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Weather perception and its impact on out-of-home leisure activity participation decisions

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ABSTRACT

Weather is fundamentally a perception rather than an objective measure. This study uses data from a four-wave travel diary survey and aims to answer two research questions, i.e. 1. How individuals from different socio-demographic groups perceive weather. 2. How an individual's weather perception affects his/her leisure activity participation decision. A thermal indicator, Universal Thermal Climate Index (UTCI) is used as a synthetic index that represents the thermal environment. Panel static/dynamic ordered Probit model is used to model leisure activity participation. The results show that the reference thermal environment, in general, corresponds to the historical mean of the thermal environment. Moreover, the effect of subjective weather perception on leisure activity participation is non-linear and asymmetric. Only 'very disappointed weather' and 'very satisfied weather' significantly influence leisure activity participation. The intra-individual heterogeneity in the effect of 'very good weather' has a smaller magnitude than that of 'very bad weather'.

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KEYWORDS
Weather perception; leisure activity participation; intra-individual heterogeneity

1. Introduction

Individuals are exposed to various weather conditions when travelling. A body of literature has recently emerged focussing on how variations in weather conditions influence individuals' travel behaviour (e.g. Koetse and Rietveld 2009; Böcker, Dijst, and Prillwitz 2013). Several studies have focussed on the impacts of extreme weather conditions such as snow and thunderstorms (Cools et al. 2010). Liu, Susilo, and Karlström (2014b) used the Swedish National Travel survey and found substantial seasonal variations of trip frequency per individual; for example, there were more cycling trips but fewer walking and public transport trips in summer compared to winter. On the other hand, Saneinejad, Roorda, and Kennedy (2012) argued that variations in temperature played only a small part in affecting daily commuter trip rates when all modes were considered. Similarly, Khattak and de Palma (1997) showed that commuters' travel changes in response to weather were limited, implying that such travel choices (e.g. mode choice, departure time choice, etc.) in response to bad weather conditions were also influenced by habit. Additionally, the perceived stress underlying activity participation decisions was found to be significantly affected by rain but the magnitude was small (Chen and Mahmassani 2015). Liu, Susilo, and Karlström (2014a) also found that monthly variation in temperature played a more important role in affecting individuals' activity

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participation than the daily variation in temperature. This indicates that individuals' activity participation varies more substantially according to the variation of climate than to the variation of daily weather. In terms of mode choice, cycling share varied significantly between seasons, especially for recreational trips (Richardson 2000; Bergström and Magnusson 2003). On the other hand, although motorised modes can provide protection against adverse weather, drivers were also exposed to dangerous road conditions and were potentially more stressed than in normal weather conditions. Focussing on leisure activities, Spinney and Millward (2011) identified that the weather's impact on different types of leisure activity participations are distinct, therefore highlighting the need to investigate the impact of the weather on leisure activities that are relevant for public health.

In exploring the relationship between weather and individuals' activity-travel behaviour, most of the existing literature has used objective meteorological measures such as temperature and precipitation. However, as stated in 'future research' in many of those studies, weather is fundamentally a 'subjective' experience/perception rather than an objective measure that affects individual's everyday travel decisions. Böcker, Dijst, and Prillwitz (2013) provided a systematic review on the impact of weather on travel behaviour in which they identified that most existing studies used objective meteorological measures to represent weather. Moreover, the effects of objective meteorological measures often vary among countries, regions and seasons (e.g. Liu, Susilo, and Karlström 2014a, 2014b). Only a few studies have incorporated knowledge in meteorology and showed that thermal indicators can better represent the perceived weather environment and avoid interdependency between objective weather measures and meteorological measures (Creemers, Wets, and Cools 2015). Indeed, a strong wind on a 30°C day may be perceived as cool and encourage leisure travel, while a strong wind at −10 °C can be perceived as cold and unsuitable for travel. However, as stated by Creemers, Wets, and Cools (2015) and Liu, Susilo, and Karlström (2014c), the thermal indicator that represents precisely the true 'perceived thermal environment' is almost unobtainable in most travel survey data, as the thermal indicator is not only dependent on objective meteorological measures but also on clothing types and other weather adaptation strategies that are adopted by a given individual. Even if the 'perceived thermal environment' can be precisely derived from the objective meteorological measures, the perception of this thermal environment may also vary among different socio-demographic groups due to the differences in various factors such as physical conditions and ethnic group. Tam et al. (2013) found that a remote Aboriginal group in Canada was least affected by weather in shaping their well-beings, which indicates that weather perception is related to lifestyle and acclimatisation.

The instruments of weather perception are typically qualitative and are usually measured in Likert scales. Questions about perception are becoming increasingly available in travel surveys. A commonly hypothesised process is that individuals would make travel decisions based on weather perception which is influenced by objective weather conditions. Some studies (e.g. Thorsson, Lindqvist, and Lindqvist 2004; Knez et al. 2009) have identified considerable variability among individuals in weather perception even under the same weather conditions. This indicates that different weather adaptations and physical conditions may significantly affect an individual's weather perception. To the best of the authors' knowledge, only a few travel behaviour studies have measured subjective weather perception (Cools and Creemers 2013; Böcker, Dijst, and Faber 2014). In most cases, these studies used a stated preference survey (e.g. Cools et al. 2010). Thus, to what extent the weather perception would influence individuals' actual travel behaviour is largely unknown. Theoretically, using instruments of weather perception provides more accurate and interpretable weather effects than using objective meteorological measures or thermal indicators, since the instruments of weather perception naturally define an individual's reference point of his/her perceived weather, which is usually latent or unobserved when objective meteorological measures or thermal indicators are used.

Another concern that is commonly shared by previous studies is the use of data only containing one-day observations of activity-travel behaviour from a given individual. Given the fact that an individual's activity-travel behaviour may vary from day-to-day (Dharmowijoyo, Susilo, and Karlström 2014; Susilo and Axhausen 2014), multi-day observations from the same individual would provide more insights into how a given individual perceives weather in different weather conditions, as well as how weather affects his/her actual travel behaviour. In other words, the inter/intra-personal heterogeneity in subjective weather perception can be better controlled by using multi-day travel diary data.

Thus, in this study, two research aims will be addressed: 1. To explore the variation of weather perception under different objective weather conditions for individuals with different socio-demographics, and 2. To explore how an individual's actual travel behaviour, in this study leisure activity participation, varies given the weather perception of the individual. Leisure activity participation was chosen because previous studies (e.g. Sabir 2011) revealed that decisions regarding leisure activity participation are highly influenced by weather conditions. Data derived from a four-week travel diary survey were used. The survey collected the in-home and out-of-home activity-travel diary of 75 respondents, as well as their answers to the instruments of weather perception in March, May and June 2014. The relatively long time period of 28 days (two waves of two-week surveys) allows us to control inter/intra individual heterogeneity in a more comprehensive manner. The results would reveal the effects of objective meteorological measures on the instrument of weather perception, and how these effects differ between individuals with a different socio-demographic profile. The results also reveal the non-linear and asymmetric effect of weather perception on individuals' leisure activity participation decisions.

The next section offers a brief review of the dataset used in this study. Section three answers the first research issue: how individuals from different socio-demographic groups perceive weather differently; section four answers the second: how individuals' leisure activity participation is affected by weather perception. Section five concludes the findings.

2. The travel diary dataset and weather-related questions

2.1. The longitudinal travel diary dataset

A four-wave travel diary survey used in this study was originally carried out in order to investigate individuals' behavioural responses to an extension of a new tramline in the Solna municipality, Stockholm. Several weather-related questions were also included together with the travel diary. The respondents were randomly selected and the sample consists of individuals who live approximately 500 metres from the new tram stations. Meanwhile 20% of the total sample consists of individuals who live more than a kilometre away from the new tram stations who act as a control sample. The study area is illustrated in Figure 1. The survey used a self-reported two-week travel diary via paper and pencil in four waves. The implementation of this panel survey spanned a total of seven months starting from October 2013 to June 2014. The first wave (14th–27th October, 2013) of the travel survey took place just before the opening date (28th October, 2013) of the new tramline extension. The following waves took place afterwards. In this study, only the travel diary data from the third (17th–30th March, 2014) and fourth (26th May–8th June, 2014) waves were used. This was five months after the opening date of the tramline extension. Thus, the influence of the newly extended tramline on individuals' travel behaviour change was believed to be negligible. Additionally, no major infrastructure changes took place between waves 3–4. Moreover, this seven-month period minimises an issue of sample ageing when implementing a panel survey (Raimond and Hensher 1997). A total of 67 individuals participated in all waves and 75 individuals participated in both waves 3 and 4. A detailed description of this panel survey can be found in Ahmad Termida et al. (2016).

2.2. Weather-related questions and weather data

In this survey, two weather related questions were included and were answered by each respondent every day during these two-week survey periods. The first question (the instrument of weather perception) is: *How did the weather make you feel on the given day*? This was measured on a five-point

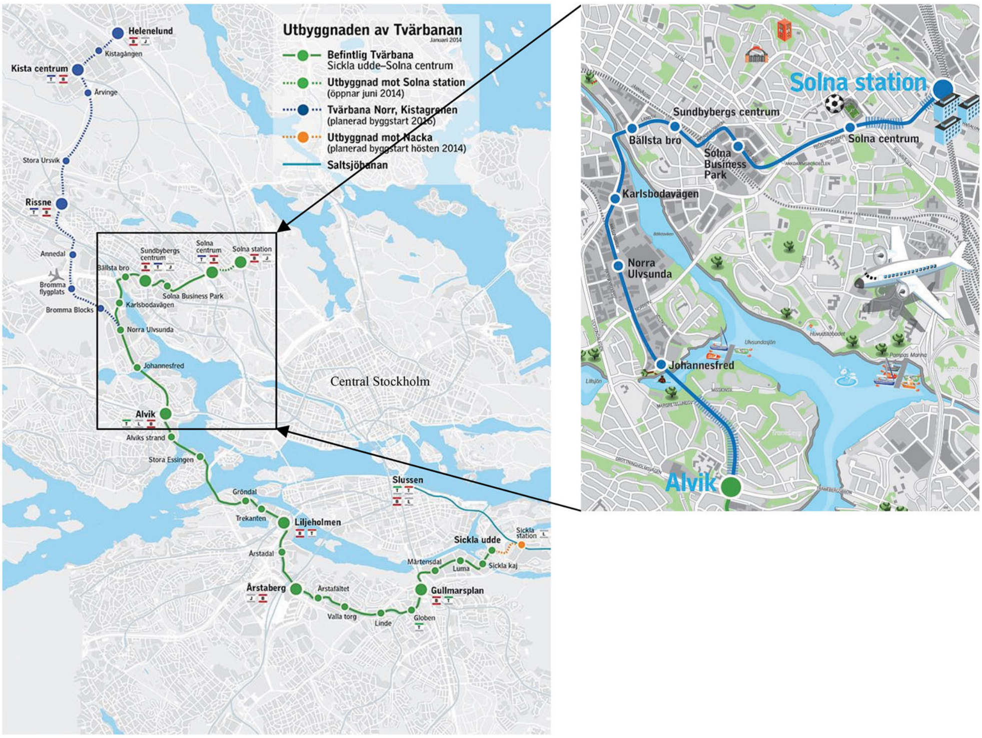

Figure 1. The area of this study (Ahmad Termida et al. 2016).

Likert scale ranging from '*very disappointing weather*' to '*very satisfying weather*'. Respondents were then asked whether they had access to the weather forecast: *Do you check the weather forecast on these days in weeks 1/2? If yes, today I checked the weather forecast for today/tomorrow/two days later/three days later/more than three days later*. However, due to the massive number of missing values for this question, it is not considered in this study. An intuitive interpretation of such a high number of missing values is that the respondents were usually asked to fill in the questionnaire at the end of the day or even the day after, and it is very likely that the respondents had already forgotten whether they had checked the weather forecast when they filled in the questionnaire. This indicates that information regarding the weather forecast may be more easily obtained through smartphone applications than the traditional travel diary via paper and pencil. On the other hand, the fact that respondents often forgot whether they had checked the weather forecast may, in itself, indicate that the weather forecast does not strongly affect individuals' travel scheduling decisions, or individuals, in most cases, make travel decisions based on the weather conditions at their departure time or during the trip.

Another issue is that each question was answered by the respondent once per day in the travel diary survey. Thus, their subjective weather perception was only available on a daily level. Although the weather perception almost certainly varies at different times of the day according to the weather conditions at any given time, it is difficult and expensive in practical terms to obtain an instrument of weather perception multiple times within a day. However, given the fact that the instrument of weather perception is typically qualitative and ordinal, it is assumed that the obtained Likert scale score represents the respondent's perception of the overall weather on the given day. Thus, the weather perception at a daily level can still be interpreted as their subjective feelings towards the variation in the weather all day.

The objective meteorological data come from the Swedish Meteorological and Hydrological Institute (SMHI 2014). Several meteorological measures, including the daily mean air temperature, daily precipitation amount (mm), hourly wind speed (km/h) and hourly relative humidity, were collected. The hourly recorded wind speed and relative humidity were aggregated into a daily level where only hourly records between 7:00–20:00 were used, given the fact that most recorded activities from the travel diary took place during the day. The weather records in the weather station nearest to the study area were used to represent the daily weather conditions in the study area given the fact that weather in general does not spatially vary across the study area due to its small size.

3. The variations of individuals' weather perception under different weather conditions

The first research question that will be addressed is how the weather perception would vary among individuals from different socio-demographic groups. The instruments of weather perception (answers from the five-point Likert scale question) were matched with the objective meteorological data. After data screening, only respondents who provided no fewer than 14 days of Likert scale scores (out of 28 possible travel days) were selected in order to avoid too few observations from any given individual. Fifty-one respondents met this standard and were selected from 75 respondents. Seven rainy days were observed during the wave 3 period (17th–30th March, 2014), while six rainy days were observed during the wave 4 period (26th May–8th June, 2014). The air temperatures observed during the wave 3 period range from -2 °C to 9 °C, while in the wave 4 period, the air temperatures ranged from 7 °C to 17 °C. Despite the substantial increase in air temperatures between waves 3–4, no systematic changes of the instruments of weather perception are found. This indicates that an individual's reference of a neutral weather condition, which refers to the weather condition that makes him/her feel '*indifferent*', almost certainly depends on the months/seasons. A natural hypothesis is that this neutral weather condition varies according to the local climate of a given month/season.

3.1. Overall effects of objective meteorological measures on weather perception

In order to explore the relationship between the objective meteorological measures and the weather perception instrument, a panel ordered Probit model is applied. The dependent variable is the instrument of weather perception for a given individual on any given day, which is typically ordinal, while the explanatory variables are objective meteorological measures. The panel ordered Probit model has the following general model structure:

$$y_{ik}^{*} = X_{ik}\beta + \eta_i + \varepsilon_{ik} \tag{1}$$

$$y_{ik} = \begin{cases} 1 \text{ (very disappointed)}, & \text{if } -\infty < y_{ik}^{*} < \mu_1 \\ 2 \text{ (disappointed)}, & \text{if } \mu_1 < y_{ik}^{*} < \mu_2 \\ \quad \ldots & \\ 5 \text{ (very satisfied)}, & \text{if } \mu_4 < y_{ik}^{*} < +\infty \end{cases} \tag{2}$$

In Eq. (1), i refers to the individual index, k refers to the day index. y_{ik}^{*} to the latent variable associated with the observed subjective weather perception and y_{ik} for individual i on day k. β is the vector of coefficients of explanatory variable sets. X_{ik}. $\mu_1, \mu_2, \mu_3, \mu_4$ denote the threshold parameters to be estimated. η_i denotes the random error term at the individual level. ε_{ik} is the random error term which is assumed to be independent and identically distributed (iid) across all observations. All of the random error terms are assumed to be normally distributed. The individual level random error term, η_i, captures the unobserved heterogeneity at the individual level (such as specific characteristics/preferences for a given individual). Alternatively, this panel data can also be considered as observing the instruments of weather perception from different individuals on a given day. Thus, i can also be treated as the day index, while k is the individual index. The day level random error term subsequently captures the unobserved heterogeneities at the day level (such as special events on a given day). Thus, two models are estimated which are known as the individual panel model and day panel model.

Objective meteorological measures are then used to construct the explanatory variables which describe the weather conditions on any given day. Since objective meteorological measures are often interrelated, thermal indicators that incorporate knowledge in biometeorology are better able to represent the thermal environment (Creemers, Wets, and Cools 2015). Thus, the thermal indicator, the Universal Thermal Climate Index (UTCI) is calculated by the air temperature, relative humidity and wind speed. The UTCI is expressed as an equivalent ambient temperature (°C) of a reference environment providing the same physiological response of a reference person as the actual environment (Blazejczyk et al. 2012). The use of the UTCI transforms the measured objective meteorological measures into a synthetic index that represents the thermal environment that is experienced by a given individual. An available programme that calculates the UTCI can be found on the UTCI official website (UTCI 2014). Note that the UTCI is not the perceived thermal environment since the influence of clothing type, weather adaptation strategies and physical conditions, among others, are not reflected in this index. Descriptive figures on weather variables, UTCI and number of leisure trips per day are presented in Figure 2. It can be seen that leisure activity participation is positively influenced by UTCI.

In order to test the hypothesis that the reference neutral weather condition corresponds to the local climate, UTCI values were then separated into a long-term variation measure (climate measure) and a short-term variation measure (daily measure). UTCI values were calculated for the period 17th–30th March (wave 3) and the period 26th May–8th June (wave 4) from 1994 to 2013. The long-term variation of UTCI is presented as the mean of the UTCI values for each of the two periods from 1994 to 2013. The climate measure is therefore defined as the mean of the past thermal environment. The mean

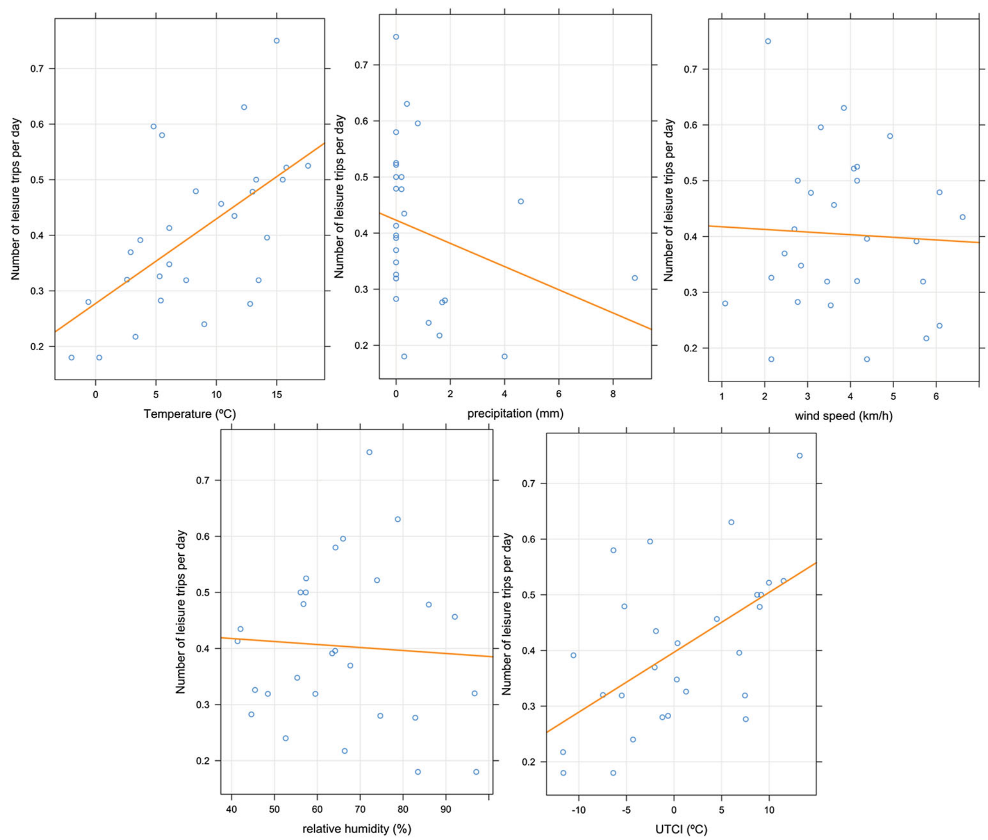

Figure 2. The scatterplot between weather variables and number of leisure trips per day.

of the past thermal environment (UTCI) in the wave 3 period (17th–30th March) is −6.92 °C and the mean in the wave 4 period (26th May–8th June) is 7.85 °C. A significant effect of this long-term variation measure would indicate that individuals' weather perceptions vary between months/periods with higher or lower climate thermal environments. Thus, the hypothesis should be rejected. The daily measure was presented in terms of a Z-score expressing the deviation in the daily thermal condition in units of standard deviation against its historical mean value in the given period. A significant effect of this daily measure would indicate that individuals are sensitive to 'unusual' thermal conditions from the locals' perspective. The use of these two variables is similar to the set-up of the mean-variance model, which is widely used to explore preferences of travel time uncertainty (e.g. Fosgerau and Karlström 2010). Other than these two variables constructed from the UTCI, daily precipitation amount is also added to capture the effects of inconvenience and uncomfortable feelings due to precipitation.

The estimation results of the individual panel and day panel models are presented in Table 1. As previously discussed, the individual panel model captures the unobserved intra-individual heterogeneity, while the day panel model captures the unobserved intra-day heterogeneity.

As shown in Table 1, the coefficients of long-term variations in UTCI are not significant at the 10% level in either model. This indicates that individuals adjust their expectations/reference points concerning the thermal environment according to the time of year. The reference point, in general, corresponds to the historical mean UTCI value. In other words, it seems that the long-term variation of UTCI has no influence on how individuals measure their weather perception, or, at least, the dependency is very weak. The short-term variation of UTCI is positive and significant in both models. It is no surprise that a 'warmer than usual' UTCI value would increase the probability of an individual choosing '*very satisfying weather*' in Sweden, a Nordic country. Precipitation, not surprisingly, leads to a significant decrease in the probability of an individual choosing '*very satisfying weather*'. Both the variations at individual and at day levels are considerable, suggesting strong intra-individual/intra-day effects.

3.2. Individual level effects of objective meteorological measures

Although the panel ordered Probit model reveals the general trend of how each objective meteorological measure influences weather perception, the effect of each meteorological measure might

Table 1. Estimation results of individual/day panel ordered Probit models.

	Individual panel model		Day panel model	
Explanatory variables	Estimates	T-value	Estimates	T-value
Long term variation of UTCI	0.003	0.747	0.010	1.422
Short term variation of UTCI	0.248	8.569	0.301	7.401
Daily precipitation amount	−0.145	−9.813	−0.133	−5.293
Thresholds μ	Ref	/	Ref	/
μ between *very disappointed* and *disappointed*	−2.527	−20.689	−2.417	−25.323
μ between *disappointed* and *neither*	−1.158	−15.127	−1.421	−22.225
μ between *neither* and *satisfied*	−0.090	−0.941	−0.061	−1.124
μ between *satisfied* and *very satisfied*	1.029	10.332	0.971	16.295
Estimated standard error				
Individual level error term	0.5139	9.854	/	/
Day level error term	/	/	0.417	8.479
iid error term	1	fixed	1	fixed
Model fit				
Number of observations	1416		1416	
Number of individuals	51		/	
Number of days	/		28	
Log-likelihood at converge	−1727.42		−1780.36	
Log-likelihood at zero	−1949.66		−1927.76	

differ between individuals. Thanks to the long time period (4 weeks) observed for any given individual, the effects of the meteorological measures at the individual level can be obtained by estimating the ordered Probit models using only the observed days from a given individual. The number of observed days from a given individual is 28 (4 weeks) in most cases, while for some respondents who only reported on some days during the survey period, the worst case is 14 observations. Note that the estimated coefficients from two different respondents cannot be compared directly, since the coefficients are not the marginal effects in ordered Probit models. Thus, the marginal effect of each weather parameter (long-term UTCI/short-term UTCI/precipitation) on the expected value of subjective weather perception is calculated. The marginal effect of a given meteorological measure *i* on the probability of observing a given respondent on day *k* choosing weather perception score *n* is $n = 1$ (*very disappointing*), 2 (*disappointing*), 3 (*indifferent*), 4 (*satisfying*) and 5 (*very satisfying*):

$$M_{k,n,i} = -\beta_i[\phi(\mu_n - X_k\beta) - \phi(\mu_{n-1} - X_k\beta)] \tag{3}$$

Where $\phi(\cdot)$ denotes standard normal probability density function. The marginal effect of a given meteorological measure *i* on the expected value of the weather perception score is then:

$$E_i = \sum_{k=1}^{K}\left(\sum_{n=1}^{5} M_{k,n,i} \times n\right)/K \tag{4}$$

K is the total number of observed days for the given respondent.

The individual level marginal effect E_i denotes the amount of change in the weather perception score due to one unit change in the objective meteorological measure *i* for a given individual. In this paper, one unit of 'long-term UTCI' is 1 °C, while one unit of 'short-term UTCI' is one standard deviation of a Z score. One unit of 'precipitation' is one millimetre. This marginal effect reveals the individual preference/sensitivity of the variation of objective weather condition towards weather perception. In total, 51 marginal effects are derived from 51 respondents for each meteorological measure. The histograms of these individual marginal effects are portrayed in Figure 3.

It is clear from Figure 3 that the individual marginal effects of 'short-term UTCI' and 'precipitation' have relatively wide distributions (a large standard deviation), which corresponds to the findings from some studies (e.g. Thorsson, Lindqvist, and Lindqvist 2004) showing that individuals' weather perception varies considerably between individuals. The distribution of the marginal effects of 'long-term UTCI' is slightly right skewed. Although three respondents have a relatively high marginal effect of 'long-term UTCI' greater than 0.1 (0.1 denotes that a 1 °C increase of 'long-term UTCI' corresponds to a 0.1 unit increase in the weather perception score), the histogram concentrates close to zero (90% confidence interval: −0.064–0.093). The distribution also indicates that one level change in the weather perception score (e.g. from *disappointing* to *indifferent*) requires considerable changes in the historical mean of the UTCI. With a 20 °C increase/decrease of the historical mean of the UTCI, which is from summer to winter, nearly 80% of respondents (38 out of 51) would not raise/lower their subjective weather scores. For the effect of 'short-term UTCI', the individual marginal effects seem to be normally distributed but slightly left skewed. The mean marginal effect of 'short-term UTCI' is 0.18 and the corresponding 90% confidence interval is −0.813–0.462. The marginal effect of 'precipitation' is mainly distributed between −0.3–0.1, with two exceptions smaller than −0.4. The corresponding 90% confidence interval is −0.31–0.051.

Since those individual marginal effects are attached to each individual socio-demographic profile, the role of socio-demographics can be tested through the ANOVA test of the individual marginal effects. The results are presented in Table 2.

As shown in Table 2, no ANOVA tests are significant in the marginal effects of 'long-term UTCI'. This shows that no systematic preference differences between socio-demographic groups are found. The difference between age groups in the marginal effect of 'short-term UTCI' is highly significant.

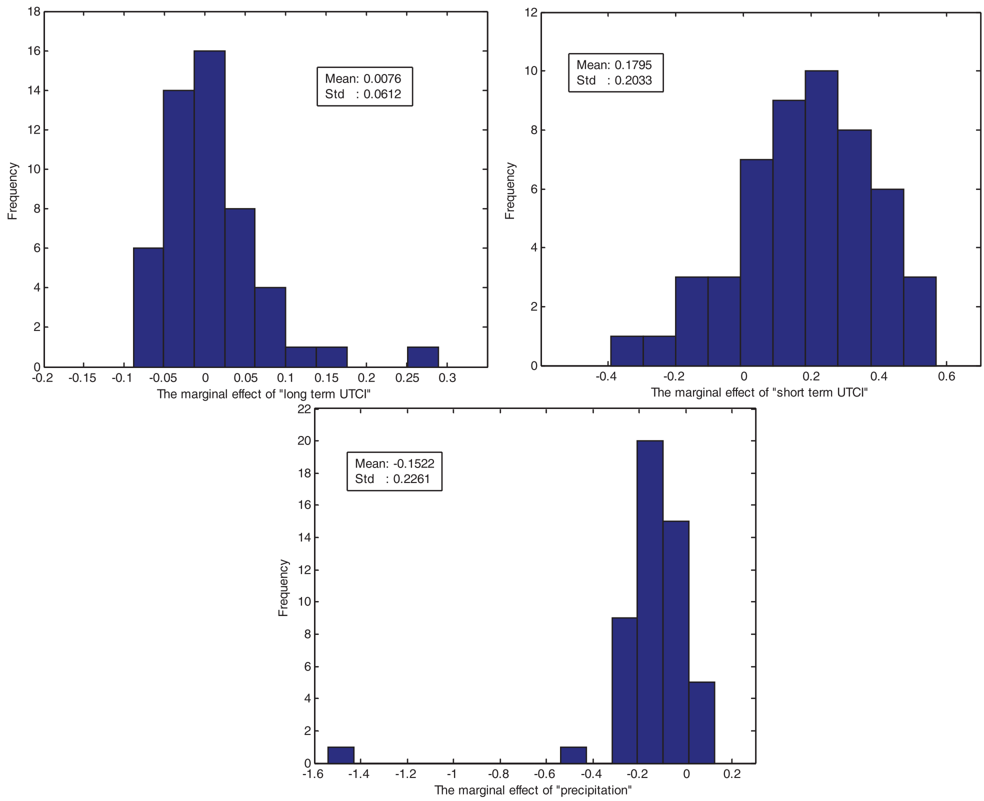

Figure 3. The distributions of individual marginal effects.

Table 2. Test of roles of individual socio-demographics.

Individual socio-demographic variables	Group (N. respondents)	Mean of the marginal effect in each group		
		Long term UTCI	Short term UTCI	Precipitation
Gender	Male (12)	−0.0026	0.1538	−0.1016
	Female (39)	0.0108	0.1874	−0.1678
Age	< 20 (5)	−0.0291	−0.0518**	−0.0710
	21–35 (10)	0.0360	0.1749**	−0.1727
	36–50 (15)	−0.0060	0.1223**	−0.2028
	51–65 (12)	0.0224	0.2617**	−0.1317
	> 65 (9)	−0.0004	0.2988**	−0.1176
Children in household	No child (40)	0.0132	0.2039*	−0.1272*
	With children (11)	−0.0125	0.0907*	−0.2430*
Living status	Living single (15)	−0.0016	0.1586	−0.0923
	Living with partner (36)	0.0115	01882	−0.1771
Monthly income	< 25,000 SEK (12)	0.0116	0.2320*	−0.1143
	25,000–65,000 SEK (26)	0.0065	0.2106*	−0.1395
	> 65,000 SEK (11)	0.0017	0.0558*	−0.2460

Note: Numbers with two stars denote that the ANOVA test is significant at 1% level. Numbers with one star denote that ANOVA test is significant between 1% and 10% level. Numbers without stars denote that ANOVA test is not significant at 10% level.

The weather perception scores of elderly people (age > 65) increase the most, 0.2988, given one unit increase in the Z-score of UTCI. This is then followed by old adults (age 51-65), 0.2617. Teenagers' weather perception scores are least influenced by the variation of the Z-score of UTCI. Intuitively, elderly people may be more sensitive to changes in the thermal environment compared to teenagers due to their physical condition. Respondents from households without children are in general more sensitive to variations in the Z-score of UTCI compared to those with children. Presumably, respondents with children are more likely to avoid travelling on 'colder than usual' days in order to protect children in the first place. Therefore, they are less likely to perceive an extreme thermal environment. At the same time, people without children are much more flexible in (re-)arranging their activity-travel patterns, while individuals with children have much stricter time–space constraints. The high-income group is in general less sensitive to the variation of the Z-score of UTCI compared to the low and medium income groups, potentially because the high-income group is likely to be more flexible in coping with bad weather, having a good car, a nice house etc. Respondents with children in their households tend to have much lower subjective weather scores in rainy conditions than those without children in their households, as they are more aware of the difficulties imposed on the children's travel by precipitation. Other socio-demographic variables show no significant roles in affecting their precipitation preference.

4. The roles of weather perception on individuals' leisure activity participation

The second research question investigates how an individual's leisure activity participation is influenced by his/her weather perception. Unlike studies on weather perceptions using stated preference data (e.g. Cools and Creemers 2013), the relationship between the weather perception and the actual (revealed) travel behaviour is more difficult to uncover since the revealed behaviour is influenced by several non-weather factors; these are not controlled as they are in the stated preference survey. However, the advantage of using actual travel behaviour is also apparent as it provides more realistic and reliable choice observations than that in the stated preference situation. The following paragraphs provide a general description of how weather perception will be treated in the context of the dynamics of leisure activity participation where several key factors influencing this decision are taken into account.

One key observation of activity participation is that a given individual's activity participation schedule, especially for non-mandatory activities such as out-of-home leisure activities, varies between days (Kitamura et al. 2006; Bayarma, Kitamura, and Susilo 2007), implying that there are considerable interactions between activities across days for their multi-day activity pattern. In this study, out-of-home leisure activities are the type of activities of which the main activity purposes are optional and can be re-scheduled. The destination usually varies substantially regarding location and time; examples include sports, eating outside, visiting friends, discretionary shopping, etc. Given that many activities on a particular day are mandatory (e.g. work and school), non-mandatory activities can be viewed as certain repertoires that the individual can choose when and where to conduct. These decisions have day-to-day variability and are believed to be highly influenced by the scheduled mandatory activities, which usually refer to the space–time constraints (e.g. Susilo and Kitamura 2005; Susilo and Dijst 2010), and the previous activity participation, which is known as state-dependence, habit persistence or need (e.g. Ramadurai and Srinivasan 2006; Arentze and Timmermans 2009). When investigating the impact of weather perception on leisure activity participation, the space–time constraints and the state-dependence, habit persistence or need should also be considered, since the choice of leisure activity participation may be more influenced by those factors than by the weather on a given day.

Thus, in this study, a random effect dynamic ordered Probit model is used to model an individual's leisure activity participation on a given day. The dependent variable of interest is the number of out-of-home leisure activities conducted on a given day for a given respondent. The model has the following structure:

$$y^*_{i,t} = X_{i,t}(\beta + \xi_i) + y_{i,t-1}(\gamma + \theta_i) + \nu_i + \varepsilon_{i,t} \tag{5}$$

$$\xi_i \sim \mathit{Normal}\,(0, \sigma_\xi),\ \theta_i \sim \mathit{Normal}\,(0, \sigma_\theta)$$

The latent dependent variable $y^*_{i,t}$ is associated with the observed number of leisure activities $y_{i,t}$ using the following formula:

$$y_{i,t} = \begin{cases} 0, \text{ if } -\infty < y^*_{i,t} < \mu_0 \\ 1, \text{ if } \mu_0 < y^*_{i,t} < \mu_1 \\ \quad \cdots \\ m, \text{ if } \mu_{m-1} < y^*_{i,t} < +\infty \end{cases} \tag{6}$$

Where i is the individual index and t is the day index. $X_{i,t}$ refers to the time variant explanatory variables influencing the decision to participate in the leisure activity. As discussed previously, $X_{i,t}$ includes work/study durations on day t, the number of continuous working days until day t since the last non-work day and four dummy variables representing the weather perception scores (*very disappointing/disappointing/satisfying/very satisfying*). $y_{i,t-1}$ refers to the number of leisure activities conducted during the previous day. The model structure implies that the number of leisure activities on day t is influenced by the space–time constraints (time needed to spend on mandatory activities on day t), the habit persistence (number of continuous working days until day t), weather perception and participation in the leisure activity on the previous day (state-dependence). The asymmetric effect of weather perception scores is considered in the different magnitudes of the effects of '*very disappointing weather*' and '*very satisfying weather*'. β and γ are the corresponding parameters for $X_{i,t}$ and $y_{i,t-1}$. ξ_i and θ_i are individual level error terms that capture the intra-individual heterogeneity of time variant variables and lagged variables. It is worth noting that coefficients $\beta + \xi_i$ and $\gamma + \theta_i$ remain constant for a given respondent i for all his/her time periods. Thus, a significant σ_ξ or σ_θ would indicate substantial intra-individual variations in the corresponding time variant variable. ν_i and $\varepsilon_{i,t}$ are the individual specific and the iid error terms which are assumed to be normally distributed and independent from each other. m is the highest category of number of leisure activities which, in this study, refers to more than three leisure activities for a given individual on a given day.

It is worth noting that participating in a leisure activity on a given day t is certainly not only influenced by leisure activity participation in the previous day t-1 but also, theoretically, the leisure activity participation from day 0 to day t-2. Using lagged effects is one alternative, that is to treat the previous days' outcomes as explanatory variables, $X_{i,t} = f(y_{i,t-1}, y_{i,t-2} \ldots)$, and to estimate a static panel version model. Such lagged effect variables can be the number of leisure activities conducted in the previous week or the number of days that the respondent has not conducted leisure activities on since the respondent last conducted leisure activities, etc. Examples of using lagged effect variables in mode choice models are Cherchi, Börjesson, and Bierlaire (2013) and Cherchi and Cirillo (2014). However, by doing so, the probability of having n leisure activities in day t is then not only conditional on that probability in day t-1 but also that probability in day t-2, t-3 etc. To the best of the authors' knowledge, obtaining consistent estimators given such a time serial correlation in the family of ordered Probit models is not tractable due to the well-known initial condition problem (Anderson and Hsiao 1982), especially when the time period is not very long (14 days in our case). On the other hand, from a Markov chain perspective, assuming the number of leisure trips on day t is only conditional on that number on day t-1 is still valid since the effects of the number of leisure trips from day t-2 to day 1 are all implicitly reflected in the probability function of the observation on day t-1. Thus, a random effect dynamic ordered Probit model where the outcome y_t is only dependent on the previous day's outcome, y_{t-1}, is chosen.

Generally, any given respondent has two time periods: wave 3 (17th–30th March, 2014) and wave 4 (26th May–8th June, 2014). Time periods in which the given respondent is engaging in long distance travel (such as having a vacation) are excluded and are not used for estimation. Note that all respondents are recruited from the study area (shown in Figure 1) which is an urban area with a good transit supply. The distance between the home of the respondent and the closest public transport station ranges from 20 m to 800 m. Thus, those factors are relatively controlled in this study and no land use variables are introduced in the model.

The initial condition problem of the model described in Eq. (5) and Eq. (6) can be solved by specifying the distributions of the error terms conditional on the initial condition of the model (Wooldridge 2005):

$$\begin{cases} \nu_i \sim Normal(\alpha_0 y_{i,0} + Z_i\alpha_1, \sigma_\nu^2) \\ \varepsilon_{i,t} \sim Normal(0,1) \end{cases} \tag{7}$$

In Eq. (7), $y_{i,0}$ is the number of leisure activities conducted on day 0 of each period for individual i. Z_i represents the individual specific explanatory variables. In this study, Z_i includes the individual socio-demographic variables. The list of variables used in the model is shown in Table 3. α_0, α_1 and σ_ν are parameters to be estimated. The random part of ν_i is donated as κ_i, so $\kappa_i \sim Normal(0, \sigma_\nu^2)$.

The maximum simulated likelihood estimator of the model described above is $\sqrt{N}$-consistent and asymptotically normal (Wooldridge 2005). The individual likelihood function has a straightforward expression:

$$L_i = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left[\prod_{Period}\prod_{t=1}^{T} L_{i,t}^{k}\phi(\xi_i)\phi(\theta_i)\phi(\kappa_i)\right] d\xi_i d\theta_i\, d\kappa_i \tag{8}$$

Where $L_{i,t}^{k}$ is the likelihood of observing respondent i on day t choosing to have kth category of the number of leisure activities:

$$\begin{aligned} L_{i,t}^{k} &= \Phi(\mu_k - X_{i,t}(\beta+\xi_i) - y_{i,t-1}(\gamma+\theta_i) - \alpha_0 y_{i,0} - Z_i\alpha_1 - \kappa_i) \\ &\quad - \Phi(\mu_{k-1} - \mu_k - X_{i,t}(\beta+\xi_i) - y_{i,t-1}(\gamma+\theta_i) - \alpha_0 y_{i,0} - Z_i\alpha_1 - \kappa_i) \end{aligned} \tag{9}$$

The likelihood function has a very similar expression as the panel static random effect ordered Probit model, with the exception of the term $\alpha_0 y_{i,0}$; additionally, $L_{i,0}^{k}$ is excluded in the likelihood function.

Table 3. Variables used in the model.

	Variable category	Variable descriptions
$y_{i,t}$	N_leisure (C)	Number of leisure activities conducted for individual i in day t
$y_{i,t-1}$	N_leisure_previous (C)	Number of leisure activities conducted for individual i in the previous day
$y_{i,0}$	N_leisure_0	Number of leisure activities conducted for individual i in day 0 of the given period
$X_{i,t}$	Work_duration **(C)**	Working hours on day t
	Work_period (C)	Number of days work since last non-work day
	Very_disappointing_weather (D)	The subjective weather score is 'very disappointed' for individual i on day t
	Disappointing_weather (D)	The subjective weather score is 'disappointed' for individual i on day t
	Ref_weather (D)	The subjective weather score is 'indifference' for individual i on day t (reference)
	Satisfying_weather (D)	The subjective weather score is 'satisfied' for individual i on day t
	Very_Satisfying_weather (D)	The subjective weather score is 'very satisfied' for individual i on day t
Z_i	Male (D)	The respondent i is male (reference)
	Female (D)	The respondent i is female
	Age $\leq$ 20 (D)	The respondent i is no older than 20
	Age21_35 (D)	The respondent i is between 21 and 35 years old
	Age36_50 (D)	The respondent i is between 36 and 50 years old (reference)
	Age51_65 (D)	The respondent i is between 51 and 65 years old
	Age $>$ 65 (D)	The respondent i is over 65 years old
	without_car (D)	The respondent i's household has no cars (reference)
	with_car (D)	The respondent i's household has cars
	Single_child (D)	The respondent i is single and with children
	Single_nochild (D)	The respondent i is single and without children
	Partner_child (D)	The respondent i has partner and with children
	Partner_nochild (D)	The respondent i has partner and without children (reference)

Table 4. Estimation result of the random effect dynamic ordered Probit model.

	Estimates	T-value
Lagged effect		
$y_{i,t-1}$	0.275**	2.979
Standard error of $y_{i,t-1}$	0.250**	3.171
$y_{i,t-1\_}$ age > 65	−0.500**	−2.420
Standard error of $y_{i,t-1\_}$ age > 65	0.296	1.563
Time variant variables: $X_{i,t}$		
Work_duration	−0.002**	−4.329
Standard error of work_duration	0.001**	2.738
Work_duration_age ≤ 20	−0.001	1.135
Work_period	0.076**	2.400
Very_disappointing_weather	−1.031	−1.381
Standard error of very_disappointing_weather	1.147*	1.754
Disappointing_weather	0.050	0.347
Satisfying_weather	−0.015	−0.148
Very_satisfying_weather	−0.189	−0.972
Very_satisfying_weather_age > 65	−0.818**	−2.789
Very_satisfying_weather_with_car	0.404*	1.770
Very_satisfying_weather_single_nochild	0.851**	2.808
Time invariant variables: Z_i		
$y_{i,0}$	0.086	0.934
Age > 65	0.601**	2.533
Thresholds		
μ_1	0.639**	4.879
μ_2	2.152**	14.576
μ_3	2.979**	16.774
μ_4	3.772**	13.401
Standard deviations		
Individual level error term κ_i	0.515**	6.121
iid error term $\varepsilon_{i,t}$	1	Fixed
Model fit		
Number of observations	1202	
Number of individuals	51	
Log-likelihood at converge	−866.6	
Log-likelihood at zero	−1046.6	
McFadden's rho	0.172	

Note: ** denote that the corresponding variable effect is significant at 1% level. * denote that the corresponding variable effect is significant between 1% and 10% level. Numbers without stars denote that the corresponding variable effect is not significant at 10% level.

The integrals in Eq. (8) are handled by a simulation approach, which draws realisations from the distributions of ξ_i and θ_i to construct the likelihood function. 200 scrambled Halton draws (Bhat 2003) are used for each error term. The coefficients of $X_{i,t}$ are also extended as a function of individuals' socio-demographic variables, so the effects of time variant variables vary between respondents from different socio-demographic groups:

$$\beta = \beta_0 + Z_i\beta_1 \tag{10}$$

The exhaustive set of such parameter expansions is particularly extensive. The full set model shows that many β_1s are not significant. Consequently, only the result of the best model is reported, as shown in Table 4. The model selection is conducted using the following steps: 1. Removing the variables in $Z_i\beta_1$ that have t-values smaller than one from the full set model, and 2. Using the likelihood ratio test to test one by one whether the left insignificant variables should be kept. Note that all β_0s are kept in the model regardless of their significance levels.

The final log-likelihood is −866.6, while the log-likelihood when all β, γ, α_0 and α_1 are zero yields −1046.6. The model has a decent fit with a McFadden's rho of 0.172. The estimation result can be interpreted as follows

The effect of $y_{i,t-1}$ is significantly positive, indicating that the number of leisure activities conducted on a given day is significantly influenced by the leisure activity participation status on the previous day. However, this finding is slightly surprising since it is commonly believed that leisure activity participation is a need which takes time to accumulate in order to trigger participation in the next leisure activity (Arentze, Ettema, and Timmermans 2011). Thus, a negative effect is expected. However, one trend observed from the data is that many leisure activities were observed in a time period covering several days, suggesting that the need to conduct leisure activities can last across days. As a result, observing a non-zero variable $y_{i,t-1}$ may indicate the beginning of a leisure activity participation period, thus one may find a positive effect of the variable $y_{i,t-1}$. Besides, elderly people (age > 65) seem to have a much weaker lagged effect compared to adults, showing that elderly people are likely to have slightly fewer leisure activities if they conducted leisure activities on the previous day. Elderly people presumably need more rest after conducting leisure activities on the previous day compared to adults (age 36-50). The standard error of lagged effect as well as that of lagged effect for elderly people are significant, indicating considerable intra-individual heterogeneity of the estimated lagged effects. The coefficient of $y_{i,0}$ is insignificant, suggesting that although $y_{i,t-1}$ is significant, such a lagged effect does not extend to the beginning of the period. In other words, the effect of previous leisure activity participation does not last as long as the whole period (two weeks). The effect of work duration, as expected, is significantly negative (−0.002). Longer work duration leads to tighter time constraints for leisure activity participation. Similarly, long work periods contribute to the accumulation of the need for leisure activity participation, thus encouraging leisure activity participation. Furthermore, it is worth noting that no socio-demographic variables significantly interact with these two effects, showing that no differences between socio-demographic groups are observed.

The weather perception scores show clear asymmetric and non-linear effects. The coefficients of '*satisfying weather*' and '*disappointing weather*' are not significant with very small t-values, indicating that small deviations against '*indifferent weather*' do not necessarily influence actual behaviour. '*Very disappointing weather*' has a negative effect, −1.031, on leisure activity participation with a significant standard error estimate (1.147) therefore indicating that the effect of '*very disappointing weather*' differs significantly among individuals. However, since no interaction effects between '*very disappointing weather*' and socio-demographic variables have been found to be significant, this intra-individual heterogeneity cannot solely be attributed to individuals' socio-demographic variables, but are more likely to be influenced by other unobserved social and psychological factors. The coefficient of '*very satisfying weather*' is insignificant but several interaction effects between socio-demographic variables and '*very satisfying weather*' are significant. '*Very satisfying weather*' has a smaller effect on leisure activity participation for elderly people than for their younger counterparts. Respondents who have cars in their households are more likely to conduct leisure activities compared to those without cars in their households when they perceive '*very satisfying weather*'. Presumably, respondents with cars have better accessibility to leisure spots such as parks and resorts, etc., thus they are likely to conduct more leisure activities given '*very satisfying weather*'. Similarly, respondents who live alone and without children are more likely to conduct leisure activities than those who are living with their partner/spouse and children when they perceive '*very satisfying weather*'. A plausible explanation would be that those who live alone and without children have a more flexible time schedule and fewer obligatory tasks, such as taking care of children/partners at home than those who are living with their partner/spouse and children. The standard deviation of '*very satisfying weather*' is insignificant. The result of another model specification (not shown in this paper), which removes the interaction effects between '*very satisfying weather*' and socio-demographic variables, demonstrates a significant standard deviation of '*very satisfying weather*' (0.312, t-value 1.759), although the magnitude is not as high as that of '*very disappointing weather*'. This indicates that the intra-individual heterogeneity in the effect of '*very satisfying weather*' does exist and can be attributed to the socio-demographic variables.

After controlling for all the time variant variables, the study identified that elderly people tend to have more leisure activities per day in general. The remaining unobserved heterogeneity at the individual level (standard deviation 0.515) is around half of the white noise (standard deviation fixed at 1), after controlling for all the time variant/invariant variables.

5. Conclusion and discussion

Using a four-week travel diary survey conducted in Solna municipality in Stockholm in March, May and June 2014, this paper aims to answer two research questions: 1. how individuals from different socio-demographic groups perceive weather differently, and 2. how individuals' leisure activity participation is affected by their weather perception. The procedure of linking objective meteorological data and the instrument of weather perception is discussed. The instrument of weather perception is typically ordinal and is often available only at the daily level, while the objective meteorological data is often available at an hourly level. Aggregating hourly weather data into its daily equivalent and mapping it with weather perception instruments is an acceptable procedure, as discussed in Section 2. Meteorological measures (temperature, wind speed and relative humidity) are then used to construct a thermal indicator, the UTCI. The use of a thermal indicator has the advantage of incorporating knowledge in biometeorology and can avoid interrelated effects of meteorological measures. Ordered Probit models are used to explore the roles of objective weather conditions on weather perception. The results reveal that the reference thermal environment in general corresponds to the historical mean of UTCI in the given period. The marginal effects of objective weather measures on the instrument of weather perception vary substantially between individuals, suggesting also a non-linear effect. Such heterogeneity can be found between individuals from different socio-demographic groups.

The effects of weather perception are investigated within the context of the dynamics of leisure activity participation where the decision to participate in leisure activities is assumed to be determined by the time–space constraints on the given day, leisure activity participation in the past and the weather condition on the given day. One finding is the non-linear and asymmetric effects of weather perception scores. Only '*very disappointing weather*' and '*very satisfying weather*' significantly influence leisure activity participation. '*Very disappointing weather*' shows a more substantial effect than '*very satisfying weather*'. Besides, results from the mixed model reveal that the effect of '*very disappointing weather*' differs significantly between individuals. This heterogeneity cannot solely be attributed to the socio-demographic variables, but is more likely to be influenced by other unobserved social and psychological factors. On the contrary, the intra-individual heterogeneity in the effect of '*very satisfying weather*' can mainly be explained by the socio-demographic variables. These findings suggest a complex relationship between objective weather measures and leisure activity participation. Objective weather measures have a non-linear and individual-specific effect on weather perception, while weather perception also exhibits a non-linear, asymmetric and individual-specific effect on leisure activity participation. As a result, a direct inclusion of a linear combination of objective weather measures in the transport models can indicate a potential biased weather effect being estimated. Transport models with weather perception as an intermediate variable linking objective weather measures and travel behaviour variables can provide better and more interpretable transport demand forecasts under different weather scenarios.

The results also suggest a decreasing leisure travel demand in '*very disappointing weather*' in general, but an increasing leisure travel demand in '*very satisfying weather*' for only a sub-group of the population, those with cars in their households and those living alone and without children. Households with cars conducting more leisure activities in '*very satisfying weather*' may also indicate substantial car leisure trips on those days. Extra traffic and network management efforts at parks or scenic spots may be necessary on days with a comfortable thermal environment, especially in the colder months (e.g. a warm and sunny day in February in Sweden). The developed model can also be used to predict leisure activity demands for a synthetic population. Given possible future weather scenarios, the weather perception scores of each agent in the synthetic population can be predicted given the observed and historical objective meteorological data, using the individual models developed in section 3. The predicted weather perception scores can be used as inputs in the model developed in section 4 to generate leisure activity demand.

Estimation results from section 4 also show that leisure activity on the previous day, work duration on the given day and the number of consecutive working days play important roles, indicating the importance of considering space–time constraint, habit and/or travel need in modelling leisure activity participation, although it is not limited to these subjects. These findings highlight the need to incorporate these aspects in the modelling efforts of future research on investigating the impact of weather. Given that leisure activities are highly subject to cultural and regional characteristics, the composition of leisure activities (e.g. percentage of sports, eating out, visiting friends, etc.) may differ significantly in various regions, resulting in regional differences of estimated weather impacts.

Finally, one should also be aware of the limitations of this study. Weather perception, in this study, is represented by the weather perception scores from the five Likert scale questions. However, from a psychological perspective, the factors representing weather perception are often latent and correlated with other psychological factors such as happiness and life satisfaction (Connolly 2013). Integrating those factors measured by several weather and well-being related questions into the model system would forward the current dynamic model into a hybrid dynamic model, similar to the development from the mixed logit model to the hybrid choice model (Walker 2001), and should thereafter yield more insightful results. Subjective weather perception may also change within a day according to the temporal weather condition and the activity participated in, such as the time during a leisure activity. New data collection methodologies are needed in order to obtain the instrument of weather perception multiple times within a single day. Besides, in many circumstances, several travel decisions are made jointly. For example, a leisure activity participation decision is likely to be made together with a decision regarding the duration of the leisure activity and/or mode choice. In a '*very satisfying weather*' condition, individuals may choose to walk in nature for the whole day instead of going to the park in the morning and playing football in the afternoon. Thus, the modelling framework should also model this joint decision in order to obtain more detailed and reliable weather effects. These topics are plausible directions for future research.

Disclosure statement

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