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Weather variability and travel behaviour – what we know and what we do not know

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ABSTRACT

Given that severe weather conditions are becoming more frequent, it is important to understand the influence of weather on an individual's daily activity-travel pattern. While some previously rare events are becoming more common, such as heavy rain, unpredicted snow, higher temperatures, it is still largely unknown how individuals will change and adapt their travel patterns in future climate conditions. Because of this concern, the number of research studies on weather and travel behaviour has increased in recent decades. Most of these empirical studies, however, have not used a cost–benefit analysis (CBA) framework, which serves as the the main tool for policy evaluation and project selection by stakeholders. This study summarises the existing findings regarding relationships between weather variability and travel behaviour, and critically assesses the methodological issues in these studies. Several further research directions are suggested to bridge the gap between empirical evidence and current practices in CBA.

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Weather; travel behaviour; large-scale transport model; transport policy; cost–benefit analysis

Introduction

As a result of global warming and climate change, it is expected that severe weather events will become more frequent. Maximum and minimum temperatures will become more extreme, while precipitation patterns will tend to shift towards more intensive individual storms (Collins et al., 2013). Travellers' reactions, and ways in which they may adapt to a warmer and more extreme future climate, are becoming popular topics in the travel behaviour area. Weather and climate are considered to influence travel behaviour, and have been investigated in various studies that suggest an impact of non-trivial magnitude (see reviews, Böcker, Dijst, & Prillwitz, 2013; Dijst, Böcker, & Kwan, 2013; Koetse & Rietveld, 2009). Many studies have focused on the disruptions caused by extreme weather conditions (e.g. Fu, Lam, & Meng, 2014; Lam, Shao, & Sumalee, 2008; Zanni & Ryley, 2015) while less attention has been paid to everyday weather conditions (e.g. Böcker, Dijst, & Faber, 2014; Sabir, 2011). The impact of everyday weather on transport systems may be

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substantial, although not particularly noticeable because the variation of everyday weather influences the individual's travel patterns throughout the year. Extreme weather may have a strong negative impact on transport systems in a sub-region, and its impact is often long-term (Van Leeuwen, Koetse, Koomen, & Rietveld, 2009). Since extreme weather events will become more frequent in the future, travel behaviour adaptation to these extreme events is expected, resulting in more substantial travel behaviour changes in future extreme weather conditions, compared to travel behaviour changes in response to the variations in current weather conditions.

Studies focusing on weather impacts on travel behaviour differ from each other in a variety of perspectives. Some use different representations of weather and investigate weather impacts on users of different travel modes. The impact of weather has been found to be stronger on active and open-air transport modes, particularly cycling, than in-vehicle modes (Sabir, 2011). The most commonly investigated weather dimensions (meteorological variables) are temperature, precipitation, wind speed and snowfall (in Nordic countries and Canada). The impacts of humidity, fog, sunshine and cloud are less often investigated (for a detailed summary of study locations and weather dimensions, please see Table 1). Despite the inclusion of various weather dimensions, its effects are often not well distinguished. In that sense, an increase of temperature in summer is often assumed to have the same effect on travel behaviour as an increase of temperature in winter. Moreover, studies tend to focus mainly on western temperate and cold countries but empirical evidence from the global south is lacking (Böcker, Dijst, et al., 2013).

Table 1 summarises a non-exhaustive set of empirical findings with respect to the focus on travel behaviour dimensions, weather dimensions, the study location, the data source and the methodology issues.

In general, these studies have used data collected from two sources: passively generated data and survey data. Studies using passively generated data usually focus on aggregated-level indicators, such as bicycle flow, for example, the number of cyclists crossing a section of a specific cycle lane during a certain period (Brandenburg et al., 2007; Nosal & Miranda-Moreno, 2014). These indicators reflect the level of a given transport service under different weather conditions. Other studies have utilised traditional survey data that include detailed individual characteristics. An on-site survey can also collect information on weather perception (e.g. Sihvola, 2009; Thorsson et al., 2007). These types of data can help researchers to further understand how weather affects travel decision-making processes. However, most travel surveys collect only one-day travel behaviour of a given respondent, while passively generated data (e.g. GPS trajectories on travel routes) normally record multi-day travels of a given individual. Future studies combining survey data with passively generated data have the potential to better unravel the complex relationships between weather and travel behaviour.

Studies carried out in different countries, for example, those in tropical areas versus temperate areas, or developing countries versus developed countries, may also yield distinct results since inhabitants in different regions may have different weather adaptation strategies, resulting in different perceptions of "normal"/"cold"/"warm". Variations in culture, land use and transportation networks may also affect the impact of weather in different regions. So far, most studies (Table 1) have focused on a single travel behaviour dimension, such as mode choice or trip distance, while only a few have developed models

Table 1. Empirical studies assessed, sorted by travel mode groups, indicators and weather dimensions.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Weather impacts on walk mode/pedestrian					
Sabir (2011)	The Netherlands	Mode choice, route choice, trip distance, destination choice, daily trip frequency	Hourly temperature: (–) Wind speed: () Precipitation: (–) Precipitation duration: () Snow: (+) Visibility: ()	Matching closest station data according to time of the day	Multinomial Logit model, Tobit model, Negative binomial model
Böcker, Dijst, Faber, and Helbich (2015)	Greater Rotterdam, The Netherlands	Mode choice with emotion	Hourly air temperature: (+) Precipitation: (+) wind speed: (+) clearness index: ()	Matching closest station data according to time of the day	Structural Equation model
Saneinejad, Roorda, and Kennedy (2012)	Toronto, Canada	Mode choice	Hourly temperature: () Precipitation: (+) Wind speed: ()	Matching a close station data according to time of the day	Multinomial Logit model
Liu, Susilo, and Karlström (2015a)	Sweden	Mode choice	Daily temperature, normalized: () Precipitation: () Snow: (+)	Matching closest station data according to day	Multinomial Logit model
Clifton, Chen, and Cutter (2011)	Sydney, Australia	Mode choice and trip generation rates	Classified weather type via cluster analysis: Summer cool with light rain(+) Autumn very rainy (+)	Matching closest station data according to day	Linear regression
Böcker, Prillwitz, and Dijst (2013)	Randstad, Holland	Mode choice and travel distance	Projected 2050 climate: ()	Weather matching to each trip (details not mentioned)	Multinomial Logit model and Tobit model
de Montigny, Ling, and Zacharias (2012)	Nine cities in Europe	Walk rate (walk count)	Hourly temperature: (+) Ground with sunshine: () Precipitation: (–)	Measured locally and verified by nearby station data	Poisson regression
Aultman-Hall, Lane, and Lambert (2009)	Downtown Montpelier, Canada	Automated hourly pedestrian counts	Hourly temperature: (bell-shape ∩) relative humidity: (–) precipitation: (–) wind speed: ()	Matching station data from 3 mi away from counting site according to time of the day	Descriptive on Factor of mean index
Nikolopoulou and Lykoudis (2007)	Athens, Greece	Square attendance	Hourly air temperature: - in summer and + in winter) Sun radiation: (- in summer and + in winter) Wind speed: () Relative humidity: ()	Matching a close station data according to time of the day	Linear regression

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Lin (2009)	Taiwan	Square attendance	Sunshine hours: (+) Physiologically equivalent temperature: (+)	Measured at the spot	Linear regression
Thorsson, Honjo, Lindberg, Eliasson, and Lim (2007)	Sweden and Japan	Square attendance	Air temperature (mixed) Various thermal index (mixed)	Record at the study spot	Linear regression
Nikolopoulou, Baker, and Steemers (2001)	Cambridge, UK	Square attendance	Hourly temperature: (+)	Matching a close station data according to time of the day	Descriptive analysis
Weather impacts on bicycle/cyclist counts					
Sabir (2011)	The Netherlands	Mode choice, route choice, trip distance, destination choice, daily trip frequency	Hourly temperature: (+ bell shape) Wind speed: (−) Precipitation: (−) Precipitation duration: (−) Snow: (−) Visibility: (−)	Matching closest station data according to time of the day	Multinomial Logit model, Tobit model, Negative binomial model
Böcker et al. (2015)	Greater Rotterdam, The Netherlands	Mode choice with emotion	Hourly air temperature: (+) Precipitation: (−) Wind speed: () Clearness index: ()	Matching closest station data according to time of the day	Structural Equation model
Saneinejad et al. (2012)	Toronto, Canada	Mode choice	Hourly temperature: (+) Precipitation: (−) Wind speed: (−)	Matching a close station data according to time of the day	Multinomial Logit model
Liu et al. (2015a)	Sweden	Mode choice	Daily temperature, normalized: (+) Precipitation: (−) Snow: (−)	Matching closest station data according to day	Multinomial Logit model
Clifton et al. (2011)	Sydney, Austrilia	Mode choice and trip generation rates	Categorised weather types via cluster analysis: Summer cool with light rain: (+)	Matching closest station data according to day	Linear regression
Böcker, Prillwitz, et al. (2013)	Randstad, Holland	Mode choice and travel distance	Projected 2050 climate: (+)	Weather matching to each trip (details not mentioned)	Multinomial Logit model and Tobit model
Flynn, Dana, Sears, and Aultman-Hall (2012)	Vermont, U.S.A.	Bicycle commuting choice	Daily temperature: (+) Precipitation: (−) Snow: (−) Wind speed: (−) Daylight hour: ()	Matching closest station data according to time of the day	Logistic regression

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Heinen, Maat, and van Wee (2011)	Delft and Zwolle, The Netherlands	Longitudinal bicycle mode choice	Daily temperature: (+) Precipitation: (–) Precipitation length: (–) Wind speed: (–) Darkness: (–) Sunshine hours: (+)	Matching closest station data according to day	Multinomial Logit model with generalized estimating equations
Nankervis (1999)	Melbourne, Australia	Students' bicycle commute choice	Daily temperature: (+) Wind speed: (–) Precipitation: (–)	Details not mentioned	Descriptive analysis
Helbich, Böcker, and Dijst (2014)	Greater Rotterdam, The Netherlands	Binary choice on bicycle considering spatial heterogeneity	Daily temperature: (+) Precipitation: (–) Wind speed: (–)	Matching a close station data according to day	Geographically weighted Multinomial Logit model
Ahmed, Rose, and Jakob (2013)	Victoria, Australia	Cycle to commute	Survey question "weather as a factor influencing bicycle to commute": (+)	Not relevant[a]	Binary Logit model
Parkin, Wardman, and Page (2008)	England and Welsh	Share of wards cycling to work	Temperature: (+) Rainfall: (–) Sunshine hours: ()	Matching weather at regional level	Binary Logit model
Bergström and Magnusson (2003)	Luleå and Linköping, Sweden	Cycling share and cycling distance	Seasons: Summer (+)	Not relevant	Descriptive analysis
Winters, Friesen, Koehoorn, and Teschke (2007)	Canada	Revealed preference on the cycling frequency	Historical climate data: Historical average temperature: (+) Historical wind speed: () Historical number of rainy days in each season: (–) Historical number of snowy days in each season: (–)	Matching closest station data	Multilevel logistic regression
Brandenburg, Matzarakis, and Arnberger (2007)	Vienna, Austria	Bicycle counts volume	Physiologically equivalent temperature: (+)	Matching station data 6 km away from studying site according to time of the day	Descriptive analysis and correlation
Gebhart and Noland (2014)	Washington, DC, USA	Bikeshare trip countsvolume	Hourly temperature: (+) Precipitation: (–) Snow: (–) Thunderstorm: () Wind speed: (–) Fog: () Relative humidity: (–) Darkness: (–)	Matching closest station data according to time of the day	Negative binomial model

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Miranda-Moreno and Nosal (2011)	Montreal, Canada	Hourly bicycle ridership (flow)	Hourly temperature: (+) Precipitation: (−) Humidity: ()	Matching a close station data according to time of the day	Linear regression
Nosal and Miranda-Moreno (2014)	Four cities in USA	Standardized bicycle count volume at studying spot	Hourly temperature: (+) Relative humidity: (−) Precipitation: (−) Lagged precipitation: (−)	Matching a close station data according to time of the day	Linear regression
Phung and Rose (2008)	Melbourne, Australia	Daily bicycle count volume at studying spot	Temperature: (+ bell shape) Daily rainfall: (−) Wind speed: (−) Sunshine hours: (+) Humidity: ()	Details not mentioned	Linear regression
Richardson (2000)	Melbourne, Australia	Average daily cycling trips	Daily temperature: (+ bell shape ∩) Wind speed: () Rainfall: (−)	Matching a close station data according to day	Adjusting factors for different weather conditions
Thomas, Jaarsma, and Tutert (2013)	The Netherlands	Daily bicycle volume count at certain bicycle path	Daily temperature: (+) Precipitation: (−) Wind speed: (−) Sunshine hours: (+)	Matching a "not so close" station data (35 km) according to day	Linear regression
Weather impacts on private car/traffic flow					
Sabir (2011)	The Netherlands	Mode choice, route choice, trip distance, destination choice, daily trip frequency	Hourly temperature: (−) Wind speed: (−) Precipitation: (+) Precipitation duration: (+) Snow: (−) Visibility: ()	Matching closest station data according to time of the day	Multinomial Logit model, Tobit model, Negative binomial model
Böcker et al. (2015)	Greater Rotterdam, The Netherlands	Mode choice with emotion	Hourly air temperature: () Precipitation: () Wind speed: () Clearness index: ()	Matching closest station data according to time of the day	Structural Equation model
Saneinejad et al. (2012)	Toronto, Canada	Mode choice	Hourly temperature: (−) Precipitation: (−) Wind speed: ()	Matching a close station data according to time of the day	Multinomial Logit model
Liu et al. (2015a)	Sweden	Mode choice	Daily temperature, normalized: (−) Precipitation: () Snow: ()	Matching closest station data according to day	Multinomial Logit model

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Clifton et al. (2011)	Sydney, Australia	Mode choice and trip generation rates	Classified weather type via cluster analysis Summer very rainy & humid and very windy (+) Summer dry & very hot dry (+) Spring very rainy (+)	Matching closest station data according to day	Linear regression
Böcker, Prillwitz, et al. (2013)	Randstad, Holland	Mode choice and travel distance	Projected 2050 climate: (−)	Weather matching to each trip (details not mentioned)	Multinomial Logit model and Tobit model
Aaheim and Hauge (2005)	Bergen area, Norway	Mode choice	Daily temperature: (−) Precipitation: (+)	Not mentioned	Multinomial Logit model
Anta, Perez-Lopez, Martinez-Pardo, Novales, and Orro (2015)	Barcelona, Spain	SP and RP mode choice between private car and public transport	SP options related to weather levels, Regular weather (−)	Not relevant	Combined SP-RP Multinomial Logit model
Cools (2009)	Belgian	Traffic volume	Temperature: (+) Daily precipitation: (−) Snow: (−) Cloudiness: (−) Sunshine duration: () Visibility: () Wind speed: (−)	Matching closest station data according to day	Linear regression
Keay and Simmonds (2005)	Melbourne, Australia	Traffic volume	Temperature: (+) 3-hour measured rainfall: (−) Wind speed: (−) Cloud: (−) Poor surface condition: (−)	Matching a close station data according to day	Linear regression
Datla and Sharma (2010)	Alberta, Canada	Traffic volume	Daily temperature: (+) Precipitation: () Snow: (−)	Matching closest station data according to day	Linear regression
Chung, Ohtani, Warita, Kuwahara, and Morita (2005)	Tokyo, Japan	Traffic volume	Hourly precipitation (−)	Matching closest station data according to time of the day	Descriptive analysis
Hassan and Barker (1999)	Lothian Region, Scotland	Ratio of traffic count to its historical value	Daily temperature: (+) Rain: (−) Snow: (−) Sunshine hours: (+)	Matching closest station data according to day	Descriptive analysis

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Akin, Sisiopiku, and Skabardonis (2011)	Istanbul, Turkey	Traffic speed and density	Rain: (–) fog/mist/haze, or snow (–)	Station data	Log-linear regression
Edwards (1999)	Wales	Traffic speed at spot	Manual observed weather type: Wet weather: (–) Misty weather: (–)	Manual observations of the weather at spot	Linear regression
Kyte, Khatib, Shannon, and Kitchener (2001)	Interstate freeway in U.S.A	Free-flow traffic speed	Snow measured every 5 minutes: (–) Wind speed: (–) Poor visibility: (–)	Details not mentioned	Linear regression
Oh, Shim, and Cho (2002)	Incheon, Korea	Traffic free-flow speed and traffic volume relationship	Rain: (–) Snow: (–)	Details not mentioned	Linear regression
Vlahogianni and Karlaftis (2012)	Athens, Greece	Freeway lane speed at certain spot	Precipitation intensity level on lane speed: (–)	Matching a close station data according to time of the day	Recurrence quantification analysis
Kilpeläinen and Summala (2007)	Finland	Choice of acquiring weather forecast and weather perception on driver behaviour	Weather perception has an insignificant effect on drivers' on-road behaviour	Not relevant	Logistic regression
Sihvola (2009)	Finland	Choice on weather forecast, driver's mode choice, perceived weather condition	Adverse weather leads to longer following distance, avoid overtaking, attention to road surface, driving slower	Not relevant	Descriptive analysis
Weather impacts on public transport					
Sabir (2011)	The Netherlands	Mode choice, route choice, trip distance, destination choice, daily trip frequency	Hourly temperature: (–) Wind speed: () Precipitation: (+) Precipitation duration: () Snow: () Visibility: ()	Matching closest station data according to time of the day	Multinomial Logit model, Tobit model, Negative binomial model
Böcker et al. (2015)	Greater Rotterdam, The Netherlands	Mode choice with emotion	Hourly air temperature: (+) Precipitation: (+) Wind speed: () Clearness index: ()	Matching closest station data according to time of the day	Structural Equation model
Saneinejad et al. (2012)	Toronto, Canada	Mode choice	Hourly temperature: () Precipitation () Wind speed: ()	Matching a close station data according to time of the day	Multinomial Logit model

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Liu et al. (2015a)	Sweden	Mode choice	Daily temperature, normalized to its historical mean: () Precipitation: (+) Snow: ()	Matching closest station data according to day	Multinomial Logit model
Clifton et al. (2011)	Sydney, Austrilia	Mode choice and trip generation rates	Classified weather type via cluster analysis Autumn very rainy (+)	Matching closest station data according to day	Linear regression
Böcker, Prillwitz, et al. (2013)	Randstad, Holland	Mode choice and travel distance	Projected 2050 climate: ()	Weather matching to each trip (details not mentioned)	Multinomial Logit model and Tobit model
Aaheim and Hauge (2005)	Bergen area, Norway	Mode choice	Daily temperature: (–) Precipitation: (+)	Not mentioned	Multinomial Logit model
Anta et al. (2015)	Barcelona, Spain	SP and RP mode choice between private car and public transport	SP options related to weather levels: Regular weather (+)	Not relevant	Combined SP-RP Multinomial Logit model
Arana, Cabezudo, and Peñalba (2014)	Gipuzkoa, Spain	Transit ridership	Daily mean temperature: (+) Relative humidity: (–) Precipitation: (–) Wind speed: (–)	Matching climate data from one close station according to day	Linear regression
Guo, Wilson, and Rahbee (2007)	Chicago, U.S.A.	Transit ridership	Daily temperature: (+) Rain: (–) Snow: (–) Wind speed: (–) Fog: (+)	Matching closest station data according to time of the day	Linear regression
Hofmann and Mahony (2005)	Ireland	Bus ridership, headway, bunching, travel time	Rain on ridership: (–) Rain on headway: (+ higher headway regularity) Rain on bunching: () Rain on bus travel time reliability: (- travel time variability)	Matching station data 10 km away from boarding station according to time of the day	Descriptive analysis
Singhal, Kamga, and Yazici (2014)	New York, U.S.A	Daily and hourly subway ridership	Temperature deviation normalized to its historical mean: (- for both too cold and too warm extremes) Rain: (–) Wind speed: (–) Snow: (–) Fog: ()	Matching a close station data according to time of the day	Linear regression

(*Continued*)

Table 1. Continued.

	Study location	Travel/traffic indicators	Weather effects found	Weather and transport data matching	Modelling technique
Weather impacts on activity participation and scheduling					
Cools and Creemers (2013)	Flemish, Belgian	SP on mode, departure time, destination and route choices	SP options related to weather conditions: significant weather effect	Not relevant	Pearson chi-square independence test and Multinomial Logit model with generalized estimating equations
Chen and Mahmassani (2015)	San Francisco Bay Area, U.S.A	Activity stress defined on activity scheduling theory	Interpolated rainfall: insignificant	Matching closest station data according to time of the day	Mixed Logit model
Eliasson, Knez, Westerberg, Thorsson, and Lindberg (2007)	Gothenburg, Sweden	Activity participation	Subjective weather perception, Clearness index: (+) Temperature (+) Wind speed (–)	Manual observations of the weather at spot	Linear regression
Khattak and Palma (1997)	Brussels, Belgian	Frequencies of change in travel mode, departure time and route choice due to adverse weather	Adverse weather on mode change: (+) Adverse weather on departure time change: (+) Adverse weather on route change: (+)	Not relevant	Ordered Probit model
Liu, Susilo, and Karlström (2015b)	Sweden	Daily activity duration, number of trips and trip chains, travel time and mode share	3-hour measured temperature, relative humidity, precipitation, wind speed, visibility, snow (different effects on work and non-work activity participations)	Matching closest station data according to time of the day	Structural Equation model
Liu, Susilo, and Karlström (2014)	Sweden	Daily activity duration, number of trips, travel time and mode share	3-hour measured temperature, relative humidity, precipitation, wind speed, visibility, snow (different effects on routine and leisure activity participations)	Matching closest station data according to time of the day	Simultaneous Tobit model
Liu, Susilo, and Karlström (2015d)	Sweden	Trip chaining decision	UTCI: (–) Precipitation: (–) Wind speed: () Visibility: () Snow: (+)	Matching closest station data according to time of the day	Ordered Probit model

Note: a "–" sign indicates that the given weather variable/effect is negatively correlated with the Travel/Traffic Indicators while a "+" indicates that the given weather variable/effect is positively correlated with the Travel/Traffic Indicators. A blank parenthesis indicates that the given weather variable/effect has an insignificant effect on the Travel/Traffic Indicators.

[a]The term "not relevant" means that the weather data and travel data are collected at the same time or there is no meteorological weather data used, e.g. weather perception in stated preference survey. Therefore, no weather and travel data matching is needed.

involving several travel behaviour dimensions (e.g. Böcker et al., 2015; Liu et al., 2015a). Since travel is a derived demand of activity participation, studies that jointly model activity time use and activity participation with travel mode choice and trip distance seem to better describe weather impacts. For instance, a decreased walk share with the increase of temperature (Sabir, 2011) could be the result of changing activity location; for example, more long distance trips result in a lower walk share.

Although much effort has been put into quantifying the impact of weather on travel behaviour, the resulting information is rarely transferred or integrated into the existing transport planning process. Given the significant weather impacts on travel behaviour, it is likely that future travel demand could vary in a warmer climate scenario (Böcker, Prillwitz, & Dijst, 2013), and thus lead to variations in, for example, traffic flow, bicycle usage, and transit ridership, resulting in changes in various transport externalities, such as road congestion, emissions, and safety. Figure 1 presents the dynamic interactions between weather and travel behaviour.

As shown in Figure 1, different weather dimensions, such as temperature, precipitation and wind speed, can affect individuals' travel decisions resulting in changes to travel mode, trip frequency, destination, etc. Changes in travel behaviour could then lead to changes in transport system usage, such as more or less traffic and more or less transit ridership in adverse weather conditions. Most studies have investigated weather impacts on traffic flow and transit ridership through a direct approach such as regression analysis using data from single or several intersections or stations (e.g. Akin et al., 2011; Guo et al., 2007). Few studies have investigated weather impacts on traffic networks by integrating findings from travel behaviour models into transport demand–supply

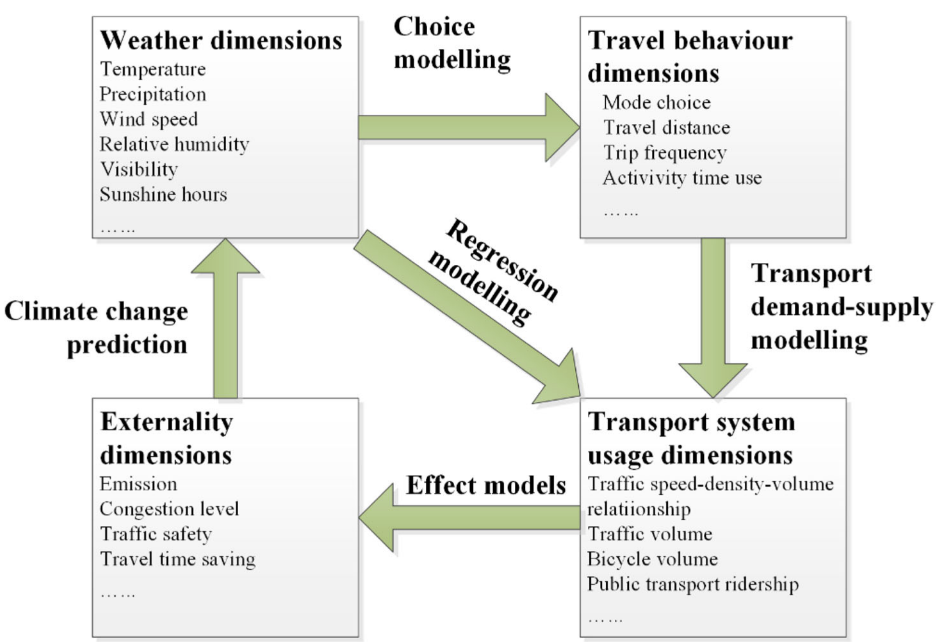

Figure 1. The dynamic relationship between weather and transport system.

models. Therefore, the induced externalities such as emissions, which may again influence the future climate, are difficult to quantify.

This paper aims to provide a systematic summary and discussion of weather-related issues in travel behaviour analysis, transport models and transport appraisal. It focuses on the discussion and critical evaluation of existing studies investigating the relationship between weather and travel behaviour, and relationships between weather and transport system usage. This paper also assesses the potential of including weather impacts on transport externalities through a cost–benefit analysis (CBA) framework. Understanding these issues would be helpful in bridging the gap between existing knowledge of travel behaviour regarding plausible weather variability impacts and the absence of weather-related factors in transport appraisal and its related policy measures.

The next section comprises a review of studies investigating the relationship between weather and travel behaviour. This is followed by a discussion of studies investigating the relationship between weather and transport system usage. Then, the potential consequences of ignoring the impacts of weather in transport appraisal are presented. Finally, this paper concludes by summarising the findings from the previous sections.

Weather impacts on travel behaviour dimensions

Among various travel behaviour dimensions, mode choice is the measure focused on by most studies (e.g. Sabir, 2011; Saneinejad et al., 2012). It is not surprising that leisure travel is more elastic than commuting in response to changes in weather conditions (Liu et al., 2015b). Cycling has been found to be the most elastic towards these changes in weather. Studies in the Netherlands, Canada and Sweden have showed that bicycle usage positively correlates with temperature until the temperature reaches 25°C (Liu et al., 2015a; Sabir, 2011; Saneinejad et al., 2012). Snow is the major factor that negatively impacts on bicycle usage (Cools, Moons, Creemers, & Wets, 2010). Precipitation and wind speed are two other major weather factors that negatively affect both commute and non-commute cycling (Aaheim & Hauge, 2005; Flynn et al., 2012; Heinen et al., 2011). Their impacts are nonlinear; that is, there is a sharp decline of cycling demand at the slightest hint of rain followed by much steadier reductions (Phung & Rose, 2008). Saneinejad et al. (2012) showed an increasing probability of travellers choosing to walk on rainy days. Most studies focusing on mode choice did not find significant impacts of wind speed and relative humidity on walking, although Sabir (2011) found an increasing walk share in heavy wind. The usage of private cars is higher in low-temperature conditions (Saneinejad et al., 2012; Liu et al., 2015a), and people tended to switch from walking and cycling to cars and public transport during rainy days (Sabir, 2011).

A few studies have investigated the weather impacts on travel scheduling and travel distance/travel time by mode. Walking and car travel distances are shorter in warmer temperatures, while cycle travel distances become longer (Bergström & Magnusson, 2003); snow corresponds to an increase in walking distance at the expense of car distance (Sabir, 2011). Snow also encourages trip chaining with all types of purposes, including commute, errands and discretionary (Liu et al., 2015d). Weather has been found to significantly influence drivers' behaviours, including a 6–7 km/h speed reduction and an increase in drivers' perceived accident risk (Kilpeläinen & Summala, 2007). Drivers are also likely to change route in adverse weather conditions (Sumalee, Uchida, & Lam, 2011).

Most of these studies have investigated the roles of multiple weather dimensions on one or a few travel behaviour dimensions. However, various issues may arise when this approach is adopted.

Matching weather to travel survey data

Most studies used objective meteorological indicators to represent weather dimensions, such as temperature, wind speed or relative humidity. These were assigned to each trip by matching the meteorological indicators from the weather station closest to the trip departure point and selecting the weather variable present at the departure time (see, e.g. Liu et al., 2014; Sabir, 2011; Saneinejad et al., 2012). It was assumed that each traveller would base his or her travel decision on the weather conditions that prevailed at the departure place and time. Different interpolation methods were used to match weather data from sparsely distributed weather stations to trip origins/destinations. Chen and Mahmassani (2015) interpolated weather over the study area based on the observed meteorological indicators at the stations. Jaroszweski and McNamara (2014) used a weather radar approach, though their focus was on traffic accidents. Nevertheless, these techniques tried to assign the most "accurate" weather information to each spot by assuming a certain spatial distribution of the meteorological indicators.

Another issue is whether to match the weather information to the departure time and location, or arrival time and location, or a certain point of time during the trip. Chen and Clifton (2011) argued that travellers would assess the weather conditions based on the conditions prior to travel. Chen and Mahmassani (2015) assumed that travellers would anticipate the weather conditions and they therefore matched weather according to the destination location and time, although they also admitted that "more research is needed to examine how weather is incorporated in travel decision processes" (Chen & Mahmassani, 2015, p. 58). Based on a stated preference survey, Cools and Creemers (2013) showed that "planned" travel decisions are often changed at the last minute in response to an adverse weather presented. Sihvola (2009) interviewed the drivers and found a substantial number of drivers changing their travel plans (i.e. their route or departure time). However, more empirical evidence is needed from revealed preference studies.

Weather dimensions separately or in combination

Since weather dimensions are recorded in terms of observed meteorological variables (e.g. temperature, wind speed), it is logical to assess the effect of each individual meteorological variable on travel behaviour (see review, Böcker, Dijst, et al., 2013). Studies tend to use a linear function of weather dimensions (variables), which assumes that each meteorological variable has a single and independent effect on the travel behaviour indicator of interest. To capture the bell-shape effect of certain meteorological variables, mostly temperature and precipitation, the continuous measures are often segmented into different intervals, and different parameters are estimated for each interval. For example, Sabir (2011) found a bell-shape effect of temperature on bicycle usage which increased along with the temperature up to 25°C and decreased when the temperature rose above 25°C. Different classifications of the variable levels may also affect the interpretation of the model results and their application to demand forecasting. For instance, studies in the

Netherlands (Böcker et al., 2015; Sabir, 2011) classified "temperature ≥25°C" as an interval, while Saneinejad et al. (2012) in Toronto classified "temperature 25–30°C, 31–35°C and ≥35°C" as three intervals.

More importantly, different meteorological variables often naturally correlate, indicating that the effects of meteorological variables are interrelated. Phung and Rose (2008) found a combined negative effect of wind and light rain on bicycle flow. A few weather studies in travel behaviour have used data mining techniques. Clifton et al. (2011) used a two-step clustering technique to classify various types of weather conditions based on observed meteorological variables. However, it is worth mentioning that data mining techniques including clustering, factor analysis, Bayesian inference, etc. have long been used to identify weather types in climatology (see review, Tian, Zheng, Yang, Ji, & Wang, 2014). Recent advances in thermal comfort studies have shown that various weather parameters have a joint effect on individuals' perception of the thermal environment (see review, Chen & Ng, 2012). Thermal comfort indexes have been used to explain variations in demand for activity space usage long before their application to travel behaviour studies (e.g. Lin, 2009; Nikolopoulou, Baker, & Steemers, 2001). Creemers, Wets, and Cools (2015) pioneered weather-related travel behaviour studies by introducing different thermal comfort constructs and comparing their performance in travel behaviour models. They concluded that physiologically equivalent temperature, among various thermal comfort indexes, is the most suited to represent weather in travel behaviour models. Liu et al. (2015d) used the Universal Thermal Climate Index (UTCI) instead of temperature, wind speed and relative humidity to represent thermal comfort when investigating trip chaining behaviour. However, in most travel behaviour studies related to weather, thermal comfort measures have not replaced observed meteorological variables.

Another issue is that most of these studies did not separate the effects of weather and of climate. In studies directly using meteorological variables or using thermal comfort measures, one cannot separate these two effects. For instance, 10°C in summer in a country of cold climate may have a completely different effect from 10°C in winter in the same country. The former may be interpreted as "cold in summer" while the latter may be interpreted as "warm in winter". Sabir (2011) used dummy variables to represent that trips took place in different seasons (seasonal dummies), together with the temperature variables in a travel behaviour model, and found significant effects of the seasonal dummies. However, this approach hinders the interpretation of the effect of temperature variables because their parameters should then be interpreted as the effects of changing temperature values in different temperature intervals after controlling for the season, which does not seem to be reasonable. Liu et al. (2015d) proposed an alternative approach; that is, to allow the parameters of different temperature intervals to interact with the parameters of seasonal dummies. Liu et al. (2014, 2015b) proposed another approach to separate the effect of climate and the effect of weather. They used the mean of historical meteorological variables or thermal comfort measures in a given month and given location of each trip as a variable to represent climate effect. They used the standardised deviation against this variable to represent the weather effect. This assumes that travellers recognise the historical meteorological variables and will respond to changes in them. In general, there is still no consensus on how the effect of climate should be represented. Furthermore, variations in climate are often seasonal, and correspond with other non-weather-related factors that exhibit a seasonal pattern.

For instance, the estimated effect of "summer" compared to that of "winter" may also capture the effects of summer holidays. It is not possible and not meaningful to separate the effect of climate and the effect of non-weather-related events because they always co-occur.

Fundamentally, weather is perceived by travellers and this perception affects travellers' travel decision-making. Studies on weather perception have tended to originate from the discipline of psychology (e.g. Connolly, 2013; Thorsson et al., 2007; Thorsson, Lindberg, Björklund, Holmer, & Rayner, 2011; Thorsson, Lindqvist, & Lindqvist, 2004) although a few have come from the field of travel behaviour and mobility (Böcker et al., 2014; Liu, Susilo, & Karlström, 2015c). Weather perception naturally defines a reference point of "good/bad" weather. Therefore, prospect theory (Kahneman & Tversky, 1979) and latent variable models (Everitt, 1984) are likely to also be applied to model weather perception.

Weather perception, as one element, has been shown to strongly influence an individual's mood and happiness. For instance, sunshine can directly increase the level of happiness by impacting on mood (Cunningham, 1979). However, this can be because a sunny day is associated with higher possibilities of outdoor leisure activities which provide more happiness (Keller et al., 2005). Indeed, weather, well-being and travel patterns are inter-related. Psychologists tend to explore the role of weather on well-being while treating travel patterns as mediating effects (see reviews, Kööts, Realo, & Allik, 2011), but travel behaviour analysts tend to explore the role of weather on travel patterns while treating well-being as control variables. However, to the authors' knowledge, only a few travel behaviour studies have included questions regarding the subjective perception of weather (e.g. "Does today's weather make you feel cold?") and investigated its relationship to travel patterns. Liu, Susilo, and Termida (2015) included one weather perception question "How did the weather make you feel on the given day?" and found that an extreme value of this question (very satisfied/very unsatisfied) was associated with changes in leisure activity participation, with a larger magnitude for "very unsatisfied" with the weather. Böcker et al. (2015) included a measure of perceived temperature and showed that weather-exposed cyclists experienced thermal conditions as significantly colder than the more weather-protected users of motorised transport modes. Eliasson et al. (2007) included a 5-Likert scale question "What is your perception of the weather today?" and found a clear correlation between the response to the question and the number of attendances at an urban outdoor environment. Thorsson et al. (2007) included a series of 5-Likert scale subjective weather questions "How do you experience the current weather today, calm or windy, cold or warm, good or bad for outdoor activity?" and showed clear climatic and cultural differences in weather perception between Japan and Sweden.

Travel behaviour dimensions separately or in combination

It has been shown that most studies have focused on only one or two travel behaviour dimensions, mostly mode choice, number of trips and trip distance (see Table 1). However, the effect of a given weather dimension on one travel behaviour dimension may have an indirect influence on another travel behaviour dimension, and vice versa. For instance, travellers may choose a closer destination on rainy days which indirectly increases the likelihood of walking. Ignoring the indirect effect could potentially lead to a biased interpretation of estimated weather effects (Liu et al., 2015b). Most existing weather–travel behaviour studies used the multinomial Logit model for mode choice, negative binomial model/ordered Probit model for trip frequency and the Tobit model for trip distance (see Table 1). However, multivariate econometric models that are able to capture the indirect effect and model several joint travel behaviour dimensions (such as joint mode choice and departure time choice (Habib, Day, & Miller, 2009) and joint car choice and car distance travelled (Fang, 2008)) have the potential to offer more insights into joint activity-travel behaviour changes under different weather conditions.

Moreover, most previous studies analysed travel behaviour changes trip by trip separately and not within a daily aggregated travel pattern. In studies analysing daily aggregated travel patterns, either daily aggregated weather information was assigned to each individual, or the average of weather information (measured at each trip departure/arrival time) was matched to all trips made by a given individual. The advantage of analysing daily aggregated travel patterns, rather than focusing on each individual trip, is that travellers' daily space–time constraints can better be incorporated into the analysis than by analysing trip-level travel patterns (Liu et al., 2015b). For instance, if a traveller has had a long working day, he/she may be too tired to respond to opportunities offered by "good"/"better weather than usual" and will use a car rather than cycling. Helbich et al. (2014) also argued that daily aggregated weather should be used because transport mode choice is frequently decided in a longer term context rather than instantaneously. Moreover, travellers' daily time use may also be affected by weather conditions. Connolly (2008) found that men spent an extra half an hour working on rainy days compared to sunny days. However, daily aggregated weather information may not capture the actual weather conditions experienced by the traveller, given that weather conditions may vary dramatically within a day. This clearly introduces errors in the analysis. Furthermore, some of the weather effects may not only have an instantaneous effect but may also affect trips when the given weather condition ends. For instance, snow may accumulate on the ground, thus hindering cyclists even when the snowfall is over. In this case, daily aggregated snow depth may capture the effect.

Weather impacts on transport system usage dimensions

In studies focusing on traffic volume, pedestrian rate, bicycle counts and transit ridership, weather information is either measured at the study locations (e.g. Akin et al., 2011; Edwards, 1999), or taken from a nearby weather station (e.g. Keay & Simmonds, 2005; Kim, Mahmassani, & Dong, 2010). Since the study location is pre-known (fixed) and individual information is not available, it is a common practice to regress a relationship between the recorded weather conditions at the study location at that point of time and the travel indicator (flow or count).

Studies summarised in Table 1 have shown that the number of walking trips is positively associated with temperature and negatively correlated with snowfall (Aultman-Hall et al., 2009; de Montigny et al., 2012). The impact of weather on road traffic has been extensively studied among all travel modes. Snowfall corresponds to a significant reduction in traffic volume of up to 70% (Cools, 2009; Hanbali & Kuemmel, 1993; Maze, Agarwai, & Burchett, 2006). Precipitation plays a minor role in weekday traffic volume (<5% in most studies) and a moderate role in weekend traffic (Chung et al., 2005;

Kim et al., 2010). Road capacity also drops during rainy days (Brilon, Geistefeldt, & Regler, 2005). Meanwhile, adverse weather conditions, mainly precipitation, also correspond with a mild speed reduction, ranging from 2% to 12% in different studies (Kyte et al., 2001; Maze et al., 2006; Oh et al., 2002). These empirical findings all suggest that different traffic speed–flow–density relationships should be used for traffic assignment models in normal and adverse weather conditions. This is particularly important for simulations of peak-hour traffic, as road capacity drop is expected in adverse weather conditions, whereas the demand for commute car trips may not drop.

Bicycle flow is more elastic than traffic volume towards adverse weather conditions. Thomas et al. (2013) found that almost 80% of the fluctuation in daily bicycle flow can be explained by changes in weather conditions. Rainfall and temperature have a relatively strong effect on the propensity to cycle to work, with a similar magnitude to that of the effect of hilliness (Parkin et al., 2008). Wind speed has a moderate effect on bicycle flow (Tin, Woodward, Robinson, & Ameratunga, 2012). Relative humidity and cloud level also have significant effects on hourly bicycle flow but with relatively small marginal effects (Gallop, Tse, & Zhao, 2012). These effects differ significantly between weekdays and weekends, indicating the different roles of weather in utilitarian cycling and leisure cycling. A moderate pedestrian volume reduction is also found on rainy days (de Montigny et al., 2012). Transit ridership decreases during rainfall and in snowy conditions (Guo et al., 2007; Hofmann & Mahony, 2005); this effect is much stronger on weekends (Singhal et al., 2014). Singhal et al. (2014) also found significant differences between weather impacts on hourly ridership and weather impacts on daily ridership, indicating time-dependent weather impacts.

Understanding weather impacts on the transport system usage using transport models

The studies discussed above have adopted direct regression models to investigate the role of weather on transport systems usage. However, changes in traffic volume/bicycle flow/transit ridership under adverse weather conditions are the result of travellers' complex travel decision-making, such as cancelling the trip, changing travel mode, changing destination, changing route and rescheduling the trip. A traditional transport four-step model normally includes trip generation, mode choice, destination choice and route choice (often the shortest path). Therefore, using the transport model to assess the impacts of weather on traffic volume/bicycle flow/transit ridership has the advantage of considering some travel behaviour changes (although four-step models are criticised as not being behavioural models, since they are based on trip-based models not activity based) rather than the empirical relationship between weather and traffic volume/bicycle flow/transit ridership. However, few transport models currently include weather as an input.

Most large-scale transport models build upon the well-known nested-Logit model structure (Ben-Akiva, 1974; Ben-Akiva & Lerman, 1985) due to its ability to accommodate a large number of alternatives. Examples of these large-scale demand models include: TRB in USA (TRB, 2007), Sampers in Sweden (Algers, Mattsson, Rydergren, & Östlund, 2009) and DNM in Denmark (Larson & Filges, 1996). These large-scale nested-Logit models often involve thousands of alternatives regarding destination choice, mode choice, departure time choice and trip frequency choice, etc. The models are often estimated via sampling of alternatives (Ben-Akiva & Lerman, 1985). However, it is difficult in practice to include weather dimensions as attributes in these models because a weather dimension at a given time often has the same value for traffic zones close to each other, since weather data are often available only at the regional level. This means that the parameter of a given weather dimension must differ between alternatives (since only the differences in choice attribute values matter). Consider the simplest example when only one weather dimension, for example, temperature, is included. Then for a nested-Logit model with a large choice set (for instance destination choice), the generic parameter of that weather attribute may be difficult to estimate since a large portion of alternatives (zones) may have the same value of temperature. Alternatively, weather measures can interact with other generic parameters such as the travel time parameter. Such an approach can capture the heterogenous weather impacts on travel time sensitivity.

Since the transport models are calibrated by travel survey data in which good weather and adverse weather conditions are sampled, the predicted or simulated travel choices are interpreted neither as travel choices in good weather nor as travel choices in bad weather, but a kind of average of travel choices in good and bad weather, depending on the proportions of samples under good/bad weather. The corresponding aggregated measures from the models, such as mode share and origin–destination demand, are also not aggregated measures in good/bad weather.

Although most transport models tend to focus on peak-hour traffic or commute trips which are less affected by weather (Liu et al., 2015b), many of these models also have detailed model components for leisure trips (for instance, Sampers in Sweden). However, to what extent the model components of leisure trip demand are biased due to the absence of weather variables is largely unknown, so are the policy evaluations related to those modelled leisure trips.

Another important question concerns whether route choice should be modelled as a behavioural model. Although some empirical evidence (e.g. Sabir, 2011; Zhang & Chen, 2009) has revealed potential route choice changes due to adverse weather, current practice mainly adopts non-behavioural roles in route choice (e.g. the shortest path according to generalised route cost) for the traffic assignment package. Above all, a holistic framework is needed to incorporate the influence of weather in large-scale transport models, from both demand and supply perspectives.

Considering weather in CBAs and transport appraisal

CBA has long been used to guide project selection and policy evaluation. As climate change is becoming a serious concern, it is important for transport policies and investments to cope with the climate change. As discussed above, the absence of weather variables in large-scale transport models hinders the incorporation of weather in transport appraisal and policy evaluation; almost no CBA considers the influence of weather on social benefits and cost estimates. Figure 2 illustrates the potential issues of considering weather in different components of CBAs.

In Figure 2, two other components: general parameters (e.g. future discount rates and marginal costs of public funds) and investment costs (e.g. increased construction costs in adverse weather conditions) are not discussed as they are beyond the scope of this paper. However, it is worth noting that weather may significantly affect these parameters,

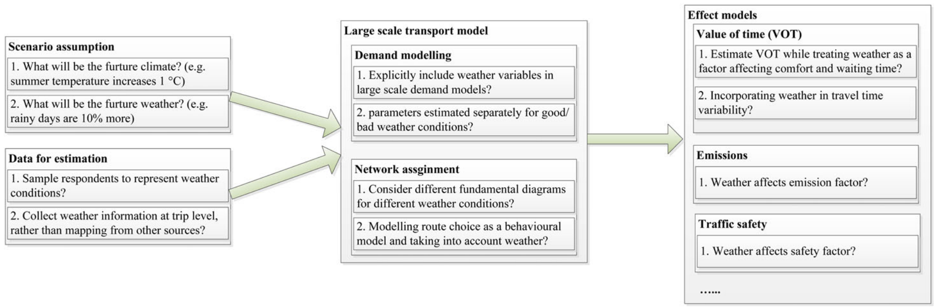

Figure 2. How can weather be incorporated in different components in CBA.

e.g. Brekke and Johansson-Stenman (2008) discussed the choice of future discount rates in climate change policies. As presented in Figure 2, beside the components of "large-scale transport model" and "data for estimation" which are discussed extensively above, the other two components (scenario assumption and effect models) also receive attention.

As CBA often involves predictions of future scenarios, appropriate assumptions of future climate and future weather are needed. However, given the fact that future climate and weather are also strongly affected by human activity, the relationship between weather/climate and human activity (including transportation) is reciprocal. One approach is to adopt existing knowledge from climate prediction models. However, considerable uncertainty exists in both the climate prediction and the transport models. The predicted outcome from such a climate-transport model would need to be interpreted with caution. Nevertheless, scenario analyses are required to represent several possible projected futures.

The results of CBAs are often sensitive to the specification of effect models (including value of time (VOT), emissions, social cost of accidents, value of noise, etc.). Effect models utilise the output of large-scale transport models and convert this output into monetary values for CBA comparison. Various effect models are believed to be affected by weather: including VOT, emission factors, traffic safety and other wider economic benefits/losses (e.g. health benefits of more cycling in good weather, and losses from road network disruption due to adverse weather). The impact of weather and climate on VOT is largely unknown, given that most existing studies evaluated VOT through stated preference data with no assumptions of weather conditions. However, precipitation can potentially affect VOT through its indirect impact on comfort and waiting times. Studies regarding VOT have incorporated comfort level and waiting times to further differentiate VOT, mainly for the public transport mode (Börjesson & Eliasson, 2014; Østli, Harkjerr, & Killi, 2015) and bicycle mode (Björklund & Carlén, 2012; Börjesson & Eliasson, 2012). The theoretical derivation of VOT, which stems from the time allocation problem (Becker, 1965), suggests that more comfort and less waiting time lowers VOT. Therefore, it seems plausible that VOT tends to be higher in adverse weather conditions, although empirical evidence is still lacking. Recent advances in scheduling models also incorporate travel time variability (see review: Carrion & Levinson, 2012). It is plausible that weather may significantly affect travel time variability (e.g. travel time may become more uncertain in adverse weather conditions).

Weather variables have been shown to affect the emission factors (emission per km drive). By utilising vehicle field testing data, Boulter and McCrae (2007) showed that various types of emission factors are affected by weather variables. Hot exhaust emission normally decreases with increasing temperature for both petrol and diesel cars; more so for diesel cars. Adverse weather conditions, such as precipitation and snow, trigger the use of in-vehicle air conditioning, wipers and window defrosters, thus increasing hot exhaust emissions from the auxiliary system. Cold start emissions are well known to be larger in lower temperatures (Andree & Joumard, 2005), while evaporative emissions increase with increasing temperature (Hausberger, Wiesmayr, Bukvarevic, Tripold, & Brenner, 2005). Liu, Susilo, and Karlström (2016) showed that passenger transport CO_2 emissions can be underestimated up to 10% in Sweden in a warmer future climate (mean monthly temperature +1–5°C), when weather impacts on emission factors and travel patterns are both considered. Consider a scenario where emissions are underestimated in a CBA; a project with actual high emissions may get a higher rank than it should be since a considerable share of emissions (which should low the rank of this project) are underestimated. This would increase the probability that projects with considerable adverse environmental effects are selected.

The impact of weather on traffic safety has been studied extensively (see review: Theofilatos & Yannis, 2014). According to Theofilatos and Yannis (2014), it is clear that precipitation increases accident frequency, but has no clear effect on the severity of the accident. Therefore, with the same level of traffic, more traffic accidents are expected on rainy days than on sunny days. However, there is no consensus on the effects of other weather parameters. Since the large-scale transport models do not consider weather, the simulated level of traffic from those models does not represent the level of traffic in good or bad weather. The estimated loss in traffic safety based on the large-scale transport models may differ significantly from the true value depending on the scenario assumptions (e.g. the proportion of rainy days next year).

Although weather is absent in policy evaluations based on CBA, local policies from individual studies (mostly targeting cycling mode) often take weather into account. For instance, Thomas et al. (2013) pointed out that the effect of policy interventions on cycling demand is difficult to measure, not least because of difficulties in controlling for changing context variables, such as weather conditions. Ahmed et al. (2013) mentioned that investments in developing end of trip facilities would be beneficial if the aim is to increase commuter cycling, particularly for female cyclists who were found to be more deterred by unfavourable weather conditions than males. Gebhart and Noland (2014) argued that the design of bike-share systems can benefit from understanding users' cycling behaviours under various weather conditions. Helbich et al. (2014) suggested that adjacent, more compact urban morphologies have the potential to alleviate undesirable weather exposures and could enhance environmentally friendly and more sustainable transport modes. Presumably, bicycle demand clearly exhibits a variation pattern with weather, which makes bicycle planning more likely to incorporate weather elements.

Discussion and conclusion

There is no doubt that weather significantly influences transport systems in terms of both demand and supply. As transport policies aim at building up economically, socially and environmentally sustainable transport systems, understanding the influence of weather on individual travel is necessary for promoting active transport modes, such as walking and cycling. With increasing contributions from the fields of travel behaviour, transportation engineering, psychology, economics and meteorology, a general picture has emerged of how weather affects our transport system. Given the fact that future weather will become more extreme, understanding how weather influences travel behaviour is vital for planners and policy-makers to achieve a sustainable transport system in a warmer and more extreme future climate. This paper has summarised and assessed these contributions from the individual behaviour and policy analysis points of view. From an individual behaviour point of view, despite extensive empirical evidence concerning the correlations between weather variables and travel patterns, there is still a lack of theoretical understanding on how weather is perceived by travellers and affects their travel decisions, together with other traditional determinants such as travel time and cost. From a policy analysis point of view, despite increasing evidence on the impacts of weather on traffic volume, bicycle flow and transit ridership, large-scale transport models, which serve as the main tool of national policy evaluations, rarely consider weather.

From an individual behaviour point of view, researchers seek to improve the accuracy of estimated weather effects. Spatially, various mapping techniques have been used to connect weather data from sparse weather stations to each individual trip (Chen & Mahmassani, 2015; Jaroszweski & McNamara, 2014). Spatial-dependent models were used to take into account the spatial heterogeneity of weather effects (Helbich et al., 2014). Temporally, continuously measured meteorological variables have become increasingly available to measure the actual weather at the departure/arrival locations (Chen & Clifton, 2011; Singhal et al., 2014). The impacts of weather on day-to-day variations in travel patterns have been analysed to consider not only instantaneous weather effects but also weather effects on dynamic day-to-day travel patterns (Liu et al., 2015c). However, there is still no consensus on how weather is incorporated into travel decision processes, as travellers may adapt their travel patterns according to the weather forecast, weather prevailing at departure, or weather at the destination, depending on the nature of the trip (Cools & Creemers, 2013). More fundamentally, several psychologists (Thorsson et al., 2007, 2011) have pointed out that weather should be evaluated as a perception because essentially it is a perceived feeling rather than an objective measure. However, so far, relevant empirical evidence is only available on activity participation (e.g. pedestrian density in open squares, Lin, 2009; Thorsson et al., 2007). More relevant empirical evidence on travel behaviour is needed.

From a policy analysis point of view, there is a gap between empirical evidence of traffic flow/travel behaviour studies and current practices of CBA that do not consider the effects of weather. This paper has summarised several potential issues that can be improved regarding including weather in large-scale transport models. First, it is difficult to estimate generic weather parameters in large-scale demand models. Second, traffic assignment packages could use different traffic speed–flow–density relationships according to weather conditions. Third, there are uncertainties surrounding scenario assumptions regarding future weather and climate (Collins et al., 2013), making these difficult to represent in transport models.

These uncertainties could lead to an over/underestimation of CBA results through complex mechanisms. Ignoring weather impacts in the CBA process could have several policy implications. Given the fact that the future climate will be warmer, and future weather will be more extreme, the cost of certain transport projects may be underestimated, while the benefits may be overestimated. Liu et al. (2016) showed that, if weather elements are ignored, transport models' assessments of future passenger transport CO_2 emissions may be considerably underestimated. External costs of CO_2 emissions, underestimated by CBAs, would lead to projects with considerable environmental impacts being selected.

Several potential research directions may be identified. First, evidence is needed on stated and revealed preferences regarding how individuals incorporate weather information when making travel decisions. The decision-making mechanism may differ according to various attributes such as trip purpose, suggesting different criteria for different trip purposes and socio-demographics. Deterministic mapping and probabilistic mapping (e.g. latent class modelling) can both be potential alternatives. Second, understanding the spatial and temporal variations of the impacts of weather is vital for policy evaluation. Given that local weather and infrastructure may form a particular micro-meteorological environment which is perceived by individuals living close to the particular area, spatial variation is expected between urban and rural areas, and coastal and inner land areas. Weather should also be evaluated in a day-to-day travel pattern dynamic context, as weather is known to strongly affect leisure activity which exhibits a clear dynamic nature. Third, weather perception enables the "empirical weather–travel pattern relationship" to be enriched by behavioural theory; for example, prospect theory. Therefore, further studies in this direction can help to explain the spatial and temporal variations of the "empirical weather–travel pattern relationship". Fourth, more studies are needed to enable transportation engineers and economists to consider weather impacts and uncertainty in terms of CBA, given the existence of considerable empirical evidence of the impacts of weather. Correspondingly, more studies are required in data collection, scenario assumption, transport models and effect models, and a general framework is needed to guide those improvements.

Finally, it is worth mentioning that weather may affect travel from a much wider perspective. For instance, various modern technologies, such as autonomous cars, can change the picture of current transport systems, but autonomous cars must also be able to cope with adverse weather. The travel equity issue also tends to be influenced by weather, as active transport users are weather-exposed; ageing or disabled travellers may find themselves less able to cope with adverse weather conditions than young and healthy travellers. Better weather information provision and infrastructures prepared for adverse weather can better protect pedestrians and cyclists and reduce accident rates in adverse weather conditions, thus providing wider social and economic benefits.

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