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The Impact of Weather Conditions on Mode Choice in Different Spatial Areas

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Abstract: This article investigates if the impact of weather conditions on mode choice (walking, riding a bike, driving a car, and using public transport) differs across spatial areas. For this purpose, a survey-based data set with more than 500,000 trips in Germany was enriched with weather conditions prevailing at the closest weather station to the point of departure at the moment of the start of the trip. In addition, the points of departure of each trip were classified into seven different spatial areas. The analysis relied on separate multinomial logit models carried out for each spatial area with mode choice as the dependent variable. The independent variables consisted of non-weather-related factors such as sex, age, car availability, level of education, etc., and various weather-related variables such as air temperature, amount of precipitation, and wind speed. The results show that weather conditions have a rather marginal impact on mode choice, with the exception of riding a bike, which constitutes the mode of transport that is most affected by weather conditions in all spatial areas. However, the impacts tend to be smaller in densely populated urban metropolises than in peripheral, rural areas. In particular, precipitation and wind speed do not appear to affect cyclists in metropolitan areas as much as in peripheral, rural regions.

Keywords: weather impact; mode choice; spatial areas

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1. Introduction

Various scholars have demonstrated the importance of the effect of weather conditions on people's mobility behaviour in the past two decades [1,2]. In general, active modes such as walking and cycling appear to be more sensitive to weather conditions than travelling by car or public transport [3]. In fact, most studies found bicycle usage to be most affected by weather conditions, with temperature having a positive impact, while wind speed and rain negatively affected cycling [4–7]. The impacts of weather conditions on public transport are less clear, with some studies showing a positive impact of temperature on bus ridership [8], while others found that heat negatively affects bus usage [9], and others pointed out the importance of ensuring the availability of car sharing systems in bad weather conditions [10]. Consequently, the impacts of weather on mode choice on the whole are larger in places with a relatively high share of active modes in the modal split [11].

Almost all of this research focuses on urban agglomerations such as the city of Melbourne [5], the city of Washington [4], the city of London [7], the cities of Munich and Berlin in Germany (Schmöller et al. 2015), the city of Brisbane in Australia [12], the area of Randstad in the Netherlands [13], greater Rotterdam [3], or the cities of Utrecht, Stavanger, Oslo, and Stockholm [11]. While some studies distinguished different areas within a city [14,15], only one [16] investigated the impact of weather conditions in different regions of a country. They found that cycling and walking in spring and autumn are more affected by temperature variations in northern Sweden than in central and southern Sweden [16]. Against this background, Dragana, Ivan, Vladimir and Jadranka [2], who conducted an extensive literature review of investigations of the impacts of weather conditions on travel demand, also concluded that future studies should address the impact of weather conditions on a detailed temporal and spatial level.

Hence, very little is known about the potentially different impacts of weather conditions on mobility behaviour in the suburban and rural parts of a country. However, mobility behaviour can differ considerably between urban and rural areas of a country due to, among other aspects, differences in infrastructures, the availability of public transport, or rates of car ownership. In Germany, for instance, 42% of the households in large metropolises do not have a car, while in small cities and villages in rural regions, only 10% of the households do not own a car [17]. Therefore, understanding how people in different spatial areas adapt their mobility behaviour to weather conditions is important for improving transport demand models and infrastructure planning and for the development of mitigation and adaption strategies to climate change, which will lead to different future weather conditions.

Against this background, the main purpose of this paper is to shed light on how weather conditions influence mobility behaviour in different spatial areas of a country. For this purpose, the grid-cell-based data set of the Mobility in Germany survey 2017 was used. The grid cells were classified into seven different spatial areas and enriched with data from the nearest weather station of the German Weather Service. Separate multinomial logit models were run for each spatial area to determine the specific impacts of weather conditions on mode choice.

The remainder of the paper is structured as follows: After this brief introduction, the process of data preparation and the resulting data set are explained in the Materials and Methods section. Subsequently, the results of the descriptive analyses and the multinomial logit models are presented in the Results section. Finally, the most important conclusions that can be drawn on the basis of the empirical results are outlined in the Conclusions and Discussion section.

2. Materials and Methods

First, the trip data set and the spatial area categories used in this analysis are described in more detail. Subsequently, it is explained how the trip data set was enriched by weather conditions. Finally, it is outlined how the statistical approach of multinomial logit models was applied for mode choice modelling in this paper.

2.1. Mobility in Germany 2017

This paper deployed the so-called B3 local data set of the survey Mobility in Germany 2017 CfV [18]. The main objective of the survey was to capture people's mobility behaviour on an average day in Germany. For this purpose, a specific sample design was developed so that the survey participants were representative of the population of Germany in terms of age and sex as well as federal state and spatial area of the place of residence. To correct minor over- or under-representation, the data set contains specific person and trip weights. Furthermore, the participants were assigned different days of the week in different months and seasons of the year to complete their travel diaries. Hence, travel diaries were reported for different days from May 2016 to September 2017 so that daily, weekly, monthly and seasonal effects should be included evenly in the data set.

Altogether, around 316,000 people from 156,000 households contributed their travel information. They were asked to report all of their trips on a specific day, including the exact addresses of the points of departure and arrival of each trip. Based on this information, trip origins and destinations were spatially located in the Inspire grid system of the European Union EC [19]. The data set available to the public does not contain the addresses provided due to privacy protection laws, but rather the grid cells of the Inspire system that were assigned to the points of departure and arrival of each trip. In addition, participants were asked various questions on their sociodemographic background, their household structure, their mobility routines, their access to public transport as well as car and bicycle ownership.

However, not all of the survey participants reported the exact addresses of their points of departure and arrival, meaning the data set does not include grid cells for all of the trips reported. The grid cells of the points of departure, however, were needed to identify the nearest weather stations. In addition, to have more trips in the final data set, it was decided that for trips not longer than 5 km, the grid cell of the point of arrival could be used if the grid cell of the point of departure was missing. The distance of 5 km was deemed as short enough for the weather conditions at the point of arrival of a trip to be the same or very similar to those at its point of departure. Hence, all trips that did not provide information on the grid cell of the point of departure and that were not longer than 5 km and provided information on the grid cell of the point of arrival were deleted and excluded from the data set.

The remaining 533,563 trips were made by 214,558 people. Unfortunately, the exclusion of many trips brought about a bias in the final data set in terms of trip length, the day of the week on which the trip was conducted, the sex and age of the participants and further variables. Therefore, an iterative proportional fitting procedure was developed to adjust the person and trip weights so that they met the actual marginal distributions of the variables of sex, age, driving license, car availability, day of the week of the trip start, month of the trip start, trip start time, trip arrival time, trip purpose, trip duration, trip length, household size, number of cars in the household, economic status of the household, spatial area type and mode of transport in the original data set.

Thus, the adjusted person and trip weights ensured that the final data set after the exclusion of many trips still represented people's mobility behaviour on an average day in Germany.

2.2. Spatial Areas

The spatial grid cells of the trip data set were classified into the seven spatial area categories of the RegioStaR7 typology that was developed by the Federal Ministry of Transport and Digital Infrastructure of Germany BMVI [20]:

1. Metropolis (urban);
2. Central city (urban);
3. City (urban);
4. Small city/village (urban);
5. Central city (rural);
6. City (rural);
7. Small city/village (rural).

Hence, this classification contains four different categories in urban regions and three categories in rural regions. It relies not only on the number of inhabitants of a certain area but also on its importance as a regional or local hub and its proximity to other hubs within Germany or in the border regions of neighbouring countries. The objective is to provide a relatively fine-grained classification with respect to the centrality of an area in an urban or a rural region (see BMVI [20] for more details).

The Federal Ministry of Transport and Digital Infrastructure also provides a publicly accessible document that lists the spatial area type for each county in Germany BMVI [20]. This information was used to link the grid cells of the trip data set to the spatial area categories. Each grid cell was assigned to the spatial area category of the county that the largest part of the grid cell belongs to.

Figure 1 illustrates the results of this classification.

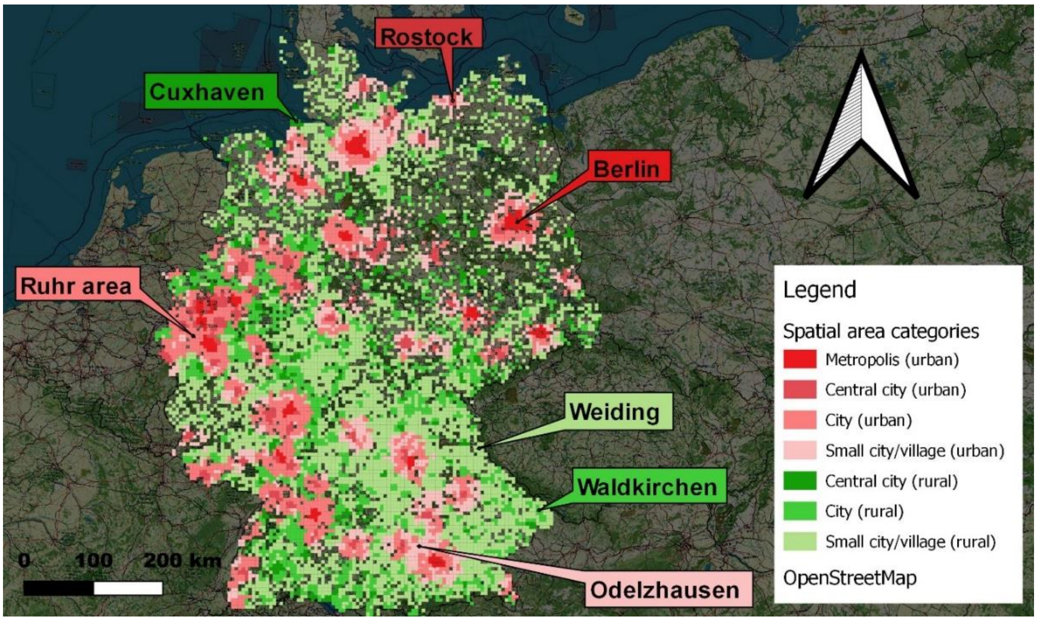

Figure 1. Spatial area categories of the points of departure. Source: CfV [18] for the trip departure locations, DWD [20] for the spatial area categories and OpenStreetMap for the map background.

The examples in Figure 1 serve to illustrate the meaning of the seven spatial area types. The Metropolis category denotes the most densely populated urban areas in Germany such as the capital city of Berlin. A central city in an urban region does not have to be a large city but rather encompasses regional hubs, such as the city of Rostock, which only has around 200,000 inhabitants. The two further categories of the urban regions refer to cities and villages that are relatively close to larger urban agglomerations, which includes many cities in the Ruhr area or also the village of Odelzhausen located right in the middle between the two cities of Augsburg and Munich.

In contrast, a central city in a rural region functions as a regional hub without proximity or fast connections to larger urban agglomerations. The city of Cuxhaven with around 50,000 inhabitants in the north of Germany serves as a prime example for this category. The two other categories of rural regions encompass rather peripheral cities and villages such as Waldkirchen and Weiding, located in the border region to the Czech Republic.

Table 1 illustrates the number of trip starts located in the different spatial areas as well as the respective modal split in the final data set. As could be expected, the share of walking, cycling and public transport usage is lower in more peripheral and rural areas, while car usage increases.

Table 1. Modal split * and absolute sum of trips per spatial area type.

Mode	Spatial Area Type						
	Urban				Rural		
	Metropolis	Central City	City	Small City/Village	Central City	City	Small City/Village
Walking	26%	24%	22%	22%	22%	22%	21%
Bicycle	14%	14%	11%	10%	13%	10%	9%
Car (passenger)	10%	14%	17%	16%	16%	17%	17%
Car (driver)	24%	33%	42%	46%	41%	46%	48%
Public Transport	26%	15%	8%	6%	8%	5%	5%
Sum of trips	98,676	84,390	141,081	32,448	30,803	75,329	70,836

* The modal split shares were calculated with the readjusted trip weights.

2.3. Weather Data

The German Weather Service provides measurements of diverse weather conditions via its open data platform DWD [21]. However, some weather conditions such as snow or black ice are only measured at rather few stations, which leads to very large distances to the grid cells of certain trip departures. Yet, the larger the distance between a grid cell and a weather station, the higher the uncertainty that the weather conditions measured at the station accurately reflect the weather conditions at the point where the trip began. Furthermore, some of the stations include missing values for certain days or time periods. Therefore, in order to produce a consistent data set with the maximum possible number of trips, stations with more than 20 missing days were excluded. Eventually, there remained weather stations with measurements of wind speed, air temperature and relative humidity and a maximum distance of 15.55 km to the points of the trip departures.

Figure 2 illustrates the locations of the weather stations that provided data on wind speed and air temperature.

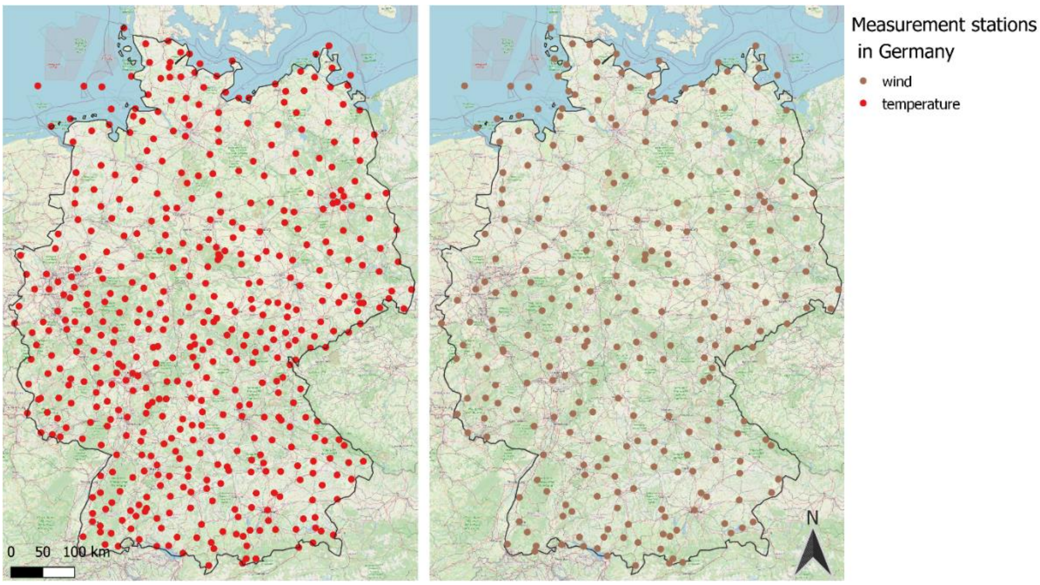

Figure 2. Locations of 493 measurement stations for temperature and 288 for wind. Source: DWD [21] for the weather station locations and OpenStreetMap for the map background.

In addition, precipitation constitutes a special case for which the German Weather Service does not only provide weather station measurements but also grid-cell-based data. In fact, the amount of precipitation measured at specific weather stations is distributed over a grid cell system covering the entire area of Germany with the help of radar technology that continuously detects the reflection of the precipitation in the atmosphere (see DWD [22] for more details). This allowed us to locate each grid cell of the trip data set via its centre in one of the grid cells of the precipitation data set so that the precipitation value of the departure hour/the departure day of each trip could be added to the trip data set.

Figure 3 shows how the grid-cell-based precipitation data look on an arbitrarily chosen day.

Hence, each trip in the data set was enriched with information on the weather conditions prevailing at the point of departure in terms of air temperature, wind speed, relative humidity and the amount of precipitation. While air temperature, wind speed and precipitation were available at both hourly and daily temporal resolution, relative humidity was only available at an hourly temporal resolution. Based on this information, further variables were calculated for both temporal resolutions in order to analyse the effect of extreme weather conditions. Table 2 provides an overview of the weather variables that were added to the trip data set.

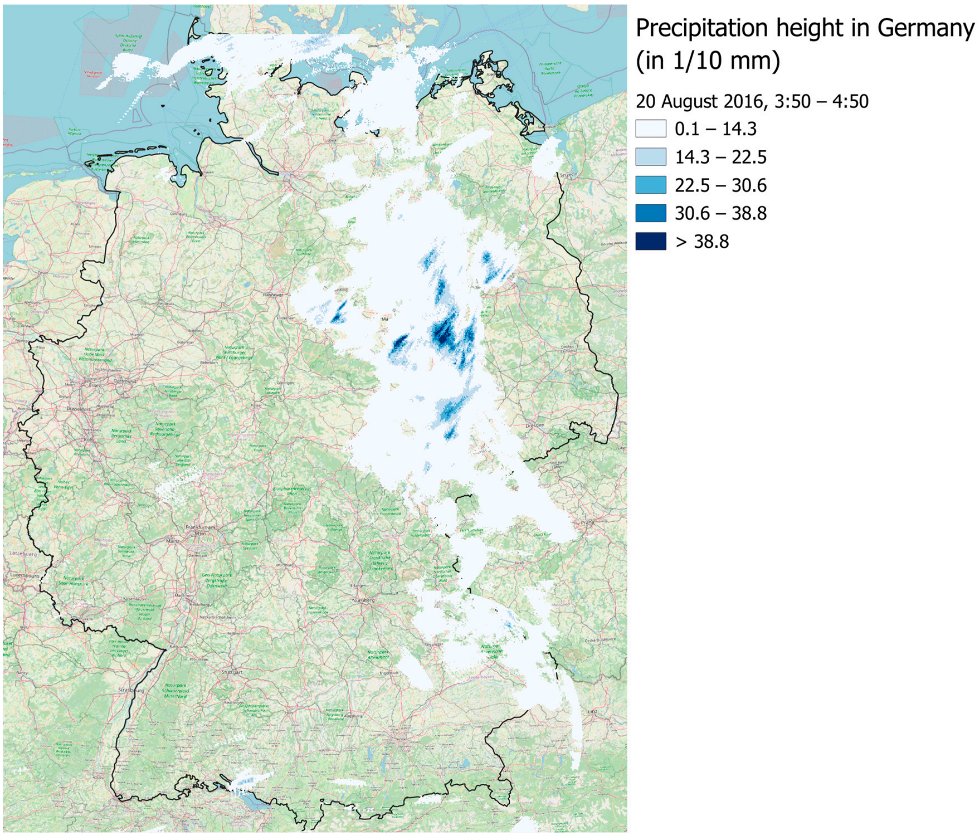

Figure 3. Illustration of precipitation data at a specific point in time. Source: DWD [21] for the precipitation data and OpenStreetMap for the map background.

In the case of air temperature, an hourly resolution refers to the maximum air temperature in the hour of the day in which the trip began. In contrast, daily resolution denotes the maximum air temperature on the day on which the trip was conducted. In a similar manner, the mean wind speed in the hour in which the trip began as well as the mean wind speed on the day on which the trip was conducted were added to the data set. Finally, the sum of precipitation in the hour in which the trip began and the overall sum of precipitation on the day on which the trip was conducted was merged to the trip data set.

Table 3 displays the average weather conditions for the different seasons of the year in our final data set.

The seasonal patterns are the same in both temporal resolutions. Air temperatures are highest in summer and lowest in winter, wind speed is highest in winter and precipitation is highest in summer and lowest in autumn.

2.4. Mode Choice Modelling

In order to analyse the impact of weather conditions on mode choice, separate multinomial logit models were estimated for each of the seven spatial area types. For these analyses, trips that were made as a car passenger (93,874) were excluded because modelling the choice situation for passenger trips properly requires specific information on household structure, etc., that the data set at hand did not contain. In addition, trips longer than 50 km (22,704) were excluded as the mode of choice situation for long-distance trips differs from the one in daily mobility behaviour, and this paper focuses on the latter.

Hence, mode choice with the categories of walking, riding a bike, driving a car and public transport constitutes the dependent variable in the multinomial logit models. Each of the models determines the choice probability (P_{iq}) as follows:

$$P_{iq} = \frac{e^{B_{ki}\ X_{miq}}}{\sum_{A_j\ \varepsilon\ A(q)} e^{B_{kj}\ X_{mjq}}} \tag{1}$$

with

- i denoting the mode choice of interest from the available alternatives A (walking, riding a bike, driving a car or using public transport);
- q referring to observation q;
- B_{ki} being a vector of alternative specific coefficients (β_{0i}, β_{1i}, β_{2i}, …, β_{Mi},);
- X_{miq} constituting a vector of the explanatory variables (x_{1iq}, x_{2iq}, …, x_{Miq}).

Table 2. Overview of weather variables.

Weather Condition	Type/Scale	Unit	Value Range	Temporal Resolution	Meaning
Temperature	Interval	°Celsius	−20.4–36.8	Hourly	Maximum air temperature in the hour of the day in which the trip began
Temperature	Interval	°Celsius	−20.3–36.8	Daily	Maximum air temperature on the day on which the trip was conducted
Wind speed	Ratio	Meter per second	0–24.1	Hourly	Mean wind speed in the hour in which the trip began
Wind speed	Ratio	Meter per second	0.1–19.5	Daily	Mean wind speed on the day on which the trip was conducted
Precipitation	Ratio	Millimetre	0–682	Hourly	Sum of precipitation in the hour in which the trip began
Precipitation	Ratio	Millimetre	0–1771	Daily	Sum of precipitation on the day on which the trip was conducted
Relative humidity	Interval	Percentage	5–100	Hourly	Mean relative humidity in the hour of the day in which the trip began
Heat	Dummy	Not applicable	0 (no), 1 (yes)	Hourly	Indicates whether the trip began in an hour in which the maximum air temperature was at least 30 °C
Heat	Dummy	Not applicable	0 (no), 1 (yes)	Daily	Indicates whether the trip was conducted on a day on which the maximum air temperature was at least 30 °C
Heat period	Dummy	Not applicable	0 (no), 1 (yes)	5-day-period	Indicates whether the trip was conducted on a day that belongs to a 5-day-period in which the maximum air temperature was at least 30 °C on each day
Temperature one day ago	Interval	°Celsius	−16.8–36.8	Daily	Maximum air temperature one day before the day on which the trip was conducted
Temperature two days ago	Interval	°Celsius	−10.8–36.8	Daily	Maximum air temperature two days before the day on which the trip was conducted
Heavy rain	Dummy	Not applicable	0 (no), 1 (yes)	Hourly	Indicates whether the trip began in an hour with at least 15 mm of precipitation
Heavy rain	Interval	Percentage	0–83	Daily	Indicates the share of hours with at least 15 mm of precipitation of the day on which the trip was conducted

Table 3. Weather conditions per season of the year.

Weather Conditions	Hourly Temporal Resolution (Mean Values per Season)				Daily Temporal Resolution (Mean Values per Season)			
	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter
Mean of maximum air temperature (in °Celsius)	15.2	20.8	7.0	3.9	18.1	23.9	9.3	6.2
Mean of mean wind speed (in m/s)	3.6	3.4	3.2	4.0	3.2	3.0	3.1	3.8
Mean of precipitation (in mm)	0.7	1.0	0.5	0.7	14.8	25.8	12.1	15.1

Table 4 presents further independent variables (X_{mig}) that, in addition to the weather conditions, were included in the models.

Table 4. Further independent variables in the mode choice models.

Name	Type/Scale
Sex	Nominal
Age group	Ordinal
Economic status	Ordinal
Education	Ordinal
Occupation status	Nominal
Car availability	Dummy
Weekend	Dummy
Trip purpose	Nominal
Trip length	Ratio
Season of the year	Nominal

The multinomial logit models were estimated with the multinom function of the R package "Feed-Forward Neural Networks and Multinomial Log-Linear Models" (version 7.3-14), better known as nnet. R version 4.0.3 was used on a Windows 10 64 bit platform.

3. Results

To shed light on the impact of weather conditions on mobility behaviour, descriptive analyses were conducted as well as multinomial logit models, with mode choice as the dependent variable. In fact, many different model specifications with weather conditions in hourly and daily temporal resolutions as well as weather conditions on interval and ratio scales or classified into specific categories were tested. All multinomial logit models achieved a good model fit, with McFadden's Pseudo R^2 ranging from 0.36 to 0.44. Indeed, the differences were so small that it was impossible to select the best model based on the model fit.

Hence, there is no clear empirical evidence showing that people adjust their mobility behaviour to the weather conditions prevailing in the specific hour in which a trip is conducted rather than to the overall weather conditions expected on that day and vice versa. However, from a theoretical point of view, we find it more plausible that more people make their mode choices for the day early in the morning or in the evening of the previous day instead of making spontaneous decisions just before the start of each trip.

Therefore, the following presentation of the results of the descriptive analyses and the multinomial logit models relies on the daily weather conditions.

3.1. Descriptive Analyses

Figure 4 illustrates the modal split per spatial area type and categorized weather conditions.

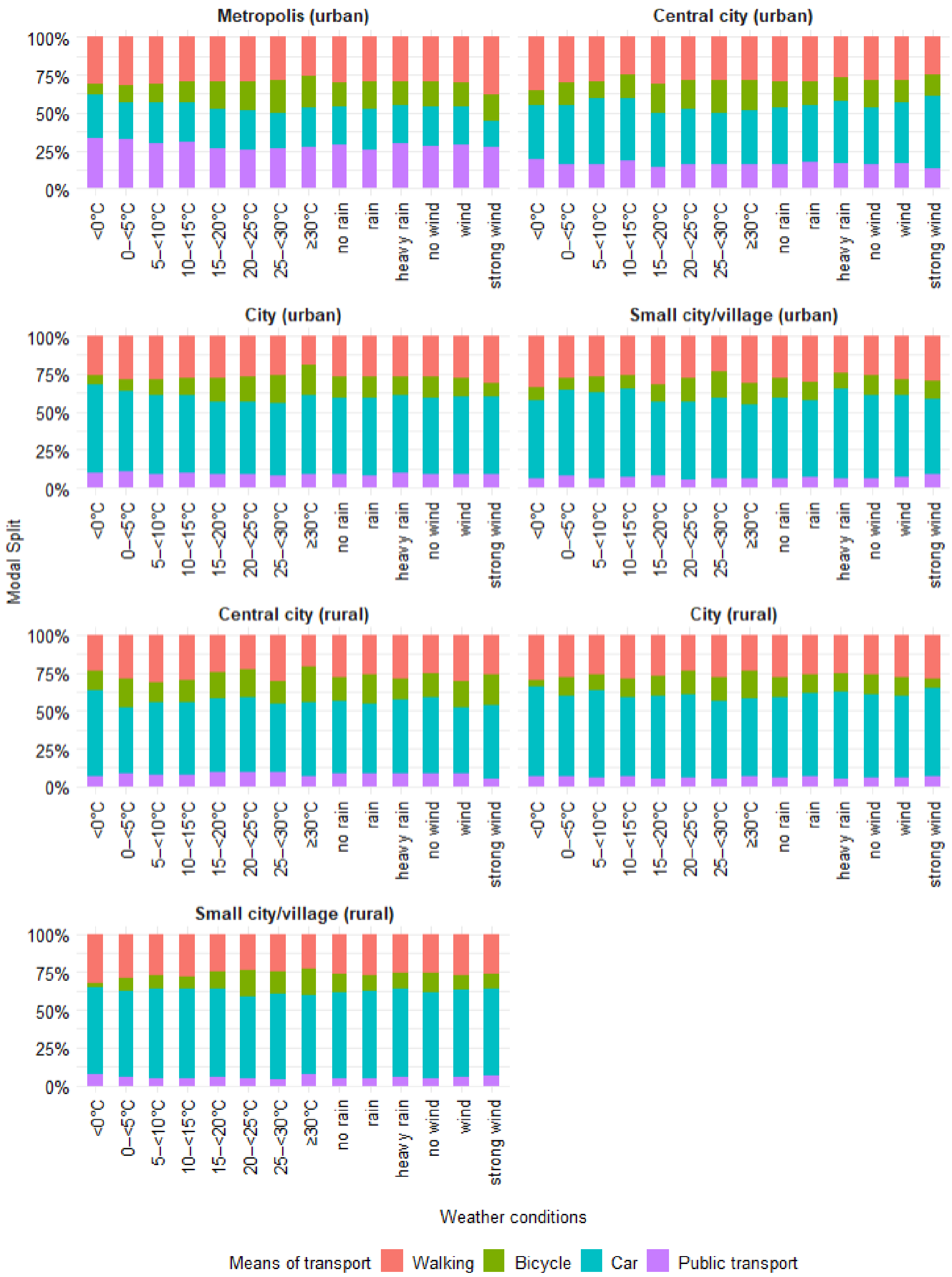

Figure 4. Modal split by spatial area type and weather conditions in daily temporal resolution. The precipitation categories refer to <1 mm (no rain), 1 mm–<15 mm (rain) and ≥15 mm (heavy rain). The wind speed categories refer to <3.4 m/s (no wind), 3.4 m/s–<8 m/s (wind) and ≥8 m/s (strong wind).

Temperature appears to have the most distinguishable effect on the modal split. Higher temperatures imply a higher share of cycling and a lower share of car usage in the modal split. This effect occurs in all spatial area types, albeit on a different level, as bicycle shares in urban and central area types are generally higher than in rural and peripheral areas even within the same categories of temperature. The effects of rain and wind speed are less distinguishable. Only in central cities in urban regions does it look like increasing rain and wind speed have a negative impact on cycling shares and a positive one on car usage.

In preparation for the estimation of the multinomial logit models, it was determined whether the different weather variables were distributed evenly over the seven spatial area types in the four seasons of the year or if there was potential bias in the data set. This was carried out via visual inspections of the plotted data. Figure 5 illustrates that the number of trips (weighted) per spatial area type was distributed quite evenly over the degrees of maximum air temperature in the different seasons.

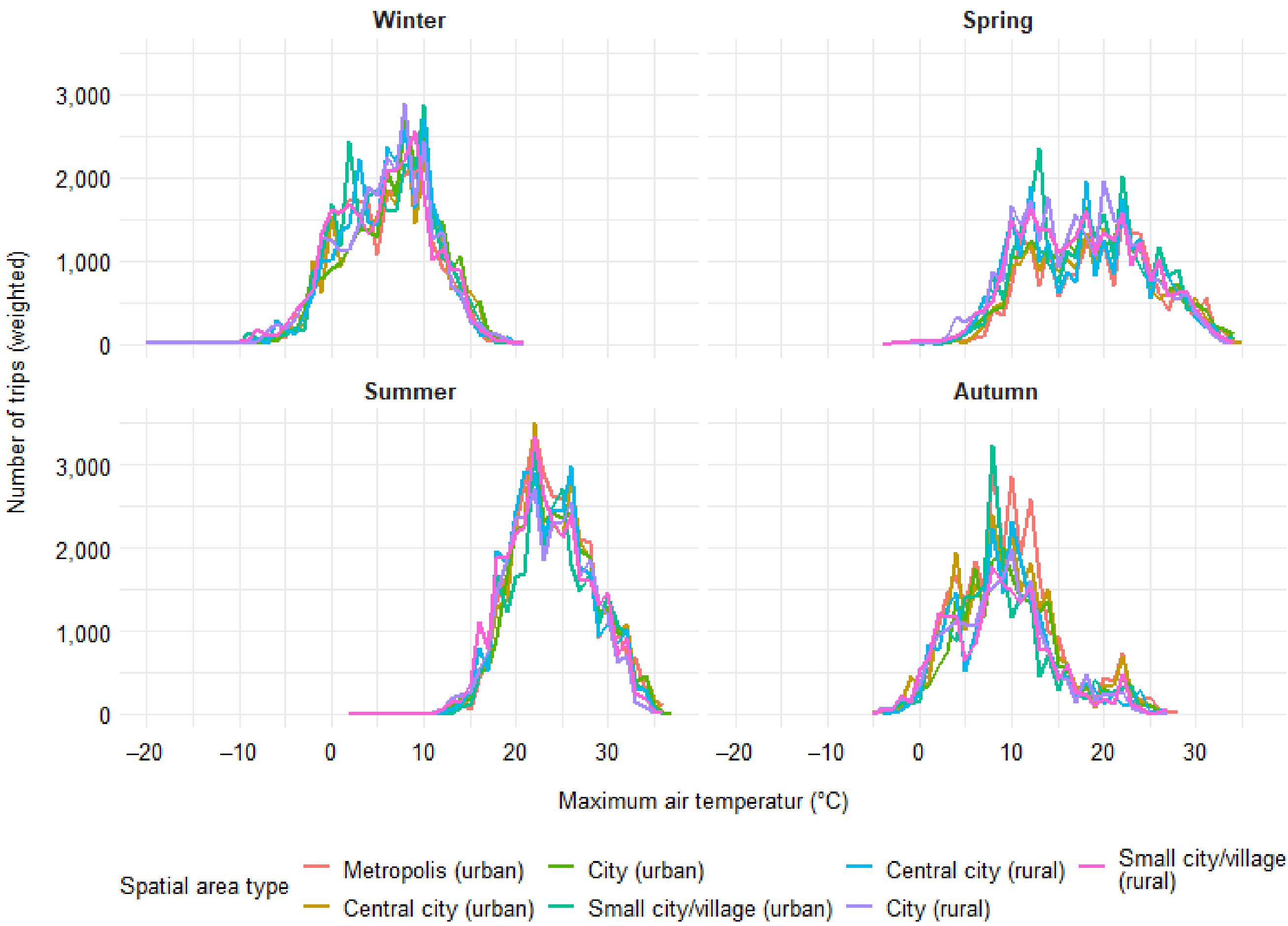

Figure 5. Number of trips (weighted) per spatial area type and temperature in daily temporal resolution and season of the year.

In contrast, Figure 6 clearly shows that there were considerably more trips on days without rain in metropolises (urban) and central cities (urban) in autumn than in spring in the data set.

For the spatial area types of city and small city/village in both urban and rural regions, however, it can be observed that there were more trips without rain in spring than in autumn.

Figure 7 outlines that the numbers of trips on days without wind, with wind and with strong wind were distributed rather evenly over all spatial area types in winter and summer.

However, there were considerably more trips on days without wind in metropolises (urban) in autumn than in summer and also clearly more trips on days with wind in metropolises (urban) in autumn than in any other regions. In contrast, there were less trips on days without wind in all spatial area types in rural regions in autumn than in spring.

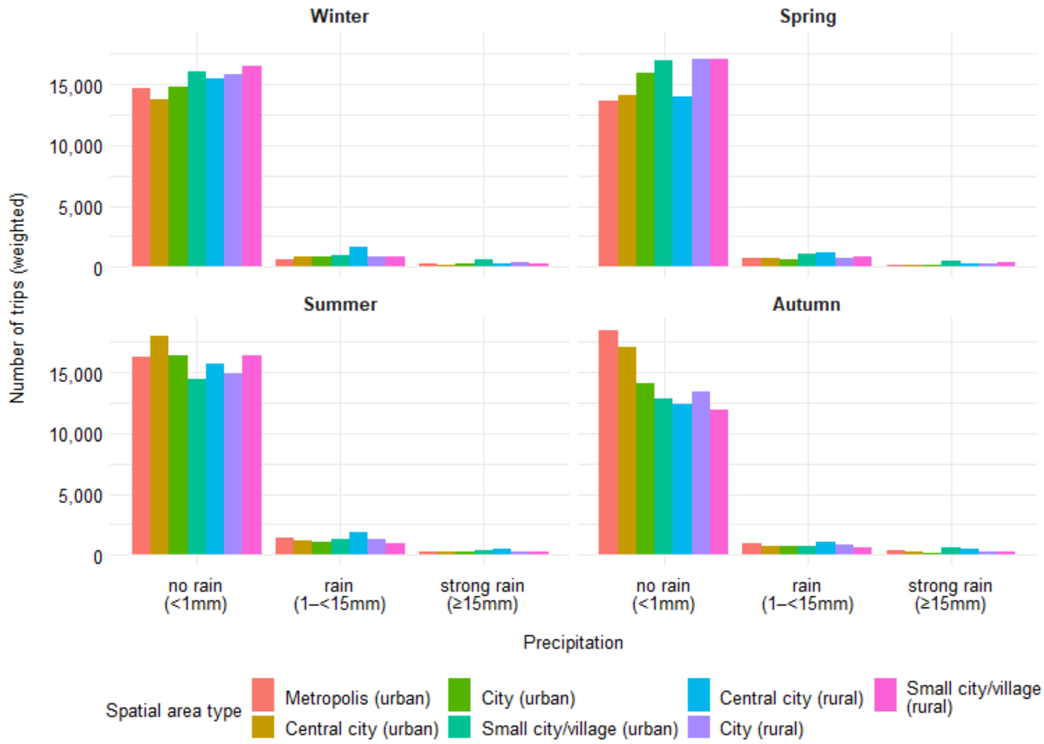

Figure 6. Number of trips (weighted) per spatial area type and precipitation category in daily temporal resolution and season of the year.

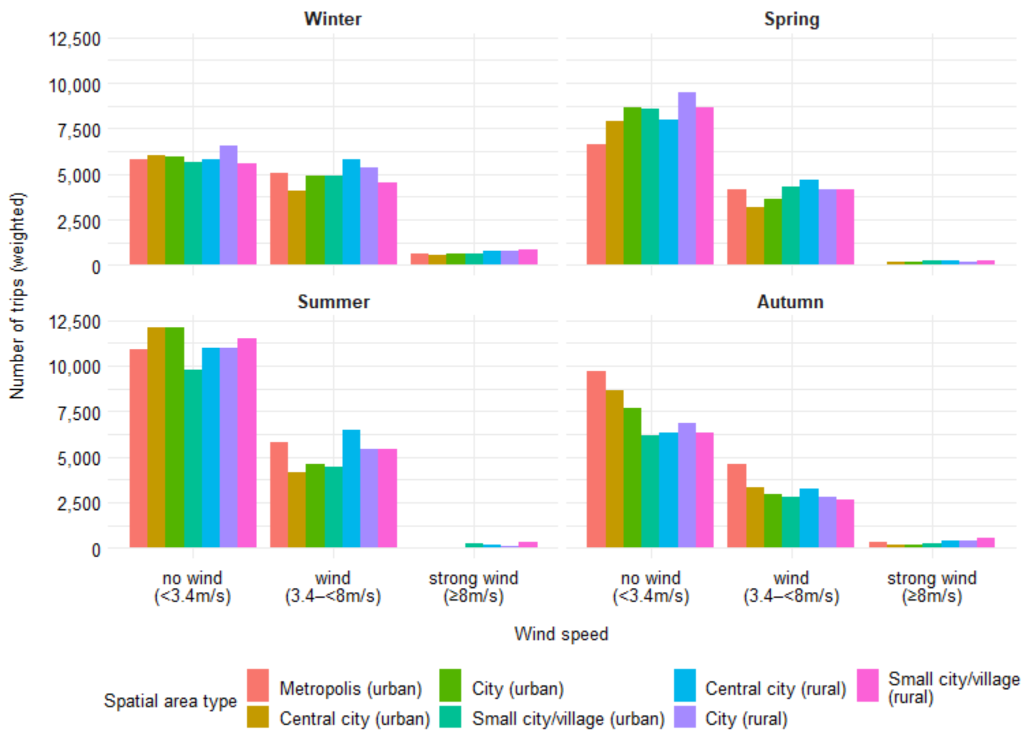

Figure 7. Number of trips (weighted) per spatial area type and wind speed category in daily temporal resolution and season of the year.

In summary, the number of trips in the different spatial area types in the data set did not distribute evenly with regard to precipitation and wind speed over the different seasons of the year. This could have influenced the results of the multinomial logit models and thus should be kept in mind.

3.2. Multinomial Logit Models

The full model results are provided in Tables A1–A4 in Appendix A and show that weather variables generally have a lower and often insignificant impact on mode choice in comparison to more usual variables in transportation research such as car availability, trip length, economic status and occupation. Still, weather variables have an impact, and as analysing this impact constitutes the focus of this paper, Table 5 only illustrates the β coefficients of the different seasons of the year and of the weather variables. As the β coefficients were calculated using maximum likelihood estimation, a two-tailed Wald Test was applied to investigate the significance of the estimated parameters.

As can be seen in Formula (1), the β coefficients of the different variables determine the choice probability of the four modes of transport distinguished. A positive β coefficient means that higher values of the variable in question increase the choice probability of the respective mode, while negative β coefficients decrease the choice probability. The further the β coefficient is away from 0, the stronger its positive or negative effect on the choice probability. Therefore, the following interpretations of the results illustrated in Table 5 focus on the β coefficients.

Over all spatial area types, no other mode has as many significant effects as riding a bicycle. Generally, spring, summer and autumn have a positive effect on bicycle usage in comparison to winter. Only in central cities in rural regions is the effect of autumn in comparison to winter negative, while in central cities in urban regions, the effects of summer and autumn are not significant, and in metropolises (urban), the effect of autumn is not significant. This could indicate that bicycle usage in densely populated urban areas is more stable over the course of a year and less affected by weather conditions than in more peripheral and rural areas. Indeed, the coefficients of the different weather condition variables also are less often significant in metropolises than in all other spatial area types. In particular, metropolises (urban) constitute the only spatial area type in which the coefficients of precipitation and wind speed on bicycle usage are not significant.

It could be suspected that this smaller impact of weather conditions on bicycle usage in metropolises (urban) relies on short trip lengths. However, further analyses of the mean length of a trip by bicycle showed rather small differences. Furthermore, the difference between the mean bicycle trip length in the different seasons of the year in metropolises (urban) was 1 km smaller than in all other spatial area types, except for central cities in urban regions (see Table A5 in the Appendix A). Hence, the additional trip length analyses provide more evidence for the conclusion that cyclists in metropolises are less affected by weather conditions than their counterparts in more peripheral and rural regions, at least with regard to precipitation and wind speed.

Except for central cities in rural regions, temperature has a positive and significant effect in all spatial area types. In contrast, precipitation has a negative effect on bicycle usage in almost all spatial area types. Only in metropolises (urban) is the effect positive but not significant, and in cities (urban), it is positive and significant. This could point to an interaction effect with the season of the year as in both spatial area types, most days with rain took place in summer. However, in both cases, the coefficient is very small, indicating negligible effects. Wind speed has a negative and significant effect on bicycle usage in all spatial area types, except for metropolises (urban) where the effect is not significant and central cities in rural regions where the effect is positive and significant. Again, this might point to an interaction effect, as most of the days with wind in central cities in rural regions took place in summer.

Table 5. Marginal effects of the weather condition variables and the seasons of the year.

Independent Variables		Dependent Variable: Mode Choice (Ref. Car Driver)					
		Walk	**Bicycle**	**Public Transp.**	**Walk**	**Bicycle**	**Public Transp.**
		Metropolis (urban)			**Central city (urban)**		
Season (ref. winter)	Spring	0.13 *	0.12 *	0.08	−0.00	0.09 *	−0.28 *
	Summer	0.20 *	0.16 *	0.12 *	0.02	0.09	−0.10
	Autumn	−0.02	−0.07	−0.06	−0.12 *	−0.03	−0.14 *
Temperature		−0.00	0.02 *	−0.01 *	0.01 *	0.02 *	0.01 *
Precipitation		0.00 *	0.00	0.00 *	−0.00	−0.01 *	−0.00
Wind speed		0.00	−0.01	−0.05 *	0.02 *	−0.07 *	−0.03 *
Temperature (one day ago)		0.02 *	−0.01	−0.02 *	−0.03 *	0.01	−0.00
Temperature (two days ago)		−0.02 *	0.01	0.02 *	0.02 *	0.01 *	0.00
Heat (ref. no)	Yes	0.24 *	−0.03	0.10	0.05	−0.49 *	−0.53 *
Heat period (ref. no)	Yes	−0.45 *	−0.39 *	−0.39 *	0.31 *	0.34 *	0.55 *
Heavy rain		−0.04 *	−0.02 *	−0.04 *	−0.02 *	0.03 *	−0.01
		City (urban)			**Small city/village (urban)**		
Season (ref. winter)	Spring	0.07	0.24 *	−0.05	0.18 *	1.03 *	0.23 *
	Summer	0.14 *	0.25 *	−0.06	0.28 *	1.20 *	−0.06 *
	Autumn	−0.07 *	0.29 *	−0.08	0.26 *	0.72 *	−0.63 *
Temperature		−0.02	0.04 *	−0.01	−0.01 *	0.01 *	−0.09 *
Precipitation		0.00 *	0.00 *	0.00 *	−0.01 *	−0.01 *	0.00
Wind speed		−0.01	−0.03 *	−0.03 *	0.03 *	−0.04 *	−0.03 *
Temperature (one day ago)		0.01 *	0.02 *	0.00	−0.01 *	0.04 *	0.02 *
Temperature (two days ago)		0.00	−0.00	0.01 *	0.02 *	−0.05 *	0.07 *
Heat (ref. no)	Yes	0.07	−0.19 *	0.13	0.37 *	−0.23 *	0.16
Heat period (ref. no)	Yes	−0.68 *	−0.34 *	−1.40 *	0.49 *	0.55 *	0.20
Heavy rain		−0.05 *	−0.08 *	−0.03 *	0.07 *	0.08 *	−0.04 *
		Central city (rural)			**City (rural)**		
Season (ref. winter)	Spring	−0.48 *	0.13 *	−0.05	0.07 *	0.42 *	0.21 *
	Summer	−0.73 *	0.26 *	−0.46 *	0.29 *	0.35 *	−0.10
	Autumn	−0.33 *	−0.11 *	−0.18 *	−0.05	0.34 *	0.05
Temperature		0.01 *	0.00	−0.09 *	0.00	0.02 *	0.01
Precipitation		−0.00 *	−0.00 *	−0.01 *	0.00	−0.01 *	−0.00 *
Wind speed		0.07 *	0.04 *	0.03 *	0.02 *	−0.06 *	−0.02 *
Temperature (one day ago)		−0.03 *	−0.04 *	0.12 *	−0.00	−0.02 *	−0.01
Temperature (two days ago)		0.04 *	0.02 *	0.00	−0.02 *	0.01 *	−0.01
Heat (ref. no)	Yes	0.11	0.73 *	−0.01	−0.16 *	−0.16 *	−0.48 *
Heat period (ref. no)	Yes	−0.64 *	−0.64 *	1.44 *	2.03 *	1.31 *	−0.15
Heavy rain		−0.01 *	0.00	−0.01	−0.02 *	0.07 *	−0.01
		Small city/village (rural)					
Season (ref. winter)	Spring	−0.09 *	0.17 *	0.19 *			
	Summer	−0.30 *	0.23 *	−0.41 *			
	Autumn	−0.13 *	0.16 *	−0.06			
Temperature		−0.01 *	0.03 *	0.03 *			
Precipitation		−0.00 *	−0.01 *	−0.00			
Wind speed		0.01	−0.11 *	0.05 *			
Temperature (one day ago)		0.01 *	−0.01	−0.03 *			
Temperature (two days ago)		0.00	0.02 *	0.01			
Heat (ref. no)	Yes	0.36 *	0.17 *	0.53 *			
Heat period (ref. no)	Yes	−1.61 *	−5.38 *	−3.69 *			
Heavy rain		0.01 *	0.04 *	−0.07 *			

* $p < 0.05$.

The temperature variables one and two days ago were included in order to account for potential lag effects of temperature. One might, for instance, expect that people use a bicycle on a day with relatively low temperatures if that day was preceded by two days with relatively warm temperatures. However, the coefficients of these variables point in different directions, indicating that there either is no lagging effect or that the variables have to be specified in another way to properly capture it. Therefore, these two variables will not be considered any further in the interpretation of the model results.

Additionally, the interpretation of the effects of the dummy variables of heat and heat period on bicycle usage is not straightforward. Except for metropolises (urban), the effects of both heat and heat periods are significant in all other spatial area types. However, in two cases, the effect of heat is positive, while that of heat periods is negative, and in three cases, the effect of heat is negative, while that of heat periods is positive. This is counterintuitive and does not make sense at first glance. It could be assumed that there is an interaction effect of heat with trip purposes or the day the of the week on which a trip is conducted. While leisure trips on weekends by bicycle might be positively affected by hot weather, heat might have a negative impact on trips to work during the week. However, further analyses did not reveal any distinct interaction effects between heat and heat periods and day of the week and trip purposes.

The effect of heavy rain on bicycle usage is significant in all spatial areas except for central cities in rural regions. However, only in metropolises and cities in urban regions is the effect negative as one would expect, while in the other spatial areas, it is positive. This counterintuitive positive effect could be the result of heavy rain occurring most often in the summer season, which generally has a positive impact on bicycle usage. However, heavy rain occurs most often in summer in all spatial area types, which indicates that there might be more complex interactions effects with other variables than just the season of the year.

Walking in comparison to car usage is positively affected by the season of spring and summer in comparison to winter in metropolises and small cities/villages in urban regions and in cities in rural regions. In these spatial areas, the active modes of walking and cycling generally seem to benefit from more pleasant weather conditions in spring and summer. In contrast, in central cities and small cities/villages in rural regions, spring, summer and autumn have a negative impact on walking in comparison to winter.

This indicates the presence of different mobility groups or mobility behaviours in the spatial areas. Indeed, further analyses of the modal split per temperature in the different spatial areas (see Figure 4) support this conclusion. In metropolises (urban), walking and cycling appear to be used by different groups of people so that the overall share of active modes increases in the warmer times of the year. However, in small cities/villages (rural), there appears to be a substitution effect between walking and cycling so that the share of cycling increases at the expense of walking when the weather becomes warmer in spring and summer. This difference is quite distinct between the most central and urban spatial area type of metropolises and the most peripheral and rural spatial area type of small cities/villages, while it gets blurred in the spatial area types in between.

The coefficients of temperature, precipitation and wind speed are in most cases lower and less often significant for walking than for cycling over all spatial area types. This suggests that weather conditions generally have a lower impact on walking than on bicycle usage, irrespective of the spatial area type. In contrast, the coefficients of heat, heat periods and heavy rain for walking are more often significant and as large as the ones for cycling or even larger. However, even within the same spatial area types, the coefficients of these variables often point in different directions, not allowing for any straightforward interpretation.

The most distinct and significant effects of the seasons of the year and the weather conditions on public transport usage in comparison to car usage can be observed in small cities/villages (urban) and in central cities (rural). In central cities in rural regions, rising temperatures lead to a decreasing usage of public transport, as do spring, summer and autumn in comparison to winter, too. Taking into account the coefficients on walking and cycling, it can be concluded that public transport usage is replaced by cycling in the warmer times of the year in central cities in rural regions. In contrast, in small cities/villages in urban regions, public transport usage seems to be replaced by both walking and cycling in summer and autumn in comparison to winter.

4. Conclusions and Discussion

The main research objective of this paper was achieved by shedding light on the impacts of weather conditions on mode choice in different spatial areas. In a nutshell, four main conclusions can be drawn from the analysis. First, weather conditions have an impact on mode choice, but a lesser one than more directly mobility-related variables such as car availability or trip length. The impact of weather conditions is generally larger on active modes of travelling such as walking and cycling than on public transport and car usage. However, the generally lower impact of weather conditions on mode choice might be due to various interaction effects with other variables or due to the way in which the weather conditions were specified in this study, which brings us to the next conclusion.

Second, the different seasons of the year appear to have a stronger impact on mode choice than daily weather conditions such as temperature, precipitation and wind speed. This indicates that people do not change their mobility behaviour from day to day if the weather changes but rather adjust their behaviour to more long-term changes in weather conditions that they expect or experience over several weeks or months. Therefore, the different seasons of the year as a proxy for more long-term changes in weather conditions were more efficient in capturing the impact on mode choice than the direct daily weather conditions in this study.

Third, weather conditions can affect mode choice in different ways in different spatial areas. Different groups of people have different mobility routines in diverse spatial areas and thus react differently to changes in weather conditions. While the shares of walking and cycling in the modal split both increase at the expense of public transport and car usage with warmer weather conditions in densely populated metropolises, there appears to be a substitution effect from walking to cycling as it gets warmer in small cities/villages in rural regions.

Fourth, bicycle usage appears to be less affected by weather conditions in densely populated urban areas such as metropolises than in all other spatial area types. In particular, precipitation and wind speed do not seem to deter cyclists in metropolises as much as in more peripheral and rural spatial areas.

This supplements the findings of [11], who found that weather conditions have the largest impact in cities with a high share of active modes such as the city of Utrecht in the Netherlands. If the spatial area types used in this paper were applied to the city of Utrecht, it would certainly not fall into the category of metropolises. Therefore, the results of this paper supplement the findings of [11] with regard to the lower impact of precipitation and wind speed on cyclists in large urban metropolises.

The results of this paper also supplement the work of [16], which showed that temperature variations have a higher impact on activity modes in northern Sweden than in central and southern Sweden in spring and autumn. In particular, the specific findings on different mobility groups in densely populated metropolises and the most rural and peripheral areas illustrate the importance of looking at the impacts of weather conditions on mobility behaviour in different spatial areas. In addition, the findings of this paper on the impact of weather conditions on cycling in densely populated metropolises support the results of [23], who found that bicycle usage is likely to increase in the city of Berlin, Germany, due to the warmer and dryer weather conditions which are expected to be brought about by climate change.

These findings are also relevant with regard to policy implications against the background of climate change. By and large, it is expected that climate change will bring about higher temperatures throughout the year in Germany, as well as higher variations in precipitation and wind speed, which is to say more days without rain and little or no wind but also more days with heavy rain and stormy wind conditions. Based on the results of this study, it can be concluded that this could lead to higher shares of the active modes in the modal split in densely populated metropolises, which should be considered in infrastructure planning and in the development of climate change adaptation strategies.

However, in more peripheral and rural areas with stronger impacts of precipitation and wind speed on mode choice and a substitution effect between walking and cycling, the implications are less clear. While more dry and windless days will have a positive impact on cycling, days with heavy rain might have a negative impact if they do not occur in summer. To avoid the danger of a decreasing share of active modes in the modal split and to possibly increase their share, improving the multimodal compatibility of public transport, walking and cycling might constitute a viable option for public transport providers.

Finally, there are some limitations of this study that highlight the need for further research. While many different specifications (hourly/daily temporal resolution, numerical/categorial, etc.) of the weather variables have been tested in various model runs, it seems like none of the specifications were good enough to adequately capture the influence of specific weather conditions such as heat or heavy rain. It could be suspected that more sophisticated statistical approaches than multinomial logit models are needed to properly capture the effect of weather conditions on mode choice. However, [11] implemented a structural equation model with trip purpose, trip chain, trip length and mode choice as the dependent variables and still did not achieve fully satisfying results.

Therefore, further research should attempt to identify better ways of operationalising weather conditions so that these can be included in transport models. Additionally, studies carried out in places with more hot days than Germany could help to shed light on the impact of heat on mode choice. The findings of this study indicate that there is a significant impact. However, it probably interacts with many other variables such as hour of the day, day of the week, trip purpose, etc. Unfortunately, the number of hot days in the data set at hand is not large enough to allow for a more fine-grained investigation of these potential interaction effects. Data from places with more hot days could help to overcome this difficulty.

In addition, further studies of the impact of weather conditions on mode choice in different spatial areas in other countries could lead to interesting results. In particular, it would be interesting to see if studies in countries with much larger metropolitan areas and more remote peripheral regions such as the USA or China produce similar results to this paper. Furthermore, studies conducted in countries near the equator could help to reveal if the impact of daily weather conditions on mobility behaviour is higher if the weather in general is characterized by less distinct seasonal variations.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Full model results for metropolises (urban) and central cities (urban).

Independent Variables		Dependent Variable: Mode Choice (Ref. Car Driver)					
		Metropolis (Urban)			**Central City (Urban)**		
		Walking	**Bicycle**	**Public Transp.**	**Walking**	**Bicycle**	**Public Transp.**
Intercept		3.08 *	2.02 *	2.75 *	2.84 *	1.92 *	1.45 *
Sex (ref. man)	Woman	0.24 *	0.19 *	0.22 *	0.36 *	0.03	0.55 *
Age (ref. 0–17)	18–29	−0.02	−1.15 *	0.09	0.12	−0.35 *	−0.07
	30–39	−0.04	−1.35 *	−0.29 *	0.06	−0.60 *	−0.22
	40–49	0.00	−1.19 *	−0.34 *	−0.21	−0.58 *	−0.05
	50–59	0.08	−1.09 *	−0.36 *	−0.12	−0.52 *	−0.10
	60–69	−0.22	−0.90 *	−0.11	0.06	−0.40 *	0.17
	70–79	0.17	−1.00 *	0.12	0.48 *	−0.09	0.49 *
	≥80	0.35 *	−0.60 *	0.22	0.86 *	−0.44 *	1.19 *
Economic status (ref. very low)	Low	−0.01	−0.05	−0.46 *	0.38 *	0.36 *	0.41 *
	Middle	0.01	−0.12 *	−0.44 *	0.27 *	0.52 *	0.31 *
	High	0.02	0.13 *	−0.44 *	0.23 *	0.61 *	0.03
	Very high	−0.24 *	0.13 *	−0.31 *	0.13 *	0.53 *	0.09
Education (ref. no school certificate)	Basic school certificate	0.05	0.74 *	0.31 *	−0.25 *	0.59 *	0.21 *
	Middle school certificate	−0.06	0.66 *	0.44 *	−0.31 *	0.44 *	0.34 *
	High school certificate	−0.07	1.24 *	0.56 *	−0.44 *	0.76 *	0.39 *
	University degree	0.13	1.54 *	0.79 *	−0.08	1.19 *	0.55 *
	Other certificate	0.56 *	1.46 *	1.20 *	−0.82 *	0.61 *	−0.30 *
Occupation status (ref. employed)	Education	0.31 *	0.04	0.63 *	0.13 *	0.58 *	1.15 *
	Housekeeping	0.44 *	0.12	0.29 *	0.06	0.00	−0.21 *
	Retired	0.46 *	0.08	0.12 *	−0.11 *	0.02	0.19 *
	Other	0.39 *	0.21 *	0.38 *	−0.09 *	0.01	0.36 *
Car availability (ref. no)	Yes	−2.76 *	−2.96 *	−3.61 *	−3.27 *	−3.70 *	−4.26 *
Weekend (ref. no)	Yes	0.42 *	0.40 *	−0.21 *	0.49 *	0.50 *	−0.10 *
Trip purpose (ref. work)	Education	1.49 *	1.52 *	0.72 *	0.58 *	0.18 *	0.00
	Shopping and other errands	−0.01	−0.87 *	−0.69 *	−0.09 *	−1.13 *	−0.76 *
	Other purpose	0.51 *	−0.31 *	−0.17 *	0.50 *	−0.58 *	−0.43 *
Trip length		−0.34 *	−0.11 *	0.01 *	−0.22 *	−0.09 *	0.03 *
Season (ref. winter)	Spring	0.13 *	0.12 *	0.08	−0.00	0.09 *	−0.28 *
	Summer	0.20 *	0.16 *	0.12 *	0.02	0.09	−0.10
	Autumn	−0.02	−0.07	−0.06	−0.12 *	−0.03	−0.14 *
Temperature		−0.00	0.02 *	−0.01 *	0.01 *	0.02 *	0.01 *
Precipitation		0.00 *	0.00	0.00 *	−0.00	−0.01 *	−0.00
Wind speed		0.00	−0.01	−0.05 *	0.02 *	−0.07 *	−0.03 *
Temperature (one day ago)		0.02 *	−0.01	−0.02 *	−0.03 *	0.01	−0.00
Temperature (two days ago)		−0.02 *	0.01	0.02 *	0.02 *	0.01 *	0.00
Heat (ref. no)	Yes	0.24 *	−0.03	0.10	0.05	−0.49 *	−0.53 *
Heat period (ref. no)	Yes	−0.45 *	−0.39 *	−0.39 *	0.31 *	0.34 *	0.55 *
Heavy rain		−0.04 *	−0.02 *	−0.04 *	−0.02 *	0.03 *	−0.01
AIC (Akaike Information Criterion)		187,404.3			175,787.2		
McFadden's Pseudo R^2		0.37			0.37		

* $p < 0.05$.

Table A2. Full model results for city (urban) and small city/village (urban).

Independent Variables		Dependent Variable: Mode Choice (Ref. Car Driver)					
		City (Urban)			Small City/Village (Urban)		
		Walking	Bicycle	Public Transp.	Walking	Bicycle	Public Transp.
Intercept		3.16 *	2.21 *	1.67 *	3.09 *	2.66 *	0.97 *
Sex (ref. man)	Woman	0.07 *	−0.24 *	−0.02	0.12 *	−0.20 *	0.04
Age (ref. 0–17)	18–29	−1.57 *	−1.94 *	−0.96 *	−3.55 *	−3.12 *	−3.51 *
	30–39	−1.45 *	−1.61 *	−0.98 *	−3.62 *	−3.01 *	−3.00 *
	40–49	−1.65 *	−1.32 *	−1.01 *	−3.65 *	−3.05 *	−4.08 *
	50–59	−1.38 *	−1.20 *	−0.77 *	−2.99 *	−2.84 *	−3.88 *
	60–69	−1.64 *	−1.01 *	−0.73 *	−3.12 *	−3.03 *	−4.20 *
	70–79	−1.66 *	−0.78 *	−0.22	−3.15 *	−2.87 *	−2.83 *
	≥80	−1.67 *	−1.41 *	−0.10	−2.52 *	−2.91 *	−2.86 *
Economic status (ref. very low)	Low	0.45 *	0.40 *	0.50 *	0.39 *	−0.09	0.86 *
	Middle	0.39 *	0.38 *	0.30 *	0.30 *	0.26 *	0.48 *
	High	0.42 *	0.68 *	0.42 *	0.17 *	0.15 *	0.32 *
	Very high	0.48 *	0.64 *	0.57 *	−0.28 *	−0.44 *	0.59 *
Education (ref. no school certificate)	Basic school certificate	0.12	−0.17	−0.25 *	1.67 *	1.61 *	1.48 *
	Middle school certificate	0.04	−0.19	−0.10	1.58 *	1.41 *	2.12 *
	High school certificate	−0.00	−0.06	0.07	1.51 *	1.74 *	2.07 *
	University degree	0.11	0.03	−0.15	1.94 *	1.77 *	2.74 *
	Other certificate	0.12	−0.67 *	0.01	2.12 *	0.97 *	2.89 *
Occupation status (ref. employed)	Education	0.06	0.56 *	1.33 *	0.51 *	0.43 *	1.16 *
	Housekeeping	0.14 *	0.41 *	0.64 *	−0.54 *	−0.36 *	−0.38 *
	Retired	0.62 *	0.38 *	0.28 *	0.09 *	0.52 *	0.10
	Other	0.44 *	0.55 *	0.90 *	−0.28 *	−0.28 *	−0.02
Car availability (ref. no)	Yes	−2.89 *	−3.19 *	−4.51 *	−2.33 *	−3.03 *	−3.10 *
Weekend (ref. no)	Yes	0.47 *	0.43 *	−0.28 *	0.63 *	0.77 *	0.14 *
Trip purpose (ref. work)	Education	1.69 *	0.56 *	0.54 *	0.76 *	0.19	1.22 *
	Shopping and other errands	0.11 *	−0.87 *	−1.05 *	−0.08 *	−0.79 *	−1.18 *
	Other purpose	0.98 *	−0.41 *	−0.76 *	1.28 *	0.03	−0.26 *
Trip length		−0.24 *	−0.09 *	0.06 *	−0.28 *	−0.11 *	0.04 *
Season (ref. winter)	Spring	0.07	0.24 *	−0.05	0.18 *	1.03 *	0.23 *
	Summer	0.14 *	0.25 *	−0.06	0.28 *	1.20 *	−0.06 *
	Autumn	−0.07 *	0.29 *	−0.08	0.26 *	0.72 *	−0.63 *
Temperature		−0.02	0.04 *	−0.01	−0.01 *	0.01 *	−0.09 *
Precipitation		0.00 *	0.00 *	0.00 *	−0.01 *	−0.01 *	0.00
Wind speed		−0.01	−0.03 *	−0.03 *	0.03 *	−0.04 *	−0.03 *
Temperature (one day ago)		0.01 *	0.02 *	0.00	−0.01 *	0.04 *	0.02 *
Temperature (two days ago)		0.00	−0.00	0.01 *	0.02 *	−0.05 *	0.07 *
Heat (ref. no)	Yes	0.07	−0.19 *	0.13	0.37 *	−0.23 *	0.16
Heat period (ref. no)	Yes	−0.68 *	−0.34 *	−1.40 *	0.49 *	0.55 *	0.20
Heavy rain		−0.05 *	−0.08 *	−0.03 *	0.07 *	0.08 *	−0.04 *
AIC (Akaike Information Criterion)		148,448.7			132,634.8		
McFadden's Pseudo R^2		0.40			0.44		

* $p < 0.05$.

Table A3. Full model results for central cities (rural) and cities (rural).

Independent Variables		**Dependent Variable: Mode Choice (Ref. Car Driver)**					
		Central City (Rural)			**City (Rural)**		
		Walking	**Bicycle**	**Public Transp.**	**Walking**	**Bicycle**	**Public Transp.**
Intercept		2.59 *	1.67 *	−0.87 *	2.98 *	2.42 *	1.90 *
Sex (ref. man)	Woman	0.41 *	−0.04	0.57 *	0.18 *	−0.15 *	0.06
Age (ref. 0–17)	18–29	−0.47 *	−0.63 *	0.07	−0.91 *	−1.07 *	0.07
	30–39	−0.10	0.01	−0.37 *	−0.77 *	−0.43 *	0.64 *
	40–49	−0.27 *	0.04	−0.02	−0.55 *	−0.36 *	0.08
	50–59	−0.29 *	−0.13	0.12	−0.59 *	−0.26	0.72 *
	60–69	−0.23	0.18	−0.66 *	−0.41 *	−0.46 *	0.31
	70–79	−0.04	0.23	0.16	−0.42 *	−0.26	0.10
	≥80	0.12	0.41 *	0.22	−0.26	−0.93 *	0.11
Economic status (ref. very low)	Low	0.09 *	0.40 *	0.80 *	−0.10 *	−0.88 *	−0.42 *
	Middle	−0.09 *	0.12 *	0.40 *	−0.12 *	−0.46 *	−0.32 *
	High	−0.34 *	−0.04	0.52 *	−0.47 *	−0.55 *	−0.80 *
	Very high	−0.01	0.21 *	0.85 *	−0.12 *	−0.12	−0.99 *
Education (ref. no school certificate)	Basic school certificate	−0.48 *	0.04	0.46 *	0.10	−0.08	−0.78 *
	Middle school certificate	−0.61 *	−0.17	0.84 *	−0.01	−0.24 *	−1.13 *
	High school certificate	−0.28 *	0.30 *	0.42 *	−0.05	−0.01	−0.94 *
	University degree	−0.25 *	0.24 *	1.05 *	0.09	0.25 *	−0.71 *
	Other certificate	0.14	0.43 *	0.21	0.69 *	0.42 *	−1.19 *
Occupation status (ref. employed)	Education	−0.03	0.64 *	0.84 *	0.45 *	1.34 *	1.47 *
	Housekeeping	0.19 *	0.30 *	0.42 *	0.15 *	0.59 *	0.70 *
	Retired	0.44 *	0.19 *	0.75 *	0.32 *	0.96 *	0.70 *
	Other	0.55 *	1.09 *	0.97 *	−0.11 *	0.46 *	0.16
Car availability (ref. no)	Yes	−2.63 *	−2.72 *	−4.62 *	−3.10 *	−3.04 *	−4.64 *
Weekend (ref. no)	Yes	0.38 *	0.60 *	0.07	0.65 *	0.42 *	−0.15 *
Trip purpose (ref. work)	Education	1.44 *	1.11 *	1.68 *	0.91 *	−0.39 *	0.46 *
	Shopping and other errands	−0.09 *	−0.98 *	−0.29 *	0.21 *	−0.93 *	−0.92 *
	Other purpose	0.54 *	−0.66 *	−0.06	1.04 *	−0.48 *	−0.71 *
Trip length		−0.22 *	−0.07 *	0.04 *	−0.22 *	−0.07 *	0.05 *
Season (ref. winter)	Spring	−0.48 *	0.13 *	−0.05	0.07 *	0.42 *	0.21 *
	Summer	−0.73 *	0.26 *	−0.46 *	0.29 *	0.35 *	−0.10
	Autumn	−0.33 *	−0.11 *	−0.18 *	−0.05	0.34 *	0.05
Temperature		0.01 *	0.00	−0.09 *	0.00	0.02 *	0.01
Precipitation		−0.00 *	−0.00 *	−0.01 *	0.00	−0.01 *	−0.00 *
Wind speed		0.07 *	0.04 *	0.03 *	0.02 *	−0.06 *	−0.02 *
Temperature (one day ago)		−0.03 *	−0.04 *	0.12 *	−0.00	−0.02 *	−0.01
Temperature (two days ago)		0.04 *	0.02 *	0.00	−0.02 *	0.01 *	−0.01
Heat (ref. no)	Yes	0.11	0.73 *	−0.01	−0.16 *	−0.16 *	−0.48 *
Heat period (ref. no)	Yes	−0.64 *	−0.64 *	1.44 *	2.03 *	1.31 *	−0.15
Heavy rain		−0.01 *	0.00	−0.01	−0.02 *	0.07 *	−0.01
AIC (Akaike Information Criterion)		164,623.5			145,521.1		
McFadden's Pseudo R^2		0.36			0.39		

* $p < 0.05$.

Table A4. Full model results for small cities/villages (rural).

Independent Variables		Dependent Variable: Mode Choice (Ref. Car Driver)		
		Small City/Village (Rural)		
		Walking	Bicycle	Public Transport
Intercept		2.97 *	2.00 *	−0.41 *
Sex (ref. man)	Woman	0.38 *	−0.08 *	0.24 *
Age (ref. 0–17)	18–29	0.41 *	−0.90 *	−0.78 *
	30–39	−0.25	−0.95 *	−0.15
	40–49	−0.21	−0.60 *	−0.38
	50–59	0.15	−0.24	0.14
	60–69	0.20	−0.31	0.40 *
	70–79	0.24	−0.66 *	1.17 *
	≥80	0.39 *	−1.04 *	0.98 *
Economic status (ref. very low)	Low	−0.13 *	0.32 *	0.34 *
	Middle	0.04	0.19 *	−0.07
	High	0.01	0.16 *	0.04
	Very high	−0.20 *	0.24 *	−0.60 *
Education (ref. no school certificate)	Basic school certificate	−0.51 *	−0.40 *	0.32 *
	Middle school certificate	−0.46 *	−0.31 *	0.33 *
	High school certificate	−0.47 *	−0.45 *	0.06
	University degree	−0.21	−0.21	0.56 *
	Other certificate	−0.74 *	−0.89 *	0.70 *
Occupation status (ref. employed)	Education	−0.11	0.20 *	1.56 *
	Housekeeping	−0.01	0.19 *	0.68 *
	Retired	0.40 *	0.74 *	−0.11
	Other	0.24 *	0.13 *	0.48 *
Car availability (ref. no)	Yes	−3.33 *	−3.19 *	−4.39 *
Weekend (ref. no)	Yes	0.65 *	0.43 *	0.04
Trip purpose (ref. work)	Education	0.96 *	0.02	1.60 *
	Shopping and other errands	−0.21 *	−0.63 *	−0.72 *
	Other purpose	1.08 *	0.14 *	−0.56 *
Trip length		−0.23 *	−0.07 *	0.05 *
Season (ref. winter)	Spring	−0.09 *	0.17 *	0.19 *
	Summer	−0.30 *	0.23 *	−0.41 *
	Autumn	−0.13 *	0.16 *	−0.06
Temperature		−0.01 *	0.03 *	0.03 *
Precipitation		−0.00 *	−0.01 *	−0.00
Wind speed		0.01	−0.11 *	0.05 *
Temperature (one day ago)		0.01 *	−0.01	−0.03 *
Temperature (two days ago)		0.00	0.02 *	0.01
Heat (ref. no)	Yes	0.36 *	0.17 *	0.53 *
Heat period (ref. no)	Yes	−1.61 *	−5.38 *	−3.69 *
Heavy rain		0.01 *	0.04 *	−0.07 *
AIC (Akaike Information Criterion)		132,047.6		
McFadden’s Pseudo R^2		0.43		

* $p < 0.05$.

Table A5. Mean length (in km) of bicycle trips per spatial area type and season of the year.

Spatial Area	All Seasons	Winter	Spring	Summer	Autumn
Metropolis (urban)	4.0	3.5	4.5	4.1	3.6
Central city (urban)	4.1	3.8	4.5	4.2	3.5
City (urban)	4.4	3.8	4.9	4.5	3.6
Small city/village (urban)	5.4	4.0	5.3	6.3	5.0
Central city (rural)	4.2	3.6	4.7	4.4	2.8
City (rural)	4.8	3.8	5.2	5.1	3.7
Small city/village (rural)	5.1	4.0	5.4	5.5	3.9

References

1. Liu, C.; Susilo, Y.O.; Karlström, A. Weather variability and travel behaviour–what we know and what we do not know. *Transp. Rev.* **2017**, *37*, 715–741. [CrossRef]
2. Dragana, P.; Ivan, I.; Vladimir, Đ.; Jadranka, J. Impact of Weather Conditions on Travel Demand–The Most Common Research Methods and Applied Models. *Promet Traffic Transp.* **2020**, *32*, 711–725. [CrossRef]
3. Böcker, L.; Dijst, M.; Faber, J. Weather, transport mode choices and emotional travel experiences. *Transp. Res. Part A Policy Pract.* **2016**, *94*, 360–373. [CrossRef]
4. Gebhart, K.; Noland, R.B. The impact of weather conditions on bikeshare trips in Washington, DC. *Transportation* **2014**, *41*, 1205–1225. [CrossRef]
5. Phung, J.; Rose, G. Temporal variations in usage of Melbourne's bike paths. In Proceedings of the 30th Australasian Transport Research Forum, Melbourne, Australia, 25–27 September 2007.
6. Saneinejad, S.; Roorda, M.J.; Kennedy, C. Modelling the impact of weather conditions on active transportation travel behaviour. *Transp. Res. Part D Transp. Environ.* **2012**, *17*, 129–137. [CrossRef]
7. Wadud, Z. Cycling in a changed climate. *J. Transp. Geogr.* **2014**, *35*, 12–20. [CrossRef]
8. Arana, P.; Cabezudo, S.; Peñalba, M. Influence of weather conditions on transit ridership: A statistical study using data from Smartcards. *Transp. Res. Part A Policy Pract.* **2014**, *59*, 1–12. [CrossRef]
9. Lanza, K.; Durand, C. Heat-Moderating Effects of Bus Stop Shelters and Tree Shade on Public Transport Ridership. *Int. J. Environ. Res. Public Health* **2021**, *18*, 463. [CrossRef] [PubMed]
10. Turoń, K. Car-Sharing Systems in Smart Cities: A Review of the Most Important Issues Related to the Functioning of the Systems in Light of the Scientific Research. *Smart Cities* **2023**, *6*, 796–808. [CrossRef]
11. Böcker, L.; Uteng, T.P.; Liu, C.; Dijst, M. Weather and daily mobility in international perspective: A cross-comparison of Dutch, Norwegian and Swedish city regions. *Transp. Res. Part D Transp. Environ.* **2019**, *77*, 491–505. [CrossRef]
12. Syeed, K.; Bunker, J.; Yigitcanlar, T. Modelling and analysing effects of complex seasonality and weather on an area's daily transit ridership rate. *J. Transp. Geogr.* **2016**, *54*, 310–324. [CrossRef]
13. Böcker, L.; Prillwitz, J.; Dijst, M. Climate change impacts on mode choices and travelled distances: A comparison of present with 2050 weather conditions for the Randstad Holland. *J. Transp. Geogr.* **2013**, *28*, 176–185. [CrossRef]
14. Tao, S.; Corcoran, J.; Hickman, M.; Stimson, R. The influence of weather on local geographical patterns of bus usage. *J. Transp. Geogr.* **2016**, *54*, 66–80. [CrossRef]
15. Tao, S.; Corcoran, J.; Rowe, F.; Hickman, M. To travel or not to travel: 'Weather' is the question. Modelling the effect of local weather conditions on bus ridership. *Transp. Res. Part C Emerg. Technol.* **2018**, *86*, 147–167. [CrossRef]
16. Liu, C.; Susilo, Y.O.; Karlström, A. The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in Sweden. *Transp. Policy* **2015**, *41*, 147–158. [CrossRef]
17. Nobis, C.; Kuhnimhof, T. *Mobilität in Deutschland–MiD Ergebnisbericht*; BMDV: Berlin, Germany, 2018.
18. Clearingstelle für Verkehr. Institut für Verkehrsforschung [CfV]. Mobilität in Deutschland 2017/Zeitreihendatensatz. Available online: https://daten.clearingstelle-verkehr.de/279/ (accessed on 10 August 2021).
19. European Commission [EC]. INSPIRE KNOWLEDGE BASE. Infrastructure for Spatial Information in Europe. Available online: https://inspire.ec.europa.eu/guide-users/57732 (accessed on 19 July 2021).
20. Bundesministerium für Verkehr und Digitale Infrastruktur [BMVI]. Regionalstatistische Raumtyoplogie (RegioStaR). Available online: https://www.bmvi.de/SharedDocs/DE/Artikel/G/regionalstatistische-raumtypologie.html (accessed on 10 July 2021).
21. German Weather Service [DWD]. CDC (Climate Data Center). Available online: https://www.dwd.de/EN/climate_environment/cdc/cdc_node_en.htm (accessed on 20 July 2021).

22. German Weather Service [DWD]. Analysen Radarbasierter Stündlicher (RW) und Täglicher (SF) Niederschlagshöhen. Available online: https://www.dwd.de/DE/leistungen/radolan/radolan.html (accessed on 18 July 2021).
23. Galich, A.; Nieland, S.; Lenz, B.; Blechschmidt, J. How Would We Cycle Today If We Had the Weather of Tomorrow? An Analysis of the Impact of Climate Change on Bicycle Traffic. *Sustainability* **2021**, *13*, 10254. [CrossRef]