Spatial Heterogeneity of Weather impacts on Cycling Flows within Gothenburg, Sweden – A Geographic Framework for Local Pattern Analysis

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Abstract

Background: In the past decade, the phenomenon of spatial heterogeneity has started to gain traction in studies of cycling and weather. Cycling is usually the mode of transportation that is most affected by inclement weather and the scientific consensus about how weather impacts cycling behaviour on a general scale is for the most part well-established. On a regional scale, weather effects have been found to be more adverse in low-density rural communities, whilst the impact is less severe in more compact cities. However, to this date, little is known about how, and even if weather produces heterogonous cycling patterns on a local city scale.

Method: Given the lack of precedent to studies of spatial heterogeneity on a local scale, this study developed and applied a framework to investigate the presence of the phenomenon. The framework consists of two parts. First, a cartographic exploration of correlation coefficients linked to cycle-measurement stations around the city of Gothenburg. Second, a weather sensitivity analysis was conducted to identify if urban areas with similar characteristics was associated with spatial heterogeneity. Properties of the urban environment were quantified with a modified Local Climate Zone system to capture the dominant urban characteristics that surrounds every cycle-measurement station and their corresponding cycleway segment.

Results: Findings made in this showed that the impact of the weather indices temperature, sunshine, precipitation and gustiness varies across the city of Gothenburg. The pattern of spatial heterogeneity was especially pronounced in relation to gustiness. Coastal environments characterized by openness were consistently more sensitive to higher wind speeds. The duration of sunshine was also more important to urban areas with a low density. Two precipitation indices were considered, along with the binary occurrence of a precipitation event. The duration of precipitation had the most negative impact on cycle frequencies and the effect was stronger than even the binary occurrence of a precipitation event. Surprisingly, in the densest built environments, cycling appears to be more sensitive to precipitation than areas characterized by openness.

Discussion: These results have some important implications for planning authorities. First, weather is not an entirely uncontrollable phenomenon in relation to cycling. It is possible to identify areas that are more affected by certain weather conditions and thus take appropriate action. Second, this study found evidence that spatial heterogeneity exists, but the robustness of the proposed framework needs refining before the results can be regarded as conducive.

Conclusions: This study could be used as a way forward for professionals who struggle to find out where they should intervene to empower cycling. The framework proposed in this study can also be used to identify urban environments that are more adversely affected by certain weather conditions without actual measurements of the cycle volume in these areas. Further developments are recommended, but the framework in this study could be a cost-effective way of identifying especially weather sensitive areas of the urban environment.

Keywords: *spatial heterogeneity, cycling, weather, local climate zones, explorative GIS*

Preface

This thesis was written during the spring semester of 2019 as part of the Master's Programme in Geography at the University of Gothenburg. Being a cycling enthusiast myself, I got inspired to explore the connection between weather and cycling in the urban environment. Since I ride my bicycle daily, I often observe cyclists make submit to the prevailing weather conditions in ways that was somewhat obvious but nonetheless sparked my curiosity. Therefore, I would like to thank Fredrik Larsson at Gothenburg's Urban Transportation Administration for providing me with the necessary cycle data and thus enabled me to conduct this research.

I would also like to thank my supervisor David Rayner at the Department of Earth Sciences who has been indispensable to the development of this unprecedented endeavour. Thank you, David, for all your support throughout the duration of writing this thesis. I would also like to thank Sofia Thorsson at the Urban Climate Research Group of the department for showing an early interest to my research before the onset on this study. Without your encouragement, I'm not sure that I would've found the aim of this study feasible.

Likewise, I would like to extend some appreciation to my fellow students in fashionably named study room "the Coprolite" for keeping me motivated through thick and thin. Our philosophical discussions during the lunches indeed helped with the mood.

Filip Olsson

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1. Introduction

Cycling as a mode of transportation offers a range of benefits, not only for the individual that uses a bicycle regularly, but also for society at large. For the individual traveller, cycling is low-cost vehicle that improves the health of the rider. In tandem, society are exposed to less pollution – both with regards to emissions and noise. Moreover, active transportation like cycling is often the fastest travel mode in cities (Handy, 2014) and a greater number of cyclists on the road may also alleviate congestion (Bernardo & Bhat, 2014). However, the built environment may only be favourable for cycling if the urban structure is dense, the topography is relatively flat and the distance between locations are short (Handy, 2014; Heinen, van Wee, & Maat, 2010; Saelens, Sallis, & Frank, 2003). But even under optimal conditions, the choice to cycle may be held back by societal attitudes against cycling (Fernández-Heredia, Monzón, & Jara-Díaz, 2014; Gatersleben & Appleton, 2007; Heinen et al., 2010). Beyond all these perspectives on cycling, there is also an aspect that's often glossed over – if it's taken into consideration at all. Cyclists are at the mercy of the prevailing weather conditions more than any other traveller (Böcker, Dijst, & Prillwitz, 2013a; Liu, Susilo, & Karlström, 2017). It's not that the relationship between cycling and weather hasn't been studied, in fact, scientific inquiries into the relationship goes back several decades. Back then, temperature and cloud cover were found to have an impact on cyclists, whereof commuters were less affected by inclement weather (Hanson & Hanson, 1977). Recently, in a comprehensive literature review, Böcker, Dijst, & Prillwitz (2013) found that weather has profound effects on open-air travel behaviour. They also identified that the association may not be entirely linear in all cases. Furthermore, the effect of weather on a regional scale has been found to vary according to location (Helbich, Böcker, & Dijst, 2014; Liu, Susilo, & Karlström, 2014, 2015). Other studies, have on an intra-city scale also indicated that a spatial component could be affecting cyclists, but these studies often aggregate data and compare utilitarian paths with recreational (Miranda-Moreno & Nosal, 2011; Thomas, Jaarsma, & Tutert, 2013). Moreover, how cyclists are affect also varies across seasons (Liu et al., 2015; Tin Tin, Woodward, Robinson, & Ameratunga, 2012).

The city of Gothenburg is undergoing densification at the intermediate city scale to achieve, amongst other things, shortened travel distances between residences and workplaces (Gothenburg City, 2014). In the city's Cycle Programme, density is also among the motivating factors but so are also the previously mentioned health benefits, reductions in noise and air pollution that increased cycle volumes could entail (Månsson & Junemo, 2015). The most important target is however, to reframe the public's perception of cycling – as to view the city of Gothenburg as a bike-friendly city. This is an especially important aspect according to Bernardo & Bhat (2014).

Much less attention is however devoted to how inclement weather conditions affects cycling behaviour in the city. At present, the Cycle Programme only mentions weather indirectly with regards to weather-protected parking, whilst the City's travel survey in 2017 briefly mentions that cycling volumes decrease at the cities permanent cycle-measurement stations when it's cold and rainy (Urban Transport Administration, 2017). The only explicit effort to avert negative weather impacts is road maintenance during the winter months. Indeed, this is a good measure because snow covered ground has been shown to substantially reduce the number of cyclists on the road (Liu et al., 2015). Another winter-related initiative is the campaign 'winter-cyclists', launched by the County Administrative Boards (2018). The campaign provided winter tires and reflective vests to 250 cyclists to encourage riders to extend their cycling across all seasons. The gains that stands to be made with measures aimed at winter-cycling are enormous, given that cycling during winter is very low compared to rest of the year. However, snow is usually only a problem during winter and it's a rare event compared to all other weather parameters.

Cycling is the mode of transportation that is most negatively affected by weather in Sweden (Liu et al., 2017). But how the Urban Transport Administration describes weather impacts above, suggests that weather is mostly being treated as an uncontrollable natural phenomenon (see Spencer, Watts, Vivanco, & Flynn, 2013). Yet, the neglect of weather impacts is perhaps not so surprising, even though the scientific consensus mostly has established how weather affects cyclists. A plausible reason for the lacking focus on cycling and weather by city planners could be the general character of the association. Most studies of cycling and weather find connections on a global scale, i.e. they do not disaggregate their analysis to smaller spatial units. A study also speculates that differences in response to weather could be related to local microclimates within a city (Helbich et al., 2014). Hence, it is possible that the built environment could be connected to how cyclist responds to weather, depending on the spatial setting. This phenomenon is called spatial heterogeneity and refers to how the same variables can produce a variety of results in spatially separate places.

Most inquiries into the relationship between cycling mobility and weather usually develop a logit- or logistic model (see Liu, Susilo, & Karlström, 2017), but Pearson's r has also been used to find associations (e.g. Nankervis, 1999; Pang, Zablotskaia, & Zhang, 2016; Tin Tin, Woodward, Robinson, & Ameratunga, 2012). Due to the novelty of spatial heterogeneity research on a local scale, the simplest tool is more than appropriate and therefore, this study will utilize the correlation coefficient. If weather systematically produces heterogeneous cycling flows in different areas, it is important to identify generic markers of the built environment where it occurs. Currently, no one has tried to link weather and cycling to the built environment through a research methodology proposed by Stewart & Oke in 2012, called the Local Climate Zone system, but this study will evaluate if it's possible. Knowledge about weathers effect on cycling flows in different LCZs could be important to e.g. city planners and transportation authorities, and thoughtful consideration of the spatial impact could be imperative to the prosperity of cycling in cities like Gothenburg.

1.1 Aim

This study seek to identify whether spatial heterogeneity exists in the relationship between weather and cycling on a local scale. A city contains a multitude of varying microclimates. Therefore, it is expected that cycle-measurement stations in similar urban settings will experience weather impacts approximately the same, due to the characteristics of their surrounding environment. Spatial variations are also expected within and between seasons- i.e. periods of homologues cycle behaviour.

To achieve this ambition, this study will lay the foundation of an explorative framework. This proposed framework should allow spatially heterogeneous cycling responses in relation to different weather conditions to be encapsulated. Guiding this research are the following questions:

- Do spatially separated cycle-measurement stations produce a variety of responses to weather?
- If so, how is this variability related to the urban environment?
- Also, how alike are the response of stations to weather when their surrounding environments are similar?

2. Background

This section covers a description of Gothenburg's weather. It then goes on to a literature review of the current scientific theory of different weather parameters association to cycling. The limitations and gaps in the current research is also highlighted. It ends with an overview regarding what we know about the spatial

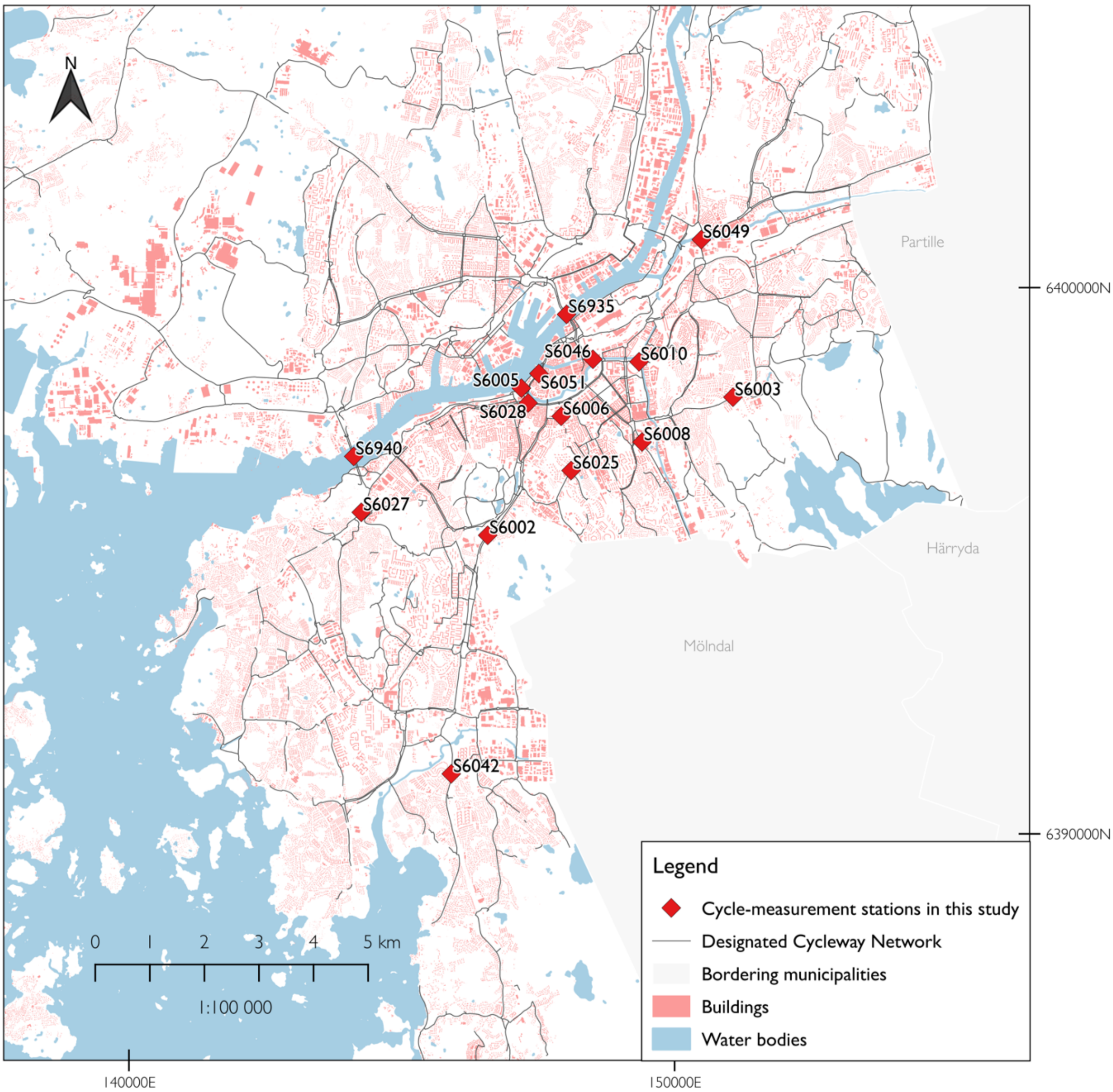

Figure 1. Location of the cycle-measurement stations within the study area of Gothenburg (see forthcoming section 3.1.1). Data source: Lantmäteriet (GSD-Fastighetskartan, 2017), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), OpenStreetMap contributors (Municipal boarders). Projection: SWEREF 99 12 00.

heterogenic relationship between cycling and weather.

2.1 Study Area – The city of Gothenburg

There is a total of 31 cycle-measurement stations within the study area of Gothenburg. However, not every station is permanent. Some stations were temporary, some have been removed due to construction whilst other station have been added with time. Therefore, only 15 stations were included in this study. These stations are permanent and have consistent data records. Most stations are found in or near the city centre but no stations are located on the island of Hisingen (Fig. 1). For more detail on the cycle data, see section 3.1.1.

2.1.1 Weather and Climate of Gothenburg

The city of Gothenburg, Sweden, is a coastal city with a mild, temperate climate. The city has distinct seasonal patterns due to its latitude. During the normal period 1961-1990, mean temperatures reached a minimum of -1.2°C in winter and a maximum of 17°C in summer. Annual mean temperature was 7.7°C (SMHI, 2014). Regarding precipitation, the annual amount in Gothenburg is about

757.8mm, which is almost 219mm above the normal national average. Most rainfall occurred in fall (82.7mm) and the driest month was the winter month February, with 39.6mm (SMHI, 2014). Average wind speeds barely vary over a year. During the normal period, the annual mean wind speed was about 5.2m/s, whereof early spring and fall were slightly windier.

Related to the seasons are also cyclical variations in the amount of daylight. At the lowest point in winter, there's just an average of 5 daylight hours, which jumps to roughly 20 at summer solstice. This also affects sunshine hours on an average year. The mean duration, according to the normal period, had a minimum of 1.3h in winter and an average max of 8.9h in June. The annual average for Gothenburg was 1722h of sunshine (Josefsson, 1993).

Compared to the normal period, the time series considered in this study is approximately normal regarding annual temperature (0.58 degrees above) and annual precipitation (30mm higher). However, the summers were unusually warm with roughly 1.97 degrees Celsius above normal, average wind speeds were almost half as strong and there were about 160 fewer annual hours of sunshine.

2.2 The relationship between Cycling and different types of Weather

2.2.1 Temperature

By far, the most common weather parameter to analyse in relation to cycling is air temperature. Most often, maximum air temperature is considered, because it is often found to have a better fitted association to cycling than mean or minimum air temperature. Many studies identify a parabolic effect of temperature onto the volume of cyclists (Böcker et al., 2013a; Miranda-Moreno & Nosal, 2011). This is indicative of a range where temperature is favourable for cycling, down to – and up to a certain threshold. In the range between these perceived thresholds, cycling frequencies can increase as a linear function of temperature (Flynn, Dana, Sears, & Aultman-Hall, 2012; Tin Tin et al., 2012). However, these thresholds tend to vary across space. For example, in Auckland, New Zeeland, no parabolic relationship were identified (Tin Tin et al., 2012). Which according to the authors may be due to a lack of extreme temperatures at the investigated location. In Washington DC, Gebhart & Noland (2014) found that average trip distance significantly decrease below 9.4°C and above 31.7°C, and yet, the warmer it is, the longer distances cyclists tend to cycle (Gebhart & Noland, 2014) . Other studies have reported an upper threshold of 30.4°C in Singapore (Meng, Zhang, Wong, & Au, 2016), 25°C in London (Wadud, 2014) and in Montreal, Canada, 28°C in combination with relative humidity levels above 60% (Miranda-Moreno & Nosal, 2011). This indicates that the decline in cycling frequencies during elevated temperature events may be a universal phenomenon even though the threshold varies.

On the other end of the spectrum, a lower cut-off point has not been found. Although the number of cyclists decrease as it gets colder, the decline always seems to level out and become stable at some point. Most likely, this is due to the resilience of the cyclists who are still roaming the roads as temperatures are below freezing. This is confirmed in Calgary, Canada by Amiri & Sadeghpour (2015). They found that 90% of commuting cyclists who self-identify as frequent winter cyclists feel comfortable cycling below -20°C or even colder. In Sweden, a cultural difference can also be discerned whereas cyclists who live in colder regions are more aware of fluctuation in air temperature (Liu et al., 2015).

In cities, the temperature can vary in accordance with the built environment. Morning and evening temperatures can be much higher in dense urban environments where large buildings and paved surfaces traps heat inside the urban canyon (Coutts, Beringer, & Tapper, 2007). At noon, differences often dissipate. The same process can also work to produce daytime cold islands in narrow canyons due to shading and high thermal admittance of building materials (Erell & Williamson, 2007).

2.2.2 Precipitation

Regarding precipitation and cycling, researchers often find a relatively large reduction of cyclists when it rains (Liu et al., 2017; Tin Tin et al., 2012) and cyclists often state in surveys that precipitation is the most deterring factor (Heinen et al., 2010; Nankervis, 1999). According to the findings of Flynn et al. (2012), the likelihood to cycle are twice as high on mornings without rain. Even though the relationship is negative on the surface, there are several nuances of how precipitation affects cycling. For example, in the Netherlands, Thomas, Jaarsma, & Tutert (2013) considered both the amount and duration of precipitation and found, much to their surprise, that the negative effect of precipitation was small. Another study also found that annual precipitation appears to play a significant role (Winters, Friesen, Koehoorn, & Teschke, 2007). Henceforth, cities with more days of precipitation experience a larger reduction in cycling volumes. In a comparison of different seasons and regions of Sweden, a study found that cycling indeed is the transport mode that has the largest negative influence from precipitation, which seems to encourage a shift to public transportation (Liu et al., 2015).

In more detail, Phung & Rose (2007) constructed a logistic model and used 2 binary categories for the amount of precipitation and found that heavier rains (>10mm) affects cycling more negatively than light rains (<10mm). They also found that precipitation had the most negative effect of all the considered weather parameters (Phung & Rose, 2007). Using 5 discrete categories for the amount of rain, Wadud (2014) found that the greatest reduction in cycling volumes occurred at 1-2mm. A lagged effect was also identified. It was found that precipitation in the previous hour had almost the same strength of deterrence as did 1-2mm of rain (Wadud, 2014). This relationship was also identified for precipitation in the previous three hours by Nosal & Miranda-Moreno (2014). They also found that a rain event that only occurred in the afternoon did not reduce cycling volumes. Likely because the cyclists got caught in unexpected rain showers (Nosal & Miranda-Moreno, 2014). A support for this proposition can be found in a study by Meng et al. (2016), who showed that 66.5 percent of cyclists would modal shift if the weather forecast predicted rain later that day. Weather forecasts have also in general been shown to increase the likelihood of changes in travel behaviour, regardless of how the information was obtained (Cools & Creemers, 2013). Moreover, travel decisions under rainy conditions are typically made by qualitative assessment based on the available information (Chen & Mahmassani, 2015). Recently, individual characteristics have also been linked to how weather information influence travel behaviour (Li, Chen, Li, & Godding, 2018). For example, Böcker, Dijst, Faber, & Helbich (2015) found that women and older people experience thermal conditions as colder than other demographics.

Furthermore, with a novel analytical approach to the relationship between cyclists and weather, Corcoran et al. (2014) found that in Brisbane, Australia, rental bicycle trips are reduced during rain, but that a noteworthy number of short trips persist under rainy conditions in the city centre. In a literature review by Böcker et al. (2013), it's also highlighted that precipitation in some places only affect clothing behaviour for light rains and an adjustment of the departure time. The degree to which bicycle trips are postponed or cancelled due to precipitation was not identified by any study considered here, rather, studies tend to focus on modal shift.

2.2.3 Wind

The effect of winds onto cycling has been studied by a lesser extent, but the consensus is nonetheless that wind has a negative impact on cycling and even more so for higher wind speeds. Nankervis (1999) find empirical support for the negative relationship, but he argues that these findings are inconclusive because the decision to cycle aren't swayed as much by wind in comparison to other weather parameters. Other authors found that wind speeds are significantly correlated with a reduction in the number of cyclists, but the marginal effect is lower than for other weather parameters (Gebhart & Noland, 2014; Tin Tin et al., 2012). A nearly linear relationship has also been found by both Wadud (2014) and Flynn et al. (2012). The latter saw that an increase of 0.4m/s decreased the likelihood of cycling by 5%. Tin Tin et al. (2012) studied cycling volumes at a permeant cycle-measuring station near the coast in New Zeeland and found that, in an open and exposed environment, gustiness had a highly significant impact on cycle frequencies. This is interesting regarding spatial heterogeneity, which we will return to in an upcoming section.

It is possible that the mixed results reported by different studies are related to the built environment. So, to get a better grip on what effect wind might have on cycling, we can turn to other sources. Wind speeds are affected by the frictional forces imposed by roughness elements like buildings and vegetation (Hong, Lin, Wang, & Li, 2012; Oke, Mills, & Voogt, 2017). This in turn generates wind turbulence which is affected by the height of buildings in relation to the width of the street (H/W ratio) and/or the density of the roughness elements which can be measured by how much of the sky is visible from the ground, i.e. sky view factor (Nakamura & Oke, 1988). For example, in a narrow street canyon, winds may skim across the top of high buildings if the direction of the flow is perpendicular, but if the wind enters the canyon at an angle, the wind will funnel through the canyon and effectively increase the original wind speed. Wind that flows from an open area straight onto a tall building, for example at the quay, will also produce intense wind speeds due to the negative pressure near the facets, which creates a suction force (Oke et al., 2017). The varying degree of roughness elements in different cities was proposed by Helbich et al. (2014) as an explanation to why the impact of wind is more negative in low-density areas, especially near the coast line.

Furthermore, since the urban environment also affects the direction of the wind, this could be important knowledge but no study was found to consider this perspective in a real-world setting. However, a lab study found that crosswinds striking a cyclist at an angle of 30 degrees at speeds of 8-10 m/s will make the bicycle unstable and force the rider to a considerable effort just to keep the bicycle in balanced (Schwab, Dialynas, & Happee, 2018). Thus, it could be important to know how, not only wind speeds, but the direction of the wind affects cyclist.

It is also possible that wind also have an interaction effect with other weather parameters. Studies also suggests (Böcker et al., 2013a; Liu et al., 2014; Phung & Rose, 2007) that wind chill could be experienced as pleasant during hot summer days, whilst the opposite could be the case on colder days or days with precipitation.

2.2.4 Sunshine

Duration of sunshine has been studied in relation to cycling, but the variable often gets too little attention. Although two literature reviews found that sunshine has been studied to some extent, almost nothing is said about its association to cycling (Böcker et al., 2013a; Liu et al., 2017). A reason for the lack of attention regarding sunshine could be data availability, as mentioned by Mathisen, Annema, & Kroesen (2015).

In London, a small but positive influence was found between cycling and duration of sunshine (Wadud, 2014). Thomas et al. (2013) found that the duration of sunshine is more important to some cyclists, depending on the type of cycleway, i.e. utilitarian and reactional, whereof sunshine was more important for the latter. Furthermore, they also found that sunshine is the second most important weather parameter in regards to its positive influence on cycling frequencies (Thomas et al., 2013). In

Auckland, a city with a oceanic/subtropical climate, Tin Tin et al. (2012) found that sunshine also had a positive effect on cycling, the effect was particularly pronounced in winter and spring. Note however that, compared to Gothenburg, an average winter in Auckland is comparable to mid-spring and mid-fall in Gothenburg's temperate climate.

Moreover, sunshine can have other effects on cycling behaviour that are worth consideration. Sunshine affects the visual perception of the urban environment, making it more aesthetically pleasing for the rider and thus influences how the current weather is perceived, even though the air temperature may remain constant (Böcker, Dijst, & Faber, 2016; Böcker & Thorsson, 2014). However, a study of cyclists in three Swedish cities, made the interesting discovery that sunshine appeared to produce less positive emotions directly after a commute (Ettema, Friman, Olsson, & Gärling, 2017).

Sunshine is also indirectly linked to the cyclist through the built environment. For example, vegetation can protected a cyclist from intense sunshine during summer, and in winter, when trees defoliate, they allow more sunshine to reach the rider (Böcker & Thorsson, 2014). Tall structures and dense urban environments will also block sunlight from reaching the ground (Erell & Williamson, 2007).

2.2.5 Other weather parameters

Given how prevalent relative humidity is in the weather-cycling literature, it's important to explain why its excluded from analysis in this study. Relative humidity is a function of temperature and moisture in the atmosphere (Lawrence, 2005). For example, if the temperature increases whilst the amount of moisture in the atmosphere remains the same, relative humidity will decrease. During the night, the opposite occurs as temperature decreases, which inflates relative humidity. This is also related to the built environment, since areas with more pervious surfaces and vegetation have a stronger evaporation compared to paved areas of a city (Kuttler, Weber, Schonnefeld, & Hesselschwerdt, 2007). Therefore, the line was drawn at temperature and precipitation, since its possible that relative humidity wouldn't conduce to other findings than those yielded by its parental variables.

That said, specific cases of relative humidity could be interesting, for example dew-point could've been used as an estimate of frost risk, and by extension slipperiness, during colder seasons. But this falls beyond the scope of this study since this risk is not an issue during warmer seasons. The same goes for snow covered ground. Other variables that have been included in previous research are; daylight i.e. elapsed time between sunrise and sunset, atmospheric pressure, visibility, fog, darkness and cloud cover. Very little is however known about the association between these parameters and cycling. But this is not necessarily an issue, given that many of these variables have multicollinearity relations to other weather effects, i.e. for example cloud cover and sunshine. Something noteworthy regarding darkness, a study in Gothenburg investigated cycling safety and found that darkness amongst other factors significantly heightens the risk of accidents (Dozza, 2017). This was likely also connected to the drinking behaviour of the cyclists.

2.3 Seasonal effects on Cycling behaviour

Even though cycling has been studied extensively in relation to weather, studies seldom evaluate the impact in detail across all seasons of a year. That said, most studies identify a substantial increase of cyclist during warmer months compared to colder months, but the increase levels off in summer (see Böcker, Dijst, & Prillwitz, 2013; Liu, Susilo, & Karlström, 2015). Moreover, seasonality has a greater effect in regions with a climate similar to that of North America and the Scandinavian countries, but consequently, the impact of day-to-day weather tends to be smaller in these regions (Böcker et al., 2013a). Other findings suggest that recreational cyclist are more affected by both seasonal variations and weather (Tin Tin et al., 2012).

Proximity may also be important from a seasonal perspective. When studying commuters to a University in Toronto, Canada, Nahal & Mitra (2018) found that a higher density of bicycle infrastructure within 500 m of the shortest route to the University positively affected the decision to cycle during all seasons.

Studies of the Randstad region, Holland and Bodø in northern Norway have also used a predictive model to show how climate change could affect cycling in the future. With regards to seasonality, it was predicted that more people will choose to cycle in winter but less will opt for the bicycle in summer because of the expected temperature increase along with more precipitation (Böcker, Prillwitz, & Dijst, 2013b; Mathisen, Annema, & Kroesen, 2015). In a comparison of different regions during different seasons, Liu, Susilo, & Karlström (2015) made the interesting discovery that the impact of precipitation onto cyclists becomes positive during winter in the central region of Sweden. No theory was disclosed to why this occurred, nor was any information available to determine whether Gothenburg fell into this category.

Some studies also focus on the demographic and psychological side of cycling. In a comparison of different transportation modes in three Swedish cities, Ettema, Friman, Olsson, & Gärling (2017) found no difference regarding the travel satisfaction between seasons, but in regards to cyclist, a negative impact on the mood was found during sunshine, which they speculate could be related to uncomfortable feelings of warmth. This could possibly also be connected to higher air temperatures according to the authors (Ettema et al., 2017). On the same topic, a study found that weather preferences may play a role in how people are affected by the seasons. Thermal conditions were more likely to be perceived as colder by people who held summer as their favourite season, compared to people with other favourite seasons (Böcker et al., 2016). Moreover, a study by Shirgaokar & Nurul Habib (2018) found that men are twice as likely to be year-around cyclists than women. Plausibly related to this is that women overall tend to experience thermal conditions as colder during travel (Böcker et al., 2016).

Furthermore, experienced cyclists, as suggested by the riders age also increase the likelihood to cycle across all-seasons. Meanwhile, income appears to have no effect on the inclination to cycle whilst a small signal implies that people with a lower education less often are found to choose the bicycle as their mode of transportation (Shirgaokar & Nurul Habib, 2018).

2.4 Spatial heterogeneity and Cycling

Although the general weather impacts on cycling are well understood, much less is known about the spatial impact of weather. Only two studies have been identified with a focus on cycling, weather and spatial heterogeneity, but these studies were conducted on a regional scale (Helbich et al., 2014; Liu et al., 2015). However, they did find evidence of spatial variation in relation to location. These two studies will be described in more detail shortly. Vandenbulcke et al. (2011) analysed cycling from a perspective of spatial heterogeneity at a regional scale but didn't consider weather. At a city scale, both Feuillet et al. (2015) and Yang, Lu, Cherry, Liu, & Li (2017) studied cycling with spatial heterogeneity in mind but weather was yet again disregarded. Other studies of cycling and weather have made partial findings of spatial heterogeneity with regards to weather and cycling (Corcoran et al., 2014; Miranda-Moreno & Nosal, 2011; Nosal & Miranda-Moreno, 2014; Thomas et al., 2013; Tin Tin et al., 2012), but the focus of these studies was primarily on other relationships on a variety of scales.

Helbich, Böcker, & Dijst (2014) studied the Randstad region, the Netherlands, with a geographically weighted logit model and found that location highly matters in relation to weather. All weather parameters appeared to be more important in open and weather-exposed peripheral areas, whilst the effect in dense city centres were weaker

(Helbich et al., 2014). Liu, Susilo, & Karlström (2015) divided Sweden into southern, central and northern regions to find that weather affects cyclists in different regions differently during different seasons. Cyclists in central and southern Sweden were less aware of changes in temperature. Both precipitation and snow covered ground strongly discouraged cycling, which corresponds with increases in public transportation and walking (Liu et al., 2015). Also in the Netherlands, Thomas, Jaarsma, & Tutert (2013) used long-term time series data to study the influence of weather onto cycling in the rural surroundings of two medium sized cities. With a prime focus on temporal fluctuations, they separated utilitarian and recreation cycle paths to find that these classes seem to experience weather conditions in a similar fashion, but the demand for recreational cycle facilities in response to weather revealed a downward trend compared to utilitarian routes (Thomas et al., 2013).

Only two articles that studied weather and cycling spatially were explicitly conducted within city limits. Both made partial findings that possibly can be attributed to spatial heterogeneity. With a novel flow-co-map analysis, based on data from Brisbane's Bicycle Sharing stations, Corcoran et al. (2014) found that, with regards to precipitation, relatively short trips continue to occur in certain parts of Brisbane, whilst a considerable system-wide reduction of longer trips are found during strong wind events in excess of 15,3 m/s. Considering five cycle counting stations in Montreal, Canada, Miranda-Moreno & Nosal (2011) observed vastly different magnitudes of regression coefficients between stations in response to rain in the previous 3 hours. They found that the station near the central business district had much more demarked reductions in cycle frequencies compared to a station at the verge of a residential area. The change was -21.8% and -10.5% respectively. Miranda-Moreno and Nosal speculate that demographic differences between the two areas could explain the variation, and suggests that professionals may be less willing to cycle in the rain. Socio-economic characteristics have been showed to produce spatial heterogeneity (Feuillet et al. 2015). Nonetheless, the authors do also emphasize that built environment characteristics must be studied in more depth to make concrete findings of its effect on cycling under different weather conditions (Miranda-Moreno & Nosal, 2011).

How spatial variations in cycling relates to weather in different built environments have also been brought up by another study. Helbich et al. (2014) suggests, based on the regional cycling-weather patterns they found in Randstad, that spatially heterogenic cycling patterns in response weather could be linked to local micro-climates within a city. A review (Böcker et al., 2013a) also highlight the lack of knowledge concerning the role of microclimates in relation to weather and cycling. To get an idea of the different microclimates within a city, Local Climate Zones can be used as a logical division of the quantifiable urban structure. The LCZ classification scheme was developed by Stewart & Oke (2012) as a standardized technique to identify uniform areas where certain urban properties cluster spatially. Since weather does produce spatially heterogenic cycling flows at regional scales, it's interesting to see whether these variations can be described with LCZs to replicate the results at a local city scale.

3. Method

The flow chart in figure 2, contains a summary of all taken steps. Basically, the methodology in this study relies on two paths. First, the production of the *station dataset* which contains all cycling and weather variables. These variables have been processed, standardized and validated. Second, to capture the variety of urban characteristics found at different stations, an adaption of the Local Climate Zone (LCZ) *classification scheme* was used (Stewart & Oke, 2012). Stations with similar characteristics, i.e. those stations that fulfil the same LCZ criteria are then collapsed into a LCZ dataset. Both individual stations and stations aggregated by LCZ class are correlated with the weather parameters. This study used the Pearson *r* product-moment correlation coefficient, or for short, Pearson *r,* to measures the association between a pair of two random variables (Asuero, Sayago, & González, 2006).

Finally, the respective Pearson *r* values were *mapped* for each station and every weather parameter. The combined LCZ stations aren't mapped, but instead their Pearson *r* values are *standardized* in a matrix table according to class. Taken together, the resulting maps and the matrix were used to analyse the spatial heterogenic effects of weather on cycling.

3.1 Dataset description

3.1.1 Cycling flow data

Data for cycling volumes were provided by Gothenburg's Urban Transport Administration on a daily aggregate level for weekdays during the period 2016-01-01 to 2018-09-07, i.e. the most recent extent at the onset of this study. Delimitation to weekdays was deemed appropriate since most commutes are undertaken during weekday. The cycle-measurement stations in Gothenburg show distinct intraday and intraweek patterns of being primarily used by utilitarian commuters (Dozza, 2017). Commuters are also been regarded as less affected by weather (Thomas et al., 2013). Calendar events that occurred on weekdays were also excluded, resulting in what can be regarded as a dataset with a homogenous population. Furthermore, a daily level of analysis is enough to explore whether spatial heterogeneity exists at all.

The dataset consists of 24 094 866 observations distributed over a total of 31 counting stations. Some stations were temporary and others were affected by construction and hence lacked data records.

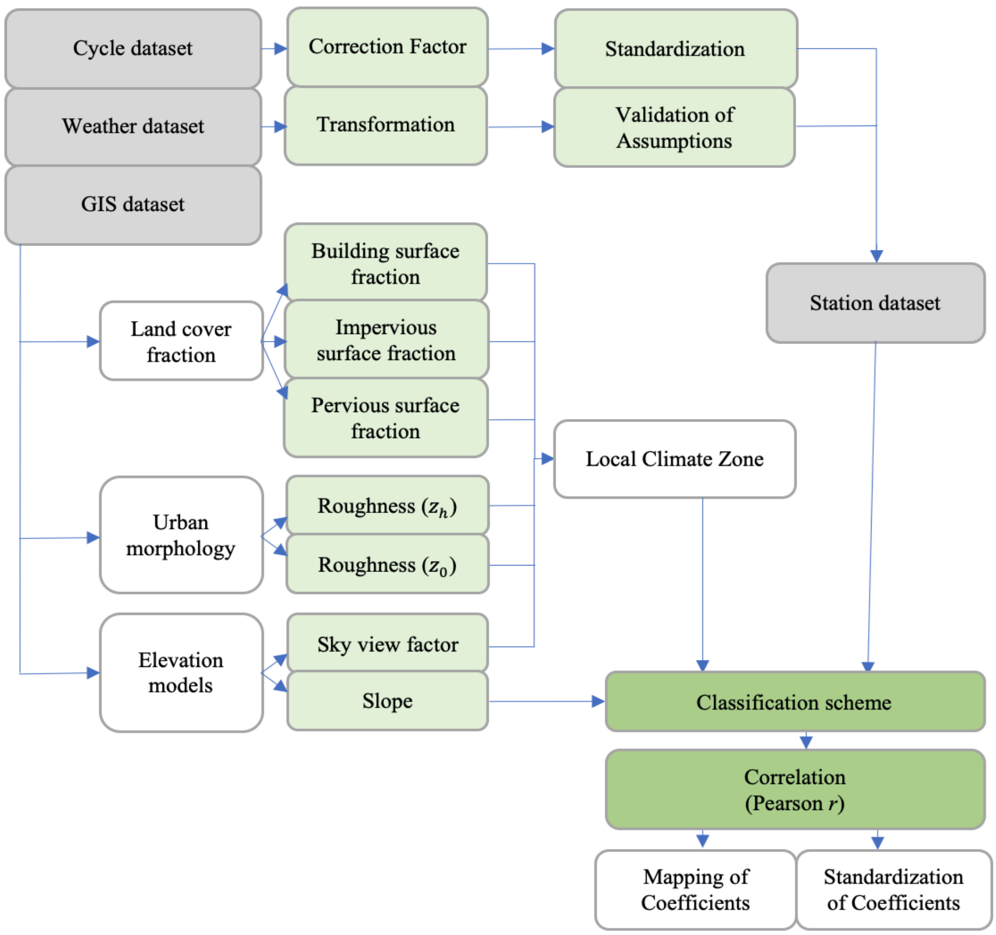

Figure 2. Flow chart providing an overview of the methodology in this study. Light green boxes are associated with data processing whilst dark green boxes highlight analytical steps.

Other than that, no systematic data errors were found in the dataset. Out of the 31 counting stations, only 14 stations retain at least 90 percent of the data for the period, but there are also a few stations have a counter in each direction. These twin-stations were aggregated and the original stations was discarded, yielding a total of 15 stations with 17 172 663 observations. Finally, every station was coded and denoted by *S* followed by four numbers.

3.1.2 Weather Data

To allow for normalizations of some variables, weather data was collected from the Swedish Meteorological and Hydrological Institute (SMHI) on an hourly basis for each weather parameter since 2008-01-01. The following weather parameters were collected from station 71420: precipitation, relative humidity, average wind speed, gust, and air temperature. Sunshine records were not available at this station and were therefore sampled from the nearby station 71415. In addition to this, as a measure of available daylight, sunrise and sunset times were generated for Gothenburg. This was done with a spreadsheet from NOAA (https://www.esrl.noaa.gov/gmd/grad/solcalc/NOAA_Solar_Calculations_year.xls). This data was then used to calculate the fraction of sunshine on a given day, depending on the hours of available daylight, which normalized the sunshine variable and removed seasonal differences caused by daylight hours.

The weather parameters were aggregated to a daily level and processed to construct a total of 11 variables that coincide with the cycle data. However, many of these variables are only versions of the same weather parameter, wind has for example 4 different constructs; wind speed, average maximum wind speed, average gust and maximum gustiness. Relative humidity will not be used either, as explained earlier. Hence, not all the 11 constructed variables will enter analysis.

3.1.3 Local Climate Zone & Slope data

From the Urban Climate Research Group at the University of Gothenburg, a raster dataset with a 1-meter resolution per pixel was collected. The dataset spans the entire municipality of Gothenburg and contains seven classes of land cover fraction, and the heights of ground, buildings and vegetation. In addition to this and because the elevation of the City's two major bridges wasn't present in the dataset; a LIDAR dataset were therefore utilized to create rasters with a 1-meter resolution to cover the bridges geographical extent. This data was the finest available to this study but other sources have been used to successfully make an LCZ classification of an entire city, see for example Geletič & Lehnert (2016) or Unger, Lelovics, & Gál, (2014).

Furthermore, the dedicated cycle network as well as the coordinates for the cycle stations were provided by Gothenburg's Urban Transport Administration. The locational data is necessary to quantify the urban properties in the Local Climate Zone scheme, applied in this study.

3.2 Data normalization & processing

3.2.1 Weather & transformations

Most studies exclude variables either based on high correlations between independent variables or because of their insignificant contribution to their models (eg. the wind variable in Miranda-Moreno & Nosal, 2011). However, this study is interested in comparing the strength of correlations, and as Böcker et al. (2013) points out, all weather factors are always co-varying with one another.

To determine which of the different versions of the 11 variable constructs were to be included in the forthcoming analysis, the underlying assumptions of the statistical test i.e. Pearson *r*, were used for guidance. These assumptions are: (1) a linear relationship exists; (2) joint distribution of a variable pair have a normal distribution; (3) variables are measured at a continuous scale; (4) each pair of variables are sampled independently

(Havlicek & Peterson, 1977). Regarding the latter, there are four weather categories that easily can be distinguished as being independent observations. These are temperature, precipitation, sunshine and wind speed. Next, we turn to look at normality.

Researchers has for a long time battled with the distributions of weather parameters. Depending on the foci of a given study, the natural variability that's inherent to different weather phenomenon should be reproduced accurately (Ailliot, Allard, Monbet, & Naveau, 2015). How a variable is defined depends ultimately on the chosen analytical tool. With regards to joint distribution of normality, precipitation is an especially complex variable to define. Since most previous studies of weather and cycling have relied on a logistic model, they often opt for a simple binary o binominal coding of precipitation. This does however transform the variable into a discrete distribution, which makes the statistical significance suspicious in a Pearson *r* model. It is also important to point out that precipitation usually has a zero-inflated exponential distribution, i.e. it's extremely positively skewed to the right. By excluding days without a precipitation event, the distribution immediately starts to change towards an exponential transform of a Gaussian distribution. However, this means that we are only concerned with the association between cycling and when it's raining. To work around this issue, a binary rain test were applied (section: 3.5.2).

So, a lot of power transformations were evaluated for every variable. None of the transformations were however, regarding precipitation, powerful enough to approximate normality. So, a rank-based inverse normal (RIN) transformation was applied. Given that we are interested in bivariate correlation, RIN transformations are appropriate since it manages the risk of making type I errors whilst it maintains power and the level of measurement (Bishara & Hittner, 2012). The equation for the RIN transformation are,

$$f(x) = \Phi^{-1}\left(\frac{x_r - 1/2}{n}\right) \tag{1}$$

where x_r is the ascending rank of x, the inverse normal cumulative distribution function is described by Φ^{-1} and n is the sample size. Still, depending on the original kurtosis of the underlying distribution, a RIN transformation might not suffice (Bishara & Hittner, 2012). However, because all zero-inflation records were excluded, the excess original kurtosis was significantly reduced, which produced a satisfying distribution after the application of the RIN transformation. It is however still important to keep in mind that the p-values can be suspect, but this is necessarily not an issue if they are highly significant. A table of all p-values are therefore provided in the appendix (table 6).

The RIN transformation was eventually applied to precipitation (mm), precipitation (length) as well as the sunshine fraction of daylight, hereon after just referred to as sunshine. The latter had a degree of a zero-inflation distribution but the excess kurtosis was much less than for precipitation, even when all events of zero sunshine were excluded. But since no other power trans-formation was strong enough to produce a satisfying approximation of normality for sunshine, the RIN transformed variables were utilized.

The temperature variable was converted to a standardized normal distribution – or a z distribution, for two reasons. First, out of all the considered weather parameters, temperature is especially well-suited for this transformation due to its relatively predictable nature. Second, this transforming of temperature allows the variable to be interpreted as warmer or colder than normal on a continuous scale. The process used here is similar to Liu et al. (2014). The z-scored temperature variable was generated with the following equation based on 10-years of data, let *d* denote a given day of the year,

Table 1
Descriptive normality statistics of the transformed weather variables with outliers removed.

Statistics	Ta_{max} (z-scored)	$Precip_{mm}$ (RIN)	$Precip_{len}$ (RIN)	$Gust$ (LN)	$Sunshine_{/Daylight}$ (RIN)
Valid *n*	981	487	486	972	787
Mean	0.095	4.405	5.092	1.733	0.428
Median	0.098	4.356	5.298	1.726	0.429
Skewness	-0.015	0.076	0.254	0.036	-0.044
Std, Error of Skewness	0.078	0.111	0.111	0.078	0.087
Kurtosis	-0.301	-0.427	-0.673	-0.337	-0.184
Std, Error of Kurtosis	0.156	0.221	0.221	0.157	0.174
Mean-median ratio	**-0.036**	**0.011**	**-0.039**	**0.004**	**-0.003**
Z-score Skewness	**-0.192**	**0.685**	**2.288**	**0.462**	**-0.506**
Z-score Kurtosis	**-1.929**	**-1.932**	**-3.045**	**-2.146**	**-1.057**

NOTE: The mean-median ratio and z-scores for skewness and kurtosis are adjusted to show deviations from 0. Used transformations are shown in parenthesis. Bold text indicate that normality was met.

$$Ta_{\max(z)} = \frac{x_i - \mu_d}{\sigma_d} \tag{2}$$

where x_i is the unique observed value of temperature, μ_d is the aggregate daily mean of a given day, and finally σ_d is the standard deviation of the same aggregate day.

Out of all the wind speed variables, mean gustiness had the fit best to cycling. Just like the other variables, gustiness was tested with a series power transformations. Although the square root is used more extensively by researchers (Ailliot et al., 2015), the transformation with the best approximation of normality got selected, which was the natural logarithm.

3.2.2 Meeting the Assumptions

Even though Pearson's correlation coefficient is robust against violations of assumptions (Havlicek & Peterson, 1977), for the sake of validity, the assumptions should be met. In addition to these assumptions, it is important to identify extreme outliers, because these can cause arbitrary de/inflations of the *r* values (Asuero et al., 2006). Therefore, after the transformations were applied, outliers were identified and rejected at ±1.5·IQR. The number of valid *n* per weather parameter after all processing is found in table 1.

There are several ways to judge whether data meet the assumptions of a statistical test, depending on sample size, one could use a statistical test like the Shapiro-Wilks test ($n < 50$) or a Kolmogorov-Smirnov test ($n > 50$) to determine normality (Henderson, 2006). However, there's an argument to be made that both these tests are too conservative at determining normality since both test may become unreliable for larger sample sizes e.g. $n > 300$ (Kim, 2013). Indeed, this is the case in this study since the smallest $n = 486$.

Therefore, this study makes use of a few less conservative methods to determine the joint normality assumption of Pearson's *r*. First, the joint normality distribution of a covariate pair is influenced by the univariate distribution of each independent variable. The univariate normality of each independent variable can be determined by inspection of the median-mean ratio, and the standardized skewness and kurtosis statistics. Both the mean and the median are measures of central tendency. If the distribution is perfectly symmetrical, then the mean and median will equate to the same value. In table 1, this value is 0, which describes the ratio between the two statistics. All values fell within ±0.05 of 0, which indicates a symmetrical distribution. In addition to the mean-median ratio, the skewness and kurtosis statistics can be z-scored to determine normality. Kim (2013) suggests that the distribution is non-normal if the z-score exceeds an absolute z-score value of 3.29 which corresponds to an alpha of 5 percent. Only the z-scored kurtosis of the transformed precipitation length comes close to this threshold, but is fine with a slight margin. Finally, we turn to the Q-Q plots to decide whether the weather variables have a univariate normal distribution (Fig. 3). A Q-Q plot represents a normal distribution by a straight line running through the data. If the data is normally distributed, then it should cluster around the centre line. What we are trying to avoid are is a clear S-shaped curve around the centre line, as well as too large departures from the centre line towards the tail ends. Judging from the Q-Q plots in figure 3, no distinct S-shapes are found. However, some variables do deviate from the centre line at one end. This indicates that the kurtosis deviates from normal. But if we refer to table 1, we can determine from the kurtosis statistics that this deviation isn't significant enough to reject the null hypothesis and hence, we can conclude that our data approximate univariate normality.

Although studies have found parabolic relationships between cycling and weather, the association can still be linear as shown by other studies. The scatter plots in figure 3 show for the sake of space the aggregate mean of all stations together with each weather parameter. We can determine from the scatter plots that a correlation exists, which justifies the fitting of a linear model. The points are mostly found within an ellipsoid shape with a demarked linear function, which indicate that the joint distribution also doesn't differ significantly from normal (Field, 2009). Also, note that precipitation length seems to be measured at an ordinal level. However, this is not the case but rather a result of the variable being measured in hours. Thus, the variable for duration of precipitation suffers from some discretization but it can still be regarded as a quantitative variable.

3.2.3 Cycle data processing

Since there are 15 stations in the dataset, the first part of processing was to get acquainted with the data to understand its natural variation. But first, cycling counts were matched to the corresponding weather variables of each day. On average, 651 days of the 981 days in the time series contain cycle counts due to the exclusion of holiday events and weekends. The cycle stations were graphically studied together with the different weather parameters. The expected covariance was confirmed by visual inspection, the cycle volume does, for example rise and fall together with temperature and cycle counts drop during precipitation events (Fig. 4).

However, another unrelated variation

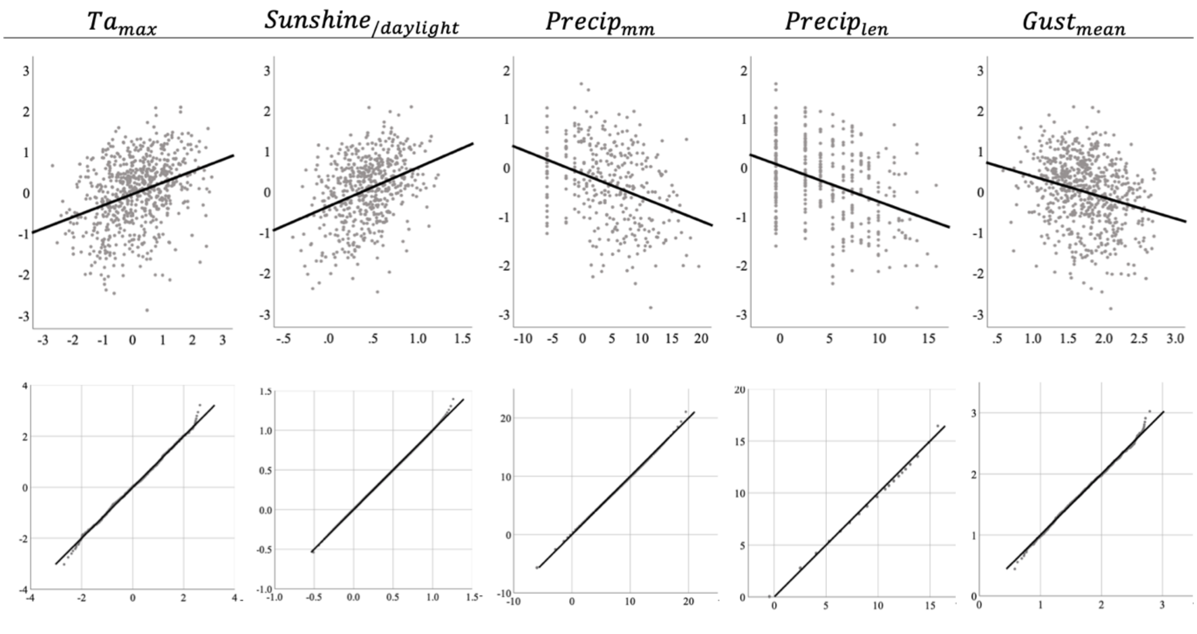

Figure 3. Scatter plots (upper row) with the standardized cycle counts on the y-axis and a weather index on the x-axis, fitted with a least square regression line. At the lower row are Q-Q plots for the five transformed weather parameters.

was revealed. During periods with no significant changes in weather, i.e. mostly neutral weather conditions, cycle counts seemed to display an intrinsic pattern of weekly variation. For example, during the two dry weeks in figure 4, the cycle count is higher mid-week. The pattern also appears to vary between different months and seasons. This variance couldn't possibly be related to weather, but was rather a phenomenon of cycle behaviour itself. To isolate these intrinsic cycling variations, the raw data was processed into ratios. The arithmetical means for each unique week were calculated, and averaged ratios were calculated for each weekday of each month. Let *d* denote day-of-week, $y = \{1 \ldots n\}$ is the *n* years of data and *m* is the month-of-year in equation,

$$R_{d,y,m} = \sum \frac{x_{d,y,m}}{\bar{x}_{y,m}} \tag{3}$$

where every unique cycle count ($x_{d,y,m}$) is divided by their corresponding week-average ($\bar{x}_{y,m}$), accumulated over the full time-series. Only full weeks of observation were permitted to avoid errors, hence, $\bar{x}_{y,m}$ is the weekly average for 5 days of cycle counts. The resulting, $R_{d,y,m}$ is the weekday in the *n*-th week of the *n*-th month in the *n*-th year. The value of $R_{d,y,m}$ enters the following equation,

$$CF = R_{d,m} = \frac{1}{n} \sum R_{d,y,m} \tag{4}$$

where the *correction factor* is abbreviated CF whereof $CF = R_{d,m}$ is the average weekday ratio in *n*-th month of a standardized year, which is given by the $R_{d,y,m}$ summed over the *n* of weeks in every month. In other words, we are left with the average ratio of each weekday – i.e. Monday thru Friday, in every normalized month of a normalized year. This processing removes most of the influence that weather may have and unveils cycling's intrinsic variation. The result of this process found clear weekly pattern that must be addressed (Fig. 5). Most weeks show distinct patterns where Wednesdays and Fridays usually have lower cycle volumes than other weekdays. This is interesting in and of itself, since it appears that cyclists seem to have a preference to cycle on certain days, regardless of the predominant weather conditions in every month.

The raw cycle data were finally treated with the correction factor. This was done by dividing the observed cycle count value by the correction factor. This treatment reduced the cycle count whenever the correction factor was ≥1 and increased the volume whenever the correction factor was ≤ 1. With the correction factor applied, the treated cycle data was standardized into z-scores based on the following equation,

$$Cycle_{z-score} = \frac{(x_i/CF) - \bar{x}_{3w}}{s_{3w}} \tag{5}$$

where the subscript $_{3w}$ denote that both the standard deviation and arithmetic sample mean encompasses one adjacent week in either direction of the centroid week where the corrected cycle count x_i is located. This is important, since we are concerned with weather-related anomalies in the cycle frequencies. Thus, a three-week span as the basis of standardization is wide enough to detect weather responses at the cycle-measurement stations, but narrow enough to avoid most of the seasonal and annual anomalies.

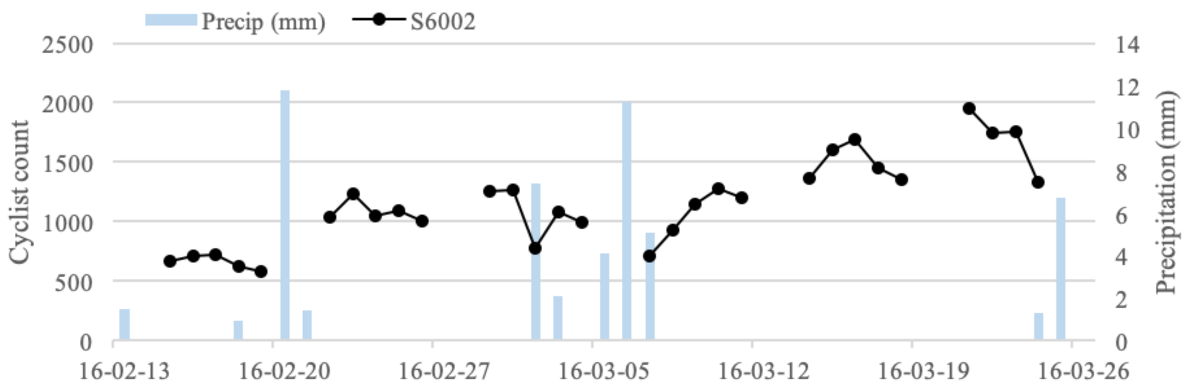

Figure 4. An excerpt of the raw cycle and precipitation data. The figure exemplifies that an intrinsic weekly pattern of variation may exist. Furthermore, the figure shows that cycle counts respond to weather – in this case, a rain event.

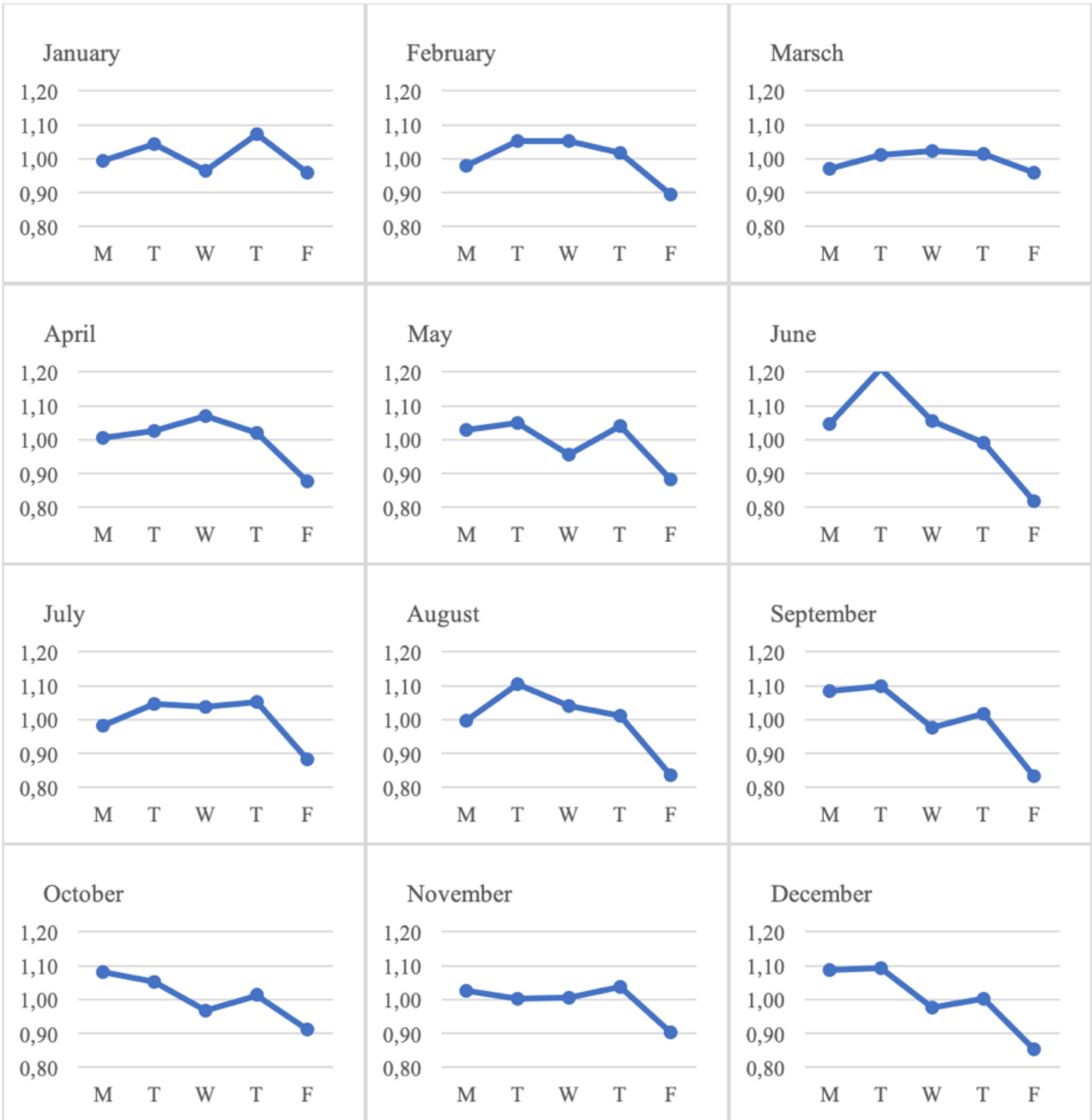

Figure 5. The normalized ratio of the intrinsic weekly pattern per month.

Table 2

Adapted Local Climate Zone classification scheme used by this study. Disregarded properties have their values dashed.

			Geometric and land cover properties							Radiative properties*		
Local Climate Zone	Description	Dominant feature**	Sky view factor	Aspect Ratio*	Building surface fraction (%)	Impervious surface fraction (%)	Pervious surface fraction (%)	Height of roughness elements (z_h)	Terrain roughness (z_o)	Surface admittance	Surface albedo	Anthro-pogenic heat output
LCZ 1	Compact high-rise	Built	0.2–0.4	-	40–60	40–60	< 10	> 25	8	-	-	-
LCZ 2	Compact midrise		0.3–0.6	-	40–70	30–50	< 20	10–25	6–7	-	-	-
LCZ 3	Compact low-rise		0.2–0.6	-	40–70	20–50	< 30	3–10	6	-	-	-
LCZ 4	Open high-rise		0.5–0.7	-	20–40	30–40	30–40	>25	7–8	-	-	-
LCZ 5	Open midrise		0.5–0.8	-	20–40	30–50	20–40	10–25	5–6	-	-	-
LCZ 6	Open low-rise		0.6–0.9	-	20–40	20–50	30–60	3–10	5–6	-	-	-
LCZ 7	Lightweight low-rise		0.2–0.5	-	60–90	< 20	<30	2–4	4–5	-	-	-
LCZ 8	Large low-rise		>0.7	-	30–50	40–50	<20	3–10	5	-	-	-
LCZ 9	Sparsely built		> 0.8	-	10–20	< 20	60–80	3–10	5–6	-	-	-
LCZ 10	Heavy industry		0.6–0.9	-	20–30	20–40	40–50	5–15	5–6	-	-	-
LCZ A	Dense trees	Openness	<0.4	-	<10	<10	>90	3–30	8	-	-	-
LCZ B	Scattered trees		0.5–0.8	-	<10	<10	>90	3–15	5–6	-	-	-
LCZ C	Bush, scrub		0.7–0.9	-	<10	<10	>90	<2	4–5	-	-	-
LCZ D	Low plants		>0.9	-	<10	<10	>90	<1	3–4	-	-	-
LCZ E	Bare rock or paved		>0.9	-	<10	>90	<10	<0.25	1–2	-	-	-
LCZ F	Bare soil or sand		>0.9	-	<10	<10	>90	< 0.25	1–2	-	-	-
LCZ G	Water		>0.9	-	<10	<10	>90	–	1	-	-	-

*Excluded properties.

**Binary simplification of the 17 discrete Local Climate Zones.

3.3 Seasonal sub-sampling of Data

With the weather and cycle data prepared, the last step was dividing the data into sub-samples to identify seasonality in our correlations. A possibility is to divide the dataset into dynamically-defined seasons based on meteorological transitions. This would accurately represent the seasonality of weather but it may not reflect cyclist behaviour. Moreover, using meteorological seasons would produce a fluid division of the data and thus complicate replication studies in the future. Thus, a better division of the dataset is instead along some culturally perceived seasons. People are habitual creatures that are driven, amongst other things by norms and attitudes towards cycling. People who cycle for more purposes than just their commute are more likely to cycle full-time, regardless of distance (Heinen, Maat, & Wee, 2011). Thus, it is possible that people who only use their bicycle to commute, often make modal shifts over a year. For example, people might shift back to their bicycle only when they think spring has arrived, even if the winter was unusually mild and calm. This could partially explain the bimodality of the raw cycle volumes in figure 6.

Therefore, a good approximation of both variations in weather and cycling behaviour was to use the conventional divisions of seasons with a modification to summer. Sweden has a long tradition of what may be called the industrial vacation period. This usually occurs, starting from around week 26 and goes on for eight consecutive weeks to, about halfway through august. Hence, the industrial vacation period of eight weeks replaces summer, and we can refer to this season as *industrial summer*. This effectively extends spring season forward to make up the gap and the fall season were extended backwards for the same reason (Fig. 6). The distribution of cyclists across all seasons were calculated per station, both how cyclist distribute *within* every station and how the distribute *between* stations and across the seasons. These distributions are presented in the results.

3.4 Adaption of the Local Climate Zone system

The original Local Climate Zone (LCZ) system is divided into 10 types of built environment (denoted 1-10) and 7 land cover types (denoted A-G). The system is based on the principle that certain characteristics of the urban environment tend to cluster in certain parts of a city, creating zones of relative uniform character (Oke et al., 2017). Furthermore, these zones are known to influence the microclimate within them, for example: temperature, moisture or wind speeds. It is also possible to combine different LCZs to better describe an urban environment (Stewart & Oke, 2012). To classify these Local Climate Zones, specific criterion of the 10 properties in table 2 have to be met, but according to the systems' developers (Stewart & Oke, 2012), the classification scheme is

Figure 6. The raw cycle data compressed to a year. The correlational seasonality is sub-sampled according to the seasons shown in the plot, where summer is replaced by the industrial vacation period and both spring and fall is somewhat extended.

inherently generic and therefore seldom captures and classifies the LCZs of any given city without some adjustments.

Given that this study is concerned with weather impacts on cyclists, some major adaptations are required. First, since cyclists' ride on a cycleway through the built environment, it is not meaningful to move too far in a perpendicular direction from the road. Rather, it's more important to encompass the whole road segment that is connected to the point where the station is located. Therefore, we can disregard the radiative properties due to distance issues, because a minimum radius of 200-meters is suggested, and because of how the radiate properties flow across a continuous urban surface (Stewart & Oke, 2012). Instead, a perpendicular minimum distance of 30m in either direction of the road is considered, which for an urban canyon can be regarded as microclimatic (Oke et al., 2017, p. 19). Moreover, the microclimatic scale was also believed to have an effect on cyclists in Helbich, Böcker, & Dijst (2014). So, this effectively means that the road has a 60m buffer. Other adjustments to the classification scheme were to exclude the aspect ratio. This is also known as the height/width ratio but, due to difficulties of quantification, this property had to be excluded. Also, the sky view factor (SVF) measures approximately the same aspect of the built environment. The final adjustment was to add an overarching category to the LCZ system since the excluded properties were expected to cause every station to meet the criterion of more LCZ classes than could be combined in a meaningful way. The added overarching class is called the *dominant feature*. No adjustments were made to the generic LCZ system regrading property values, henceforth, table 2 contain a replication of the original system along with the modifications made to the classification scheme by this study.

3.4.1 LCZ Data processing

The quantification of the geometric properties was done with the QGIS toolkit UMEP (Universal Multi-Scale Environmental Predictor) and vector data analysis. The calculation of sky view factor is immensely cumbersome to compute as it can take several days to complete for larger areas. Therefore, the stations were used as points with a 30-meter radius buffer for the SVF calculation. The tool calculates how much of the sky that is visible from every pixel. After the removal of SVF values at rooftops, the resulting mean of the SVF value per station were added to the classification scheme. The height of roughness elements (z_h) and the terrain roughness (z_o) also had to be calculated from the station points. The roughness quantification was done with the of rule-of-thumb approach to determine packing density of roughness features within the buffer (Oke et al., 2017; Stewart & Oke, 2012).

To quantify the geometric land cover properties, the corresponding road segment connected to each station were cut at major intersection of the cycle network where it is possible for cyclists to change route. A 30-meter buffer were cast around the road segment (Fig. 7) and the land cover area occupied by buildings, impervious- and pervious surfaces were calculated within the buffered-cycle ways. The fraction covered by these properties was then calculated as a function of the total area covered by the whole buffer.

3.4.2 Classification: Dominant Feature Class

With all properties added to a spreadsheet, every station got scored by how many property criterion per LCZ they fulfilled in table 2. Hence, all LCZ class outputs that a station met the criterion for are presented in table 3. As expected, a few stations met the criteria for two or more Local Climate Zones due to the unmodified original values and the exclusion of four properties. This was however not a problem since we are interested in the dominant feature class. This meant that every station was weighed by how many LCZ classes they obtained. If all or most obtained LCZ classes fell into the LCZs 1–10, it was classified as *Built*. If an equal amount of LCZs are obtained by a station, its classified as *Mixed* and finally, if the weight fell on the LCZ A–G classes, the stations was classified as characterized by *Openness* (table 3).

3.4.3 Classification: Slope Character

In addition to the LCZ system, an important property for cycling were added to the classification, namely topography. A review of cycling identifies that hilliness have a negative impact on cycling, but for more experienced riders, presence of slopes can be an attractive attribute (Heinen et al., 2010).

Based on the cycleway segments connected to every station, the slope was calculated through a topographic profile where each line of the cycleway segment is placed upon the elevation model. Thereafter, the degree of slope is calculated according to changes in height between every pixel where the cycleway segment intersects the elevation model. Due to the high resolution of the elevation model, some pixels produced extremely high slope values. This was probably caused by the two datasets being inaccurately overlapped in some areas. Therefore, the resulting slope values in the topographic profile was purged from outliers at ±IQR·1,5.

To determine the slope characteristics of each segment, the standard deviation (sigma) of slopes was used. This is meaningful since it captures whether the terrain is relatively homogenous, i.e. flat or heterogeneous i.e. hilly or steep based on the value of the standard deviation. For example, a sigma value of 0 would indicate perfect flatness. To the left in figure 7, the topographic profile for the flattest station (S6010) and the steepest station (S6940) are shown. The figure tells us that we expect a lower standard deviation at S6010 and a higher at S6940, and their respective sigma values were in fact 0.507 and 1.773.

The stations then had their slope character classified based on their relation to each other. The stations with the lowest 25 percent of sigma values got classified as *Flat,* the middle 50 percent was classified as *Hilly*, whilst the highest 25 percent was classified as *Steep*. Finally, the dominant feature class was

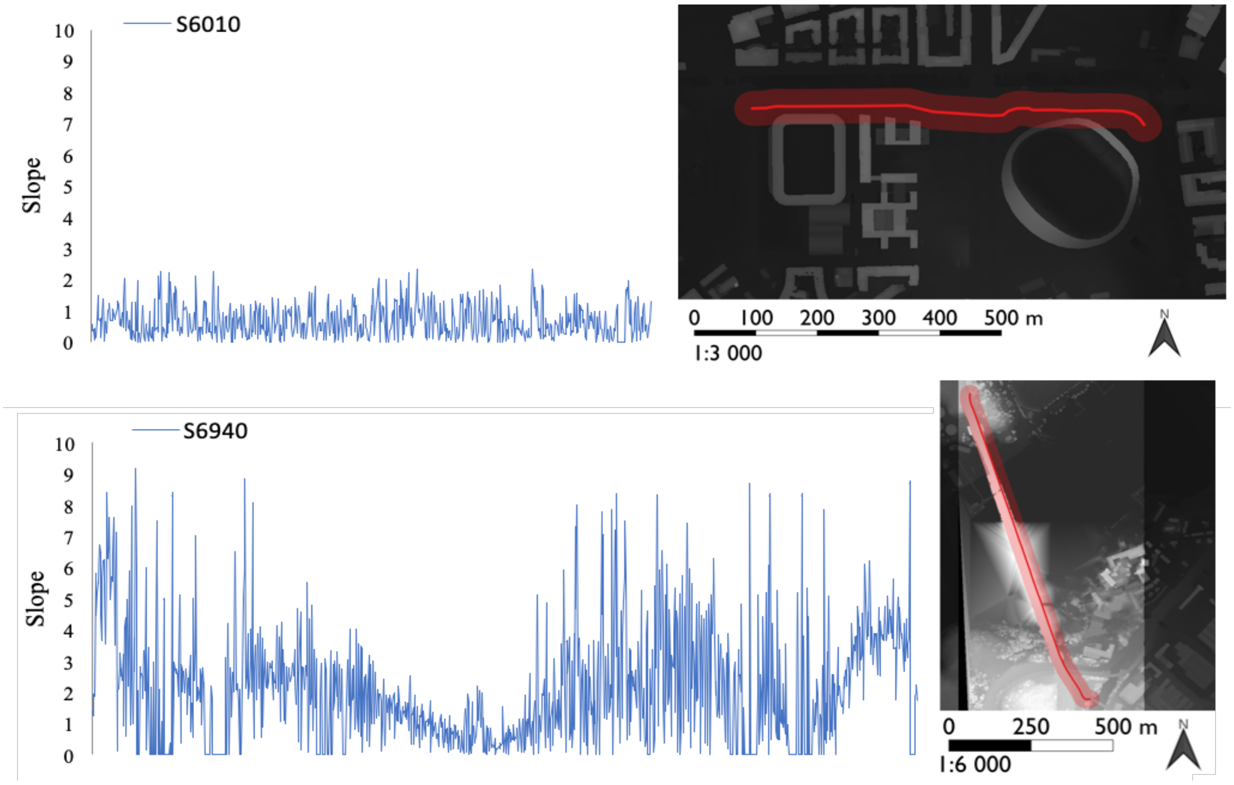

Figure 7. Left: the topographical profile of the slope character of the flattest and steepest stations in the dataset. Right: the cycleway segments overlaid on top of the elevation model, used to produce the topographical profiles. In addition, the extent of the buffer used to calculate some of the LCZ properties are shown in a transparent red colour.

Table 3
Final classification of the stations according to the modified LCZ classification scheme.

Fulfilled Criterion per LCZ	Dominant feature	S6002	S6003	S6005	S6006	S6008	S6010	S6025	S6027	S6028	S6042	S6046	S6049	S6051	S6940	S6935
LCZ 1																
LCZ 2						×	×							×		
LCZ 3					×					×			×			
LCZ 4																
LCZ 5	Built	×			×									×		
LCZ 6		×	×					×	×	×			×			
LCZ 7																
LCZ 8																
LCZ 9													×			
LCZ 10								×					×	×		
LCZ A										×						×
LCZ B		×					×	×	×	×		×	×			
LCZ C		×									×					
LCZ D	Openness														×	
LCZ E				×												×
LCZ F																
LCZ G																
Dominant feature selection		*Mix*	*Built*	*Open*	*Built*	*Built*	*Mix*	*Built*	*Mix*	*Mix*	*Open*	*Open*	*Built*	*Built*	*Open*	*Open*

NOTE: Every × signals that the station has met the criterion for this Local Climate Zone.

combined with the slope character of the cycleway segment. The classified stations were mapped and is presented in figure 9 of the results.

3.5 Data analysis

3.5.1 Bivariate Correlation

The bivariate correlation Pearson's r seeks to determine the degree of association between a pair of two variables. The degree of association is given by r which assumes a value between -1 and 1. If either of these values are reported, then the association between a pair of variables is either perfectly negative or perfectly positive as all data congregate at a line. The null hypothesis of Pearson's r is a correlation coefficient of 0. In other words, if a pair of variables obtains an r value of 0, then the variables have no association at all. The coefficient is thereafter tested for statistical significance, in this study, an alpha (α) of 5 percent was selected, i.e. $p=0.05$ or less must be obtained for a correlation to be significant.

In a previous section, we determined that the assumptions of Pearson's r were mostly met. Regarding normality, basic moments of the variable distributions did not differ significantly from normal. This was done, amongst other things by transforming the variables. Therefore, it is important to emphasize that Pearson's r is an invariant estimator (Rodgers & Nicewander, 1988), i.e. the association can be interpreted as if the variables were untransformed since the equation of Pearson's r in essence is a function the mean and standard deviation, which acts to equalize the units of measurement by adjusting the scale of the variables (Rodgers & Nicewander, 1988). However, some weather parameters and especially temperature is serially correlated, i.e. past values of the variable can be used to predict future temperature values. This indeed violates some assumptions of the significance test of Pearson r which is important to bear in mind.

Apart from the importance of meeting the assumptions underlying Pearson's r, there are other guidelines to consider. In this study, we are using the correlation coefficient to perform multiple tests which entails justifications of the statistical significance of the test. First, an adjustment of the alpha value must be considered to avoid type I errors (Onwuegbuzie, 1999). The Bonferroni correction is commonly used to do this. However, making the adjustment will inflate the risk of making type II errors. The exploratory design of this study does not justify the application of an adjustment to the alpha value (Armstrong, 2014).

Second, since the sample size can cause virtually any correlation to become significant as $n \to \infty$, Daniel (1998) suggests that the slope of r should be considered alongside the p-value. A table of critical r values for $\alpha = 5\,\%$ is provided in Daniel (1998). For example, during the sub-sampled season referred to as industrial summer, precipitation events average $n \approx 50$ which enlists a critical absolute value of $r \geq .276$. By comparison, the average of the full samples, i.e. the total effect, is $n \approx 500$ and has a critical value of $r \geq .088$. This slope criterion for statistical significance was kept, thus, every Pearson coefficient had their statistical significance evaluated based on both their p-value as well as the critical slope value.

3.5.2 Binary rain test

Since both precipitation variables were treated in a manner that removed zero-inflation, an additional test is required to analyse the impact of wet days, compared to dry days. This was done by converting the fraction of variance explained by the binary precipitation value to a pseudo equivalent r value. Two residuals were calculated for every station. One conditional that disregarded precipitation events;

$$Unconditional = \sum \left(\frac{x}{\bar{x}}\right) \tag{6}$$

and one conditional that accounted for precipitation events.

$$Conditional = \sum \left(\frac{x_{dry}}{\bar{x}_{dry}}\right) + \sum \left(\frac{x_{wet}}{\bar{x}_{wet}}\right) \tag{7}$$

The variance (σ^2) of both residuals was calculated and inserted into the final equation,

$$pseudo\ r = \sqrt{(R^2)} = \frac{Unconditional - Conditional}{Unconditional} \tag{8}$$

where the equivalent r was given by the square root of the explained variance. This r value was also sign corrected to reflect the negative impact of days with a precipitation event on cycling.

4. Results

4.1 Orientation

Because no previous studies were found to have developed, at a local scale, a robust framework for determination of spatial heterogeneity in cycling volumes under different weather conditions, this study will lay the foundation for such an endeavour. This framework is dynamic, designed for local analyses and makes interpretations straightforward. The solution is twofold.

First, most statistical tests aren't designed to be geographical and thus, the location of the data is usually not relevant to the test (Harris & Jarvis, 2014). The statistical test Pearson r is indeed not designed with geography in mind, yet mapping the coefficients given in r per cycle-measurement station renders them spatial and allows for patterns to be explored. This approach – i.e. explorative GIS analysis, relies on a visual model, where spatial patterns are studied through an interpretive mode of analysis (Aitken & Kwan, 2010). Second, the coefficients are quantitatively evaluated in a matrix to emphasize where the effects of weather are either the strongest or weakest. More detail of how this was done is presented in a subsequent section (see 4.4).

The results are introduced in three parts. First, some descriptive statistics of the global station averages are presented, followed by an explorative GIS analysis of the total weather impact for the whole time-series (Fig. 8) Along with these results, the results of the modified Local Climate Zone (LCZ) classification is presented (Fig. 9) as well as how cycle volumes distribute across seasons, both *within* (Fig. 10) and *between* stations (Fig. 11). Second, the results of the sub-sampled seasonal maps are presented for every weather index (Fig. 12-16). These maps are also explored for spatial heterogeneity with the framework. Lastly, the strength of spatial heterogeneity in different urban environments is presented in a matrix (table 5), along with all statistically significant coefficients. This is the last part of the heterogeneity framework and allows for a quantitative assessment of sensitivity to spatial heterogeneity occurrences. Inspiration to this approach was found in Mathisen, Annema, & Kroesen (2015). The results are presented in accordance with the research questions, reproduced below:

- Do spatially separated cycle-measurement stations produce a variety of responses to weather?
- If so, how is this variability related to the urban environment?
- Also, how alike are the response of stations to weather when their surrounding environments are similar?

4.2 Part I: Overall & Total effects

4.2.1 Main findings of Total Heterogeneity

The descriptive statistics for the global station average and the results of the binary rain test are presented in table 4. Regarding the total effect, the global r of all stations reveal that the duration of precipitation had the strongest absolute correlation (r = -0.36) and gustiness had the weakest (-.24). Furthermore, sunshine had marginally more positive impact on cycling than temperature. The range statistic, i.e. the difference between the minimum and maximum coefficients can be regarded as an indicator that spatial heterogeneity could be present. Looking at the range, temperature had the most universal effect on cycling due to its relatively narrow range (~0.07) whilst sunshine had the widest range (~0.13). However, apart from temperature, all weather parameters had a range statistic greater than ~0.10. The global stations averages in regards to the season will also be used for context in a part II.

Turning to the results of the binary rain test in table 4, the equivalent r showed that Badhusgatan (S6051) had the lowest reduction in cycle volumes (-.17) between dry and wet days, whereas Säröleden (S6042) had the greatest reduction (-.37) whenever a precipitation event occurred. However, the average equivalent r value of -.28 are lower than the obtained global r values of the other precipitation indices. Recall that both amount and duration of precipitation only considered cycling frequencies during days with precipitation events. Hence, these findings regarding precipitation unveil that the character of precipitation, i.e. how much it rains or length of rains had more association to cycling than the binary occurrence of a precipitation event in and of itself. Next, we turn to the maps.

4.2.2 Cartographic exploration: Total effect

To aid the explorative GIS analysis, the rose-styled coefficients were overlaid with a ring legend. To find appropriate scaling of these rings, the absolute r values of all coefficients were used to derive three percentile rings that approximate the recommended thresholds for small ($|r| \geq .1$), medium ($|r| \geq .3$) and large ($|r| \geq .5$) effect sizes in behavioural sciences (Cohen, 1992), where cycling as a phenomenon arguably resides. The size of the whole circle corresponds to the obtained maximum coefficient value.

Overall, apart from for gustiness, most coefficients of the total time-series approx-

Table 4
Left: Descriptive statistics of the aggregated Global r, given by all 15 stations.
Right: The pseudo equivalent r from the Binary rain test (section 3.5.2).

		Global Station Averages					Binary Rain test	
Weather		**Mean**	**Std.**	**Min**	**Max**	**Range**	**Station**	**Equivalent *r***
Ta_{max}	Total	0.32	0.02	0.29	0.36	0.07	*S6002*	-0.31
$Sunshine_{/daylight}$	Total	0.34	0.04	0.27	0.41	0.13	*S6003*	-0.30
$Precip_{mm}$	Total	-0.33	0.04	-0.26	-0.38	0.11	*S6005*	-0.26
$Precip_{len}$	Total	-0.36	0.03	-0.3	-0.42	0.11	*S6006*	-0.29
$Gust_{mean}$	Total	-0.24	0.03	-0.17	-0.29	0.12	*S6008*	-0.29
Ta_{max}	Winter	0.11	0.03	0.06	0.18	0.13	*S6010*	-0.29
$Sunshine_{/daylight}$	Winter	0.04	0.05	-0.05	0.15	0.19	*S6025*	-0.24
$Precip_{mm}$	Winter	-0.31	0.04	-0.24	-0.39	0.15	*S6027*	-0.35
$Precip_{len}$	Winter	-0.36	0.06	-0.28	-0.52	0.24	*S6028*	-0.27
$Gust_{mean}$	Winter	-0.13	0.04	-0.05	-0.21	0.16	*S6042*	-0.37
Ta_{max}	Spring	0.45	0.03	0.41	0.52	0.11	*S6046*	-0.26
$Sunshine_{/daylight}$	Spring	0.49	0.04	0.42	0.56	0.14	*S6049*	-0.31
$Precip_{mm}$	Spring	-0.37	0.04	-0.30	-0.43	0.13	*S6051*	-0.17
$Precip_{len}$	Spring	-0.44	0.04	-0.38	-0.50	0.12	*S6940*	-0.27
$Gust_{mean}$	Spring	-0.26	0.04	-0.19	-0.32	0.14	*S6935*	-0.28
Ta_{max}	Industry	0.19	0.06	0.09	0.30	0.20	**Mean**	-0.28
$Sunshine_{/daylight}$	Industry	0.38	0.11	0.26	0.60	0.34	**Std.**	0.05
$Precip_{mm}$	Industry	-0.45	0.06	-0.34	-0.54	0.20	**Min**	-0.37
$Precip_{len}$	Industry	-0.40	0.09	-0.16	-0.49	0.34	**Max**	-0.17
$Gust_{mean}$	Industry	-0.29	0.08	-0.16	-0.38	0.23	**Range**	0.20
Ta_{max}	Fall	0.37	0.03	0.30	0.41	0.11		
$Sunshine_{/daylight}$	Fall	0.30	0.03	0.25	0.35	0.10		
$Precip_{mm}$	Fall	-0.29	0.06	-0.18	-0.37	0.20		
$Precip_{len}$	Fall	-0.37	0.07	-0.21	-0.47	0.27		
$Gust_{mean}$	Fall	-0.31	0.03	-0.27	-0.39	0.12		

imated a moderate correlation onto cycling since most coefficients values are found around the median (|.33|) ring (Fig. 8). Concerning spatial patterns, the gust variable is the only weather parameter that clearly displays a negative association with demarked spatial variance. Its coefficients approximate a moderate correlation at stations S6002, S6005, S6935 and S6940. All stations except S6002 are located near the Göta älv and the latter two stations are found at the two major bridges.

Stations S6002 and S6042 experience the most positive influence of sunshine, both stations experienced a substantial moderate correlation (S6002 $r = +.39$; S6042 $r = +.41$). The nearby station at Långedragsvägen (S6027) approximated the same spatial effect from sunshine (+.38). The other weather parameters had less pronounced spatial patterns. Duration of precipitation had the most negative correlations on cycling overall, except for S6027 and S6940 whose coefficients were below the moderate strength threshold. Compared to duration, the effect of precipitation amount was more constant. A slightly more negative association to precipitation appeared to be concentrated to central, inland stations. No obvious spatial pattern was identified in relation to temperature.

4.2.2 Dominant features & Slope characteristics

The results from the modified Local Climate Zone classification (section 3.4) are presented in figure 9. The dominant feature and slope characteristic is shown per station. Starting with the roughness characteristics, the most common class are Built/Hilly ($n = 4$), and in total $n = 6$ stations were classified as Built and

$n = 7$ as Hilly. The spatial distribution of these are varied, nonetheless most Built classes were found in or near the city centre, apart from S6003 and S6049 to the east, north-east. Out of the $n = 5$ Open stations, all – except S6042 in the south – run alongside waterbodies. Additional attention should be steered towards the southward stations. S6002 runs north into the built city and connects in the south to the map insert of S6042. These stations had the longest cycleway segments and had, from the location of S6002 and downwards, a relatively flat and open environment. Regarding Dag Hammarskjöld (S6002), the urban environment became increasingly more built in the direction of the city centre, which is reflected by its Mixed classification. This characteristic of partial built/openness is reflected in every station with a Mixed class.

The terrain character show that the city centre is mostly classified as Hilly. Out of the $n = 4$ Flat stations, two are found near Mölndalsån just east of the city centre and the remaining two corresponds to stations S6002 and S6042 in the south. The steepest ($n = 4$) stations are the cities two major bridges, Älvsborgsbrons neighbouring station S6027 and S6025 which, is located outside the Department of Earth Science at the University of Gothenburg.

4.2.3 Cyclists' seasonal distribution

The distribution of cyclists between stations, (Fig. 11), reveal the usage of every station in this study during the considered time series. The height of a column in the histograms refers to how large a share of the total cycle volume in the city that station had during a given season. Station S6006 at Vasagatan had the largest usage by cyclists and other frequently used stations are found near this station. Note also that S6006 and station S6008 east of Vasagatan also appears to capture a larger share of cyclists during winter seasons. Even though the summer season was shortened to only encompass the industrial vacation period, the results show that an inverse pattern can be discerned where stations farther away from the city centre capture a larger fraction of the total cycle volume in the summer.

Figure 10 considers the seasonal distribution within every station. Overall, a clear pattern emerges regardless of where stations are located. On average, the volume of winter cyclist are around 10 percent of the total volume per station. Furthermore, a majority of all stations had slightly more cyclist in spring and fall, albeit the industrial summer volume is quite similar in relation to these seasons. However, station S6042 clearly deviates from this pattern as the station have a pronounced bump during its industrial summer. Station S6935 at the northern bridge, as well as S6051 just south of it also deviates slightly since more cyclists are concentrated to spring at these locations.

Indeed, if the seasons were kept at the conventional length of three months each, it is likely that the minor difference between summer and its adjacent seasons would dissipate. However, the three southwestern stations would still retain a larger volume during summer since figure 6 show that the first modal peak starts to decrease in June and the second modal peak occurs sometime near the end of August. Nonetheless, the relative length of the seasons used in this study were necessary to obtain correlations that reflect both relatively homogenous periods of cycle volumes as well as climatological conditions.

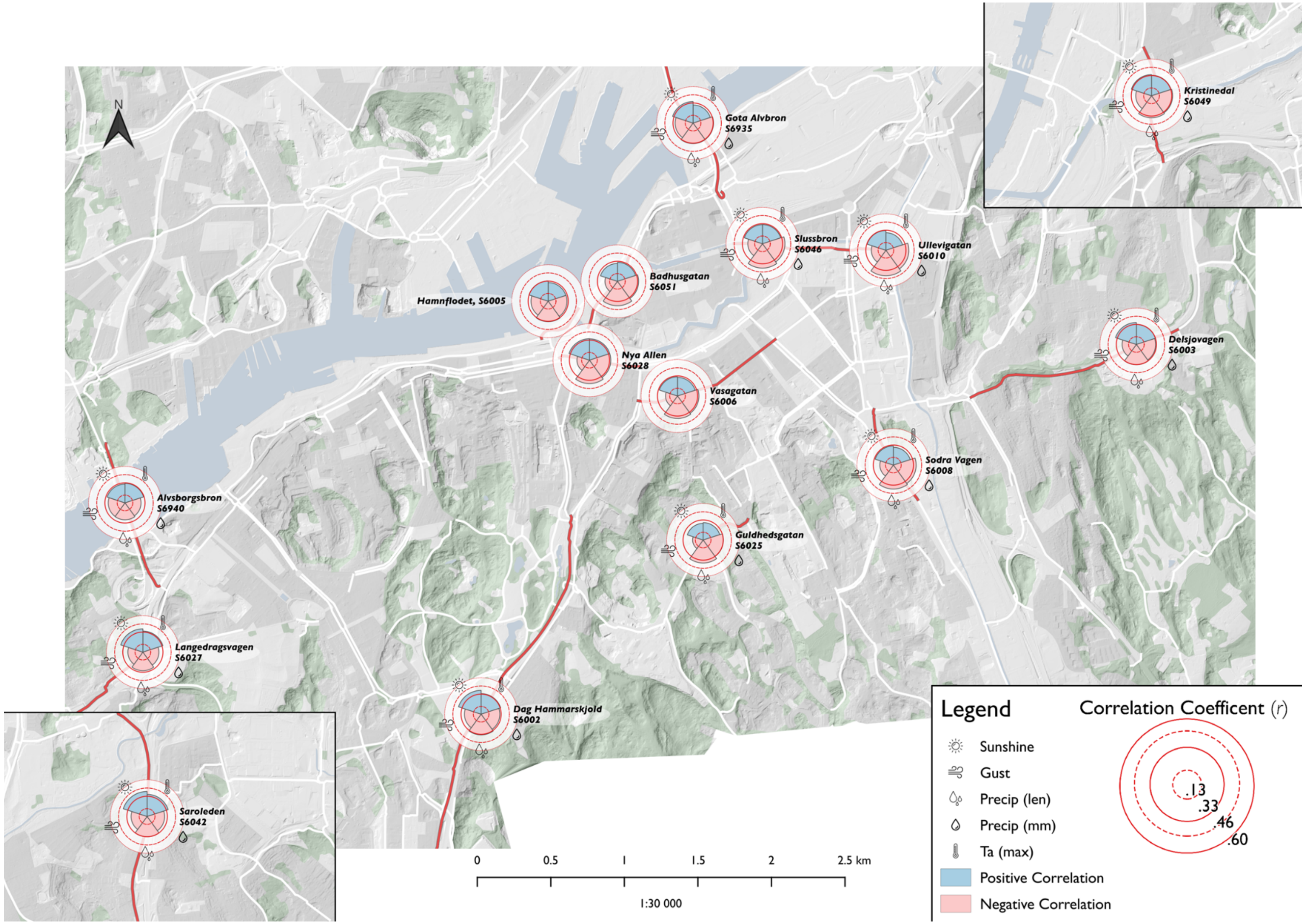

Figure 8. Total weather effects per cycle-measurement station. The coefficients encompass the whole time-series. The ring legend reflects a small correlation at $|.13|$ *a moderate correlation at* $|.33|$*and a large correlation at* $|.46|$*. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.*

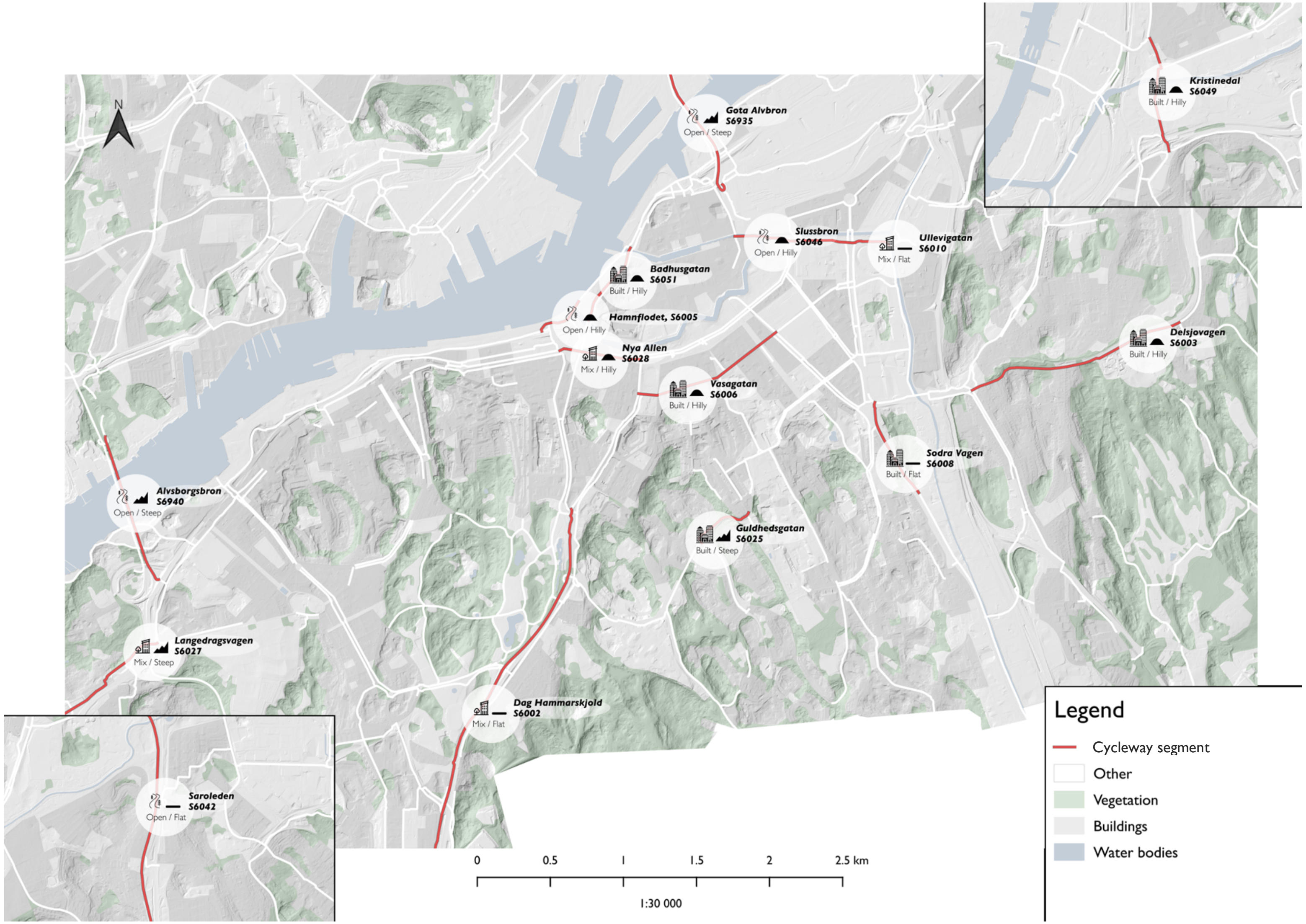

Figure 9. Dominant feature characteristics per station, obtained through the modified Local Climate Zone system (see section 3.4). Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

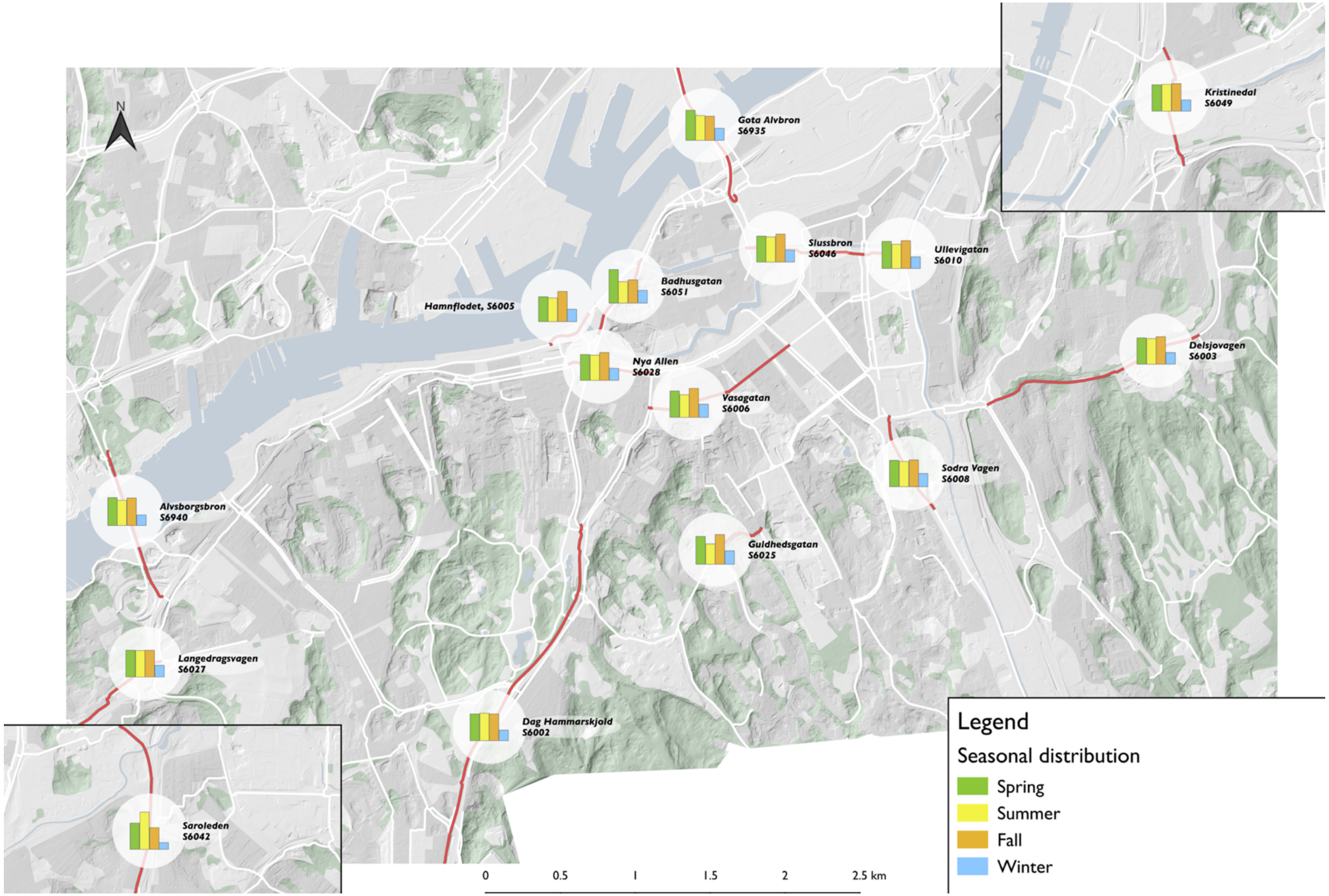

Figure 10. Seasonal distribution of cyclists within every station. Height of a histogram column represents the seasonal share. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

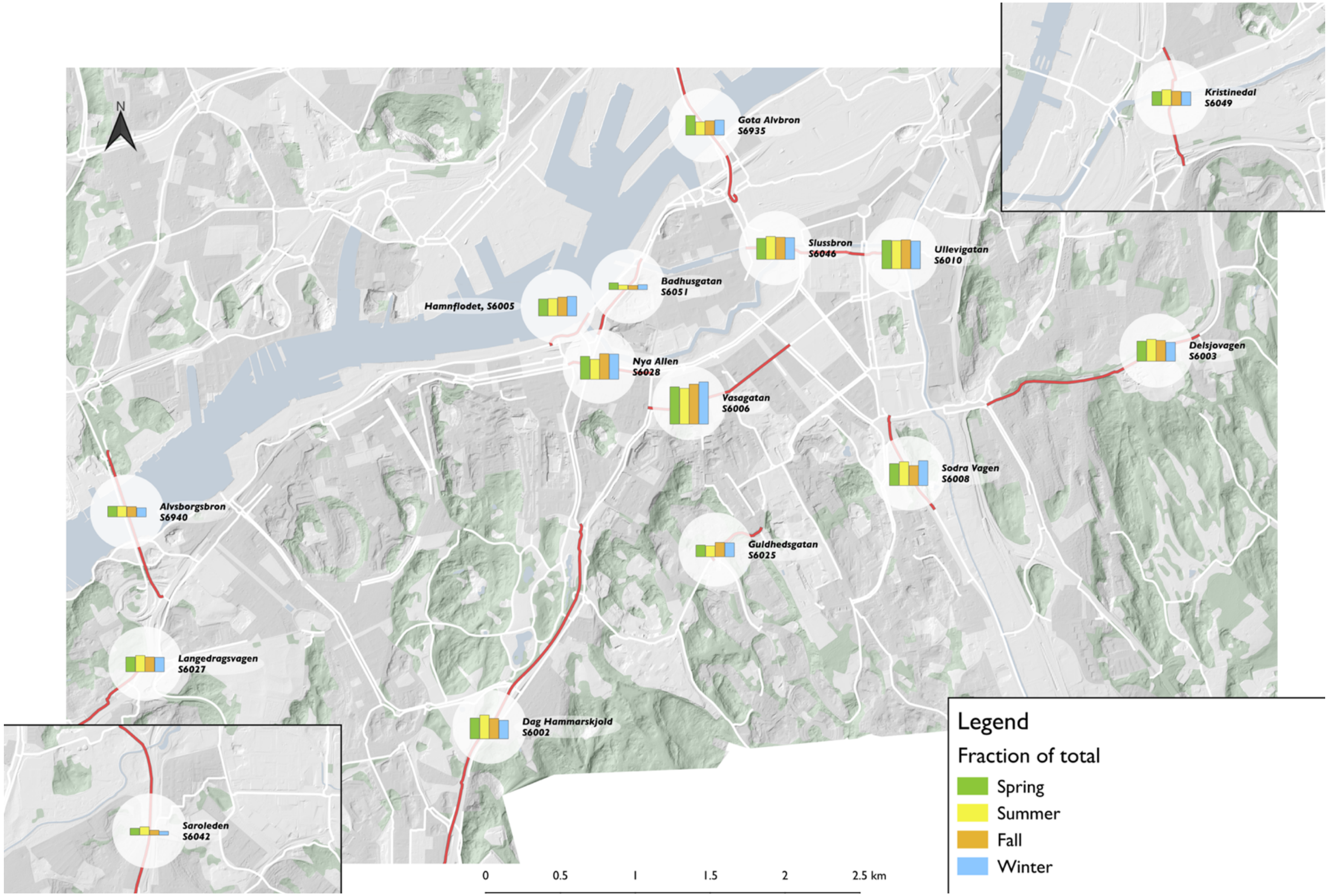

Figure 11. Distribution of the total cycle volume between stations. Height of a histogram column represents the seasonal share. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

4.3 Part II: Seasonal Coefficients in detail

In this section, the mapped coefficients are presented per weather index over the seasons. Focus of these results are on stations with spatial variance in contrast to the global *r* averages and other levels of aggregation, e.g. dominant Local Climate Zone features or slope characteristic (appendix: table 7).

4.3.1 Seasonality map: Temperature

The global average *r* of temperature had the least impact on cycling in winter (*r* = +.11) and the greatest impact on cycling in spring (+.45), which is indicative of a large effect (table 4). In fall, a stable moderate correlation is obtained (+.37), whilst the global *r* for the industrial summer average had a small correlational strength. However, the range of coefficients are about ~.2 for summer, while the range for other seasons average ~.12 between stations. This is useful guidance for the exploration heterogeneity in the mapped coefficients.

A couple of stations revealed correlations well above the global *r* during the industrial summer (Fig. 12). The *r* values for stations S6027, S6028 and S6042 had correlations that hovers close to the median ring, which suggests a moderate (.33) yet positive association. Two are western stations en-route to the ocean while S6028 connects Järntorget with downtown. Moreover, station S6002, located near the big park Slottskogen with its path running north into the city centre and south towards S6042 had a *r* of +.24, just shy of the other protruding stations during industrial summer. Regarding temperature and the other seasons, no obvious patterns of spatial heterogeneity were identified. For example, during fall, variation between stations is hard to find since most coefficients are evenly spread within a narrow range. Apart from the few exceptions mentioned earlier, the impact of temperature in winter and industrial summer barely reach the threshold for a small (±.13) correlation strength.

4.3.2 Seasonality map: Sunshine

Sunshine had some of the strongest correlation coefficients (table 4). Overall, spring and industrial summer experienced the most benefit from sunshine with most values of *r* approximating a large (*r* = +.46) effect from sunshine. The greatest *r* value in this study was obtained at S6027 (+.60) during the industrial summer. In stark contrast, the global *r* for winter was +.04 which yield no effect at all. Only cyclists at Götaälvbron (S6935) appeared to experience a small (+.15) positive effect from sunshine during winter (Fig. 13). Concerning the range of *r* for all other seasons, spring and fall had range values of ~.14 and ~.10 respectively, indicating a small presence of spatial heterogeneity (table 4). Industrial summer had however a coefficient range of ~.34. Exploring the mapped coefficients confirms demarked patterns of spatial heterogeneity in this season (Fig. 13). These spatial variations are in summer quite similar to those of temperature, apart from those west, southwestern stations previously mentioned, S6003 in the eastern city also stands out. This station is the closest to the vast natural environment at the city's outskirts, a popular place with trails for exercise and lakes for swimming and barbecue.

In fall, except for the major bridges (average of +.27), there is a weak signal that all peripheral stations have a slightly more moderate impact from sunshine. For example, stations S6006 and S6025 in the dense city centre had a substantial yet small effect at +.25, whilst most stations further away from downtown on average approximate a moderate (+.33) benefit. In fact, most peripheral stations with a slightly higher impact from sunshine during fall are either classified as Open or Mixed.

4.3.3 Seasonality map: Precipitation (mm)

Apart from stations S6027 and S6940, the negative coefficients for amount of precipitation appeared to be quite alike when stations are compared per season (Fig. 14). Most stations approximate a moderate (*r* = -

.33) to large (-.46) impact from the amount of precipitation over a year. The most negative coefficient was obtained at S6028 with a strength of -.54 which corresponds to a large effect. According to table 4, the global *r* showed that fall (-.29) is the season with least impact from precipitation, closely followed by winter (-.31). In spring, a substantial moderate correlation was found at global *r* = -.37 and industrial summer approximated a large (-.45) negative effect from the amount of precipitation.

The range of coefficients were wide enough across all seasons to indicate some spatial heterogeneity (table 4). However, obvious spatial deviance was only observed at station S6027 and S6940 whose correlation was substantial yet small at about -.18 during fall (Fig. 14). The former also had a higher initial reduction of cyclists according the equivalent *r* (table 4). Upon closer inspection, the stations revealed a consistent pattern in relation to their dominant feature class. If all stations with a Built classification are aggregated, regardless of slope character, they had a correlational strength that was marginally higher in comparison with other dominant classes (appendix: table 7).

4.3.4 Seasonality map: Precipitation (length)

For the most part, the duration of precipitation revealed a similar pattern as that of amount, but with one important difference, i.e. the correlation coefficients are more pronounced. According to the global *r,* only the industrial summer was exempt from this pattern and hence was more affected by the amount rather than the duration (table 4). Some noteworthy differences are that the steepest bridge (S6935) only had a weak (*r* = -.16) impact of rain duration during industrial summer (Fig. 15 compared to the approximately large impact of the global *r* (table 4). Whereas global *r* obtained a moderate impact during winter, station S6051 near the river had a substantial large correlation of -.52 in winter.

The previously observed pattern for dominant LCZ features was present, but for duration of precipitation another interesting finding was made. If instead the coefficients are aggregated based on centre versus periphery, an average increase in negative *r* values are revealed for the city centre. During the industrial summer and fall, the negative increase is about ~.09. Furthermore, during the same seasons, aggregation on topography revealed, that Flat and Hilly stations are also more affected by the duration of precipitation (appendix: table 7). With regards to spatial heterogeneity, these results suggest that packing density of urban facilities are important to the decline of cyclists during periods of lengthy precipitation events in the city centre.

4.3.5 Seasonality map: Gusty winds

The wind speed results had, in comparison to the other weather parameters, less powerful coefficients. The strongest association between cycling frequencies and gustiness were found for the industrial summer and fall, with a global *r* of -.29 and -.31 respectively (table 4). Spring had a global average of -.26 whilst winter had the weakest global impact at -.13 in strength. Even though gustiness had less powerful coefficients in relation to other weather parameters, gust is the variable that unveil the most distinct pattern of spatial heterogeneity across the seasons (Fig. 16).

Stations of the Built class are compared to Open class stations clearly less affected by the gust speed. The Open stations S6005, S6935 and S6940 near the river all have coefficients that approximate a moderate (*r* = -.33) impact from gusts. Furthermore, open and mixed inland stations located farther away from downtown also have values of *r* that almost reach a moderate (-.33) impact in spring and summer (Fig. 16). Although the impact is more pronounced for these peripheral stations, those with a Built classification like S6003 and S6049 in the east had a slightly weaker association. Another interesting finding was that gusty winds during fall had approximately constant correlations across all stations, which indicate that strong winds is a city-wide issue in fall.

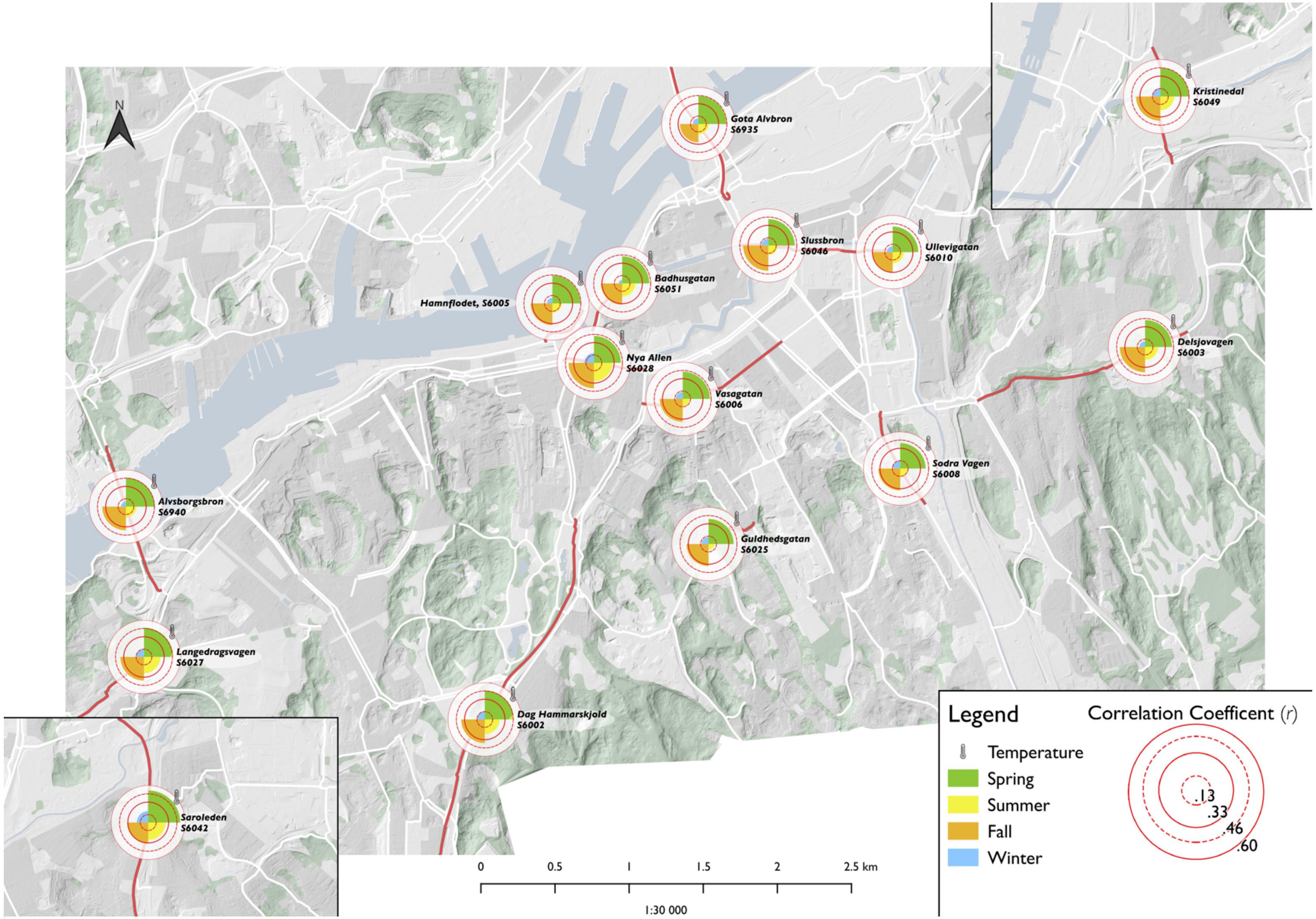

Figure 12. Seasonal effects of temperature. All coefficients are positive. Correlations obtained with the sub-sampled time-series data (section 3.3). The ring legend reflects a small correlation at |.13| a moderate correlation at |.33|and a large correlation at |.46|. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

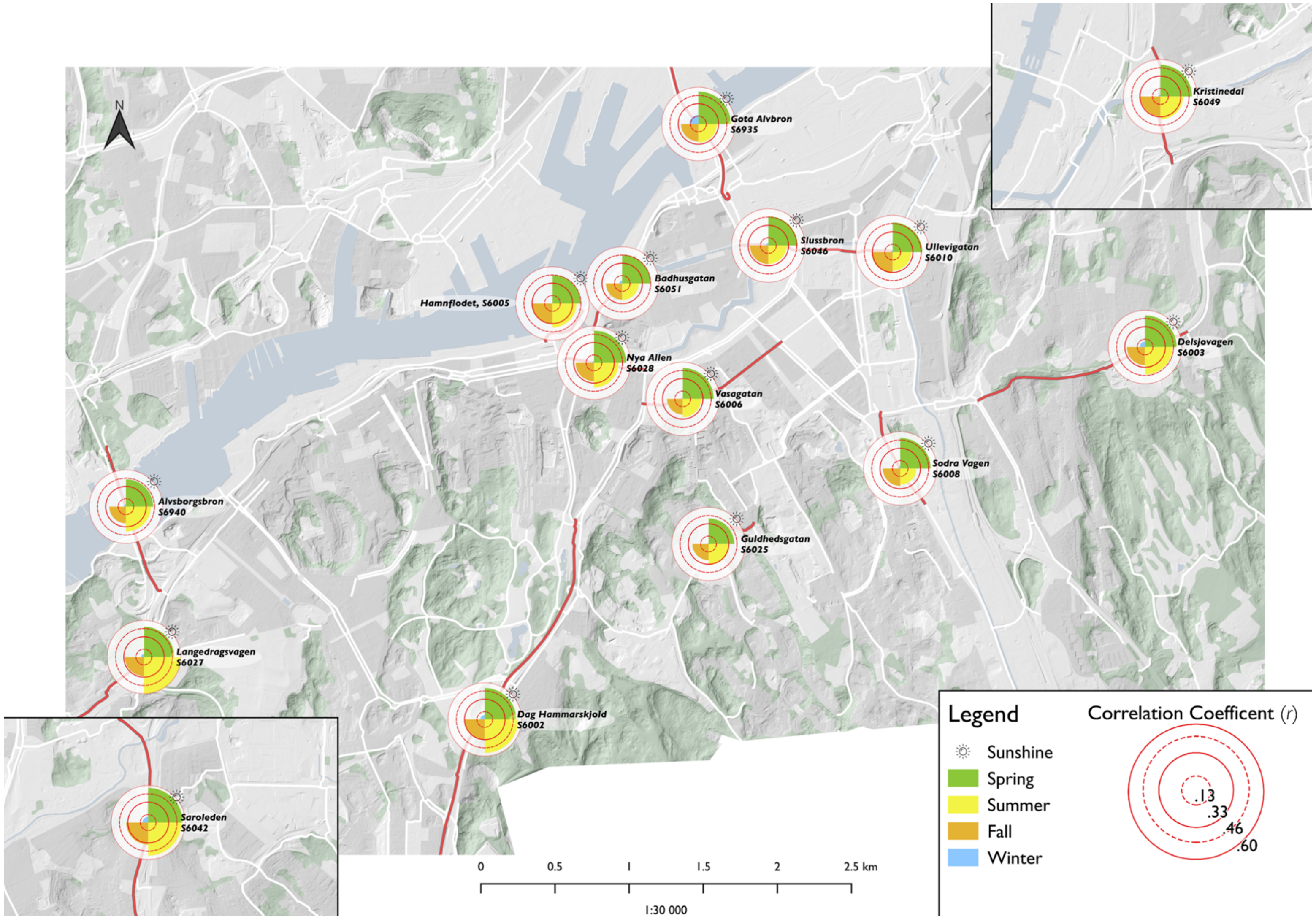

Figure 13. Seasonal effects of sunshine fraction of daylight. All coefficients are positive. Correlations obtained with the sub-sampled time-series data (section 3.3). The ring legend reflects a small correlation at |.13| a moderate correlation at |.33| and a large correlation at |.46|. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

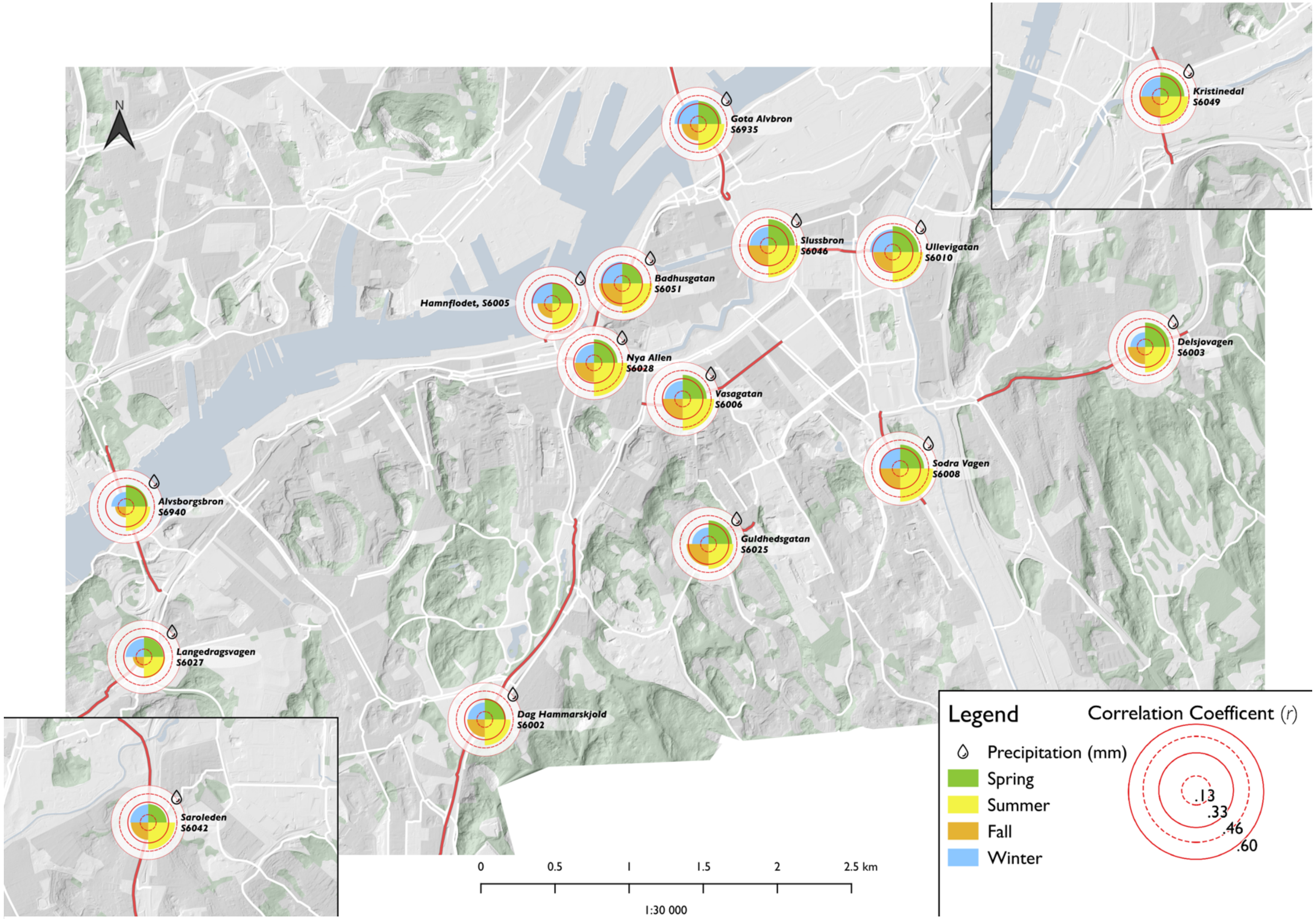

Figure 14. Seasonal effects amount of precipitation. All coefficients are negative. Correlations obtained with the sub-sampled time-series data (section 3.3). The ring legend reflects a small correlation at |.13| a moderate correlation at |.33| and a large correlation at |.46|. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

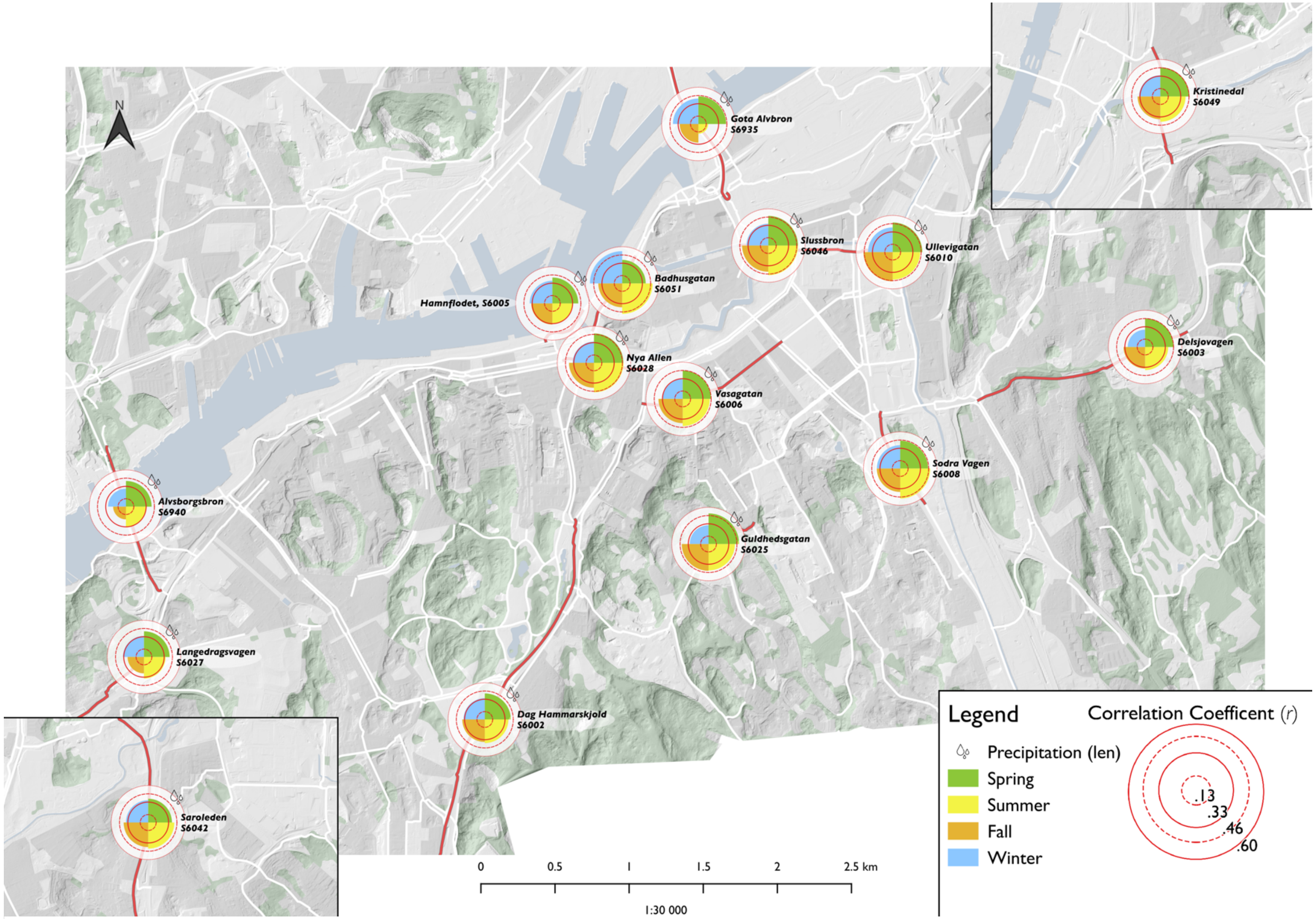

Figure 15. Seasonal effects duration of precipitation. All coefficients are negative. Correlations obtained with the sub-sampled time-series data (section 3.3). The ring legend reflects a small correlation at |.13| a moderate correlation at |.33| and a large correlation at |.46|. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

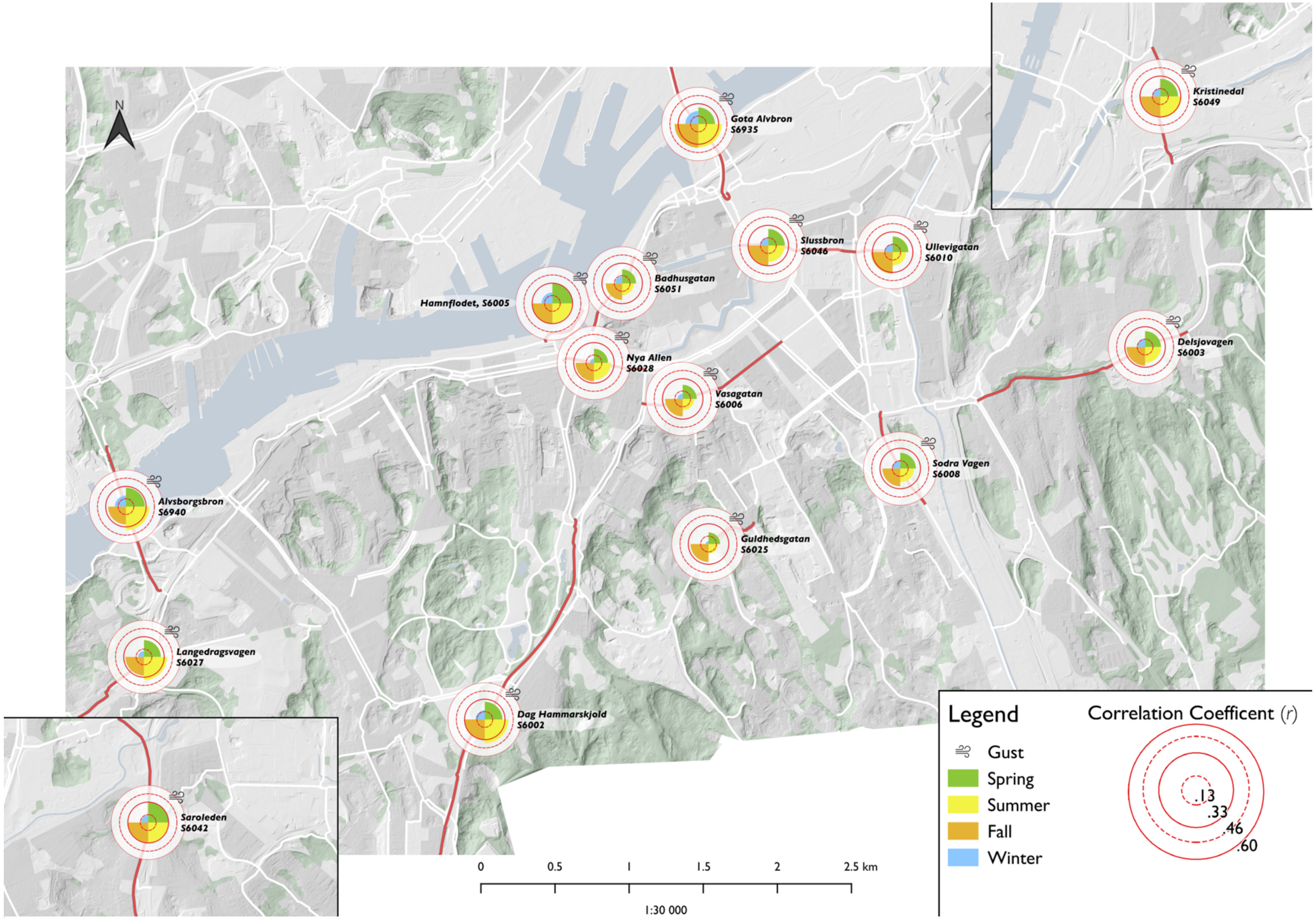

Figure 16. Seasonal effects average gust winds. All coefficients are negative. Correlations obtained with the sub-sampled time-series data (section 3.3). The ring legend reflects a small correlation at |.13| a moderate correlation at |.33| and a large correlation at |.46|. Data source: Lantmäteriet (GSD-Terrängkartan, 2014), Urban Transport Administration (Cykelmätstationer, 2017; Cykelbana, n.d.), Urban Climate Group, University of Gothenburg (DEM). Projection: SWEREF 99 12 00.

Table 5

Heterogeneity matrix: weather sensitivity in different urban environments. The original coefficient slope is superimposed over the z-scored coefficients. Only statistically significant correlations at p=0.05 and their critical slope value are shown in the matrix. For every row, more sensitivity is emphasised in red whenever a class is $+1\sigma$ *from the row mean, while less sensitivity is emphasised with blue* (-1σ)*. Number of stations per class is given in parenthesis next to the class.*

	Weather	Open/Flat (1)	Open/Hilly (2)	Open/Steep (2)	Mix/Flat (2)	Mix/Hilly (1)	Mix/Steep (1)	Built/Flat (1)	Built/Hilly (4)	Built/Steep (1)
Total	Ta_{max}	0.36	0.32	0.32	0.32	0.35	0.34	0.29	0.33	0.29
Total	$Sunshine_{/daylight}$	0.41	0.32	0.34	0.37	0.35	0.38	0.31	0.34	0.27
Total	$Precip_{mm}$	-0.28	-0.34	-0.30	-0.35	-0.35	-0.26	-0.37	-0.35	-0.33
Total	$Precip_{len}$	-0.33	-0.37	-0.31	-0.39	-0.38	-0.30	-0.39	-0.37	-0.38
Total	$Gust_{mean}$	-0.26	-0.27	-0.29	-0.26	-0.21	-0.25	-0.22	-0.23	-0.17
Winter	Ta_{max}									
Winter	$Sunshine_{/daylight}$									
Winter	$Precip_{mm}$	-0.29	-0.33	-0.32	-0.33	-0.30	-0.30	-0.33	-0.31	
Winter	$Precip_{len}$	-0.36	-0.37	-0.37	-0.38	-0.34	-0.34	-0.38	-0.37	-0.31
Winter	$Gust_{mean}$									
Spring	Ta_{max}	0.52	0.45	0.47	0.45	0.44	0.47	0.41	0.46	0.41
Spring	$Sunshine_{/daylight}$	0.56	0.46	0.49	0.50	0.52	0.49	0.50	0.52	0.42
Spring	$Precip_{mm}$	-0.30	-0.39	-0.37	-0.39	-0.38	-0.32	-0.39	-0.38	-0.38
Spring	$Precip_{len}$	-0.38	-0.46	-0.44	-0.46	-0.48	-0.42	-0.45	-0.45	-0.50
Spring	$Gust_{mean}$	-0.32	-0.30	-0.29	-0.27	-0.23	-0.27	-0.25	-0.26	
Industry	Ta_{max}	0.28		0.21	0.23	0.30	0.27		0.21	
Industry	$Sunshine_{/daylight}$	0.53	0.37	0.39	0.46	0.40	0.60	0.26	0.37	0.34
Industry	$Precip_{mm}$		-0.48	-0.41	-0.48	-0.54	-0.34	-0.54	-0.49	-0.40
Industry	$Precip_{len}$		-0.42	-0.30	-0.43	-0.48	-0.35	-0.49	-0.44	-0.43
Industry	$Gust_{mean}$	-0.33	-0.30	-0.40	-0.33		-0.38	-0.22	-0.26	
Fall	Ta_{max}	0.34	0.40	0.35	0.37	0.41	0.38	0.36	0.40	0.36
Fall	$Sunshine_{/daylight}$	0.35	0.32	0.31	0.35	0.30	0.31	0.28	0.31	0.26
Fall	$Precip_{mm}$	-0.28	-0.29		-0.32	-0.31		-0.34	-0.31	-0.36
Fall	$Precip_{len}$	-0.40	-0.39		-0.44	-0.40		-0.38	-0.38	-0.43
Fall	$Gust_{mean}$	-0.32	-0.35	-0.35	-0.35	-0.30	-0.30	-0.29	-0.31	-0.29

4.4. Part III: Matrix of Spatial Heterogeneity

The purpose of the heterogeneity matrix (table 5) is to support the explorative analysis and provide an overview of weather sensitivity, dependent on similarities of the urban environment. The results are presented for the aggregated coefficients according to their dominant feature class. The disaggregated stations, sorted by dominant features are provided in table 8 of the appendix.

4.4.1 Class Sensitivity Analysis

The matrix in table 5 contains the obtained r values that are statistically significant at $p=0.05$ and the critical r value for coefficients, according to their sample size. These r values are superimposed over the standardized coefficients with sign correction, i.e. the impact is always less as $|r| \rightarrow 0$. For example; the first row of total effects had an average r of +.32, meanwhile, class Open/Flat had a standardized z value of 1.39 at r = +.36 and Built/Steep had a z value of -1.55 with r = +.29. Both classes are $\pm 1\sigma$ from the row mean. But because Open/Flat is farther away from $|r| = 0$, and its level of deviation was beyond 1 sigma from row mean, this class is considered to show evidence of more sensitivity to weather. In contrast, Built/Steep showed less sensitivity to weather in this example. This is summarized by the following equation,

$$sensitivity = sign(r)\frac{\sum(r_i - \mu_{r,row})}{\sum(\sigma_{r,row})} \tag{9}$$

where spatial heterogeneity is determined by the level of *sensitivity* a class reveal in its association to the weather indices. More sensitive classes are highlighted in the matrix by a red color-coding, whilst less sensitive classes are coded in blue.

Note however that the sensitivity is weighted by row, therefore the matrix will always detect at least one sensitivity occurrence per weather index. But this is not an issue since we seek to evaluate whether spatial heterogeneity can be associated to the urban environment at all. More conservative approaches to the identification of weather sensitivity is discussed in section 5.4.

4.4.2 Significance of the Coefficients

Missing values in table 5 corresponds to all non-significant correlations that were excluded from the sensitivity analysis. For the total effect, all class coefficients are statistically significant across every variable. Regarding the seasons, temperature is only significant at $p=0.05$ across all dominant feature classes in spring and fall. Only six classes had significant correlation in summer. Sunshine did not have any statistical significance during winter. But for all other seasons, statistical significance was found across every class. Just like temperature and sunshine, gustiness had no statistically significant correlations in winter. Only in fall, statistical significance was obtained across all classes for the wind variable, whilst Built/Steep never met significance at $p=0.05$ in spring or industrial summer. Both precipitation variables were the only variables to obtain statistical significance during winter, whereof only Built/Steep didn't obtained significance. Not due to the alpha value (p=.013), but because the coefficient slope didn't exceed the critical r value. These results are corroborating with both the individually mapped coefficients and the global r.

4.4.3 Main findings of Weather Sensitivity

For temperature and sunshine, most sensitivity was found in the Open and Mixed classes. The effect was stronger in spring and the industrial summer. Overall, the Built class category were found to be the least sensitive to both temperature and sunshine. The most contrasting sensitivity were identified between Open and Built classes during spring, whereof flat terrain and openness appeared to favour much more sensitive. Steep terrain in a built environment revealed the opposite effect. An interesting seasonal finding was that Open/Flat appeared to become increasingly less sensitive to temperature as the seasons changed through spring, industrial summer to fall. Moreover, during fall season, all classes characterized by a hilly terrain had experienced more impact from an elevated temperature. Recall from figure 9 that all Hilly classes are located in the city centre and towards to eastern periphery.

Moving to the two precipitation indices, the direction of sensitivity is reversed. Classes characterised by more packing density of buildings were more sensitive to precipitation events. However, the Mix/Steep class differ from the rest of the dense classes as it consistently showed less sensitivity to precipitation across all seasons. Open classes were never more sensitive in their association to either precipitation index. Moreover, a flat terrain was especially less sensitive to both the amount and the duration of a precipitation event.

Findings for gust showed an average decrease in sensitivity as roughness increased: Open ($\sim|.27|$), Mix ($\sim|.24|$) Built ($\sim|.21|$). Yet again, weather sensitivity was concentrated to one dominant feature since all association to more wind speed sensitivity were found in the Open classes, out of which the steeper class obtained the most sensitivity. Most negative impact was found at Open/Steep, which corresponds to Gothenburg's two major bridges.

5. Discussion

5.1 What was done in this study?

In this study, five weather indices were correlated by 15 cycle-measurement stations with the Pearson correlation coefficient. These coefficients were mapped and quantitatively analysed with a proposed framework to reveal patterns of spatial heterogeneity at a local scale. This was done by analysing linear association between cycling and weather on the full time-series as well as the sub-sampled seasonal data. The resulting coefficients were mapped according to season and explored to identify local effects of the weather indices. Coefficients were also aggregated according to urban characteristics to analyse how weather sensitivity differs across the defined classes. The study is, to the author's knowledge, unique and therefore lacks precedent.

The discussion is structured to follow a similar structure as that of the results. In the first part, the global effect is discussed alongside the result of the explorative GIS analysis. Then in the second part, the sensitivity analysis is considered along with its limitation. Finally, the broader implications for future research and society is discussed.

5.2 Part I: Main findings in relation to previous research

The first part of the results were conducted at the whole dataset and presented the global stations averages, followed by an exploration of mapped station coefficients. This part of the analysis is most comparable to previous research of cycling and weather.

5.2.1 Effects of Temperature

Regarding temperature, this study standardized the variable based on ten years of data and thus, the original temperature in degrees Celsius was lost. Instead, the temperature variable represented each day as colder than usual, or warmer than usual on a continuous scale. This approach has been utilized before to study mobility and weather (Liu et al., 2014, 2015). Most studies of cycling and weather use logit- or logistic models on grouped temperature data and therefore can identify parabolic relationships (Gebhart & Noland, 2014; Liu et al., 2017; Meng et al., 2016; Miranda-Moreno & Nosal, 2011). However, this study used linear correlation (Flynn et al., 2012; Nankervis, 1999). Therefore, we must consider the global *r* per season to compare findings. By plotting the coefficient slopes per season against the original mean temperature of each season (Fig. 17), it becomes clear that a parabolic relationship likely exists between unstandardized temperature and cycle volumes in Gothenburg as well. However, this study cannot make any conclusive inference in this regard.

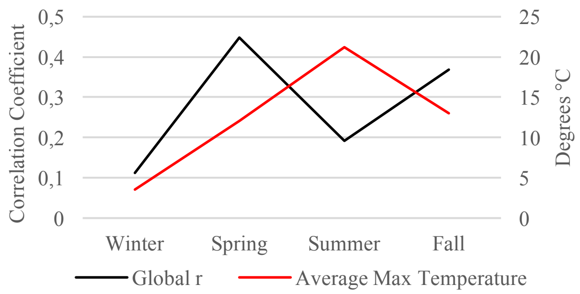

Figure 17. Post-hoc seasonal plot of the aggregate station average (global r) plotted against the untreated maximum temperature of the considered time-series.

It is nonetheless possible to suggest that unusual temperatures have a direct effect on cyclists i.e. cyclists are more sensitive to increases in temperature than decreases. Unusually high temperatures revealed a small association to cyclists during summer which suggests that a turning point have been reached and higher temperatures start to be disincentive to cycling. However, temperature is only statistically significant in certain environments of the city, indicating that the turning point may vary across the city during summer (table 5). In winter, the association is insignificant and the coefficient slope of the global *r* barely approximate a small impact (table 4 & 5). With regards to winter, these results corroborate with Liu, Susilo, & Karlström (2015) who found that cyclists in southern and central Sweden are less aware of differences in temperature. It is therefore likely that frequent winter cyclists in Gothenburg feel comfortable cycling, regardless if the winter is unusually warm or cold. This reasoning is also in line with the findings of Amiri & Sadeghpour (2015). Moreover, the opposite is likely occurring during summer. Judging from the correlation coefficient of the global r, it appears that higher than usual temperatures had much less impact on cycling in this season. The industrial summer was also the only season to reveal a pattern of spatial heterogeneity towards the coastline (Fig. 8), which implies that cycling is more resistant to unusual heat in these areas during summer.

Although the total effect of temperature didn't produce any obvious patterns (Fig. 8), it produced some variation during the industrial summer (Fig. 12). Stations at Långedragsvägen (S6027), Nya Allén (S6028) and Säröleden (S6042), almost obtained a moderate correlation, while Dag Hammarskjöld (S6002) had slightly association to temperature. Other stations had much lower coefficients during the industrial summer season. Of the more affected stations, all but Nya Allén (S6028) had their largest fraction of Gothenburg's total cycle volume in the summer (Fig. 11). Moreover, the internal seasonal distribution of cyclist at stations S6002 and S6042 show that they are important industrial vacation stations (Fig. 10). Therefore, it is likely that all these deviant stations are important recreational locations in the industrial summer. For example: riders at Säröleden (S6042) pass in the south a couple of bathing sites, a camping area and a marina. Långedragsvägen (S6027) are en-route from the central city towards the popular bathing site Saltholmen, where also a relatively large marina is located. It is thus likely that these stations maintain a substantial influence from an unusually high temperature, even during summer, since cyclist know that they will be able to cool down as they reach the coastline. The central city cycleway at station Nya Allén (S6028) is boarded with trees that block out the sun, moreover it connects two popular downtown areas with a high concentration of shopping, restaurants and pubs. In this area, it is possible that more people chose to cycle to the city for a drink, even on weekdays during the industrial summer, whenever the temperature is higher than usual. Dozza (2017) found that more cyclist get into accidents late at night in Gothenburg and suggests that intoxication could be the reason behind it. Moreover, the Dag Hammarskjöld station (S6002) were also found to have a greater influence from temperature in summer. This station is located near the city's biggest park Slottskogen, where many people go for a variety of recreational purposes during good weather conditions. However, the stations also lead to Järntorget in the north and could thus also be affected by night-time activates in the city.

5.2.2 Effects of Sunshine

The sunshine variable was constructed to capture how long the sun was shining as a fraction of available daylight. This was done because a full day of sunshine in early spring may only equate to half a day of sunshine around summer solstice. In contrast to previous findings, the results from the global *r* in this study found that sunshine had the most positive impact on cyclists in Gothenburg. Previous studies in a European setting found sunshine to be the second most important variable associated to cycling (Thomas et al., 2013) or to have a small yet positive influence (Wadud, 2014). However, in Auckland, NZ, sunshine was found to have the most positive impact (Tin Tin et al., 2012).

It was mentioned above that both stations S6002, S6027, S6028 and S6042 can be regarded as mostly recreational during the industrial summer. In that regard, these results corroborate with the findings made by Thomas et al. (2013) who showed that recreational paths had more positive influence from sunshine. Moreover, Delsjövägen (S6003), a Built/Hilly station in eastern Gothenburg had a pronounced moderate total correlation to sunshine (Fig. 8). Although its classification is Built, the station had a land cover of vegetation that is on par with the Open dominant feature classes. Referral to table 3 also reveal that S6003 only obtained LCZ 6, which is described as open low-rise by Stewart & Oke (2012). A possible explanation to the high influence of sunshine at S6003 could be that the built environment, with its high fraction of vegetation, is perceived by cyclists as aesthetically pleasing during sunshine (Böcker et al., 2016; Böcker & Thorsson, 2014). This reasoning can possibly also be extended to other areas farther from the city centre. Henceforth, in general, more people could be encouraged to cycle during sunshine in greener areas. In fact, a study found that the share of cyclist in greener areas are generally higher compared to other modes of transportation (Böcker et al., 2015).

Cartographic exploration of the seasonal coefficients also showed that sunshine had the most powerful impact on cycling at stations farther from the city centre (Fig. 13), and of the Open dominant feature class (Fig. 9). This spatial heterogeneity indicates that cyclist may prefer to ride in areas where they are more exposed to sunshine, rather than in dense urban environments where sunlight could be blocked by buildings. Furthermore, since the spatial heterogeneity of sunshine closely resembles those patterns identified for temperature, it is possible that the central city is experienced or perceived as colder on sunny days if the solar rays doesn’t reach the rider (e.g. Böcker et al., 2016; Ettema et al., 2017). Stronger coefficients outside the city centre could also be related to the fact that sunshine is a good indicator of clear and calm weather and hence suggest that many cyclists could simply be opportunists in these areas.

5.2.3 Effects of Precipitation

Because the amount, as well as the duration of precipitation are quite alike, they will be discussed together. With few exceptions, many studies found precipitation to be the strongest deterrent of cycling (Heinen et al., 2010; Liu et al., 2015, 2017; Nankervis, 1999; Phung & Rose, 2007). This study can confirm those results for the city of Gothenburg, whereof the duration of precipitation appears to have a stronger negative association to cycling than the amount on a given day. Moreover, both indices deterred on average more cyclists than the binary occurrence of precipitation (table 4). There are however a few noteworthy discrepancies. Flynn et al. (2012) found the likelihood to cycle on a morning with dry weather conditions to be twice as high. Even though this study did not conduct the exact same test, the equivalent *r* for the rain test, found that the global station average only was -.28. A simple post-hoc check showed that the *r* equivalent had to be at least -.43 or more to reduce the number of cyclist by half on a wet day. Only the station at Säröleden (S6042) came close to this value (-.37) in the binary rain test (table 4). Recall that the precipitation variables were processed to only consider cycling days when a rain event occurred. Thus, the motivation for the binary rain test were to enable a comparison of dry and wet days.

Furthermore, since this study found duration of precipitation to have more negative effect than the amount. A possible explanation could be the lagged effect on cyclists, observed by both Nosal & Miranda-Moreno (2014) and Wadud (2014). The former found that rain in the previous hour had the same negative effect as 1-2mm of precipitation. On the other hand, Nosal & Miranda-Morena (2014) found the negative effect of rain to remain up to three hours after the event occurred. Hence, it is likely that, the longer it rains, potential cycle trips are either shifted to other transport modes, postponed or simply cancelled all together (Böcker et al., 2013a; Liu et al., 2015). However, both Nosal & Miranda-Moreno and Wadud conducted their studies on hourly data, whereof this study utilizes daily data. Therefore, the lagged effect of precipitation is likely to have a greater impact in their studies due to their design. Nonetheless, a plausible explanation to why the length of precipitation still had a more negative association to cycling in this study is that drizzling rains can spread over a whole day, and will therefore affect cyclists for longer durations of time. Meanwhile, heavy precipitation events can occur during a brief period, whereas the remainder of the day can favourable for cycling. That said, most of the difference is likely negligible due to the multicollinearity between the daily precipitation variables.

Compared to the total effect of precipitation, the patterns of spatial heterogeneity were easier to decipher from the exploration of the seasonal maps, since the range of coefficient were much greater per season than the total effect, apart from spring (Fig. 8, 14 & 15). The two bridges showed clear patterns of spatial effects. For example, Götaälvbron (S6935) had a small association to the precipitation length during the industrial summer, whilst the average station had a substantial moderate correlation (Fig. 15). The fraction of the total cycle volumes is indeed lower at Götaälvbron during the summer season (Fig. 11), but it doesn't explain why this station had a much lesser impact. The other Open/Steep station: Älvsborgsbron (S6940), which also is the steepest bridge in Gothenburg, had a consistent usage by cyclist across all seasons (Fig. 11). And since Älvsborgsbron often is the least affected station by precipitation, especially in fall (Fig. 14 & 15), the cyclists who chose to ride over the bridge could be regarded as experienced and well prepared to combat inclement weather conditions as well as the steep incline. This also suggests that both bridge stations could primarily be utilized by utilitarian all-seasons cyclists, according to Shirgaokar & Nurul Habib (2018) this category of cyclists are more likely to cycle in all kinds of weather.

Another spatial pattern surfaced during the explorative GIS analysis. The marginal effect of precipitation on cyclist in the city centre was slightly higher, and thus indicate that less cycling is conducted within the dense urban centre when it rains. This pattern could be related to proximity with public transportation (Gatersleben & Appleton, 2007). If a potential cyclist has public transportation as a readily available option near their residence, it could be possible that they will take the tram or a bus instead of their bicycle, whenever a precipitation event occurs. However, a study found that short trips in the city remains during rain (Corcoran et al., 2014). Even though this study isn't equipped to support any finding that relates to trip distance, the immediate reduction of cyclists is slightly less at Built classes on wet days, according to the equivalent *r* (appendix: table 7). Meanwhile, cyclists who live farther away may not have the same accessibility to public transportation and may thus opt to adjust their clothing behaviour by a larger extent (Böcker et al., 2013a). Furthermore, since the effect of precipitation during the industrial summer is approximately moderate at most peripheral stations, while the correlation more often is large in the city centre, it could be possible that cyclist don't mind the rain as much if they ride in areas characterized by more openness or greenery.

5.2.4 Effects of Gusty winds

The literature review in this study unravelled a contentious relationship between cycling and wind speeds in previous research. The global *r* of gustiness in this study are aligned with the findings of both Gebhart & Noland, (2014) and Tin Tin, Woodward, Robinson, & Ameratunga (2012). They found a negative association between cycling and wind, but the marginal effect was lower than other weather parameters, whereof the latter found a highly significant impact of wind speeds. Tin Tin et al., considered a cycle-measurement station located at the quay, directly exposed to the ocean beyond the shore. Compared to this study, four stations are located near Göta älv, whereas all but one station had a total impact that approximated a moderate correlation from gust during exploration (S6005, S6935 & S6940 in Fig. 8). Also, these riverside stations were also classified by the modified LCZ scheme as Open (Fig. 9). In fact, if the critical slope value is disregarded, the riverside stations characterized by openness were the only ones that obtained statistically significant coefficients during winter at $p=0.05$ in relation to gusty winds (appendix: table 6). Previous research of spatial heterogeneity found that low-density rural communities along the coast were more negatively affected by wind conditions (Helbich et al., 2014). Furthermore, the system-wide reduction in cycle volumes during strong winds found by Corcoran, Li, Rohde, Charles-Edwards, & Mateo-Babiano (2014) was only found during fall in Gothenburg in this study. However, the sensitivity analysis produced conflicting results since gustiness were still more impactful in fall at most Open classes (table 5). These result nonetheless give merit to the suggested theory (Helbich et al., 2014), that roughness of the urban structure protects cyclists from the worst wind effects.

Compared to the city centre, there were stations of the Built class with slightly stronger coefficients at the periphery. A possible explanation for this spatial variance could be that the buildings in these locations are either spaced far apart, or often aligned with the predominant wind direction in Gothenburg, causing winds to channel through the urban canyon at high speeds (Oke et al., 2017). This plausible explanation is better encapsulated by the Mixed classes. For example: station S6010 is located near the Gamla Ullevi stadium. From the dominant feature classification (table 3), it fulfilled the criterion for both LCZ 2: compact midrise and LCZ B: scattered trees (table 2), which is a relatively good description of the area. The stadium is a stand-alone tall building which can produce strong wind turbulence whilst the area for the most part is open with a few trees boarding the cycleway. This reasoning was also used on a regional scale by Helbich, Böcker, & Dijst (2014). They noticed that cities with tall buildings spaced far apart were more affected by winds, compared to denser cities. This study is in accordance with their results on a local scale.

Regarding seasonal differences of gustiness (Fig. 16), the Built class stations in the city centre consistently showed lower coefficient scores compared to the Open classes across all seasons (Fig. 8 & 16). Only in fall did the difference decrease. A steep terrain combined with openness also seemed to exacerbate the negative impact, because the steep and less dense classes consistently had coefficients that approximated a moderate correlation to gust, apart from in winter. However, even though Guldhedsgatan (S6025) also is a station with steep characteristics, also being of the Built dominant feature appeared to protect cyclists enough to reduce the association dramatically. However, the findings made in this study are inconclusive regarding route choice, but it is possible that commuting cyclists do choose different routes based on their local knowledge whenever their experience of prevailing weather conditions affects them negatively (see Skov-Petersen, Barkow, Lundhede, & Jacobsen, 2018). On a general note, it is possible that some heterogeneity effects could represent a shift in route choice rather than modal change or trip cancellation.

5.3 Part II: Weather effects in similar Urban Environments

The matrix of spatial heterogeneity was used to derive how weather sensitive different environments are, according to their urban characteristics. Stations were aggregated according their dominant feature class from the modified LCZ classification scheme (section 3.4). The analysis was design so that some dominant feature classes would always deviate and reveal either more- or less sensitivity to a given weather parameter. A disaggregated sensitivity matrix is available in the appendix (table 8). Comparison of every station, sorted by dominant feature will show that the sensitivity retained by the aggregated classes in table 5.

5.3.1 Differences in Weather Sensitivity between Urban Environments

Even with classes aggregated based on similarities, the results remained consistent with the findings made during exploration of the mapped coefficients. Regarding temperature, no statistical significance was find during winter, which suggests that changes in temperature indeed makes no differences to cyclists in Gothenburg (table 5). In spring, all classes became significant and openness favoured cycling much more than the built environment. Especially more sensitive was the Open/Flat class in relation to temperature. However, in the subsequent seasons, the association to temperature became neutral and eventually less sensitive. Meanwhile, note that the more sensitive association to sunshine remained over the year for the Open classes, which suggests that the duration of sunshine becomes increasingly more important to cyclists as time goes by. This cross-over also indicates a degree of collinearity between these two weather parameters that could be important. For example, cyclists that are eager to bring their bikes out as temperature starts to increase early in the year will possibly only continue to ride later in the year if the sun is shining during summer and fall. Furthermore, Open/Flat is the only more sensitive at 2 sigmas' in relation to temperature during spring (table 5), whereas no other obvious patterns of spatial heterogeneity were identified in spring during the cartographic exploration (Fig. 12). Therefore, the sensitivity analysis indicate that spatial heterogeneity may still be present during the season (table 5).

A surprising explorative finding that were confirmed by the heterogeneity matrix was that the Built classes were the only ones that were more sensitive to precipitation (table 5). Indeed, the availability of public transportation is higher in the central city where the bulk of Built classes are located. Yet, as implied earlier, one might have expected the dense urban structure to protect cyclists and thus unveil a pattern where these cyclists ride their bike, even when it rains. A similar finding was recently made by Miranda-Moreno & Nosal (2011) who unwittingly found evidence of spatial heterogeneity in Montreal, Canada. They identified a great variance in the magnitude of their coefficients between a station that served a residential area and another one that served the downtown central business district. They went on to speculate that the functionality of these two areas could explain the difference, since the CBD mostly attract professionals whilst the residential area has a more heterogeneous population. However, in the case of Gothenburg, no such mono-functional area met inclusion criteria. Therefore, the variance in magnitude is unlikely to be explained by population composition alone. Based on findings made in this study, the reasons for why openness has a lower association to precipitation is hard to speculate. Apart from proximity to public transportation, the difference between centre and periphery could also be related to local cultural expressions (e.g. Heinen, Maat, & Wee, 2011; Spencer, Watts, Vivanco, & Flynn, 2013) or anything else for that matter.

Regarding sunshine sensitivity, it is perhaps not surprising that Open and Mixed classes consistently showed more association to sunshine, in part because denser urban environments are usually characterized by less greenery. Areas characterized by openness may also be perceived as less hectic environments, and could therefore be better suited for a pleasant ride whenever the opportunity presents itself.

Moreover, sunshine not only had the largest global *r* coefficient, but it was also the only statistically significant weather parameter across every season, except in winter. Therefore, sunshine appears to be an especially important factor for cyclists in Gothenburg. Yet, the impact of sunshine still revealed clear patterns of weather sensitivity. During spring, the greatest difference in sensitivity were identified between the Open and Built classes. The latter had a demarked magnitude of less sensitivity to sunshine. And the coefficient range between the highest and lowest obtained coefficient was ~.14 between these two classes. The coefficient range is even greater during the industrial summer, as the difference between the least sensitive (Built/Flat) and the most sensitive (Mix/Steep) classes is ~.27 in magnitude. Since it is likely that a lot of people are on vacation during the industrial summer, the vast difference and henceforth spatial heterogeneity between these urban environments could be related to recreational activities. Indeed, Thomas, Jaarsma, & Tutert (2013) showed that sunshine is particularly important for recreational cyclists in the Netherlands. Furthermore, the heterogenic variance remains in fall, but judged by the strength of the correlations, the difference is now smaller as the positive effect of sunshine has been reduced. Possibly because of what we will delve into next.

Gustiness during fall season was the only season with statistical significance across all dominant feature classes (table 5). Moreover, the magnitude of station coefficients is on average slightly greater in fall compared to other seasons (table 4). Much like the effects of sunshine, most sensitivity were found in the Open and Mixed classes. By contrast, the Built classes was always less sensitive and Built/Steep even lost statistical significance regarding gustiness during spring and the industrial summer. Considering the Mixed dominant feature, only Mix/Flat (Ullevigatan, S6010 and Dag Hammarskjöld, S6002) were more sensitive to the effects of gustiness. In addition to what was discussed earlier regarding S6010 (section 5.2.4), it's possible that winds doesn't on top of roughness features (Oke et al., 2017). Hence, the cycleway will remain exposed to high wind speeds. Apart from spring, stations classified as Open/Steep were the only class that consistently showed more sensitivity in relation to gusty winds. Thus, the sensitivity analysis supports the findings made by the cartographic exploration: steepness combined with openness seems to exacerbate the impact of wind on cyclists. It should however be noted that there is a free-of-charge ferry between the two bridges, near stations S6005 and S6051. This ferry is an option for cyclists wanting to cross the river. However, the former station often experience the same magnitude in its coefficients as the bridges (Fig. 16). Moreover, station S6005 is characterized as Open/Hilly which is amongst the most sensitive classes. Thus, it's unlikely that cyclists who ride in strong winds take the detour to the ferry. Rather, other reasons are likely the culprit for the negative effect near the river. The most probable explanation is that the cycle ways along the river is hardly protected by any roughness features at all and cyclists are also forced to ride close to the quay for some cycleway segments, leaving them directly exposed to the elements.

5.4 Evaluation of Methodology & Limitations

Because no previous research was identified to develop a framework for spatial heterogenic analysis of cycle flows, this study proposed such a model. The framework make use of the correlation coefficient to measure the magnitude of association between a dataset of weather parameters and a dataset with permanent cycle- measuring stations. The resulting coefficients are then mapped to allow for pattern exploration. Thereafter, the station coefficients are aggregated according to their dominant feature from a modified Local Climate Zone (LCZ) system, standardized per row of weather parameter and added to a matrix where weather sensitive stations are highlighted.

The modified LCZ classification of every stations is part of the pre-processing. In this study, six properties of the urban environment were quantized according to the original values provided by Stewart & Oke (2012). These properties are related to a total of 17 Local Climate Zones, where each property have a different range criterion that must be met. So, each station got scored by how many times they fulfilled the criterion for a LCZ. To simplify the classification, the first 10 classes got referred to by their dominant feature: *Built* environment. The last 7 classes were characterized by their dominant feature: *Openness*. However, many stations met the criteria for several LCZs and sometimes by an equal amount of the Built and Open dominant feature classes. The pragmatic solution to those stations were to classify them as *Mixed.*

There are a few plausible reasons for why some stations met the criterion for many more than one LCZ. First, the original classification values were not adjusted to the context of Gothenburg and stations could therefore have been misclassified. Second, the urban environment surrounding the stations were quantified along the cycleway segment connected to the stations or based on the point location of the station. This goes against how Stewart & Oke recommends the scheme should be used. Nevertheless, it wasn't meaningful to follow the uniformity of the urban structure rather than the cycleway, since every cyclist moves through a varying landscape during their ride. This aspect should however be evaluated in future studies to identify the best way of quantification. For example, what scale should be considered of the cycleway network? In this study, only the cycleway segment connected to each station between major intersections was considered. However, it is possible that a larger extent is indeed needed to fully capture the average cyclist passing a station. Thus, it may be possible to utilize every cycleway within a given distance as the basis of classification.

Moreover, cyclist is also affected by topography. Therefore, the slope characteristics of each station were added to their LCZ type. This was done by calculating the topographic slope profile of the cycleway segment connected to each station. To capture the slope characteristics of that segment, the standard deviation – or sigma value – was chosen as the best indicator. This statistic was chosen because it reveals how much the terrain varies. For example, the average-slope could yield a low gradient if the cycleway were mostly flat but with a steep terrain towards one end. Thus, the logic for selecting sigma is that it will increase depending on how much relief each topographic slope profile is characterized by. This study did however produce a lot of outliers due to the fine resolution of the raster geodata, but these were appropriately handled.

The slope characteristics of each station were eventually classified depending on their relative difference to each other. That is, the first quartile got classified as flat, the 50% of values that fell in the middle were classified as hilly whilst all values beyond the third quartile got classified as steep. This however poses a problem since the division of classes was based on the sampled 15 stations. Hence, it is very likely that a few stations got misclassified, for example as hilly or steep even though they are relatively flat. To overcome this issue, the topographic profile of every cycleway segment in the city should've been quantified. By doing so, the resulting classification of the 15 stations would've been more accurate since their slope characteristics would be determined based on the whole population of slope profiles. Another approach would've been to assign arbitrary cut-off values based on the observed topography of the flattest and steepest cycleway in the station sample. In the end, the result of the combined LCZ and slope characteristics were indeed different enough to identify classes with association to spatial heterogeneity in the *r* matrix.

The basic functionality of the matrix used to identify heterogenic sensitivity between the classes was simple. Statistically significant coefficients were standardized per row in a matrix. Whenever a class deviated by more than one standard deviation, it was color-coded as either red or blue. Depending on the sign (+/-) of the correlation, the sensitive classes had their spatial heterogeneity determined by 1 sigma from the row mean, whereof less sensitivity was found whenever $|r| \rightarrow 0$, and more if $|r| \rightarrow \pm 1$. This method worked well and did confirm that some urban environments are statistically associated to the heterogeneous patterns that were identified during exploration of the maps. However, it is possible that the approach was too responsive and since it always identified weather sensitive classes, even when the range of coefficients was arguably too narrow. To overcome this, a more robust approach to establish the presence of spatial heterogeneity would be to utilize the critical values of z, for example $z_{\alpha=10\%} = 1.28$ or $z_{\alpha=5\%} = 1.645$ for a two-tailed probability test. Nonetheless, since part of the aim of this study was to explore whether specific urban forms were associated with spatial heterogeneity depending on similarities in their urban characteristics, this method of detecting sensitivity was appropriate.

An alternative to the sensitivity analysis of the urban environment is to explore the impact of weather indices during different seasons. By standardizing every seasonal weather index on the total effect, the analysis would reveal where a weather parameter has more impact, meanwhile the influence of spatial heterogeneity is reduced.

5.4.1 Recommendations for Further Research

In summary, this study laid the foundation for a framework to analyse spatial heterogeneity at a local scale. The proposed methodology successfully captured and identified interesting results of heterogeneous responses by different stations in relation to weather. The findings made by this study has made it clear that when roughness elements of the built environment are considered, it is possible to unveil areas that are sensitive to certain weather conditions. Regarding gustiness, it becomes clear that location is important for cyclists. The implications of these gusty wind findings to other researchers are important to emphasize. Previous research often reject wind variables in relation to cycling, either because they overlook the variable or because they make insignificant findings. However, researcher could wrongfully be rejecting wind variables because they sample and aggregate data to a city-wide scale from cycle-measurement stations surrounding by a high density of roughness elements. It is therefore important to consider the spatial heterogeneity of cycling and winds in the study design.

Future research is recommended to build upon the proposed framework of spatial heterogeneity. Evaluation of the appropriate scale for quantifying the urban environment surrounding the cycle-measurement station should be undertaken. Moreover, the resulting association of spatial heterogeneity according to class characteristics should be validated through replication and additional testing. It is also important to find a robust standard for the sensitivity matrix. This study proposed that a critical value of $z_{\alpha=10\%} = 1.28$ or $z_{\alpha=5\%} = 1.645$ z should be used. Finally, in this study, the correlation coefficient was used to explore spatial heterogeneity. It is however possible to apply logit- or logistic regression, which is commonly used to study cycling and weather (see Liu, Susilo, & Karlström, 2017), and insert those coefficients into the framework. Moreover, it could also possible to use the relative percentage of change in cycle volumes (Miranda & nodal 2011), instead of the z-scored cycle volumes used in this study.

5.5 Implications for Society & Planning Authorities

With regards to the spatial impact of weather, understanding how cyclists are influenced is vital for promoting active modes of transportation (Liu et al., 2017). Therefore, some recommendations are proposed to retain cycle volumes. It is important to recognize that the urban environment produces a variety of microclimates which can be related to local weather effects. Planning authorities should for instance appreciate that weather is not an uncontrollable natural phenomenon that affects cyclists, and residents should be made aware of how their local environment produce local weather patterns that is different from other areas of the city. Recognizing the limitations of current infrastructure in specific urban environments in relation to all weather indices should lead to better planning strategies that are climate sensitive. Moreover, cyclists themselves may come to understand that certain weather conditions are only less favourable to cycling where they reside, and that riding a bicycle could be more favourable just around the block.

Indeed, Gothenburg has more annual precipitation than the Swedish national average, which has been linked to lower cycling volumes in general (Winters et al., 2007). Therefore, improved local weather forecast may be needed to avoid unnecessary reductions in cycle volumes whenever the threat of precipitation is looming. For instance, detailed hourly maps of weather forecasts should be recommended to cyclists to allow them to determine whether a precipitation event is likely to occur on their frequented routes or only in other areas of the city. Moreover, the city of Gothenburg could launch a campaign like the winter-cyclists' initiative, but instead of providing winter tires and reflective vests, a campaign could provide raincoats suitable for cycling.

Moreover, the infrastructure must be prepared to better handle the adverse effects of weather. Urban environments where gusty winds consistently are problematic for cyclists should be protected by low vegetation or fences that reduce wind speed rather than trying to block it entirely. A solid wall could for example cause winds to channel onto cyclists and effectively produce the opposite than the intended results, whereas vegetation has been proved to effectively reduce wind speeds in an urban environment (Hong et al., 2012). Since this study found that sunshine has a stronger association to cycling in areas characterised by openness, it is also worth considering how vegetation can be introduced in dense urban areas. More greenery could influence more people to cycle in built environments whenever sunshine hits the city, due to the aesthetic properties of vegetation. In addition to this Ettema, Friman, Olsson, & Gärling (2017) suggested that intense sunshine could lead to uncomfortable feelings of warmth for cyclists. Thus, tall vegetation could also cast protective shadows on the cyclists. During the summer season, it is also possible that outdoor bathing opportunities near the city centre could encourage more people to cycle since it would provide an opportunity to cool down whenever the temperature is unusually high.

It could also be worthwhile to improve the guidepost system boarding the cycle ways. For example, a guidepost could be a cost-effective measure to reduce the deterrent effect of a steep terrain when a cyclist easily can choose an alternative route to their destination. Therefore, the density of guidepost should increase and the distance to certain locations should be included in the signage.

Whenever infrastructure or the built environment cannot be adjusted to combat inclement weather, it becomes important to re-frame the publics' perception of weather effects (Heinen et al., 2010). For example, during days with strong winds, better guidepost could be used, as mentioned above, to redirect cyclists into urban environments that are known to be less affected by winds. Doing so would send the message that city planners acknowledge the problem and are actively working to reduce the barriers to cycling. So, even when the root cause of weather-related issues cannot be affected, the negative impact of weather can still be resisted. This argument stems from the findings made by Thorsson, Lindqvist, & Lindqvist (2004). They saw that people adjust their location within a park to improve their thermal comfort whenever they become too cold or too hot. This behaviour could also be catered for by designing the cycle network to allow for route-choice decisions based on the comfort of the cyclists.

6. Concluding Remarks

This study is a contribution to the emerging field of spatial heterogeneity regarding cycling and weather. Since this study lacks precedent, the proposed framework should lay the foundation for further developments in the field. Replication of the results in this study should be conducted to validate the robustness of the weather sensitivity findings in certain urban environments.

Citywide, this study could conclude that, duration of precipitation is the most influential deterrent of cycling in Gothenburg during all seasons. Apart from precipitation, no other weather condition had a statistically significant impact on cycling during the winter season. Gustiness also had a negative association, but the magnitude of its impact was lower. Regarding positive influences, sunshine was the most influential benefactor of cycling citywide. The effect of temperature fell just behind. These weather parameters also revealed spatially heterogeneous patterns when the respective stations had their correlations analysed during cartographic exploration.

Daily weekday cycling in various urban areas were found to respond differently to certain weather conditions, depending on their urban characteristics. Sunshine always had more positive influence in areas characterized by openness and unexpectedly, open areas appeared to be less sensitive in relation to precipitation. Meanwhile, dense urban environments in the city centre were more sensitive to precipitation. Furthermore, gustiness had the most negative impact on open areas near Göta älv in Gothenburg. Other inland areas that were characterized by some openness were also slightly more affected by wind speeds. Apart from the industrial summer season, temperature revealed no obvious patterns of spatial heterogeneity. However, in summer, those stations that had the strongest correlations to sunshine also retained some influence on days with unusually high temperatures. To summarize, parts of the city that is mostly characterized by openness is more sensitive to all weather conditions, except for precipitation which had a more pronounced impact on the dense urban centre.

When the stations were aggregated based on their environmental similarities, the weather sensitivity analysis conducted through the heterogeneity matrix confirmed the explored spatial patterns. Openness were indeed associated to more sensitivity in relation to all weather indices, apart from precipitation where the sensitivity was low. Moreover, a steep topography combined with openness was consistently found to be associated with more sensitivity to gustiness, unless the area had a high roughness from buildings. Apart from winter, sunshine was the only weather parameter that obtained more sensitive results across all seasons in open urban environments. Precipitation was the only statistically significant weather index during winter, and stations characterized by a higher density of buildings were always more sensitive to precipitation across all seasons. However, apart from precipitation, denser areas appeared to have a lower weather sensitivity in general.

Finally, this study urges planning authorities to recognize how weather affects different urban environments and that the adverse effects of weather can be reduced to encourage cycling. The applied framework can be adapted by professionals to identify areas that most likely are sensitive to certain weather effects, even in areas without measurement of cycling volumes since the sensitivity may be inferred from similar urban environments. Moreover, promoting map-based weather forecasting to cyclists who may not be aware that precipitation can be local to other parts of the city would increase the spatial awareness in society and thus, possibly retain a larger cycle volume during inclement weather conditions. Provision of raincoats suitable for cycling through directed campaigns could also be a means to reduce the adverse effect of precipitation events. Regarding the impact of gustiness, protective features like low density bushes is recommended to cushion the impact of wind in areas characterized by openness. Measures with cushioning effects on wind speeds should also be applied where vegetation aren't appropriate, for example at weather exposed bridges. Where it is possible, vegetation should always be the preferred protective measure since the findings in this study indicates that greenery could make a bicycle trip more aesthetically pleasing during sunshine. Since temperature appeared to reveal no obvious patterns of spatial heterogeneity in relation to cycling, the best solution is likely to continue to improve infrastructure and to implement more campaigns aimed at swaying the public's perception of cycling until more people continue to cycle, even as the temperature begins to drop. Improved guideposts boarding the cycleway could also be an effective measure to reduce the negative impact of a steep topography. Guidepost could also be a cost-effective measure to communicate the spatial heterogeneity of certain weather conditions in different urban environments.

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8. Appendix

Table 6

A full report of the obtained p-values for the correlation coefficient per station. Bold text is statistically significant at α = 5%.

Weather		S6002	S6003	S6005	S6006	S6008	S6010	S6025	S6027	S6028	S6042	S6046	S6049	S6051	S6940	S6935
Ta_{max}	Total	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Sunshine_{/daylight}$	Total	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Precip_{mm}$	Total	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Precip_{len}$	Total	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Gust_{mean}$	Total	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Ta_{max}	Winter	0.107	0.267	0.267	0.166	0.122	0.239	0.168	0.12	**0.048**	**0.02**	0.164	0.106	0.515	0.318	0.286
$Sunshine_{/daylight}$	Winter	0.503	0.431	0.943	0.993	0.745	0.797	0.931	0.673	0.78	0.39	0.74	0.77	0.683	0.751	0.208
$Precip_{mm}$	Winter	**0.01**	**0.033**	**0.001**	**0.006**	**0.002**	**0**	**0.013**	**0.006**	**0.005**	**0.006**	**0.005**	**0.004**	**0.003**	**0.029**	**0**
$Precip_{len}$	Winter	**0.001**	**0.011**	**0**	**0.002**	**0**	**0**	**0.004**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0**	**0.007**	**0**
$Gust_{mean}$	Winter	0.062	0.143	**0.028**	0.292	0.101	0.105	0.568	0.244	0.413	0.148	0.12	0.114	0.196	**0.027**	**0.014**
Ta_{max}	Spring	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Sunshine_{/daylight}$	Spring	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Precip_{mm}$	Spring	**0**	**0**	**0.001**	**0**	**0**	**0**	**0**	**0.001**	**0**	**0.002**	**0**	**0**	**0.001**	**0**	**0**
$Precip_{len}$	Spring	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Gust_{mean}$	Spring	**0**	**0**	**0**	**0**	**0**	**0**	**0.008**	**0**	**0.001**	**0**	**0**	**0**	**0.001**	**0**	**0**
Ta_{max}	Industry	**0.009**	**0.022**	0.108	0.212	0.167	0.052	0.317	**0.003**	**0.004**	**0.006**	0.103	**0.016**	**0.025**	0.065	0.117
$Sunshine_{/daylight}$	Industry	**0**	**0**	**0**	**0.001**	**0.004**	**0.001**	**0**	**0**	**0**	**0**	**0.001**	**0**	**0.004**	**0**	**0.004**
$Precip_{mm}$	Industry	**0.002**	**0.003**	**0.002**	**0**	**0**	**0**	**0.003**	**0.013**	**0**	**0.005**	**0**	**0.001**	**0**	**0.004**	**0.009**
$Precip_{len}$	Industry	**0.005**	**0.006**	**0.016**	**0.001**	**0**	**0.001**	**0.002**	**0.011**	**0.001**	**0.007**	**0**	**0.003**	**0**	**0.016**	0.345
$Gust_{mean}$	Industry	**0**	**0.005**	**0.001**	**0.043**	**0.015**	**0.017**	0.091	**0**	**0.008**	**0.001**	**0.004**	**0**	**0.046**	**0**	**0**
Ta_{max}	Fall	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
$Sunshine_{/daylight}$	Fall	**0**	**0.001**	**0**	**0.004**	**0.002**	**0**	**0.003**	**0**	**0.001**	**0**	**0.001**	**0**	**0.004**	**0.002**	**0.002**
$Precip_{mm}$	Fall	**0.007**	**0.008**	**0.028**	**0.002**	**0.002**	**0.003**	**0.001**	0.091	**0.003**	**0.009**	**0.001**	**0.002**	**0.001**	0.102	**0.013**
$Precip_{len}$	Fall	**0**	**0.001**	**0.001**	**0**	**0.001**	**0**	**0**	**0.012**	**0**	**0**	**0**	**0**	**0**	0.051	**0.005**
$Gust_{mean}$	Fall	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.001**	**0**	**0**

Table 7
Other aggregations of the 15 station coefficients, utilized to guide the explorative analysis.

	Weather	Periphery*	Centre*	Range	Open	Mixed	Built	Range Open vs. Built	Flat	Hilly	Steep	Range Flat vs. Steep	Pseudo binary *r*	
Total	Ta_{max}	0.33	0.31	0.03	0.32	0.26	0.31	0.01	0.32	0.32	0.31	0.01	*Open*	-0.29
Total	$Sunshine_{/daylight}$	0.36	0.31	0.05	0.34	0.29	0.32	0.03	0.36	0.33	0.33	0.03	*Mix*	-0.30
Total	$Precip_{mm}$	-0.3	-0.35	0.05	-0.31	-0.26	-0.34	0.03	-0.33	-0.34	-0.3	0.04	*Built*	-0.27
Total	$Precip_{len}$	-0.32	-0.38	0.06	-0.33	-0.29	-0.37	0.04	-0.37	-0.37	-0.32	0.05		
Total	$Gust_{mean}$	-0.26	-0.22	0.04	-0.27	-0.19	-0.21	0.06	-0.25	-0.23	-0.25	0	*Flat*	-0.31
Winter	Ta_{max}	0.12	0.11	0.01	0.11	0.1	0.1	0.01	0.13	0.11	0.1	0.03	*Hilly*	-0.27
Winter	$Sunshine_{/daylight}$	0.07	0.01	0.06	0.06	0.04	0.02	0.04	0.06	0.02	0.06	0	*Steep*	-0.28
Winter	$Precip_{mm}$	-0.29	-0.32	0.03	-0.31	-0.25	-0.3	0.01	-0.32	-0.3	-0.3	0.02		
Winter	$Precip_{len}$	-0.34	-0.37	0.04	-0.36	-0.29	-0.36	0	-0.37	-0.36	-0.34	0.03		
Winter	$Gust_{mean}$	-0.14	-0.11	0.03	-0.16	-0.09	-0.1	0.06	-0.13	-0.12	-0.13	0		
Spring	Ta_{max}	0.47	0.43	0.04	0.46	0.36	0.43	0.03	0.45	0.44	0.45	0		
Spring	$Sunshine_{/daylight}$	0.51	0.48	0.03	0.49	0.4	0.48	0.01	0.51	0.49	0.47	0.04		
Spring	$Precip_{mm}$	-0.35	-0.38	0.03	-0.36	-0.29	-0.38	0.02	-0.36	-0.38	-0.36	0.01		
Spring	$Precip_{len}$	-0.43	-0.46	0.03	-0.43	-0.36	-0.45	0.02	-0.43	-0.45	-0.44	0.01		
Spring	$Gust_{mean}$	-0.29	-0.25	0.04	-0.3	-0.21	-0.24	0.06	-0.28	-0.26	-0.26	0.02		
Industry	Ta_{max}	0.22	0.17	0.06	0.18	0.2	0.16	0.02	0.21	0.19	0.17	0.03		
Industry	$Sunshine_{/daylight}$	0.46	0.32	0.14	0.39	0.37	0.33	0.06	0.41	0.35	0.41	0		
Industry	$Precip_{mm}$	-0.41	-0.49	0.08	-0.44	-0.36	-0.47	0.03	-0.47	-0.48	-0.39	0.08		
Industry	$Precip_{len}$	-0.35	-0.45	0.1	-0.35	-0.33	-0.44	0.09	-0.43	-0.43	-0.32	0.12		
Industry	$Gust_{mean}$	-0.35	-0.23	0.12	-0.33	-0.25	-0.23	0.11	-0.29	-0.26	-0.32	0.03		
Fall	Ta_{max}	0.37	0.37	0	0.36	0.3	0.37	0.02	0.35	0.38	0.36	0		
Fall	$Sunshine_{/daylight}$	0.31	0.29	0.02	0.31	0.26	0.28	0.03	0.33	0.3	0.28	0.05		
Fall	$Precip_{mm}$	-0.26	-0.32	0.07	-0.26	-0.22	-0.33	0.07	-0.3	-0.31	-0.25	0.06		
Fall	$Precip_{len}$	-0.32	-0.4	0.08	-0.33	-0.3	-0.38	0.05	-0.4	-0.38	-0.3	0.1		
Fall	$Gust_{mean}$	-0.32	-0.3	0.02	-0.33	-0.26	-0.29	0.04	-0.32	-0.3	-0.32	0.01		

**The two major bridges (S6935 and S6940) was regarded as peripheral stations even though they could've been separated to the centre (S6935) and periphery (S6940).*

Table 8

Disaggregated station coefficients, sorted by dominant feature class. The original coefficient slope is superimposed over the z-scored coefficients. Only statistically significant correlations at p=0.05 and their critical slope value are shown in the matrix. For every row, more sensitivity is emphasised in red whenever a class is $+1\sigma$ *from the row mean, while less sensitivity is emphasised with blue* (-1σ).

Weather		S6042 Open/ Flat	S6005 Open/ Hilly	S6046 Open/ Hilly	S6935 Open/ Steep	S6940 Open/ Steep	S6002 Mix/ Flat	S6010 Mix/ Flat	S6028 Mix/ Hilly	S6027 Mix/ Steep	S6008 Built/ Flat	S6003 Built/ Hilly	S6006 Built/ Hilly	S6049 Built/ Hilly	S6051 Built/ Hilly	S6025 Built/ Steep
Ta_{max}	Total	0.36	0.3	0.31	0.3	0.32	0.34	0.29	0.35	0.34	0.29	0.33	0.3	0.33	0.31	0.29
$Sunshine$	Total	0.41	0.33	0.31	0.35	0.31	0.39	0.32	0.35	0.38	0.31	0.36	0.31	0.34	0.29	0.27
$Precip_{mm}$	Total	-0.28	-0.31	-0.37	-0.33	-0.26	-0.31	-0.38	-0.35	-0.26	-0.37	-0.31	-0.35	-0.34	-0.35	-0.33
$Precip_{len}$	Total	-0.33	-0.34	-0.4	-0.34	-0.28	-0.34	-0.42	-0.38	-0.3	-0.39	-0.33	-0.37	-0.36	-0.4	-0.38
$Gust_{mean}$	Total	-0.26	-0.28	-0.24	-0.29	-0.27	-0.27	-0.24	-0.21	-0.25	-0.22	-0.23	-0.2	-0.26	-0.2	-0.17
Ta_{max}	Winter															
$Sunshine$	Winter															
$Precip_{mm}$	Winter	-0.29	-0.34	-0.3	-0.39			-0.37	-0.3	-0.3	-0.33		-0.29	-0.31	-0.35	
$Precip_{len}$	Winter	-0.36	-0.37	-0.35	-0.41	-0.29	-0.35	-0.4	-0.34	-0.34	-0.38	-0.28	-0.32	-0.34	-0.52	-0.31
$Gust_{mean}$	Winter															
Ta_{max}	Spring	0.52	0.45	0.43	0.45	0.47	0.47	0.42	0.44	0.47	0.41	0.44	0.44	0.46	0.44	0.41
$Sunshine$	Spring	0.56	0.46	0.47	0.53	0.44	0.51	0.48	0.52	0.49	0.5	0.51	0.5	0.51	0.47	0.42
$Precip_{mm}$	Spring	-0.3	-0.33	-0.43	-0.37	-0.36	-0.34	-0.42	-0.38	-0.32	-0.39	-0.4	-0.39	-0.39	-0.32	-0.38
$Precip_{len}$	Spring	-0.38	-0.42	-0.48	-0.45	-0.42	-0.42	-0.48	-0.48	-0.42	-0.45	-0.46	-0.46	-0.47	-0.38	-0.5
$Gust_{mean}$	Spring	-0.32	-0.32	-0.27	-0.27	-0.31	-0.29	-0.25	-0.23	-0.27	-0.25	-0.26	-0.23	-0.28	-0.23	
Ta_{max}	Industry	0.28					0.24		0.3	0.27		0.21		0.22	0.21	
$Sunshine$	Industry	0.53	0.39	0.3		0.4	0.54	0.3		0.6		0.45	0.3	0.37		0.34
$Precip_{mm}$	Industry		-0.42	-0.51		-0.39	-0.42	-0.49	-0.54	-0.34	-0.54	-0.41	-0.51	-0.45	-0.49	-0.4
$Precip_{len}$	Industry	-0.42	-0.33	-0.48		-0.34	-0.38	-0.45	-0.48	-0.35	-0.49	-0.38	-0.44	-0.41	-0.49	-0.43
$Gust_{mean}$	Industry	-0.33	-0.32	-0.27	-0.38	-0.38	-0.38	-0.22	-0.28	-0.38	-0.22	-0.26		-0.34		
Ta_{max}	Fall	0.34	0.35	0.41	0.3	0.38	0.38	0.33	0.41	0.38	0.36	0.41	0.37	0.39	0.34	0.36
$Sunshine$	Fall	0.35	0.34	0.3	0.28		0.33	0.34	0.3	0.31	0.28	0.3		0.32		
$Precip_{mm}$	Fall	-0.28		-0.33			-0.29	-0.31	-0.31		-0.34	-0.28	-0.32	-0.32	-0.37	-0.36
$Precip_{len}$	Fall	-0.4	-0.34	-0.43	-0.3		-0.37	-0.47	-0.4	-0.27	-0.38	-0.35	-0.39	-0.37	-0.39	-0.43
$Gust_{mean}$	Fall	-0.32	-0.33	-0.32	-0.39	-0.29	-0.33	-0.35	-0.3	-0.3	-0.29	-0.3	-0.28	-0.32	-0.27	-0.29