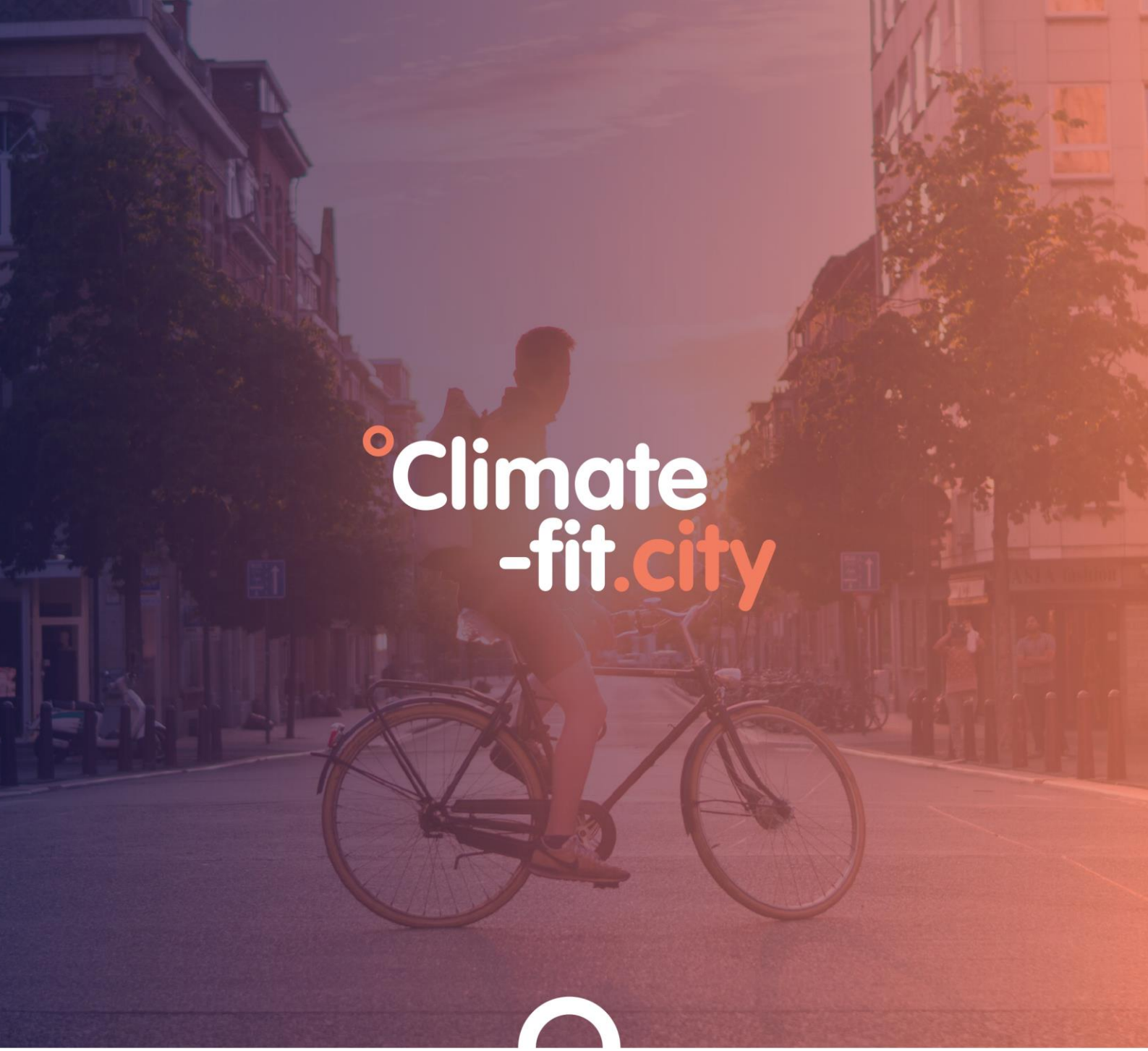

Active Mobility – Bremen

Service Report

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v.01	22/08/2019	-
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v.03	17/09/2019	Correction of a typo in the headings of Figure 18 and Figure 19.

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INTRODUCTION

This report is part of the *Climate-fit.city Active Mobility Service*, a prototype urban climate service. The service has been developed as part of the Climate-fit.city project (http://climate-fit.city/), which has received funding from the European Union's Horizon 2020 Research and Innovation Programme, under the Grant Agreement number 730004. The *Climate-fit.city Active Mobility Service* is supposed to support urban developers, traffic planners, public authorities, awareness raisers, and stakeholders in their efforts to further enhance the attractiveness of active mobility in cities, particularly of urban cycling.

Active mobility, like cycling, is an important alternative to car use, especially in cities. It improves health, saves space and is environmentally friendly. The attractiveness of urban cycling is influenced by a number of factors, including, amongst others, safety, existing infrastructure, and convenience. Also meteorological conditions affect the behaviour of cyclists. Several studies have found a non-linear relationship between temperature and cycling demand and a negative influence of rain and wind. Hence, climate change may alter the attractiveness of urban cycling by leading, for instance, to a rise in days with increased heat stress or to changes in (extreme) precipitation or wind patterns. Taking climatic aspects into account thus represents a relevant factor when trying to enhance the comfort and attractiveness of cycling.

This report shows how sensitively cyclists in Bremen respond to variations in meteorological conditions. Moreover, it provides information on Bremen's current and future climatic attractiveness for cycling as well as spatial and temporal variations of this attractiveness. Bremen's climatic attractiveness for cycling is assessed from both, a rather objective and a more subjective perspective. The latter is derived from the observed behaviour of cyclists in Bremen.

The report is structured into three parts. Part A presents the key data used by the *Active Mobility Service*. Part B shows the results of the analyses undertaken within the service. Part C provides some supplementary analyses and material as well as technical details on the methods used. Note that most of the analyses presented in this report have a focus on working days and commuter traffic.

Based on the findings presented in this report, *Bike Citizens Analytics,* a tool that visualises bicycle traffic data for urban planning[1], has been enhanced by cycling-tailored climatic information. The new climatic features in *Bike Citizens Analytics* are currently implemented as a prototype version. They enable further interactive in-depth analyses to be performed on the effects of meteorological conditions on bicycle traffic.

Note that this version of the *Climate-fit.city Active Mobility Service* is a prototype that comes with a few limitations. Details on these limitations can be found in chapter 3 of this report.

[1] See e.g. https://www.bikecitizens.net/partner/cities/.

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PART A | DATA

1 Data on bicycle traffic

Two different sources of bicycle traffic data are used in the *Active Mobility Service*: (i) data from the permanent bicycle traffic monitoring stations of the City of Bremen and (ii) data on trips tracked by the Bike Citizens App. Data from the permanent monitoring stations are available for a longer period, resulting in more robust estimates. Data on trips tracked by the Bike Citizens App, on the other hand, allow for spatial analyses.

1.1 Bicycle traffic monitoring stations

Data from up to eight locations of permanent bicycle traffic monitoring stations – hereafter referred to as *counting stations* – are available for the period 12/11/2010 to 31/12/2018. As illustrated in Table 1, the implementation dates and, thus, the lengths of the available time series data differ according to the station. The earliest implementation date was 12/11/2010, the latest 01/06/2012. The highest available temporal resolution is 15 minutes. The data were provided by the City of Bremen. Latest figures are also publicly available[2].

Table 1: List of permanent automatic counting stations in Bremen

Name	Date of implementation	Share in total counts (%) [a)]	Share in total counts on non-workdays [a)] / Share in total counts on workdays
Langemarckstraße (east & west)	01/06/2012	13.3	0.903
Radweg Kleine Weser	18/04/2012	10.7	1.012
Graf-Moltke-Straße (east & west)	16/04/2012	7.2	1.055
Schwachhauser Ring	14/03/2012	5.0	1.347
Wachmannstraße (north & south)	24/04/2012	15.3	0.819
Hastedter Brückenstraße	23/11/2011	7.7	1.135
Osterdeich	24/11/2011	10.4	1.226
Wilhem-Kaisen-Brücke (east & west)	12/11/2010[b)]	30.4	0.960

[a)] for the period 01/01/2013-31/12/2018 (days with missing values at one or more stations are removed);
[b)] the station at the east side of the Wilhem-Kaisen-Brücke was implemented later (01/10/2011);
Data source: City of Bremen

The fourth column in Table 1 presents the proportion between the station's share in total counts on workdays and the station's share in total counts on non-workdays. This figure helps to characterize the stations with respect to leisure and commuter traffic. Values clearly above 1 suggest a comparatively high share of leisure cyclists at this station. That is, the station's share in citywide counts on non-workdays clearly exceeds the station's share in citywide counts on workdays. Although there are some stations in Bremen that

[2] https://vmz.bremen.de/radzaehlstationen/.

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gain in relative importance on non-workdays (e.g. *Schwachhauser Ring*, *Osterdeich*, and *Hastedter Brückenstraße*), there is no station with a very clear focus on leisure traffic. An overview on the locations of the counting stations is given in Figure 1.

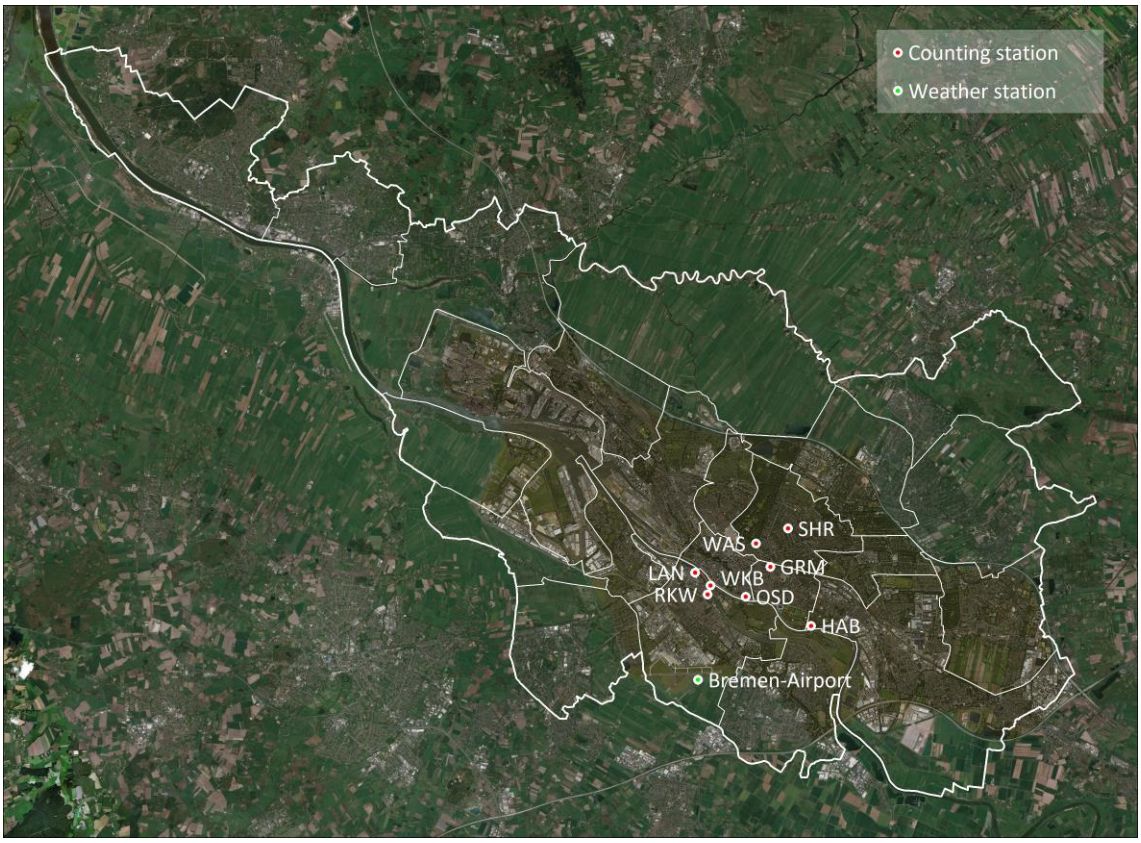

Figure 1: Location of the counting stations (and the used weather station; see chapter 2.1). Abbreviations of stations: LAN … Langemarckstraße, RKW … Radweg Kleine Weser, GRM … Graf-Moltke-Straße, SHR … Schwachhauser Ring, WAS … Wachmannstraße, HAB … Hastedter Brückenstraße, OSD … Osterdeich, WKB … Wilhem-Kaisen-Brücke. Data sources: location coordinates for counting stations provided by the City of Bremen; location coordinates for the weather station from the German Weather Service (DWD)[3]; satellite image and administrative borders from OpenStreetMap.

The plots in Figure 2 show some basic characteristics of the data measured by the counting stations for the period 2013-2018. Plot (a) illustrates the average daily counts per month, plot (b) presents the year-to-year evolution of the average daily counts, and plot (c) shows the average hourly counts per day. Each time, the shown figures refer to the sum across all counting stations listed in Table 1. All three plots differentiate between workdays and non-workdays.

As illustrated in Figure 2.a, the highest average daily counts are usually observed between May and September, with average daily counts on workdays showing a bend in July due to holidays. The fewest cyclists typically pass the counting stations in January, February and December. Within the considered period, the highest average daily counts were observed in 2018, exceeding the figures of 2013 by about 20 % (see Figure 2.b). As expected, there are typically two clear bicycle traffic peaks in the course of a workday: one

[3] ftp://opendata.dwd.de/climate_environment/CDC/help/stations_list_soil.txt (latest visit: July 2019).

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in the morning and one in the late afternoon. On non-workdays, by contrast, average hourly counts at stations peak in the early afternoon (see Figure 2.c).

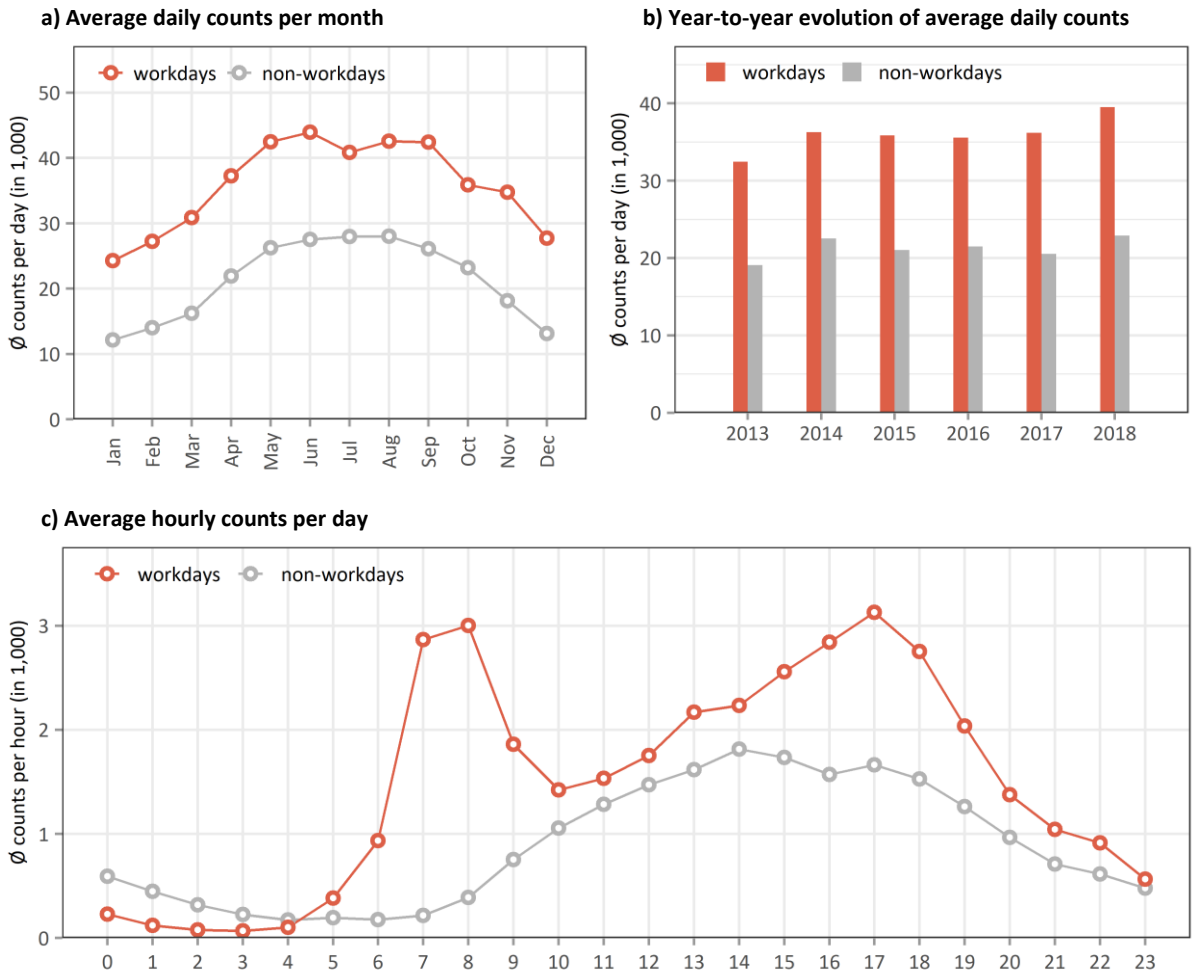

Figure 2: Some basic characteristics of the data from all counting stations for the period 2013-2018 (days with missing values at one or more stations are removed). (a) Average daily counts per month. (b) Year-to-year evolution of average counts per day. (c) Average hourly counts per day. Data source: City of Bremen.

In the *Active Mobility Service*, data from the counting stations are used to assess (i) how sensitively Bremen's daily bicycle traffic volume responds to variations in meteorological conditions (see chapters 4.1 and 7), and (ii) how cyclists in Bremen perceive the city's climatic attractiveness for cycling (see chapter 5.2).

1.2 Tracked trips (Bike Citizens App)

The second kind of data on bicycle traffic used by the *Active Mobility Service* is trips tracked by the Bike Citizens App (Figure 3.a). This data set includes the trips of people who used the Bike Citizens App with tracking mode in Bremen and its near surroundings between 01/01/2016 and 31/12/2018. Each track is identified by a track ID and consists of single points with the following information: longitude and latitude, metres in altitude, and time difference to the preceding point. In addition, information on the start and end time as well as the duration of each track is available. To preserve anonymity, tracks do not include the starting and end points.

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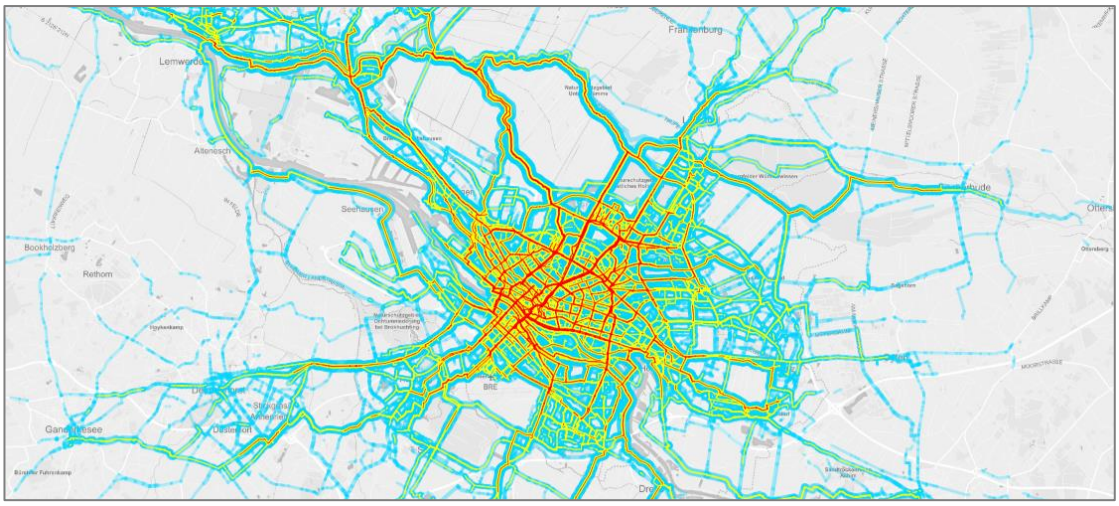
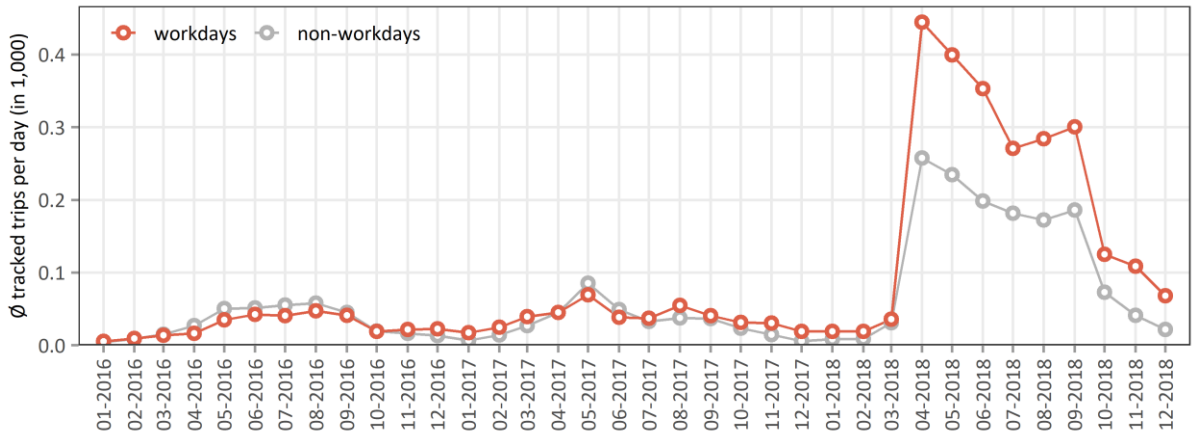
a) Illustration of the trips tracked with the Bike Citizens App



b) Month-to-month evolution of average daily tracked trips



c) Month-to-month evolution of average daily counts at stations

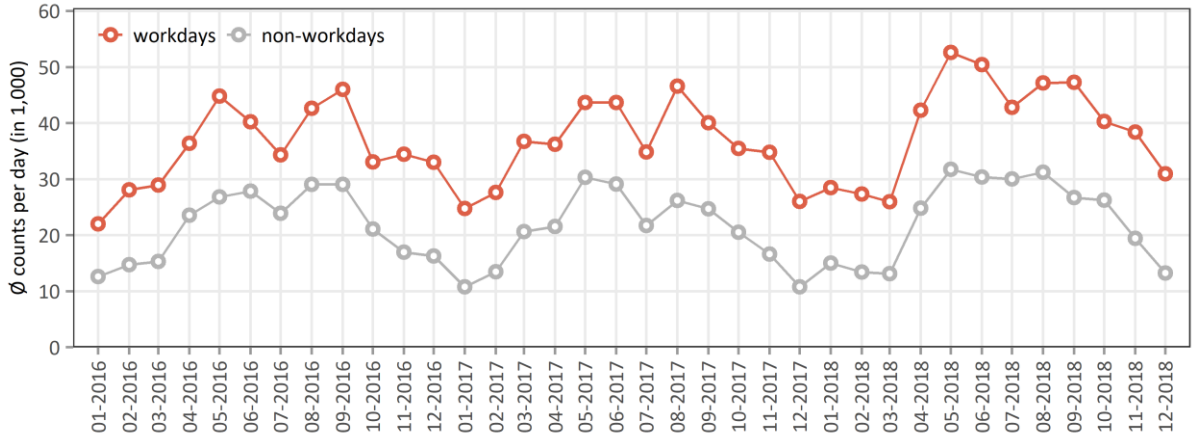


Figure 3: (a) Trips tracked with the Bike Citizens App between 01/01/2016 and 31/12/2018 (visualization by Bike Citizens Analytics: the more red, the higher the number of tracked trips) (b) Month-to-month evolution of average daily tracked trips (2016-2018). (c) Month-to-month evolution of average counts at stations (2016-2018). Data sources: Bike Citizens and City of Bremen.

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Figure 3.b shows the month-to-month evolution of the average number of daily tracked trips between 01|2016 and 12|2018. For comparison, the month-to-month evolution of the average number of daily counts at all stations is presented in Figure 3.c. There was a huge increase in the average number of daily tracked trips in April 2018 due to the start of the campaign "*Mondfahrt auf Erden*" [*moon ride on earth*] (see Figure 3.b). With this campaign, cyclists in Bremen were challenged to altogether cycle the distance to the moon (i.e. 720,000 km) within 6 months and record their trips with the Bike Citizens App. Thus, between April and September 2018 the recording-behaviour of App-users was influenced by this campaign, which needs to be accounted for in the subsequent analyses. After the end of the campaign, the number of tracked trips remained at a higher base level than before the campaign.

In the *Active Mobility Service*, tracked trips are used as an alternative source of data to quantify how sensitively Bremen's daily bicycle traffic volume responds to variations in meteorological conditions (see chapters 4.1-4.3). The great advantage of this kind of data is its spatial information, which allows assessing potential spatial differences in the sensitivity of Bremen's bicycle traffic volume towards variations in meteorological conditions. Spatial analyses, however, require large amounts of data in order to provide meaningful and robust results. Such a critical mass of tracked trips was mainly reached during and after the campaign "*Mondfahrt auf Erden*". That is why all spatial analyses based on tracked trips only refer to this period.

2 Meteorological data

2.1 Meteorological data for past time horizons

The *Active Mobility Service* uses four different meteorological variables, i.e. wet-bulb globe temperature (WBGT) as a measure of thermal comfort (see Box 1), wind speed, precipitation, and snow depth.

Box 1: Explanation on wet-bulb globe temperature

What is the wet-bulb globe temperature?

The wet-bulb globe temperature (WBGT) is a kind of apparent temperature index and represents the ISO-standard for quantifying human thermal comfort (ISO 1989). It considers the familiar ambient (dry) temperature, the cooling ability of evaporation and wind as well as the exposure to solar radiation. The index is used by various authorities to measure thermal comfort and offer guidance with respect to workload and exercises in direct sunlight. The US National Oceanic and Atmospheric Administration (NOAA), for instance, points out that WBGT values between 29.4 °C and 31.1 °C stress the body after 30 minutes of working or exercising in direct sunlight. With WBGT values between 31.1 °C and 32.2 °C, this time span drops to 20 minutes. When WBGT values are above 32.2 °C the body is stressed after 15 minutes of physical activity[4]. For details on the calculation of WBGT within Climate-fit.city services see Lauweat et al. (2018).

[4] https://www.weather.gov/tsa/wbgt

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Meteorological variables related to thermal comfort, i.e. WBGT and wind speed, are simulated by the urban boundary layer climate model *UrbClim* (De Ridder et al. 2015). They are available hourly with a 100 m spatial resolution. The *UrbClim* model is driven by ERA5 (European Centre For Medium-Range Weather Forecasts 2017), the latest global reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). For a brief explanation on reanalysis data see Box 2. Note that at the time of running the *UrbClim* simulations within the Climate-fit.city project, only a first batch of ERA5 data, covering the period 01|2000-10|2018, had been released. When complete, the ERA5 dataset will cover the period from 1950 to within 3 months of real time. As terrain input data *UrbClim* by default uses CORINE 2012 land use maps[5], EEA 2012 soil sealing maps[6] and MODIS satellite-based vegetation cover maps (Friedl et al. 2010). For further information on *UrbClim* see Lauweat et al. (2018, 2019).

Meteorological variables related to precipitation and snow depth are taken from a local measurement station. Hourly precipitation data and daily data on snow depth come from the measurement station *Bremen-Airport* of the German Meteorological Service (DWD Climate Data Center (CDC) 2018a,b, 2019a,b). All data are open source[7]. The location of the station is illustrated in Figure 1. Table 2 summarizes the meteorological data used by the *Active Mobility Service* for Bremen.

Table 2: Overview on the meteorological data used by the Active Mobility Service for Bremen

MET variable	Data source	Spatial resolution	Temporal resolution	Available period
WBGT	UrbClim-ERA5	Grid (100 m)	Hourly	2000-2018
Wind speed	UrbClim-ERA5	Grid (100 m)	Hourly	2000-2018
Precipitation	DWD	Point	Hourly	1995-2018
Snow depth	DWD	Point	Daily	1890-2018

Box 2: Explanation on reanalysis data

What are reanalysis data?

Reanalysis data are synthesized weather records. "*[They] are produced by a numerical weather prediction (NWP) model – the same type of model used in weather forecasting – driven by historical weather observations from satellites, aircraft, balloons, and surface stations. The model and data-assimilation system are 'frozen' in time to provide as consistent a record as possible; only the observational data change. With this approach it is possible to generate a time series of gridded atmospheric variables, including temperature, pressure, wind, humidity, precipitation, and others, extending back several decades"* (Brower et al. 2013).

2.2 Meteorological data for future time horizons

The *Active Mobility Service* not only provides information on Bremen's current climatic attractiveness for cycling, but also on its projected future climatic attractiveness. This future attractiveness is assessed based on the projected climate change between the reference period 1981-2010 and the future period 2036-

[5] http://land.copernicus.eu/pan-european/corine-land-cover/clc-2012
[6] https://land.copernicus.eu/pan-european/high-resolution-layers/imperviousness/status-maps/2012
[7] ftp://opendata.dwd.de/climate_environment/CDC/ (latest visit: July 2019).

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2065. Two different Representative Concentration Pathways (RCPs) are considered: RCP4.5 and RCP8.5 (see also Box 3).

Box 3: Explanation on Representative Concentration Pathways

What are Representative Concentration Pathways (RCPs)?

Various factors have to be taken into account when projecting the climate of the future, including the evolution of greenhouse gas emissions, technological developments, population growth, economic development, changes in land use, etc. In order to ensure the comparability of outputs from different modelling systems a standardized set of scenarios is used. RCPs are such a standardized set of scenarios. They define scenarios on possible future emissions and concentrations of greenhouse gases in the atmosphere. Overall, there are four representative pathways: RCP2.6, RCP4.5, RCP6 and RCP8.5. The number behind the RCP relates to the amount of radiative forcing produced by greenhouse gases in 2100 (Wayne 2013).

RCP4.5 is a moderate emission scenario with effective climate change mitigation measures. RCP8.5 represents the business-as-usual scenario with unbridled emissions. The future projections used in the *Active Mobility Service* consider all publicly available global and regional climate model outputs from the CMIP5 and EURO-CORDEX databases[8]. The figures outlined in this service report represent the mean over these considered models, i.e. the multi-model ensemble mean. For details on the methodology of downscaling climate projections and generating the future climate data used in the *Active Mobility Service* see Lauweat et al. (2018).

3 Limitations of the prototype version

The prototype version of the *Active Mobility Service* has a few limitations that need to be considered when interpreting the tables and figures in this service report. As mentioned in chapter 2.1, ERA5 reanalyses data was only available for the period 01|2000-10|2018 when running the *UrbClim* simulations for this prototype version of the *Active Mobility Service*. For reasons of consistency, all analyses based on past meteorological data are thus limited to the period 2000-2017. That is the reason, why in this prototype version the statistical evaluations of the *current climate* in chapter 5 are not based on a 30-year period as common in climate statistics, but only an 18-year period. However, the climate change signals themselves were calculated based on the comparison of two 30-year periods (see chapter 2.2 and Lauweat et al. 2018). Furthermore, no climate change projections are available for the meteorological parameter *snow depth*.

As illustrated in Figure 3 (see chapter 2.1), the campaign "*Mondschein auf Erden*" had a strong impact on trips tracked with the Bike Citizens App. The subsequent statistical analyses explicitly take into account and control for the structural break caused by this campaign. Nevertheless, it is hard to say to what extent users of the App continued with their usual cycling behaviour and just tracked more heavily and to what extent users actually changed their cycling behaviour due to the campaign. Thus, the results based on the analyses of tracked trips might be somewhat limited in their representativity.

[8] CMIP5 – Coupled Model Intercomparison Project Phase 5; https://cmip.llnl.gov/cmip5/
EURO-CORDEX – Coordinated Downscaling Experiment (European Domain); https://www.euro-cordex.net/

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PART B | CYCLING – WEATHER – CLIMATE

4 Sensitivity of the city's cyclists towards meteorological conditions

This section deals with the sensitivity of Bremen's cyclists to meteorological conditions. First, we look at the cyclists' sensitivity at an aggregate – more or less citywide – level. The effects of meteorological conditions on total bicycle traffic volume (chapter 4.1) as well as average cycling speed and trip distance (chapter 4.2) are presented. Subsequently, potential spatial differences in the sensitivity of the bicycle traffic volume towards meteorological conditions are illustrated (chapter 4.3). All analyses refer to workdays only. Selected results for non-workdays can be found in the supplements (chapter 7).

4.1 Effect of meteorological conditions on total bicycle traffic volume

The *Active Mobility Service* uses a statistical model to estimate how sensitively the city's daily bicycle traffic volume (BTV) responds to variations in different meteorological indicators (see chapter 9.1 for technical details). By considering only workdays, the model primarily focuses on commuter traffic. Saturdays, Sundays and official holidays are excluded from the analysis. Two different data sources on bicycle traffic volume are used for analysing the sensitivity towards variations in meteorological conditions: data from counting stations (see chapter 1.1) and data on trips tracked by the Bike Citizens App (see chapter 1.2). This means, the city's daily bicycle traffic volume is either measured as the daily sum of counts over all considered counting stations or as the daily sum of the number of tracked trips.

The statistical model uses a number of relevant factors to explain variations in the city's daily bicycle traffic volume (see Table 3). These include (i) socio-economic variables like the number of inhabitants, (ii) calendric variables such as school holidays, bridging days[9], weekdays and hours of daylight, and (iii) meteorological variables. Overall, the effect of four meteorological indicators is studied: mean WBGT between 06:00 and 20:00 ($WBGT_{mean}$), the maximum of mean hourly wind speeds between 06:00 and 20:00 (WS_{max}), the number of hours with precipitation between 06:00 and 20:00 (PRH), and snow depth at 07:00. As mentioned in chapter 2.1, data on precipitation and snow depth stem from a local measurement station, whereas data on WBGT and wind speed come from the urban climate model *UrbClim*. *UrbClim* output is available at a 100 m resolution. To estimate the effect of variations in meteorological conditions on total bicycle traffic volume, *cycling-weighted* citywide averages of the respective indicators are used. The weighting is done according to the spatial distribution of bicycle traffic volume measured in terms of tracked trips. That is, those grid cells frequented more heavily by cyclists get more weight when calculating the citywide average of the respective indicator.

The applied statistical model provides the sensitivity of the city's daily BTV towards the four considered meteorological indicators. For illustrating these sensitivities, we make use of response function plots. Box 4 contains a guideline on how to read and interpret these plots.

[9] Bridging days are workdays that fall between a public holiday and a typical non-workday. For example, a Friday that is preceded by a public holiday is a bridging day. Many people use them to take the day off and have a "long" weekend.

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Box 4: Interpretation guideline for response function plots

How to read a response function plot?

Throughout this chapter, we use similar-looking plots to illustrate how sensitively the city's daily bicycle traffic volume (BTV) responds to variations in particular meteorological (MET) indicators. The illustrated response functions are derived from a statistical model that uses a number of relevant factors – day of the week, hours of daylight, the city's population, school holidays, WBGT, precipitation, wind, etc. – to explain variations in the city's daily BTV. The consideration of all these factors within our statistical model allows us to "control" for them and hold them fixed when plotting the response of the city's daily bicycle traffic volume to variations in a particular MET indicator. Hence, when interpreting the illustration of a response function within this chapter, be aware that it shows the response of the city's daily BTV to variations in the considered MET indicator, while holding all other factors of the model fixed.

The black line in Figure 4 represents the response of the city's daily BTV (plotted on the vertical axis) to variations in the considered MET indicator (plotted on the horizontal axis). The steeper the slope of the line, the more sensitive is the city's daily BTV to variations in the considered MET indicator. Grey-shaded areas around the black line display the confidence interval and thus reflect the uncertainty accompanied by the estimation of the response.

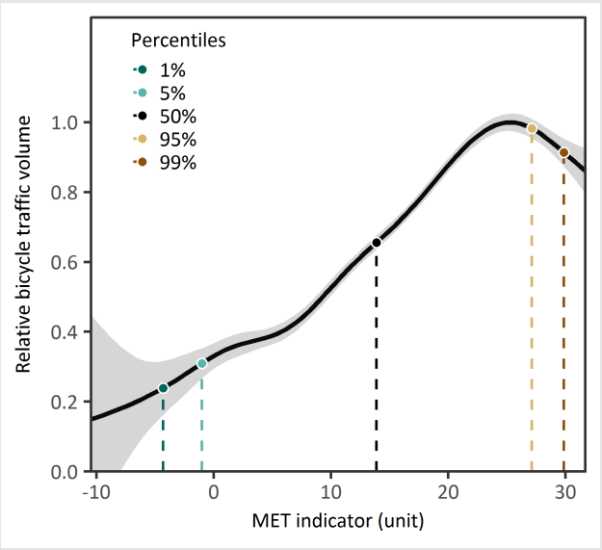

Figure 4: Example of a response function plot (design based on Marí-Dell'Olmo et al., 2018)

Note that the city's daily BTV – displayed on the vertical axis – is measured in relative terms. A value of 1 is assigned to the highest daily BTV that results from systematically varying the considered MET indicator while holding all other factors fixed. Hence, those values of the considered MET indicator that are associated with a relative BTV of 1 are perceived as *optimal* conditions for cycling by the city's cyclists. A relative BTV of, for example, 0.6 indicates a reduction by 40 % compared to the city's daily BTV under optimal conditions of the considered MET indicator.

To get an impression on how often particular values of the considered MET indicator occurred within the model calibration period, selected percentiles of the MET indicator's distribution (1 %, 5 %, 50 %, 95 %, and 99 %) are displayed in addition to the response function. The 5th percentile, for example, indicates the value of the considered MET indicator below which 5 % of all values observed within the model calibration period were found. In our example plot, 5 % of the observed values of the considered MET indicator fall below -1.2. Hence, in 5 % of days the MET indicator did not exceed -1.2, whereas in 95 % of days it exceeded this value in the calibration period. The other quantiles are to be interpreted in the same way.

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Table 3: Variables used to explain variations in the city's daily bicycle traffic volume

Type	Name	Description
Socio-economic	Population	Number of the city's inhabitants per year
Calendric	Christmas holidays	A variable indicating school holidays at Christmas
Calendric	Winter holidays	A variable indicating school holidays in January/February
Calendric	Easter holidays	A variable indicating school holidays at Easter
Calendric	Pentecost holidays	A variable indicating school holidays around Pentecost
Calendric	Summer holidays	A variable indicating school holidays in summer
Calendric	Autumn holidays	A variable indicating school holidays in autumn
Calendric	Bridging days	A variable indicating bridging days
Calendric	Weekday	A variable indicating the weekday (Monday, Tuesday, etc.)
Calendric	Day length	Hours of daylight
Meteorological	WBGT ($WBGT_{mean}$)	Mean wet-bulb globe temperature in °C between 06:00 and 20:00
Meteorological	Wind speed (WS_{max})	Maximum mean hourly wind speeds in km/h between 06:00 and 20:00
Meteorological	Precipitation hours (PRH)	Number of hours with precipitation > 0.1 mm between 06:00 and 20:00
Meteorological	Snow depth (SD)	Depth of snow in cm at 07:00

Figure 5 shows the resulting response functions when measuring the city's daily BTV in terms of counts at stations on workdays. As illustrated in plot (a), higher WBGT values result in higher values of the city's BTV. In other words, the higher the perceived temperatures the more cyclists. At the upper end of the WBGT spectrum observed in the calibration period, the curve flattens to a vertical line. That means, from a certain point on, further increases in the perceived temperature do not have a noticeable effect on the city's daily BTV anymore. According to the response function in Figure 5.a, Bremen's cyclists perceive a mean WBGT of about 25 °C during the day as optimal. In contrast, a mean WBGT of 0 °C during the day typically causes the city's BTV to drop by about 45 % compared to WBGT conditions perceived as optimal (all other factors being equal).

Note that cities with a hotter climate than Bremen often show an inverted u-shaped response function, where further increases in (perceived) temperature beyond a certain threshold cause the bicycle traffic volume to decrease again. This is for example the case in Vienna, where daily BTV decreases with rising perceived temperatures when mean WBGT values during the day exceed the optimum of about 25 °C (see Köberl and Kortschak 2019). A mean WBGT of 30 °C, for instance, leads to a reduction in Vienna's BTV of about 9 %. Cyclists in Bremen have not experienced such hot conditions yet.

The other three meteorological indicators – wind speed, precipitation and snow on the ground – all show a negative effect on the city's daily BTV, as one might expect. With respect to wind speed, the impact of the wind's cooling effect is already largely captured by WBGT (see also Box 1). Hence, what remains is the effect of an increase in air resistance in the case of headwind. Wind variability below mean hourly speeds of about 15 km/h during daytime hardly effects the city's daily BTV. Exceptionally windy days, by contrast, cause BTV to drop by more than 30 % compared to days with no strong winds (all other factors being equal). Precipitation as well shows a noticeable effect on the city's BTV. The more hours of precipitation a day, the higher the losses in daily BTV. It drops by about 10 % in case of one hour with precipitation during the day and by more than 40 % in case of an entirely rainy day, compared to a day with virtually no precipitation (all other factors being equal). Similar orders of magnitude are also found for the effects of snow on the

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ground. Compared to a winter day with no snow, BTV drops by about 16 % in case of 1 cm and by almost 40 % in case of 7 cm snow on the ground (all other factors being equal).

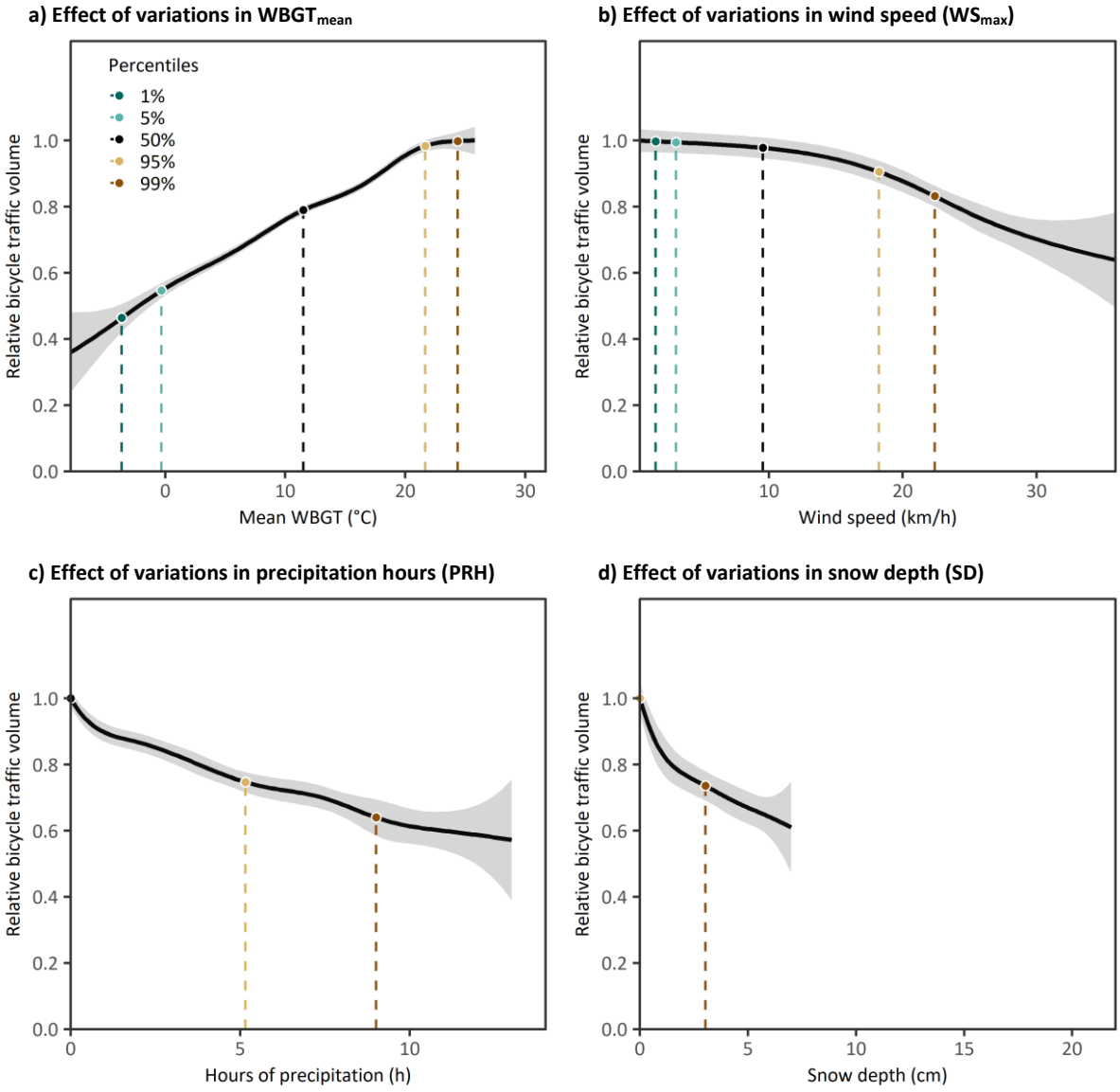

Figure 5: Effect of variations in MET indicators on the city's daily BTV, where BTV is measured in terms of counts at all counting stations. The plots refer to workdays only. Period of model calibration: 06|2012-10|2018. Plot design based on Marí-Dell'Olmo et al. (2018).

Table 4 provides a numerical illustration of the response functions shown in Figure 5. The displayed figures refer to the effects on the city's daily BTV due to deviations of the considered meteorological indicators from the values perceived as optimal by cyclists in Bremen. As already evident from the graphical illustrations, the largest effects result from the (seasonal) variations in perceived temperatures.

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Table 4: Effect of variations in MET indicators on the city's daily BTV, where BTV is measured in terms of counts at considered counting stations. Figures refer to workdays only. Period of model calibration: 06|2012-10|2018.

$WBGT_{mean}$ [°C]	Effect on BTV [compared to optimal WBGT conditions]
25	**±0 %**
20	-5 %
15	-16 %
10	-24 %
5	-35 %
0	-45 %
-5	-57 %

WS_{max} [km/h]	Effect on BTV [compared to optimal WS conditions]
0	**±0 %**
10	-2 %
15	-6 %
20	-12 %
25	-22 %
30	-30 %
35	-35 %

PRH [h]	Effect on BTV [compared to optimal PRH conditions]
0	**±0 %**
1	-10 %
5	-25 %
10	-39 %
13	-43 %

SD [cm]	Effect on BTV [compared to optimal SD conditions]
0	**±0 %**
1	-16 %
5	-33 %
7	-39 %

Additional in-depth analyses of the BTV's meteorological sensitivity reveal that the effect of precipitation varies over the course of a day. Figure 6 shows how precipitation sums of more than 1 mm within three hours affect the city's daily BTV, depending on whether taking place in the morning (06:00-09:00), at noon (11:00-14:00) or in the afternoon (16:00-19:00). Precipitation during the morning hours causes daily bicycle traffic to drop by more than 20 % compared to days with no significant precipitation amounts in the morning, at noon or in the afternoon. Precipitation at noon or in the afternoon, by contrast, only leads to a reduction of daily bicycle traffic by about 13 % or 14 %. Hence, rain in the morning clearly exceeds the effect of rain at noon or in the afternoon, with the difference being statistically significant. Note that this effect is only observed on workdays (see Figure 33 in chapter 7).

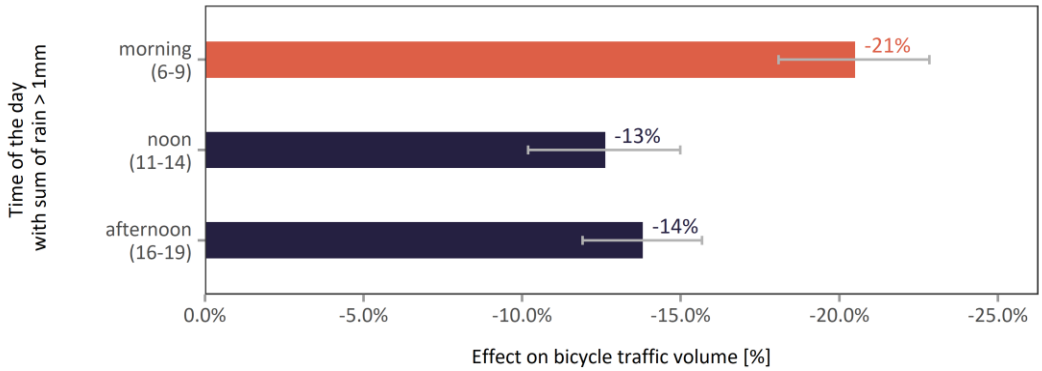

Figure 6: Effect of precipitation on the city's daily BTV, depending on the time of the day. BTV is measured in terms of counts at considered counting stations. Figures refer to workdays only. Error bars display the 95 % confidence interval and thus reflect the uncertainty accompanied by the estimation. Period of model calibration: 06|2012-10|2018.

Figure 7 shows the effect of variations in meteorological indicators on the city's daily BTV when measuring BTV in terms of the number of tracked trips[10] instead of counts at stations. Note that the period available for model calibration is shorter than in the case of counts at stations and ranges from 01|2016 to 10|2018. Compared to the period 06|2012 to 10|2018, this slightly reduces the spectrum of observed meteorological conditions and associated responses in the case of wind speed and precipitation duration. The citywide

[10] The statistical model using tracked trips as a measure of daily BTV additionally accounts for structural breaks in the data, caused for instance by the campaign "*Mondfahrt auf Erden*" (see Figure 3.b).

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daily maximum of mean hourly wind speed only reached 31 km/h instead of 36 km/h in the shorter calibration period. In addition, the highest number of precipitation hours observed in the shorter calibration period during daytime was 12 instead of 13 hours.

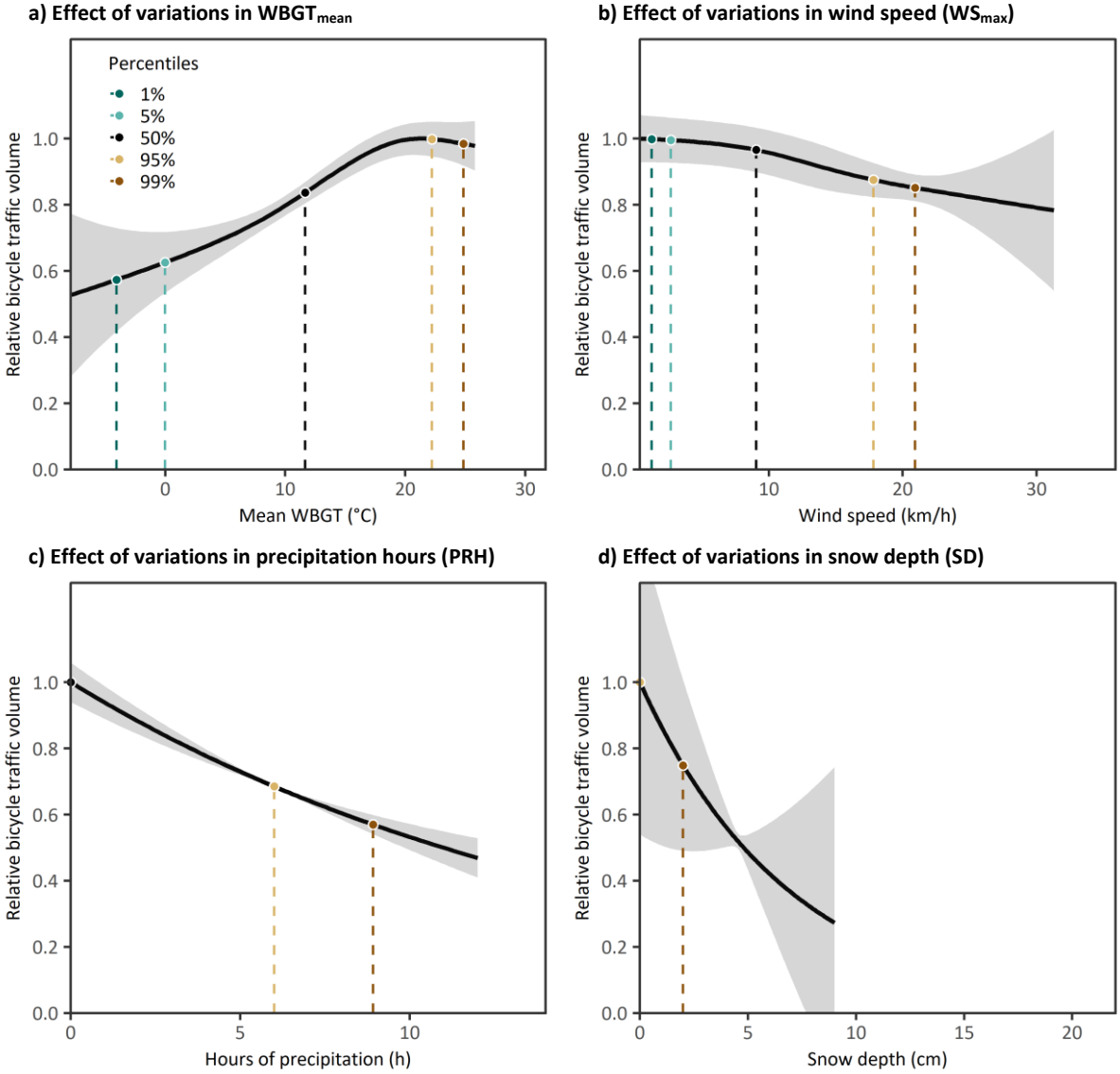

Figure 7: Effect of variations in MET indicators on the city's daily BTV, where BTV is measured in terms of the number of tracked trips. Plots refer to workdays only. Period of model calibration: 01|2016-10|2018. Plot design based on Marí-Dell'Olmo et al. (2018).

The group characteristics of cyclists tracking their trips may differ from the group characteristics of cyclists captured by the counting stations (e.g. smaller fraction of elderly people, etc.). The same holds true for the sensitivity towards meteorological conditions. To allow for direct comparison between the sensitivity of tracked trips and the sensitivity of counts at stations, Figure 8 shows the respective response functions for the calibration period 01|2016-10|2018 next to each other. As long as the grey-shaded areas around the response functions overlap, differences between the two curves are not statistically significant. As shown in the single plots of Figure 8, most differences observed between the sensitivity of tracked trips and the sensitivity of counts at stations are within the uncertainty bounds.

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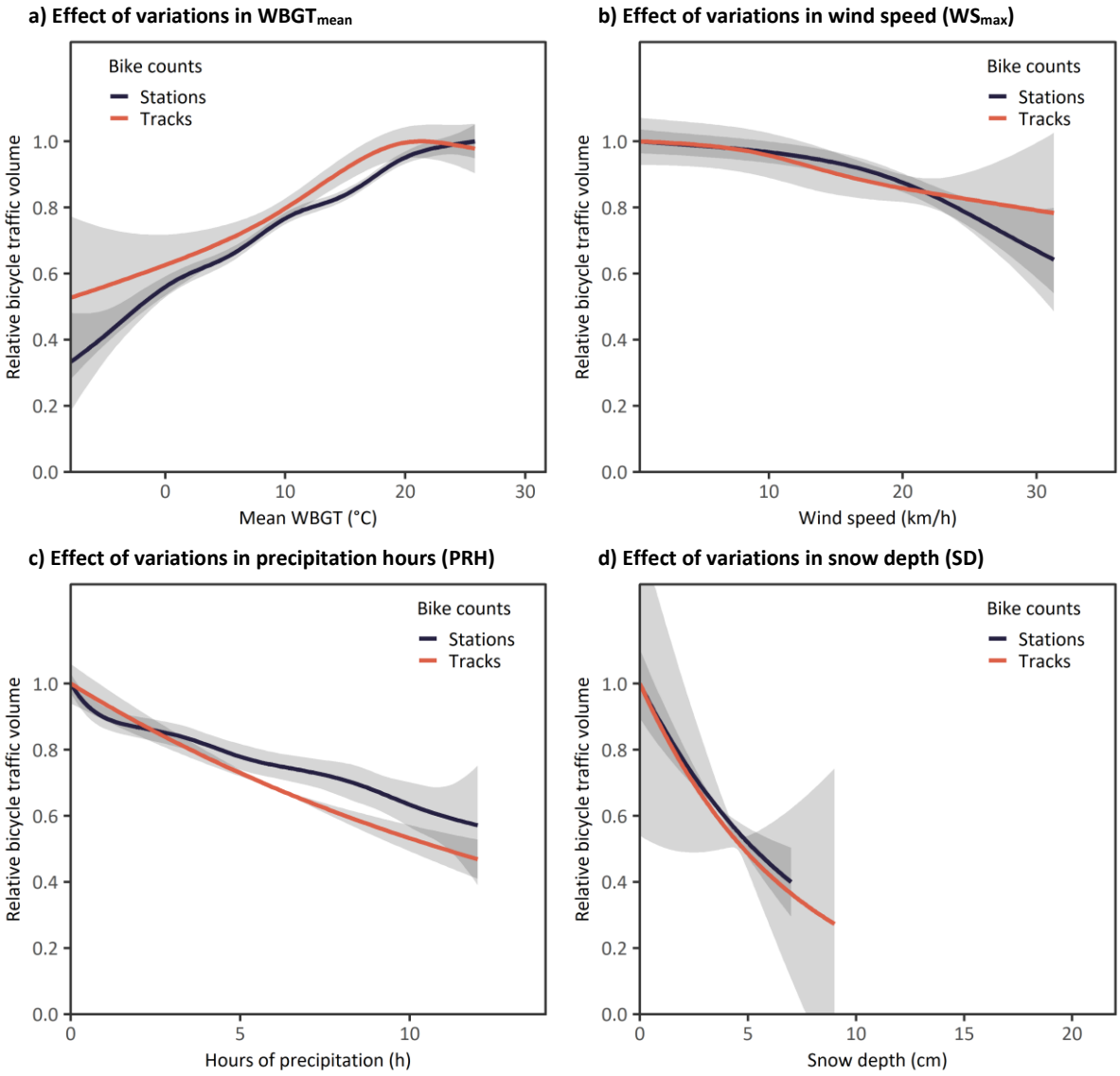

Figure 8: Effect of variations in MET indicators on the city's daily BTV, using different sources for BTV measurement: Data from measurement stations ("Stations") vs. tracked trips from Bike Citizens ("Tracks"). Plots refer to workdays only. Period of model calibration: 01|2016-10|2018. Due to some days with missing values at counting stations and their exclusion from model calibration, the response function for counts at stations towards snow depth covers a somewhat smaller spectrum than the respective response function for tracked trips.

Figure 9 once again illustrates the response functions of the city's daily BTV, with BTV being measured in terms of counts at stations. The dark-blue lines indicate the response functions that result from the long calibration period used in Figure 5, i.e. 06|2012-10|2018. The orange-red lines, by contrast, display the response functions resulting from the shorter calibration period used in Figure 8, i.e. 01|2016-10|2018. Besides the slightly reduced spectrum of observed wind speeds and precipitation durations, the only difference arises with respect to snow depth. In recent years, BTV seems to have become somewhat more sensitive towards variations in snow depth. Note, however, that this difference might be the result of an artefact. In the shortened calibration period, the number of days to analyse the response of cyclists towards snow on the ground is low (i.e. only 14 days with a non-cero snow depth). This limited amount of observations makes the estimates less robust.

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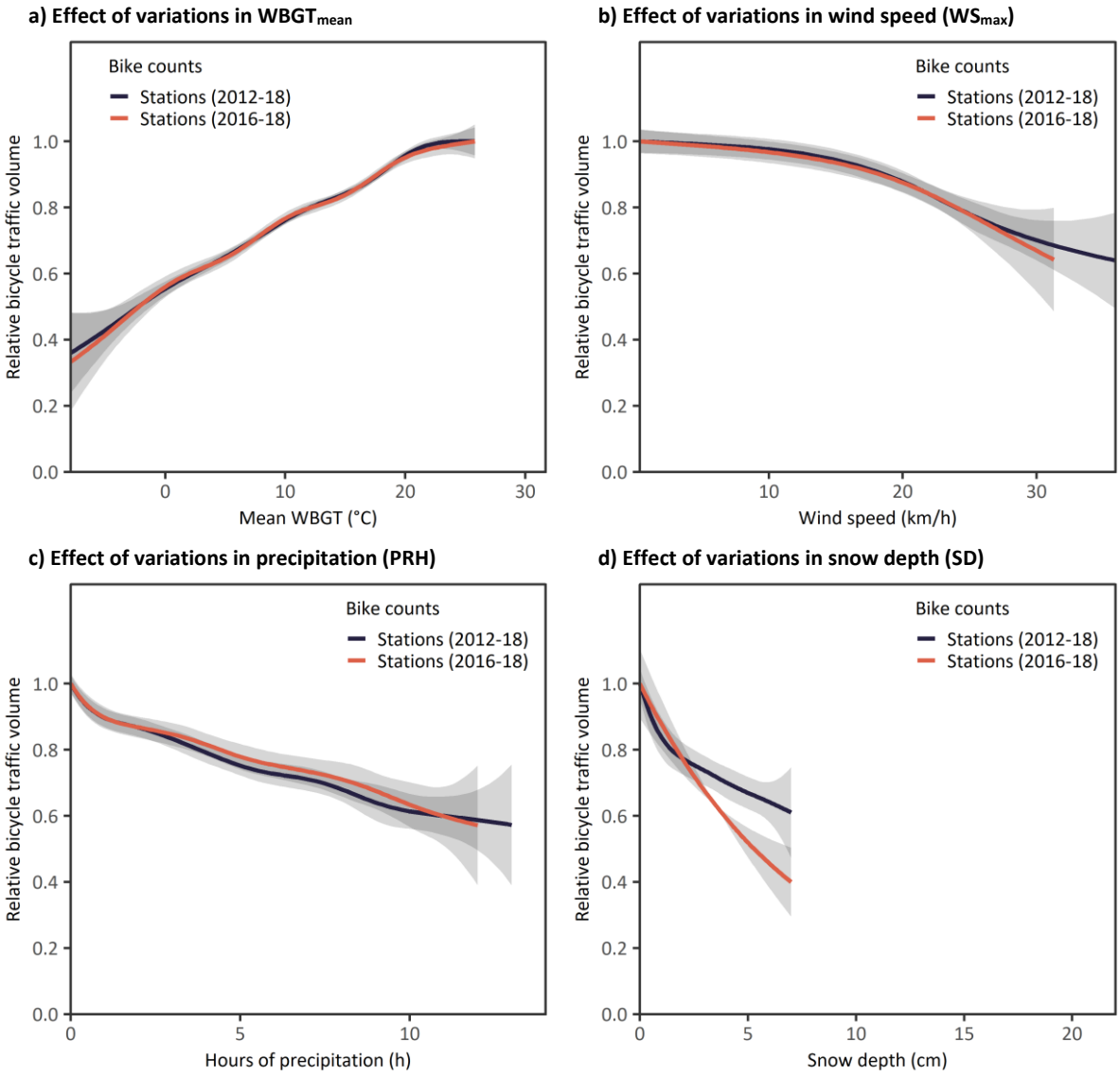

Figure 9: Effect of variations in MET indicators on the city's daily BTV, where BTV is measured in terms of counts at considered counting stations. Comparison of two different periods of model calibration: 2012-2018 and 2016-2018. Plots refer to workdays only.

Table 5 illustrates the role and importance of the meteorological indicators in explaining variations in the city's daily BTV. The adjusted R^2 may take on values between 0 and 1 and indicates how much of the observed variation in the city's daily BTV can be explained by the applied statistical model. When measuring BTV in terms of counts at stations and using the period 06|2012 to 10|2018 for model calibration, the resulting model explains 88 % of the variation in the city's daily BTV. Without considering any meteorological indicators, the model would only be able to explain 52 % of the variation in BTV. By taking meteorological conditions into account, the model is able to explain additional **75 %** of the variance that would remain unexplained otherwise.

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Table 5: 'Explained variation' (adj. R^2) and improvement in 'explained variation' due to the consideration of MET indicators

BVT measured by …	Period of model calibration	Adj. R^2 (model with MET)	Adj. R^2 (model without MET)	Change in adj. R^2 due to MET
… counting stations	06|2012-10|2018	0.881	0.522	+0.359
… counting stations	01|2016-10|2018	0.889	0.533	+0.356
… tracked trips	01|2016-10|2018	0.978	0.959	+0.019

In the case of tracked trips, the improvement due to additionally considering meteorological conditions is somewhat less pronounced, but still clearly visible. The amount of explained variation in BTV rises from 96 % to 98 %. This means, that additional **46 %** of the otherwise still unexplained variance can be explained by taking meteorological conditions into account. Note that the high adjusted-R^2-values in the case of tracked trips – both with and without meteorological variables – arise from dummies that account for the promotion campaign "*Mondfahrt auf Erden*". As shown in Figure 3.b (chapter 1.2), this campaign caused high jumps in the number of tracked trips and accounting for them explains a large part of the variation in the number of daily tracked trips.

4.2 Effect of meteorological conditions on trip distance and cycling speed

The data on tracked trips allow investigating the effect of variations in meteorological conditions on average trip distance and average cycling speed. Again, statistical models are used to estimate how sensitive average trip distance and average cycling speed are to variations in meteorological conditions. The models work on a daily resolution and only consider workdays.

Figure 10 illustrates the response functions for those meteorological indicators that show a statistically significant influence on either average trip distance or average speed of those cyclists tracking their trips with the Bike Citizens App. The vertical axis on the left side of each plot measures daily average trip distance or daily average cycling speed in relative terms. The value 1 represents the highest average trip distance or cycling speed that results from systematically varying the considered meteorological indicator while holding all other factors fixed. The vertical axes on the right side, by contrast, measures average trip distance or cycling speed in absolute terms.

Only WBGT shows a statistically significant influence on average trip distance and average cycling speed. As illustrated in Figure 10.a, average trip distance increases with WBGT. Compared to days with WBGT values perceived as optimal by the cyclists, average trip distance drops by about 35 % in case of a mean WBGT of 0 °C during daytime (all other factors being equal). Expressed in absolute terms, average trip distance drops below 4.8 km with mean WBGT being less than 0 °C during daytime. For comparison, on days with WBGT conditions perceived as optimal, average trip distance of tracked cyclists amounts to 7.3 km[11].

[11] One may expect a bias in the average trip distance due to the campaign "*Mondfahrt auf Erden*", as one of the challenges included to track the longest trip. However, with 6.0 km the daily average trip distance during the campaign (Apr.-Sep. 2018) was even a bit shorter than the daily average trip distance of 6.5 km outside the campaign (Apr.-Sep. 2016 and Arp.-Sep. 2017).

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The impact of WBGT on average cycling speed is, by contrast, negligible over most parts of the WBGT spectrum (see Figure 10.b). Only on cold days, there is a more or less noticeable decrease in average cycling speed, presumably due to worsening road conditions (e.g. icy roads).

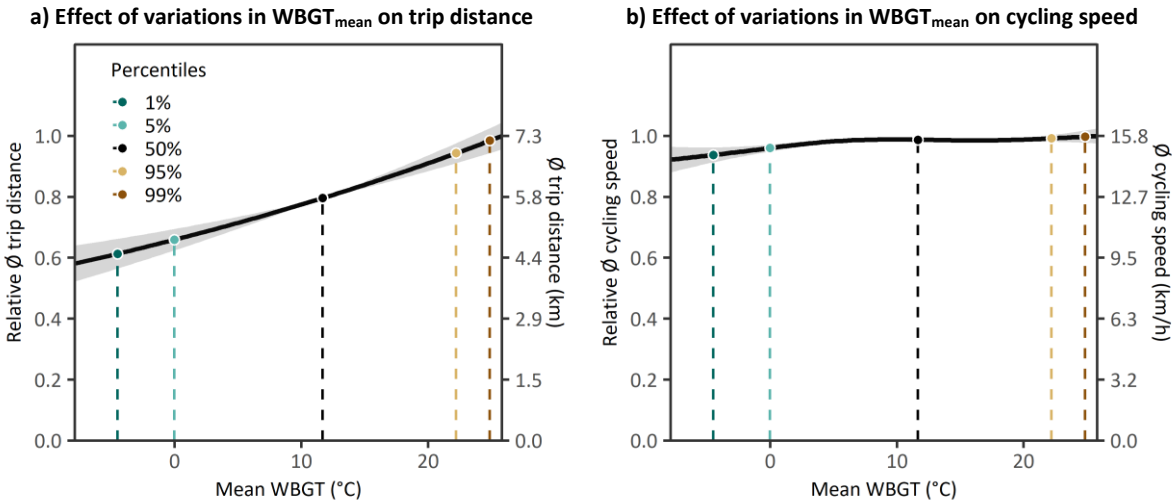

Figure 10: Effect of variations in MET indicators on average trip distance and average cycling speed of tracked trips. Plots refer to workdays only. Period of model calibration: 01|2016-10|2018. Plot design based on Marí-Dell'Olmo et al. (2018).

4.3 Effect of meteorological conditions on the spatial distribution of cyclists

The results in chapter 4.1 show the sensitivity of the city's daily BTV towards meteorological conditions on an aggregate – more or less citywide – level. This section, by contrast, illustrates whether there are spatial differences in how sensitively the city's daily BTV responds to variations in meteorological conditions. In these spatial analyses, BTV is measured in terms of tracked trips. As mentioned in chapter 1.2, spatial analyses require large amounts of data to provide meaningful and robust results. Since such a critical mass of tracked trips was mainly reached during and after the campaign "*Mondfahrt auf Erden*", the following analyses are limited to the period 04|2018-10|2018 and thus only comprise the summer season.

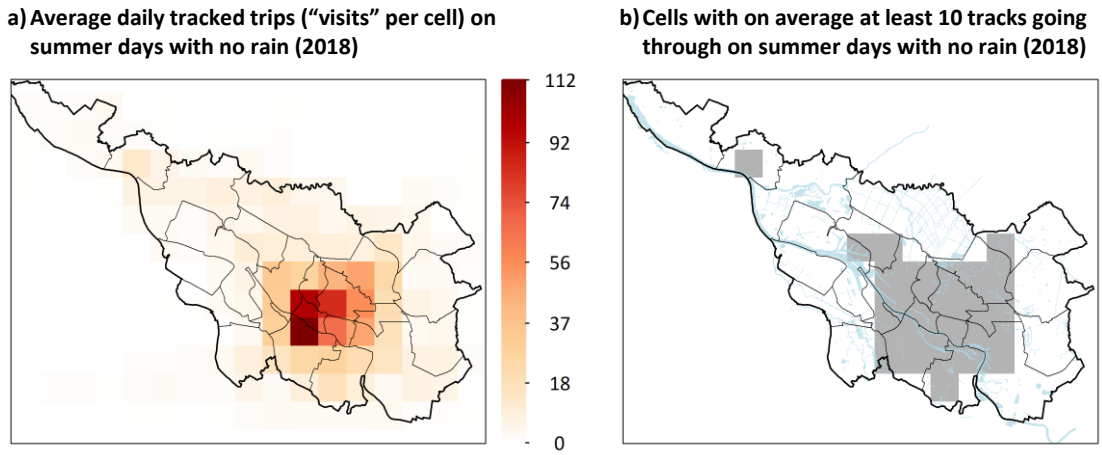

Figure 11: (a) Average daily tracked trips per cell on summer days with no rain and (b) cells with on average at least 10 tracks going through on summer days with no rain. Both plots only refer to data from 2018. Administrative borders and waterbodies: OpenStreetMap.

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The analyses are carried out for two different levels of spatial detail: raster cells of 2 km squared and districts. In the case of the raster level, we only consider cells that show at least 10 tracks going through them on summer days without rain. The remaining raster cells are excluded from the analysis due to too low amounts of tracks for meaningful results (for further technical details see chapter 9.2). Figure 11 illustrates the number of average daily tracked trips per cell on summer days without rain (left plot) and the cells considered in the spatial analysis (right plot).

Figure 12 shows the sensitivity of daily BTV in terms of tracked trips towards variations in meteorological conditions per analysed raster cell (a) and per district (b). The sensitivity per cell or district is measured in relation to the citywide average as derived from the statistical model in chapter 4.1. That is, a value exceeding 1 indicates the cell's or district's sensitivity to be above the citywide average whereas a value smaller than 1 indicates the cell's or district's sensitivity to be below the citywide average. As shown in the figures, the sensitivity of daily BTV towards variations in meteorological conditions varies over the city. In the city centre, daily BTV responds less sensitively to variations in meteorological conditions than in the outer parts of the city. Reasons for spatial differences in the meteorological sensitivity of daily BTV may include, amongst others, spatial differences in

(i) the bicycle infrastructure (number of cycle paths, number of (roofed) bicycle parking areas, frequency of snow removal of cycling paths, exposure to strong wind, etc.),
(ii) the demographic, socioeconomic and psychographic characteristics of the residents (age, sex, family status, attitude, etc.),
(iii) the scale of structures (small-scale structures with shorter distances increase the probability for taking the bike despite suboptimal meteorological conditions),
(iv) etc.

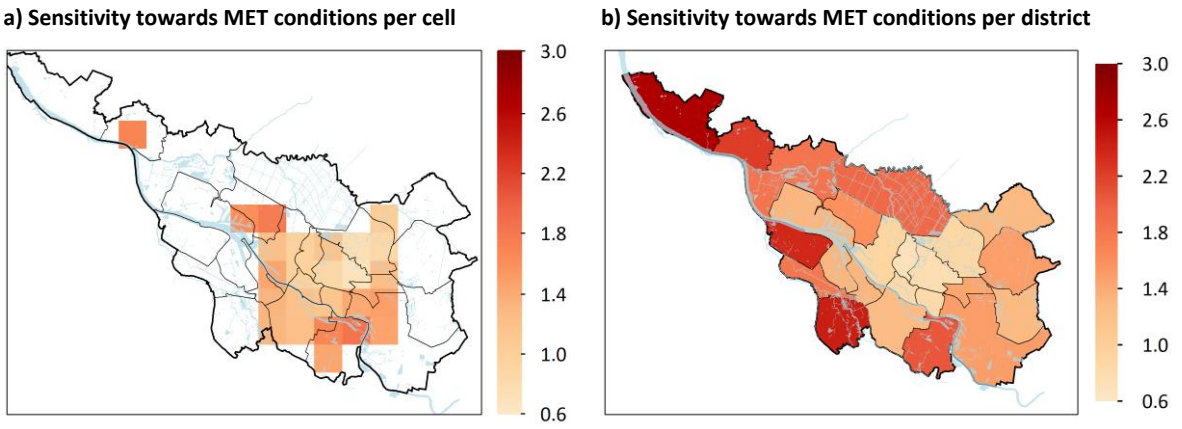

Figure 12: Sensitivity of tracked trips towards variations in MET conditions on workdays in the period 04|2018-10|2018, per cell (a) and per district (b). The sensitivity per cell/district is measured relative to the citywide sensitivity. Administrative borders and waterbodies: OpenStreetMap.

Using the *Bike Citizens Analytics* tool, further interactive visual in-depth analyses regarding the effects of meteorological conditions on bicycle traffic can be performed. The tool visualizes trips tracked by the *Bike Citizens App* and allows comparing the cycling intensity per stretch of road, based on meteorological conditions. Predefined filters are available for the parameters wet-bulb globe temperature ($WBGT_{mean}$), wind speed (WS_{max}), precipitation (*PRH*), and snow depth (*SD*). Using these filters, workdays characterized by particular meteorological conditions can be selected and the corresponding cycling intensities compared to each other.

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By way of example, Figure 13 shows a comparison of the relative cycling intensities on "*dry*" workdays and "*wet*" workdays. The filter "*dry*" workdays includes all workdays with virtually no precipitation during daytime, whereas the filter "*wet*" workdays refers to workdays with at least five hours of precipitation during daytime. Cycling intensities are illustrated by the thickness of the streets. Stretches of roads entirely yellow indicate that there is no difference between the relative cycling intensity on "*dry*" and "*wet*" workdays. Red and blue wrappings, by contrast, indicate shifts in the relative cycling intensities when comparing "*dry*" and "wet" workdays. The thicker the wrapping, the more pronounced is the shift. Stretches of roads with a blue wrapping show a higher relative cycling intensity on "*wet*" workdays than on "*dry*" workdays. A red wrapping, by contrast, indicates a higher relative cycling intensity on "*dry*" workdays than on "*wet*" workdays. In other words, bluely wrapped roads are over-proportionally used on "*wet*" workdays, whereas redly wrapped roads are under-proportionally used on "*wet*" workdays. The illustrated map section in Figure 13 shows the "Bürgerpark" in its centre. On "*wet*" workdays, cyclists tend to avoid the unpaved ways inside the park and rather use the roads alongside the park.

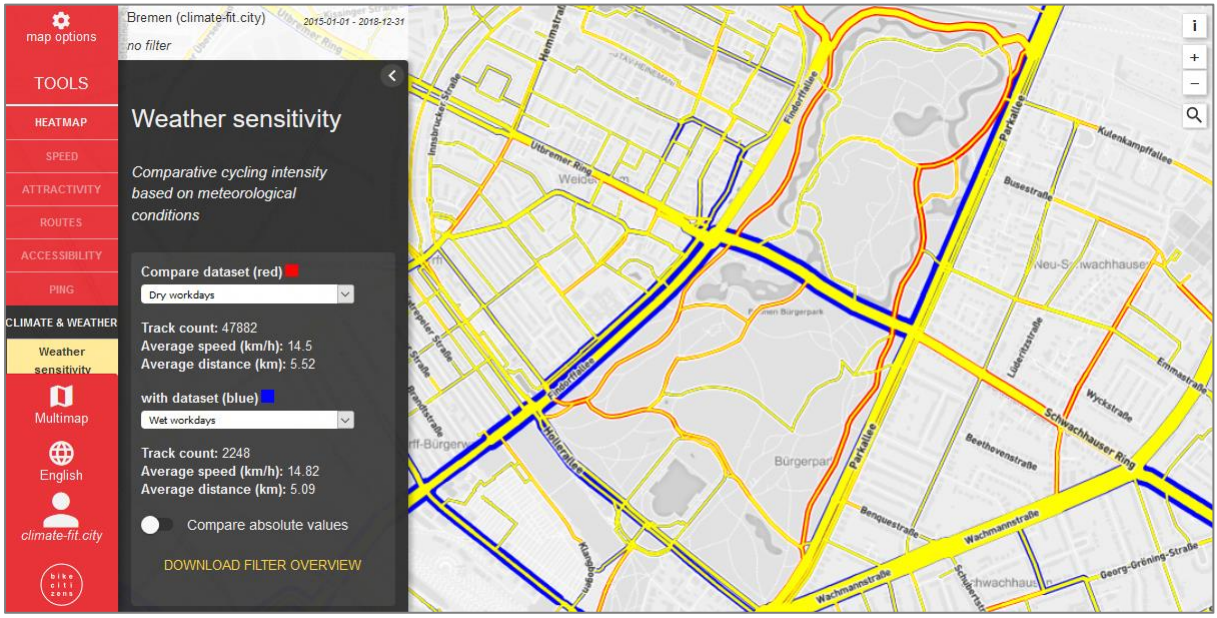

Figure 13: Comparison of relative cycling intensities on "dry" workdays (red), i.e. workdays with no precipitation during daytime (06:00-20:00) and "wet" workdays (blue), i.e. workdays with at least five hours of precipitation during daytime (06:00-20:00). Screenshot of Bike Citizens Analytics with zoom to the "Bürgerpark".

5 The city's climatic attractiveness for cycling

The *Active Mobility Service* assesses a city's climatic attractiveness for cycling from two different perspectives: a rather *objective* one and a more *subjective* one. The *objective* perspective on the city's climatic attractiveness for cycling consists of information derived from climate data only. This includes various evaluations of cycling-relevant meteorological indicators under current and future climatic conditions. The *subjective* perspective, by contrast, describes the city's climatic attractiveness as *perceived* by its cyclists. It is derived by merging climate data with the response functions calculated in chapter 4.1. Whereas *objective* climatic attractiveness is displayed in the original units of measurement of the considered meteorological indicators (e.g. °C, km/h), *subjective* or *perceived* climatic attractiveness is measured in terms of *relative BTV* (see chapter 5.2 for further details). Both, *objective* and *perceived* climatic attractiveness are assessed

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under current and future climatic conditions, where the latter refers to the period 2036-2065. Climate projections for two different Representative Concentration Pathways (RCPs) are considered, i.e. RCP4.5 (moderate emissions) and RCP8.5 (high emissions) (see chapter 2.2).

The reason for providing two different measures of climatic attractiveness is to allow for better comparability between cities. Since the sensitivity of BTV to variations in meteorological conditions is supposed to differ across cities, the *perceived* climatic attractiveness will not only display differences in the cities' climates but also differences in how sensitively the cities' cyclists respond to variations in meteorological conditions. Hence, a comparably low *perceived* climatic attractiveness of a city may either result from a high frequency of unfavourable meteorological conditions or from a high sensitivity of the city's BTV to variations in meteorological conditions (or a combination of both). The *Active Mobility Service* allows for differentiating between these two effects by providing information on both, the city's *objective* and *perceived* climatic attractiveness.

5.1 "Objective" climatic attractiveness today and in future

Figure 14 presents evaluations of the meteorological indicators, whose effect on the city's daily BTV was illustrated in chapter 4.1. This includes the mean wet-bulb globe temperature in °C between 06:00 and 20:00 ($WBGT_{mean}$), the maximum mean hourly wind speeds in km/h between 06:00 and 20:00 (WS_{max}), the number of hours with precipitation > 0.1 mm between 06:00 and 20:00 (PRH) and snow depth in cm at 07:00 (SD). In case of $WBGT_{mean}$ and WS_{max}, which both present *UrbClim* outputs, cycling-weighted citywide averages are used for the analyses. Apart from snow depth, evaluations are presented for both, current and future climatic conditions. For snow depth, no climate projections are available within this prototype version of the *Active Mobility Service*. Thus, evaluations only refer to current climatic conditions.

Plot (a) displays the annual cycle – i.e. monthly averages – of $WBGT_{mean}$ under current and future climatic conditions. January usually shows the lowest, July by contrast the highest values of $WBGT_{mean}$. Under current climatic conditions, the monthly averages range from 1.8 °C to 18.8 °C. Due to climate change, the annual average of $WBGT_{mean}$ is projected to rise from 10.4 °C to 12.3 °C (RCP4.5) and 12.7 °C (RCP8.5), respectively. On a monthly basis, the highest increases are expected for September and December, the lowest for May. This overall warming trend is also reflected in the frequency of cold and hot days. Whereas the number of days per year with $WBGT_{mean}$ below or equal 0 °C is projected to decrease noticeably, the number of days per year with $WBGT_{mean}$ equal or above 25 °C is expected to increase sharply (Figure 14.b). However, days with $WBGT_{mean}$ equal or above 30 °C will remain an exception. The problem of heat stress is thus a much less significant issue for Bremen than for cities farther south, such as Vienna (see also Köberl and Kortschak 2019).

Besides $WBGT_{mean}$, the average daily number of hours with precipitation during daytime and the average annual number of days with at least 1, 5 or 10 hours of precipitation are as well projected to increase in future (Figure 14.c and Figure 14.d). The same holds true for the average annual number of days with high wind speeds (i.e. maximum mean hourly wind speeds of at least 18 km/h[12]). This increase is particularly pronounced under RCP8.5. By contrast, the average annual number of days with maximum mean hourly wind speeds of not more than 10 km/h is expected to remain more or less the same in future (Figure 14.e). Note, however, that projections on wind speed are characterized by high uncertainties.

[12] This represents the 95 % quantile under current climatic conditions.

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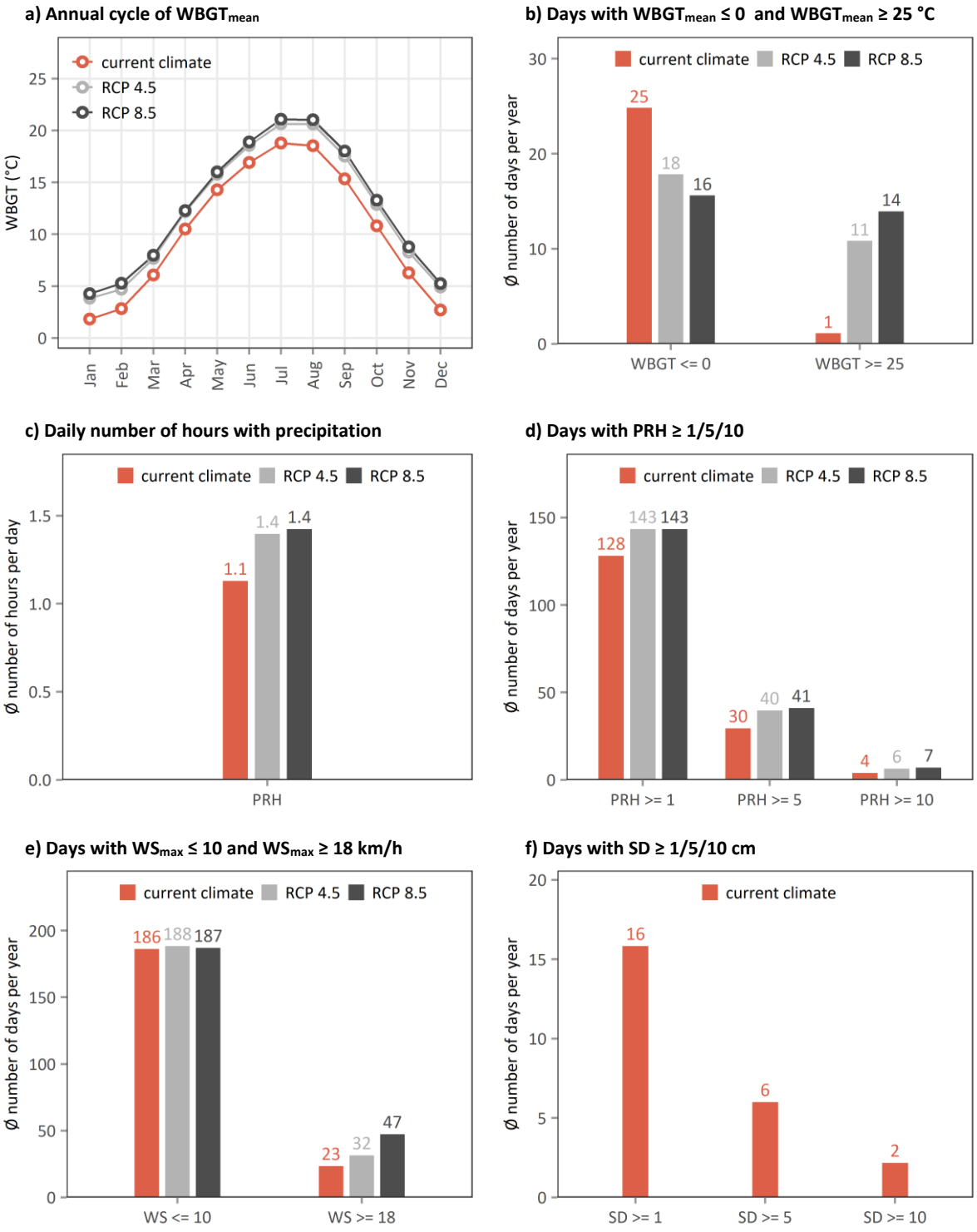

Figure 14: Analyses of the MET indicators WBGT$_{mean}$, PRH, WS$_{max}$, and SD under current and future (Ø 2036-2065) climatic conditions. (a) Annual cycle of WBGT$_{mean}$. (b) Average annual number of days with WBGT$_{mean}$ ≤ 0 °C and with WBGT$_{mean}$ ≥ 25 °C. (c) Average daily number of hours with precipitation. (d) Average annual number of days with PRH ≥ 1, PRH ≥ 5 and PRH ≥ 10. (e) Average number of days with wind speeds ≤ 10 km/h and wind speeds ≥ 18 km/h. (f) Average number of days with snow depth ≥ 1 cm, snow depth ≥ 5 cm and snow depth ≥ 10 cm (only for current climatic conditions).

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As already mentioned, the prototype version of the *Active Mobility Service* does not include future projections on snow depth. Under current conditions, 16 days with a snow depth of at least 1 cm are on average observed per year (Figure 14.f). Year-to-year variability is, however, high, with the annual number of days with a snow depth of at least 1 cm ranging between 3 and 77.

Figure 15 provides detailed information on the typical spatial distribution of heat on hot days under current and future climatic conditions. It shows the indicator $WBGT_{mean}$ on a 100 m resolution, averaged over all days with a cycling-weighted citywide $WBGT_{mean}$ of at least 25 °C. The plots allow identifying those regions of the city with the highest exposure to heat on hot days. They are also available as selectable layers within *Bike Citizens Analytics*.

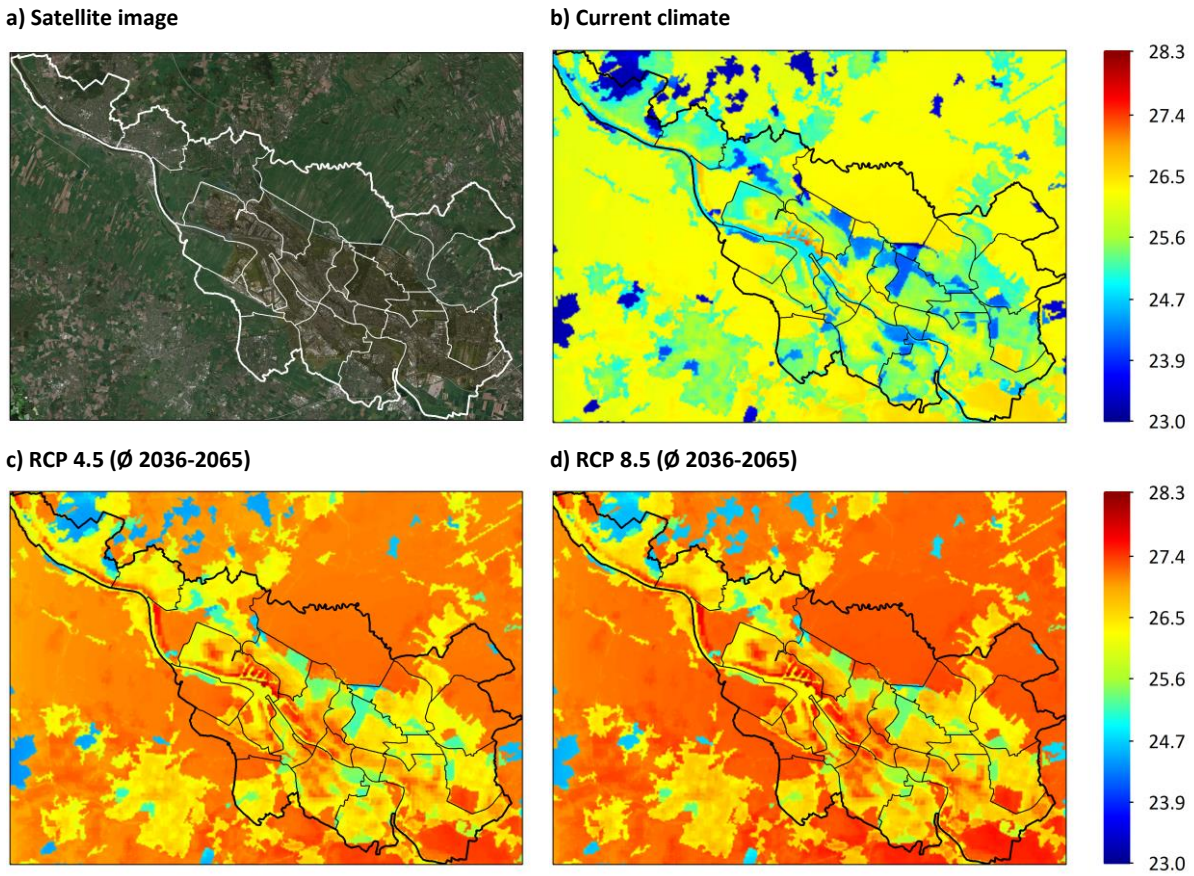

Figure 15: Typical heat distribution on hot days under current and future climatic conditions (in °C); i.e. $WBGT_{mean}$ averaged over days with cycling-weighted citywide $WBGT_{mean} \geq 25$ °C (roughly corresponds to the 99th percentile under current climatic conditions). Resolution: 100 m. Data sources: WBGT data from UrbClim, satellite image and administrative borders from OpenStreetMap.

Figure 16 to Figure 19 once again show the typical spatial distribution of heat stress on hot days under current and future climatic conditions, but zooming into particular regions of the city. In addition, black lines display roads open to cyclists in order to allow identifying those (stretches of) roads that are most prone to heat stress on hot days.

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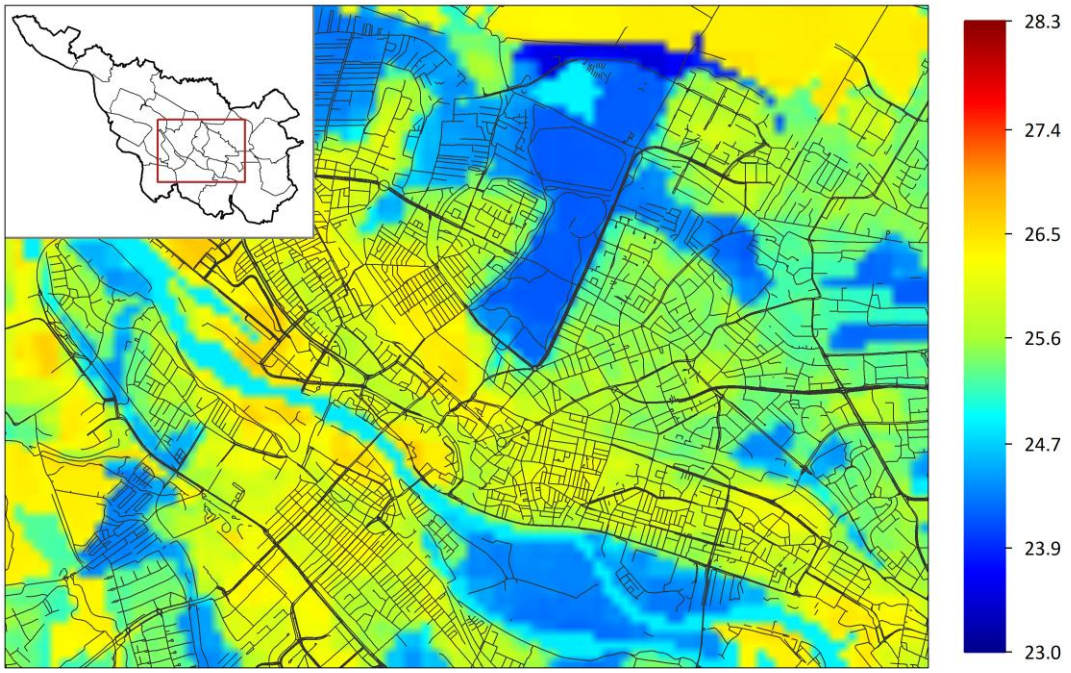

Figure 16: Typical heat distribution on hot days under current climatic conditions (in °C); i.e. $WBGT_{mean}$ averaged over days with cycling-weighted citywide $WBGT_{mean} \geq 25$ °C (roughly corresponds to the 99th percentile). Resolution: 100 m. Zoom into the city's centre. Black lines indicate roads open to cyclists. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

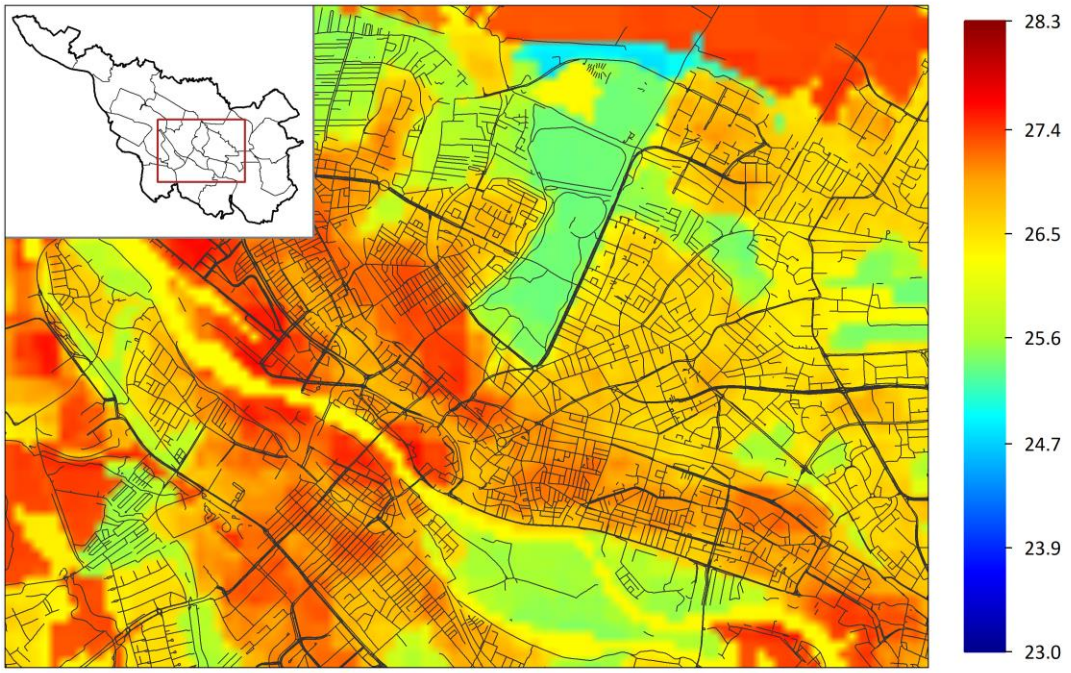

Figure 17: Typical heat distribution on hot days under future (Ø 2036-2065; RCP8.5) climatic conditions (in °C); i.e. $WBGT_{mean}$ averaged over days with cycling-weighted citywide $WBGT_{mean} \geq 25$ °C (roughly corresponds to the 99th percentile). Resolution: 100 m. Zoom into the city's centre. Black lines indicate roads open to bikers. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

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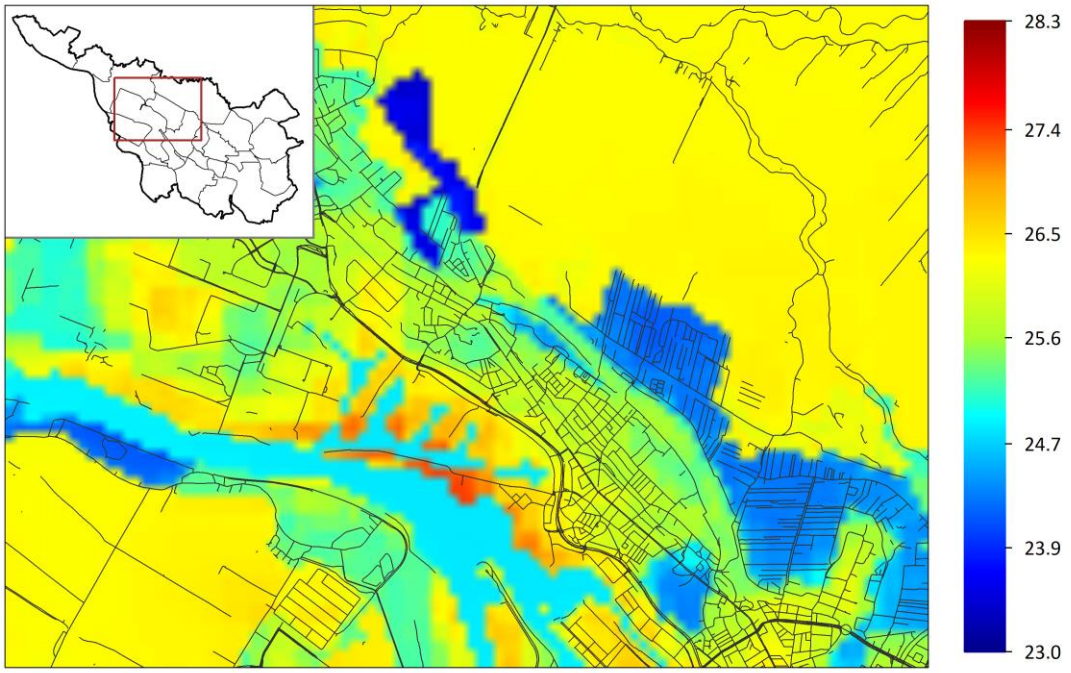

Figure 18: Typical heat distribution on hot days under current climatic conditions (in °C); i.e. $WBGT_{mean}$ averaged over days with cycling-weighted citywide $WBGT_{mean} \geq 25$ °C (roughly corresponds to the 99th percentile). Resolution: 100 m. Zoom into the city's northwest. Black lines indicate roads open to bikers. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

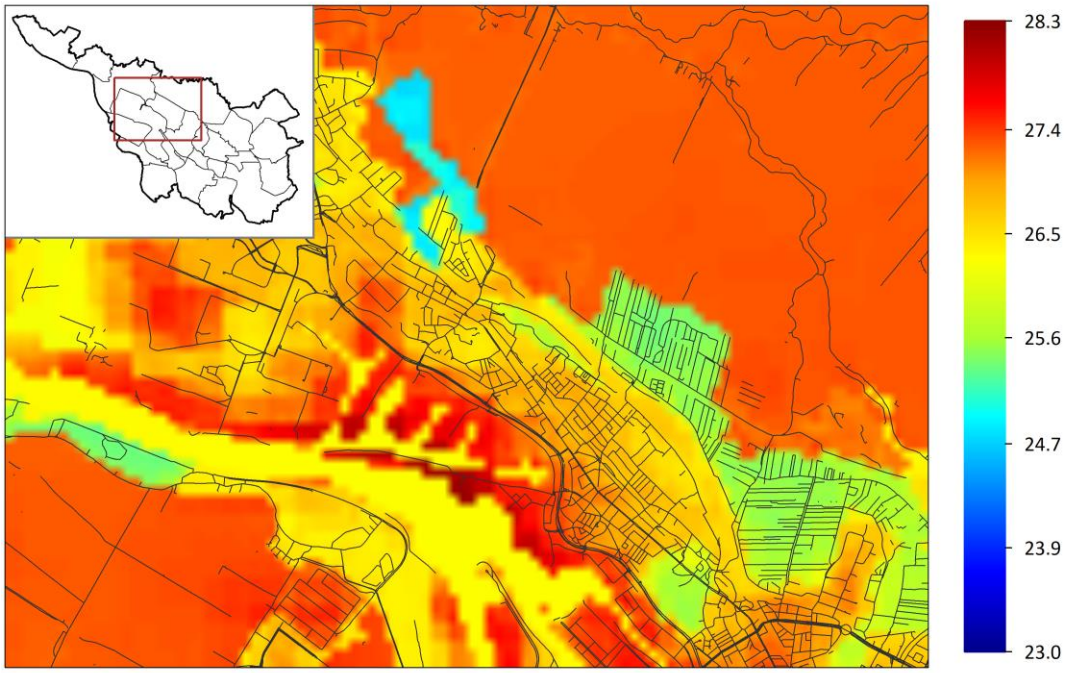

Figure 19: Typical heat distribution on hot days under future (Ø 2036-2065; RCP8.5) climatic conditions (in °C); i.e. $WBGT_{mean}$ averaged over days with cycling-weighted citywide $WBGT_{mean} \geq 25$ °C (roughly corresponds to the 99th percentile). Resolution: 100 m. Zoom into the city's northwest. Black lines indicate roads open to bikers. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

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Figure 20 provides further information on spatial differences in the exposure to heat. It shows the average annual number of days with a mean wet-bulb globe temperature during daytime (i.e. between 06:00 and 20:00) of at least 25 °C at a 100 m resolution. Thus, it adds spatial detail to the information provided by the bars on the right side of Figure 14.b. Again, the information is shown for current as well as future climatic conditions.

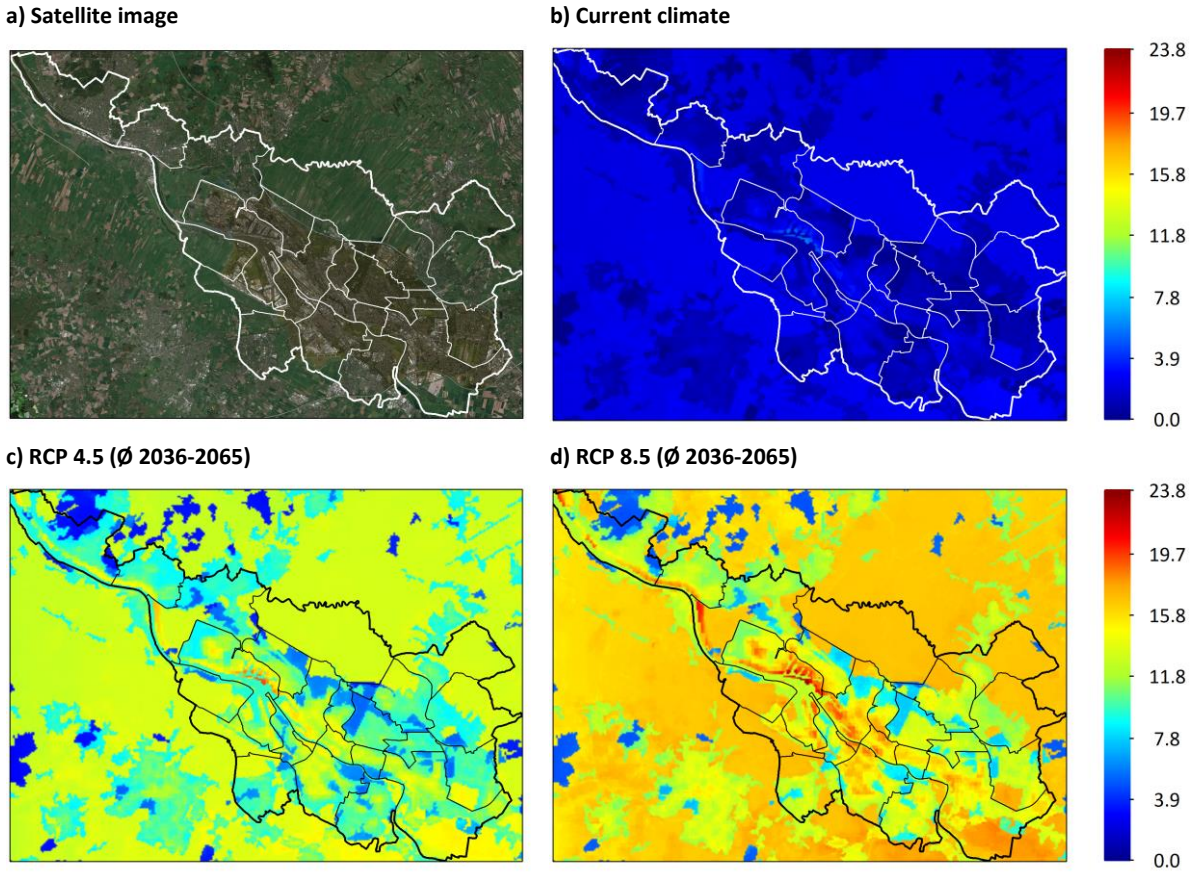

Figure 20: Average annual number of days with $WBGT_{mean} \geq 25$ °C under current and future climatic conditions (in °C). Resolution: 100 m. Data sources: WBGT data from UrbClim, satellite image and administrative borders from OpenStreetMap.

Figure 21 to Figure 24 once again show the average annual number of days with a mean wet-bulb globe temperature during daytime of at least 25 °C under current and future climatic conditions, but zooming into the centre of the city. Note that Figure 21 and Figure 22 both display the same data, i.e. the number of days with mean WBGT during daytime of at least 25 °C under current climatic conditions, but use a different colour scaling. In Figure 21, the applied colour scaling is adjusted to the range of values observed under current climatic conditions and thus allows for a better discriminability of spatial differences. Figure 22, by contrast, uses the same uniform colour scaling as applied in Figure 20, Figure 23 and Figure 24. This colour scaling covers the whole range of values under current and future climatic conditions and allows for easy visual comparability of different time horizons.

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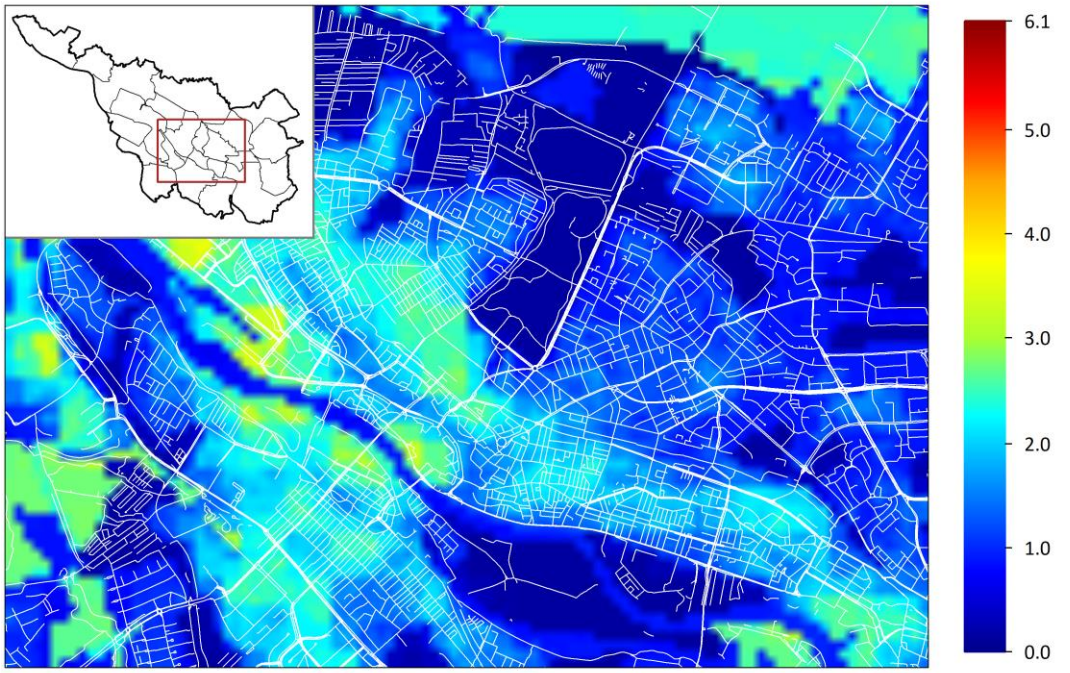

Figure 21: Average annual number of days with $WBGT_{mean} \geq 25$ °C under current climatic conditions. Note: for a better discriminability of spatial differences, the colour scaling differs from Figure 20. Resolution: 100 m. Zoom into the city's centre. White lines indicate roads open to bikers. Data sources: WBGT data from UrbClim roads and administrative borders from OpenStreetMap.

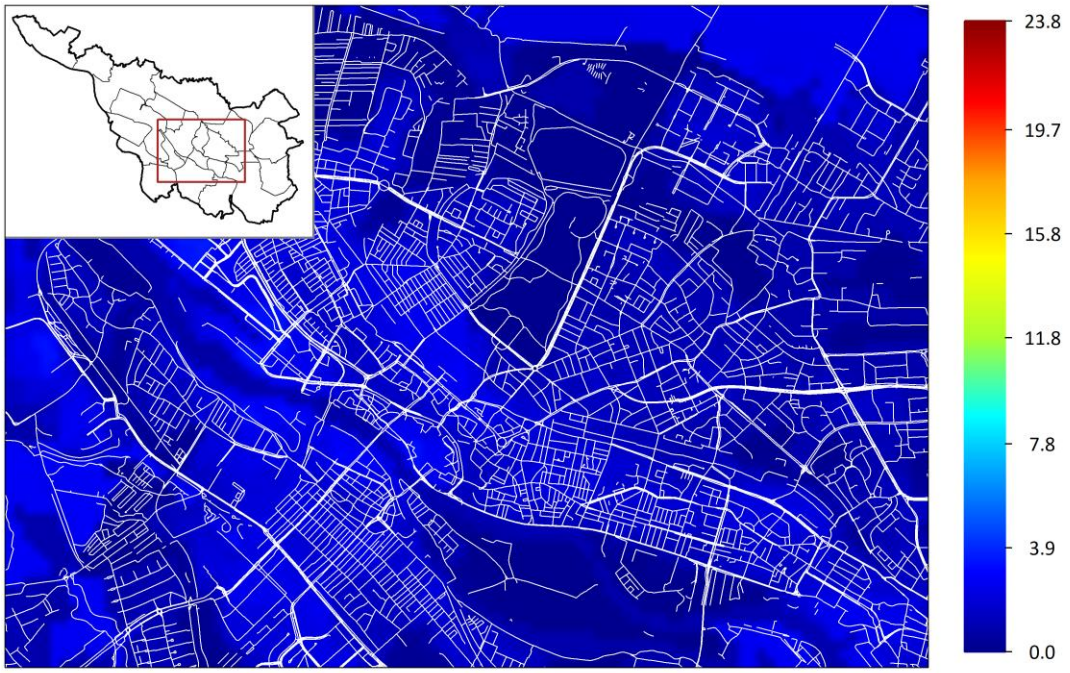

Figure 22: Average annual number of days with $WBGT_{mean} \geq 25$ °C under current climatic conditions. Note: the same colour scaling as in Figure 20 is used. Resolution: 100 m. Zoom into the city's centre. White lines indicate roads open to bikers. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

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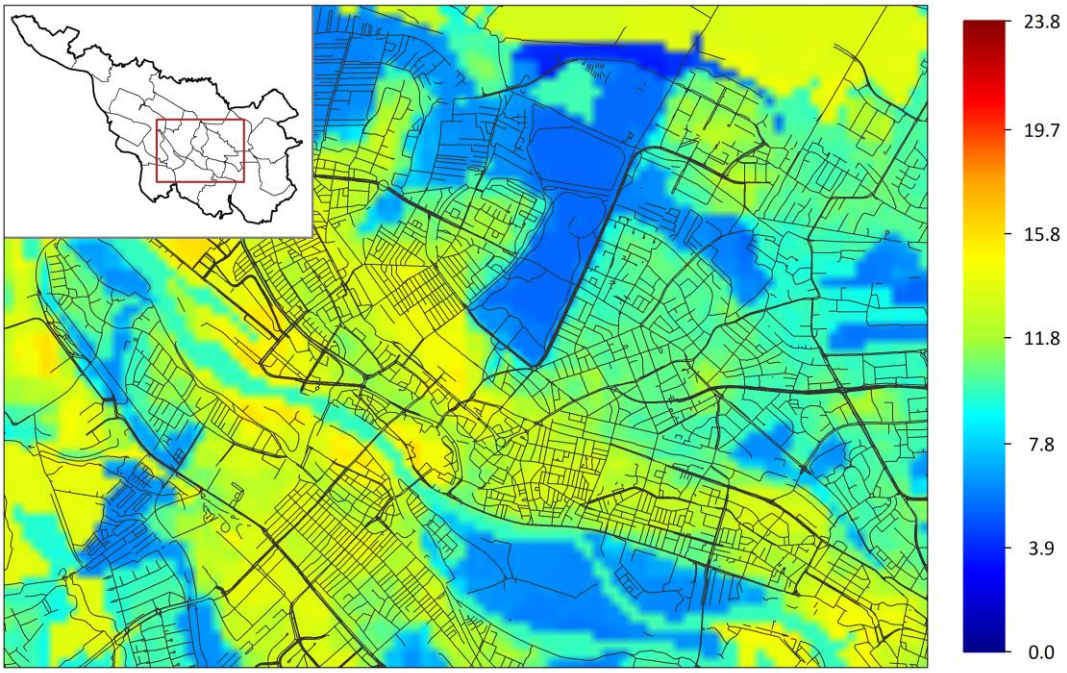

Figure 23: Average annual number of days with $WBGT_{mean} \geq 25$ °C under future climatic conditions (Ø 2036-2065; RCP4.5). Resolution: 100 m. Zoom into the city's centre. Black lines indicate roads open to bikers. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

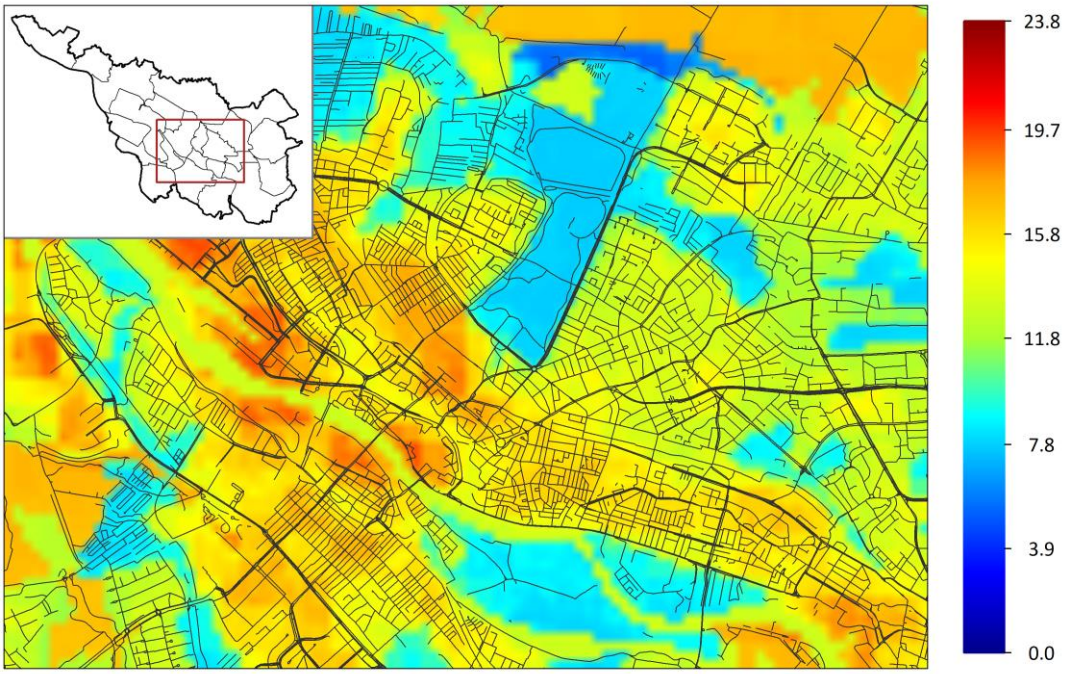

Figure 24: Average annual number of days with $WBGT_{mean} \geq 25$ °C under future climatic conditions (Ø 2036-2065; RCP8.5). Resolution: 100 m. Zoom into the city's centre. Black lines indicate roads open to bikers. Data sources: WBGT data from UrbClim, roads and administrative borders from OpenStreetMap.

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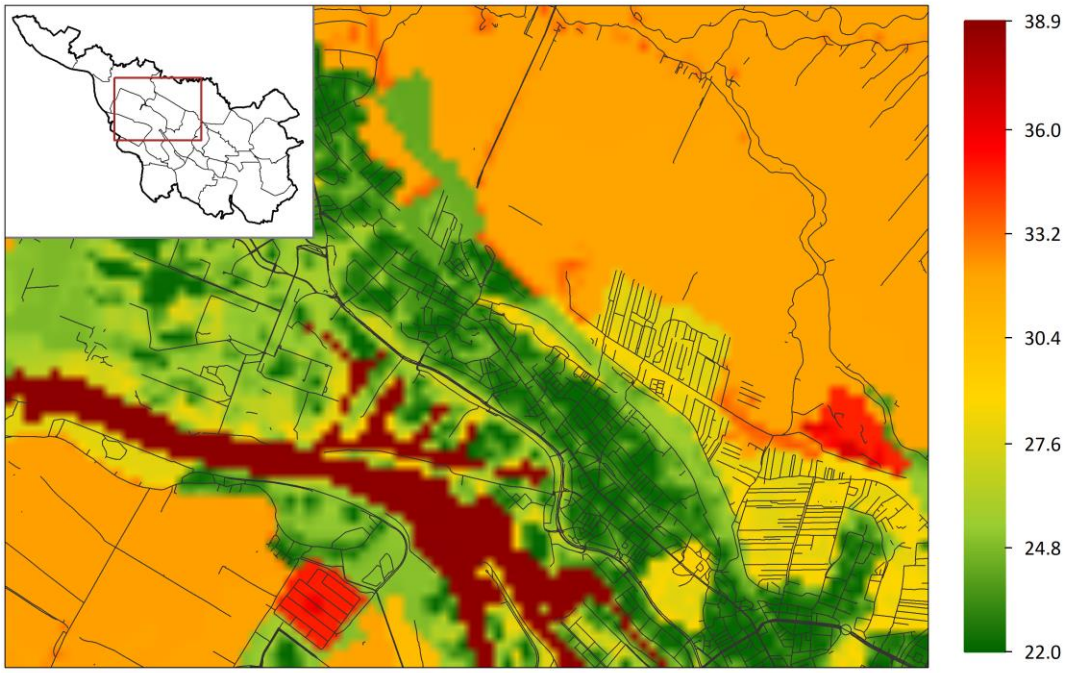

Figure 25: Typical wind speeds on particularly windy days under current climatic conditions (in km/h); i.e. WS_{max} averaged over days with cycling-weighted citywide $WS_{max} \geq 23$ km/h (roughly corresponds to the 99th percentile). Resolution: 100 m. Zoom into the city's northwest. Black lines indicate roads open to cyclists. Data sources: wind data from UrbClim, roads and administrative borders from OpenStreetMap.

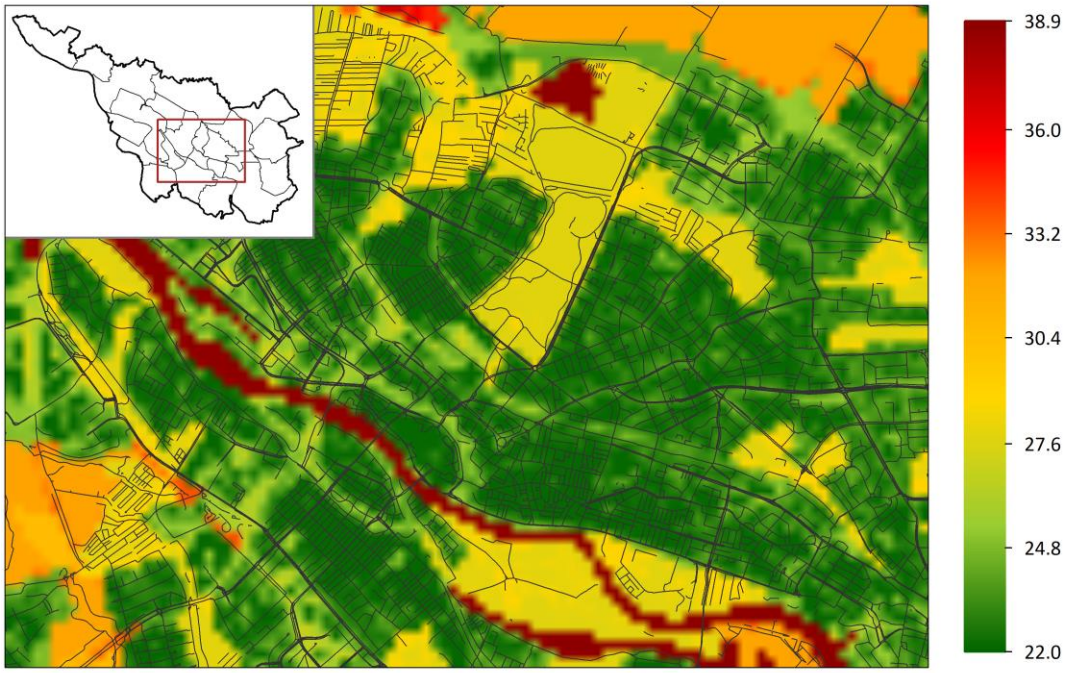

Figure 26: Typical wind speeds on particularly windy days under current climatic conditions (in km/h); i.e. WS_{max} averaged over days with cycling-weighted citywide $WS_{max} \geq 23$ km/h (roughly corresponds to the 99th percentile). Resolution: 100 m. Zoom into the city's centre. Black lines indicate roads open to cyclists. Data sources: Wind data from UrbClim, roads and administrative borders from OpenStreetMap.

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In addition to the spatial details on heat stress, Figure 25 and Figure 26 provide information on the typical spatial distribution of wind speeds on stormy days for particular regions of the city. They show the indicator WS_{max} on a 100 m resolution, averaged over all days with a cycling-weighted citywide WS_{max} of at least 23 km/h. Both figures refer to current climatic conditions. In addition to the distribution of wind speeds, black lines display roads open to cyclists.

Cycling-tailored urban climate data, as presented in Figure 15 to Figure 26, can also be accessed via *Bike Citizens Analytics*. With its split-screen function, the tool allows for a visual comparison of urban climate data and cycling intensities. An example of this split-screen function is illustrated in Figure 27. The left screen in Figure 27 shows the typical spatial distribution of thermal comfort on hot days under current climatic conditions, where thermal comfort is represented by the mean wet-bulb globe temperature during daytime (06:00-20:00). The right screen visualizes the typical distribution of cycling intensities based on the trips tracked by the *Bike Citizens App*. This kind of information can support the identification of regions with priority needs for adaptation measures (i.e. regions that are both, heavily frequented by cyclists and frequently exposed to unfavourable climatic conditions).

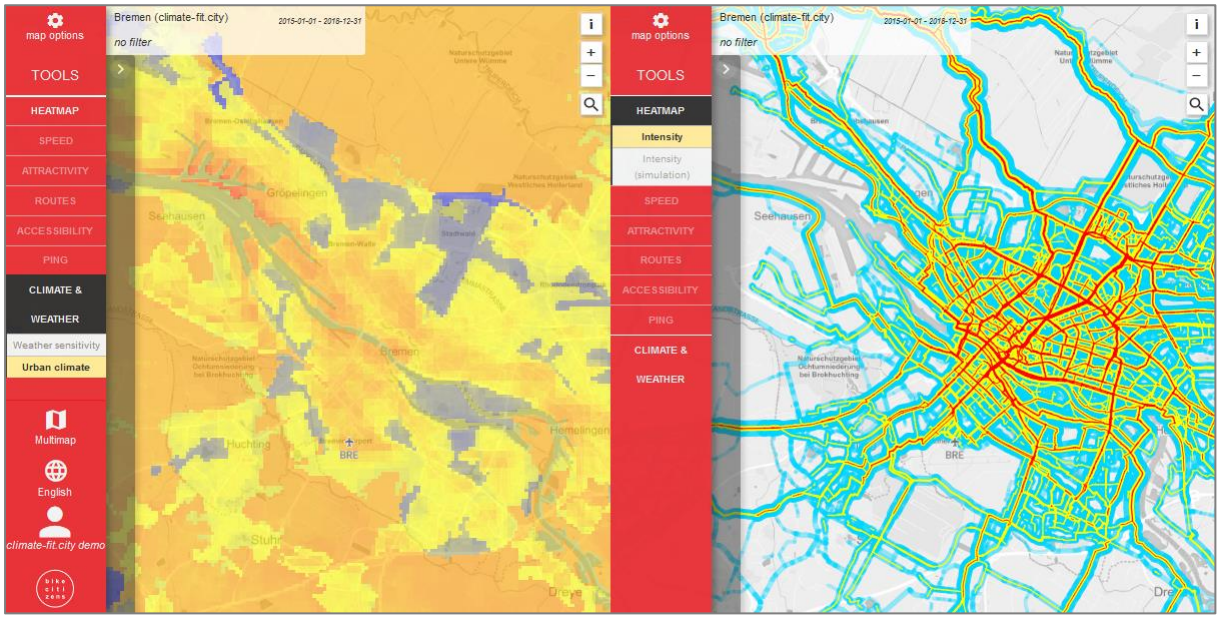

Figure 27: Example of the split-screen function within Bike Citizens Analytics. Left screen: typical heat distribution on hot days under current climatic conditions on 100 m resolution (i.e. $WBGT_{mean}$ averaged over days with cycling-weighted citywide $WBGT_{mean} \geq 25$ °C). Right screen: typical distribution of cycling intensities based on the trips tracked by the Bike Citizens App.

5.2 "Subjective" climatic attractiveness today and in future

The *subjective* or *perceived* climatic attractiveness represents the assessment of the city's current and future climatic conditions based on how sensitively the city's cyclists respond to variations in meteorological conditions nowadays (see chapter 4.1)[13]. The *perceived* climatic attractiveness is measured in relative

[13] For assessing the perceived climatic attractiveness, we use the sensitivities resulting from measuring BTV in terms of counts at all stations. Response functions are extrapolated in a linear fashion at their margins to account for meteorological conditions that have not been observed within the model calibration period.

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terms. A value of 1 corresponds to the city's BTV that would be expected if meteorological conditions were optimal throughout the year. Figure 28 shows the city's climatic attractiveness as perceived by its cyclists under current (orange-red bars) and future (grey bars) climatic conditions.

Based on their observed cycling habits, cyclists in Bremen assess the city's current climatic attractiveness with a value of about 0.68. Remember that a value of 1 represents the highest possible score. It would result if cyclists perceived the climatic conditions as optimal throughout the whole year or if they were completely insensitive towards variations in meteorological conditions. Bremen's climatic attractiveness, as perceived by its cyclists, varies with the course of the year. Whereas the climatic conditions in January are the least appreciated ones by cyclists in Bremen (0.49), climatic conditions typically experienced in July and August rank among the most valued ones (0.84).

A perceived annual climatic attractiveness of 0.68 indicates that there is still some theoretical potential for increases in bicycle usage by further reducing the cyclists' sensitivity towards variations in meteorological conditions. This theoretical potential amounts to an increase in the current average annual bicycle traffic volume by about 47 %.

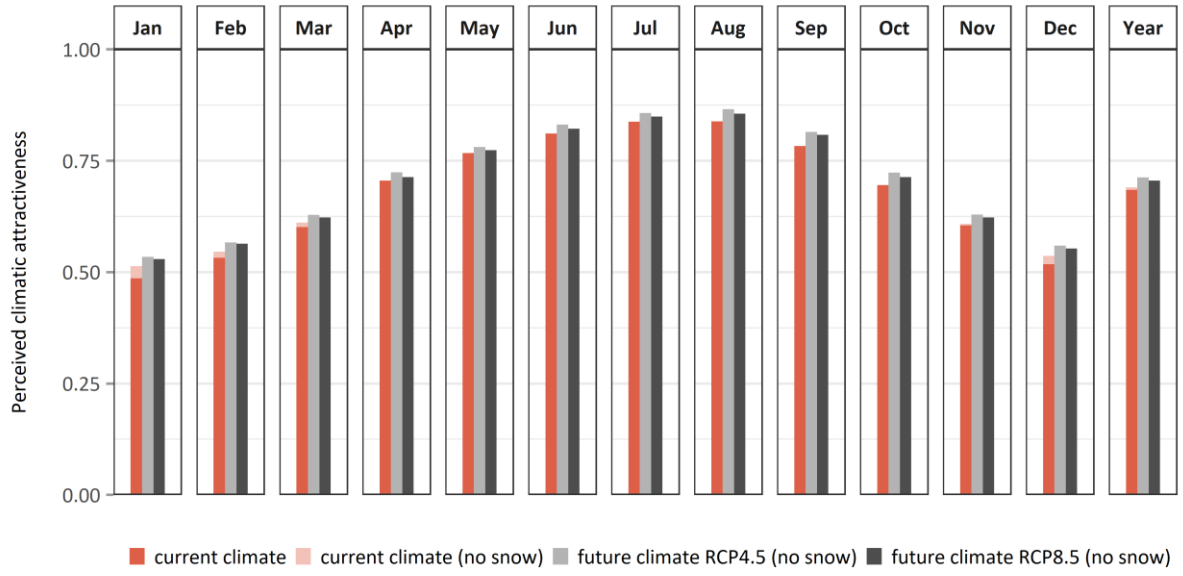

Figure 28: The city's climatic attractiveness as perceived by its cyclists under current and future (Ø 2036-2065) climatic conditions. A value of 1 corresponds to the expected BTV under permanent optimal climatic conditions.

As already mentioned, no projections on snow depth are available for future climatic conditions in this prototype version of the *Active Mobility Service*. Hence, the *perceived* climatic attractiveness under future conditions is assessed without considering the effect of snow on the ground. For reasons of comparability, Figure 28 thus also shows the *perceived* climatic attractiveness under current climatic conditions when assuming no days with snow on the ground. Bars in orange-red show the actual perceived attractiveness of the current climatic conditions whereas bars in bright-red show how attractive climatic conditions would be perceived in case of no days with snow on the ground. Without snow on the ground climatic attractiveness would, for example, be assessed with about 0.51 instead of 0.49 in January.

Bremen's *perceived* climatic attractiveness for cycling is projected to increase in future. This rise in *perceived* climatic attractiveness covers all months and is mainly due to the expected increase in WBGT (see also Figure 14.a and Figure 14.b). Although RCP8.5 shows a somewhat more pronounced warming trend

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than RCP4.5, the increase in *perceived* climatic attractiveness is nevertheless smaller due to the projected higher rise in days with strong wind speeds (see also Figure 14.e). Note however, that wind projections are characterized by high uncertainties.

Table 6 gives an overview on the frequency of meteorological conditions that cause the city's daily BTV to drop by a particular percentage when occurring on a workday. This percentage drop is measured compared to the BTV expected under optimal climatic conditions. The frequency of occurrence of such meteorological conditions – measured in days per year – is shown for current as well as future (Ø 2036-2065) climatic conditions. Days with high drops in BTV may represent a challenge for the city's traffic system, as a high number of "fair-weather-cyclists" will switch to alternative modes of transportation (e.g. public transportation and cars).

Taking the effect of snow on the ground into account, there are currently about 50 days per year with meteorological conditions that cause the city's BTV to drop by more than 50 % when occurring on a workday (compared to the expected BTV under optimal meteorological conditions). Disregarding the effect of snow on the ground, there are only 45 days per year. Under future climatic conditions, this frequency is expected to drop to about 40 days per year under RCP 4.5, but rise to 50 days per year under RCP8.5 due to the more frequent occurrence of stormy days.

Table 6: Frequency of MET conditions causing considerable drops in the city's BTV compared to optimal MET conditions

Change in BTV (compared to optimal MET conditions)	Frequency of occurrence (days/year)			
	Current climatic conditions	Current climatic conditions (no snow)	Future* climatic conditions RCP 4.5 (no snow)	Future* climatic conditions RCP 8.5 (no snow)
> -50 %	~50	~45	~41	~50
> -60 %	~18	~8	~8	~17
> -70 %	~6	~0	~0	~3
> -80 %	~1	~0	~0	~0
> -90 %	~0	~0	~0	~0

*) Future climatic conditions: Ø 2036-2065

6 "MET-adjusted" bicycle traffic data

The final component of the *Active Mobility Service* consists of weather-adjusted bicycle traffic statistics. The effect of atypical weather conditions – i.e. weather conditions deviating from the norm –is removed from the bicycle traffic data. This shows, whether an increase or decrease in the bicycle traffic volume can be traced back to particularly favourable or unfavourable meteorological conditions. We use the average meteorological conditions of the period 2000-2017 to represent the norm.

Figure 29 shows the month-to-month evolution of average daily counts on workdays at all stations in the period 01|2015-10|2018. Actually observed counts are illustrated in grey, weather-adjusted counts in orange-red. The weather-adjusted figures show, how many cyclists would have been counted at all stations if the weather conditions had been as usual. In May 2018, for instance, the weather-adjusted counts are clearly below the actually observed counts. Thus, the particularly bike-friendly weather contributed significantly to the outstanding performance at the counting stations in this month. Large positive weather

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effects are also identified for December 2015 and September 2016. In April 2016, July 2015 or September 2017, by contrast, counts at stations would have been higher if the weather conditions had been as usual.

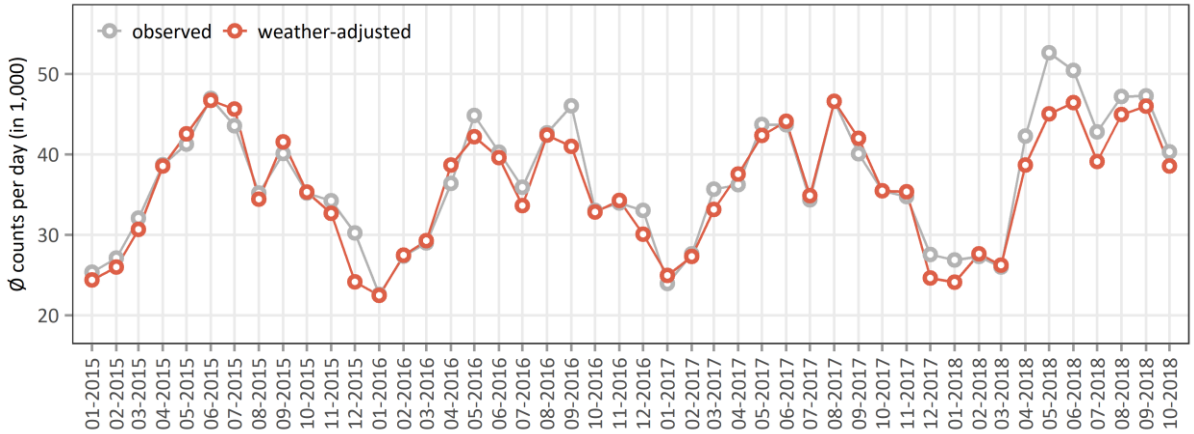

Figure 29: Observed and weather-adjusted month-to-month evolution of average daily counts on workdays at all stations in the period 01|2015-10|2018. The weather-adjustment uses the average meteorological conditions of the period 2000-2017 as reference conditions.

Analysed on an annual level, below-average weather conditions for cycling in 2013 somewhat dampened actual counts at stations on workdays (see Figure 30). That is, counts would have been slightly higher if the weather conditions had been as usual. In contrast, the weather conditions in 2014 and 2018 were particularly bike-friendly and significantly boosted actual counts at stations. Hence, parts of the increases observed in the original figures from 2013 to 2014 and from 2017 to 2018 are attributable to atypical weather conditions. Even in the weather-adjusted statistics, there remains to be a rise in counts in the respective years, but it is less pronounced than in the original figures.

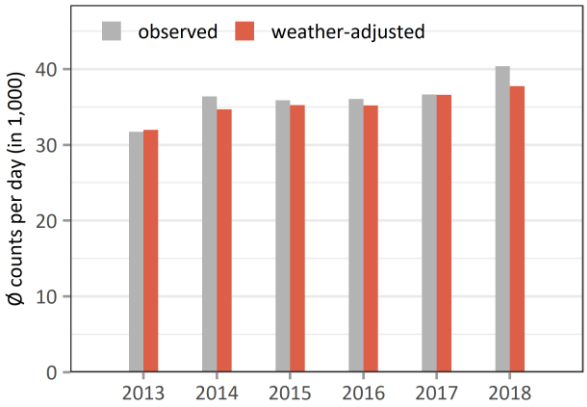

Figure 30: Observed and weather-adjusted year-to-year evolution of average daily counts on workdays at all stations in the period 2013-2018. The weather adjustment uses the average meteorological conditions of the period 2000-2017 as reference conditions.

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PART C | SUPPLEMENTS & TECHNICAL DETAILS

7 Supplement: Some analyses for non-workdays

Throughout the whole report, analyses have primarily focused on workdays. This section includes some additional results for non-workdays.

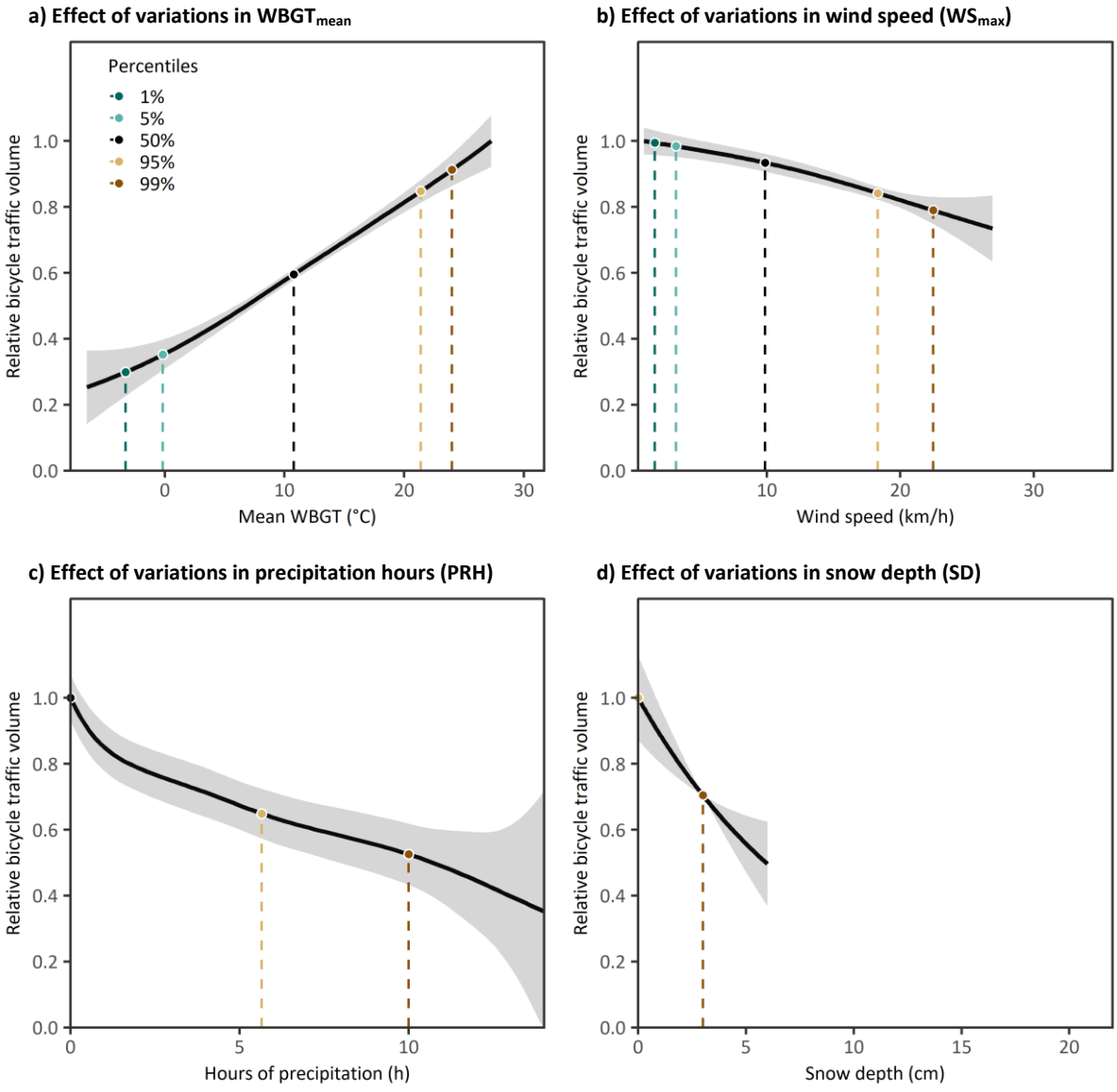

Figure 31: Effect of variations in MET indicators on the city's daily BTV, where BTV is measured in terms of counts at all counting stations. The plots refer to non-workdays only. Period of model calibration: 06|2012-10|2018. Plot design based on Marí-Dell'Olmo et al. (2018).

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Figure 31 shows how sensitively the city's daily BTV – measured in terms of counts at stations – responds to variations in meteorological conditions on non-workdays. It represents the non-workday-equivalent to Figure 5. For an easier comparison, Figure 32 displays the response functions for workdays (dark-blue) and non-workdays (orange-red) next to each other.

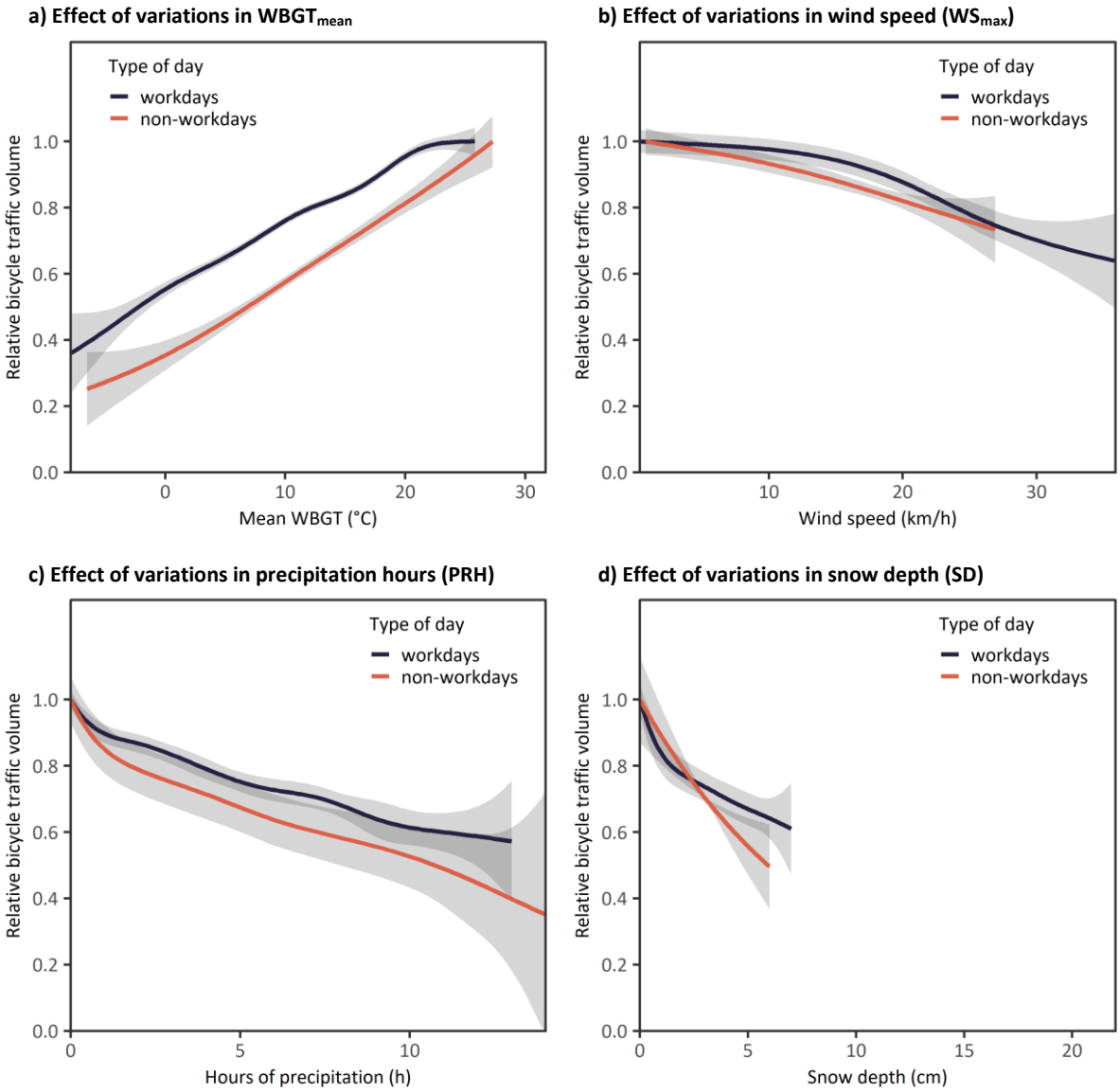

Figure 32: Effect of variations in MET indicators on the city's daily BTV, where BTV is measured in terms of counts at considered counting stations. Comparison between workdays and non-workdays. Period of model calibration: 06|2012-10|2018.

On non-workdays, BTV tends to respond more sensitively to variations in meteorological conditions than on workdays. This particularly holds true for the response to variations in the perceived temperature (see Figure 31.a). Over most parts of the WBGT spectrum, the response function shows a somewhat steeper slope on non-workdays than on workdays. The difference is most pronounced at the upper end of the WBGT spectrum, where there is no flattening of the curve on non-workdays. In the case of wind speed,

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precipitation duration and snow depth, differences are, however, mostly within the uncertainty bounds (see Figure 31.b-d).

Other than on workdays, there is no significant difference in the effect of precipitation over the course of the day (see Figure 33). It does not really matter whether precipitation takes place either in the morning (06:00-09:00), at noon (11:00-14:00) or in the afternoon (16:00-19:00). In each case, it causes daily BTV on non-workdays to drop by more or less 20 % compared to days with no significant precipitation amounts in the morning, at noon or in the afternoon. On workdays, by contrast, rain in the morning clearly exceeds the effect of rain at noon or in the afternoon (see Figure 6).

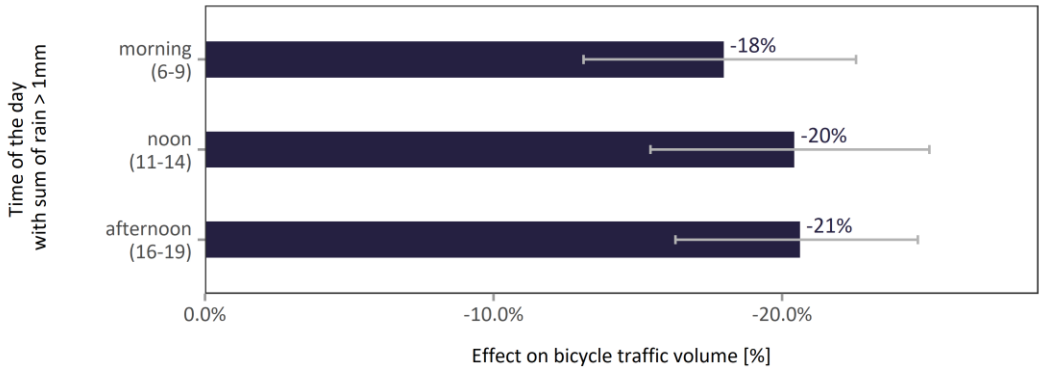

Figure 33: Effect of precipitation on the city's daily BTV, depending on the time of the day. BTV is measured in terms of counts at considered counting stations. Figures refer to non-workdays only. Period of model calibration: 06|2012-10|2018.

Figure 34 and Figure 35 provide weather-adjusted bicycle traffic statistics for non-workdays. Considered at a monthly level, particularly bike-friendly weather conditions boosted actually observed counts at stations for instance in December 2015, May 2017 and May 2018. May 2015, September 2015 and July 2017, by contrast, rank among those months where counts at stations would have been noticeably higher on non-workdays if the weather conditions had been as usual.

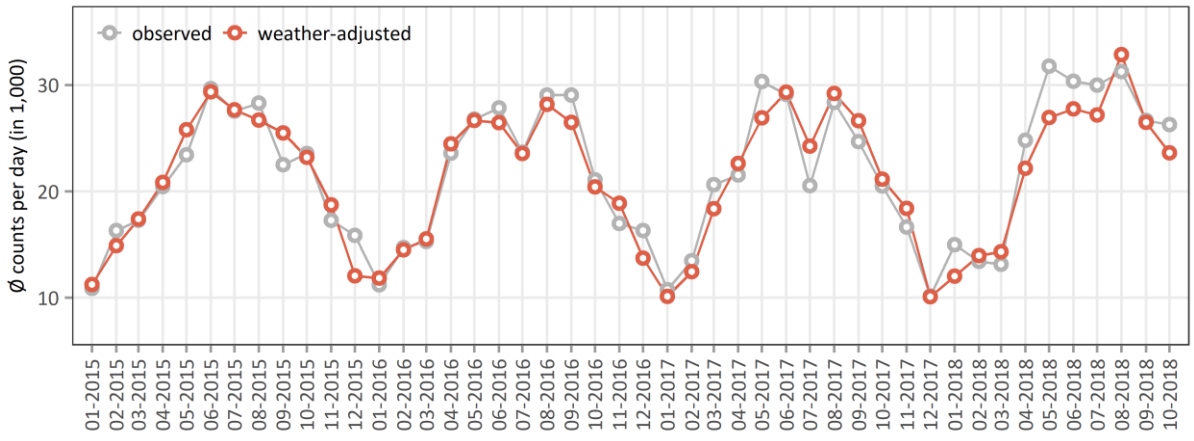

Figure 34: Observed and weather-adjusted month-to-month evolution of average daily counts on non-workdays at all stations in the period 01|2015-10|2018. The weather-adjustment uses the average meteorological conditions of the period 2000-2017 as reference conditions.

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Analysed on an annual level, below-average weather conditions for cycling somewhat dampened actual counts at stations on non-workdays in 2013, 2015 and 2017 (see Figure 35). That is, counts would have been a bit higher if the weather conditions had been as usual. In contrast, the weather conditions in 2014 and 2018 were particularly bike-friendly on non-workdays and significantly boosted actual counts at stations. Hence, parts of the increases observed in the original figures from 2013 to 2014 and from 2017 to 2018 are attributable to atypical weather conditions. Even in the weather-adjusted statistics, there remains to be a rise in counts in the respective years, but it is less pronounced than in the original figures.

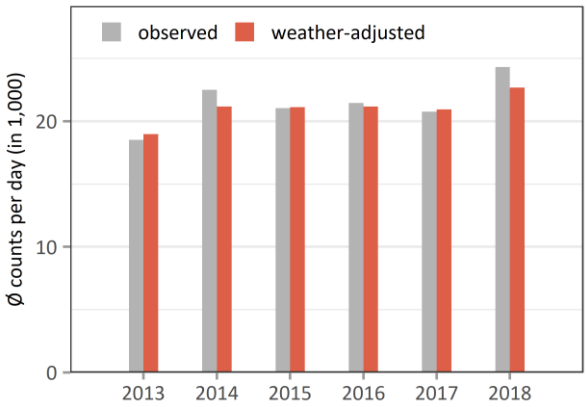

Figure 35: Observed and weather-adjusted year-to-year evolution of average daily counts on non-workdays at all stations in the period 2013-2018. The weather adjustment uses the average meteorological conditions of the period 2000-2017 as reference conditions.

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8 Supplement: Sensitivity at single counting stations

In chapter 4.3, we show spatial differences in the sensitivity of the city's daily BTV towards variations in meteorological conditions, with BTV measured in terms of tracked trips. As these analyses are limited to the summer half year 2018 and may include effects of the campaign "*Mondfahrt auf Erden*", the present chapter additionally presents the differences in the sensitivity of BTV at the single counting stations for the period 06|2012-10|2018.

Principally, results at district level cannot be transformed one-to-one to station-level, as the sensitivity at each station depends on the kind of routes passing by. That is, for example, whether a station is characterized by a high share of cyclists with short trip distances or by a high share of inbound/outbound commuters. Nevertheless, we would expect some similarities between results at district level and results at station level, as long as

(i) there is enough similarity between the sensitivity of tracked trips and the sensitivity of counts at stations (see also chapter 4.1) and

(ii) spatial differences in the summer half year 2018 are more or less representative for spatial differences throughout the year.

Figure 36 to Figure 38 show the response functions of daily BTV at each single station next to the response functions of daily BTV at all stations. The latter corresponds to the response functions displayed in Figure 5 in chapter 4.1. Counting stations are grouped together according to their sensitivity towards variations in meteorological conditions. Figure 36 shows the counting stations with a meteorological sensitivity above the all-station-average, Figure 37 the stations with a sensitivity below the all-station-average, and Figure 38 the stations with a sensitivity close to the all-station-average. Table 7 expresses the meteorological sensitivity of each counting station by one single number, using the concept of "perceived" climatic attractiveness introduced in chapter 5.2. For calculating the "perceived" climatic attractiveness, the same meteorological input data[14] is used across all stations. Thus, differences in the "perceived" climatic attractiveness at single counting stations solely reflect differences in their meteorological sensitivities (i.e. response functions). The lower the "perceived" climatic attractiveness, the higher the station's sensitivity towards variations in meteorological conditions.

It becomes evident from Figure 36 to Figure 38 and Table 7 that the counting stations *Wachmannstraße (WAS)* and *Graf-Moltke-Straße (GRM)* rank among the least sensitive ones, whereas the stations *Hastedter Brückenstraße (HAB)* and *Radweg Kleine Weser (RKW)* represent the most sensitive ones. Overall, sensitivity differences are mainly found with respect to perceived temperature (WBGT). During the warm season, daily BTV at the station HAB, for instance, responds much more sensitively to variations in the perceived temperature than daily BTV across all stations (see Figure 36.a). That is, during the warm season increases in the perceived temperature lead to much higher increases in BTV at the station *Hastedter Brückenstraße (HAB)* than at all stations. A reason might be the station's closeness to the *Werdersee*, the biggest recreational lake in Bremen. The same holds true for the counting station *Radweg Kleine Weser (RKW)*.

[14] I.e. cycling-weighted citywide averages in case of WBGT and wind speed, and data from the measurement station Bremen-Airport in case of precipitation and snow.

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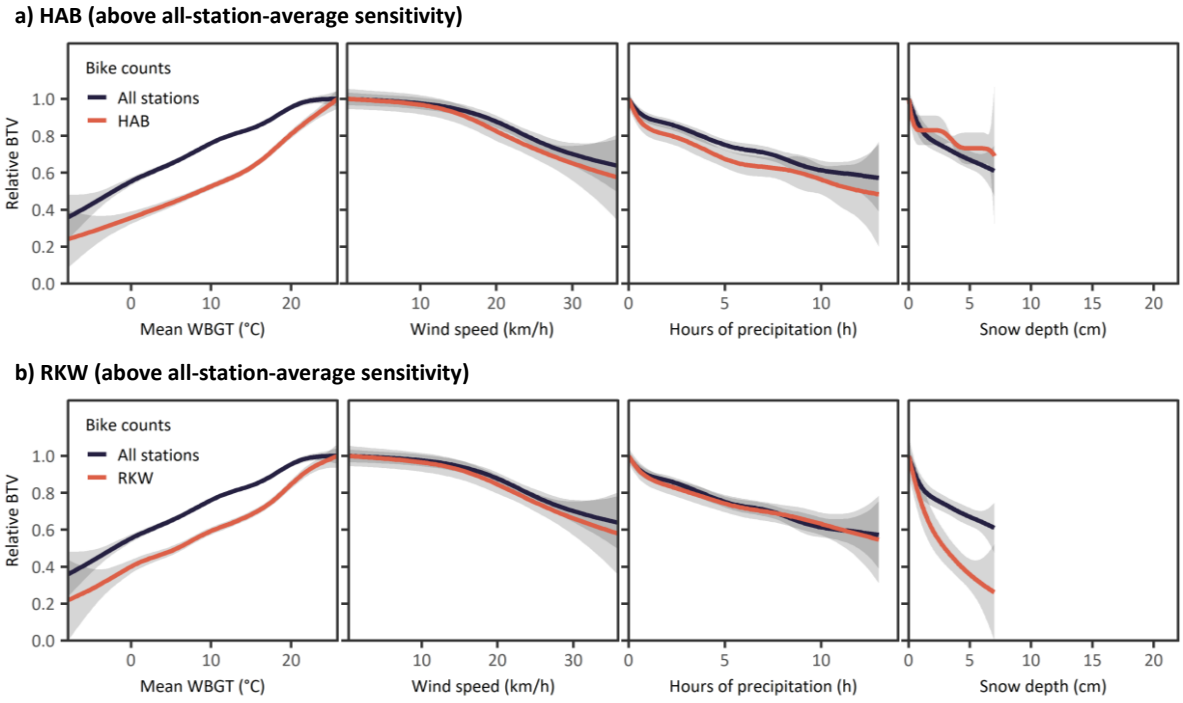

Figure 36: Effect of variations in MET indicators on daily BTV at single stations compared to the effect on daily BTV at all stations (= city's BTV). Overview of the counting stations with a sensitivity above the all-station-average. The plots refer to workdays only. Period of model calibration: 06|2012-10|2018.

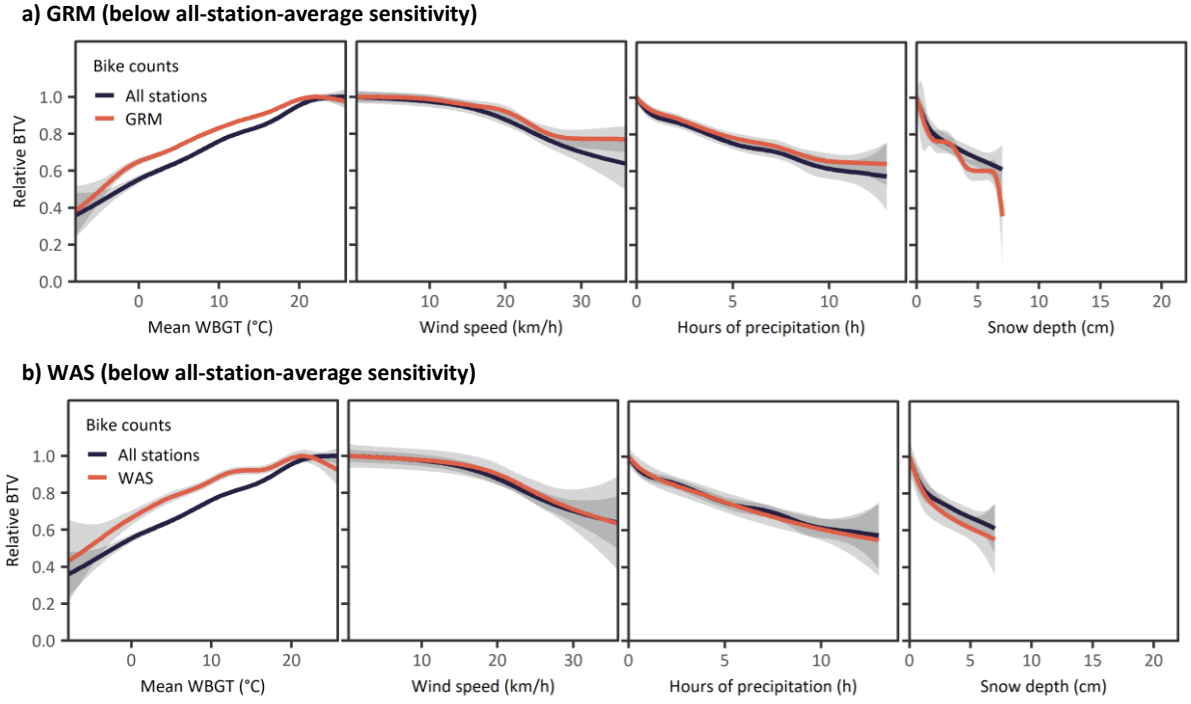

Figure 37: Effect of variations in MET indicators on daily BTV at single stations compared to the effect on daily BTV at all stations (= city's BTV). Overview of the counting stations with a sensitivity below the all-station-average. The plots refer to workdays only. Period of model calibration: 06|2012-10|2018.

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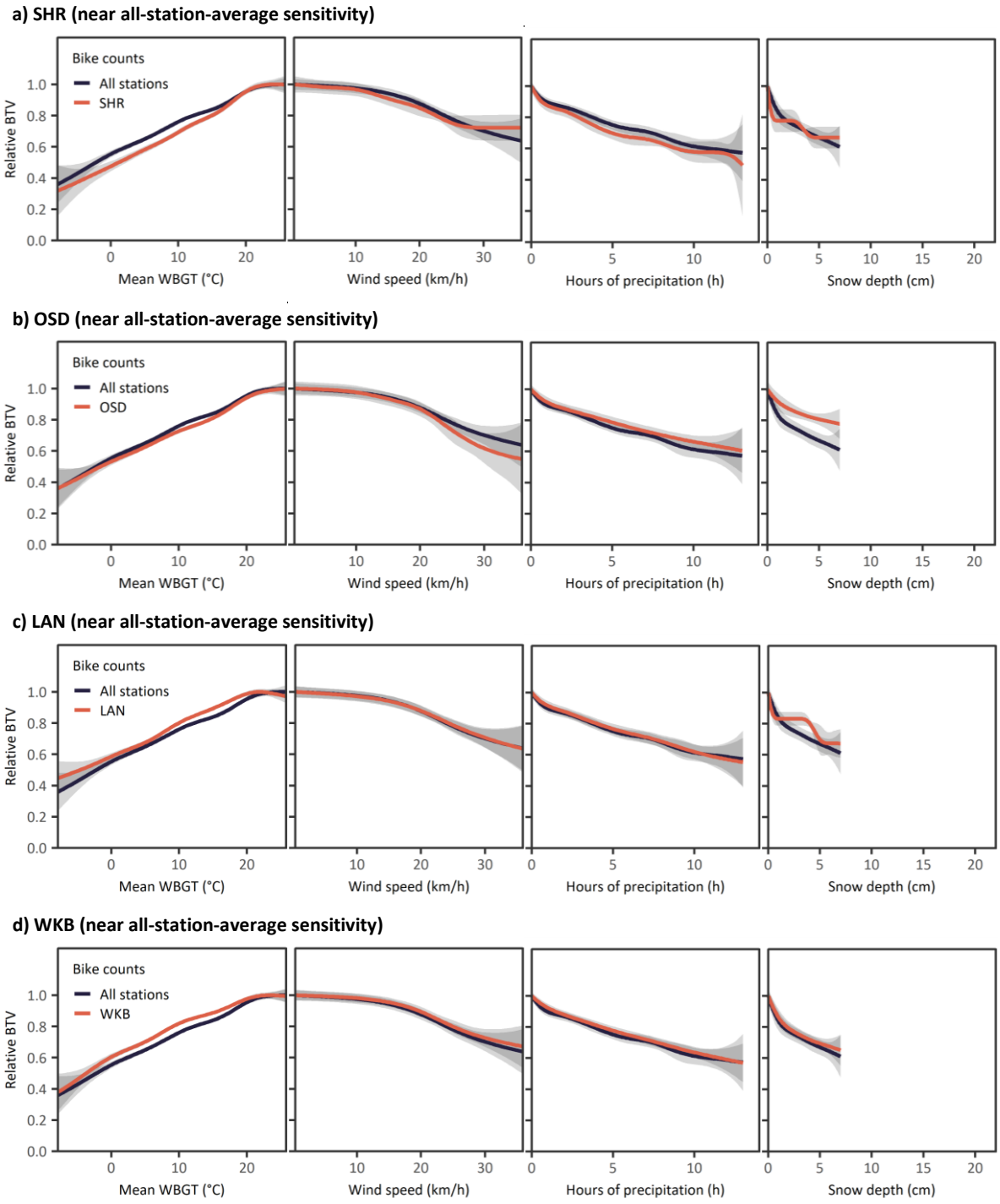

Figure 38: Effect of variations in MET indicators on daily BTV at single stations compared to the effect on daily BTV at all stations (= city's BTV). Overview of the counting stations with a sensitivity close to the all-station-average. The plots refer to workdays only. Period of model calibration: 06|2012-10|2018.

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Table 7: Ranking of the counting stations according to their sensitivity towards variations in meteorological conditions

Name	"Perceived" climatic attractiveness [a)]	Sensitivity category
Hastedter Brückenstraße (HAB)	0.50	**above** all-station-average sensitivity
Radweg Kleine Weser (RKW)	0.54	**above** all-station-average sensitivity
Schwachhauser Ring (SHR)	0.63	**near** all-station-average sensitivity
Osterdeich (OSD)	0.67	**near** all-station-average sensitivity
All stations	**0.68**	all-station-average sensitivity
Langemarckstraße (LAN)	0.72	**near** all-station-average sensitivity
Wilhem-Kaisen-Brücke (WKB)	0.74	**near** all-station-average sensitivity
Graf-Moltke-Straße (GRM)	0.76	**below** all-station-average sensitivity
Wachmannstraße (WAS)	0.77	**below** all-station-average sensitivity

[a)] The "perceived" climatic attractiveness is calculated using the same meteorological input data across all stations. Differences in the "perceived" climatic attractiveness thus solely reflect differences in the sensitivities (i.e. response functions) of the stations.

Comparing the results for the single counting stations with the results at district level shows wide agreement. Based on the spatial differences found for tracked trips on district level for the summer half year 2018 (see Figure 39), we would expect the stations *Wachmannstraße (WAS)*, *Graf-Moltke-Straße (GRM)* and *Schwachhauser Ring (SHR)* to rank among the less sensitive ones, and the stations *Radweg Kleine Weser (RKW)* and *Hastedter Brückenstraße (HAB)* to rank among the more sensitive ones. The results for the single counting stations confirm most of this expectation (see Table 7). Only the station *Schwachhauser Ring (SHR)* turns out to respond more sensitively to variations in meteorological conditions than expected from the results at district level.

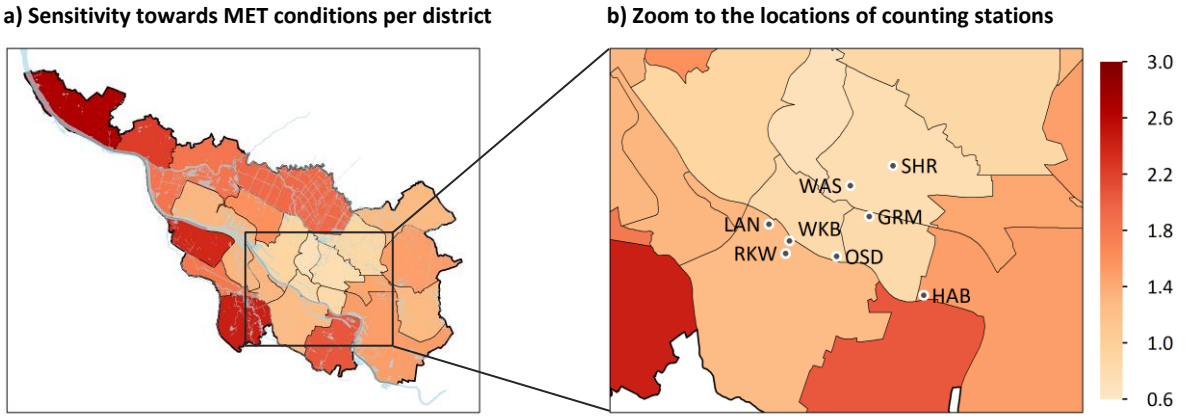

Figure 39: (a) Sensitivity of tracked trips towards variations in MET conditions on workdays for the period 04|2018-10|2018, per district (equivalent to Figure 12.b) and (b) locations of the counting stations. Administrative borders and waterbodies: OpenStreetMap.

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9 Technical details: Methodology

This chapter provides some technical details on the statistical models used in the *Active Mobility Service*. For technical details on the urban climate model *UrbClim,* see De Ridder et al. (2015). Details on the methodology of downscaling climate projections and generating the future climate data used in the *Active Mobility Service* can be found in Lauweat et al. (2018).

9.1 Statistical model: meteorological sensitivity of total bicycle traffic volume

So-called generalized additive models (GAM) are used in chapter 4.1 to explain variations in the city's daily BTV and assess its sensitivity towards meteorological conditions. GAMs are generalized linear models in which the regressand – the city's daily BTV in this case – linearly depends on unknown smooth functions of some regressors or explanatory variables. Hence, potential non-linear effects of particular meteorological indicators can be easily considered. The selection of regressors entering the final model is a result of

(i) experience from the literature (Ahmed et al. 2010; Böcker and Thorsson 2014; Brandenburg et al. 2007; El-Assi et al. 2015; Flynn et al. 2012; Helbich et al. 2014; Phung and Rose 2007; Thomas et al. 2013),
(ii) experience from the pilot city Vienna (see Köberl and Kortschak 2019), and
(iii) city-specific adjustments (e.g. with respect to different types of school holidays).

The general model structure looks as follows:

$$\log(BTV) \sim s(MI_1) + s(MI_2) + MI_3 + (MI_4 > a) + C_1 + C_2 + \cdots \qquad \textit{Eq. 1}$$

where BTV is the city's daily bicycle traffic volume, MI_i are different meteorological indices, C_i are other explanatory variables, s denotes a smooth function, and a_i defines a threshold.

The final model used to explain variations in the city's BTV on workdays takes the following form (see Table 3 for a description of the single explanatory variables):

$$\begin{aligned} \log(BTV) \sim & s(WBGT_{mean}) + s(PRH) + s(WS_{max}) + s(SD) + population + christmas.holidays \\ & + winter.holidays + easter.holidays + pentecost.holidays + summer.holidays \\ & + autmn.holidays + weekday + bridging.day + s(day.length) \end{aligned} \qquad \textit{Eq. 2}$$

Note that the statistical model that uses tracked trips as a measure of the city's daily BTV additionally includes dummy variables accounting for structural breaks in the data (such as the campaign "*Mondfahrt auf Erden*"). With additional explanatory variables, the risk of overfitting increases. That is why the holiday-variable with the lowest statistical significance (i.e. *pentecost.holidays*) is excluded from the model for tracked trips.

As described in chapter 4.1, data on WBGT and wind speed come from the urban climate model *UrbClim* (driven by ERA5 reanalysis data), whereas data on precipitation and snow depth stem from a local measurement station. As an alternative to the local measurement station, we also could have used ERA5 reanalysis data – available on a 30 km grid – as a source for precipitation and snow depth data. However, measurements from the local station revealed slightly better model performances in this case.

GAMs are also applied for investigating the effect of variations in meteorological conditions on average trip distance and average cycling speed on workdays (see chapter 4.2). In those cases, the final model

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specifications only include statistically significant meteorological indicators but no calendric or socio-economic parameters as explanatory variables:

$$\log(distance) \sim s(WBGT_{mean}) \quad \textit{Eq. 3}$$

$$\log(speed) \sim s(WBGT_{mean}) \quad \textit{Eq. 4}$$

where *distance* is the daily average trip distance and *speed* is the daily average cycling speed.

9.2 Statistical model: spatial characteristics of meteorological sensitivity

As described in chapter 4.3, potential spatial differences in the sensitivity of daily BTV – measured in terms of tracked trips – are analysed on a 2 km x 2 km grid and on district level. The GAM fitted to explain variations in the citywide daily BTV serves as a starting base. It is used to simulate BTV for each workday in the period 04|2018-10|2018 and for each considered grid cell or district in a first step. These simulations are split into a calendric effect (CE) and a meteorological effect (ME). In a second step, we assess how well the citywide model simulates BTV for each individual cell or district by fitting the following model:

$$log(BTV_j) \sim \mathrm{CE_j} + \mathrm{ME_j} \quad \textit{Eq. 5}$$

where BTV_j denotes cell/district j's daily bicycle traffic volume measured in terms of the number of tracked trips passing through cell/district *j*, CE_j is the calendric effect for cell/district j as simulated by the citywide model, and ME_j refers to the meteorological effect for cell/district j as simulated by the citywide model. If the coefficients resulting for the calendric effect and the meteorological effect are both 1, the citywide model fits perfectly for describing BTV in the respective cell/district. That is, calendric effect and meteorological effect of the respective cell/district equal the citywide effects. If, by contrast, the coefficient resulting for the meteorological effect exceeds 1, BTV in the respective cell/district responds more sensitively to variations in meteorological conditions than citywide BTV. If the coefficient is below 1, the meteorological sensitivity of BTV in the respective cell/district lies below the citywide average.

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11 Abbreviations

BTV	Bicycle traffic volume
CE	Calendric effect
CMIP	Coupled Model Intercomparison Project
CORDEX	Coordinated Regional Climate Downscaling Experiment
ECMWF	European Centre for Medium-Range Weather Forecasts
EEA	European Environmental Agency
ERA5	ECMWF ReAnalysis 5
ME	Meteorological effect
MET	Meteorological
PRH	Hours with precipitation (precipitation hours)
RCP	Representative Concentration Pathway
SD	Snow depth
WBGT	Wet-bulb globe temperature
WS	Wind speed

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