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# DOCTORAL PROGRAMME

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**Information Management**  
Specialization in Geographic Information  
Systems

**CLIMATE CHANGE AND IMPACTS IN THE URBAN  
SYSTEMS**

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## ABSTRACT

Urban systems are not only major drivers of climate change, but also impact hotspots. The processes of global warming and urban population growth make our urban agglomerations vulnerable to chain reactions triggered by climate related hazards. Hence, the reliable and cost-effective assessment of future climate impact is of high importance. Two major approaches emerge from the literature: i) detailed spatially explicit assessments, and ii) more holistic approaches consistently assessing multiple cities. In this multidisciplinary thesis both approaches were addressed. Firstly, we discuss the underlying reasons and main challenges of the applicability of downscaling procedures of climate projections in the process of urban planning. While the climate community has invested significant effort to provide downscaling techniques yielding localised information on future climate extreme events, these methods are not widely exploited in the process of urban planning. The first part of this research attempts to help bridge the gap between the communities of urban planners and climatologists. First, we summarize the rationale for such cooperation, supporting the argument that the spatial scale represents an important linkage between urban and climate science in the process of designing an urban space. Secondly, we introduce the main families of downscaling techniques and their application on climate projections, also providing the references to profound studies in the field. Thirdly, special attention is given to previous works focused on the utilization of downscaled ensembles of climate simulations in urban agglomerations. Finally, we identify three major challenges of the wider utilization of climate projections and downscaling techniques, namely: (i) the scale mismatch between data needs and data availability, (ii) the terminology, and (iii) the IT bottleneck. The practical implications of these issues are discussed in the context of urban studies.

The second part of this work is devoted to the assessment of impacts of extreme temperatures across the European capital cities. In warming Europe, we are witnessing a growth in urban population with aging trend, which will make the society more vulnerable to extreme heat waves. In the period 1950-2015 the occurrence of extreme heat waves increased across European capitals. As an example, Moscow was hit by the strongest heat wave of the present era, killing more than ten thousand people. Here we focus on larger metropolitan areas of European capitals. By using an ensemble of eight EURO-CORDEX models under the RCP8.5 scenario, we calculate a suite of temperature based climate indices. We introduce a ranking

procedure based on ensemble predictions using the mean of metropolitan grid cells for each capital, and socio-economic variables as a proxy to quantify the future impact. Results show that all the investigated European metropolitan areas will be more vulnerable to extreme heat in the coming decades. Based on the impact ranking, the results reveal that in near, but mainly in distant future, the extreme heat events in European capitals will be not exclusive to traditionally exposed areas such as the Mediterranean and the Iberian Peninsula. Cold waves will represent some threat in mid of the century, but they are projected to completely vanish by the end of this century. The ranking of European capitals based on their vulnerability to the extreme heat could be of paramount importance to the decision makers in order to mitigate the heat related mortality. Such a simplistic but descriptive multi-risk urban indicator has two major uses. Firstly, it communicates the risk associated with climate change locally and in a simple way. By allowing to illustratively relate to situations of other capitals, it may help to engage not only scientists, but also the decision makers and general public, in efforts to combat climate change. Secondly, such an indicator can serve as a basis to decision making on European level, assisting with prioritizing the investments and other efforts in the adaptation strategy. Finally, this study transparently communicates the magnitude of future heat, and as such contributes to raise awareness about heat waves, since they are still often not perceived as a serious risk.

Another contribution of this work to communication of consequences of changing climate is represented by the MetroHeat web tool, which provides an open data climate service for visualising and interacting with extreme temperature indices and heat wave indicators for European capitals. The target audience comprises climate impact researchers, intermediate organisations, societal-end users, and the general public.

**Keywords:** urban climate; downscaling; climate change; impact assessment; adaptation planning; urban planning, heat waves, ranking, communication of climate change



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## **LIST OF ACRONYMS**

**AHWI** – Apparent Heat Wave Index

**ANN** – Artificial Neural Network

**CC** – Climate Change

**CCA** – Canonical Correlation Analyses

**CDF** – Cumulative Distribution Function

**CDO** – Climate Data Operator

**CORDEX** – Coordinated Regional Climate Downscaling Experiment

**CW** – Cold Wave

**CWMId** – Cold Wave Magnitude Index daily

**DG** – Directorates-General

**DMI** – Danish Meteorological Institute

**DRM** – Disaster Risk Management

**EC** – European Commission

**EEA** – European Environmental Agency

**EOF** – Empirical Orthogonal Function

**ESG** – Earth System Grid

**ETCCDI** – Expert Team on Climate Change Detection and Indices

**EU** – European Union

**FAO** – Food Agriculture Organization

**GAM** – Generalized Linear Models

**GCM** – Global Circulation/Climate Model

**GDP** – Gross Domestic Product

**GFCS** – Global Framework for Climate Services

**GIS** – Geographic Information System

**HSD** – Heat-induced Sleeping Discomfort

**HW** – Heat Wave

**HWMI<sub>d</sub>** – Heat Wave Magnitude Index daily

**I/O** – Input/Output

**IPCC** – Intergovernmental Panel on Climate Change

**IPSL** – Institute Pierre Simon Laplace

**IT** – Information Technology

**KNMI** – Koninklijk Nederlands Meteorologisch Instituut

**LAM** – Limited Area Models

**LCDM** – Land Cover Deltatron Model

**LMA** – Large Metropolitan Area

**MME** – Multi Model Ensemble

**MOS** – Model Output Statistics

**MRE** – Monitoring, Reporting and Evaluation

**NASA** – National Aeronautics and Space Administration

**NetCDF** – Network Common Data Form)

**NRC** – National Research Council

**NSRP** – Neymar-Scott Rectangular Pulses

**NWP** – Numerical Weather Prediction

**OCT** – Open City Toolkit

**OECD** – Organisation for Economic Co-operation and Development

**OGC** – Open Geospatial Corporation

**PCA** – Principal Component Analyses

**PerfectProg** – Perfect Prognosis

**PMP** – Precipitation

**RCM** – Regional Circulation/Climate Model

**RCP** – Representative Concentration Pathways

**SMHI** – Swedish Meteorological and Hydrological Institute

**SRES** – Special Report on Emission Scenarios

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**SREX** – Managing the risks of extreme events and disasters to advance climate change adaptation– Special Report

**SVD** – Singular Value Decomposition

**SW** – Soft Ware Probable Maximum

**UCAR** – University Corporation for Atmospheric Research

**UCM** – Urban Canopy model

**UHI** – Urban Heat Island

**UK** – United Kingdom

**UN** – United Nations

**UNFCCC** – United Nations Framework Convention on Climate Change

**US** – United States

**WEF** – World Economic Forum

**WG** – Weather Generators

**WGBT** – Wet-Bulb Globe Temperature

**WMO** – World Meteorological Organization

**WSDI** – Warm Spell Duration Index

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# 1 Introduction

## 1.1 Scientific Background

### 1.1.1 Climate Change

Continued warming of our planet is evident and captured in the observations. According to (Hansen et al., 2010), during the 1966-2015 period the global annual-mean surface air temperature increased by 0.17 °C per decade. This warming is even stronger (0.21 °C) when only the land area is considered. Another study by (Papalexiou et al., 2018) found a global increase of 0.19 °C per decade during the past 50 years, but with an acceleration up to 0.25 °C per decade in the last 30 years. Climatologists expect the global mean warming to be approximately 2 °C by 2050 (IPCC, 2014; Lelieveld et al., 2016), and the warming by the end of the century might reach up to 5.8 °C (Patz et al., 2005). Even if society acts responsibly and manages to keep global warming under the 2 °C increase relative to preindustrial era, a regional warming might strongly overpass this threshold (Seneviratne et al., 2010). While the global warming rate remains uncertain and climate projections vary in dependency of the used models and scenarios, there is a general agreement on overall warming trend (Tebaldi et al., 2006; Min et al., 2011; Fischer, 2014). Moreover, even a relatively small rise in average global temperature triggers significantly more severe extreme events (Katz et al., 2002; Russo et al., 2015). It was demonstrated by (Diffenbaugh et al., 2007) that severity of the hottest months and days of the year already increased.

Zhang et al., (2011) reported that since 1950 more than 70% of the sampled global land area undergone a significant increase in the occurrence of temperature extremes. A recent study utilizing data of about 9000 globally placed stations shows positive trends in the approximately 80% of studied area (Papalexiou et al., 2018). Moreover, in some regions, the exceedance of the 90th percentile of daily temperatures relative to the 1961–1990 reference period is expected to occur in 70% of the time for the last three decades of this century (Russo & Sterl, 2012; Zhang et al., 2011).

A general warming can be found for mid latitudes (Fischer et al., 2013), and more specifically for the Mediterranean area (Patz et al., 2005; Russo et al., 2014; Papalexiou et al., 2018), Western and Southern US (Patz et al., 2005), Indonesia, Africa, and both Americas (Russo et al., 2014), and Europe (e.g. Lhotka et al., 2018; Russo et al., 2014; Papalexiou et al., 2018) large portions of Russia (Russo et al., 2015), or Australia, Nepal, Myanmar, portions of China, Kazakhstan and Mongolia (Papalexiou et al., 2018). When the severe RCP8.5 scenario became a reality, the northern part of Brazil was also found to expect to suffer extreme heatwaves regularly (Russo et al., 2014). In fact, the heat impacts in Latin America (and generally in all humid regions) will be more severe, which is confirmed by modelling when the humidity is taken in the account (Russo et al., 2017). In contrary, Alaska, north-east Australia, and northern parts of Norway, Sweden and Finland show decreasing trends (Papalexiou et al., 2018).

Nearly all the regions exhibit stronger warm extremes and weaker cold extremes (Zhang et al., 2011), and warming is projected to accelerate in the future with steep growth in numbers of warm days and nights (Lelieveld et al., 2016). In the future, the increased persistency of large synoptic phenomena in the atmosphere might cause higher extreme temperatures and more severe heat waves (Barriopedro et al., 2011; Tomczyk & Bednorz, 2016; Pereira et al., 2017). The extreme climate events and their associated risks represent a more serious threat to natural and human systems than the changes in climatic mean (Weber & Sonka, 1994; Easterling et al., 2007; Meehl et al., 2000; Tebaldi et al., 2006; Zhou et al., 2004; Zwiers et al., 2011; Mekasha et al., 2014; Seo et al., 2016).

### **1.1.2 Climate Change and Heat Waves**

The Intergovernmental Panel on Climate Change (IPCC) have confirmed that the trends in global temperature experienced over the last century cannot be explained solely on the basis of inherent variability of the climate system (Houghton et al., 2001). Since then, many others have started to argue about the importance of anthropogenic influence in this process. The World Meteorological Organization (WMO, 2015) states that from 79 scientific studies published in the Bulletin of the American Meteorological Society in a period between 2011 and 2014, the majority confirmed that extreme meteorological events were magnified by anthropogenic factors. However, regardless of what is the real trigger in that phenomenon, climate change is a fact and society needs to address this issue and its consequent threats. The *Met Office* Hadley Centre, HadCRUT4.4.0.0, (Morice et al., 2012) projected that the global average temperature would probably cross the symbolic threshold of 1 °C above the pre-industrial era in 2015. This scenario was recently preliminary confirmed by WMO (WMO, 2015). Worldwide, the period between 2011 and 2015 has been the warmest on record with the highest global average temperature estimates most likely assigned to year 2015. The warming of 2015 is a flag of great importance because it represents global warming of 1 °C (UK Met Office, 2015), which represents the half of internationally agreed limitation in order to avoid dangerous climate change (UNFCCC, 2011). According to WMO, this is caused by an extremely strong El Nino phenomenon, which is itself a result of greenhouse warming (Cai et al., 2014).

The last five years were outstanding in terms of occurrence of many extreme meteorological events – the heat waves in particular. Only in 2015 major heat waves have stroked India in May and June with average maximum temperatures over 42 °C, and locally exceeding 45 °C, which caused over 2300 deaths (Hussain et al., 2016). Heat waves also occurred in Europe (Duchez et al., 2016), northern Africa and Middle East where many new temperature records were set. In May extremely high temperatures were reported in Burkina Faso, Niger and Morocco. Portugal and Spain were exposed to unusually high temperatures as well. In July, Denmark, Morocco and Iran were affected by heat waves. The month of August brought a heat wave to Jordan and, simultaneously, the city of Wroclaw (Poland) experienced some all-time high temperatures with a peak of 38.9 °C on the 8<sup>th</sup> of August. The heat spread up over Eastern Europe in September, and the record high temperatures were exceeded in South Africa on a regular basis in spring 2015 (WMO, 2015).

According to the analysis of the last half decade many extreme events, especially those related to temperature extremes, have had resolutely increasing probability of occurrence as an impact of anthropogenic climate change. These probabilities have grown by a factor of 10 or higher in some cases. The most steadily growing increase in these probabilities has been on extreme heat (WMO, 2015).

### **1.1.3 Urbanization and Population Boom**

In parallel with climate change, we are witnessing a population boom and the vast majority will concentrate in large metropolitan agglomerations. In 2007, first time in history, the urban population exceeded the rural one. Therefore, the human kind became predominantly urban based. The number of rural dwellers has been growing since 1950 and it is projected to reach its peak in near future (UN, 2014). However, this report also states that in early twenties of the century, the global rural population will start to decline towards 3,2 billion in 2050.

In 2014, about 3.9 billion people, representing 54% of global population, were urban dwellers. Half of the urban population is resided in small agglomerations up to half-million inhabitants. Roughly one of eight urban dwellers is an inhabitant of a megacity (settlements with population of 10 million or more). The number of megacities nearly tripled since 1990. Currently, we have 28 megacities on the planet, and they are home to 453 millions of people. The United Nations (UN, 2014) projected that by year 2030 there will be 41 megacities on the Earth. In previous decades, the largest agglomerations were located in developed regions, but currently the world's largest cities are in global South. The projections say that by 2050 the urban systems will be home to 66% of global population, representing 6.3 billion urban dwellers (UN, 2014).

Cities are commonly associated with the concentration of economic activity, and thus provide its inhabitants with higher level of literacy, education, better healthcare, access to social services and opportunities for cultural and political participation. However, urban environment is nowadays more unequal than rural areas, and a large proportion of urban poor is living in metropolitan systems with sub-standard conditions. The urban poor are especially vulnerable to extreme weather events, and climate change related disasters caused population loss in some cities. If poorly planned and managed, urban expansions may lead to sprawl, pollution and environmental degradation (UN, 2014).

The official outcome of RIO+20 conference entitled *“The Future We Want”* clearly states that the development of sustainable urban systems is crucial and that cities can lead the way to an economically, socially and environmentally friendly future if the holistic approach to urban planning and management will be applied (UN, 2012).

### **1.1.4 Climate Change and Cities**

Cities and climate change are mutually connected. Urban systems act as important economic hubs and, as such, they are very demanding on resources. Globally, the energy consumption of urban agglomerations is up to 80% of the total energy production, which represents approximately 71–76% of global CO<sub>2</sub> emissions (UN, 2014). This illustrates the important role of urban areas as drivers of global warming, but also their potential for mitigating high carbon

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dioxide emissions. The urbanized areas are not only major drivers of climate change, but simultaneously they are hot spots of climate change impact. Cities are challenged by intersecting issues related to increasing risk of climate hazards and continuing processes of population boom and urbanization (GERISC, 2015).

Providing services like public transport, housing, electricity, water and sanitation is typically cheaper and more environmental friendly in dense urban systems than in rural areas. These services require certain infrastructure. For example, the energy infrastructure leverages economic development, health and quality of life in general. Disruptions of electricity, gas and fuel supplies can have serious consequences on business, healthcare, energy services, schools, street lighting, water treatment and supply, public transport, road traffic management and public safety. For instance, extreme temperature can possibly impact the production of electricity, depending on the particular location and overall context (Rosenzweig et al., 2011). The foreseen life time of infrastructure components varies between 5 and 50 years (in some cases 100 years). Therefore, the current decision making will define not only the safety, but also the contribution of the energy sector on greenhouse warming (IPCC, 2014).

In general, urban systems are hot spots of various disaster risks, which make them especially vulnerable to chain reactions (WEF, 2015). In addition, many of the world's agglomerations are from historical reasons located in areas highly exposed to multiple hazards (Akbari et al., 1999; Haigh, 2012). Most likely, cities will be increasingly exposed to impacts of climate change in form of urban flooding, flash floods, river floods, and heat waves causing high levels of air pollution triggering serious health problems. Climate change has major economic consequences in form of reduction in labour productivity, disruption of transport systems and significant losses in energy production and its supply chains (Confalonieri et al., 2007).

According to Hartmann et al., (2013), one of the major symptoms of climate change relevant for urban systems are heat waves. Their frequency probably increased since the middle of twentieth century. Constant grown of urban population is driving the replacement of natural vegetation cover by artificial surfaces (EC-DG Environment, 2012). This accelerates the urban heat island phenomenon, and reduces the capacity of natural retention and infiltration of precipitation. One of the most direct consequences is an increase in the seasonal mean temperatures (Collins et al., 2013). Furthermore, increasing temperatures and changes in rainfall variability will only amplify this problem (Revich & Shaposhnikov, 2012). This also indicates that the magnitude of impacts is a function of both the societal and the climatological factors (Rosenzweig et al., 2011).

The impact of climate change in urban areas is often worsened by systematic interaction within the inner city environment, and by processes occurring in rural areas surrounding the urban settlements (OECD, 2014). The local authorities should plan and manage the urban system aiming to improve the resilience to extreme meteorological events. Adaptation measures should focus on a regional and local scale in order to solve issues related to the connection of fresh air zones inside and outside the urban agglomeration boundaries (GERISC, 2015). The capacity of local governments to face the impacts of climate change will be tested for the combination of increasing occurrence of natural disasters, insufficient management strategies and rapid urbanization (Tanner et al., 2009). The mortality due to natural disasters is highest in developing



countries, while overall economic damage is greatest in developed regions. One of the key reasons of life losses is an absence of efficient early-warning systems (Zommers, 2012).

Under good and qualified management, the process of urbanization can provide an opportunity to economic growth with simultaneous positive environmental development. In the same time, rapid urbanization can strengthen the magnitude of almost every global risk, and local impacts can also be further amplified by unsustainable production and consumption patterns (GERISC, 2015).

### 1.1.5 Natural Hazard Assessment

When the climate change and the evaluation of climate impacts are discussed, the assessment of associated potential natural disasters is in the centre of attention. Diagram below (Figure 1) depicts the essential components of assessment of natural hazards related to climate change. Taking into consideration the realistic time and resources constraints, the majority of our effort will be devoted to the key generic steps: “Weather and Climate Events” and “Exposure” components, rather than attempt to execute a complete assessment of potential natural hazards related to climate change.

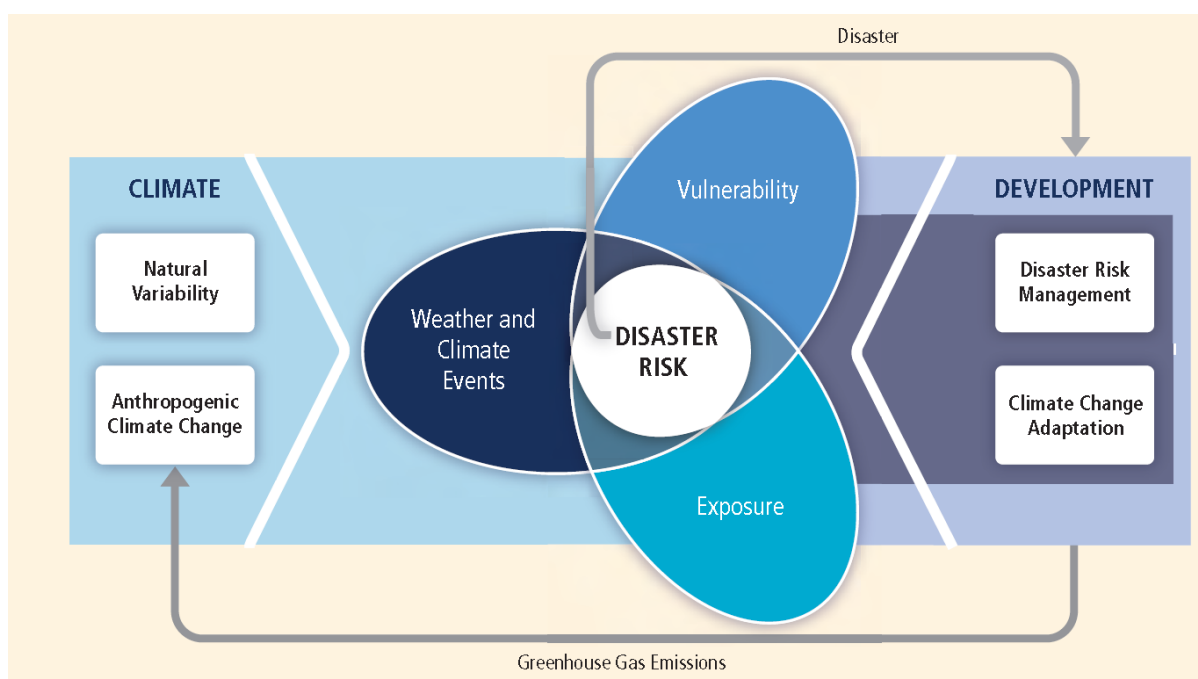


Figure 1 - Scheme of natural hazard assessment (IPCC, SREX, 2001).

### 1.1.6 Modelling of the Impacts of Future Climate

The general recipe for estimating the impact of future climate events (not considering the Exposure and Vulnerability parts of Natural Hazard Assessment) consists of deployment of the ensemble of numeric physical models, establishing the robust metrics able to detect the extremes of interest, and the interpretation of obtained results. The members of a Climate

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Model Ensemble should be ideally validated against reliable observational datasets or, for data scarce regions, against reanalyses products (so-called hind cast procedures). When the model runs for a historical period are found valid, also the future projections are considered as a reliable base of future climate behaviours assessment. Regarding the future periods, considering that our planet is undergoing global warming and local climate exhibits increased variability, the models have to incorporate future scenarios reflecting the directions and magnitude of changes in the evolution of the climate variables relevant to climate impacts of interest. The numerical models provide the simulated climate variables (e.g. daily maximum near-surface temperature, daily precipitation, etc.) but the bigger impacts are commonly associated with the occurrence of extreme events, for example, the prolonged periods of extreme heat or drought. For that purpose, robust and understandable Climate Indices have to be deployed to consistently capture the impacts (e.g. Zhang et al., 2011). The definition of extreme in long time-span is challenging – current extremes are likely to become the future norms (Argüeso et al., 2016). Moreover, the climate indices should be chosen from widely utilized indicators to allow for comparison amongst the studies. For example, in plain words, the term “Heat Wave” can mean various different things (Zhang et al., 2011). The suit of selected climate indices also should be aligned with the purpose of the study. Nevertheless, generally, the climate indicators represent the quantification of climate related natural hazards.

### **1.1.7 Multi-Model Ensemble Problem**

Multi-Model Ensembles are broadly defined as a set of model runs originating from structurally different models. In context of climate ensembles, the projections come from numerical models parametrizing or resolving the selected relevant process. Various types of climate ensembles are recognised, for example, the superensembles (contain more sets of initial conditions for each particular model), or the perturbed physics ensembles (composed from multiple runs of single model but with different settings of parameters) (Tebaldi & Knutti, 2007). The principle that using a combination of multiple models outperforms any single projection or forecast is anchored on the assumption that errors tend to cancel out in the ensemble, when the individual members are independent. Thus, with increasing number of simulations, the overall uncertainty should decrease. The usage of this approach is not at all limited solely to the domain of climate and meteorological science. The examples manifesting the improvement in skill, reliability and consistency of prediction can be found in the public health sector (Early warning system for Malaria occurrence (Thomson et al., 2006)) or in agriculture (crop yield projection by (Cantelaube et al., 2004)). The ensemble problem is also related to the field of machine learning, where, for instance, all the trees of random forest can be seen as an individual members of a large ensemble.

To understand why are climate Multi-Model Ensembles (MMEs) somewhat particular, the model structure and model uncertainties should be addressed. Undoubtedly, the different groups around the world develop different circulation models relatively independently. However, there is a whole list of unavoidable similarities. For instance, the parallel developed models aim to provide similar resolution and thus they cannot resolve (therefore they have to parametrize) the same physical phenomenon. The theoretical arguments derived from state-of-the-art physics are likely to be the same. Additionally, the computational methods (including the same known shortcomings) are unavoidably common to many circulation models (Tebaldi, 2007). On the top

of that, in the spirit of open science, especially in case of successful models, the entire model components are open and therefore borrowed by other modelers in order to improve and speed up their own development efforts. All abovementioned is resulting in presence of the persistent bias in climate MME (Tebaldi, 2007).

When designing the model, certain choices have to be made and they may implicitly exhibit uncertainty. This uncertainty is difficult to capture by changing parameters within a single model. Such an uncertainty contains not only the theoretical aspects like assumptions, simplifications or choices in parametrizations of physical processes, but also the implications of practical decisions such as numerical aspects of the choice of the grid, the resolution or the truncation. These abovementioned uncertainties are attributed to model structure (Tebaldi & Knutti, 2007). In order to understand and quantify the uncertainty in climate change projections, the structural uncertainties should be deeply investigated. Without such an evaluation it is not possible to guarantee that results do not strongly exhibit artefacts of the individual structures. This represents the strongest argument supporting the utilization of ensembles of different models (Tebaldi & Knutti, 2007). In climate modelling, the total uncertainty is composed of partial uncertainties of completely different nature and origin: firstly, natural fluctuation emerging in climate in the absence of any radiative forcing of the planet. This uncertainty is commonly referred to as the internal variability of the climate system. Secondly, the response uncertainty. It is a model uncertainty in the response to the same radiative forcing. Thirdly, we recognize uncertainty originating in scenarios for future emissions of greenhouse gases, related to potential anthropogenic influence based on the future socio-economic and technological evolution (Hawkins & Sutton, 2012). The proportional influence of all three abovementioned components of uncertainty depends on the prediction lead time and also varies with spatial and temporal scale (Räisänen & Palmer, 2001). The model and scenario derived uncertainties play an important role in long term predictions (e.g. many decades) at regional and larger scales. On the other hand, in context of projections covering upcoming one or two decades at regional spatial scale, the model uncertainty and inner-variability are the most influential (Hawkinson & Sutton, 2012). It should be noted that in the context of climate MME, the uncertainty due to inter model variance and the internal variability of each model should be kept separated. This recommendation is based on the fact that the first mentioned component is not a fundamental property of the climate system, whilst the second one is (Hawkins & Sutton, 2012). Understanding the uncertainty in climate modelling is crucial not only in order to be detected, quantified and attributed, but also for purposes of the adaptation and mitigation planning (Deser et al., 2012).

### **1.1.8 Adaptation and Mitigation**

It is important to describe the concept of sustainable city in terms of efforts towards urban development satisfying environmental, socio-cultural and economic needs of inhabitants, in order to highlight the interactions of mitigation and adaptation measures when applied at different scales (Georgescu et al., 2015).

Strategies to mitigate negative impacts of urbanization on the environment (e.g. urban heat or air pollution) commonly account for direct modifications of surface's properties and surface energy balance (Oke, 2006). For instance, covering the roofs with high albedo materials

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increases the reflectance and therefore, diminishes the heat storage and consequent sensible heat (Akbari et al., 1999). Furthermore, deployment of highly permeable concrete or tarmac also decreases the amount of heat stored in urban fabric and enables larger surface evaporation (Stempihar et al., 2012). The urban green rises the intensity of the latent heat fluxes and provides direct shading from the vegetation canopy (Dimoudi & Nikolopoulou, 2003). Moreover, in the mitigation and adaptation portfolio, recent technologies complement above-mentioned well established methods (Georgescu et al., 2015). Specifically, these technologies encompass utilization of phase change solar energy storing materials (Santamouris et al., 2011), photovoltaic pavements and canopies (Golden et al., 2007) and waste usage for power generation purposes (Persson & Werner, 2012). In the city context, deployment of these technologies may change water and surface energy cycles, which subsequently mitigates the urban heat island (UHI) effect and therefore, reduces an energy demand and green gas emissions (Georgescu et al., 2015). Also, the anthropogenic heat when put in use for power generation, can be seen as an energy-saving opportunity (Salamanca et al., 2014). The physical principles behind those processes and impacts of related adaptation approaches are well known at various spatial extents, but multi-scale impacts on urban systems need further investigation (Georgescu et al., 2015).

When choosing an appropriate adaptation strategy, the scale interdependency should be considered. Certain approaches (e.g. green roofs) provide micro-scale benefits, where most of the profit is given to selected stakeholders concentrated in vicinity of building rooftop. In contrary, the urban planners should be aware of synoptic and global climate because those may significantly narrow down the portfolio of applicable micro-scale solutions (Georgescu et al., 2015). For instance, in urban systems periodically exposed to dust storms, the effect of installation of highly reflective roofs will be significantly lowered by decrease in albedo due to fine particle deposition (Getter & Rowe, 2006). Moreover, climatological impacts occurring at the larger scale may unexpectedly influence a metropolitan system. For example, high reflectivity can detrimentally influence a hydrology cycle in urban area and as such cause decrease in regional-scale precipitation (Bala & Nag, 2012). Specific climatic conditions predefine effective adaptations. The strategies should be harmonious with large spatial sustainability context. Hence, for example, utilizing non-native flora (aiming for local temperature reduction) with high water demand in arid zones may result to reduction in city water supply (Ruddell & Dixon, 2014). According to Georgescu et al. (2015), the balance between localized cooling and water scarcity in cities should be subject to further research.

Even individual building can have decadal or century-times scale impact. Decisions of urban planners also have climate-related spatial impacts and planning process should consider the limits on parallel or concurrent development resulting from scale interdependent phenomena (Mills et al., 2010). Buildings relatively taller than surrounding constructions would alter shading, near-surface temperature and the wind regime which consequently influence the thermal comfort and the air quality in the area, particularly in case of cumulated impacts related to the rapid development. As an example can serve the study of Pearl River delta in East China, which documents the impact of the sum of rapid development onto regional air quality (Lu et al., 2009). The decision makers should be aware of scale interdependency dimension of development in order to optimize strategies across various spatial scales. Georgescu et al. (2015), clearly states

that not all the adaptation and mitigation measures should be given an equal weight across all spatial scales. In addition, there is still demand for deeper analysis, tool development and coordinated efforts, which should rise from the collaboration between global climate and urban communities and related disciplines.

Downscaling methods have been proposed to obtain regional and local-scale weather and climate data. Many well established researchers clearly state that there is a strong need of finer scale information on climate elements, particularly in areas of complex topography and with highly heterogeneous land cover (e.g. Giorgi et al., 2001; Mearns et al., 2003; Wilby et al., 2004). Describing in more detail the areas where information is needed, authors typically provide examples such as coastal areas, river mouths, islands or mountain regions. Until today, the urban systems are not explicitly mentioned on such lists, even though they fulfil the requirements of the above definition (considering the term “topography” in a broader sense). There are examples of successful applications of downscaling methods in the context of urban systems (e.g., Kusaka et al. (2012), predicting heat stress for Tokyo, Osaka and Nagoya metropolises). Furthermore, one of the most frequently mentioned main constraints of the application of downscaling techniques is the lack/scarcity of the observational data within the downscaling domain. However, the city, the smart city in particular, is an example of data generator, and as such perhaps this constrain is not potentially that disconcerting.

The problematics of scientific background is in reality far more complex and include many other aspects, namely the physical principles of heat wave formation, the urban specific temperature related physical processes, urban heat island phenomenon, impacts of extreme heat, the relation of heat and air pollution, physiological functioning of human bodies and health consequences, aging trends in European society, the different impact groups within a urban space, relation between climate science and urban planning, importance of data scale for mitigation and adaptation planning, definition of extremes, the issues of downscaling and comparative ranking, and the communication of climate change. These topics are addressed in more detail in the following chapters of the thesis.

## **1.2 Problem Statement**

The key messages of previous paragraphs frame the scope and relevance of this study. The planet is currently undergoing a process of climate change and greenhouse warming. The heatwaves are one of the most amplified symptoms of this change. Human kind is currently predominantly urban based, and the majority of ever continuing population growth will take place in urban agglomerations. In warming Europe, we are witnessing a growth in urban population with aging trend, which will make the society more vulnerable to extreme heat waves. In the period 1950-2015 the occurrence of extreme heat waves increased across European capitals. As an example, Moscow was hit by the strongest heat wave of the present era, killing more than ten thousand people. Cities are especially vulnerable to impacts of climate change. Urban systems are not only major drivers of climate change, but also impact hot spots. Furthermore, the impacts are commonly managed in city scale. In the same time, when managed in a sophisticated manner, urbanization can provide an opportunity to mitigate natural risks related to climate change. The prevention, mitigation and adaptation measures are and will be managed by local authorities and commonly at city scale. Therefore, assessing climate

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change impacts on quality of life and on infrastructures in urban systems is an important area of research. Not only the processes and their impacts on all levels (local, meso and global scale), but also the interactions between those should be subject to detailed analysis. While global and regional climate projections are currently available, local-scale information is lacking. Such a detailed information is crucial for impact assessment studies, particularly in urban areas. The assessment of vulnerability of European capitals to extreme heat could be of paramount importance to the decision makers in order to mitigate the heat related mortality, especially with the foreseen increase of global mean temperature.

### **1.3 Research questions**

This research work adds to the body of knowledge on climate change and impacts in the urban systems by addressing the key question:

- Which are the current and future impacts of extreme temperatures in the main European metropolitan systems?

Three research questions emerge from this general question:

- Which European capitals will be affected by more intense and frequent heat waves towards the end of the century?
- Which European capitals will be affected by more intense and frequent cold waves towards the end of the century?
- How can such information be deployed to different stakeholders (such as impact researchers, city planners, decision makers and citizens) in a simple and effective manner?

### **1.4 Objectives**

The main objective of this thesis is to assess current and future impacts of extreme temperatures in European capitals.

A number of detailed objectives emerge from this general objective:

- To analyse how is the climate information being incorporated into the decision process and urban planning.
  - To rank the European capitals in terms of impacts of extreme temperatures.
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- To compare the impacts of extreme temperatures in European capitals by taking into account the population exposure.
- To provide recommendations and tools that can help urban inhabitants, city planners, and decision makers to adapt or mitigate the impacts of extreme temperature events.

In order to address the proposed objectives, the research methodology includes three main stages. First, a thorough literature review and discussion on the multidisciplinary issues involved are undertaken. This stage is crucial, because it is expected to contribute to the selection of appropriate methods, tools and information sources, which may be useful not only in the following research stages, but also for impact researchers and city planners.

Secondly, climate projections data for Europe from Multi-Model Ensembles are collected, and a set of indices of extreme temperatures and heat waves (HWs) and cold waves (CWs) indicators are computed. A ranking procedure is then proposed, accounting for the different spatial extents of European capitals, the length of each assessed period (near past, near future, and future), and different impacts' magnitudes of HWs and CWs. The ranking procedure is then extended to account for population exposure. The results of this research stage are expected to provide further insights on the impacts of extreme temperatures and related population exposure across all the European capitals. Moreover, we expect to raise awareness about HWs, since they are still often not perceived as a serious risk (Keramitsoglou et al., 2017).

Finally, the third stage is dedicated to the development of a Web tool, in order to provide an open data climate service for visualising and interacting with extreme temperature indices and HWs indicators for European capitals. We expect that this tool may contribute to the effective communication of the complex issue of climate change to a large audience.

## **1.5 Thesis outline**

The thesis is organised in five chapters and appendixes. The first chapter discusses the motivation and relevance of the research work, states the objectives and the research questions, and briefly summarises the methodological stages. This chapter ends with a brief overview of each of the main chapters, and their links to published or submitted scientific articles.

Chapter 2 is mainly based on the article "Climate projections and downscaling techniques: a discussion for impact studies in urban systems" published in the International Journal of Urban Sciences (Smid & Costa, 2017). This chapter provides a literature review on the thesis topics, particularly on localised climate projections, emphasising their statistical downscaling, and on the relations between the fields of climate science, urban planning and policy making. Section 2.1 is dedicated to downscaling procedures of climate projections data. Further details on the most significant statistical downscaling procedures are disclosed in Appendix A. In Section 2.2, emphasis is given to recent advancement in urban studies incorporating climate projections. Chapter 2 also includes a discussion on the applicability of climate data to urban planning practice where three main bottlenecks of wider utilization of localized climate projections in planning of adaptation and mitigation measures and urban design in general are formalized.

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Chapter 3 is an extension of the submitted article “Ranking European Capitals by Exposure to Heat Waves and Cold Waves”. This section presents the research on the impact of future heat waves and cold waves in 31 European capital cities using an ensemble of 8 GCM/RCM models under the RCP8.5 scenario from EURO-CORDEX. In section 3.5 we introduce a ranking procedure based on the ensemble predictions, and population density as a proxy to quantify the future exposure. Section 3.6 covers the obtained results. The ranking of European capitals based on their exposure to extreme heat is of paramount importance to decision makers in order to mitigate the heat related mortality, especially with the foreseen increase of global mean temperature. Furthermore, this simple comparative indicator is expected to help communicating the global, complex and impersonal issue of climate change locally thus contributing to raise awareness and call for action.

Chapter 4 is devoted to the Web tool developed as an integrated part of the Open City Toolkit (OCT) of the Geoinformatics: Enabling Open Cities (GEO-C) project [642332 — GEOC — H2020-MSCA-ITN-2014; <http://www.geo-c.eu/>]. The architecture, functionalities and the purpose of the Web tool are detailed in this chapter, which is an extension of the submitted article “MetroHeat web tool: a communication service of climate change impacts on temperature over European capitals”.

Finally, Chapter 5 states the conclusions of this study by summarising the main findings and contributions of the research work, and by pointing out a number of suggestions for further research.



## 2 Literature Review

In the warming world, we are witnessing an urban population boom and an increasing number of megalopolis areas (Yang & Chen, 2007). Projections indicate that by 2050 urban systems will be home to 66% of the global population, representing 6.3 billion urban dwellers (UN, 2014). Urban systems act as important economic hubs and, as such, they provide its inhabitants with higher quality of life, including health, cultural and psychological aspects (Murray, 2011). Urbanized areas are not only major drivers of climate change (CC), but are simultaneously hot spots of CC impact, and many of the world's agglomerations are located in areas highly exposed to multiple hazards (Akbari et al., 1999; Haigh & Amaratunga, 2012). CC impacts on urban systems may cause the stagnation of the state or entire country (Malakar & Mishra, 2017). Climate change has major economic consequences in the form of reduction in labour productivity, disruption of transport systems and significant losses in energy production and its supply chains (Confalonieri et al., 2007). Mortality due to natural disasters is highest in developing countries, while overall economic damage is greatest in developed regions (Kousky, 2014). However, economic development significantly decreased disaster damage (Choi, 2016).

All the above-mentioned illustrates the importance of CC impact assessment in urban contexts. While impact assessments are commonly based on the output of state-of-the-art GCM-RCM simulations (Regional Circulation Models nested within General Circulation Model) providing information at scales varying between 12.5 and 50 km, the process of urban planning operates with finer scales exploiting detailed knowledge of neighbourhoods sometimes even at sub-street level. The GCM-RCMs are numerical coupled models describing atmosphere, oceans, land surface, sea ice and interactions among those earth systems. Those models remain essential tools to assess climate change (Fowler et al., 2007). However, their coarse resolution and inability to resolve sub grid scale features limits their usability. A large portion of impact studies operates on scales finer than common resolution of global or even regional model outputs (Wilby et al., 2004).

The strong need for higher resolution climate data for impact assessment is a long time well-known issue (e.g., Cohen, 1996; Kim et al., 1984). This interest originated in the recognized discrepancy of course resolution GCMs (hundreds of kilometres) and the scale of interest of impact studies (an order or two orders of magnitude finer scale) (Hostetler, 1994). The impact applications are highly sensitive to local climate variation, and as such they require information proportional to the point climate observations. The fine-scale variations are parametrized in lower resolution models. The requirement of fine-scale information emerges particularly in regions of complex topography (Giorgi & Bi, 2000; Mearns et al., 2003; Wilby et al., 2004). Describing areas where information is needed in more detail, authors typically provide examples such as coastal areas, river mouths, islands or mountain regions. Until today, urban systems are not explicitly mentioned on such lists, even though they fulfil the requirements of the above definition (considering the term 'topography' in a broader sense).

When choosing an appropriate adaptation strategy, scale interdependency should be considered. Certain approaches (e.g. green roofs) provide micro-scale benefits, where most of the advantage is given to selected stakeholders concentrated in the vicinity of building rooftops.

On the contrary, urban planners should be aware of synoptic and global climate change because this may significantly narrow down the portfolio of applicable micro-scale solutions (Georgescu et al., 2015). For instance, in urban systems periodically exposed to dust storms, the effect of installation of highly reflective roofs will be significantly lowered by the decrease in albedo due to fine particle deposition (Getter & Rowe, 2006). Moreover, climatological impacts occurring at a larger scale may unexpectedly influence a metropolitan system. For example, high reflectivity can detrimentally influence a hydrology cycle in an urban area and as such cause a decrease in regional-scale precipitation (Bala & Nag, 2012). Georgescu et al. (2015), clearly states that not all adaptation and mitigation measures should be given an equal weight across all spatial scales. In addition, there is still demand for deeper analysis, tool development and coordinated efforts, which should rise from the collaboration between global climate and urban communities and related disciplines.

GCM-RCM outputs are still insufficient for the analysis of many regional and local climate aspects, such as extremes. GCMs of very high resolution would indeed improve the simulations of regional and local aspects (Christensen et al., 2007), but they remain unreachable due to the enormous computational cost (Fowler et al., 2007), which leads to the accommodation of downscaling techniques (Rummukainen, 2010).

## **2.1 Downscaling of climate projections**

In this study the term “Downscaling” refers to techniques improving spatial or/and temporal resolution of climate projections. Principally any data can be refined by downscaling techniques (Rummukainen, 2010). Coarse GCM output might be satisfactory, for example when the variation within a single grid cell is low or in case of global assessment. The main advantage of information directly obtained from GCM is the certainty that physical consistency remains unattached (Mearns et al., 2003). GCMs are valuable predictive tools, but they cannot account for fine-scale heterogeneity and reflect on features like mountains, water bodies, infrastructure, land-cover characteristics, convective clouds and coastal breezes. Bridging this gap between the resolution of climate models and regional and local scale processes represents a considerable challenge. Moreover, the uncertainties that characterize the GCMs/RCMs are generally aggravated when these models are downscaled, which is the crucial step for identifying the city-specific impacts and, consequently, to identify vulnerabilities. Hence, the climate community put significant emphasis on the development of techniques for downscaling (Fowler et al., 2007).

There is no consensual and unique classification scheme to be applied in attempts to comprehensively review and summarize the downscaling techniques. In many studies (e.g. Fowler et al., 2007; Khan et al., 2006; Trzaska & Schnarr, 2014), the methods are categorized into two main groups: Dynamical downscaling and Statistical downscaling. Dynamic downscaling is based on RCMs or fine spatial-scale numerical atmospheric models, such as Limited Area Models (LAM) (Feser et al., 2011; Fowler et al., 2007). Statistical downscaling is based on observed relationships between climate at fine and coarse resolutions that are used to transform global climate models’ output to finer resolution. Alternatively, Mearns et al. (2003) distinguish three groups of approaches: High resolution GCMs; Nested LAM and RCMs; and Empirical/Statistical and statistical/dynamical methods. Within the group of Statistical downscaling, many approaches can be distinguished and classified according to different criteria. For example, Wilby et al. (2004) provide background information and guidance on the application of some Statistical downscaling methods, but also listed alternatives to downscaling techniques (thus somehow excluding those from the family of downscaling methods) including spatial interpolation of grid points (sometimes named ‘unintelligent downscaling’), climate sensitivity analysis (frequently addressed as bottom-up approach), spatial/temporal analogues using historical data and simple change factor (known as Delta method). Giorgi et al., (2001) provide a survey of statistical downscaling techniques focusing on studies published between 1995 and 2000. More detailed review of downscaling techniques in field of climate projections can be found in appendix A.

### **2.1.1 Dynamical downscaling**

In a nutshell, dynamical downscaling represents a group of methods originally used in numerical weather forecasting (Rummukainen, 2010). The first studies establishing the foundation of

regional modelling are Dickinson et al., (1989) and Giorgi & Bates, (1989). Since then, the field has undergone massive development (e.g., Christensen et al., 2007; Feser et al., 2011; Giorgi et al., 2001; Hong & Kanamitsu, 2014; Xue et al., 2014; Wang et al., 2004). Dynamical models address data and physical processes equivalent to GCMs, but at finer scales, and provide results only for selected limited regions of the globe (Trzaska, & Schnarr, 2014). RCMs utilize the same physical-dynamical definitions of the key climate processes as GCMs. Atmospheric fields representing the output of a global model (e.g. surface pressure, wind, temperature and humidity) are loaded into vertical and horizontal boundaries of the RCM. Administering of boundary conditions represents a major challenge of dynamical downscaling (Rummukainen, 2010). The physics-based equations and locally specified data are used to gain regional climate outputs (Trzaska, & Schnarr, 2014). The unresolved inner-cell variabilities are pushed to RCM output rather than fully taken into account. All the inner-cell fine scale processes are approximated in a procedure called parametrization (Rummukainen, 2010).

Two major streams are recognizable in dynamical downscaling. In the first, the resolution is increased over the entire domain of the atmospheric global model (e.g., Christensen et al., 2007). The second strategy is based on the utilization of a global model with variable grid cell size (Fox-Rabinovitz et al., 2008; Lal et al., 2008). This technique maintains a coarse grid over the majority of the globe, but increases the resolution within a particular area of interest (Rummukainen, 2010).

The earlier RCMs resolution used to vary between 100 to 50 km, and at its best 25 km grid cells (Rummukainen, 2010). The more recent development proved that RCMs are capable of delivering high resolution results (20 km or less) (Leung et al., 2003; Mearns et al., 2003). Consequently, increasing resolution also entails increasing computational cost and data volume. RCMs also require a high level of expertise to interpret the results. Moreover, the RCM experiments require high frequency (e.g. 6 hours) GCM fields supply for boundary conditions. These data are not usually stored due to mass-storage demand (Mearns et al., 2003). Due to these practical limitations, the regional dynamical downscaling models remain out of reach for a vast majority of researchers. Accordingly, the emphasis in this paper is given on the application of statistical downscaling techniques.

### **2.1.2 Statistical downscaling**

Statistical downscaling, also known as ‘Empirical/statistical’ or ‘Statistical/dynamical’ downscaling (Mearns et al., 2003), is based on the perspective that regional climate is mainly conditioned by two factors: the large-scale climate and the local/regional features such as topography, land-sea distribution or land use (Fowler et al., 2007; Mearns et al., 2003; Zorita & Von Storch, 1999; Wilby et al., 2004). The large scale climate variables are used as ‘predictors’ to regional or local variables named ‘predictands. Fowler et al. (2007) expressed the essence of the idea of statistical downscaling as the following descriptive equation:

$$R=F(X)$$

where R represents the local climate variable which is subject to downscaling, X is the set of large climate variables, and F is a function which relates R and X being validated by the use of point observations or/and gridded reanalysis data. This equation represents the most common

form, but other relationships have been used, such as relationships between predictors and the statistical distribution parameters of the predictand (Pfizenmayer & von Storch, 2001), or the frequencies of extremes of the predictand (Katz & Group, 2002).

Statistical downscaling allows one to simultaneously simulate multiple outputs such as precipitation, maximum and minimum temperatures, solar radiation, relative humidity and wind speed (e.g. Parlange & Katz, 2000), which is of great importance, particularly for impact studies (Wilby et al., 2004). It is also possible to downscale predictors independently, but in such a case, it is crucial to ensure that inter-variable relationships remain intact.

The performance of downscaling techniques depends on the choice of the regional domain (Wilby & Wigley, 2000), which in practice is often not considered (Benestad, 2001), and also depends on the regionalization methods (Wilby et al., 2004). Gutiérrez et al. (2013) assessed the performance of statistical methods commonly used for downscaling temperature (including Analogue methods, Weather typing techniques, Multiple linear regression, and Regression conditioned on weather types) with respect to their robust applicability in climate change studies. These authors established a new validation framework exploiting the anomalous warm historical periods. Based on this framework the study concluded that regression methods are the most appropriate in regard to climate change studies. Weather typing was found to underestimate the temperature in moderately warmer conditions and Analogue methods, even though best reproducing the observed distributions, significantly underestimate the temperatures for warm periods in comparison with observed values.

Operational weather forecasting approaches, such as Perfect Prognosis (Perfect Prog) (Von Storch et al., 1993) and Model Output Statistics (MOS) (Wilks, 1995, 1999), may also be incorporated in statistical downscaling (e.g., Feddersen & Andersen, 2005). These approaches, also named statistical post-processing methods, have been successful in correcting many deficiencies inherent to forecasts from numerical weather prediction models (Marzban et al., 2006). Both groups of methods use large multiple regression equations, taking advantage of the correlations between predictand and regressors. The classification has its foundation in the character of the employed predictors (Maraun et al., 2010).

Perfect Prog was developed to exploit the deterministic nature of dynamical Numerical Weather Prediction (NWP) models. Large scale observational data are often replaced by the reanalysis products, and the MOS approach is also rooted in NWP (Glahn & Lowry, 1972). The main principle is to exploit statistical relationships between local observational data and simulated output of the numerical model, in order to correct for RCMs errors (Maraun et al., 2010). This approach allows for the impact of a particular dynamical model to be directly reflected at different projections. A limitation of MOS models is that the data set must contain both the historical records of the predictand and the corresponding stored records of the forecast produced by the dynamical model.

### **2.1.3 Discussion of downscaling approaches**

The choice of an appropriate method, or even deciding whether or not it is convenient to apply a downscaling procedure, is often not straightforward (Mearns et al., 2003). Nevertheless, frequently, the global or continental scale information is implemented directly, which negatively

affects the resulting local scale impact maps (Trzaska, & Schnarr, 2014). We acknowledge that the most cutting edge approach to provide future localised climate information is to combine dynamical downscaling with further statistical advancement and bias corrections, as Lemonsu et al., (2013) did when assessing the evolution of Parisian climate. However, these authors had access to a luxurious retrospective dataset with high spatial-temporal resolution for evaluation purposes. Moreover, their skills, expertise and the access to (funding, time and computational power) resources were arguably outstanding. Those advantages are usually associated with larger cities hosting universities and other institutions able to help with such sophisticated planning. Smaller urban systems often struggle to obtain such support, mainly in terms of expertise (Georgi et al., 2006). This is of high importance since consistent long-term urban policy should be based on systematic local participation.

On the other hand, the major practical limitation of regional dynamical downscaling, which is its high computational demand (Mearns et al., 2003; Fowler et al., 2007; Rummukainen, 2010), is not so impactful in the case of empirical/statistical downscaling techniques. Furthermore, statistical downscaling allows to simultaneously simulate multiple outputs such as precipitation, maximum and minimum temperatures, solar radiation, relative humidity and wind speed (e.g. Parlange & Katz, 2000), which is of great importance, particularly for impact studies (Wilby et al., 2004). This flexibility, together with their reachability to wider urban stakeholder communities, determines the focus of this paper in terms of practical bottlenecks discussed below. In the following, we outline the strengths and weaknesses of statistical downscaling approaches.

The climate community invested significant effort to compare the methods of statistical downscaling (e.g., Benestad, 2001; Dibike & Coulibaly, 2005; Huth, 1999; Khan et al., 2006; Schoof & Pryor, 2001; Widmann et al., 2003; Wilby & Wigley, 1997; Zorita & Von Storch, 1999). Schoof (2013) provides a broad overview of statistical downscaling for studies on regional climate change, focusing on downscaling assumptions, choices of predictors and predictands, and methodological approaches.

The strengths and weaknesses of distinct approaches of statistical downscaling are summarized in Table 1. The basic assumption of stationarity is essential, but it also represents the major theoretical weakness of statistical downscaling (Wilby et al., 2004). The concept of stationarity assumes that the statistical relationship between the predictor and predictand will not change in future climate (Fowler et al., 2007). However, there is evidence that this may not occur (e.g. Fowler & Kilsby, 2002; Slonosky et al., 2001). Stationarity of the predictor-predictand relationship can be tested using long records, or a period of different climate characteristics can be used for model validation. Non-stationarity is introduced by an incomplete set of predictors, which does not reflect the low frequency behaviour, or has an inappropriate sampling or calibration period, or by real changes in the climate system. However, in projected climate change, the circulation dynamics may be robust to non-stationarities and the associated degree of non-stationarity is relatively small (Hewitson & Crane, 2006).

When applied to a changing climate, another key assumption inherent to statistical downscaling is that the predictors should 'carry the climate change signal' (Giorgi et al., 2001). Selected predictors should be physically meaningful and reflect the processes which subsequently control

variability in the climate. The selected predictor variables should also be those that are well represented by GCMs (Fowler et al., 2007). Appropriately selecting variables is in the equilibrium between the relevance in the physical climate reality and the accuracy with which the predictor is reproduced by the climate model (Wilby & Wigley, 2000). Partial correlation analysis, step-wise regression or an information criterion are examples of procedures that may be preliminarily applied in order to identify the most promising predictor variables (Wilby et al., 2003). Also, local knowledge and expert opinion are priceless information sources in attempts to assemble the most effective set of predictors (Wilby et al., 2004).

When the statistical downscaling model is not able to consolidate land surface forcing, meaning that the simulated regional climate is determined solely on the basis of free atmospheric variables, the CC scenario will omit changes in land-surface feedback. However, it is acknowledged that local land use management influences regional climate, vegetation cover and runoff regimes (e.g. Chase et al., 2001, Kalnay et al., 2006; Prudhomme et al., 2002).

Table 1 - Strengths and weaknesses of statistical downscaling methods with sample studies.

Strengths	Weaknesses	Sample studies
<b>Weather typing</b>		
<ul style="list-style-type: none"> <li>• Yields physically interpretable linkages to surface climate.</li> <li>• Versatile (e.g., can be applied to surface climate, air quality, flooding, erosion, etc.).</li> <li>• Compositing for analysis of extreme events.</li> </ul>	<ul style="list-style-type: none"> <li>• Requires additional task of weather classification.</li> <li>• Circulation-based schemes can be insensitive to future climate forcing.</li> <li>• May not capture intra-type variations in surface climate.</li> </ul>	<ul style="list-style-type: none"> <li>• <b>Empirical Orthogonal Functions (EOFs)</b> (Goodess &amp; Palutikof, 1998)</li> <li>• <b>Cluster analyses</b> (Cheng, Auld, Li, Klaassen, &amp; Li, 2007; Cheng, Yu, Li, Li, &amp; Chu, 2009; Osca, Romero, &amp; Alonso, 2013)</li> <li>• <b>Fuzzy methods</b> (Bardossy, Bogardi, &amp; Matyasovszky, 2005; Bárdossy, Stehl'ik, &amp; Caspary, 2002; Teutschbein, Wetterhall, &amp; Seibert, 2011)</li> <li>• <b>Analogue method</b> (Zorita, &amp; Von Storch, 1999)</li> <li>• <b>Hybrid approaches</b> (Enke, Deuschländer, Schneider, &amp; Küchler, 2005)</li> </ul>
<b>Weather generators</b>		
<ul style="list-style-type: none"> <li>• Production of large ensembles for uncertainty analysis or long simulations for extremes.</li> <li>• Spatial interpolation of model parameters using landscape.</li> <li>• Can generate sub-daily information.</li> </ul>	<ul style="list-style-type: none"> <li>• Arbitrary adjustment of parameters for future climate.</li> <li>• Unanticipated effects to secondary variables of changing precipitation parameters.</li> </ul>	<ul style="list-style-type: none"> <li>• <b>Markov chains</b> (Camberlin, Gitau, Oettli, Ogallo, &amp; Bois, 2014; Kim, Kim, &amp; Kwon, 2011)</li> <li>• <b>Markov processes of second order</b> (Mason, 2004; Qian, Hayhoe, &amp; Gameda, 2005)</li> <li>• <b>Markov processes of third order</b> (Dubrovský, Buchtele, &amp; Žalud, 2004)</li> </ul>



Strengths	Weaknesses	Sample studies
<b>Regression methods</b>		
<ul style="list-style-type: none"> <li>• Relatively straightforward to apply.</li> <li>• Employs full range of available predictor variables.</li> <li>• ‘Off-the-shelf’ solutions and software available.</li> </ul>	<ul style="list-style-type: none"> <li>• Poor representation of observed variance.</li> <li>• May assume linearity and/or normality of data.</li> <li>• Poor representation of extreme events.</li> </ul>	<ul style="list-style-type: none"> <li>• <b>Regression-based and Generalized Linear Models (GAM)</b> (Bergant &amp; Kajfež-Bogataj, 2005; Hellström, Chen, Achberger, &amp; Räisänen, 2001; Korhonen, Venäläinen, Seppä, Järvinen, &amp; others, 2014)</li> <li>• <b>Principal Component Analyses (PCA)</b> (Kidson &amp; Thompson, 1998; Sarhadi, Burn, Yang, &amp; Ghodsi, 2017)</li> <li>• <b>Artificial Neural Networks (ANN) and machine learning algorithms</b> (dos Santos, Mendes, &amp; Rodrigues Torres, 2016; Joshi, St-Hilaire, Ouarda, &amp; Daigle, 2015)</li> <li>• <b>Canonical Correlation Analyses (CCA)</b> (Karl, Wang, Schlesinger, Knight, &amp; Portman, 1990; Skourkeas, Kolyva-Machera, &amp; Maheras, 2013)</li> <li>• <b>Singular Value Decomposition (SVD)</b> (Chun, Sung, Woo-Seop, Oh, &amp; Hyojin, 2016; Huth, 1999; Liu &amp; Fan, 2012; Zwiers &amp; Von Storch, 2004)</li> <li>• <b>Kriging and other spatial interpolation approaches</b> (George, Janaki, &amp; Gomathy, 2016; Ramos, St-Onge, Blanchet, &amp; Smargiassi, 2015)</li> </ul>

Statistical downscaling methods tend to underestimate the variance and poorly represent extreme events. Therefore, the techniques that introduce additional variability are frequently utilized (Fowler et al., 2007). A method magnifying the variability by multiplication by a suitable factor is known as ‘Variance inflation’ (Karl et al., 1990). The randomization method adds variability in the form of white noise, and provided good results in returned values of surface temperature for central Europe (Kyselý, 2002). A more sophisticated approach to add variability to statistical models is a variant of canonical correlation analysis called ‘Expanded downscaling’ (e.g., Huth, 1999; Müller-Wohlfeil et al., 2000). Each of the abovementioned approaches have different drawbacks (Bürger & Chen, 2005). Variance inflation does not adequately reflect spatial correlations. Randomization poorly transfers change in variability that influences expected future change. Expanded downscaling is highly susceptible to the choice of statistical processes during its own application (Fowler et al., 2007).

Generic weakness of statistical downscaling is high demand on available data. On the other hand, the computational cost of statistical downscaling is relatively low. Therefore, it may appear to be an advantageous alternative for projects where the computational capacity, technical expertise or time represent significant restriction (Trzaska, & Schnarr, 2014). Statistical downscaling may be appropriate for impact studies in heterogeneous regions with complex topography and steep environmental gradient (e.g. islands, mountains, land/sea contrast), or in

cases where point scale information is required (e.g. local flooding, soil erosion, urban drainage, etc.), or to produce large ensembles and transient scenarios (Wilby et al., 2004).

## 2.2 Climate projections and urban studies

This section illustrates the variety of current approaches available to study potential impacts of CC in urban systems, thus it provides a typological summary rather than a comprehensive review of the field. The studies are organised from the point of view of the scale and the complexity of deployed downscaling techniques with highlights of unique features. We start with relatively simple studies utilizing the data from only one weather station. Then we move to works assessing climate change in more than one metropolitan system, but sometimes considering each city as a point feature. Finally, we focus on complex studies deploying various techniques of statistical and dynamical downscaling, exploiting a range of environmental indices and (apart from the climate simulations) deploying sophisticated models of future evolution of urban land cover.

The first group of urban studies commonly uses observational data from just one or few measurement stations (weather or rain gauge stations) for validation purposes. These time series are used to correct bias in dynamically simulated GCMs or RCMs in order to obtain more reliable projections of urban climate. This approach is widely used in hydrology and the term downscaling frequently refers to temporal disaggregation of the data (e.g. Hingray & Haha, 2005; Huang & Lu, 2015; Willems & Vrac, 2011).

Sunyer, Madsen, & Ang, (2012) considered future scenarios for a location north of Copenhagen (Denmark) using simulated data from a set of RCM projections of the ENSEMBLES project (Van der Linden & Mitchell, 2009) with spatial resolution of 25 km. This study compares five statistical downscaling methods: two regression models and three weather generators. The regression methods exploit the different statistical properties, namely changes in mean and changes in mean and variance. The Weather Generators (WGs) are a Markovian chain model, a semi-empirical model and a Neymar-Scott Rectangular Pulses (NSRP) model. The paper by Sunyer et al. (2012) is also outstanding for its highlights of the importance of the limitations and advantages of different downscaling techniques.

Somewhat related is a study of Onof & Arnbjerg-Nielsen, (2009), but with focus given solely to WGs. The rainfall generator in this method is composed of two features: the storm structures are captured by the hourly generator and then the disaggregator provides hourly information at finer temporal scales. Another difference from Sunyer et al. (2012) lies on the method of transformation of the areal information (RCM output) to the point scale. Here, the areal information is represented by a grid-squared product of the Danish Meteorological Office with a resolution of 10 km. For each gauge, the RCM cell containing the gauge and the eight neighbouring cells are considered. Then the mean and standard deviation over those nine grid-squares are used in the fitting of the hourly generator. This strategy was also applied by Willems & Vrac (2011). These authors used two sets of methods. One of them was the direct usage of climate models output with computation of quantile perturbations on extreme events. The study tested the assumption that the same perturbations remain constant for finer temporal scales. The second group of methods belong to the family of Weather typing approaches, which account for low accuracy of daily precipitation in current climate models by considering that

change in precipitation is not only a function of change in atmospheric circulation but it also depends on temperature rise.

Recently, Batista et al., (2016) assessed the impact of future heat in the metropolitan region of São Paulo (Brazil) based on the Indoor Perceived Equivalent Temperature (IPET) index. The IPET was computed on the adjusted cutting-edge multi model climate project CORDEX, which is an international initiative for downscaling climate projections from different parts of the world. More specifically, Batista et al. (2016) deployed CREMA (CORDEX REgCM4 hyper-Matrix experiment) simulations. This study is unique considering the use of measurements from two weather stations for validation purposes, which is justified by the varying wind conditions in the city.

Another group of studies focused on the impact of CC in urban systems by assessing multiple metropolitan areas simultaneously. Such studies, apart from their conclusions regarding specific cities, also allow for judgments at broader spatial domains (e.g. state or regional). For example, a study by Martin et al., (2012) assessed the potential temperature-related mortality under climate change for fifteen Canadian cities. This study shares some aspects with previously mentioned works, namely the strategy of the eighth neighbouring grid-cells centred at the observations' locations – in this case the airports. A distinctive feature of this work is the linkage between temperature and mortality, which was possible due to the cooperation between the authors and the Public Health Agency of Canada that provided the mortality data.

Fallmann et al., (2015) analysed various climate indices for eleven urban areas in Central Europe. This work used climate simulations of a non-hydrostatic Weather Research and Forecasting (WRF) model with the Advanced Research WRF-ARW dynamic solver version 3.1.1. of 7 km grid cell resolution. The E-OBS dataset (Haylock et al., 2008) was used for validation purposes. Another highlight of the study by Fallmann et al. (2017) is that it provides some hints on the technical / IT execution of the exercise, which is seldom addressed in scientific literature.

A very different study by Huang & Lu, (2015) assessed the effect of Urban Heat Island (UHI) on climate warming in the Yangtze river delta in China, which covers many metropolitan areas. The analyses were based on measurements from forty-one meteorological stations that uniformly covered the study area with data from 1957 to 2013. The authors provide the warming rates and estimates of the UHI contribution to observed warming. Another aspect of this study is the classification of the cities into levels according to population size and subsequently derived conclusions within those categories.

Another study for China region using climate simulations in the context of urban systems is the work of Li et al., (2015). The authors projected heat-related mortality for cardiovascular diseases and respiratory diseases. The interesting feature to be highlighted is that this work targets the specific causalities within those disease categories instead of the total heat-related mortality. On the other hand, the limitation of this study might be the usage of the ensemble consisting of only five GCMs (the rule of thumb recommends at least ten models). However, Li et al., (2016) have improved the study by utilizing thirty-one downscaled climate models for the same area. More importantly, they included the trend of aging population in the estimate of future heat-

related mortality. Consequently, this study provides the first evidence of the synergy in hybrid question of global warming and population aging in China.

Completely unparalleled is a study by Früh et al., (2011). Firstly, the RCMs runs were used as input for a dynamical model to obtain data at urban scale (horizontal resolution varies from 500 m at the outskirts to 50 m at the city centre), and then the microscale simulations covering thirty-year time slices (past and future) were delivered via the Cuboid method. This method considers the assumption that it is possible to reduce the problem into three degrees of freedom: the 2-m air temperature, the 2-m humidity and 10-m wind speed. This approach is related to the family of envelope models used in Ecology. Only a small set of meteorological conditions are being simulated and the specific day characteristics are derived by means of interpolation. According to Früh et al. (2011), this pragmatic approach provides approximated results but significantly decreases the computational cost.

A complex study by Hayhoe et al., (2004) assessed CC impacts on a medium size area of interest in California (USA), where one of the four locations considered for extreme heat analyses is located in the city of Los Angeles. This study used one lower (B1) and one higher (A1fi) Special Report on Emission Scenarios (SRES), which bracket a large proportion of various future emission scenarios. Dynamical models were statistically downscaled to a grid of  $1/8^\circ$  ( $\sim 13.5$  km) by a still popular downscaling method based on probability density functions. This approach belongs to the family of empirical-statistical downscaling techniques. Furthermore, simple regression was used to downscale to the locations of selected weather stations. The observed monthly regression relations were then applied to future projections to ensure that the approximated information on future climate shared the same weather statistics. Hayhoe et al. (2004) also reported that the extrapolation beyond the range of observed values were rarely needed because the simulated climate behaviour involves higher occurrence of warm days rather than an increase in expected absolute maxima. This study represents one of the most complex CC impact assessments in terms of impacted sectors: extreme heat, heat related mortality, snowpack, runoff, water supply, agriculture and general vegetation distribution. The most relevant conclusions in an urban context are about extreme heat and related mortality, but the authors also provide insights on future precipitation, snowpack, runoff, water supply, agriculture and vegetation cover.

Even though the study by Lee et al., (2016) is not urban specific, it used RCM simulations and has several unique aspects. The authors computed the Probable Maximum Precipitation (PMP) deploying data from 64 weather stations dispersed all over South Korea, which were interpolated into a 5x5 km grid by inverse distance weighting. The bias included in RCM simulation was corrected by the quantile-mapping method. First, the major storm events on the record were identified assuming that their associated precipitation efficiency was maximal. The storm efficiency is a function of perceptible water (total mass of water vapour in vertical column of the atmosphere). However, the direct measurement of this quantity is very challenging and perceptible water is also not a common variable provided by RCMs. The first unique feature of this study is the overcoming of the issue of lacking perceptible water information by exploiting the correlated relationship with surface dew point temperature. Second, this article provides a very detailed and intelligible explanation of a cutting edge bias correction method.

Kusaka et al., (2012) evaluated future heat stress in the world's largest metropolitan system – Greater Tokyo. This sophisticated study deploys the dynamical WRF model with 3 km horizontal spacing. The boundary forcing is created by averaging the ensemble of three different GCMs. To express estimated future heat stress this study uses the concept of Wet-Bulb Globe Temperature (WGBT). WGBT is an empirical heat index developed to control heat-related casualties in military training, and supposedly it correlates better with heat stroke occurrence than simple air temperature. Another simple but interesting indicator of future heat stress used by Kusaka et al. (2012) is the frequency of Heat-induced Sleeping Discomfort (HSD) nights. Another highlight of this work is an approach to account for the complexity of the urban system. The WRF model is coupled to a single layer Urban Canopy Model (UCM), which considers the urban geometry, green fraction and anthropogenic heat emission with diurnal variation.

There are many studies confirming that land cover has a significant impact on climate (e.g. Fallmann et al., 2017; Huang & Lu, 2015; Solecki & Oliveri, 2004). Some works proved its impact on rather local scales (Cui & Shi, 2012; Früh et al., 2011; Hu & Jia, 2010; Wolters & Brandsma, 2012; Zhang et al., 2010). Other studies provided evidence of climate being influenced by urbanization and related land cover changes on regional or even global scale (e.g. Batista et al., 2016; Da Rocha et al., 2014; Llopart et al., 2014). On the other hand, a global study by Peng et al., (2011), considering 419 large cities, states that no relation has been confirmed between the size of the metropolitan system or population density and the UHI effect. Rather than that, those authors emphasised the importance of urban design and urban vegetation cover within the city.

One of the most complex approaches for downscaling urban climate data involving land use modelling is the work of Solecki & Oliveri (2004). As a part of the New York Climate & Health Project, these authors describe a procedure to downscale CC scenarios in urban land use models. The land use models considered in this study are part of the SLEUTH program (Clarke et al., 1997), which deploys a probabilistic cellular automata protocol, and consists of two core components: the Land Cover Deltatron Model (LCDM) is nested within an Urban Growth Model (UGM). An alternative to those mostly not user friendly cellular automata models was recently introduced by Bununu (2017).

Finally, Lemonsu et al. (2013) used a very sophisticated approach to investigate the evolution of Parisian climate. This study was conducted as part of the EPICEA project (French acronym for Pluridisciplinary study of the impacts of climate change at the scale of Parisian region). The aforementioned authors combined dynamical downscaling with the quantile-quantile (q-q) correction method. The long term urban climate simulations were calculated by the SURFEX land surface modelling system. The analyses were done for a 48 km x 48 km study area with a spatial resolution of 1 km. The land use / land cover scheme followed the CORINE classification. For evaluation purposes, the high spatial-temporal resolution (8 km, hourly) retrospective dataset (1958–2008) generated by the SAFRAN system was utilized. This study by Lemonsu et al. (2013) assessed possible aspects of future climate in winter and summer seasons separately by exploiting a wide range of climate indices, and provided information on the UHI effect as well.

## 2.3 Discussion

Climate change is expected to have significant impacts on urban systems and built infrastructure (Chapman et al., 2016; Hunt & Watkiss, 2011; Rosenzweig et al., 2011), such as energy systems (Spandagos & Ng, 2017), water supply and wastewater treatment (Howard et al., 2016; Wang et al., 2016), transportation systems (Dulal et al., 2011; Kwan & Hashim, 2016; Peterson et al., 2008), public health and human comfort (Araos et al., 2016; Batista et al., 2016; Li et al., 2015; Molenaar et al., 2015).

What climate-related challenges does the city face? Where are adaptation policies and actions the most urgently needed? Those are key questions faced by decision makers but the answers often lead to short or medium term solutions. Actions like establishing a plan for the mobile dams' deployment belong to coping measures and are based on the experiences of past extreme events. Incremental adaptation represents another approach, when the already existing solutions are improved step by step considering the future evolution of the climate conditions. Coping and incremental adaptation measures certainly have their value but do not grant the functionality in the long term future. In extreme cases, these approaches might lead to a scenario where the urban system is locked-into an unsustainable situation (e.g. the capacity of already existing dykes or conventional sewerage system is not ever-increasable). On the other hand, urban systems last for decades and certain features such as valuable heritage remain for centuries. Hence, broader and systematic approach to address long term adaptation planning is needed. Transformative adaptation combines coping and incremental strategies, while addressing the root of causes and acknowledging the future potential magnitude of various risks. Transformative adaptation aims to multipurpose solutions and, as an integral part of urban planning, turns challenges to opportunities and boosts overall quality of life.

Adaptation to climate change is currently becoming an integral part of urban planning and infrastructure development at city and district levels. While the short and medium term perspective is usually considered, long-term planning often remains omitted by managers and decision makers. There are several reasons for the lack of long term adaptation planning and action. Firstly, for example in European cities, administrators operate with reduced budgets and high unemployment resulting from economic crises. Globally, while some cities already experienced dramatic impacts of CC, others view the matter as a distant future challenge, thus their focus is on more urgent problems. In fact, in scientific literature the evidence of the current lack of appropriate policy targeting the urban climate can be found (Hughes, 2017). Moreover, even though integrated long-term transformative adaptation strategy makes the action more affordable, these investments are rewarding after a long time beyond political mandates. Long term adaptation planning operates with periods of approximately 50-100 years and represent a difficult challenge owing to the uncertainty associated with future climate, as well as because of the socioeconomic evolution of complex urban environments (George et al., 2016).

### 2.3.1 Linking climate data and urban planning

Climate information should be considered in the planning practice of different sectors, such as cultural heritage protection, disaster risk reduction, food security, public health, energy, transport, tourism, water resources and coastal management. However, recommendations on how to incorporate climate data into the urban planning process often remain rather holistic. A

few major entities (e.g., WMO – World Meteorological Organization, IPCC – Intergovernmental Panel on Climate Change, FAO – Food and Agriculture Organization of the United Nations), among other authors (e.g., Akbari et al., 2016; Davoudi et al, 2009), provide general information on adaptation and mitigation planning. For example, the Implementation Plan of the Global Framework for Climate Services (WMO, 2014) provides some insights, but they are still general as they typically reflect the purpose of the actions or they are limited to a few urban systems.

Eliasson (2000) investigated if, how and when knowledge about the climate is used in the urban planning process. The study showed that the use of climatic information was unsystematic and that climatology had a low impact on the planning process. Carter et al., (2015) discuss the use of weather data and climate projections by urban planners from Greater Manchester (UK) for adaptation planning. Those authors also stress practical limitations in the data that are constraining its wider use, such as the need to provide simpler messages with an accompanying narrative to explain what CC means locally. Lorenz et al., (2017) explored the usability and adoption of climate projections within local adaptation planning in England and Germany. Their conclusions regarding the English context raised the question to what extent the discussion on the usability of climate projections at a local level is sensible at the moment. Lorenz et al. (2017) also concluded that Germany makes substantial use of past and present climate data for spatial planning, but the strictly regulated nature of planning prevents the use of climate projections, due to their inherent uncertainties.

How exactly can uncertain probabilistic information be included in a decision support system? A basic concept, still widely used in engineering, considers the climate variability but only with constant properties through time, and based on the severity of the past events. This stationarity assumption is still a common practice when designing new infrastructures (Klein Tank et al., 2009). Therefore, the capacity to endure extremes is accounted for up to a magnitude that might not be realistic at locations where that assumption is not met. In fact, urban planners often take into account spatially coarse projections of climate events and then apply general adaptation measures across the whole metropolitan area (e.g., the utilization of certain thickness of insulation of electric wires or the usage of pipes with specific diameter or/and of certain material when the replacement takes place). Such adaptation measures are not location-specific. Hence, they may be effective but not efficient. Instead (or additionally), urban planners could use localised climate projections to prioritize projects according to areas with strongest future impacts (i.e., the conjunction of hazards exposure and vulnerabilities). Detailed climate projections could assist with major infrastructures development to ensure their safety. For example, industries with high potential to contaminate water resources and soil could be located in areas of low risk of extreme climate impacts. Urban planning should give a greater emphasis to the locations exhibiting higher impacts on the vulnerable part of society, such as children, elderly and low income communities. Furthermore, close attention should be given to land-use planning to prevent new urbanization in high-risk areas (including high-risk areas in distant future).

The important reason why the localised climate information is being incorporated to urban planning rather slowly is that data providers and data users need to interact better. It can also be due to the uniqueness of each urban system, or because climate adaptation is still somewhat new in the policy making agenda (Carter et al., 2015). Climate experts often do not have a

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mandate to influence the decision-making process, while urban decision makers need assistance with data handling and interpretation. In urban space, various programs, institutes and private stakeholders typically address individual aspects of adaptation planning, but the coordination between them is generally weak (WMO, 2014). Due to the novelty of this agenda, the interaction between stakeholders should have a form of long-term bidirectional communication to allow for feedback and further adjustments. Moreover, Schoof (2013) suggested to establish new expert positions within decision-making bodies. Those climate professionals would help to increase the utility of localised climate projections.

To successfully tackle the impacts of CC in urban systems, climate projection data with a suitable spatial scale are vital. For example, while water management studies require an inter-regional approach, UHIs or stormwater related challenges are by their nature local (George et al., 2016). Local stakeholders often have very fine scale information regarding vulnerabilities to changing climate, while at the same time local decision makers have a key responsibility to deliver space-specific adaptation measures to address the environmental, social and economic implications of CC (Carter et al., 2015).

Currently, we are witnessing two parallel tendencies. The first one is a push towards localised city / district level planning (George et al., 2016), and a second one is a need for long-term adaptation planning (Davoudi et al., 2012). The lack of information that can be used as a basis for impact studies addressing these two requirements represents a certain gap. Different communities are mentioning this gap, each of them from their own perspective. The environmentalist community often refers to a gap in knowledge (e.g. Martins & Ferreira, 2011) and urban planners state that cities do not have skills and expertise, whilst decision makers address the shortage of financial resources to bridge this gap by consultancy (George et al., 2016). However, the two above-mentioned requirements are bounding this gap.

The usual approach to dealing with uncertainties in future projections of climate change and its impacts is to consider a range of possible future scenarios under different Representative Concentration Pathways (RCPs) (e.g., RCP 4.5 or RCP 8.5) described by Van Vuuren et al. (2011). The temporal scope of most of the impact studies based on such CC projections is the end of the century. These studies are particularly useful for long-term sustainable development planning, because it must account for vulnerability to extreme weather events, disaster management and adaptation, particularly in developing countries (Mirza, 2003). Nevertheless, Vautard et al., (2013) argue that the medium term future period of 2050 corresponds to the societal demand of climatic projections useful for adaptation purposes. Regardless of the time scope of the climate projections (2050 – medium term future; 2100 – distant future) or the range of possible future scenarios, important is the need for downscaling scenarios and projections at spatial scales that are relevant for adaptation policies, particularly at city scale.

Carter et al. (2015) advocate that, for effective adaptation, decision makers should develop responses to recent trends in weather and climate, as well as to future projections. Those authors support this claim on a detailed case study of CC impacts and urban adaptation responses linked to spatial planning in Greater Manchester (UK). Research methods employed included downscaling climate projections, spatial analysis with Geographic Information Systems, land use modelling, energy balance modelling, social network analysis, participatory workshops,



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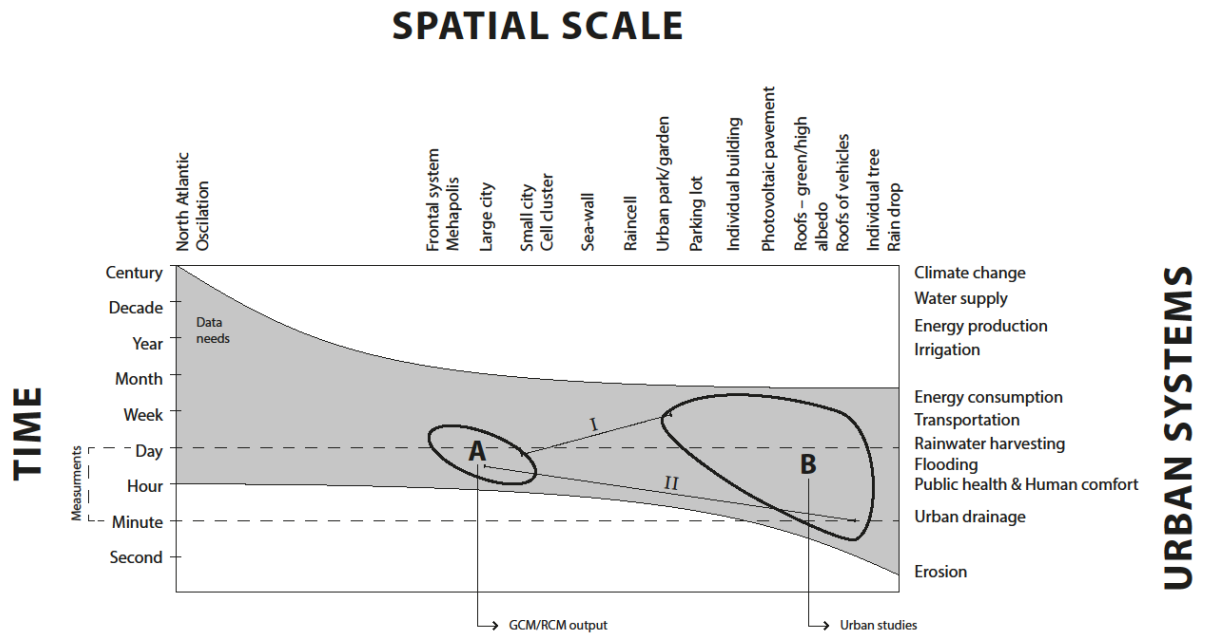
and scenario development, among other approaches. We agree that their conclusions and recommendations are relevant to cities in general.

Another successful multidisciplinary approach is the Rotterdam Climate Initiative (<http://www.rotterdamclimateinitiative.nl>), which aims to have reduced CO<sub>2</sub> emissions by 50% and to have made the region 100% climate proof by 2025. Four potential climate scenarios are used for all climate research and policy-making in the Netherlands, such as the urban CC adaptation plans (City of Rotterdam, 2013). For example, two extreme climate scenarios are used to determine the upper and lower limits for the rise in sea level and the normative river flow, as well as to analyse flood protection measures. One of the scenarios assumes 1°C temperature rise on earth in 2050 compared to 1990 and no change in air circulation patterns, and the other one assumes 2°C temperature rise, milder and wetter winters due to more westerly winds and warmer and drier summers due to more easterly winds. These CC scenarios are also linked to two socioeconomic scenarios. This combination has led to four delta scenarios looking ahead to 2050 and 2100. The Rotterdam Climate Change Adaptation Strategy is based on these delta scenarios (City of Rotterdam, 2013).

### **2.3.2 Mismatch between data needs and data availability**

In localised long-term future climate impact assessment, there is no alternative to deployment of climate projections. Swart et al., (2014) emphasised the need to enclose the gap in available climate simulations data by calling for making the projections more precise. Moreover, Olazabal et al., (2014) highlight the problem of the lack of knowledge on specific local future climate conditions. The quantitative knowledge relevant to local priorities is pivotal in urban planning, urban design and the adaptation strategy implementation processes. Space-specific information can be used for the development of map-based interfaces, which is very effective in communication. This is important because local level tools and decision support systems foster citizens' participation, and allow them to embrace the change and tackle the adaptation as a positive opportunity rather than an issue solely bringing additional costs.

Evidence based knowledge of previous events, general climate change information, localised climate projections and vulnerability assessment of exposure features represents the main components of urban adaptation strategy. While local and regional governments have very fine scale information on urban systems and their vulnerability at their disposal, data with the adequate spatial scale regarding future climate behaviour, as simulated by GCM/RCM models, are often lacking to address its relation with various aspects of urban systems. This mismatch between data needs and data availability is schematically depicted in Figure 2, which also illustrates the magnitude of the need for applying downscaling techniques to the already available GCM/RCM data.



**Figure 2 - Mismatch between data needs and data availability in urban systems.**

The discrepancy between features A and B (Figure 2) express the general mismatch at spatial and temporal scales. Ideally, A and B would overlap.

Figure 2 can provide insights on questions like: Is the available data sufficient to address a particular urban challenge? Is there a need to apply downscaling techniques, and if so, what would the satisfactory spatial and temporal target resolution be? For example, there is a great variation in the requirements on space and time resolution in hydrology. Water management operates on broader areas at catchment scales, thus the common RCM output with 50x50 km cell size might be feasible. Conversely, stormwater and urban draining analyses require a much finer spatial and temporal scale, coming down to point scale representing individual rain gauges. Similarly, on the temporal axis of Figure 2, flash floods analysis calls for hourly and sub-hourly data. Overall, the needs for urban hydrological studies are located in the right-bottom part of object B (Figure 2). For example, heat waves (in dependency on what kind of environmental index is being used) are typically defined as certain days during which the temperature does not drop under a certain threshold. Hence, daily temperature data would be effective for such an assessment and subsequent adaptation planning. Additionally, the dotted lines in Figure 2 represent examples of the mismatch between raw GCM/RCM output and the needs of urban studies. The line marked as I illustrates the situation where cutting-edge RCM simulations are available (e.g. EURO-CORDEX data with 12x12 km /day resolution) and the UHI effect is of main concern. The longer line II depicts GCM/RCM of 50x50 km / 6 hourly, and the subject to be analysed is a stormwater discharge. These illustrative examples assist in reading Figure 2, where the length of lines I and II represents the magnitude of the scale mismatch, which emphasise the current need for the deployment of downscaling techniques.

### **2.3.3 Climate change adaptation practices and scale interdependency**

Grimmond et al. (2010) identify current capabilities to observe and predict urban atmospheric processes across a range of spatial scales. In future urban climate assessment, there is a need to not only estimate the climate behaviour, but also the socioeconomic evolution of the urban system. Those two are bind since they are bidirectional inter-dependent. Therefore, the modelling should also be coupled. Land use and land cover represent prominent observable tokens of the socioeconomic situation. Generally, land use in the context of complex urban fibre is a phenomenon occurring (and being managed) at finer scale than typical GCM/RCM output, thus downscaling techniques have their value for urban planning and design. Moreover, land-use changes are not considered in RCMs, which are usually run with static vegetation (Rössler et al., 2017). For example, when designing an urban square, decision makers having the localised information on future climate conditions (including the influence of e.g. amount of sealed surface to water run-off and UHI) may design the square differently. The positioning of circumferential buildings, the excessive water draining vegetation or shading trees can be added, targeting the areas of likely future high exposure. Street design can incorporate the corridors following the main local wind directions (Georgi et al., 2016). Such decisions are difficult to be made based on coarse resolution decision making supporting materials, particularly in a city context, where conditions might differ street by street (Ali-Toudert & Mayer, 2007).

Specific climatic conditions predefine effective adaptations. The strategies should be harmonious within a large spatial sustainability context. Hence, for example, utilizing non-native flora (aiming for local temperature reduction) with high water demand in arid zones may result in the reduction of city water supply (Ruddell & Dixon, 2014). According to Georgescu et al., (2015), the balance between localized cooling and water scarcity in cities should be subject to further research.

Both climate and land cover models carry large uncertainties. This uncertainty must be kept in mind during the decision making. Hence, the action taken on the basis of localised future projections should favour the so called robust and low-regret measures. Those measures are of relatively low cost and bring large benefits. For example, instead of increasing the capacity of a sewerage system, which does not guarantee sufficient functionality under long-term climate change, the city may deploy a green infrastructure at a lower cost. Such a solution also brings additional benefits and is more flexible, therefore it allows the urban system to avoid locking itself in the unsustainable strategy (Georgi et al., 2016). Moreover, due to the complexity and long-term nature of climate, the integration of a monitoring, reporting and evaluation (MRE) system is vital (UNFCCC, 2010). MRE does not only represent a procedure to systematize experience and extend knowledge, but also provides an emphasis on learning. Hence, MRE allows for necessary continuous adjustments in future decision making (Bours et al., 2014).

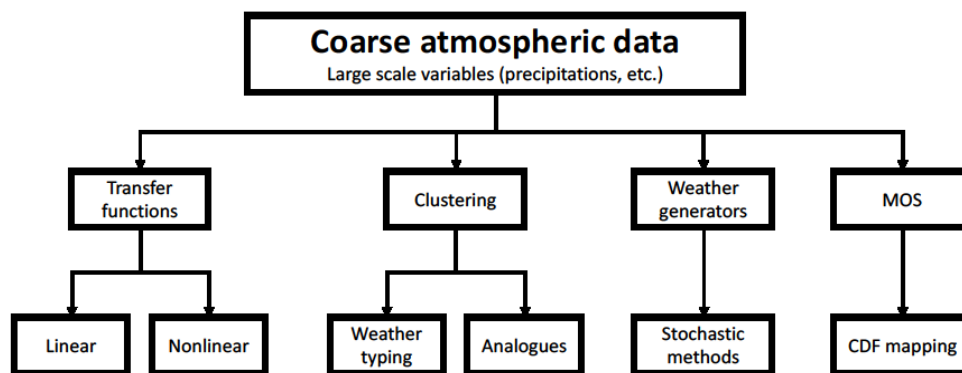
### **2.3.4 Practical bottlenecks for geographers, urban planners or statistics practitioners**

Terminology represents the very first bottleneck for everyone new to the field of downscaling of climate projections. Von Storch et al. (1991) might have been the first ones to use the term downscaling and it has been widely used since then, but the terms *disaggregation* and

*regionalization* are also frequently used in Europe. In parallel, the name *refinement* was proposed by Environment Canada (Hengeveld, 2000). Nevertheless, the downscaling concept has been increasingly utilized in Canada (Barrow et al., 2004). ‘Statistical/empirical’ downscaling is commonly addressed by simplified terms ‘statistical’ or ‘empirical’ downscaling, while ‘Dynamical downscaling’ can be referred to as ‘numerical’ downscaling (Bi et al., 2017).

Downscaling and climate modelling represent a multidisciplinary field, where researchers from various backgrounds intersect their efforts, resulting in specific terminology, which may be somewhat confusing. For instance, Polynomial Regression (also called the Surface Trend Analysis) is a statistical technique. In the context of spatial interpolation procedures, it is commonly classified as a deterministic technique, and kriging approaches are classified as stochastic. Furthermore, the terms ‘statistical’ and ‘stochastic’ (frequently used as names of sub-classes in downscaling methodological reviews) are not always considered as synonymous, even though both terms could be seen as identical since they are referring to methods handling input modelling factors as variables with certain probability distributions. In addition, recent development is moving towards multi-step methodologies containing deterministic and stochastic components. This evolution leads to the introduction of new terms like hybrid or semi-stochastic approaches, which makes the efforts of initial exploration of various downscaling methods even more challenging. Consequently, we present perhaps the most comprehensive graphic in Figure 3. Not all classification terms found in the literature are included, but it is helpful when one tries to orient oneself in the main sub-categories of statistical/empirical downscaling.

## Empirical/Statistical Downscaling



MOS: Model Output Statistics; CDF: Cumulative Distribution Function

**Figure 3 - Main families of empirical/statistical downscaling (adapted from Bi et al., 2017).**

Wilcke & Bärring, (2016) argue that many climate impact modellers are simply not able to handle the data generated by GCM-RCM simulations. This topic is seldom discussed in urban climate scientific literature (e.g., Wilcke & Bärring, 2016; Rössler et al., 2017). Here, we hypothesize that the underlying reason largely lies in certain entrance barriers within the IT domain. Sometimes, one can find pointers, for example when Fallmann et al. (2017) state that calculations were carried out using Climate Data Operators (CDO) tools. However, the comprehensive know-how

is not that straightforward to find. This IT bottleneck is possible to divide into two related areas. First, is the data structure / format, and the second is the amount of data generated by GCM-RCMs (meaning both data volume and large quantity of files).

Future climate projections data are commonly provided in NetCDF (Network Common Data Form) format. This is a set of interfaces, libraries, self-describing, machine-independent and array-oriented data formats supporting creation, access and sharing of scientific data (Rew et al., 2011). NetCDF has its origin in the University Corporation for Atmospheric Research (UCAR) consortium, under the Unidata program. NetCDF is a successor of Common Data Format developed by NASA, but it is no longer compatible (Rew et al., 2011). All above-mentioned entities represent supreme sources of information. The various versions of NetCDF data can be encountered (NetCDF-3, NetCDF-4/HDF5, NetCDF-4/HDF5 classic and 64-bit Offset format), which may easily lead to confusion (Rew et al., 2011, Appendix C). Since March, 2011 the NetCDF-4/HDF5 file format is standard and has been approved and recommended by NASA Earth Science Data Systems (<http://earthdata.nasa.gov/standards>; accessed: 13/03/2017), and NetCDF Classic and 64-bit Offset Format are standards recognized by the Open Geospatial Consortium (OGC; <http://www.opengeospatial.org>, accessed: 13/03/2017). In general, NetCDF data is binary, self/describing and portable – meaning that all computer platforms, regardless of their approaches towards integer storage, characters and floating point numbers can access such data (Rew et al., 2011). A variable represents a multidimensional array of values of the same type. The dimension specifies the variable shape, common grid and coordinate system. An attribute holds the properties of data sets (global attribute) or specific variable (e.g. units), but attributes cannot be multidimensional (Rew et al., 2011). The other important role of attributes is the implementation of conventions. Typically, it is a name of an attribute rather than the name of the variable that is subject to standardization. The NetCDF Climate and Forest Conventions dictates the organization of the data in the climate domain (Eaton et al., 2011).

The NetCDF-4/HDF5 represents the file format providing the most enhanced capabilities. The deployment of HDF5 as storage layer removes many of the restrictions common to the 64-bit offset and the classic NetCDF files. The model allows for user-defined data types including more primitive types as strings, larger variable sizes and supports multiple unlimited dimensions. Furthermore, the HDF5 storage layer allows for per-variable compression, multidimensional tailing and dynamic scheme changes, meaning that there is no need to copy data when adding a new variable. Finally, when reading and writing NetCDF-4/HDF5 files, the parallel I/O (input/output) is supported, thus the computational performance is significantly improved [7.3.4. Parallel I/O], which is of extraordinary importance when handling large multi-model ensembles of climate projections due to large number of files.

The cost of the above-mentioned power and flexibility comes in software applicability. Most of existing NetCDF software is only compatible with the classic data model and it is not capable of handling the additional complexity. This brings the necessity of installation of multiple SW libraries, but the more important challenge, reported by NetCDF users, is the shortcoming of Windows platform support in comparison with Linux (<https://earthdata.nasa.gov/standards/netcdf-4hdf5-file-format>; accessed: 15/03/2017). Additionally, some of GCM/RCM simulations come on unconventional grids (e.g. False North Pole rotated native grid for European domains of EURO-CORDEX experiment). They can be easily

re-rotated ([https://www.earthsystemcog.org/projects/cog/faq\\_data/](https://www.earthsystemcog.org/projects/cog/faq_data/); accessed: 17/03/2017), but not by tools commonly used by classical geographers, urban planners or statistics practitioners. Somewhat extensive lists of SW tools to conveniently handle NetCDF data can be found in <https://www.unidata.ucar.edu/software/netcdf/software.html> (accessed: 23/03/2017).

Apart from data format, the second practical challenge of the deployment of the full multi-model climate ensembles is simply the amount of data in terms of both-data volume and large quantity of files generated by GCM/RCMs. We will use an example to illustrate the data amount necessary to work within the context of climate projections. Multiple variables such as precipitation, maximum and minimum temperatures, solar radiation, relative humidity and wind speed are of interest for impact studies (Wilby et al., 2004). Here, for simplicity, only one variable will be considered for illustration purposes. We selected the EURO-CORDEX (Jacob et al., 2014) multi-model ensemble since it represents the cutting edge, fine scale set of climate simulations and it is openly available. Furthermore, for the sake of simplicity, we are only considering a single climate scenario (e.g. RCP 8.5), but note that in a real climate impact assessment exercise all the following numbers would be multiplied by the number of required variables, and then the data for each scenario would also be added. Searching the data internet portal (<https://esg-dn1.nsc.liu.se/projects/esgf-liu/>; accessed: 03/10/2016) with the following specifications returns approximately 620 files with 620 GB: CORDEX experiment, daily data, EUR-11 domain, historical plus RCP 8.5 runs, average temperature, time span between 1971 and 2100, and only 10 GCM/RCM models as a minimum number of ensemble members.

The data comes in the form of NetCDF-4/HDF5 files – each one containing a time slice of 5 years covering the whole European domain. In Windows environment, users have an option to add the files, one by one, to the basket as in a common e-shop. However, it is clearly convenient to migrate to the Linux environment already in this very first step. Then, the automatic *wget* download is available and requires only basic knowledge of shell scripting. This principle holds true for each subsequent step in data handling. For example, when applying spatial and temporal subsetting with focus on a particular urban system, the resulting data are not large in terms of bytes, but the number of files remains. Luckily, the climate community invested significant efforts to provide the tools for managing such a data (including e.g. merging files by time, so our 620 files potentially become just 1). But, again, those tools are not common in the tool boxes of most classical geo-practitioners.

To provide the directions to the reader searching for the right tools, we would like to highlight some (reflecting just our personal preference). To understand the data structure, time and space handling, and quick visualisation purposes, Panoply software from NASA (<https://www.giss.nasa.gov/tools/panoply/>) and Ncview by David W. Pierce ([http://meteora.ucsd.edu/~pierce/ncview\\_home\\_page.html](http://meteora.ucsd.edu/~pierce/ncview_home_page.html); accessed: 03/10/2016) represent convenient starting points. We recommend the CDO tools (Schulzweida, 2017) for pre-processing and computing many of traditionally used environmental indices. Working with CDO within the Python environment is also an option (e.g. Anaconda Python distribution). The ‘extRemes’ R package (Gilleland & Katz, 2016) allows to build indices in an R environment and contains few advanced indices (e.g. Russo et al., 2015). To calculate and interpret climate change signals and time series from climate multi-model ensembles the ‘wux’ R package (Mendlik et al.,

2016) is an interesting tool, and the recent 'spdownscale' R package (Rasheed et al., 2017) can be of priceless help when in need for statistical downscaling and bias correction.

Furthermore, somewhat related to the IT bottleneck, we would like to highlight a few methodologies that have been proposed for reducing the computational cost. When computational resources represent a constraint, the full multi-model climate ensemble can be reduced to a few representative members, while preserving crucial statistical properties (total spread / uncertainty) and simultaneously reducing structural bias in the resulting subset (Mendlik & Gobiet, 2016). These authors proposed a straightforward three-step procedure to achieve this utilizing commonly used statistical techniques: principal component analysis and cluster analysis. Other related useful approaches are provided by Wilcke, & Barring (2016) and Cannon, (2015).

## **2.4 Summary**

We introduced the rationale and problem background justifying the need for future climate impact assessment targeting metropolitan areas from a multidisciplinary point of view – climate, urban planning and policy making. The downscaling of climate projections generated by GCM/RCMs was briefly reviewed and discussed. Furthermore, focus was given to recent developments in urban climate studies making use of downscaling approaches. The reasons why fine-scale climate data is being incorporated to urban planning rather slowly are highlighted. A thorough review on the major challenges in the use of climate change impact data for urban planning is provided. Moreover, some strategies to deal with them are suggested.

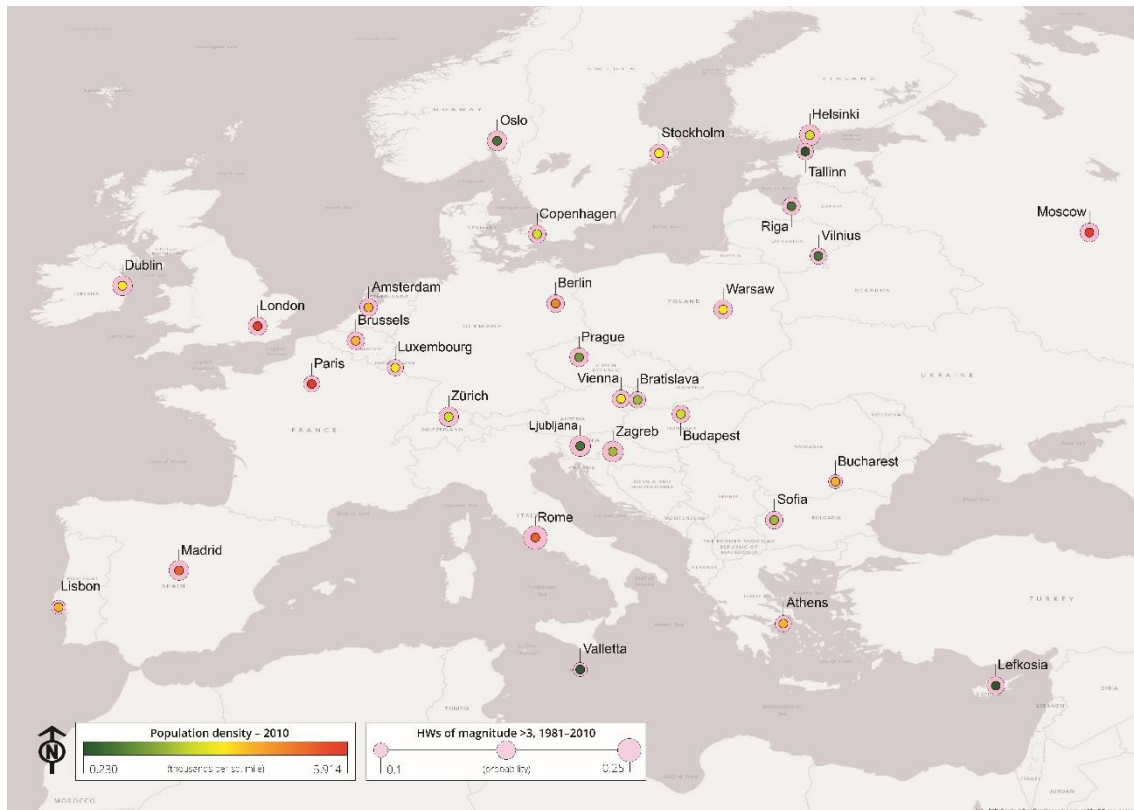
Three major practical bottlenecks of using climate projections and their downscaled derivatives in an urban context were covered, namely the terminology, the scale mismatch, and the IT aspects. In the literature, the call for multidisciplinary cooperation between the communities of climate and urban planning can be found. However, we would like to emphasize that specific IT expertise would be also required to successfully tackle the task of future climate impact assessment at an urban scale.

In this chapter, we attempt to bridge the gap between all involved expert stakeholders. By highlighting the pitfalls and providing pointers towards appropriate tools and information sources we hope this work might be useful to anyone new in the field of impact assessment using localised future climate data, regardless of the background from which he or she will tackle this multidisciplinary challenge.

### **3 Ranking European Capitals by Exposure to Heat Waves and Cold Waves**

In this study we focus on future impacts of temperature extremes in European capital cities, with emphasis on heat waves since these represents one of the most remarkable extreme climate related events regularly striking Europe (Vautard et al., 2013). Figure 4 serves as a domain map of this study localizing the target cities, indicates the population densities by colors, and also illustrates the occurrence of severe HWs between 1981 and 2010. In 2007, humankind became predominantly urban based (McCarthy et al., 2010; UN, 2014). Projections indicate that by 2050 urban systems will be home to 66% of the global population representing 6.3 billion urban dwellers (UN, 2014) with this proportion being even higher in European Union, where currently 75% of population reside in cities with expected growth to 82% by 2050 (Guerreiro et al., 2018; UN-habitat, 2010). The increasing urbanization (Estrada et al., 2017; Smid & Costa, 2017) accompanied with an aging trend of European society will lead to magnified impacts of future heat including the higher risk of future heat related mortality (Baccini et al., 2008; Hajat et al., 2014). Urbanized areas are not only major drivers of climate change, but are simultaneously hot spots of climate change impact (de la Barrera & Henriquez, 2017). The recent study by Guerreiro et al., (2018) covering 571 European cities shows that capitals are among top 100 for one or more analyzed future hazards. European capitals typically represent around 30% of national GDP (Eurostat, 2016), and they often have a critical role concentrating international and intranational flows of capital accompanied with labour activity, and as such, they are vital for national competitiveness in a globalized world (Dijkstra et al., 2013).





**Figure 4. Target cities with the population density (for 2010) indicated by colors, and severe HWs (magnitude > 3) occurrence between 1981 and 2010 illustrated by proportional sized background symbols.**

Europe was marked amongst the particularly warming regions (IPCC, 2007), with strong response to the anthropogenic climate change thus exhibiting stronger warming rate than the planetary mean (Amengual et al., 2014; Kuglitsch et al., 2010). The Heat Waves (HWs) do not only have various human, economic and environmental consequences (Argüeso et al., 2016), but they also represent one of the deadliest weather-related hazards (Habeeb et al., 2015; Revich & Shaposhnikov, 2012; Robine et al., 2008). Many efforts have been recently devoted to studying European heat (e.g. Guerreiro et al., 2018; Lhotka et al., 2018; Pereira et al., 2017; Russo et al., 2014; Schoetter et al., 2015). A detailed description of the 10 most severe HWs within European domain since 1950 can be found in Russo et al. (2015). The 2003 HW had a death toll of approximately 40,000 people in Europe, highlighting the need to implement early warning systems in European cities (García-Herrera et al., 2010). The strongest event of the present era was the 2010 HW, strongly impacting Moscow, where an extreme day temperature of 38.2 °C was recorded and more than ten thousand people died (Barriopedro et al., 2011). Since then, other intense events stroke Europe, such as the severe Central European HW events of 2013 (Holtanová et al., 2015) and 2015 (Hoy et al., 2017), or the recent heatwave of summer 2017 that impacted western and central Europe (Sánchez-Benítez et al., 2018).

Regarding the future perspective, we will encounter more frequently HWs of greater intensity and duration across entire Europe. The increase in amplitude will be most dramatic in southern-central Europe, while the extension of the duration is expected to be most pronounced in the Mediterranean (Fischer & Schär, 2010; Guerreiro et al., 2018). The future impacts in southern areas is frequently emphasized in the literature (e.g. Jacob et al., 2014; Pereira et al., 2017), and

the high populated areas of Mediterranean coast will be of concern (Fischer & Schär, 2010). The north-south gradient across the Europe is expected to remain (Fischer et al., 2012), but the strongest intensification of hot extremes may occur in mid continental latitudes (Fischer, 2014) due to higher increase in climate variability towards the north (Fischer & Schär, 2010). Extreme heat events can occur also in Northern areas currently not being strongly associated with HWs (D'Ippoliti et al., 2010).

Despite these predictions, situation in urban zones will be somewhat different. At the city level, the anthropogenic activities, such as natural-to-urban land conversion or changes in radiative substances in the atmosphere, will influence local climates (Estrada et al., 2017). In urban settings the stress of extreme heat is exacerbated by the UHI – Urban Heat Island effect. Dark surfaces (e.g. roads, parking lots or rooftops) may warm about 8 °C above the temperature of surrounding air (Patz et al., 2005). The construction of high-rise buildings and the densely build environment contribute to exacerbated heat stress. Varentsov et al., (2017) showed for Moscow that recent urban sprawl contributed by 10% on UHI increase in central metropolitan area. UHI also exhibit spatial and diurnal variation. The stronger effect is represented by nocturnal heat UHI but this is concentrated in city centers and other densely constructed areas. On the other hand, spatially larger day-time UHI has lower intensity and warming is most pronounced in residential neighborhoods less protected by shading (Lemonsu et al., 2015). However, the impacts remain unclear – for example, Schuster et al., (2014) in study of spatial variability of heat related mortality in Berlin, did not find any clear spatial trends or major clusters. Instead their results indicate large spatial variability with many hotspots.

In Europe the increased heat stress within urban areas was demonstrated, for example, for Hungary (Unger, 1996), Greece (Kamoutsis et al., 2007), or more recently for 571 cities all over Europe (Guerreiro et al., 2018). The HW impact is heterogeneous across the European cities. (Ward et al., 2016) concluded that cities located in cooler climate are more affected than settlements in warmer regions. D'Ippoliti et al., (2010) showed that the mortality was amplified by HW by 12.4% in North Continental part and even by 21.8% in Mediterranean. The trends are alarming worldwide but in the global study on modern megalopolises, Papalexiou et al., (2018) explicitly pointed out Paris with warming trend 0.96 °C per decade closely followed by Moscow, thus illustrating the importance of the issue in European context.

The largest and most densely populated urban zones exhibit the strongest UHI (Schatz & Kucharik, 2015), which supports our focus on Capitals. Moreover, under the RCP8.5 “business as usual” scenario, even for median cities there is expected 1.7% and 5.6% lost in GDP for years 2050 and 2100 respectively, and the total cost of urban impacts could be magnified by a factor 2.6 due to UHI effects (Estrada et al., 2017). These findings, together with close link between capital cities and national economies (Dijkstra et al., 2013) also justify the selection of target cities in this study.

Our primary purpose was to examine the changing characteristics of heat extremes across the European capitals with particular attention to a comparison among the cities. The quantification of cost and benefits, and the adaptation design of urban space remains the major challenge (Guerreiro et al., 2018) and our method offers a suitable

framework to assess HW risks associated with future climate in urban areas. The variations among the cities depend on wide range of geographical, socioeconomic, demographical, technological and cultural factors (Baccini et al., 2008). In future Europe, the currently relatively better adjusted (due to their historical experience with extreme heat) Southern cities will anyway need to increase their resilience which can be realized mostly via radical changes and costly, fundamental re-engineering measures (Guerreiro et al., 2018), while Central Europe is expected to have more capacity and economic power to facilitate the necessary adaptations (Guerreiro et al., 2018; Tapia et al., 2017).

In this study, we computed HWs and Cold Waves (CWs) indices on a subset with eight members of EURO-CORDEX ensemble (Jacob et al., 2014) for historical (1971-2005) and future (2006-2100) periods under the RCP8.5 (Riahi et al., 2011) “business-as-usually” scenario for 31 European capitals (EU28 plus Moscow, Oslo and Zurich). HWs and CWs indices were constructed based on the simulations of daily near-surface maximum and minimum temperatures, following the definition of the Heat Wave Magnitude Index daily (HWMId) (Russo et al., 2015). The spatial extent of Larger Metropolitan Area (LMA) for each city was based on the data from the Urban Atlas produced by the European Environmental Agency (EEA, 2012). We propose a ranking procedure for the capital cities in terms of HWs and CWs impact. We also reflected the variation in impacts of extreme heat onto different metropolitan societies by including the population density as additional exposure variable into the ranking.

This cities’ ranking has three major benefits. Firstly, it communicates the risk associated with climate change induced extreme heat locally – virtually on “people’s backyards”. Due to its simplicity and the fact that it allows to illustratively relate to situations of other Capitals, may help to engage not only scientists, but also the decision makers and general public, on efforts to combat climate change. In many cases, we are afraid that society may be often overwhelmed by either the complexity of climate related scientific findings or by constant repetition of media correctly informing on pessimistic perspective of our climate. Secondly, such an indicator can serve as a basis to decision making on European level, assisting with prioritizing the investments and other efforts in the adaptation strategy. Thirdly, this study communicates the magnitude (property of HWMId) of future heat and as such contributes to raise awareness about HWs since they are still often not perceived as a serious risk (Keramitsoglou et al., 2017).

### 3.1 Data and Methods

#### 3.1.1 Climate Simulations

To investigate impacts of extreme temperatures across the European capitals (EU28, Moscow, Oslo, and Zurich) we used the recommended multimodel ensemble approach since ensemble as a whole outperforms individual projections and provide more a reliable picture of future changes (Sillmann et al., 2013b) and multi dynamical Regional Climate Model (RCM) downscaling of individual Global Circulation Models (GCMs) is also desirable (Smid & Costa, 2017). The European branch of CORDEX experiment currently provides the largest collection of simulations and provides the data at two different resolutions – 0.11° and 0.44°. These simulations were evaluated by many. Projected climate variables were compared with the observed values (e.g. Abiodun, et al., 2017; Hofstra et al., 2009; Soares and Cardoso, 2018) and also indices constructed based on the simulations of daily minimum and maximum temperature CORDEX data were extensively validated against their counterparts computed on observational dataset (Lelieveld et al., 2016; Pereira, et al., 2017). These validation exercises are most frequently done using the Ensemble-OBS gridded observational dataset by Haylock et al., (2008). Some studies specifically assess the ability of models to project the HWs (e.g. Ouzeau et al., (2016), Vautard et al., (2013); or Lhotka et al., (2018)) and generally literature confirms the reliability of EURO-CORDEX data (e.g. Kotlarski et al., (2014)). Here we rely on these previous studies and consider the EURO-CORDEX simulations valid for analyses of future heat and cold waves.

The EURO-CORDEX models exhibit common biases underestimating heat extremes in Scandinavia, and the contrary for Southern and Central Europe, and also exhibit large-scale cooling over vast continental areas in simulations at increased resolution. Detailed bias analyses can be found in Vautard et al. (2013). Despite those systematic biases, simulated values of temperature variables were found especially reliable. Moreover, the indices used in this study (HWMId/CWMId by Russo et al., (2015) – see section 2.2.1) contain implicit bias corrections by obtaining the percentile thresholds from respective model runs instead of observations. This strategy to minimize the bias was also used by Pereira et al. (2017).

From two available EURO-CORDEX resolutions we choose the finer grid projections (~ 12.5 km). It was shown that coarser simulations project drier summer conditions (Kotlarski et al., 2014) and very persistent HWs (Vautard et al., 2013). These issues are improved in higher resolution (Kotlarski et al., 2014; Lhotka et al., 2018), and the main advantages of finer scale projections are in warm season (Soares & Cardoso, 2018; Lhotka et al., 2018). These improvements can be attributed to enhanced orography and better resolved local feedbacks and, as such, being pronounced in some coastal regions due to more accurate representation of coastline and coastal breeze (Vautard et al., 2013), and also in areas of complex terrain (Lhotka et al., 2018), which are both relevant in context of our target cities.

From full EURO-CORDEX ensemble we excluded some models due to their shortcomings in the Mediterranean area (Kotlarski et al., 2014) and in the ability to estimate the intensity of extreme events (Vautard et al., 2013). The resulting subset used in this work is composed of 8 simulations, containing different GCM/RCMs combinations performed by four different institutions (Table 2). The daily maximum and minimum near-surface temperature data for the 1971–2100 period were retrieved from ESG – Earth System Grid data repository and the details on models can be found in the EURO-CORDEX website (<http://www.euro-cordex.net>).

**Table 2 - The list of utilised GCM/RCMs combinations.**

<b>Institute</b>	<b>RCM</b>	<b>Driving GCM</b>
Royal Netherlands Meteorological Institute (KNMI)	RACMO22E	ICHEC-EC-EARTH
Danish Meteorological Institute (DMI)	HIRHAM5	ICHEC-EC-EARTH
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	ICHEC-EC-EARTH
Institut Pierre Simon Laplace (IPSL-INERIS)	WRF331F	IPSL-IPSL-CM5A-MR
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	IPSL-IPSL-CM5A-MR
Royal Netherlands Meteorological Institute (KNMI)	RACMO22E	MOHC-HadGEM2-ES
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	MOHC-HadGEM2-ES
Swedish Meteorological and Hydrological Institute (SMHI)	RCA4	MPI-M-MPI-ESM-LR

From all the Representative Concentration Pathways (RCPs) scenarios adopted by the IPCC for its 5<sup>th</sup> Assessment Report (Christensen et al., 2013) here we use RCP8.5 scenario. Unlike the SRES (Special Report on Emission Scenarios) (Nakicenovic et al., 2000) scenarios, they are not associated with particular storylines thus account for combined uncertain influence of economic, technological, demographical and policy factors (Sillmann et al., 2013b). The RCP8.5 assumes continued growth of energy demand, hence does not have any peak breaking point during the 21<sup>st</sup> century. This scenario assumes continuing trends in all anthropogenic activities influencing the climate with no mitigation policies being implemented (Riahi et al., 2011). Here, we choose this scenario because it might be more relevant in projected future heat impacts over the cities given the additional influence of the urbanization to local climates. The other reason lays in one of the major objectives of this study which is the communication of climate change. Multiple previous studies found that most severe impacts throughout the 21<sup>st</sup> century are projected under the RCP8.5 scenario (e.g. Jacob et al., 2014; Lhotka et al., 2018; Russo et al., 2015). However it is noteworthy the recent interesting finding

of Lhotka et al., (2018) for near future (2020-2049) in Central Europe the largest increment of HWs frequency exhibit the RCP4.5 “low concentration” scenario. Nevertheless, the main objective of this study is to analyse the evolution of extreme heat impacts during the entire century, and to communicate the quantified comparative hazard across the European capitals in simplistic manner, thus the RCP8.5 as an upper risk boundary was utilized in this study.

### 3.1.2 Climate Indices

Indices describing moderate climate extremes are commonly deployed to characterise the impacts of climate change, since they capture relatively frequent impact-causing events (Alexander et al., 2006). When assessing the impacts of extreme temperatures in changing climate, two main challenges are encountered. Firstly, the definition of extreme in long time-span is problematic – current extremes are likely to become the future norms (Argüeso et al., 2016). Secondly, the differences in local climates must be considered when the impact assessment aims to comparison amongst distant locations (Pereira et al., 2017) and the perception and vulnerability is not only function of local physical conditions but also of the cultural and environmental attitude of the society (e.g. Coccolo et al., 2016). These challenges, were overcome to large extent for most of the characteristics of future climate by (Alexander et al., 2006) and for HWs specifically by (Russo et al., 2014; and Russo et al., 2015).

For assessing the risks and vulnerabilities of urban populations to extreme heat the frequency and occurrence of HWs are vital (McCarthy et al., 2010). However, the term heat wave may refer to many different things in dependence of used formula (Zhang et al., 2011). The diversity in obtained results was demonstrated by Jacob et al., 2014; pointing out the projected increase in HWs occurrence ranging from 9 to 45 depending on the index formulation. To define the consistent index capturing multiday temperature extremes is, due to the dependency of these events not only on the frequency distribution but also on the day to day persistence, especially challenging (Zhang et al., 2011). There have been numerous efforts to provide a robust HW definition (e.g. Alexander et al., 2006; Frich et al., 2002; Hansen et al., 2008; Kyselý, 2010; Lhotka & Kyselý, 2015; Lhotka et al., 2018; Meehl & Tebaldi, 2004; Orłowsky & Seneviratne, 2012; Perkins et al., 2012; Russo & Sterl, 2011; Russo et al., 2014, 2015; Schär et al., 2004; Sillmann et al., 2013a). However, the currently implemented ETCCDI (Expert Team on Climate Change Detection and Indices) index – the Warm Spell Duration Index (WSDI) still exhibits some shortcomings (see IPCC, 2012; Orłowsky & Seneviratne, 2012; Russo et al., 2014) and an universally accepted HW definition is still missing, thus represents an open issue to scientific debate (Keramitsoglou et al., 2017).

In order to quantify heat wave (cold wave) intensity we deployed the HWMId (CWMId), taking into account duration and temperature anomalies of heat waves into a single number (see Russo et al., 2015). The robustness of this index was illustrated, for example, by its ability to capture the large Finish HW of 1972 which till then went largely undetected by previous indices, despite the fact that this unusual event was reported in traditional newspapers. In the same time the HWMId also demonstrated its ability to precisely detect well known historical events across the globe (Russo et al., 2015). Hence, our choice of this HW metric allows for comparison amongst large distances in space and time. Moreover, to calculate the HWMId in the reference period, the bootstrap / one “out-of-base” year cross-validation procedure illustrated in Zhang et al.,

(2005) is used, therefore avoiding potential heterogeneities between the outside and within of the base period (Sippel et al., 2015), which is in agreement with ETCCDI recommendations (Schaller et al., 2018).

According to Russo et al., (2015) the HWMI<sub>d</sub> is defined as the maximum magnitude of the heatwaves in a year, and a heatwave is defined as a climatic event equal or longer than 3 consecutive days with maximum temperature (T<sub>max</sub>) above the daily threshold for the reference period 1981-2010. The threshold is defined as the 90th percentile of the set of daily maximum temperature computed from 31 day moving windows around each day of the year, for the entire 30 years reference period. Hence, for a given day *d*, the threshold is the 90th percentile of the set of data *A<sub>d</sub>* defined as follows:

$$A_d = \bigcup_{y=1981}^{2010} \bigcup_{i=d-15}^{d+15} T_{y,i}$$

where  $\cup$  denotes the union of sets and  $T_{y,i}$  is the daily T<sub>max</sub> of the day *i* in the year *y*. The magnitude of the event is then computed as the sum of the magnitude of the consecutive days composing a heatwave, with daily magnitude calculated by

$$M_d(T_d) = \begin{cases} \frac{T_d - T_{30y25p}}{T_{30y75p} - T_{30y25p}} & \text{if } T_d > T_{30y25p} \\ 0 & \text{if } T_d \leq T_{30y25p} \end{cases}$$

with  $T_d$  being the daily T<sub>max</sub> on day *d* of the heatwave,  $T_{30y25p}$  and  $T_{30y75p}$  are, the 25th and 75th percentile values, respectively, of the time series composed of 30 year annual maximum daily temperatures within the reference period 1981–2010. The  $M_d$  function gives the magnitude of a single heat wave day. The  $M_d$  is applied to each heat wave day and the final score of the HWMI<sub>d</sub> is given by the sum of all  $M_d$  values calculated for the days composing a heat wave.

Here cold waves are defined as three consecutive days with daily minimum temperature below the daily threshold defined as the 10<sup>th</sup> percentile of daily minima, centered on a 31 day window. In analogy to the HWMI<sub>d</sub> definition the Cold Wave Magnitude Index daily (CWMID) is defined as the minimum of the magnitude of all the cold waves in a year with values smaller or equal to zero. The CWMID sums the negative magnitude of the consecutive days composing a coldwave. In this study, in order to compare the CWMID with HWMI<sub>d</sub> we take the absolute values of the CWMID. This means that CWMID values close to zero indicate cold wave with very low magnitude and high positive values correspond to severe or extreme cold waves.

The data pre-processing was executed by means of the Climate Data Operator (CDO 2018: Climate Data Operators. Available at: <http://www.mpimet.mpg.de/cdo>) software and for calculation of HWMId/CWMId the “extRemes” R package (Gilleland & Katz, 2016) was used.

### 3.1.3 Spatial Determination of Large Metropolitan Areas

The usage of larger simulated or gridded observational datasets to assess the climate change impact over the set of target cities is not new (e.g. Guerreiro et al., 2018; Habeeb et al., 2015; Mishra & Lettenmaier, 2011; Papalexiou et al., 2018). The studies vary in the way how the target city areas are defined and how the data within the selected extent are treated, often in dependence on main aim of each study. Urban zones have been determined using different approaches, such as satellite night-time lights products (e.g. Yang et al., 2017), auxiliary data such as “Gisco Urban Audit 2004” (e.g. Guerreiro et al., 2018), areal estimates as a function of population density (e.g. Estrada et al., 2017), GIS processing of OpenStreetMaps (e.g. Varentsov et al., 2017), or predefined radius around the city centre (e.g. Papalexiou et al., 2018). Here, we exploit the data of Urban Atlas (EEA, 2012) offering the spatial extent of Greater Metropolitan Areas thus containing also the new and old urbanization situated often outside the municipality boundaries, but factually co-forming the metropolis as a whole and its climate. Subsequently, for each capital city apart Moscow, we sub set the HWMId/CWMId gridded values to the smallest rectangle containing the area given by Urban Atlas. In case of Moscow, which is not covered in the product, we estimated the area based on Varentsov et al., (2017).

In contrast to recent extensive study of Guerreiro et al., (2018) using 1 grid point to represent each city, we involved in analysis all the grid cells of each selected rectangle, therefore fulfilling the requirement of de la Barrera & Henriquez, (2017) to focus on cities “*in extenso*”. For example, the rectangular subset for Lisbon contains also the Sintra mountain known for its relatively cooler and wetter microclimate (Alcoforado et al., 2014) but also being a home to significant portion of Lisbon Metropolitan Area population. Hence, we believe that this approach prevents to assess the climate impacts as too severe, which may be a case when only the central meteorological station or the associated grid cell is considered.

Finally, we computed the annual median of the grid cells for each index, thus differing from previous studies based on averaged values, such as Abiodun et al., (2017); and Papalexiou et al., (2018). By this method, schematically depicted on Figure 5, each index for each city is represented by single vector, which then serves as the input for the comparative ranking procedure.



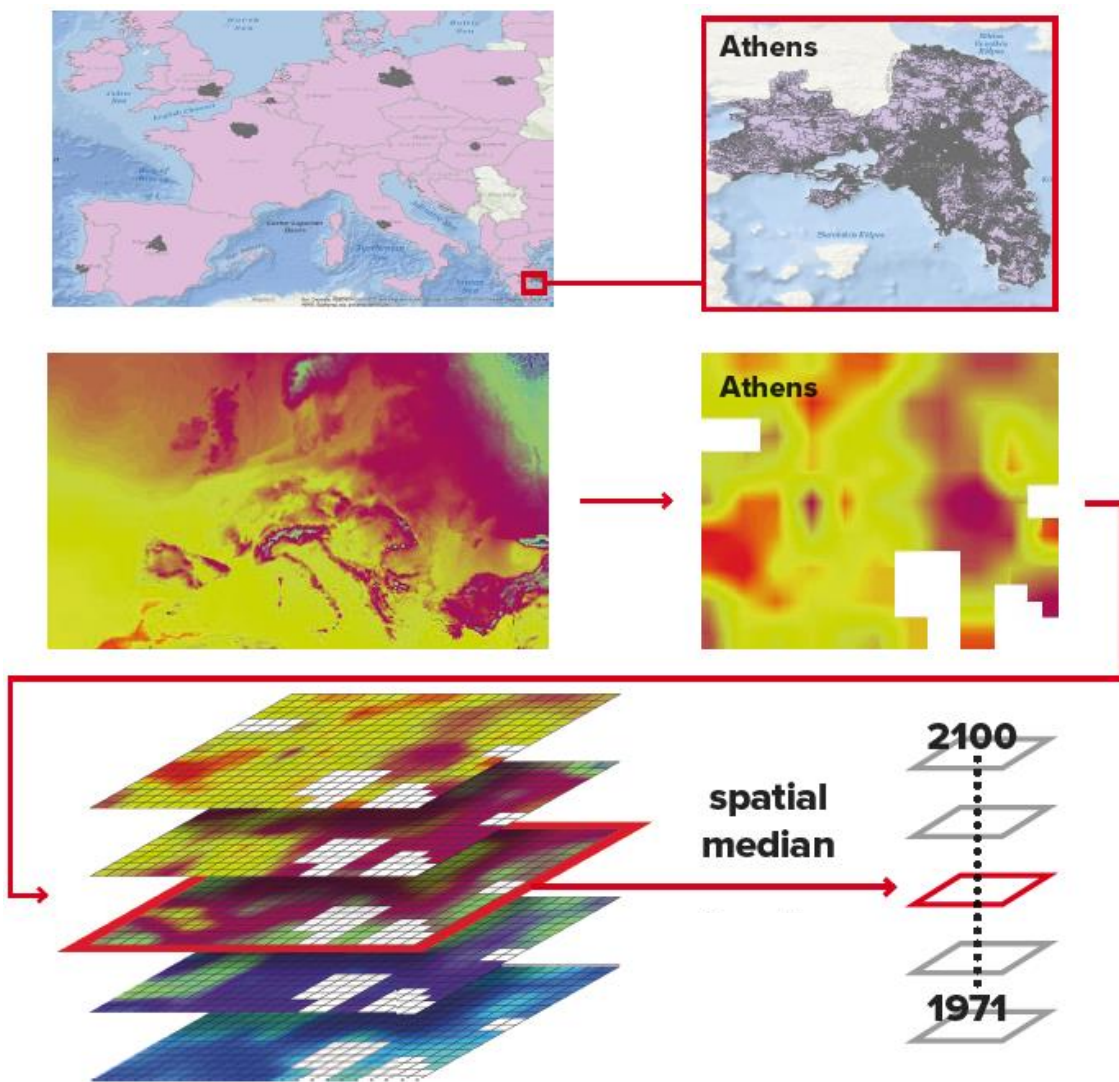


Figure 5 – Goinformatics workflow to determine the larger metropolitan areas and post-processing of the computed climate indices

### 3.1.4 Ranking Procedure

To rank the capital cities in terms of impact risks, firstly, we split the merged climate simulations covering the 1971 – 2100 period consisting of historical and RCP8.5 scenario realizations into three periods: near past (1981–2010), near future (2021-2050), and future (2071-2100). This 30 years chunks of computed indices were chosen to avoid the presence of climate change signal thus ensuring the stationarity in time series (Russo & Sterl, 2012).

Secondly, we constructed the following matrix for each 30 year period (i.e. time-slice) based on the annual spatial median of computed indices:

$$A = \{A_{ij}; i \in I; j \in J\}$$

where  $I$  stands for the set of 31 cities, and  $J$  stands for the set of annual HWMId /CWMId values in the considered period.

Subsequently, for each city, the number of HWMId/CWMId values exceeding a certain threshold were counted and divided by period length. These relative frequencies are interpreted as the probabilities of occurrence of events with given magnitudes for all cities in each time-slice. The considered magnitude thresholds were: greater than 3 labeled as “severe” events, greater than 6 labeled as “extreme” events, and greater than 9 labeled as “very severe” HWs and CWs. These thresholds are arbitrary but chosen in a way that they divide the past-present era HW magnitudes to approximately equal sized segments (the highest magnitude within computed ensemble mean between 1971 and 2020 is 11.204 for Berlin). Finally, the ensemble median of resulting probabilities was used for the final ranking and plotted on circular plots.

Exposure to Heat waves and Cold Waves has been measured by means of population density. The data about 31 target capitals were retrieved from spatially explicit dataset by Jones & O’Neill, (2016) consistent with the SSP1 Socioeconomic pathway (O’Neill et al., 2014). According to the dataset, the most densely populated city in this study is London, followed by Moscow and Paris (Figure 2). On the opposite side relatively sparsely populated cities of Lefkosia, Tallinn, and Valletta can be found. The SSP1 scenario assumes, the rapid urbanization, continuing migration, and in low fertility countries (including Europe) positive economic prospects which will allow for medium fertility level (Jones & O’Neill, 2016). This dataset offers near past, current and estimated future projections, with data spanning over the period from 1980 to 2100 by decade. Firstly, we exploited only the values for the year 2010, thus considering the population density as a static factor. In other words, we analyzed recent past exposure and analogously estimated exposure for future periods as if the population densities remain constant. The vectors of population densities expressed in thousands per km<sup>2</sup> were divided by their maximum (the value of population density of the densest populated city) therefore expressed at the standardized scale between 0 and 1, with values close to zero or one indicating low or high population density, respectively. Furthermore, the exposure measure was calculated as the product of the probabilities of occurrence of HWs with different magnitudes and standardized population density values. This was done for each target city and for all three analysed time-slices. Secondly, to assess the influence of evolving population projections, we undertaken a similar procedure, but instead of static population density data, the median of projected values within each period was utilized. For example, city specific HWs probabilities of 2071-2100 were multiplied by vectors of the same length, computed as medians of population density projections for years 2080, 2090, and 2100 with the same standardization. Then again, the final ranking was based on the ensemble median.

## **3.2 Results**

Our results provide insights regarding the future evolution of temperature related exposure of population across all the European capitals. We showed that the cold waves exhibit a decreasing trend with already relative small impacts in the mid-century and almost entirely vanishing in far future. The results clearly show a gradual increase in frequency and severity of extreme heat events. Based on the impact ranking, in near and distant future extreme heat events will be not exclusive to traditionally exposed areas such as Mediterranean and Iberian Peninsula. Severe, extreme and very extreme HWs have increasing probabilities of occurrence from 2021-2050 to 2071-2100 in most cities (Figure 6).

## Probability of HWs occurrence

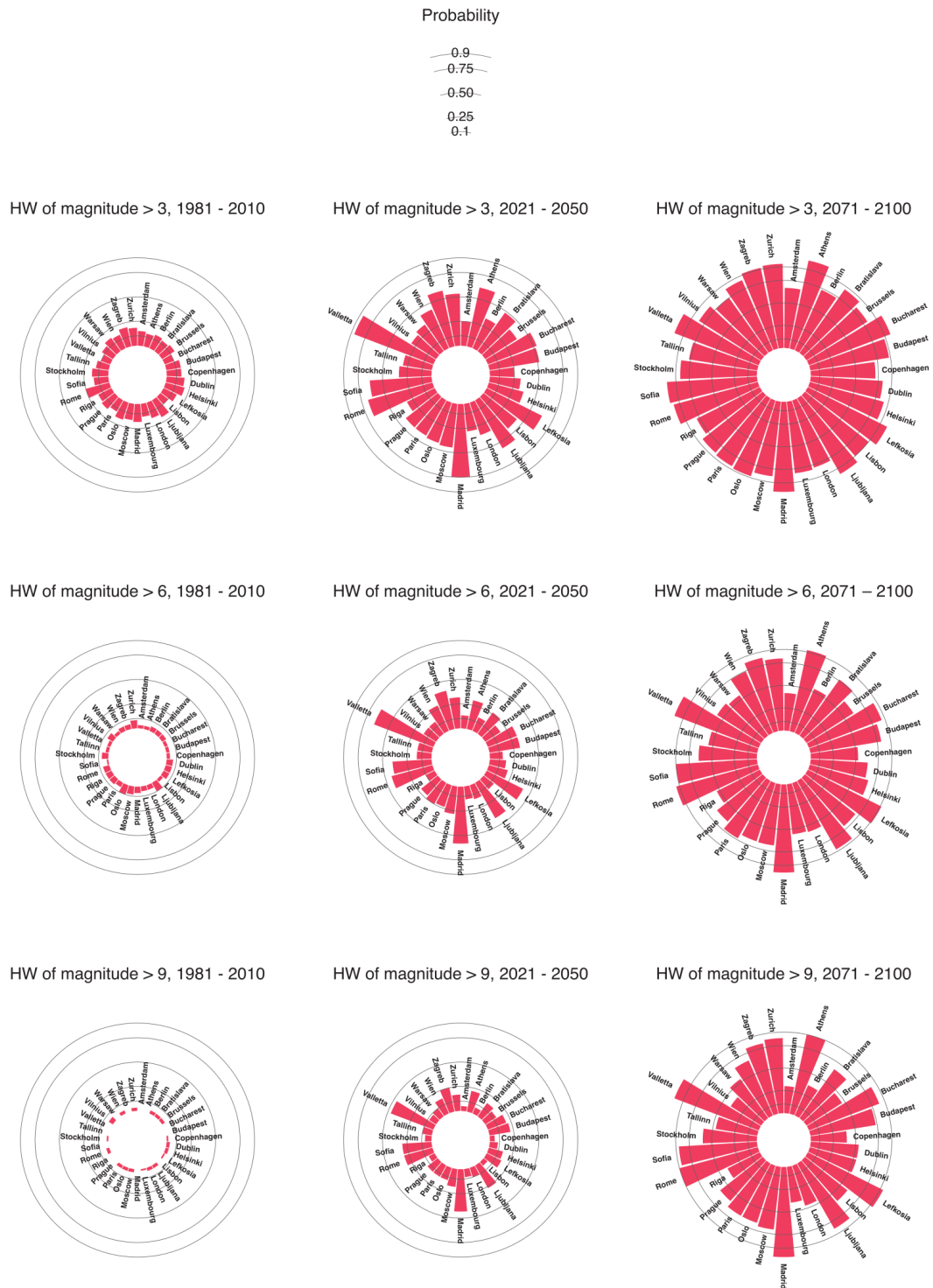


Figure 6 - Probability of HWs occurrence.

In near future (2021–2050), the occurrence of HW with magnitude greater than 6 is more likely in Madrid and Valletta (probability about 0.6), Lefkosia, Ljubljana, Rome, and Sofia (probability over 0.4) and Athens, Bucharest, Budapest, and Zurich (probability = 0.3), whereas the occurrence of HW of magnitude greater than 9 is most likely in the Valletta (probability = 0.46), Madrid (probability = 0.43), followed by Rome and Sofia (probability = 0.3). Valletta and Madrid show the highest values in probability of occurrence of heatwaves with a magnitude greater than 9 but also Ljubljana and Zagreb might be exposed to very extreme HWs. In 2071–2100, the probabilities of occurrence of HW greater than 6 are smaller than 0.5 only in Amsterdam. In distant future, the probabilities of occurrence of HW to be more severe than 9 are greater than 0.75 in the following cities: Athens, Bratislava, Bucharest, Budapest, Lefkosia, Ljubljana, Madrid, Rome, Wien, Zagreb and Zurich, but closely followed by Paris (probability = 0.73) and Lisbon (probability = 0.71).

These findings confirm that HWs will most likely strike the populous metropolises of Madrid, Rome and Athens commonly associated with extreme temperatures but also other cities, namely Wien, Zagreb, and Zurich should expect serious impacts in the future. The Maltese capital, Valletta, particularly emerges from the analyses, as it is projected to progress from a comparatively center position in the ranking for near past towards the most severe HWs by the end of this century. These impacts will be even more serious due to Valletta's geographic location in the middle of Mediterranean Sea where the humidity will enhance all the negative implication for local population (Russo et al., 2017).

Another important finding is related to relative change between near and distant future. Whereas the top ranked metropolises of Lefkosia, Madrid, Rome, Sofia and Valletta keep their leading positions, the continental European cities of Bucharest, Budapest, Ljubljana, Prague Paris and Zagreb will experience a dramatic increase in HWs occurrence. This holds true for the HWs of all the analyzed magnitudes. Somewhat special case is represented by Athens, because it is ranked in between these two groups for the period 2021-2050 (particularly for magnitudes higher 6 and 9) but will belong to the top ranked capitals towards the end of century. These relative changes between the two future periods are less striking when the population factor is taken in account. This is a direct consequence of the methodology, where the multiplication between 2 vectors (HWs probabilities and exposure factor based on population densities – both on scale between 0 and 1) naturally often yields lower results to be plotted. Hence, even though the HWs exposure evolution (the dramatic increase for continental cities towards the end of the century) remains, the relative changes on the circular plots are also decreased.

When the population densities are considered (Figure 7, and Figure 8), the less populous metropolitan areas located in warm climates (e.g. Lefkosia or Valletta) do not appear in top positions of our ranking. The cities of Athens, Rome, Wien, Zagreb and Zurich strongly emerge from the analyses as the most exposed to future HW hazard, followed by Lisbon, Ljubljana, London, Madrid, Sofia, Stockholm, and Tallinn. Moreover, the involvement of the projections of population density to the analyses brought only quantitative changes and does not change the resulting ranking order. We hypothesize that this hints the need for more elaborated demographic models rather than indicating that population density is not suitable proxy for the

population

exposure.

### Exposure to HWs – static population density

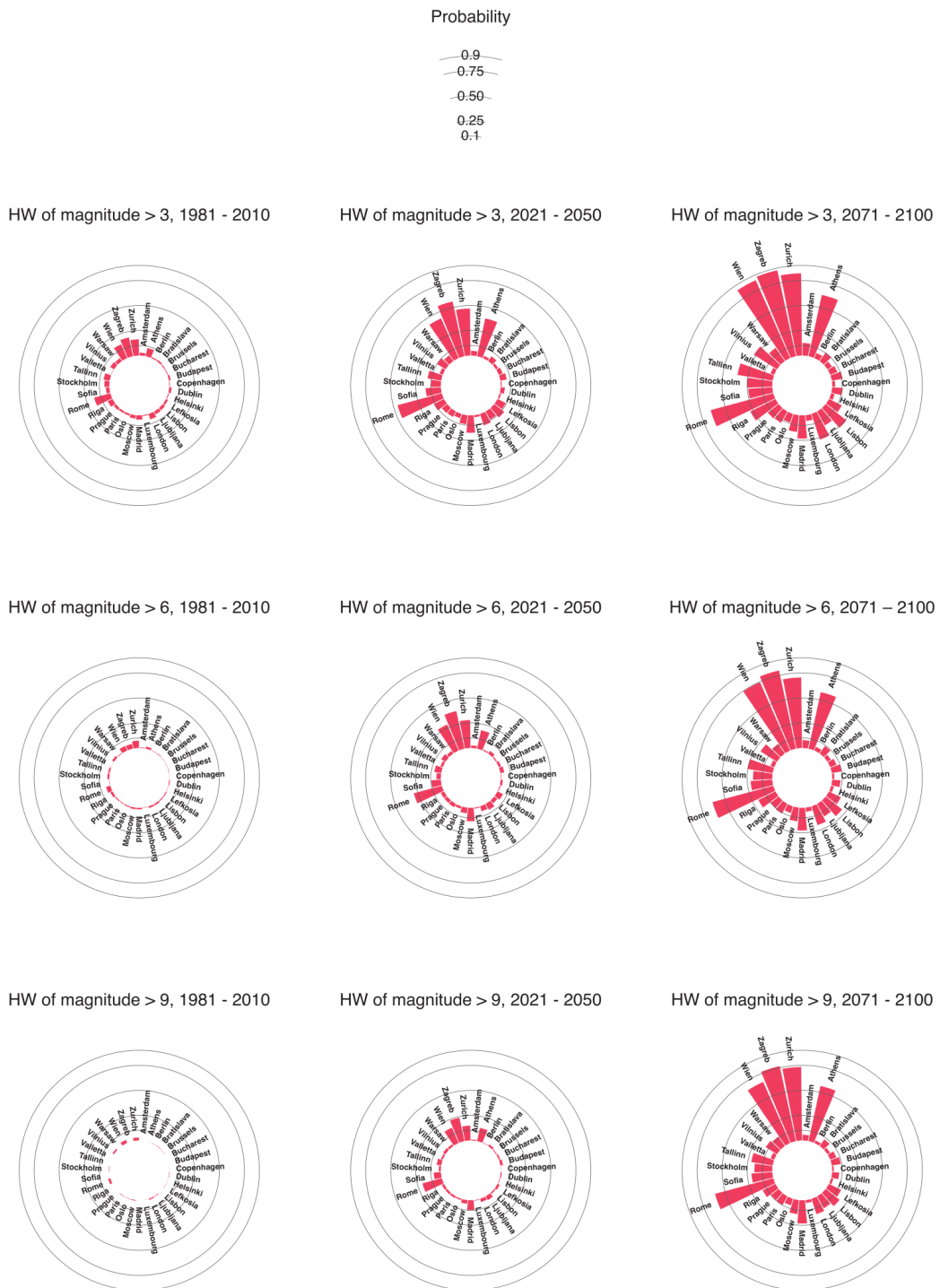


Figure 7 - Exposure to HWs – static population density.

## Exposure to HWs – dynamic population density

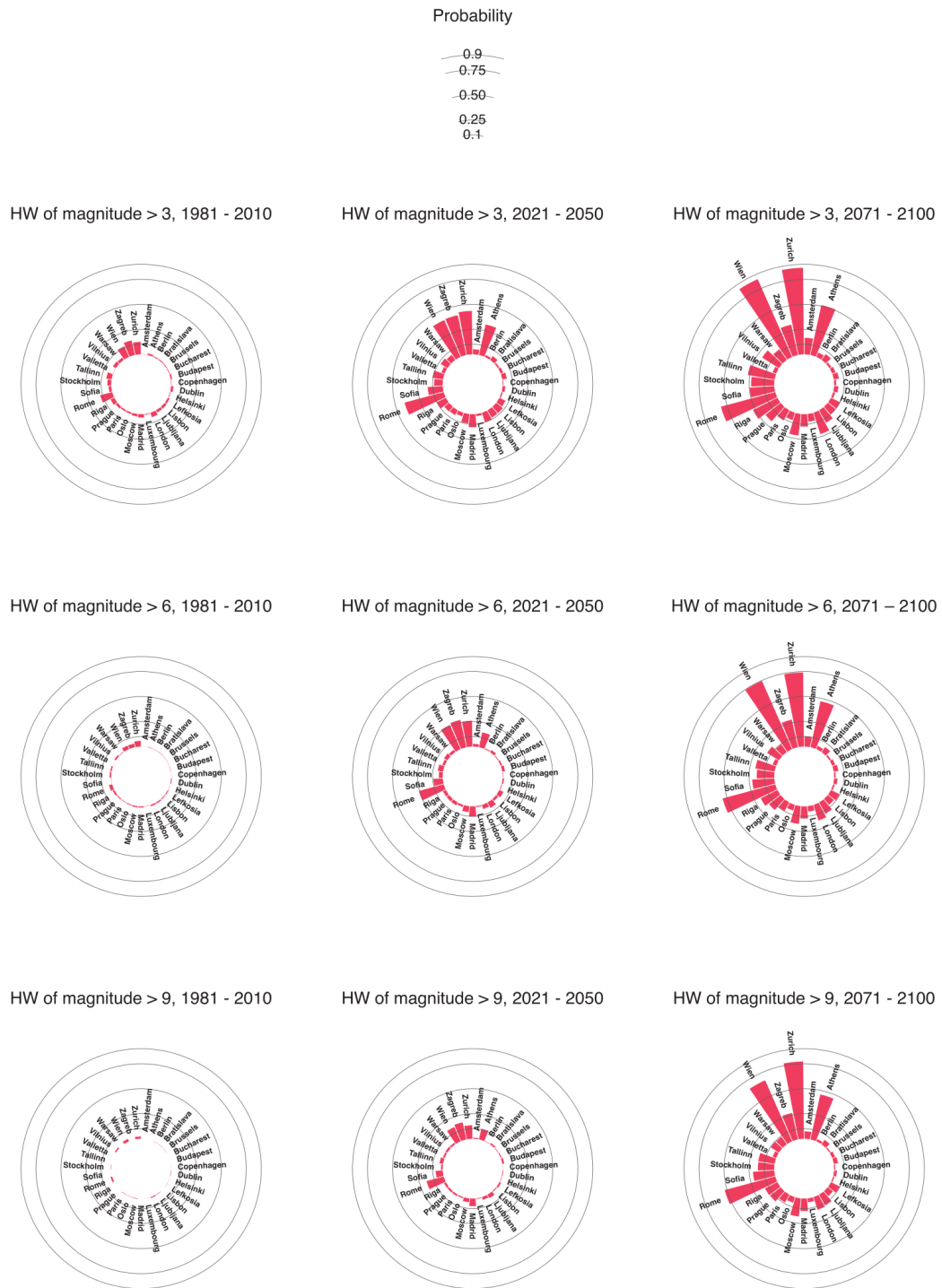


Figure 8 - Exposure to HWs – dynamic population density.

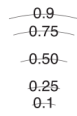
With the increasing of global mean temperature, model simulations indicate that the occurrence of CWs of magnitude greater than 3 is unlikely in all cities (Figure 9). The estimated probabilities are smaller than 0.25 in all periods and vanish to almost zero in all cities in distant future (2071-

2100). In near future (2021-2050), the occurrence of CW exceeding the magnitude 3 is more likely in the cities of Zagreb and Zurich (probability > 0.18), Budapest and Paris (probability = 0.17) and Amsterdam, Berlin, Bratislava, Prague, Sofia, Warsaw (probability > 0.13), whereas the occurrence of CW stronger than value 6 of CWMId is more likely in the cities of Amsterdam, Bratislava, Bucharest, Paris, and Wien (probability > 0.1). The estimated probabilities of CW to be greater than 9 are smaller than 0.1 in all cities and within the three periods.

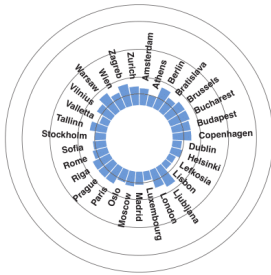


### Probability of CWs occurrence

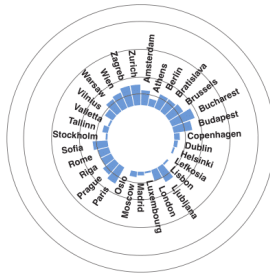
Probability



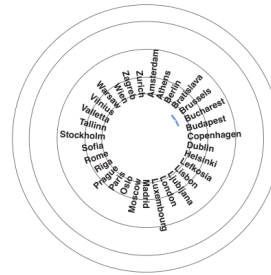
CW of magnitude > 3, 1981 - 2010



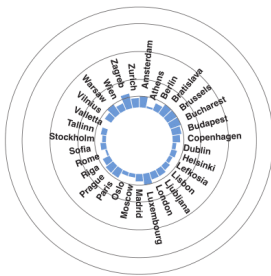
CW of magnitude > 3, 2021 - 2050



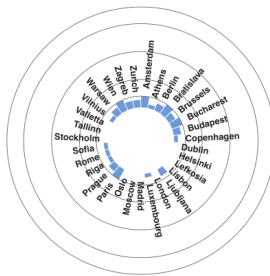
CW of magnitude > 3, 2071 - 2100



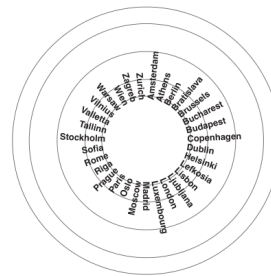
CW of magnitude > 6, 1981 - 2010



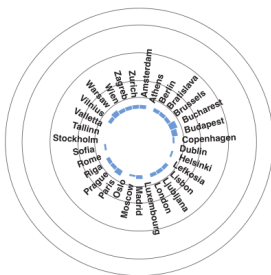
CW of magnitude > 6, 2021 - 2050



CW of magnitude > 6, 2071 - 2100



CW of magnitude > 9, 1981 - 2010



CW of magnitude > 9, 2021 - 2050



CW of magnitude > 9, 2071 - 2100

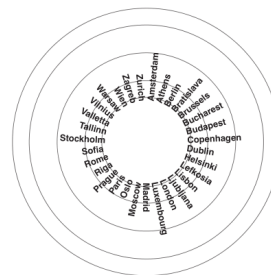


Figure 9 - Probability of CWs occurrence.

Because CWs are projected to not to be a major threat across all the European capitals, this can be considered as a positive impact climate change and the exposure considering the population data was not analyzed.

Even though, the CWs are projected to be almost absent in the future, additionally we have tested if the reduction in CWs exposure will be equal, greater or lower than increase of HWs exposure. For each city we estimated the following index for each level of magnitude (3, 6, 9):

$$RelativeEvolution = \frac{|(Pr(future HWs) - Pr(present HWs))|}{|(Pr(future CWs) - Pr(present CWs))|}$$

The results show that for events of magnitude 3, in vast majority of European capital cities the increase in HWs will heavily outweigh the change in exposure to CWs. The same holds true for waves of magnitude greater than 6 when differences between present situation and distant future are considered. However, the extreme climate events of this magnitude and their shift in the near future, for some cities (e.g. Bratislava, Dublin, Ljubljana, Stockholm, Valletta, Vilnius, Tallinn, or Zurich), exhibit the opposite tendency in the relative evolution in exposure to HWs and CWs. This tendency is observable also for very extreme events for both considered time periods. It is noteworthy that in most cases where increasing CWs exposures were stronger than their HWs counterparts, the final results are of very small absolute values when compared with opposite situation. There is a large variety of possible explanations of this phenomenon and the further analyses would be needed to understand the underlying reasons. The full results can be found in Appendix B – Figure 15.

It should be emphasized that the results interpretation should be handled with caution. For example, the large metropolitan area of Amsterdam, even though being ranked with lowest risk in comparison to other European capitals towards the end of the century, has an estimated probability of occurrence of severe HWs equal to 0.66, and for extreme HWs the probability is 0.41 (chances of very extreme events are predicted to be 0.3). Hence, the result should not be misinterpreted as the extreme heat event will be no serious threat for such locations.

### 3.3 Conclusions and Discussion

Even though HWs are often still not perceived as serious risk (Keramitsoglou et al., 2017) they were found as the deadliest form of extreme weather in US (Habeeb et al., 2015) and there is no reason to assume that this will be different in Europe. Managing the impacts in cities is of paramount importance (UN-habitat, 2010) because it is the metropolitan space where the most people will encounter the extreme heat (Schatz & Kucharik, 2015) and it is the nature of urban space what enhances the impacts of larger scale synoptic phenomenon (e.g. Arnfield, 2003; Estrada et al., 2017; Zhao et al., 2014). The alternation of climate impacts by urban space will be not always necessary negative. Impacts may be softened by the joint influence of urban space and climate warming, such as some costs associated with maintenance of rich cultural heritage of European cities (la Fuente et al., 2011), reduction in winter heating demand and saved lives (Schatz & Kucharik, 2015, Kolokotroni et al., 2012). Nevertheless, the increasing negative impacts of extreme heat will by far outweigh the positive consequences.

Specifically in urban areas, the crucial negative impacts of extreme heat include health risks, human discomfort, associated higher concentrations of pollutants, lower water quality, increase energy demand for cooling, and decrease in labor productivity (Dunne et al., 2013; Estrada et al., 2017; Zander et al., 2015). The risk of fire triggered by overload of power transmission lines (Altalo & Hale, 2004; Habeeb et al., 2015) also represent monetary costs and causes areal blackouts (Habeeb et al., 2015). Moreover, it was reported that even if the wildfire does not strike the urban zone directly, nearby agglomerations experience continued periods of extreme air pollution (Konovalov et al., 2011). Even with no fire occurrence, the episodes of extreme heat are responsible for the air quality deterioration in urban environment (Fischer et al., 2012; Nazaroff, 2013; Sarrat et al., 2006; Stathopoulou et al., 2008).

The elderly, young, the individuals with preexisting chronic conditions, communities with weak socioeconomic status, people with mental disorders and isolated individuals are commonly listed as the vulnerable disadvantaged impact groups (Basu, 2009; Habeeb et al., 2015; Keramitsoglou et al., 2017). Especially the aging factor is emphasized in many studies (e.g. Baccini et al., 2008; D'Ippoliti et al., 2010; Michelozzi et al., 2009; Son et al., 2012). The elderly population suffers the enhanced burden from heat stress because of less-well functioning thermoregulation (Flynn et al., 2005), decreased skin blood flow and reduced cardiac output (Kenney & Munce, 2003), and higher presence of preexisting chronic conditions. The risk grows with continues aging in population of highly developed countries (Michelozzi et al., 2009). Moreover, the significant portion of wealthier elders choose to retire out of the urban zones thus remaining urban elders represent an important group in danger considering also their more frequent isolation, reluctance to spend on cooling, and urban effects on local climate (Habeeb et al., 2015; Hajat et al., 2014; Michelozzi et al., 2009; Son et al., 2012).

Amongst the aforementioned consequences of extreme heat, the health impacts are of outstanding importance. In Europe, where universal healthcare generally covers the entire population, the health impacts also represent direct monetary cost to governments. The health impacts span from heat cramps which may signalize heat exhaustion and heat strokes (Michelozzi et al., 2009; Russo et al., 2017) leading to fatal congestive heart failure or acute myocardial infraction (Koken et al., 2003), to respiratory diseases. In high-income settings of European capitals only smaller proportion of fatalities occurs due to hyperthermia as such (Hajat et al., 2014). The respiratory heat-related illnesses may be associated with the systematic inflammation of airways resulting in chronic obstructive pulmonary diseases triggering dyspnea, further amplified by extreme heat conditions (Viegi et al., 2007). Furthermore, other infectious diseases associated with vector infectious agents, such as viruses, bacteria or protozoa, are thermostatically dependent (Kovats et al., 2001; Gubler et al., 2001; Patz et al., 2005). For example, the occurrence of food-born infection of Salmonellosis in Continental Europe was enhanced by 30% by elevated average temperature (Kovats et al., 2004; Patz et al., 2005).

The physiological impacts of extreme heat have stronger association with nighttime rather than day time temperatures (Tan et al., 2010; Habeeb et al., 2015; Keramitsoglou et al., 2017). In urban systems during the night, the shallow, vertically stable atmosphere layer is formed, preventing the day-time diffusion of excessive heat. The day-night temperatures asymmetry is vital for human health since the urban inhabitants are prevented to recover during nocturnal relief and people suffer the prolonged periods of extreme heat burden (Anderson & Bell, 2011;

Schatz & Kucharik, 2015; Keramitsoglou et al., 2017; Pereira et al., 2017). Moreover, both – the enhanced duration and intensity of HWs are responsible for more severe impacts (D'Ippoliti et al., 2010; Son et al., 2012). The more negative impacts are commonly associated with prolonged periods of extreme heat (D'Ippoliti et al., 2010; Kalkstein et al., 2011; Schatz & Kucharik, 2015; Zuo et al., 2015; Pereira et al., 2017), even though Gasparrini & Armstrong, (2011); estimated the HW influence on mortality as relatively small in comparison to impact of daily high temperatures.

This study does not substitute a detailed city-specific vulnerability assessment, neither explicitly quantifies the impacts in monetary or epidemiological terms. Our results provide insights regarding the future evolution of temperature related exposure of population across all the European capitals. We showed that the cold waves exhibit a decreasing trend with already relative small impacts in the midcentury and almost entirely vanishing in far future. This is in agreement with previous work on Iberian Peninsula by Pereira et al., (2017). We confirmed that HWs will most likely strike the populous metropolises of Madrid, Rome and Athens commonly associated with extreme temperatures but also other cities, namely Wien, Zagreb, and Zurich should expect serious impacts in the future. The Swiss capital – Zurich, deserves the particular attention since it was marked as the city with the most significant rise in HWs intensity (quantified as 12.9 C) from all the European capitals (supplementary of Guerreiro et al., 2018) and so far it does not represent recognized HWs impact hotspot. The Maltese capital, Valletta, particularly emerges from the analyses, as it is projected to progress from a comparatively center position in the ranking for near past towards the most severe HWs by the end of this century. These impacts will be even more serious due to Valletta's geographic location in the middle of Mediterranean Sea where the humidity will enhance all the negative implication for local population. Our results generally agree with previous studies (e.g. Peterson et al., 2012) that increase in magnitude of heat waves and decrease in magnitude of cold spells over entire European domain can be expected. Moreover, we confirm that by the end of the century the relatively higher increase in the intensity of future heat will take a place along south – northeast gradient (Pereira et al., 2017), with the most dramatic rise in HWs magnitudes in Central Europe (supplementary of Guerreiro et al., 2018), and also in south-central Europe (Fischer and Schar, 2010). To this we can add south-east European region (represented in this study by cities of Bucharest and Sofia), where we expect the HWs of comparable severity as in Mediterranean, closely followed by Moscow which is typically not included in most of European studies. The absence of humidity in our analyses represents a limitation of this work and it is one of the directions for further research. Nevertheless, in continental European areas relative humidity does not play a significant role during heat waves. For example the two most outstanding events on record (HWs of 2003 and 2010) were characterized as not humid (Russo et al., 2017).

It should be emphasized that the results interpretation should be handled with caution. For example, the large metropolitan area of Amsterdam, even though being ranked with lowest risk in comparison to other European capitals towards the end of the century, has an estimated probability of occurrence of severe HWs equal to 0.66, and for extreme HWs the probability is 0.41 (chances of very extreme events are predicted to be 0.3). Hence, the result should not be misinterpreted as the extreme heat event will be no serious threat for such locations.

We found that when the population exposure feature is taken into account, the less populous metropolitan areas located in warm climates (e.g. Lefkosia or Valletta) do not appear in top positions of our ranking. The more surprising result is that relatively highly populated areas of Budapest, Bucharest, Lisbon and Paris do not rank in high positions in HW exposure results. Moreover, the involvement of the population density projections to the analyses brought only quantitative changes and does not change the resulting ranking order. We hypothesize that this hints the need for more elaborated demographic models rather than indicating that population density is not suitable proxy for the population exposure. Finally, the relative changes between the 2 future periods described in the results section are less striking when the population factor is taken in account. This is a direct consequence of the methodology, where the multiplication between 2 vectors (HWs probabilities and exposure factor based on population densities – both on scale between 0 and 1) naturally often yields lower results to be plotted. Hence, even though the HWs exposure evolution (the dramatic increase for continental cities towards the end of the century) remains, the relative changes on the circular plots are also decreased.

Overall, the major usage of our simplistic but descriptive urban indicators (i.e. the estimated probabilities of HWs/CW for each city) is twofold. Firstly, similarly to the study of Guerreiro et al.,(2018) such a methodology can serve as a basis to decision making on European level, assisting with prioritizing the investments and other efforts in the adaptation strategy. Secondly, it communicates the risk associated with climate change induced extreme heat locally, thus helps to bridge the gap between science, policy making and general public to better comprehend the seemingly no personal issue of climate change and its impacts. The climate change communication represents the vital prerequisite for action and the fact that our indicators are comparative highly contributes to its illustrative and communication power. Finally, since our study is based on HWMId, unlike many other works, our results offer the transparent information about the magnitudes of future HWs events. For example, in comparison with (Ward et al., 2016) focused on UHI effects during the HWs, the HWMId utilizes the magnitude sum over all HW days thus better captures the cumulative burden of temporarily persistent HW episodes. However, we reached the similar finding that in comparison with population related information, it is the regional climate as the most important explanatory factor of heat impacts. The other study by (Lemonsu et al., 2013) defines HW intensity as product of maximum temperature by duration in days, but this is not suitable to analyze the longer periods. Nevertheless, we acknowledge that these authors had different aims in mind and all the rigorous assessment addressing the magnitudes or intensity aspect of HWs helps to create a more precise picture of upcoming challenges. This contributes to raise awareness about HWs since they are still often not perceived as serious risk (Keramitsoglou et al., 2017).



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## 4 MetroHeat

This section is devoted to the web tool developed as an integral part of the Open City Toolkit (OCT) of GEO-C. This work is partially based on subfield of climate science – climate services and partially on Climate Change communication which represents compelling but unwell integrated and dispersed body of literature (Moser, 2006). In this section we address the motivation and purpose behind the platform development, as well as description of target audience. Furthermore, we highlight the success factors and pitfalls being encountered when developing such a service, including implemented solutions. Finally, we describe the architecture and functionalities provided by the tool and we discuss potential limitations and further activities.

Researchers, consultants, policy makers, private stakeholders and even general public represent a growing amount of people requiring climate-related information. However, they differ in terms of their backgrounds, skills and objectives (Swart et al., 2017). In response to this demand, numerous entities developed information platforms and portals providing an ever increasing amount of climate and climate impact data during the last decade (Street et al., 2015). This phenomenon resulted in the so-called “Portal Proliferation Syndrome” diagnosis, as users do not know from where to obtain and how exactly to interpret the available climate information (Bernard, 2011; Swart et al., 2017). The purview of climate services is clearly being continuously extended by adding more actors, such as the so-called purveyors, who play the vital role of knowledge brokers by translating climate and climate impact information from a scientific-technical domain to understandable and plain text deliverables to non-scientific public, thus assisting policy makers and others to combat the consequences of climate change (Swart et al., 2017).

This evolution is also reflected in the history of released global frameworks. The World Meteorological Organization (WMO) in 2009 organized the 3<sup>rd</sup> World Climate Conference, where a Global Framework for Climate Services (GFCS) was established, aiming to strengthen production, availability, delivery, and application of science-based climate services and prediction (WMO, 2009). This framework followed-up the concept of climate services in the United States (NRC, 2001). In 2010, GFCS was complemented with a report entitled “Climate Knowledge for Action: A Global Framework for Climate Services”, and in 2014 with an Implementation Plan (GFCS, 2014). According to the WMO definition, climate services should provide one or multiple climate products, or provide advice to decision-making of individuals or organizations, simultaneously targeting the facilitation of adaptation planning (WMO, 2009). In Europe, this definition is broadened by a framework of the European Research and Innovation Roadmap for Climate Services (EC, 2015), delineating climate services as “the transformation of climate-related data – together with other relevant information – into customised products, such as projections, forecasts, information, trends, economic analysis, assessments (including technology assessments), counselling on best practices, development and evaluation of solutions and any other service in relation to climate that may be of use to the society at large. As such, these services include data, information and knowledge that support adaptation, mitigation and disaster risk management (DRM)” (Swart et al., 2017).

Under this framework, the researchers are expected to overcome not only the challenges of new raw data production, but the community is also called to deliver processed high-quality information. To achieve this, the development of the climate data infrastructure must comply with data management and preservation requirements according to open data policies (De Filippis et al., 2018). The research data infrastructure must facilitate data discovery and access but, since the interdisciplinary approach is key to overcome many challenges associated with the impacts of climate change (Hadorn et al., 2008), the infrastructure should also provide means to improve the collaboration between scientists of different background (Zhao et al., 2015).

Apart from the aforementioned frameworks, scientific literature offers recommendations for the provision of climate services. For example, Sigel et al., (2016) extensively reviewed 17 existing national portals discussing their limitation and possibilities. Bulens et al., (2013) presented the results of an experiment based on the feedback from participants thus tackling the issue from a user perspective. Houtkamp et al., (2016) analysed the user requirements and summarized learned lesson in terms of user engagement, and Swart et al., (2017) proposed a systematic evaluation framework for climate services related portals. The lively debate about climate services worldwide, particularly in Europe, highlights their usefulness for a wide range of users, but the developments are usually framed in the perspective of the data provider (Lourenço et al., (2015). Although global and European climate services do not explicitly exclude climate impact information, they are often not yet focused on it. (Swart et al., 2017). Moreover, most current services have a national, regional, or global focus. Hence, climate services targeting metropolitan communities, particularly in Europe, are still lacking.

## 4.1 Purpose

The open data climate service, MetroHeat (<https://cgranell.shinyapps.io/metroheat/>), is a web tool for visualising and interacting with extreme temperature indices and heat waves indicators, based on multi-model climate projections for major European cities.

Aligned with the previously stated definitions and motivation, the purpose of our open data, web-based climate service is threefold:

- to provide the transformed climate impacts-related data as customised products for urban stakeholders;
- to support the capacity for multidisciplinary research and cooperation;
- to contribute to the effective communication of the complex issue of climate change.

This initiative arises based on two facts – firstly even though the theory recommends the usage of full ensembles of climate simulations, in reality many climate modellers are simply not able to handle large multi-model ensembles (MME) (Wilcke & Barring, 2016). Secondly, those who have the resources and advanced skills to manage climate data or to compute derived indices mainly stores these products in personal archives (De Filippis et al., 2018). However, when these computed datasets become accessible in a user-friendly manner, they may be of further use for many stakeholders (Smid & Costa, 2017).

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MetroHeat offers intermediate products, namely a suite of extreme temperature indices computed on a subset of EURO-CORDEX ensemble data (Jacob et al., 2014), which is a cutting edge and fine scale set of climate simulations that is openly available. Users can specify the European capital cities (EU28, Moscow, Oslo, and Zurich) of their interest together with a desired time-span (annual or decadal data between 1971 and 2100). Based on the users' preferences, multiple graphics are then automatically generated and adjusted. Finally, the resulting graphics can be downloaded, either as a graphic file (e.g. PNG, JPEG, etc.) or as a table file with the raw data series (e.g. CSV).

The main barriers to the communication of climate change are people's apathy or disinterest, the overabundance of information and its complexity. The issue of climate change is global, uncertain, politically charged, and difficult to solve (Moser, 2006). The computed climate indices provide detailed insights at city level, and contribute to a better understanding of the "local" impact of climate change in a unique way, which is tailored to be understandable and accessible to a widest audience. Therefore, MetroHeat enables people to connect to this ostensibly impersonal problem.

## 4.2 Target audience

When developing climate a service or, in a broader sense, communicating climate change, the very first question to be asked is: "Who is the audience?" (Moser, 2006). Often, even in climate services developed by formal international programmes, such as the European Copernicus Climate Change Service (C3S; <https://climate.copernicus.eu>), the target users are seen primarily as a homogenous group of policy makers. Even though most climate services acknowledge the diversity amongst the target users, these services do not distinguish between them in terms of the different products or associated components that best suit their needs (Benitez-Paez et al., 2017; Swart et al., 2017). The funding is often conditioned by the creation of societal benefits from the investment, thus climate services tend to stress the societal-end users as main beneficiaries (EC, 2015).

In reality, though, the spectrum of users is very diverse, varying from climate scientist and policy makers (from Global or European to municipal and sub-municipal levels), to private companies and non-governmental organizations. For pragmatic reasons, Swart et al., (2017) categorized the users into four user groups as follows: climate scientists, climate impact researchers, intermediate organizations, and societal-end users. The climate scientists demand high-level data of high reliability, and their requirements on post-processing capabilities provided by climate services are relatively low. Similarly, the impact researchers call for high level-data. However, this group also needs impact indicators, rather than raw climate variables, and their appreciation of post-processing functionalities is expected to be somewhat higher. Under the group of intermediate organizations there are various sub-groups of knowledge purveyors and boundary workers, such as consultants. They are interested in all possible kinds of information. While their skills are not necessary matching the level of the previous two groups, the intermediate organizations play the vital role of knowledge brokers by providing the link between climate data providers and climate impact information delivery. This user group exhibits increased demand for tools to allow them to post-process the provided data by

themselves. Lastly, Swart et al., (2017) define the societal-end users as governmental or industry decision makers, which are broadly described as “people who are trying to address the impact of changing climate”. This group is also interested in all kind of available data but often lack skills, interest, and time needed to handle climate-related data. Therefore, they demand information delivered in a clear and concise manner.

Here, we expanded the classification of Swart and colleagues by an additional group of the general public. We argue that one of the primary aims of climate services, like any other form of communication of climate change-related scientific findings, is to trigger certain behavioural changes (Blix, 2004). For example, when the goal is to reduce transport emissions, all actors from vehicle manufacturers, national legislators, municipal transport and urban planners should be addressed, but special attention should be given to individual inhabitants – drivers, commuters or travellers in general. The general public can have significant influence over the decision makers’ actions. Casually educated individuals can act collectively, changing behavioural norms and mobilizing for policy changes at local and higher levels (Moser, 2006). But this connection is mutually beneficial since the effectiveness of solutions and policies highly relies individual attitude and behaviour (Heiskanen et al., 2010). Following the classification of Swart et al., (2017) classification, we argue that this user group of general public needs lower level climate impact information. Since the general public are not expected to have advanced data handling skills, emphasis should be placed on the simplicity of accessibility and interpretation of climate information. Figure 10 depicts the target users groups of MetroHeat.

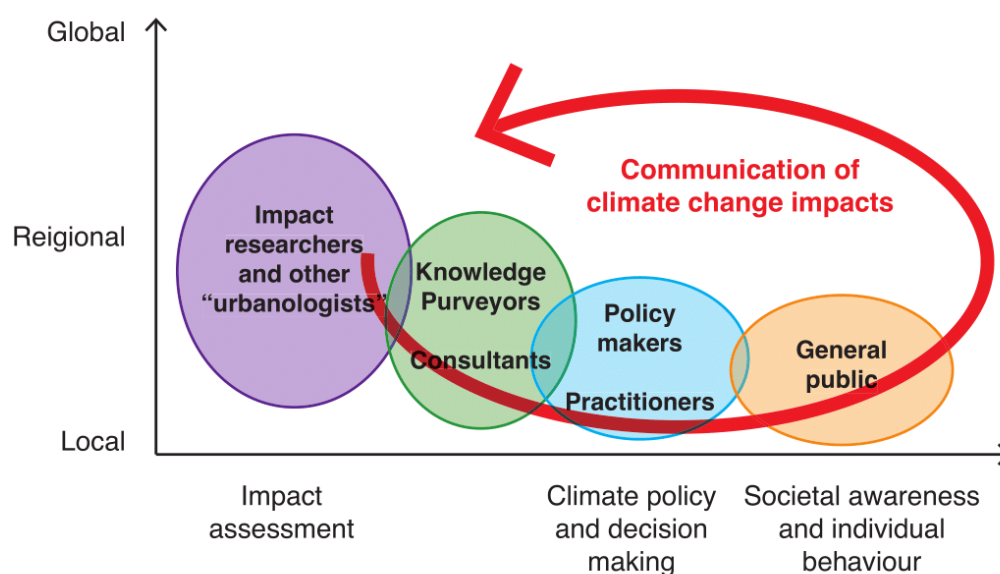


Figure 10 - Different MetroHeat user groups, their purposes and interactions.

## 4.3 Materials and methods

### 4.3.1 Suite of extreme temperature indices

The Expert Team on Climate Change Detection and Indices (ETCCDI; <http://etccdi.pacificclimate.org/index.shtml>) formalized the list of recommended climate

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indices to facilitate the coherency in climate impact modelling across the globe (Peterson, 2005). This list, currently known as “ETCCDI Indices”, has been further analysed perhaps in most detail by Zhang et al., 2011; Sillmann et al., 2013a; and Sillmann et al., 2013b. The more extreme the event is, the more relevant for the society is to define, capture and project such a phenomenon. However, the rarer the event is, the higher is the uncertainty associated with such a projection due to its position further in the tail of the distribution of the climate element. Thus, in this trade-off between the uncertainty and rarity/severity of climate events, the emphasis of ETCCDI indices (and also of this work) is given to “moderate extremes” that typically occur at least once a year (Zhang et al., 2011). MetroHeat provides 3 different ETCCDI absolute indices, 4 ECCDTI percentile-based indices, and it is complemented with the Heat Wave Magnitude Index daily (HWMId) (Russo et al., 2015).

Absolute indices represent the upper or lower extreme per chosen period of time (Sillmann et al., 2013b), and they are often used by engineers to infer the design of the infrastructures (Zhang et al., 2011). Here, we computed the maximum and minimum of daily maximum temperatures for each year (TNx and TNn respectively) and also the annual maximum of daily maximum temperature (TxX) (Alexander et al., 2006) to capture the evolution of extreme heat peaks.

In comparison with the absolute indices, the percentile-based indices have a clear advantage, as they can be used in studies of wide regions with different climate characteristics (Tank & Können, 2003). Moreover, they are better descriptors of variation in synoptic conditions facilitating the extreme events (Zhang et al., 2011). They express the percentile rates of thresholds exceedance. The thresholds of ETCCDI indices are typically defined as the 90th or 10th percentile, and days exceeding (not exceeding) a given high (low) percentile are counted. Hence, all the percentile-based indices provided by MetroHeat account for the climatic variability amongst the individual cities.

We exploited the ETCCDI percentile-based indices indicating the number of warm days (Tx90p) and warm nights (Tx90p) due to their high importance for heat impact on human health (Lubczyńska et al., 2015). Furthermore, we computed their counterparts: the number of cool days and cool nights (Tx10p and Tn10p, respectively). These indices are important because, even though the cold impacts are expected to decrease (Hajat et al., 2014; Lhotka & Kysely, 2015; Pereira et al., 2017), the cold waves influence the heating energy demand (Mishra & Lettenmaier, 2011). Furthermore, the cold related mortality was observed to supersede the heat related mortality in some European countries (Keatinge et al., 2000; O’Neill et al., 2003). For example, in the UK, the cold impacts with demographic changes are expected to remain important (Hajat et al., 2014). Moreover, the results of (Fonseca et al., 2016) suggest increasing trends in cold days and cold nights in winter time over the Iberian Peninsula. Accordingly, the Tx10p and Tn10p indices represent valuable climate information in MetroHeat.

The ETCCDI index named Warm Spell Duration Index (WSDI) still exhibits some shortcomings to characterize heat waves (see Orłowsky & Seneviratne, 2012; IPCC, 2012; Russo et al., 2014). Hence, we deployed the HWMId, which is an improvement of the Heat Wave Magnitude Index (Russo et al., 2014) anchored in Russo et al., 2015. The HWMId also utilises percentile-based local thresholds, and by default it provides not only the magnitude of heat waves, but also the duration and timing for each year (Russo et al., 2015).

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The complete suite of 8 indices provided via the web service is further detailed in Table 3, which includes their units, computational description, short explanation and literature references. The ETCCDI indices were computed by means of the Climate Data Operator (CDO 2018: Climate Data Operators. Available at: <http://www.mpimet.mpg.de/cdo>) software, and for calculation of HWMId the “extRemes” R package (Gilleland & Katz, 2016) was used. The raw climate variables underlying the intermediate products provided in MetroHeat can be retrieved from ESG – Earth System Grid data repository. Details on climate models can be found in the EURO-CORDEX website (<http://www.euro-cordex.net>), and are described by Jacob et al. (2014).

**Table 3 - Provided climate indices.**

Index	Description	Explanation	Units	References
HWMId	<i>Sum of the magnitude* of consecutive days (<math>\geq 3</math>) composing the heatwave.</i>  (*Daily magnitude relative to local IQR threshold of reference period)	The maximum magnitude of the heat waves in a year. A “heat wave” is defined as a sequence day in which the daily maximum temperature is above the 90th percentile of daily Tx for a 31-day running window centered at this day for the reference period	<i>Non-parametric ranking</i>  (values in [0, +∞[)	(Russo et al., 2015)
Tn10p	<i>Percentage of days when TN &lt; 10<sup>th</sup> percentile</i>	<i>The amount of very cold days</i>	% of days	(Alexander et al., 2006)
Tn90p	<i>Percentage of days when TN &gt; 90<sup>th</sup> percentile</i>	<i>The amount of very warm nights.</i>	% of days	(Alexander et al., 2006)

Tx10p	<i>Percentage of days when TX &lt; 10<sup>th</sup> percentile</i>	<i>The amount of days when the daily high is much <b>cooler</b> than average.</i>	% of days	(Alexander et al., 2006)
Tx90p	<i>Percentage of days when TX &gt; 90<sup>th</sup> percentile</i>	<i>The amount of days when the daily high is much <b>warmer</b> than average</i>	% of days	(Alexander et al., 2006)
TNn	<i>Annual minimum value of daily minimum temperature</i>	<i>Absolute peak – “the coldest night”</i>	°C	(Alexander et al., 2006)
TNx	<i>Annual maximum value of daily minimum temperature</i>	<i>Absolute peak – “the Warmest night”</i>	°C	(Alexander et al., 2006)
TXx	<i>Annual maximum value of daily maximum temperature</i>	<i>Absolute peak – “the hottest day”</i>	°C	(Alexander et al., 2006)

### 4.3.2 Success factors and pitfalls

Formal frameworks (e.g., European Research and Innovation Roadmap for Climate Services) and climate services literature are mainly focused on relatively large developments (e.g., C3S). They provide recommendations for development process, which we cannot fully fulfil given the available resources and time restrictions. For instance, the recommended four-step user engagement process emphasizes long-term ongoing discussion and feedback from users during the development (Houtkamp et al., 2016), which was out of our reach. However, we instead reviewed the scientific literature and identified the major pitfalls and success factors. This review exercise helped us design the MetroHeat web tool in accordance with good practices to avoid recurrent mistakes found in literature. It should be noted, though, that our rather modest web tool does not have any ambition to compete with well-established climate services, we hope that this tool has a potential to fill a certain gap. While global, European, and national climate information services are fairly available, there are only a few services focused on urban areas (Baklanov et al., 2018).

Major pitfalls emerging from the literature are duplication (i.e. production of redundant information) (Hammill et al., 2013), lack of data in easy-to-handle form (Smid & Costa, 2017), deployment of static information (e.g. reports or maps) for download (De Filippis et al., 2018), and general deficient data visualization capabilities (Swart et al., 2017). On the other hand,

successful factors that are most frequently mentioned are: to provide open access, to consider the particular needs of users, and to ensure the scientific correctness associated with trust (Swart et al., 2017).

To avoid the most commonly recognised pitfalls, the design and implementation of MetroHeat incorporated the following functionalities. We provided the capability of downloading data in CSV and XLS formats, which are widely known data structures and representations. Additionally, graphics can be downloaded in different formats, such as PNG, JPEG, SVG, or PDF files (preserving the aesthetics of the graph). Moreover, the web tool offers interactive non/static information (for further details see the Functionalities section). The different visualizations are synchronized in sense that the selection of the user on one activates the same selection on the others. Regarding the pitfall of duplication, to the best of our knowledge, there is no other service focused exclusively on European capital cities offering the pre-computed ensemble (including ensemble mean) of the selected climate indices. Climate impact researchers without skills or resources to handle large multi-model climate projections may use MetroHeat to conduct their research on specific European metropolitan systems/areas. Finally, we are definitely confident that there is no other climate service offering visualizations of the HWMI<sub>d</sub> – Heat Wave Magnitude Index daily (Section 2.1).

In an attempt to comply with the success factors that emerge from the literature we made all the data fully open and accessible. Due to restricted time and financial resources it was not possible to tailor specific sub-interfaces for each user group. Hence, we choose the strategy of maximum simplicity in terms of both – data formats and web application interface. To ensure the scientific correctness associated with trust Swart et al.; (2017) recommend the support of some widely recognised institution to ensure the quality and give the additional credibility. Even though, the MetroHeat web tool cannot provide an official link to such an institution, the presented information is supported by scientific papers previously published by ourselves and also by others. The EURO-CORDEX simulations have been validated by many (e.g. Jacob et al., 2014; Kotlarski et al., 2014; Katragkou et al., 2015; Cardoso et al., 2016; Prein et al., 2016; Soares & Cardoso, 2018). More specifically, their ability to reproduced past and project future HWs (heat waves) was shown by (Lhotka et al., 2018; Vautard et al., 2013). The credibility of climate indices computed based on EURO-CORDEX was described by (Dosio, 2016) for ETCDDI indices and for HWMI<sub>d</sub> by (Russo et al., 2015). Finally, we invested effort to provide solid visualisation capabilities ranging from the visualization of tabulated data, to various types of charts (line, bar and area), and polar charts and sparklines. All types of visualizations are automatically synchronized and adjusted on-the-fly according to the criteria selected by user (more in section 4.4.2 Implemented features). The web tool was developed within the Open City Toolkit of the GEO-C project (<http://geo-c.eu/>), funded by the European Commission (Grant Agreement number 642332 — GEO-C — H2020-MSCA-ITN-2014), which is acknowledged in the About menu of the tool.

## 4.4 MetroHeat web tool

### 4.4.1 Architecture

The MetroHeat web tool is structured in two parts. The first part represents a set of R scripts with the aim of handling intermediate tasks for data processing. These scripts take as input the results of the models ensemble, and reorganise them to best suit the MetroHeat design requirements and the purposes of the contained data visualisations while, at the same time, ensuring an adequate level of transparency towards users. The resulting processed data, ready to be consumed by MetroHeat, are publicly available in a CKAN-based catalogue (<http://giv-oc2.uni-muenster.de:5000/dataset?groups=datasets&tags=ESR09>). The public registration of the processed datasets in a CKAN-based catalogue is a requirement of the GEO-C project, which, as one of its outcomes (Granel et al., 2018), is the realisation of an Open City Toolkit (Degbelo et al., 2016). In short, the Open City Toolkit is aimed to transform the research outcomes from the GEO-C individual projects into datasets, services, applications and products that can be relevant for city developments and city stakeholders.

The second part of our MetroHeat web tool is the conceptual architecture and materialisation of the web application itself. The bottom part of diagram in Figure 11 illustrates the architecture of the MetroHeat web tool, while the top part represents the required steps for computing the input data into climate indices and pre-processing those indices for data visualisation, as described above. The CKAN-based catalogue thus acts as a nexus between the two parts of the MetroHeat web tool. As in any data science project, the first part of the web tool – data transformation, processing and preparation - was by far the most complex and time consuming of both parts, which is in line with the common assertion that data preparation and pre-processing tasks constitute a highly significant portion of any data science project.

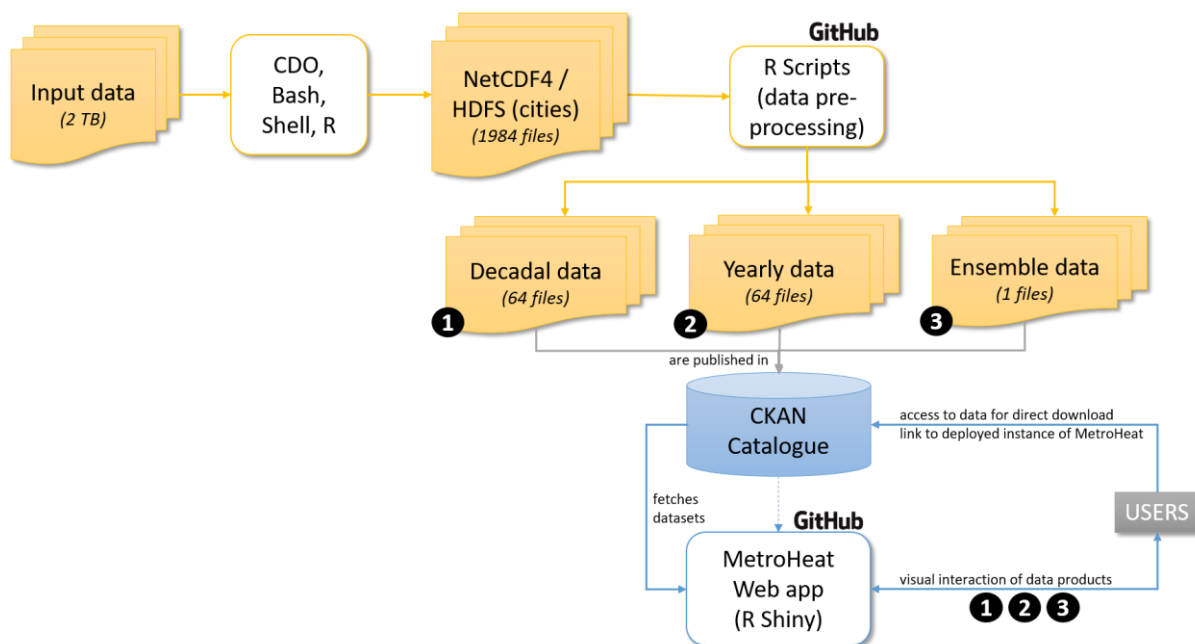


Figure 11 - MetroHeat web tool architecture.

In terms of implementation, the R scripts for data pre-processing are stored and published in GitHub (<https://github.com/cgranell/climatechange-viz>) and the web tool was entirely developed with the well-known R package “Shiny” (Chang et al. shiny: Web Application Framework for R, 2018. <https://cran.r-project.org/package=shiny>), which was designed to build interactive web applications in R. The source code of MetroHeat is also available in GitHub (<https://github.com/cgranell/climatechange-shiny-apps>). The application is deployed in a public server and fetches on the fly the input data from the CKAN catalogue instead of doing so locally. This architecture is meant to prolong the applications lifespan since its operability requires a minimum set of maintenance activities and also does not require any dedicated in-house hardware infrastructure since it is deployed in the cloud infrastructure.

#### 4.4.2 Implemented features

The MetroHeat home page is intuitively divided into three vertical areas with different purposes (See Figure 12). The features in the left panel serve as a menu to navigate between different sections which can be understood as sub-applications to access and interact with data products as explained later on. The central part is devoted to place interactive visualisations. On the right panel said various parameter selectors are located. The main parameters selected are reflected in coloured boxes placed horizontally above the central visualisation area. These information boxes are meant to always display the current user selection. In the left top corner of the central panel for data visualisation, the *Compare/Explore* button can be found. It allows to switch between graphical visualisation and tabulated data. Generated graphics were given their own interactivity. The legend items, i.e. city names, play a dual role: as a traditional legend item to color a data series, and as a way to select/unselect each data series in the graphic. When the user hovers a data series in the graphic, a tooltip automatically pops up containing condensed information (time instance and values of the selected climate index for the current selection of Capitals). Finally, the three horizontal bars icon located in top right corner of the data visualisation panel denotes additional options such as printing and graph downloading in several formats. While raw data series are downloadable in CSV and XLS data formats, the graphical output is downloadable in two raster formats (PNG and JPEG) and two vector formats (SVG and PDF) to meet up to maximum extent the need of different users, provide them with high quality graphical materials, and allow them for additional editing with tools of their own choice.



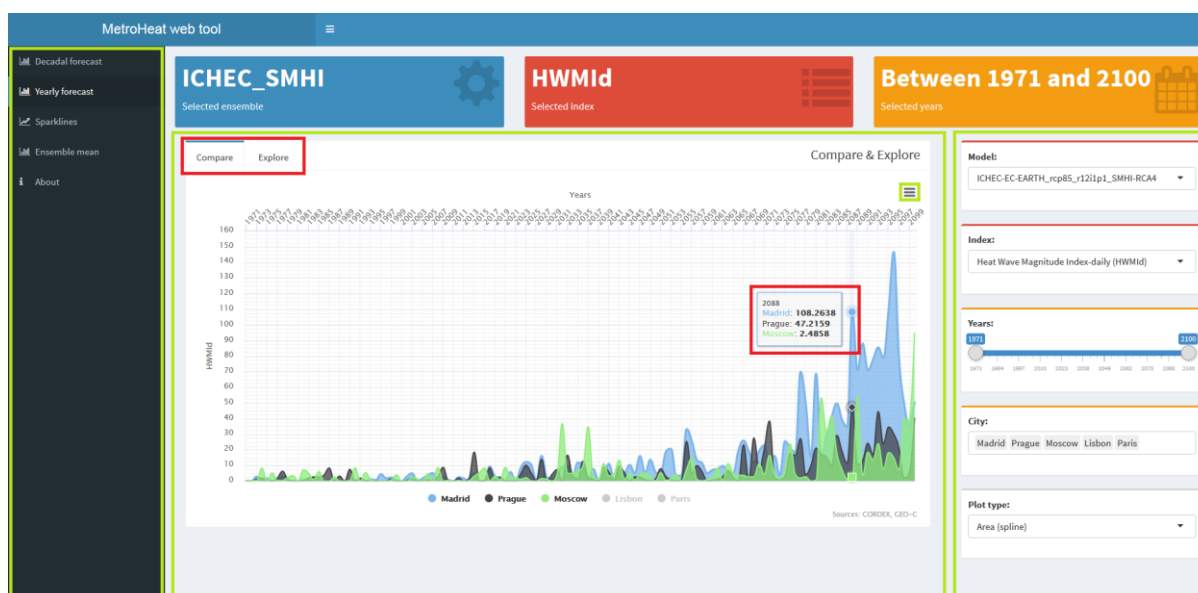


Figure 12 - MetroHeat user interface and visual disposition of functional features.

The right panel of MetroHeat contains selectors to define the content and customise the style of the data visualisations. Nevertheless, the type of selectors being visualised and even the content of these selectors depend on the active selection done by the user in the main menu (left panel). This means that the selection of the main option (data product/sub-application) in the left panel generates dynamically the set of allowed selectors on the right panel of MetroHeat. For example, if a user selects “yearly forecast”, she can choose from the collection of eight different GCM/RCMs combinations (“Model” selector) and also between eight different climate indicators (“Index” selector) referring each to distinct aspects of metropolitan local climates. Another drop-down menu (“City” selector) serves to select the metropolitan areas of users’ interest. Selecting or dropping a city from the City selector automatically updates the corresponding plot. The user can also choose any arbitrary period between 1971 and 2100 (yearly time steps) through the “Years” selector. While the previous selectors are aimed to personalise the content of the graphic, by filtering either the data series (cities) or the temporal dimension (X-axis), the last drop-down menu (“Plot type” selector) refer to visualisation options, allowing users to choose different types of plots, such as scatter plots, stacked bar charts or spline area charts (examples below in Figure 13).

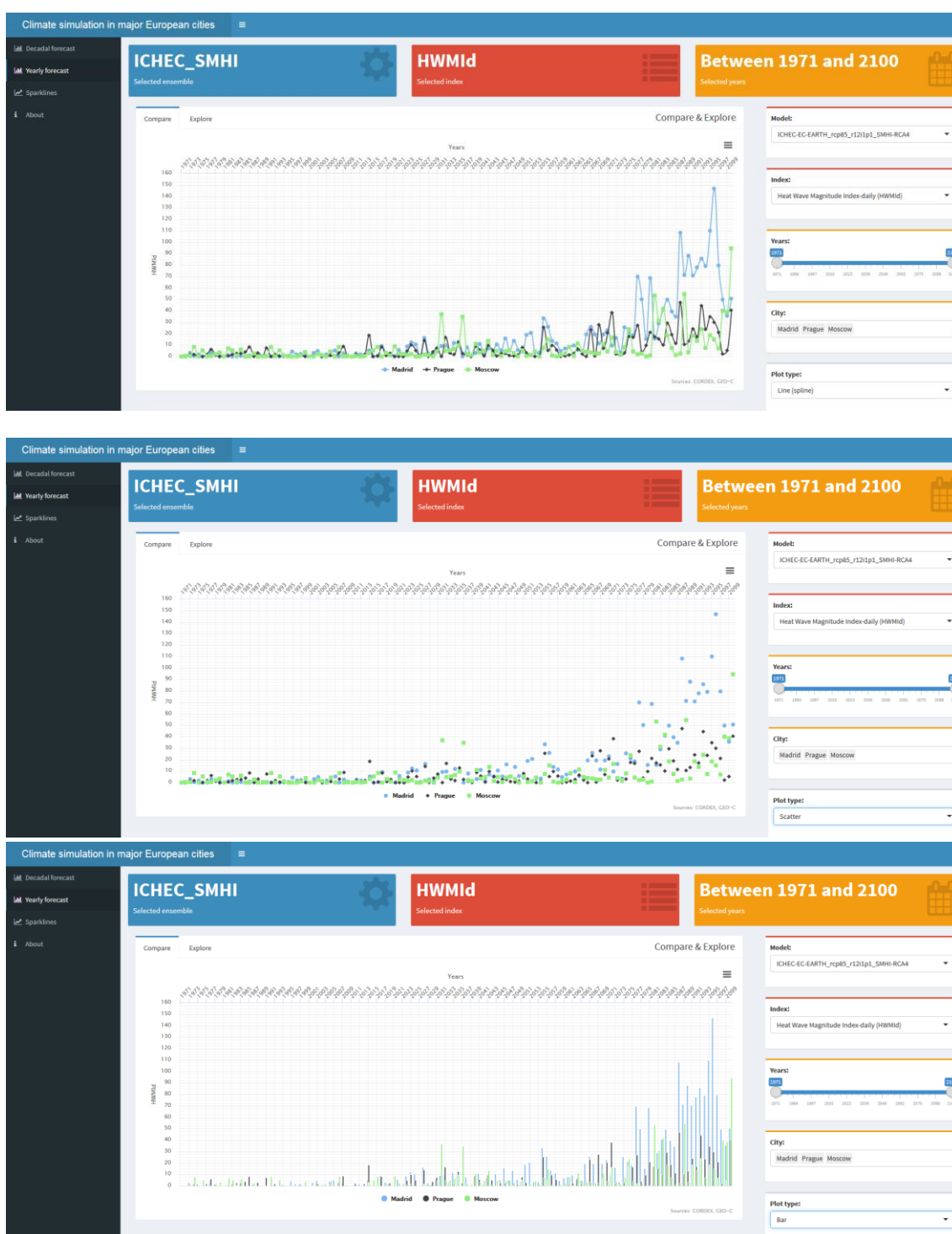


Figure 13 – The examples of different visualization capabilities.

The web tool is designed to provide all its functionalities smoothly in all common internet browsers and can be accessed via <https://cgranell.shinyapps.io/metroheat/>.

#### 4.4.3 Data products

The left panel of the MetroHeat web tool allows users to choose between the different data products – the yearly projections and their means for each decade, which better illustrates the slow variation in the climate.

These three data products are accessible through the menu options in the left panel as “Yearly forecast”, “Decadal forecast”, and “Ensemble means”. All of the three views of the MetroHeat share the same user interface for consistency. The difference lies in the content of the selectors on the right panel, which slightly change depending on the active data product, for dynamically customising the resulting plot.

Two of the data products, yearly and decadal forecast, has an additional but synchronised visualisation to inspect data differently through the menu option “Sparklines”. Sparklines allow for the general visual comparison amongst the cities but also displays multiple climate indices at the same time (see Figure 14). By synchronised visualisation we mean that the last user selection applies to the sparkline visualisation, as this visualisation mode, as illustrated in the Figure below, does not show a right panel for parameter selectors. This means the current selection in terms of models, indices, timespan, and selected cities in the yearly forecast or decadal forecast visualisation applied to filter out the input dataset for the sparklines visualisation. Technically, the sparklines visualisations in MetroHeat utilise the R package sparkline (Vaidyanathan et al., 2016).

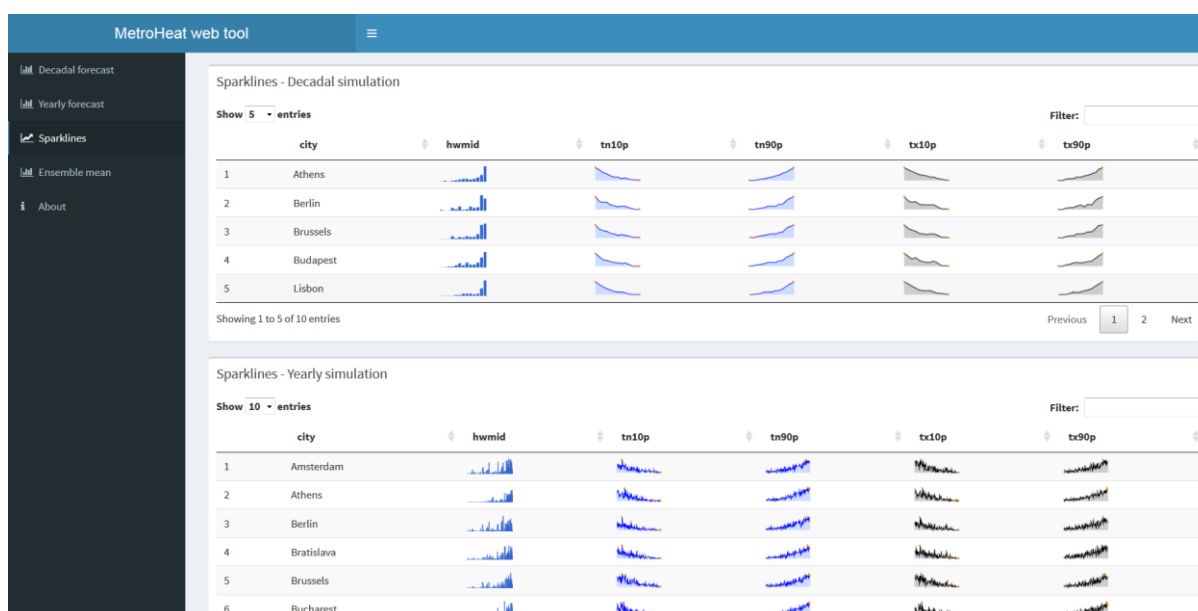


Figure 14 - Sparklines synchronized visualization.

## 4.5 Discussion

The web tool offers climate impact-related data aiming for different urban stakeholders. Urban researchers may exploit the provided intermediate products to enhance their own research. The decision makers at the European level may utilize the information to prioritize the adaptation and mitigation strategy planning. Our tool also communicates the climate impacts in a comparative manner between all European capitals. It allows a wider public to intuitively understand the implications of different extreme heat magnitudes, since citizens are generally familiar (often having personal experience) with climate across their cities. This local point of

view on the global, complex and non-personal issue of climate change, helps to raise awareness and to casually educate the public. Subsequently, this may increase the capacity and willingness of citizens to engage in the debate and influence the decision making process.

Our goal to catalyse the research of others is aligned with current open data policies, where online portals are expected to positively contribute towards reforms (Weerakkody et al., 2017). The European Commission established plans to open public data via the Communication on Open Data in 2011. However, the ambition of making data available to the community originates from a European directive in 2003 encouraging greater realization of the economic value of public data through its reuse. Open data are stimulating the innovations (van Veenstra & van den Broek, 2013; Janssen et al., 2012), supplying policy-makers with information to comprehend complex challenges (Sivarajah et al., 2016) and enhance the involvement of citizens in governmental activities (Conradie & Choenni, 2014). Furthermore, the key purpose of open data is to encourage the creative developments of further applications to serve and engage the wider society through the visualization of patterns and relationships (Martín et al., 2015; Weerakkody et al., 2017). However, to make these goals achievable, there are still bottlenecks and barriers, preventing the utilization of open data at wider scale. The most frequently listed barriers are the data structures, and the required relatively high technical and analytical skills of users (Smid & Costa, 2017; Palma, 2017). We argue that overcoming these obstacles is even more challenging in regard of climate science. Wilcke & Barring, (2016) stated that many climate impact modellers are simply not able to handle the large volumes of data, which are necessary to analyze the climate impacts. For illustration, the ensembles data of climate simulations usually comes in the form of hundreds or thousands of files, and the total data volume is in the order of Tera Bytes. Technicians are encouraged to develop applications based on open data to benefit wider society, but the raw climate data with thousands of time steps and multi-model simulations do not represent such an easy-to-use information.

Climate data are most frequently available in NetCDF binary format (Palma, 2017), which requires the installation of multiple SW libraries, and NetCDF support in terms of SW tools is much more advanced for Linux than for the Windows environment (<https://earthdata.nasa.gov/standards/netcdf-4hdf5-file-format>; accessed: 15/03/2017, Smid & Costa, 2017). Moreover, the climate projections are commonly available in geographic grids (Hijmans et al., 2005), which are sometimes unconventional (e.g. with False North Pole rotated native grids with the latitude and longitude coordinates provided each in form of matrix instead of vector). Even though there are many open climate data sets nowadays, handling them requires programming skills and complex pathways, and additional expertise to generate the impact information. Moreover, these pathways differs by various communities developing the climate models, and this results in a gap of knowledge interchange (Palma, 2017). For this reason, for example, Fofonov & Linsen (2018) developed a tool, named MultiVisA, which can be used for visualizing such climate simulation ensembles, but its main target audience are domain experts. However, the tools as ClimPick (Palma, 2017) or MultiVisa, still aim to general broad purposes. They ease the data handling and visualisation but do not provide (or allow to calculate) the domain specific indices.

Our web tool is free and publicly available, and it offers visualization capabilities of temperature impact information on all the European capital cities (EU28, Moscow, Oslo, and Zurich) in a simple,

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easy to use, and understandable form. In this sense, we acted as knowledge brokers, providing the intermediate products, thus allowing the other stakeholders (mainly urban researchers and the decision makers) to skip the strongest utilization barriers discussed above.

Somewhat more complex is to engage with the general public, since there is also the psychological dimension and not only the technical aspects playing a crucial role. The key motivation factor to engage the public is their sense of empowerment (Wang & Fesenmaier, 2003; Muntinga et al., 2011). The empowerment is defined as nexus between sense of personal competence and willingness to take action in the public domain (Zimmerman & Rappaport, 1988; Li, 2016). Li, (2015) describes empowerment as a multi-level construct consisting of the individual level, the organizational level, and the community level. Studies on empowerment span over many fields, such as health, management, education, and psychology science, but the role of public relations and engagement in the power dynamic of climate policy deserves attention as well. Public engagement fuelled by the sense of empowerment should trigger the desired change.

Regarding web tools, platforms and services, Muntinga et al., (2011) define the quantum of online engagement as an increasing scale of the involvement, from consuming to contributing, and then to creating. We recognise that in the highly scientific climate domain, the general public users cannot be expected to become content creators, which would represent the ultimate level of public engagement. However, we hope that users will acquire climate knowledge by using our web tool, thus enhancing their sense of personal competence, which subsequently allows for their enhanced willingness to engage in the public domain – between themselves and towards the decision makers. Accordingly, a more informed urban audience can better engage with climate policy decision making at city level.

According to marketing research, public complaining behaviour is an outstanding power-action. This behavioural component of psychological empowerment is a fundamental display of the publics' power (Li, 2015). Complaining allows customers to express their frustration and confront companies' wrong-doings based on their buying experiences (Li & Stacks, 2014). We argue that in regard of climate impact adaptation, one of the most frequent wrong-doings is the non-doing. Climate change adaptation and mitigation measures taken in advance will be far more cost-efficient than actions taken after the society feels the climate change direct impact. Therefore, citizens' engagement in the policy decision making process is fundamental to boost adaptation and mitigation measures. Moreover, we recognise that the absence of a platform enabling the dialog between policy makers and citizens is a major limitation of our web tool, as it would enhance the interpersonal component of public empowerment. This is due to the fact that we neither officially represent a part of decision making, nor the raw climate data producing structures. Hence, we do not have the necessary means to facilitate this important ongoing debate. Instead, our web tool engages the wider society as an integrated part of the Open City Toolkit (OCT) of the GEO-C project (Degbelo et al., 2016). The OCT is a freely available and open data based prototype with a set of the tools aiming to increase transparency, facilitate collaborations, and improve cities' actions. Therefore, our web tool contributes to raising awareness and spreading the information in a bottom-up approach via the OCT, and also through marketing efforts from the institutions involved in the GEO-C project (<http://geo-c.eu/>).

## 4.6 Conclusion

MetroHeat is an open data and open source based web tool providing impact-related customised products for urban stakeholders in all European capitals (EU28, Moscow, Oslo, and Zurich). European capitals typically represent around 30% of national GDP (Eurostat, 2016), and they often have a vital function concentrating international and intranational money flows accompanied with labour activity, and as such, they are crucial for national competitiveness in context of globalized economy (Dijkstra et al., 2013).

The underlying data is an eight-member ensemble belonging to EURO-CORDEX project. Even though, the underlying data are also freely publicly available, their original form is not easy to use, interpret or visualize. Therefore, we acted as knowledge purveyors, aiming to facilitate informed decision making, to foster multidisciplinary research and cooperation, and to raise awareness and engage the general public with complex issue of local impacts of changing climate.

In comparison with current market, well established services communicating climate change impacts have a global, national or regional focus. Despite that urban level and city administrators were identified as vital to combat the climate change impacts (Hintz et al., 2018), the climate service targeting metropolitan communities in Europe is still lacking. In terms of data handling and visualization, there has been recently tools developed such as ClimPick (Palma, 2017) or MultiVisA (Fofonov & Linsen, 2018) but these serve to broader purposes and their users are still required to possess significant expertise to extract meaningful information. Hence, we believe that MetroHeat has its use niche filling this market gap.

As final note, currently MetroHeat offers the data on past, current and future aspects of local climates related to extreme temperature, but the web tool is ready to accommodate in future also the information on other hazards, for example, droughts, floods, or sea-level rise where relevant.

## 5 Conclusion

The main objective of this thesis was to assess current and future impacts of extreme temperatures in European capitals. A literature review and discussion on the topic was undertaken, which allowed for investigating how the climate information is being incorporated into the decision process and urban planning. Within the community of urban planning there is emerging call for local climate information (George et al., 2016) and in the same time the need for long-term planning is currently emphasised (e.g. Davoudi et al., 2012). In parallel, the lively scientific debate centred on the trade-off between the reliability of statistical downscaling of climate simulations and its convenience is now lasting more than a decade. However, regardless whether the localised climate projections are delivered by means of dynamical or statistical downscaling methods, there are still certain practical barriers for the implementation of such an information in the processes of decision making, urban planning, and designing the adaptation and mitigation strategies. In this thesis we identified and formalised the practical barriers of the wider utilization of climate projections.

The first outstanding practical bottleneck is related to still persisting scale mismatch between data needs and data availability. Most of currently available downscaled products still do not offer the fine scale appropriate to complex urban environment and sufficient spatial resolution to address many of the urban challenges. For example, regarding the floods, the framework to assess the future adaptation benefits is available (Ward et al., 2016) but metropolitan adaptation to heat-waves still presents a major challenge in urban decision making (Tapia et al., 2017). The localized quantitative knowledge relevant to local priorities is pivotal in urban planning, urban design and tailoring of the adaptation strategy. Moreover, the spatially explicit information can be used for the deployment of map-based interfaces. These may serve as a basis for better informed decision making and prioritizing, but also as tools of effective communication to foster citizens participation and allow the society as a whole to embrace the change and tackle the adaptation as a positive opportunity.

The second significant practical barrier, which obstacles the wider exploitation of localized climate projections, lies within the IT domain. Wilcke & Barring (2016) argue that many climate impact modellers are simply not able to handle the data generated by GCM-RCM runs. This topic is seldom discussed in urban climate or urban planning scientific literature. Also based on our own experience, we formalised this bottleneck and divided the issue into three different areas: i) the data amount (meaning both – the data volume, and large quantity of files), ii) the common data structure/format, iii) the challenge to gain know how for the ultimately required complex workflow.

The development of new tools to handle, visualize, analyse and interpret the outputs of climate models represents an important part of the solution. Efforts are currently being done, such as those by (Hempelmann et al., 2017; Palma, 2017; Fofonov & Linsen, 2018). Likewise, some of the outputs of this thesis contribute to ease the handling of massive data produced by GCM-RCM simulations, and to reduce the need to discover the rather awkward data procedures bind

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to often locally kept data processing know-how (Hempelmann et al., 2017). Our contribution is represented by the climate communication service web tool called MetroHeat, developed as an integral part of the Open City Toolkit (OCT), synergizes with findings of Chapters 2 and 3. The most important scientific findings of Chapter 3 are complemented with a suit of climate indices descriptive to various aspects of future extreme climate behaviours across the European capital cities. The data and visualisations are available to download, thus allowing other researchers to skip an important IT bottleneck formalised in Chapter 2, and also to avoid the need for significant computational resources. The customised products can be easily used, for example, in the fields of climate adaptation, epidemiology, smart cities, or in general urban sciences. Moreover, the presented data products can serve as a basis to decision making on European level, assisting with prioritizing the investments and other efforts in the adaptation strategy. At last but not at least, in similar manner as the comparative urban indicator of Chapter 2, also the other climate indices offered via customizable comparative graphics communicate the local impacts. This is in alignment with current European data policies, which encourage the increase of the economic value of public data through its reuse. Even though the original underlying data of this research are openly accessible, they are not easy-to-use, thus we “translated” it to an intuitively understandable form. Hence, the web tool contributes also on casual public education, the engagement of wider urban population, and raising the awareness about upcoming consequences of climate change

The main scientific contribution of this research is represented by ranking procedure described in Chapter 3 and its results. Heat waves are considered by IPCC the most important and dangerous hazard related to climate change and managing the impacts of HWs in cities is of paramount importance (UN-habitat, 2010) because it is the metropolitan space where the most people will encounter the extreme heat (Schatz & Kucharik, 2015). The alternation of climate impacts by urban space, described in the Introduction, will be not always necessarily negative. The CWs impacts may be softened by the joint influence of urban space and climate warming, such as reduction in winter heating demand and saved lives (Schatz & Kucharik, 2015; (Kolokotroni et al., 2012). Nevertheless, the increasing negative impacts of extreme heat will by far outweigh the positive consequences.

Specifically in urban areas, the crucial negative impacts of extreme heat include health risks, human discomfort, associated higher concentrations of pollutants, lower water quality, increase energy demand for cooling, and decrease in labor productivity (Dunne et al., 2013; Estrada et al., 2017; Zander et al., 2015).

In Europe, where universal public health insurance generally covers entire population, the health impacts also represent direct monetary cost to governments. The health impacts span from heat cramps which may signalize heat exhaustion and heat strokes (Michelozzi et al., 2009; Russo et al., 2017) leading to fatal congestive heart failure or acute myocardial infraction (Koken et al., 2003), to respiratory diseases. In high-income settings of European capitals only smaller proportion of fatalities occurs due to hyperthermia as such (Hajat et al., 2014).

Our results provide insights regarding the future evolution of temperature related exposure of population across all the European capitals. We showed that the cold waves exhibit a decreasing trend with already smaller impacts in the midcentury and almost entirely vanishing in far future.

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We confirmed that HWs will most likely strike the populous metropolises of Madrid, Rome and Athens commonly associated with extreme temperatures but also other cities, namely Valletta Sofia, Wien, Zagreb, and Zurich should expect serious impacts in the future. The Maltese capital, Valletta, particularly emerges from the analyses, as it is projected to progress from a comparatively centre position in the ranking for near past towards the most severe HWs by the end of this century.

Currently, in places such as Valletta or Lisbon the humidity may already play an important role but in future also other locations, for example, large coastal agglomerations of Northern Europe, can be exposed to severe impacts of humid HWs.

Overall, the major usage of our simplistic but descriptive urban indicators (i.e. the estimated probabilities of HWs/CW for each city) is twofold. Firstly, similarly to the study of Guerreiro et al.,(2018) such a methodology can serve as a basis to decision making on European level, assisting with prioritizing the investments and other efforts in the adaptation strategy. Secondly, it communicates the risk associated with climate change induced extreme heat locally, thus helps to bridge the gap between science, policy making and general public to better comprehend the seemingly no personal issue of climate change and its impacts. The climate change communication represents the vital prerequisite for action and the fact that our indicators are comparative highly contributes to its illustrative and communication power. Finally, since our study is based on HWMId, unlike many other works, our results offer the transparent information about the magnitudes of future HWs events. This contributes to raise awareness about HWs since they are still often not perceived as serious risk (Keramitsoglou et al., 2017).

In summary, this thesis contributed with relevant knowledge on current and future impacts of extreme temperatures in European capitals, as well as with recommendations and tools that can help urban inhabitants, city planners, and decision makers to adapt or mitigate the impacts of extreme temperature events. This work also helps to decrease the important gap between various stakeholders and thus facilitate the forging of complex but well-rounded solutions.

## **5.1 Limitations**

This study does not substitute a detailed city-specific vulnerability assessment, neither explicitly quantifies the impacts in monetary terms. Each large urban system is unique in its complexity and the detailed city-specific vulnerability assessment would require access to dynamical model coupled with urban land cover simulations. This approach was in terms of time, expertise and computational resources out of our reach and also out of the scope of this research. The important limitation of this study is the absence of the impact assessment of the humidity aspect. Humidity is increasingly being recognised as an important factor influencing the human ability to cope with extreme heat events. This limitation is caused by difficulties related to the availability of the reliable air humidity projections for the European domain.

## 5.2 Future research

Future research should include the humidity aspect in the assessment of heat wave impacts on European urban areas. The Apparent Temperature or the Wet Bulb Temperature variables could be incorporated in a thermo-dynamical way, and be used as proxies to quantify heat related impacts on human beings. Moreover, other sophisticated indices (e.g. Apparent Heat Wave Index (AHWI) (Russo et al; 2017) would be an interesting addition to the risk assessment. With focus on the humidity impacts, the emphasis can be given to the urban systems located on coasts, or further research may be conducted on areas of interest outside of Europe.

Furthermore, the methodology presented in Chapter 3 represents a framework ready to accommodate also the information on other significant hazards such as droughts, floods, or sea level rise where relevant. When these information will be obtained in a consistent manner, the further step would be to improve the ranking algorithm to build a truly multi-hazard urban indicator. Another potential area of further research is to add the epidemiological perspective and involve the air pollution, morbidity, mortality, hospital admission, or emergency phone calls data.

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## Appendix A

### A-1 Regional and local climate modelling

The climate system is global. The fundamental aspects of climate research are observations, theory and models (Rummukainen, 2010). General Circulation Models (GCMs) are numerical coupled models describing atmosphere, oceans, land surface, sea ice and interactions among those earth systems. GCMs are essential tools to assess the climate change (Fowler et al., 2007). However, their coarse resolution and inability to resolve sub grid scale features limits their usability (Grotch & MacCracken, 1991). Nevertheless, frequently, the global or continental scale information is implemented directly, which negatively affects the resulting local-scale impact maps (Trzaska & Schnarr, 2014). A large portion of impact studies operates on scales finer than common resolution of global or even regional model outputs (Wilby et al., 2004). The strong need of higher resolution climate data for impact assessment is an issue well known for a long time (Kim et al., 1984; Gates, 1985; Robinson & Finkelstein, 1989; Lamb, 1987; Smith & Tirpak, 1989; Cohen, 1996). This interest origin in recognized discrepancy of course resolution GCMs (hundreds of km) and the scale of interest of impact studies (an order or two orders of magnitude finer scale) (Hostetler, 1994).

The impact applications are highly sensitive to local climate variation, and as such they require the information proportional to the point climate observations. The fine-scale variations are parametrized in lower resolution models. The requirement of fine-scale information emerges particularly in regions of complex topography, coastal or island areas and in regions with highly diverse land cover (Giorgi et al., 2001; Mearns et al., 2003; Wilby et al., 2004).

In reality, the climate system is defined by processes occurring on a broad range of spatial and temporal scales. Consequently, GCMs have an ability to effectively characterize large-scale climate features (e.g. general circulation of the atmosphere and the oceans). Additionally, they perform well describing sub-continental patterns. Horizontal meshes of the atmospheric component of the GCMs range from 400 to 125 km (Laprise et al., 2008). The formal resolution of GCMs varies between 200 and 100 km<sup>2</sup>, which is insufficient for the analysis of many regional and local climate aspects, such as extremes. GCMs of very high resolution would indeed improve the simulations of regional and local aspects (Rummukainen, 2010), but they remain unreachable due to the enormous computational cost (Fowler et al., 2007), which leads to the accommodation of downscaling techniques (Rummukainen, 2010).

The climate projections can be subject to downscaling on their spatial or/and temporal aspects. Spatial downscaling refers to the methods deriving the information in finer spatial resolution, acting like a “magnifying glass”, e.g. from original GCM course resolution of 500 km to obtaining grid cells of 20x20 km. Temporal downscaling derives fine-scale temporal information (e.g. daily rainfall, surface wind speed variability, storm inter-arrival times, monsoon front onset and transition times) (Mearns et al., 2003) from coarse-scale temporal GCM output (e.g. monthly or seasonal rainfall amounts) (Trzaska & Schnarr, 2014). The spatial and temporal variabilities are

closely related, meaning that the projection of short term extremes will be more precise when simulated in high spatial resolution. (Mearns et al., 2003).

Nowadays, a wide pallet of methods generating high resolution climate information is available. These techniques vary in their strengths and weaknesses – some tend to be complex and computationally expensive while others are difficult to interpret. The choice of an appropriate method, or even the decision whether or not it is convenient to apply a downscaling procedure, is often not straightforward (Mearns et al., 2003).

## **A-2 Downscaling procedures**

Principally any data can be refined by downscaling techniques (Rummukainen, 2010). The course GCM output might be satisfactory, for example when the variation within a single grid cell is low or in case of global assessment. The main advantage of information directly obtained from GCM is the certainty that physical consistency remains unattached (Mearns et al., 2003). GCMs are valuable predictive tools, but they cannot account for fine-scale heterogeneity and reflect on features like mountains, water bodies, infrastructure, land-cover characteristics, convective clouds and coastal breezes. Those heterogeneities are essential for decision making in fields of agriculture, hydrology, species distribution (Trzaska & Schnarr, 2014) and urban planning.

Bridging this gap between the resolution of climate models and regional and local scale processes represents a considerable challenge, including the application of climate change scenarios. Hence the climate community put significant emphasis on development of techniques for downscaling (Fowler, 2007).

There is no consensual and unique classification scheme to be applied in attempts to comprehensively review and summarize the downscaling techniques. In many studies (e.g. Fowler et al., 2007; Trzaska & Schnarr, 2014; De Castro et al., 2005; Shukla & Lettenmaier, 2013; Khan et al., 2006), the methods are categorized into two main groups: Dynamical downscaling and Statistical downscaling. Dynamic downscaling is based on regional climate models (RCMs) or fine spatial-scale numerical atmospheric models, such as Limited Area Models (LAM). Statistical downscaling is based on observed relationships between climate at fine and coarse resolutions that are used to transform global climate models' output to finer resolution. Alternatively, for example Mearns et al., (2003) distinguishes three groups of approaches: High resolution GCMs; Nested limited area models and RCMs; and Empirical/Statistical and statistical/dynamical methods. Within the group of Statistical downscaling, many approaches can be distinguished and classified according to different criteria. For example, Wilby et al. (2004), provide background information and guidance on the application of some Statistical downscaling methods, but also listed alternatives to downscaling techniques (thus somehow excluding those from family of downscaling methods) mentioning spatial interpolation of grid points (sometimes named "unintelligent downscaling"), climate sensitivity analysis (frequently addressed as "bottom-up" approach), spatial/temporal analogues using historical data and simple change factor (known as "Delta" method). Giorgi et al. (2001) provide a survey of statistical downscaling focusing on studies published between 1995 and 2000.

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The methodological review will be organised under the two broad categories: Dynamical downscaling and Statistical downscaling. The later will be further detailed, because it was found to be more appropriate to address the thesis objectives.

### **A-2.1 Dynamical downscaling**

The term “dynamical downscaling” mainly pertains to Limited Area Models (LAMs) or regional climate models (RCMs) (Fowler et al., 2007; Feser et al., 2011). In nutshell, those represent a group of methods originally used in numerical weather forecasting (Rummukainen, 2010). The first studies establishing the foundation of regional modelling are Dickinson et al., 1989 and Giorgi et al., 1989. Since then, the field has undergone massive development, as documented in Christensen et al., 2007; Feser et al., 2011; Giorgi et al., 1991; Giorgi et al., 2001; Grotch, 1991; Wang et al., 2004; McGregor, 1997; Meehl et al., 2007; Hong & Kanamitsu, 2014; Pielke et al., 2012; Xue et al., 2014. Dynamical models address data and physical processes equivalent to GCMs, but at finer scales, and provide results only for selected limited regions of the globe (Trzaska & Schnarr, 2014).

RCMs are complementary tools to GCMs. They provide essential input to climate impact studies and adaptation planning and as such; they contribute to both research and application works (Rummukainen, 2010). Dynamical downscaling techniques represent one of the fundamental philosophies to tackle studies of more detailed processes and simulations of regional, or even local, conditions (Rummukainen, 2010). Over the last quarter of the century, RCMs increased in spatial and temporal resolution, in periods covered in models runs and they were developed towards regional climate system models. Dynamical regionalisation procedures give capabilities to assess past and possible future climate and assist the progress of climate impact studies, thus RCMs support the climate policy and adaptation measures (Rummukainen, 2010). Dynamical downscaling was successfully implemented in the past to simulate orographic precipitation (Frei et al., 2003), extreme climate events (Fowler et al., 2007; Frei et al., 2006) and non-linear effects (e.g. anomalies related to El-Niño phenomenon) (Leung et al., 2003).

RCMs utilize the same physical-dynamical definitions of the key climate processes as GCMs (Rummukainen, 2010). Atmospheric fields representing the output of a global model (e.g. surface pressure, wind, temperature and humidity) are loaded into vertical and horizontal boundaries of the RCM. In other words, the forcing data are fed to RCMs as lateral boundary conditions. The fundamental boundary conditions usually are temperature, moisture, wind information, sea surface temperature and sea ice (Rummukainen, 2010). These lateral boundary conditions apply alongside of the RCM domain. Administrating of boundary conditions represents a major challenge of dynamical downscaling (Rummukainen, 2010). The physics-based equations and locally specified data are used to gain regional climate outputs (Trzaska & Schnarr, 2014). The major assumption used by dynamical regional models is that there is no dramatic deviation between low and high resolution circulation pattern, otherwise the consistency between course resolution forcing and high resolution output would be dubious (Mearns et al., 2003). The unresolved inner-cell variabilities are pushed to RCM output rather than fully taken into account. For example, the process of formation of rain from cloud droplets is well known, but it is not convenient to model all droplets individually. All these inner-cell fine

scale processes are approximated in a procedure called “parametrization” (Rummukainen, 2010).

The earlier RCM resolution used to vary between 100 to 50 km, and at its best 25 km grid cells (Rummukainen, 2010). The more recent development proved that RCMs are capable of delivering high resolution results (20 km or less) (Leung et al., 2003; Mearns et al., 2003). Consequently, increasing resolution also entails increasing computational cost and data volume. RCMs also require high level of expertise to interpret the results. The above mentioned restrictions are often critical for institutions in developing countries (Trzaska & Schnarr, 2014).

Two major streams are recognizable in dynamical downscaling. In the first, the resolution is increased over the entire domain of the atmospheric global model (e.g. Christensen et al., 2007). The second strategy is based on the utilization of a global model with variable grid cell size (Fox-Rabinovitz et al., 2008; Lal et al., 2008). This technique maintains a coarse grid over the majority of the globe, but increases the resolution within a particular area of interest (Rummukainen, 2010).

The temporal resolution of RCMs varies from few minutes to approximately half an hour, while GCMs data are commonly provided in six hours steps. This increases uncertainty, but there are also other technical issues associated (e.g. functional form of the blending of the boundary conditions with regional model, the width of the adjustment zone, size of the regional domain or even the domain orientation) (Rummukainen, 2010). However, studies have shown that RCMs generate additional variability not associated with the boundary forcing (e.g. Vernekar & Ji, 1999; Giorgi & Bi, 2000; Christensen et al., 2001).

The evaluation of RCMs’ performance may be based upon a technique known as “hindcast” (Christensen et al., 1997). In these experiments, the perfect boundary conditions are used meaning that, instead of simulated conditions, the compilations of observations (obtained via meteorological reanalysis) (Uppala et al., 2005; Kalnay et al., 1996; Onogi et al., 2007). are applied to drive boundary conditions. Hindcasts reduce systematic biases in large-scale forcing (Rummukainen, 2010).

RCMs are commonly addressed as “nested” regional climate models. Nesting refers to supplying the high resolution RCM with the results for a particular region from a coupled GCM, which are used as initial and boundary conditions for the RCM. Therefore, the regional model is nested inside the global simulation (Mearns et al., 2003). Utilization of more than one RCM is also an option. The model with smaller domain is nested within a domain of another RCM. This technique is called “multiple-nesting” (Rummukainen, 2010). The majority of RCM is done as “oneway” nesting experiments. Their main purpose is to generate realistic climate surfaces in high spatial resolution. An alternative is to coordinate the efforts of global and regional climate modelling and use the output of regional simulation to improve the performance of GCM. This variant is known as “tway” nesting (Rojas, 2006).

RCM climate change simulation experiments can be run in “time-slice” mode, or continuous climate projections can be generated. Time-slice mode refers to obtaining the climate change

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signals via comparison of recent past or present-day period and future scenario targeting periods of interest (Mearns, 2003). Examples of studies utilizing transient simulations are Cubasch et al., 1995; Hudson & Jones, 2002; Govindasamy et al., 2003. In order to produce scenarios for periods outside the time-slices, “pattern scaling” has been used (Fowler et al., 2007). Continuous climate projections of extended periods are convenient for analysing possible impacts with time wise longer characteristics such as impacts on forest or other ecosystems (Rummukainen, 2010).

As mentioned earlier, RCMs inhibits other uncertainties than those inherent to GCMs. This uncertainty has a small, but not ignorable impact, on future projections (e.g. Rowell et al., 2006). It can be compensated by re-tuning of the boundaries and dumping the numerical noise (Rummukainen, 2010). The inexactness associated with RCM outputs of temperature projections was found lower than the uncertainty introduced by emission scenarios, but for simulated precipitation the opposite is the true (Fowler et al., 2007). In nested regional models, the uncertainty introduced by the choice of the RCM is comparable to the uncertainty associated with global circulation model selection (Fowler et al., 2007). RCMs are still burdened with systematic errors, thus they require a bias correction and also further downscaling to finer resolution (Trzaska & Schnarr, 2014).

The first main advantage of dynamical downscaling is that the information is derived from physically-based models, and the second one is the ability of those models to provide feedback (Mearns et al., 2003). RCMs also successfully generate information on precipitation extremes at scales unavailable via GCMs (e.g. Frei et al., 2003; Huntingford et al., 2003; Christensen et al., 2003; Frei et al., 2006; Schmidli et al., 2006), and even surpass the performance of GCMs on their grid scale (Durman et al., 2001).

A technical weakness of dynamical regionalization techniques is the application of formulations of course models. Therefore, the model may require some adjustment for use at finer spatial scale. This issue emerges particularly in case of models with variable grid resolution because parametrization needs to be valid for all the scales covered by the model (Mearns et al., 2003). The other issue arises from the assumption that relationships developed in physical parametrization of RCMs for present day climate will hold under the possible future conditions. This weakness is common also to all methods of statistical downscaling (Wilby et al., 2004). The major practical limitation of regional dynamical downscaling models is their relatively high computational demand (Mearns et al., 2003; Fowler et al., 2007; Rummukainen, 2010; Trzaska & Schnarr, 2014). Moreover, the RCM experiments require high frequency (e.g. 6 hours) GCM fields supply for boundary conditions. These data are not usually stored due to mass-storage demand. (Mearns et al., 2003).

### **A-2.2 Statistical downscaling**

Statistical downscaling is also known as “Empirical/statistical” or “Statistical/dynamical” downscaling (Mearns et al., 2003). These methods are based on the perspective that regional climate is conditioned mainly by two factors: the large-scale climate and the local/regional features such as topography, land-sea distribution or land use (von Storch et al., 1993, 1999). Methods of statistical downscaling encompass the establishment of statistical models related to

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empirically observed relationships between large-scale atmospheric and local climate characteristics (Mearns et al., 2003; Wilby et al., 2004; Fowler et al., 2007; Trzaska & Schnarr, 2014). The large scale climate variables are used as “predictors” to regional or local variables – “predictands” (Wilby et al., 2004). Fowler et al., 2007 expressed the essence of idea of statistical downscaling in descriptive equation:

$$R=F(X)$$

where R represents the local climate variable which is subject to downscaling, X is the set of large climate variables, and F is a function which relates R and X being validated by use of point observations or/and gridded reanalysis data (Fowler et al., 2007). This equation represents the most common form, but other relationships have been used (e.g., relationships between predictors and the statistical distribution parameters of the predictand in Pfizenmayer & von Storch (2001), or the frequencies of extremes of the predictand by (Katz et al., 2002).

Many statistical downscaling models have been proposed for data-rich areas, utilizing a wide pallet of techniques varying from different regression methods to neural networks and analogues (Mearns et al., 2003). Statistical downscaling allows to simulate simultaneously multiple outputs such as precipitation, maximum and minimum temperatures, solar radiation, relative humidity and wind speed (e.g. Parlange & Katz, 2000), which is of great importance, particularly for impact studies (Wilby et al., 2004). It is also possible to downscale predictors independently, but in such a case, it must be ensured that inter-variable relationships remain intact.

When developing statistical downscaling models, two major aspects should be primarily considered. First, the determination of the model time-step (e.g. hourly or daily average). The second consideration is related to the required addressed periods. Sometimes, the classical climatological seasons (e.g. December – February or March-May) may not correspond to the seasonality contained in data, thus alternative delimitations may be required (Winkler et al., 1997).

The basic assumption of stationarity is essential, but it also represents the major theoretical weakness of statistical downscaling (Wilby et al., 2004). The concept of stationarity assumes that the statistical relationship between the predictor and predictand will not change in future climate (Fowler et al., 2007). There is evidence showing that this may be not always the truth (e.g. Huth, 1997; Slonosky et al., 2001; Fowler and Kilsby, 2002). Stationarity of predictor-predictand relationship can be tested using long records, or a period of different climate characteristics can be used for model validation (Charles et al., 2004). Non-stationarity is introduced by an incomplete set of predictors, which does not reflect the low frequency behaviour, or has a non-appropriate sampling or calibration period, or by real changes in the climate system (Wilby et al., 1998). However, in projected climate change, the circulation dynamics may be robust to non-stationarities and the associated degree of non-stationarity is relatively small (Hewitson & Crane, 2006).

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When applied to a changing climate, another key assumption inherent to statistical downscaling is that the predictors should “carry the climate change signal” (Giorgi et al., 2001). Selected predictors should be physically meaningful and reflect the processes which subsequently control variability in the climate. The selected predictor variables should also be those that are well represented by GCMs (Fowler et al., 2007). Appropriately selecting variables is in the equilibrium between the relevance in the physical climate reality and the accuracy with which the predictor is reproduced by the climate model (Osborn et al., 1999; Wilby & Wigley, 2000).

Partial correlation analysis, step-wise regression or an information criterion are examples of procedures, which may be preliminarily applied in order to identify the most promising predictor variables (Charles et al., 1999; Wilby et al., 2003). Also, the local knowledge and the expert opinion are priceless information sources in attempts to assemble the most effective set of predictors (Wilby et al., 2004).

When the statistical downscaling model is not able to consolidate land surface forcing, meaning that the simulated regional climate is determined solely on the basis of free atmospheric variables, the climate change scenario will omit changes in land-surface feedback. However, nowadays, it is already acknowledged that local land use management influences regional climate, vegetation cover and runoff regimes (Chase et al., 2001; Kalnay and Cai, 2003; Stohlgren et al., 1998).

Methods of statistical downscaling tend to underestimate the variance and poorly represent the extreme events. Therefore, the techniques that introduce additional variability are frequently utilized (Fowler et al., 2007). Method magnifying the variability by multiplication by a suitable factor is known as “Variable inflation” (Karl et al., 1990). The randomization method adds variability in form of white noise (e.g. Kilsby et al., 1998). The randomization technique provided good results in returned values of surface temperature for central Europe (Kysely, 2002). A more sophisticated approach to add variability to statistical models is a variant of canonical correlation analysis called “Expanded downscaling” (Bürger, 1996). This method has been employed by Huth, 1999; Dehu et al., 2000; and Müller-Wohlfeil et al., 2000. Each of the abovementioned approaches have different drawbacks (Burger and Chen, 2005). Variable inflation does not adequately reflect spatial correlations. Randomization poorly transfers change in variability that influences expected future change. Expanded downscaling is highly susceptible to the choice of statistical processes during its own application (Fowler et al., 2007).

The performance of downscaling technique depends on choice of the regional domain (Wilby & Wigley, 2000), which in practice is often not considered (Benestad, 2001), and also depends on the regionalization methods (Wilby et al., 2004). The choice of a downscaling procedure is typically conditioned by the data availability, the access to already existing models (and their documentation), and to the statistical/technical nature of the study (e.g. uni-variate or multivariate, single or multisite) (Wilby et al., 2004). Gutiérrez et al. (2013) assessed the performance of statistical methods commonly used for downscaling temperature (including analogue methods, weather typing techniques, multiple linear regression, and regression conditioned on weather types) with respect to their robust applicability in climate change studies. These authors concluded that, overall, regression methods were the most appropriate

for climate change studies, although they fail to reproduce the observed winter distribution of minimum temperature.

In general, the methodological reviews of downscaling procedures often cover various methods according to their application (e.g. downscaling for the hydrological modelling). Some of the most recent and comprehensive studies like Value-Cost Action (ES 1102) or Fischer et al., (2013) apply categorization according to Wilks, 1995 using concept of Perfect Prog and MOS. Other examples of systematic classification schemes of downscaling techniques can be found for instance in (Fowler et al., 2007) where three main categories are recognised: regression models, weather typing schemes and whether generators or in Trzaska & Schnarr, (2014) classifying also into three classes: Linear methods, Weather classifications and Weather generators.

Downscaling and climate modelling represent a multidisciplinary field, where researchers from various backgrounds intersect their efforts, resulting to specific terminology, which may be somewhat confusing. For instance, the Polynomial Regression (also called the Surface Trend Analysis) is a statistic technique. When applied for interpolation purposes, it's commonly classified as a deterministic technique. Even the terms "statistic" and "stochastic" (frequently used as names of sub-classes in downscaling methodological reviews) are not always considered as synonymous even though both terms could be expressing the same since they are referring to methods approaching various input modelling factors as variables with certain probability distribution. Furthermore, the recent development is going towards multi-step methodologies containing deterministic and stochastic component. This evolution leads to introduction of new terms like hybrid or semi-stochastic approach, which makes the efforts to systematically classify downscaling methods to previously used categories even more challenging.

For purpose of this proposal we adopted the classification of statistical downscaling methods from Fowler 2007, which is very alike the one established by Wilby et al., (2004) recognizing three main following categories:

- Regression models
- Weather typing (also called weather classifications)
- Weather generators

#### **5.2.1.1 The Delta-Change method**

This method is also known as Change Factor method (CFs) or the "perturbation" method. It is the most straightforward technique to generate finer spatial scale scenarios (Wilby et al., 2004). Differences between control and future GCM simulation are applied to baseline observations (Fowler et al., 2007). In first step, the reference climatology is identified for particular area of interest. With respect to purpose of the study, the subject of delta-change method can be for example representative long average (e.g. 1961 – 1990) or actual meteorological record (e.g. daily maximum temperatures). Afterwards, change factors in the corresponding temperature

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variable for course scale grid cell closes to target site are computed. Finally, the variable change – “delta” is simply added to each day in the baseline (Wilby et al., 2004).

The main advantage of the delta-change method is that, due to its simplicity and computationally low cost, can be applied to several coarse scale models to produce manifold climate scenarios (Fowler et al., 2007). There are also caveats associated with this method. CFs assumes that performance of GCM is more accurate in simulation of relative changes rather than absolute values, thus presuming a constant bias through the time (Fowler et al., 2007). The second caveat represents the limited abilities of this method. Even though CFs allows to scale the mean, maxima and minima of climate variables, the method is omitting the possibility of changing variability thus the resulting spatial pattern of climate stays constant (Diaz-Nieto and Wilby, 2005). Moreover, CFs are not easily applicable to precipitation records because precipitation amounts can be affected by the number of rainy days, the magnitude of extreme events and therefore yield even negative precipitation simulations (Wilby et al., 2004).

The examples of previous studies utilizing the delta method are Arnell et al., 1992; 1994; Arnell and Reynard, 1996; Diaz-Nieto and Wilby, 2005; Eckhardt and Ulbrich, 2003; Pilling and Jones, 1999; Prudhomme et al., 2002.

#### **5.2.1.2 Regression models**

The predictor-predictand relationship is determined by “transfer function” (F. Giorgi et al., 2001). This relation can have linear or nonlinear character (Wilby et al., 2004). Multiple regressions models employ grid cell values of GCMs as predictors of regional predictand like surface temperature or precipitation (e.g. Hanssen-Bauer and Forland, 1998; Hellström et al., 2001). Methods of somewhat higher complexity involve usage of principal components of pressure fields or geopotential heights (e.g. Cubasch et al., 1996; Kidson & Thompson, 1998; Hanssen-Bauer et al., 2003). Examples of even more sophisticated methods are Zorita & Von Storch (1999), using artificial neural networks (ANN), or deployment of canonical correlation analysis (CCA) (e.g. Karl et al., 1990; Wigley, 1990; Von Storch et al., 1993; Busuioc et al., 2001), or singular value decomposition (SVD) (e.g. Huth, 1999; Von Storch and Zwiers, 2001). Abauvrer and Asin, 2005 innovated this type of techniques by utilization of logistic regression to daily precipitation probability and generalized linear model (GAM) for Ebro valley. This method provided reasonable good results for seasonal characteristics and some of the daily behaviours but had a low performance in reproducing the extreme events (Fowler et al., 2007). The multi-way partial least squares regression was applied by Bergant & Kajfez-Bogataj, (2005) to regionalize temperature and precipitation in Slovenia. This approach superseded conventional regression models but was tested only on the cold season (Fowler et al., 2007). Regression approaches tend to underestimate variance in future climate (Wilby et al., 2004). Some downscaling regression models use the stochastic processes to represent unresolved variance (e.g. Charles et al., 1999; Wilby et al., 2003). Burger in 1996 and later Von Storch et al., 1999 debated the problem of under prediction of variance (Wilby et al., 2004).

The most outstanding of regression methods is Regression-Kriging (RK). In environmental science, RK became the most popular technique for its relative simplicity and also performance superseding other geostatistical techniques. Regression-kriging is especially interesting for

interpolation of climatic and meteorological data because the explanatory variables (e.g. in form of meteorological satellite data) are today increasingly collected with shrinking time intervals. Therefore, when such an auxiliary data is available, spatio-temporal regression-kriging models can be developed. The alternatives to Regression-kriging include Bayesian Maximum Entropy approach, techniques of machine learning and also other available kriging techniques, such as co-kriging. The Bayesian Maximum Entropy method can be preferred option when explanatory data are from many different sources and differ in reliability (D'Or et al., 2003). The machine learning algorithms include neural networks and decision trees. However flexible the decision trees methods are (they allow optimization for local fits), they are not principally favourable from statistical point of view because those methods omit spatial location of points when deriving the classification trees (Hengl, 2009). Co-kriging (CK) also allows to use the explanatory information, but employment of this method is most appropriate when the explanatory data are not spatially exhaustive. CK requires modelling of both – direct and cross-variograms. In general, RK is usually preferred over CK if the covariates are available in form of complete maps/images. An interesting option is the combination of regression kriging and co-kriging. In this case, RK is used in deterministic part of the model and then CK is applied in order to interpolate on residuals and add these back to improve estimated deterministic part of variation. There are a few limitations of regression kriging. This method is highly sensitive to data quality. A single bad data point can affect the result of regression and thus ruin prediction over the whole area of interest. Furthermore, the points must be well spread at the edges of the feature space. This is also supporting argument to exploit multiple predictors to fit the target (Hengl, 2009). The auxiliary maps should have a constant physical relationship with the dependent variable through time, and also a linear relationship.

### **5.2.1.3 Weather typing**

Weather typing or classification schemes connected the occurrence of “weather classes” with local climate (Fowler et al., 2007). This models group days into classes called weather states or types, based on their synoptic closeness (Wilby et al., 2004). The definition of synoptic similarity uses empirical orthogonal functions (EOFs) (Goodness and Palutikof, 1998), or indices from SLP data (Conway et al., 1996), or cluster analysis (Fowler et al., 2000, 2005), or fuzzy rules (Bardossy et al., 2002, 2005). Weather typing methods assumes that weather states will remain constant and many of these classification procedures suffer from the inherent problem of within-class variability of climate parameters (Birkmann et al., 2000). The way around this issue was suggested by Enke et al., (2005) where the schema is based on a stepwise multiple regression and predictor fields are successively chosen in order to minimize RMSE between observations and projections (Fowler et al., 2007). Analogue method was originally developed by Lorenz, (1969) for weather forecasting. Analogue approaches are weather typing schemes where predictands are chosen by matching the previous situations with state of current weather (Wilby et al., 2004). The method was rediscovered for purpose of climate applications (Zorita, 1995; Martin et al., 1997) since longer series of predictors and completed reanalysis data became available (e.g. Kalnay et al., 1996). However, analogue method is sensitive to limited pools

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observations (Timbal et al., 2003), but it is appropriate to generate multi-site and multi-variate series (Timbal and McAvaney, 2001).

#### **5.2.1.4 Weather generators (WGs)**

These models are reflecting the statistical attributes of local climate variable but not the observed events (Wilks and Wilby, 1999). Weather generators are based on Markovian processes. In principle, WGs condition their parameters on large-scale atmospheric predictors, weather states or rainfall properties (Katz et al., 1996; Semenov and Borrow, 1997; Wilks, 1999). Variables like wet-day amounts, temperatures or solar radiation are often conditioned on precipitation occurrence (Wilby et al., 2004). Weather generators appear useful particularly for temporal downscaling such as disaggregation of monthly precipitation sums (Kilsby et al., 1998). Also weather generators employing Markov process of second order (e.g. Mason, 2004) and third order (Dubrovsky et al., 2004) have been developed. These methods improved projections of precipitation occurrence and persistence (Fowler et al., 2007).

More recent evolution of these approaches represents, for example, the connection of the Neyman Scott rectangular pulse model (NSRP), which is a stochastic precipitation generator, to the weather component developed by Watts et al., 2004 (originated from WG constructed by Jones and Salmon, 1995). This methodology is described by Kilsby et al., (2007) and it shows enhanced skill in capturing the variability and projections of extremes (Fowler et al., 2007).

Major weakness of weather generators represented by their conditioning to specific local climate relationships. Therefore, they are not directly applicable in other climates. WGs also have a tendency to underestimate the inter-annual variability (Fowler et al., 2007).

Additionally, should be noted the Statistical DownScaling Model (SDSM) (Wilby et al., 2002) using circulation patterns and moisture variables to condition local parameters. SDSM also introduces the variance to projected downscaled series by stochastic inflation. This approach is a hybrid of regression methods and stochastic weather generators (Fowler et al., 2007).

### **A-2.3 Comparison of statistical downscaling methods**

The climate community invested significant effort to compare the methods of statistical downscaling. The examples of comparative studies are Wilby and Wigley, 1997; Zorita and Von Storch, 1997; Huth, 1999, Benestad, 2001; Schoof & Pryor, 2001; Dibike and Coulibaly, 2005; Khan et al., 2006 and Widmann et al., 2003.

Generic weakness of statistical downscaling is high demand on available data. Furthermore, these methods usually do not consolidate land-surface feedbacks, and they assume stationarity (Wilby et al., 2004). Statistical downscaling is straightforward when compared to dynamical methods but tends to underestimate variance in future climate (Fowler et al., 2007). On the other hand, the computational cost of statistical downscaling is relatively low. Therefore, they may appear to be advantageous alternative for projects where the computational capacity, technical expertise or time represent significant restriction (Trzaska & Schnarr, 2014).

Statistical downscaling may be appropriate for impact studies in heterogeneous regions with complex topography and steep environmental gradient (e.g. islands, mountains, land/sea

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contrast), or in cases where point scale information is required (e.g. local flooding, soil erosion, urban drainage, etc.), or to produce large ensembles and transient scenarios (Wilby et al., 2004).



## Appendix B (CWs and relative decrease/increase of HWs/CWs)

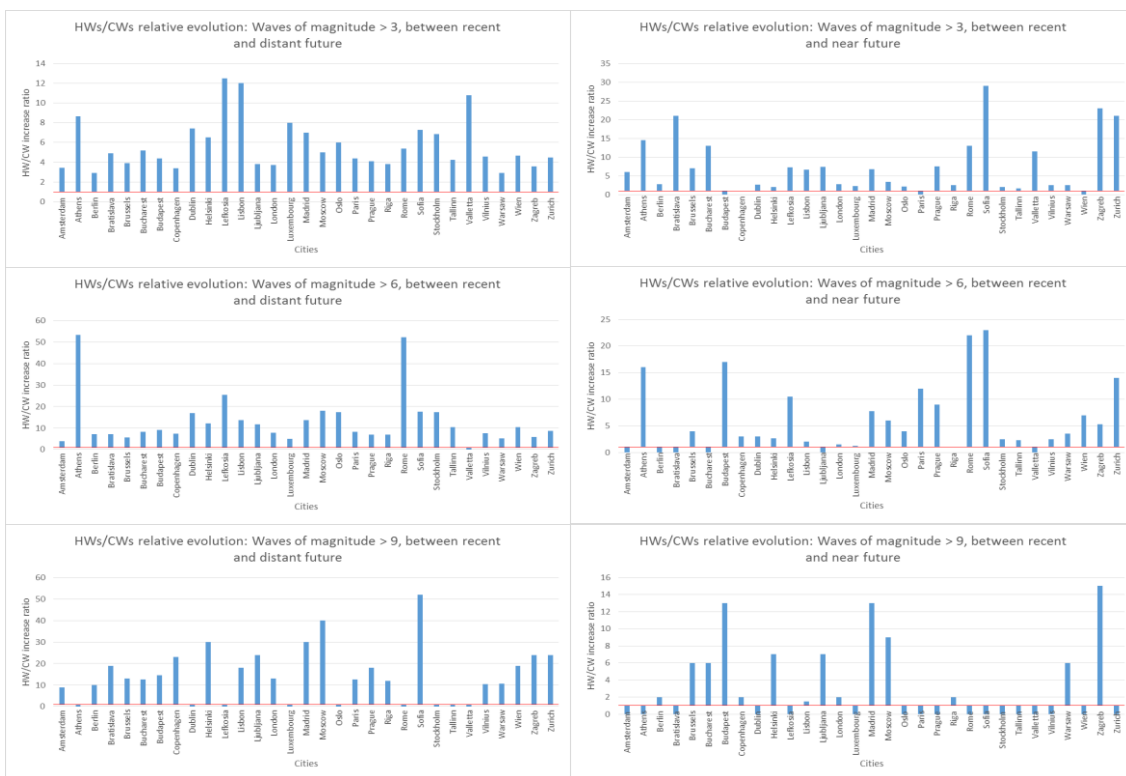


Figure 45 – Relative evolution of HWs and CWs.

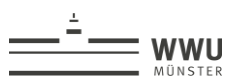
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