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Weather and daily mobility in international perspective: A cross-comparison of Dutch, Norwegian and Swedish city regions

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ABSTRACT

With climate change, weather has emerged as an important theme in transport research and planning. Although recent studies demonstrate profound weather effects on mobility in single case study areas, international cross-comparisons are required to reveal how effects differ between cities with different transport and climate regimes. This paper provides an international cross-comparison of the simultaneous effects of weather on destination choices, distances, trip chaining, and transport modes in the urban regions of Utrecht (Netherlands), Oslo and Stavanger (Norway), and Stockholm (Sweden). Hereto, regional subsamples of national travel survey data were linked to meteorological records for the three respective countries and analysed in generalised Structural Equation Models. Our findings generally indicate that light, calm, dry and warm atmospheric conditions may positively affect cycling and the selection of outdoor leisure destinations, while cold and to a lesser extent wet and windy weather conditions reduce cycling and enhance car use and travel optimising strategies like trip chaining, to reduce weather exposures. A positive effect of air temperature on cycling flattens out above 20–25 °C in most of our study areas, but hot weather does not seem to reduce cycling strongly. However, our findings also show considerable regional differences in the effects of weather on mobility. Both general effects and differences are interpreted in relation to geographical context, transport and land use, climate conditions, cultures, habits and adaptations and are discussed to formulate policies to mitigate active transport mode users' exposures to adverse weather and make walking and cycling (even more) year-round modes.

1. Introduction

Climate and transport are complexly related (Chapman, 2007). On the one hand, motorised transport is one of the largest contributors to global climate change: it roughly accounts for 23% of all anthropogenic CO_2 emissions worldwide and even 30% in developed countries (UNECE, 2018). On the other hand, many transport activities – especially walking and cycling – are weather-exposed and highly sensitive to changes in climate conditions. So far, the majority of attention has gone out to the effects of weather extremes such as heat, drought, heavy precipitation, flooding and storm on the performance and safety of transport systems

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(Transportation Research Board, 2008; Jaroszweski et al., 2010). Yet, increasingly scholars have also started looking at the effects of more gradual changes in everyday weather conditions on mobility decisions such as transport mode and destination choices, that could over time have profound impacts on mobility patterns and emissions (Sabir, 2011; Böcker et al., 2013; Creemers et al., 2014; Liu et al., 2015). Such knowledge is becoming more relevant given the fact of global warming and more importantly to support more effective policy and planning strategies that combine mitigation and adaptation elements (IPCC, 2018) in the transport sector.

The existing knowledge on weather and daily mobility – including from the Dutch (e.g. Sabir, 2011; Creemers et al., 2014; Thomas et al., 2013; Böcker and Thorsson, 2014), Norwegian (e.g. Aaheim and Hauge, 2005) and Swedish contexts (e.g. Bergström and Magnussen, 2003; Liu et al., 2015) examined in this paper – centres around the effects of weather on transport mode choices, usually based on (national) travel survey data linked to meteorological data from nearby weather stations. Findings generally indicate that warm, dry, calm and sunny weather stimulate usage of active (especially cycling) over motorised transport modes (especially car use), with effects generally being larger for recreational than for utilitarian purposes. Regarding temperature, some studies find non-linear bell-shaped effects that indicate that not only cold but also hot temperatures above optimums ranging from 24° to 33 °C decrease walking in Montpellier, VT (Aultman-Hall et al., 2009), Knoxville, TN (Burchfield et al., 2012) and cycling in Melbourne, Australia (e.g. Phung and Rose, 2008), Montreal, Canada (Miranda-Moreno and Nosal, 2011), Boulder, CO (Lewin, 2011), Portland, OR and Brisbane, Australia (Ahmed et al., 2012), Rotterdam, the Netherlands (Böcker and Thorsson, 2014) and Washington, DC (Gebhart and Noland, 2014). Others use thermal comfort indicators that combine air temperature with wind speed, humidity and solar radiation to demonstrate that thermal conditions are perceived as more than air temperature alone (Creemers et al., 2014). While most studies analyse only weather effects on mobility at the moment of travel, some show that weather variables, such as precipitation, also have *lag* and *lead effects* (Gebhart and Noland, 2014; Zhao et al., 2018).

Mobility decisions other than transport mode choices have been studied less extensively. Some find positive effects of temperature and negative effects of precipitation *on trip generation* in the Netherlands (Cools et al., 2010), Scotland (Hassan and Barker, 1999) and Melbourne, Australia (Keay and Simmonds, 2005), *on travel distance* in Norway (e.g. Aaheim and Hauge, 2005) and *on travel time* in Rotterdam, the Netherlands (e.g. Böcker and Thorsson, 2014). Others point at the significance of weather for participation in different types of activities. Warm and dry weather encourages outdoor active leisure activities around the world (e.g. Tucker and Gilliland, 2007; Chan and Ryan, 2009) and attendances of outdoor destinations in Chicago, IL (Dwyer, 1988) and a Tokyo satellite city (Thorsson et al., 2007). Cold weather and precipitation increase time spent on home-based indoor activities such as media consumption (Spinney and Millward, 2011 – in Halifax, Canada). Finally, Liu et al. (2015) find in Sweden that weather may even affect the way people spatiotemporally structure trips into more or less complex chains.

While the above-documented studies have vastly improved our understanding of weather effects on daily mobility especially over the last decade, two main issues remain under-investigated. First, there is a need for a better understanding of the potentially differential effects of weather on mobility decisions between cities, regions, countries and societies. In a literature review Böcker et al. (2013) bring together the findings from various geographical contexts. The review informally establishes a rough geographical pattern of possibly stronger day-to-day weather effects on mobility in temperate (maritime) climates, as opposed to possibly stronger seasonal mobility variances in continental climates that often feature cold (snowy) winters and hot summers. However, the authors stress that in order to confirm these and possible other geographical heterogeneities, international comparison studies are urgently required that utilise a uniform research design and model framework to analyse the effects of weather on mobility across different societal and climate contexts. While such comparison studies demonstrate their usefulness in related fields like urban climatology and biometeorology (e.g. Thorsson et al., 2007), to the authors' knowledge examples are still currently lacking in the field of weather and mobility.

A second knowledge need is for an integrated analysis of the simultaneous effects of weather on different mobility decisions. Most studies analyse the effects of weather on just one aspect of travel behaviour, or they address multiple but in separate models. This is striking as mobility choices such as transport mode choices, trip purposes, and distances are intrinsically interrelated. Liu et al. (2015) provide one example of a more integrated analysis. Based on Swedish national travel survey data examined in Structural Equation Models, they conclude that the effects of daily weather on a wide range of daily aggregated activity travel behaviours become more accentuated when analysed simultaneously. To the authors' knowledge, such integrated analysis on the trip level linked to hourly weather conditions is currently still lacking.

To address these knowledge needs, this paper examines the simultaneous effects of weather on interrelated mobility decisions regarding trip purpose, trip distance, trip chaining, and transport mode choice in Dutch, Norwegian and Swedish city regions. To establish the endogeneities between different travel behaviours and to analyse the simultaneous weather effects on these, a generalised Structural Equation Modelling (GSEM) technique in the statistical software package Stata has been used. For the analyses we draw on regional subsamples of national travel survey data for the greater city regions of Utrecht (Netherlands), Oslo, Stavanger (Norway), Stockholm (Sweden), joined with hourly meteorological records from nearby weather stations. The remainder of this paper is structured as follows. The second section will introduce and discuss our case study areas, data and modelling techniques. The third section presents our findings and discusses these in relation to the literature above. The final section provides a conclusion and more general discussion on the significance of this study, its limitations, and future research recommendations.

2. Research design

2.1. Study areas

This study is situated in four cities and their surrounding municipalities: Oslo and Stavanger in Norway, Stockholm in Sweden, and Utrecht in the Netherlands (see Fig. 1). Oslo is the capital and most populous urban region of Norway, as well as the nation's

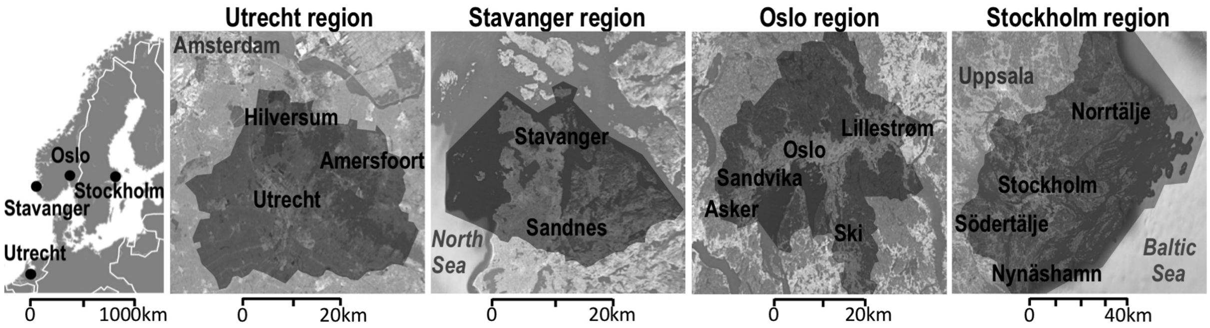

Fig. 1. Geographical situation and demarcation of selected city regions (©Google).

economic and political centre. Situated in the southeast of Norway at the inland end of a stretchy sheltered bay on hilliness terrains with elevation differences up to 500 m, Oslo has a humid continental climate with warm humid summers (highs around 22 °C; lows around 12 °C), cold winters (highs around −2 °C; lows around −7 °C), and 763 mm precipitation annually (MET, 2015). Stavanger together with neighbouring Sandnes forms Norway's third-most populous urban region and its centre for the oil sector. Situated at the weather-exposed west coast of Norway on hilliness terrains with elevation differences up to 400 m, Stavanger has a maritime climate with relatively mild summers (highs around 19 °C; lows around 12 °C) and winters (highs around 3 °C; lows around −1 °C), and 1,180 mm precipitation annually (MET, 2015). Stockholm is Sweden's capital, economic and political centre and most populous urban region. Situated at Sweden's Baltic east coast on sheltered water-rich terrains with elevation differences up to 100 m, Stockholm has a humid continental climate with warm humid summers (highs around 22 °C; lows around 13 °C), cold winters (highs around −1 °C; lows around −5 °C), and 539 mm of precipitation annually (SMHI, 2012). Utrecht is the fourth-most populous city in the Netherlands and is part of the economically significant and populous Dutch metropolitan Randstad Conurbation. Located in flat lowlands, inland, but in relatively close proximity (50 km) to the Dutch western North-Sea coast, Utrecht has a maritime climate with warm summers (highs around 23 °C; lows around 13 °C), mild winters (highs 6 °C; lows 0 °C), and 833 mm of precipitation annually (KNMI, 2015). Weather conditions in all city regions experienced by the respondents during the respective survey periods are roughly in accordance to the above-described seasonal numbers, although all regions have also been subjected to some notable temperature extremes, such as temperatures down to −18.3 °C even in Utrecht and up to 32.5 °C even in Oslo (Table 1).

The rationale for selecting these four city regions is fourfold. First, the four regions make for an interesting comparison of different climate conditions. The areas span across different inland and coastal variations of two world climate zones, some with strong seasonal variations (Oslo, Stockholm), while others being more heavily subjected to daily fluctuations of rain, sunshine clouds and wind (Utrecht and especially Stavanger). Second the international comparison of these four city regions, allows us to explore if and how cultural differences between Norway, Sweden and the Netherlands, such as cycling and outdoors cultures, play a role in differences in the effects of weather on mobility. Third, the four study areas feature different types of land use patterns and transport systems (see descriptive statistics on density and modal split in Table 1). Stavanger is a lower-density urban region that is highly dominated by car use. Public transport is minimal and subjected to a negative image. Oslo, Utrecht and Stockholm are more compactly designed, although different in size and with different transport systems. All three have just under half of all trips made by car. Utrecht boasts a large share of cycling. Because cycling is the most weather-exposed transport mode, this may have considerable implications for the effects of weather on mobility. Stockholm and Oslo have the majority of non-car trips made by public transport. Public transport demand may also be weather sensitive due to the weather-exposed access and egress part from a door-to-door perspective (e.g. Singhal et al., 2014; Arana et al., 2014). A final reason for selecting these case study areas is that all demonstrate active policy agendas on sustainable transportation and climate change adaptation.

2.2. Data

This study draws on trip-based national travel survey data from Norway (2013–2014), Sweden (2011) and the Netherlands (2010–2012), collected for one day per respondent via self-reported internet surveys (in the Netherlands[2]) or via telephone interviews (in Norway and Sweden). Based on the residential postal code, regional subsamples of these datasets are selected for the regions (see Fig. 1) around Utrecht (N = 4413 respondents/8972 trips), Stockholm (N = 2087 respondents/4650 trips), Oslo (N = 6454 respondents/14,601 trips) and Stavanger (N = 1981 respondents/5454 trips). Respondents under the age of 18 are filtered out. We focus on trips made by foot, bicycle, public transport and car. Rarer uses of other transport modes (< 2% in all datasets), such as moped, motorcycle, taxi or airplane are filtered out. Additionally, because of our focus on daily mobility, trips abroad are filtered out, as well as trips longer than 250 km. Return trips back home – except for loop-trips originating from and returning home – are also filtered out to avoid double-counting, and because mobility decisions, such as the transport mode and distance, have usually been made in prior trips.

[2] If respondents could not respond via Internet, data were collected through telephone interviews or home visit interviews (if in addition to no Internet also no telephone number is available).

Table 1
Variable descriptives.

		Utrecht (NLD)N = 4413 resp.N = 8972 trips				**Oslo (NOR)**N = 6454 resp.N = 14601 trips				**Stavanger (NOR)**N = 1981 resp.N = 5454 trips				**Stockholm (SWE)**N = 2087resp.N = 4650 trips			
		mean / %	sd	min	max	mean / %	sd	min	max	mean / %	sd	min	max	mean / %	sd	min	max
Independent variables– *at respondent level*																	
Age	(years)	47.4	16.3	18	94	48.1	16.9	18	92	49.3	15.7	18	92	49.2	16.7	18.0	84.0
Gender	male	46.9%				48.8%				51.8%				45.5%			
Work [a]	Fulltime	45.4%				64.1%				64.1%				65.2%			
Hh-type	Single	18.1%				22.0%				18.5%				25.1%			
	Couple	34.5%				34.7%				34.6%				41.0%			
	Family/other	47.4%				43.2%				46.9%				34.0%			
Hh-income [b]	Lower	12.3%				13.2%				9.2%				9.9%			
	Middle	37.1%				28.2%				26.9%				22.3%			
	Higher	50.5%				47.8%				54.4%				41.6%			
	Unknown	0.1%				10.8%				9.5%				26.2%			
Education [c]	Lower	21.8%				5.5%				6.3%				n/a			
	Middle	32.4%				28.1%				34.3%				n/a			
	Higher	45.4%				66.3%				59.4%				n/a			
Cars in hh	(# of cars)	1.3	0.8	0	10	1.1	0.8	0	≥3	1.4	0.7	0	≥3	1.2	0.8	0.0	7.0
Bicycle	yes	93.6%				75.2%				79.7%				n/a			
Pop. density	(1000 inh./ km^2)	3.6	3.3	0.0	13.2	4.1	4.8	0.0	18.1	1.9	1.5	0.0	6.2	4.8	7.3	0.0	38.8
– *at trip level*																	
Weekend	Yes	21.3%				19.1%				19.6%				22.8%			
Peak	Morning	19.6%				20.4%				19.0%				14.3%			
	Evening	13.8%				19.4%				18.0%				13.0%			
Night time	12AM-6AM	0.9%				1.3%				1.6%				2.8%			
Darkness	yes	17.2%				24.0%				22.8%				24.0%			
Air temp.	(hourly avg.)	10.9	7.3	−18.3	32.0	8.8	8.4	−18.3	32.5	10.3	5.9	−5.4	29.9	6.5	7.9	−28.6	27.9
Windspeed	(hourly avg.)	3.7	1.8	0.0	12.0	2.7	1.6	0.0	22.0	5.3	3.2	0.0	26.1	3.7	1.9	0.0	15.2
Rainfall	yes	20.4%				10.1%				17.6%				9.4%			
Snowfall	yes	1.3%				2.1%				0.3%				5.3%			
Dependent variables– *at trip level*																	
Purpose	Work/study	27.3%				28.8%				28.0%				24.9%			
	errands	25.0%				29.7%				31.1%				28.1%			
	Social	10.4%				8.0%				8.5%				7.9%			
	Leisure outdoor	9.2%				11.5%				10.1%				16.9%			
	Leisure other	28.2%				21.9%				22.3%				22.2%			

(*continued on next page*)

Table 1 (*continued*)

		Utrecht (NLD)N = 4413 resp.N = 8972 trips				**Oslo (NOR)**N = 6454 resp.N = 14601 trips				**Stavanger (NOR)**N = 1981 resp.N = 5454 trips				**Stockholm (SWE)**N = 2087resp.N = 4650 trips			
		mean / %	sd	min	max	mean / %	sd	min	max	mean / %	sd	min	max	mean / %	sd	min	max
Chain trip	Yes	50.3%				51.1%				52.8%				49.0%			
Mode	Walk	19.5%				28.9%				21.1%				30.2%			
	Bicycle	26.3%				4.5%				6.3%				2.7%			
	Public transport	4.9%				16.4%				4.5%				19.0%			
	Car	49.3%				50.3%				68.1%				48.0%			
Distance	(in km)	12.3	22.3	0	210	10.0	20.7	0	248	8.0	15.2	0	226	9.4	13.5	0	234

(a) Fulltime occupation includes full time students in Norway and Sweden but not in the Netherlands.
(b) Middle household income is €20 k-40 k in NL, NOK600k-1000 k in Norway and SEK250k-500 k in Sweden. Lower is below, higher is above.
(c) Lower education is lower vocational or lower in NL and lower secondary or lower in Norway. Middle education is middle vocational in NL and higher secondary in Norway. Higher education is higher vocational/university in both NL and Norway. Education is unknown for Sweden.

These trip-based mobility data are enriched in two subsequent steps. First, the mobility data are matched via the residential postal code with local population densities[3]. Second, via the residential postal code and departure time, these joint datasets are linked to hourly weather data at the departure time from the nearest[4] meteorological station of the Royal Dutch Meteorological Institute (KNMI, 2015), Swedish Meteorological and Hydrological Institute (SMHI, 2012), or Norwegian Meteorological Institute (MET, 2015). Following Böcker et al. (2013) the three most commonly used weather variables are extracted: average hourly air temperature, average hourly wind speed, and hourly precipitation sum. Precipitation is intersected with temperature above or below zero to create dummies for rain and snowfall. Other weather variables like fog and thunder have also been tested, but have ultimately been excluded because of infrequent occurrences and related non-significant effects. Hourly weather data are preferred over daily, because of higher temporal accuracies in the constantly changing weather exposures (following e.g. Sabir, 2011 and Creemers et al., 2014). Sensitivity analyses were carried out to check if mobility decisions during present trips are affected by weather events during prior or subsequent trips. Such lead or lagged effects of weather were not identified and have therefore been omitted from the final models.

From these combined datasets, we analyse transport mode choices, distances, trip purposes, and trip chaining as dependent variables with trips as the unit of analysis. Trip purposes are classified into five categories: work/study trips, errands (including grocery shopping and chauffeuring), social visits, leisure trips outdoors (including jogging, walking, touring and visiting parks and nature), and other leisure trips (including dining, entertainment, cultural visits, shopping trips over an hour, and sports activities that are not identified as outdoors). Trip chaining is a dummy that distinguishes trips that are part of complex home-based chains of more than one destination, from more simple home-destination-home trips. To account for possible sample biases and to measure the true effects of weather, we control for socio-demographic, transport resource (e.g. car ownership) and residential attributes of respondents (or their households), as well as timing attributes of trips (e.g. weekday or weekend, light or dark, daytime or night-time and peak or off-peak). Table 1 provides a descriptive overview of all dependent and independent variables included in the analyses and indicates whether statistics are calculated over the total samples of respondents or the total samples of trips.

As this study is cross-comparing data from different national travel survey data, we would like to discuss potential sources of selection bias that could affect our results. First, Table 1 indicates potential sample biases related to education level between the Dutch and Norwegian data, while Swedish data on education is not available. While the low share of lowly educated in the Dutch data are related to a different classification that unlike the Norwegian data includes also lower vocational education, the high share of highly educated in Norway most likely indicates a relative overrepresentation of higher educated. To verify whether this has an effect on our findings, sensitivity analyses were run of models without education as a control variable, as well as models on higher educated subsamples separately, both revealing no differences in the overall picture of weather effects on mobility. Second, for the Norwegian national travel data, survey days in winter appear to be slightly underrepresented, which is reflected by slightly higher than expected mean air temperature values in Oslo and Stavanger. However, this selection bias is minor and moreover should have if any only a minor effect on the results in this paper, as these are based on multivariate analyses of the relative effects of weather parameters on mobility rather than cross-comparisons of descriptive mobility data.

2.3. Statistical modelling techniques

In our multivariate analyses, Structural Equation Modelling (SEM) has been used via the software package Stata. Unlike ordinary, logit or multinomial logit regression techniques, SEM allows analysing the effects of a set of independent variables on not one but multiple dependent variables, as well as the endogenous relationships between these dependent variables. This statistical approach is well suited to analyse the simultaneous effects of weather, along with other independent background variables, on an interlinked choice set of trip purposes, trip chaining, trip distances and transport modes. Analysing the simultaneous effects in one integrated model is crucial to unravel how weather affects integrated mobility decisions. For example, pleasant weather conditions may enhance the selection of nearby destinations that can easily be reached by foot or bicycle, reduce trip distances, and increase the share of active transport modes, all at the same time. We have tested and confirmed the robustness of our SEM models, by comparing it to the separate effects of weather on trip chaining, distances, purposes and transport mode choices in respectively binary logit, Tobit and multinomial logit models.

Before using SEM, we need to define the endogenous relationships among dependent variables. Hereto we use common transport research insights and logic on the sequential order of decision-making. Our ultimate dependent variable is the transport mode choice. Transport mode choices differ for different distances. Active modes, especially walking, are more common on shorter distances, while motorised modes are more often used to cover longer distances. On their turn, trip distances may differ for different trip purposes. Errands trips for instance are usually shorter than work trips. The question that remains is where trip chaining comes into the decision-making process. Trip chaining is less often studied, but one may assume trip chaining as a function of purpose. Some trips such as errands trips may be more easily chained to commute trips from or towards work, while other trips like leisure and social visits may be more often made independently. This study looks at home-based trip chaining by comparing chained trips (any trip that is involved in a more complex chain than a simple home-destination-home trip) to non-chained trips (home-destination-home). Trip chaining behaviour is being recognized as a phenomenon that people schedule/optimize their daily activities. Studies have shown clear relationships between trip chaining behaviour, trip purpose and mode choice (e.g. Ye et al., 2007; Noland and Thomas, 2007), as trip chaining behaviour is found positively

[3] The sources for population density are 4-digit postal code population density in the Netherlands (CBS-Statline, 2015), traffic zone level population density in Sweden (see Algers et al., 2009) and Norwegian Statistical Bureau (ssb.no)2015 in Norway.

[4] All meteorological stations used in this study are located inside the study areas, at a maximum distance of 20km to any of the respondent's residential location.

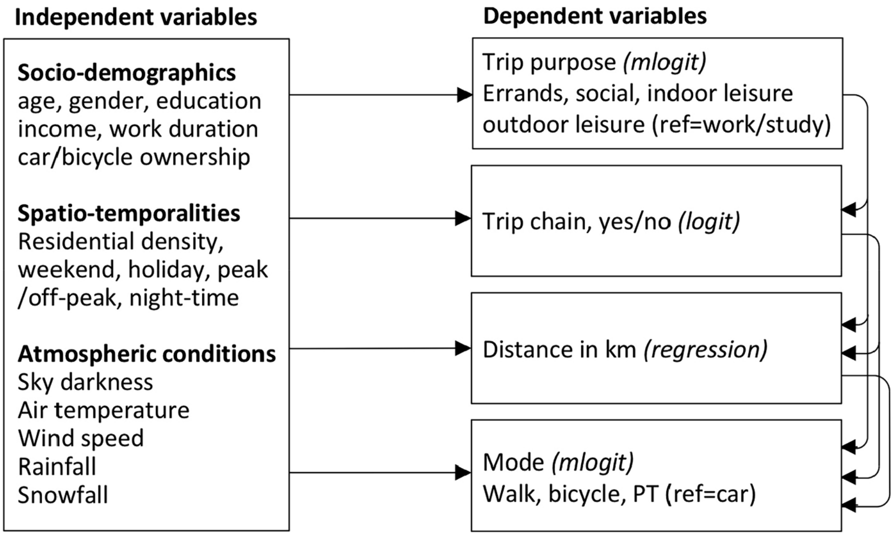

Fig. 2. Gsem model structure.

correlated with car usage and errand trip purposes. Hence, we arrive at our final model configuration where our independent variables (including weather) affect trip purpose; our independent variables and trip purpose affect trip chaining; our independent variables, trip purpose and trip chaining affect distance; and all affect transport mode choice (Fig. 2). Model configurations based on alternative causalities have been tested but were ultimately excluded due to inferior model fit and counterintuitive effects.

The final model configuration depicted in Fig. 2 poses three statistical challenges. First challenge is to address non-independence of observations. To control for intragroup correlation between trips made by the same respondent on the same day, we estimate robust standard errors that adjust for within-cluster correlations (Wooldridge, 2002) via Stata's *vce-cluster* command. Second challenge is to estimate the right statistical relationships with regard to each dependent variable's measurement level. While it is fairly straightforward in SEM to regress continuous dependent variables on a set of independent or dependent variables, this is more complicated for categorical variables. Especially when such categorical dependent variable serves at the same time as predictor in another equation (i.e. $X_{1\text{-}n}$ - > $Y_{1(\text{categorical})}$ - > Y_2). Using Stata's *gsem*-function we allocate each dependent variable the right *family link*: a standard (continuous) regression link for "distance", a binary logistic link (logit) for the dummy "trip chain", and a multinomial logistic link (mlogit) for the categorical dependent variables "trip purpose" and "mode choice". Unfortunately, this new *gsem* function does not yet come with detailed absolute model fit statistics. Third challenge is therefore to evaluate model fit. Hereto, we run several simplified (*normal-sem*) versions of our model in which we recode the categorical mediator "trip purpose" into separate dummies for utilitarian (work/study) versus non-utilitarian trips (social/leisure) and active (walking/cycling) versus motorised transport modes (car/public transport), as well as alternative configurations (e.g. cycling separately, walking separately, work separately, outdoor leisure separately). All alternative *normal-sem* models showed comparable model fits in terms of RMSEA and CFI. Moreover, they provide a logical overall picture of parameter estimates similar to our full *gsem* models and comparable findings regarding the effects of weather on mobility. This paper presents the full *gsem* model (Fig. 2) results, while reporting model[5] fit statistics for the underlying *normal-sem* models.

3. Results

This section briefly shows the descriptive relations between weather and transport mode choices for the four study areas, and subsequently discusses more deeply our multivariate generalised structural equation modelling (*gsem*) results. Fig. 3 shows that higher air temperature, calm wind conditions and no precipitation increases bicycle shares while decreasing the share of motorised transportation – in Utrecht mainly that of car use; in Oslo also that of public transport. In contrast to earlier studies, the air temperature effect appears rather linear for Utrecht[6]. For the other study areas, the positive air temperature effects seem to flatten out and possibly inverse at or above air temperatures in the range of 20–25 °C. Generally, weather effects on modal split are most pronounced for Utrecht and least pronounced for Stavanger.

As for our multivariate results, first we will briefly discuss model fit and the endogenous relations between the four dependent variables depicted in Fig. 2. Second, we will summarise, discuss and cross-compare in detail the effects of weather on mobility across our four study regions. All *normal-sem* models that the *gsem* models presented in this paper are based on, show good model fit with

[5] Using the simplified *normal-sem* model identical to our full gsem model, except for having "trip purpose" recoded into a utilitarian/non-utilitarian and transport mode into active/motorised modes.

[6] The linear air temperature effect in Utrecht also extends when adding a > 30 °C category. As it did not stand out, we omitted this category because of an insufficient number of observations for the three other study areas.

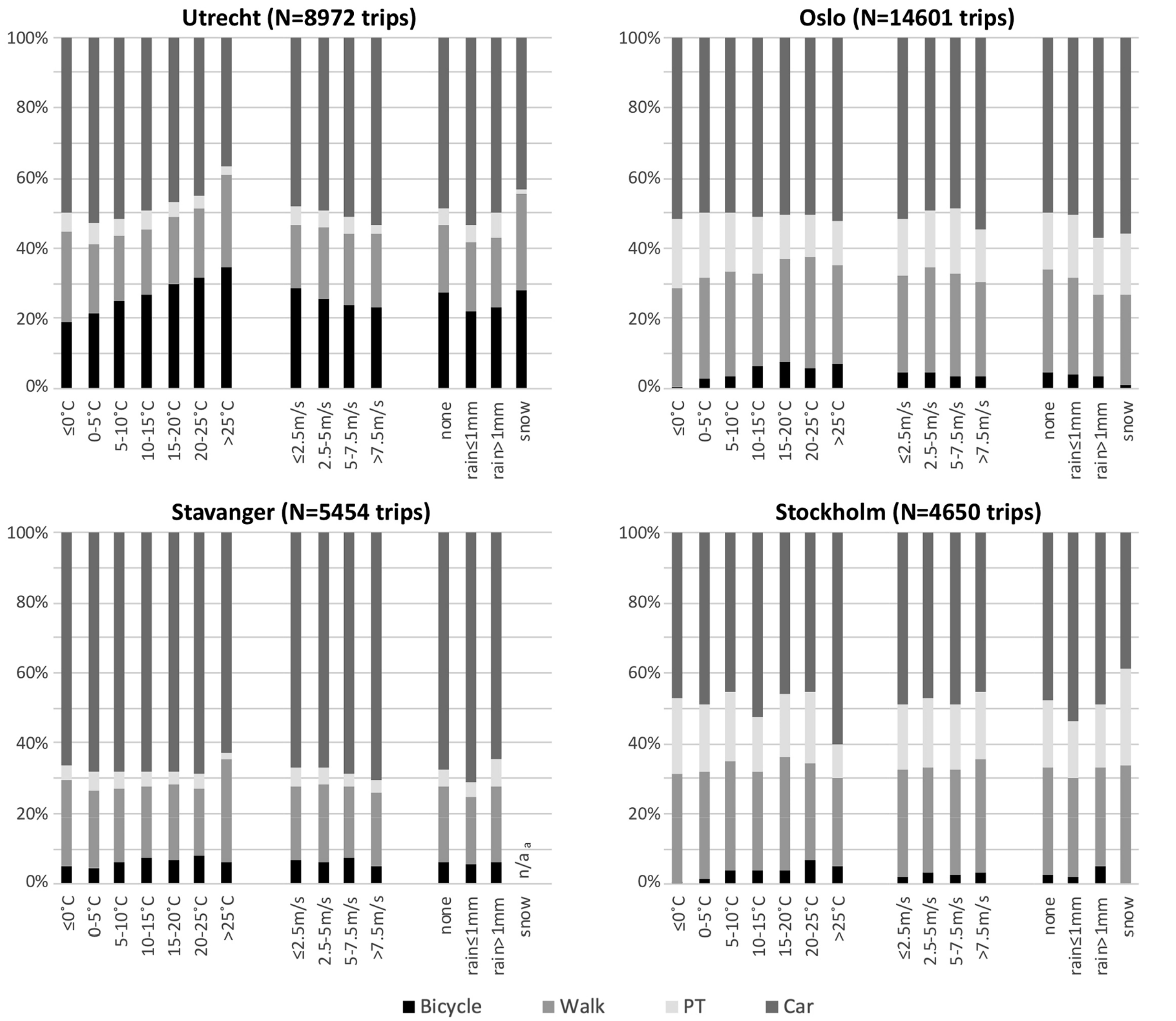

Fig. 3. Effects of air temperature (left), wind speed (middle) and precipitation (right) on modal split for the four study areas. [a]Snow effect is omitted for Stavanger due to a too small number of observations.

RMSEA values below the critical threshold of 0.05 (Utrecht: 0.01, Oslo: 0.01, Stavanger: 0.02, Stockholm: 0.00) and CFI values above the critical threshold of 0.95 (Utrecht 0.99, Oslo: 1.00, Stavanger: 0.99, Stockholm: 1.00). For the complete underlying model outcomes, the reader is referred to Appendix A, Tables A.1–A.4.

Table 2 summarises the endogenous relations between our four dependent variables trip purpose, trip chaining, trip distance and transport mode. The values in the table represent the non-standardised regression coefficients, while star signs flag their respective statistical significances. Outdoor leisure trips are least likely to be part of complex chains, except for Stockholm where other leisure trips are most often part of complex trip chains. In Utrecht, errands trips are often chained. In all regions except Utrecht, chained trips are of shorter distance than simple trips from home to a destination and back home. Of all trip purposes errands trips have the shortest distance in Oslo and Stavanger, while leisure outdoor trips have the shortest distance in Utrecht and Stockholm. Errands trips are generally of shorter distance while work trips are generally longer. In Stavanger it is social and outdoor leisure trips that have the longest distance, and in Oslo social visits. Compared to work/study trips, other trips are less often done by foot, bicycle and public transport, and thus more often by car. An exception to this are outdoor leisure trips which are least likely done by car and show the highest use of active transport modes. As expected in a European context where modal splits are not overly dominated by car use, shorter distance trips are typically more often performed by foot and bicycle while longer trips are more likely covered by car and especially public transport.

Table 3 summarises the *direct effects* of atmospheric conditions on mobility. We do this to unravel the relative impact of atmospheric parameters on different travel behavioural decisions. It should be noted that *total effects* (e.g. how rain affects transport mode choice not only directly, but also via trip chaining and or trip distance) may still be substantial, even when direct effects are not significant. Not presented here to limit paper length, the effects of other predictors (e.g. socio-demographics) on mobility are largely as expected and in line with earlier studies (see Tables A.1–A.4, Appendix A).

Table 2
Gsem model results – relations between dependent travel behaviour variables.

		Utrecht (N = 8972 trips)					Oslo (N = 14601)				
		Trip chain	Distance	Transport mode *(ref. car)*			Trip chain	Distance	Transport mode *(ref. car)*		
		(yes/no)	*(km)*	Walk	Cycle	Public	*(yes/no)*	*(in km)*	Walk	Cycle	Public
Trip purpose *(ref. work/ study)*	Errands	0.248**	−12.796**	−0.118	−0.584**	−1.514**	0.025	−6.637**	−0.595**	−1.155**	−1.745**
	Social visit	0.124	0.324	−0.180	−0.597**	−1.249**	−0.235**	3.055**	−0.452**	−1.290**	−1.106**
	Leis. outd.	0.408**	−13.069**	6.845**	2.675**	−1.019	−0.743**	−0.886	4.504**	1.526**	−1.395**
	Leis. other	0.061	−7.323**	0.119	−0.421**	−0.190	0.008	−3.437**	−0.177	−0.995**	−0.838**
Trip chain (yes/ no)			0.546	−0.537**	−0.467**	−0.051		−1.694**	−0.404**	−0.508**	−0.205**
Trip_length (in km)				−0.660**	−0.198**	0.014**			−0.556**	−0.088**	−0.002
		Stavanger (N = 5454)					Stockholm (N = 4650 trips)				
		Trip chain	Distance length	Transport mode *(ref. car)*			Trip chain	Distance	Transport mode *(ref. car)*		
		(yes/no)	*(in km)*	Walk	Cycle	Public	*(yes/no)*	*(in km)*	Walk	Cycle	Public
Trip purpose *(ref. work/ study)*	Errands	0.060	−2.991**	−0.670**	−1.353**	−1.718**	0.190	−6.715**	−0.694**	−1.340**	−1.114**
	Social visit	−0.257	3.402**	−0.588**	−1.132**	−0.988**	−0.432*	−2.449*	−0.179	−1.084*	−0.208
	Leis. outd.	−0.554**	4.203**	4.509**	1.137**	−0.914	−1.259**	−8.423**	3.032**	0.303	−0.518*
	Leis. other	−0.090	0.340	−0.309	−1.337**	−0.927**	0.532**	−4.941**	0.588**	−0.227	0.207
Trip chain (yes/ no)			−1.261**	−0.752**	−0.834**	−0.479**		−0.956**	−0.699**	−0.595*	−0.189
Trip_length (in km)				−0.423**	−0.076**	0.007*			−0.571**	−0.146**	0.011*

* Significant at $\alpha < 0.05$.
** Significant at $\alpha < 0.01$.

Of all atmospheric conditions, *sky darkness* has the most prominent effect on mobility with strong significant effects on almost all travel behaviour variables in all four study areas. Hereby, sky darkness is operationalised as the period between sunset and sunrise compared to that between sunrise and sunset. It should be noted that all underlying full models (appendix A) control for the 12AM-6AM night-time period to make sure we measure the effect of sky darkness and not that of distinctive mobility patterns or limited availability of transport alternatives at night. When it is dark, people perform fewer chained trips compared to non-chained trips, and more social and leisure trips compared to work trips. We want to express strongly that this is a relative measure of trip purpose compared to work trips. As such, darkness may for instance have a negative effect on work trips and thereby increase the relative likeliness of other trip purposes. Congruent to existing studies (e.g. Böcker and Thorsson, 2014), darkness also leads to fewer trips by active transport modes (fewer walking and cycling trips in Utrecht, fewer cycling trips in Oslo, fewer walking trips in Stockholm). In Stavanger darkness has no effect on transport mode choice. Darkness does not have a clear effect on trip distances, except for Oslo where we observe reduced distances during darkness.

A second important atmospheric condition to affect travel behaviour is *air temperature* (T_a). Existing studies generally indicate positive effects of T_a on outdoor activities and the use of active transport modes, especially cycling (e.g. Creemers et al., 2014; Thomas et al., 2013; Böcker and Thorsson, 2014; Liu et al., 2015). Some add that this effect may be bell-shaped rather than linear – i.e. a positive effect up until a certain optimum T_a value, above which outdoor activities and active modes flatten out or reduce (e.g. Aultman-Hall et al., 2009; Miranda-Moreno and Nosal, 2011; Lewin, 2011; Ahmed et al., 2012; Böcker and Thorsson, 2014). To account for and possibly detect such non-linear temperature effects, our final models include an untransformed T_a variable along with a squared T_a. Congruent to existing studies, our findings indicate a positive T_a effect on cycling shares in all study areas except Stavanger (where no significant effect is found). In Oslo and Stockholm this positive T_a effect on cycling comes at the cost of car use, and in Utrecht at the cost of both car use and walking. In Oslo and Stockholm we find that the positive effect of T_a is accompanied by a significant negative effect of T_a squared (note that the low parameter estimates 0.004 and 0.005 have to do with the unit of the analysis here being only a one squared degree difference). This indicates a nonlinear relationship with a stronger positive relative T_a effect by colder conditions than by warmer conditions and possibly a negative effect of heat. In contrast an earlier Dutch study (e.g. Böcker and Thorsson, 2014), we find no evidence for a bell-shaped T_a effect on cycling in the Utrecht region, but the referred study is from another city (Rotterdam) and is based on oversampling of hot days.

Besides affecting transport modes, T_a also negatively affects trip chaining. This could possibly indicate at a strategy of linking multiple destinations in more efficient trip chains in order to avoid additional exposure to cold weather, although no such effect is visible in the other regions. In Oslo but not in the other cities, T_a has a nonlinear positive but weakening (positive T_a; negative T_a squared) effect on outdoor leisure trips as compared to work trips. A possible explanation why outdoor leisure in Oslo is more temperature dependent (and as showed below also rain dependent) than in the other regions, could be that of all cities regions compared in this study it has perhaps the easiest access to a variety of recreational and nature areas inside and in the immediate

Table 3
SEM model results – summary of weather effects on travel behaviour.

	Trip purpose *(ref. work/study)*				Trip chain	Trip length	Transport mode *(ref. car)*		
	Errands	Social	Leis.out.	Leis.oth.	*(yes/no)*	*(in km)*	Walk	Cycle	Public
Utrecht (N = 8972)									
Sky darkness *(yes/no)*	−0.285**	0.766**	0.954**	0.570**	−0.438**	−0.022	−0.440**	−0.360**	−0.151
Air temperature T_a *(°C)*	0.000	0.022	0.019	0.034*	−0.021*	−0.058	−0.068**	0.025*	−0.001
T_a squared	0.000	0.000	0.000	0.000	0.001	0.004	0.003**	0.000	0.000
Wind speed W_s *(m/s)*	−0.018	−0.035	−0.020	−0.028	0.020	0.307*	−0.005	−0.061**	−0.060
Rainfall *(yes/no)*	0.014	−0.022	−0.063	0.033	−0.011	0.016	−0.035	−0.259**	0.082
Snowfall *(yes/no)*	0.149	−0.409	0.433	−0.179	−0.256	−3.788*	−0.014	0.273	−1.168
Oslo (N = 14601)									
Sky darkness *(yes/no)*	0.176*	0.876**	0.640**	0.461**	−0.208**	−1.655**	−0.137	−0.365*	0.028
Air temperature *(°C)*	0.021**	0.029*	0.053**	0.026**	−0.005	−0.023	0.003	0.167**	−0.001
Air temperature Squared	−0.001*	−0.001	−0.001*	0.000	0.000	0.004	−0.001	−0.004**	0.000
wind speed *(in m/s)*	−0.010	0.014	−0.041	−0.005	0.029*	−0.031	0.009	−0.024	0.020
Rainfall *(yes/no)*	−0.147	−0.113	−0.393**	0.008	−0.009	1.103	−0.083	0.005	0.077
Snowfall *(yes/no)*	−0.014	−0.022	0.140	−0.042	0.078	−0.328	−0.083	0.109	−0.200
Stavanger (N = 5454)									
Sky darkness *(yes/no)*	0.011	0.544**	0.334*	0.282*	−0.461**	−0.991	−0.056	−0.292	−0.030
Air temperature *(°C)*	0.046	0.048	0.043	0.009	−0.003	−0.159	−0.013	0.077	0.011
Air temperature squared	−0.001	−0.002	−0.001	0.001	0.000	0.011	0.001	−0.002	0.000
Wind speed *(m/s)*	0.022	0.011	−0.041*	0.021	0.028*	−0.004	−0.003	−0.011	−0.029
Rainfall *(yes/no)*	−0.015	−0.135	−0.523**	−0.293*	−0.119	0.631	0.075	−0.099	0.152
Snowfall *(yes/no)*	−0.310	−0.064	−0.866	0.184	0.146	−3.606*	0.263	1.529	−11.304**
Stockholm (N = 4650)									
Sky darkness *(yes/no)*	0.456**	0.890**	0.730**	0.387**	−0.376**	−0.404	−0.327*	0.103	−0.197
Air temperature *(°C)*	0.014	0.023	−0.005	−0.007	−0.006	−0.010	−0.006	0.165**	−0.020
Air temperature squared	0.000	0.000	0.001	0.000	0.001	0.002	−0.001	−0.005*	0.000
Wind speed *(m/s)*	0.023	−0.059	0.066*	0.038	−0.018	0.011	0.002	0.072	0.048
Rainfall *(yes/no)*	−0.108	0.266	−0.253	−0.038	0.117	−0.385	−0.147	−0.339	0.174
Snowfall *(yes/no)*	−0.161	−0.482	−0.461	−0.264	0.064	−0.386	0.037	−0.970	−0.077

* Significant at $\alpha < 0.05$.
** Significant at $\alpha < 0.01$.

vicinity of the city, allowing for spontaneous scheduling of outdoor activities. Additionally, in contrast to for instance Stavanger (which also has such natural amenities) Oslo also has some of the largest seasonal air temperature differences.

Other atmospheric conditions of importance to travel behaviour are *wind speed* (W_s) and precipitation. We analyse the effects of W_s in meter per second (m/s), and the effects of precipitation by means of binary variables indicating whether *rainfall* and *snowfall* occurred at the hour of travel or not. Alternative operationalisations of precipitation such as hourly precipitation sum and snow cover on the ground were tested but ultimately rejected due to inferior model fit and measurement uncertainty respectively. As expected and in line with the existing Dutch studies (e.g. Creemers et al., 2014; Thomas et al., 2013; Böcker and Thorsson, 2014), we find negative effects of W_s and rainfall on cycling in Utrecht, while favouring car use. Somewhat surprisingly, we cannot statistically confirm any wind or precipitation effects on transport mode choice in the three Scandinavian cities (except for a negative snowfall effect on public transport use in Stavanger[7]). The stronger rain effect in Utrecht could be related to a larger exposure to wet conditions in this study area (20.4% of recorded trips during wet conditions), especially when compared to Oslo (10.1%) and Stockholm (9.4%) (Table 1). Another more general explanation of why the effects of disadvantageous weather conditions like rain and wind are stronger in Utrecht than in the other studies may have to do with the transport regime. With a bicycle modal split share of 26.3%, Utrecht relies much more on this weather exposed transport mode than the other cities in our study with bicycle shares between 2.7% and 6.3% (Table 1). In comparison: especially in a city region like Stavanger adverse weather effects on mode choice are likely much lower, simply because people drive much of their trips regardless of weather.

Wind speed and precipitation also affect some travel behaviour decisions other than the transport mode. In line with the positive T_a effect on outdoor leisure and in congruence to existing studies (Dwyer, 1988; Thorsson et al., 2007; Lin, 2009; Spinney and Millward, 2011), we observe that rain reduces the likeliness of outdoor leisure trips in Stavanger and Oslo. In Stavanger increased W_s leads also to fewer outdoor leisure trips. This is possibly a result of Stavanger being the windiest of our study areas, as indicated in Table 1 by a W_s mean of 5.3 m/s compared to 2.7–3.7 m/s values for the other regions (plus a higher standard deviation indicating more wind variability). In the two study areas where snowfall is rarest – Stavanger and Utrecht – snowfall has a negative effect on overall trip distances. It could be that people choose destinations that are nearer as a strategy to reduce their

[7] We will not further interpret this strong negative snowfall effect on public transport in Stavanger as it is highly sensitive to possible outliers by a low number of cases, as Stavanger public transport use is limited (4.5%) and snowfall occurred minimally (0.3%) (Table 1).

exposure to snow. In Oslo and Stockholm this negative snow effect on distance is not present, possibly because people are more familiar and individually adapted to snow conditions, and because the cities are more resilient to snowfall, for instance through efficient snow clearing.

4. Conclusion and discussion

This paper set out to address two major shortcomings in current weather and mobility research: the lack of international comparison studies, and the lack of knowledge on the simultaneous effects of weather on a diverse range of travel behaviours. It is our objective to develop a better understanding of the effects of weather on destination choices, trip distances, trip chaining, and transport mode choices in the greater urban regions of Utrecht (Netherlands), Oslo, Stavanger (Norway), and Stockholm (Sweden), and how these might differ in relation to climate, transport regime, land use and culture. Regional subsamples of national travel survey data were linked to meteorological records and analysed by means of a generalised structural equation modelling technique, which enables us to analyse the effects of weather on multiple dependent travel behaviour variables simultaneously.

Our findings indicate that weather conditions in urban regions situated in different climate regimes have substantial effects on a diverse range of travel behaviour variables. Sky darkness (even when controlled for night-time hours) has negative effects on trip chaining and the use of active transport modes. Of the three classic weather parameters, especially low air temperatures and to some extend also rainfall and wind speed demonstrate the ability to reduce cycling – especially compared to car use – and the selection of outdoor leisure destinations in some of the study regions. Wind stimulates the combining of trips into more efficient trip chains, possibly to reduce weather exposure in our Norwegian study regions. In line with existing studies (e.g. Lewin, 2011; Ahmed et al., 2012), we find evidence for non-linear (bell-shaped) air temperature effects on bicycle usage (in Stockholm and Oslo) and outdoor leisure activities (in Oslo) where positive effects flatten out or slightly reverse above 20–25 °C, indicating possible negative effects of heat. With climate change projections for all four case study areas showing increasing air temperatures, and longer and more frequent periods of heat (KNMI, 2014; Andersen et al., 2018), policy makers and planners are advised to consider climate-sensitive urban design strategies (Lenzholzer and Van der Wulp, 2010), specifically along highly frequented walking and cycling infrastructures. This may include the use of lighter surfaces, compact designs and deciduous trees for shading specifically in summer, and increased use of vegetation over concrete (Konarska et al., 2014; Theeuwes et al., 2014).

However, the effects of weather on mobility are far from universal across the study regions. Differences in the statistical significance, magnitude and occasionally even the direction of effects, highlight the importance of geographical context with regard to transport and land use, climate conditions, cultures, habits and adaptations. Policy makers and planners should be aware of this and be cautious when translating research findings and policy solutions on weather and mobility from other geographical contexts to their own policy agendas. Our results reveal that the effects of weather on transport mode choices are much stronger in Utrecht than in Stavanger, even though both cities share a somewhat comparable maritime climate. A likely explanation is related to the *transport regime.* The Utrecht region has a much higher share of cycling – the most weather-sensitive transport mode identified in the literature (e.g. Koetse and Rietveld, 2009; Böcker et al., 2013) – than the other study regions, while also offering good cycling alternatives in walking on short distances and public transport on medium to long distances. In contrast, Stavanger with its lower densities, longer distances and fewer public transport options, is to a much larger extent dependent on private car use, the most weather sheltered transport mode, and therefore much less influenced by weather. A second example highlights the potential role of *habit* and *adaptation*. In Stavanger and Utrecht people reduce their exposure to snowfall by travelling shorter distances, while in Oslo and Stockholm – where snowfall is more common – such snow effect is absent, possibly because these cities and their citizens are more familiar with and resilient to snowfall. This finding bears significance for policy. Adverse weather conditions, such as snowfall may be significant mobility barriers but they are not unsurmountable: adaptive policy measures like proactive snow clearing can ameliorate its adverse effect. A third example highlights the possible importance of *climate*, *land use* and *cultural* context. We find that dry and warm but not too hot weather in Oslo and calm and dry weather in Stavanger increase the visiting of outdoor leisure destinations relative to work trips, but none of these effects in the non-Norwegian regions. An explanation could be that both Norwegian cities share a typical active outdoor culture and offer the easiest access to recreational and nature areas allowing for spontaneous weather-sensitive scheduling of outdoor activities. Of the two, Oslo has the highest air temperature differences (explaining its stronger temperature effect) while Stavanger is the windiest (explaining its stronger wind effect).

This study has some limitations. Because of comparing national travel survey datasets from different countries, the reader needs to be aware of the differing potential selection biases between these datasets, even though multivariate models controlling for background characteristics and sensitivity analyses were run to confirm the overall robustness of our findings. Moreover, nearest station matching of weather and mobility data over distances up to 20 km may result in inaccuracies between the measured meteorological data and the actual weather observed by respondents during their trips, especially when taken into account microclimatological complexities across residential environments in urban regions (Oke, 1982, Steeneveld et al., 2011). We would recommend future studies to advance the insights on how geographical, cultural, climate, transport and land use context influence the effects of weather on daily mobility developed in this paper along the following lines of inquiry. First, cross-comparison studies like in this paper, may be up-scaled to include a wider range of geographical contexts, including case study areas at lower latitudes that observe heat more frequently at present, as well as a case studies with more distinct transport and cultural contexts, for instance from the global south. Second, studies could focus more on the contextual differences within regions, by zooming into the potentially differential effects of weather on mobility of different socio-demographic, -economic and -cultural groups, especially those with different climate backgrounds (e.g. non-western immigrants), or those more vulnerable to weather (e.g. young children and the elderly). Third, studies are recommended to address microclimatological differences between residential environments, as well as to take into account other measureable attributes of residential environments besides population density, such as local land use patterns, building use diversities, and the presence and quality of walking, cycling, parking and public transport infrastructures. Finally, contextual differences in weather effects on mobility may be studied through focus groups or other qualitative approaches. This could provide a more detailed picture of the subjective experiences of weather and weather-relate comfort as well as people's habits, adaptation and coping strategies related to weather.

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Appendix A

See Tables A1–A4.

Table A1
Full gsem model results Utrecht (N = 8972).

		Dependent variables								
		Trip purpose *(ref. work/study)*				Trip chain chain	Distance	Transport mode *(ref. car)*		
		Errands	Social	Leis. outd.	Leis. other	*(yes/no)*	*(km)*	Walk	Cycle	Public
Mediators										
Purpose	Errands					0.248**	−12.796**	−0.118	−0.584**	−1.514**
(ref. work / study)	Social					0.124	0.324	−0.180	−0.597**	−1.249**
	Leis. outd.					0.408**	−13.069**	6.845**	2.675**	−1.019
	Leis. other					0.061	−7.323**	0.119	−0.421**	−0.190
Trip chain *(yes/no)*							0.546	−0.537**	−0.467**	−0.051
Trip distance *(km)*								−0.660**	−0.198**	0.014**
Control variables										
Age *(years)*		0.031**	0.017**	0.034**	0.026**	−0.005*	0.040*	−0.010**	−0.006*	−0.030**
Male *(ref. female)*		−0.390**	−0.560**	−0.279*	−0.351**	−0.196**	3.409**	−0.082	−0.141	−0.055
Fulltime work *(yes/no)*		−0.938**	−1.037**	−0.822**	−0.961**	0.226**	2.297**	−0.168	−0.395**	−0.742**
Househ. type	Single	−0.347**	0.596**	−0.246	−0.036	0.323**	0.881	0.171	−0.277	−0.302
(ref. family)	Couple	−0.219*	0.394**	0.344*	0.173	0.027	1.399*	0.120	0.062	−0.044
hh income	Middle	−0.011	−0.222	0.269	0.050	−0.396**	−1.686	0.142	−0.096	0.339
(ref. lower)	Higher	0.113	0.154	−0.141	0.035	−0.084	−0.906	−0.025	−0.235*	−0.151
	Unknown									
Education	Middle	−0.155	−0.253	0.100	−0.059	0.158	1.019	−0.037	0.014	−0.305
(ref. lower)	Higher	−0.035	−0.395**	−0.171	0.043	0.267**	3.345**	0.127	0.345**	0.023
# cars in household						0.078	1.542**	−0.755**	−1.068**	−1.293**
Owns bicycle *(yes/no)*								0.184	3.201**	−0.071
Pop.dens. *(1000 inh./km^2)*		0.000	−0.022	−0.023	0.015	0.014	−0.086	0.080**	0.046**	0.065**
Weekend *(ref. weekday)*		1.229**	2.460**	2.001**	1.898**	−0.441**	4.046**	−0.194	−0.242*	−0.301
Holidays		0.101	0.453**	0.520**	0.421**	−0.105	1.292	−0.051	−0.230*	−0.135
Peak	Morning	−1.742**	−3.661**	−2.628**	−2.818**	−0.217**	2.670**	−0.116	0.351**	0.609**
(ref. off−peak)	Evening	1.167**	1.174**	0.939**	1.053**	0.069	2.773**	0.041	0.069	0.146
Night time (yes/no)		−2.322**	−1.912**	−3.099**	−2.950**	−0.025	14.738**	0.181	0.510	0.517
Atmospheric conditions										
Sky darkness *(yes/no)*		−0.285**	0.766**	0.954**	0.570**	−0.438**	−0.022	−0.440**	−0.360**	−0.151
Air temperature T_a *(°C)*		0.000	0.022	0.019	0.034*	−0.021*	−0.058	−0.068**	0.025*	−0.001
T_a squared		0.000	0.000	0.000	0.000	0.001	0.004	0.003**	0.000	0.000
Wind speed W_s *(m/s)*		−0.018	−0.035	−0.020	−0.028	0.020	0.307*	−0.005	−0.061**	−0.060
Rainfall *(yes/no)*		0.014	−0.022	−0.063	0.033	−0.011	0.016	−0.035	−0.259**	0.082
Snowfall *(yes/no)*		0.149	−0.409	0.433	−0.179	−0.256	−3.788*	−0.014	0.273	−1.168
Constant		−0.143	−1.140**	−2.367**	−0.968**	−0.062	7.022**	2.373**	−0.301	1.150*

* Significant at $\alpha < 0.05$.
** Significant at $\alpha < 0.01$.

Table A2
Full gsem model results Oslo (N = 14601).

		Dependent variables								
		Trip purpose *(ref. work/study)*				Trip chain chain	Distance	Transport mode *(ref. car)*		
		Errands	Social	Leis. outd.	Leis. other	*(yes/no)*	*(km)*	Walk	Cycle	Public
Mediators										
Purpose	Errands					0.025	−6.637**	−0.595**	−1.155**	−1.745**
(ref. work /	Social					−0.235**	3.055**	−0.452**	−1.290**	−1.106**
study)	Leis. outd.					−0.743**	−0.886	4.504**	1.526**	−1.395**
	Leis. other					0.008	−3.437**	−0.177	−0.995**	−0.838**
Trip chain *(yes/no)*							−1.694**	−0.404**	−0.508**	−0.205**
trip distance *(km)*								−0.556**	−0.088**	−0.002
Control variables										
Age *(years)*		0.026**	0.017**	0.030**	0.021**	−0.012**	0.054**	−0.015**	−0.010*	−0.014**
Male *(ref. female)*		−0.274**	−0.456**	−0.315**	−0.416**	−0.151**	1.961**	−0.155*	0.115	−0.182**
Fulltime work *(yes/no)*		−1.269**	−1.490**	−1.207**	−1.302**	0.227**	0.732	0.000	0.017	−0.221*
Househ. type	Single	−0.608**	0.030	−0.364**	−0.192	0.230**	−0.167	0.368**	0.085	−0.030
(ref. family)	Couple	−0.563**	0.039	−0.126	−0.091	0.056	0.679	0.278**	−0.142	−0.152
hh income	Middle	0.058	0.215	0.144	0.000	0.166	−0.402	−0.447**	−0.044	−0.287*
(ref. lower)	Higher	−0.047	−0.054	−0.031	−0.067	0.203	−0.065	−0.194	0.073	−0.158
	Unknown	−0.268	−0.112	−0.209	−0.324*	−0.066	−0.309	−0.094	−0.087	0.057
Education	Middle	0.000	−0.132	−0.023	−0.028	0.439**	0.752	−0.273	0.044	−0.423*
(ref. lower)	Higher	0.293*	0.202	0.185	0.208	0.682**	0.458	−0.120	0.650	−0.259
# cars in household						−0.060	1.447**	−0.901**	−1.097**	−1.332**
Owns bicycle *(yes/no)*								0.006	1.905**	0.046
Pop.dens. *(1000 inh./km²)*		−0.011	−0.006	−0.020*	0.007	0.001	−0.295**	0.052**	0.070**	0.049**
Weekend *(ref. weekday)*		1.426**	2.184**	2.079**	1.721**	−0.310**	1.486**	−0.038	0.043	−0.160
Holidays		0.412**	0.699**	0.575**	0.406**	−0.162*	0.785	−0.227**	−0.342*	−0.319**
Peak	Morning	−1.861**	−3.727**	−2.561**	−3.306**	−0.306**	2.449**	0.274**	0.771**	0.688**
(ref. off−peak)	Evening	0.710**	0.648**	0.383**	0.466**	0.280**	2.815**	0.235**	0.437**	0.593**
Night time (yes/no)		−1.973**	−1.769**	−1.266**	−1.655**	−0.331	1.655**	0.382	1.501**	0.483*
Atmospheric conditions										
Sky darkness *(yes/no)*		0.176*	0.876**	0.640**	0.461**	−0.208**	−1.655**	−0.137	−0.365*	0.028
Air temperature T_a *(°C)*		0.021**	0.029*	0.053**	0.026**	−0.005	−0.023	0.003	0.167**	−0.001
T_a squared		−0.001*	−0.001	−0.001*	0.000	0.000	0.004	−0.001	−0.004**	0.000
wind speed W_s *(m/s)*		−0.010	0.014	−0.041	−0.005	0.029*	−0.031	0.009	−0.024	0.020
Rainfall *(yes/no)*		−0.147	−0.113	−0.393**	0.008	−0.009	1.103	−0.083	0.005	0.077
Snowfall *(yes/no)*		−0.014	−0.022	0.140	−0.042	0.078	−0.328	−0.083	0.109	−0.200
Constant		0.255	−1.228**	−1.414**	−0.109	−0.008	6.926**	3.265**	−2.969**	2.169**

* Significant at $\alpha < 0.05$.
** Significant at $\alpha < 0.01$.

Table A3
Full gsem model results Stavanger (N = 5454).

		Dependent variables								
		Trip purpose *(ref. work/study)*				Trip chain chain	Distance	Transport mode *(ref. car)*		
		Errands	Social	Leis. outd.	Leis. other	*(yes/no)*	*(km)*	Walk	Cycle	Public
Mediators										
Purpose	Errands					0.060	−2.991**	−0.670**	−1.353**	−1.718**
(ref. work /	Social					−0.257	3.402**	−0.588**	−1.132**	−0.988**
study)	Leis. outd.					−0.554**	4.203**	4.509**	1.137**	−0.914
	Leis. other					−0.090	0.340	−0.309	−1.337**	−0.927**
Trip chain *(yes/no)*							−1.261**	−0.752**	−0.834**	−0.479**
Trip distance *(km)*								−0.423**	−0.076**	0.007*
Control variables										
Age *(years)*		0.025**	0.005	0.032**	0.024**	−0.007	0.014	−0.008*	0.000	−0.019**
Male *(ref. female)*		−0.174	−0.073	−0.298*	−0.219*	−0.098	1.196**	−0.423**	−0.317*	−0.248
Fulltime work *(yes/no)*		−1.445**	−1.509**	−1.153**	−1.564**	0.074	1.106	0.008	0.033	−0.468*
Househ. type	Single	−0.528**	0.223	−0.465*	−0.246	0.322*	1.116	0.154	−0.413	−0.189
(ref. family)	Couple	−0.631**	0.142	−0.127	−0.320*	0.022	0.904	0.028	−0.013	−0.078
hh income	Middle	0.149	−0.104	−0.176	−0.086	0.292	0.442	−0.382	−0.137	−0.219
(ref. lower)	Higher	0.125	−0.313	−0.087	−0.083	0.467*	0.633	−0.220	0.225	−0.361
	Unknown	0.431	0.086	0.319	0.196	0.161	−0.078	0.089	−0.192	0.269
Education	Middle	0.197	−0.044	0.142	0.034	−0.054	−1.275	−0.160	0.020	−0.665*
(ref. lower)	Higher	0.590*	0.181	0.389	0.475	0.137	−0.348	0.066	0.243	−0.518

(continued on next page)

Table A3 (*continued*)

		Dependent variables								
		Trip purpose *(ref. work/study)*				Trip chain chain	Distance	Transport mode *(ref. car)*		
		Errands	Social	Leis. outd.	Leis. other	*(yes/no)*	*(km)*	Walk	Cycle	Public
# cars in household						0.024	0.918*	−0.583**	−0.879**	−1.449**
owns bicycle *(yes/no)*								−0.145	1.358**	−0.325
Pop.dens. *(1000 inh./km^2)*		0.012	0.035	−0.013	0.048	−0.019	−0.404**	0.121**	0.073	0.014
Weekend *(ref. weekday)*		1.491**	2.158**	2.223**	1.647**	−0.516**	0.772	−0.114	0.166	−0.459
Holidays		0.074	0.496**	0.310	0.105	−0.258*	0.802	−0.145	−0.259	−0.313
Peak	Morning	−1.837**	−4.335**	−2.502**	−3.316**	−0.186*	1.604*	−0.309*	0.348*	0.387*
(ref. off−peak)	Evening	0.993**	0.783**	0.860**	0.799**	0.005	1.883**	0.073	0.274	0.263
Night time (yes/no)		−2.173**	−2.478**	−2.340**	−1.564**	−0.188	7.084*	0.885*	1.279**	0.676
Atmospheric conditions										
Sky darkness *(yes/no)*										
Air temperature T_a *(°C)*										
T_a squared		0.011	0.544**	0.334*	0.282*	−0.461**	−0.991	−0.056	−0.292	−0.030
Wind speed W_s *(m/s)*		0.046	0.048	0.043	0.009	−0.003	−0.159	−0.013	0.077	0.011
Rainfall *(yes/no)*		−0.001	−0.002	−0.001	0.001	0.000	0.011	0.001	−0.002	0.000
Snowfall *(yes/no)*		0.022	0.011	−0.041*	0.021	0.028*	−0.004	−0.003	−0.011	−0.029
		−0.015	−0.135	−0.523**	−0.293*	−0.119	0.631	0.075	−0.099	0.152
Constant		−0.310	−0.064	−0.866	0.184	0.146	−3.606*	0.263	1.529	−11.304**
		−0.412	−0.673	−1.665**	−0.342	0.196	5.041*	2.248**	−1.525*	2.304**

* Significant at $\alpha < 0.05$.
** Significant at $\alpha < 0.01$.

Table A4
Full gsem model results Stockholm (N = 4650).

		Dependent variables								
		Trip purpose *(ref. work/study)*				Trip chain chain	Distance	Transport mode *(ref. car)*		
		Errands	Social	Leis. outd.	Leis. other	*(yes/no)*	*(km)*	Walk	Cycle	Public
Mediators										
Purpose	Errands					0.190	−6.715**	−0.694**	−1.340**	−1.114**
(ref. work /	Social					−0.432*	−2.449*	−0.179	−1.084*	−0.208
study)	Leis. outd.					−1.259**	−8.423**	3.032**	0.303	−0.518*
	Leis. other					0.532**	−4.941**	0.588**	−0.227	0.207
Trip chain *(yes/no)*							−0.956**	−0.699**	−0.595*	−0.189
Trip distance *(km)*								−0.571**	−0.146**	0.011*
Control variables										
Age *(years)*		0.025**	0.014*	0.017**	0.011*	−0.001	−0.032*	−0.020**	0.015	−0.023**
Male *(ref. female)*		−0.146	−0.190	−0.218	−0.079	−0.375**	1.090**	−0.320**	−0.506*	−0.421**
Fulltime work *(yes/no)*		−1.436**	−1.393**	−1.617**	−1.398**	0.496**	0.358	−0.050	−0.164	−0.326*
Househ. type	Single	−1.020**	0.125	−0.498*	−0.222	−0.153	−0.043	0.023	−0.228	0.404
(ref. family)	Couple	−0.835**	−0.244	−0.178	−0.175	−0.144	1.620**	0.211	−0.621*	0.508**
hh income	Middle	−0.609*	−0.940**	−0.515	−0.052	0.401	−0.994	−0.627*	−0.400	−0.532*
(ref. lower)	Higher	−0.758**	−0.766*	−0.887**	−0.209	0.491*	−2.122*	−0.806**	0.070	−0.308
	Unknown	−0.886**	−0.581	−0.656*	−0.092	0.148	−1.146	−0.329	−0.010	0.034
# cars in household						0.012	1.107**	−0.823**	−0.914**	−1.313**
Pop.dens. *(1000 inh./km^2)*		0.001	0.001	−0.020*	−0.003	−0.002	−0.159**	0.020*	0.039**	0.029**
Weekend *(ref. weekday)*		1.961**	3.086**	2.651**	1.992**	−0.795**	2.295**	−0.074	−0.628	−0.525**
Holidays		0.242	0.670**	0.334*	0.363*	−0.313**	0.440	0.322*	0.115	−0.081
Peak	Morning	−1.630**	−3.461**	−2.375**	−2.825**	−0.138	3.998**	0.317	1.071**	0.867**
(ref. off−peak)	Evening	1.680**	1.883**	1.360**	1.497**	0.120	3.173**	0.183	0.065	0.487**
Night time (yes/no)		−3.199**	−3.074**	−1.845**	−1.945**	−0.561*	6.733**	0.476	0.821	−0.192
Atmospheric conditions										
Sky darkness *(yes/no)*		0.456**	0.890**	0.730**	0.387**	−0.376**	−0.404	−0.327*	0.103	−0.197
Air temperature T_a *(°C)*		0.014	0.023	−0.005	−0.007	−0.006	−0.010	−0.006	0.165**	−0.020
T_a squared		0.000	0.000	0.001	0.000	0.001	0.002	−0.001	−0.005*	0.000
Wind speed W_s *(m/s)*		0.023	−0.059	0.066*	0.038	−0.018	0.011	0.002	0.072	0.048
Rainfall *(yes/no)*		−0.108	0.266	−0.253	−0.038	0.117	−0.385	−0.147	−0.339	0.174
Snowfall *(yes/no)*		−0.161	−0.482	−0.461	−0.264	0.064	−0.386	0.037	−0.970	−0.077
Constant		1.082*	−0.431	0.492	0.632	0.011	13.602**	4.228**	−1.456	2.062**

* Significant at $\alpha < 0.05$.
** Significant at $\alpha < 0.01$.

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