Integrated Weather Effects on Cycling Shares, Frequencies, and Durations in Rotterdam, the Netherlands

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ABSTRACT

With the increasing societal interest in climate change, health, accessibility, and liveability and subsequent policy aims to promote active transport modes over car usage, many scholars have investigated the relationship between weather and cycling. Existing studies, however, hardly address the effects of weather on cycling durations and often lack assessments of the combined effects of different meteorological variables and potential nonlinearity of these effects. Drawing on travel diary data from a panel study of 945 Greater Rotterdam respondents (the Netherlands), this paper investigates and compares the effects of different meteorological variables, singly as well as combined, on cycling frequencies, cycling durations, and the exchange between cycling and other transport modes. Results show linear negative effects of precipitation sum and wind speed and nonlinear bell-shaped effects of thermal variables on cycling and opposite effects on car usage. Out of three thermal variables investigated, mean radiant temperature (radiant heat exchange between humans and the environment) and physiological equivalent temperature (an index combining the effects of air temperature, mean radiant temperature, air humidity, and wind speed) better explain cycling behavior than just air temperature. Optimum thermal conditions for cycling were found on days with maximum air temperatures around 24°C, mean radiant temperatures around 52°C, and physiological equivalent temperatures around 30°C. Policy and planning implications are highlighted that could reduce cyclists' exposures to disadvantageous weather conditions such as heat, precipitation, and wind, at present and in a potentially changing climate.

1. Background

Recently, scholars and policy makers have shown increasing interest in climate change adaptation and mitigation. Although large uncertainties and regional variations exist, climate changes (i.e., overall warmer temperatures and changes in precipitation patterns) have been projected and can already be observed today (e.g., Stocker et al. 2013). These weather changes are expected to have an impact on daily lives, especially those aspects that take place outdoors. One sector that may be particularly affected is the transportation sector (Koetse and Rietveld 2009). Of particular interest are the effects on cycling, which provide large societal benefits in terms of CO_2 emission reduction and improved accessibility, liveability, and health. Intuitively, cycling should be highly affected by weather due to cyclists' direct exposure. Yet, despite many recent contributions, scientific knowledge about this relationship is still somewhat limited.

Existing studies demonstrate the effects of daily weather [exceptions include, e.g., Sabir (2011), Tin Tin et al. (2012), and Gebhart and Noland (2013), who analyze weather also on an hourly level] on a wide range of travel behaviors, including transport mode choices, trip generation, and to a lesser extent distances traveled [for detailed literature reviews, see Koetse and Rietveld (2009), Heinen et al. (2010), and Böcker et al. (2013)]. Findings generally indicate that warm sunny or dry weather enhances walking and cycling, while cold, wet, or windy weather has the opposite effects—the effects typically being larger for recreational than for utilitarian purposes (e.g., Hanson and Hanson 1977; Nankervis

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1999; Bergström and Magnusson 2003; Aaheim and Hauge 2005; Gallop et al. 2012; Sabir 2011; Flynn et al. 2012; Sears et al. 2012; Thomas et al. 2013). In contrast, studies pay less attention to time spent traveling. However, the effects of weather may be inherently related to time. People may tolerate traveling in the open air during weather conditions like heat, cold, or heavy rain for a short period of time, but may not want to expose themselves for too long.

Studies on weather and travel behavior show two important meteorological shortcomings. First, studies often assume linear weather effects on travel behaviors, whereas in reality these effects may be nonlinear through optimums or thresholds. However, some recent studies demonstrate that not only lower but also high temperatures may negatively affect cycling, for instance above air temperatures of 24°C in Portland (Ahmed et al. 2012), 28°C in Melbourne (Phung and Rose 2008) and Montreal (Miranda-Moreno and Nosal 2011), and 32.2°C in Boulder, Colorado (Lewin 2011). Second, except for a few studies demonstrating the effects of weather on cycling using weather ratings (e.g., Nankervis 1999) or thermal indices (e.g., Brandenburg and Arnberger 2001; Brandenburg et al. 2004), weather and climate change are solely described and discussed in terms of absolute values and trends—in either averages or extremes—of individual meteorological variables, such as air temperature, wind speed, radiation, or precipitation. However, in order to evaluate the impact of weather on people's thermal comfort, health, and well-being, as well as travel behaviors, it is necessary to analyze the combined effects (e.g., Thorsson et al. 2011; Böcker et al. 2013).

To address these shortcomings in this paper we analyze and compare the impact of precipitation and the single as well as combined (via the physiological equivalent temperature index) impacts of air temperature, mean radiant temperature (radiant heat exchange between humans and environment), air humidity, and wind speed on cycling frequencies, time spent cycling, and the exchange between cycling and other transport modes. This work results from interdisciplinary research collaboration between transportation and climatology scientists with the ambition to integrate and expand on knowledge about the complex link between weather and cycling. This knowledge could be used to give guidance on how to plan and design sustainable, healthy, accessible, and attractive urban areas at present and in a changing climate.

2. Data and methods

Selected for this study was the greater Rotterdam area situated on the west coast of the Netherlands. The area is part of the Randstad, the densely populated economic heart of the Netherlands. Typical for the Netherlands, cycling shares are relatively large (around 20%). The region is characterized by a warm-temperate (maritime) climate (Geiger and Pohl 1954) with mild winters (average lows of 1°C and highs of 6°C), warm summers (average lows of 12°C and highs of 21°C), and relatively stable year-round precipitation patterns (KNMI 2013). The rationale for selecting Rotterdam is threefold. First, it is a metropolitan region with a wide variety of population categories (see section 2b). Second, it offers a wide variety of high-density as well as lower-density residential environments (Fig. 1). Third, the region demonstrates an active policy on sustainable transportation and climate change adaptation.

a. Meteorological attributes

Hourly meteorological data (air temperature, air humidity, wind speed, global radiation, and precipitation) for greater Rotterdam were obtained from the Dutch Meteorological Institute (KNMI 2013) from August 2012 through February 2013. The meteorological station is located at the northern edge of Rotterdam (51°57′N, 4°27′E) approximately 20 km from the sea (Fig. 1). Figure 2 describes observed daily maximum air temperature $T_{a(\max)}$, average wind speed $W_{s(\mathrm{avg})}$, precipitation sum $P_{(\mathrm{sum})}$, and the occurrence of snow cover on the ground during the study period, along with normal air temperatures for the period 1980–2010. After a wet July month (not included in this research), warmer-than-average sunny weather occurred in late August [with a peak in $T_{a(\max)}$ of 34°C; 10°C above average] as well as early September and late October. After a warmer and much wetter than average December month, mid-January provided unusually cold winter weather (up to 10°C below average) with continuous snow cover and frost even during daytime.

Weather effects on mobility were analyzed using daily meteorological variables aggregated from hourly meteorological data over the 18-h period between 0600 LT and 2400 LT, the time interval in which the majority of mobility takes place (LT is local time). The reason for using daily over hourly variables is threefold. First, some of our analyses (cycling frequencies and total cycling durations) can only be analyzed on the daily level. For uniformity, interpretability, and model comparison it is preferred to also perform the other analyses on the daily level. Second, transport mode choices are often made on the daily rather than instantaneous level. For instance, when deciding in the morning to take the bicycle to work, one probably also keeps in mind the predicted weather later that day when returning home. Third, usage of daily aggregates will allow for better comparison with existing studies, as well as better compatibility with climate change

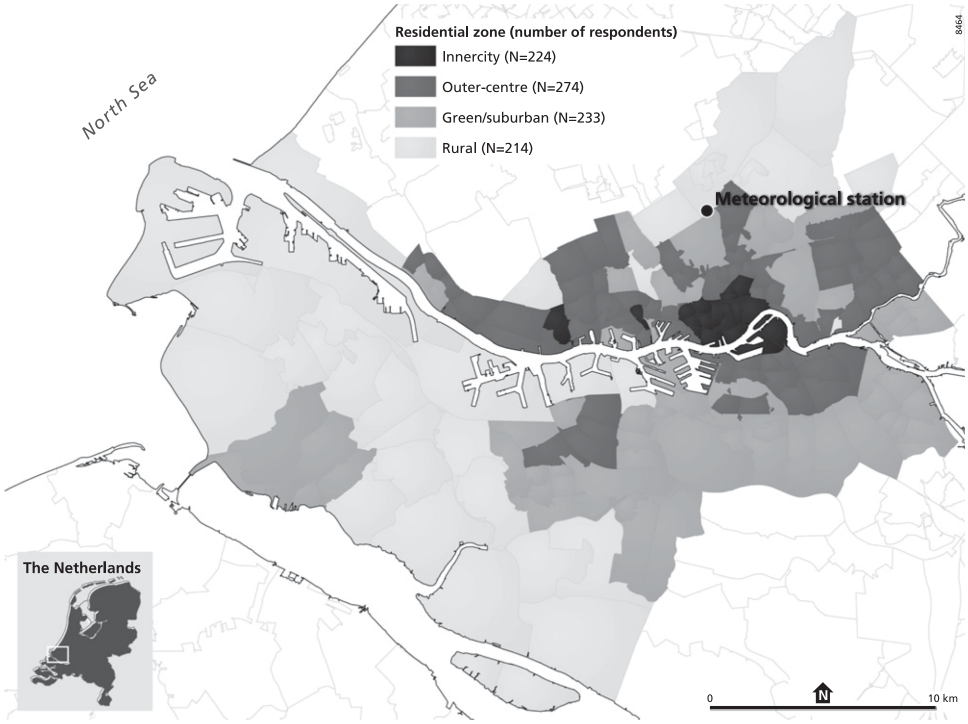

FIG. 1. Greater Rotterdam study area.

projections. We are aware that weather characteristics aggregated over the course of a day may not always correctly describe the weather experienced at a specific moment. For mode choices, we also tested an analysis with weather variables on the hourly level. This hourly model revealed the same picture and performed roughly the same; hence the daily level model was preferred.

For $W_{s(\mathrm{avg})}$ the daily average (in $\mathrm{m\,s^{-1}}$) was aggregated; for $P_{(\mathrm{sum})}$ the daily sum is in millimeters.[1] Thermal conditions were investigated using daily maximums rather than averages because these better describe the type of day. For instance, a clear day with cold (at night) and hot conditions (during the day) may result in a similar temperature average as a cloudy day with mild conditions at night as well as during the day. Thermal conditions were analyzed in three ways: by means of maximum daily *air temperature* [$T_{a(\max)}$], *mean radiant temperature* [$T_{\mathrm{mrt}(\max)}$] and *physiological equivalent temperature* [$\mathrm{PET}_{(\max)}$].

Mean radiant temperature (T_{mrt}) is one of the most important meteorological variables governing the human energy balance and outdoor thermal comfort (heat load), especially during warm and sunny days (Mayer and Höppe 1987). It is a sum of the exposure to all shortwave and longwave radiation fluxes (direct, diffuse, reflected, and emitted) in a given surrounding area. The value of T_{mrt} is directly influenced by the surface geometry (buildings, vegetation, and topography) and surface materials, which also makes it a good measure to identify built geometries causing increased risks. Compared to T_a, T_{mrt} shows large spatial variations over a short distance during the day (e.g., Thorsson et al. 2011; Lindberg and Grimmond 2011a). The calculation of T_{mrt} was done using SOLWEIG1D (Lindberg 2012), a subversion of SOLWEIG version 2.3 (Lindberg et al. 2008; Lindberg and Grimmond 2011b). SOLWEIG1D calculates the T_{mrt} for a person residing in a specific site (point) and requires observation data on air temperature, air humidity, and solar radiation (global and diffuse components). In addition, geographical information (latitude, longitude, and height above sea level) and information about surface characteristics (sky view factor, albedo, and emissivity) along with information about the proportion of radiation received by the human body in each direction (angular factors) and absorption coefficients for shortwave and longwave radiation are needed. In this study the T_{mrt} was calculated for a person standing/walking in a constantly sun-exposed environment with a sky view factor (SVF) of 0.6 (selected to represent the general SVF for the area). Angular factors were set to 0.22 for radiation fluxes from the four

[1] For precipitation we also analyzed the effects of precipitation duration, but in the end total sum was preferred because of better performance in the models.

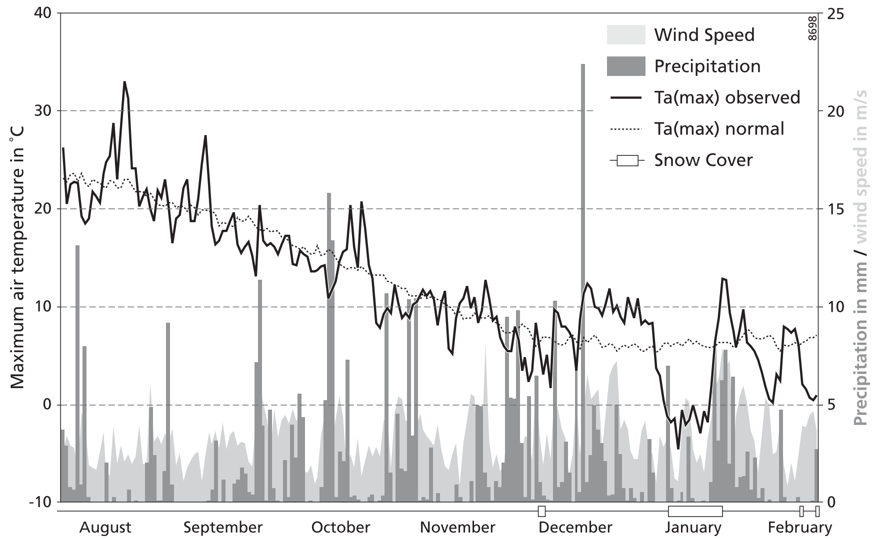

FIG. 2. Rotterdam weather conditions during survey period. Source: Helbich et al. (2014). Based on KNMI's (2013) publically available weather data. Key: $T_{a(\max)}$, observed = observed daily maximum air temperature; $T_{a(\max)}$, normal = daily maximum air temperature averages for the period 1980–2010.

cardinal points (east, west, north, and south) and 0.06 for radiation fluxes from above and below. Standard values of absorption coefficients for shortwave and longwave radiation were used (i.e., 0.7 and 0.97, respectively) (Höppe 1992; VDI 1998). Albedo and emissivity for buildings and vegetation were set to 0.20 and 0.95, respectively according to Oke (1987). For detailed equations and model validation, see Lindberg et al. (2008) and Lindberg and Grimmond (2011b).

Mayer and Höppe's (1987) physiological equivalent temperature index quantifies the combined effect of T_a, W_s, T_{mrt}, and air humidity. A PET value of, for instance, 30°C means that the human body perceives the combined outdoor thermal conditions as a fictive indoor environment with an air temperature of 30°C (Mayer and Höppe 1987). In calculating the PET, characteristics of human beings are set as constants: 80 Watts for internal heat production, 0.9 clo (1 clo = $0.155\,\mathrm{m^2\,°C\,W^{-1}}$) for clothing heat transfer resistance. PET values between 18° and 23°C indicate comfortable conditions. Higher (lower) values indicate increasing probability of heat (cold) stress (Matzarakis and Mayer 1996).

b. *Mobility attributes and modeling techniques*

This research draws on travel diary data from a panel study among 945 Greater Rotterdam residents, who were selected with the assistance of a questionnaire agency from an existing Internet panel. Respondents aged 18 years and older were randomly selected from four different types of residential environments in the greater Rotterdam area: inner city, outer center, green/suburban, and rural (see Fig. 1). We oversampled for non-native Dutch originating from hotter climates (mainly Surinamese, Dutch-Antillean, Indonesian, Turkish, and Moroccan) and older age groups (aged 65 or higher) because of generally lower response rates for these groups in research (Adler et al. 2002), as well as to account for specific weather preferences (e.g., potentially lower heat or heavy wind tolerances among elderly or higher heat tolerances for ethnic groups originating from hotter climates).

Respondents were assigned randomly to six sample days—two in summer (August–September), two in autumn (October–November), and two in winter (December–February)—in which they completed records of all their travel and destination activities. As a result, all days during the data period were covered, with the single exception of the Christmas holiday. Records were only registered during periods that were typically regular working weeks for the respondent, including weekends but excluding holidays. Extra diaries were distributed during hot summer days and cold (snow covered) winter days in order to obtain sufficient response numbers during these interesting but rarely occurring weather extremes. Sample attrition was 13.1% between waves 1 and 2 and 13.0% between waves 2 and 3 and appeared to be random rather than biased when various key sociodemographics were considered. For this reason we also included in our final sample respondents who only completed one or two seasons. Table 1 specifies the composition of the final sample of 945 respondents after cleaning the data for unreliable records and records featuring trips

TABLE 1. Sample composition and representativeness. A dash indicates that data are not publicly available.

		Sample (N = 945)	Population[a]
Gender	Male	49.2%	49.2%
	Female	50.8%	50.8%
Age	18–25	8.7%	12.6%[b]
	25–45	33.4%	28.2%
	45–65	42.9%	27.1%
	65–80	13.9%	10.9%
	>80	1.2%	4.1%
Ethnicity	Native Dutch	89.6%	69.2%
	Non-native Dutch	10.4%	30.8%
Education	Higher	35.3%	8%[c]
	Average	35.9%	20%[c]
	Lower	28.1%	72%[c]
	Unknown	0.6%	0%[c]
Household composition and size	Family with child(ren) < age 5	8.4%	—
	Family with child(ren) aged 5–12	9.4%	—
	Dual-earner couple	12.6%	—
	Single-earner couple	7.7%	—
	Non-working couple	12.2%	—
	Working single	16.3%	—
	Non-working single	11.2%	—
	Other (incl. single parent)	22.2%	—
	Average household size	2.37	2.15
Net monthly household income	<2000€	29.5%	—
	€2000–€3000	24.0%	—
	€3000–€4000	19.0%	—
	>€4000	11.1%	—
	Unknown	16.3%	—
	Average in euros	—	€2767

[a] Total 2010 population statistics for the Rotterdam Rijnmond COROP region (Source: Netherlands Central Bureau for Statistics; http://statline.cbs.nl/statweb/).
[b] The 12.6% in the total population is aged 15–25 instead of 18–25.
[c] Statistic for the entire Netherlands population.

outside the Netherlands subject to different weather conditions. Generally the sample is well balanced with substantial shares for various sociodemographic groups. Additionally, the sample is reasonably representative when compared to the general population in this region, with the exception of lower educated and nonnative Dutch being somewhat underrepresented, which is quite typical for Internet surveys (Adler et al. 2002).

Our multivariate analysis considered the marginal effects of weather on mode choices, cycling frequencies, and cycling durations, as well as its relative contribution compared to various background variables. These include classical individual and household background variables (e.g., age, gender, income, etc.), spatiotemporal attributes (e.g., residential environment, weekend/weekday, time of the day, etc.), and attitudes that may intermediate the role of weather effects on mobility (e.g., favorite season, environmental concern, and whether a person is more urban or countryside oriented). These are listed in Fig. 3. Mode choices are analyzed on the trip level, while cycling frequencies and durations are analyzed per person per day. The trip-level attributes of trip purpose and type, as well as the spatiotemporal attributes related to time of the day, are only included in the trip-level mode choice analysis. All other attributes are included in all three analyses.

To test the effects of weather on mode choices a multinomial LOGIT model was used. This model, based on utility maximization, is similar to binary logistic regression, except that it allows a categorical variable with more than two alternatives. The reference category is the car, allowing for comparison with earlier studies. For daily cycling frequencies and durations, negative binomial and TOBIT models (respectively) were used. These were preferred over standard Poisson (count data) and ordinary least squares (OLS) (interval/ratio data) regression, as they better handle the dependent variables' absence of negative values and excess of zeros due to people not making cycling trips on a day (Cameron and Trivedi 1998; Greene 1997). Because this is a panel study and each respondent performs several trips during several days, trips performed by one respondent may not be strictly independent. To relax the usual requirement of independent observations, all statistical analyses in this paper were performed with the Stata software package "vce-cluster" command (clustered by respondent ID). The estimation of equal robust standard errors per respondent corrects for intragroup correlation (Wooldridge 2002).

For all analyses we estimated separate models for the different trip purposes of work, errands, social visits, and leisure, because existing literature indicates that the weather effects are smaller for utilitarian trips than for leisure (e.g., Aaheim and Hauge 2005; Sabir 2011). However, for the overview and focus of the paper these separate trip purpose models will not be presented but only discussed in text. Additionally, separate models were estimated for $T_{a(\max)}$, $T_{\mathrm{mrt}(\max)}$, and $\mathrm{PET}_{(\max)}$, which because of multicolinearity (Pearson r, $T_{a(\max)}$, $T_{\mathrm{mrt}(\max)}$ = 0.81; $T_{a(\max)}$, $\mathrm{PET}_{(\max)}$ = 0.96; $T_{\mathrm{mrt}(\max)}$, $\mathrm{PET}_{(\max)}$ = 0.90) are analyzed one at a time. Finally, to check for potential nonlinear effects, for each of the three thermal variables, we estimated models in two different ways: untransformed (describing a linear relationship) and transformed (describing a bell-shaped relationship). To model the bell-shaped effect, use is made of a Gaussian function (see Fig. 4), in which $f(x)$ indicates the transformed thermal variable as a function of its original, a is the position of the center of the peak

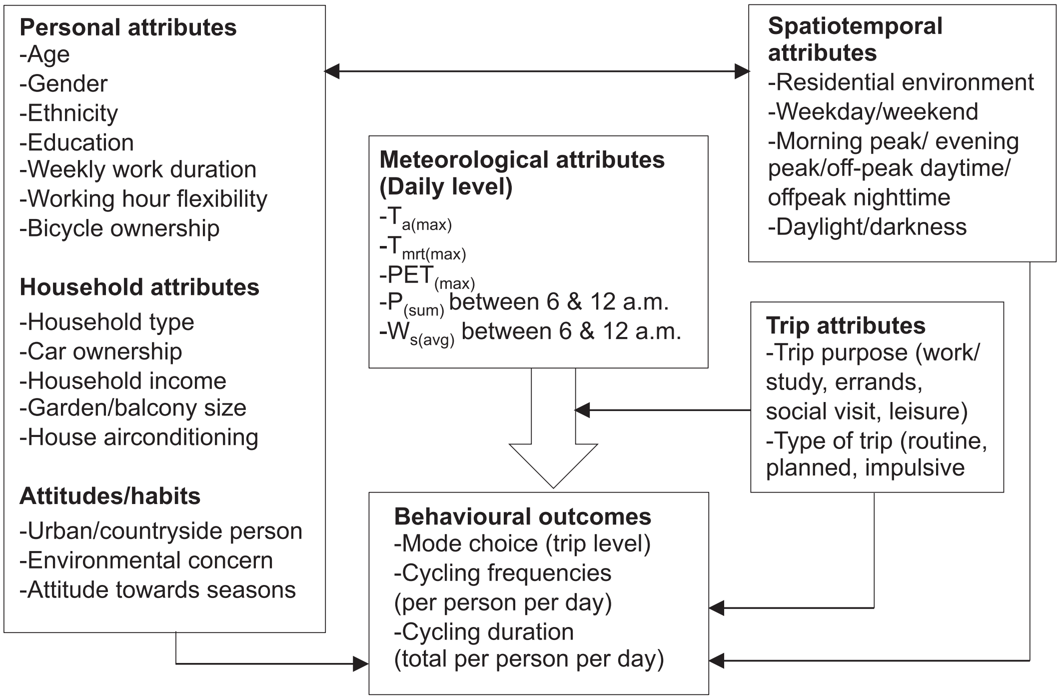

FIG. 3. Overview of all variables used in the models. Key: $T_{a(\max)}$ = maximum daily air temperature; $T_{\mathrm{mrt}(\max)}$ = maximum daily mean radiant temperature; PET = maximum daily physiological equivalent temperature; $W_{s(\mathrm{avg})}$ = daily average wind speed; $P_{(\mathrm{sum})}$ = daily precipitation sum.

(optimal thermal condition for cycling), and b is the full width at half maximum (FWHM) (see Fig. 4). For each model, various values for a and b were tested until a maximum model log likelihood was reached.

3. Results

a. *Weather and cycling: Descriptive results*

Figures 5, 6, and 7 provide schematic descriptive overviews of the effects of weather on mode choices and cycling frequencies and durations, calculated for the full Greater Rotterdam sample (all trip purposes combined). The modal splits in Fig. 5 show that, overall, around half of all trips are made by car. As is typical for the Netherlands, cycling also has considerable shares (around 20%). Weather conditions generally seem to have a clear effect on mode choices. Of all transport modes, cycling appears to be the most sensitive to weather.

The three thermal variables have an initially positive effect on cycling shares until a certain thermal optimum. Thereafter the effect is negative. This is congruent with the—sometimes described as parabolic (e.g., Phung and Rose 2008)—effect of T_a on cycling, often indicated but less often empirically demonstrated in the literature. Cycling shares seem to peak on days with $T_{a(\max)}$ values between 20° and 25°C, $T_{\mathrm{mrt}(\max)}$ values between 55° and 60°C, and $\mathrm{PET}_{(\max)}$ values between 23° and 29°C, which according to the literature should be classified as ''slightly warm'' (Matzarakis and Mayer 1996). Note that here we refer to maximum temperatures. Cycling in the morning or evening those days may occur during more comfortable thermal conditions. Where cycling peaks, a dip in car usage is observed and to a lesser extent walking, while public transport is affected to a minimum during hot days.

In line with the literature (e.g., Aaheim and Hauge 2005; Sabir 2011), $P_{(\mathrm{sum})}$ and $W_{s(\mathrm{avg})}$ both negatively affect cycling shares in a more linear way, mostly at the cost of car usage. When it comes to the effects of $W_{s(\mathrm{avg})}$, it should be noted that days with high $W_{s(\mathrm{avg})}$ correlate to some extent with rainy (Pearson $r = 0.36$) and cloudy weather conditions, which may be additional contributors to the here observed decrease in cycling shares.

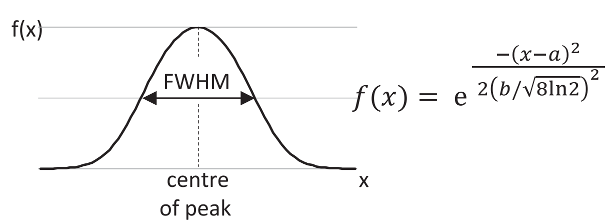

FIG. 4. Gaussian function.

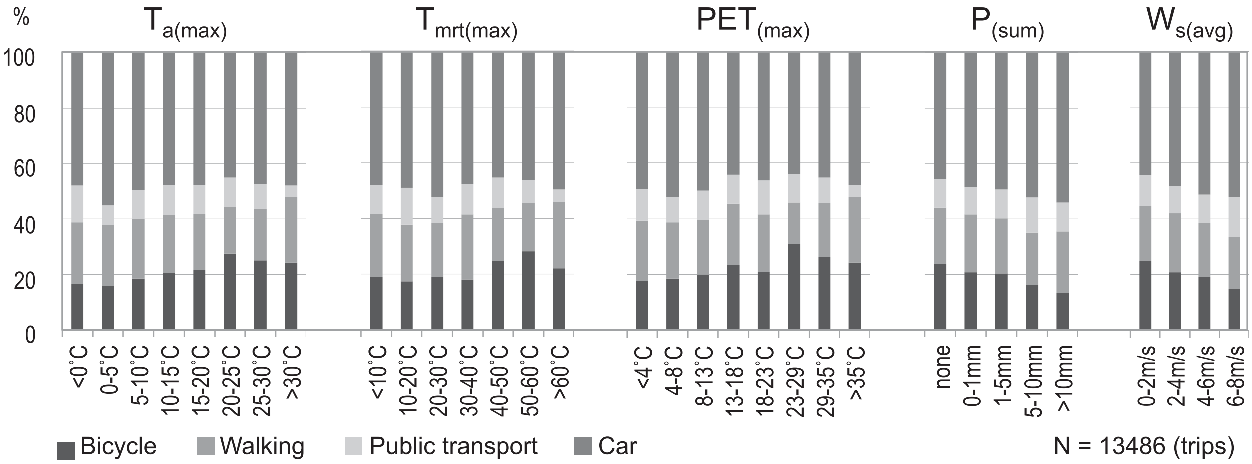

FIG. 5. Weather effects on modal split. Key is as in Fig. 3.

Figure 6 presents the effects of weather conditions on the number of bicycle trips per person per day. It represents actual bicycle frequencies (demand) rather than mode shares, discussed above. Generally, weather effects on cycling frequencies show a similar pattern as observed for cycling shares, but the effects seem to be a bit more pronounced. Congruent with the modal split descriptives, daily $P_{(\mathrm{sum})}$—especially on days with over 5 mm of precipitation—and $W_{s(\mathrm{avg})}$ show negative effects.

Regarding thermal conditions, cycling frequencies increase until the same optimum temperatures found earlier for the modal split shares are reached. But rather than the parabolic relationship indicated in the literature, thermal conditions seem to demonstrate a bell-shaped effect on cycling, which flattens out on the lower extreme. This is especially visible when looking at the graphs for $T_{a(\mathrm{max})}$ and $T_{\mathrm{mrt(max)}}$. It seems that, at least within the wide range of thermal conditions observed during our study period, a core of weather-tolerant cyclists exists who keep cycling, regardless of the thermal conditions. Remarkably, the $\mathrm{PET}_{(\mathrm{max})}$ graph reports a dip in cycling frequencies at days with $\mathrm{PET}_{(\mathrm{max})}$ values between 18° and 23°C, which according to the literature should be classified as comfortable thermal conditions (Matzarakis and Mayer 1996). However, the exceptionally high cycling peak in the next class may indicate that the observed anomaly is related to arbitrarily chosen interval classes. Also, it should be noted that here we refer to descriptives that take no account of simultaneous effects of temperatures, precipitation, and wind speeds. These descriptive graphs should therefore be interpreted as indicators of general trends rather than exact representations of individual classes.

Figure 7 presents the effects of weather on daily cycling durations. A roughly comparable picture arises for the cycling frequencies, with more or less similar bell-shaped effects for the thermal variables and negative effects for $P_{(\mathrm{sum})}$ and $W_{s(\mathrm{avg})}$. One exception is that the hottest

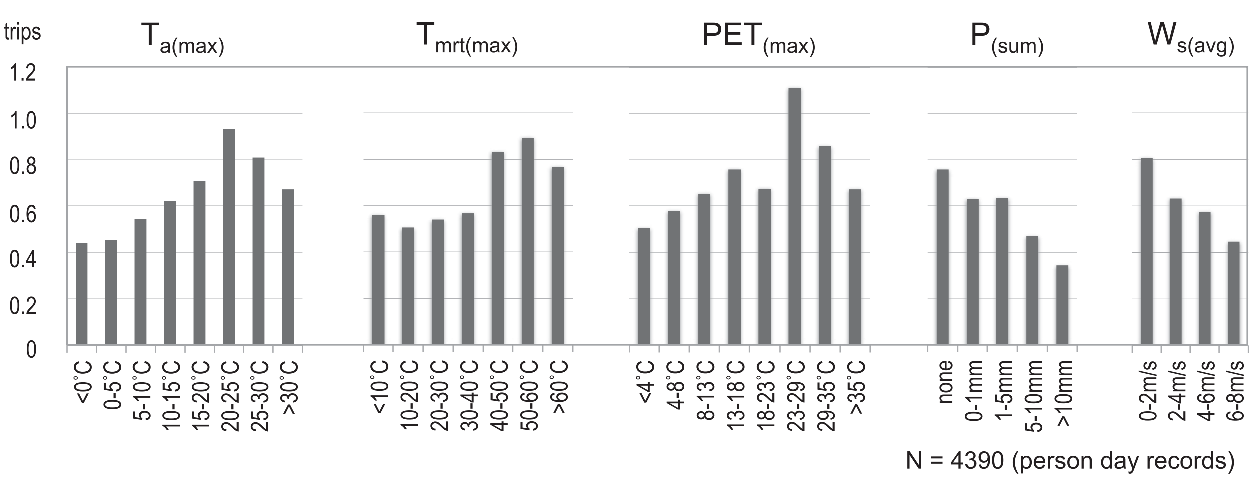

FIG. 6. Weather effects on number of cycling trips per person per day. Key is as in Fig. 3.

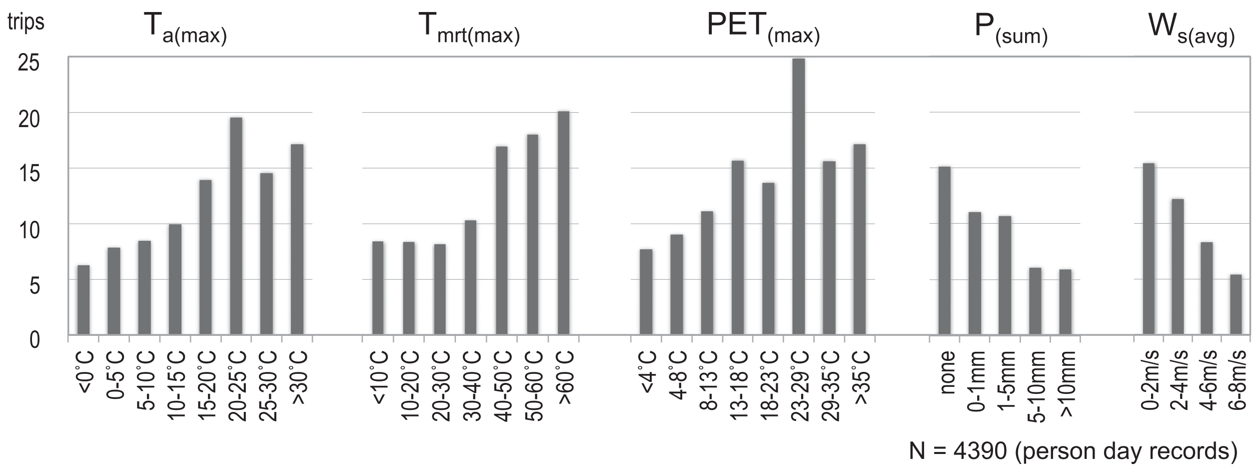

FIG. 7. Weather effects on time spent cycling per person per day. Key is as in Fig. 3.

thermal classes for $T_{a(max)}$, $T_{mrt(max)}$, and $PET_{(max)}$ no longer show a decline over the preceding classes. A closer look at the raw mobility data for these hot days revealed that these higher cycling durations are mostly related to distinct leisure activity patterns involving recreational cycling tours and cycling trips to more distant natural recreation areas, including beaches. Overall, the weather effects for cycling durations appear to be even more prominent than for cycling frequencies. This is, for instance, clearly demonstrated when comparing the slope in the graphs for $W_{s(avg)}$. It seems that during calm, dry, and pleasant thermal conditions people cycle not only more frequently, but also longer.

b. Multivariate results

This section presents a multivariate analysis of the effects of weather on cycling. Tables 2, 3, and 4 summarize the effects of weather and weather-related parameters on mode choices, cycling frequencies, and cycling durations. To not distract from the main meteorological focus of this paper, the tables do not display the full underlying models, which also include all other independent background attributes[2] listed in Fig. 3. These full models, as well as the separate models estimated for the different trip purposes,[3] can be requested by sending an e-mail to the authors.

1) WEATHER EFFECTS ON CYCLING SHARES COMPARED TO OTHER TRANSPORT MODES

Table 2 presents a summary of the effects of meteorological variables on transport mode choices, as well as the effects of whether or not a trip was made in daylight and whether or not snow cover occurred on the ground. The parameter estimate (B) indicates the change in log odds of choosing a transport mode over the car for a one-unit parameter change. The z statistic indicates the ratio between the parameter estimate and the robust standard errors clustered per respondent. Statistically significant effects have been marked with asterisks. Overall, meteorological variables have a clear effect on the exchange between cycling and the car, even when corrected for various background characteristics, as well as snow cover on the ground and daylight. The exchange between the car and other transport modes is less affected by weather.

Regarding the thermal conditions, the bell-shaped transformed variables for $T_{a(max)}$, $T_{mrt(max)}$, and $PET_{(max)}$ (see section 2b) demonstrate more significant effects and provide better overall model performance than the untransformed originals. This indicates that the effect of thermal conditions on transport mode choice is bell-shaped rather than linear. The positive parameter estimates for the transformed variables imply that the effects of thermal conditions on cycling follow the bell-shaped curve. More precisely, the best model fit was reached for bell-shaped variables with an optimum of 24°C for $T_{a(max)}$ (FWHM = 25°C), 52°C for $T_{mrt(max)}$ (FWHM = 25°C), and 30°C for $PET_{(max)}$ (FWHM = 42°C). These optimums are roughly in line with the optimum intervals found in the descriptives. When comparing the three bell-shaped thermal parameters, $T_{mrt(max)}$ and $PET_{(max)}$ provide higher significance levels and better or similar model fit—indicated

[2] The respective effects of these sociodemographic, household, trip, and urban form attributes on mode choice outcomes are generally in line with the literature (e.g., Hanson 1982; Cervero and Seskin 1995; Dieleman et al. 2002).

[3] In line with the literature (e.g., Hanson and Hanson 1977; Aaheim and Hauge 2005; Sabir 2011), it was shown that mode choices for leisure trips and social visits are more strongly affected by weather conditions than mode choices for utilitarian trips from/to work, study, and especially errands.

TABLE 2. Weather effects on transport mode choice. One asterisk (*) indicates $p < 0.10$, two (**) $p < 0.05$, and three (***) $p < 0.01$. $T_{a(\max)}$ = maximum daily air temperature; $T_{\mathrm{mrt(max)}}$ = maximum daily mean radiant temperature; $\mathrm{PET}_{(\max)}$ = maximum daily physiological equivalent temperature; $W_{s(\mathrm{avg})}$ = daily average wind speed; $P_{(\mathrm{sum})}$ = daily precipitation sum.

	Multinomial LOGIT model (Car = ref.)							
	Cycling			Walking			Public transport	
	B		z	B		z	B	z
T_a model								
$T_{a(\max)}$ (bell-shaped, with optimum = 24°C; FWHM = 25°C)	0.284	*	1.76	−0.239		−1.48	0.256	1.32
$W_{s(\mathrm{avg})}$ (0600–2400 LT)	−0.061	*	−1.91	−0.044		−1.43	−0.014	−0.33
P_{sum} (0600–2400 LT)	−0.036	**	−2.41	−0.004		−0.30	0.025	1.31
Snow cover	−0.152		−0.89	0.084		0.57	0.283	1.41
Daylight	0.523	***	6.21	0.312	***	3.54	0.101	1.04
n = 13 486 (trips); Wald chi-square = 3176***; pseudo R^2 (McFadden) = 0.21								
T_{mrt} model								
$T_{\mathrm{mrt(max)}}$ (bell-shaped, with optimum = 52°C; FWHM = 25°C)	0.245	**	2.11	−0.197	*	−1.83	−0.024	−0.17
$W_{s(\mathrm{avg})}$ (0600–2400 LT)	−0.050		−1.46	−0.052	*	−1.66	−0.022	−0.53
$P_{(\mathrm{sum})}$ (0600–2400 LT)	−0.034	**	−2.26	−0.005		−0.39	0.021	1.11
Snow cover	−0.212		−1.40	0.141		1.13	0.137	0.77
Daylight	0.514	***	6.14	0.316	***	3.60	0.144	1.45
n = 13 486 (trips); Wald chi-square = 3242***; pseudo R^2 (McFadden) = 0.21								
PET model								
$\mathrm{PET}_{(\max)}$ (bell-shaped, with optimum = 30°C; FWHM = 42°C)	0.391	***	2.60	−0.211		−1.39	0.037	0.19
$P_{(\mathrm{sum})}$ (0600–2400 LT)	−0.041	***	−2.73	−0.013		−0.95	0.020	1.04
Snow cover	−0.130		−0.83	0.135		1.03	0.164	0.89
Daylight	0.514	***	6.12	0.315	***	3.57	0.139	1.41
n = 13 486 (trips); Wald chi-square = 3173***; pseudo R^2 (McFadden) = 0.21								

by the Wald chi-square statistic[4]—than $T_{a(\max)}$. The only thermal variable that is significant on the 99% confidence interval is $\mathrm{PET}_{(\max)}$. This indicates that combining meteorological variables (T_a, T_{mrt}, humidity, and W_s) within PET seems to lead to a better explanation of the exchange between cycling and the car. However, T_{mrt} is the dominant component within the PET and the most important component of thermal comfort and heat load (Mayer and Höppe 1987). Moreover, the T_{mrt} model as a whole, including $W_{s(\mathrm{avg})}$ as a separate meteorological variable, performs better (higher Wald chi-squared score) than the PET model, in which $W_{s(\mathrm{avg})}$ has been integrated within the $\mathrm{PET}_{(\max)}$.

In line with the descriptives, $W_{s(\mathrm{avg})}$ and $P_{(\mathrm{sum})}$ negatively affect cycling shares as compared to the car. The $W_{s(\mathrm{avg})}$ effect is significant only in the T_a model (with 90% confidence) and not in the T_{mrt} model. This may be explained by the higher negative correlation between $W_{s(\mathrm{avg})}$ and $T_{\mathrm{mrt(max)}}$ (Pearson $r = -0.29$) than between $W_{s(\mathrm{avg})}$ and $T_{a(\max)}$ (Pearson $r = -0.17$). The significant negative effect of $W_{s(\mathrm{avg})}$ on cycling found in the T_a model may be partially associated with potentially unpleasant or threatening cloudier skies, while in the T_{mrt} model these cloudier skies are better captured by $T_{\mathrm{mrt(max)}}$. For $P_{(\mathrm{sum})}$ the negative effects on cycling shares are significant (with a confidence interval of 95% or higher) in all models. Snow cover on the ground seems to affect cycling negatively, potentially related to slippery conditions. However, the effect is not statistically significant, possibly because slippery conditions also negatively affect car usage (nonsignificant positive effects are shown for walking and public transport shares relative to the car). An especially notable observation is the strong positive effect of daylight on both cycling and walking shares in comparison to the car. It seems that after sunset, active transport modes become less attractive. This may partially be related to colder thermal conditions at night, but also to reduced visibility or potential safety issues.

[4] The Wald chi-square evaluates to what extent a chosen model performs better than a baseline model in which all estimated parameters are set to zero. If none of the parameters would add anything to the chosen model, the Wald chi-square would be zero. A higher Wald chi-square indicates a better model fit.

2) Weather effects on cycling frequencies

Table 3 presents a summary of meteorological effects on the number of cycling trips per person per day. Rather than relative cycling shares, this is an analysis of cycling demand in absolute terms. The parameter estimate (B) indicates the change in the expected log count of the number of bicycle trips per person per day for a one-unit parameter change. Robust standard errors (S.E.) clustered per respondent and z statistics indicating

TABLE 3. As in Table 2, but for weather effects on number of cycling trips per person per day.

	Negative binomial model			
T_a model	B		Robust S.E.	z
$T_{a(\max)}$ (bell-shaped, with optimum = 24°C; FWHM = 25°C)	0.475	***	0.116	4.09
$W_{s(\mathrm{avg})}$ (0600–2400 LT)	−0.041		0.025	−1.64
P_{sum} (0600–2400 LT)	−0.040	***	0.013	−3.13
Snow cover	−0.278	**	0.133	−2.09
n = 4389 (person-day records); Wald chi-square = 407***				
T_{mrt} model				
$T_{\mathrm{mrt}(\max)}$ (bell-shaped, with optimum = 52°C; FWHM = 25°C)	0.425	***	0.079	5.41
$W_{s(\mathrm{avg})}$ (0600–2400 LT)	−0.020		0.026	−0.77
$P_{(\mathrm{sum})}$ (0600–2400 LT)	−0.036	***	0.013	−2.83
Snow cover	−0.379	***	0.117	−3.24
n = *4389* (person-day records); Wald chi-square = 428***				
PET model				
$\mathrm{PET}_{(\max)}$ (bell-shaped, with optimum = 33°C; FWHM = 39°C)	0.544	***	0.093	5.85
$P_{(\mathrm{sum})}$ (0600–2400 LT)	−0.037	***	0.012	−3.01
Snow cover	−0.315	***	0.118	−2.67
n = 4389 (person-day records); Wald chi-square = 415***				

the ratio between parameter estimates and standard errors are also presented.

Overall, weather seems to have a clear effect on cycling frequencies. In line with the descriptives and the effects on cycling mode shares, thermal conditions demonstrate a bell-shaped effect on cycling frequencies (all significant with 99% confidence). The highest cycling frequencies occur on days with values of 24°C for $T_{a(\max)}$, 52°C for $T_{\mathrm{mrt}(\max)}$, and 33°C for $\mathrm{PET}_{(\max)}$. This 33°C for $\mathrm{PET}_{(\max)}$ is slightly higher than the optimums found in the descriptives and the mode choice model. It seems that although cycling mode shares start decreasing above 30°C PET, cycling frequencies in absolute terms start decreasing above 33°C PET—thermal conditions classifying as "warm," two classes above "comfortable" in the literature (Matzarakis and Mayer 1996). Similar to the cycling shares, cycling frequencies $T_{\mathrm{mrt}(\max)}$ and $\mathrm{PET}_{(\max)}$ seem to also be better indicators (higher z statistics as well as overall model Wald chi-squared) than $T_{a(\max)}$.

As for cycling mode shares, $P_{(\mathrm{sum})}$ shows significant linear negative effects on cycling frequencies (all with 99% confidence). Earlier, a negative effect of snow cover could not be statistically confirmed on cycling shares relative to the car. In contrast, when it comes to absolute cycling frequencies, snow cover demonstrates a highly significant negative effect in all models, suggesting an influence of slippery conditions. It seems that $W_{s(\mathrm{avg})}$ negatively affects cycling frequencies, but these effects are not statistically significant.

3) WEATHER EFFECTS ON CYCLING DURATION

Table 4 presents a summary of meteorological effects on total hours cycling per person per day. The parameter estimate (B), similar to standard OLS regression, indicates the predicted change in cycling hours per person per day for a one-unit parameter increase. Robust standard errors (S.E.) clustered per respondent and t statistics indicating the ratio between parameter estimates and standard errors are also presented.

Overall, weather strongly affects daily cycling durations. All included meteorological attributes show significant effects. Generally, the effects of weather on cycling durations show a similar picture as cycling shares and frequencies. Thermal conditions show bell-shaped effects on cycling durations (all significant with 99% confidence). Approximately in line with the descriptives, the longest daily cycling durations occur on days with maximum values of 24°C for $T_{a(\max)}$, 52°C for $T_{\mathrm{mrt}(\max)}$, and 31°C for $\mathrm{PET}_{(\max)}$. Both $P_{(\mathrm{sum})}$ and snow cover on the ground demonstrate highly significant negative effects on cycling durations (all with 95% or 99% confidence). Also, $W_{s(\mathrm{avg})}$ shows a negative effect on cycling durations, which, in contrast to the cycling frequencies, is significant (with 99% confidence in the T_a model and with 90% confidence in the T_{mrt} model). In line with the descriptives, it seems that $W_{s(\mathrm{avg})}$ affects cycling durations more strongly than cycling frequencies. This indicates that people do still make bicycle trips on windy days but that those trips are shorter than on calm days.

4. Discussion and conclusions

This paper aims to investigate the complex link between weather and cycling. Drawing on travel diary data from a triple-wave panel study among 945 respondents

TABLE 4. As in Table 2, but for weather effects on the number of hours spent cycling per person per day.

	TOBIT model			
	B		Robust S.E.	t
T_a model				
$T_{a(\max)}$ (bell-shaped, with optimum = 24°C; FWHM = 25°C)	0.581	***	0.108	5.40
$W_{s(\mathrm{avg})}$ (0600–2400 LT)	−0.061	***	0.020	−3.03
P_{sum} (0600–2400 LT)	−0.026	***	0.010	−2.64
Snow cover	−0.276	**	0.107	−2.59
n = 4389 (person-day records); Wald chi-square = 235***; pseudo R^2 (McFadden) = 0.087				
T_{mrt} model				
$T_{\mathrm{mrt(max)}}$ (bell-shaped, with optimum = 52°C; FWHM = 25°C)	0.482	***	0.076	6.37
$W_{s(\mathrm{avg})}$ (0600–2400 LT)	−0.038	*	0.020	−1.84
$P_{(\mathrm{sum})}$ (0600–2400 LT)	−0.022	**	0.010	−2.29
Snow cover	−0.411	***	0.097	−4.23
n = 4389 (person-day records); Wald chi-square = 244***; pseudo R^2 (McFadden) = 0.089				
PET model				
$\mathrm{PET}_{(\max)}$ (bell-shaped. with optimum = 31°C; FWHM = 42°C)	0.695	***	0.102	6.82
$P_{(\mathrm{sum})}$ (0600–2400 LT)	−0.026	***	0.010	−2.69
Snow cover	−0.299	***	0.099	−3.02
n = 4389 (person-day records); Wald chi-square = 240***; pseudo R^2 (McFadden) = 0.088				

from Greater Rotterdam, the Netherlands, and after controlling for various individual, household, and trip background characteristics, we analyzed the effects of aggregated daily weather conditions on cycling. Daily weather data produced results similar to those of hourly weather data and were preferred because of uniformity and compatibility and because they are more in line with the moment of transport mode decision-making. To provide a complete picture of cycling behavior, unlike most existing research, an analysis was made not only of cycling frequencies, but also of cycling durations and the exchange between cycling and other transport modes. The results demonstrate a clear overall effect of daily weather conditions on transport mode choices in general and cycling in particular. Congruent with the literature (e.g., Nankervis 1999; Bergström and Magnusson 2003; Aaheim and Hauge 2005; Sabir 2011), daily precipitation sum [$P_{(\mathrm{sum})}$] and average wind speed [$W_{s(\mathrm{avg})}$] demonstrate linear negative effects on cycling, mostly benefiting car usage. Cycling durations seem to be more significantly affected by $W_{s(\mathrm{avg})}$ than cycling shares and frequencies. This indicates that on windy days people not only cycle less often, but also for shorter durations. Thermal conditions affect cycling in a nonlinear bell-shaped way. Congruent with some recent studies (e.g., Phung and Rose 2008; Ahmed et al. 2012; Lewin 2011), a thermal optimum for cycling can be identified (days with maximum air temperatures around 24°C). Below and above this temperature cycling shares, frequencies, and durations decrease and car usage increases. Compared to the exposed bicycle, the car offers its user better protection from wind, precipitation, and cold as well as heat.

In contrast with most existing studies on weather and transportation, when analyzing thermal conditions we not only take into account the daily maximums for air temperature [$T_{a(\max)}$], but also for mean radiant temperature [$T_{\mathrm{mrt(max)}}$], which combines the effects of air temperature (via emission of long-wave radiation from the sky and surrounding surfaces) and solar radiation (direct, diffuse, and reflected), and physiological equivalent temperature [$\mathrm{PET}_{(\max)}$], which combines the effects of T_a, T_{mrt}, W_s, and humidity. Weather may be perceived as warmer during calms and sunshine than during cloudy and windy conditions, despite a similar T_a. The use of PET and T_{mrt} provides a more comprehensive account of weather conditions, although it should be mentioned that in order to calculate these indices, assumptions needed to be made regarding the urban geometry and human parameters such as shape, heat production, and clothing. Our results demonstrate that $T_{\mathrm{mrt(max)}}$ and $\mathrm{PET}_{(\max)}$ provide better explanations for cycling shares, frequencies, and durations than just $T_{a(\max)}$, confirming the importance of combined weather effects. Nevertheless, $T_{a(\max)}$, although somewhat weaker, also demonstrates significant effects. In general, T_a may therefore still be a powerful indicator as it is easily interpretable, free of assumptions, widely accessible, and easily compatible with weather forecasts and climate change scenarios.

Insights from this paper are relevant to policy makers in several ways. When analyzing cycling trends over time, as in when evaluating the effects of cycling policies, for example, the insights presented here could be used to disentangle cycling trends from the noise caused by short-term weather fluctuations. Similarly, the insights could be used to improve annual modal split estimations by adjusting for weather conditions—particularly when these are based on origin-destination survey data conducted over the course of less than a full year, or during years with abnormal weather conditions. Additionally, the effects of weather on cycling are relevant in the context of climate change. Most of the year, a warmer future climate may have positive effects on cycling. However, in summer heat may pose a threat. A brief calculation based on Dutch Meteorological Institute climate change projections for the Netherlands (KNMI 2009) reveals that the number of days with maximum air temperatures of 25°–30°C and 30°–35°C—days on which optimum conditions for cycling are exceeded—is expected to increase respectively from 24 currently to 30–47 in 2050 and from 4 currently to 7–14 in 2050, depending on whether mild (+1°C global temperature rise; no changing prevailing wind patterns) or severe (+2°C global temperature rise, changing prevailing wind patterns) climate change scenarios are utilized. A potential future increase in overall precipitation and extreme precipitation events plus changes in solar radiation/cloudiness may further (negatively) impact cycling. Policy makers are advised to consider (thermal) climate adaptations in urban design, for instance through usage of deciduous trees in urban areas and along cycling infrastructures, which provide cooling in summer when foliated—mainly through shading but also through transpiration—while retaining valued sunshine in winter when defoliated (e.g., Lindberg and Grimmond 2011a; Konarska et al. 2014). In addition to alleviating heat and solar radiation, trees can be used to regulate wind and humidity and to protect from sudden (summer) downpours. Wind barriers and precipitation shelter, in the form of trees or other, particularly along main cycling infrastructures, could be additional interventions to reduce cyclists' weather exposures, which may lead to increased bicycle-over-car usage.

This research explores the complex integrated weather effects on travel behavior. Future research could further elaborate this topic into several directions. First, the notions of combined weather and nonlinearity explored in this study could further be investigated. Studies could further explore the effects of precipitation combined with thermal conditions, as well as the existence of (combined) precipitation, wind, or thermal thresholds triggering sudden travel behavior changes. Also, studies may explore the effects of weather variability (e.g., showers versus continuous rain; wind gusts; sunny spells during cloudy days), as well as lagged weather effects (e.g., first warm sunny spring day after a long winter). Second, research could investigate integrated weather effects on other related travel behavior decisions, such as choices for destinations, departure times, speeds, and routes. Such analyses may require other data collection techniques (e.g., smart GIS interfaces), as well as more precise spatial and temporal resolutions. Third, research on the integrated effects of weather on a wide range of (travel) behavioral activities may further focus on the development of new or the fine-tuning of existing meteorological indices to the specific the activities one wants to address. For instance the PET may be better recalibrated to cycling (or other outdoors activities). Fourth, research into the integrated effects of weather should be explored not only objectively, but also in terms of peoples' subjective interpretations of weather in connection with emotional experiences during travel or outdoors activities. Such subjective accounts have been studied qualitatively (e.g., Spencer et al. 2013) but may also be integrated into quantitative travel surveys or diaries. Fifth, to better explore thermal optimums and potential negative effects of heat, especially in the light of climate change, future research is strongly recommended in hotter climate regimes where people experience heat more regularly. Finally, to better guide climate adaptation policies, studies could further investigate the effects of spatial design interventions, such as the usage of trees, wind barriers, and precipitation shelters, on the (experienced) weather exposure of cyclists.

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