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Geographic heterogeneity in cycling under various weather conditions: evidence from Greater Rotterdam

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ABSTRACT

With its sustainability, health and accessibility benefits, cycling has nowadays been established on research and policy agendas. Notwithstanding the decision to cycle is closely related to local weather conditions and interwoven with the geographical context, research dealing with both aspects is scarce. On the basis of travel diary data, we assess the association of three weather conditions, namely air temperature, wind speed, and precipitation, on cycling trips for leisure and commute purposes for the Greater Rotterdam area, the Netherlands. Besides region-wide logit models and autologistic regressions, place-specific associations of weather conditions are explored through geographically weighted logit models. Considering the entire Rotterdam area, results confirm significant weather effects on cycling while highlighting the necessity to model the residents' locational component. When the confounding effects of individual and household characteristics are controlled, a key finding is that weather effects appear to vary across space, specifically between the more densely settled central environments and the surrounding lower-density areas. Additionally, the results show differences between leisure and commute trips, in which leisure trips appear to be more weather sensitive and show more pronounced spatial patterns.

1. Introduction

Over the last decade, scientific as well as societal interest in climate change adaptation and mitigation has risen extensively. Although uncertainties exist, renewed climatological research reveals evidence for global temperature rise, changes in precipitation patterns, and increased frequencies of extreme weather phenomena (e.g., IPCC, 2007). 'Affecting' as well as 'being affected by', the transport sector is evidently related to climate change in a complex manner (Koetse and Rietveld, 2009; Böcker et al., 2013). In this regard, sustainable, healthy and accessible active transport modes like cycling, recently received a great deal of interest in transport geography and transport studies (e.g., Buehler and Pucher, 2010; Aldred, 2013; Heinen et al., 2013). The effects of weather on these desirable, but also weather-exposed, active transport modes compared to motorised transport are of particular interest. Findings generally indicate warm, calm, dry or sunny weather to stimulate cycling, while cold, wet, windy or cloudy weather have reverse effects (e.g., Müller et al., 2008; Koetse and Rietveld, 2009; Böcker et al., 2013). Recreational trips are typically more affected than utilitarian trips (e.g., Hanson and Hanson, 1977; Nankervis, 1999; Bergström and Magnussen, 2003; Sabir, 2011; Tin Tin et al., 2012).

While many of these contributions control for various confounders (e.g., socio-demographic or household characteristics), the locational component and the spatial variations in weather effects on behavioural outcomes have been largely underexplored. Some empirical results demonstrate different effects of weather on cycling between different spatial settings (e.g., Brandenburg et al., 2004; Phung and Rose, 2008; Thomas et al., 2013). However, so far only limited use has been made of detailed local spatial variation beyond the level of predefined or administrative units and as a consequence significant place-specific associations remain unclear. Such place-specific insights could help policy makers to set up appropriate planning provisions and formulate context-specific policies.

To address these shortcomings, this paper aims to analyse the spatial variation in weather effects on cycling. The analysis draws on unique travel diary data amongst 950 Greater Rotterdam respondents, geo-referenced by residential location, which is coupled to weather data from a local weather station. The first objective is to analyse the effects of air temperature, wind speed, and precipitation on commute as well as leisure cycling per person per day utilising region-wide logit models accounting for

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geographically correlated decision patterns. The second objective is to explore whether and how these effects differ across space. Hereto, we complement the region-wide models with place-based spatial varying coefficient models (i.e., geographically weighted logit models; GWLM), frequently used in housing (e.g., Helbich et al., 2014) and health studies (e.g., Chi et al., 2013), but a fairly new approach in the transport domain (e.g., Wang and Khattak, 2013). The paper is organised as follows. While Section 2 briefly reviews the literature, Section 3 outlines the research design. Section 4 discusses key results. Finally, Section 5 highlights major conclusions and outlines future research avenues.

2. Literature review

To better understand the potential spatial differences in weather effects on cycling, this section elaborates on theoretical insights regarding urban microclimates and empirical findings regarding spatially differentiated weather effects on cycling. Essential microclimate processes are highlighted in Fig. 1, however, for more elaborative discussions see Stewart and Oke (2012) and Theeuwes et al. (2014). During daytime, urban canyons – i.e., areas between buildings facades – may heat more quickly than surrounding lower density or natural areas due to multiple reflections of solar radiation (a) and the absorption of heat in building surfaces (b), although these processes may be counteracted when urban canyons receive considerably less direct solar radiation due to building shadows (c). In contrast, natural areas reflect more of the radiation back into sky and additionally cool due to evapotranspiration – i.e., vegetation's transpiration and water evaporation (d). During nighttime, urban canyons cool much less than natural areas, due to limited sky view (f versus e), and solar energy storage in building surfaces (b). In addition to altering temperatures, urban geometries may also affect wind as well as precipitation patterns. As buildings form obstacles to wind and precipitation, densely built-up areas generally offer more shelter than more open and exposed rural areas. However, tall freestanding buildings direct relatively strong wind caught at higher altitudes downwards and potentially creates uncomfortable drafts and gusts at street level (Blocken and Carmeliet, 2004).

The meaning of these theoretical microclimate differences for cycling or other outdoor activities is shown in several studies. Their findings are either directly or indirectly related to differences in exposure to weather between different areas. A few studies link spatially differentiated weather effects directly to physical attributes of the built environment. For instance, Miranda-Moreno and Nosal (2011) find that the negative effect of rain on cycling is more than twice as strong for a bicycle path connecting a low-density residential area, than for a path connecting a less weather-exposed dense residential area in Montreal (Canada). For Melbourne, Australia, Phung and Rose (2008) report that weather-exposed cycling trails along the bay have a relatively high optimal riding temperature of 32.5 °C (compared to 28 °C for other investigated trails) and are, due to its weather exposure, exceptionally sensitive to precipitation and wind speed. Similarly, Nikolopoulou and Lykoudis (2007) analyse the effects of thermal conditions and wind speed on pedestrian activity at a seashore boulevard and a sheltered inner-city plaza in Athens, Greece. Although looking at pedestrians, their findings may also be indicative for other weather-exposed travel, such as cycling. They find that thermal conditions have a positive effect on attendances in winter, particularly in the sunlit parts, and a negative effect in summer. Due to its cooling effect, higher wind speeds increase the percentage of people in the sun, but nevertheless negatively affect overall attendance. The associations appear to be much stronger in the exposed seashore plaza than the inner-city plaza.

Other studies attribute observed spatial differences to the way places and routes are used and by whom. Studies from Vienna, Austria (Brandenburg et al., 2004), Melbourne (Phung and Rose, 2008), and the Netherlands (Thomas et al., 2013) find large weather effects on paths primarily used for recreational purposes and paths used at off-peak times, compared to paths used primarily for commuting and paths used at peak times. Brandenburg et al. (2004), additionally, find differences in recreation cyclist counts between two recreational areas. One area has most of its visitors living nearby, which results in less sensitivity to cloudy or slightly rainy weather. For the other area, visitors have to cycle further, in which case cyclists are not only exposed for a longer period of time, but also cloudy or slightly rainy weather brings in more uncertainty, which reflects in a stronger negative association with

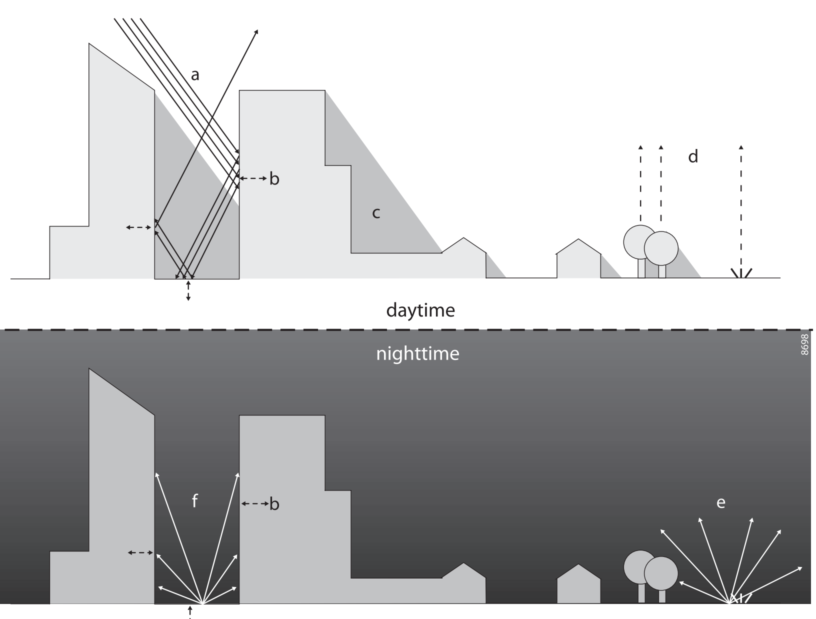

Fig. 1. Urban microclimate processes (individual letters are explained in the text).

cycling. Miranda-Moreno and Nosal (2011) report that a path frequented by professionals employed at Montreal's central business district, is most strongly affected by rain, potentially because of a larger aversion to rain amongst business people. Finally, a study from Bergen, Norway, finds evidence for relatively minor weather effects in the outskirts, compared to the city centre (Aaheim and Hauge, 2005). However, the authors argue that rather than being related to weather exposures, the observed difference may be a result of the relatively minor bicycle usage in these car-oriented low-density areas, with long travel distances, regardless of the weather.

Based on the above-mentioned theoretical insights and empirical evidences, a few expectations can be formulated regarding spatially varying cyclists' weather sensitivities in Greater Rotterdam. It is expected that temperature plays a smaller role in densely built-up areas in comparison to city outskirts. Not only is the city centre potentially less cold, which in the temperate Rotterdam climate may be a contributor to cycling most of the year, except for some hot periods in summer; city centre cyclists may also be less exposed to weather in general, due to relatively shorter travel distances and shelter opportunities. Similarly, because walls or roofs in narrow urban canyons break winds and provide shelter, cyclists in more compact densely built urban areas with narrow streets are expected to be less deterred by rain and heavy winds. However, an exception to this may be central districts with freestanding high-rise buildings, which may provide uncomfortable turbulent and gusty wind conditions. Finally, because of the larger effect of weather on leisure cycling, it is hypothesised that the expected spatial patterns are more pronounced for leisure trips than for commute trips.

3. Research design

Besides the study area, this section introduces the meteorological data, aspects of the data gathering via a travel diary survey, and the statistical modelling.

3.1. Study area and data

The study area for this analysis is Greater Rotterdam, located on the Dutch west coast. It is part of the densely populated and economically important Randstad, which in addition to Rotterdam contains the cities of Amsterdam, The Hague, and Utrecht. The rationale for selecting Greater Rotterdam is fourfold: First, the area is characterised by rich population diversity in terms of ethnicity, age cohorts, and socio-economic status. Second, the area comprises a large diversity in built environments, potentially resulting in different travel patterns (Fig. 2). The city centre consists of a mixture of modern high-rise areas in downtown Rotterdam rebuilt after the Second World War, directly linked to compact historic as well as modern, mid-rise build-up areas. Additionally, there are several flanking old towns (e.g., Schiedam) and more typical suburban satellite towns (e.g., Barendrecht), as well as some remote villages and rural districts. Third, Rotterdam's location close to the North Sea provides impetus for variable weather conditions. Its maritime climate is characterised by 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 seasonal precipitation patterns (KNMI, 2013). Finally, regional policy-makers vigorously promote active policies on sustainable transport and climate change adaptation.

A travel diary survey, conducted during the period from August 2012 to February 2013, forms the basis of this research. A total of 950 residents aged over 18 years completed travel diaries during six randomly assigned days – two in summer, autumn and winter. Irregular days on which respondents reported ill or on holiday were reassigned. Due to anticipated lower response rates of non-native Dutch and older age cohorts (>65 years), both groups have been oversampled. Moreover, a spatially well-balanced selection of the probands is achieved through sample stratification in accordance to the core city, outer parts, suburbia, and rural areas. Data are analysed at the daily level in terms of whether or not respondents used the bicycle for all trip purposes combined (i.e., work, errands, social, and leisure trips), for leisure (i.e., all leisure trips including fun shopping, but excluding social visits) or for work purposes (i.e., travelling from/towards a reported work location or for business). These records have been linked to the residential location's geographical coordinates, through usage of the nation-wide cadastre database (Basisregistraties Adressen en Gebouwen). To respect privacy issues but still permitting precise spatial analysis, trips are linked to 6-digit postal codes, which in the Netherlands contain approximately 17 addresses.

After data cleaning (e.g., removing incomplete or unreliable records), 4317 person-day-records have been considered for further analysis. Although it is not the purpose of this study to strive for exact representativeness, we checked whether our sample mirrors the population accurately by comparing it to regional statistics (CBS, 2013). For instance, the gender proportion (51% female) and average household size (2.37 persons per household) more or less reflect the region's population averages of 51% and 2.15 respectively. No large sample biases are noticeable, except for some underrepresentation of lower educated (28.1% compared to 72.0%) and non-native Dutch people (10.4% compared to 30.8%), which is quite typical for Internet surveys (Adler et al., 2002). Moreover, to purely measure the effects of weather on cycling, all multivariate analyses control for classical background characteristics, such as age, gender, number of cars per household and weekly work duration in hours (Table 1). Exceptions are income and education, which based on preliminary statistical tests, indicated no association with cycling.

Subsequently, the mobility data have been matched by day to meteorological data, obtained from the Dutch Meteorological Institute's Rotterdam weather station (KNMI, 2013). The spatially closest official weather station is located in the northern part of the study area (Fig. 2). One measuring station secures that weather is treated uniformly and allows investigating how weather effects differentiate across space. Daily maximum air temperature in °C ($T_{a(\max)}$), average wind speed in m/s ($W_{s(\text{avg})}$), and precipitation sum in mm ($P_{(\text{sum})}$) have been aggregated from hourly averages between 6 am and 12 am, representing the interval in which most mobility takes place. A daily level of analysis is used here rather than an hourly level, because transport mode choices are frequently decided on a daily rather than instantaneous basis. Also a daily level analysis allows for better comparisons with existing studies and climate change projections. Fig. 3 describes the meteorological conditions during the survey period. During this period, the Rotterdam area had been subjected to a complete range of combinations in weather conditions natural to its regional climate. It started with warmer-than-average sunny weather in late August, continuing on a less pronounced level in early September and late October. December was relatively warm (+10 °C) and wet while, mid-January was abnormally cold with snow, frost and daily maximums down to −4 °C. Table 1 describes all weather and control variables used in the analyses.

3.2. Statistical analysis

Based on the utility-based choice theory (Ben-Akiva and Bierlaire, 1999), conventional binomial logit regressions (LR) serve as baseline. Despite the numerous applications of LR in combination with spatially referenced data, the exact residential location of people is mostly neglected and non-spatial statistical models

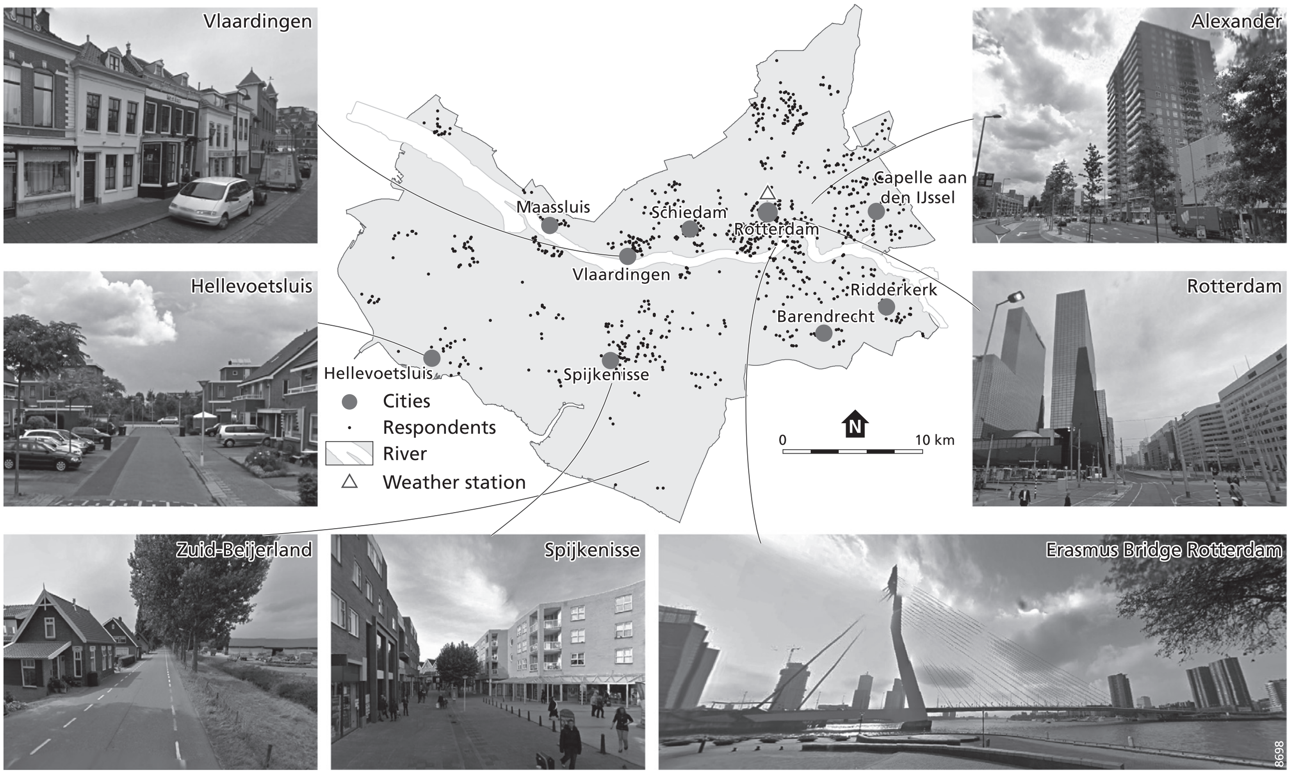

Fig. 2. Location of the respondents and impressions of the build-up environments (Google Street View).

Table 1
Data description and descriptive statistics.

Description	Min.	Mean	Max.	% per category 0	% per category 1
Response variables					
Cycling on a day (1 = yes, 0 = no)				75	25
Cycling on a day for commuting (1 = yes, 0 = no)				92	8
Cycling on a day for leisure (1 = yes, 0 = no)				91	9
Control variables					
Age in years	18.000	48.250	87.000		
Gender (1 = male, 0 = female)				49	51
BMI class (1 = obese; 0 = not obese)				22	78
Weekly work duration in hours (continuous)	0.000	21,660	70.000		
Number of cars in the household (continuous)	0.000	1.178	4.000		
Weather variables					
Daily maximum air temperature (Gaussian transformation continuous[a])	0.027	0.579	1.000		
Daily average wind speed between 6 am and 12 am in m/s (continuous)	0.873	3.106	8.076		
Daily precipitation sum between 6 am and 12 am in mm (continuous)	0.000	1.588	22.400		

[a] It should be noted that the daily maximum air temperature is processed by means of a Gaussian transformation. This justifies that temperature is not linearly related to cycling, but is instead bell-shaped, with an optimal temperature of 24 °C and a mean width at half maximum of 25 °C. The curve with these two estimates provides the best fit.

are estimated. However, due to spatial autocorrelation (SAC), referring to the systematic coincidence between locational and travel decision similarities (Páez and Scott, 2005), the model assumption of independence between observations falls too short (Anselin, 2009). SAC causes estimated parameters not to be reliable possibly leading to incorrect conclusions (Augustin et al., 1996). Besides a spatially filtered LR (Moniruzzaman and Páez, 2012), the autologistic model (ALR), introduced by Besag (1974), is a simple alternative by extending the LR through an autocovariate term. It is assumed that an inverse distance weighed binary response variable employed as independent variable absorbs remaining SAC not explained by the predictors and enhance the model's explanatory power (Augustin et al., 1996).

Even though an ALR effectively corrects for residual SAC, it still assumes that a single equation reflects the complex relationship between mode choice, weather conditions, and control variables. As recently shown by Wang and Khattak (2013), such a holistic and stationary perspective is too simplistic and does not reflect place-based particularities. If spatial heterogeneity is actually present but not accounted for, the estimates are biased (Páez and Scott, 2005). In accordance to Morency et al. (2011), continuous spatial varying coefficient models have the ability to consider, besides classical confounding effects, the geographical context affecting travel behaviour. One classic approach to analyse spatial heterogeneity is Casetti's (1972) spatial expansion method where non-spatial attributes are interacted with polynomial terms of the

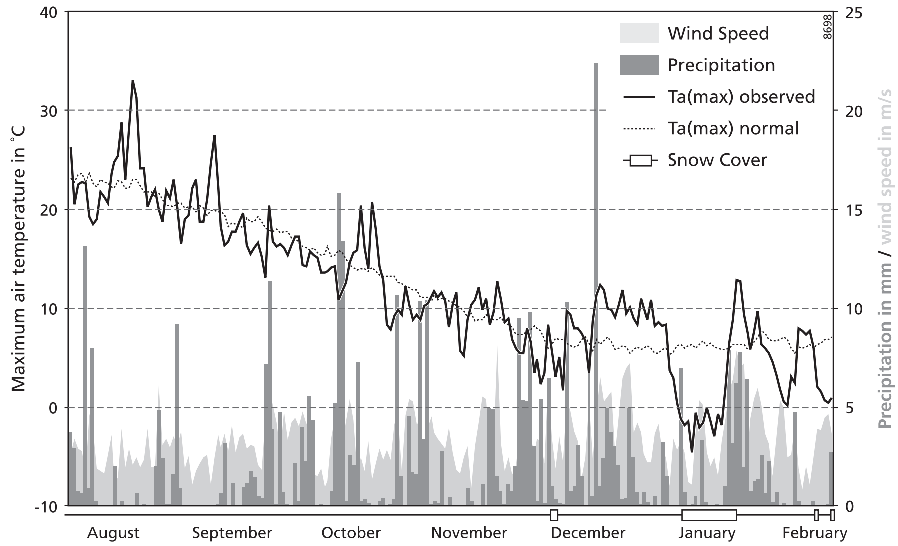

Fig. 3. Weather conditions within greater Rotterdam.

coordinates. However, Fotheringham et al. (2002) argue that the spatial expansion method is not feasible to model spatial variation precisely.

To circumvent these shortcomings and to go beyond the exploration of broad patterns, a geographically weighted logit model (GWLM; Fotheringham et al., 2002; Atkinson et al., 2003) has been applied to explore spatial heterogeneity in the regression parameters. A GWLM is in principle a spatial disaggregation of a generalised linear model. Instead of using the entire sample, the GWLM considers a subset of the data to model smooth parameter variation across space. The data subsets are determined by means of a window moving from regression point i to j, each time estimating a regression. Additionally, sample points farther away from a regression point receive lower weights than more adjacent ones through a Euclidean distance-based kernel function. In transport geography exponential distance decay functions are generally agreed (e.g., Handy and Niemeier, 1997). As compared to the kernel type, the kernel bandwidth, referring to the number of sample points considered in each local model, is of critical importance. In addition to a pre-specified fixed bandwidth, an adaptive bandwidth is frequently utilised through optimising a statistical performance criterion (i.e., the corrected Akaike Information Criterion; AICc). Besides reducing the volatility of the regression coefficients, an adaptive bandwidth has the striking property that the kernel width depends on the density of the sample (Fotheringham et al., 2002). In areas having densely distributed sample points a smaller bandwidth is required to model changes over small distances; otherwise missed by an overly large bandwidth setting. Consequently, for areas featuring a sparse sample the bandwidth is larger. Besides reducing spatial dependency implicitly through kernel functions and keeping the common interpretation of LRs valid, a GWLM results in a series of mapable regression parameters. Finally, to receive area-wide parameters at unsampled locations, geostatistical interpolation (i.e., kriging) can be utilised as post-processing step. Even though GWLMs have matured, some caution concerning an uncritical interpretation of the estimates remains. Among others, Wheeler and Tiefelsdorf (2005) as well as Páez et al. (2011) refer to multicollinearity problems among local parameter estimates. In particular, Wheeler and Tiefelsdorf (2005) found that GWLMs themselves artificially introduce multicollinearity effects, even if the explanatory variables are uncorrelated. Therefore, Páez et al. (2011) advise against using GWLMs for inference and recommend them as exploratory tool, although the model limitations are significantly reduced with larger samples like ours.

4. Results and discussion

This section outlines main empirical results. While Section 4.1 focuses on the region-wide models, Section 4.2 discusses spatial variations in weather effects on cycling.

4.1. Region-wide models

An initial descriptive analysis reveals that 25% of all respondents use the bicycle at least once per day. For commute and leisure purposes this is respectively 8% and 9%. A multivariate logistic regression model (LR)[1] is estimated to analyse the effects of weather on cycling for all trip purposes combined, while simultaneously controlling for socioeconomic and demographic confounding characteristics. Included in the model are only those independent variables significant on the 0.1 level. Subsequently, for reasons of cross-comparison, similar versions of this base-model are estimated for the work and leisure purposes. The LR models are presented in Table 2 on the left. Testing the assumptions of the LRs, the significant Moran's I statistics of the residuals ($p < 0.001$) indicate that the LR models, independently of the trip purpose, are faced with autocorrelated residuals. In order to correct these shortcomings, extra autocovariates with inverse distance weighing up to 3000 m are introduced as autologistic regressions (ALRs) (Table 2, middle). These autocovariates are always highly significant ($p < 0.001$), successfully correcting for autocorrelation (i.e., the Moran's I statistics are not significant anymore), and result in a considerably lower number of significant predictor variables (Table 2). Additionally, model comparisons by means of the corrected Akaike Information Criterion (AICc) constantly favour the ALR models. In the remainder of this paper we will focus primarily on the three meteorological variables. The effects of the other control variables are logical and in line with general transportation literature (e.g., Hanson, 1982; Dieleman et al., 2002).

In congruence with, for instance Phung and Rose (2008), Lewin (2011) and Ahmed et al. (2010), air temperature demonstrates a

[1] Region-wide binomial logistic regression models were also compared to region-wide Poisson and negative binomial models and revealed similar results with regard to the effects of weather on cycling, confirming the robustness of logistic regression.

Table 2
Results of the cycling models.

	LR		ALR		GWLM
	Estimate	Std. error	Estimate	Std. error	Median estim.
All trips					
Intercept	−0.250	0.194***	−2.360	0.241***	0.043
Obese	−0.577	0.095**	−0.279	0.110*	−0.511
Male	−0.213	0.077***	−0.075	0.091	−0.160
Age	−0.010	0.003***	−0.004	0.003	−0.010
Work duration	−0.010	0.002***	−0.004	0.003	−0.013
Number of cars	−0.329	0.048***	−0.185	0.055***	−0.570
Temperature	0.942	0.122***	1.428	0.146***	1.007
Wind speed	−0.029	0.029	−0.067	0.034*	−0.024
Precipitation	−0.031	0.014*	−0.031	0.017#	−0.013
Autocovariate	n.a.		3.783	0.131***	n.a.
AICc	4651		3581		2475
Leisure trips					
Intercept	−2.525	0.299***	−4.218	0.333***	−2.445
Obese	−0.808	0.156***	−0.573	0.162***	−0.785
Male	−0.050	0.113	0.073	0.119	−0.143
Age	0.006	0.004	0.012	0.004**	0.007
Work duration	−0.009	0.003**	−0.004	0.004	−0.008
Number of cars	−0.085	0.069	0.060	0.071	−0.173
Temperature	1.112	0.182***	1.262	0.190***	1.083
Wind speed	−0.063	0.044	−0.080	0.046#	−0.045
Precipitation	−0.057	0.025*	−0.058	0.027*	−0.035
Autocovariate	n.a.		2.549	0.151***	n.a.
AICc	2609		2316		1736
Commute trips					
Intercept	−1.651	0.301***	−3.779	0.345***	−1.566
Obese	−0.282	0.148#	0.078	0.161	−0.179
Male	−0.481	0.124***	−0.341	0.133*	−0.455
Age	−0.020	0.004***	−0.017	0.005***	−0.020
Work duration	0.013	0.004***	0.023	0.004***	0.012
Number of cars	−0.263	0.074***	−0.040	0.076	−0.388
Temperature	0.677	0.192***	0.838	0.205***	0.881
Wind speed	0.008	0.045	−0.010	0.047	0.043
Precipitation	−0.038	0.024	−0.039	0.025	0.001
Autocovariate	n.a.			3.258	0.175***
AICc	2339		1946		1512

*** Signif. codes < 0.001.
** Signif. codes < 0.01.
* Signif. codes < 0.05.
# Signif. codes < 0.10.

highly significant bell-shaped effect on cycling, which appears to be less strong for work compared to leisure trips (e.g., Hanson and Hanson, 1977; Bergström and Magnussen, 2003). Also confirming previous studies (e.g., Sabir, 2011), wind speed and precipitation have negative effects on cycling, although less profound than temperature. When looking solely at commute purposes, the effects of precipitation and wind are not significant. In contrast to other purposes, which might be more easily postponed, cancelled, or conducted by another transport mode, the journey to work is less flexible and more of a routine, and hence is carried out in its regular fashion, regardless of wind or rain.

4.2. Place-based models

Region-wide models confirm a statistical association between weather conditions and cycling and trend surface regressions point towards some spatial variation. However, to provide a more focused place-based analysis, additional geographically weighted logit models (GWLMs) have been estimated (Table 2, right). It must be noted that, in accordance to Páez et al. (2011), the GWLMs are exclusively employed for exploratory purposes to map spatial variations within the meteorological predictors and thus statistical significances regarding the effects of individual parameters are not derived. Each GWLM is calibrated with an exponential kernel function and an adaptive bandwidth. The AICc minimisation shows that for all trips a local subsample of 86 nearest neighbours, for leisure trips 118 neighbours, and for commutes 106 neighbours are paramount. Again, the AICc are considerably reduced compared to the ALRs, clearly supporting a place-based modelling approach. Except the GWLM for all trips showing minor residual SAC, being just significant at the 0.05 level, the remaining GWLMs are well-behaved.

In addition to Table 2 listing median estimates, the GWLMs provide parameter surface maps. These maps visualise for each independent variable how its parameter estimate differs spatially. Figs. 4–6 visualise the parameter surfaces for the effects of air temperature, wind speed, and precipitation on cycling for leisure, work and all purposes combined. The maps can be interpreted as follows. Dark shaded areas indicate a relatively large positive/negative effect and thus a relatively strong weather effect on cycling. Light shaded areas indicate a relatively weak weather effect, with parameter estimates equal to zero or even slightly counterintuitive (i.e., slightly negative in case of air temperature or marginally positive in case of precipitation or wind speed).

4.2.1. Spatial variations in temperature effects on cycling

Indicated by the overall dark shaded areas in Fig. 4, air temperature has overall a positive bell-shaped effect on cycling. This confirms earlier findings that higher air temperatures increase the likelihood for cycling until a certain optimum (24 °C), after which the cycling probability decreases (e.g., Phung and Rose, 2008;

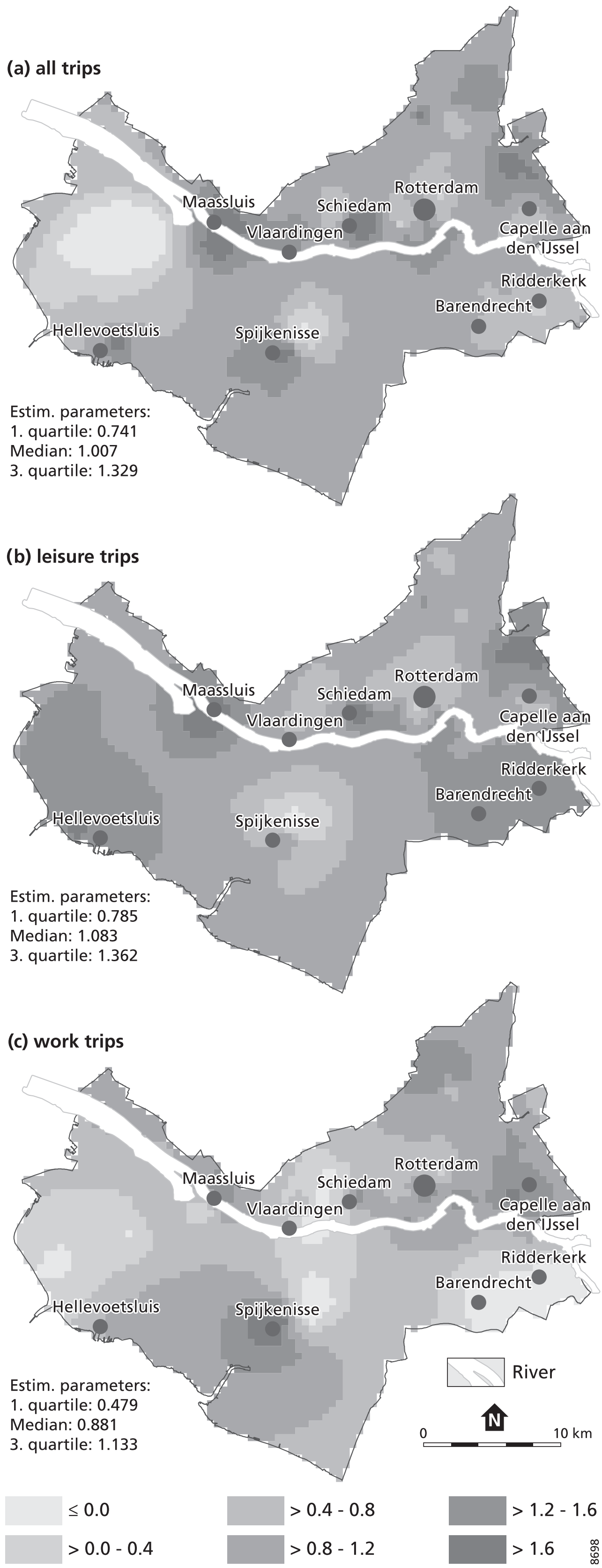

Fig. 4. Air temperature effects on cycling for different trip purposes.

Ahmed et al., 2010; Lewin, 2011). However, a more focused look at the spatial pattern of the parameters reveals noticeable geographic heterogeneity. The slightly lighter shaded area around the Rotterdam city centre, as well as some of the historic and compact secondary towns like Vlaardingen (for photo impressions, see Fig. 1), indicate a relatively low parameter magnitude for temperature. According to our expectation, it seems that temperature plays a less important role for cyclists in these more densely and compactly built areas, compared to cyclists in more remote lower density areas, such as Hellevoetsluis to the west or the area south of Spijkenisse to the south (Fig. 1). Urban morphological differences could explain why the negative effects of cold weather are less strong in compact central districts. First, due to relatively narrow urban canyons and the lack of evapotranspiration (e.g., Stewart and Oke, 2012), these compact districts are potentially warmer places than the more open and remote outskirts, particularly in the evening, night, and early morning. Second, as distances cycled in the city centre are generally shorter (Cervero and Kockelman, 1997), people may also better tolerate unpleasant temperatures.

In line with our expectations, the above-described spatial pattern of smaller positive bell-shaped temperature effects in central areas and larger effects in more remote areas appears to be most pronounced for leisure trips, which of all trip purposes seem most weather-sensitive (e.g., Hanson and Hanson, 1977; Bergström and Magnussen, 2003; Sabir, 2011). However, when looking at work trips or all trips combined, some counterintuitive anomalies in weather effects can be identified. For instance, relatively small positive bell-shaped temperature effects are in the western coastal area north of Hellevoetsluis (Fig. 1), where larger effects would be expected based on the areas' relatively low density, remoteness, and large weather-exposure. However, in accordance to, for example, Aaheim and Hauge (2005), this may be related to the long distances and resulting car dominance and disadvantaged position of the bicycle for purposes other than leisure, regardless of the weather.

4.2.2. Spatial variations in wind effects on cycling

Indicated by the dark shaded areas in Fig. 5, overall the effects of wind speed on cycling are largely negative in most parts of the study area. But, even more than for temperature, a highly differentiated spatial pattern is observed. With respect to all trips combined, a pattern roughly similar to that of temperature is noticeable. As expected, the effects of wind speed seem to be most negative in the remote, low-density, and weather-exposed areas, particularly along the coast north of Hellevoetsluis. These large negative effects of wind, particularly along the coast, are in line with earlier studies from Melbourne (Phung and Rose, 2008) and Athens (Nikolopoulou and Lykoudis, 2007), which document relatively large negative wind effects on exposed cycling or pedestrian activities and weather exposed waterfronts compared to more sheltered locations. At the same time, compact centrally located historic towns like Vlaardingen, Schiedam, and Spijkenisse (Fig. 1) are only marginally affected by wind, with parameter estimates equal to zero or even slightly positive. Their urban morphologies of relatively narrow streets and compact mid-rise built-up areas offer obstacles to wind and relative wind shelter for cyclists within the urban canyons (Blocken and Carmeliet, 2004). However, Rotterdam city centre deviates. The centre, as well as the adjacent area to the northeast named Rotterdam Alexander, demonstrate a relative strong negative effect of wind speed on cycling. This may seem remarkable, as a densely built city centre would be expected to provide many obstacles and therefore shelter against wind. However, in the specific case of Rotterdam, the city centre and Rotterdam Alexander, consist of many relatively freestanding high-rise buildings (Fig. 1), which, combined with some open spaces, such as major rivers, and a dominant wind from sea, may create a highly turbulent and potentially uncomfortable gusty environment for cycling.

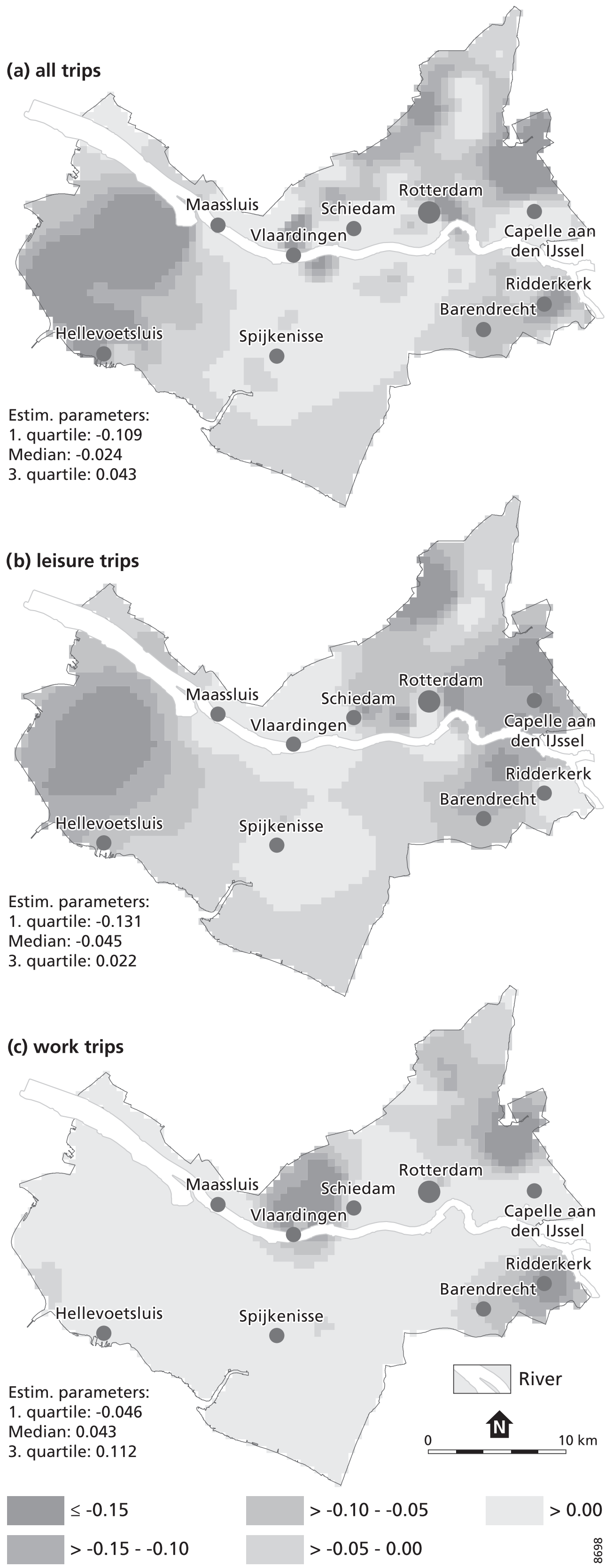

Fig. 5. Wind effects on cycling for different trip purposes.

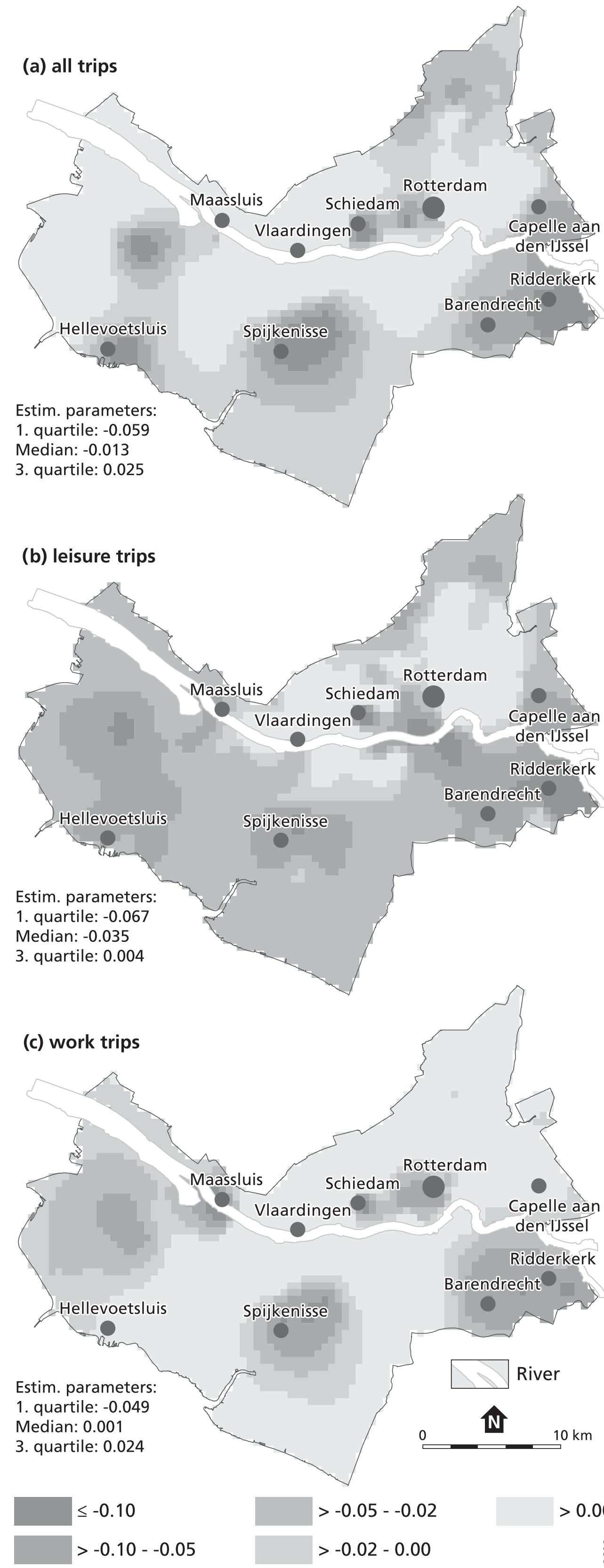

Fig. 6. Precipitation effects on cycling for different trip purposes.

When comparing the effects of wind speed on cycling for work and leisure trips, some notable differences can be identified. The pattern revealed for leisure trips is more or less in line with the overall pattern of wind effects on cycling discussed above. However, a different picture arises for work trips. In congruence with existing research (e.g., Nankervis, 1999; Sabir, 2011), work trips are less negatively affected by wind speed than other trips. In much of the study area parameter estimates are around zero or even above, indicating a counterintuitive positive effect of wind. Also the observed spatial pattern differs. Bicycle trips to work are most negatively affected by wind, not in the city centre and the remote parts to the west, but in towns directly surrounding the Rotterdam city centre, such as Vlaardingen and Ridderkerk. A potential explanation is that people in those towns may commute a relatively long distance by bicycle into the city centre when wind conditions are mild, but choose another mode when winds or drafts get unpleasant, particularly when maybe they have to cross a major river bridge on their way (Fig. 1). As for temperature, the lack of a negative wind effect on work trips in the weather-exposed areas to the west of the study area, may be related to the overall unattractiveness of the bicycle due to longer distances, regardless of the weather.

4.2.3. Spatial variations in precipitation effects on cycling

Fig. 6 presents parameter surface maps for precipitation. The dark shaded areas confirm the overall negative effect of precipitation on cycling in the literature (e.g., Bergström and Magnussen, 2003; Sabir, 2011; Tin Tin et al., 2012). However, also for precipitation, spatial heterogeneity should not be underestimated. The spatial pattern is somewhat similar as observed for wind and temperature. As reported for Montreal (Miranda-Moreno and Nosal, 2011), the less densely built areas to the north, southeast, south, and southwest, are more strongly affected by precipitation than the more densely built Rotterdam city centre, its adjacent neighbourhoods, and some of the compact secondary towns like Vlaardingen. Confirming our expectation, less shelter opportunities and longer travel distances in those more remote parts of the study area seem to result in a larger sensitivity of cyclists to rainy weather.

The different trip purposes indicate some notable differences. In line with Bergström and Magnussen (2003), Sabir (2011), and Thomas et al. (2013), clearly indicated by the dark shaded areas, leisure trips are more negatively affected than other trips. Also the above-described spatial pattern of remote areas being more influenced than central ones is most pronounced for leisure trips. For work trips on the other hand, precipitation seems to exert more modest negative, negligible or even counterintuitive positive effects. Nevertheless, also for bicycle work trips it seems that the negative effects of precipitation are strongest in the more remote less densely built parts of the study area to the south and west. An exception are the relatively small precipitation effects for bicycle work trips in some less densely built parts of the study area outside towns to the south and very north, where larger negative precipitation effects would be expected based on the exposure of these areas to weather. Again, an explanation might be the relative unattractiveness of the bicycle compared to other transport modes, irrespective of the weather, due to relatively long commute distances in these areas or the relatively low number of respondents in those areas.

5. Conclusions and discussion

Recently, geographic heterogeneity has become an increasingly important aspect in transport studies (e.g., Morency et al., 2011; Wang and Khattak, 2013), likewise echoed in a call by Wang et al. (2013). Despite this recent interest, hardly any attention has been devoted to the role of place-based analysis of weather effects on cycling, even though along with microclimate conditions (Stewart and Oke, 2012) cyclists' weather exposures may strongly vary across space. To address this research gap, this study aims to assess the impact of weather conditions on cycling focusing on leisure trips and commuting from a spatially explicit analysis perspective. Drawing on travel diary data from Greater Rotterdam, the Netherlands, geocoded by residential location, this paper extends previous studies in two ways: First, by estimating region-wide autologistic regression models (ALRs). Second, by complementing the ALRs with spatial varying coefficient models – more specifically geographically weighted logit models (GWLMs) – to explore spatial heterogeneity in trip-based mode choices.

In line with previous research (e.g., Hanson and Hanson, 1977; Nankervis, 1999; Bergström and Magnussen, 2003; Sabir, 2011; Tin Tin et al., 2012), the ALRs indicate that air temperature has a supportive effect on cycling while wind speed and precipitation have a statistically significant inhibitory effect. In accordance to Hanson and Hanson (1977) and Sabir (2011), among others, these effects are generally larger for leisure than for work trips. Furthermore, the models provide clear evidence that, even while controlling for various socio-demographics including differences in household type and car ownership, location highly matters in choice for cycling, yielding well-behaved, more parsimonious, and better performing regressions compared to traditional non-spatial logit specifications.

More important, the GWLMs provide valuable place-based insights and show profound spatial differences in weather effects within the study area. We find evidence that temperature plays a smaller role in the more central parts of the study area compared to the more open and remote areas. During colder periods, centrally located densely built environments provide more pleasant warmer microclimates, particularly during early mornings, evenings, and at night, while during hot weather city centre microclimates may not be as negative as often thought, because buildings provide shade (Theeuwes et al., 2014). Also wind seems to play a stronger role in the more weather-exposed remote areas (i.e., near the coast) than in more central areas. One major exception is a relatively strong negative wind effect in downtown Rotterdam and its adjacent neighbourhood Alexander to the east. This may be a result of the relatively open-plan high-rise built-up environments of both areas, which may cause uncomfortable turbulent wind environments at street level. As with the effects of wind, precipitation has a stronger negative effect on cycling in the outskirts than in central areas. An additional reason for the observed patterns may be that cyclists better tolerate precipitation, but also wind speed and extreme temperatures, in central areas, due to the shorter travel distances related to the compact design. When looked at different trip purposes, the observed pattern of relatively weak weather effects in central versus relatively strong effects in peripheral areas is more clearly visible for leisure than for work trips.

This analysis demonstrates the added value of place-based mode choice models providing a detailed and especially mapable picture of peoples' habitual travel behaviours linked to weather conditions. These insights serve as vital information for planners and policy-makers to formulate more context-specific transport policies. For instance, adjacent more compact urban morphologies have the potential to alleviate undesirable weather exposures and could enhance environmental friendly and more sustainable transport modes. Hereby, it is important to look at the effects of all weather parameters simultaneously, and not, for instance, overlook potential wind discomfort generated by high-rise constructions. Also, it is important not to generalise findings carelessly. In different urban fabrics, hotter (or future) climate regimes, or when not designed carefully, these urban benefits may easily diminish or reverse through negative factors like excessive urban heat and reduced air quality.

Despite these promising results, this study has some limitations. First, due to restrictions related to the local modelling approach, the nested hierarchical data structure of trips, day-records, and persons could not be considered. However, robustness tests performed with region-wide hierarchical models revealed similar estimated parameters. Second, the ALRs arbitrarily assume a given neighbourhood definition, lacking a theoretical basis, even though sensitivity analysis cannot confirm significant differences in the estimations. Likewise, the counterintuitive effects in some areas might be caused by local multicollinearity, a known GWLM deficit (e.g., Wheeler and Tiefelsdorf, 2005; Páez et al., 2011), or they result of omitted variables describing, for instance, the cycling infrastructure, not accessible in this research for entire Greater Rotterdam. However, Heinen et al. (2013) report insignificant effects for variables describing cycling infrastructure (e.g., availability of bicycle storage outside). Third, weather conditions are exclusively measured at one location. This unitary availability of local meteorological data might be problematic as it neglects local microclimates. On the plus side, it allows for uniformly comparing and interpreting spatial differences in weather effects.

Besides eradicating these shortcomings, several opportunities for future research arise. New data collection techniques such as GPS tracking may form the basis for a place-based analysis by georeferenced route locations, rather than residential locations. This provides a more exact representation of the environments people are exposed to en-route. It would also open up ways to directly assess the effects of land use patterns and lower-scale street designs, and could provide a more rigorous understanding of localised weather exposures and interrelated mode and route decisions. Finally, usage of other weather-exposed transport alternatives, such as walking may also be analysed.

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