_3.0	-1078,760	124,159	0,000
Thunderstorm_2.0	480,157	146,082	0,001
Wind_2.0	-328,364	38,289	0,000
Wind_3.0	-570,005	168,310	0,001
ar.L1	0,631	0,002	0,000

Table G.3: AR(1) model results with weather variables

	Model: A20 Westbound
No. Observations	29927
Log-Likelihood	-170494
Durbin-Watson	2,062

	Coeff	Std error	p-value
maxWind	-3,411	0,355	0,000
Temperature	14,611	1,082	0,000
Sunshine	0,302	1,181	0,798
Precipitation	-20,320	4,614	0,000
Sight	-1,755	0,252	0,000
Thunder	-69,482	22,879	0,002
SlipperinessDummy	-109,459	67,260	0,104
SnowHeight	-12,454	1,352	0,000
ar.L1	0,611	0,002	0,000

	Model: A20 Eastbound
No. Observations	29927
Log-Likelihood	-169846
Durbin-Watson	2,093

	Coeff	Std error	p-value
maxWind	-3,573	0,367	0,000
Temperature	14,231	1,198	0,000
Sunshine	-1,382	1,121	0,217
Precipitation	-17,084	5,178	0,001
Sight	-1,179	0,282	0,000
Thunder	14,171	20,582	0,491
SlipperinessDummy	-14,914	104,013	0,886
SnowHeight	-11,783	1,447	0,000
ar.L1	0,634	0,002	0,000

Table G.4: AR(1) model results with significant weather variables

	Model: A20 Westbound
No. Observations	29927
Log-Likelihood	-170495
Durbin-Watson	2,063

	Coeff	Std error	p-value
maxWind	-3,419	0,352	0,000
Temperature	14,688	1,029	0,000
Precipitation	-20,518	4,598	0,000
Sight	-1,751	0,251	0,000
Thunder	-73,938	22,808	0,001
SnowHeight	-12,795	1,349	0,000
ar.L1	0,611	0,002	0,000

	Model: A20 Eastbound
No. Observations	29927
Log-Likelihood	-169847
Durbin-Watson	2,093

	Coeff	Std error	p-value
maxWind	-3,559	0,365	0,000
Temperature	13,994	1,164	0,000
Precipitation	-16,835	4,796	0,000
Sight	-1,193	0,279	0,000
SnowHeight	-12,190	1,450	0,000
ar.L1	0,633	0,002	0,000

Table G.5: Least squares regression model results with weather code variables

	Model: A20 Westbound
No. Observations	22874
R-squared	0,001
Log-Likelihood	-170707
Durbin-Watson	2,064

	Coeff	Std error	p-value
Slipperiness_1.0	-95,367	188,569	0,613
Slipperiness_2.0	0,000	0,000	
Snow_1.0	96,651	133,338	0,469
Snow_2.0	-92,288	79,685	0,247
Snow_3.0	-355,345	121,721	0,004
Thunderstorm_1.0	53,179	108,870	0,625
Thunderstorm_2.0	-100,493	102,266	0,326
Wind_1.0	46,413	108,870	0,670
Wind_2.0	-21,359	69,319	0,758
Wind_3.0	-465,973	172,139	0,007

	Model: A20 Eastbound
No. Observations	22786
R-squared	0,001
Log-Likelihood	-170100
Durbin-Watson	2,095

	Coeff	Std error	p-value
Slipperiness_1.0	90,273	188,981	0,633
Slipperiness_2.0	0,000	0,000	
Snow_1.0	137,892	133,630	0,302
Snow_2.0	-95,987	79,859	0,229
Snow_3.0	-438,236	121,987	0,000
Thunderstorm_1.0	57,155	109,108	0,600
Thunderstorm_2.0	122,827	102,489	0,231
Wind_1.0	65,753	109,108	0,547
Wind_2.0	-151,056	69,471	0,030
Wind_3.0	81,836	188,981	0,665

A6 Flevoland

Table G.6: AR(1) model results with weather and weather code variables

	Model: A6 Westbound
No. Observations	29182
Log-Likelihood	-142979
Durbin-Watson	2,045

	Coeff	Std error	p-value
maxWind	-1,405	0,141	0,000
Temperature	9,188	0,480	0,000
Sunshine	-0,138	0,443	0,755
Precipitation	0,337	2,835	0,906
Sight	-0,629	0,100	0,000
Thunder	15,452	9,169	0,092
SlipperinessDummy	-26,531	15,504	0,087
SnowHeight	-1,094	0,636	0,085
Slipperiness_1.0	-49,669	39,869	0,213
Slipperiness_2.0	-258,650	23,637	0,000
Snow_1.0	-58,089	18,423	0,002
Snow_2.0	-385,318	45,391	0,000
Snow_3.0	-1,127	40,892	0,978
Thunderstorm_1.0	-31,331	8,469	0,000
Wind_1.0	52,153	7,567	0,000
Wind_2.0	-25,957	25,409	0,307
Wind_3.0	50,651	8,951	0,000
ar.L1	0,658	0,002	0,000

	Model: A6 Eastbound
No. Observations	28462
Log-Likelihood	-146340
Durbin-Watson	2,137

	Coeff	Std error	p-value
maxWind	-0,266	0,212	0,210
Temperature	12,908	0,615	0,000
Sunshine	3,704	0,595	0,000
Precipitation	-7,639	3,710	0,039
Sight	0,245	0,142	0,085
Thunder	43,138	14,809	0,004
SlipperinessDummy	27,017	34,884	0,439
SnowHeight	-2,149	1,279	0,093
Slipperiness_1.0	5,277	50,338	0,917
Slipperiness_2.0	-209,960	33,050	0,000
Snow_1.0	-2,571	29,549	0,931
Snow_2.0	-408,799	96,151	0,000
Snow_3.0	-64,717	35,773	0,070
Thunderstorm_1.0	-7,628	10,024	0,447
Wind_1.0	32,547	8,541	0,000
Wind_2.0	-65,101	32,724	0,047
Wind_3.0	-3,535	11,795	0,764
ar.L1	0,586	0,002	0,000

Table G.7: AR(1) model results with significant weather and weather code variables

	Model: A6 Westbound
No. Observations	29182
Log-Likelihood	-142982
Durbin-Watson	2,046

	Coeff	Std error	p-value
maxWind	-1,432	0,132	0,000
Temperature	9,214	0,460	0,000
Sight	-0,631	0,098	0,000
Slipperiness_2.0	-259,021	23,709	0,000
Snow_1.0	-63,453	18,392	0,001
Snow_2.0	-413,990	42,027	0,000
Thunderstorm_1.0	-32,216	8,404	0,000
Wind_1.0	52,114	7,521	0,000
Wind_3.0	52,230	8,913	0,000
ar.L1	0,658	0,002	0,000

	Model: A6 Eastbound
No. Observations	28462
Log-Likelihood	-146346
Durbin-Watson	2,138

	Coeff	Std error	p-value
Temperature	13,226	0,361	0,000
Sunshine	3,890	0,587	0,000
Precipitation	-4,709	3,668	0,199
Thunder	45,599	14,638	0,002
Slipperiness_2.0	-207,577	32,660	0,000
Snow_2.0	-447,545	86,798	0,000
Wind_1.0	36,814	7,435	0,000
Wind_2.0	-62,427	32,179	0,052
ar.L1	0,588	0,002	0,000

Table G.8: AR(1) model results with significant weather variables

	Model: A6 Westbound
No. Observations	29182
Log-Likelihood	-143086
Durbin-Watson	2,059

	Coeff	Std error	p-value
maxWind	-1,384	0,143	0,000
Temperature	9,596	0,458	0,000
Sunshine	-0,209	0,445	0,638
Precipitation	0,962	2,804	0,731
Sight	-0,565	0,097	0,000
Thunder	9,354	8,926	0,295
SlipperinessDummy	-45,364	14,886	0,002
SnowHeight	-1,888	0,581	0,001
ar.L1	0,674	0,002	0,000

	Model: A6 Eastbound
No. Observations	28462
Log-Likelihood	-146375
Durbin-Watson	2,142

	Coeff	Std error	p-value
maxWind	-0,398	0,210	0,058
Temperature	13,743	0,548	0,000
Sunshine	3,589	0,589	0,000
Precipitation	-6,651	3,684	0,071
Sight	0,239	0,125	0,056
Thunder	37,220	14,742	0,012
SlipperinessDummy	24,842	35,417	0,483
SnowHeight	-2,278	1,025	0,026
ar.L1	0,592	0,002	0,000

Table G.9: AR(1) model results with significant weather variables

	Model: A6 Westbound
No. Observations	29182
Log-Likelihood	-143087
Durbin-Watson	2,059

	Coeff	Std error	p-value
maxWind	-1,377	0,135	0,000
Temperature	9,578	0,441	0,000
Sight	-0,570	0,095	0,000
SlipperinessDummy	-46,073	14,844	0,002
SnowHeight	-1,861	0,579	0,001
ar.L1	0,674	0,002	0,000

	Model: A6 Eastbound
No. Observations	28462
Log-Likelihood	-146376
Durbin-Watson	2,142

	Coeff	Std error	p-value
Temperature	14,050	0,301	0,000
Sunshine	3,700	0,586	0,000
Thunder	19,839	14,410	0,169
SnowHeight	-2,585	0,997	0,010
ar.L1	0,593	0,002	0,000

Table G.10: Least squares regression model results with weather code variables

	Model: A6 Westbound
No. Observations	22204
R-squared	0,009
Log-Likelihood	-142976
Durbin-Watson	2,078

	Model: A6 Eastbound
No. Observations	21632
R-squared	0,003
Log-Likelihood	-146353
Durbin-Watson	2,15

	Coeff	Std error	p-value
Slipperiness_1.0	-18,785	12,990	0,148
Slipperiness_2.0	-89,980	11,198	0,000
Snow_1.0	-23,397	5,104	0,000
Snow_2.0	-141,309	28,628	0,000
Snow_3.0	-5,798	12,849	0,652
Thunderstorm_1.0	-12,844	2,234	0,000
Wind_1.0	13,695	1,991	0,000
Wind_2.0	-15,566	9,185	0,090
Wind_3.0	12,271	3,291	0,000

	Coeff	Std error	p-value
Slipperiness_1.0	-0,771	18,003	0,966
Slipperiness_2.0	-84,289	15,520	0,000
Snow_1.0	2,673	7,073	0,705
Snow_2.0	-174,716	39,677	0,000
Snow_3.0	-26,369	17,808	0,139
Thunderstorm_1.0	-5,983	3,097	0,053
Wind_1.0	11,038	2,760	0,000
Wind_2.0	-25,975	12,730	0,041
Wind_3.0	0,555	5,338	0,917

A37 Drenthe

Table G.11: AR(1) model results with weather and weather code variables

	Model: A37 Eastbound
No. Observations	28462
Log-Likelihood	-135482
Durbin-Watson	2,13

	Coeff	Std error	p-value
maxWind	-0,331	0,118	0,005
Temperature	5,091	0,325	0,000
Sunshine	-1,265	0,332	0,000
Precipitation	-4,983	1,385	0,000
Sight	-0,294	0,071	0,000
Thunder	11,551	11,400	0,311
SlipperinessDummy	-66,670	9,023	0,000
SnowHeight	-2,014	0,272	0,000
Slipperiness_2.0	-354,232	16,723	0,000
Slipperiness_3.0	-573,060	15,319	0,000
Snow_1.0	161,813	46,255	0,000
Snow_2.0	-161,797	25,741	0,000
Snow_3.0	-481,546	25,723	0,000
Thunderstorm_1.0	-139,250	44,163	0,002
Thunderstorm_2.0	-41,586	86,796	0,632
Wind_1.0	9,188	38,590	0,812
Wind_2.0	-62,733	92,443	0,497

Table G.12: AR(1) model results with significant weather and weather code variables

	Model: A37 Eastbound
No. Observations	28462
Log-Likelihood	-135481
Durbin-Watson	2,13

	Coeff	Std error	p-value
maxWind	-0,348	0,117	0,003
Temperature	5,102	0,324	0,000
Sunshine	-1,291	0,331	0,000
Precipitation	-4,980	1,371	0,000
Sight	-0,292	0,071	0,000
SlipperinessDummy	-66,722	9,015	0,000
SnowHeight	-1,978	0,272	0,000
Slipperiness_2.0	-354,240	16,712	0,000
Slipperiness_3.0	-573,098	15,307	0,000
Snow_1.0	161,294	46,356	0,001
Snow_2.0	-161,828	25,733	0,000
Snow_3.0	-481,710	25,714	0,000
Thunderstorm_1.0	-137,920	44,348	0,002
ar.L1	0,629	0,002	0,000

Table G.13: AR(1) model results with significant weather variables

	Model: A37 Eastbound
No. Observations	28462
Log-Likelihood	-135620
Durbin-Watson	2,145

	Coeff	Std error	p-value
maxWind	-0,461	0,119	0,000
Temperature	5,305	0,335	0,000
Sunshine	-1,295	0,335	0,000
Precipitation	-4,826	1,373	0,000
Sight	-0,297	0,073	0,000
Thunder	10,353	11,448	0,366
SlipperinessDummy	-102,300	7,114	0,000
SnowHeight	-2,752	0,208	0,000
ar.L1	0,648	0,002	0,000

Table G.14: AR(1) model results with significant weather variables

	Model: A37 Eastbound
No. Observations	28462
Log-Likelihood	-135619
Durbin-Watson	2,145

	Coeff	Std error	p-value
maxWind	-0,449	0,119	0,000
Temperature	5,264	0,336	0,000
Sunshine	-1,206	0,336	0,000
Precipitation	-4,692	1,370	0,001
Sight	-0,302	0,073	0,000
SlipperinessDummy	-102,012	7,138	0,000
SnowHeight	-2,731	0,208	0,000
ar.L1	0,648	0,002	0,000

Table G.15: Least squares regression model results with weather code variables

	Model: A37 Eastbound
No. Observations	21877
R-squared	0,012
Log-Likelihood	-135481
Durbin-Watson	2,17

	Coeff	Std error	p-value
Slipperiness_2.0	-118,928	16,264	0,000
Slipperiness_3.0	-206,941	15,415	0,000
Snow_1.0	105,308	41,862	0,012
Snow_2.0	-43,844	20,612	0,033
Snow_3.0	-154,522	39,468	0,000
Thunderstorm_1.0	-60,701	31,645	0,055
Thunderstorm_2.0	-36,638	52,952	0,489
Wind_1.0	2,132	16,420	0,897
Wind_2.0	-25,880	48,338	0,592

A58 Zeeland

Table G.16: AR(1) model results with weather and weather code variables

	Model: A58 Westbound
No. Observations	28462
Log-Likelihood	-143984
Durbin-Watson	1,739

	Coeff	Std error	p-value
maxWind	-1,310	0,212	0,000
Temperature	10,867	0,783	0,000
Sunshine	-1,601	0,500	0,001
Precipitation	3,932	3,547	0,268
Sight	-0,535	0,183	0,003
Thunder	3,318	15,989	0,836
SlipperinessDummy	-68,327	34,239	0,046
SnowHeight	-2,215	1,114	0,047
Slipperiness_1.0	-333,906	87,550	0,000
Slipperiness_2.0	0,000		
Snow_1.0	-129,761	114,947	0,259
Snow_3.0	-402,973	82,504	0,000
Thunderstorm_1.0	-23,606	140,390	0,866
Thunderstorm_2.0	-184,100	101,310	0,069
Wind_1.0	28,193	155,300	0,856
Wind_2.0	14,489	106,529	0,892
Wind_3.0	0,000	0,000	
ar.L1	0,828	0,001	0,000

	Model: A58 Eastbound
No. Observations	28462
Log-Likelihood	-143148
Durbin-Watson	1,615

	Coeff	Std error	p-value
maxWind	-0,558	0,189	0,003
Temperature	8,935	0,876	0,000
Sunshine	-0,261	0,447	0,559
Precipitation	-2,195	2,318	0,344
Sight	-0,679	0,173	0,000
Thunder	41,090	11,993	0,001
SlipperinessDummy	-34,322	27,345	0,209
SnowHeight	-2,285	1,283	0,075
Slipperiness_1.0	-83,376	193,461	0,666
Slipperiness_2.0	0,000	0,000	0,014
Snow_1.0	-207,292	86,107	0,016
Snow_3.0	-448,703	83,544	0,000
Thunderstorm_1.0	-111,344	116,651	0,340
Thunderstorm_2.0	411,396	106,612	0,000
Wind_1.0	-90,081	66,000	0,172
Wind_2.0	38,557	100,438	0,701
Wind_3.0	0,000	0,000	
ar.L1	0,840	0,001	0,000

Table G.17: AR(1) model results with significant weather and weather code variables

	Model: A58 Westbound
No. Observations	28462
Log-Likelihood	-143984
Durbin-Watson	1,739

	Coeff	Std error	p-value
maxWind	-1,232	0,207	0,000
Temperature	10,795	0,782	0,000
Sunshine	-1,528	0,499	0,002
Sight	-0,572	0,181	0,002
SlipperinessDummy	-67,686	34,269	0,048
SnowHeight	-2,911	1,110	0,009
Slipperiness_1.0	-334,826	87,695	0,000
Snow_3.0	-369,743	85,192	0,000
ar.L1	0,828	0,001	0,000

	Model: A58 Eastbound
No. Observations	28462
Log-Likelihood	-143152
Durbin-Watson	1,616

	Coeff	Std error	p-value
maxWind	-0,548	0,182	0,003
Temperature	6,927	0,851	0,000
Sight	-0,416	0,169	0,014
Thunder	64,206	11,667	0,000
Slipperiness_2.0	0,000	0,000	0,000
Snow_1.0	-236,134	89,060	0,008
Snow_3.0	-560,176	66,621	0,000
Thunderstorm_2.0	401,997	107,140	0,000
ar.L1	0,840	0,001	0,000

Table G.18: AR(1) model results with weather variables

	Model: A58 Westbound
No. Observations	28462
Log-Likelihood	-143983
Durbin-Watson	1,739

	Coeff	Std error	p-value
maxWind	-1,313	0,211	0,000
Temperature	10,854	0,781	0,000
Sunshine	-1,551	0,500	0,002
Precipitation	4,242	3,539	0,231
Sight	-0,537	0,182	0,003
Thunder	4,931	16,000	0,758
SlipperinessDummy	-66,186	34,405	0,054
SnowHeight	-3,359	0,970	0,001
ar.L1	0,829	0,001	0,000

	Model: A58 Eastbound
No. Observations	28462
Log-Likelihood	-143142
Durbin-Watson	1,615

	Coeff	Std error	p-value
maxWind	-0,539	0,188	0,004
Temperature	7,168	0,874	0,000
Sunshine	-0,674	0,445	0,130
Precipitation	1,605	2,418	0,507
Sight	-0,427	0,172	0,013
Thunder	-5,140	12,229	0,674
SlipperinessDummy	-20,102	27,958	0,472
SnowHeight	-3,140	1,126	0,005
ar.L1	0,841	0,001	0,000

Table G.19: AR(1) model results with significant weather variables

	Model: A58 Westbound
No. Observations	28462
Log-Likelihood	-143981
Durbin-Watson	1,739

	Model: A58 Eastbound
No. Observations	28462
Log-Likelihood	-143142
Durbin-Watson	1,615

	Coeff	Std error	p-value
maxWind	-1,257	0,206	0,000
Temperature	10,943	0,780	0,000
Sunshine	-1,588	0,500	0,001
Sight	-0,579	0,181	0,001
SnowHeight	-3,201	0,968	0,001
ar.L1	0,829	0,001	0,000

	Coeff	Std error	p-value
maxWind	-0,507	0,181	0,005
Temperature	6,907	0,850	0,000
Sight	-0,431	0,169	0,011
SnowHeight	-3,142	1,125	0,005
ar.L1	0,841	0,001	0,000

Table G.20: Least squares regression model results with weather code variables

	Model: A58 Westbound
No. Observations	21841
R-squared	0
Log-Likelihood	-143965
Durbin-Watson	1,74

	Model: A58 Eastbound
No. Observations	21842
R-squared	0
Log-Likelihood	-143129
Durbin-Watson	1,615

	Coeff	Std error	p-value
Slipperiness_1.0	-132,062	78,886	0,094
Slipperiness_2.0	0,000	0,000	
Snow_1.0	-39,263	28,615	0,170
Snow_3.0	-69,684	50,921	0,171
Thunderstorm_1.0	-29,091	48,923	0,552
Thunderstorm_2.0	1,866	72,013	0,979
Wind_1.0	13,704	36,006	0,704
Wind_2.0	4,441	30,251	0,883
Wind_3.0	0,000	0,000	
Wind_3.0	-465,973	172,139	0,007

	Coeff	Std error	p-value
Slipperiness_1.0	-28,647	75,902	0,706
Slipperiness_2.0	0,000	0,000	
Snow_1.0	-39,491	27,533	0,151
Snow_3.0	-82,849	48,995	0,091
Thunderstorm_1.0	-51,667	47,072	0,272
Thunderstorm_2.0	24,168	69,289	0,727
Wind_1.0	-36,375	34,644	0,294
Wind_2.0	-11,996	29,107	0,680
Wind_3.0	0,000	0,000	
Wind_3.0	81,836	188,981	0,665

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Table G.21: AR(1) model results with weather and weather code variables

	Model: A30 Southbound
No. Observations	29927
Log-Likelihood	-152491
Durbin-Watson	2,002

	Model: A30 Northbound
No. Observations	29927
Log-Likelihood	-150194
Durbin-Watson	1,983

	Coeff	Std error	p-value
maxWind	-1,125	0,226	0,000
Temperature	5,046	0,624	0,000
Sunshine	-3,775	0,600	0,000
Precipitation	-6,392	2,205	0,004
Sight	0,226	0,131	0,084
Thunder	22,201	17,735	0,211
SlipperinessDummy	7,876	25,332	0,756
SnowHeight	-1,616	0,714	0,024
Slipperiness_1.0	0,000	0,000	0,952
Slipperiness_2.0	-236,698	70,425	0,001
Snow_1.0	-217,700	557,921	0,696
Snow_2.0	-215,968	109,981	0,050
Snow_3.0	-1102,246	31,353	0,000
Thunderstorm_1.0	-106,614	104,702	0,309
Thunderstorm_2.0	-152,985	67,794	0,024
Wind_1.0	46,283	65,515	0,480
Wind_2.0	25,030	132,032	0,850
Wind_3.0	-494,412	115,152	0,000
ar.L1	0,665	0,002	0,000

	Coeff	Std error	p-value
maxWind	-0,832	0,206	0,000
Temperature	4,979	0,533	0,000
Sunshine	-3,593	0,536	0,000
Precipitation	-7,914	1,620	0,000
Sight	0,157	0,114	0,169
Thunder	9,628	14,923	0,519
SlipperinessDummy	-5,743	18,570	0,757
SnowHeight	-2,695	0,550	0,000
Slipperiness_1.0	0,000		
Slipperiness_2.0	-216,810	74,899	0,004
Snow_1.0	-221,894	306,121	0,469
Snow_2.0	-110,495	75,645	0,144
Snow_3.0	-939,711	28,354	0,000
Thunderstorm_1.0	-139,115	119,656	0,245
Thunderstorm_2.0	2,475	61,151	0,968
Wind_1.0	20,842	33,151	0,530
Wind_2.0	0,673	112,670	0,995
Wind_3.0	-265,446	83,498	0,001
ar.L1	0,648	0,002	0,000

Table G.22: AR(1) model results with significant weather and weather code variables

	Model: A30 Southbound
No. Observations	29927
Log-Likelihood	-152495
Durbin-Watson	2,002

	Model: A30 Northbound
No. Observations	29927
Log-Likelihood	-150194
Durbin-Watson	1,983

	Coeff	Std error	p-value
maxWind	-0,929	0,201	0,000
Temperature	5,810	0,470	0,000
Sunshine	-3,966	0,596	0,000
Precipitation	-6,222	2,130	0,003
SnowHeight	-1,375	0,711	0,053
Slipperiness_2.0	-237,155	69,931	0,001
Snow_2.0	-222,408	104,755	0,034
Snow_3.0	-1109,876	31,191	0,000
Thunderstorm_2.0	-144,242	64,397	0,025
Wind_3.0	-515,042	91,149	0,000
ar.L1	0,666	0,002	0,000

	Coeff	Std error	p-value
maxWind	-0,692	0,182	0,000
Temperature	5,495	0,412	0,000
Sunshine	-3,899	0,535	0,000
Precipitation	-8,244	1,350	0,000
SnowHeight	-2,967	0,503	0,000
Slipperiness_2.0	-217,194	74,942	0,004
Snow_3.0	-924,729	27,851	0,000
Wind_3.0	-271,540	60,598	0,000
ar.L1	0,648	0,002	0,000

Table G.23: AR(1) model results with weather variables

	Model: A30 Southbound
No. Observations	29927
Log-Likelihood	-152501
Durbin-Watson	2,006

	Model: A30 Northbound
No. Observations	29927
Log-Likelihood	-150193
Durbin-Watson	1,984

	Coeff	Std error	p-value
maxWind	-1,231	0,222	0,000
Temperature	5,025	0,622	0,000
Sunshine	-3,628	0,598	0,000
Precipitation	-4,905	1,749	0,005
Sight	0,244	0,131	0,061
Thunder	15,636	17,211	0,364
SlipperinessDummy	7,936	25,366	0,754
SnowHeight	-2,872	0,526	0,000
ar.L1	0,670	0,002	0,000

	Coeff	Std error	p-value
maxWind	-0,896	0,203	0,000
Temperature	5,133	0,534	0,000
Sunshine	-3,906	0,536	0,000
Precipitation	-7,610	1,399	0,000
Sight	0,157	0,114	0,169
Thunder	9,369	14,775	0,526
SlipperinessDummy	-5,830	18,651	0,755
SnowHeight	-3,647	0,438	0,000
ar.L1	0,652	0,002	0,000

Table G.24: AR(1) model results with significant weather variables

	Model: A30 Southbound
No. Observations	29927
Log-Likelihood	-152504
Durbin-Watson	2,006

	Model: A30 Northbound
No. Observations	29927
Log-Likelihood	-150194
Durbin-Watson	1,983

	Coeff	Std error	p-value
maxWind	-0,998	0,199	0,000
Temperature	5,778	0,471	0,000
Sunshine	-3,680	0,598	0,000
Precipitation	-5,225	1,714	0,002
SnowHeight	-2,821	0,527	0,000
ar.L1	0,670	0,002	0,000

	Coeff	Std error	p-value
maxWind	-0,751	0,180	0,000
Temperature	5,492	0,410	0,000
Sunshine	-3,732	0,535	0,000
Precipitation	-8,624	1,348	0,000
SnowHeight	-3,374	0,440	0,000
ar.L1	0,652	0,002	0,000

Table G.25: Least squares regression model results with weather code variables

	Model: A30 Southbound
No. Observations	22481
R-squared	0,003
Log-Likelihood	-152577
Durbin-Watson	2,011

	Coeff	Std error	p-value
Slipperiness_1.0	0,000	0,000	
Slipperiness_2.0	-77,014	28,408	0,007
Snow_1.0	-5,299	151,656	0,972
Snow_2.0	-61,873	35,746	0,083
Snow_3.0	-386,541	61,913	0,000
Thunderstorm_1.0	-40,754	71,491	0,569
Thunderstorm_2.0	-70,532	49,204	0,152
Wind_1.0	40,133	37,335	0,282
Wind_2.0	5,445	49,204	0,912
Wind_3.0	-224,922	87,559	0,010

	Model: A30 Northbound
No. Observations	22482
R-squared	0,002
Log-Likelihood	-150267
Durbin-Watson	1,988

	Coeff	Std error	p-value
Slipperiness_1.0	0,000	0,000	
Slipperiness_2.0	-74,267	25,626	0,004
Snow_1.0	-34,101	136,804	0,803
Snow_2.0	-41,791	32,245	0,195
Snow_3.0	-333,814	55,850	0,000
Thunderstorm_1.0	-38,584	64,490	0,550
Thunderstorm_2.0	-18,077	44,385	0,684
Wind_1.0	-27,971	33,679	0,406
Wind_2.0	-2,329	44,385	0,958
Wind_3.0	-65,843	78,984	0,405

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Table G.26: AR(1) model results with weather and weather code variables

	Model: A31 Westbound
No. Observations	29927
Log-Likelihood	-153033
Durbin-Watson	1,918

	Coeff	Std error	p-value
maxWind	9,772	0,249	0,000
Temperature	-2,342	1,684	0,164
Sunshine	2,188	0,972	0,024
Precipitation	-6,472	2,087	0,002
Sight	-0,953	0,207	0,000
Thunder	-94,587	45,087	0,036
SlipperinessDummy	-310,501	19,331	0,000
SnowHeight	-5,528	2,823	0,050
Slipperiness_2.0	-584,975	65,137	0,000
Slipperiness_3.0	-818,058	94,886	0,000
Snow_1.0	268,449	82,486	0,001
Snow_2.0	-479,509	96,526	0,000
Snow_3.0	-107,295	225,527	0,634
Thunderstorm_1.0	2,914	191,972	0,988
Thunderstorm_2.0	0,000	0,000	0,001
Wind_1.0	-346,168	63,186	0,000
Wind_2.0	1409,043	18,890	0,000
ar.L1	0,864	0,001	0,000

	Model: A31 Eastbound
No. Observations	29927
Log-Likelihood	-146555
Durbin-Watson	2,021

	Coeff	Std error	p-value
maxWind	4,785	0,174	0,000
Temperature	-4,986	1,054	0,000
Sunshine	1,498	0,690	0,030
Precipitation	-13,666	2,320	0,000
Sight	-0,837	0,148	0,000
Thunder	-2,391	34,158	0,944
SlipperinessDummy	-252,864	11,766	0,000
SnowHeight	-3,854	1,410	0,006
Slipperiness_2.0	-455,060	53,756	0,000
Slipperiness_3.0	-440,889	52,372	0,000
Snow_1.0	353,904	50,032	0,000
Snow_2.0	-293,381	67,528	0,000
Snow_3.0	-221,443	277,232	0,424
Thunderstorm_1.0	36,469	137,446	0,791
Thunderstorm_2.0	0,000	0,000	0,913
Wind_1.0	-136,340	53,953	0,012
Wind_2.0	1585,084	12,037	0,000
ar.L1	0,829	0,001	0,000

Table G.27: AR(1) model results with significant weather and weather code variables

	Model: A31 Westbound
No. Observations	29927
Log-Likelihood	-153012
Durbin-Watson	1,898

	Coeff	Std error	p-value
maxWind	7,632	0,259	0,000
Sunshine	0,704	0,997	0,480
Precipitation	-8,171	2,112	0,000
Sight	-0,713	0,196	0,000
Thunder	-68,075	49,449	0,169
SlipperinessDummy	-190,814	27,246	0,000
Slipperiness_2.0	-570,764	70,912	0,000
Slipperiness_3.0	-795,297	99,052	0,000
Snow_1.0	-293,676	152,142	0,054
Snow_2.0	-633,438	74,386	0,000
Thunderstorm_2.0	0,000	0,000	0,171
Wind_1.0	-327,185	62,534	0,000
Wind_2.0	1382,047	19,604	0,000
ar.L1	0,866	0,001	0,000

	Model: A31 Eastbound
No. Observations	29927
Log-Likelihood	-146555
Durbin-Watson	2,016

	Coeff	Std error	p-value
maxWind	4,731	0,173	0,000
Temperature	-4,437	1,046	0,000
Sunshine	1,379	0,690	0,046
Precipitation	-17,047	2,218	0,000
Sight	-0,904	0,148	0,000
SlipperinessDummy	-252,264	11,817	0,000
SnowHeight	-5,028	1,385	0,000
Slipperiness_2.0	-454,811	53,502	0,000
Slipperiness_3.0	-440,888	52,025	0,000
Snow_1.0	368,838	49,226	0,000
Snow_2.0	-288,668	64,554	0,000
Wind_1.0	-136,323	54,137	0,012
Wind_2.0	1585,639	12,039	0,000
ar.L1	0,826	0,001	0,000

Table G.28: AR(1) model results with weather variables

	Model: A31 Westbound
No. Observations	29927
Log-Likelihood	-152924
Durbin-Watson	1,91

	Coeff	Std error	p-value
maxWind	9,839	0,240	0,000
Temperature	-1,650	1,677	0,325
Sunshine	2,143	0,955	0,025
Precipitation	-14,450	1,896	0,000
Sight	-0,938	0,206	0,000
Thunder	-43,233	45,708	0,344
SlipperinessDummy	-6,226	36,130	0,863
SnowHeight	-4,967	3,137	0,113
ar.L1	0,870	0,001	0,000

	Model: A31 Eastbound
No. Observations	29927
Log-Likelihood	-146435
Durbin-Watson	2,021

	Coeff	Std error	p-value
maxWind	4,799	0,175	0,000
Temperature	-5,976	1,073	0,000
Sunshine	1,641	0,685	0,017
Precipitation	-16,292	2,197	0,000
Sight	-0,624	0,151	0,000
Thunder	-4,629	33,264	0,889
SlipperinessDummy	-22,019	15,867	0,165
SnowHeight	-4,277	1,482	0,004
ar.L1	0,841	0,001	0,000

Table G.29: AR(1) model results with significant weather variables

	Model: A31 Westbound
No. Observations	29927
Log-Likelihood	-152927
Durbin-Watson	1,91

	Coeff	Std error	p-value
maxWind	9,697	0,238	0,000
Sunshine	1,826	0,946	0,054
Precipitation	-15,833	1,859	0,000
Sight	-1,038	0,187	0,000
ar.L1	0,871	0,001	0,000

	Model: A31 Eastbound
No. Observations	29927
Log-Likelihood	-146440
Durbin-Watson	2,02

	Coeff	Std error	p-value
maxWind	4,921	0,175	0,000
Temperature	-5,332	1,073	0,000
Sunshine	1,877	0,686	0,006
Precipitation	-17,575	2,153	0,000
Sight	-0,778	0,150	0,000
SnowHeight	0,396	1,507	0,793
ar.L1	0,841	0,001	0,000

Table G.30: Least squares regression model results with weather code variables

	Model: A31 Westbound
No. Observations	21907
R-squared	0,002
Log-Likelihood	-152945
Durbin-Watson	1,912

	Coeff	Std error	p-value
Slipperiness_2.0	-73,367	38,417	0,056
Slipperiness_3.0	-67,823	34,213	0,047
Snow_1.0	-51,844	82,396	0,529
Snow_2.0	-92,576	45,357	0,041
Snow_3.0	38,352	98,482	0,697
Thunderstorm_1.0	30,456	59,776	0,610
Thunderstorm_2.0	0,000	0,000	
Wind_1.0	6,317	59,776	0,916
Wind_2.0	206,506	41,723	0,000

	Model: A31 Eastbound
No. Observations	21882
R-squared	0,007
Log-Likelihood	-146404
Durbin-Watson	2,03

	Coeff	Std error	p-value
Slipperiness_2.0	-87,361	28,718	0,002
Slipperiness_3.0	-60,180	25,575	0,019
Snow_1.0	-25,972	61,593	0,673
Snow_2.0	-103,421	33,906	0,002
Snow_3.0	21,269	73,617	0,773
Thunderstorm_1.0	1,643	44,684	0,971
Thunderstorm_2.0	0,000	0,000	
Wind_1.0	10,549	44,684	0,813
Wind_2.0	348,048	31,189	0,000

A7 Groningen

Table G.31: AR(1) model results with weather and weather code variables

	Model: A7 Westbound
No. Observations	29927
Log-Likelihood	-143738
Durbin-Watson	1,952

	Coeff	Std error	p-value
maxWind	-0,300	0,140	0,033
Temperature	2,715	0,400	0,000
Sunshine	-0,874	0,404	0,030
Precipitation	-1,044	2,346	0,656
Sight	-0,027	0,084	0,752
Thunder	-18,690	6,663	0,005
SlipperinessDummy	-14,932	9,670	0,123
SnowHeight	-2,277	0,695	0,001
Slipperiness_2.0	-356,828	16,664	0,000
Slipperiness_3.0	-523,635	13,384	0,000
Snow_1.0	97,334	141,894	0,493
Snow_2.0	-98,831	31,830	0,002
Snow_3.0	-90,786	184,506	0,623
Thunderstorm_1.0	-82,567	68,093	0,225
Thunderstorm_2.0	-27,274	55,799	0,625
Wind_1.0	-58,998	61,123	0,334
Wind_2.0	7,016	34,965	0,841
ar.L1	0,642	0,001	0,000

	Model: A7 Eastbound
No. Observations	28462
Log-Likelihood	-120531
Durbin-Watson	2,113

	Coeff	Std error	p-value
maxWind	-0,217	0,164	0,185
Temperature	1,988	0,463	0,000
Sunshine	-1,410	0,463	0,002
Precipitation	-2,300	2,770	0,406
Sight	0,051	0,095	0,592
Thunder	-24,439	17,663	0,166
SlipperinessDummy	-15,950	12,158	0,190
SnowHeight	-1,880	0,779	0,016
Slipperiness_2.0	-390,356	15,678	0,000
Slipperiness_3.0	-518,096	15,034	0,000
Snow_1.0	78,544	306,279	0,798
Snow_2.0	-203,220	31,019	0,000
Snow_3.0	-295,893	97,339	0,002
Thunderstorm_1.0	-86,765	54,099	0,109
Thunderstorm_2.0	-27,904	196,845	0,887
Wind_1.0	-37,237	70,013	0,595
Wind_2.0	26,861	41,408	0,517
ar.L1	0,638	0,001	0,000

Table G.32: AR(1) model results with significant weather and weather code variables

	Model: A7 Westbound
No. Observations	29927
Log-Likelihood	-143732
Durbin-Watson	1,953

	Coeff	Std error	p-value
maxWind	-0,358	0,116	0,002
Temperature	2,655	0,315	0,000
Sunshine	-0,810	0,399	0,042
Thunder	21,273	6,620	0,001
SnowHeight	-2,392	0,662	0,000
Slipperiness_2.0	-349,102	16,661	0,000
Slipperiness_3.0	-527,236	12,936	0,000
Snow_2.0	-96,138	31,656	0,002
ar.L1	0,642	0,001	0,000

	Model: A7 Eastbound
No. Observations	28462
Log-Likelihood	-120532
Durbin-Watson	2,113

	Coeff	Std error	p-value
Temperature	1,805	0,256	0,000
Sunshine	-1,441	0,460	0,002
SnowHeight	-1,948	0,754	0,010
Slipperiness_2.0	-404,956	14,916	0,000
Slipperiness_3.0	-527,633	14,141	0,000
Snow_2.0	-211,377	30,547	0,000
Snow_3.0	-303,823	95,470	0,001
ar.L1	0,639	0,001	0,000

Table G.33: AR(1) model results with significant weather variables

	Model: A7 Westbound
No. Observations	29927
Log-Likelihood	-143822
Durbin-Watson	1,96

	Coeff	Std error	p-value
maxWind	-0,464	0,139	0,001
Temperature	3,087	0,393	0,000
Sunshine	-0,833	0,408	0,041
Precipitation	-1,201	2,360	0,611
Sight	-0,045	0,085	0,592
Thunder	11,983	6,628	0,071
SlipperinessDummy	2,668	9,631	0,782
SnowHeight	-2,598	0,660	0,000
ar.L1	0,655	0,001	0,000

	Model: A7 Eastbound
No. Observations	28462
Log-Likelihood	-120607
Durbin-Watson	2,13

	Coeff	Std error	p-value
maxWind	-0,414	0,163	0,011
Temperature	2,426	0,465	0,000
Sunshine	-1,441	0,469	0,002
Precipitation	-2,011	2,701	0,457
Sight	0,029	0,097	0,763
Thunder	-14,689	17,893	0,412
SlipperinessDummy	-4,890	13,365	0,714
SnowHeight	-2,754	0,694	0,000
ar.L1	0,656	0,001	0,000

Table G.34: AR(1) model results with significant weather variables

	Model: A7 Westbound
No. Observations	29927
Log-Likelihood	-143823
Durbin-Watson	1,96

	Coeff	Std error	p-value
maxWind	-0,504	0,112	0,000
Temperature	2,939	0,309	0,000
Sunshine	-0,840	0,404	0,037
SnowHeight	-2,595	0,660	0,000
ar.L1	0,655	0,001	0,000

	Model: A7 Eastbound
No. Observations	28462
Log-Likelihood	-120608
Durbin-Watson	2,13

	Coeff	Std error	p-value
maxWind	-0,413	0,131	0,002
Temperature	2,545	0,363	0,000
Sunshine	-1,411	0,465	0,002
SnowHeight	-2,799	0,694	0,000
ar.L1	0,656	0,001	0,000

Table G.35: Least squares regression model results with weather code variables

	Model: A7 Westbound
No. Observations	22741
R-squared	0,008
Log-Likelihood	-143742
Durbin-Watson	1,975

	Model: A7 Eastbound
No. Observations	19071
R-squared	0,01
Log-Likelihood	-120556
Durbin-Watson	2,151

	Coeff	Std error	p-value
Slipperiness_2.0	-134,511	17,983	0,000
Slipperiness_3.0	-179,813	16,692	0,000
Snow_1.0	44,684	47,578	0,348
Snow_2.0	-54,473	22,747	0,017
Snow_3.0	61,113	50,863	0,230
Thunderstorm_1.0	-27,508	35,966	0,444
Thunderstorm_2.0	-8,701	37,323	0,816
Wind_1.0	-36,345	30,873	0,239
Wind_2.0	3,388	21,549	0,875

	Coeff	Std error	p-value
Slipperiness_2.0	-128,773	17,994	0,000
Slipperiness_3.0	-182,089	16,702	0,000
Snow_1.0	65,218	47,608	0,171
Snow_2.0	-84,439	22,761	0,000
Snow_3.0	20,386	50,895	0,689
Thunderstorm_1.0	-10,473	35,988	0,771
Thunderstorm_2.0	-7,746	60,220	0,898
Wind_1.0	-1,685	30,892	0,957
Wind_2.0	15,354	21,562	0,476

H Case Studies

In this Appendix, all plots that are used for the case studies in the research of Chapter 7. Per road segment, a Section is included. Per Section, plots are found for the counts on the days 4-1-2016, 5-1-2016, 7-1-2016, 10-12-2017, 11-12-2017 and 18-01-2018.

The legend in Figure H.1 is applicable for the plots in all Sections. The 95% confidence interval is the confidence interval for the average demand pattern, as described in Chapter 5.

A20 Zuid-Holland

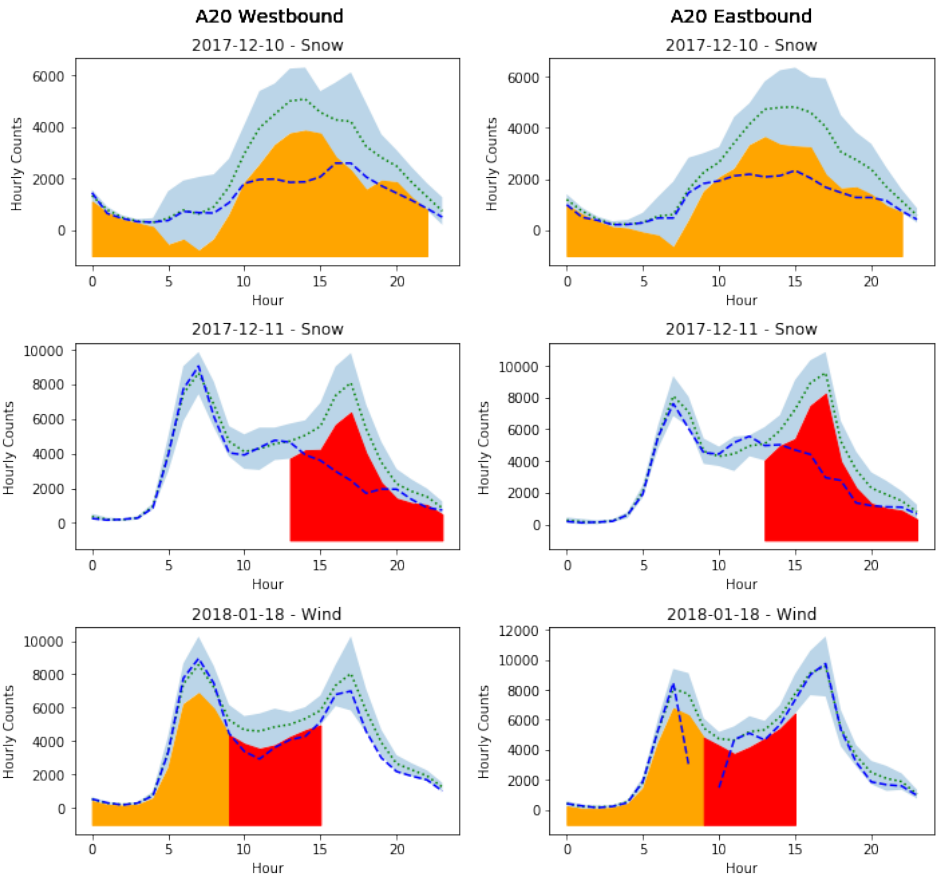

Figure H.2: Case study for the A20

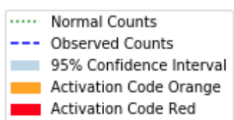

Figure H.1: Legend for case study plots

A6 Flevoland

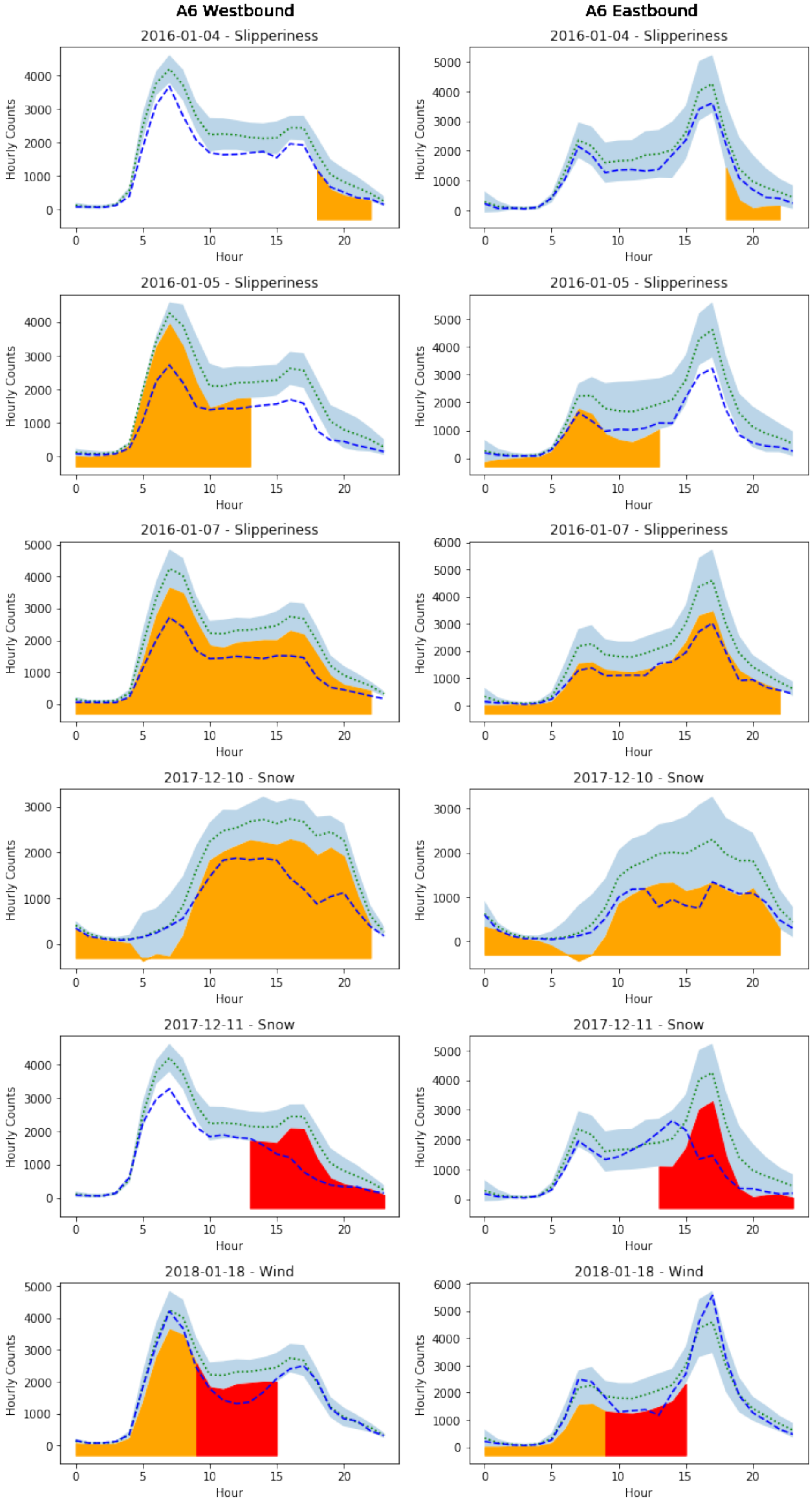

Figure H.3: Case study for the A6

A37 Drenthe

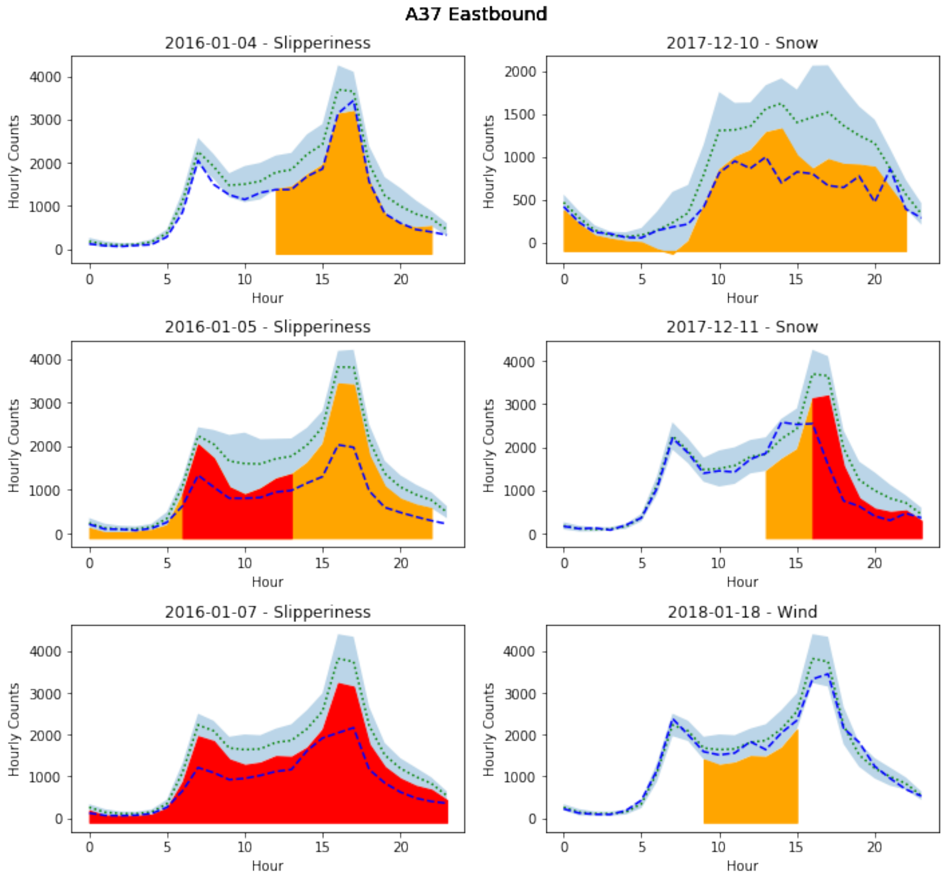

Figure H.4: Case study for the A37

A58 Zeeland

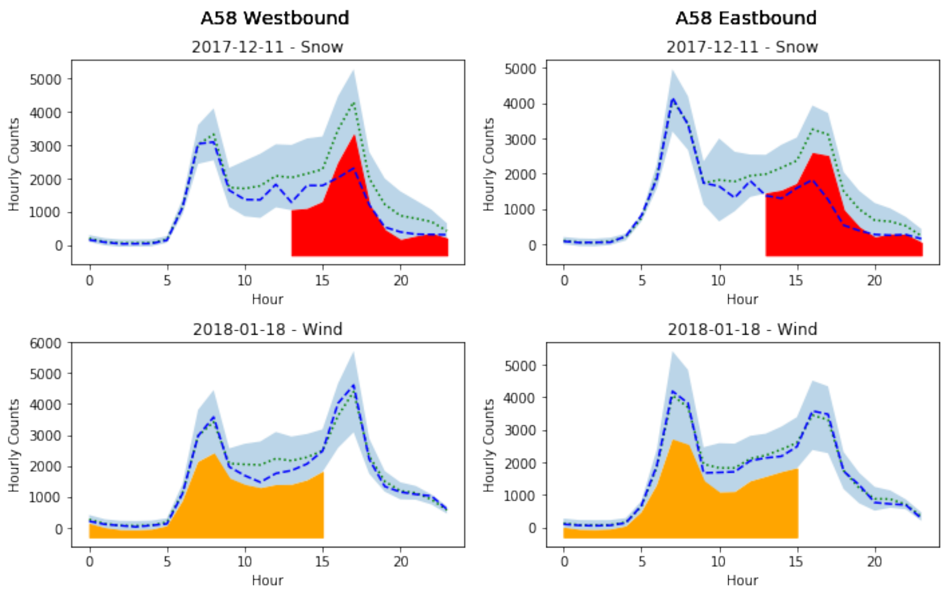

Figure H.5: Case study for the A58

A30 Gelderland

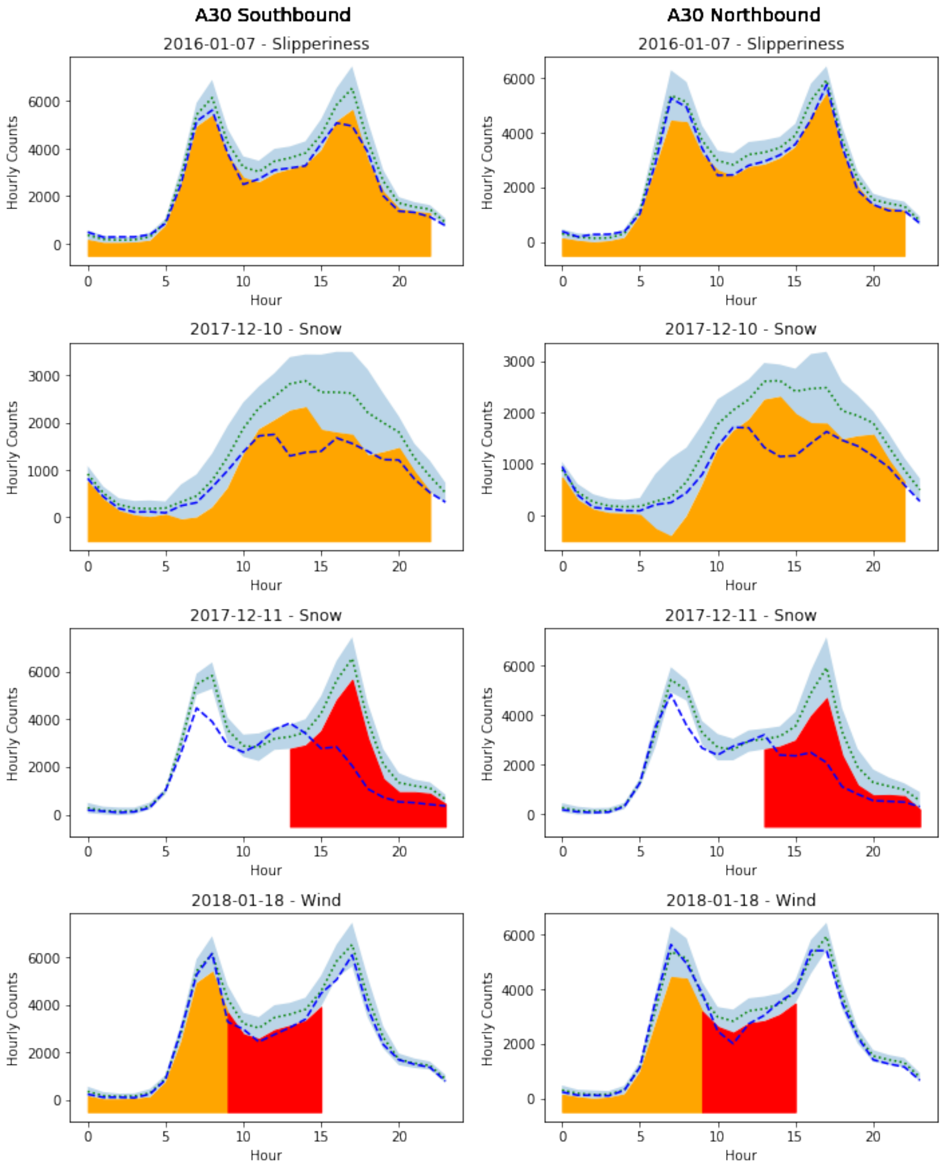

Figure H.6: Case study for the A30

A31 Friesland

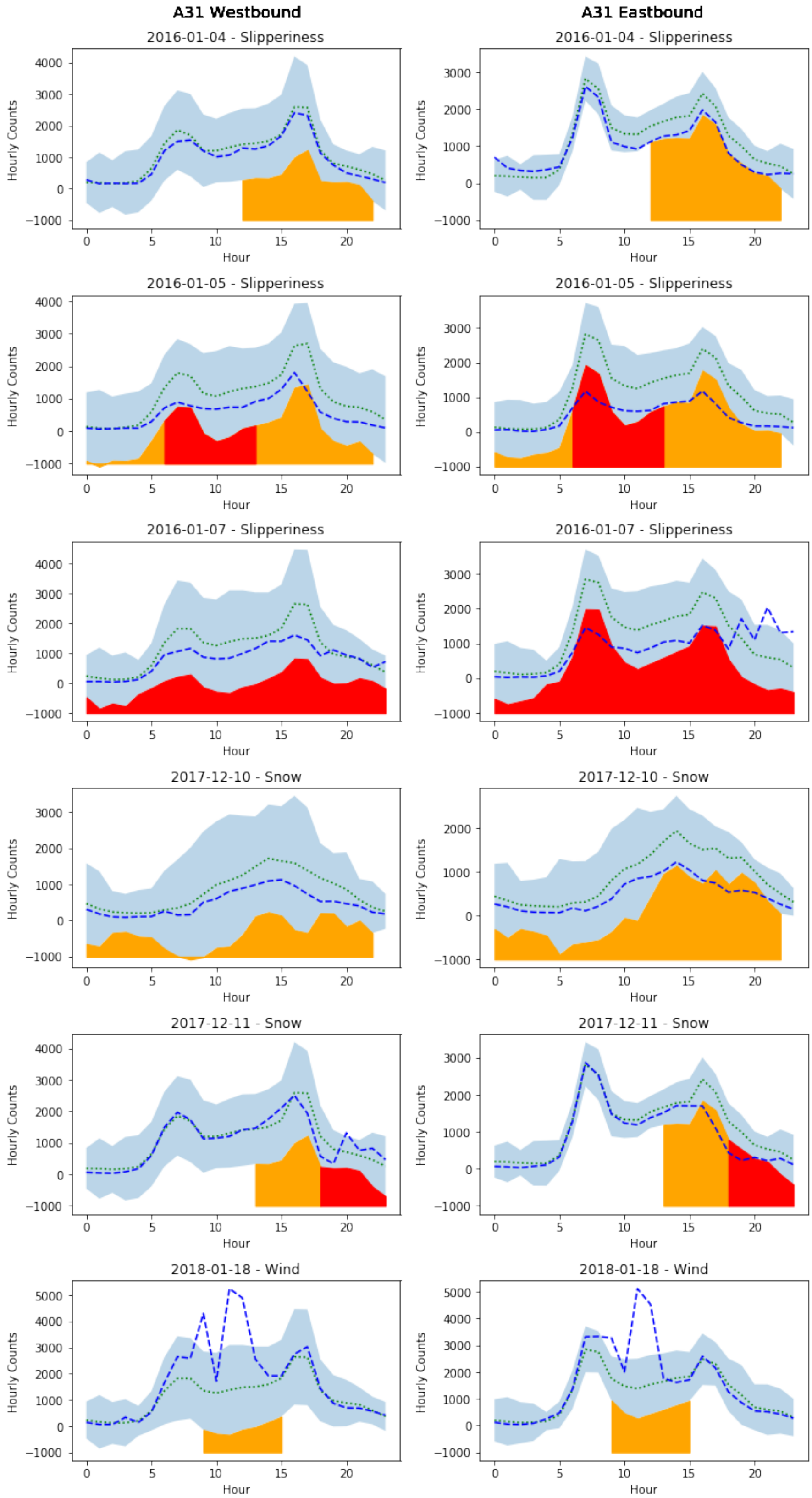

Figure H.7: Case study for the A31

A7 Groningen

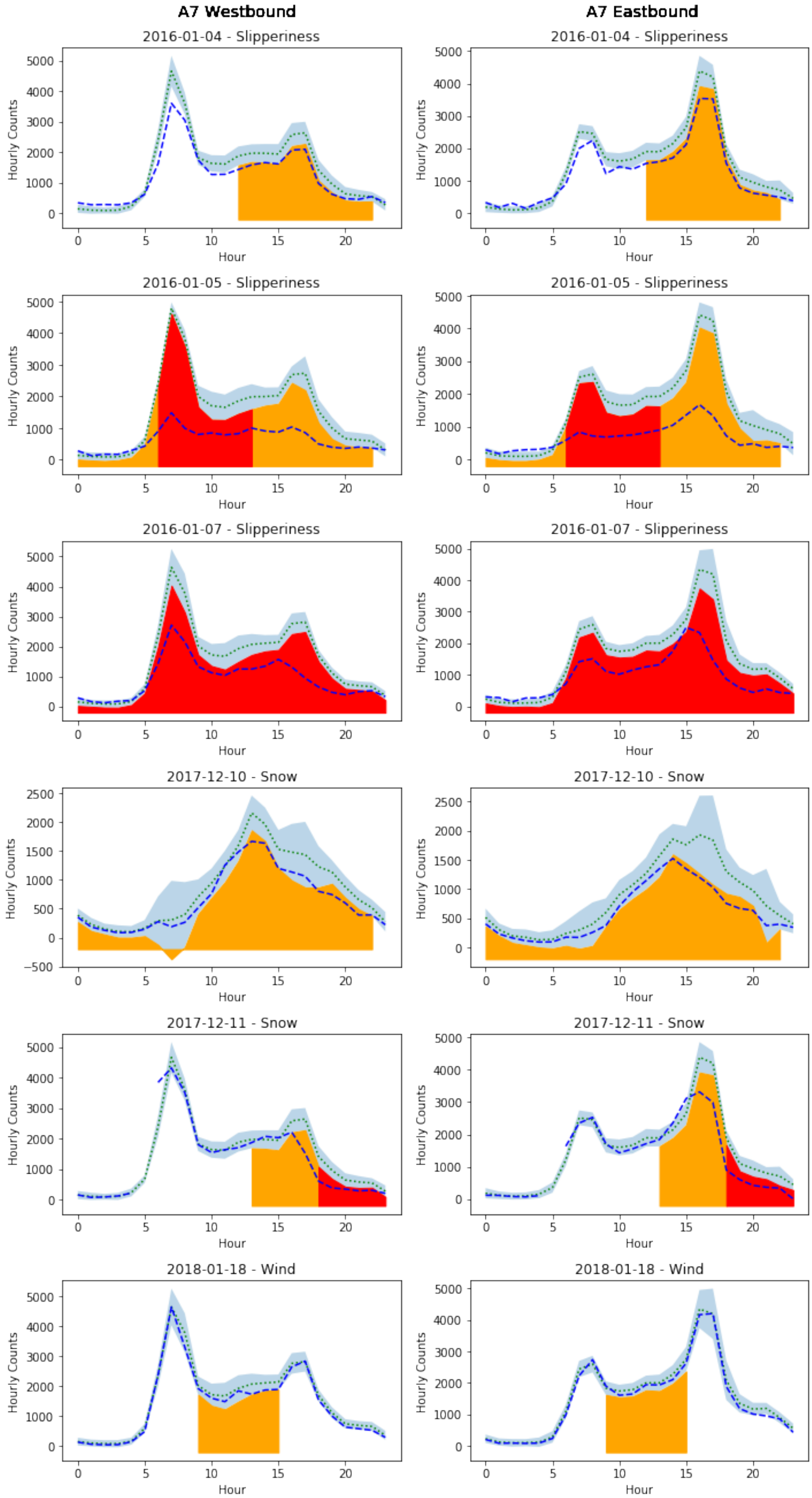

Figure H.8: Case study for the A7

I Reliability

In this Appendix, the plots are found that show the correlation between the reliability of a previous code and the impact on the counts for the next code.

A20 Zuid-Holland

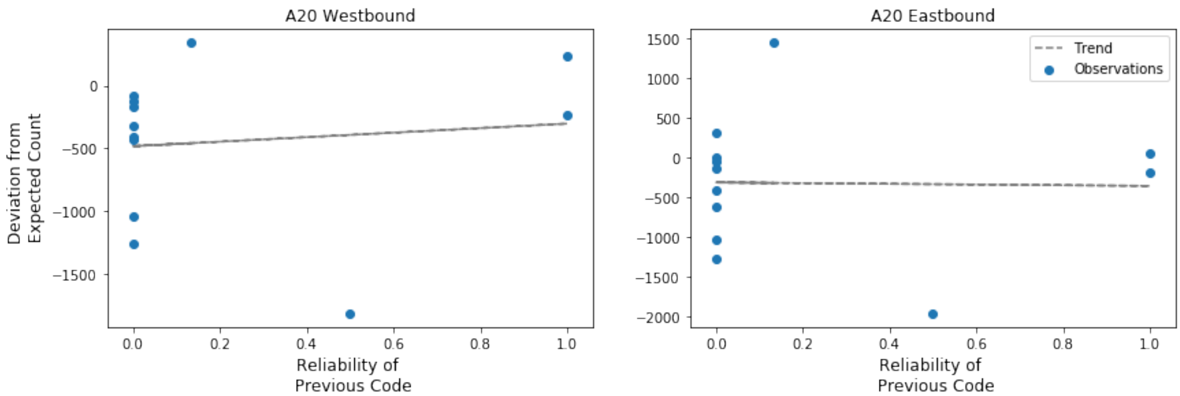

Figure I.1: Reliability of previous code in relation to deviation from expected counts for the A20

A6 Flevoland

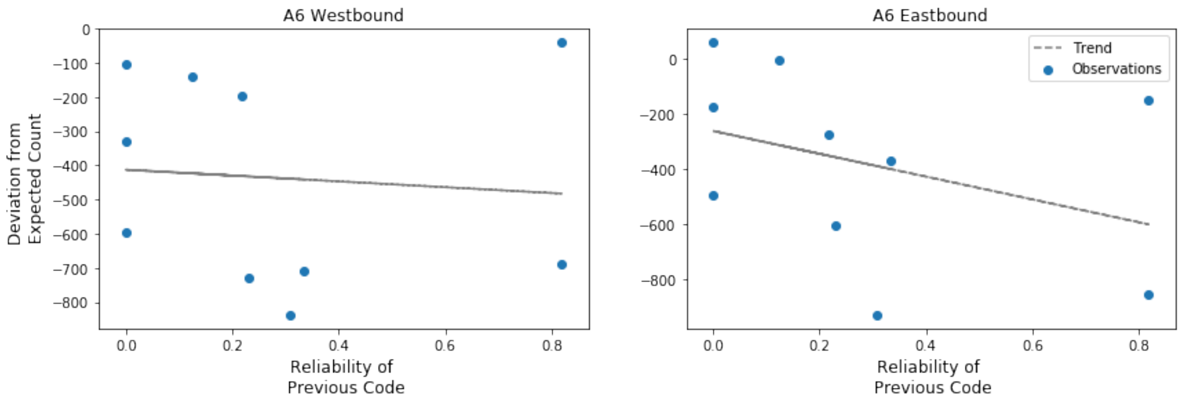

Figure I.2: Reliability of previous code in relation to deviation from expected counts for the A6

A37 Drenthe

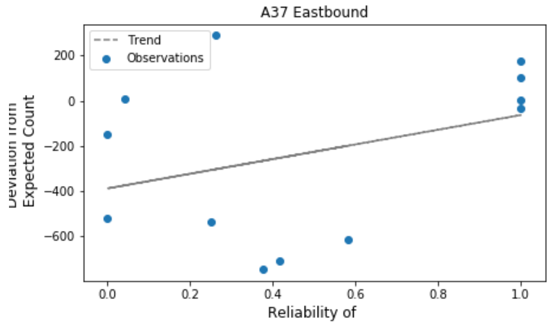

Figure I.3: Reliability of previous code in relation to deviation from expected counts for the A37

A58 Zeeland

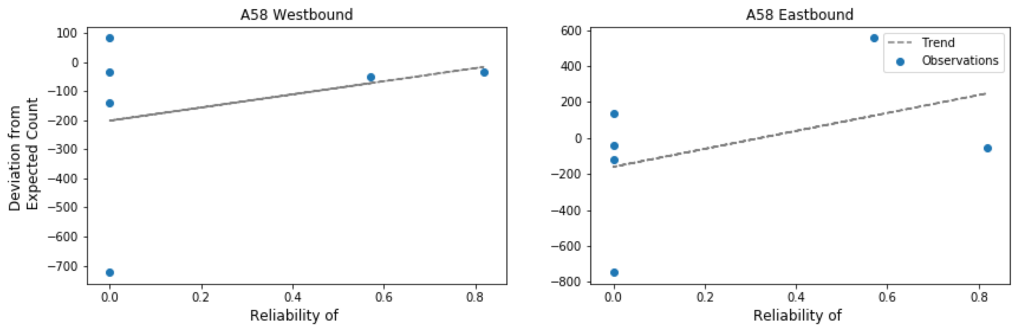

Figure I.4: Reliability of previous code in relation to deviation from expected counts for the A58

A30 Gelderland

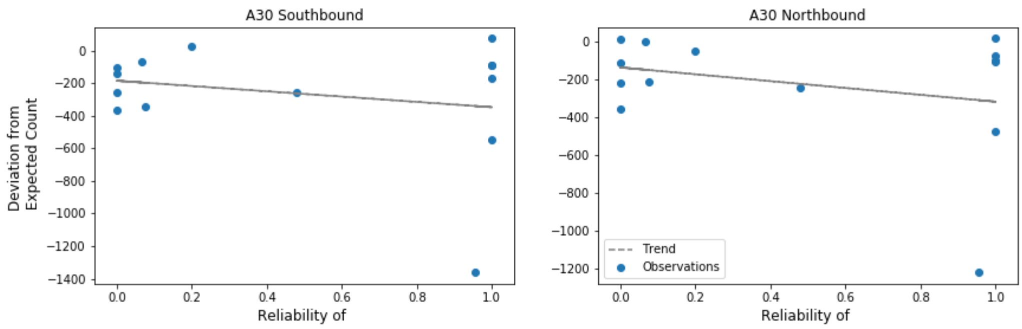

Figure I.5: Reliability of previous code in relation to deviation from expected counts for the A30

A31 Friesland

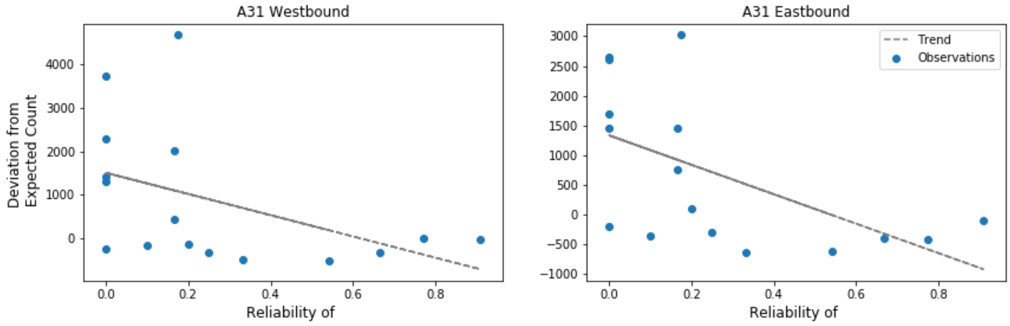

Figure I.6: Reliability of previous code in relation to deviation from expected counts for the A31

A7 Groningen

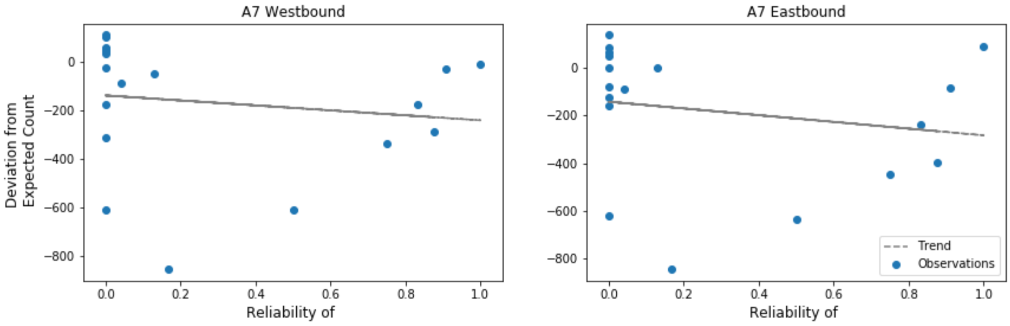

Figure I.7: Reliability of previous code in relation to deviation from expected counts for the A7

J Scientific Paper

Impacts of Weather Codes on Travel Behavior

Jeroen Delfos[1]

Abstract— **In this paper an analysis is presented on the impacts of weather codes on travel behavior. Loop detector data of seven segments in different provinces in the Netherlands are analyzed with regression models with autoregressive errors. Weather codes were found to be significantly influencing travel demand. Particularly codes orange for slipperiness and snow, and codes red for slipperiness, snow and wind yield significant results for most road segments. Furthermore, some trip rescheduling behavior was observed. The unreliability of the previous weather code was found to reduce the impacts for the next weather codes. The analysis of Twitter data was not useful to confirm hypotheses on the incentives for changing travel behavior. As this study is the first revealed preference study into the effects of weather codes, lots of research gaps remain. Secondary roads were not included in the study, which might be affected in other ways than highways. Furthermore, interaction effects between time and weather effects might explain some of the unexplained variability of the model results.**

I. Introduction

Multiple researches have been studying the effects of weather on travel behavior. Both stated preference [2], [8] as well as revealed preference [3], [9] approaches were used, which pointed out that travelers tend to plan less trips during adverse weather conditions. A weather alarm was found to have an additional impact on travel behavior, when this variable was introduced in a stated choice experiment [10]. However, this result has not been verified with a revealed preference study. Insights into the impacts of a weather alarm and weather codes in general provide relevant information for road authorities (e.g. Rijkswaterstaat for the Netherlands), when forecasting traffic volumes during extreme weather conditions. Furthermore, results are interesting for the institute that issues these weather codes (e.g. KNMI for the Netherlands), as this institute hopes that advices that are accompanying a weather code are taken seriously by travelers.

In the Netherlands, weather codes are issued since 1998 in case of expected adverse weather conditions [7]. The currently used systematics are in place since 2015, and follow the decision tree as schematized in Figure 1. Four code colors are available, with green being active when no anomalies are occurring. Code yellow indicates a chance on dangerous weather conditions. Citizens are asked to be alert, especially when in traffic. Code orange is issued when chances are high that dangerous or extreme weather conditions will occur. In this case, citizens are asked to be prepared. Code red is also called a weather alarm, indicating that citizens should take action. Weather conditions under code red can cause damage and injury such that it can be disruptive for the society. Codes are issued when certain threshold values for weather characteristics are exceeded (see KNMI and Ministry of I&E [6, p.26-27]). Before a code red is issued, an impact analysis is conducted by the KNMI in cooperation with departmental coordination centers, the national crisis center, the road authority, the police, fire department and rail authority. Based on the threshold values and impact analysis the KNMI decides on the choice to issue a weather alarm.

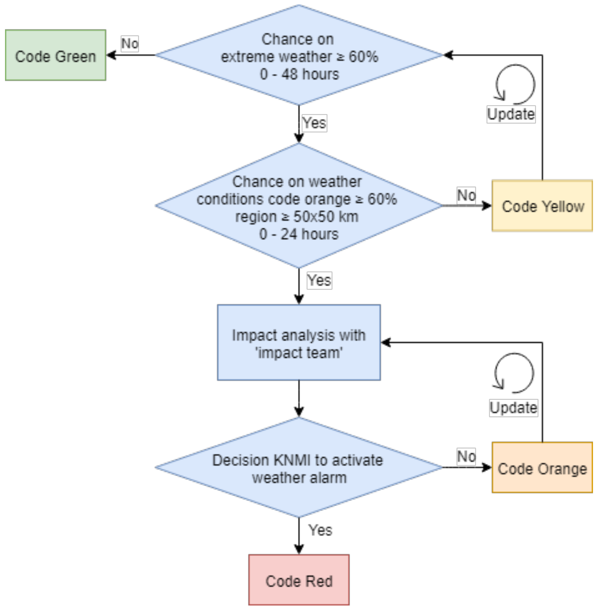

Fig. 1. Decision tree for the activation of weather codes [7]

II. Theoretical Framework

A theoretical approach is adopted to analyze the impacts of weather codes on travel behavior. Hypotheses are tested, that follow from existing literature. Preceding research that studied the impacts of weather conditions on road traffic volumes found that traffic volumes decreased in the case of adverse weather [2], [5]. Furthermore, Stralen, Calvert, and Molin [10] found that travelers travel less when a weather alarm is issued. When we assume that this decreased travel demand is a result of the advice from the KNMI to avoid to make a trip, we can interpret the impact of a weather code as the compliance of a traveler towards the advice that is given along with the weather code. Chorus, Arentze, and Timmermans [1] mentions four factors that influence compliance with a travel advice, being the unreliability of information, the preference for a travel alternative, the relative

*This work was part of a master thesis, executed under the supervision of the TU Delft and in cooperation with CGI

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importance for travel times and the relative importance for travel time uncertainty. This study will take the unreliability of information into account, as this factor can be directly related to the interpretation of the advice as given by the KNMI, while the other factors can be seen as effects of the weather characteristics corresponding with the weather code, rather than effects that are induced by the weather code itself. Therefore, the latter factors are included as an error term in the theoretical model.

Travelers' perception of weather codes is seen as a proxy for unreliability of information. We assume that this perception is formed by the sentiment that is prevailing during a certain weather code and the reliability of a previous weather code. With the reliability we mean the degree to which the measured weather characteristics indeed exceeded the threshold values of a weather code. These two parts are expected to be interrelated, as we expect that the sentiment towards a weather code will be relatively negative when a previous weather code was unreliable. When the previous weather code was unreliable, we expect that people will perceive the next weather code as less reliable.

In this study, we take the choice to make a trip (i.e. frequency choice) and the departure time choice of road users as the dependent variables, representing travel behavior, as these two variables can be observed through traffic counts.

When we schematize the hypotheses that follow from literature and from the stated assumptions, Figure 2 is derived. This framework will be used for structuring the study in this article.

III. Data and Methods

This Chapter will elaborate on the used data and subsequently the methods with which the data is manipulated to come to results with regards to the influences of weather codes on travel behavior. Furthermore, this Chapter will explain

Data

Since this research tries to unravel the effects of weather codes on travel behavior from a revealed preference perspective, revealed preference data is needed. Historical data for traffic counts, weather characteristics and issued weather codes are used for the period of 2015 until April 2018.

Traffic data has been supplied by the Nationale Databank Wegverkeersgegevens (NDW). Vehicle speeds and counts are registered through loop detectors that are integrated in the road surface. The data is aggregated per minute, and is available for all major roads in the Netherlands, on multiple segments.

It is chosen to analyze the main highways of the Netherlands. To choose the segments that will be analyzed, requirements are specified that will help to analyze only segments that will provide insights in the effects of weather codes on travel behavior:

1) The measurement locations must have measurement data in the period between 2015 and now. This period is aligned with the period for which detailed weather code data is available.
2) The measurement locations must be in different provinces. This will make sure that the variety of weather codes is as big as possible, since weather codes are issued per province.
3) The traffic flow on the measurement locations have to be as least as possible influenced by factors other than weather. Roads were congestion and disruptions occur regularly are to a lesser extent suitable for analyzing weather effects on traffic volumes.
4) The measurement location of the traffic flow and the weather characteristics must be in the same region, such that it can be assumed that the weather at a measurement location was similar to the weather at the measurement location for measuring traffic volumes.

The NDW was consulted on requirement three, which resulted in a list of segments that were relatively unaffected by congestion. From this list, the A20, A6, A37, A58, A30, A31 and the A7 were selected as the segments that were the least affected by congestion, while situated in different provinces. For these measurement points, data was available for the years of 2015 to 2018. Furthermore, weather measurement stations were found in no further away than 20km. The measurement locations are depicted in Figure 3

Fig. 3. Measurement Locations for weather (red) and traffic (yellow)

Before traffic data can be used for the proposed analyses the data has to be prepared, in order to exclude factors that are not related to weather, but do influence traffic counts. Firstly, the demand patterns for all segments are visually inspected to spot any anomalies. For example the opening of the A4 in December 2015 led to a decrease in travel demand for the A20. Correction factors are used to correct for this, and other anomalies. This is done by calculating the average counts for the same months as the period of the anomaly, in other years. Subsequently, the factor is calculated by which the period of the anomaly should be factorized in order to have an average count that is the same as the average counts of the periods without anomalies. All hours in the period with anomalies are corrected with this factor. After this, the

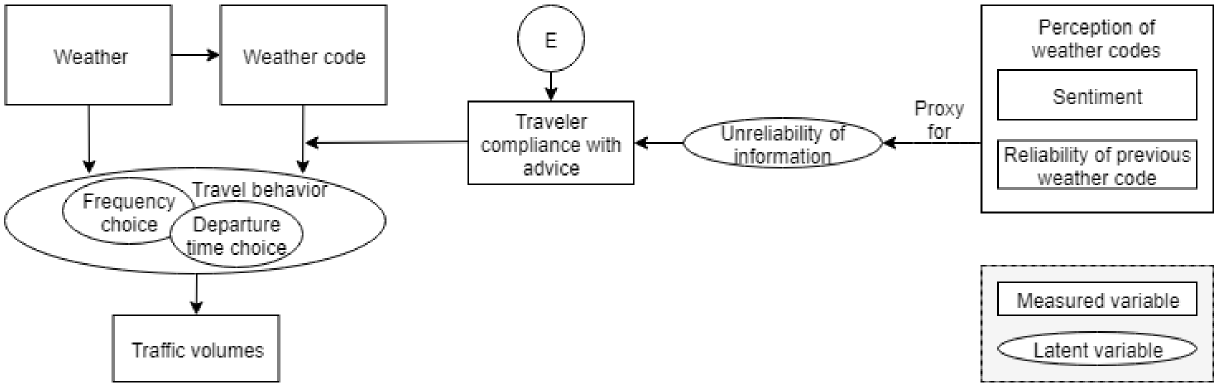

Fig. 2. Theoretical Framework for the influences of weather and weather codes on travel behavior

data is deseasonalized, by correcting the data for daily and weekly patterns. This is necessary in order to avoid that low temperatures, or low amounts of sunshine are linked to low counts, while they are actually linked to night times. Another example is that fog is often occurring during the morning peak. However, fog is not leading to a morning peak, while the time of day is. The deseasonalization of the data follows the following process:

$$
\begin{gathered}
C_t = \frac{1}{N} \textstyle\sum_{i=1}^{N} c_{i,t}, \text{ with } i = 0, 1..., 168 \\
D_t = c_t - C_t
\end{gathered} \tag{1}
$$

With C_t the average count at time t for each hour of the week, N the amount of observations, $c_{i,t}$ the i^{th} observation of counts at time t and D_t the deseasonalized counts at time t.

Weather data was supplied by the KNMI, for the measurement locations of all segments. Average and maximum wind speeds, precipitation, temperature, sunshine duration, horizontal sight, and dummies that indicate whether snow or slipperiness was present were available. With the temperature, precipitation and the dummy for the presence of snow, snow height was calculated and added to the variables as well.

Sentiment data was found on Twitter, when searching for the words 'code' and 'knmi' within the period for which a weather code was active. The data was imported by downloading the full feed of tweets as a text file, as the Twitter API does not allow for accessing more than the first 40 tweets for a certain query. After the text was downloaded, the list of tweets was split into separate tweets which allows for searching for combinations of words, after which irrelevant text was deleted.

The reliability of a weather code was measured by comparing the observed weather characteristics with the threshold values of the issued weather code. When weather characteristics exceeded the threshold values of the issued weather code, the reliability variable was 1, while it was zero if the threshold values were not exceeded. The reliability of a weather code was expressed as the mean value of the reliability over all hours for which a weather code was active, during one day.

Methods

Different methods were used for different parts of the study. Firstly, the influences of weather codes on traffic volumes are statistically tested, in order to be able to assess the impacts of weather codes on trip frequency choice. This is done with linear regression (see Equation (2)), and regression with autoregressive errors, as these methods provide both insights into the significance and impacts of variables. As follows from the theoretical framework, weather variables need to be taken into account when analyzing the impacts of weather codes. For the regression model with autoregressive errors, two model specifications are applied. The first one handles both weather and weather code variables simultaneously (see Equation (3)), yielding the 'best fit' for all included variables. The second model first handles weather variables, and subsequently regresses the weather code variables on the residuals (see Equation (4)). This model specification gives the minimal influences of the weather code variables. This is done to assess the impacts of a weather code under the assumption that travelers are primarily and firstly influenced by the weather itself.

$$
y_t = \sum_{w=1}^{W} \beta_w x_{wt} + \sum_{q=1}^{Q} \beta_q x_{qt} + \epsilon_t \tag{2}
$$

With y_t being the estimated deseasonalized count, β_w and β_q being the coefficients for weather variable w and weather code variables q respectively, x_{wt} and x_{qt} being the observed value for the weather and weather code variables respectively at time t and ϵ_t being the error term at time t which is normally distributed with a zero mean.

$$
\begin{gathered}
y_t = \textstyle\sum_{w=1}^{W} \beta_w x_{wt} + \sum_{q=1}^{Q} \beta_q x_{qt} + u_t \\
u_t = \phi_1 u_{t-1} + \epsilon_t
\end{gathered} \tag{3}
$$

With all symbols having the same meaning as in Equation (2), but with the error term u_t being the autoregressive error term at time t, which is described by the coefficient ϕ_1

times the error term of the previous observation u_{t-1} plus a normally distributed error term ϵ_t.

$$\hat{y}_t = \sum_{w=1}^{W} \beta_w x_{wt} + u_t$$

$$y_t - \hat{y}_t = \sum_{q=1}^{Q} \beta_q x_{qt} + \epsilon_t \tag{4}$$

$$u_t = \phi_1 u_{t-1} + \epsilon_t$$

With all symbols having the same meaning as in Equations (2) and (3), but with $\hat{y}_t$ being the estimate for the regression model with autoregressive errors on weather variables only and $y_t - \hat{y}_t$ representing the residuals.

Secondly, the trip scheduling choice is analyzed by assessing the demand patterns during a set of days for which weather codes were issued and comparing these demand patterns with the expected demand patterns for days without a weather code. Thirdly, the influence of perception of reliability on the impact of weather codes is analyzed, by checking the correlation between the reliability of the previous code with the influence of the next weather code, and statistically testing this with linear regression. Lastly, Twitter data is manually sorted on sentiment, and checked to see whether people developed a certain sentiment towards a weather code because of the perceived reliability.

Thirdly, the influence of reliability on the compliance rate is assessed. By comparing the thresholds of a certain weather code with the actual measured weather conditions, a reliability score can be assigned to each weather code. Subsequently, it can be assessed whether a low reliability of a weather code negatively influences the impact of the next weather code. If the reliability of the previous weather code correlates with the impact of the weather code on traffic counts, chances are high that the reliability of the previous weather code indeed changes the compliance rate of travelers towards the travel advice of a weather code.

Lastly, sentiment can be seen as a proxy for the unreliability of information. Several methods will be used to analyze this sentiment:

1) Counts of words that are often paired with negative sentiment are counted. The occurrence of these 'negative words' can indicate the amount of tweets with a negative sentiment during a day with a weather code.
2) A sample set of tweets will be manually assessed on their sentiment. Subsequently, the prevailing words in the tweets of both neutral and negative sentiment can be compared. These words can then be used as input to determine the sentiment of tweets outside the sample set.
3) A manual inspection of all the tweets can be done if the first two methods do not provide any outcomes. All tweets will be reviewed and labeled with a sentiment by the author of this paper.

For the analysis, three classes are distinguished. A tweet is either positive, negative, or neutral towards the weather code as issued by the KNMI. A positive tweet might for example state that it was a good choice that the KNMI issued a weather code. A negative tweet might for example state that the weather code was not necessary. A neutral tweet does not hold an opinion towards the weather code. An example of this is the statement that the KNMI issued or a code, or a description of the weather circumstances for the day.

IV. Results

This Section will present the results for the analyses on the impacts of weather codes.

Weather Codes and Frequency Choice

The linear regression model yielded significant coefficients for the majority of weather and weather code variables. However, the significance of these results are likely to be overestimated, as autocorrelation was found between the residuals [4]. Durbin-Watson statistics between 0.3 and 0.8 were found, indicating this autocorrelation.

To cope with this autocorrelation, regression with autoregressive errors is performed. Both the simultaneous model of Equation (3) as well as the sequential model of Equation (4) yield significant results, with Durbin-Watson statistics close to 2, indicating that chances are low that the residuals are autocorrelated. Furthermore, the log-likelihood of the simultaneous and the sequential models were closer to zero, indicating a better model fit in comparison to the linear regression model with normal errors.

All seven road segments were analyzed. The amount of times that a weather code yields significant results (i.e. was found to be statistically influencing travel demand), is shown in Figure 4. From this, we can see that codes for slipperiness and snow are most often significant. Codes for thunderstorms and wind are less often impacting travel demand significantly. Furthermore, the expected pattern can be observed with respect to the code color, as codes red are most significant, followed by codes orange. The sequential model gives the lower bound of the influence of weather codes, from which it can be observed that codes orange for slipperiness and snow, and codes red for slipperiness, snow and wind are significant for most road segments.

For weather codes, all the hypotheses are that a weather code will result in less travel demand during the active period of a weather code. However, this is not always the case. Code yellow for snow, orange for thunderstorms, and code yellow, orange and red for wind are yielding unexpected signs. All codes for slipperiness yield the expected sign. Furthermore, the codes orange and red for snow, and codes yellow for thunderstorms yield the expected sign as well. For these codes we can conclude that they have a clear and significant effect on the traffic volumes.

When looking at the KDE plots as depicted in Figure 8, we can see that for the most weather types, the impacts of codes red are higher than codes orange and yellow. A more surprising result can be observed when looking at the differences in densities between the simultaneous and the sequential model. For all the weather codes the sequential model has coefficients that are closer to zero than the coefficients of the simultaneous model, which is logical, since the model specification allows the assignment of measured impacts to the weather variables first. In most of the plots, it can be observed that the sequential model has a more concentrated density, meaning that over the segments, there is more consensus on the impacts of the weather codes.

Weather Codes and Departure Time Choice

The demand pattern for six weather codes days were analyzed. Table I gives a list of the six days, and their corresponding codes. For these days, the hypothesis was tested that travelers will reschedule trips towards a period outside of the period in which a weather code is active. This will result in above average counts for the periods just outside the period in which a the weather code was active. A graphical display of this assumption can be found in Figure 5.

TABLE I
CASE STUDY SELECTION

Weather Code	Date
Slipperiness Orange	04-01-2016
Slipperiness Orange/Red	05-01-2016
Slipperiness Orange/Red	07-01-2016
Snow Orange	10-12-2016
Snow Orange/Red	11-12-2016
Wind Orange/Red	18-01-2016

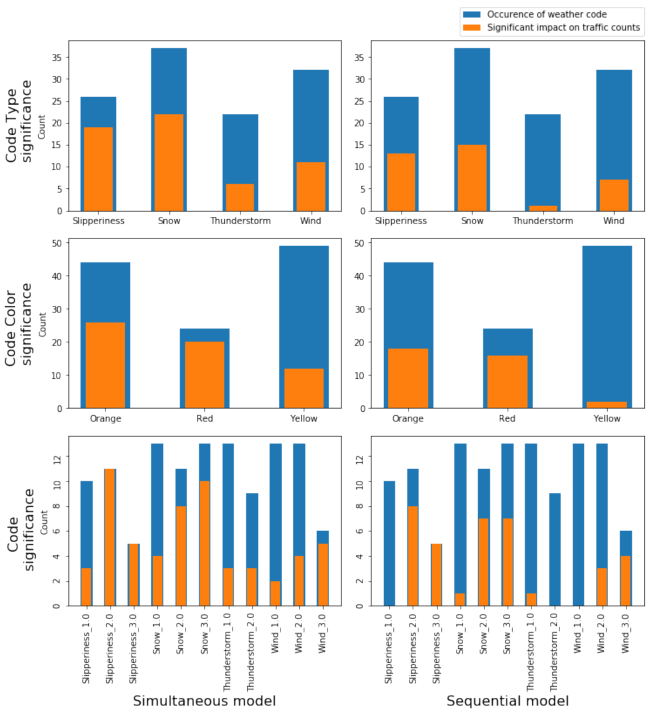

Fig. 4. Significance of weather code variables

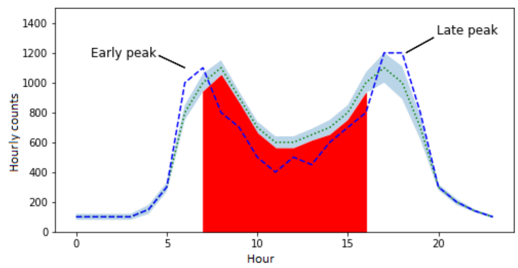

Fig. 5. Graphical representation of the second hypothesis

A few cases can be found in which peaks are slightly moved towards hours in which no code was active, and hereby confirm our hypothesis. For the A20 in the eastbound direction and the A30 in southbound direction on 11-12-2017, a small peak can be observed at around midday, just before the code red is active. A similar effect can be seen for the same date on the A6 in the eastbound direction. However, here the peak is located just inside the period of the code red. It seems that here, travelers decided to travel before the usual evening peak to avoid traffic, instead of avoiding traveling during code red. The A37 yields a similar pattern for 11-12-2017. Here, some travelers chose to travel before the afternoon peak, during code orange. Hereby, these travelers avoided the evening peak as well as traveling in code red. For the code red for wind on 18-01-2018, it can be observed for the A6 in eastbound direction that travelers postponed their trip towards the hours after the weather code was terminated. This effect is to a lesser extend visible for the A30 in northbound direction.

Generally we can see that rescheduling only can be observed in cases of codes red. this is also the case when a code orange is preceding or succeeding the code red. Codes orange themselves do not lead to rescheduling behavior amongst travelers.

The plots for the discussed cases are found in Figure 6.

Perception and Weather Codes

The correlation between the reliability of the previous code and the impact on counts for the next code are checked by plotting the measurements with the reliability and the deviation from the expected counts on the x-axis and y-axis respectively. When combining all the observations of all segments, Figure 7 is derived. Here we can see a relatively high amount of positive deviations for reliability values between 0 and 0.2. When we statistically test the trend line, the trend coefficient yields significance on a 95% confidence interval, with a p-value of 0.034. This implies that low reliability for the previous weather code impacts the compliance of travelers towards the advices given during weather codes.

Three methods were used to analyze Twitter data. The first two methods as mentioned in Section III were not able to provide results. This was due to the fact that the query gave a relatively low amount of tweets, from which most tweets were neutral statements. Therefore, it was difficult to attribute characteristics to the negative tweets, since there were only

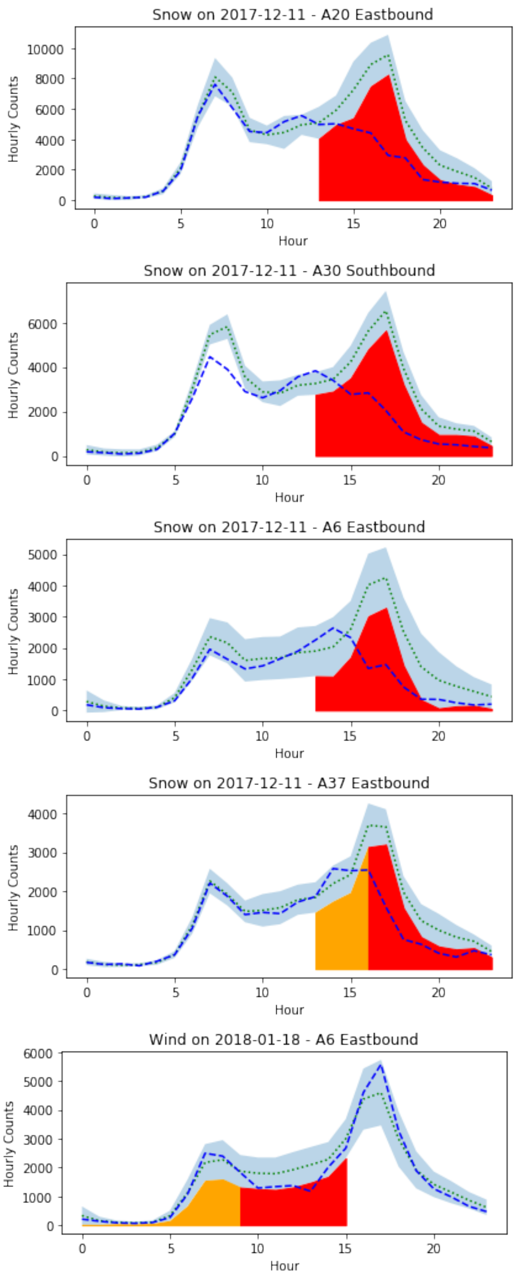

Fig. 6. Travel demand patterns for case study days

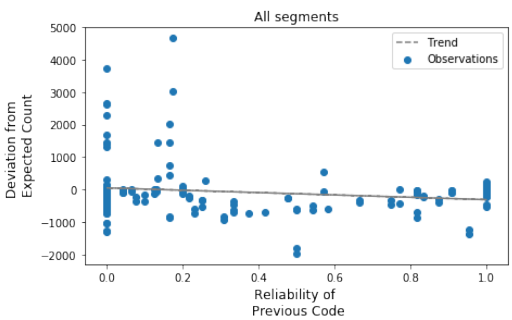

Fig. 7. Reliability of previous code in relation to deviation from expected counts for all road segments

a few negative tweets found. Therefore, the third, manual, method was used to analyze the tweets.

Twitter data from three dates were, which differ in code characteristics (see Table II), is analyzed. For these days, respectively 206, 725 and 507 tweets were available. The tweets that were assessed to be negative with regards to the weather code are presented in Table III, at the end of this paper. For 09-12-2017 only two negative tweets were found that had both the words 'code' and 'knmi' in them. For 11-12-2017 this number was 10, while 18-01-2018 yields 6 negative tweets. Some tweets are about the unreliability of weather codes. In other tweets, people express that they don't agree with the danger that the KNMI warns for. Besides this, several tweets express their dissatisfaction on the timing of the code red.

TABLE II

SELECTED DAYS FOR THE SENTIMENT ANALYSIS

Date	Reliability previous code	Reliability code	Impact	Weather code
09-12-2017	low	medium	medium	Snow/slipperiness orange
11-12-2017	medium	high	high	Snow/slipperiness orange/red
18-01-2017	low	low	low	Wind orange/red

With a dataset as small as 18 observations it is difficult to confirm or deny the hypotheses. It can be seen that for 18-01-2018 half of the negative tweets were complaints about the timing of the code. For this day, we see a low reliability, although there was in fact a very heavy storm. This can be explained by the used method for measuring reliability, which takes into the average reliability over all hours that the code was active. If a code is active longer than necessary, reliability is going down.

The most negative tweets are found for 11-12-2017. This contradicts the hypothesis that more negative tweets will be observed at weather codes with a low reliability, since the reliability for the code on 11-12-2017 was high. Since the total amount of tweets were highest for this day, the amount of negative sentiment might be more related to the total attention that is given to the weather code.

V. CONCLUSION

This paper looks at the influences of weather codes on travel behavior from three perspectives that follow from the theoretical framework of Figure 2. First, the impacts of a weather code on trip frequency choice was assessed. As a linear regression model yields unreliable results, due to autocorrelated errors, two regression models with autoregressive errors were used. The first model simultaneously modeled weather and weather code variables, resulting in a 'best fit' for the variable coefficients. From this model we can conclude that weather codes have a significant influence on travel demand during the hours for which a weather code was active. Weather codes for slipperiness and snow were most often significant. Codes red were most often significant, followed by codes orange. The same patterns hold for the model for which weather and weather code variables were modeled sequentially, with a regression model with autoregressive errors, and a linear regression model respectively. From this model we obtained the minimal influence of weather codes. The same patterns hold as for the simultaneous model. However, a decreased influence can be observed, leading to only codes orange for slipperiness and snow and codes red for slipperiness, snow and wind to be significant for most occurrences.

Although a decrease in travel demand can be observed for hours with one of these weather codes, this does not necessarily mean that travelers canceled trips. In theory, the decrease in counts might be compensated by an increase in trips outside the time period for which a weather code was active. Therefore, the departure time choice was assessed as the second perspective. From visual inspections of the demand patterns on days with codes orange for slipperiness and snow, and codes red for slipperiness, snow and wind, it can be concluded that rescheduled trips do not compensate the decrease in counts for hours with a weather code. This means that travelers are actually canceling trips because of weather codes. However, some rescheduling activity can be observed, as cases were found in which counts were above average for the hours just before or just after the active period of a weather code. With this, we can conclude that both the departure choice as well as frequency choice are affected by weather codes.

The third perspective is that of the influence of perception of reliability on the compliance towards advice, which in turn is assumed to influence the impact of weather codes on travel behavior. The reliability of the previous weather code was found to be affecting the impact of the next weather code. A low probability of the previous weather code is often found to coincide with a low impact of the next weather code on traffic counts. Furthermore, sentiment data is analyzed from Twitter. A set of 18 tweets was found with a negative sentiment regarding weather codes, out of a total of 1438 tweets for three days with a weather code. With this relatively small dataset, drawing conclusions is hard. It could however be observed that a low reliability does not always lead to more negative sentiment.

For weather code orange and red for slipperiness, orange and red for snow and red for wind, the majority of road segments yielded significant impacts on travel demand, with on average respectively 331, 575, 287, 702 and 500 counts less when modeling weather and weather codes simultaneously. When modeling these variables sequentially, respectively 125, 139, 99, 301 and 296 less counts were observed. Although rescheduling behavior is observed, this behavior does not compensate for the trips that were not undertaken during the active period of a weather code. This means that part of the travelers takes the warnings of weather codes seriously, and cancel trips. However, the majority of travelers is not influenced by weather codes. The analysis on reliability of weather codes shows that this incompliance with advices of the KNMI could partly be due to perceived unreliability. Although efforts were made, additional reasons for incompliance were not found in tweets that had a negative sentiment towards weather codes.

VI. Discussion

This paper adds knowledge to the research field of the impacts of weather related circumstances on travel behavior. It does this by looking at revealed preference data, which has not been done when analyzing effects of weather codes, or more generally, weather related travel advices.

The analyses focus on travel behavior on highway roads of the Netherlands. Travel behavior on secondary roads might differ from the observed patterns. Travel behavior changes under the effect of weather codes is expected to yield different results for other modes as well. The research in this paper does not provide insights in these differences.

While travel demand patterns can be influenced by a number of factors, this research included only some factors. This leads to limitations for the interpretation of the value of the observed absolute changes in demand.

Thunderstorms and slipperiness were included in the weather variables as dummies. Historical data from the KNMI did not allow us to differentiate between 'some thunder' and 'heavy thunder'. First of all, this might have reduced the significance of the results for these weather variables. Secondly, this has implications for the way we can measure the reliability of weather codes for these weather types.

VII. Recommendations

The approach taken in this research provided new insights, but also had its limitations. The wish to include data for different provinces, which allowed us to assess more weather codes, led to the choice to only include highway segments. As demand patterns can be different for secondary roads, it would be interesting to do similar analyses for these secondary roads. This statement is supported by Stralen, Calvert, and Molin [10], who found that a weather alarm was of significant influence for the choice of avoiding the motorway.

Autoregression played a part in the models with which the impacts of weather codes on travel demand were calculated. However, it is likely that there time plays a bigger role in the composition of travel demand. For example, the combination of weather characteristics with time might have a specific effect on travel demand. Besides this, combinations of different weather characteristics might alter travel demand. We could for example hypothesize that the combination of warm weather and sunshine leads to more people traveling towards for example beaches.

The research in this report does not differentiate on travel purpose. Stated preference work points out that differences can be measured between changes in travel behavior for utilitarian and recreational trips, when varying the weather circumstances [10]. We can imagine that people who feel less obligated to make a trip are more likely to be influenced by weather codes as well. The research in this report does not touch upon such hypotheses.

The research in this report assumes that travelers are primarily influenced by weather, and subsequently can be additionally influenced by weather codes. However, no research has been found that confirms this assumption by means of a stated choice experiment. It's recommended for future research to look into the causal relationships into the field of weather, weather codes and their impacts on travel behavior.

Although substantial efforts were made, the research in this report yielded summary conclusions with respect to the relation between sentiment and compliances rates. It proved to be hard to use Twitter data for this purpose. However, the insights that the research aimed to give might be valuable for insights into the best way of communicating about the weather codes. Furthermore, insights into the motivations for the choice of travelers to (not) make a trip during the active period of a weather code might be revealed if the sentiment amongst travelers can be analyzed. Future research might be conducted with the help of surveys, that collect data during, or just after the occurrence of a weather code. This survey should be aimed at revealing travelers opinions with regards to the KNMI issuing the code and the motivations for (not) making a trip during a weather code. On the other hand, artificial intelligence (AI) is increasingly powerful in analyzing text, which might make it possible to analyze tweets more accurately in the future.

The KNMI states that it hopes that advices that are given with weather codes are taken seriously by travelers. As seen in the analyses of this report, low reliability of the previous weather code is often paired with a low compliance rate towards travel advices. As the compliance rate is seen as a proxy for how serious travelers take the advice of the KNMI, this means that it is important for the KNMI that weather codes are reliable. Making the weather code more location specific and more time specific might be helpful for this reliability. Nowadays, weather codes are issued per province, while extreme weather can occur very local. Furthermore, the timing of a weather code is often unclear. Even the official documentation of the KNMI does not always provide an answer on the precise activation time of a weather code. This makes it harder for travelers to reschedule their trip towards a time outside the activation period.

For the RWS, we can conclude that, as some weather codes influence travel behavior, weather codes are a valuable variable to include in traffic forecasting models. The RWS can expect less traffic in the case of weather codes red for slipperiness, snow and wind, and for codes orange for slipperiness and snow. If this updated traffic forecasting model is combined with models that can predict congestion or chances on accidents, the chances on congestion and accidents during weather codes can be more accurately predicted.

As the RWS is aiming to reduce the amount of trips during the active period of weather codes, it might be useful to search for other ways to reduce the amount of trips during extreme weather. The weather code and its advices are reducing the amount of trips, but still the larger share of trips is undertaken. Apparently, the majority of travelers is not willing to change travel behavior due to advises from the KNMI.

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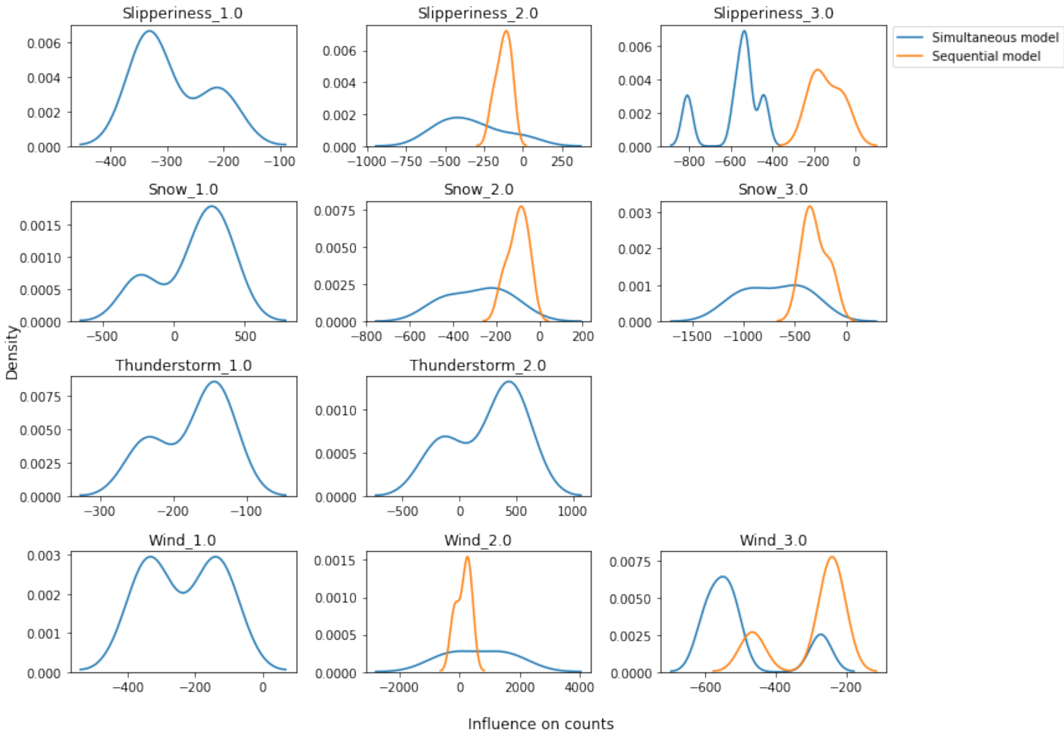

Fig. 8. KDE for weather code variables

TABLE III
LIST OF NEGATIVE TWEETS DURING THE SELECTED DATES WITH THE WORDS 'CODE' AND 'KNMI'

Date	Negative Tweet
09-12-2017	code oranje. dan weet je dus dat niets maar dan ook niets gebeurd meestal.
	geen paniek. het komt geregeld voor dat een code oranje voorbarig is gebleken en dat het toch nog een prachtige, zonnige dag werd.
11-12-2017	anno 2017. zoek ”winter 1963”. we zijn volgens mij de weg kwijt. code rood = zoveel overlast dat de maatschappij ontwrichtend kan zijn.
	overal is er chaos met sneeuw en hier ligt het alweer te smelten. gisteren code oranje en gladde wegen, maar ik heb helemaal niks gemerkt.
	code rood afgegeven door knmi... nou hier in fryslan ligt niets hoor...
	code rood. code rood! code rood!!! code rooooooooood!!!!!! serieuze vraag aan het knmi: is er ook nog een code zwart, voor ”nu zijn jullie allemaal serieus fucked”? want code rood voor een paar sneeuwvlokken maak je je wereldwijd toch een piepklein beetje belachelijk mee...
	okay. code rood knmi. klinkt alsof nederland vergaat. wat nu? wat betekent code rood in landen waar dagelijks zo'n dik pak sneeuw ligt? zoveel vragen!
	komt het knmi even aanzetten met code rood. hele dag nog heen sneeuwvlok gevallen
	typisch nederlands: mensen afraden de weg op te gaan, aanraden thuis te werken. maar dan niet de code rood afkondigen die dit rechtvaardigt, knmi
	het knmi maakt de mensen weer is gek met hun code oranje! de meeste wegen zijn heel goed begaanbaar! maar natuurlijk zullen collega's die ver af wonen er weer zijn en diegene die relatief dichtbij wonen zeggen dat ze er niet doorkomen...
	ohh.. ahhh...men waar blijft de voorspelde code rood?!?!?!?
	knmi geeft opnieuw code oranje af wegens verwachte sneeuwval. een instantie die opgedoekt kan worden. steeds weer code oranje of rood en gebeurt er niets. dus opdoeken met de instantie die verkeerde info verstrekt en mensen op het verkeerde been zet
18-01-2018	de volgende keer moet er bij deze extreme weersomstandigheden eerder code rood worden afgegeven. daarnaast moet de overheid de scholen verplicht gesloten houden, en een verbod van vrachtwagens om te rijden! alleen waarschuwen werkt niet!
	het is hier nu bijna windstil. gaan we die code ook nog even publiekelijk intrekken a.u.b.?
	knmi, zijn jullie vergeten code rood in te trekken?
	trekt maar in weer in die code rood voor vleuten/de meern/utrecht het valt hier nu reuze mee
	hee, knmi, eerst code oranje afkondigen, waarmee velen naar school/werk moeten, en dan code rood waardoor iedereen thuis moet blijven? beetje moeilijk als je al op werk/school bent!
	knmi met die weeralarmen geloof ik niet meer. paniekzaaierij. wat vroeger winter was met een dagje sneeuw is vandaag de dag ineens een code rood waard...

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