How does weather affect bikeshare use? A comparative analysis of forty cities across climate zones

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Abstract

This study examines the effect of weather on bikeshare use. We employ data from forty Public Bicycle Sharing Programs located in forty cities (16 countries) across five different climate zones, spanning tropical to boreal climates. Our curated dataset is longitudinal and consists of nearly 100 million cycling trips. Key findings include: (a) the most significant variable, particularly on weekdays, is the time of day, followed by precipitation; (b) in most cities, usage increases on weekdays and weekends up to a point around 27 to 28° C, before declining; (c) usage by hour usually follows a bimodal or trimodal daily pattern on weekdays, except for schemes which are too small to serve a commuter function (weekend and weekday usage is similar in small schemes); (d) weekend usage peaks at around 2 to 3 pm in most schemes, except those in hotter climates where the peak is around 5 pm; (e) precipitation negatively affects female ridership more than male ridership; and, (f) a changing climate is likely to affect cycling by boosting ridership in cold climates and lowering ridership in warm climates, but the effects will likely be small. In the spirit of reproducibility, all data and R code are publicly available.

Introduction

Individual trip-making is known to be conditioned by a range of "fixed" factors, including: gender, age, occupation, household characteristics, the built and natural environment, and, crucially, the presence of specialised infrastructure (Böcker et al. 2012; Liu et al. 2016). A variety of attitudes, habits, norms, and beliefs also affect travel decisions (Willis et al. 2015; Pojani et al. 2017). Empirical evidence has also shown that weather too affects where, when, and how we move around cities (Tao et al. 2018; Wei et al. 2019). Inclement local conditions, or even predictions of poor weather, can induce re-scheduling, re-routing, or cancellation of

planned journeys (Singhal et al. 2014). Weather or, eventually, changes in climate, can also lead travellers to switch modes, for example from bicycles to cars or vice versa (Wadud 2014). Individual travel decisions, when aggregated, have important implications across transportation systems in terms of traffic congestion, environmental pollution, and travel experience (Koetse and Rietveld 2009; Böcker et al. 2016). Empirical research on the weather-transport relationship is increasing but remains fragmented in terms of locations and methodologies (Corcoran et al. 2018). With climate breakdown looming, investigating in a more systematic manner the effect of weather on urban transport has become critical.
Cycling - arguably the most sustainable travel mode in existence - is likely to be more vulnerable to weather variations than driving or riding public transport, given that cyclists are exposed to the full effects of the ambient conditions. In some cities at least, weather is a key factor in deciding whether to cycle or not (An et al. 2019). However, weather effects on cycling in different climatic zones are yet to be empirically measured and compared in a single study. Without this understanding, cities cannot promote bicycle ridership or mitigate its potential loss. In this study, we conduct such a measurement, employing data from forty Public Bicycle Sharing Programs (PBSPs) located in forty cities (16 countries) across five climate zones,[1] ranging from the topical monsoonal climate of Kaohsiung (Taiwan) to the Continental climate of Minneapolis (USA) and from the Steppe climate of Valencia (Spain) to the Boreal climate in Trondheim (Norway) (Figure 1). The choice of our case study cities was principally driven by digital data availability across the world's climate zones.
Our analytic approach has a number of advantages:

1) We employ '*big data*' which capture every cycling trip within a twelve-month period, rather than merely a sample of trips, as typically captured by traditional travel surveys. Often, surveys rely on participants' travel diaries, and human memory is notoriously fallible. The advent of modern PBSPs may have rendered surveys obsolete. While the patterns of walking - another most sustainable travel mode - are difficult to measure, bikeshare data provide an excellent proxy estimator for utility cycling. There are now more than 1,000 bikesharing systems worldwide (Table 1). The trip data which they generate are openly available since the launch of the third generation of bikesharing systems in 2005 (Antoniades and Chrysanthou 2009). Modern bicycle stations are fully automated and computerized, and monitor and record the usage of the systems in real-time. Hence it has become possible for researchers to obtain detailed statistics on bicycle journeys. Some studies have already exploited the data harvested from digital PBSP stations to investigate bicycle travel demand and geographic patterns of cycling in specific cities (e.g., see Mateo-Babiano et al. 2016).

2) Our method is *longitudinal* and seeks to capture the longer term histories of individual travellers. More specifically, we use the concept of travel trajectories, which are a set of spatio-temporal points describing an individual cyclist travelling through a network. We embed these travel trajectories within a novel visualization framework, which unveils travel habits (and changes therein) in relation to weather. By contrast, much existing work tends to be cross-sectional in nature. As such, it provides single snapshots wherein the effect of weather, which requires longitudinal data to be discerned, remains underexplored. Digital bikesharing station data offer a new and exciting al-

ternative to the traditional cross-sectional survey for the combined study of weather and cycling (and travel behaviour more generally).

3) Our study is *international and comparative.* Up to now research has mostly proceeded on a case-by-case basis, and the effects of weather and climate on cycling have rarely been considered on such a large scale (Böcker et al. 2019 is an exception). Rather than analysing cycling patterns in a single case study city, as most existing studies have done, we examine multiple case studies in contrasting climate zones (Table 2). This approach brings to the fore the role of climate in addition to weather. By way of definition, weather refers to short-term changes in the atmosphere whereas climate describes the weather of a place averaged over a period of time (often 30 years). Both are expected to affect cycling patterns and behaviour (on weather, see An et al. 2019; Böcker et al. 2012; Hanson and Hanson 1977; Meng et al. 2016; on climate see, Chan and Wichman 2020; Wadud 2014; Winters et al. 2006). Fortunately, global weather observation data are now publicly available (Jendritzky et al. 2012).

4) We go beyond describing the current situation by *predicting the effect of a changing climate* on bikeshare usage. Existing studies show that, in the future, some cities will change places in the climate zone categorisation altogether (Irfan et al. 2019; Climate Central 2020). This will likely affect temperature ranges, rainfall, and other weather patterns in these cities (e.g., 'the rainy season' may shift from certain months to other months). To model climate change, we raise the temperatures in each case study city by a few degrees and thus show that a warmer climate leads to a cycling decline in some places, but it is a boon to cycling in others. However, climate change may manifest itself as an increase in extreme weather events - heatwaves, floods, and storms - rather than as a gradual increase in average temperatures (Coumou and Rahmstorf 2012). Hence the importance of investigating the effects of weather on cycling.

People living in naturally hot or naturally cold environments, such as Saudi Arabia or Finland, have developed a certain level of resilience to heat or cold. For example, a study on cycling uptake set in Singapore found that the local climate and the weather variations therein pose less of a barrier than factors such as safety and convenience, which are nearly universal. This is because people acclimatised to the tropics have a higher tolerance to heat than residents of temperate climates (Lee and Pojani 2019). However, there are upper (Raymond et al., 2020) and lower limits (Roberts, 2007) to human thermal tolerance: human life is sustainable only below an internal temperature of 42 degrees Celsius and above an internal temperature of 30 degrees Celsius. In a warming world, human resilience may not be sufficient in hot climates.

Our methodology is further detailed below. We have purposely refrained from prefacing the methodology with a literature review expounding the available studies on cycling and weather. While this is customary in academic articles, in this case the literature is too fragmented, as noted, and therefore the findings are confusing if presented in narrative format. Instead, we summarise the main findings of prior studies in Table 3. To compile the table, we have consulted empirical studies rather than relying on reviews. To our knowledge, this is a comprehensive listing of published academic articles that examine the associations between cycling and weather.

As seen, the most consistent findings are the following: (a) temperature has a bell-shaped effect on cycling but the limits on either side vary by climate zone, as people acclimatise to their local weather conditions (Helbich et al (2014), Pucher and Buehler (2006), Nankervis (1999)); (b) precipitation is a deterrent to cycling but less so in places accustomed to rain and snow (Rose et al (2011)); (c) the effect of weather is weaker for utilitarian trips, such as the work commute, than for leisure trips (Hong et al (2020)); (d) in northern latitudes, cycling peaks in summer and drops in winter (Gebhart and Noland (2014)); and (e) women are more affected by inclement weather (Nahal and Mitra (2018)).

Note that using a personal bicycle to cycle may differ from bikesharing in a variety of ways. For example, bikesharing users may be technology enthusiasts. Bikesharing may be more often used as a solution to the first mile / last mile problem rather than in full origin-destination trips and as such it may be differently impacted by weather (e.g., one may discard a shared bicycle at any point during a trip if it starts to rain whereas a privately-owned bicycle is more likely to be returned to the home). Notwithstanding these differences, as seen in Table 3, the findings of studies employing bikesharing data are quite similar to the findings of studies employing bicycle counts, intercept surveys, travel diaries, or census data.

Methodology

As noted, this study draws on data from forty PBSPs located in forty cities (16 countries) and across five different climate zones (Figure 1). Cycling data from PBSPs span the period (July 2016 to December 2019).[2]

The forty cities come from many different geographic contexts; for example, from European, North American and Asian countries. The largest cities (New York, London and Paris) have populations of the order of 10 million people while the smallest (Lillestrom and Créteil) are in the range of 50 to 100 thousand residents. Some cities such as Toyama have densities as low as 330 residents per square kilometre while the densest such as New York City have a density of over 10,000 residents per square kilometre. Similarly, the percentage of commuter cyclists who are female has been used as a way to measure the "bike friendliness" of a city (Aldred et al, 2016). Examples from our cities measured in 2016 are 22% in Brisbane (Australian Bureau of Statistics, 2017) and 39% in Vancouver (Statistics Canada, 2017), which would be considered at the low and high end respectively. More information on city populations is available in the supplementary data.

PBSP trip data

We obtained cycling trip level data for the forty PBSPs in two ways: First, for 11 schemes, we simply downloaded open-source 'flow data'; and second, for the remaining 29 schemes we collected 'stock data' from the operators' websites.[3] These websites provide real-time snapshots of bicycle and space availability at each station. The data collection timelines vary slightly by system depending on availability.

The 29 JCDecaux schemes included in our sample provide 'stock data' at a 1 minute resolution covering the calendar year 2017. Data from the Melbourne scheme[4] covers the period from July 2016 to June 2017; data from the Kaohsiung scheme also covers the period from July 2016 to June 2017. The 'flow data' derived from 'stock data' necessarily includes manual redistribution of bicycles.[5]

The 11 cities which offer actual 'flow data' include: Washington D.C., Vancouver, New York City, Minneapolis, Los Angeles, Chicago, London, Oslo, Trondheim, Bergen, and Toronto. The calendar year considered was 2017, except for the Norwegian schemes where the data are from 2019. The largest scheme for which 'flow data' are available is in New York, with 16,360,422 trips recorded in total.[6]

Overall, 97,824,175 cycling trips were analysed.[7]

Weather and climate data

The Köppen climate classification is the most widely employed in the world (Köppen 1884; 2011). It delineates five major climate types based on the annual and monthly averages of temperature and precipitation. However, it is inappropriate for assessing an outdoor activity such as cycling, which is sensitive to small changes in temperature and precipitation. For example, New York and Brisbane are lumped into the same classification ('Cfa', Humid Subtropical) although New York has distinct seasons with cold and snowy winters whereas Brisbane has mild seasonal variation with warm and clear winters. For this reason, we employed the Trewartha climate classification instead of Köppen. Trewartha is considered as a "truer" reflection of the global climate (Trewartha and Horn 1980; Belda et al. 2014). Brisbane and Melbourne are classified as 'Cf' (Humid Subtropical) in Trewartha, but may be different at lower levels of subclassification: third and fourth letters may be added such as 'a' for hot and 'b' for warm for the warmest months.

As of September 2020, there were a total of 1,999 active PBSP schemes in the world (Meddin et al., 2020),[8]the majority of which are hosted in B and C climates, in other words subtropical or temperate and continental (Table 1 and Figure 1). We gathered forty PBSP examples from five (out of six) Trewartha climate zones (Table 2 and Figure 1). Our sample is fully representative of PBSPs, with online data available in climate classifications A through E. Six schemes located in type F (polar) climates did not offer online data at the time of writing.

Weather observation data (temperature, humidity, precipitation, wind, and solar radiation) are recorded by the European Centre for Medium Range Weather Forecasting and made available through the Copernicus Climate Data Store. We obtained hourly precipitation data and the historical Universal Thermal Climate Index (UTCI) from this source (di Napoli 2020).[9] By way of explanation, the UTCI measures heat stress from the environment to the human body (Jendritzky et al. 2012). This index was specifically developed to measure thermal comfort for outdoor activities (Bröde et al. 2012). It conveniently captures most weather variables (air temperature, humidity, solar radiation, and wind). The UTCI was developed by the International Society of Biometeorology as a bioclimate index to describe the heat load that the human body experiences trying to maintain a thermal equilibrium with the outdoor environment. It has been evaluated across different climate regions and on various spatial and temporal scales. (di Napoli et al. 2018).

Therefore, we argue that its use is appropriate in a study on cycling.

Analysis procedure

To reiterate, this study examines how weather affects bike share usage.[10] We developed a model which predicts hourly bikeshare demand as a function of time of day, time of year, day of week, UTCI, and precipitation variables. As a starting point, we applied a Generalized Additive Model contained in the *mgcv* R package (Wood 2001). For each city, the model predicts weekday and weekend usage:

$$usage(h) \quad = \quad s(u_{\mathrm{h}}) \; + \; p_{\mathrm{h}} \; + \; s(h) \; + \; s(j_{\mathrm{h}}) \; + \; \epsilon$$

where:

$usage(h)$ = number of trips within half an hour of hour h

u_{h} = UTCI temperature at hour h

p_{h} = total precipitation in the previous hour[11]

j_{h} = Julian date[12]

ϵ = Error term

Bikeshare usage is modelled for each hour with a non-zero number of trips. [13] In theory, other factors in addition to UTCI, precipitation, and season can affect bikeshare usage, as operators try to increase ridership or revenue. These factors include economic and legal incentives such as: longer opening hours; increases or decreases in fees; incentives for students; introduction of ‘tap and go’ riding with credit card support; competitions and promotions; competing bikesharing, dockless bike sharing and electric scooter schemes; legal changes, such as around mandatory helmet laws and the provision of helmets; public transport strikes; force majeure events, such as terrorist attacks on public transport or pandemics; changes in public transport prices (e.g., free tram/bus zones); addition of credit card facilities to stations; and/or large group events. However, to the extent of our knowledge, none of these changes have occurred in any of forty schemes during the years examined.[14]

Other factors, such as air pollution levels and public holidays may certainly affect usage in the studied cities. However, these were considered too difficult to incorporate in our model. A more complex model would also incorporate the effect of wind speed and direction on certain trips. In any case, the patterns of usage are already very clear with the studied variables.

In addition to modelling current bikeshare usage, we considered the effect on trip frequency of UTCI increases or decreases by one or two degrees Celsius, holding all other factors constant, including precipitation. Finally, for a subset of our database we examined gender differences. For a portion of the trips in New York and Chicago, gender data are publicly available.[15] Based on these additional data, we developed a four-variable model for weekends and weekdays. We then examined the coefficients of the precipitation terms in the models to test for a significant difference between males and females in the weekend and weekday models.

We have visualised the model results using the *vis.gam* function in the R *mgcv* package. In this case, *vis.gam* is used to provide a contour plot of the fitted usage variable versus two predictor variables. For our plots, we have chosen three pairs: UTCI and Precipitation, to illustrate 'weather' effects; Hour and Julian date, to illustrate 'temporal' effects, and Hour and Precipitation, as these are generally the two most significant variables.

Note that the R^2 value increases for larger bikesharing systems and the error term is relatively smaller for larger systems. This means that the effects of temporal and weather variables are better modelled for larger systems, as random variation is minimised.

Findings and discussion

The travel patterns of all cycling trips in all forty systems are shown in Figure 2, a-f. The weekday model R^2 values range from 0.911 in London to 0.085 in Créteil. This means that the weekday models explain between 8.5% and 91.1% of the variance in usage. Créteil's is a very small system with only 4,936 trips during 3,005 usage hours in 2017. The next lowest R^2 value is 0.304 for Santander. Weekend model R^2 values range from 0.932 in London to 0.174 in Créteil. In other words, the weekend models explain between 17.4% to 93.2% of the variance in usage. In all of the models, each of the four predictor variables was found to be significant at $p<.05$, except for precipitation in the two Créteil models ($p=0.07$).

In 38 of the 40 weekday models, and 32 of the 40 weekend models, the most significant variable is the 'hour' (i.e., the time of the day). Typically, weekend usage peaks around 2 to 3 pm, while weekday usage has a bimodal peak around business hours. In Kaohsiung, the only system in a tropical climate, the weekend usage peaks later in the day, at around 5 pm. In this study, all modelling is carried out assuming all other variables are equal. In reality, a siesta tradition may develop in a city if the temperature became too extreme, and this would change the hourly modelling. Similarly, we would expect systems like Minneapolis which operate only a few months per year to extend their operating months in the presence of warmer weather. After the 'hour', the second most significant variable is usually the 'precipitation' (in 28 of the 40 weekday and weekend models). For weekdays, the daily and yearly patterns are fixed and extremely predictable. In some cities, the 'date' variable is very significant.

We also modelled usage as a function $s(u_\mathrm{h})$ of the UTCI hourly variable alone. We found that there is usually a turning point in the range of 15 to 35 degrees Celsius where the modelled usage is always decreasing regardless of temperature changes.[16] Examining the turning point sheds further light on usage patterns. To find out the turning point for each city, we estimated the usage for a range of temperatures between 10 and 50 degrees Celsius. We found that for cities where a turning point exists, the value ranges from 19 (Göteborg) to 33.7 (Minneapolis) during weekdays, and from 22.5 (Lillestrøm) to 32.8 (Washington, D.C.)

during weekends. The mean turning points values are 27.0 (weekdays) and 28.2 (weekends). In Brisbane, the turning points are the closest to the general sample means: 27.8 (weekdays) and 28.5 (weekends). Some cities, including Göteborg and Dublin, have no clear turning points. In Dublin, 'precipitation', 'hour', and 'Julian date' are far more significant than temperature during weekdays. During weekends, 'hour' and 'precipitation' are the most significant variables. The turning point is 19.8 degrees Celsius on weekdays whereas on weekends usage keeps increasing alongside temperature. However, the maximum UTCI value for Dublin is only 28.6 degrees Celsius. These findings are in line with the 'stress category' classification where UTCI values of 9-26 degrees Celsius are classified as "no heat stress", 26-32 as "moderate heat stress", 32-38 as "strong heat stress", 38-46 as "very strong heat stress" and 46+ as "extreme heat stress" (di Napoli et al. 2018). A similar pattern is found in electricity-demand forecasting (Clements et al. 2016).[17]

Next, we focus on a few selected cities from each climate classification. Figure 3 shows the models for New York. This city is an example of the 'Dc' (continental) climate classification. Its weekday pattern is bimodal and very focused around business hours, whereas the weekend pattern is focused around afternoon riding, although some people are still out riding after midnight. Similarly, An et al. (2019) and Heaney et al. (2019) found that a higher temperature (up to 26-28° C) predicts more cycling trips in New York. The average daily temperature affects cycling trips more during weekends than weekdays. Rainy, humid, windy and especially snowy weather lead to fewer cycling trips (An et al. 2019).

Figure 4 shows the Seville models. This is an example of the "Cs" (Mediterranean) climate classification. Among the case studies, Seville has the highest UTCI temperature value of 46.9 degrees in July 2017. The tradition of the siesta is clear in the afternoon dip in ridership, and trimodal weekday peaks at 9am, 2pm and 8pm. The Seville model is based on 2,570,212 trips. Valencia is the sole example of a type B system in the data – a 'BS' classification (Steppe). The model is based on 4,363,268 trips (Figure 5). As in Seville, a clear trimodal peak is visible in Valencia on weekdays.

In Paris, a 'Do' classification (Oceanic), there is a considerable drop in demand around Julian date 210 due to traditional August holidays in France (Figure 6). Brisbane is an example of the 'Cf' climate classification (Humid Subtropical). The Brisbane plots, shown in Figure 7, are based on 604,196 trips.[18] As with most cities, the weekday model is bimodal (suggesting commuter trips) with peaks around 8 am and 5 pm. There is a drop-off in usage around Christmas and New Year, as these holidays occur in summertime in Australia. Similarly, Corcoran et al. (2014) found that in Brisbane, rainfall affects ridership, especially during weekends whereas temperature exerts much less influence on cycling trips (both utilitarian and recreational).

The cycling trip patterns in Kaohsiung, the only example of a Tropical / Monsoon climate, are shown in Figure 8. Trondheim is the only example of a Boreal climate, and the models are shown in Figure 9. Despite their very different climatic settings, both Trondheim and Kaohsiung exhibit a normal bimodal travel pattern during weekdays and a unimodal pattern during weekends. The peak is at about 4 pm in Trondheim and at 5 pm in Kaohsiung. The Kaohsiung plot that links precipitation to UTCI is somewhat unusual because it has two peaks (at 21.5 and 32.3 degrees) whereas most other cities have just one peak. Also, fewer people ride in the monsoon season (around Julian Date 250), which is strong in Taiwan and involves typhoons. Other studies set in tropical climates have found that cyclists here prefer relatively lower temperatures (29.5–31.5° C) and humidity (52.3%–62.7%) and no rainfall, although high UTCI does not eliminate ridership altogether because people tend to acclimatise to their living environments (Meng et al. 2016; Lee and Pojani 2019).

When we uniformly raise the UTCI temperatures in each city to check the potential effect of climate change on cycling, we find that a uniform 1 degree Celsius increase in UTCI results in changes in weekday ridership from -0.6% to 2.0% and in weekend ridership from -0.4% to 2.8% . A uniform 2 degree increase in UTCI changes weekday ridership by -1.4–4.0% and weekend ridership by -0.9–5.6% . Ridership increases are realised in colder climates whereas decreases occur only in Valencia and/or Seville. Although we did not check other base years due to computational storage and capacity limitations, a pattern of increased usage is likely to be correct for the small temperature increases modelled here. Heaney et al.'s study (2019), based on New York data, reached similar conclusions to ours: climate change is predicted to produce cycling increases in winter, spring, and fall, and declines in summer, but, with no policy changes, the net increase may reach only up to 3.1% by 2070. Readers are invited to download our full dataset if they wish to model the effect of precipitation changes, or hourly usage changes. With regard to gender differences (Table 4), a one-tailed z-test indicates that females are more sensitive to precipitation, confirming the findings of prior studies (see for example, Aaheim et al. 2005; Saneinejad et al. 2012; Nahal and Mitra 2018). However, the difference with males is statistically significant ($p < 0.01$) only during weekdays in New York and during weekends in Chicago.[19]

Conclusion

The key findings of this large-scale, longitudinal, and comparative study include: (a) the most significant variable in most models, particularly on weekdays, is the hour, followed by precipitation; (b) in most cities, usage increases on weekdays and weekends up to a point around 27 to 28° C, before declining; (c) weekday usage by hour usually follows a bimodal or trimodal daily pattern, except for schemes which are too small to serve a commuter function and therefore have similar usage on weekends and weekdays (see also O'Brien et al. 2014); (d) weekend usage peaks at around 2 to 3 pm in most schemes, except those in hotter climates where the peak is around 5 pm; (e) precipitation negatively affects female ridership more than male ridership, with the effect being statistically significant for some cities and models; and (f) global warming is likely to lead to ridership increases in colder climates and declines in warmer climates, but the effects will be relatively small.

Drawing on the results across our case study cities, and in line with prior studies, we found that temperature broadly exerts a bell-shaped effect on cycling. However, the limits on either side vary but are not closely connected to the climate zone or climatic norms. For example, Trondheim and Ljubljana revealed greater sensitivity to lower temperatures than Dublin and Kaohsiung – all places with very different climates. In very cold cities such as Minneapolis, Kazan, and Vilnius the bikesharing schemes close in winter as the roads become icy and dangerous. We also found that, generally, precipitation (rain and/or snow) is a deterrent to cycling. While this finding generally confirms prior studies, our cross-climatic comparative framework reveals a more nuanced picture. In cities such as Dublin, Seville, and Valencia people cycle even in wet weather, whereas in places like Melbourne, Chicago, and Vancouver people avoid cycling when it rains or snows. In the latter, a smaller amount of precipitation appears to exert greater impacts on cycling. This cannot be chalked up to the fact that in more temperate climates, people are more accustomed to precipitation (which has been the assumption so far). While Dublin is notoriously rainy, Seville and Valencia are rather dry but here rain does not make much of a difference to the cyclists. The difference could be that Seville and Valencia have large systems and safe cycling infrastructure whereas Melbourne only had a small system not useful for commuters. With regard to seasonality, we found that in cities located in more temperate climates, such as Paris and Brussels, cycling peaks in summer and drops in winter. Conversely, those located in more tropical settings – e.g., cities such as Brisbane and Kaohsiung – experience little seasonal variation in cycling. In making these broad observations we do acknowledge the range of additional factors that are important and act to shape ridership dynamics alongside that of weather and climate including the size of the scheme and the quality of redistribution, to name but a select few.

Taken together our findings are not surprising. However, they are conclusive given the type and amount of data employed in this study. Stakeholders who are pondering whether to introduce or expand a bikesharing system in their area may wish to consult our findings for cities with a similar climate and culture. Alternatively, they can apply our analysis procedure to their longitudinal dataset of bikeshare usage and weather. It must be noted, however, that in the future, the picture we have painted may look very different if regulatory and infrastructural interventions in favour of utilitarian cycling in general, and bikesharing in particular, take place in cities. Cycling needs to become a normative and integral part of transport planning. Planners need to secure strong political support for cycling, as well as unity and collaboration within the cycling communities of individual cities. In nearly all places, funding for bicycle transport needs to increase (Butterworth and Pojani 2018). While we cannot change the weather, we can and should transform our institutional and political environments, if bicycle travel is to become a widespread form of transport.

Future studies may extend our analytic approach by including additional variables (e.g., land use, topography, culture, and specialised infrastructure) provided that 'big data' is available which can be matched with bikesharing data. To this end, we provide our R code as part of the supplementary materials by way of encouraging researchers to build on the present study. As digital bikesharing becomes more widespread around the world, and more data is captured, a broader range of settings can be examined, and for longer periods of time. Finally, predicting the effect of global warming on bikeshare usage will be a crucial task in the years to come.

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Tables

Table 1. PBSPs by climate zone and continent.

Trewartha Type	*Climate*	*North America*	*South America*	*Africa*	*Asia*	*Oceania*	*Europe*
Type A	Tropical Wet (Ar) Wet and dry (Aw)	9	20	3	44	2	0
Type B	Dry (arid and semi-arid) Steppe (BS) Desert (BW)	16	6	3	136	0	24
Type C	Subtropical Mediterranean (Cs) Humid (Cf)	58	34	2	509	9	121
Type D	Temperate and continental Continental (Dc) Oceanic (Do)	110	0	0	182	4	675
Type E	Boreal	4	0	0	1	0	21
Type F	Polar Tundra (Ft) Ice cap (Fi)	0	0	0	2	0	4

Table 2. Case study cities.

City	*Trewartha climate classification*	*Mean UTCI*	*Rain total (mm)*
Amiens, France	Do (Oceanic)	6.5	744
Bergen, Norway	Dc (Continental)	-1.1	2303
Besançon, France	Do (Oceanic)	8.6	1167
Brisbane, Australia	Cf (Humid Subtropical)	19.9	943
Brussels, Belgium	Do (Oceanic)	6.0	752
Cergy-Pontoise, France	Do (Oceanic)	7.7	666
Chicago, USA	Dc (Continental)	3.6	1179
Créteil, France	Do (Oceanic)	7.9	732
Dublin, Ireland	Do (Oceanic)	2.7	939
Göteborg, Sweden	Dc (Continental)	-0.1	1086
Kaohsiung, Taiwan	Aw (Tropical)/Am (Monsoon)	26.6	2720
Kazan, Russia	Dc (Continental)	-2.6	654
Lillestrøm, Norway	Dc (Continental)	1.4	970
Ljubljana, Slovenia	Dc (Continental)	8.5	1403
London, UK	Do (Oceanic)	5.3	713
Los Angeles, USA	Cs (Mediterranean)	18.3	309
Lund, Sweden	Dc (Continental)	1.2	858
Luxembourg, Luxembourg	Do (Oceanic)	5.8	802
Lyon, France	Do (Oceanic)	9.3	840
Marseille, France	Cf (Humid Subtropical)	8.2	383
Melbourne, Australia	Cf (Humid Subtropical)	10.7	745
Minneapolis, USA	Dc (Continental)	3.0	983
Mulhouse, France	Do (Oceanic)	8.7	961
Namur, Belgium	Do (Oceanic)	5.3	853
Nancy, France	Do (Oceanic)	6.6	864
Nantes, France	Do (Oceanic)	8.8	601
New York, USA	Dc (Continental)	8.3	1157
Oslo, Norway	Dc (Continental)	2.0	1297
Paris, France	Do (Oceanic)	7.8	728
Rouen, France	Do (Oceanic)	6.8	847
Santander, Spain	Do (Oceanic)	12.2	1173
Seville, Spain	Cs (Mediterranean)	18.1	340
Toronto, Canada	Dc (Continental)	3.0	968
Toulouse, France	Do (Oceanic)	10.4	826
Toyama, Japan	Cf (Humid Subtropical)	10.9	2605
Trondheim, Norway	E (Boreal)	1.0	1083
Valencia, Spain	BS (Steppe)	16.3	279
Vancouver, Canada	Do (Oceanic)	6.5	2118
Vilnius, Lithuania	Dc (Continental)	1.0	915
Washington, D.C., USA	Do (Oceanic)	11.6	1062

Table 3. Main findings of prior studies on the relationship between cycling and weather. Studies employing bikesharing data are highlighted in grey.

Study (by date)	*Setting (place & climate zone)*	*Key findings*
Hanson and Hanson (1977)	Uppsala, Sweden Continental (Dc)	Bicycle use declined with falling temperatures. Work commutes were less sensitive to weather than recreational trips. Even when the temperature was below freezing, 20-25% of all trips to work were made by bicycle.
Bergström and Magnusson (2003)	Luleå and Linköping, Sweden Boreal (E) and Continental (Dc)	The number of bicycle trips decreased by nearly half from summer to winter. Temperature and precipitation (rain and snow) were the most important factors to those who cycled to work in summer but not in winter.
Aaheim et al. 2005	Bergen, Norway Continental (Dc)	Weather had little effect on cycling. Precipitation had a stronger negative effect among older women, and in the case of recreational trips. Cycling for work-related trips increased with higher temperatures.
Pucher and Buehler (2006)	50 states, USA and 13 provinces, Canada Varies	Either excessively high or low temperatures deterred cycling, while precipitation of any amount (rain or snow) discouraged cycling.
Brandenburg et al. (2007)	Vienna, Austria Continental (Dc)	Cycling, especially for recreational reasons, was mostly performed during mild weather (i.e., sunny, temperature higher than 5° C, few clouds and no precipitation).
Winters et al. (2007)	53 larger cities, Canada Varies	Fewer people cycled in cities with more days of precipitation or freezing temperatures. Average summer maximum temperature and average wind speed did not influence cycling.
Parkin et al. (2008)	8,800 wards, England and Wales Oceanic (Do)	Rainfall had a negative impact on the propensity to cycle to work. Higher mean temperatures were linked with a greater volume of cycling to work.
Nankervis (1999)	Melbourne, Australia Humid Subtropical (Cf)	Cycling was at its highest in summer/autumn, declined in winter, and resurged in spring. Wind, rain, and temperature were significant in relationship to cyclist numbers. Cyclists were particularly sensitive to extremes of temperature, with cold being more powerful.

Sabir et al. (2010)	National, Netherlands Oceanic (Do)	Precipitation enhanced the modal shift from bicycle to public transport and car.
Rose et al. (2011)	Melbourne, Australia. and Portland, USA Humid Subtropical (Cf) and Oceanic (Do)	Warmer temperatures and lower rainfall led to increased bicycle traffic in both cities. The effect of temperature was stronger in Portland.
Miranda-Moreno and Nosal (2011)	Montreal, Canada Continental (Dc)	When the temperature doubled, up to 50% increase in cycling could be expected. Temperatures higher than 28° C, humidity greater than 60% , and rain had a negative effect. Lagged effects of rain were also observed. Cycling volumes peaked in the summer months.
Goetzke and Tilmann (2011)	20 cities, Germany Continental (Dc)	Bad weather was unconducive to cycling.
Lewin (2011)	Boulder, Co, USA Continental (Dc)	There was a strong linear relationship between high temperatures and cycling volumes, with a slight decrease in cycling at temperatures greater than 90º F. Cycling also decreased on days with rain or snow but this effect was not linear.
Tin Tin et al. (2012)	Auckland, New Zealand Humid Subtropical (Cf)	For a 1° C increase in temperature, the cycling volume increased by 3.2% (hourly) and 2.6% (daily). For a 1h increase in sunshine, the cycling volume increased by 26.2% (hourly) 2.5% (daily). For a 1 mm increase in rainfall, the cycling volume decreased by 10.6% (hourly) and 1.5% (daily). For a 1 km/h increase in wind speed, the cycling volume decreased by 1.4% (hourly) and 0.9% (daily).
Flynn et al. (2012)	Vermont, USA Continental (Dc)	Participants were nearly twice as likely to commute by bicycle when there was no morning precipitation. A 1° F increase in temperature raised the likelihood of cycling by about 3% . A 1 m/h increase in wind speed decreased cycling likelihood by about 5% , and 1 inch of snow on the ground reduced the likelihood of cycling by about 10% .

Saneinejad et al. (2012)	Toronto, Canada Continental (Dc)	At temperatures higher than 15° C cycling became insensitive to temperature. At temperatures below 15° C cycling decreased. Wind speed and rain negatively affected cycling. Younger cyclists were more sensitive to colder temperatures than older cyclists. Women were about 1.5 times more negatively affected by cold temperatures than men.
Thomas et al. (2013)	Ede and Gouda, Netherlands Oceanic (Do)	Most daily fluctuations in cycling (80%) could be explained by weather conditions. Temperature had the largest (positive) effect, whereas the effect of precipitation was small. Recreational demand was much more sensitive to weather than utilitarian demand.
Nosal and Miranda-Moreno (2014)	Montreal, Ottawa, Vancouver, Green Route, Canada and Portland, USA Varies	Temperature was positively associated with cycling, whereas humidity was negatively associated, with a non-linear association in most cases. Precipitation had a significant negative impact on cycling flows, and its effect increased with rain intensity. Lagged effects of rain were also observed. Bicycle flows were more sensitive to weather on weekends than on weekdays.
Corcoran et al. (2014)	Brisbane, Australia Humid subtropical (Cf)	Rainfall affected cycling trips, especially during weekends. Strong winds (over 5.5 km/h) considerably reduced the number of longer-distance cycling trips. Temperature exerted much less influence on cycling trips (both utilitarian and recreational).
Gebhart and Noland (2014)	Washington, D.C., USA Oceanic (Do)	Cycling trips peaked during summer months. More and longer trips were made when temperatures were in the 80-89° F (26.7-31.7° C) range. The number of trips was higher for temperatures in the 90° F range (32.2-37.2° C) as compared to the 50° F range (10-15° C). Trip frequency was about 0.75% less when it was raining. Humidity led to decreases in ridership. The effects of fog and thunderstorms were not significant.
Helbich et al. (2014)	Rotterdam, Netherlands Oceanic (Do)	Air temperature has a bell-shaped effect on cycling, and the effect is weaker for utilitarian compared to leisure trips. Wind speed and precipitation have negative effects on cycling, although less strong than temperature. During work commute trips, the effects of precipitation and wind are not significant. Temperature, wind, and precipitation are less important to cyclists in denser and more compact areas than to cyclists in sprawling suburbs.

Rudloff and Lackner (2014)	Vienna, Austria Continental (Dc)	The demand for bicycles and stations depends on weather: warmer temperatures encourage use whereas precipitation discourages use; the correlation between wind and demand is very low.
Amiri and Sadeghpour (2015)	Calgary, Canada Boreal (E)	More than 70% of participants (frequent cyclists) had a high tolerance to cold, and a third were comfortable with cycling in temperatures up to -20° C. Icy roads were the greatest safety concern in winter cycling.
Motoaki and Daziano (2015)	Ithaca, NY, USA Continental (Dc)	More experienced cyclists were less affected by adverse weather conditions. Rain deterred cyclists with lower skills from cycling 2.5 times more strongly than those with better cycling skills. Snow was almost 4 times more deterrent to the less experienced cyclists.
Meng et al. (2016)	Singapore Tropical Wet (Ar)	Cyclists preferred relatively lower temperature (29.5–31.5° C) and humidity (52.3% – 62.7%) and no rainfall. Wet weather forecasts led cyclists to change travel mode.
Schmiedeskamp and Zhao (2016)	Seattle, Wa, USA Oceanic (Do)	There was a roughly linear increase in bicycle volume with increased day length (in the warmer season). There was an inverse relationship between precipitation and bicycle counts but people were more sensitive to the presence of precipitation than to the intensity. Temperature had a positive relationship with cycling, and there was no leveling off in counts at very high temperatures (85° F).
De Chardon et al. (2017)	75 cities, Europe, United States, Canada, Brazil, Australia, Israel Varies	Weather impacted cycling but the effect was not always strong. Warmer temperatures increased cycling volumes but benefits peaked between 18 and 33° C. An increase in wind speed of 1 km/h, above the mean, was associated with a 2% decrease in cycling. Humidity was not significant.
Lu et al. (2017)	Ningbo, China Humid subtropical (Cf)	Rain negatively and significantly affects bikesharing use.
Nahal and Mitra (2018)	Toronto, Canada Continental (Dc)	Cyclists, women in particular, were the most likely to change their commute modes in winter.
Kim (2018)	Daejeon, South Korea Continental (Dc)	Higher temperature was positively correlated with cycling volume but temperatures over 30° C reduced cycling. Relative humidity, precipitation, wind speed, and the thermal heat index were negatively correlated with cycling.

Zhao et al. (2018)	Seattle, Wa, USA Oceanic (Do)	Rainfall and especially snowfall had significantly negative impacts on cycling. There were significant lagging weather effects. Cycling was most impacted by weather in spring (due to capricious conditions). Daily cycling in summer fluctuated up and down when the average daily temperature exceeded 20° C. Cycling volumes were more stable (but lower) in winter.
Böcker et al. (2019)	Oslo and Stavanger, Norway, Continental (Dc) and Mediterranean (Cs) Stockholm, Sweden, Continental (Dc) Utrecht, Netherlands Oceanic (Do)	Dry and warm weather positively affected cycling, while cold and (to a lesser extent) wet and windy weather reduced cycling rates. The positive effect of temperature flattened out above 20-25°C. Hot weather did not reduce cycling considerably.
An et al. (2019)	New York, USA Continental (Dc)	A higher temperature (up to 28° C) predicts more cycling trips. The average daily temperature affected cycling trips more during weekends than weekdays. Rainy, humid, windy and especially snowy weather led to fewer cycling trips.
Heaney et al. (2019)	New York, USA Continental (Dc)	Cycling significantly increased as temperatures increased but declined at temperatures above 26-28° C. Due to climate change, cycling may increase in winter, spring, and fall, and decline in summer. The net increase may be up to 3.1% by 2070.
Lee and Pojani (2019)	Singapore Tropical Wet (Ar)	High temperature, combined with high humidity or heavy tropical rains, was an important - though not crucial - factor in the decision to cycle.
Cervero et al. (2019)	36 cities, England and Wales Oceanic (Do)	Rain worked against bicycle commuting. Warmer temperatures encouraged cycling, at least during spring.
El-Assi et al. (2019)	Toronto, Canada Continental (Dc)	There was a significant correlation between temperature and cycling activity. In the warmer seasons, trips were concentrated within three peaks (morning, midday, and afternoon). In the colder seasons, the midday peak declined.
Tu et al. (2019)	Shanghai, China Humid subtropical (Cf)	Rain negatively affects bikesharing use. The effect of weather on bike trip density is much stronger on rainy days.

Hong (2020)	Glasgow, Scotland Oceanic (Do)	Seasonal cycling patterns were evident. Average cycling counts peaked in summer (June-August, below 20° C on average) and were the lowest in December. Rain had a negative effect on cycling volumes but commuting trips were less sensitive to rain.
Lepage and Morency (2021)	Montreal, Canada Continental (Dc)	Presence of rain and rain in the three previous hours decreases bikesharing demand. High temperatures (over 25 degrees Celsius) induce a 22% increase in bikesharing demand but increases are lower for temperatures higher than 28 degrees Celsius. Wind speed influences bikesharing demand especially for stations father from the downtown.

Table 4. Bikeshare usage by gender for select PBSPs.

City	Gender	Weekday slope	Weekday slope SE	Weekend slope	Weekend slope SE
New York	Male	-0.42644	0.01603	-0.52349	0.02476
New York	Female	-0.51771	0.01854	-0.53310	0.02694
Chicago	Male	-0.28442	0.01456	-0.6850	0.0374
Chicago	Female	-0.31127	0.01625	-0.82321	0.04550

Note: the term ‘slope’ refers to the regression line slope (not the physical slope in the city’s terrain).

Figures

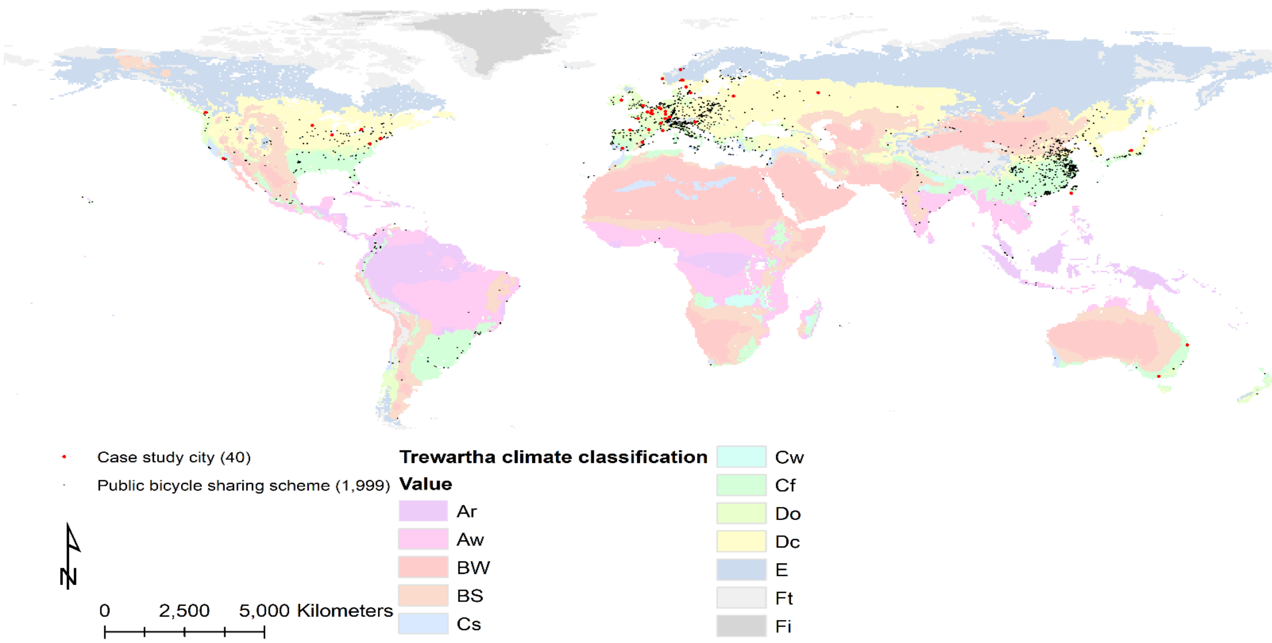
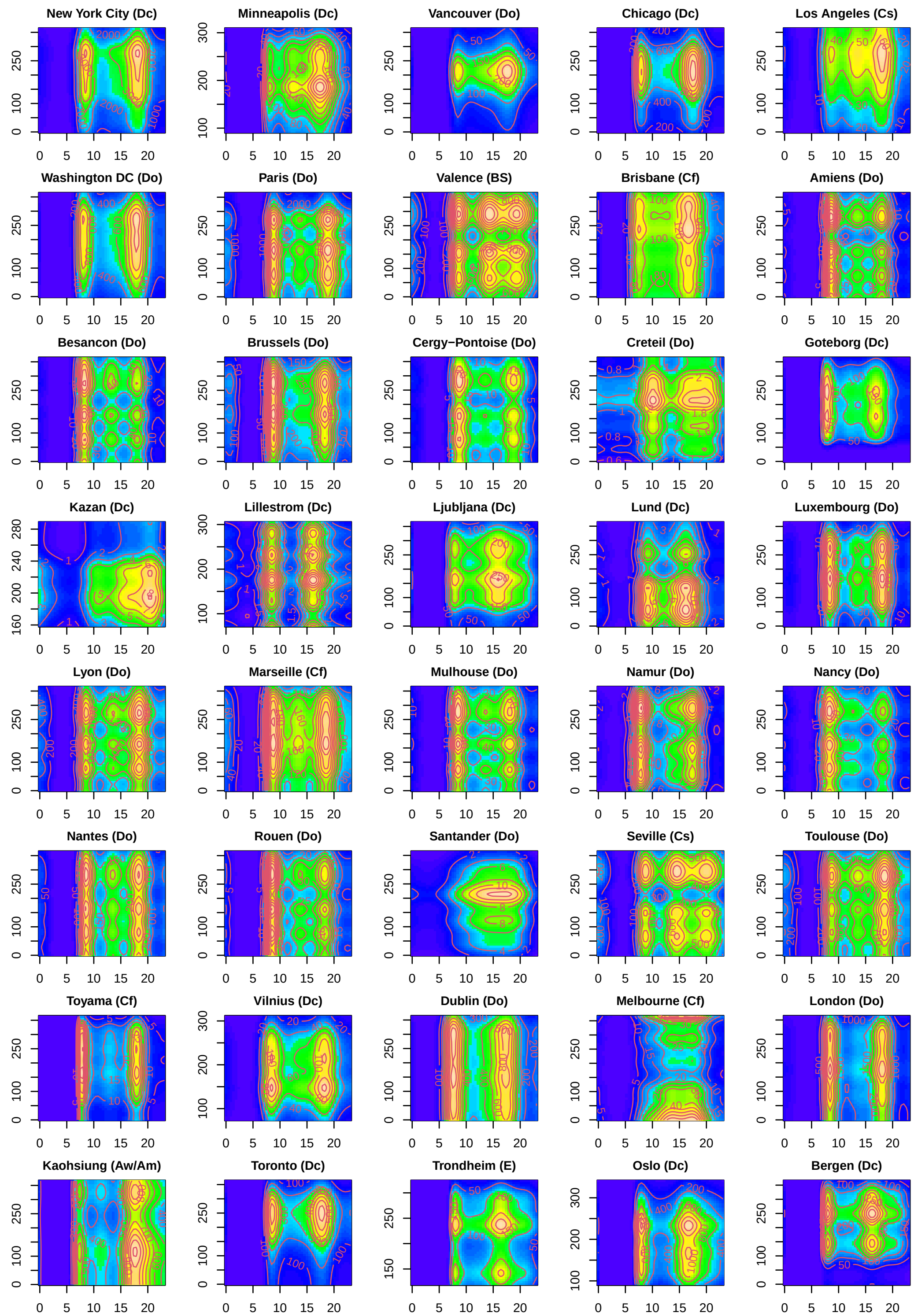


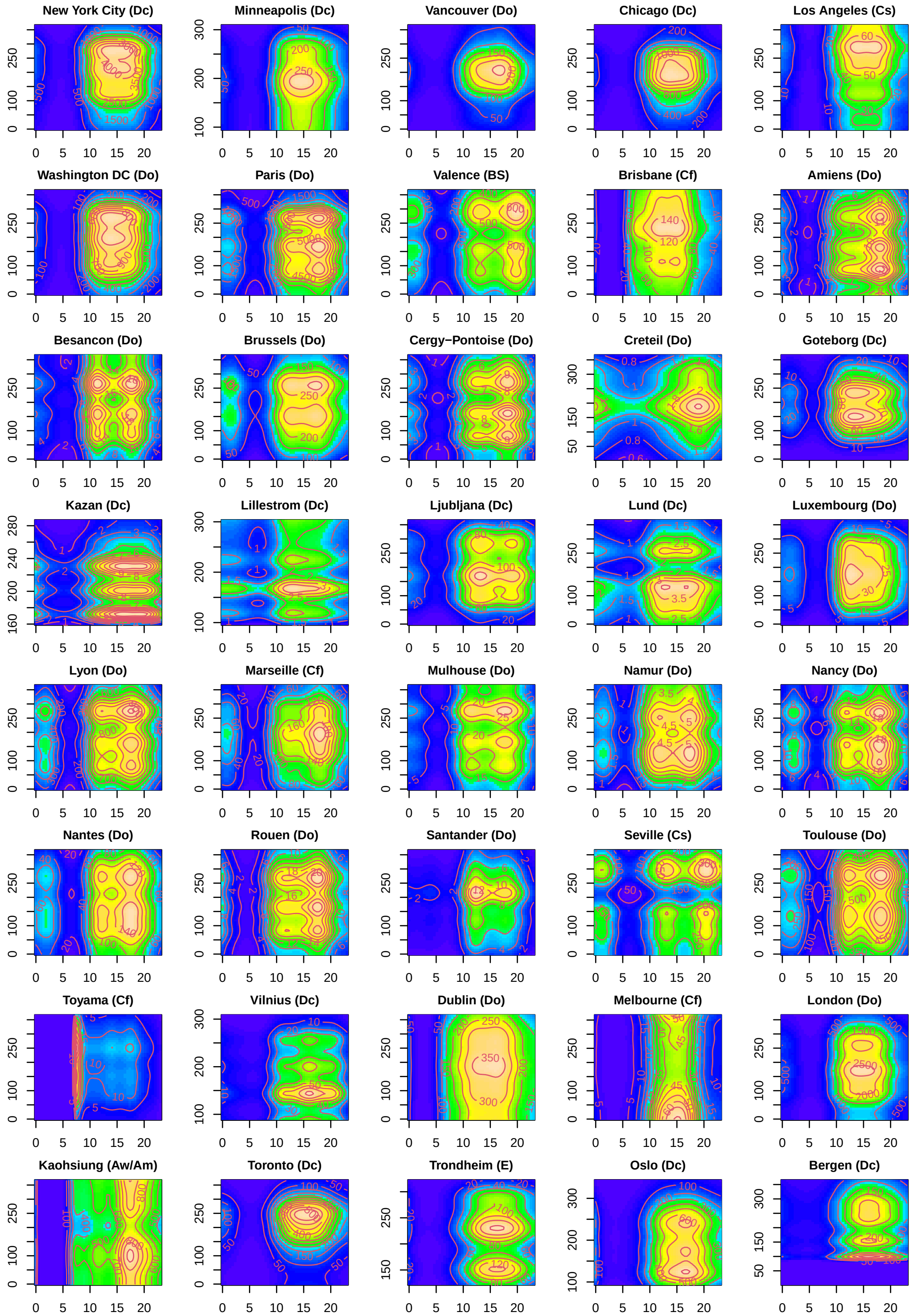
Figure 1. Global distribution of PBSPs and location of our forty case study cities mapped against the Trewartha climate classification.

In all figures, Season number (0-365) represents Julian dates, Hours are numbered 0-23, Precipitation is in millimetres, and UTCI is in degrees Celsius.

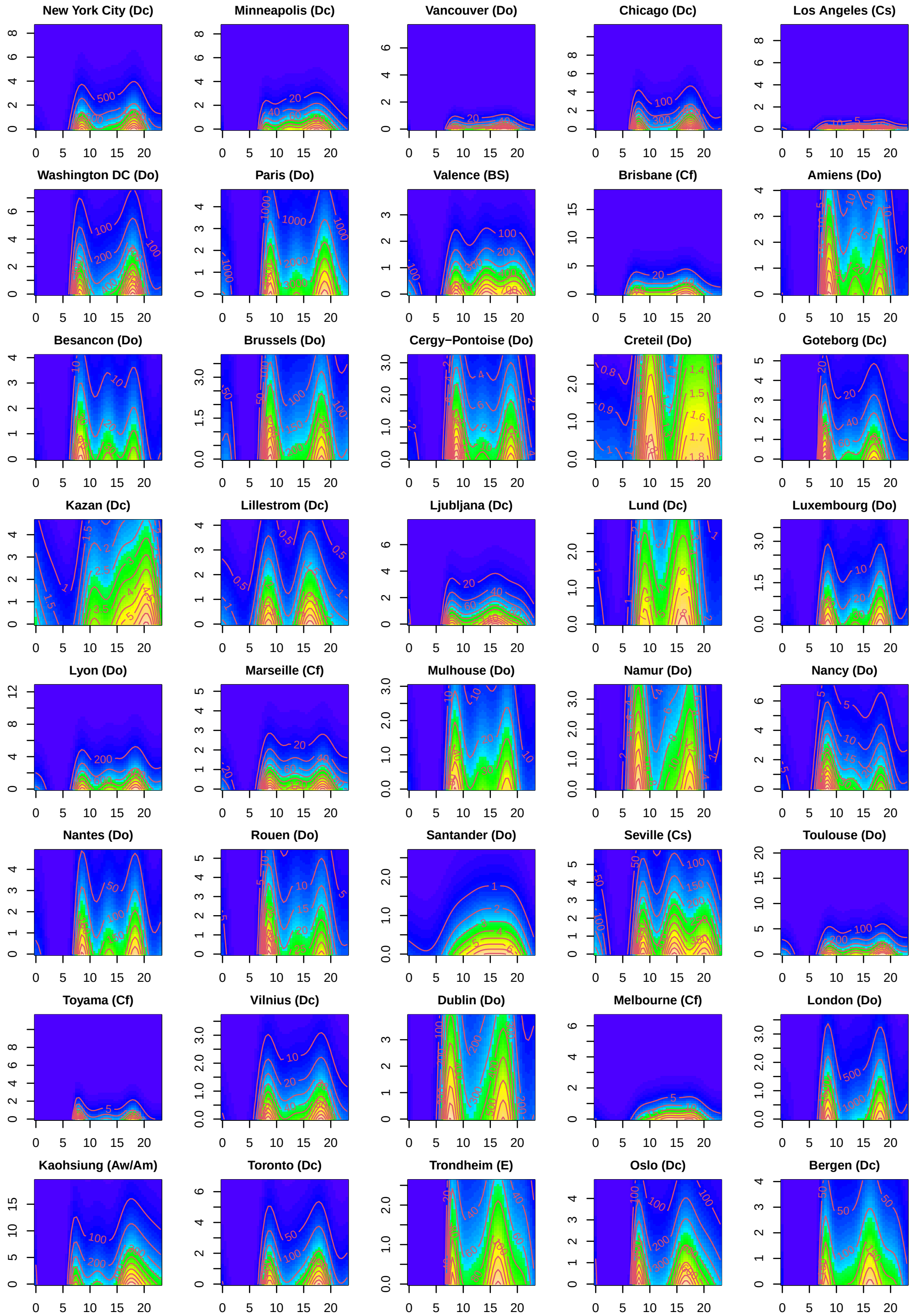
Figure 2 (a-f). Travel pattern variations by weather variables for all cycling trips.



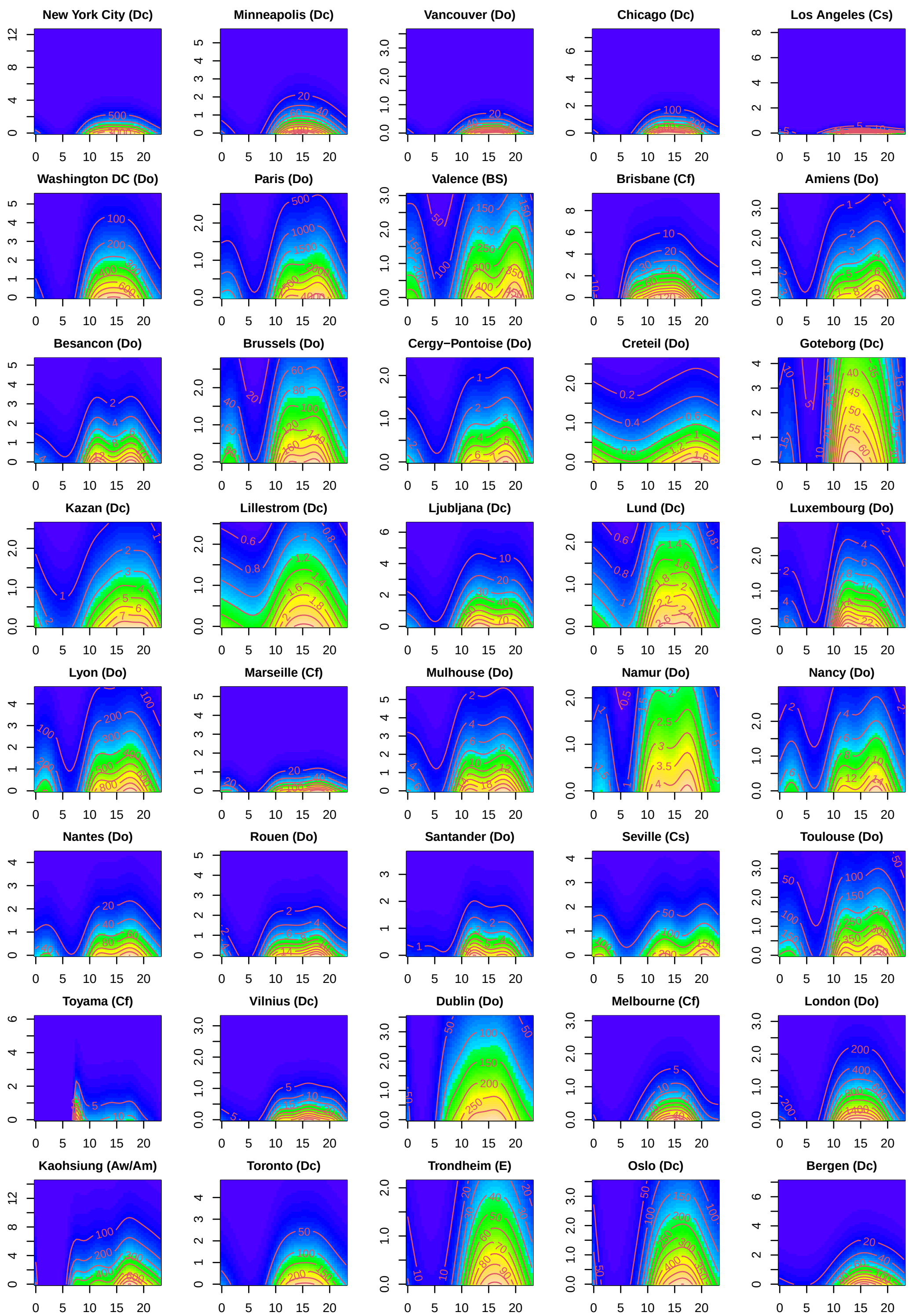
(a) Bike share usage by season (x) and hour (y), weekdays



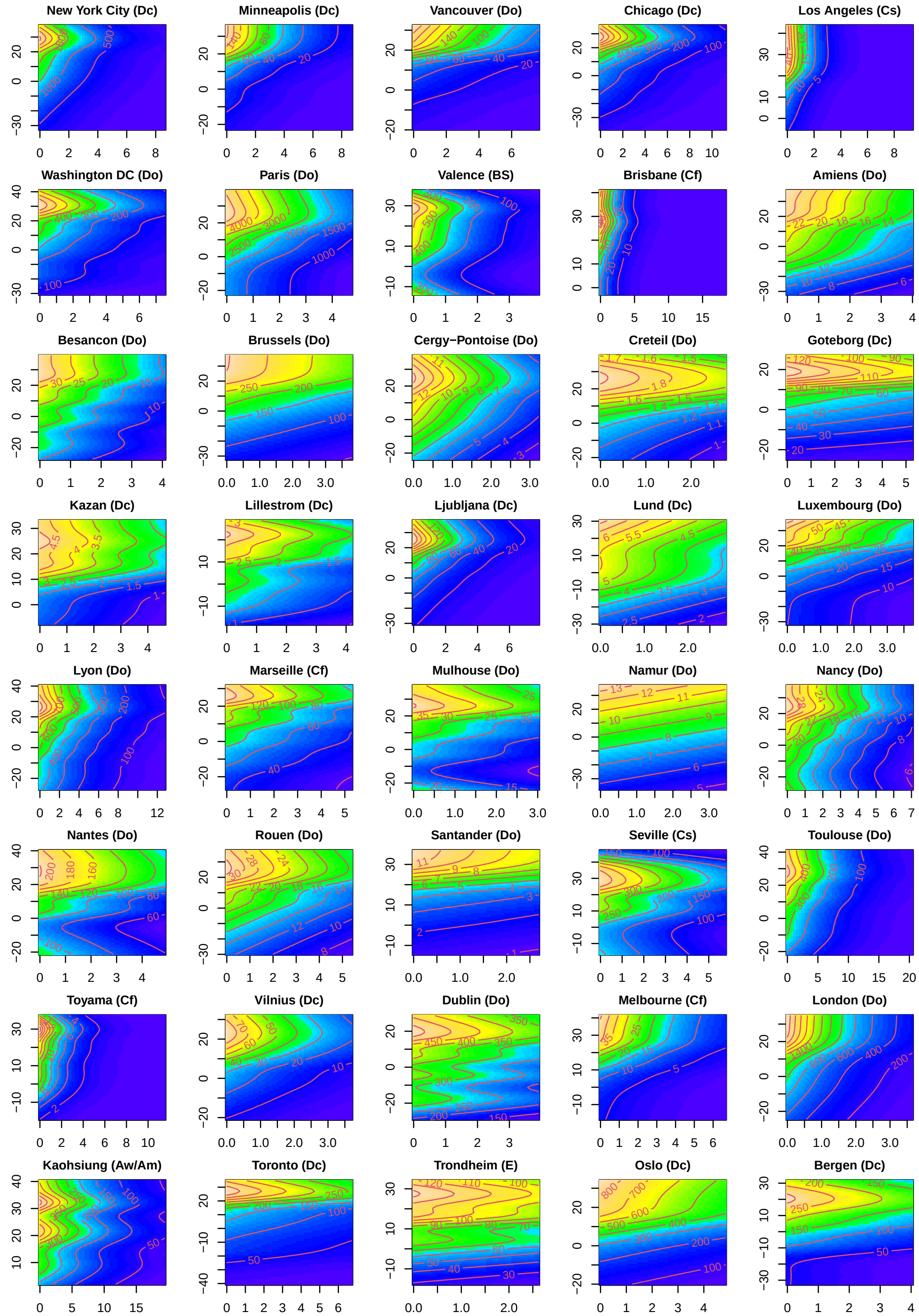
(b) Bike share usage by season (x) and hour (y), weekends



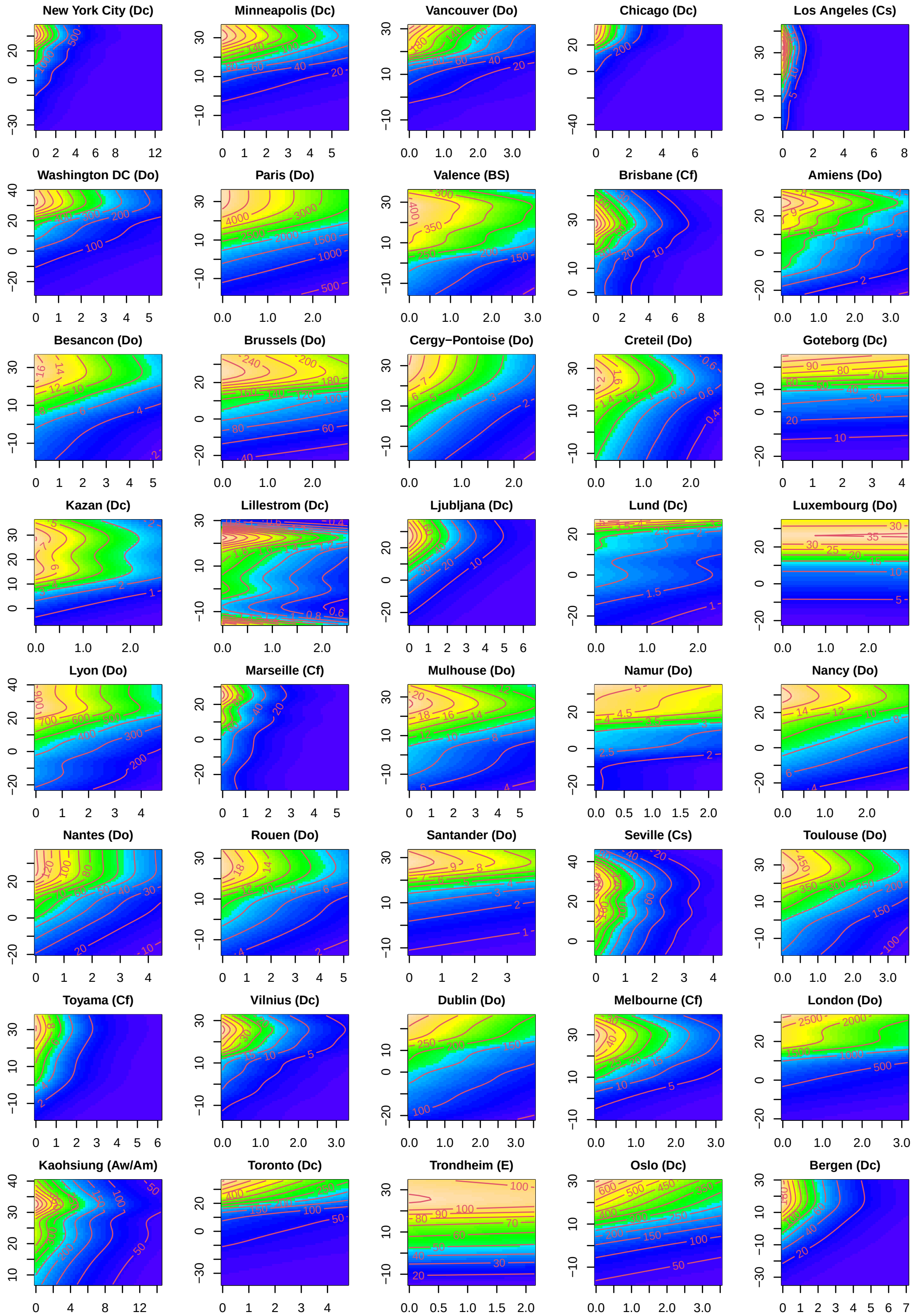
(c) Effect of precipitation (y) on bike share usage by hour (x), weekdays



(d) Effect of precipitation (y) on bike share usage by hour (x), weekends



(e) Effect of Universal Thermal Climate Index (x) and precipitation (y) on bike share usage, weekdays



(f) Effect of Universal Thermal Climate Index (x) and precipitation (y) on bike share usage, weekends

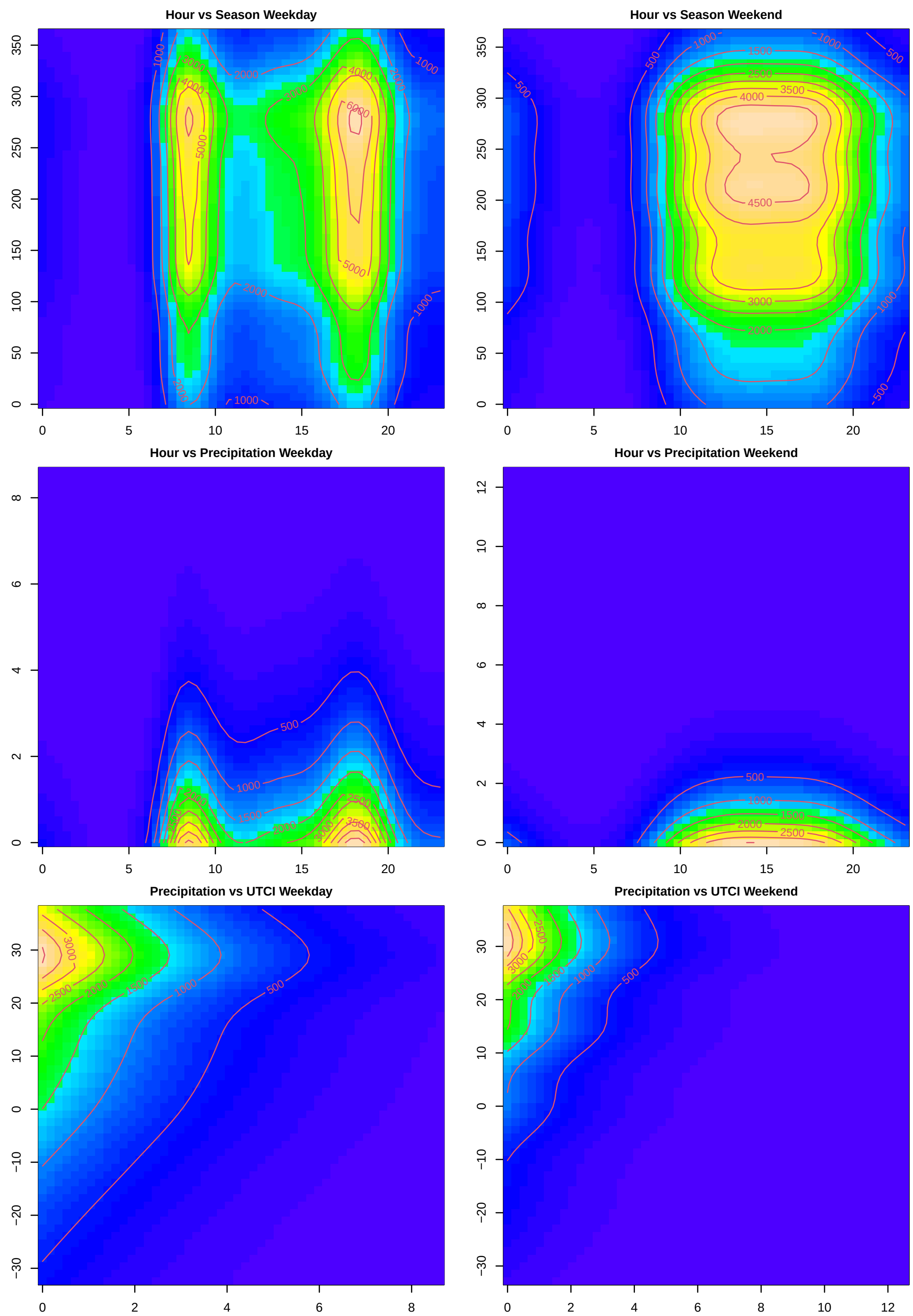


Figure 3. Travel patterns in a *Continental* climate – New York City (Dc)

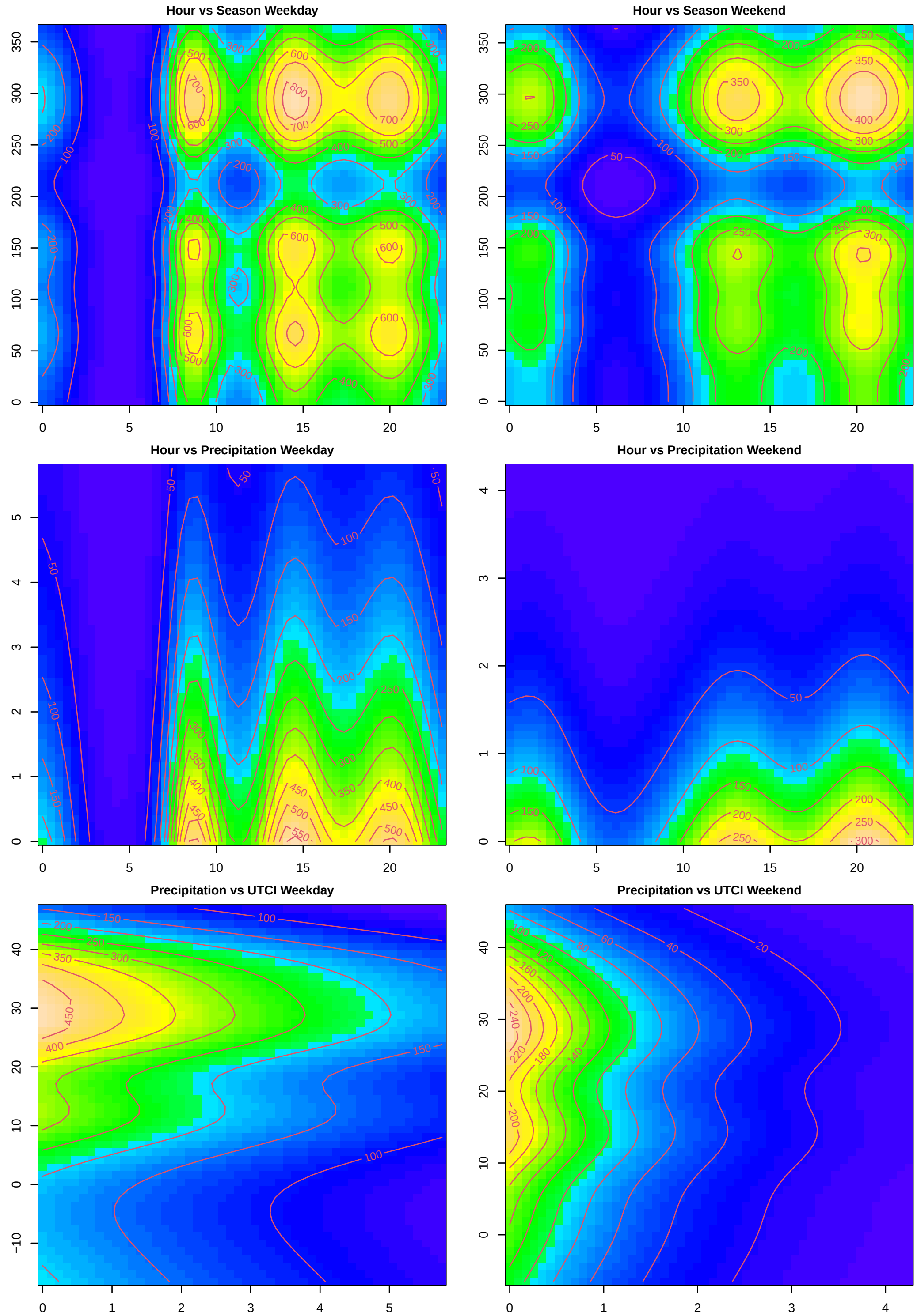


Figure 4. Travel patterns in a *Mediterranean* climate – Seville (Cs)

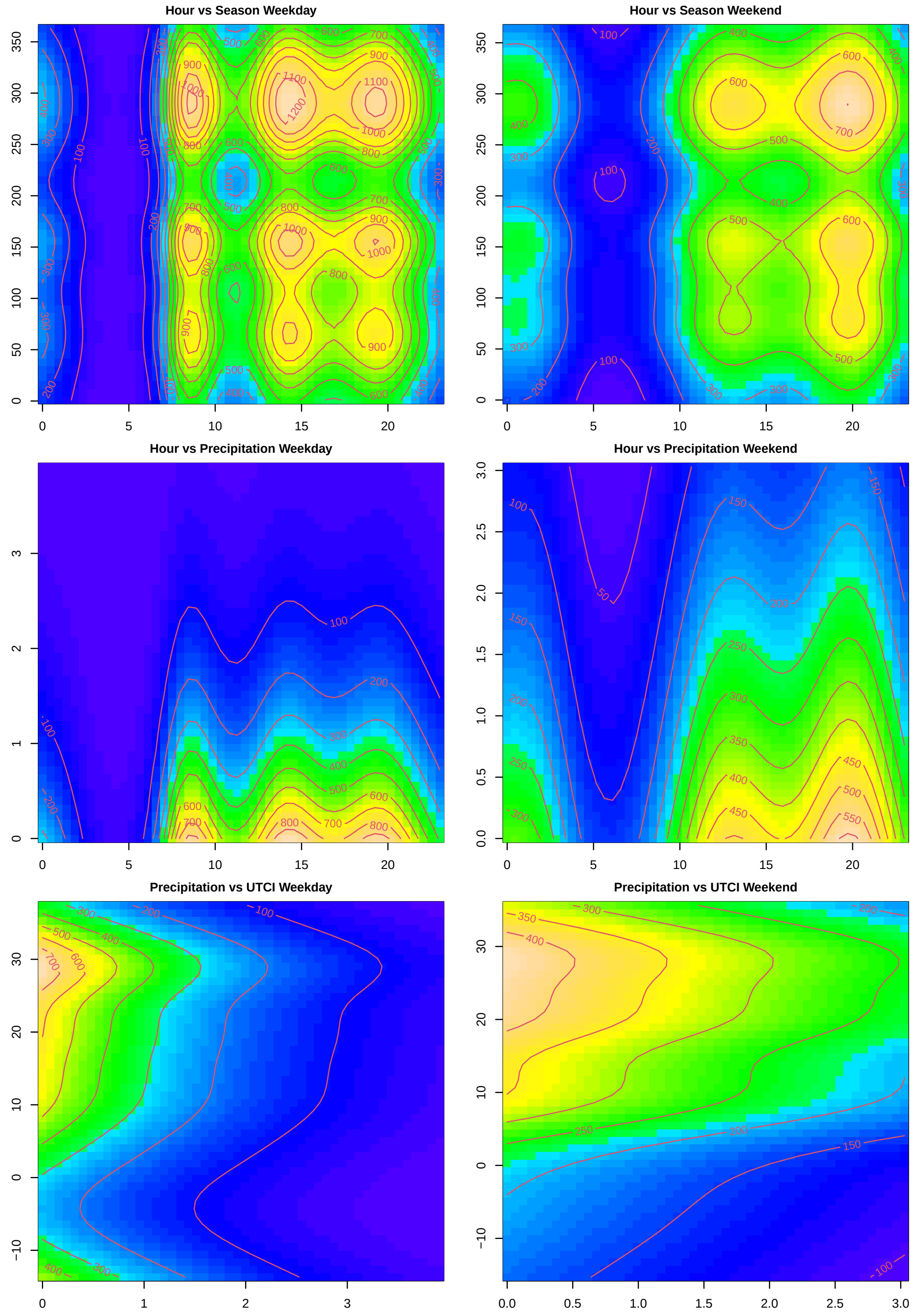


Figure 5. Travel patterns in a *Steppe* climate - Valencia (BS)

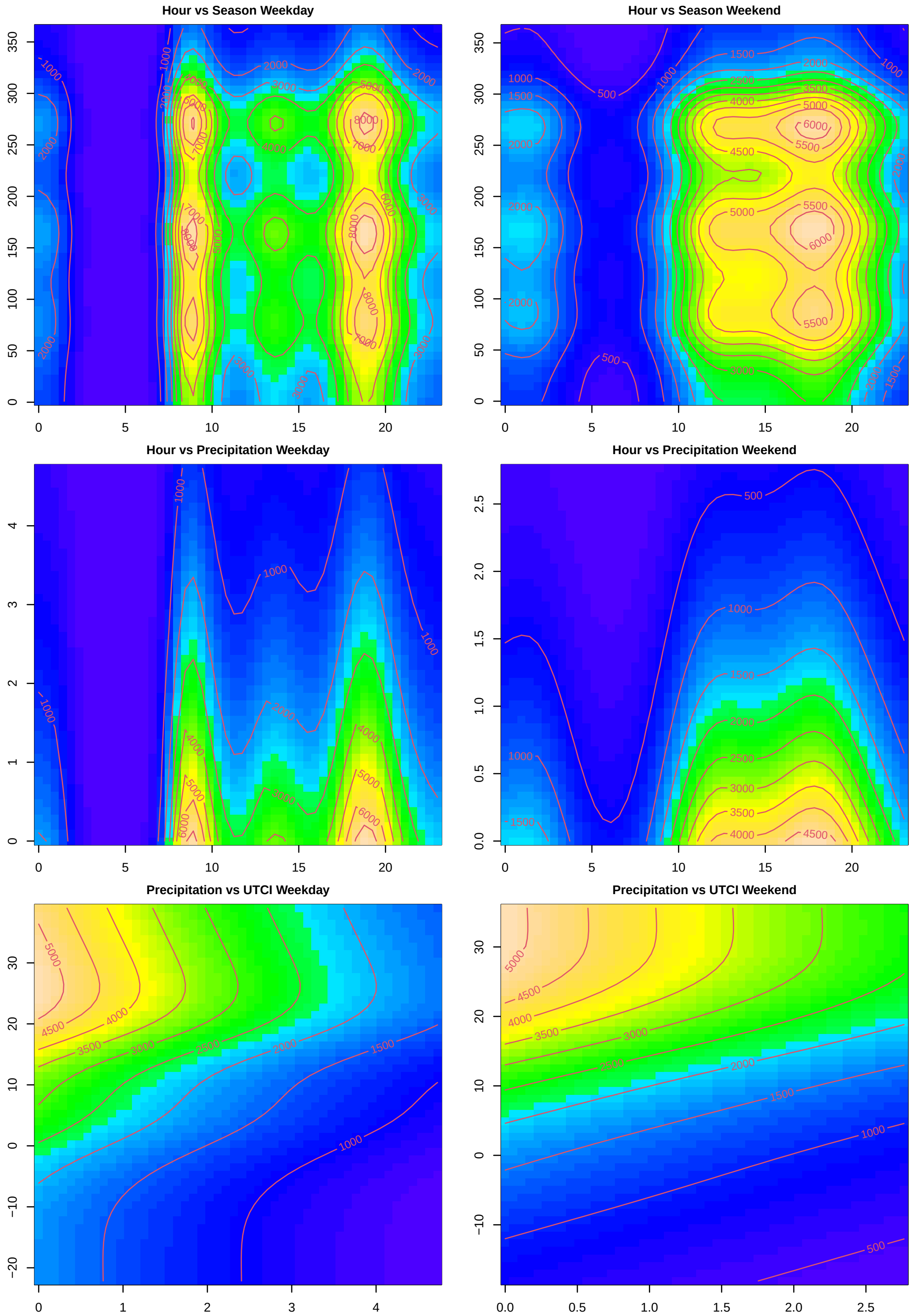


Figure 6. Travel patterns in an *Oceanic* climate – Paris (Do)

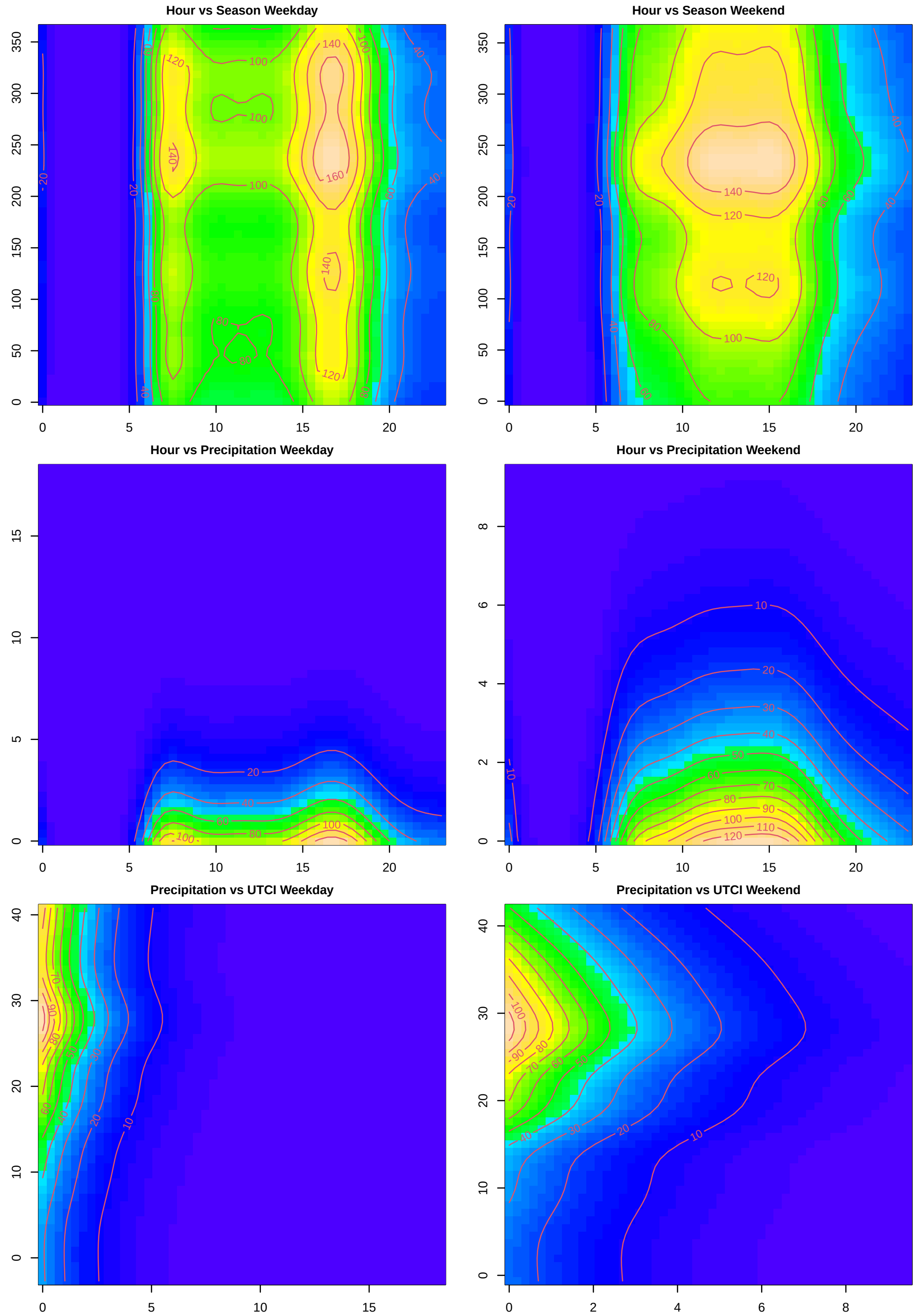


Figure 7. Travel patterns in a *Humid Subtropical* climate – Brisbane (Cf)

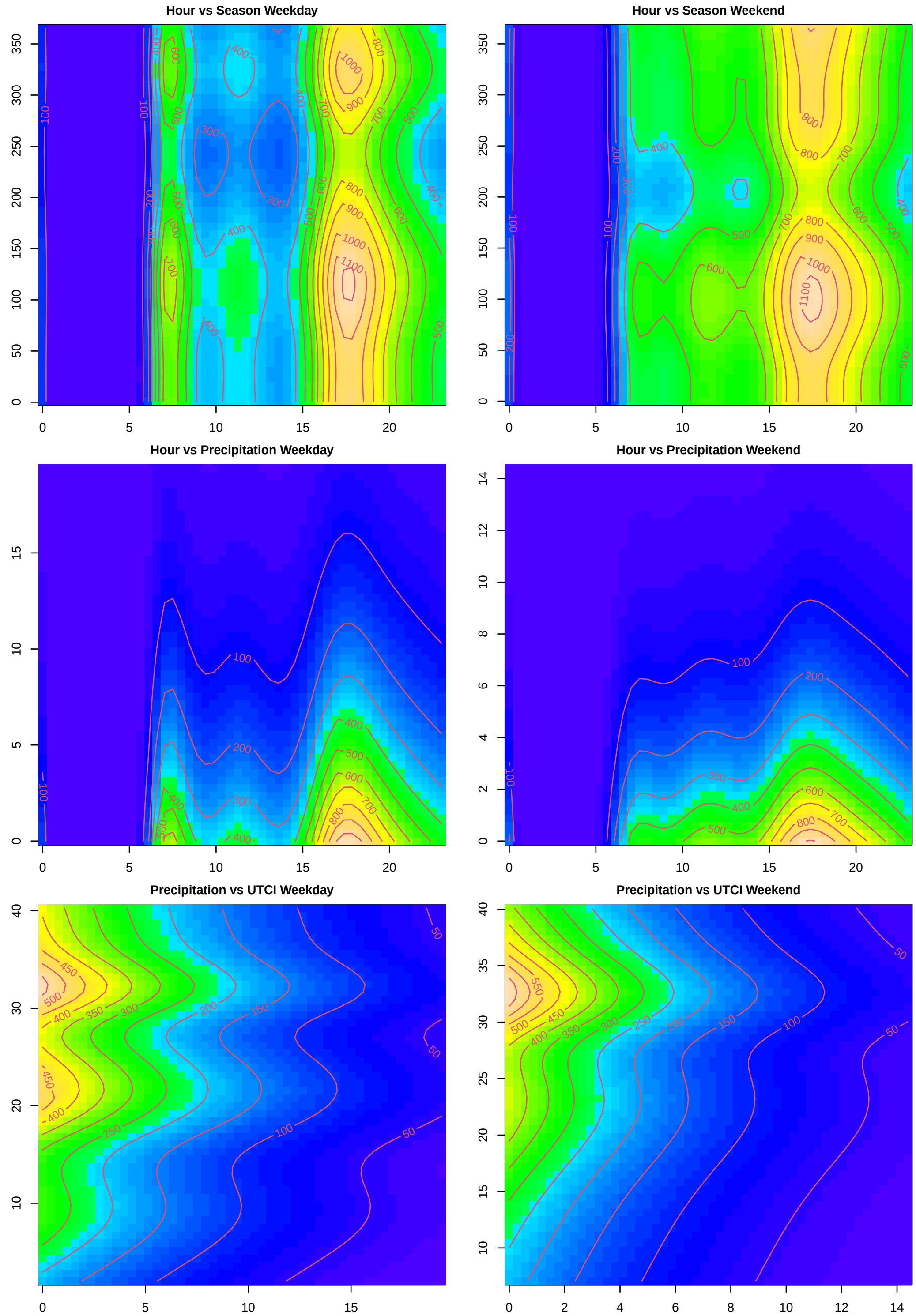


Figure 8. Travel patterns in a *Tropical / Monsoon* climate – Kaohsiung (Aw/Am)

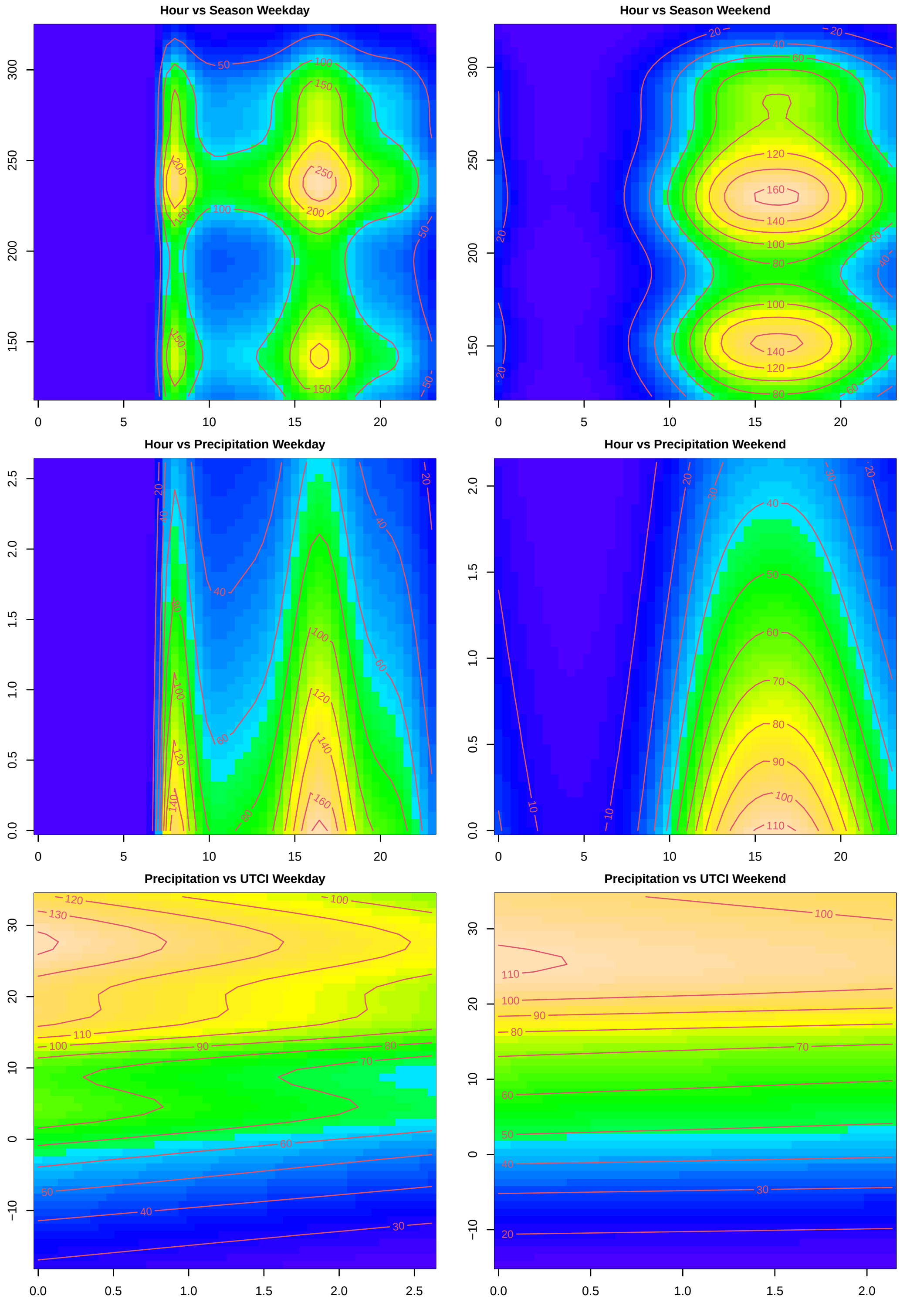


Figure 9. Travel patterns in a *Boreal* climate – Trondheim (E)

Notes

[1]The climate zone classification employed in this paper is Trewartha including both current and future prediction (Belda et al. 2014)

[2]We have collected PBSP data for dozens of systems dating back to March 2012. However, due to space, computing, and network limitations we could not develop models using UTCI and precipitation data for a longer timeline.

[3]Stock data are measured at one specific time, and represent the cycling trips at that point in time (say, 15 July 2017), which may have accumulated in the past. Flow data are measured over an interval of time.

[4]This scheme closed in November 2019.

[5]The Stockholm system was ultimately excluded because it has only one station and therefore only loop trips were available.

[6]The New York data required some cleaning; for example, some days in March 2017 recorded zero trips, which was not the result of any system outage.

[7]nextbike, a large company which operates PBSPs in more than 200 cities and 25 countries worldwide, is notably absent from this study. Its data are not easily scrapable as nextbike does not report the exact number of bicycles available at a given time but only an approximation. Therefore, neither stock nor flow data could be computed.

[8]This is based on the Meddin Bike-sharing World Map https://bikesharingworldmap.com.

[9]The European Centre for Medium Range Weather Forecasting provides UTCI data worldwide at hourly and 0.25 degree resolution (di Napoli 2020).

[10]This is as opposed to recreational usage with a personal bicycle. We discuss patterns of utility cycling, e.g., for commuting, observed in some bikeshare schemes.

[11]For instance, to model bikeshare usage from 2:30 to 3:30 we account for rain from 1:30 to 2:30. The one hour lag period for the precipitation was chosen based on an analysis of correlation of precipitation with bikeshare usage across the 28 JCDecaux schemes.

[12]The Julian date is expressed as an integer ranging from 0 to 365 (inclusive).

[13]Here, $s(x)$ is a spline-based smooth function fit to the variable x, using the *mgcv* default thin plate regression spline. The precipitation variable p_h is fit with a linear term. The model fit would be improved if significant public holidays, such as Christmas, were treated as weekend days, but this was too difficult to achieve across forty cities. In *mgcv*, a Gaussian family and log link function are employed to model Usage.

[14]Unusual usage patterns such as on 8th October and 10th December, 2017 in the Los Angeles scheme, where more than 100 hires per hour were recorded for several hours, were excluded.

[15]The Minneapolis PBSP has made gender data publicly available but for a year that falls outside this study's timeline. Gender data is also collected in some JCDecaux systems.

[16]The weekday Kaohsiung model and weekend Seville model have two local maxima at 21.5 and 32.3 degrees, and 14.9 and 28.8 degrees, respectively. This may be due to local climatic patterns.

[17]The Clements et al. (2016) study is set in Brisbane and applies a piecewise linear model of electricity demand with temperature ranges of 9–15, 9–20, 22–26, and 22–30 degrees Celsius.

[18]We were also able to obtain monthly usage data from the Brisbane City Council website which indicated the exact number of trips taken in 2017 was 656,767. In each month during 2017, the ratio of the number of estimated trips to actual trips is between 89.4% and 94.2%.

[19]For weekend riding in New York, the test returns $p = 0.39$; for weekdays in Chicago $p = 0.11$.