Influence of the urban green vegetation fraction on the urban heat island effect across Europe

A.M. Droste[1], R.J. Ronda[1], N.E. Theeuwes[1], G.J. Steeneveld[1]

[1] *Meteorology and Air Quality group, Wageningen University, The Netherlands*
Arjan.Droste@wur.nl

Abstract

The difference in temperature between an urban area and its rural surroundings is known as the Urban Heat Island (UHI). In the light of climate change and the ongoing world-wide urbanisation, it is important to take measures to reduce the UHI. Studies have shown that increased vegetation fraction in cities correlates with a reduction in mean UHI values. Though this relation has been researched for single cities and countries, it is yet unknown whether this relation is universal across different climate zones. This study researches the applicability of measurements from hobby meteorologists combined with ECMWF model data to calculate the UHI in an innovative new approach. We research the influence of the vegetation fraction of neighbourhoods on the maximum UHI, in order to establish a statistical relationship between vegetation and UHI reduction. This analysis is performed for several European cities in varying climates (Rotterdam, the Netherlands; Oslo, Norway; Madrid, Spain) to determine the role of climate zones on this relationship. Our results establish that using the ECMWF operational model data as means of rural background temperature is a valid new way of calculating UHI. For Rotterdam we find a significant (R^2 of 72%) relationship between vegetation and maximum UHI reduction, but we are unable to reproduce a significant relation for the cities of Madrid and Oslo. Water availability for the rural surroundings, the anthropogenic water flux and the regional climate appear to play a large role in the way vegetation affects the UHI.

1. Introduction

From 2008 onwards, over half of the world's population has been living in cities, and projections show urbanisation to increase even further (United Nations, 2011). This rapid urbanisation, combined with climate change, can bring various health issues related to the Urban Heat Island (UHI) effect: the phenomenon of temperatures being several degrees higher in cities than in the rural surroundings. During heat waves the UHI can cause excess mortality (Poumadère et al., 2005) and thermal discomfort and stress (Bell, 1981), so adaptation and mitigation measures are required to reduce the impact and magnitude of the UHI. One such mitigation option is increasing the vegetation fraction in cities. Its effect is well researched in several individual cities (e.g. Florence by Petralli et al., 2014), and for cities in the Netherlands a robust relation was found where the 95 percentile of UHI decreases with 0.6 °C for every 10% vegetated surface (Steeneveld et al., 2011; Heusinkveld et al., 2014). However, whether such a universal relation exists for other cities in other climate zones, and whether this relation is different in different climate zones, is still unknown. To this end we research the influence of vegetation on the UHI in 3 distinctly different European cities: Rotterdam, Madrid and Oslo. Rotterdam is situated close to the Dutch North Sea coast, with a temperate maritime climate (Köppen class Cfb) and prevailing south-westerly winds. Madrid is situated inland, with an average altitude of 660 metres above sea level, and a dry Mediterranean climate (Köppen class Csa). Oslo lies in the Oslofjord in the southern part of Norway, with a steep topographical gradient from 0 metres at the harbour to 300 metres close to the northern city border, and a humid continental climate (Köppen class Dfb).

An issue in determining the UHI is choosing the rural reference station, which heavily influences the UHI magnitude (Sakikabara and Owa, 2005). We explore an innovative method for calculating UHI using the operational model data of the European Centre for Medium-ranged Weather Forecasting (ECMWF) as rural reference.

2. Methodology and data

2.1 Urban data

The urban temperature records are obtained from the Wunderground website (www.wunderground.com), an online platform where weather hobbyists can upload records of their own private weather station. This platform provides a unique and extensive database of urban records without the need for expensive measurements. Steeneveld et al. (2011) have used these data to successfully determine UHI for various cities in the Netherlands. To ensure quality we apply various filters on the data: We remove outliers; hours with fog or rain which might potentially contaminate the dataset (approximately 15% of the hours are removed). Due to the significant differences in elevation within the cities of Oslo and Madrid the temperature records of these stations have all been adiabatically corrected to sea level for legitimate comparison between the stations. After selecting and filtering the station data, we have 8 Wunderground stations in Rotterdam; 28 in Madrid and 18 in Oslo. The time of interest is January 2010 up to September 2014.

In addition to the Rotterdam Wunderground stations we make use of a network of weather stations in Rotterdam maintained by Wageningen University and Technical University Delft. These stations were placed for the Climate-

Proof Cities project (CPC, Van Hove et al., 2015) and make up a network of 13 stations plus an additional rural reference station. UHI calculated using this reference station is used to check the accuracy of the ECMWF UHI values. In Madrid we use data from the WMO stations at Barajas airport for validation of the ECMWF data. In Oslo we use 3 additional urban stations from the Norwegian Weather Service, as well as the rural Bjørnholt station to serve as reference.

2.2 ECMWF data

We make use of the operational ECMWF model data as an alternative venue for calculating the UHI, using it as a rural background. The model has a spatial resolution of 0.15° in latitude and longitude, and a temporal resolution of 6 hours (output at 0, 6, 12 and 18 UTC). The variables of interest from the model include the 10-metre temperature, the zonal and meridional components of the wind (u and v) and the average surface geopotential. The latter is scaled to the gravitational constant (g, 9.81 ms^{-2}) to obtain information about the elevation. The relatively coarse temporal resolution limits the possibilities for UHI analysis. We require the daily maximum UHI, so for our analysis we use the UHI at 0 UTC. From theory it follows that the UHI is largest after sunset, and Kim and Baik (2002) report that the maximum UHI is 3.3 times more likely to occur during the night than during the day. For all cities involved, 0 UTC is indeed after sunset, even in Oslo during summer.

2.3 Vegetation fraction

We use the method by Steeneveld et al. (2011) to determine the green vegetation fraction in a square with sides of 600 metres around each station. We use the reflective properties of vegetation in the Red, Green and Blue (R, G, B) spectrum to count green pixels in Google Earth imagery:

Green% = R>1.15B & G>1.01R & G>1.01B

Each pixel that meets the conditions set by this function is classified as a green pixel. The green fraction is expressed as the fraction of these green pixels to the total amount of pixels per image. We made an effort to make every Google Earth image as recent as possible, during the summer or spring months, where vegetation is the most active. For Madrid we use a different equation, since the typical vegetation tends to be darker, which gets filtered out by the initial equation:

Green% = G > B & G > R & (G - R+B/2 > 20) & (R + B < 200)

The equations estimate the green fraction accurately, though for certain types of darker vegetation, mainly trees, the green fraction is underestimated. For stations where this was the case, the images have been manually greened to improve the resulting green vegetation fractions.

3. Results

For each of the cities up for research we have created a contour plot of the average urban air temperature varying over the day and year; various regression plots relating the 95 percentile of the daily maximum UHI (i.e. the UHI at 00 UTC) and a plot of the mean monthly UHI against the mean monthly rural background temperature. The latter is introduced in Zhou et al. (2013), who find a hysteresis-like curve of the average UHI. In each city we compare the results of using the ECMWF data to measurement data from WMO stations close to the city in question.

3.1 Rotterdam

Figure 1a shows the resulting regression between the 95 percentile of UHI and the green vegetation fraction. Take note that we have used only stations from the urban canopy layer in this analysis: when including all stations the relationship deteriorates significantly, with R^2 values decreasing with 16% for the reference station case. Removing the outlier at the far right with vegetation fraction of 48% does not impact the regression significantly. The ECMWF data and the measured Reference data perform nearly equally, with both having an R^2 value of near 0.73. The magnitude of the UHI is significantly different between the ECMWF and reference stations however: the ECMWF 95 percentile of UHI does not go beyond 5 °C, whereas the Reference data has values up to 7 °C UHI for several stations. Other studies of the Rotterdam UHI (e.g. Steeneveld et al., 2011; Heusinkveld et al., 2014; Van Hove et al., 2015) point in the direction of this 7 degrees UHI, indicating that 5 °C is likely an underestimation related to the warm bias found in many climate models (Jacob et al., 2007). The regression slope indicates how much the 95 percentile of UHI decreases with every added percentage vegetation. Steeneveld et al. (2011) found that the UHI decreases with roughly 0.6 °C per 10% added vegetation. Our results are close to this value, though the choice of rural reference heavily influences the regression slope. The ECMWF slope is steeper than the reference regression slope (0.75 °C versus 0.5 °C reduction per 10% vegetation), because it calculates a very low UHI to those stations with relatively high vegetation fractions, whereas these same stations still have a significant UHI (order of 3 °C) when calculated with the Reference data.

Figure 1b shows the seasonality of the average UHI for Rotterdam, plotted against the background temperature The seasonal differences between the ECMWF and the Reference station data are small: the ECMWF seems to overestimate the mean UHI during October until February, when the Reference data gives values close to 0 °C. The structure of both plots is the same, with the direction and relative intensity of the UHI following the same pattern. The direction of the hysteresis curve is clockwise, which is in agreement with the findings of Zhou et al.

(2013), who find a clockwise direction for the majority of cities in their research. The maximum magnitude of the hysteresis effect is about 1.1 °C for the Reference data and 0.6 °C for the ECMWF, due to the higher winter UHI intensity. This hysteresis effect means that for the same air temperature, differences in radiation uptake and partitioning or wind speed (advection) cause a difference in mean UHI intensity at night. Autumn and spring have roughly the same rural air temperature, and the difference in UHI is likely caused by radiation: there is more insolation during the spring months, which translates to more nocturnal heat release by the urban fabric.

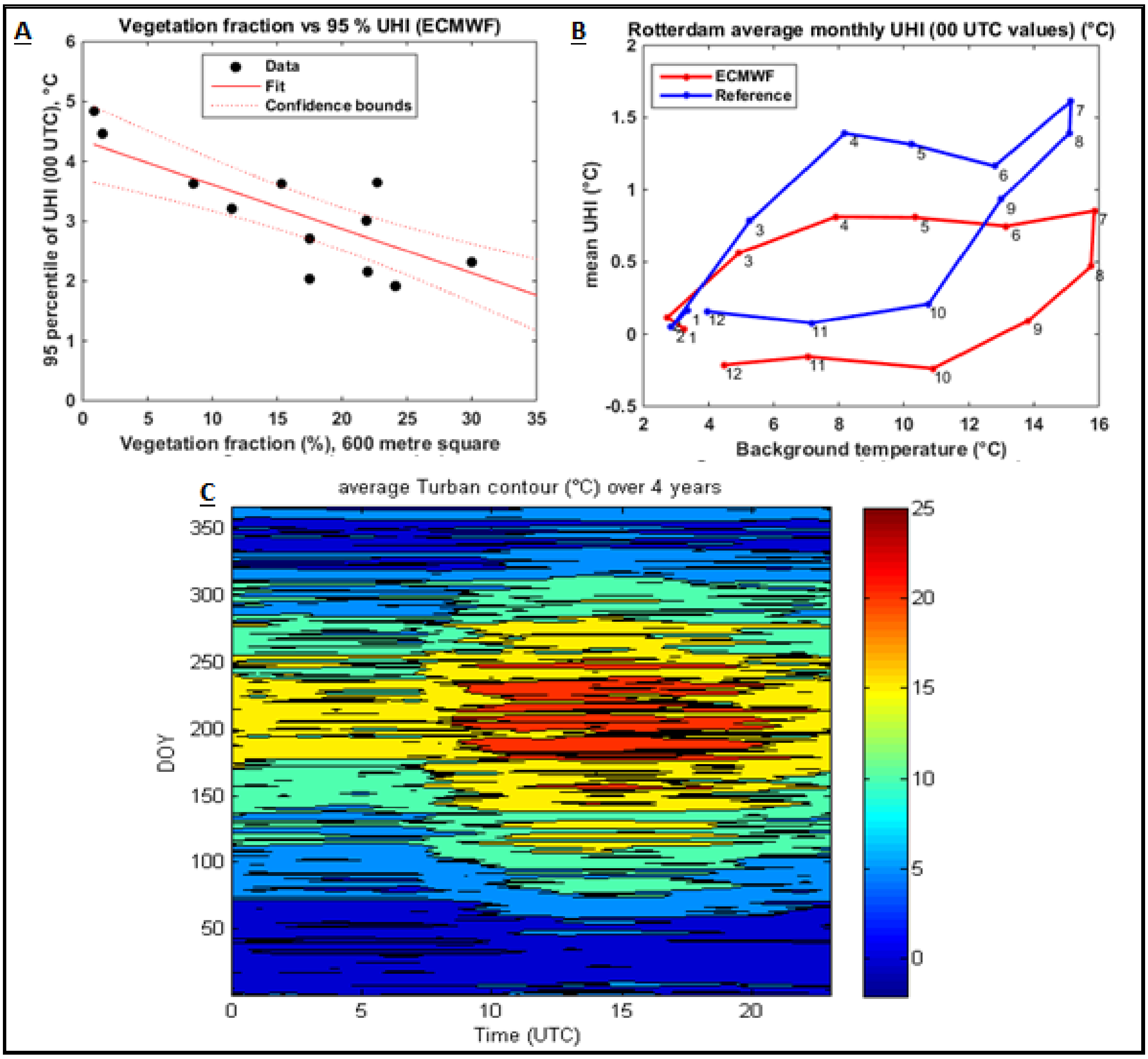

Figure 1: Rotterdam: Statistical regression of UHI of urban canopy stations (ECMWF data used) against vegetation fraction (A); Seasonality of the UHI (B, number markers indicate the month of the year), and average urban temperature throughout the year (C, with time in UTC on the x-axis and the Day of the Year (DOY) on the y-axis) of Rotterdam. All UHI values calculated at 00 UTC.

Figure 1c shows the diurnal cycle of the urban temperature throughout the year. Considering the difference between spring (DOY 90 to 150) and autumn (DOY 275 to 330) at 0 UTC, May (DOY 120 to 150) seems to be significantly warmer at night (typical temperature around 10 °C) than October or November (typical temperature around 7 to 8 °C), even though the rural background temperature is roughly equal. In July and August the UHI intensity is the largest, confirming theory: the insolation is large, causing increased heat uptake by the urban fabric during the day and subsequent nocturnal release, increasing UHI. There is a curious peak in UHI intensity in April, seen in both the ECMWF and the Reference data. At this time of year the solar radiation is not at its peak yet, but is starting to increase, and air temperatures are generally low. A high UHI indicates either a high city temperature, which we deem unlikely due to the aforementioned weaker solar radiation input, or a low rural background temperature.

Oke (1982) reports that in temperate latitudes the highest UHI intensities are most often found during summer and autumn; Georgescu et al. (2012, in Zhou et al., 2013) also report summertime maxima and less intense UHI during spring and autumn for the USA; Kim and Baik (2002) conversely report weakest UHI in the summertime for Seoul, and moderate UHI in spring. Offerle et al. (2006) performed flux measurements in Lodz, Poland, and their results show that April and May have a significantly higher sensible heat flux during the day than October and November. This could indicate that during the day the urban canopy layer warms up and retains some of that heat during the night due to heating from the built environment, giving rise to high urban heat islands even in spring.

A second explanation can be related to the vegetation: the Reference station of Rotterdam has a grass-cover all around it, which is active early in the year, whether the city also contains some shrubs and trees, which start actively growing later in the year. Active vegetation has a higher latent heat flux than inactive or dead vegetation, which decreases the sensible heat flux if the net radiation is equal. This causes evaporative cooling of the surface layer and therefore colder rural air temperature compared to the urban environment.

3.2 Madrid

Figure 2a shows the relation between 95 percentile UHI and the vegetation fraction for the Madrid stations (ECMWF data). The regression model is not significant: i.e. a constant value has more predictive power than the statistical model. R^2 values range are 6.9% for Barajas and 9.1% for the ECMWF data, with only canopy stations included. With all stations included, R^2 is around 1%. Performing the regression using median UHI instead of 95 percentile slightly increases the model reliability: R^2 values go up to around 12% and the p-values decrease slightly, but not well enough to speak of a significant statistical relationship.

Our hypothesis is that this could be due to the different type of vegetation in the city. Madrid has more trees and shrubs than Rotterdam, which has predominantly grass. Moreover, Madrid is situated in a dry climate, meaning that the rural surroundings are not irrigated naturally. Therefore, the vegetation is no longer active in summertime to decrease rural temperatures, whereas in the city itself gardens and parks will be watered by the inhabitants and the municipality. We have repeated the regression looking only at the growing season of vegetation in spring and early summer (the MAMJ months). However, results do not change: R^2 values are still lower than 10% for both ECMWF and Barajas with similar p-values. Looking at the median UHI for the growing season we once again see a slight improvement, similar to the relation of the median with the all-year data. No statistical significant relationship can be established between the green vegetation cover and the UHI for Madrid.

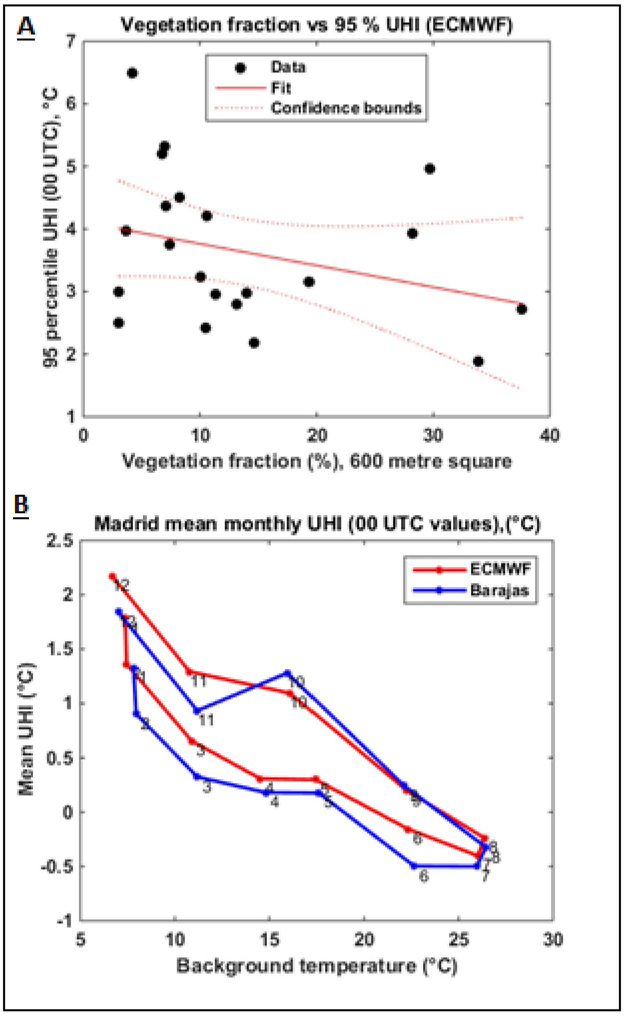

Figure 2: Madrid: Regression of 95 percentile UHI (ECMWF, only canopy stations) against vegetation fraction (A) and seasonal trend of the mean UHI in Madrid (B). The number markers indicate the month.

Figure 2b shows the seasonal UHI plot for Madrid. The plot shows an interesting pattern: the highest UHI intensity in winter and autumn, and the lowest (negative!) intensity during summer. The ECMWF data gives higher UHI values than Barajas airport for the winter months, and the opposite is true for the summertime where Barajas gives stronger negative UHI intensities. The direction of the hysteresis plot is counter-clockwise, as opposed to the results of Rotterdam. This indicates that spring has lower UHI (or negative UHI in this case) than the autumn for the same rural air temperature.

Zhou et al. (2013) have considered Madrid specifically in their analysis, and they find a negative UHI intensity during the summer as well, with typical values of between -1 and -2 °C. In our results we find summertime UHI intensities of around -0.5°C, which is markedly less. Zhou et al. (2013) also have a different course of their hysteresis curve, which moves clockwise with peak UHI lying in spring (though small, on the order of 0.5 °C) and wintertime UHI close to 0 °C. Their hypothesis for the hysteresis curve is related to different phenological phases in urban and rural areas, meaning that the onset of the growing season might be different between these areas, similar to our hypothesis for Rotterdam.

A second possible cause for the negative UHI intensity in summer is the anthropogenic water flux. The irrigation in the city during the dry summer months causes an influx of water in the urban environment that is absent in the rural environment. The potential evaporation is very high during the hot summer months, so any additional water will be evaporated, changing the flux partitioning. Moreover, in southern European countries it is common to clean the streets with water, which provides another anthropogenic water flux into the urban system (Grimmond et al., 2010). This increased latent heat compared to the dry rural area causes city temperatures to be lower, causing a negative UHI.

3.3 Oslo

Performing the regression for the 95 percentile UHI for Oslo (fig. 3a) gives no significant results for either reference data set: both ECMWF and the Bjørnholt WMO station show a scattered UHI without pattern (R^2 around 0.09 for only canopy stations). Plotting the same regression for the median UHI only deteriorates the relation, R^2 going down to 0.02. The regression line seems to be trending upwards, though the slope is not significant and therefore no true conclusions should be made about this characteristic. It could partially be explained by the Norwegian Weather Service stations: they seem to give lower air temperatures than the Wunderground stations, most likely due to being well-ventilated and therefore less prone to heat up. The Alna station, located near the railway station, is one of these, and has the lowest green cover and a low UHI. Removing these stations from the regression does not improve the regression line (since the weak pattern vanishes) but does make the line straight again, suggesting no actual relation.

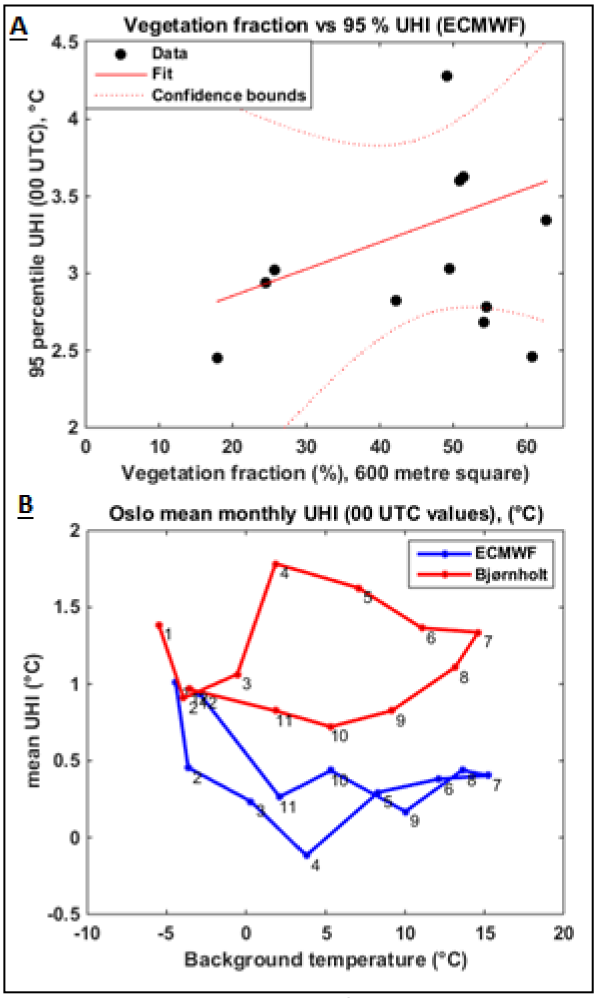

Figure 3: Oslo: Regression of 95 percentile UHI (ECMWF) against vegetation fraction (A) and seasonal trend of the mean UHI for Oslo (B)

Figure 3b shows the seasonal plots for the ECMWF data and the Bjørnholt reference data. There is no strong hysteresis effect visible as was the case for Rotterdam, and maximum UHI seems to occur during the winter (ECMWF) or spring (Bjørnholt). Remarkable is that the two data sources have an opposite hysteresis direction: While the ECMWF data shows a counter-clockwise direction, the Bjørnholt plot is going clockwise, which strokes with the findings by Zhou et al. (2013). This large difference between the datasets shows that the choice of reference station is very crucial in determining the UHI magnitude (which Sakikabara and Owa, 2005, already warned for), and conclusions should therefore be drawn with care. For the ECMWF data the standard deviation of the UHI is larger than the hysteresis effect (on the order of 0.5 °C), and what we see in the plots could therefore just as well be caused by statistical error rather than actual physical phenomena. For Bjørnholt this error is relatively smaller and the hysteresis shape could generally be trusted. In April the UHI is at its peak, which we have also observed in Rotterdam, with minimum UHI during the autumn and slightly increasing in winter again. The high winter UHI could be caused by Bjørnholt's remote location (to the north of Oslo), rather than something happening in the city itself. A plot of the temperature values of Bjørnholt and the ECMWF has shown that Bjørnholt is nearly 4 degrees colder during the yearly minima, which occur in these winter months. The UHI in winter can be caused by anthropogenic heat release during winter, which governs the UHI at higher latitudes due to the limited radiation (Oke, 1982). The water influence of the Oslofjord likely plays a large role in the local urban climate as well, cooling the city during summer and heating it up during winter, giving rise to the wintertime UHI.

4. Conclusions

We have researched the influence of urban vegetation on the maximum Urban Heat Island in 3 different cities across Europe, and have assessed the value of using ECMWF model output to serve as rural background values to calculate the UHI. Our results show that the ECMWF is a good alternative for UHI calculations, though the resulting UHI values are generally lower than those calculated from reference measurements.

We find a robust statistical relationship between vegetation fraction and the UHI for the city of Rotterdam, with between 0.5 °C and 0.75 °C maximum UHI reduction for every 10% additional vegetated surface. This is close to Steeneveld et al. (2011) who found 0.6 °C reduction per 10% vegetation. For Madrid and Oslo we are unable to produce a significant statistical relationship. In Madrid, the UHI is negative during summer, likely caused by the water shortage in the rural surrounding and the anthropogenic water flux in the city, causing elevated evaporation and therefore cooler temperatures. In Oslo, the UHI is largest in springtime, and the seasonality of the UHI intensity could be caused by the large influence of the water of the Oslofjord bordering the city, cooling the urban fabric during summer and warming it during winter. Our results suggest regional climate has a large influence on the way vegetation affects the UHI.

5. Acknowledgments

We thank all the weather hobbyists uploading their personal weather station data to the Wunderground platform for providing such a versatile and extensive source of urban meteorological data; Jan Elbers for maintaining the Rotterdam CPC data network and providing information; Bert van Hove for sharing methods and suggestions about the Rotterdam data analysis and the Norwegian Weather Service for the data for Oslo.

6. References

Bell P. A., 1981: Physiological, Comfort, Performance, and Social Effects of Heat Stress. *Journal of Social Issues*, **37**, 71–94,

Georgescu M. Mahalov, A. and Mousaoui M., 2012: Seasonal hydro-climatic impacts of Sun Corridor expansion. *Environmental Res. Letters*, **7**

Grimmond C. S. B., Blackett M., Best M. J., Barlow J., Baik J. J., Belcher S. E., Bohnenstengel S. I., Calmet I., Chen F., Dandou A., Fortuniak K., Gouvea M. L., Hamdi R., Hendry M., Kawai T., Kawamati Y., Kondo H., Krayenhoff E. S., Lee, S. H., Loridan, T., Martilli A., Masson V., Miao S., Oleson K., Pigeon G., Porson A., Ryu Y. H., Salamanca F., Shashua-Bar, L., Steeneveld, G. J., Tombrou, M., Voogt, J., Young, D. and Zhang, N., 2010: The international urban energy balance models comparison project: first results from phase 1. *J. Appl. Meteor.*, **49**, 1268-1292

Heusinkveld B. G., Steeneveld G. J., Van Hove L. W. A., Jacobs C. M. J. and Holtslag A. A. M., 2014: Spatial variability of the Rotterdam urban heat island as influenced by urban land use. *J. Geophys. Res. Atmos*., **119**, 677-692

Jacob D., Bärring L., Christensen O. B., Christensen J. H., De Castro M., Déqué M., Giorgi F., Hagemann S., Hirschi M., Jones R., Kjellström E., Lenderink G., Rockel B., Sánchez E., Schär C., Seneviratne S. I., Somot S., Van Ulden A. and Van den Hurk B., 2007: An inter-comparison of reguibal climate models for Europe: model performance in present-day climate. *Clim. Change,* **81**, 31-52

Kim Y. and Baik J., 2002: Maximum urban heat island intensity in Seoul. *J. Appl. Meteor.*, **41**, 651–659.

Offerle B., Grimmond C.S.B., Fortuniak K., Klysik K. and Oke T.R., 2006: Temporal variations in heat fluxes over a central European city centre. *Theor. Appl. Climatol.*, **84**, 103–115

Oke T. R., 1982: The energetic basis of the urban heat island. *Quart. J. R. Met. Soc.*, **108**, 1-24.

Petralli M., Massetti L., Brandani G. and Orlandini S., 2014: Urban planning indicators: useful tools to measure the effect of urbanization and vegetation on summer air temperatures. *Int. J. Climatol.*, **34**, 1236–1244

Poumadère M., Mays C., Le Mer S. and Blong R., 2005: The 2003 Heat Wave in France: Dangerous Climate Change Here and Now. *Risk Analysis*, **25**, 1483–1494.

Sakakibara Y and Owa K., 2005: Urban-rural temperature differences in coastal cities: influence of rural sites. *Int. J. Climatol*., **25**, 811-820.

Steeneveld, G. J., Koopmans S., Heusinkveld B. G, Van Hove L. W. A. and Holtslag A. A. M (2011). Quantifying urban heat island effects and human comfort of variable size and urban morphology in the Netherlands. *J. Geophys. Res*., **116**

United Nations, department of social and economic affairs, 2012: World urbanization prospects: the 2011 revision: highlights. http://esa.un.org/unup/pdf/WUP2011_Highlights.pdf (retrieved on 17-9-2014)

Van Hove L.W.A., Jacobs C.M.J., Heusinkveld B.G., Elbers J.A., Van Driel B.L. and Holtslag, A.A.M., 2015: Temporal and spatial variability of urban heat island and thermal comfort within the Rotterdam agglomeration. *Building and Environment*, **83**, 91-103.

Zhou B., Rybski D. and Kropp J.P., 2013: On the statistics of urban heat island intensity. *Geophys. Res. Letters*, **40**, 5486-5491.